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REVIEW

# From data to decision: How wearable plant sensors help improving proactive irrigation strategies and water use efficiency

Mustafa A.J. Al-Sammarraie[1], Ali Irfan Ilbas[2]* and Zeki Gokalp[2]

**Affiliations:** [1]University of Baghdad, College of Agricultural Engineering Sciences, Baghdad, Iraq
[2]Faculty of Agriculture, Erciyes University, Kayseri, Türkiye

## Abstract

Wearable sensors are a revolutionary tool in agriculture because they collect accurate data on plant environmental conditions that affect plant growth in real-time. Moreover, this technology is crucial in increasing agricultural sustainability and productivity by improving irrigation strategies and water resource management. This review examines the role of wearable sensors in measuring plant water content, leaf and air humidity, stem flow, plant and air temperature, light, and soil moisture sensors. Wearable sensors are designed to monitor various plant physiological parameters in real-time. These data, obtained through wearable sensors, provide information on plant water use and physiology, making our agricultural choices more informed and accurate. Internet of Things (IoT) technologies can improve irrigation strategies and reduce water consumption by analyzing data from wearable sensors and adapting it to automate the irrigation system. The review also highlights the importance of using Artificial Intelligence (AI) to predict plant water needs accurately. This review concludes that wearable sensors provide accurate and real-time data on the stress state of plants and their surroundings, improving water management efficiency and agricultural production sustainability. These IOT and AI-enabled technologies are a crucial milestone toward smart and sustainable agriculture, which shows the importance of innovation in responding to enhanced climate threats.

**Keywords:** artificial intelligence, climate challenges, irrigation systems, water consumption, wearable sensors

## Introduction

Food security is vital to people's lives. In 2022, the number of people suffering from food insecurity reached 250 million, proving the importance of food (Yan *et al.*, 2024). Plants are an important food source as they meet the different demands of consumption (Zhang *et al.*, 2023). Plants are exposed to pathogens and animal factors, which are classified as biotic stresses, while they are exposed to environmental factors (drought, salinity, etc.), which are classified as abiotic stresses (Coatsworth *et al.*, 2023). These stresses negatively affect productivity by negatively impacting crop growth. Therefore, it is important to study the mechanisms of plant growth and their responses to these stresses. Monitoring plant phenotypes over the long term is important to understand how they interact with the environment, as plant growth is a slow and subtle response to external stimuli (Bahuguna and Jagadish, 2015).

The plant phenotype includes all external and internal characteristics that indicate the plant structure (Dejonghe and Russinova, 2017). Nutritional information of a plant includes N, P, and K, while physiological information includes indicators such as proteins, nitrogen, alcohol, and antioxidants. Physical characteristics that are crucial to understanding plant growth and development include leaf thickness, which affects photosynthetic efficiency, and fruit size, which determines the quality of production and reproductive success. There is also stem diameter. This is one of the important factors that influences the plant's ability to support its upper parts and vitality. An important indicator of a plant's health and ability to transport nutrients and water is its stem flow rate. Finally, the hydraulic conductivity of the roots helps the plant absorb water and minerals from the soil, thus maintaining a healthy balance for growth (Busby *et al.*, 2017).

Wearable sensors provide information about plant status. These sensors can be installed on different parts of the plant (leaves, stems, or roots). A combination of different sensors can be used to obtain real-time physiological (biophysical or biochemical) information and monitor plant status (Zhao *et al.*, 2020; Al-sammarraie and Ilbas, 2024; Zhou *et al.*, 2024). Conventional sensors have a rigid

*Corresponding Author: Ali Irfan Ilbas. Email: iilbas@erciyes.edu.tr

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mechanical structure, which can cause biological rejection or tissue damage when in prolonged contact (Aroca and Calbo, 2016; Moreno-Moreno *et al.*, 2018). Therefore, there is a need to monitor plant physiological data over the long term. Wearable sensors are flexible electronic sensors with the ability to bend and fold freely. Researchers have designed flexible wearable electronic sensors to monitor plant phenotypes without destroying them. Since the mechanical properties of these sensors are like plant tissues, they can be integrated with plants without the need for rigid mechanical structures (Qu *et al.*, 2023). Plant monitoring electronics can be attached to plant parts without the need for equipment, solving the incompatibility problem with traditional sensors and enabling the detection of multiple indicators to monitor plant growth and response to climate change. The objective of the review is to examine how wearable sensors and AI technologies that provide accurate measurements of factors such as plant water content, soil and air moisture, temperature, and light can be used in water resource management in agriculture.

## Review methodology

This review discusses the role of wearable sensors in increasing agricultural sustainability and productivity by improving irrigation strategies and water resource management, drawing on multiple databases, including Web of Science, Scopus, IEEE Xplore, Google Scholar, and ScienceDirect. This review examines wearable sensors for measuring plant water content, leaf and air humidity, stem water flow, plant and air temperature, light, and soil moisture. The review also highlights the importance of using artificial intelligence to accurately predict plant water requirements. These technologies represent a step toward smarter, more sustainable agriculture and highlight the importance of innovation in addressing growing climate challenges.

### APPLICATION OF WEARABLE PLANT SENSORS IN PLANT MONITORING

Wearable plant sensors are biocompatible and flexible, enabling long-term real-time monitoring. Plant monitoring has helped in gathering information about the growth environment and plant physiology by attaching these flexible devices to the tissues and organs of the plants. Wearable plant sensors use various techniques to acquire and process different data, including (Zhang *et al.*, 2023; Yan *et al.*, 2024):

1. Sensor placement: Different wearable sensors are attached to a plant part (leaves, stems, or branches) without causing any damage.
2. Measured parameters: Key parameters measured include leaf moisture, transpiration rates, stem flow, photosynthesis rates, and thermal measurements (plant and air temperature).
3. Wireless data transmission: Sensors transmit the collected data wirelessly to a central system using different protocols such as Wi-Fi, Bluetooth, or LoRa, allowing for real-time monitoring.
4. Cloud-based data management: The collected data are stored and processed in cloud-based systems, allowing users to easily access and analyze the data.

