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Review

An Overview of Smart Irrigation Management for Improving Water Productivity under Climate Change in Drylands

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Abstract: Global drylands, covering about 41% of Earth's surface and inhabited by 38% of the world's population, are facing the stark challenges of water scarcity, low water productivity, and food insecurity. This paper highlights the major constraints to agricultural productivity, traditional irrigation scheduling methods, and associated challenges, efforts, and progress to enhance water use efficiency (WUE), conserve water, and guarantee food security by overviewing different smart irrigation approaches. Widely used traditional irrigation scheduling methods (based on weather, plant, and soil moisture conditions) usually lack important information needed for precise irrigation, which leads to over- or under-irrigation of fields. On the other hand, by using several factors, including soil and climate variation, soil properties, plant responses to water deficits, and changes in weather factors, smart irrigation can drive better irrigation decisions that can help save water and increase yields. Various smart irrigation approaches, such as artificial intelligence and deep learning (artificial neural network, fuzzy logic, expert system, hybrid intelligent system, and deep learning), model predictive irrigation systems, variable rate irrigation (VRI) technology, and unmanned aerial vehicles (UAVs) could ensure high water use efficiency in water-scarce regions. These smart irrigation technologies can improve water management and accelerate the progress in achieving multiple Sustainable Development Goals (SDGs), where no one gets left behind.

Keywords: drylands; food insecurity; irrigation management; smart irrigation; sustainable development goals; water scarcity

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1. Introduction

Drylands (hyper-arid, arid, semiarid, and dry sub-humid parts) occupy 41% of Earth's surface, supporting 38% of global population [1,2]. Agriculture and pastoralism are the major livelihood sources for most of the population, largely dependent upon natural resources [3]. About 70% of the world's drylands exist in developing countries where people are confronting the stark challenge of poverty, food insecurity, malnourishment, poor economic conditions, and marginalization [4,5]. Water availability and agricultural productivity are the most pressing issues associated with drylands and land degradation [6]. Globally, water scarcity is already affecting 1–2 billion people, and a majority of them are concentrated in drylands, where the supply of water is insufficient to meet the user demands [7]. Future climate projections also suggest that in coming decades more people will be facing huge shortages of water. Consequently, climate change and water management decisions will adversely affect drylands and their inhabitants [8]. As global population is increasing rapidly, agricultural productivity in drylands needs improvement to meet food security demands. Therefore, adopting smart irrigation approaches is a viable option to better utilize the available water resources and improve water productivity in drylands. Water scarcity has become one of the critical issues and threatens the sustainable development in drylands [9]. Water scarcity occurs when water demand becomes equal or even exceeds the total available fresh water resources [10]. Water scarcity should be considered from both physical and economic perspectives [11]. Physical water scarcity has two aspects: green water scarcity (soil moisture in root zone is insufficient to meet crop water demands), and blue water scarcity (both surface and ground water availability is unable to meet human water needs) [12]. The economic water scarcity occurs when water resources are physically available, but lack of institutional capacity and socioeconomic conditions limit the use of that water [13]. Water scarcity negatively impacts social integrity and sustainable economic development, especially in drylands. The primary sector, which is seriously affected, is agriculture, utilizing more than 80% of total fresh water [14]. Intensification of agricultural water scarcity could affect food production and threaten food security in drylands in the future [15]. Further, it may seriously impact the associated Sustainable Development Goals of SDG-2 (Zero hunger), SDG-6 (Clean water), SDG-7 (Clean and affordable energy), SDG 15.3 (Desertification control) and SDG-14 (Life below water), which are directly or indirectly dependent on water availability [16,17].

Since the available water resources are limited and to obtain more yields with less water use, efficient management of available water with improved water productivity is direly needed to meet future food demands [18]. Managing irrigation efficiently is challenging in drylands because there are so many factors to take into account, such as crop type, climate, soil type, and irrigation methods [19]. Drylands are characterized by high potential evapotranspiration, low and erratic rainfall and high temperature [20]. Additionally, predicted extreme weather events due to climate change will further worsen the situation. Besides hostile environmental conditions, increasing water scarcity in these regions is posing serious threats to irrigated agriculture and sustained food production [16]. Although agriculture consumes about 80% of the total water utilized in the agriculture sector globally [14], this irrigation generates a lower return per unit of water used than other economic sectors [21]. The use of traditional irrigation methods and low water use efficiency (35–40%) caused by poor management are major constraints to sustainable crop production in drylands [22,23]. Moreover, farmers in these regions still rely on traditional irrigation systems that manifest the lowest WUE. This situation puts enormous pressure on the agriculture sector to become more efficient in irrigation water use and evoked the call for a "Blue Revolution" in water-limited agricultural regions "to produce more crop per drop of water." Efficient water-saving irrigation approaches, especially the application of smart irrigation systems, have the potential to meet this critical challenge in dryland productivity.

