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Review

Advanced Monitoring and Management Systems for Improving Sustainability in Precision Irrigation

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Abstract: Globally, the irrigation of crops is the largest consumptive user of fresh water. Water scarcity is increasing worldwide, resulting in tighter regulation of its use for agriculture. This necessitates the development of irrigation practices that are more efficient in the use of water but do not compromise crop quality and yield. Precision irrigation already achieves this goal, in part. The goal of precision irrigation is to accurately supply the crop water need in a timely manner and as spatially uniformly as possible. However, to maximize the benefits of precision irrigation, additional technologies need to be enabled and incorporated into agriculture. This paper discusses how incorporating adaptive decision support systems into precision irrigation management will enable significant advances in increasing the efficiency of current irrigation approaches. From the literature review, it is found that precision irrigation can be applied in achieving the environmental goals related to sustainability. The demonstrated economic benefits of precision irrigation in field-scale crop production is however minimal. It is argued that a proper combination of soil, plant and weather sensors providing real-time data to an adaptive decision support system provides an innovative platform for improving sustainability in irrigated agriculture. The review also shows that adaptive decision support systems based on model predictive control are able to adequately account for the time-varying nature of the soil–plant–atmosphere system while considering operational limitations and agronomic objectives in arriving at optimal irrigation decisions. It is concluded that significant improvements in crop yield and water savings can be achieved by incorporating model predictive control into precision irrigation decision support tools. Further improvements in water savings can also be realized by including deficit irrigation as part of the overall irrigation management strategy. Nevertheless, future research is needed for identifying crop response to regulated water deficits, developing improved soil moisture and plant sensors, and developing self-learning crop simulation frameworks that can be applied to evaluate adaptive decision support strategies related to irrigation.

Keywords: precision irrigation; adaptive decision support systems; model predictive control; crop yield; water savings; sustainability

1. Introduction

Globally, 70% of water use is applied in irrigation of crops, making irrigation the largest consumptive user of fresh water [1]. Over 80% of freshwater withdrawals in developing countries is applied in irrigation [2]. Irrigated agriculture provides 40% of the world's food from less than 20% of the cultivated area highlighting the importance of irrigation in global food security [3].

Irrigated crop production globally extends over 275 million hectares, with an estimated annual increase of 1.3% [2]. Global climate change may further increase irrigation water demand due to a greater variation in annual precipitation amounts [4]. Postel [5] suggested that irrigation will provide 46% of the global crop water requirement by 2025, which was computed as 28% in 1995, resulting in a decline of rain-fed agriculture. Food production in the developing world, notably in South, Southeast and East Asia, is at present heavily reliant on irrigation. The total irrigated area in Asia is 230 million ha, which represents over 70% of the global irrigated area. Of the 230 million ha of irrigated land area, 60% is located in China and India [3]. It is estimated that 75% of the grain production in China is dependent on irrigation [2]. Sarma [6] noted that India uses as much as four times more water to produce one unit of a major food crop as compared to the USA and Europe. This implies that an improvement in water use efficiency in the developing world would conserve at least half of the water presently applied in irrigation.

It is estimated that a water volume of 2630 km^3 is abstracted yearly from surface and ground water sources for irrigated crop production. The absence of surface water sources in a number of communities has further increased the pressure on groundwater resources. This has resulted in the over-abstraction of global groundwater sources which is calculated to be as much as 163 km^3 per annum [2]. A global shortage in freshwater sources is predicted unless action is taken to improve water management and increase water use efficiency. This has necessitated greater regulatory demands for environmental protection of freshwater [7]. It is reported that only half of the total freshwater volume abstracted for irrigation globally reaches the targeted crops [2]. These have brought about the need to devise procedures to use the limited water more efficiently while maximizing crop yield and quality.

Conventional irrigation practice involves applying water uniformly over every part of the field without taking into account the spatial variability in soil and crop water needs; this consequently leads to overirrigation in some parts of the field while other parts of the field are underirrigated [8]. The risks associated with overirrigation include surface runoff, deep percolation and leaching of nitrates and nutrients. Those associated with underirrigation are more subjective and include reduction in crop yields and quality, as well as inefficient use of fertilizer and other supplemental inputs for crop production [9].

The irrigation process requires a high level of 'precision' in order to optimize the water input and crop response, while minimizing adverse environmental impacts. Precision irrigation is an evolving field with active interest by both industry and academic researchers. It is conceptualized by some researchers as the use of efficient irrigation application systems, whereas others view it as the variable application of irrigation based on predefined maps or sensor feedback [10]. Smith et al. [11] suggested that 'precision' involves the accurate determination, quantification of crop water needs and the precise application of the optimal water volume at the required time. This implies that varying water application spatially is not the sole requirement for the achievement of 'precision' in the irrigation process. Hence, precision irrigation can be defined as the process of accounting for the field-scale spatial variability in crop water need and applying the right amount of water to match the spatial crop water need at the right time [9]. The advantages associated with precision irrigation include increased crop yields, improved crop quality, improved water use efficiency/savings, reduction of energy costs and reduction of adverse environmental impacts [12]. Pierce [13] viewed precision irrigation as a tool for improving sustainability in irrigated agriculture in terms of improved irrigation water use efficiency and improved environmental quality of irrigated fields.

The balance of several core aspects is however important for the successful implementation of a robust precision irrigation system. Implementing a precision irrigation system involves efforts on real-time monitoring of crop and soil conditions, scheduling irrigation and control of the irrigation application equipment. Research has been mainly focused on the sensing and control aspects of precision irrigation with much advancements in the last decade [12]. Research is limited, however, in the development of appropriate irrigation scheduling tools for the precision irrigation process [14]. Irrigation scheduling is the process by which a producer determines when to apply irrigation and the amount of irrigation water to apply [15]. Hornbuckle et al. [16] suggested that the irrigation scheduling endeavour should be treated as an all-encompassing decision support system for irrigation management. A robust decision support system is important in the successful implementation of precision irrigation. The need for a decision support system capable of real-time management decisions of when, where and how much to irrigate while also considering uncertainty in climatic inputs, the time-varying nature of cropping systems, as well as equipment and operational limitations cannot be overemphasized. Rhodig and Hillyer [17] noted that the development of an optimal decision support tool for precision irrigation will involve the combination of appropriate modeling and management tools. The decision support tools available for precision irrigation management are presently inflexible and difficult to adapt to varying cropping scenarios [18].

In recent years, there has been a number of in-depth reviews on precision irrigation (e.g., [9,16]), and our intention is not to repeat the areas they addressed. Rather, our aim is to provide an in-depth technical analysis of the considerations necessary for the development of a practical and robust decision support system for precision irrigation in order to improve sustainable irrigated agriculture. To that end, the review will focus on the following critical aspects of precision irrigation: (1) monitoring considerations; (2) present limitations and state of the art in decision support; and (3) opportunities for improving sustainability. We will however include brief sections on the concept of spatial variability and the control of water application in precision irrigation.

2. Spatial Variability: The Long-Term Challenge of Irrigated Agriculture

The underlying argument for precision irrigation is the presence of within-field spatial variability that influences crop water demand. The spatial variability in crop water demand may have a direct influence on the crop yield, quality and the environmental quality of irrigated fields [19]. The soil water presents the sole source of water available for direct plant uptake and therefore its spatial variability will have a direct influence on crop water demand. Soil and landscape characteristics like soil texture, topography, abiotic and management factors (e.g., compaction, tillage) and hydraulic properties vary spatially across a field [11]. These have a direct influence on the water-holding capacity of the soil. Hedley and Yule [20] reported that the spatial variation in the soil water retention characteristics was strongly correlated with the spatial variation in soil texture across a field, noting that areas with heavier soils within a field had a larger water-holding capacity in comparison to those with light textured soils. The advent of rapid non-invasive technologies for mapping soil properties, specifically electrical conductivity mapping, can reveal within-field variability that can guide in variable rate irrigation management. These have been successfully applied by Hedley and Yule [21] and Daccache et al. [8]. Readers are directed to [22,23] for a comprehensive overview of electrical conductivity mapping.

The variability in yield across a field has also been found to be strongly correlated with the spatial variability in water available for crop use. The spatial variability in crop yield is a function of the interplay between water stress, nutrients, in addition to soil's physical and chemical properties [24]. The yield map can be correlated with the soil electrical conductivity (EC) map. These similarities can be explained through the spatial variability of soil properties that exists across a field. The water-holding capacity of the soil is a major factor affecting yield, and the yield map will likely show a strong correlation to soil EC [25]. Irmak et al. [26] noted that the spatial variability in soil water retention characteristics played a dominant role in explaining the spatial yield variability observed in soybean. Martinez-Casasnovas et al. [27] suggested yield mapping as an important tool in variable rate irrigation management.

