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How much is enough in watering plants? State-of-the-art in irrigation control: Advances, challenges, and opportunities with respect to precision irrigation

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With a rapidly expanding global population placing an ever growing demand on freshwater resources, an increased focus on irrigation techniques tailored to the specific needs of plant appears as one solution to minimize overall freshwater consumption. Precision irrigation methods seek to realize an acceptable compromise between yield and irrigation water consumption through control of the timing and quantity of water supplied to plants. The goal is to maintain the water content of the soil, achieve specific water use efficiency with regard to yield or maintain the physiological response of the plant to water stress within predetermined limits. Reliance on soil moisture measurements to establish irrigation water demand inadequately addresses heterogenous distribution of water in soil. Growing research interest is observed detailing the determination of plant water status directly from physiological responses. This paper reviews irrigation control approaches based on different plant water status assessment techniques. A distinct focus is made on application scale of the discussed control approaches, an aspect that has not been considered intensively enough in previous discussions of irrigation control approaches. A discussion of the observed strengths and shortcomings and technological advances supporting the various methods used to quantify plant water status extends the review. Emerging trends that are likely to have an impact on plant water status determination and optimal timing and quantification of irrigation water requirements are integrated to show latest results. A peek into the future of precision irrigation foresees greater reliance on plant-based signals, both in characterization of the control variable, namely the plant water status, and in generation of controller outputs in terms of quantity and timing.

KEYWORDS

precision irrigation, irrigation control, deficit irrigation, water status, irrigation management, industry 4.0

1 Introduction

As the world advances further into the 21st century, a rapidly growing global population continues to exert greater demand on agricultural food production (van Dijk et al., 2021). The effects of climate change provide an additional challenge to traditional rain- and reservoir-based crop production, making the case for use of irrigation either exclusively throughout the growing season, or as a supplement to natural precipitation (Wada et al., 2013; Rosa et al., 2020). Maintaining crop yields from the available land area, using a diminishing quantity of the required freshwater for irrigation is a delicate balancing act that has acted as a motivation for extensive research in precision irrigation approaches, with the overall goal of maximizing water use efficiency of irrigated crops, while simultaneously meeting the rising global food demand.

While water treatment and desalination provide alternatives to cover the freshwater need, existing techniques are costly and energy intensive, particularly at low to medium scale (Arborea et al., 2017; Hagenvoort et al., 2019; Arena et al., 2020; Oubelkacem et al., 2020; Ofori et al., 2021). Concerns about the safety of treated wastewater, even with application of advanced treatment methods, have resulted in a call to more rigorous regulation and combination of treatment processes (Rizzo et al., 2020). Freshwater generation *via* atmospheric water harvesting (Tu et al., 2018; Lu et al., 2022) offers a novel, but energy intensive alternative which is currently limited to smaller production units (LaPotin et al., 2021). As a conclusion optimization of crop irrigation appears to be the most suitable solution to achieve a sustainable compromise between increasing freshwater demand for food production and the associated energy and environmental costs to realize adequate global food supply.

In the history of mankind, adequate food production has been a fundamental requirement in the growth and advancement of human society. As early as 5000 BC, early agricultural civilizations in Egypt and Mesopotamia had come upon the idea of expanding the extent of arable land through use of irrigation, making use of the floodwaters of the Nile, Tigris, and Euphrates which was diverted into arable farmlands bordering the rivers through an extensive network of canals (Bazza, 2007). Through the use of intricate systems of canals, with later additions of reservoirs, dikes, and overflow canals, flooding could be mitigated (Grenfell et al., 1900; Westermann, 1919). Similar implementation of surface irrigation was also recorded in ancient China, Crete, India, and Persia (Biswas, 1970). Irrigation control in this case was focused on direction of irrigation water to specific locations, regulation of irrigation duration and mitigation of flooding. Surface irrigation methods involving use of flooded basins, furrows, dykes, dams, and artificial reservoirs remain the predominant form of irrigation to date (Jägermeyr et al., 2015). Control methods aimed at more efficient use of irrigation water have been targeted at regulating the timing, duration, and frequency of supply to the fields through control of gates, sluices, valves, and pumps.

Introduction of new methods of water application to plants in the field, namely through sprinklers and drip lines, provided new opportunities for more accurate control of irrigation water supply, allowing the regulation of water supply down to the individual plant level. These developments on the actuation side of irrigation have been accompanied by corresponding developments in sensing and control approaches.

The incorporation of spatial variability in the management of irrigation is a key concept in distinguishing between traditional irrigation and precision irrigation (Sadler et al., 2005; Smith and Baillie, 2009). In Smith et al. (Smith et al., 2010), a distinction is made between traditional definitions of precision irrigation, which focus on maximizing efficiency through precise determination of volume, location and timing of irrigation, with uniform application over the entire system, and an updated definition that incorporates spatial and temporal variation in irrigation treatment. The focus is shifted from field level to management zones within the field (Gonzalez-Dugo et al., 2014; Fernández, 2017), or to individual plant level (Kizer et al., 2018; Klein et al., 2018). Camp et al. describe precision irrigation as "site-specific water management, specifically the application of water to a given site in a volume and at a time needed for optimum crop production, profitability, or other management objectives at that specific site" (Camp et al., 2006). In this review, the supporting technologies are considered with regard to their flexibility in allowing variable precision irrigation of individual plants or zones, rather than achieving efficiency through generation of uniform irrigation schedules.

Traditional definitions of precision irrigation consider the "precise amount" of water to be applied to be the full amount of water required to meet the plant demand, which has commonly been determined based on the relationship between crop evapotranspiration and environmental factors (Morillo et al., 2015; Morales et al., 2016). Current irrigation practices that explore the cultivation of irrigated crops under regulated water deficit provide a new Frontier for precision irrigation, where the required amount to be delivered is determined with a goal of avoiding irreversible water stress damage, without necessarily fully matching evapotranspiration-based plant demands. This provides further avenues for improvement of water use efficiency. Deficit irrigation-based applications of precision irrigation approaches have been employed in control of both pre- and post-harvest yield quality (Pérez-Pastor et al., 2007; Lipan et al., 2019; Venturi et al., 2021). The observed effect of deficit irrigation approaches on crop maturation (Zegbe-Domínguez et al., 2003; Cui et al., 2008) is an additional research target, with the possibility to enhance economic outcomes for the farmer by matching harvest timing to periods of greatest market demand. In this review, precision

irrigation control approaches incorporating regulated water deficit are emphasized.