## Measured parameters from plant

### THE WATER CONTENT OF THE PLANT

Water quality is an important factor affecting plant growth. Water accounts for 80% to 90% of the total water content of plants. The water content of plants should be carefully controlled by good management. Wearable sensors assess the water content of plants (Atherton *et al.*, 2012). Atherton *et al.* (2012) constructed a sensor consisting of a microheater and two thermometers, the previous two elements are made of thin films (Fig. 1A). The thermometers record changes in the temperature of the heater in the leaves and can be placed on the leaf surface to measure water content, but it may be affected by environmental factors such as ventilation or solar radiation. Palazzari *et al.* (2017) developed a leaf sensor to monitor changes in leaf and air temperature associated with water stress, thus contributing to the support of automated irrigation systems (Fig. 1B). The sensor is linearly accurate ($R^2$ = 0.97) in measuring temperature change with water stress in the plant. The sensitivity is 1.89% per degree Celsius, and it is responsive to changes quickly. Regarding the working life of the sensor, it is least intrusive on leaf growth and is therefore suitable for long-term use. Windt *et al.* (2021) exploited a nuclear magnetic resonance (nMR) device to record water content data in rice (Fig. 1C). Liquid proton density linearly correlates with water content ($R^2$ = 0.99) and concurs with gravimetric readings. The sensor also accurately quantifies minute osmotic challenge-induced water content alterations (e.g., dehydration) with high precision. The sensor is also constructed for use in field environments with a rechargeable battery and has thermal stability. These wearable sensors demonstrate the potential of this technology for water resource management to increase productivity.

The difference between the saturated water vapor pressure and the actual water vapor pressure at a given temperature is known as vapor pressure deficit (VPD), and it affects how stomata open and close in plants and how efficiently they use water (Yuan *et al.*, 2019). There is a negative correlation between VPD and plant water content, as high VPD for prolonged periods or at very high levels leads to higher water loss from the stomata, leading to water stress, which is harmful to plant health and may in some cases lead to the death of plants, given that the effect of VPD varies with exposure time, degree of altitude, and type of plant. Vurro *et al.* (2019) developed a gas sensor to monitor VPD in plants using an organic electrochemical transistor (Fig. 2A). In this case, Oren *et al.* (2017) fabricated a wearable sensor using graphene, the pattern reached a resistivity of 0.22 ± 0.12 kΩ $sq^{-1}$ (Fig. 2B).

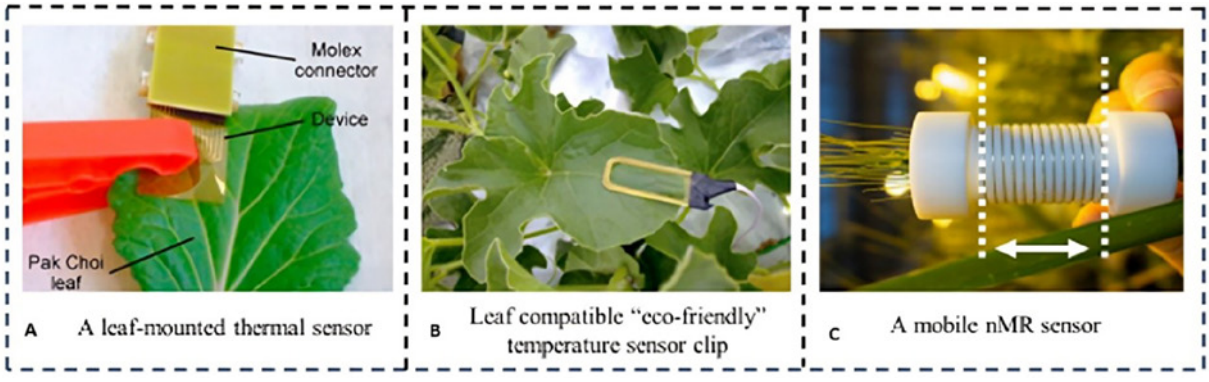



**Fig. 1.** Various wearable sensors for plant monitoring.

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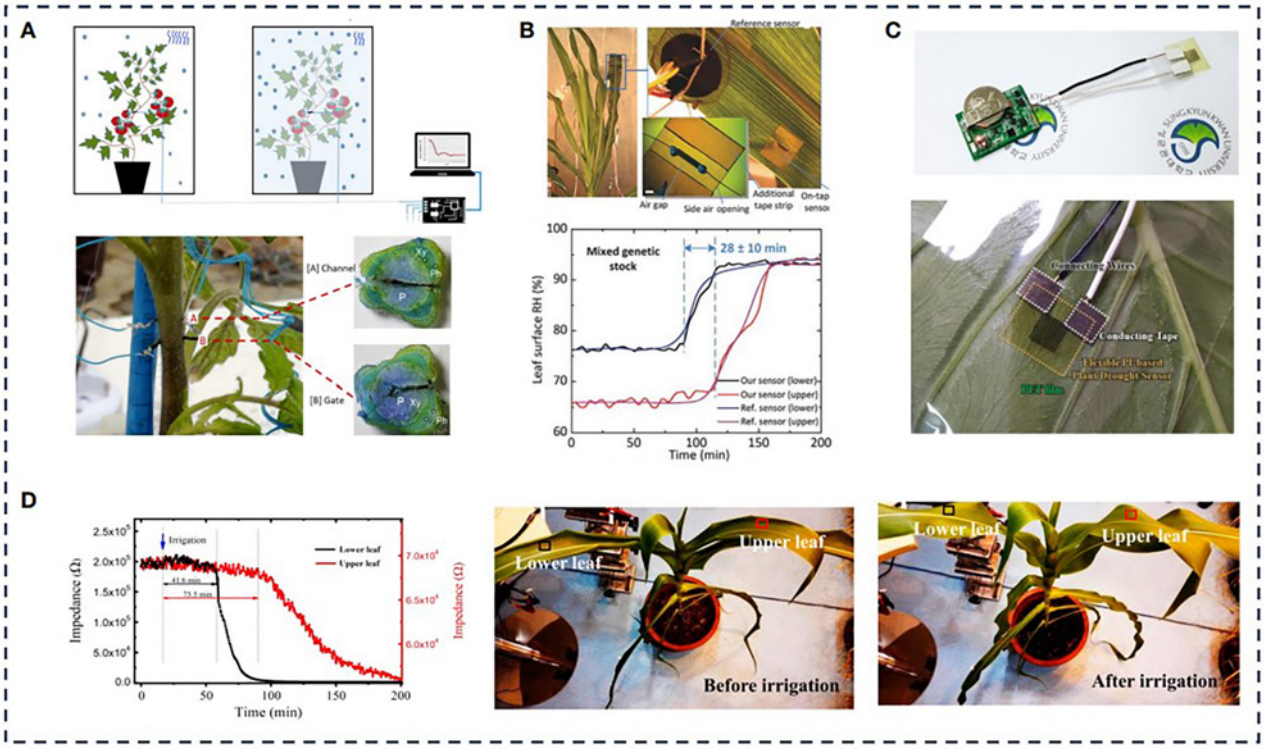



**Fig. 2.** Various wearable sensors for measuring water content.

Im *et al.* (2018), a flexible plant drought sensor with the polyimide (PI) was designed to monitor plant stomatal responses using water evaporation (Fig. 2C). From the results of the experiment, it was found that the sensor is sensitive to relative humidity. In another study, Kim and Andrew (2020) prepared chlorinated PEDOT electrodes using a vapor printing technique and monitored the blade capacitance and impedance signals. For 130 days, plant dehydration and UV damage were monitored using bioimpedance spectroscopy. Based on the results obtained from the leaf data, it was found that drought reduced the water content and capacitance value. Lan *et al.* (2020) designed a graphene oxide (GO)-based capacitive humidity sensor with high sensitivity. These sensors were placed on plant leaves to directly monitor stomatal transpiration. Peng *et al.* (2024) also managed to monitor leaf capacitance in real time using wearable electrodes. It was found that the leaf moisture content had a positive correlation with the capacitance value.