A robust precision irrigation system will be able to meet the spatially varying crop water demand across a field at the right time. This requires accurate knowledge of the within-field variability. This is addressed by applying the concept of irrigation management zones/units in precision irrigation. The irrigation management zones are a group of homogeneous units with similar soil water retention characteristics [21]. It is however important that these management zones are large enough to be managed individually while remaining relatively homogeneous in order to reflect the spatial soil variation across the units. The delineation of irrigation management zones based on real-time sensor data has also been demonstrated. This is achieved by applying infrared thermometry/thermography to assess the spatial variation in crop canopy temperature across a field [28]. The crop canopy temperature of a healthy transpiring crop will often be less than that of the ambient air. When crop transpiration is reduced as a result of water deficits, the crop canopy temperature is expected to increase. The characterization of crop water status as a function of the canopy and ambient temperature is the basis for using infrared thermometry/thermography as a mapping tool for precision irrigation [29]. Shaughnessy et al. [30] and Evett et al. [31] have successfully applied this procedure in generating dynamic maps to guide variable rate water application for field crops grown under a center pivot system. It should, however, be noted that infrared temperature measurements are usually taken over a short period, mostly at midday when the crop is expected to experience the highest evaporative demand. Hence, this method is well suited for crop production systems in which the soil moisture dynamics has relatively long time constants.

3. Spatial Scales of Irrigation Management

Centre pivot, lateral move and low energy precision application (LEPA) moving machines can be modified to apply spatially variable irrigation [32]. These systems are particularly suited to variable rate water application because of their current level of automation and large coverage area with a single lateral pipe. Fixed irrigation systems also have potential to be deployed for variable rate water application as they can be very accurate and can be automated based on sensor feedback [2]. Implementing a spatially varied irrigation system requires an understanding of the characteristics of the irrigation application system deployed including the spatial scales covered by the water application equipment. The spatial scale associated with the variability in crop water requirements and its impact on yield should also be identified [32].

O'Shaughnessy et al. [33] suggested that the size and numbers of irrigation management zones that can be controlled in a precision irrigation strategy will determine the overall flexibility of the system. For moving application systems, the width of the management zone is dependent on the number of drops or nozzles within an individually controlled set (i.e., sprinklers controlled by a single solenoid valve) and the length will be dependent on the pattern of variability in the direction of the traveling sprinkler. The wind speed and the overlap from the wetted sprinkler patterns between management zones will also affect the accuracy of the water volume applied. Raine and McCarthy [32] noted that the spray diameter and overlap achieved by moving application systems make it impossible to target water applications on a single crop basis using these systems. Hedley et al. [2] suggested that the economic benefits of spatially varied irrigation should be an important consideration even when the system is considered achievable from a technical standpoint. The spatial scales associated with moving and fixed irrigation systems is presented in Table 1. Smith et al. [11] concluded that the spatial resolution of a precision irrigation system will be influenced by the spatial scales associated with the application system, spatial resolution of the infield sensors and the spatial scales associated with the variability in crop water requirements.

Table 1. Spatial scales of fixed and moving irrigation systems.

System	Spatial Unit	Order of Magnitude of Spatial Scale (m^2)
Sprinkler–solid set	Wetted area of single sprinkler	100
Centre pivot, lateral move	Wetted area of single sprinkler	100
LEPA-bubbler	Furrow dyke	1
Traveling irrigator	Wetted area of sprinkler	5000
Drip	Wetted area of an emitter	1 to 10
Micro-spray	Wetted area of single spray	20

LEPA: low energy precision application. Source: Raine and McCarthy [32].

4. Control of Water Application in Precision Irrigation

The water application system used in the precision irrigation process must be able to control the water application volume applied per unit time to each defined irrigation management unit within a field [13]. The development of variable rate water application systems has been mostly focused on continuous move systems [11].

The control of water application on continuous move systems (centre pivot, linear move, boom and reel) is based on databases of spatially referenced data defining irrigation management units [20]. The volume of water applied to each management unit can be achieved by varying the application rate of sprinklers or controlling the ground speed of continuous move systems [13].

The application rate of sprinklers is mostly varied through the pulse modulation of the sprinkler nozzles. This involves the application of normally opened solenoid valves to control flow through an individual or group of sprinkler heads. The solenoid turns the flow of water either on or off at a sprinkler location in order to achieve a desired application depth within a specified cycle time. The cycle time is the total number of switching (either to on or off phase) required by the solenoid valves during a pulse cycle [34]. Evans et al. [34] applied the pulse modulated sprinkler control on a linear move sprinkler system. Daccache et al. [8] also applied a pulsed modulated sprinkler control on a boom and reel irrigation system. Field evaluation of both systems indicated a satisfactory performance over a range of water application rates. They however noted a problem with sprinkler overlap at the edge of the irrigation management units.

The variation in irrigation volume applied by a continuous move system can also be achieved by varying its travel speed. The sprinklers on the manifold of the irrigation system are usually operated at a specified flow rate and pressure. An increase in travel speed of the system reduces the application depth and a decrease in the travel speed increases the application depth [35]. This type of system cannot be applied in situations where variable application depths are needed along the length of the irrigation system [34]. Al-Karadsheh [9] evaluated the performance of speed control in achieving variable water application rate on a linear move system. The wetted diameter of the sprinklers was reported to be between 15.2 and 21.3 m. He reported that the system needed to travel a minimum distance of 16 m before a desired change in application volume can be reached. This suggests that this system is not suitable for use in applications where the management units are small in scale.

The adaptation of fixed irrigation systems for variable rate water application has been achieved (e.g., [36]). Variable water rate application in these systems is usually achieved either by individual nozzle or emitter control, or zone management [13]. Readers are referred to [13] for a comprehensive review of such systems. Miranda et al. [37] described a distributed control system implemented to achieve variable rate water application in a fixed irrigation system operating in predefined management zones. Their results indicated that the system was able to apply the irrigation volume required in each zone. Goumopoulos et al. [38] also implemented a variable rate water application setup for a fixed irrigation system capable of zone-specific irrigation of strawberries. Individual nozzle control in a micro-sprinkler system has been demonstrated by Coates et al. [39]. They reported individual control of 54 nodes in a vineyard with the system. The nozzle connected to each node was capable of achieving a unique water application volume. They concluded that the water requirements of each defined zone in the vineyard can be individually met by the irrigation system. The authors reported a payback period of between 3.5 and 4.5 years for the system.

5. Monitoring

The routine or continuous monitoring of moisture fluxes in the soil–plant–atmosphere system is a fundamental aspect of managing crop production in irrigated agriculture. Monitoring can essentially be viewed as the application of various sensing technologies in determining and characterizing the spatiotemporal field-scale moisture dynamics and plant water use. These sensing methods can be classified under three broad headings: soil-based, weather-based and plant-based sensing [40]. Soil-based sensing typically involves the use of sensors to determine the soil moisture content or potential. This information is then used to infer the amount of water available for plant use and its temporal dynamics. The weather-based sensing involves the use of the crop evapotranspiration to determine the temporal crop water use. The evapotranspiration is determined using climatic variables such as radiation, rainfall and wind speed [41,42]. The plant-based sensing involves the determination of plant water status which is usually related to plant physiology. Measurements of canopy temperature, stomatal resistance, sap flow, leaf turgor pressure, stem diameter and leaf thickness are used to infer plant water status [43].

Recent advances in remote sensing has enhanced the possibility of monitoring the spatial nature of both soil and crop water status. Remote sensing encompasses non-contact technologies that are capable of sensing radiation reflected or emitted from agricultural fields. They are deployed using satellites, aerial platforms and tractors [44]. These technologies have a high spatial resolution and are well suited for regional soil and crop water evaluation [45]. This review focuses on sensing technologies that can be applied in monitoring field-scale soil and crop water dynamics. Readers are referred to [44,46] for a comprehensive review of remote sensing technologies applicable in precision agriculture.

5.1. Soil-Based Sensing

The knowledge of soil moisture fluxes comprising of the depletion and refill of soil water can be used to monitor crop water use hence making it a useful tool in irrigation scheduling and management decisions [47]. Several methods have been developed for measuring soil moisture content; they are indirect methods which rely on the strong relationship between a particular property of the soil and the soil moisture content. Moreover, they are able to provide continuous monitoring and are non-destructive [48]. In precision irrigation, the commonly applied method for monitoring the temporal dynamics of field-scale soil moisture is the dielectric-based method [20]. This is because of the ease of their deployment in large-scale soil moisture sensor networks [49]. Thus, the proper deployment and management of this technology can optimize the sustainability of irrigated agriculture. Consequently, this section will outline a brief description of this method including a consideration of the factors affecting sensor performance. For a more detailed description of other state-of-the-art soil moisture sensing technologies, readers are referred to [50,51].

