



RESEARCH ARTICLE

# Comparative evaluation of economic returns and water-saving efficiency of IoT-based smart drip irrigation and conventional irrigation methods in maize (*Zea mays* L.)

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## Abstract

Precision irrigation is critical for improving water productivity in maize under conditions of increasing water scarcity and climate variability. This study evaluated the impact of internet of things (IoT)-based smart drip irrigation and irrigation scheduling strategies on yield, water-use efficiency and economic returns of hybrid maize. Eight irrigation treatments, including IoT-based sensor-controlled drip irrigation, pan evaporation (PE)-based scheduling, irrigation water/cumulative pan evaporation ratio (IW/CPE) methods, conventional drip irrigation, surface irrigation and flood irrigation, were evaluated under field conditions. In the IoT-based treatments, soil moisture sensors continuously monitored root-zone moisture and automatically initiated irrigation when soil water depletion reached either 60 % or 80 % of the available soil water (ASW), representing moderate and high allowable depletion levels respectively. In contrast, conventional drip irrigation was operated using fixed irrigation schedules without real-time soil moisture sensing or automated feedback control. Results indicated significant differences ( $p \leq 0.05$ ) among treatments. The IoT-based drip irrigation at 60 % ASW depletion recorded the highest grain and straw yields, with grain yield increasing by 39 % compared with flood irrigation. The same treatment achieved the highest water-use efficiency, producing 2.62 times more grain per unit of water applied and reducing irrigation water use by 47 %. Economic analysis showed that IoT-based irrigation generated the highest profitability, with net returns increasing by 88 % over flood irrigation. The results demonstrate that sensor-based automated drip irrigation scheduled at 60 % allowable soil water depletion is an efficient and economically viable strategy for improving maize productivity, water-use efficiency and water conservation under water-limited conditions.

**Keywords:** economic analysis; internet of things-based irrigation; irrigation scheduling; precision agriculture; water scarcity; water use efficiency

## Introduction

Water is one of the most critical natural resources for agricultural production and global food security. Agriculture accounts for nearly 70 % of global freshwater withdrawals and approximately 90 % of consumptive water use worldwide (1). Rapid population growth, urbanisation, climate change and increasing food demand have intensified pressure on available freshwater resources, making efficient water management a major challenge for sustainable agriculture (1, 2). According to the United Nations, the global population is projected to exceed 9.7 billion by 2050, necessitating substantial increases in agricultural productivity while simultaneously reducing pressure on natural resources (3). Consequently, improving irrigation efficiency has become a critical priority for ensuring food security and sustainable agricultural development.

Irrigation plays a vital role in agricultural production, particularly in arid and semi-arid regions where rainfall is insufficient to meet crop water requirements. However, conventional irrigation methods such as flood and surface irrigation continue to dominate agricultural practices in many developing countries, including India. These methods are characterised by low application efficiency and substantial water losses through evaporation, runoff and deep percolation (4). Irrigation efficiencies below 50 % have frequently been reported, resulting in considerable wastage of water resources and reduced crop productivity (5). Furthermore, excessive irrigation can contribute to nutrient leaching, waterlogging, soil degradation and salinity development, thereby threatening long-term agricultural sustainability (6).

To overcome these limitations, drip irrigation has emerged as one of the most efficient irrigation methods available. By delivering water directly to the crop root zone, drip irrigation minimises evaporative and runoff losses while maintaining favourable soil moisture conditions (7). Previous studies have reported significant improvements in water-use efficiency and crop productivity under drip irrigation compared with conventional irrigation systems (5, 8, 9). Nevertheless, conventional drip irrigation systems are generally operated manually or according to fixed irrigation schedules and therefore cannot adequately respond to temporal variations in soil moisture, weather conditions and crop water requirements. Consequently, periods of over-irrigation and under-irrigation may still occur, limiting irrigation efficiency and crop performance (6, 10). Furthermore, manual irrigation management increases labour requirements and often limits the effectiveness of irrigation scheduling, particularly in large-scale farming systems (11).

Recent advances in information and communication technologies (ICT), wireless sensor networks and the internet of things (IoT) have facilitated the development of smart irrigation systems capable of real-time monitoring and automated irrigation management. The IoT refers to interconnected devices that collect, transmit and process data through internet-based communication networks (12). These capabilities have enabled the development of sensor-based irrigation systems that dynamically adjust water application according to crop water demand.

Unlike conventional drip irrigation systems, which are generally operated manually or according to fixed time-based schedules, IoT-enabled drip irrigation integrates soil moisture sensors, wireless communication modules, microcontrollers and automated control units. The system continuously monitors root-zone soil moisture and automatically initiates irrigation when predefined soil moisture thresholds are reached, thereby matching irrigation application with actual crop water requirements in real-time.

Soil moisture sensors continuously monitor root-zone water availability and transmit the information to a microcontroller or cloud platform. Irrigation is automatically initiated when soil moisture falls below a predefined threshold corresponding to the allowable soil water depletion level and is terminated once the desired moisture level is restored (11, 13). Irrigation scheduling was based on allowable depletion of 60 % and 80 % of the available soil water (ASW) in the crop root zone. Irrigation was automatically initiated when the respective depletion threshold was reached, corresponding to moderate (60 % ASW depletion) and relatively high (80 % ASW depletion) levels of allowable soil water depletion. This real-time feedback mechanism allows irrigation scheduling according to actual crop water requirements, thereby reducing water wastage, minimising moisture-related crop stress and improving irrigation efficiency. In addition, wireless communication technologies enable remote monitoring and control, providing farmers with enhanced operational flexibility and decision-making capability (12, 14).

The effectiveness of irrigation management is closely linked to soil-plant-water relationships and the soil-plant-atmosphere continuum (SPAC), which describes the continuous movement of water from the soil through plant roots and tissues to the atmosphere via transpiration. Soil moisture availability within the root zone directly influences plant water uptake, nutrient transport, photosynthesis, biomass accumulation and ultimately crop

productivity. When soil moisture declines below critical levels, plant water uptake is restricted, resulting in stomatal closure, reduced photosynthetic activity, impaired nutrient transport and decreased crop growth. Conversely, excessive irrigation may reduce soil aeration, promote nutrient leaching and increase water losses through deep percolation and evaporation (6, 10). Therefore, maintaining optimum root-zone soil moisture is essential for sustaining efficient water movement through the SPAC and maximising crop productivity while conserving water resources. In this context, continuous soil moisture monitoring provides a scientific basis for precision irrigation scheduling and sensor-based irrigation systems help avoid both over-irrigation and under-irrigation by enabling timely irrigation decisions based on actual root-zone moisture conditions.

Previous studies have demonstrated that advanced irrigation technologies can substantially improve agricultural water management; however, their objectives, methodologies and reported outcomes vary considerably. Conventional irrigation methods are generally associated with low water-use efficiency, whereas drip irrigation systems improve irrigation performance through precise water delivery to the root zone (8, 9). More recently, IoT-based irrigation systems have extended these benefits by incorporating real-time sensing, automated control and data-driven irrigation scheduling (11, 12). Previous studies reported substantial improvements in irrigation scheduling and water-use efficiency through sensor-guided irrigation management (11, 13), whereas other researchers emphasised the broader role of IoT technologies in precision agriculture and resource optimisation (12, 15). Nevertheless, many studies have primarily focused on sensor development, communication architecture, automation strategies or system performance rather than comprehensive evaluations of agronomic outcomes. Moreover, several investigations have been conducted under laboratory, greenhouse, or small-scale experimental conditions, limiting the applicability of their findings to practical field environments (12, 16).

Maize (*Zea mays* L.) is one of the most important cereal crops worldwide and contributes substantially to food security, livestock feed production and industrial applications (17). The crop is highly sensitive to irrigation management, particularly during critical growth stages such as tasseling, silking and grain filling. Water stress during these stages can significantly reduce grain yield and quality (10, 18, 19). Therefore, precise irrigation scheduling is essential for maximising maize productivity while minimising water consumption.

Despite considerable progress in drip irrigation and IoT-enabled irrigation technologies, limited field-based studies have simultaneously evaluated crop productivity, water-use efficiency, water savings and economic performance under identical agronomic conditions, particularly in maize cultivated under tropical environments. Most studies have focused on individual aspects such as water savings, sensor performance, communication efficiency, or crop yield rather than providing integrated assessments of agronomic and economic performance within a single experimental framework (20–22).

Furthermore, direct field-based comparisons between IoT-enabled smart drip irrigation and conventional drip irrigation under identical agronomic conditions are limited (14, 22). Consequently, robust field-based evidence regarding the agronomic effectiveness, water-saving potential and economic viability of IoT-enabled smart

irrigation systems for maize production remains limited. Although previous studies have generally reported positive effects of drip and sensor-based irrigation on water conservation and crop productivity, the magnitude of these benefits varies considerably among studies. Some researchers have reported substantial reductions in irrigation water use and significant improvements in yield and water-use efficiency under sensor-guided irrigation systems (11, 13), whereas others observed only modest yield advantages despite considerable water savings (10, 20). Such variations may be attributed to differences in climatic conditions, soil characteristics, crop type, irrigation thresholds, sensor accuracy and management practices. Furthermore, most studies have evaluated either engineering performance or agronomic responses separately, making it difficult to comprehensively assess the practical effectiveness of IoT-enabled irrigation systems under field conditions. Therefore, additional field-based investigations integrating water use, crop productivity and economic performance are required to establish the overall benefits of smart irrigation technologies.

Therefore, this study was undertaken to evaluate the effectiveness of an IoT-enabled smart drip irrigation system and compare its performance with conventional drip, surface and flood irrigation methods in hybrid maize under field conditions. The specific objectives were to assess the effects of different irrigation methods and soil moisture depletion levels on crop growth, yield attributes, grain yield, water-use efficiency, water savings and economic returns. The study hypothesised that sensor-based automated irrigation scheduling would maintain more favourable root-zone moisture conditions, thereby enhancing crop productivity, water-use efficiency and economic returns compared with conventional irrigation practices. The findings are expected to provide field-based scientific evidence on the agronomic, water-use and economic benefits of IoT-enabled irrigation systems and support the adoption of precision irrigation technologies for sustainable maize production under water-limited conditions.

## Materials and Methods

A field experiment was conducted during the summer season of 2023 at the Research Farm of the Agricultural College and Research Institute, Madurai, Tamil Nadu, India (9°58.22' N, 78°12.25' E; 147 m above mean sea level). The experimental site is situated in the Southern Agro-Climatic Zone of Tamil Nadu and is characterised by a semi-arid climate with moderate rainfall and temperatures favourable for maize cultivation. The soil of the experimental field was sandy clay loam in texture. Prior to the initiation of the experiment, soil samples were collected randomly from five locations within the field at a depth of 0–15 cm and composited for analysis. The initial physicochemical properties of the experimental soil, including pH, electrical conductivity (EC), organic carbon and available nitrogen (N), phosphorous (P) and potassium (K) contents, are presented in Table 1.