An important indicator of a plant's health and ability to transport nutrients and water is its stem flow rate (Miner *et al.*, 2017). Li *et al.* (2022) makes a humidity sensor with GO. From the test results, it was found that the device's sensitivity to humidity reached 7945 W/%RH, enabling dynamic monitoring of plant internal water migration (Fig. 2D).

To provide accurate moisture measurements, there must be a strong connection between the product and the sensor. Long-term use of sensors can easily initiate the plant's self-healing process, making the moisture measurement data less accurate. As a result, flexible sensors must be developed that are compatible with the properties of the products and minimize the harmful effects of long-term use.

## Leaf temperature

There is a difference between the temperature of the plant and the surrounding air, and analyzing this difference can assess water stress in the plant (Daskalakis *et al.*, 2017). Wearable sensors are less affected by environmental conditions than traditional infrared thermography methods (Leinonen *et al.*, 2006). Agricultural applications use wired communication technologies because they are cheap and easy to use and contribute to improving the storage and transmission of data for leaf temperature sensors. Daskalakis *et al.* (2017) developed a sensor based on the wireless backscattering method to measure the temperature of the leaf (Fig. 3A-i). As shown in Fig. 3A-ii, these sensors were fabricated using nanoparticle inkjet printing technology. Two sensors are placed on the upper and lower surfaces of the leaf to measure the air and leaf temperatures. For communication, the backscattered Morse code was modified to transmit a carrier signal at a frequency of 868 MHz. In this case, the Morse code corresponds to the air temperature value (Fig. 3A-iii). The sensor stands tall enough to record ambient air and leaf temperature differences accurately enough to assess water stress, and the sensor can measure small differences in upper and lower leaf surface temperatures.

Palazzari *et al.* (2017) designed a temperature sensor consisting of four sensors that can be easily attached to the leaf edge, as shown in Fig. 3B-i. These sensors were tested on the leaves of a watermelon plant (Fig. 3B-ii). The results showed that the temperature differences recorded by the four sensors were affected by rainfall and water stress conditions (Fig. 3B-iii). The sensor exhibited proper response to temperature changes associated with rainfall and water stress, with sensitivity to temperature gradients associated with micro-environmental conditions. The sensors lend themselves to easy leaf-mounting, with the implication of potential long-term deployment with minimal environmental impact.

Radio frequency identification (RFID) technology is gaining increasing attention due to its low maintenance and installation costs. Palazzi *et al.* (2019) developed a standalone leaf-adaptive temperature sensing system consisting of an EM4325 sensor chip and an RFID transceiver (Fig. 3C-ii). As shown in Fig. 3C-iii, the difference between the air temperature and the pumpkin leaf was measured after the sensor was attached to the plant leaves. Group 1 was irrigated after the sensors were installed, but Group 2 was not, which made it under drought stress. Analysis showed that the

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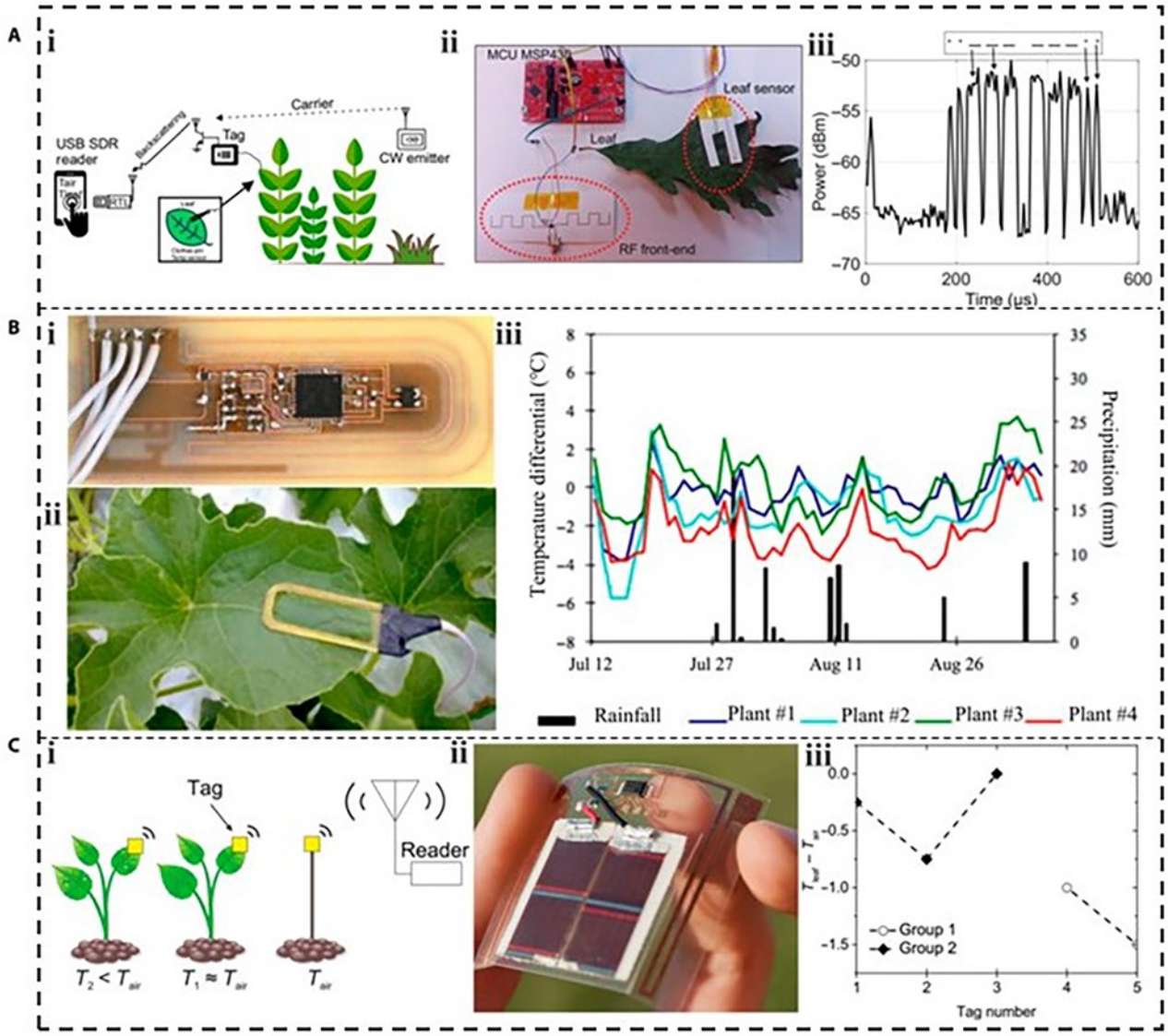