5.1.1. Dielectric Soil Moisture Sensors

Dielectric soil moisture sensors operate by exploiting the dielectric properties of soil and its constituents [52]. The relative dielectric permittivity of a substance is used to describe the effect of an electromagnetic field on its molecular structure. It is a dimensionless constant greater than one, made up of a real and imaginary part [53]. The apparent relative dielectric permittivity of soil, $\varepsilon'_{\mathrm{soil}}$ is a function of its constituents majorly being water, air and solid particles. The relative dielectric permittivity of the other constituents except water has a negligible effect as they have small values in the range of 1–7. The one of water, $\varepsilon'_{\mathrm{water}}$ having a value of approximately 80 has the most remarkable effect. It is therefore possible to correlate the volumetric moisture content (VMC) to $\varepsilon'_{\mathrm{soil}}$ using empirical equations at a frequency range of between 50 MHz and 17 GHz. At this high frequency range, $\varepsilon'_{\mathrm{soil}}$ is highly stable and it usually referred to as the apparent dielectric permittivity of soil [54].

A range of electromagnetic sensors exploits this property to provide a non-destructive in situ measurement of soil moisture contents. They include time domain reflectometry (TDR) sensors, time domain transmission (TDT) sensors and capacitance sensors.

5.1.2. Factors Affecting the Performance of Dielectric Soil Moisture Sensors

The accuracy of data from soil moisture sensors is important in the precision irrigation process. Over estimation of soil moisture status may lead to a delay in irrigation scheduling decisions and consequently affect crop yield and quality. Underestimation of soil moisture status on the other hand may lead to application of irrigation too often or when not required by the crops. This will result in water/energy wastage and adverse environmental effects.

Dielectric soil moisture sensors measure the soil moisture content for the soil volume corresponding to their sphere of influence. The various factors affecting the performance of dielectric soil moisture sensors include bulk electrical conductivity (salinity), soil texture, bulk density and temperature. A variation in any of these factors around the sphere of influence of the dielectric sensor will have an effect on its performance. These properties vary with location and depth in a soil profile and it is important to take them into account when calibrating dielectric soil moisture sensors [55]. These sensors often rely on site-specific calibration, but they often come with 'universal' calibrations which can be used where absolute accuracy is not required. The accuracy of calibration equations supplied by manufacturers of these sensors are usually between a range of $\pm$4 - 2% VMC when applied in non-saline soils [56]. Site-specific calibration equations which are developed by comparing the sensor output to gravimetrically derived soil moisture content can be applied when a higher level of accuracy is required [57]. In addition, for capacitance type probes, it is essential that the probe access tubes are fitted correctly without air gaps to ensure robust soil water measurements. For a detailed technical description of factors affecting the performance of dielectric sensors, readers are referred to [58,59].

5.2. Proximal Sensing and Mapping of Soil Moisture

The recent advances in rapid mapping and positioning technologies enables the spatial characterization of soil moisture retention properties to inform precision irrigation decisions. The electromagnetic induction (EM) technique is used in combination with accurate positioning systems to quantify soil moisture variability at resolutions less than 10 m. It also provides a highly accurate digital elevation map (DEM) [2].

The EM sensor maps the soil's apparent EC which is influenced by soil texture and moisture in non-saline soils [48]. Those same factors correlate highly to the soil's water-holding capacity. Based on the EC maps, a targeted soil sampling can be conducted at different parts of the field. Topographic features that are likely to influence field-scale soil moisture dynamics are derived using the DEM [60].

The EC maps enable the grouping of discrete units known as management units with similar available water-holding capacity (AWC) characteristics which can then be used in selecting soil moisture monitoring sites. This has been demonstrated by [34,61]. The data from soil moisture sensors located in the management units can also be used in generating dynamic application maps based on a relationship between the soil moisture depletion and the mapped EC values. These application maps serve as an input into the precision irrigation control system. Hedley and Yule [21] applied soil moisture sensors and an EC map in generating dynamic water status maps for a 35.2 ha irrigated maize field. Daccache et al. [8] applied a similar method in producing dynamic soil moisture maps for various fields.

The electric resistivity tomography technique can also be applied in deriving the EC map of a field. Hedley et al. [2] reported that the method has a good vertical resolution but it cannot be deployed on a moving platform for rapid non-invasive mapping. It has been applied by Kelly et al. [62] in positioning soil moisture sensors to support irrigation decisions.

The ground-penetrating radar (GPR) can also be applied in monitoring the field-scale soil moisture status [50]. It can be mounted on a vehicle or moving irrigation system for mapping soil moisture in a field. The GPR is however affected by high clay content, is not amenable to automation and requires further development to improve its viability in precision irrigation applications [63].

The deployment of soil moisture sensors in management units defined by these mapping techniques enables the dynamic updates of soil moisture maps which can aid variable rate water application.

5.3. Weather-Based Sensing

Weather-based sensing involves the use of climatic variables in determining ET which is indicative of the crops' daily water use. Evaporation accounts for the direct evaporation of water to the air from the soil surface or canopy interception of either precipitation or applied irrigation. Transpiration accounts for the uptake of water by a plant and the subsequent loss of water as vapor through stomata in its leaves, required for metabolic cooling of the leaf to maintain photosynthesis without the leaf overheating [41]. Evapotranspiration is generally viewed as a combination of the evaporation of water from the soil, evaporation from the canopy surface and plant transpiration [64].

The evaporation and transpiration process occur simultaneously and are often difficult to distinguish. The predominance of each of these processes however varies at different crop growth stages. At the initial crop growth stage, water is lost mainly in form of evaporation from the soil surface. As the development of the crop progresses, transpiration becomes the major medium of water loss to the atmosphere [45].

The ET process is largely dependent on solar radiation, vapor pressure deficit of the atmosphere at any given time and wind speed. It is also influenced by soil water content, the rate at which water can be taken up from the soil by the plant roots and crop characteristics (type, variety and growth stage) [64]. Readers are directed to [41,65] for a further discussion on the ET process.

The temporal dynamics of evapotranspiration on hourly or daily timescales is appropriate for quantifying crop water use in the precision irrigation process. The United Nations Food and Agriculture Organization Penman–Monteith (FAO-PM) equation presents a procedure for computing hourly or daily ET values using standard climatological measurements of solar radiation, air temperature, humidity and wind speed made at a height of 2 m above a fully transpiring grass surface [41]. These data can be obtained from automatic weather stations installed on a specific field or from a metrological network. The equation provides a basis from which reference ET (ET from the well-watered grass surface) for different time periods can be calculated and to which ET from other crops can be computed using crop coefficients, K_c [66]. The crop coefficients are specific to each crop and crop canopy cover, which is dependent on the crop growth stage. The K_c curve defined for a crop over its growth stage is generalized for regions with similar climates. The K_c is however dependent on the canopy dynamics including cover fraction, leaf area index and greenness which may vary across regions with similar climates [67]. This introduces errors into ET estimates derived using the standard FAO-PM crop coefficient approach. The FAO-PM method presents a relatively easy procedure for determining the temporal dynamics of crop water use. The crop coefficient used in determining the actual ET of a particular crop however needs to be estimated at each growth stage. It is noted in Allen et al. [41] that reference ET can be overestimated by as much as 20% during conditions of low evaporative demand.

Remote sensing provides a means of overcoming the shortcomings of the FAO-PM crop coefficient approach of estimating crop ET by providing real-time feedback on daily crop water use as influenced by actual crop canopy dynamics, local climatic conditions and field spatial variability [68]. The remotely sensed normalised difference vegetation index (NDVI) computed from crop canopy reflectance measurements in the red and near-infrared (NIR) wavelengths has been found to be a useful tool in computing accurate crop coefficients for a broad range of crops [69]. Singh et al. [70] has demonstrated the use of the calculated reference ET and the remotely sensed NDVI in estimating the water use of cotton. A similar procedure has also been demonstrated by Farg et al. [67] for estimating the daily water use of wheat.

The surface renewal analysis method presents an opportunity for assessing the real-time temporal dynamics of crop water use. The surface renewal (SR) method is used to determine the sensible heat which can then be applied to the energy balance equation to determine the latent heat (i.e., ET) [71]. It is based on analyzing the temperature time series generated from monitoring the change in heat content of air parcels that interact with the crop canopy. When an air parcel comes in contact with the crop canopy, the air temperature remains constant for a brief time period known as the quiescent period. The temperature of the air parcel however increases after this time period as energy is transferred to it from the crop canopy. The increase in temperature continues until the air parcel is replaced by cooler air from the atmosphere. At this time, the temperature of the air shows a sharp drop [72]. A high frequency trace of this temperature renewal event exhibits a ramp-like function. Applying structure function theory to the ramp function enables the determination of the sensible heat flux. The instrumentation requirement for an SR system is minimal, consisting of small diameter fine wire thermocouples or a two-dimensional sonic anemometer and a high frequency data acquisition system (2 Hz to 10 Hz) [71]. Standard climatological measurements are also required to obtain the other parameters in the energy balance equation.