Previous contributions in the review of precision irrigation approaches have addressed model-based and sensor-based monitoring (Adeyemi et al., 2017; Liang et al., 2020; Plaščak et al., 2021; Bwambale et al., 2022), specific control algorithms applied in irrigation scheduling (Romero et al., 2012; Abioye et al., 2022), and technological advances supporting future development in precision irrigation control (Neupane and Guo, 2019; Bodkhe et al., 2020; Han et al., 2020). This review similarly provide a comprehensive summary of monitoring, control, and actuation approaches applied in precision irrigation control. Additionally, the implementability of deficit irrigation-based strategies for increased water use efficiency is addressed, allowing the extension of achievable water savings thus contributing to sustainable expansion of global food production without exhausting available freshwater resources.

2 Precision irrigation control approaches

Control techniques are broadly classified as open or closed loop, defining the existence of any kind of calculated or otherwise technically realized feedback (output to the input of the system considered). Open loop precision irrigation control relies on an accurate understanding (in the best case: a model) of plant water requirements, while closed loop methods include sensing mechanisms to dynamically adjust the control input to the irrigation system based on measured values.

The performance of precision irrigation control approaches depends on the definition of plant water requirements. The characterization of plant water demand and the subsequent responses to the water application is described in Kögler (Kögler and Söffker, 2017) along a soil-plant-atmosphere continuum. This paper similarly groups approaches in precision irrigation into soil-based, plant-based, and atmosphere-based approaches. Further distinction is made between approaches targeted at enhancing precise delivery at field level, within irrigation management zones and at individual plant level.

2.1 Soil-based approaches

Growing plants obtain water required for their growth from the soil. The soil moisture content has therefore been applied as a measure of the water status of the plant, with a plant-specific lower limit describing the minimum moisture content required to maintain the plant above wilting point (Briggs and Shantz, 1911) and a soil-specific maximum water holding capacity, also referred to as the field capacity (Veihmeyer and Hendrickson, 1931). The main goal of traditional irrigation methods is to maintain soil moisture content at field capacity during the growth phases, with scheduling of irrigation events based on plant growth models such as FAO Aquacrop (Steduto et al., 2009) or multivariable models simulating soil moisture, plant growth, and evapotranspiration such as DSSAT (Hoogenboom et al., 2019).

Model-based predictive control approaches applied in precision irrigation allow the integration of soil moisture models in a predictive control scheme, which allows forecasting of moisture content and update of control actions based on measured variables. Spatial and temporal variability is accounted for using regression models (Hedley C. and Yule I., 2009), a predictive model with weekly measurement-based updates performing online optimization (Nahar et al., 2019), employment of Kalman filters (Roy, 2014), and application of deep belief networks and macroscopic cellular automata, with dynamic environmental measurements providing additional data for prediction (Song et al., 2016).

The learning capabilities of neural networks allows the adaptation of plant growth models for the design of precision irrigation controllers. Specific neural-network based approaches allow online updating of control decisions based on measured real-time conditions, resulting in more accurate behavior. These capabilities are utilized by Capraro et al. (Capraro et al., 2008) in the development of an adaptive closed loop controller that allows for modification of control actions when environmental perturbations such as rainfall or extreme temperatures cause a change in irrigation requirements. Long short term memory neural networks are employed for prediction of soil moisture content (Adeyemi et al., 2018) or soil matric potential Jimenez et al. (2020) with varying performance, both in terms of water savings and prediction accuracy. These are attributed to soil characteristics and duration of the prediction window. Difference in performance of neural network-based predictive models are also reported by (Gu et al., 2021), with larger estimation errors observed at lower soil moisture content levels, affecting performance of the precision irrigation scheduling system.

A major challenge in the use of model-based methods for precision irrigation is that the control performance is limited by the accuracy of prediction or estimation achieved by the model. Incorporation of soil moisture data into irrigation management decisions offers a significant performance improvement in soil-based precision irrigation approaches. Sensor readings have been used to calibrate and refine model output, as described in (Tseng et al., 2018), where soil moisture measurements are used in labelling images acquired from an unmanned aerial vehicle for training a deep learning-based predictive algorithm. Conversely, application of predictive models can be integrated in sensor-based control approaches to reduce the quantity of sensor readings required to make an accurate assessment of soil water content, as proposed in (De Benedetto et al., 2013b) and (Andugula et al., 2017).

Soil-based closed loop control methods integrate soil moisture measurements in the control loop. On/off switching algorithms triggered by designated soil moisture sensors with preset static thresholds have been employed in precision irrigation control by Xiao et al. (Xiao et al., 2010). Use of dynamic switching thresholds allows real-time response to field conditions, with the adaptation of the thresholds accomplished in Capraro et al. (Capraro et al., 2008) by neural networks, and numerical simulation employed by Egea et al. (Egea et al., 2017). An alternative approach involves placement of sensors at varying depths to track infiltration rate, allowing anticipatory switching (Benzekri and Refoufi, 2006; Zhao et al., 2007; Liu and Xu, 2018).