A smart irrigation system applies water in the right amount, at the right time and place, in a field [24]. Smart irrigation offers better irrigation decision-making by using several factors, including soil and climate variation, soil hydraulic properties, plant responses to water deficits, and changes in weather factors, that can help save water and increase yields [25]. By using smart irrigation systems, farmers can save precious resources without exposing plants to moisture deficiencies [26]. Smart irrigation has been argued as a way to manage soil variability and gain economic benefits by fulfilling the specific irrigation demands of individual crops [27]. It is also implied that the smart irrigation system will be managed in such a way that will enable nutrients and water to be delivered directly to the plant roots [28]. To the best of our knowledge, studies addressing the issue of low water productivity in dryland agriculture and its improvement through adoption of smart irrigation approaches is limited. Therefore, the specific objectives of this article were (i) to present an overview of the constraints of low water use efficiency in dryland agriculture, (ii) to assess the conventional irrigation scheduling methods, and (iii) to examine the feasibility and benefits of smart irrigation systems for better irrigation management to enhance water productivity in water-scarce regions.

2. Major Constraints of Agricultural Productivity in Drylands

2.1. Land Degradation

Natural processes such as vegetation loss, wildfires, overgrazing, climate change, wind and water erosion and other adverse/destructive anthropogenic activities cause land degradation (Figure 1) [3,29]. This causes a substantial decline in the functional capabilities of those specific areas, negatively influences agricultural activities and productivity and natural resources management, creates economic loss, and loss in biological activity [30]. Generally, land degradation is more critical or serious in dryland, semiarid and arid areas [31]. These include some parts of central Asia, China, Africa and the Mediterranean basin [32]. Land degradation in Africa highly impacts Somalia, Eritrea, and Ethiopia (horn of Africa) [33]. A prominent sign of land degradation is the occurrence of unexpected climatic conditions and vegetative stress [34]. Moreover, low levels of soil nitrogen and organic carbon (C) show a state of land degradation that leads to very low soil fertility [35]. Stavi and Lal [36] reported that land degradation increases by 5–10 million hectares every year globally. Ibrahim et al. [37] found that the increase in land degradation observed in the Africa Saharan region was mainly due to the increase in drought frequency from 1968–1990.