The SR technique requires that measurements are taken at a minimum height above the crop canopy. It is assumed that the canopy is homogeneous and able to absorb all the momentum transferred to it by the ambient airflow [73]. This assumption introduces errors in ET estimates over fields with variable canopy structures. Castellvi and Snyder [74] concluded that the technique can be applied for estimating ET from short and dense canopy crops as they are mostly decoupled from the environment. The technique also requires calibration using an eddy covariance system or a lysimeter. This may limit its practicality for farm-scale deployment. The SR methodology proposed by Castellvi [75], however, does not require calibration. Rosa and Tanny [76], Shapland and Snyder [72], and Rosa et al. [77] have reported highly accurate hourly ET estimates from various crops using a surface renewal analysis system.

5.4. Plant-Based Sensing

The importance of plant-based monitoring becomes emphasized when studying the effect of water deficit on plants and its relation to plant water status. The temporal dynamics of crop water use can be monitored using a number of plant-based methods. They include methods that require direct contact with the plant and those that require only proximal contact with the plants [78]. The contact sensors are useful in monitoring the temporal dynamics of the plant water status while the proximal sensors are capable of assessing the spatial nature of crop water status across a field and hence well suited for the precision irrigation process [11]. A good understanding of the various aspects of plant water status and plant drought physiology is important in the successful application of these systems. Readers are directed to [79,80] for a comprehensive overview of plant-based sensing methods applicable in irrigation management. Plant-based sensing systems measure either the plant water content, plant water potential or the plant physiological response to moisture deficits. A summary of various plant-based sensing systems is given in Table 2. It should be noted that many of these require skilled manpower and considerable management time for their operation.

Table 2. Summary of plant-based monitoring methods.

Plant-Based Measurement	Advantage	Disadvantage
Plant water potential methods		
Leaf turgor pressure sensors [81,82]	Capable of real-time measurements and can characterize leaf water dynamics	Point-based and requires scaling to canopy level
Plant water content methods		
Leaf thickness sensors [83]	Relatively cheap and can be automated	Leaf thickness not sensitive to changes in plant water status. Sensors also largely inaccurate. Low spatial resolution
Stem diameter variation [84,85]	Sensitive to water deficits and can be automated	Limited by diurnal hysteresis. Low spatial resolution
Plant response to water deficits		
Xylem cavitation [86]	Sensitive to onset of water stress and moderately cheap instrumentation	Only useful during drying and inadequate characterization of cavitation-water status relationship. Low spatial resolution
Sap flow [87,88]	Highly accurate method capable of quantifying plant transpiration	Point-based technique requiring replication to improve spatial resolution. Irrigation thresholds difficult to define. Also requires considerable time and expertise in its operation
Thermal sensing (proximal) [89,90]	Simple procedure with high spatial and temporal resolution	Largely empirical and difficult to implement in humid climates

5.5. Thermal Sensing

Plant canopy temperature is a widely accepted variable indicative of plant water status. The stomata controls evaporative cooling of the leaves based on soil water status and prevailing environmental conditions. It closes due to increased water deficits and a reduction in plant transpiration causing an increase in plant canopy temperature [91]. The measurement of the crop canopy temperature by infrared thermometry which is then normalized using an index such as the crop water stress index (CWSI) can be used in determining the plant water status and its response to water deficits [79].

The CWSI is a well-established method of accounting for the variation in canopy temperature as a function of prevailing microclimatological conditions and water deficits [92]. It relates the difference in the crop canopy temperature measured using infrared thermometry to the air temperature as a function of atmospheric vapor deficit [93]. This temperature difference is then related to an upper and lower temperature baseline to determine a water stress index. The upper baseline represents a non-transpiring crop and the lower baseline represents a fully transpiring crop under the same prevailing environmental condition [30]. The CWSI is a dimensionless value of between 0 and 1, with a value of 0 indicating a well-watered crop and a value of 1 indicating a severely water-stressed crop [93].

Biotic factors can also induce stress in a plant thus affecting transpiration rate, crop water use and canopy temperature. These biotic factors also affect leaf colour and morphology which in turn affects the optical properties of the crop canopy [94]. In order to successfully apply infrared thermometry as a tool for assessing plant water status, it is important to differentiate between abiotic (such as water stress) and biotic stresses (such as plant diseases and pest infestation). Multiband optical sensors could be applied in detecting various crop diseases and crop infestation within a field by computing vegetation indices based on canopy reflectance measurements [33]. This has been applied by Garcia-Ruiz et al. [95] for detecting citrus greening and by Yang et al. [96] for detecting infestation of green bugs and aphids in wheat. It may be useful to outfit precision irrigation systems with these sensors.

The main advantage of thermal sensing for precision irrigation application is related to the non-contact and real-time capability of the system. Infrared thermometry and thermography provide the opportunity to map the spatial variation in crop water status which can guide in variable rate irrigation management. The use of thermal sensing for guiding zone-specific water application has been demonstrated as noted in Section 2.

A major problem faced in applying the thermal sensing approach is the establishment of the baseline temperatures. In climates in which the air humidity is often high, variations in wind speed and net radiation introduce significant errors in the estimation of the lower limit baseline temperature [97]. A number of studies have been conducted to develop procedures for enhancing the possibility of applying measurements of crop canopy temperature in inferring plant water status in humid regions. Jones [98] provides an excellent summary of these research efforts. They include the use of well-watered plots to substitute for empirical non-water stressed baselines, although these well-watered plots are rarely available in practice. The use of artificial reference surfaces for measuring baseline temperatures has been proposed but it is reported that these artificial reference surfaces differ significantly in thermal and radiative properties in comparison to real leaves. A modeling approach to simulating the canopy resistance of well-watered plants has also been investigated but this is limited by the difficulties encountered in correctly modeling stomata behavior and hence canopy resistance. The possibility of including a wide range of metrological data including net radiation and vapor pressure deficit in deriving CWSI models for humid climates has also been investigated. The mathematical complexity typical of the models however limit their practical application.

Another problem commonly encountered in applying infrared measurements of canopy temperature in inferring plant water status is the inclusion of soil temperature and other background temperature including the sky and stems in the measured canopy temperature. This usually leads to errors in estimation of the canopy temperature as the soil and background temperature are usually many degrees different from the canopy temperature [90]. Jones [99] proposed the use of narrow acceptance angle infrared sensors that can be positioned to view only single leaves as a solution to this problem. It has however been found that the temperature estimates of single leaves determined by this method is mostly not representative of the temperature of the plant canopy. A dense deployment of infrared sensors may seem an alternative but this may be prohibitive in terms of cost for practical applications.

The advancements in the field of thermal imagery and the recent availability of low-cost thermal cameras has presented the possibility of overcoming the problems associated with the inclusion of soil and background temperatures in the measured canopy temperature. Thermal imagery allows for the average temperature of a defined area to be obtained and also the separation of background temperature from the area of interest. The temperature of a large number of individual leaves making up a canopy can be included in an image while the soil and background temperature can be discarded by applying automated image processing techniques [92]. Gonzalez-Dugo et al. [100] has demonstrated the use of thermal imagery in mapping the crop water status in a commercial orchard in Spain. They also demonstrated the rapid mapping of field-scale crop water status by deploying thermal imaging equipment on an unmanned aerial vehicle (UAV).

Plant-based sensing methods including thermal sensing only provide information on the need for irrigation and provide no information on the volume of irrigation application needed. They are used in combination with soil-based sensing for this reason [19].

6. Decision Support

A decision support system for irrigation management and scheduling provides a framework for incorporating various tools and techniques for site-specific irrigation decisions. The widespread commercial adoption of precision irrigation will be predicated on the development of robust and optimal decision support systems [19].

A number of decision support systems schedule irrigation at predefined intervals and apply predefined irrigation volumes. They do not incorporate any form of sensor feedback on plant water status, soil water status and climatic variables [101]. This 'open-loop' strategy is largely designed based on heuristics and historical data. Mareels et al. [102] suggested that this is an inefficient approach often leading to overwatering and waste of fertilizer and other supplemental crop inputs.

Closed-loop irrigation strategies aim to irrigate: when the soil moisture content reaches a certain threshold [103–105]; when plant sensors indicate a certain stress threshold [93,106,107] or with feedback from crop simulation models with the aim of attaining a certain yield, crop physiological response or economic objective [108]. These closed-loop irrigation strategies have been shown to improve water use efficiency in the production of horticultural crops under protected environments. Environmental conditions in such production systems can be controlled based on plant feedback which eliminates the stochastic plant response often encountered in field-scale crop production [109]. Belayneh et al. [110] implemented a wireless sensor network of soil moisture sensors for closed-loop irrigation control in a pot-in-pot nursery. A significant reduction in water use was achieved by the system. The authors also reported a 2.7-year payback period for the system. Chappell et al. [111] reported water savings of 83% for a closed-loop irrigation control system implemented in a protected crop production system. They noted that there was less occurrence of plant diseases in the nursery due to the elimination of over-watering. Saavoss et al. [112] reported a 65% increase in profit due to the implementation of a wireless sensor network-based closed-loop control system in a nursery. The authors noted that the increase in profit was due to improvement in crop quality and yield resulting from the precise control of irrigation applications.