**Fig. 3.** Wearable sensors to measure plant leaf temperature.

leaf temperature in Group 1 was about −1.25°C lower than the air temperature, and in Group 2 it was about −0.33°C lower. In addition, the difference between the air temperature and the pumpkin leaf showed a negative relationship with the level of water stress. It is a precision reader of the air temperature difference and the pumpkin leaf, with the ability to read minute changes (a difference ranging from −1.25 to −0.33°C). It is therefore sensitive enough to detect variations in water stress levels. Low maintenance costs, as well as ease of installation, also contribute to its long operational lifespan in the field.

## Disclosure of growth environment information

Growth and physiological processes are greatly influenced by changes in soil conditions and temperature (Hackenberger *et al.*, 2018; Jasim *et al.*, 2022). Monitoring these variables can improve plant productivity using wearable sensors. This uses techniques such as spectroscopy (Mulla, 2013), machine vision (McCarthy *et al.*, 2010), and aerial instruments (Primicerio *et al.*, 2012) to avoid the delays that occur with conventional monitoring techniques. Dong *et al.* (2023) constructed a sensor that measures leaf and fruit temperature around the clock using a porous matrix (Fig. 4A-i). The fruit temperature sensor adapts to the surface contours to transform the plane shape into three-dimensional (Fig. 4A-ii). Laboratory experiment results show that these two sensors effectively monitor the micro-environment temperature.

In recent years, sensors have seen great development in monitoring operations, which has led to more competition in the market. Multi-functional sensors have been introduced into agricultural operations that can monitor plant physiology and environmental conditions simultaneously. Nassar *et al.* (2018) developed a wearable sensor to measure temperature and humidity on plant surfaces to monitor climate and growth rate (Fig. 4B). Zhao *et al.* (2019) developed a lightweight and flexible plant sensor that can monitor light, temperature, humidity, and plant growth (Fig. 4C), which helped to understand plant growth in different environments. Lu *et al.* (2020) exploited ZnIn2S4 nanosheets and developed a flexible sensor for continuous monitoring of the transpiration status of plants (Fig. 4D). The system includes humidity, temperature, and light sensors, which are embedded in a 50 μm thick PI film. Laser-induced graphene and screen-printed silver paste are used. A PET layer is covered over the light sensor, thus protecting it from water. The electrode has a planar structure that provides a moisture detection range of up to 90% and a highly sensitive light response within 4 ms. This development in sensors reflects

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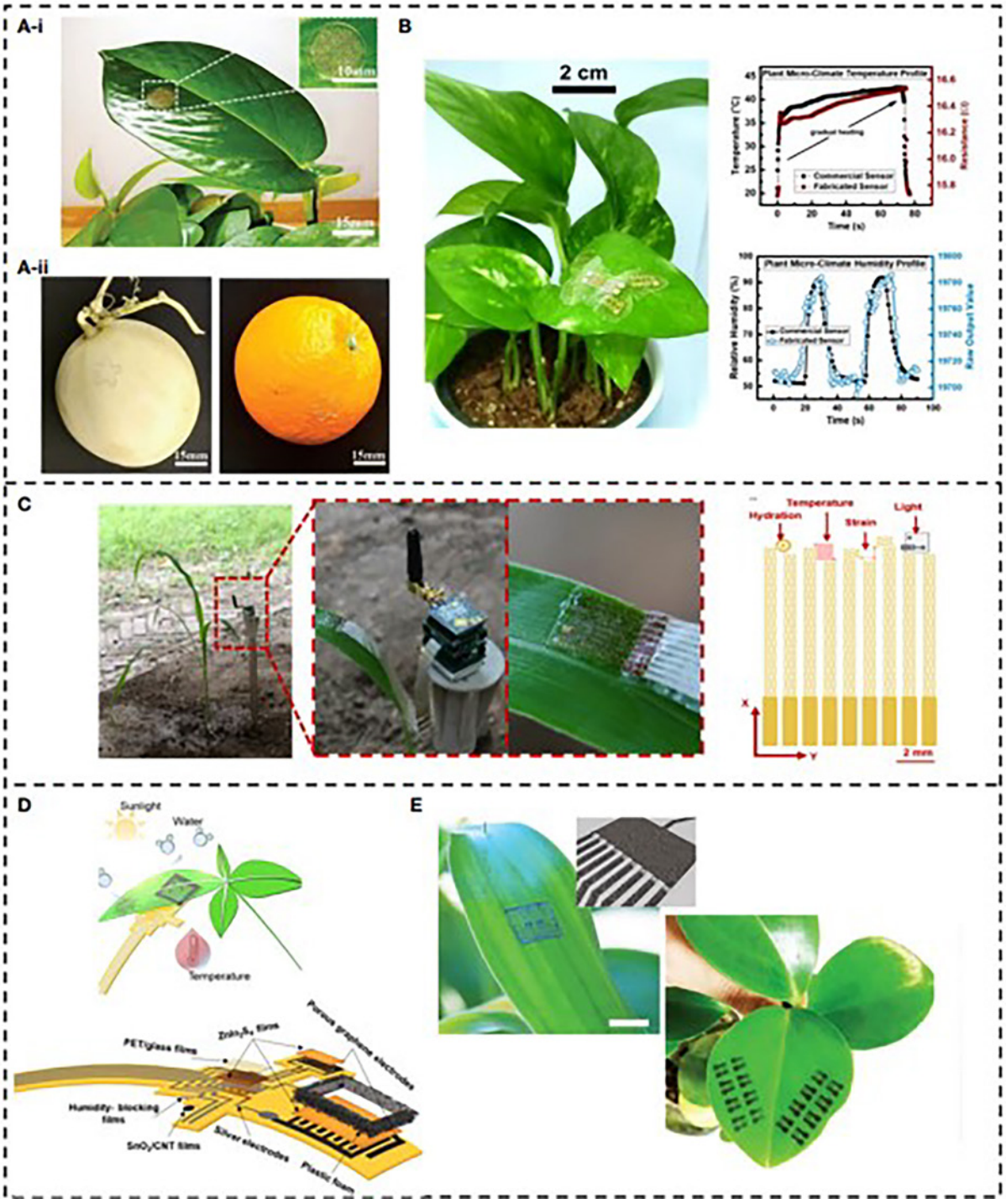



**Fig. 4.** Various wearable sensors to monitor plant growth environment information.

the continuous innovation in the field of smart agriculture and enhances the effectiveness of agricultural resource management.