Development of a large variety of soil moisture sensors with greater accuracy and reliability has facilitated the precision control of irrigation based on real-time conditions. A major challenge to implementation of sensor-based control approaches has been the unit cost of sensors, which limits the economic viability of field scale application of appropriately accurate and precise sensors. New low-cost soil moisture sensors have been developed in recent times based on sensing approaches commonly used in commercially available sensors, including frequency domain reflectometry (FDR) (Xiao et al., 2010), time domain reflectometry (TDR) (Wei et al., 2013), impedance spectroscopy (Umar and Setiadi, 2015), and capacitance-based methods (Kojima et al., 2016; Gao et al., 2018). Novel approaches in the measurement of soil moisture content have also been developed in recent times, such as a time-domain multiplexing approach described in Saeed et al. (Saeed et al., 2019) and a high frequency double-resonance tuning approach developed by Qinglan et al. (Qinglan et al., 2020). Ding and Chandra introduce a Wi-Fi-based measurement system that relies on radio-frequency propagation (Ding and Chandra, 2019). Development of more precise calibration techniques and incorporation of fault detection mechanisms generates an opportunity for improvement of measurement accuracy and flexibility of application in both novel and existing soil moisture sensors (Oates et al., 2016; Chen L. et al., 2019; González-Teruel et al., 2019; Nagahage et al., 2019). Additionally, dynamically variable irrigation thresholds based on plant growth requirements can be incorporated through calibration based on plant measurements. This is employed in Lou et al. (Lou et al., 2016) to generate a set of soil potential thresholds that allows precision irrigation through different plant growth stages.

Location and distribution of moisture sensors within the field has traditionally relied on expert knowledge from manufacturers or farmers. Approaches for optimizing the spatial distribution of soil moisture sensors for improved mapping of water content include use of clay percentile (Zhao W. et al., 2017), analysis of soil elevation maps combined with measurement of electrical conductivity (Adamchuk et al., 2010), and application of graph-theoretical methods (Roy, 2014).

Field level precision irrigation based on soil moisture content relies on accurately modeling and/or measurement of soil water dynamics, incorporating the effects of precipitation, irrigation, leaching, run-off, and drainage to establish the moisture available within the root zone of the plant. Precision irrigation control approaches are therefore employed primarily to address accuracy of moisture content measurement and monitoring, and the scheduling the timing and quantity of field-level irrigation events. Remote sensing techniques capable of extracting soil moisture characteristics with increasing precision and more frequent intervals is a key factor in the further development of soil-based precision irrigation at field level. Electromagnetic surveys have been applied in (Hedley et al., 2013) to assess the spatio-temporal dynamics of soil moisture and water table depth for precision irrigation control. Satellite data are also used to determine the soil water index, which is used as an indicator of soil moisture content (Termite et al., 2019).

Zone level precision irrigation relies on accurate demarcation of the field into homogeneous management zones based on physical and chemical characteristics of the soil (Bazzi et al., 2018; de Lara et al., 2018; Chen S. et al., 2019). Integration of plant-related measurements to complement soil sensor measurements has been explored in (Rojo et al., 2016; Ortuani et al., 2019; Vera et al., 2019; Serrano et al., 2020) for better zone delineation as a means to increasing irrigation efficiency. Recent research investigates the adoption of Bayesian maximum entropy (Han et al., 2020) and clustering approaches (Haghverdi et al., 2015; Oldoni and Bassoi, 2016; Ohana-Levi et al., 2019; Javadi et al., 2022) for achievement of optional zoning. To address challenges arising from static management zone delineation based on spatial characterization, dynamic determination of zone boundaries has been explored with integration of real-time soil and plant sensor measurements (Scudiero et al., 2018; Fontanet et al., 2020) or use of deep learning approaches (Song et al., 2016).

With regard to the current status of soil-based precision irrigation control approaches summarized in Table 1, it can be stated that the maintenance of soil moisture level between a user-defined lower boundary related to the wilting point and an upper boundary defined by the soil water capacity has been employed as the basis for control decisions. Challenges related to soil water dynamics arising from inherent hydraulic characteristics or changes in the spatial envelope defining root-available water have been addressed. Optimization of location and distribution of soil moisture sensors to allow accurate mapping of soil moisture distribution while minimizing the required number of sensors is a potential area for further work in the implementation of sensor-supported soil-based precision irrigation control. Variations in the upper soil moisture boundary during scheduling of irrigation quantity has not been considered in literature, signifying a gap in the application of soil-based precision irrigation methods to deficit irrigation strategies. Additionally, a significant gap

TABLE 1 Summary of soil-based precision irrigation control approaches.

Author	Year	Sensing/Measurement			Application scope			Modeling/Control approach
		Soil	Plant	Atm	Field	Zone	Plant	
Adeyemi et al.	2018	x		x	x			MPC with NN-based prediction
Andugula et al.	2017	x				x		Gaussian process regression
Bazzi et al.	2019	x				x		Fuzzy C-means algorithm
de Benedetto et al.	2018	x			x			Kriging with external drift
Benzekri and Refoufi	2006	x		x	x			Anticipatory on/off control
Capraro et al.	2008	x				x		on/off control with dynamic thresholds
Chen et al.	2020					x		Genetic algorithm
Egea et al.	2017	x			x			on/off control
Gu et al.	2021	x		x	x			NN-based on/off control
Hedley and Yule	2009	x				x		Daily prediction of soil water status
Jimenez et al.	2020	x			x			LSTM neural network
Liu and Xu	2018	x					x	On/off control
Lou et al.	2016	x	x		x			On/off control
Nahar et al.	2019	x		x	x			MPC with closed loop scheduling
Roy	2014	x			x			MPC with stochastic receding horizon
Song et al.	2016	x		x	x			Deep belief network (DBN)
Termite et al.	2019	x		x	x	x		Feedforward NN; ANFIS
Tseng et al.	2018		x		x		x	Deep convolutional neural network
Wei et al.	2013	x			x			On/off control
Xiao et al.	2010	x			x			on/off control
Xiao et al.	2010	x			x	x		on/off control
Zhao et al.	2007	x			x			On/off, Time control and fuzzy hybrid control

exists in soil-based approaches applied at individual plant level. Advancements in the field of wireless sensor networks, remote sensing and machine learning approaches are expected to drive future developments in soil-based precision irrigation control, allowing for more localized decision support systems and greater adaptability to individual plant water requirements.

2.2 Atmosphere-based approaches

Atmosphere-based precision irrigation control approaches involve balancing the water supplied to the plant with the water released to the atmosphere through evapotranspiration. Achievement of the high accuracy required in precision irrigation is either accomplished by refining evapotranspiration models for use in open loop control or by incorporation of sensor feedback in closed loop control.

