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Review

Smart irrigation monitoring and control strategies for improving water use efficiency in precision agriculture: A review

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ABSTRACT

The demand for freshwater resources has increased in recent times and has been exacerbated by escalating global population and increasing drought indices in the world's agricultural zones. Irrigated agriculture is inevitably a wasteful water user that has deprived other sectors of the scarce resource. Improving water use efficiency in irrigated agriculture is therefore crucial for sustainable agricultural production to thrive. There is potential to improve water use efficiency through smart irrigation systems, especially with the advent of wireless communication technologies, monitoring systems, and advanced control strategies for optimal irrigation scheduling. This paper reviews state-of-the-art smart monitoring and irrigation control strategies that have been used in recent years for irrigation scheduling. From the literature review, closed-loop irrigation control strategies are efficient than open-loop systems which do not cater for uncertainties. It is argued that combining soil-based, plant, and weather-based monitoring methods in a modelling environment with model predictive control can significantly improve water use efficiency. This review shall help researchers and farmers to choose the best irrigation monitoring and control strategy to improve irrigation scheduling in open field agricultural systems.

1. Introduction

Agriculture is the backbone of most economies in the world as it contributes significantly to the Gross Domestic Product (GDP) and provides food security (World Bank, 2020d). Conversely, agriculture has been regarded as a significant water user sector as it abstracts 70% of the world's freshwater resources to irrigate 25% of the world's croplands (FAO, 2020a, 2017a; Khokhar, 2017). Climate change and increasing population do impose additional pressure to resources, such as water availability, that are vital for agricultural production (Ungureanu et al., 2020). According to the Anon (2019), the world population will hit 9.7 billion by 2050 translating into increased demand for nutritious food and water resources. The Food and Agricultural Organization (FAO) forecasts a more than 50% increase in irrigated food production by 2050, which will require a 10% increase in water abstracted for agriculture, provided water productivity improves (FAO, 2020b). The land on which food is cultivated does not expand, which means agricultural cropping systems need to utilize the available water and land resources efficiently to feed the future population. Understanding the mechanisms that can improve water use efficiency and result in significant water savings and higher yield is therefore paramount.

Water use efficiency in irrigated agriculture is the ratio of estimated irrigation water requirements to the actual water withdrawal (FAO, 2020a). Water use efficiency is dimensionless and can be applied to plant, field, scheme, as well on basin and country scale. Agronomists, however, define water use efficiency in terms of crop yield per amount of water used to produce the yield (Hatfield and Dold, 2019; Sharma et al., 2015; Ullah et al., 2019; and Unver et al., 2017). Water use efficiency has gained significant attention from researchers as water scarcity continues to vary in both space and time across the world due to the effects of climate change (Hess and Knox, 2013). Competition from other sectors of the economy for the scarce water resource has made agriculturalists, irrigation engineers, and policy-makers revisit the way water is used in agriculture. Apparently, state of the-art approaches to water management and systems will need to be adopted to address declining land base and water allocations to meet agricultural

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production needs. Precision agricultural technologies are key in ensuring a higher water use efficiency (Evans and Sadler, 2008).

Precision agriculture is at the centre to shape itself to provide solutions to the overarching problems in agriculture. Yin et al. (2021) described precision agriculture as the "use of technologies that integrate sensors, information systems, enhanced machinery, and informed management to improve production by accounting for dynamics within sustainable agricultural systems". Precision agriculture and smart irrigation, in particular, enables farmers to save precious resources without subjecting plants to moisture deficiency (Pierce, 2010). Smart irrigation involves the application of water at the right time, in the right amounts, and at the right spot in the field (Singh et al., 2019). Therefore, it requires the use of monitoring and control strategies for optimum irrigation scheduling taking into consideration the variation in soil moisture conditions, changing weather patterns, and plant physiological conditions. Conventional irrigation systems apply irrigation water without considering the spatiotemporal variation of soil characteristics and changes in weather variables that affect crop evapotranspiration (Vories et al., 2021). This subsequently leads to spatial variation in the actual depth of irrigation water received by plants. Applying more than required irrigation water results in fertilizer leaching, deep percolation, and surface ponding and runoff while inadequate irrigation may lead to plant stress that may result in a reduction in crop yield and quality.

Implementing an optimised irrigation schedule through a smart irrigation system requires sensors to monitor soil, plant, weather conditions. On the other hand, irrigation control deals with the allocation of inputs and making necessary adjustments according to the crop response to save irrigation water while mitigating the effects of disturbances and uncertainties (Abioye et al., 2020a; Zazueta et al., 2008).

Over the past few years, several survey articles have been published on improving water use efficiency in irrigated agriculture (Chai et al., 2014; Hatfield and Dold, 2019; Howell, 2001; Taheripour et al., 2016; Ullah et al., 2019). Other past reviews have focused on the use of smart technologies like smart sensors, Internet of Things (IoT), Wireless Sensor Networks (WSN) in agriculture (Adeyemi et al., 2017; Hamami and Nassereddine, 2020; Koech and Langat, 2018; Li et al., 2020; Velmurugan et al., 2020; and Zinkernagel et al., 2020). One of the most recent survey papers in the realm of smart irrigation was performed by Abioye et al. (2020b). The authors highlight the application of monitoring and control strategies in precision irrigation. In our opinion, the authors give a valuable start to fellow researchers interested in smart irrigation. However, concerning the application of monitoring and control strategies for water use efficiency improvement, to the best of our knowledge, there appear to be very limited systematic literature reviews. The authors fail to show how monitoring and control strategies water use efficiency in precision agriculture. This review further builds upon existing literature by combining both smart strategies used in monitoring crop water use and irrigation control techniques to improve water use efficiency.

2. Real-time irrigation scheduling

Irrigation scheduling is the decision of when and how much water to apply to the field and thus has a direct effect on water use efficiency (Broner, 2005); and (Koech and Langat, 2018). The quantity of water to be applied is estimated using a criterion to determine the irrigation requirement and strategy to prescribe how much to apply. Efficient application of irrigation water requires an understanding of the dynamics of plant water use, which has a relationship with the weather, soil characteristics, and plant physiology. Efficient irrigation scheduling applies irrigation water at the right time and in the right quantity to optimize production and offset adverse environmental impacts. On the other hand, poor irrigation scheduling results in under-watering or waterlogging which affects water use efficiency (Hassan et al., 2021).

Real-time irrigation scheduling is pertinent in saving water by applying the quantity required to meet plant needs. Several irrigation scheduling tools have been developed to help irrigators apply water precisely to crops (Andales et al., 2019). Growers who do not use any irrigation scheduling tool often rely on their experience to schedule irrigation (Anon, 2010). Recent research has proved that growers who rely on heuristic methods of scheduling like manual, time-based, and volume-based irrigation scheduling register significant water losses (García et al., 2020). An effective real-time irrigation scheduling event requires monitoring of the factors that affect plant growth and a control strategy for the delivery of the right amounts of irrigation water.