The field experiment was conducted during the summer season of 2023 on sandy clay loam soil to evaluate the performance of IoT-based drip irrigation, conventional drip irrigation and surface irrigation methods in maize. The experiment was laid out in a randomised block design (RBD) comprising 8 treatments and 3 replications. Maize hybrid COH(M) 8, a medium-duration hybrid, was used as the test crop. The crop was sown on 03 April 2023 and harvested on 21 July 2023, with a crop duration of 109 days. Sowing was carried out at a spacing of 60 × 25 cm using a seed rate of 20 kg ha<sup>-1</sup>. The total net cropped area of the experiment was approximately 200 m<sup>2</sup>. Each experimental plot measured 8.33 m<sup>2</sup> (3.0 × 2.78 m) and consisted of five rows of maize. Growth, yield and yield-attributing observations were recorded from the central rows of each plot, excluding border plants to minimise edge effects. The effective net sampling area was 5.0 m<sup>2</sup> per plot. To prevent lateral movement of water and avoid interference among irrigation treatments, a buffer zone of 0.5 m was maintained between adjacent plots and 1.0 m between replications. Peripheral bunds and drainage channels were provided around the experimental area to ensure proper drainage and prevent waterlogging.

The treatments comprised T<sub>1</sub>: IoT-based drip irrigation at 60 % depletion level; T<sub>2</sub>: IoT-based drip irrigation at 80 % depletion level; T<sub>3</sub>: drip irrigation at 60 % pan evaporation (PE); T<sub>4</sub>: drip irrigation at 80 % PE; T<sub>5</sub>: drip irrigation as normal practice; T<sub>6</sub>: surface irrigation at 0.6 irrigation water/cumulative pan evaporation ratio (IW/CPE) ratio; T<sub>7</sub>: surface irrigation at 0.8 IW/CPE ratio; and T<sub>8</sub>: flood irrigation as farmers' practice (conventional method). The land was prepared by 4–5 deep ploughings using a disc plough, cultivator and rotavator to obtain a fine tilth. Ridges and furrows were formed to facilitate sowing and efficient irrigation management. Prior to sowing, urea was applied based on soil test recommendations and incorporated into the soil. The recommended fertiliser dose of 135 : 62.5 : 50 kg N : P<sub>2</sub>O<sub>5</sub> : K<sub>2</sub>O ha<sup>-1</sup> was adopted for maize cultivation. Nitrogen was supplied through urea in three splits at sowing, knee-high and tasselling stages. The entire dose of P (P<sub>2</sub>O<sub>5</sub>) and K (K<sub>2</sub>O), along with 45 kg urea ha<sup>-1</sup>, was applied as a basal dose at sowing. Weed management was carried out through the application of Atrazine at 500 g ha<sup>-1</sup> as a pre-emergence herbicide at three days after sowing. Coragen insecticide was applied at 900 mL ha<sup>-1</sup> for effective management of insect pests. No major disease incidence was observed during the crop growth period. Necessary prophylactic plant protection measures were adopted uniformly across treatments. All agronomic practices, including nutrient management, weed control and plant protection measures, were carried out according to the recommendations of the Tamil Nadu Agricultural University Crop Production Guide (22).

Irrigation scheduling was carried out to ensure the timely application of water according to crop requirements, thereby improving water use efficiency (WUE) and crop productivity. Efficient irrigation scheduling was achieved by considering soil moisture status, atmospheric evaporative demand and irrigation water requirements

**Table 1.** Initial physical and chemical properties of the experimental soil

| Available nutrients | kg ha <sup>-1</sup> | Physical and chemical properties               | Value |
|---------------------|---------------------|------------------------------------------------|-------|
| 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 <sup>-3</sup> )             | 1.40  |
| Organic carbon (%)  | 0.61                | Electrical conductivity (dS m <sup>-1</sup> )  | 0.78  |
|                     |                     | Basic infiltration rate (mm hr <sup>-1</sup> ) | 6     |

Values represent the mean of three composite soil samples collected before sowing.

while avoiding moisture stress and waterlogging conditions (23, 24). The experiment evaluated four irrigation approaches: IoT-based drip irrigation, PE-based drip irrigation, surface irrigation based on the IW/CPE ratio and conventional flood irrigation. In the IoT-based drip irrigation treatments ( $T_1$  and  $T_2$ ), one Irrrometer 200SS Watermark soil moisture sensor was installed in each treatment plot at a depth of 30 cm below the soil surface within the active root zone of maize. The sensors were positioned within the wetted zone of the drip irrigation system and connected to the controller through a wired communication network for reliable transmission of soil moisture data. Soil moisture depletion from field capacity was continuously monitored and used for automated irrigation scheduling. The field capacity of the experimental soil was determined as 25.89% volumetric water content. Irrigation was automatically initiated when 60% and 80% of the ASW had been depleted from field capacity in  $T_1$  and  $T_2$  respectively, following standard soil-water relationship principles (23). The opening and closing of solenoid valves were automatically controlled through the IoT-enabled controller based on real-time sensor feedback, ensuring precise water application according to crop water requirements. Similar sensor-based automated irrigation approaches have been reported to improve irrigation efficiency and water management in agricultural systems (11, 25). In the PE-based drip irrigation treatments ( $T_3$  and  $T_4$ ), irrigation water was applied once every three days based on cumulative pan evaporation values recorded using a Class A open pan evaporimeter. The irrigation depth was calculated as 60% and 80% of cumulative pan evaporation for  $T_3$  and  $T_4$  respectively, following Food and Agriculture Organization (FAO) irrigation scheduling procedures (23). Treatment  $T_5$  received drip irrigation at three-day intervals according to the prevailing farmer practice. For the surface irrigation treatments, irrigation was scheduled using the IW/CPE approach with a fixed irrigation depth of 50 mm. In  $T_6$  (0.6 IW/CPE ratio), irrigation was applied when the cumulative pan evaporation reached 83.3 mm, whereas in  $T_7$  (0.8 IW/CPE ratio), irrigation was applied when the cumulative pan evaporation reached 62.5 mm. The IW/CPE scheduling approach was adopted following the methodology which relates irrigation timing to atmospheric evaporative demand (24, 26). Treatment  $T_8$  received conventional flood irrigation at three-day intervals according to the prevailing farmer practice.

Drip irrigation systems were used in treatments  $T_1$  to  $T_5$  to deliver water directly to the crop root zone with high application efficiency. Irrigation scheduling in  $T_1$  and  $T_2$  was based on real-time soil moisture monitoring through the IoT-enabled sensor network, whereas treatments  $T_3$  to  $T_7$  were irrigated according to PE and IW/CPE-based scheduling using the daily water balance method. Flood irrigation in  $T_8$  was applied following the conventional irrigation practice adopted by local farmers. All irrigation treatments were maintained throughout the crop growth period according to their respective treatmentschedules.

### Design and development of the internet of things (IoT)-based smart irrigation system

The IoT-based smart irrigation system was developed to automate irrigation scheduling using real-time soil moisture measurements and environmental parameters. The system architecture comprised a central control unit integrated with sensing, communication and irrigation control modules. The overall architecture of the IoT-based smart water management system is presented in Fig. 1.

The data acquisition system consisted of an Irrrometer 200SS Watermark soil moisture sensor, ESP32 microcontroller, ESP8266 Wi-Fi communication module, Arduino Nano controller,

solenoid valves, motor driver module, water flow sensor, power supply unit, display module and global system for mobile (GSM) communication module. The soil moisture sensor continuously monitored moisture conditions within the crop root zone, while the ESP32 microcontroller processed sensor inputs and executed irrigation control functions. Sensor data were transmitted to the cloud platform through the ESP8266 Wi-Fi module for real-time monitoring and storage. The Arduino Nano controlled the operation of solenoid valves based on predefined irrigation thresholds and the motor driver module regulated pump operation. Water application was quantified using a water flow sensor, whereas the display module enabled on-site monitoring of system status and irrigation parameters. The entire system was powered through a 230 V three-phase electrical supply and housed within a weatherproof metallic enclosure to ensure reliable field operation. The assembled IoT-based smart irrigation unit is shown in Fig. 2.

The control unit supported manual, automatic and reset operating modes and was programmed to schedule irrigation according to soil moisture depletion levels, cumulative pan evaporation and IW/CPE-based irrigation criteria. The software platform was customised for the study and incorporated both web-based and mobile-based interfaces to facilitate remote monitoring and control. The software architecture and data flow process are illustrated in Fig. 3. Integration with a cloud-based analytics platform enabled real-time data acquisition, storage, visualisation and automated irrigation management.

For soil moisture monitoring, one Irrrometer sensor was installed in each IoT-based treatment plot at a depth of 30 cm below the soil surface within the active root zone of maize. The sensors were positioned within the wetted zone of the drip irrigation system to accurately capture soil moisture dynamics. Sensor readings were continuously transmitted to the controller and cloud platform for irrigation decision-making. When soil moisture declined below the predefined threshold, the controller automatically activated the pump and opened the corresponding solenoid valve to initiate irrigation. Irrigation was terminated automatically once the soil moisture content reached the prescribed field capacity level. The volume of water applied during each irrigation event was measured using the water flow sensor and recorded on the cloud server. The installed data acquisition system and experimental field setup are presented in Fig. 4.

### Harvesting and threshing

The maize crop was harvested manually at physiological maturity when the husk leaves had turned brown and the cobs attained harvest maturity. Harvested cobs were sun-dried for 3–4 days to reduce grain moisture content and facilitate efficient shelling. The cobs from each net plot were harvested, threshed and cleaned separately for yield estimation.

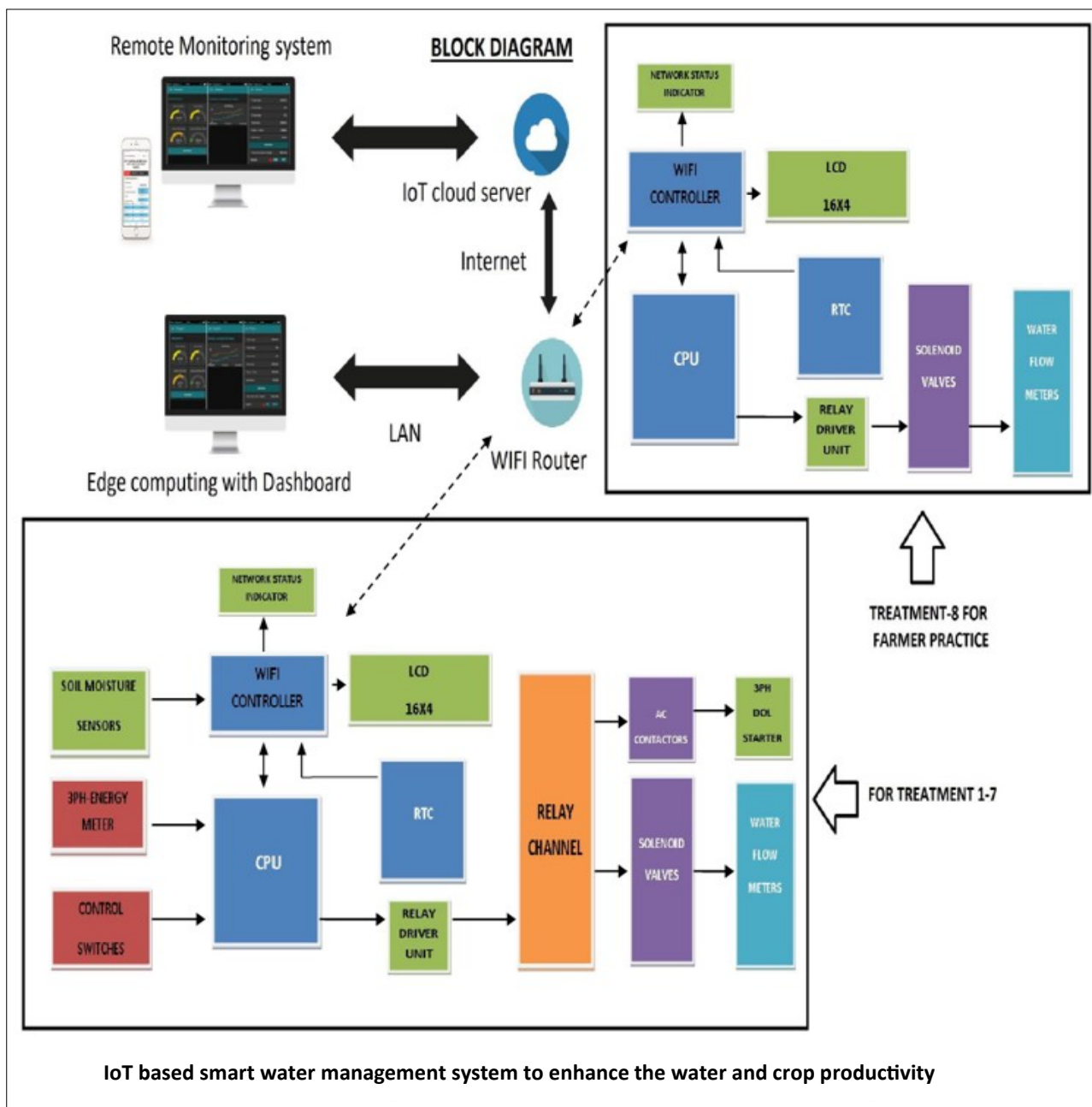
### Biometric observations

Five representative plants were randomly selected and tagged in each experimental plot for recording growth observations. Growth parameters were measured at 30 days after sowing (DAS), 60 DAS and harvest, whereas yield attributes, grain yield, straw yield, water use, WUE and economic parameters were recorded at harvest.