Wearable sensors provide monitoring of various plant growth environments for a comprehensive assessment of plant growth status. However, the size and quality of these sensors are limited by the limited materials and preparation processes, which increases the burden on plants. As a result, the future focus in developing these technologies will be on lightweight, compact, flexible, and multifunctional electronics, which is a major focus in this field. These sensors are a crucial tool for improving plant nutrient management, as they can increase the bioavailability of nutrients required for good growth and improve yield quality. It is also important to consider the impact of abiotic factors such as drought and salinity, which pose significant challenges in food plant production. Therefore, improving the resilience of agricultural production systems to these conditions is crucial to maintaining food security worldwide.

## AIR TEMPERATURE

The process of photosynthesis is influenced by air temperature and thus affects plant growth. Whether high or low temperatures, unsuitable temperatures can deteriorate plant health. Nassar *et al.* (2018) designed a wearable sensor to measure the temperature and humidity sensors on plant surfaces. Fig. 5A-i shows a gold

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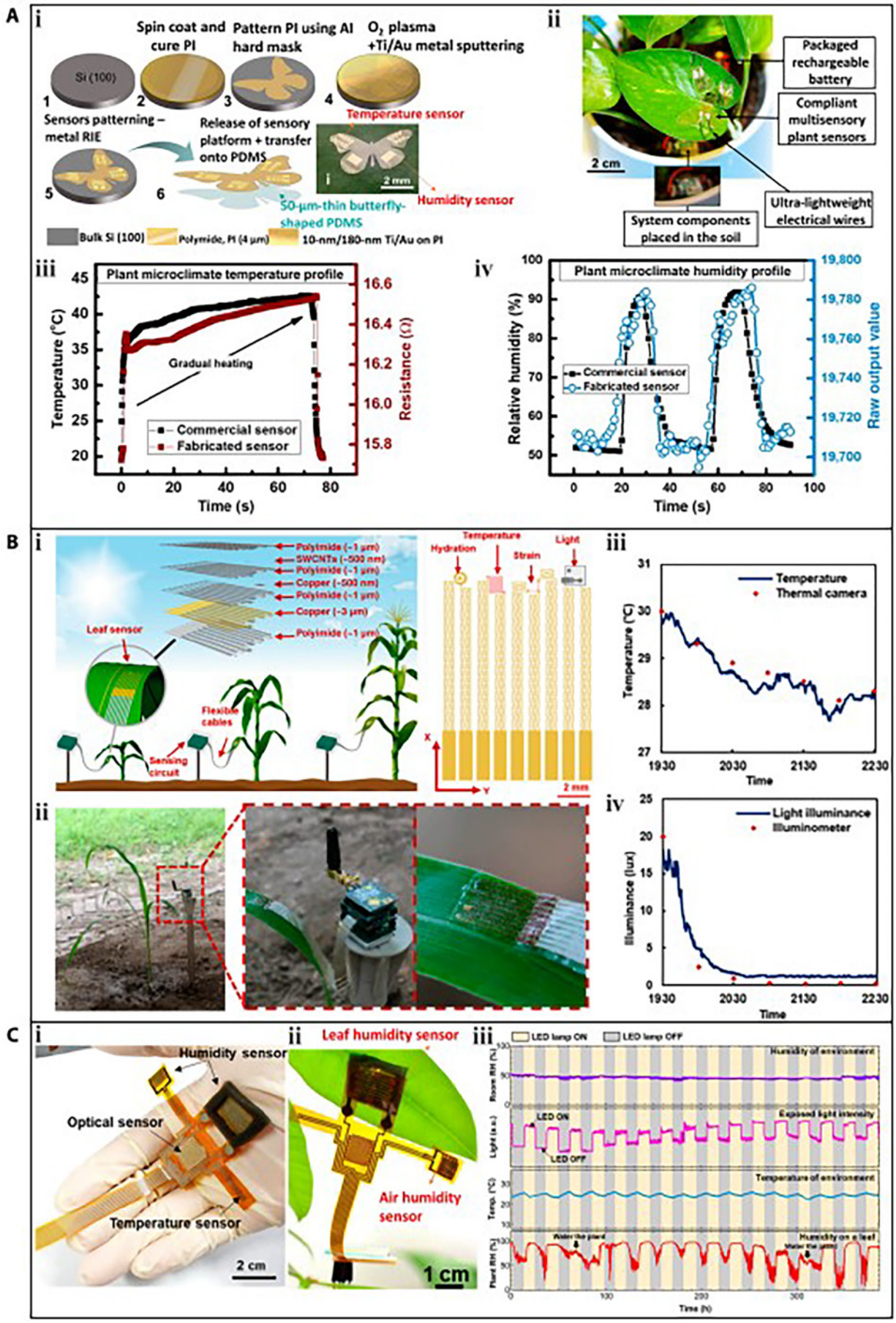



**Fig. 5.** Wearable sensors to measure air temperature, humidity, and light.

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layer covering lightweight butterfly-shaped polymer-reinforced (PI) electrodes. A gold serpentine pattern acts as a temperature sensor between these electrodes, causing its resistance to increase with temperature at a rate of 0.032 Ω per degree Celsius. The lightweight silver epoxy wires connected the sensor platform to the data acquisition circuits to be mounted on the surface of a *Scindapsus aureus* leaf (Fig. 5A-ii). As shown in Fig. 5A-iii, the results showed that the resistance of the new temperature sensor increased in tandem with the temperature measured by the existing temperature sensor. These results demonstrated that the fabricated sensor had good reliability.

The main feature of wearable plant sensors is multifunctionality. As shown in Fig. 5B-i, the sensor is lightweight and flexible, which can monitor different plant phenotypes such as elongation and humidity and environmental factors such as light and air temperature. To detect temperature, the sensor is composed of a zigzag-shaped copper layer. Fig. 5B-ii installed this sensor outdoors on a corn leaf to monitor the air temperature in real-time. Fig. 5B-iii shows that the obtained temperature data show good agreement with the data obtained using a thermal imaging camera (Zhao *et al.*, 2019).