3. Monitoring in smart irrigation systems

To improve water use efficiency, it is pertinent to monitor specific factors that influence crop growth and development. Monitoring in the perspective of smart irrigation also entails real-time data collection on the status of soil, plant, and weather parameters cropped area through the use of state-of-the-art communication technologies (Abioye et al., 2020b). The development of a real-time monitoring system involves the integration of sensors with a wireless sensor communication network or IoT framework. Wireless networks are very significant in real-time monitoring for smart irrigation since they have sensing, processing, and transmission capabilities (Hamami and Nassereddine, 2020). The wireless sensor network comprises various sensor nodes connected through a wireless connection module (Hamami and Nassereddine, 2020). Monitoring in smart irrigation can either be soil-based, weather-based, or plant-based monitoring as depicted in Fig. 1.

3.1. Soil moisture monitoring

Soil moisture monitoring involves measuring either the soil water potential or the soil water content, it has been used widely for irrigation scheduling (Delgoda et al., 2016). Monitoring the soil moisture in the plant root zone is important as it helps in understanding the moisture dynamics and its relationship with the volume of irrigation water and plant water uptake. Several options exist for determining soil moisture levels. The direct soil moisture measurement (gravimetric sampling) and indirect methods like eletromagetic property, heat conductivity, neutron count, water potential, and electrical resistance.

With advances in microcomputer and communication technology, varieties of soil sensors for example ground, aerial and satellite moisture sensors are gaining momentum in the suite of irrigation tools (Earth Observation System, 2020a). Soil moisture sensors have a small footprint on the field with sensors at multiple depths, soil moisture dynamics can be captured. Installing the sensors at different depths increases the accuracy and also helps in understanding the changes in soil water content in response to irrigation and crop water use (Soulis et al., 2015). Soil sensors give a wide range of data on the soil's physical, chemical, and mechanical properties taken as optical, radiometric, mechanical, acoustic, electrical, electromagnetic, pneumatic, or electrochemical measurements (Zinkernagel et al., 2020). The measured variables helps in the determination of parameters such as the Maximum Allowable Depletion (MAD) (Li et al., 2020). Detailed descriptions of the functionality of soil moisture sensors and their characteristics can be found in Pardossi et al. (2009); and Pardossi and Incrocci (2011); and Thompson et al. (2017). Fig. 2 presents the most commonly used soil moisture sensors in research and vegetable production.

Determination of spatiotemporal variability of soil moisture content is vital for various applications, this has prompted the development of different measurement techniques over the last years. Soil moisture content is measured as Volumetric Moisture Content (VMC). Soil moisture content sensors infer volumetric moisture content based on changes in the thermal properties or electrical properties of the soil (Peddinti et al., 2020). The electrical-based sensors used to measure Volumetric Moisture Content rely on the propagation of electromagnetic waves in the soil. These sensors fall into various types i.e, Frequency Domain Reflectometry (FDR), Time-Domain Reflectometry (TDR), capacitance,

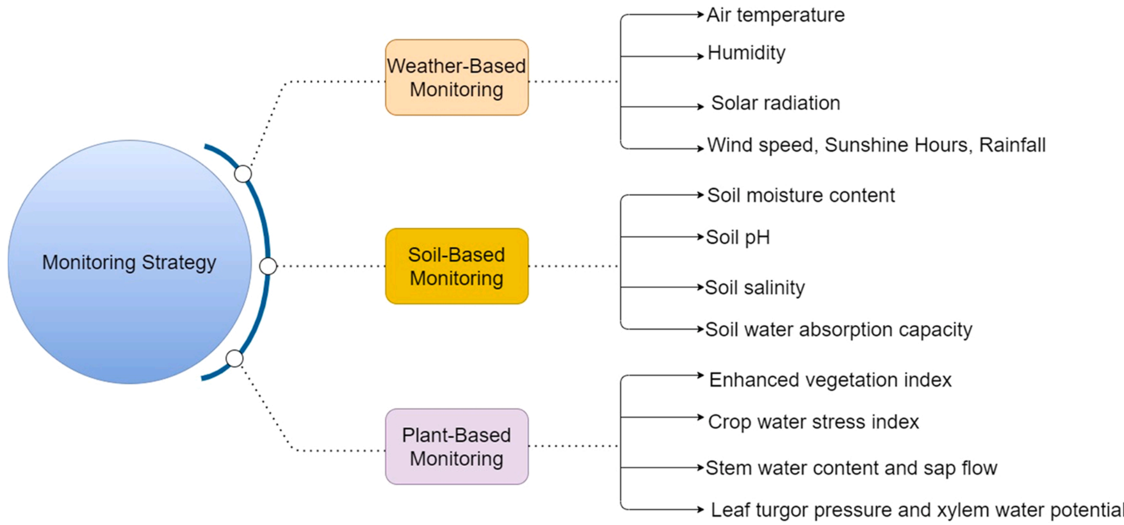

Fig. 1. Monitoring methods in smart irrigation.