Common models of evapotranspiration incorporated into precision irrigation include FAO's Penman-Monteith model (Allen, 1998; Fourati et al., 2014; Robinson et al., 2017; Pereira et al., 2020), the Hargreaves-Samani model (Hargreaves and Samani, 1985; Gordin et al., 2019; Pelosi et al., 2019; Domínguez-Niño et al., 2020) and the Surface Energy Balance model (SEBAL) (Bastiaanssen et al., 1998; Gobbo et al., 2019). Both the Penman-Monteith and Hargreaves-Samani models generate an estimated reference evapotranspiration rate, which is multiplied by a crop-specific coefficient to predict the actual evapotranspiration rate of the crop. The Hargreaves-Samani model provides a simpler approach due to its ability to provide an estimate based solely on temperature values, as compared to the Penman-Monteith approach, where several environmental, geographic and soil-related variables are required. Better temporal stability in evapotranspiration prediction accuracy using the Hargreaves-Samani approach has also been reported in (Lorite et al., 2015), making it a more reliable option for control approaches integrating longer prediction windows. The SEBAL approach directly computes the actual evapotranspiration rate from thermal imagery without requiring specific soil- or crop-related coefficients, making it more readily applicable to new or inadequately researched crop varieties for which physiological coefficients are yet to be established.

Machine learning approaches have more recently been applied in estimation of evapotranspiration, and hence plant water requirements, based on weather data (Sidhu et al., 2020; Farooque et al., 2021). Linker et al. use temperature forecasts to

TABLE 2 Summary of atmosphere-based precision irrigation control approaches.

Author	Year	Sensing/ Measurement			Application scope			Modeling/Control approach
		Soil	Plant	Atm	Field	Zone	Plant	
Barker et al.	2018			x		x	x	VRI with remote sensing-based water balance model
Bhatti et al.	2019			x				satellite and airborne imagery-based VRI
Dominguez-Nino et al.	2020	x		x		x		model-predictive control (IRRIX software)
Farooque et al.	2021			x				deep learning model-based ET prediction
Fourati et al.	2014	x		x	x	x		FAO56 ET model-based on/off control
Gobbo et al.	2019	x		x		x		VRI with dynamic zone delineation
Gordin et al.	2019	x		x	x	x		Hargreaves-Samani ET model-based on-off control
Incrocci et al.	2014	x		x		x	x	Soil moisture-based vs. ET-based automated drip irrigation
Linker et al.	2018			x	x			MPC with real-time multi-objective optimization
Lorite et al.	2015			x	x			weather forecast-based on/off irrigation control
Lozoya et al.	2016	x		x	x	x		model-predictive control with soil moisture measurement
Ma et al.	2017	x		x	x			weather forecast-derived ET-based deficit irrigation
Pelosi et al.	2019		x	x	x			calibrated Hargreaves-Samani for ET modeling
Robinson	2017			x	x	x		plant-specific Penman-Monteith model-based control
Roy	2014	x		x	x	x		stochastic receding horizon approach
Sidhu et al.	2020			x	x			Regression-based on/off scheduling
Tsakmakis et al.	2016	x		x	x	x		interoperable model coupling for irrigation scheduling (IMCIS)

estimate evapotranspiration values, which are applied in precision scheduling of irrigation to achieve targeted optimal combinations of yield and irrigation amount selected by the farmer (Linker et al., 2018). Estimation of evapotranspiration using remote sensing data is employed in Barker et al. (Barker et al., 2018) for variable rate irrigation control. In Ma et al., the Root Zone Water Quality Model is calibrated using lysimeter measurements for estimation of plant evapotranspiration, which is then applied in irrigation scheduling (Ma et al., 2017). The authors suggest further improvement of irrigation scheduling by inclusion of weather forecasting data. Improvements in water use efficiency are observed in this case. However, due to the implementation of an open-loop control, real-time evapotranspiration values play no role in the decision-making, making the system susceptible to environmental variations. For greenhouse-based applications (Incrocci et al., 2014), developed a data-driven evapotranspiration model for precision irrigation control, achieving a 45% reduction in seasonal water use.

An alternative atmospheric-based approach relies on prediction of precipitation rather than evapotranspiration (Roy, 2014; Tsakmakis et al., 2016). Roy introduces a stochastic weather forecasting module for predicting precipitation (Roy, 2014) using publicly available weather forecasts. Tsakmakis et al. use a weather prognostics model based on the air pollution model (Hurley, 2005), which predicts precipitation by solving given scalar equations. Irrigation scheduling is adjusted based on predicted timing and quantities of precipitation.

Hybrid approaches combining ET estimation with soil moisture sensing (Lozoya et al., 2016; Nocco et al., 2019; Bhatti et al., 2020) or plant-based methods (Tsakmakis et al., 2016; Gobbo et al., 2019) have also been used to achieve greater accuracy in precision irrigation control. These allow compensation of weather-related disturbances to the evapotranspiration model by integrating the dynamic behavior of soil moisture or of the plant. However their reliability depends on the accuracy of crop coefficients used in determination of actual evapotranspiration.

A major challenge in atmospheric-based precision irrigation approaches arises from the difficulty in differentiating between evaporation (from the soil surface) and transpiration (from the plants), requiring dynamic adjustment of irrigation control algorithms as plant cover increases during the growth season. A recent approach described by Chen et al. (Chen et al., 2020) involves the partitioning of evapotranspiration values into its two components through machine learning techniques. This could provide a key to achieving greater accuracy in precision irrigation control, allowing the focusing of water delivery to meet actual plant demand rather than maintaining constant soil moisture levels, including in areas where no plant growth is present. A summary of existing atmosphere-based control approaches is provided in Table 2.

2.3 Plant-based approaches

To alleviate the gaps inherent in soil-based and atmospheric-based precision control approaches, plant-based precision irrigation control has been widely seen as the best approach in accurately determining and meeting plant water requirements (Jones, 2004). The timing and quantity of irrigation is based on the plant physiological response to lack of water, which results in changes in leaf surface temperature, water potential, or turgor (Ayars and Phene, 2007).