In field-scale crop production, the crop needs vary over time and space due to both biotic and abiotic factors [9]. McCarthy et al. [113] noted that in these crop production systems, closed-loop strategies are unable to account for unknown crop dynamics, the stochastic nature of climatic variables and crop response, and the time-varying nature of the soil-plant-atmosphere system. This last point is especially due to crop growth, crop management and infestation of pests and diseases.

The closed-loop systems are also unable to consider equipment and other operational limitations. McCarthy et al. [114] concluded that an optimal decision support system must be 'adaptive' with the ability of accommodating the temporal and spatial variability within the field. The decision support system must also have the capability of modifying irrigation decisions in response to crop physiology, uncertainties in climatic inputs, soil, irrigation systems and water supply limitations, economic considerations and the quality of sensor feedback.

6.1. Adaptive Decision Support

The characteristics of a cropping system varies over time. Within a cropped system, the properties that will typically vary within and between seasons include crop growth, soil properties (due to addition of nutrients and other management processes) and climate. This will have a direct influence on the irrigation timing and volume required for optimal crop growth [11].

An adaptive decision support system is able to continuously re-adjust the irrigation scheduling algorithm in order to retain the desired performance of the irrigation system [114]. The adaptive decision support system is able to utilize historical or real-time sensor data to arrive at irrigation timing and volume that adequately accounts for the temporal and spatial variability in the field [114]. In control theory an adaptive control system is generally accepted as a control system able to adjust its controller parameters based on sensor feedback from a process, such that the controlled process behaves in a desirable way [11]. McCarthy et al. [108] noted that an adaptive decision support system for irrigation may either be sensor-based if they use direct sensor measurements for the irrigation strategy or model-based if they use a calibrated simulation model to aid irrigation decisions.

The development of adaptive decision support systems presents an opportunity to improve sustainability in precision irrigation through improved water use and crop productivity. They will also enhance synergistic applications of data available from soil, plant and weather sensors to arrive at optimal irrigation scheduling decisions [108].

In this section we will present a brief discussion on state-of-the-art of adaptive decision support systems. We will thereafter discuss the opportunities these systems present in improving sustainability in irrigated agriculture. Readers are referred to [113] for a comprehensive overview on the application of advanced process control to irrigation, details on methods of operation and a consideration of fundamental control concepts as they apply to irrigation scheduling.

6.1.1. Mechanistic Models

A number of irrigation decision support systems are based on complex physical models which closely resemble the actual physical system [115]. They are able to incorporate the physiological and morphological representation of the plant into the decision support tool. Barnard and Bauerle [116] described an irrigation scheduling system based on the spatially explicit biophysical model, MAESTRA (Multi-Array Evaporation Stand Tree Radiation A), which couples the within-canopy photosynthesis and stomatal conductance. Data on leaf temperature, canopy aerodynamics and environmental variables are used as inputs into the model to predict the plant transpiration. They reported that the model-based tool applied between 18% and 56% more water than a sensing-based method for scheduling irrigation in four species. They, however, noted that the model-based approach produced greater tree growth. Asher et al. [117] described a mechanistic model capable of inferring crop water requirements. The model employs leaf temperature data as input for determining the crop aerodynamic characteristics which is then used in the Penman–Monteith equation for calculating the actual crop ET. A major drawback of these mechanistic models is that they include static parameters which, once identified, are assumed to remain constant over the cropping season. This is rarely so in practice as the cropping system varies over time due to both biotic and abiotic factors.

6.1.2. Simulations

Crop simulation models based on first principle physical models of crop phenology, soil physics and hydrology can be applied in simulating the crop response to irrigation and cropping system management [115]. These simulation models provide the opportunity to evaluate the benefit of several precision irrigation strategies as they eliminate the need for time-consuming field experiments [118]. They can be interfaced with real-time sensor feedback from soil or plant sensors and weather data to determine daily irrigation requirements of crops. They can also be used in predicting the yield impact of an irrigation strategy. This is achieved by employing weather forecast data in computing a daily soil moisture balance and assessing the impact of soil moisture deficits on crop growth [118].

DeJonge et al. [14] investigated the effect of variable rate irrigation management on corn production in Iowa using the CERES-maize model. Corn yield was compared for a period of 28 years under simulated scenarios of no irrigation, scheduled uniform irrigation and precision irrigation. They reported no significant difference in corn yield and water use between the uniform irrigation and precision irrigation scenarios. Thorp et al. [24] described a methodology for applying the Decision Support System for Agrotechnology Transfer (DSSAT) crop growth model in analyzing variable rate management practices including irrigation on crop growth and yield. The platform enabled the evaluation of precision irrigation strategies on crop performance in predefined management zones. These systems are however incapable of real-time decision support and can only be applied using historical data.

McCarthy et al. [114] proposed a simulation framework, VARIwise, capable of real-time decision support in precision irrigation. The simulation framework is capable of incorporating real-time data input from field sensors in arriving at irrigation decisions. The combination of different sensor inputs into the simulation framework enables adaptive decision support with the system being able to re-adjust irrigation decisions based on plant feedback and also explore optimal control strategies.

Simulation models for use in irrigation decision support require extensive calibration and validation to establish model accuracy. The limitation in data available for this endeavour often limit the use of the platforms to specific crops.

6.1.3. Artificial Intelligence

Artificial intelligence presents the potential of solving problems in precision irrigation which are complex, non-linear and ill-defined [119]. Artificial intelligence algorithms are able to emulate the human decision-making process when applied to a particular problem domain. They have been deployed for implementing adaptive decision support in irrigation in form of artificial neural networks, fuzzy logic and expert systems with mixed success to date [118–120].

- Artificial Neural Networks

Artificial neural networks (ANN) are non-linear mapping structures employed in modeling when the underlying data relationship is not well defined. ANN are able to identify and learn correlations between input data and corresponding target output values. They are able to predict the outcome of new independent data sets making them a useful tool in predictive modeling [121]. ANN are well suited for the irrigation decision support problem that can often be complex and stochastic in nature. These networks are also adaptive in nature and are able to continuously learn in order to provide optimal solutions to target problems in dynamic systems.

Karasekreter et al. [122] implemented an ANN for scheduling irrigation in a strawberry orchard using soil moisture and its physical properties as model inputs. The system was able to achieve water savings of 20.5% and an energy saving of 23.9%. ANN however require large datasets for training and are unable to describe the physical dynamics of a system. This makes their use limited in real-time decision support tools.

- Fuzzy Logic

Fuzzy logic is an artificial intelligence algorithm that can be used to model a process and relate it to human experience in arriving at decisions. A fuzzy logic system is made up of a set used to classify input data into membership classes, a decision rule that is applied to each set which culminates in a human-like decision output from the system [123]. A detailed description of the process is given in [124].

Mousa and Abdullah [123] successfully applied a fuzzy logic model in scheduling irrigation in drip and sprinkler irrigation systems using ET, soil moisture data and crop growth stage as model inputs. Prakashgoud and Desai [124] employed a fuzzy logic system using soil moisture data, leaf wetness and climatological data as model inputs in order to implement irrigation scheduling decisions. The system was capable of maintaining soil moisture thresholds in the specified range. Giusti and Marsili-Libelli [125] described an adaptive irrigation decision support system implemented with fuzzy logic. The system incorporates a predictive model of the soil moisture and an inference system for maintaining the soil moisture within an acceptable threshold. The system was reported to adapt irrigation decisions to rainfall uncertainty and produced water savings of 13.55% over a simulation period of 168 days.

The accuracy of fuzzy logic systems is largely tied to an in-depth knowledge of the system. They also lack an inner mechanistic structure with the domain of applicability limited to the range of training data used in setting them up. Delgoda et al. [115] suggested that the points mentioned makes decision making with a fuzzy system an ad hoc process limiting its application in adaptive decision support.

- Expert Systems

An expert system is a tool able to emulate the reasoning process a human expert would employ in a decision-making process in his/her field of expertise. It captures the human decision-making expertise and heuristics representing it in a series of rules and facts [126]. An expert system typically consists of a knowledge base component and an inference engine that acts as a reasoning tool [127]. Expert systems are especially suited to dynamic problems that are of a complex nature. They are also well suited to dealing with incomplete and uncertain data [128]. This makes them well suited for irrigation decision support which often requires the input of experts to arrive at optimal decisions.