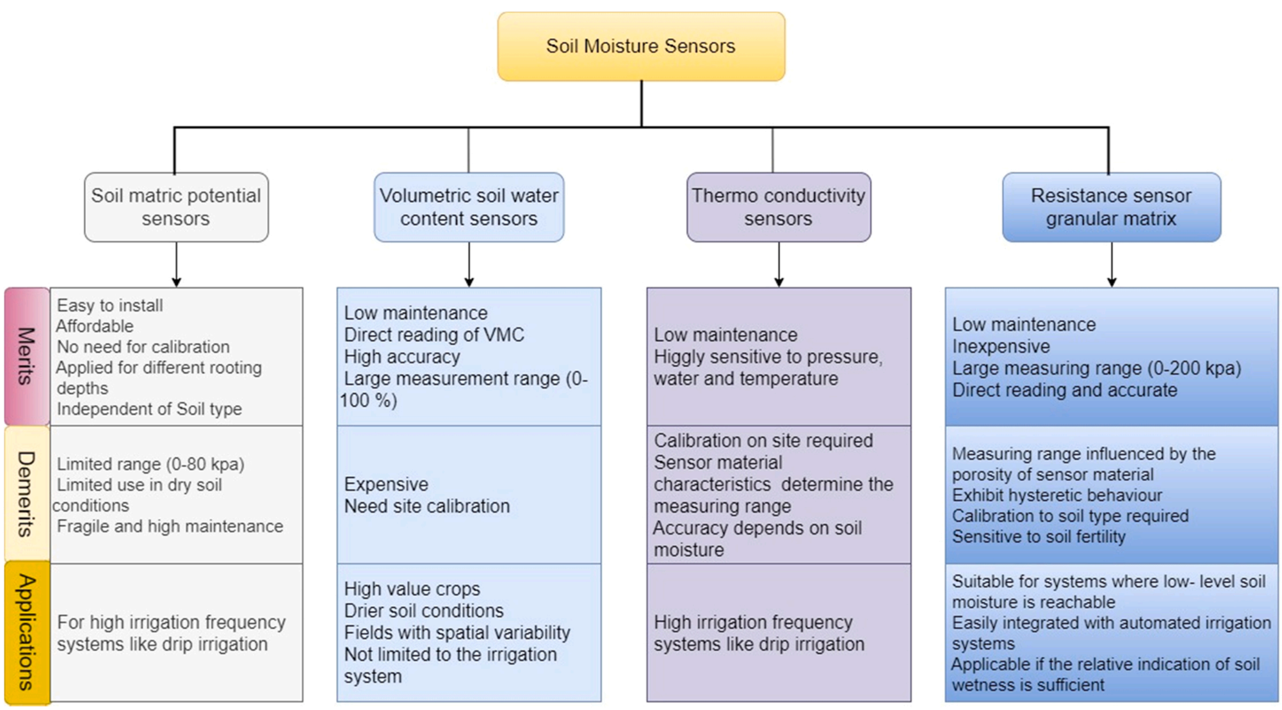

Fig. 2. Soil moisture sensors in research and vegetable production.
Adapted from: (De Pascale et al., 2018; Thompson et al., 2017; Zinkernagel et al., 2020).

and resistance sensors. Frequency Domain Reflectometry sensors are capable of determining the bulk dielectric constant by measuring the frequency variations of an electro-magnetic pulse propagated into the soil (Fertinnowa, 2020b).

Lozoya et al. (2016) used FDR sensors to measure field volumetric soil moisture content. The sensor node was implemented with a low-cost Arduino Mega board based on an ATmega 328 microcontroller. The sensors were placed on crop root level and had a volumetric moisture content range of 0 – 50% with 0.1% resolution. To optimize water use efficiency in vegetables, Yadav et al. (2020) used six (6) capacitance soil moisture-based sensors with a data logger at three (3) locations. The authors programmed irrigation scheduling using upper field capacity and lower thresholds of soil available water. The results revealed an improvement in water use efficiency compared to conventional methods of irrigation scheduling. Domínguez-Niño et al. (2020) reported that using capacitance-type soil moisture sensors combined with FAO's soil water balance model provided a sound basis for automated irrigation scheduling in orchards.

The disadvantage associated with soil moisture-based irrigation scheduling is that plant water uptake and stress does not only respond to the soil water content but also to atmospheric conditions, nutrient availability, root zone salinity, and pest and disease infestation. With variation in soil characteristics, accurate irrigation schedules are established if many representative monitoring sites are established rather than using a single point. Recently, researchers are combining remote sensing with ground sensors to solve the problem of heterogeneity (Ahmad et al., 2021; Babaeian et al., 2019; Klemas et al., 2014).

Liao et al. (2021) in experimenting with a smart irrigation system in a greenhouse using soil moisture sensors used a logic diagram to describe the irrigation scheduling process as shown in Fig. 3.

3.2. Weather-based monitoring

Weather-based monitoring involves real-time estimation of reference evapotranspiration ET using measured weather parameters and thus indicates the water lost by the plants and the soil environment (Abioye et al., 2020b; Adeyemi et al., 2017). The quantity of water lost through evapotranspiration depends on humidity, wind speed, solar radiation, and air temperature. The temporal dynamics of evapotranspiration on hourly or daily timescales is appropriate for determining crop water use in smart irrigation systems. Where soil or plant measurements are not possible, weather parameters are used to give an approximate irrigation schedule (White and Raine, 2008). The FAO Penman-Monteith equation discussed in Allen et al. (1998), presents a procedure for calculating hourly or daily evapotranspiration values using standard climatological measurements of air temperature, solar radiation, humidity, and wind speed. The daily crop water use can then be estimated using Eq. 1.

$$ET_c = K_c * ET_0 \tag{1}$$

Where;$ET_c =$ Crop evapotranspiration (mm day^{-1})K_c = Crop coefficientET_0 = Reference evapotranspiration (mm day^{-1}).

Most real-time weather-based monitoring systems have an automatic weather station with sensors for humidity, temperature, wind speed, rainfall, solar radiation, and atmospheric pressure (Adeyemi et al., 2017). Dataloggers are configured to automatically acquire data at a set interval and the data is then transmitted via a communication system to an online data access portal. The data logger manages communication protocols with the remote server using a WSN or IoT framework. The data is sent to smart irrigation controllers that combine with site-specific variables such as soil type to adjust irrigation schedules (Hydropoint, 2017b). The factors that affect the performance and choice of a weather monitoring system range from robustness, accuracy, installation and maintenance requirements, measurement suite, remote data acquisition, season capabilities, and power requirements.

(Khoa et al., 2019) implemented smart water management in farming using an IoT platform. The authors proposed a novel topology of sensor nodes using affordable and efficient components. With a LoRa LPWAN (Long Range Low Power Wide Area Network) technology transmission module, the authors reported good performance of the system. Similarly, Wasson et al. (2017), used a weather-based monitoring system and transmitted the real-time air temperature, solar radiation, wind speed, and humidity data via a wireless communication standard. Coelho et al. (2020) developed a system for monitoring soil moisture and environmental parameters using the IoT. Data acquisition was carried out employing sensors connected to a micro-controller system, and the signals were transmitted through a radio frequency module using the LoRaWanTM protocol.

Irrigation schedules developed using weather measurements are widely used, however, the soil characteristics often used for estimating soil water volume are based on the soil texture and yet soil structure and organic matter content affect available soil moisture.

3.3. Plant-based monitoring

Irrigation scheduling can be achieved by monitoring the plant-water-status indices. The relationship between crop water stress and soil water deficit makes it possible to estimate irrigation scheduling. The sensitivity of the measurement made to determine water deficit in a plant at a particular crop stage influences the efficiency of plant-based irrigation scheduling (Gu et al., 2020). Jones (2004) classified plant-based monitoring into plant-water-status monitoring which involves direct measurement of leaf, xylem, or stems water potential and plant physiologic monitoring that involves stomatal conductance, thermal sensing, sap flow, and xylem cavitation measurements.