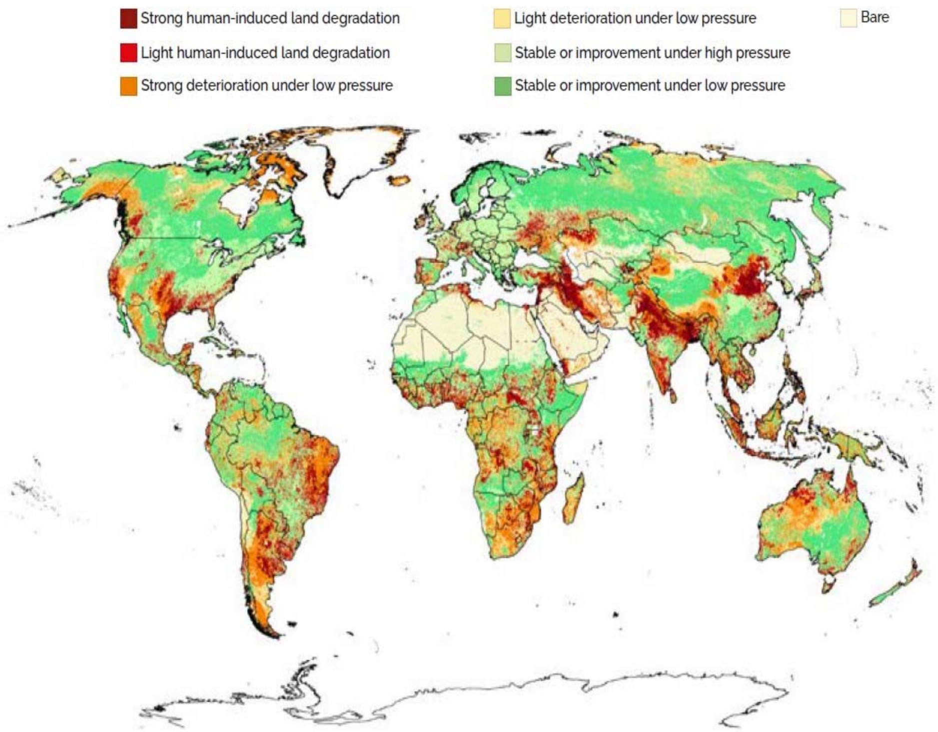

Figure 1. Global distribution of land degradation based on severity of human-induced pressure [29].

To gain insight into land degradation intensity, statistical methods and models have been utilized using data collected over the years. These models allow precise predictions about land degradation intensity [38]. Normalized difference vegetation index (NDVI) is one of the methods used to measure the vegetation mass over a specific area [39]. NDVI represents the vegetation state of an area in terms of numerical values. If numerical values are negative, it means there is a reduction in vegetation. A study carried out by Ibrahim et al. [37] using residual trend analysis of NDVI showed substantial evidence of soil degradation in sub-Saharan West Africa. The study also highlighted the drought occurrence caused by vegetation decline in Africa. Pravalie et al. [40] reported that the impending increase in land degradation is posing serious threats to the people of developing countries. Disease proliferation, decrease in crop yields and increasing armed conflicts are the major outcomes of land deterioration. A possible solution to land degradation is to achieve a state of land degradation neutrality (LDN) [41]. LDN is a state where land is retained in a stable condition capable of enduring biological functions including facilitating appropriate food security [42]. Sustainable land management practices such as soil amendments (addition of biochar, manuring, composting) to restore degraded lands could be used to decrease the effects of land degradation [43].

2.2. Water Scarcity Issues and Sustainable Development Goals

Water availability is one of the main indicators of land degradation, and upsurge in land degradation is potentially aggravating water scarcity [44,45]. Availability of water is jeopardized by lessening of ground and surface water due to reduction in biomass [46]. This results in less water available for agricultural (Figure 2) [16] and domestic use. Scarcity of water is an indicator of safe water; hence, water scarcity is a deficiency in fresh water resources to meet the standard water demand [11]. Successful achievement of SDGs is dependent upon the water security of both human and environmental systems (Figure 3) because water is directly linked to all SDGs [7]. The leading reasons for water scarcity are droughts, climate change, and inaccessibility and inadequate management of resources [47]. Rosa et al. [16] reported that in 2012, almost 2.3 billion people did not have access to safe water. Access to safe water is an important factor as it decreases disease frequency and social problems, including unemployment, malnutrition, and poverty [48]. Agriculture and industrial sectors use the largest proportion of water, and this water is usually drawn from below ground, lakes and rivers [49]. Falkenmark [50] reported that water scarcity poses substantial threats to the agriculture sector, which requires sufficient quantity of water for irrigation. Crop production and food security are directly dependent on sufficient water availability [51]. Water scarcity leads to plant stress, resulting in various environmental problems, such as intensified soil erosion and salt concentration [52]. Increasing climate change, land degradation, and population necessitate the development of effective management systems to wisely mitigate water scarcity [53–55].

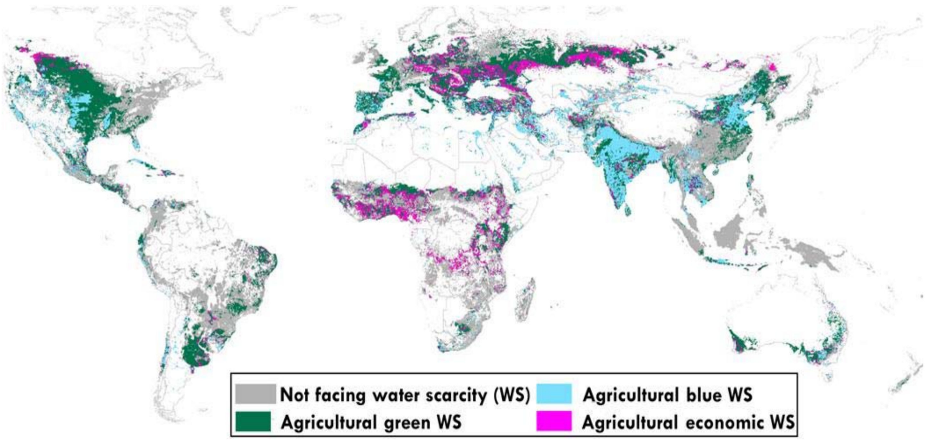

Figure 2. The global distribution of agricultural blue water scarcity (BWS), green water scarcity (GWS), and economic water scarcity (EWS) [16].