A flexible, multi-modal sensing system was developed to maintain the material and its shape. This system included three humidity sensors, an optical sensor, and a temperature sensor (Fig. 5C-i) (Lu *et al.*, 2020). All three sensors had to be built on a flexible PI substrate with a thickness of 50 μm. Silver electrodes for the temperature sensor were placed on the PI substrate. Next, $SnO_2$ nanoparticles and single-walled carbon nanotubes (SWCNTs) were deposited on silver electrodes. This was a tool used to measure temperature. Finally, a passivation layer was coated on the temperature sensor. This prevents moisture and scratches on the temperature sensor. The weight of the integrated sensing system for real-time monitoring was about 0.3 g (Fig. 5C-ii). It was fixed on the lower epidermis of *Phaleria macrocarpa* leaves. The third row of Fig. 5C-iii shows that the air temperature reached a constant temperature of about 25°C for about 16 days.

### AIR HUMIDITY

Air humidity affects the stomata condition of plants and plays an important role in water absorption and mineral nutrient transport, thus affecting the transpiration rate (Zhang *et al.*, 2023). Fig. 5A-i shows that the flexible multi-sensing platform includes a finger-shaped humidity sensor. This sensor increases its capacity as humidity increases and is sensitive to up to 1.6% relative humidity. The sensor was installed on a plant leaf to monitor the environment in real-time (Fig. 5A-ii). The flexible multi-mode sensing system (Fig. 5C-i) includes two humidity sensors constructed by laser scanning with LIG electrodes on a PI substrate. The humidity sensing part of both sensors consists of ZnIn2S4 nanosheets. One sensor is exposed to the atmosphere to measure air humidity, while the other is directly attached to the lower epidermis of *P. macrocarpa* leaves. According to the second row of Fig. 5C-iii, the air humidity was maintained at a constant level throughout the plant growth period and the light was turned on and off repeatedly. As shown in the first row of Fig. 5C-iii, the data recorded by the smaller sensor confirmed the constant air humidity level. However, as shown in the fourth row of Fig. 5C-iii, the leaf humidity increased rapidly when the light was on, causing the stomata to open for photosynthesis. Conversely, the leaf moisture content decreased after the light source was turned off (Lu *et al.*, 2020).

## Light

One of the major environmental factors that influence plant growth is light. Photosynthesis helps plants produce food by converting light into chemical energy. However, excess light can cause physical damage, such as leaf burns. As a result, it is important to monitor the light intensity in the environment surrounding plants (Zhang *et al.*, 2023). As shown in Fig. 5B-i, a flexible multi-mode sensing system uses a silicon-based phototransistor to detect light. This transistor is 20 μm thick and has been mechanically polished, making it lighter and more flexible. During field experiments, the phototransistor was able to detect light attenuation at sunset (Fig. 5B-ii), and these measurements were consistent with those made by a commercial light meter (Fig. 5B-iv) (Zhao *et al.*, 2019). As shown in Fig. 5C-i, the flexible multi-mode sensing system also contains an optical sensor. This sensor creates a light-sensing component by printing silver electrodes on a PI substrate and depositing ZnIn2S4 nanosheets on the silver electrodes. The optical sensor, which can detect light at a frequency of up to 50 Hz, exhibited a fast response time of about 4 ms. The wearable sensor was able to accurately detect daytime and nighttime periods because an 18-W artificial light source was automatically turned on and off every 12 h (Fig. 5C-iii) (Lu *et al.*, 2020).

Wearable sensors to measure water content, plant temperature, humidity, light, and water vapor pressure deficit (VPD) possess numerous important advantages over traditional methods. While traditional methods such as soil electrical conductivity, infrared thermography, or laboratory testing are point or indirect measurements and tend to be influenced by environmental factors such as temperature, humidity, and solar radiation, wearable sensors provide real-time and continuous measurement directly from the plant surface or plant organs, and hence more accurate detection of physiological and environmental changes. In terms of accuracy, such tools can measure subtle fluctuations in temperature, water level, and humidity with precision instruments that offer early warning of water stress or fluctuating environmental conditions – a task difficult to achieve using traditional methods, subject to time lag and the effects of environmental interference. From an operational life viewpoint, wearable sensors have flexible and lightweight structures that support continuous use for weeks to months and operate in variable field conditions compared to traditional devices that must be calibrated and serviced at intervals. Additionally, the sensors leverage wired and wireless data communication technologies to facilitate proper transmission of information for collection and timely analysis of farm information and expanding farmers' ability to act fast and well-informed to adjust irrigation practices and management of resources. Contrarily, traditional practices lean on slow or indirect gathering of information, reducing the effectiveness of agricultural interventions. Therefore, wearable sensors are a paradigm shift in monitoring plant health and the environment with high accuracy, high sensitivity, and long working life, which are essential tools for smart and sustainable agriculture compared to conventional methods lacking these attributes.

However, despite the advantages of wireless transmission and cloud-based data management offered by these systems, data security and transmission stability must be considered to make wearable sensor systems dependable in agricultural environments. This means using strong encryption schemes to protect sensitive data from unauthorized access when being transmitted wirelessly, employing countermeasures to indicate jamming, such as spread spectrum technologies and adaptive transmission protocols, and regularly updating hardware and software to combat security loopholes. These are imperative in guaranteeing the reliability and security of agricultural sensor networks, especially due to the susceptibility of extreme environmental conditions and potential cyber-attacks. This enhances the effectiveness and reliability of smart monitoring systems and ensures their subsequent accurate and reliable operation (Li *et al.*, 2022; Lu *et al.*, 2020).

## Soil moisture sensors integrated with wearable plant sensors

A soil moisture sensor is a device used to measure the moisture content of soil. These sensors provide critical data that aid in irrigation management by indicating when and how much water to apply to plants. They play a vital role in optimizing water use,

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**Fig. 6.** Types of soil moisture sensors a: FDR; b: TDR; c: VH400.

improving plant yields, and reducing water waste. There are several types of soil moisture sensors and they include time domain reflectometry (TDR) which provides fast and accurate soil moisture readings but is generally more expensive (Fig. 6b); frequency domain reflectometry (FDR) which allows measurements to be made at different depths in the same location but requires soil-specific calibration (Fig. 6a); Capacitive sensors (e.g., VH400) measure the dielectric constant of the soil, which is related to the moisture content (Fig. 6c). These sensors are known for their fast response and insensitivity to salinity, although the data loggers used with them can be expensive (Garg *et al.*, 2016).