Canopy temperature-based crop water stress indices (CWSI), both based on theoretical (Idso et al., 1981) and experimental models (Jackson et al., 1981) have been employed in irrigation scheduling since the early 1980s. Due to their reliance on canopy temperature measurements taken at a specific time of day (typically midday), they are constrained in their adaptability to dynamically varying stress conditions. Applications of CWSI in precision irrigation control are described in O'Shaughnessy et al. (O'Shaughnessy et al., 2012b), where a cumulative time threshold is incorporated in the determination of irrigation timing, and in Osroosh et al. (Osroosh et al., 2015), where a dynamic threshold is implemented to account for changes in water stress thresholds at different growing stages. A recent approach described by Andrade et al. (Andrade et al., 2018) is the implementation of machine learning algorithms for forecasting of crop water stress indices based on historic data.

Advancements in canopy temperature measurements have contributed greatly to the development of plant-based precision irrigation approaches. High resolution satellite thermal images have been used for mapping of plant water stress levels for site-specific irrigation scheduling, with the capability to replace locally obtained leaf water potential (LWP) measurements (Meron et al., 2010). At a local level, thermal imagery obtained from unmanned aerial vehicles (UAVs) (Gonzalez-Dugo et al., 2013; Martínez et al., 2016; Matese et al., 2018) or all-terrain vehicles moving within the irrigated field (Gutiérrez et al., 2018) has been used in mapping of plant water requirements for generation of irrigation management zones. At plant level, surface temperature sensors mounted on individual leaves have been applied to allow continuous monitoring of stress status (Rojo et al., 2016; Kizer et al., 2018).

Determination of plant water status by measurement of water potential in a pressure chamber was first described by Dixon and Joly in 1895 (Dixon and Joly, 1895). Various approaches have been developed for determination of water potential, with measurements taken either from the leaves or from the stem (SWP). Water potential measurement is done either directly on the plant (Mirás-Avalos et al., 2016; Blanco-Cipollone et al., 2017) or estimated from multispectral imagery (Baluja et al., 2012; Zhao T. et al., 2017; Beeri et al., 2018; Helman et al., 2018; Tung et al., 2018). Precision irrigation control approaches based on use of plant water potential-based thresholds for triggering of irrigation events are described by (Acevedo-Opazo et al., 2010; Bellvert et al., 2015; Mirás-Avalos et al., 2016) and (Ruiz-Sánchez et al., 2018). The application of machine learning approaches enables integration of historical water potential measurements to predict spatial variations in water requirements, as described in (Pôças et al., 2020). An alternative method involves the use of water potential thresholds as the standard for calibration of other measurement approaches, such as trunk diameter shrinkage and growth rate (Livellara et al., 2011). Near infra-red spectroscopy measurements have also been applied in precision irrigation control, as described by (Diago et al., 2018).

Water is required for the maintenance of turgor pressure in plants. Plant water status can therefore be monitored or measured through measurement of turgor. Developments related to leaf turgor measurements and potential application in precision irrigation are described in (Martínez-Gimeno et al., 2016; Rodriguez-Dominguez et al., 2019). A novel approach employing ultrasonic sensing techniques for determination of leaf water content as related to turgor pressure is described in (Álvarez-Arenas et al., 2016), allowing for non-contact application of turgor-based precision irrigation control.

Other emerging methods of assessing plant water status that could provide useful feedback for precision irrigation control include measurement of leaf thickness (Seelig et al., 2011), trunk diameter (Conejero et al., 2011; Meng et al., 2017), leaf reflectance (Katsoulas et al., 2016) and various applications of image analysis (Hendrawan and Murase, 2009; Chen et al., 2018; Mateo-Aroca et al., 2019; Xu et al., 2020). The demarcation of irrigation management zones based on plant-based sensors is also a potential area of exploration (Bazzi et al., 2018), allowing the realization of zone-based irrigation control that better matches the plant water requirements.

In general, while plant-based approaches (summarized in Table 3) provide the closest match to plant water requirements, there still exist open questions regarding the determination of appropriate irrigation quantity, the distinguishing of physiological responses to water stress from other stresses, and the dynamic adaptation of irrigation control to account for physiological coping mechanisms employed by plants in response to water stress.

The interaction between the soil, plant and atmosphere provides a broad spectrum of combinations for precision irrigation control approaches. Selection of a suitable approach depends on the specific soil, plant and environmental characteristics under consideration, as well as the desired scale of application. While significant progress has been made in development of field-level and zone-based precision irrigation applications using all three approaches, there remains a significant gap in plant-level precision irrigation control, which has the potential to further improve the efficiency of irrigation water supply to meet actual plant demand.

TABLE 3 Summary of plant-based precision irrigation control approaches.

Author	Year	Sensing/ Measurement			Application scope			Modeling/Control approach
		Soil	Plant	Atm	Field	Zone	Plant	
Acevedo-Opazo et al.	2010		x	x			x	SWP-based regulated deficit irrigation
Andrade et al.	2018	x	x	x		x		ANN-based model predictive control
Bellvert et al.	2015		x			x		regulated deficit irrigation with dynamic management zones
Blanco-Cipollone et al.	2017		x	x			x	deficit irrigation with on/off control and static thresholds
Gonzalez-Dugo et al.	2013		x		x	x	x	canopy-air temperature differential-based CWSI thresholding
Gutierrez et al.	2018		x	x	x			reduced error pruning tree-based VRI
Kizer et al.	2018		x	x	x			CWSI- and stem water potential-based VRI
Livellara et al.	2011		x	x			x	variable rate drip irrigation
Martinez et al.	2016		x	x	x		x	IR image-based deficit irrigation
Matese et al.	2018	x	x		x			stem water potential-based on/off control
Meron et al.	2010	x	x			x		inverse distance-weighted interpolation of CWSI data
Miras-Avalos et al.	2016	x	x	x	x			SWP-based regulated deficit irrigation
O'Shaughnessy et al.	2012	x	x		x	x		CWSI- and time threshold-based on/off control
Osroosh et al.	2015	x	x	x	x	x	x	adaptive on/off control with dynamic threshold
Pocas et al.	2020		x		x			Bayesian and Tree-based regression algorithms
Rojo et al.	2016	x	x			x		unsupervised fuzzy classification-based VRI
Ruiz-Sanchez et al.	2018	x	x			x	x	Takagi-Sugeno-Kang fuzzy inference system
Tung et al.	2018		x			x	x	Modified partial least squares regression-based LWP modeling

3 Advances in precision irrigation

The development of precision irrigation control has benefited from technological advances in various fields. In this section, the technological advances contributing to precision irrigation control are discussed under three main categories: sensor development and data acquisition, data processing and control approaches, and actuating devices. Specific elements of Industry 4.0 are directly addressed in each section.