Liu et al. [12] described the common indicators employed to evaluate water scarcity, such as IWMI, (a system that evaluates the economic and physical changes influencing the availability of water within a country), the criticality ratio (a ratio of water consumption to the available water resources) and Falkenmark indicator (which compares the quantity of available water against the number of people who consume that water). Water stress and crowding indices may also be employed to measure water scarcity in a country. These indices also estimate the decrease or increase in water scarcity. Efforts are required to curtail the water scarcity issues. In this regard, implementing efficient water use practices and managing water in high-risk regions are important aspects to address [45]. These efforts could decrease water scarcity and increase access to adequate agricultural and drinking water. Moreover, by taking care of structural and social customs, governments can effectively resolve major conflicts. Hence, joint efforts are needed from governments and research institutes to resolve the water scarcity problem successfully [56].

Figure 3. Interlinkage of SDGs and water highlighting the importance of water security for humans and environment.

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2.3. Climate Variability

Variations/changes in climatic conditions often impact human, biological and agricultural systems through decreasing water resources, rising global temperatures, heavy precipitation, elevation in permafrost thawing, worsening water and air quality, rise in sea level, health risk, food supply and availability, intense drought, disturbing rainfall periods, and devastating effects on coastal infrastructure [57,58]. East Africa is an example of climatic anomalies, and the progression of increased rainy seasons, droughts and temperatures is detrimental to the development of this area [59]. In Tanzania, crop data techniques predicted a yield reduction of 7.6%, 8.8%, and 13% in rice, sorghum and maize by 2050, respectively [3]. The impacts of variation in climatic events are significantly negative [60], for example, the Mediterranean Basin has shown a prominent rise in average temperatures beyond global changes, with significant impacts on plant processes and water resources [61]. Climatic variation may induce a significant reduction in crop growth and productivity and increase vector-borne diseases, thus threatening food security [62]. Heavy rain and early frost may have negative effects on flowering periods and induce frost damage, while dry seasons or droughts largely decrease the decomposition of soil organic matter [63]. Such alterations induce negative impacts on biological systems. Fitness of the population is one of the main factors negatively affecting community structures and population dynamics [64]. Thus, it becomes vital to develop mitigation practices to decrease climate change impacts on agriculture. Several mitigation protocols for climate change impacts suggested by Haussmann et al. [65] and Gomez-Zavaglia et al. [66] are: (i) developing skills for water management, (ii) improving methods of breeding selection, (iii) capacity building of farmers, (iv) genetically improved seeds with better adaptation to increased temperatures, (v) reducing livestock and crop emissions, (vi) changes in net irrigation, and (vii) sequestering carbon in soils.

2.4. Overexploitation of Groundwater

Increasing economic growth has resulted in continuous demand for water, leading to groundwater overexploitation, especially in big cities [67]. Both humans and the environment rely heavily upon groundwater; therefore, understanding its environmental implications is vital [68]. Over-pumping of water is a global issue, primarily caused via agricultural water use. Among its effects are the drying of wetlands and streams, phreatophytic vegetation elimination, soil subsidence, storage loss, decline in groundwater level, increased pumping cost, and soil salinization [69,70]. Recently, the exploitation of groundwater resources has become increasingly critical, especially in semiarid and arid coastal areas. In these regions, the coastal aquifers are at risk due to the intrusion of salty marine water. For example, Tripoli in northwestern Libya has been experiencing progressive seawater intrusion into its coastal aquifers since the 1930s due to its ever-growing demand for water [71]. Groundwater overexploitation not only causes water-quality degradation and aquifer depletion but also influences the ecological stability of wetlands and streams, resulting in substantial losses of biodiversity and habitat. Therefore, societies should realize that water resources are vulnerable and finite and discover methods to resolve the stresses of human development on nature's tolerance. Educating the public about human influences on the environment is the first step toward sustainable water use.