Modern irrigation operations face many problems that affect water use efficiency, such as inefficient water use and labor-intensive monitoring. Irrigation management becomes more complex due to the lack of real-time data and the inappropriate allocation of resources. Solving these problems requires innovative solutions to improve irrigation management, especially using technologies such as machine learning and artificial intelligence. These technologies can increase resource use efficiency, make better decisions, solve environmental problems in agriculture, reduce water waste, and increase plant productivity (Gierz *et al.*, 2024).

## Artificial intelligence applications in irrigation management

AI technologies in irrigation management have been rapidly evolving (Fig. 7), transforming and digitizing the agricultural sector by providing and analyzing real-time data, which helps in making informed decisions (Wei *et al.*, 2024). Using AI-based predictions, applications have been developed to monitor plant health and detect disease outbreaks (Al-Sammarraie and Jasim, 2021; Bondad *et al.*, 2023), as well as to optimize resource use (Ibrahim *et al.*, 2019; Al-Sammarraie *et al.*, 2024). These data-driven approaches allow users to make accurate decisions on planting dates, irrigation methods, fertilization, or pesticide use, to improve plant yields and reduce environmental impact (Ibrahim *et al.*, 2018; Vallejo-Gomez *et al.*, 2023). AI technologies are well suited to handling big data, complementing real-time data capture devices such as sensor or optical capture technologies. Farm managers' goals for using AI in irrigation management include optimizing water use, scheduling irrigation to increase productivity, and reducing labor costs (Asher *et al.*, 2018; Ara *et al.*, 2021).

Drip irrigation systems are a means to reduce water usage as well as precisely control soil moisture content and plant growth (Al-Sammarraie *et al.*, 2021; Klyushin and Tymoshenko, 2021). By monitoring plant development in real-time, AI can assess water usage and adjust drip irrigation systems more efficiently (Graf *et al.*, 2020). Artificial neural network (ANN) assisted irrigation analytics to generate moisture maps that help optimize daily and spatial water usage (Dursun and Özden, 2014). Jayaraman *et al.* (2022) studied machine learning algorithms for water quality improvement. Meanwhile, Kumar *et al.* (2023) estimated soil moisture availability and temporal usage. Parra *et al.* (2020) used AI to predict production efficiency based on irrigation systems in orchards. AI modeling can predict transpiration and optimize water use using weather variables, plant growth conditions, and soil parameters (Chen *et al.*, 2020). Using an Arduino microcontroller, Biswas *et al.* (2021) estimated the amount of water needed using IoT data such as temperature, humidity, soil moisture, and sunlight. This data was sent to a central server to make accurate predictions about future irrigation needs. This facilitated water management practices. Agricultural planning requires accurate estimates of evapotranspiration, which impacts irrigation water planning to increase water use efficiency (Saggi and Jain, 2019). A smart and precise irrigation strategy using IoT to improve water use efficiency in irrigation systems was presented by other authors (Thakur *et al.*, 2020). This method is based on automatically determining soil moisture levels to irrigate the field and provide the required amount of water.

The main benefits of using AI in agriculture are improved irrigation schedules and reduced labor costs. Spatial moisture maps generated using machine learning methods reduce the costs associated with irrigation control systems (Dursun and Özden, 2014). By providing precise irrigation control based on changing conditions, this system can reduce unnecessary irrigation and lower overall operating costs by reducing daily water and energy consumption by up to 38%. Additionally, by automating the climate in greenhouses, the need for labor can be reduced, potentially increasing the profits of the greenhouse sector (Hemming *et al.*, 2020). This shift demonstrates how AI applications can help achieve agricultural sustainability goals while also saving significant resources. Sun *et al.* (2025) developed the PlantRing system, a wearable sensor and AI integration system. It consists of wearable flexible sensors, a wireless communication module, and cloud data analysis software. It is used to accurately monitor plant growth and water status under adverse field conditions to enable improved irrigation strategies using advanced analytics.

To reduce farmers' dependence on agricultural labor and increase plant productivity, the use of AI-based ICT has been of great help (Kumar and Prakash, 2020; Al-Sammarraie *et al.*, 2022). Shen *et al.* (2022) also proposed a method that allows real-time adjustment of irrigation plans and implementation of optimal irrigation schedules, especially in arid and semi-arid regions. The developed model combines irrigation forecasts with a dynamic irrigation system that creates a long-term memory network to adapt to changing conditions. This model showed that winter wheat increased plant yield by 10.3 and 4.4%, respectively, and net profit by 19.1 and 7.4%, respectively, over a 3-year growth cycle.

Fig. 8 shows the various steps required to create a smart irrigation system. The process begins with selecting the sensors needed to

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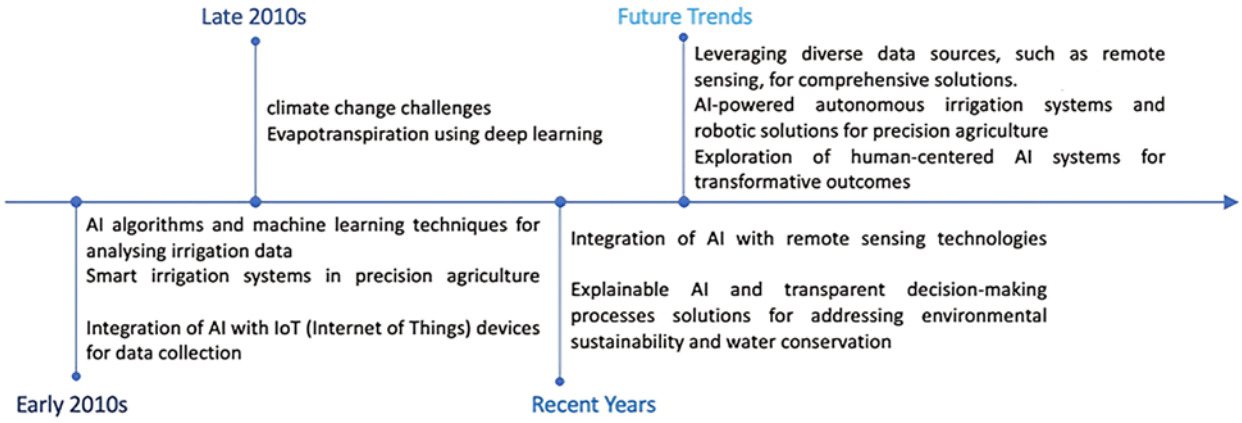