Expert systems applied in irrigation decision support can be classified as either 'expert systems proper' or hybrid expert systems. A detailed review on the application of expert systems in irrigation decision support is given in [128,129]. The 'expert systems proper' class of irrigation decision support tools schedule irrigation based on soil moisture and climatic data. They are unable to consider the time-varying nature of the cropping system (crop growth, disease and pest infestation) to arrive at optimal irrigation decisions. They are also unable to account for the stochastic nature of climatic variables and are not well suited for real-time applications [129].

Hybrid expert systems which are also referred to as model-based expert systems combine algorithmic techniques and a knowledge-based component in solving problems relevant to its application domain. Its advantage in irrigation is that optimal irrigation decision can be made by combining expert knowledge with data feedback from infield sensors, data-driven models and crop simulation models [130]. Thomson and Ross [131] described a model-based expert system designed for decision support in irrigation management. The system employs feedback from soil moisture sensors to adjust the input of a crop simulation model, PNUTGRO (peanut crop growth simulation model), and also incorporates the capability of sensor feedback validation. The system was reported to maintain soil moisture at the defined thresholds. Goumopoulos et al. [38] developed an expert system-based adaptive decision support platform for zone-specific irrigation of strawberry plants. The system includes a wireless sensor network of soil, climate and plant sensors providing feedback for the decision support system. It also includes a machine learning process capable of inferring new rules and extending the knowledge base from logged data sets. The system was reported to reduce irrigation water consumption by around 20%. A hybrid expert system based on real-time soil moisture data with the capability of incorporating plant models is described in Kohanbash et al. [132].

The performance of an expert system is largely dependent on the effectiveness of the knowledge acquisition process. An error in this process will drastically affect the system reliability and its performance.

6.1.4. Learning Control

Learning control decision support strategies perform systems identification using sensor feedback without defining a mathematical model [113]. Systems identification models a dynamic system based on a time series of measured input/output data [133]. A comprehensive overview on the theory of systems identification is presented in [134].

Iterative learning control can be applied in systems with ill-defined models that operate repetitively and assume the same initial condition after each iteration. It is well suited to the irrigation problem as irrigation scheduling and application is a repetitive problem over the crop season. The time-varying nature of the soil–plant–atmosphere system can also be viewed as an ill-defined problem. The strategy is also able to improve system performance by eliminating the effects of a repeating disturbance with undefined dynamics. Applied to irrigation, this may be a measured crop response that reoccurs as a consequence of irrigation. The temporal changes in crop water use and weather conditions are not considered [113].

McCarthy et al. [114] noted that a drawback of the iterative learning approach may be the inefficient systems identification resulting from the slow system dynamics of the crop system in response to irrigation events. This results from the evaluation of the effect of only one irrigation volume on plant response at any water application event. They suggested that this drawback may be eliminated by applying the process of iterative hill climbing control. This learning control strategy employs an adaptive varied identification process. A range of irrigation volumes are applied at each irrigation event to a number of test cells on the field. The response in the test cell that best matches the desired system performance is identified as the optimal irrigation process. They reported that the iterative hill climbing control procedure was capable of maximizing cotton yield when used with a combination of plant and soil sensors to provide feedback for the identification procedure. Their conclusions were however based on results from a simulation study and a field-based validation of the procedure was not reported.

The results of the learning control procedure are based solely on sensor measurements and may be largely affected by sensor drift as a model of the crop response is not developed from the identification procedure. This method can be considered more of a "brute force" approach than a scientifically based approach to scheduling irrigation.

6.1.5. Model Predictive Control

Model predictive control (MPC) is an industrial control approach employed in decision support for large-scale multivariable problems with multiple constraints. It has been successfully implemented in the food industry, petrochemical industry and power generation among others [135]. Model predictive control employs a plant model and optimization algorithm to calculate plant inputs in order to achieve a future value of a performance criterion. The system performance is predicted over a finite horizon subject to constraints on both the inputs and outputs of the plant [101]. Readers are directed to [135–137] for an in-depth review of the theory of model predictive control and its application in various industries.

In the case of irrigation, applying a soil moisture balance model, the plant input will be the irrigation amount, the plant output will be the soil moisture deficit, and both crop ET and precipitation values will be considered as disturbances as they cannot be controlled. A prediction of future input values and disturbances is required in an MPC system in order to determine the optimal system output [138]. This highlights the need for the incorporation of weather forecast data into the MPC framework for irrigation decision support.

Model predictive control appears to be well suited to the domain of irrigation decision support. The irrigation problem has input constraints in terms of optimal irrigation volume and output constraints in terms of soil moisture thresholds and the desired plant response to water deficits [135]. Ooi et al. [139], Lozoya et al. [101] and Saleem et al. [135] described a model predictive control framework for irrigation scheduling based on a soil moisture balance model. They employed a system identification procedure to generate a grey box model of the soil–plant–atmosphere system with a network of soil moisture sensors providing real-time feedback to the control algorithm. They all reported the ability of the MPC platform to sufficiently predict crop irrigation needs and also observations of significant water savings. The authors of the discussed systems however fail to account for the stochastic nature of rainfall and crop water use in the system dynamics. Delgoda et al. [138] noted that an adequate consideration of the uncertainty in rainfall and ET inputs into the water balance model employed in the MPC framework will improve the capability of the MPC system.

Delgoda et al. [115] addressed the drawbacks noted in the above MPC frameworks by employing disturbance affine feedback control, an uncertainty modelling technique widely applied in MPC to account for the stochastic nature of rainfall and crop water use. A simple order model of soil moisture dynamics is included in the system to enable online calculation of model parameters, hence accounting for the time-varying nature of soil-plant-atmosphere system. The authors reported an optimal performance of the system in humid regions where considerable uncertainties in climatic variables exist.

6.2. Commercial Sensor Applications in Adaptive Decision Support

Manufacturers of sensors and a number of system integrators are showing considerable interest in developing innovative tools that will further optimize irrigation water use.

A sensor integration project is described by AgSmarts (Memphis, TN, USA). Moving irrigation systems are equipped with sensors which provide data on crop growth stage and soil profile. Aquaspy soil moisture sensors (San Diego, CA, USA) positioned in various parts of the field also provide data on soil moisture status which is applied in irrigation timing and calculation of irrigation volumes. These irrigation decisions are automatically adjusted based on the varying water requirements at each crop growth stage [140].

Omica, Italy has deployed a wireless sensor network of Libelium environmental and soil moisture sensors (Zaragoza, Spain) on a maize farm in Italy to support irrigation decisions. The sensors are interfaced to a geo-referenced decision support system which enables zone-specific irrigation management. The system is able to predict crop yield based on irrigation timing and application volumes combined with historical yield data. This can then be applied in optimizing the decision support system towards achieving a desired crop yield goal.

Most decision support systems presently produced for commercial use provide on/off irrigation control based on specified thresholds and plant/crop sensor feedback. The incorporation of predictive models into these systems will enhance the possibility of improving irrigation water use and crop yield [141].

7. Opportunities for Improving Sustainability

Sustainability is premised on the principle of meeting the needs of the present generation without compromising the ability of future generations to meet their own needs. Sustainable agriculture is focused on developing farming practices that are safe and do not have an adverse impact on the environment [142].

Pretty [143] suggested that sustainable agriculture integrates the main goals of environmental health and economic profitability. The efficient and effective use of water is considered the main driver for improving sustainability in irrigated agriculture. This will involve the use of less water for irrigating crops and also preserving the quality of water sources. Conventional irrigation practices apply water uniformly over a field resulting in a high volume of water use. Overirrigation may also result from this practice which causes leaching of nitrates and nutrients into ground water sources. An important consideration would also be the use of less energy for operating water pumps and irrigation application equipment. Soil erosion continues to be a serious threat to sustainability in irrigated agriculture. This can be eliminated by applying precise irrigation volumes to reduce surface runoff.

Precision irrigation presents a promising platform for improving sustainability in irrigated agriculture. This is especially hinged on the possibility of eliminating the adverse environmental impacts related to conventional irrigation practices with the adoption of precision irrigation. The economic profitability of the adoption of precision irrigation is however a very important point to consider. This will be manifested in terms of improved crop yields and increased water savings including the associated reduction in energy consumption resulting from the optimal matching of irrigation inputs to the spatial water demands of the field, thus reducing costs [11].

Precision irrigation is predicated on the hypothesis that the crop water requirements vary spatially across a field. In heterogeneous crops such as fruit orchards, this variability is also due to physiological factors such as leaf area and fruit load [144]. It is assumed that varying water application across the field to meet this spatial crop water need will improve crop yield and reduce the costs of associated inputs. Smith et al. [11] noted that the evidence to support this hypothesis in commercial crop production is not readily found in literature.