2.5. Socioeconomic Drivers

The adverse impacts on water availability, agricultural productivity, and economic feasibility have been correlated with the displacement of residents [49]. Countries dependent on other countries' agricultural productive capabilities are also seriously affected. Food insecurity and hunger are common outcomes of poor agricultural production phases for millions who are dependent on agriculture [72]. The 1980s famine in Africa resulted from a decline in agricultural productivity [73,74]. Generally, droughts indicate decreased food security [75]. Between 1992 and 1995, drought periods aggravated already problematic conditions in Africa. There was income loss for farmers, a rise in unemployment, and a decline in maize export to neighboring states. Moreover, there was an emergence in incurred service debts through farmers [76]. Gebremskel et al. [33] stated that drought periods in East Africa have caused more than 0.5 million deaths and financial losses up to US $1,500,000. Several rural residents heavily rely on land productivity. Thus, rising water scarcity, land degradation and drought frequency cause adverse effects on people's lives [77]. Couttenier et al. [78] reported that social conflict could erupt as a result of decreased availability of farmland and water (e.g., civil war in Darfur). Rifts for agricultural resources and farmland often generate deadly circumstances. Ongoing conflicts among Fulani herdsmen farmers in Nigeria are another example of such conflicts. These conflicts resulted in 68% of total deaths in north-central Nigeria [79].

2.6. Droughts

Drought is a condition of abnormally dry weather sufficiently prolonged, lacking water to induce hydrologic imbalance and constraining agricultural activities in the affected region [80]. Drought types such as inter-annual droughts stay longer and decrease crop productivity, whereas inter-seasonal drought may be short and controlled via efficient water management [81]. Hermans and McLeman [82] reported that repeated occurrence of drought contributed towards degradation of land. Henchiri [83] reported that sub-Saharan Africa has faced long periods of drought with greater intensity. Nijbroek et al. [84] demonstrated that Namibia is an arid country and faced drought for many years, as well as neighboring counties of South Africa being liable to droughts repeatedly triggered by El Niño—Southern Oscillation (ENSO), a system of warm seawater that passes over the Pacific about every 10 years. Climate change could trigger desertification, induce natural calamities and environmental susceptibility. An increase in drought frequency is also expected because of climate change [85]. Droughts cause extreme distress to food security, agricultural productivity, and the economy [81]. Losses of up to US $120,000,000,000 were noted over a period of 30 years in Europe. In southern Africa, more than 10,000,000 tons of food was needed in terms of aid to drought-affected areas [3]. Africa has an unpleasant history of droughts with devastating effects on food security [86]. The most disturbing drought was during 1991–1992. It caused a huge loss in agricultural productivity, massive unemployment, and economic despair. Given the detrimental effects of drought, it is important to improve agricultural practices in response to droughts. One such practice is environmental restoration. Land restoration helps to reduce land degradation impacts [87]. Rigorous land restoration can be attained through tree plantations in degraded lands. Alternatively, in situ planting of seeds that could lead to natural regeneration may also be used [87]. Predicting droughts is also useful for proper mitigation. Recently, scientists in Kenya introduced a technology by satellite analysis, which can forecast droughts with 90% accuracy [88]. Moreover, better water management techniques and planting drought-resistant trees and crops may remove the distressing damage droughts have on the agriculture. Thus, most African nations should focus on irrigation as a method to reduce drought impacts (Figure 4) [89].

Figure 4. Countries affected by drought in 2020–2022 [89].

2.7. Conventional Technology

In dryland regions, most farmers employ old farming techniques that result in failure to manage food for increasing populations [90]. The traditional farming techniques generate little food [3]. Agriculture conservation (crop rotation, soil cover and minimum tillage) could help to enhance crop yields with increasing profitability and decreasing soil degradation [91]. Some techniques are not used by subsistence farmers mainly because of unfamiliarity [92]. The implication of microbial-resistant varieties or seeds is less common in Africa [93]. These advancements have the capability to improve yield and increase stress tolerance. Nonetheless, most farmers in rural areas are lacking access to services and information to be effectively used in their favor [94]. Sarkar et al. [95] reported that the use of modern techniques is helpful and provides opportunities to farmers for increasing the crop yields. Digitizing farming methods permits farmers to guess the yield and weather forecast, select suitable crops according to the area, and improve irrigation systems. Nuclear technology is also used as a tool to increase yield via radioactive isotope utilization. These are used as early detectors and tracers of the existence of diseases. Moreover, applying nuclear technology in agricultural practices can increase crop productivity by 40%, improve soil structure and texture, and decrease labor and input costs [96]. Nonetheless, the main hindrance is that modern farming techniques and technologies are not available to the majority of farmers in dryland areas.