**Fig. 7.** Evolution of AI algorithms and use cases in agriculture over time.

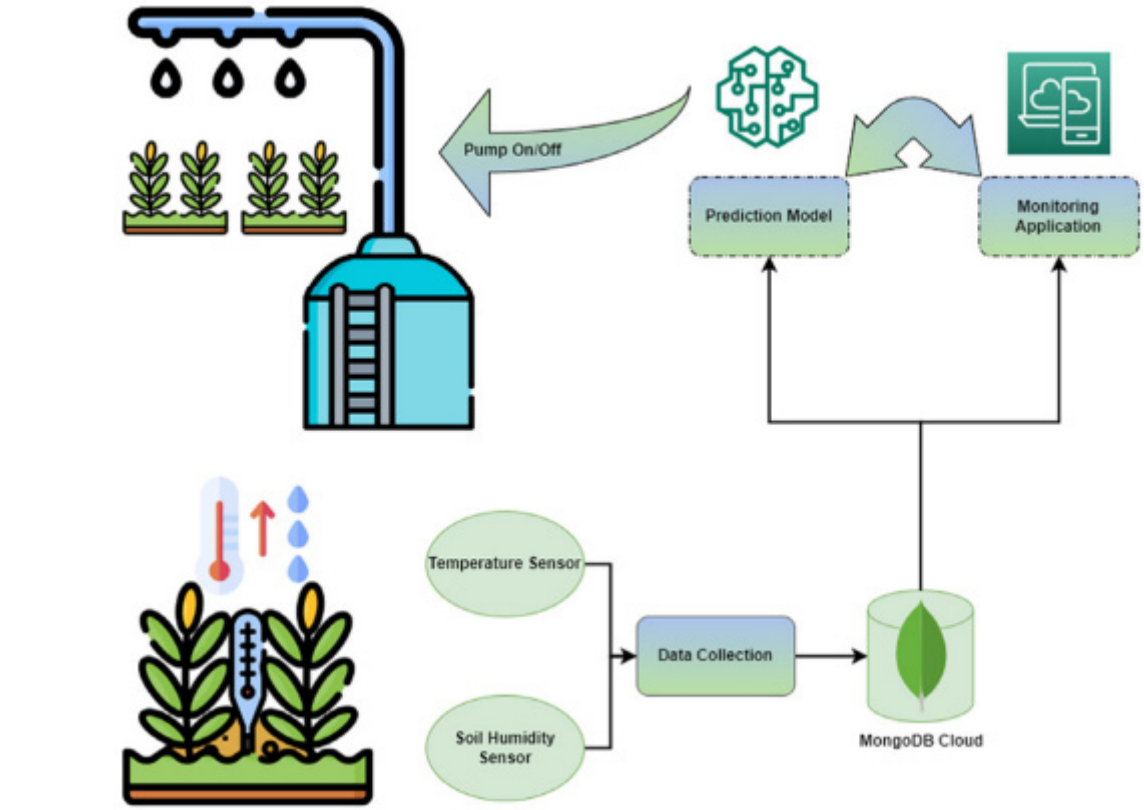



**Fig. 8.** Proposed smart irrigation system.

build the model, where a soil moisture sensor is used to determine the soil moisture level, in addition to temperature, humidity, and rainfall sensors. After connecting these sensors to the Arduino board, the board is programmed to activate the sensors, allowing for the collection and transmission of various data in real-time. In the next stage, the data are stored using Node-Red and MongoDB, where data were collected over several months, which helped train the system to predict when to start or stop pumping. The same methodology can be applied by adding data from wearable sensors to estimate the amount of irrigation required. The smart irrigation system consists of four main components, including a moisture content measurement unit that uses electronic sensors planted in the soil to measure its water content, a receiver that receives and analyzes the data from the measurement units, and an operating program that receives the data and estimates the plants' water needs. Finally, there are smart controllers that monitor weather and soil conditions to automatically adjust the irrigation schedule according to environmental variables (Tace *et al.*, 2022).

The process begins with the installation of ground or wearable sensors on plants or soils, where the sensors take repeated measures of environmental and physiological parameters. The data are transmitted to a local processor or cloud platform through wired or wireless communication technologies. In the cloud platform, the data are processed and analyzed with advanced algorithms for biomarker extraction from the plants and assessing their water status. As per the analysis results, the system makes recommendations or actual instructions to smart irrigation systems to make proactive changes in the amount of irrigation water and timing, thus giving an immediate and efficient response to any

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changes in plant or environmental factors. The system assists in improving water use efficiency, reducing wastage, and optimizing plant productivity, which benefits farmers and enhances food security. It also offers the ability to experience automated and dynamic irrigation control, with remote view capabilities, thus being a feasible and efficient system in various agricultural environments (Tace *et al.*, 2022).

In the end, wearable plant sensors allow it to transition from calendared, traditional irrigation towards data-driven, anticipatory strategies. Based on real-time measurement of plant water status and environmental conditions, these sensors allow early detection of water stress and timely irrigation interventions. With wireless networks and cloud management platforms, they can automate irrigation decisions, reduce water waste, and maximize water use. Field demonstrations have verified that such sensor-based practices can save large quantities of water while maintaining or increasing crop yield, showing a real and working change in irrigation practice made possible by wearable plant sensors (Dong *et al.*, 2023; Yan *et al.*, 2024).

## Conclusions

Using AI to make water use in agriculture more efficient is a strategic move. Using machine learning and big data analytics, farmers can make informed choices that help reduce water consumption and increase agricultural productivity. This integration not only improves environmental sustainability but also helps solve growing climate problems. Results show that combining wearable sensors with AI makes measurements more accurate and provides a better understanding of how much water a water plant needs. These technologies increase agricultural sustainability and reduce waste by reducing water consumption. The ability to continuously monitor environmental conditions allows farmers to make more effective and faster decisions. In addition, the article explains that the use of these technological products in modern agriculture may reveal new ways to improve productivity and reduce environmental impact. The trend towards the use of these innovations indicates a positive shift towards smarter and more sustainable agriculture. While wearable sensors and AI hold high promise in improving water efficiency and agricultural sustainability, they are faced with technical, economic, and social limitations to their widespread adoption. Technically, sensors are not robust against harsh field conditions, whereas AI models are difficult to interpret in a manner that is meaningful for farmers. Economically, the exorbitant cost and lack of training programs are obstacles, especially in rural areas and developing countries. Socially, farmers face resistance to change due to their reliance on traditional methods, coupled with a lack of digital literacy and data protection concerns. To surmount these obstacles, more advanced and user-friendly technologies, financial and technical support, better digital infrastructure, and awareness and training activities to achieve user trust are necessary. This paves the way for smart and sustainable agriculture to meet future challenges.

### CONFLICT OF INTEREST

The authors declare no conflicts of interest.

### ETHICS STATEMENT

The authors confirm that the research meets any required ethical guidelines, including adherence to the legal requirements of the study country.

### AUTHOR CONTRIBUTIONS

All authors contributed to the study's conception and design. The manuscript has been written and finalized by the authors.

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