3.1 Advances in sensing

3.1.1 Remote sensing

Greater availability of satellite data has provided a significant boost to integration of remote sensor data in precision irrigation applications. The soil moisture and ocean salinity (SMOS) satellite (Kerr et al., 2010) launched by the European Space Agency and the soil moisture active and passive (SMAP) (Entekhabi et al., 2010) satellite by NASA have in particular been instrumental in furthering research on remote measurement and monitoring of soil water content. Drought assessment using soil water deficit indices derived from SMOS Martínez-Fernández et al. (2016) and SMAP (Zhu et al., 2019) enables the tracking of changes in soil moisture content over time, enabling precision irrigation management. In (Brocca et al., 2018), satellite data are used to quantify amount of irrigation water supplied at various sites, demonstrating the potential of applying remote sensing data to monitoring and control tasks associated with precision irrigation. The challenge of downscaling regional scale satellite data for local application, such as in precision irrigation, is presented in (Peng et al., 2017), with a discussion of satellite-based, geoinformation-based, and model-base approaches. A key limitation of microwave satellites is that soil moisture information describes the surface condition rather than root zone characteristics. The Global Land Evaporation Amsterdam Model (GLEAM) (Martens et al., 2017) provides a set of algorithms allowing estimation of root-zone soil moisture and evaporation from satellite data, allowing for incorporation into precision irrigation strategies. Termite et al. (Termite et al., 2019) describe the harnessing of machine learning capabilities in analysis of satellite imagery to predict soil moisture dynamics for application in irrigation decision support systems.

3.1.2 Wireless sensor networks

Advancements in wireless sensor network technology have led to improved collection and analysis of sensor data for high resolution mapping of soil moisture (Zhao et al., 2007; Xiao et al., 2010; Hedley et al., 2013). Real-time communication between sensors, actuators, and human users is easily achievable over locally available telecommunications

infrastructure and interfaces can be implemented on mobile hand-held devices (Işık et al., 2017). An expansion of sensor networking has seen the rise of Internet-of-Things-based sensing applied for monitoring of plant water requirements, whether *via* soil-based, atmosphere-based, or plant-based measurements (Vasisht et al., 2017; Goap et al., 2018; Munir et al., 2018). Integration of wireless sensor networks has also found application in dynamic delineation of irrigation management zones for zone-based precision irrigation control in Sapna et al. (Sapna et al., 2020).

3.2 Advances in data processing and control

3.2.1 Big data

The vast quantities of data generated from networked sensors generate a need for expanded processing and storage capabilities. In this respect, cloud computing approaches provide a viable solution, finding application in monitoring of real-time irrigation status (López-Riquelme et al., 2017; Vaishali et al., 2017) and modeling of plant water requirements for soil-based (Raikar et al., 2018; Mezouari et al., 2020), plant-based (Roopaei et al., 2017), and atmosphere-based (Bendre et al., 2015) precision irrigation control approaches. Data analysis techniques applied on Big Data applications are also proving beneficial in management of precision irrigation control systems (Zhang et al., 2017).

3.2.2 Machine learning and artificial intelligence

Machine learning involves generation of self-modifying or adapting algorithms whose performance accuracy increases with experience (Marsland, 2014). Machine learning techniques have been crucial in development of dynamic control approaches through integration of learning capabilities. Applications in the area of precision irrigation are primarily in predictive modeling of soil moisture dynamics (Hinnell et al., 2010; Adeyemi et al., 2018) and optimized irrigation scheduling (Jimenez et al., 2018; Murthy et al., 2019). Recent research involves application of Machine learning algorithms to identify new parameters that can be employed in characterization of plant water content, primarily through image analysis (Hendrawan and Murase, 2009).

3.2.3 Multi-agent systems

Multi-agent systems expand the capabilities of artificial intelligence by introducing multiple autonomous intelligent agents capable of interacting with each other. Multi-agent systems have been employed in simulation of plant growth response to multiple irrigation strategies, allowing the selection of optimal precision irrigation approaches for specific conditions (Isern et al., 2012; Belaqziz et al., 2013; Zaryouli et al., 2020). With the incorporation of real-time sensed variables describing plant response to water application, multi-agent systems have additionally been proposed for dynamic tuning of irrigation scheduling algorithms (Villarrubia et al., 2017; Wanyama and Far, 2017; González-Briones et al., 2019), allowing for constant adaptation of water supply to plant needs. Further research in incorporation of artificial intelligence in plant-based precision irrigation control could be useful in enabling further individualization of plant water requirement estimation, resulting in precision irrigation control applications that more closely meet individual plant needs.

An emerging field in precision irrigation control is the modeling of irrigation-related parameters using hybrid automata. Here, plant, soil, and atmosphere-related parameters are modeled using finite state-machines, with individual states described using simple linear models, enabling the modeling and control of complex dynamic systems, as described in Lozoya et al. (Lozoya et al., 2019) and Jihin et al. (Jihin et al., 2019). Future work in this area would involve integration of the generated plant models in precision irrigation control algorithms, with the aim of predicting plant water requirements and adaptively adjusting irrigation scheduling based on plant response.