3. Traditional Approaches Used for Irrigation Scheduling

The amount of water and its application timing is crucial in irrigation scheduling (IS), either in agriculture or landscapes [97,98]. Irrigation water requirement is measured following a criterion that determines irrigation needs and methods to apply a calculated amount of water [18]. In order to use irrigation water efficiently, we have to understand the dynamics of plant water use, together with weather, plant physiology, and soil properties. Among the various irrigation scheduling approaches developed and suggested, three types are most important: weather-based, soil moisture-based, and plant water status-based [28,99].

3.1. Weather-Based Irrigation Scheduling

In weather-based irrigation planning, reference evapotranspiration (ET_0) is calculated by measuring the weather elements that reflect the amount of water lost via plants and soil [28]. Solar radiation, humidity, air temperature and wind speed influence the quantity of water lost through evapotranspiration. In the absence of soil and plant measurements, weather attributes are used to determine irrigation schedules based on evapotranspiration [100]. Reference evapotranspiration can be calculated following the FAO Penman–Monteith equation by measuring the solar radiation, wind speed, air temperature and humidity [100,101]. Daily crop water use can be calculated by:

$$ET_c = K_c \times ET_0$$

where ET_c = crop evapotranspiration (mm day^{-1}), K_c = crop coefficient, and ET_0 = reference evapotranspiration (mm day^{-1}).

The method is strongly dependent on (1) the accurate calculation of ET_0, (2) better Kc curve development over the entire crop-growing season, (3) determination of soil water-holding capacity by analyzing soil properties, and (4) quantifying site-specific rainfall [102]. Mostly, real-time weather monitoring systems are equipped with an automatic weather station containing sensors for temperature, rainfall, wind speed, humidity, atmospheric pressure, and solar radiation [103]. These data loggers are designed to obtain data automatically at periodic intervals, and these data are transferred to an online data access portal. Data loggers communicate with remote servers using a wireless sensor network (WSN) or Internet of Things (IoT) framework [18]. WSN is one of the most popular technological methods that is used to precisely monitor the weather and environmental parameters [104–108]. These data finally reach smart irrigation controllers, which in combination with site-specific variables (e.g., soil type), set up the irrigation schedule. The selection and performance of a weather monitoring system depends upon different accuracy, installation, robustness, data acquisition, maintenance, and power requirements. An IoT-based weather monitoring system demonstrated by Wasson et al. [109] monitors and analyzes the crop environment in terms of wind speed, temperature, solar radiation, soil moisture, and humidity using various weather-based sensors connected through a wireless network for data transfer and web-based services. Likewise, Khoa et al. [110] implemented an IoT platform for smart irrigation management. They suggested an innovative topology of sensor nodes with low cost. The authors were satisfied with the performance of the LoRa LPWAN (long-range low-power wide area network) technology transmission module system. A multiagent-based monitoring approach consisting of an open-source platform (PANGEA) was used to collect data on weather elements and soil moisture via different sensors. This platform is equipped with several master and slave nodes connected through sensors for data transfer [111]. Many researchers [112–114] have also employed WSN and IoT based platforms for weather-based monitoring and reported satisfactory performance of the systems. Although weather-based irrigation scheduling is widely practiced, the heterogeneity of soil properties used to estimate soil water volume affects the amount of available soil water. In addition to that, spatiotemporal, variability in large-scale evapotranspiration is another challenge confronted by this approach.

3.2. Plant-Based Irrigation Scheduling

Plant-based irrigation scheduling mainly relies on several indices indicating plant water status [115]. The relationship between soil moisture deficit and crop water stress helps to determine irrigation scheduling. Plant-based irrigation scheduling is sensitive to measurements conducted at a specific crop stage to determine water deficit in plants [18]. Since varying plant species, plant tissues, and crop growth stages have variable sensitivity to moisture deficit, several plant-based stress measurements have been suggested for irrigation scheduling [99]. There are two principal categories based on plant variable measurements used for irrigation scheduling: firstly, plant water status-based direct measurements including leaf, stem, and xylem water potential status and indirect measurements pertinent to leaf thickness, turgor pressure, and trunk diameter [116,117]; and secondly, plant physiology-based estimates including sap flow, stomatal conductance, xylem cavitation, and thermal sensing [118]. A leaf turgor pressure sensor estimates the relative change in leaf turgor pressure to determine leaf water stress [119]. In addition to transpiration water loss, root water uptake and cellular osmotic pressure determine the magnitude of turgor pressure. For example, a ZIM probe (leaf turgor pressure sensor) is a noninvasive leaf patch clamp pressure probe that can detect leaf turgor pressure. ZIM probes are capable of measuring even minute shifts of turgor pressure within leaves in real time [119,120].