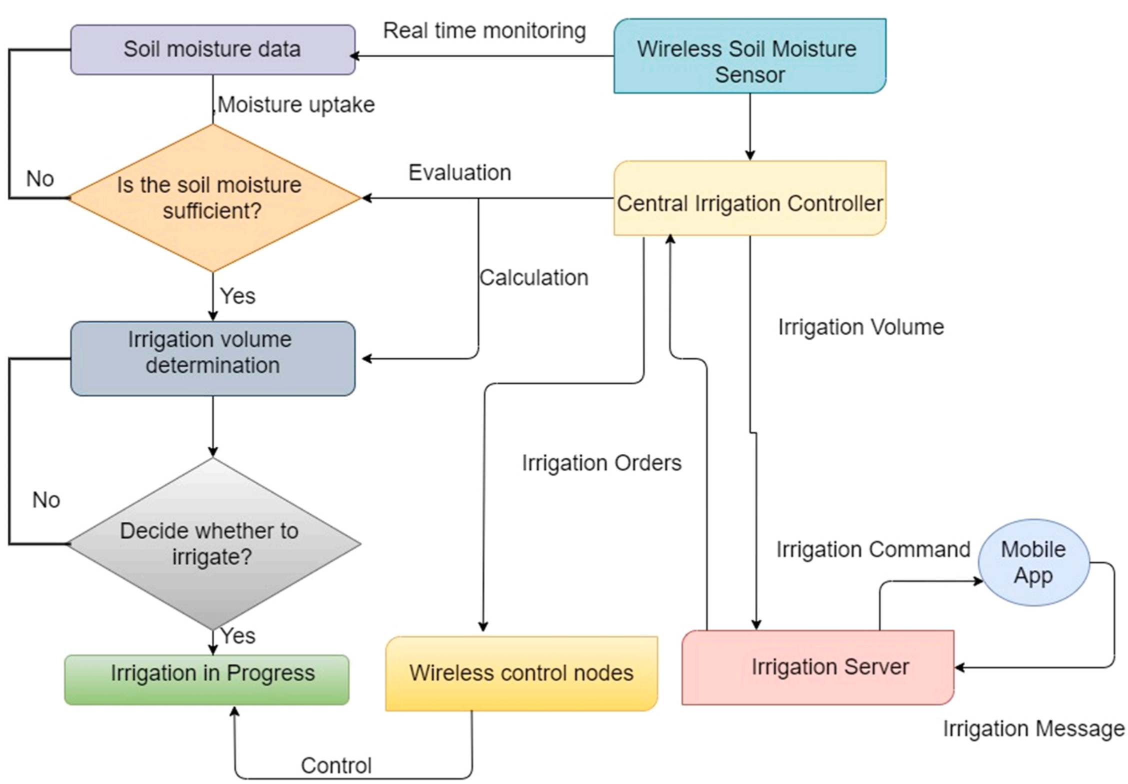

Fig. 3. Soil moisture-based irrigation scheduling.
Adopted from Liao et al. (2021).

3.3.1. Leaf turgor pressure sensors

Leaf turgor pressure sensors detect leaf water stress by measuring relative changes in leaf turgor pressure (Zimmermann et al., 2013). The magnitude of turgor pressure is dictated by rootwater uptake, transpirational water loss and by the celluar osmotic pressure. An example of the leaf turgor pressure sensor is the non-invasive leaf patch clamp pressure probe also know as the ZIM-Probe. The ZIM-probe provides real-time measurements of even minute changes in turgor pressure within leaves (Zimmermann, 2011, 2013). It consists of two stamps that are each equipped with a magnet. One stamp also contains a sensitive pressure sensoring-element, which sends detected pressure changes to the ZIMtransmitter and telemetric unit. The counter stamp contains a screw thread, which enables adjustment of the distance between the two magnets as depicted in Fig. 4. The ZIM-probe has been successfully tested under laboratory, greenhouse and field conditions on a variety of herbaceous and woody plant species (e.g. grapevine, barley, arabidopsis, tomato, tobacco, banana, paprika, wheat, maize, beech, oak, populus, olive, avocado, plum, orange, grapefruit, and eucalyptus).

3.3.2. Leaf thickness sensors

Advances in electronic technologies have enabled researchers to develop small leaf thickness sensors. (Afzal et al., 2017; Seelig et al., 2012) developed tiny leaf sensors and evaluated them on a tomato plant (Solanum lycopersicum) and cowpea (Vigna unguiculata) respectively. Seelig et al. (2012) observed that irrigation timing based on leaf thickness measurements improved water use efficiency by 25–45% compared to the preset irrigation scheduling treatments. Afzal et al. (2017) reported that the daily CAP variations decreased when soil moisture was below the wilting point and completely ceased below the soil volumetric water content of 11%, suggesting that the effect of water stress on CAP was observed through its impact on photosynthesis. The results suggest that leaf thickness and CAP can be used for estimating plant water status. These studies suggested leaf thickness variations as a feasible plant-based method for monitoring water status.

3.3.3. Sap flow sensors

The development of reliable heat pulse and energy balance thermal sensors for sap-flow measurement in the stems of plants has opened up an alternative approach to irrigation scheduling based on measurements of sap-flow rates (Jones, 2004). Because sap-flow rates are expected to be sensitive to water deficits and especially to stomatal closure, many workers have tested the use of sap-flow measurement for irrigation scheduling and control in a diverse range of crops, including grapevine (Jones, 2004). The Dynagage Sap Flow Sensors are the latest technology for measuring the sap flow, and thus the water consumption of plants (Ecotechtonic, 2016). These energy balance sensors measure the amount of heat carried by the sap which is converted into real-time sap flow in grams or kilograms per hour. The sensors are non-intrusive and not harmful since the plants are heated up 1 °C to 5 °C typically. The principles of heat balance sensors are scientifically proven and references exist for most major crops and many tree species. Unlike other methods, Dynagages require no calibration since sap flux is directly determined by the energy balance and rates of heat convection by the sap flow (Dynamax Inc, 2007). The need for this new technology is great because it is an affordable and practical way to measure the water use by plants of agricultural, economic and ecological importance. Plants in greenhouses, nurseries or in natural environments can be measured with the same ease.

Fig. 4. ZIM-Probe (http://www.zim-plant-technology.com).

3.3.4. Xylem cavitation sensors

In transpiring plants, water in the xylem vessels is under tension. This tension is directly proportional to the water deficit to such an extent that the water columns can fracture, or 'cavitate'(Jones, 2004). The cavitation events lead to the explosive formation of a bubble, initially containing water vapour. These cavitation events can be detected acoustically in the audio or ultrasonic-frequencies, and the resulting embolisms may restrict water flow through the stem. Substantial evidence, though largely circumstantial, now indicates that the ultrasonic acoustic emissions (AEs) detected as plants become stressed do indeed indicate cavitation events and that AE rates can be used as an indicator of plant 'stress'.