3.3 Advances in actuation

Delivery of irrigation water involves control of suitable individual or combinations of pumps, valves, gates, and drip lines through connected actuators in the form of motors, mechanisms, and/or linkages. To ensure that the required amount of irrigation water is delivered in a timely manner to the required location, improvements at the delivery end play a significant role. A common unifying factor is uniform supply of irrigation water, with precision control approaches mainly concerned with on/off switching of actuators to accomplish scheduling and determine irrigation quantity.

3.3.1 Variable rate irrigation

The achievement of precision irrigation requires variable delivery of water to different locations, based on localized requirements. The development of variable rate irrigation is described in Mulla and Khosla (Mulla and Khosla, 2015) as one of the major contributors to the widespread adoption of precision agriculture. In variable rate irrigation, the amount of water delivered by individual nozzles or groups of nozzles is independently adjustable, allowing for delineation of a field into different irrigation management zones. This is a widely used approach in cases where variations in scheduling or frequency of irrigation for different zones within the field may not be desired. Implementation of variable rate irrigation has been achieved by a number of researchers through modification of commercially

available sprinkler irrigation systems to supply preset quantities of water under the control of a programmable system (McCann et al., 1997; Camp et al., 1998; Chávez et al., 2009) or development of new systems with variable rate irrigation capabilities (Han et al., 2009). With hardware capable of supplying different amounts of water, precision irrigation control is transformed into a zoning/mapping operation, with regions requiring similar quantities of irrigation water (based on soil properties or plant requirements) clustered together. Delineation of irrigation management zones has been accomplished through measurement of soil properties at different locations within the area under irrigation to generate databases that are used to determine location-specific irrigation settings (Hedley C. B. and Yule I. J., 2009; Chávez et al., 2009; Moral et al., 2010; Nahry et al., 2011; Liakos et al., 2015; Boluwade et al., 2016). Aggregation of on-site sensor measurements with satellite data to develop decision support and zone management systems for use in precision irrigation control is described by multiple researchers as well (Zhang et al., 2009; Jiang et al., 2011; De Benedetto et al., 2013a; Barker et al., 2018).

Variable rate irrigation approaches relying on characterization of soil properties for zoning result in generation of prescription maps for precision irrigation applications. Such approaches, however, fail to respond to the dynamics of plant water requirements. Recent approaches incorporate plant-based measurements to dynamically update zoning maps generated from soil properties. O'Shaughnessy et al. use real-time plant water stress readings taken during irrigation events to dynamically update the zoning maps used for precision irrigation control (O'Shaughnessy et al., 2012a). In Goumopoulos et al., a wireless sensor network integrating measurements from soil, plant, and atmosphere is applied in generation of irrigation management zones and used for control of a wireless actuator network for precision irrigation within a greenhouse (Goumopoulos et al., 2014).

3.3.2 Agricultural robots

Introduction of robotic agents in automation of irrigation water delivery is an emerging area of research interest. With appropriate path planning and field preparation, greater flexibility in geographical location of irrigation heads is achievable, and the role of such robots is easily expandable to include multiple functions, such as sensing of soil and plant characteristics, collection of samples, and delivery of agricultural chemicals. Jafari et al. introduce an autonomously guided vehicle for relocation of sprinkler heads within an irrigated field (Jafari et al., 2013). The replacement of manual labour with robotic actuation improves on accuracy and speed of irrigation, as well as minimizes wastage of water. Gealy et al. develop a hand-held robotic device used for fine-tuning emitter settings in a modified drip irrigation system (Gealy et al., 2016). Water delivery can be set to match individual plant requirements by adjustment of flow settings at each emitter. Thayer et al. introduce a routing algorithm to allow a similar robotic device for precision adjustment of emitter settings to operate autonomously within a vineyard (Thayer et al., 2018). Developments in collaborative robotics provide further opportunities for integration of robotic actuation in precision irrigation. Dusadeerungsikul et al. (Dusadeerungsikul et al., 2019) discuss the development of a collaborative control protocol which integrates robotic agents into a smart greenhouse to create a cyber-physical system that includes human and robotic agents. The described system primarily serves a monitoring and detection role with response provided by human operators. The system however is an indicator of the potential application of collaborative robots in a precision irrigation scenario, whether in sensing or actuation.

Current research involving collaborating robotic fleets, otherwise described as swarm robotics, is an emerging area of interest that could further influence future developments in precision irrigation control. The scalability, flexibility, and robustness in solution of complex tasks could be employed in tailoring precision control decisions to allow more individually adapted irrigation on larger scale (Albani et al., 2017). This is facilitated by having specialized functions distributed among a larger number of robots, which can then be deployed as and when needed with coordinated communication (Emmi et al., 2014). Of particular interest are swarms composed of aerial and ground robots, which could integrate airborne sensing capabilities with ground-based application tasks, allowing real-time, closed-loop precision irrigation control (Grassi et al., 2017; Vu et al., 2017; Potena et al., 2019).

4 Challenges and opportunities

Irrigation control has primarily been targeted at minimization of water consumption at the expense of yield, or maximization of yield at the expense of water consumption. Research on the effect of targeted water stress during specific growth periods however indicates that it is possible to achieve equivalent or even greater yield while reducing water consumption through strategic alternation of moderate drought stress and recovery periods (Blum et al., 1990; Cui et al., 2009; Niu et al., 2018). With the ongoing depletion of global freshwater supplies, minimization of water consumption will remain an overarching target of precision irrigation, with advancements in technology increasingly targeting more efficient use of every applied drop of water. An emerging Frontier that presents interesting research questions is the individualized direct control of plant growth and development by targeted application of environmental stresses, such as is accomplished through deficit irrigation. This has been suggested in various research works (Hunt and Nicholls, 1986; Kang and Wang, 2017; Sánchez-Blanco et al., 2019). Kögler and Söffker compare such targeted growth control based on precise irrigation sequencing to sports training (Kögler and Söffker, 2020). Development of more