### Growth parameters

#### Plant height

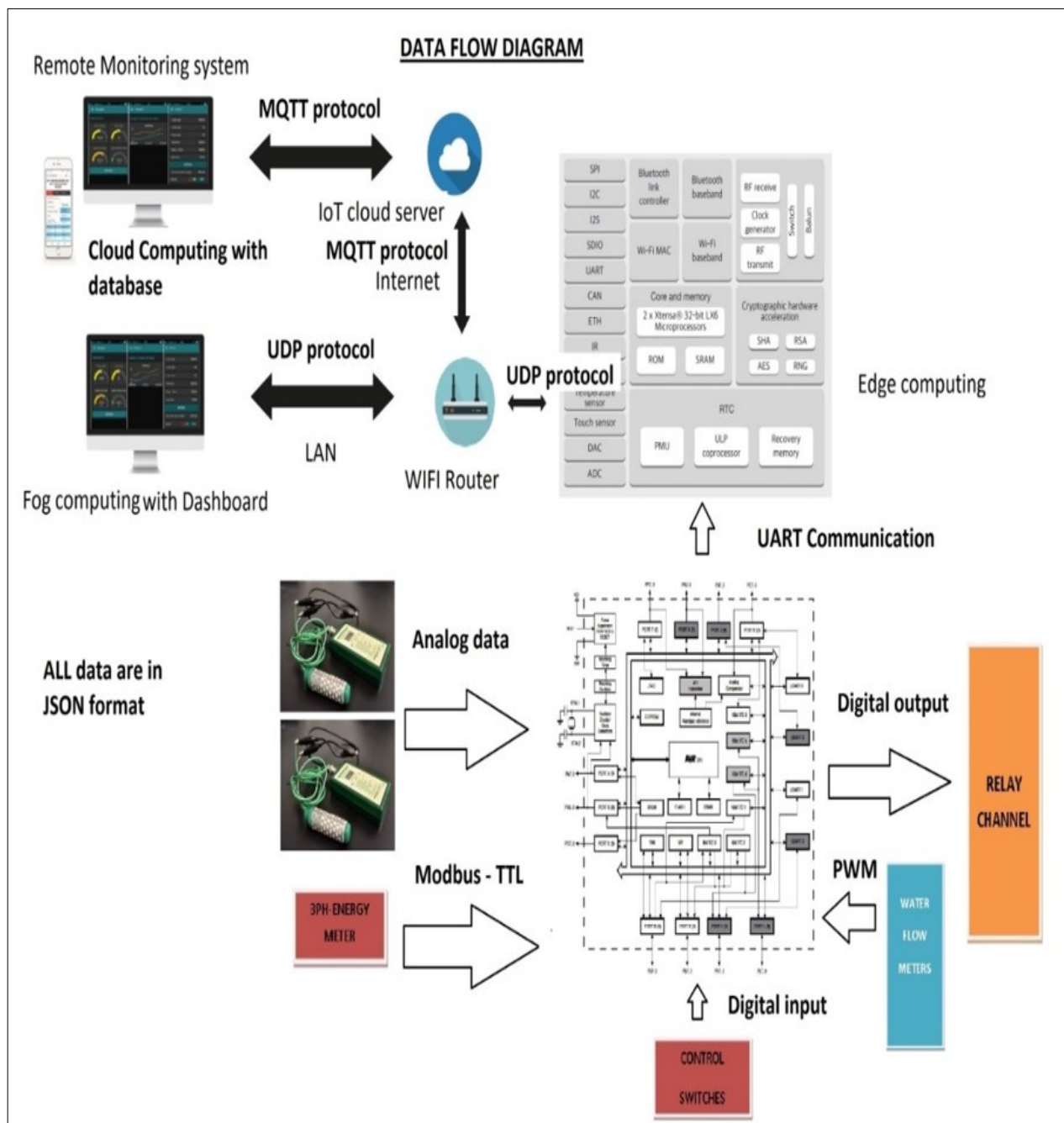
Plant height was measured from the ground level to the tip of the



**Fig. 1.** Internet of things (IoT) based smart water management system.



**Fig. 2.** Internet of things (IoT) based smart irrigation unit.



**Fig. 3.** Internet of things (IoT) based smart irrigation data flow diagram.



**Fig. 4.** Experiment field at Agricultural College and Research Institute (AC & RI), Madurai.

tallest leaf in each tagged plant at 30 DAS, 60 DAS and harvest. The mean plant height was expressed in centimetres (cm). Plant height is an important growth parameter reflecting crop response to soil moisture availability and irrigation management (27, 28). The mean plant height was computed using the following formula:

$$PH = \frac{\sum H_i}{n}$$

where,

PH = Mean plant height (cm)

$H_i$  = Height of the  $i^{\text{th}}$  sampled plant (cm)

$n$  = Number of plants observed (5)

#### Leaf area index

Leaf area index (LAI) was determined at 30 DAS, 60 DAS and at harvest following the standard method (29). The number of fully expanded green leaves per plant was recorded, along with the length and maximum width of the third fully expanded leaf from the top. The LAI was used as an indicator of canopy development, light interception and crop growth response to irrigation treatments.

LAI was calculated using the following formula:

$$LAI = \frac{(L \times B \times K \times N)}{A}$$

where:

L = leaf length (cm)

B = maximum leaf width (cm)

K = correction factor (0.75, dimensionless)

N = number of green leaves per plant (count)

A = ground area occupied per plant ( $\text{cm}^2$ )

#### Dry matter production

Plant samples were collected at 30 DAS, 60 DAS and at harvest from each treatment. The sampled plants were initially shade-dried and subsequently oven-dried at 60 °C until a constant weight was achieved. Dry weights of shoot and root components were recorded separately and summed to obtain total dry matter per plant. Dry matter production (DMP) was expressed on a hectare basis ( $\text{kg ha}^{-1}$ ) for statistical analysis following (27). This parameter represents the total biomass accumulation per unit area and is an important indicator of crop growth performance under different irrigation treatments.

Dry matter production was calculated using the following formula:

$\text{DMP (kg ha}^{-1}\text{)} = \text{Dry matter per plant (kg)} \times \text{Plant population per hectare}$

where:

Dry matter per plant = total oven-dry weight of shoot + root ( $\text{kg plant}^{-1}$ )

Plant population per hectare = number of plants in 1 hectare ( $\text{plants ha}^{-1}$ )

#### Yield attributes and yield

Yield attributes, namely cob length, number of kernels per cob and 100-kernel weight, were recorded at harvest from tagged plants in each experimental plot, as these parameters are key determinants of grain yield in maize. For each treatment, five representative cobs were randomly selected from the net plot and used for detailed observations. Similar approaches for evaluating maize yield components have been widely reported in agronomic studies (30, 31). Cob length was measured from the base to the tip of the cob using a graduated measuring scale and expressed in

centimetres (cm). The number of kernels per cob was determined by manual counting of all kernels from each selected cob and the mean value was expressed on a per cob basis (kernels per cob). For estimation of 100-kernel weight, grains were randomly selected from the bulk seed lot of each treatment; 100 kernels were counted and weighed using an electronic balance and the results were expressed in grams (g per 100 kernels). All yield attributes were averaged across sampled cobs and subjected to statistical analysis to evaluate treatment effects. These parameters were used as key yield components for assessing crop performance under different irrigation regimes.

#### Grain and straw yield ( $\text{kg ha}^{-1}$ )

The maize cobs harvested from each net plot were sun-dried for 3–4 days to reduce moisture content and facilitate efficient shelling. The dried cobs were then manually threshed and the grains were cleaned and weighed separately for each treatment. The grain yield obtained from each net plot was recorded and subsequently converted to a hectare basis using standard agronomic procedures and expressed in kilogram per hectare for statistical analysis. After cob removal, the remaining plant biomass (stover) from each plot was collected, sun-dried for two consecutive days and weighed separately. Straw yield was estimated from the net plot biomass, converted to a hectare basis and expressed in kilogram per hectare.

The conversion of net plot yield to hectare basis was carried out using standard agronomic methods commonly followed in maize yield studies (28).

where:

$$\text{Grain yield (kg ha}^{-1}\text{)} = \frac{\text{Grain yield from net plot (kg)} \times 10000}{\text{Net plot area (m}^2\text{)}}$$

$$\text{Straw yield (kg ha}^{-1}\text{)} = \frac{\text{Straw yield from net plot (kg)} \times 10000}{\text{Net plot area (m}^2\text{)}}$$

Grain yield from net plot = Grain weight harvested from the net plot (kg)

Straw yield from net plot = Weight of dried stover obtained from the net plot (kg)

Net plot area = Effective harvest area used for yield estimation ( $\text{m}^2$ )

10000 = Area equivalent to one hectare ( $\text{m}^2$ )

#### Water use and water use efficiency

Total water use (TWU) for each treatment was calculated as the sum of irrigation water applied and effective rainfall received during the crop growth period.

$$TWU = IW + ER$$

where, TWU = total water use (mm), IW = irrigation water applied (mm), ER = effective rainfall (mm).

Irrigation water applied under all treatments was measured using a flow sensor installed in the irrigation system. The volume of water delivered during each irrigation event was automatically recorded and summed to obtain the seasonal irrigation water applied.

The recorded water volume (L) was converted into irrigation depth (mm) using the relationship:

$$1 \text{ L m}^{-2} = 1 \text{ mm water depth}$$

Thus, irrigation water depth was obtained by dividing the total volume of water applied (L) by the plot area (m<sup>2</sup>). Effective rainfall was estimated using the water balance approach based on rainfall, PE, crop coefficient (K<sub>c</sub>) and soil water-holding capacity following the standard procedure (32).

#### **Irrigation scheduling**

The automated irrigation system comprised watermark soil moisture sensors, a microcontroller-based irrigation controller, solenoid valves and a flow sensor for measuring irrigation water applied. Irrigation events and water application data were automatically recorded and stored for subsequent analysis.