3.3.5. Stem diameter variation

Stem and fruit diameters fluctuate diurnally in response to changes in water content, and so suffer from many of the same disadvantages as other water status measures. Nevertheless, the diurnal dynamics of changes in diameter, especially of fruits, have been used to derive rather more sensitive indicators of irrigation need, where the magnitude of daily shrinkage has been used to indicate water status, and comparisons of diameters at the same time on succeeding days give a measure of growth rate. Although changes in growth rate provide a particularly sensitive measure of plant water stress, such daily measurements are not particularly useful for the control of high-frequency irrigation systems. Nevertheless, several workers have achieved promising results for low-frequency irrigation scheduling by the use of maximum daily shrinkage (MDS).

New trends in plant-based monitoring involve the use of optical sensors to assess the status of plant water stress, drought, nutrient level, and pest and disease infestation. Optical sensors are broadly classified into contact or non-contact sensors. Whereas contact sensors are physically mounted so that they are in contact with the plant, non-contact sensors are either proximal (handheld, fixed or vehicle-mounted) or remote (aerial and satellite-based data acquisition) (Adeyemi et al., 2017).

Several researchers including Aleotti et al. (2018), Jia et al. (2019), and Uddin et al. (2017) have generated irrigation maps through monitoring vegetation using unmanned aerial vehicles with high-resolution cameras. Similarly, Lozoya et al. (2019) employed spectral reflectance sensors to estimate the health status of the plant in a controlled environment agriculture experiment. The authors found out that the two methods achieved similar spectral results on the health status of the plant, which could be integrated with soil moisture sensing for optimal irrigation control.

The major constraint in the application of plant-based sensors for commercial irrigation scheduling is that they do not provide a direct measurement of the quantity of irrigation water to be applied (White and Raine, 2008). It requires using plant-based irrigation scheduling conjunctively with soil moisture measurement and the soil water balance model.

Table 1 summarizes the monitoring strategies that have been employed in recent years to schedule irrigation.

4. Irrigation control strategies for smart irrigation systems

For irrigation to be sustainable, control strategies that apply irrigation water precisely have to be adopted. An irrigation controller is an essential part of the irrigation system and helps to achieve labour savings in addition to applying the required volume of irrigation water for a specified period leading to high efficiency in water, energy, and fertilizer use (Boman et al., 2018). Irrigation control strategies are divided into open-loop systems and closed-loop systems. While open-loop systems apply a preset action like in simple irrigation timers, closed-loop systems receive feedback from sensors, make decisions and apply the resulting decisions to the irrigation system. Fig. 4 presents a detailed classification of irrigation control strategies derived from literature studies.

4.1. Open-loop irrigation control

In an open-loop system, the operator decides on the amount of water that will be applied and when the irrigation will take place (Boman et al., 2018). This information is then programmed into the controller and the water is applied according to the desired schedule. Open-loop systems are either time-based or volume-based as shown in Fig. 5 (Abioye et al., 2020b). Open-loop systems have a clock that is used to start and stop irrigation events (Zazueta et al., 2008).

Sudarmaji et al. (2019) developed and used time-based automatic irrigation systems for both drip and sprinkler irrigation, the system was found to apply water according to the set time times. Similarly, Montesano et al. (2016) compared time-based irrigation control with soil moisture-based control and reported low water use efficiency with 18% leaching compared to soil moisture-based control in a soil-less lettuce experiment. Since there is no soil moisture and weather monitoring in an open-loop system, sensors are not required. This makes the system inexpensive however with constraints of failing to respond to varying soil and environmental conditions.

4.2. Closed-loop irrigation control

In closed-loop systems, a control strategy for irrigation decisions is developed. Having defined the strategy, the control system takes over and makes irrigation scheduling decisions (Boman et al., 2018). Sensors help to provide feedback to the controller on which the irrigation decisions are based. Feedback and control in a closed-loop system are done continuously and therefore, require data acquired by monitoring devices like soil moisture, air temperature, solar radiation, wind speed humidity, and rainfall as well as system parameters like pressure and flow. In closed-loop control, a decision of whether or not to initiate an action is based on a comparison between the current state of the system and the specified desired state (Boman et al., 2018). Fig. 6 is a schematic presentation of a closed-loop control system.

Closed-loop control strategies are further subdivided into linear control, intelligent control, optimal control, and other control strategies as depicted in Fig. 5.

4.2.1. Linear control

Linear control in closed-loop irrigation is further classified as linear quadratic control and Proportional-Integral-Derivative (PID) control. Proportional integral derivative-based irrigation controllers have been widely used in irrigation research and other industrial applications because of their simplicity, low cost, and extensive control algorithm (Aguilar et al., 2015). "The principle of PID controller is to read a sensor, then compute the desired actuator output by calculating proportional, integral, and derivative responses and summing those three components to compute the output" (National Instruments Corperation, 2020c). Although PID controllers suffer setbacks when faced with external disturbances and non-linear systems, it is more efficient because of its control ability on the actual output of a process.

Lacasta et al. (2014) implemented a decentralized feedback discrete PID controller integrated with the hydraulic model to achieve a reliable complete simulation tool for predictive purposes. The results showed that the PID controllers effectively captured the stochastic phenomena and provided the correct gate movements to obtain the desired water levels. Likewise, Arauz et al. (2020) designed a PI controller for irrigation canals based on linear matrix inequalities. The authors solved an Linear Matrix Inequalities-based optimal control problem to obtain sparse feedback that provided the PI tuning; the results indicated a 30% improvement in PID tuning and were able to satisfactorily control canal water levels. Azar et al. (2020) designed and manufactured a smart irrigation mobile robot with a soil moisture sensor. The authors introduced a simulation analysis of the designed smart irrigation mobile robot by using One-degree-of-freedom (1-DOF) PID controller. The results indicated that the smart irrigation mobile robot produced the desired output parameters.

Nonetheless, classical closed loop controllers such as PID find it hard to control multi-variable and moving processes with time delays (Abioye et al., 2020a, 2020b). Improving the controller performance requires linking feedback paths or cascading several PID controllers. Given the non-linearity of PIDs, there are inadequate gain selections of the control systems. Hybrid fuzzy PID is required for optimal control of irrigation systems. Tuning a PID requires the integration of intelligent algorithms

Table 1
Summary of monitoring strategies for irrigation scheduling.