Evans and King [18] reviewed much of the work prior to that date focused on analysing the improvements in crop yield and water savings achievable with precision irrigation and suggested that the greatest savings are likely to occur in humid climates by the increased utilization of stored moisture and in-season precipitation. Results from simulation- and field-based case studies they reviewed showed water savings of 0% to 26% for well-watered crop production employing precision irrigation strategies. No significant improvements in crop yields resulting from the adoption of precision irrigation were reported. They concluded that in arid and semi-arid regions, precision irrigation is more suited to maximize net return rather than yield and it may have greater potential in reducing irrigation water use in humid climates when irrigating to maximally utilize in-season precipitation. They further noted that the economic benefit of adopting precision irrigation for field-scale crop production is limited. This is because the cost of equipment, maintenance and management is much greater than the revenue improvements achieved as a result of improved yield and water savings. The payback period of implementing the technology may also exceed the useful life of the water application equipment, typically placed at 15 years. A payback period ranging from 5 to 20 years is noted in Smith et al. [11] for the adoption of precision irrigation for crop production in New Zealand.

Evans et al. [145] reviewed the adoption trends of spatially varied irrigation in the USA covering a period of 20 years. They noted that about only 200 of the 175,000 moving irrigation systems in the USA were fitted with variable rate water application technology. They suggested higher net returns on investment as a stimuli for adoption of precision irrigation by growers. Growers that had adopted the technology reported no significant savings in water and energy use in non-limiting water situations. They noted that in more than 20 years of research pertaining to variable rate irrigation management, the economic benefit was yet to be demonstrated. This was attributed to the marginal water savings (5%–15%) which is insufficient to realize a payback for the initial investment in the water application technology. They concluded that an economic strategy that optimizes net return rather than total returns for the technology should be adopted as a long-term investment goal.

Heeren et al. [146] conducted a simulation study to assess the reductions in pumping costs through the adoption of precision irrigation in 49,224 centre-pivot irrigated fields in Nebraska, USA. The study focused on applying variable rate water applications in mining undepleted available water. They noted that the reduction in pumping costs achieved from the adoption of precision irrigation in all fields may be negligible in comparison to the cost of variable rate water application equipment. They concluded that the adoption of this technology will be economically justifiable only with an increase in energy costs.

An economic evaluation of spatially varied irrigation applications is presented in Lee [147]. The study assessed energy savings resulting from pumping lesser volumes of water for irrigation on a 67-acre field in Wyoming. The cost of installing the variable rate water application equipment on the field was reported as $29,513 with a useful equipment life of 15 years. The yearly return for the equipment based on energy savings achieved was computed as $1816.71, which equates to a payback period of 16.25 years. This suggests that a payback will only be realized for the technology outside the useful life of the equipment.

Precision irrigation offers the benefit of providing water conservation benefits by avoiding overirrigation and the associated adverse environmental impacts [18]. Sadler et al. [148] discussed water conservation strategies where precision irrigation can potentially reduce the total water applied and improve the environmental quality of irrigated fields. They suggested that programing zero irrigation amounts to non-cropped areas will improve water conservation using precision irrigation. They also noted that adjusting spatial water application based on the infiltration rate of the soil and soil water storage capacity will reduce the occurrence of surface runoff and soil erosion. Surface runoff and leaching were identified as the major avenues for loss of nutrients from the soil. They suggested the occurrence of this can be eliminated by spatial application of precise irrigation volumes based on the soil water-holding characteristics. They presented several case studies in which the adoption of precision irrigation has been demonstrated to enhance the environmental quality of irrigated fields. They concluded that precision irrigation has the capability of improving water use efficiencies while reducing the adverse environmental impacts associated with conventional irrigation practices.

The results from the above studies show that precision irrigation is a proven tool for improving sustainability in irrigated agriculture in terms of enhancing environmental health. Its economic justification in terms of significant yield improvements and water savings is however limited.

Evans and King [18] suggested that the lack of significant improvements in yield response when employing precision irrigation may result from the fact that the yield response to the water curve near maximum yield (100% ET) is almost flat, with small changes in water applied using precision irrigation having little effect on yield. The majority of these precision irrigation studies have used only soil data for irrigation management. The local microclimate and crop genetics may however have a direct influence on the yield response of the crops.

Soil moisture status may also not provide a complete indication of crop water status, rather the plant may be the best indicator of water availability. The decision support systems employed by current precision irrigation systems assume that the soil–plant–atmosphere system never varies with time. The characteristics of the crop, soil and climate vary within the season altering the timing and optimal amount of irrigation volume required at any irrigation application event.

We argue that the incorporation of multiple sensed variables (plant, soil and weather data) will enhance the possibility of arriving at optimal irrigation decisions and hence an improvement in economic outcomes. This should be integrated with a decision support system that has the capability to adapt to the time-varying nature of the cropping system. The decision support system should also have the capacity to 'learn' in order to improve its performance based on experience and a target crop production function. We discuss how this can be achieved by exploiting improvements in monitoring and management considerations.

7.1. Monitoring Considerations

A precision irrigation system is designed to apply water at a differential rate in response to the temporal and spatial variation in crop water need across a field. This process is supported by a number of sensors providing data to a real-time decision support system. These sensors include weather stations, soil moisture sensors, environmental sensors, plant sensors and thermal sensors which may be integrated into a wireless sensor network. A careful design of these sensing systems including a consideration of factors affecting their performance is crucial in realizing the goal of improved water use through precision irrigation.

Dielectric soil moisture sensors sense the water content of the immediate soil in their zone of influence. The zone of influence reported for most commercial dielectric soil moisture sensors corresponds to a cylindrical measurement volume of 1.5 L [149]. It is therefore important to install the sensors in areas representative of the soil moisture available for plant use. The normal practice employed by most users is to place the sensors in the driest regions of the field or in the regions comprising of a soil profile with the lowest available water-holding capacity [150]. Adopting this approach will most likely lead to wetter regions in the field receiving more frequent irrigation which will consequently result in overirrigation. A more efficient approach is to define irrigation management zones and place a number of sensors in each management zone to give the average soil moisture estimate. This may however be limited by cost.

A structured installation profile is also necessary in order to capture soil water movement and availability. It is recommended that sensors should be installed at each soil horizon along the plant rooting zone [151]. An accepted convention is the installation of sensors at three to four depths along the rooting zone (1 per 25% of total rooting depth). The sensor located on the uppermost soil profile is able to detect precipitation events, the sensor in the deepest part of the profile is able to detect drainage and the other sensors located midway in the soil profile are able to capture soil moisture dynamics useful in supporting irrigation scheduling decisions [152]. The variation in soil properties at the different rooting depths should also be taken into account. With an increasing knowledge of the site, it is usually possible to install the sensors at two depths and still adequately capture the soil moisture dynamics. The soil moisture sensors should also be deployed using soil-specific calibration equations to enable accurate estimates of soil moisture content.

The actual crop evapotranspiration can vary spatially and temporally under conditions of unrestricted water supply. These variations can be the result of several factors including differences in crop genetics, plant density, weed competition, pest intensity, nutrient availability and stage of growth [18]. Addressing the variation in ET across a field may result in significant water savings.

The accurate measurement of evapotranspiration is crucial in arriving at optimal irrigation decisions [71]. The FAO-PM procedure for calculating ET which is applied in many precision irrigation systems relies on information from weather stations applied in calculating a reference ET which is adjusted for specific crops using crop coefficients. This calculated ET is assumed to be uniform for every part of the field. This will however result in the application of inaccurate irrigation volumes to replace crop water use, owing to the spatial nature of the actual ET. The application of the NDVI technique in determining site-specific crop coefficients provides a platform for overcoming this challenge. The surface renewal analysis procedure also presents a promising tool for quantifying the actual crop ET. It is however best suited to homogeneous, short and dense canopies.

Plant-based measurements provide the best indication of plant water status as they provide a direct measure of the plants' response to soil moisture availability and climatic demand. An efficient plant-based monitoring system should however respond sensitively to the slightest change in water deficits.

Measurements of leaf water potential and sap flow are contact methods which give direct information on plant water status but their spatial resolution is limited as many samples are required to effectively monitor the dynamics of field-scale plant water status [153]. Infrared thermometry has provided a robust platform for assessing plant water status. The (CWSI calculated from the infrared measurements of crop canopy temperature can adequately quantify field-scale crop water status with high spatial and temporal resolution. This presents a robust and cost-effective tool for use in precision irrigation. Its application in humid regions is however marred with difficulties.

A systems engineering approach can be applied in overcoming the difficulties encountered with applying the CWSI in humid climates. A mathematical model derived using this approach may adequately simulate the real-time dynamics of the baseline temperatures required for computing the index.

A summary of the technology gaps and refinements necessary in monitoring tools in order to achieve robust precision irrigation management is presented in [11]. They include the limited volume of influence, high cost and the need to improve the measurement accuracy of soil moisture sensors. The refinements recommended include the development of low cost soil measurement sensors with a wider volume of influence, low cost and resilient wireless communication networks able to link spatially deployed soil moisture sensors and the development of smart calibration software in order to improve the accuracy of soil moisture sensors. The technology gaps identified in plant sensing technology include the limited knowledge of irrigation thresholds and quantity, and low spatial resolution. The refinements recommended include the integration of plant-based sensing with soil moisture sensing tools in order to determine irrigation volumes, calibration of infra-red thermography against physiologically explicit plant measurements in order to determine critical thresholds and the deployment of IR thermography tools on low altitude UAVs to further enhance spatial coverage.