T<sub>1</sub>: Irrigation was initiated when 60 % of the ASW was depleted from field capacity and continued until field capacity was restored.

T<sub>2</sub>: Irrigation was initiated when 80 % of the ASW was depleted from field capacity and continued until field capacity was restored.

$$ASW = FC - PWP$$

Where

FC = Field capacity (%)

PWP = Permanent wilting point (%)

Available soil water was calculated following standard soil-water relationship procedures (23).

#### **Pan evaporation (PE)-based drip irrigation**

Daily PE data were recorded using a Class A open pan evaporimeter. The cumulative pan evaporation (CPE) over a three-day interval following the principles (23). The CPE was calculated as:

$$CPE = PE_1 + PE_2 + PE_3$$

where, CPE (mm) over three days and PE<sub>1</sub>, PE<sub>2</sub> and PE<sub>3</sub> are the daily PE values (mm). Irrigation was applied when the predetermined CPE level was attained.

The depth of IW was computed based on CPE as:

$$IW = CPE \times F$$

where F is the PE factor (0.60 or 0.80 depending on the treatment).

Treatment-specific irrigation scheduling formulas

$$IW_{60} = CPE \times 0.60$$

$$IW_{80} = CPE \times 0.80$$

Irrigation was applied at three-day intervals based on the calculated irrigation depth.

#### **Surface irrigation based on irrigation water/cumulative pan evaporation ratio**

Surface irrigation treatments were scheduled using the IW/CPE ratio approach (24, 26). The CPE was calculated as:

Cumulative pan evaporation (CPE)

$$CPE = \sum_{i=1}^n P E_i$$

where,

CPE = cumulative pan evaporation (mm)

PE<sub>i</sub> = daily pan evaporation on the *i*<sup>th</sup> day (mm)

n = number of days between two successive irrigations

#### **Irrigation water depth (IW)**

In the surface irrigation treatments (T<sub>6</sub> and T<sub>7</sub>), a fixed irrigation

water depth of 50 mm was applied at each irrigation event. Irrigation water depth refers to the depth of water applied uniformly over the soil surface to replenish the moisture depleted from the root zone. The selected irrigation depth should be sufficient to restore soil moisture within the effective root zone without causing excessive deep percolation losses or waterlogging conditions (24, 26).

The irrigation water depth applied at each irrigation event was expressed as:

$$IW = d$$

where:

IW = depth of irrigation water applied (mm)

d = predetermined irrigation depth (mm)

In the present study, the value of d was fixed at 50 mm for all surface irrigation treatments. The irrigation depth was selected based on the soil water-holding capacity of the experimental field, effective rooting depth of maize and the recommendations commonly adopted for IW/CPE-based irrigation scheduling in field crops (24, 33).

The volume of water required per plot was calculated using the relationship:

$$V = A \times IW$$

Where,

V = volume of irrigation water (L)

A = plot area (m<sup>2</sup>)

IW = irrigation depth (mm)

Since 1 mm of water applied over 1 m<sup>2</sup> area is equivalent to 1 L of water, the volume of water required for each irrigation event was determined accordingly. The irrigation water applied was measured using a calibrated water flow sensor installed in the irrigation system to ensure accurate water application and recording.

The fixed irrigation depth was subsequently combined with CPE values to determine irrigation timing under the IW/CPE scheduling approach. This method has been widely used for irrigation scheduling because it relates irrigation frequency to atmospheric evaporative demand and provides a reliable estimate of crop water requirements (24, 26).

#### **Irrigation water/cumulative pan evaporation ratio**

The irrigation scheduling criterion is expressed as:

$$IW/CPE = \frac{IW}{CPE}$$

where,

IW = depth of irrigation water applied at each irrigation event (mm)

CPE = cumulative pan evaporation between two successive irrigations (mm)

$$CPE = \frac{IW}{IW/CPE \text{ ratio}}$$

$$CPE = \frac{50}{0.6} = 83.3 \text{ mm}$$

For T<sub>6</sub> (0.6 IW/CPE ratio):

For  $T_7$  (0.8 IW/CPE ratio):

$$\text{CPE} = \frac{50}{0.8} = 62.5 \text{ mm}$$

Accordingly, irrigation was applied whenever the CPE reached 62.5 mm and a fixed depth of 50 mm irrigation water was applied. This approach schedules irrigation according to atmospheric evaporative demand and provides a reliable means of maintaining soil moisture at desired levels throughout the crop growth period (24, 26).

$T_8$ : Surface irrigation under farmer's practice

Irrigation was applied according to the conventional irrigation schedule followed by local farmers throughout the crop growth period.

### Irrigations

The number of irrigation events applied under each treatment was recorded throughout the crop growth period. An irrigation event was considered each time water was applied according to the respective treatment schedule. In the IoT-based treatments, irrigation frequency was determined automatically based on predefined soil moisture threshold levels, whereas in the PE-based and IW/CPE-based treatments, irrigation scheduling was followed according to CPE criteria. For conventional drip irrigation and farmer's practice treatments, irrigation was applied based on the recommended fixed irrigation schedule.

The total number of irrigations received by each treatment during the crop season was computed and used for comparative analysis of irrigation performance, irrigation frequency and overall WUE. The scheduling and interpretation of irrigation frequency followed standard irrigation management principles widely adopted in field crop studies (23, 26).

### Water use efficiency

Water use efficiency (WUE) was calculated to assess the efficiency of water utilisation for grain production. It was computed as the ratio of grain yield to the total water used during the crop growth period and expressed as kilograms per hectare per millimetre (34).

$$\text{WUE} = \frac{\text{Grain yield (kg ha}^{-1}\text{)}}{\text{Total water used (mm)}}$$

$$\text{WUE} = \text{Grain yield kg ha}^{-1} / \text{Total water use (mm)}$$

Total water use (TWU) was calculated as the sum of irrigation water applied and effective rainfall received during the crop growth period. Higher WUE values indicate greater efficiency of water use in converting available water into economic yield.

### Water saving

Water saving was estimated by comparing the TWU of each irrigation treatment with that of the farmer's practice treatment ( $T_8$ ). Water saving was computed following the approach (5). The percentage of water saving was calculated using the following equation:

$$\text{Water saving (\%)} = \frac{\text{TWU}_{\{T8\}} - \text{TWU}_{\{Ti\}}}{\text{TWU}_{\{T8\}}} \times 100$$

where,

$\text{TWU}_{T8}$  = total water use under the farmer's practice treatment (mm)

$\text{TWU}_{Ti}$  = total water use under the respective treatment ( $T_1$ – $T_7$ ) (mm)

Total water use (TWU) was calculated as the sum of irrigation water applied and effective rainfall received during the crop growth period. The water-saving percentage was computed separately for each treatment relative to the farmer's practice treatment. Higher values indicate greater water conservation compared with the conventional irrigation practice.

### Energy use efficiency (EUE)

Energy use efficiency (EUE) was calculated to assess the productivity of energy consumed under different irrigation treatments. It was expressed as grain yield produced per unit of electrical energy consumed during the crop growth period.

$$\text{EUE} = \frac{\text{GY}}{\text{EC}}$$

where:

EUE = energy use efficiency (kg kWh<sup>-1</sup>)

GY = grain yield (kg ha<sup>-1</sup>)

EC = total electrical energy consumption for irrigation (kWh ha<sup>-1</sup>)

The total electrical energy consumption was estimated based on the operating time of the irrigation pump and its rated power capacity. Energy use was computed for each irrigation event and summed over the entire crop season to obtain seasonal energy consumption. Higher EUE values indicate more efficient utilisation of electrical energy for crop production. The methodology for energy-based evaluation of irrigation systems followed standard agronomic energy auditing approaches (35, 36).

### System reliability and operational efficiency

System reliability and operational efficiency were evaluated based on the successful execution of scheduled irrigation events and the overall performance of the automated irrigation system under field conditions. These indicators were used to assess the effectiveness of sensor-based monitoring, communication, controller operation and irrigation execution in the IoT-enabled irrigation system, following methodologies commonly adopted in automated irrigation and smart water management studies (11, 25).

$$\text{SR (\%)} = \frac{N_s}{N_t} \times 100$$

$$\text{OE (\%)} = \frac{I_a}{I_s} \times 100$$

where:

SR = System reliability (%)

OE = Operational efficiency (%)

$N_s$  = Number of successful irrigation operations

$N_t$  = Total number of scheduled irrigation operations

$I_a$  = Number of irrigation events successfully executed

$I_s$  = Number of irrigation events scheduled

Higher values indicate stable system performance and effective synchronisation between sensing, control, communication and irrigation application components. Since all scheduled irrigation events were successfully executed, both parameters attained 100 % under the IoT-based treatments.

## Economic data collection

Economic analysis was carried out to evaluate the profitability and economic feasibility of different irrigation treatments in maize cultivation. Data on the cost of cultivation were collected throughout the crop growth period and included expenses incurred on land preparation, seed, fertilisers, plant protection chemicals, irrigation, labour, machinery operations and other agronomic inputs. In the case of IoT-based irrigation treatments, additional costs associated with the installation of soil moisture sensors, microcontroller units, solenoid valves, communication modules and other automation components were also included. The economic indicators considered in the study were cost of cultivation, gross return, net return and benefit-cost (B : C) ratio, following standard agricultural economic procedures (28, 37).

The cost of cultivation was calculated as the sum of fixed and variable costs incurred during crop production.

$$\text{Cost of cultivation} = \text{Fixed cost} + \text{Variable cost}$$

The gross return was calculated by multiplying the grain yield obtained from each treatment by the prevailing market price of maize grain.

$$\text{Gross return} = \text{Grain yield} \times \text{Market price}$$

The net return was computed by subtracting the cost of cultivation from the gross return.

$$\text{Net return} = \text{Gross return} - \text{Cost of cultivation}$$

The B : C ratio was calculated as:

$$\text{B : C ratio} = \frac{\text{Gross return}}{\text{Cost of cultivation}}$$

A higher net return and B : C ratio indicate better economic performance and greater profitability of the irrigation system. The economic analysis was used to compare the financial viability of IoT-based smart irrigation, conventional drip irrigation and surface irrigation methods.

## Statistical analysis

The data recorded on growth, yield attributes, yield, WUE, water saving and economic parameters were subjected to analysis of variance (ANOVA) appropriate for a RBD following the standard procedure (28). The significance of treatment effects was tested at the 5 % probability level ( $p \leq 0.05$ ). Whenever significant differences among treatments were observed, treatment means were compared using the least significant difference (LSD) test at the 5 % level of significance. Standard error of difference (SEd) and critical difference (CD) values were calculated for mean separation.

## Result

The results of the present investigation on the influence of different irrigation methods and irrigation scheduling approaches on hybrid maize are presented in Tables 2–7. The study evaluated the performance of IoT-based soil moisture sensor-guided drip irrigation, PE-based drip irrigation, conventional drip irrigation, surface irrigation based on the IW/CPE ratio and farmer's practice irrigation with respect to growth attributes, yield attributes, grain yield, straw yield, water use, WUE, water saving and economic returns.

Significant variations were observed among irrigation treatments for most of the parameters studied. The response of hybrid maize to different irrigation methods and scheduling levels was reflected in plant growth, biomass accumulation, yield formation, water productivity and economic performance. The results of individual parameters are presented in the following sections.

The growth parameters of hybrid maize, namely plant height, LAI and DMP, were significantly influenced by irrigation methods and irrigation scheduling levels throughout the crop growth period (Table 2). Plant height increased progressively from 30 DAS to harvest under all treatments. At harvest, the highest plant height was recorded under  $T_1$  (217.33 cm), which was 26.4 % higher than that of the farmer's practice treatment,  $T_8$  (172.00 cm).