Monitoring strategy	Characteristics	Key findings/water savings	Reference
Soil moisture sensing	Automatic and precise control of irrigation depth to avoid water leakage or deficiency	30% increase	Liao et al. (2021)
	Commercial nursery, Sprinkler irrigation	50% reduction in irrigation volume	Wheeler et al. (2020)
	Plum crop, drip irrigation	Improved Water savings	Millán et al. (2019)
	Cotton, Open field, Centre Pivot irrigation	Irrigation scheduling was successful, water savings generally improved	Sui (2017)
	Straw berry	58.8% water saving	Guéry et al. (2018)
Weather-based scheduling	Cantaloup plant, greenhouse	30% water savings	Abioye et al. (2021)
	Baby Packchoi production, greenhouse	A good tool for the decision support system to guarantee the crop water requirements are met.	Guo et al. (2021)
	Maize, irrigation scheme	Considering irrigation scheduling, yield and IWP showed very satisfactory results.	Cruz-Blanco et al. (2014)
Plant-Based Scheduling NDVI	Automated greenhouse	NDVI Sensors ensure an optimal irrigation process	Lozoya et al. (2019)
Plant-based scheduling-CWSI Algorithm	Apples	Real-time monitoring of water demand was possible through the adaptive nature of the algorithm, through the use of a dynamic non-stressed threshold.	Osroosh et al. (2015)
Plant-based scheduling	Cotton	10% reduction in irrigation water	Meeks et al. (2020)

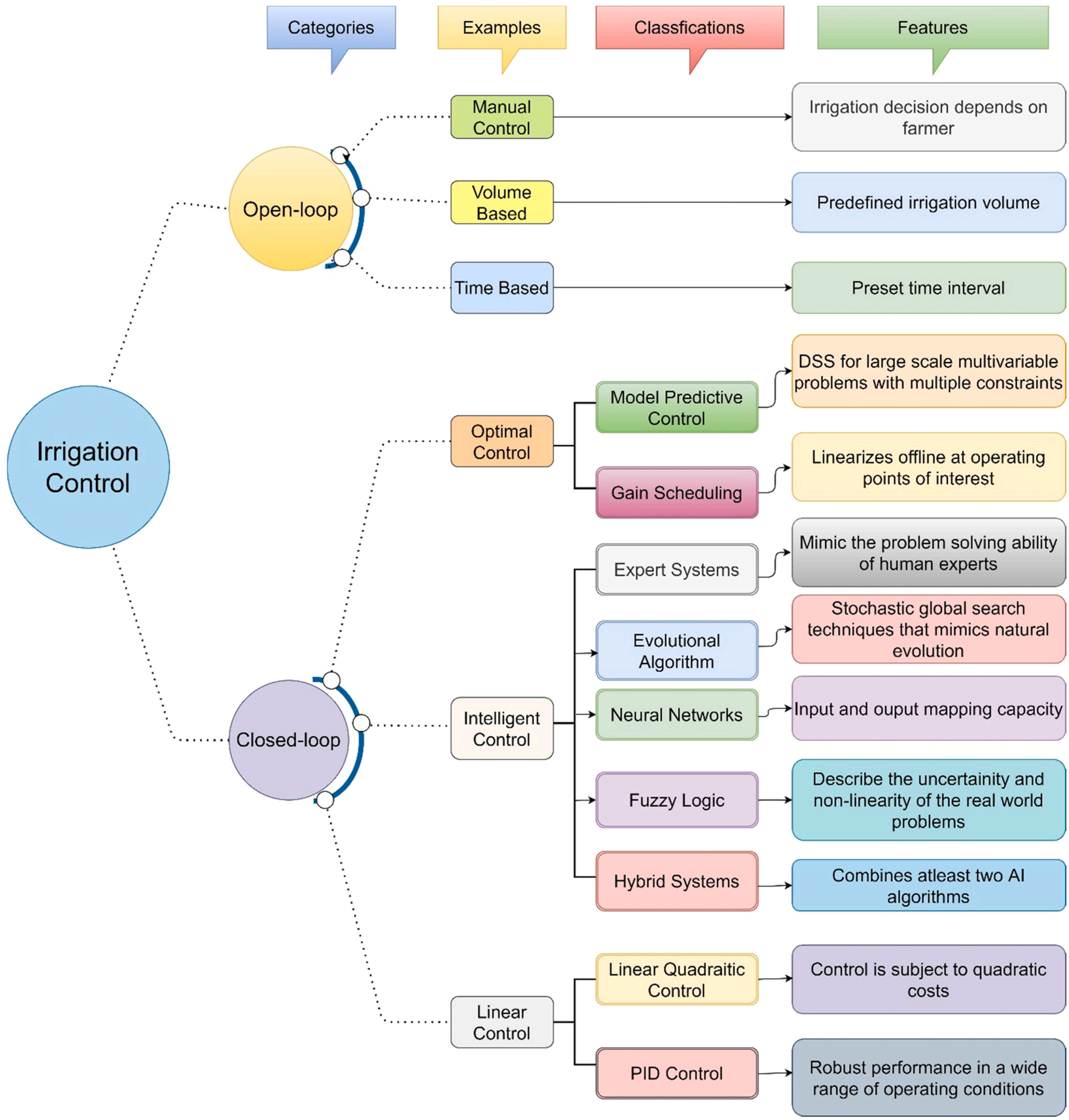

Fig. 5. Classification of irrigation control strategies.
Adapted from (Abioye et al., 2020b; Boman et al., 2018; McCarthy et al., 2013).

such as hybrid fuzzy PID for optimal control of irrigation systems (Chao et al., 2019; Maghfiroh et al., 2020).

4.2.2. Artificial intelligence in closed-loop irrigation

(Mccarthy, 2004) defined Artificial Intelligence (AI) as the science and engineering of making intelligent machines, especially intelligent computer programs. AI is an evolving technology in the agricultural domain. AI-based machines and systems, have taken today's agricultural production systems to a different level. This technology has enhanced crop production and improved real-time monitoring, harvesting, processing and irrigation, and marketing (Talaviya et al., 2020). AI has the capability of solving multivariate, non-linear, and time-variant complex problems affecting the irrigation system. AI algorithms can mimic the human decision-making process when applied to a certain problem domain. AI has been implemented in irrigation systems for adaptive decision-making processes in a form of ANN, fuzzy logic, and expert systems (Adeyemi et al., 2017).

Artificial Neural Network (ANN) is a variation of the machine learning model that resembles the neural network of the human brain (Campos et al., 2020). While synapses connect the neurons in a human brain, in ANN, synapses are replaced by weights and biased connections. This helps to map the relationship between inputs and outputs (Campos et al., 2020). ANN-based controllers have learning and adaptation capabilities to the variable dynamics which makes them suitable for irrigation control systems (Abioye et al., 2020b).