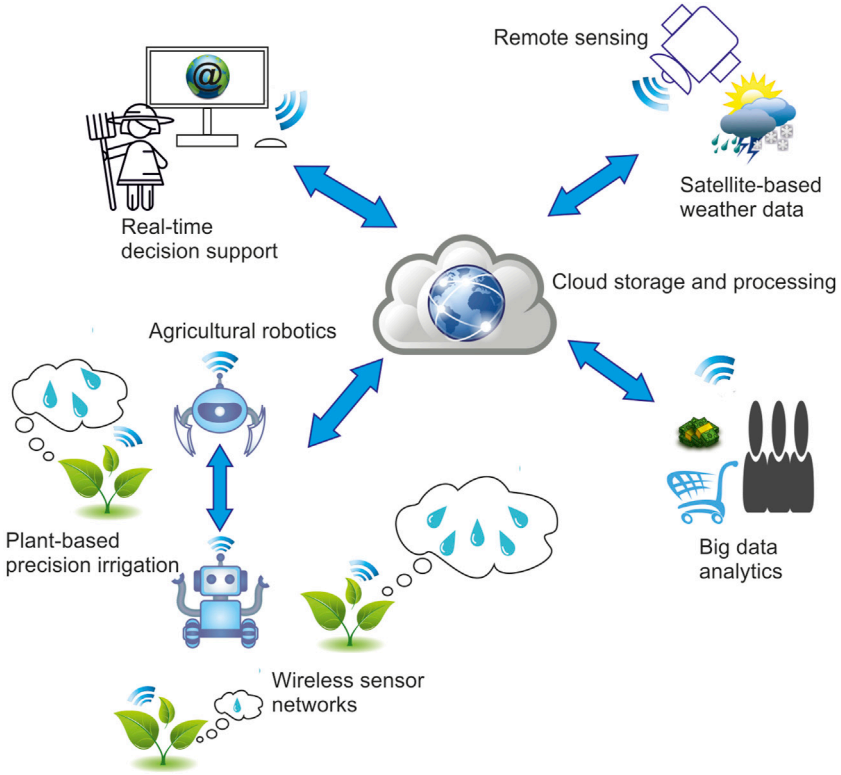

FIGURE 1
Agriculture 4.0- The future of precision irrigation control, with cloud-based data storage and processing, real-time communication between plant-based sensors, intelligent agents (including robots), supported by weather data and market analytics.

efficient precision irrigation technology and more accurate models representing the complex relationship between plant growth and irrigation water supply is necessary to achieve this. More direct targeting of irrigation application to the specific plants that require it, with quantity and timing selected to just avoid the region of drought stress within which physiological damage or yield reduction occurs, could result in significant water savings and more reliable projection of irrigation water use throughout the growing season.

Integration of networking and remote access into precision irrigation solutions has led to a new set of challenges related to data security. Wireless sensor networks, Internet-of-Things enabled devices, and cloud-based systems can be particularly vulnerable to cyber security threats such as distributed denial of service (DDoS) attacks, integration into malicious botnets (Antonakakis et al., 2017) and exploitation by ransomware creators. This creates an additional layer of considerations to be included in design of precision irrigation control systems.

Legal challenges stemming from ambiguity in regulatory frameworks governing implementation of new technology could be a setback in some precision irrigation applications, such as those involving robotic actors and artificial intelligence. Progress has been made in enacting legislation to govern operation of unmanned aerial vehicles within the European Union (European Commission, Directorate-General for Mobility and Transport, 2019a; European Commission, Directorate-General for Mobility and Transport, 2019b). Social and ethical issues stemming from implementation of artificial intelligence and autonomous robotic agents are also a cause of concern, with questions arising regarding data privacy, accountability in decisions involving human interaction and accessibility of criteria applied in decision-making (Müller, 2020).

Despite existing challenges, a wealth of opportunities abounds in precision irrigation research and implementation. Recent advances in high resolution remote sensing technology could also play an important role in precision irrigation. In particular, the use of satellite data to infer soil moisture is particularly practicable in introduction of precision irrigation principles in decision support systems for large scale irrigation platforms. Termite et al. apply machine learning techniques to infer soil moisture status from satellite imagery, providing crucial information for irrigation management at a municipality level (Termite et al., 2019).

Further opportunities exist in application of cloud-based data storage and processing, allowing for reduction in setup and

operational costs through remote sharing of data and processing power. Enhanced accumulation of soil, plant, and environmental data facilitated by networked devices expands available agricultural data from which new models and control approaches can be generated and tested. On the actuation front, assistive technologies such as subsurface water retention technology (SWRT) (Roy et al., 2019), which uses an impermeable membrane to extend the duration of water availability to plants, could be integrated into precision irrigation scheduling approaches.

What then, does the future hold for precision irrigation control? The incorporation of elements of Industry 4.0 in agricultural applications (also referred to as Agriculture 4.0) provides a guiding framework (see Figure 1). Plant-level sensors would give individual plants or plant monitoring units the ability to communicate their needs in real time. This information would be collected and processed in real time in an interconnected network of devices and agents. Artificial intelligence would then interpret the collected data and combine it with accurate, dynamic growth models encompassing specific scenarios with regard to exactly how much water should be consumed during the entire growth season, what yield is to be produced from each sector, by which date the crops should be arriving at specific developmental stages (including targeted harvest dates), and employing additional soil-specific and weather-specific information to tailor the prescription to each field, growing season, and set of user preferences. A robust, adaptable controller would then generate a database containing the specific irrigation needs of each individual, and delivery of water would be implemented by opening of irrigation valves at the individual plant level, activated either remotely from a cloud-connected platform, or on site by swarms of mobile robots, each responsible for specific zones within the field. After all, the best-placed entity to answer the question "how much water is too much water" is the individual plant, communicating its needs in real time and determining when it wishes to be watered, how much water it requires, and how much thirst it can take before compromising the final expected yield.

Author contributions

The contribution of the authors to the work is as follows: Conceptualization, DS and LO; Resources, DS; Data Curation, LO; Writing—Draft preparation, Review and Editing, LO and DS; Proofreading—DS; Supervision, DS; Project Administration, DS; Funding Acquisition, DS.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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