**Table 2.** Influence of irrigation methods and level on plant height (cm), leaf area index ( $\text{m}^2$ ) and dry matter production (Kg/ha) of hybrid maize

| Treatment                                                 | Plant height |        |            | Leaf area index |        |            | Dry matter production |        |            |
|-----------------------------------------------------------|--------------|--------|------------|-----------------|--------|------------|-----------------------|--------|------------|
|                                                           | 30 DAS       | 60 DAS | At harvest | 30 DAS          | 60 DAS | At harvest | 30 DAS                | 60 DAS | At harvest |
| $T_1$ : IoT-based drip irrigation at 60 % depletion level | 83.40        | 204.00 | 217.33     | 1.87            | 3.22   | 5.20       | 3305                  | 12297  | 18344      |
| $T_2$ : IoT based drip irrigation at 80 % depletion level | 82.03        | 185.10 | 200.33     | 1.85            | 2.77   | 4.62       | 3294                  | 12208  | 18123      |
| $T_3$ : Drip irrigation at 60 % PE                        | 81.70        | 179.40 | 190.68     | 1.31            | 2.04   | 3.99       | 3232                  | 11603  | 16344      |
| $T_4$ : Drip irrigation at 80 % PE                        | 81.97        | 179.93 | 191.93     | 1.53            | 2.09   | 4.46       | 3256                  | 11865  | 16718      |
| $T_5$ : Drip irrigation as normal practice                | 81.13        | 179.03 | 189.23     | 1.43            | 2.26   | 3.64       | 3201                  | 11188  | 15437      |
| $T_6$ : Surface irrigation at 0.6 IW/CPE ratio            | 77.37        | 163.43 | 173.83     | 1.16            | 2.06   | 3.54       | 3133                  | 10884  | 13455      |
| $T_7$ : Surface irrigation at 0.8 IW/CPE ratio            | 78.13        | 170.93 | 181.37     | 1.27            | 2.23   | 3.59       | 3107                  | 10003  | 12659      |
| $T_8$ : Flood irrigation as farmer's practice             | 67.53        | 160.73 | 172.00     | 1.14            | 2.03   | 3.30       | 3155                  | 9345   | 11765      |
| SEd ( $\pm$ )                                             | 1.84         | 6.07   | 6.58       | 0.116           | 0.193  | 0.252      | 28.58                 | 122.47 | 163.30     |
| LSD ( $p = 0.05$ )                                        | 3.91         | 12.87  | 13.95      | 0.246           | 0.409  | 0.535      | 60.58                 | 259.63 | 346.18     |
| CV (%)                                                    | 2.83         | 4.19   | 4.20       | 9.84            | 10.11  | 7.64       | 1.09                  | 1.34   | 1.30       |

DAS: days after sowing; IoT: Internet of things; PE: pan evaporation; IW/CPE: irrigation water/cumulative pan evaporation ratio.

Treatment T<sub>2</sub> recorded a plant height of 200.33 cm, representing a 16.5 % increase over T<sub>8</sub>. Among the PE-based irrigation treatments, T<sub>4</sub> and T<sub>3</sub> recorded plant heights of 191.93 and 190.68 cm, corresponding to increases of 11.6 % and 10.9 % respectively, over T<sub>8</sub>. The lowest plant height was observed under the farmer's practice treatment. Leaf area index increased steadily from 30 DAS to harvest across all irrigation treatments. At harvest, the highest LAI was recorded under T<sub>1</sub> (5.20), followed by T<sub>2</sub> (4.62). Compared with T<sub>8</sub> (3.30), T<sub>1</sub> and T<sub>2</sub> increased LAI by 57.6 % and 40.0 %, respectively. Treatments T<sub>4</sub> and T<sub>3</sub> recorded LAI values of 4.46 and 3.99, representing increases of 35.2 % and 20.9 %, respectively, over the farmer's practice treatment. Dry matter production increased significantly with crop growth under all irrigation treatments. At harvest, T<sub>1</sub> recorded the highest DMP (18344 kg ha<sup>-1</sup>), followed by T<sub>2</sub> (18123 kg ha<sup>-1</sup>). Compared with T<sub>8</sub> (11765 kg ha<sup>-1</sup>), T<sub>1</sub> and T<sub>2</sub> increased DMP by 55.9 % and 54.0 % respectively. Treatments T<sub>4</sub> and T<sub>3</sub> also recorded higher DMP, with increases of 42.1 % and 38.9 % respectively, over the farmer's practice treatment.

### Yield attributes

The yield attributes of hybrid maize, namely cob length, cob girth and test weight, were significantly influenced by irrigation methods and irrigation scheduling approaches (Table 3).

Among the treatments, T<sub>1</sub> (IoT-based drip irrigation at 60 % depletion level) recorded the highest cob length (22.67 cm), followed by T<sub>2</sub> (20.30 cm). Compared with the farmer's practice treatment, T<sub>8</sub> (17.03 cm), T<sub>1</sub> and T<sub>2</sub> increased cob length by 33.1 % and 19.2 % respectively. Treatments T<sub>4</sub>, T<sub>3</sub>, T<sub>5</sub>, T<sub>7</sub> and T<sub>6</sub> recorded increases of 12.6 %, 9.8 %, 8.5 %, 2.3 % and 1.0 % respectively, over T<sub>8</sub>. Cob girth was also significantly affected by irrigation treatments. The maximum cob girth was recorded under T<sub>1</sub> (16.37 cm), followed by T<sub>2</sub> (15.20 cm). Compared with T<sub>8</sub> (13.37 cm), T<sub>1</sub> and T<sub>2</sub> increased cob girth by 22.4 % and 13.7 % respectively. Treatments T<sub>4</sub>, T<sub>3</sub>, T<sub>5</sub>, T<sub>7</sub> and T<sub>6</sub> recorded increases of 11.7 %, 6.4 %, 5.5 %, 4.9 % and 3.0 %

respectively, over the farmer's practice treatment. Test weight differed significantly among irrigation treatments. The highest test weight was recorded under T<sub>1</sub> (27.82 g), followed by T<sub>2</sub> (27.40 g). Compared with T<sub>8</sub> (23.80 g), T<sub>1</sub> and T<sub>2</sub> increased test weight by 16.9 % and 15.1 % respectively. Treatments T<sub>4</sub>, T<sub>3</sub>, T<sub>5</sub>, T<sub>7</sub> and T<sub>6</sub> recorded increases of 12.7 %, 12.6 %, 7.7 %, 3.9 % and 2.2 % respectively, over the farmer's practice treatment. Overall, higher values of cob length, cob girth and test weight were recorded under the IoT-based drip irrigation treatments (T<sub>1</sub> and T<sub>2</sub>) than under the conventional irrigation treatments.

### Irrigations

The number of irrigation events varied among irrigation methods and scheduling approaches (Table 4). The highest number of irrigations was recorded under T<sub>5</sub> (drip irrigation as normal practice), which received 24 irrigations during the crop growth period. Treatments T<sub>3</sub> (drip irrigation at 60 % PE) and T<sub>4</sub> (drip irrigation at 80 % PE) each received 21 irrigations representing a reduction of 12.5 % compared with T<sub>5</sub>. Among the IoT-based irrigation treatments, T<sub>1</sub> (IoT-based drip irrigation at 60 % depletion level) received 16 irrigations, whereas T<sub>2</sub> (IoT-based drip irrigation at 80 % depletion level) received 12 irrigations. Compared with T<sub>1</sub>, irrigation frequency was reduced by 25.0 % under T<sub>2</sub>. Relative to T<sub>5</sub>, the number of irrigations was reduced by 33.3 % and 50.0 % under T<sub>1</sub> and T<sub>2</sub> respectively. The lowest irrigation frequency was recorded under T<sub>6</sub> (surface irrigation at 0.6 IW/CPE ratio), which received six irrigations, followed by T<sub>7</sub> (surface irrigation at 0.8 IW/CPE ratio) with 8 irrigations. Compared with T<sub>5</sub>, irrigation frequency was reduced by 75.0 % and 66.7 % under T<sub>6</sub> and T<sub>7</sub> respectively. Treatment T<sub>8</sub> (flood irrigation as farmer's practice) received 12 irrigations, which was 50.0 % lower than T<sub>5</sub>. The IoT-based smart irrigation system performed efficiently and consistently throughout the crop growth period. All scheduled irrigation events were successfully executed in both IoT-based treatments without any interruption in sensor operation, controller performance, communication, or solenoid valve

**Table 3.** Influence of irrigation methods and yield attribute of hybrid maize

| Treatment                                              | Cob length (cm) | Cob girth (cm) | Test weight (g) |
|--------------------------------------------------------|-----------------|----------------|-----------------|
| T1 : IoT based drip irrigation at 60 % depletion level | 22.67           | 16.37          | 27.82           |
| T2 : IoT based drip irrigation at 80 % depletion level | 20.30           | 15.20          | 27.40           |
| T3 : Drip irrigation at 60 % PE                        | 18.70           | 14.23          | 26.80           |
| T4 : Drip irrigation at 80 % PE                        | 19.17           | 14.93          | 26.83           |
| T5 : Drip irrigation as normal Practice                | 18.47           | 14.10          | 25.63           |
| T6 : Surface irrigation at 0.6 IW/CPE ratio            | 17.20           | 13.77          | 24.33           |
| T7 : Surface irrigation at 0.8 IW/ CPE ratio           | 17.43           | 14.03          | 24.73           |
| T8 : Flood irrigation as Farmer's Practice             | 17.03           | 13.37          | 23.80           |
| SEd (±)                                                | 0.75            | 0.78           | 0.71            |
| LSD ( $p = 0.05$ )                                     | 1.58            | 1.65           | 1.50            |
| CV (%)                                                 | 4.85            | 6.56           | 3.34            |

IoT: Internet of things; PE: pan evaporation; IW/CPE: irrigation water/cumulative pan evaporation ratio.

**Table 4.** Influence of irrigation methods and scheduling approaches on number of irrigations in hybrid maize

| Treatment      | Irrigation method and scheduling approach         | Number of irrigations |
|----------------|---------------------------------------------------|-----------------------|
| T <sub>1</sub> | IoT-based drip irrigation at 60 % depletion level | 16                    |
| T <sub>2</sub> | IoT-based drip irrigation at 80 % depletion level | 12                    |
| T <sub>3</sub> | Drip irrigation at 60 % PE                        | 21                    |
| T <sub>4</sub> | Drip irrigation at 80 % PE                        | 21                    |
| T <sub>5</sub> | Drip irrigation as normal practice                | 24                    |
| T <sub>6</sub> | Surface irrigation at 0.6 IW/CPE ratio            | 6                     |
| T <sub>7</sub> | Surface irrigation at 0.8 IW/CPE ratio            | 8                     |
| T <sub>8</sub> | Flood irrigation as farmer's practice             | 12                    |

PE: pan evaporation; IW/CPE: irrigation water/cumulative pan evaporation ratio.

actuation. Treatment T<sub>1</sub> recorded 16 successful irrigation events out of 16 scheduled events, while treatment T<sub>2</sub> recorded 12 successful irrigation events out of 12 scheduled events. Consequently, both system reliability and operational efficiency were 100 % in T<sub>1</sub> and T<sub>2</sub>. These results indicate effective synchronisation among soil moisture sensing, data transmission, controller decision-making and automated water application, ensuring timely irrigation according to the prescribed soil moisture depletion thresholds.