In recent years, various studies have explored the applicability of

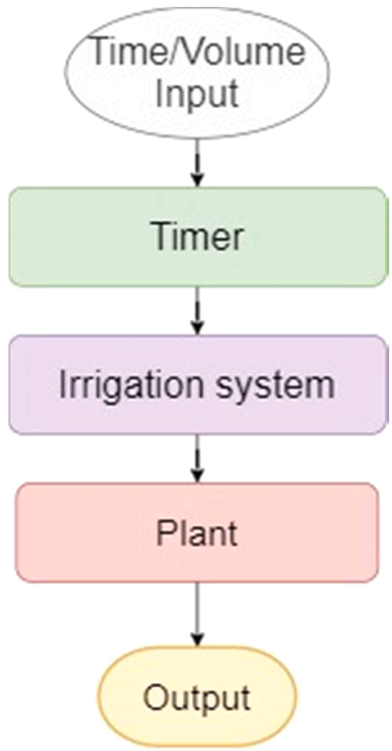

Fig. 6. Block diagram for an open-loop control system.

Artificial Neural Networks in irrigation scheduling. King et al. (2020) used ANN modelling to develop and evaluate data-driven models for predicting the reference canopy temperatures needed to compute crop water stress index for sugarbeet and wine grape. The data-driven models developed by the authors were able to estimate reference temperatures, enabled automated calculation of the crop-water-stress index for effective assessment of crop water stress. Adeyemi et al. (2018) modelled soil moisture content using Dynamic Neural Networks and reported significant water savings in an AQUACROP simulation of a potato growing season. Similarly, Karasekreter et al. (2013) registered 20.5% and 23.9% in water and energy savings when an ANN for scheduling with soil moisture and physical parameter inputs was implemented in a strawberry orchard. The major drawback with ANN systems is that large datasets for ANN model training are required. The accuracy of the ANN-based irrigation scheduling depends on how representative the data is of the physical system and thus data collection using precision instruments needs to be carefully undertaken.

Fuzzy logic-based methodology focuses on decision making by allowing the expression of logical values between true and false and describes the uncertainty and non-linearity of real-world problems (Krishnan et al., 2020). "A fuzzy logic system is made up of a set used to classify input data into membership classes, a decision rule is applied to each set which culminates in a human-like decision output from the system" (Adeyemi et al., 2017). Fuzzy logic has been applied in irrigation control and has been recommended by researchers. For example, Mendes et al. (2019) developed a fuzzy inference system that decided when to increase or decrease the speed of the central pivot by considering the spatial variability of the field. The system was reported to work efficiently. Fuzzy irrigation controllers can accurately calculate the required amount of irrigation water and address the non-linearity associated with the process (Abioye et al., 2020b). Although Fuzzy Logic-based irrigation controllers have been reported by researchers as efficient, the accuracy and performance of the prediction entirely depend on the expertise of the designer about plant dynamics and fuzzy rule formulation.

Another aspect of Artificial Intelligence in irrigation control is expert systems. An expert system is a computer program that uses artificial intelligence (AI) technologies to simulate the judgment and behavior of a human or an organization that has expert knowledge and experience in a particular field (Janjanam et al., 2021). Typically, an expert system incorporates a knowledge base containing accumulated experience and an inference or rules engine – a set of rules for applying the knowledge base to each particular situation that is described to the program. The system's capabilities can be enhanced with additions to the knowledge base or to the set of rules. Current systems may include machine learning capabilities that allow them to improve their performance based on experience, just as humans do. An expert-controlled irrigation system aims to provide farmers with the expertise on how to determine the exact quantity of crop water needed at the right time, weather, and growing medium such as humidity, temperature, and soil types (Nada et al., 2014). Several researchers including (Eid and Abdrabbo (2018); Hazman (2015); Ragab et al. (2018); Shahzadi et al., 2016) have used expert systems for various applications in agriculture. The performance of an expert system is largely dependent on the effectiveness of the knowledge acquisition process. Process errors pose a great threat to expert systems reliability and performance.

4.2.3. *Model predictive control*

Model Predictive Control (MPC) has its roots in optimal control. The principle of MPC is to use a dynamic model to forecast system behaviour and optimize the forecast to produce the best decision-the control move at the current time (Rawlings et al., 2018). Model predictive control is a very flexible optimal control framework based on solving constrained optimal control problems online repeatedly (Mao et al., 2018). MPC has been widely used in modern manufacturing industries due to its ability to handle multivariate processes and to address state and input constraints (Ding et al., 2018; Lozoya et al., 2014, 2016; Puig et al., 2012). In a control problem, the goal of the controller is to calculate the input to the plant such that the output follows the desired reference (Anon, 2018). MPC uses a model of the plant to make predictions about future plant output behaviour and an optimizer that ensures that the predicted future plant output tracks the desired reference (Anon, 2018). Fig. 7 is a schematic presentation of a model predictive control process.

Several researchers such as; Abioye et al. (2021); Ding et al. (2018); Lozoya et al. (2014); McCarthy et al. (2014); Puig et al. (2012); Saleem et al. (2013); and Zhang et al. (2015) have used Model Predictive Control strategies in irrigation scheduling in controlled environment agriculture. MPC has shown better performance in controlling air temperature in greenhouses compared to Proportional Integral Derivative control. However, the applications in irrigation are still minimal with many studies stopping at the simulation phase, and thus the impact on water use efficiency and water productivity is not known. More so, the MPC methods often used are Classical and Improved MPC. There is a need to evaluate stochastic and Hybrid MPC strategies for efficient irrigation scheduling in open-field agriculture. There are many uncertainties and unpredictable disturbances from the environment exist unlike in a greenhouse environment. A summary of irrigation control strategies as used in irrigation are presented in Table 2.

5. Opportunities for improving water use efficiency in open field smart irrigation systems

The need to improve water use efficiency in irrigated agriculture has gained serious attention from researchers in recent years. This is because agriculture has been reported to be a significant water user sector and yet spatiotemporal water scarcity indices are on the rise leaving little or no water for agricultural production. Producing more crop per drop requires that soil and weather parameters are precisely monitored and irrigation scheduled to meet the crop water demand. Commercial automated irrigation systems offered by major irrigation companies are programmed to irrigate at time intervals for predefined periods, and it is usually based on the user's empirical knowledge of crop needs, soil

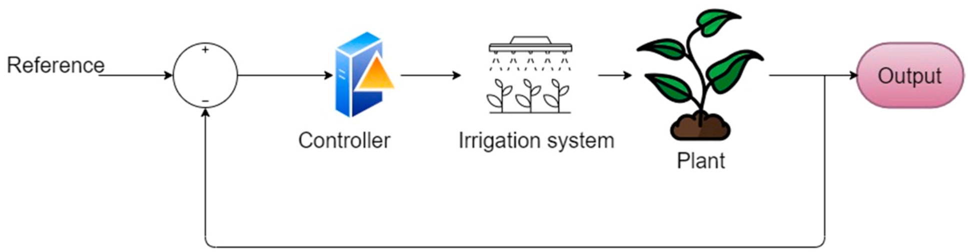

Fig. 7. Block diagram for a closed-loop control system.