A combination of multiple sensor inputs deployed at a density that captures spatial variability is therefore likely to yield the most robust and accurate solution for precision irrigation. This will ensure that the decision support system is robust to data availability, gaps and deficiencies. This will include data from soil, weather and plant sensors [11]. An important consideration will also include developing cost-effective and user-friendly tools which will enhance the adoption of these adaptive systems by farmers.

7.2. Management Considerations

Management can perhaps be viewed as the most vital aspect of a precision irrigation system. Management acts as an interface between monitoring and decision support, culminating into irrigation decisions. This enables the implementation of vital management decisions of when and where to apply irrigation and also the irrigation volumes to be applied. The decision support system is perhaps the management backbone of a precision irrigation system and its proper implementation is vital for improving sustainability in irrigated agriculture.

The adaptive decision support tools discussed have the capability of improving crop yield and water savings when deployed as part of a precision irrigation system. Smith et al. [11] noted that the simulation of adaptive decision support strategies can be used in identifying optimal irrigation scheduling decisions. A simulation tool capable of representing a range of field conditions at different spatial and temporal scales is considered ideal. Such a simulation framework is presented in [114].

Model-based decision support systems using feedback from multiple sensors may present a platform for arriving at optimal water applications. MPC appears to be ideally suited for achieving the aim of improving sustainability in irrigated agriculture. A decision support system based on MPC employs an optimization algorithm to implement an input strategy with the best performance.

McCarthy et al. [113] noted that MPC implemented for a precision irrigation system could involve the use of real-time data from field sensors to calibrate a crop or soil model and then optimizing this calibrated model to arrive at optimal irrigation scheduling decisions. A combination of data from soil moisture sensors, thermal sensors and weather sensors would be appropriate for MPC. The data from the sensors would most likely be required daily, as measurements are not required at a high temporal resolution to calibrate the model. A dense deployment of these sensors is however required to account for the spatial nature of field-scale crop water use. The thermal sensors may be mounted on a moving platform for spatial data collection across the field.

Equipment availability, irrigation system capacity and other operational considerations can be incorporated as system-level constraints in an MPC-based decision support system. These constraints can be considered to arrive at future irrigation scheduling decisions [113].

MPC uses a model's simulation to determine the optimum irrigation application timing and volume. When combined with a soft sensing system, variables that are not directly measured can be controlled and optimized. This presents a possibility of applying decision support systems based on MPC in realising a desired crop yield and also a water-saving goal [136].

There has been considerable research into water use procedures that can achieve improved water savings in irrigated agriculture, particularly deficit irrigation. Deficit irrigation (DI) is an irrigation strategy in which a crop is exposed to a level of water stress at certain growth stages in its development (regulated deficit irrigation) or throughout its growth season. The growth stage in which the plant is subjected to water stress is predetermined as a drought tolerant stage. The goal of deficit irrigation is that there will be little adverse effect on yield and irrigation water can be conserved [154]. Evans and

King [18] suggested deficit irrigation as a tool for improving water use in precision irrigation. They noted that it can be applied in maximizing net returns and conserve large amounts of water in arid and semi-arid regions.

It is however important to investigate the response of different crops to water deficits including timing tolerances in order to develop optimal deficit irrigation strategies that can be integrated into the precision irrigation decision support framework. It is also important to investigate the economics of yield reduction associated with deficit irrigation strategies. O'Shaughnessy et al. [33] suggested that implementing deficit irrigation as part of precision irrigation management will involve the continuous assessment of crop stress and growth stage throughout the growing season. This will be instrumental in avoiding temporary severe stress which could result in uneconomic reduction in crop yield or quality.

The high cost of the component technologies of precision irrigation including soil, plant and weather sensors, decision support systems and variable rate water application systems is presently a constraint to the wide-scale adoption of this technology by farmers [148]. The minimal yield improvements and water savings currently achieved through field-scale precision irrigation may not justify the initial capital investment required for its adoption. As fresh water resources become scarcer, it is expected that more premium will be placed on water abstracted for irrigated agriculture. Regulatory agencies may also require farmers to continuously demonstrate the efficient use of water. These factors may promote the adoption of precision irrigation by farmers [155].

A conceptual model-based decision support system that uses the full range of plant, weather and soil data for irrigation management is illustrated in Figure 1. This is currently being developed by the authors. It involves the integration of various sensing systems, dynamic modeling, machine learning and model predictive control into an adaptive decision support system for precision irrigation.

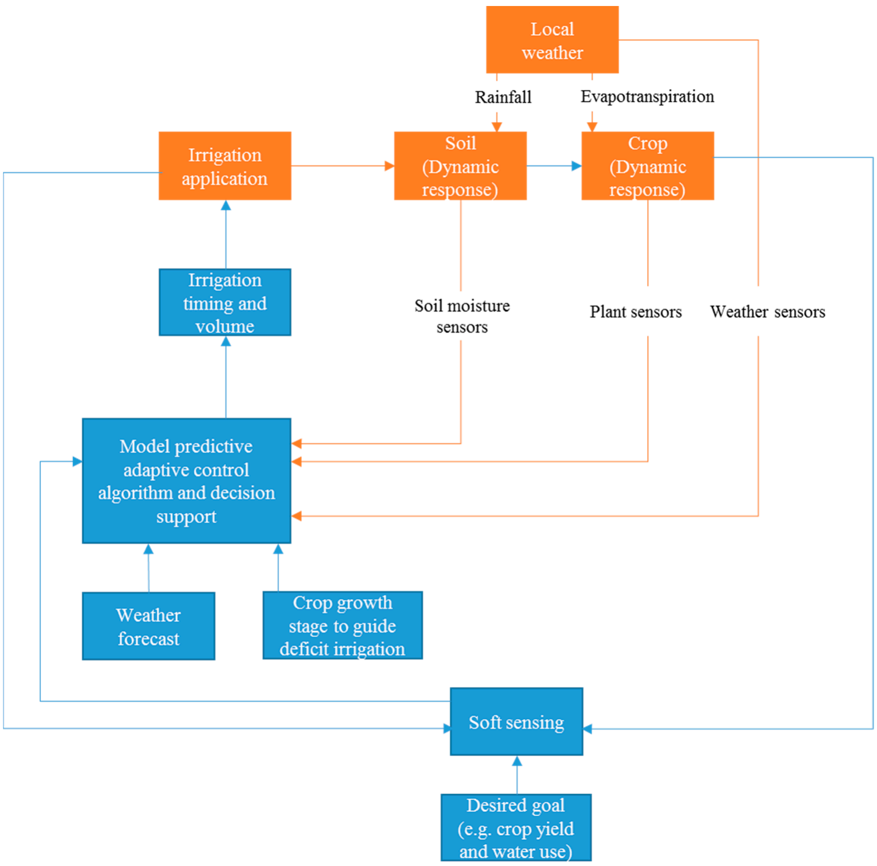

Figure 1. Conceptual model-based decision support system for precision irrigation. Elements in blue represent novel ideas from the Authors and elements in orange are from the decision support system presented in McCarthy et al. [114].

8. Conclusions

Technological innovations that can improve sustainability in irrigated agriculture form an important vehicle for actualizing the optimal use of limited water resources. Precision irrigation has been demonstrated as such an innovation, though presently the economic benefit related to the adoption of this technology at field-scale crop production is minimal. This is because the potential for yield improvements and water savings may not cover the cost of technology required for its implementation.

The application of adaptive control techniques to irrigation decision support and improvements in monitoring tools has the capability of dealing with the time-varying and stochastic nature of the soil–plant–atmosphere system while also considering operational limitations in arriving at optimal irrigation decisions. This ultimately presents a platform for actualizing the environmental and economic goals of sustainability in irrigated agriculture.

A robust design of monitoring tools including a proper combination of soil, weather and plant sensors is however vital for the proper operation of an adaptive decision support system. The decision support system should be able to account for the varying crop water requirements within season as a result of both biotic and abiotic factors. The decision support system should also consider agronomic objectives to ensure the optimal irrigation strategy is delivered by the precision irrigation system.

The high cost of sensors and the requirement for dense deployment in order to obtain data at high spatial resolutions is presently a constraint. The large dataset required for the calibration of crop simulation models is also another significant problem. Future research needs include the development of cost-effective soil moisture sensors with wider spheres of influence, identification of irrigation thresholds for plant-based sensors and the development of self-learning crop simulation models that are able to infer relationships from a limited data set. The field evaluation of adaptive decision support systems would also be beneficial in quantifying their sustainability improvement potential.

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