#### Grain yield, straw yield, water use, water-use efficiency and water saving

Grain yield and straw yield were significantly influenced by irrigation methods and irrigation scheduling approaches (Table 5). Among the treatments, T<sub>1</sub> (IoT-based drip irrigation at 60 % depletion level) recorded the highest grain yield (7050 kg ha<sup>-1</sup>) and straw yield (11069 kg ha<sup>-1</sup>), followed by T<sub>2</sub> (6746 and 10557 kg ha<sup>-1</sup> respectively). In comparison with the farmer's practice treatment, T<sub>8</sub> (5069 and 7604 kg ha<sup>-1</sup>), T<sub>1</sub> increased grain yield and straw yield by 39.1 % and 45.6 % respectively, whereas T<sub>2</sub> increased grain yield and straw yield by 33.1 % and 38.8 % respectively. The lowest grain yield and straw yield were observed under T<sub>8</sub>. The error bars presented the standard error of the mean (SEm ± 64.64 kg ha<sup>-1</sup> for grain yield and SEm ± 85.38 kg ha<sup>-1</sup> for straw yield), indicating low variability among replications (Fig. 2). Furthermore, the observed differences among treatment means were greater than the corresponding LSD values (196.06 kg ha<sup>-1</sup> for grain yield and 259.01 kg ha<sup>-1</sup> for straw yield), confirming that the irrigation treatments exerted a significant effect on both grain and straw yield at the 5 % probability level. The relatively small error bars and low coefficient of variation values (1.86 % for grain yield and 1.56 % for straw yield) further indicate the reliability and precision of the experimental data. The error bars presented in Fig. 5 represent the standard error of the mean.

Total water use differed markedly among irrigation treatments. The highest total water use was recorded under T<sub>8</sub> (809.69 mm), whereas the lowest was observed under T<sub>1</sub> (430.10 mm). Despite receiving 46.88 % less total water than T<sub>8</sub>, treatment T<sub>1</sub> produced 39.1 % higher grain yield, demonstrating superior water productivity under sensor-guided irrigation. Relative to T<sub>8</sub>, total water use was reduced by 46.9 % in T<sub>1</sub>, followed by T<sub>2</sub> (40.6 %), T<sub>6</sub> (37.6 %), T<sub>3</sub> (35.4 %), T<sub>7</sub> (31.5 %), T<sub>4</sub> (30.4 %) and T<sub>5</sub> (23.5 %). Water-use efficiency exhibited an inverse trend to total water use. The highest WUE was recorded under T<sub>1</sub> (16.39 kg ha<sup>-1</sup> mm<sup>-1</sup>), followed by T<sub>2</sub> (14.03 kg ha<sup>-1</sup> mm<sup>-1</sup>). Compared with T<sub>8</sub> (6.26 kg ha<sup>-1</sup> mm<sup>-1</sup>), WUE increased by 161.8 % in T<sub>1</sub>, 124.1 % in T<sub>2</sub>, 86.9 % in T<sub>3</sub>, 82.7 % in T<sub>4</sub>, 70.9 % in T<sub>6</sub>, 61.2 % in T<sub>7</sub> and 50.2 % in T<sub>5</sub>. Water-saving percentage ranged from 23.54–46.88 % among the irrigation treatments. The highest water saving was recorded under T<sub>1</sub> (46.88 %), followed by T<sub>2</sub> (40.63 %) and T<sub>6</sub> (37.64 %). Treatments T<sub>3</sub>, T<sub>7</sub>, T<sub>4</sub> and T<sub>5</sub> recorded water savings of 35.40 %, 31.46 %, 30.44 % and 23.54 % respectively. As the reference treatment, T<sub>8</sub> recorded no water saving.

#### Treatment-wise expenditure incurred in hybrid maize cultivation

The expenditure incurred in hybrid maize cultivation varied among irrigation treatments owing to differences in irrigation infrastructure, sensor installation, irrigation operations and weed management costs (Table 6). The total cost of cultivation ranged from ₹54910 ha<sup>-1</sup> to ₹58589 ha<sup>-1</sup> across the treatments. Among the treatments, T<sub>2</sub> (IoT-based drip irrigation at 80 % depletion level) recorded the lowest cost of cultivation (₹54910 ha<sup>-1</sup>), followed by T<sub>1</sub> (₹55290 ha<sup>-1</sup>), T<sub>3</sub> and T<sub>4</sub> (₹55115 ha<sup>-1</sup> each) and T<sub>5</sub> (₹55875 ha<sup>-1</sup>). The highest cost of cultivation was recorded under T<sub>8</sub> (flood irrigation as farmer's practice) (₹58589 ha<sup>-1</sup>). Compared with T<sub>8</sub>, the cost of cultivation was reduced by 6.3 % in T<sub>2</sub>, 5.6 % in T<sub>1</sub>, 5.9 % in T<sub>3</sub> and T<sub>4</sub>, 4.6 % in T<sub>5</sub>, 2.3 % in T<sub>6</sub> and 1.3 % in T<sub>7</sub>. The expenditure on drip irrigation materials was ₹4186 ha<sup>-1</sup> in treatments T<sub>1</sub>–T<sub>5</sub>, whereas no

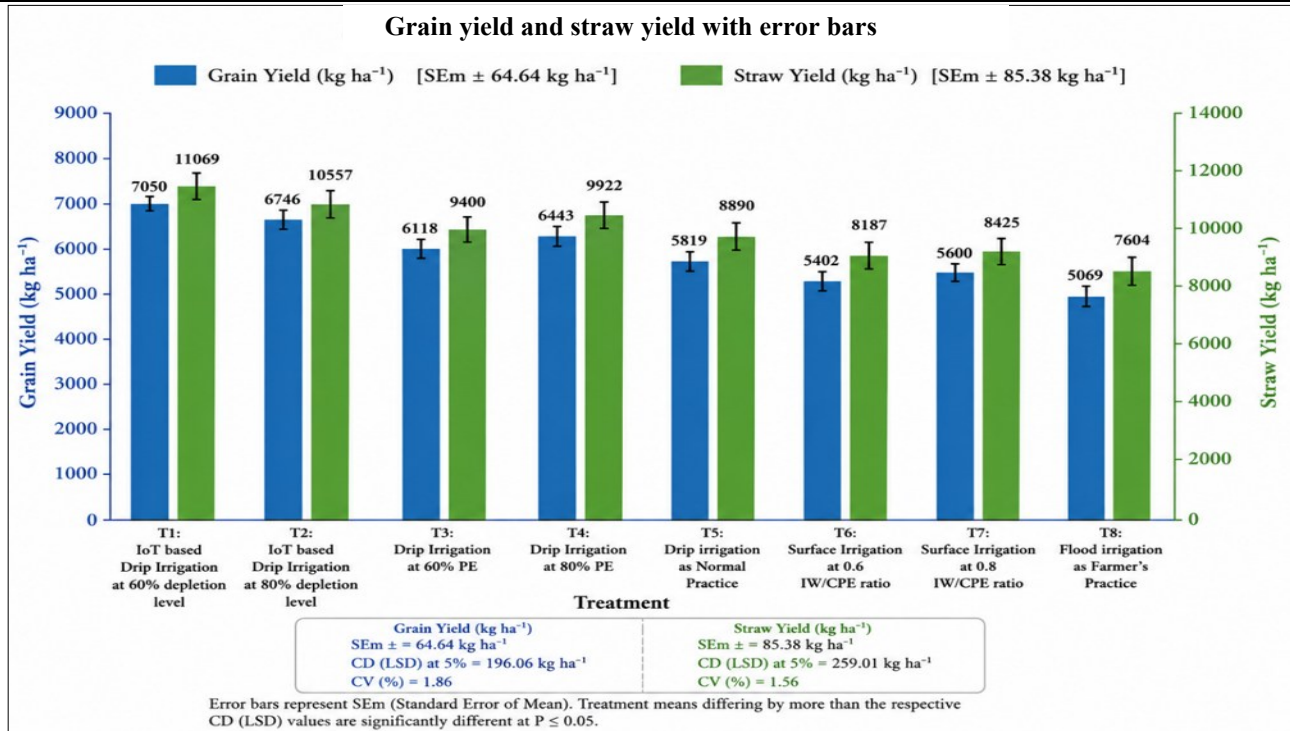
**Table 5.** Influence of irrigation methods and levels on yield, water use and water use efficiency of hybrid maize

| Treatment                                             | Grain yield<br>(kg ha <sup>-1</sup> ) | Straw yield<br>(kg ha <sup>-1</sup> ) | Effective<br>rainfall (mm) | Irrigation water<br>(mm) | Total water<br>used (mm) | WUE<br>(kg ha <sup>-1</sup> mm <sup>-1</sup> ) | Water saving<br>(%) |
|-------------------------------------------------------|---------------------------------------|---------------------------------------|----------------------------|--------------------------|--------------------------|------------------------------------------------|---------------------|
| T1: IoT based drip irrigation at 60 % depletion level | 7050                                  | 11069                                 | 209.69                     | 220.41                   | 430.10                   | 16.39                                          | 46.88               |
| T2: IoT based drip irrigation at 80 % depletion level | 6746                                  | 10557                                 | 209.69                     | 271.01                   | 480.70                   | 14.03                                          | 40.63               |
| T3: Drip irrigation at 60 % PE                        | 6118                                  | 9400                                  | 312.13                     | 210.96                   | 523.09                   | 11.70                                          | 35.40               |
| T4: Drip irrigation at 80 % PE                        | 6443                                  | 9922                                  | 284.65                     | 278.60                   | 563.25                   | 11.44                                          | 30.44               |
| T5: Drip irrigation as normal practice                | 5819                                  | 8890                                  | 225.70                     | 393.35                   | 619.05                   | 9.40                                           | 23.54               |
| T6: Surface irrigation at 0.6 IW/CPE ratio            | 5402                                  | 8187                                  | 204.95                     | 300.00                   | 504.95                   | 10.70                                          | 37.64               |
| T7: Surface irrigation at 0.8 IW/CPE ratio            | 5600                                  | 8425                                  | 154.95                     | 400.00                   | 554.95                   | 10.09                                          | 31.46               |
| T8: Flood irrigation as farmer's practice             | 5069                                  | 7604                                  | 209.69                     | 600.00                   | 809.69                   | 6.26                                           | 0                   |
| SEm ±                                                 | 64.64 kg ha <sup>-1</sup>             | 85.38 kg ha <sup>-1</sup>             |                            |                          |                          |                                                |                     |
| CD (LSD) at 5 %                                       | 196.06 kg ha <sup>-1</sup>            | 259.01 kg ha <sup>-1</sup>            |                            |                          |                          |                                                |                     |
| CV (%)                                                | 1.86                                  | 1.56                                  |                            |                          |                          |                                                |                     |

IoT: Internet of things; PE: pan evaporation; IW/CPE: irrigation water/cumulative pan evaporation ratio; WUE: water use efficiency.