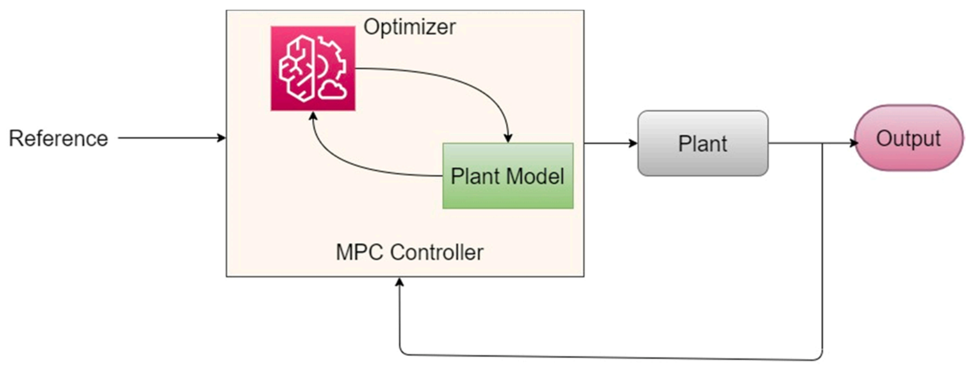

Fig. 8. Schematic presentation of a model predictive control process.

Table 2
Irrigation control strategies used in recent studies.

Crop	Scale	Control strategy	Findings	Reference
Strawberry (*Fragaria ananassa*)	Poly-tunnel	Proportional-Integral Derivative	Potential to match water requirements to the water supply while responding to solar radiation levels.	Goodchild et al. (2015)
No crop	Lab setup	Proportional-Integral Derivative	Ability to reduce water wastage	Sheikh et al. (2018)
No crop	Lab setup	Proportional-Integral	PID Smart irrigation mobile robot performed as expected with forward and circular motions.	Azar et al. (2020)
Cow peas (*Vigna unguiculata*)	Open field	Fuzzy Logic	Obtain a higher level of accuracy to expertly use water for irrigation	Krishnan et al. (2020)
Faba bean (*Vicia faba*)	Open field	Expert system	Optimum irrigation schedule for Faba bean crop.	Hazman (2015)
Onion (*Allium cepa*) Cabbage (*Brassica oleracea*)	Open field	Time-based	The system can supply water continuously for the plants at a particular time.	Sudarmaji et al. (2019)
Lettuce (*Lactuca sativa*)	Greenhouse	Time-based, sensor-controlled	Improved weight and quality of lettuce, less irrigation water used.	Montesano et al. (2016)
Soy (*Glycine max*), cotton (*Gossypium*), corn (*Zea mays*)	Open field	Fuzzy logic	Fuzzy logic can solve uncertainties and non-linearities of an irrigation system and establish a control model for high-precision irrigation.	Mendes et al. (2019)
Sugarbeet,(*Beta vulgaris*) Grapevines (*Vitis vinifera*)	Openfield	Artificial Neural Network	Neural network models with one hidden layer with four neurons for sugar beet and five neurons for wine grape provided excellent predictions of well-watered canopy temperature.	King et al. (2020)
Rice *(Oryza sativa)*	Open field	Artificial Neural Networks	The proposed model was able to predict the timing and quantity of irrigation water	Sidhu et al. (2020)
No crop	Irrigation canal	Gain Scheduling	Controlling a multi-pool canal system.	Bolea and Puig (2016)
Mustard leaf*(Brassica juncea)*	Greenhouse experiment	Model Predictive control	Accurately approximated the behaviour of discrete-time linear quadratic regulator based controller and resulted in 30% water savings	Abioye et al. (2021)
Green Pepper *(Capsicum annuum Group)*	Open field	Model Predictive Control	Achieved a higher control efficiency and significantly reduced the control effort	Lozoya et al. (2014)
Apples*(Malus domestica)*	Open field	Grey box Model Predictive Control	Model performed satisfactorily	Delgoda et al. (2016)
Maize(*Zea mays*)	Open field	Evolutionary Algorithms	Algorithms can solve the deficit irrigation problem with excellent results.	De Paly and Andeas (2009)
Maize(*Zea mays*)	Open field	Evolutionary Algorithms	An efficient tool for planning irrigation schedules by considering crop water needs.	Belaqziz et al. (2014)

characteristics, and weather factors. Some farmers use either soil moisture-based scheduling or weather-based scheduling. These methods have been reported to save water. Consequently, closed-loop-based feedback control strategies have been proposed for smart irrigation as opposed to open-loop systems which are characterized by over and under irrigation.

Several studies have developed process dynamics models on which closed-loop irrigation schedules are based (Delgoda et al., 2016; Ding et al., 2018; Goodchild et al., 2015; Lozoya et al., 2016; Lozoya et al., 2019; Saleem et al., 2013; Karasekreter et al., 2013; Ragab et al., 2018; Zhang et al., 2015). The system dynamics estimated and formulated in these studies are based on the soil water balance model without capturing the dynamic nature of weather, soil characteristics, and plant water use. Capturing weather and plant water use dynamics ensures that all disturbances to the system are well incorporated in the algorithm which improves the accuracy.

Therefore, there is a need to address this gap by developing a mathematical model that incorporates the dynamics of soil moisture content, weather, and crop growth parameters obtained from a combination of weather, soil, and plant sensors in open field experiments. A novel irrigation control strategy based on a hybrid model predictive control needs to be evaluated in an open field irrigation environment and the resulting water use efficiency and water productivity determined.

6. Conclusions

In this manuscript, a review of smart irrigation monitoring and control strategies for improving water use efficiency in precision agriculture has been presented. The review has been developed around monitoring strategies for irrigation scheduling and irrigation control techniques. In addition, a discussion on opportunities for future research based on research gaps has been established. In this regard, it is concluded that a combination of weather-based, soil-based, and plant-based monitoring strategies coupled with a discrete model predictive control strategy needs to be studied in an open field environment. Unlike controlled environment agriculture research, open field agricultural irrigation systems are faced with uncertainties that need to be studied. Future research will thus focus on developing process dynamics models for irrigation scheduling and establishing the effects of smart monitoring and control strategies on water use efficiency and water productivity in open field agricultural systems.

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Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Author contributions

Conceptualization, E.B.; Methodology, E.B.; Formal analysis, E.B.; Investigation, E.B.; writing – original draft preparation, E.B.; Writing – review and editing, F.K.A, G.K.A. .; Visualization, F.K.A.; Supervision, F. K.A, G.K.A. .; Project administration, F.K.A; Funding acquisition, F.K.A, G.K.A. All authors have read and agreed to publish the manuscript.

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