**Table 6.** Treatment-wise expenditure incurred in hybrid maize cultivation (₹ ha<sup>-1</sup>)

| Particulars/Treatment                                            | T1    | T2    | T3    | T4    | T5    | T6    | T7    | T8    |
|------------------------------------------------------------------|-------|-------|-------|-------|-------|-------|-------|-------|
| Drip irrigation materials                                        | 4186  | 4186  | 4186  | 4186  | 4186  | 0     | 0     | 0     |
| Sensor, flow meter, water flow sensor and Installation materials | 2739  | 2739  | 284   | 284   | 284   | 284   | 284   | 284   |
| Preparatory cultivation                                          | 13850 | 13850 | 13850 | 13850 | 13850 | 13850 | 13850 | 13850 |
| Sowing                                                           | 9300  | 9300  | 9300  | 9300  | 9300  | 9300  | 9300  | 9300  |
| Irrigation                                                       | 0     | 0     | 0     | 0     | 0     | 600   | 800   | 1200  |
| Crop maintenance                                                 | 5500  | 5500  | 5500  | 5500  | 5500  | 5500  | 5500  | 5500  |
| Fertiliser application                                           | 6475  | 6475  | 6475  | 6475  | 6475  | 6475  | 6475  | 6475  |
| Weeding                                                          | 3390  | 3010  | 5670  | 5670  | 6430  | 11370 | 11750 | 12130 |
| Plant protection                                                 | 2250  | 2250  | 2250  | 2250  | 2250  | 2250  | 2250  | 2250  |
| Harvesting                                                       | 7600  | 7600  | 7600  | 7600  | 7600  | 7600  | 7600  | 7600  |
| Total cost                                                       | 55290 | 54910 | 55115 | 55115 | 55875 | 57229 | 57809 | 58589 |

**Fig. 5.** The error bars represent the standard error of the mean (SEM ± 64.64 kg ha<sup>-1</sup> for grain yield and SEM ± 85.38 kg ha<sup>-1</sup> for straw yield).

expenditure was incurred under the surface and flood irrigation treatments (T<sub>6</sub>–T<sub>8</sub>). Additional expenditure on sensors, flow meters, water-flow sensors and installation materials amounted to ₹2739 ha<sup>-1</sup> in the IoT-based treatments (T<sub>1</sub> and T<sub>2</sub>), compared with ₹284 ha<sup>-1</sup> in the remaining treatments. Irrigation expenditure varied among treatments and ranged from ₹0 to ₹1200 ha<sup>-1</sup>. No irrigation expenditure was recorded in treatments T<sub>1</sub>–T<sub>5</sub>, whereas expenditures of ₹600, ₹800 and ₹1200 ha<sup>-1</sup> were recorded under T<sub>6</sub>, T<sub>7</sub> and T<sub>8</sub> respectively. Weed management expenditure showed considerable variation among treatments, ranging from ₹3010 ha<sup>-1</sup> in T<sub>2</sub> to ₹12130 ha<sup>-1</sup> in T<sub>8</sub>. Compared with T<sub>8</sub>, weed management expenditure was reduced by 75.2 % in T<sub>2</sub>, 72.1 % in T<sub>1</sub>, 53.3 % in T<sub>3</sub> and T<sub>4</sub>, 47.0 % in T<sub>5</sub>, 6.3 % in T<sub>6</sub> and 3.1 % in T<sub>7</sub>. The costs incurred for preparatory cultivation, sowing, crop maintenance, fertiliser

application, plant protection and harvesting remained uniform across all treatments.

### Economics of hybrid maize under different irrigation methods and scheduling approaches

The economics of hybrid maize cultivation were influenced by irrigation methods and scheduling approaches (Table 7). The cost of cultivation ranged from ₹54910 ha<sup>-1</sup> to ₹58589 ha<sup>-1</sup> across the treatments. The lowest cost of cultivation was recorded in T<sub>2</sub> (IoT-based drip irrigation at 80 % depletion level; ₹54910 ha<sup>-1</sup>), followed by T<sub>1</sub> (IoT-based drip irrigation at 60 % depletion level; ₹55290 ha<sup>-1</sup>), whereas the highest cost was observed under T<sub>8</sub> (flood irrigation as farmer's practice; ₹58589 ha<sup>-1</sup>). Among the treatments, T<sub>1</sub> recorded the highest gross return (₹157116 ha<sup>-1</sup>), net return

**Table 7.** Influence of irrigation methods and levels on economics of hybrid maize

| Treatment                                                          | Cost of cultivation<br>(₹ ha <sup>-1</sup> ) | Gross return<br>(₹ ha <sup>-1</sup> ) | Net return<br>(₹ ha <sup>-1</sup> ) | B : C ratio |
|--------------------------------------------------------------------|----------------------------------------------|---------------------------------------|-------------------------------------|-------------|
| T <sub>1</sub> : IoT based drip irrigation at 60 % depletion level | 55290                                        | 157116                                | 101826                              | 2.84        |
| T <sub>2</sub> : IoT based drip irrigation at 80 % depletion level | 54910                                        | 150315                                | 95406                               | 2.74        |
| T <sub>3</sub> : Drip irrigation at 60 % PE                        | 55115                                        | 136237                                | 81122                               | 2.47        |
| T <sub>4</sub> : Drip irrigation at 80 % PE                        | 55115                                        | 143479                                | 88364                               | 2.60        |
| T <sub>5</sub> : Drip irrigation as normal practice                | 55875                                        | 129548                                | 73673                               | 2.32        |
| T <sub>6</sub> : Surface irrigation at 0.6 IW/CPE ratio            | 57229                                        | 120237                                | 63008                               | 2.10        |
| T <sub>7</sub> : Surface irrigation at 0.8 IW/ CPE ratio           | 57809                                        | 124604                                | 66795                               | 2.16        |
| T <sub>8</sub> : Flood irrigation as farmer's practice             | 58589                                        | 112794                                | 54205                               | 1.93        |

IoT: Internet of things; PE: pan evaporation; IW/CPE: irrigation water/cumulative pan evaporation ratio.

(₹101826 ha<sup>-1</sup>) and benefit-cost (B : C) ratio (2.84). This was followed by T<sub>2</sub>, which registered a gross return of ₹150315 ha<sup>-1</sup>, net return of ₹95406 ha<sup>-1</sup> and B : C ratio of 2.74. The lowest gross return (₹112794 ha<sup>-1</sup>), net return (₹54205 ha<sup>-1</sup>) and B : C ratio (1.93) were recorded under T<sub>8</sub>. Compared with T<sub>8</sub>, T<sub>1</sub> increased gross return by 39.3 %, net return by 87.9 % and B : C ratio by 47.2 %. Similarly, T<sub>2</sub> increased gross return by 33.3 %, net return by 76.0 % and B : C ratio by 42.0 % over T<sub>8</sub>. The PE-based drip irrigation treatments, T<sub>3</sub> and T<sub>4</sub>, increased net returns by 49.7 % and 63.0 % respectively, compared with the farmer's practice. Likewise, the surface irrigation treatments T<sub>6</sub> and T<sub>7</sub> recorded 16.2 % and 23.2 % higher net returns respectively, than T<sub>8</sub>. The treatment-wise expenditure analysis revealed that variations in cultivation cost were primarily associated with irrigation infrastructure, irrigation operations and weed management expenses (Table 6). The lowest weeding cost was recorded in T<sub>2</sub> (₹3010 ha<sup>-1</sup>), followed by T<sub>1</sub> (₹3390 ha<sup>-1</sup>), whereas the highest weeding expenditure was observed under T<sub>8</sub> (₹12130 ha<sup>-1</sup>). Compared with T<sub>8</sub>, weeding costs were reduced by 75.2 % in T<sub>2</sub> and 72.1 % in T<sub>1</sub>. Overall, IoT-based drip irrigation treatments (T<sub>1</sub> and T<sub>2</sub>) achieved higher economic returns and B : C ratios while maintaining lower cultivation costs than the conventional farmer's practice. This demonstrated the economic advantage of sensor-based irrigation scheduling in hybrid maize cultivation.

## Discussion

The superior performance of IoT-based drip irrigation treatments demonstrates the importance of precise soil moisture management in enhancing maize productivity, WUE and economic returns. Among the irrigation treatments, IoT-based drip irrigation at the 60 % depletion level (T<sub>1</sub>) consistently produced superior growth, yield attributes, grain yield, water productivity and profitability. The improved performance may be attributed to the maintenance of optimum soil moisture conditions throughout the crop growth period, which created a favourable environment for physiological processes governing plant growth and yield formation.

Enhanced plant height, LAI and DMP under T<sub>1</sub> indicate that sensor-based irrigation scheduling effectively maintained soil moisture within the optimum range of crop water requirements. Adequate soil moisture availability improves root activity and nutrient mobility, facilitating greater absorption of N, P and K from the soil solution. Improved nutrient availability, coupled with enhanced stomatal conductance, supports greater photosynthetic activity and carbon assimilation, leading to increased biomass accumulation and canopy development. Compared with the farmer's practice (T<sub>8</sub>), T<sub>1</sub> substantially improved vegetative growth, indicating that real-time soil moisture monitoring and automated irrigation scheduling reduced moisture-related constraints on crop development. Similar observations were reported by previous researchers, who demonstrated that sensor-based irrigation systems improve crop growth through precise water management (11). Likewise, earlier studies reported that automated irrigation scheduling maintains favourable root-zone moisture conditions and enhances crop performance (13).

The attainment of 100 % system reliability and operational efficiency demonstrates the robustness and dependable field performance of the developed IoT-based irrigation system. The uninterrupted functioning of soil moisture sensors, communication modules, microcontrollers and solenoid valves ensured accurate

monitoring of root-zone soil moisture and successful execution of all scheduled irrigation events. Reliable system operation is essential for precision irrigation because irrigation decisions depend entirely on the accurate acquisition and transmission of soil moisture information. The high reliability and operational efficiency observed in the present study indicate that the automated irrigation system effectively translated sensor readings into timely irrigation actions without failure or delay. Similar observations were reported previous researchers (11), who demonstrated stable performance of sensor-based irrigation systems under field conditions. Likewise, another studies highlighted that reliable IoT-enabled automation improves irrigation precision, reduces human intervention and enhances resource-use efficiency (25). Therefore, the present findings confirm the suitability of IoT-based irrigation systems for efficient and dependable irrigation management in maize cultivation under semi-arid conditions.

The superior yield attributes and grain yield observed under T<sub>1</sub> may be attributed to the maintenance of favourable soil moisture conditions during critical reproductive stages such as tasseling, silking and grain filling. Adequate water availability during these stages enhances pollen viability, silk receptivity, kernel set and assimilate translocation towards developing grains. Maintenance of optimum root-zone moisture also minimises reproductive stress and promotes efficient grain filling, resulting in improved cob development, test weight and final yield. Similar observations were reported by previous researchers, who demonstrated that adequate moisture availability during reproductive growth significantly improves maize yield components (19). Likewise, previous studies reported that optimum irrigation scheduling enhances grain formation and overall maize productivity (10).

The reliability of the treatment effects was further supported by the error-bar analysis presented in Fig. 2. The relatively small error bars associated with grain yield (SEm ± 64.64 kg ha<sup>-1</sup>) and straw yield (SEm ± 85.38 kg ha<sup>-1</sup>), together with the low coefficient of variation values (1.86 % and 1.56 %, respectively), indicate high experimental precision and consistency among replications. Furthermore, the clear separation of treatment means beyond the respective LSD values confirms that the observed differences among irrigation treatments were statistically significant and reflected genuine treatment responses rather than experimental variability.

The improved performance of IoT-based irrigation can also be explained through the soil-plant-atmosphere continuum (SPAC). The SPAC concept describes the continuous movement of water from the soil through plant roots, vascular tissues and leaves before being released into the atmosphere through transpiration. Under sensor-guided irrigation, soil moisture was maintained within an optimum range, ensuring uninterrupted water flow throughout the continuum. This stable moisture regime prevented hydraulic limitations commonly associated with moisture deficit or excessive soil wetness. By avoiding repeated cycles of over-irrigation and under-irrigation, the sensor-based system minimised physiological stress, maintained favourable stomatal conductance, enhanced nutrient transport and improved photosynthetic efficiency. Consequently, plants sustained greater biomass accumulation and reproductive development, resulting in superior grain and straw yields. Similar benefits of precise irrigation scheduling on crop productivity and WUE have been reported and other studies on maize under drip irrigation systems (38).

The reduction in irrigation frequency and TWU under IoT-

based treatments further highlights the effectiveness of real-time irrigation scheduling. Irrigation was applied only when soil moisture depletion reached predetermined thresholds, thereby synchronizing irrigation application with actual crop water requirements. This approach minimised non-beneficial water losses through runoff, evaporation and deep percolation. As a result, a greater proportion of the applied water contributed directly to crop growth and yield formation, leading to substantially higher WUE. Similar improvements in irrigation efficiency have been reported previously, who emphasised that precise irrigation scheduling improves crop water productivity by reducing non-beneficial water losses (6). Earlier studies also demonstrated that sensor-based irrigation technologies significantly reduce water use while maintaining or improving crop productivity (13, 39).

Although PE-based drip irrigation treatments ( $T_3$  and  $T_4$ ) improved crop performance compared with conventional irrigation methods, they remained inferior to sensor-based treatments. Pan evaporation-based scheduling estimates atmospheric evaporative demand but does not directly account for actual root-zone soil moisture variability. Consequently, irrigation may be applied when sufficient moisture remains available in the root zone or delayed when localised moisture depletion occurs. Such limitations reduce the ability of PE-based scheduling to accurately synchronise irrigation with crop water demand. In contrast, soil moisture-based irrigation scheduling responds directly to actual root-zone conditions, resulting in more efficient water management and improved crop performance.

The IoT-based smart irrigation system demonstrated excellent operational stability throughout the crop growth period, achieving 100 % system reliability in both  $T_1$  and  $T_2$ , as all scheduled irrigation events were successfully executed without sensor, communication, controller, or solenoid valve failures. The uninterrupted functioning of the system ensured continuous monitoring of root-zone soil moisture and timely irrigation application according to the predefined depletion thresholds. Reliable operation is a critical prerequisite for the successful adoption of sensor-based irrigation systems because irrigation decisions are entirely dependent on accurate sensor measurements and effective communication between sensing and control components. Similar findings were reported previously which observed stable field performance of wireless sensor-based irrigation systems and emphasised the importance of reliable sensor-controller integration for precision water management (11). Likewise previous researcher reported that the integration of IoT-enabled monitoring and automated control mechanisms improved the dependability of irrigation scheduling and reduced the need for manual intervention (25). The high reliability observed in the present study may be attributed to the robust integration of watermark soil moisture sensors, ESP32 microcontroller, wireless communication modules and automated valve control, which ensured uninterrupted data acquisition and irrigation execution under field conditions. These results indicate that the developed IoT-based irrigation system is technically feasible and capable of supporting precision irrigation management for maize cultivation under semi-arid conditions.

The treatment-wise expenditure analysis revealed that cultivation costs varied primarily due to differences in irrigation infrastructure, irrigation operations and weed management expenses. Although  $T_1$  and  $T_2$  required additional expenditure for soil moisture sensors, flow meters, automation devices and installation

materials, their overall cultivation costs remained lower than those of the conventional flood irrigation treatment. Reduced irrigation frequency and automated irrigation scheduling minimised labour requirements associated with irrigation operations, thereby lowering recurring operational costs. Similar economic benefits of drip irrigation systems have been reported previously that observed lower labour and management costs under micro-irrigation systems compared with conventional irrigation practices (8).

A substantial reduction in weed management expenditure was observed under IoT-based and drip irrigation treatments. Localised application of water restricted moisture availability in non-cropped areas, thereby reducing weed emergence and growth. Compared with flood irrigation, weeding costs were reduced considerably under  $T_1$  and  $T_2$ , contributing significantly to lower cultivation costs. Furthermore, maintenance of optimum soil moisture conditions reduced the likelihood of excessive canopy humidity and prolonged soil saturation, conditions that often favour pest and disease development. Although plant protection costs remained similar across treatments, improved irrigation management may indirectly contribute to healthier crop growth and lower pest incidence.

The superior economic performance of IoT-based irrigation treatments was primarily driven by the combined effects of higher grain yield, improved water productivity and reduced operational expenses. Among all treatments,  $T_1$  recorded the highest gross return, net return and B : C ratio. The additional investment associated with sensors and automation components represented only a small proportion of the total cultivation cost and was more than compensated by the increase in crop productivity and reductions in irrigation and weed management expenses. Compared with conventional drip irrigation treatments, the additional investment for IoT components generated substantially greater net returns, demonstrating a favourable cost-benefit relationship.

The economic advantage of sensor-based irrigation can also be explained through improved regulation of the SPAC. Maintenance of optimum root-zone moisture enhanced physiological efficiency by improving nutrient uptake, stomatal conductance, photosynthetic activity and assimilate translocation. These physiological benefits translated into greater biomass accumulation, higher grain yield, improved WUE and ultimately superior economic returns. Similar observations were reported by early researchers, who highlighted the role of precise irrigation management in improving both water productivity and farm profitability (5).

The additional investment required for IoT components was economically justified by the substantial increase in net returns obtained under sensor-based irrigation. The expenditure on sensors, flow meters, water-flow sensors and installation materials in the IoT-based treatment ( $T_1$ ) was ₹2739 ha<sup>-1</sup>, compared with ₹284 ha<sup>-1</sup> in the conventional drip irrigation treatment ( $T_5$ ), resulting in an additional investment of ₹2455 ha<sup>-1</sup>. However,  $T_1$  generated a net return of ₹101826 ha<sup>-1</sup> compared with ₹73673 ha<sup>-1</sup> under  $T_5$ , providing an additional net income of ₹28153 ha<sup>-1</sup>. Thus, the additional IoT investment yielded more than eleven times its cost within a single cropping season, indicating immediate recovery of the investment and a highly favourable return on investment. This short payback period highlights the economic feasibility and practical viability of adopting IoT-based irrigation technology for maize cultivation,

particularly under conditions of increasing water scarcity, rising labour costs and the growing need for efficient resource management. Overall, the findings demonstrate that integration of IoT-based soil moisture monitoring with drip irrigation improves SPAC functioning, enhances physiological efficiency, optimises water use, reduces production costs and increases farm profitability. The technology offers a practical and economically viable strategy for sustainable maize production while addressing the challenges of water scarcity, labour shortages and the need for efficient resource management.

## Conclusion

The present study demonstrated that irrigation method and scheduling significantly influenced the growth, yield, water-use efficiency (WUE), water conservation, system performance and economic returns of hybrid maize. Among the treatments evaluated, internet of things (IoT)-based drip irrigation scheduled at 60 % soil moisture depletion emerged as the most effective irrigation strategy. Compared with conventional flood irrigation, this treatment increased grain yield by 39.1 %, improved WUE by 161.8 % and achieved 46.9 % water savings. The IoT-based irrigation system also exhibited reliable field performance, demonstrating the technical feasibility of sensor-based automated irrigation under practical farming conditions. The superior performance of the system was attributed to continuous soil moisture monitoring and automated irrigation scheduling, which maintained optimum root-zone moisture conditions, improved water availability to the crop and enhanced overall crop growth and productivity. By minimising both over-irrigation and under-irrigation, the sensor-guided approach improved water productivity while reducing unnecessary water use. Economic analysis further confirmed the advantage of IoT-based irrigation, which generated substantially higher profitability and benefit–cost ratio than conventional irrigation methods, indicating its economic viability despite the additional investment required for sensors and automation components. Overall, the integration of soil moisture sensors with drip irrigation provides a sustainable, water-efficient, technically reliable and economically viable irrigation strategy for hybrid maize production. The technology offers considerable potential to enhance agricultural water management, improve crop productivity and support climate-resilient and precision agriculture under increasing water scarcity and rising labour costs.

## Recommendations

Based on the results of the present investigation, it can be concluded that irrigation methods and irrigation scheduling play a crucial role in improving maize productivity, water-use efficiency and farm profitability. Among the treatments evaluated, IoT-based drip irrigation at 60 % soil moisture depletion level emerged as the most effective irrigation strategy, resulting in superior crop performance, enhanced water productivity, higher economic returns and substantial savings in irrigation water. Therefore, the adoption of sensor-based IoT irrigation systems is recommended for hybrid maize cultivation, particularly in water-limited regions where efficient utilisation of available water resources is essential. The technology offers significant potential for improving irrigation management through real-time monitoring, automated decision-making and precise water application based on crop requirements. From a scalability perspective, IoT-based irrigation

systems can be adapted to smallholder, medium-scale and commercial farming operations through modular and customisable sensor, controller and automation configurations. Integration of IoT technologies with existing drip irrigation infrastructure can reduce installation costs and enhance implementation feasibility. Wider adoption may be promoted through farmer training programs, extension services, technical support mechanisms and government subsidy schemes that help overcome financial and technical barriers associated with initial investment. The development of low-cost, energy-efficient and user-friendly IoT platforms will further improve accessibility, particularly for resource-constrained farmers. In addition, validation of IoT-based irrigation systems across diverse agro-climatic regions, soil types and cropping systems is recommended to establish region-specific guidelines and support large-scale deployment. Such scalability-focused initiatives will facilitate broader adoption of precision irrigation technologies and contribute to sustainable agricultural intensification, improved water resource management, enhanced climate resilience and long-term agricultural sustainability.

## Future scope

Although the present study demonstrated the advantages of IoT-based drip irrigation in improving yield, WUE and economic returns in hybrid maize cultivation, further research is required to broaden its applicability and technological advancement. Future studies should evaluate the performance of IoT-based irrigation systems across diverse soil types, climatic conditions, cropping systems and agroecological regions to develop location-specific recommendations. Advanced research should focus on sensor optimisation, including improvements in soil moisture sensor accuracy, calibration stability, durability, long-term reliability and optimal placement within the crop root zone. In addition, the development of intelligent irrigation scheduling algorithms capable of integrating real-time soil moisture data, crop water requirements, weather forecasts and evapotranspiration estimates could substantially improve irrigation precision. The incorporation of artificial intelligence, machine learning, digital twins and predictive analytics for automated decision-making offers significant potential for adaptive and self-learning irrigation systems. Future investigations may also explore the integration of IoT platforms with remote sensing technologies, unmanned aerial vehicles (UAVs), satellite-based monitoring and cloud-based decision support systems for real-time crop and water management. Research on energy-efficient communication protocols, solar-powered sensor networks, low-cost automation systems, integrated fertigation management, long-term sustainability and economic feasibility will further support large-scale adoption. Such advancements will contribute to the development of climate-resilient, resource-efficient, intelligent and data-driven irrigation systems for sustainable agricultural production.

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## Authors' contributions

PP and PK conducted the research experiments. PP and BS prepared the manuscript. NA performed the data analysis. MM, SA and JASR revised the manuscript for language and editorial quality. All authors have read and approved the final manuscript.

## Compliance with ethical standards

**Conflict of interest:** Authors do not have any conflict of interest to declare.

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## Declaration of generative AI and AI-assisted technologies in the writing process

The authors used ChatGPT (OpenAI, GPT-5.5) to assist with language editing and manuscript preparation. All AI-generated suggestions were critically reviewed, revised and verified by the authors, who take full responsibility for the content of the manuscript.

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