Due to advanced electronic technologies, researchers have developed small leaf sensors and tested them against cowpea (*Vigna unguiculata* L.) and tomato (*Solanum lycopersicum* L.) plants. Leaf thickness-based irrigation timing improved WUE by 25–45% compared to preset irrigation plans [121]. In another study, Afzal et al. [122] reported that leaf thickness and leaf electrical capacitance (CAP) could be employed for leaf water status monitoring. Based on energy balance and heat pulse, thermal sensors have been developed to determine sap flow from plant stems, assisting irrigation scheduling. Sap-flow methods are able to provide in situ measurements of plant water use and transpiration dynamics. The Dynagage sap-flow sensors are the latest ones used to estimate sap flow and thus the water consumption by plant. The amount of heat utilized by the sap is measured by the energy balance sensors and gives the real-time sap flow in grams or kilograms per hour. These sensors require no calibration and offer an efficient and affordable method to determine the water use of plants [28]. During transpiration, the water in the xylem subjected to tension is directly proportional to the deficit in water to the point where the water columns can rupture or cavitate [123]. This cavitation leads to the eruptive formation of a bubble that contains water vapor [124]. Audio or ultrasonic frequency signals can detect these cavitation events, and the associated embolisms can hinder water flow [116]. Detection of such ultrasonic acoustic emissions (AEs) indicates plant stress and cavitation events. Thus, the AE rate can be used as a sensor to detect plant stress.

Stem Diameter Fluctuations

Stem and fruit diameter experience diurnal fluctuations due to changing water content [125]. Various water stress indicators can be determined by analyzing the daily patterns of stem diameter variation (SDV) [126]. The maximum daily shrinkage (MDS) and stem growth rate (SGR) are commonly used indicators for scheduling irrigation [115]. Currently, different optical sensors are used to detect plant water status, nutrient level and health condition. Two types of optical sensors (contact and noncontact) are primarily used [18]. Contact sensors are physically connected to plants, whereas noncontact sensors are vehicle-mounted, fixed, handled, or remotely controlled (aerial vehicles or satellite data) [28]. In many studies, monitoring through unmanned aerial vehicles (UAVs) with high-resolution cameras helped to generate irrigation maps over large cropped areas [127,128]. In another study, Lozoya et al. [129] used a sensor network to control green pepper growth under four different irrigation designs.

Bauer and Aschenbruck [130] employed IoT and sensor network integration to monitor leaf area for optimizing irrigation. Several factors other than water content can affect the SDV-derived index, such as plant age, crop load, and field management practices. Furthermore, SDV estimates are usually affected by small raindrops and animals [131]. Canopy temperature measurement is another key method commonly employed for irrigation scheduling. Major canopy temperature-based methods include the crop water stress index (CWSI), temperature–time threshold (TTT), and temperature stress day (TSD) [132–134]. Infrared thermometers and thermal cameras are used to detect temperature. However, diurnal dynamics of temperature remain a major challenge for all the canopy temperature-based methods [99]. A major drawback of using plant-based sensors for irrigation management is that they lack direct estimates of irrigation water amount to be applied. Soil textural variability is another challenge affecting the accurate estimation of irrigation amounts needed.

3.3. Irrigation Scheduling Based on Soil Moisture

Soil moisture monitoring is one of the fundamental approaches used for irrigation scheduling, and it is conducted by determining the soil water content or the soil water potential [135]. Monitoring soil moisture at high spatial and temporal resolution is critical for optimal irrigation scheduling [28]. Different types of sensors, such as time-domain transmission, neutron probes, granular matrix, and capacitance, are commonly implemented for soil moisture determination [136]. Gravimetric sampling to estimate soil moisture fluxes and a tensiometer is also used to measure soil matric potential, reflecting the amount of soil water available for plant use [99]. With the advancement of technology, satellite and groundwater sensors are becoming popular as irrigation tools. Soil moisture sensors can be installed at multiple depths in the field and capture soil moisture dynamics. They enhance accuracy and improve understanding of changes appearing in soil water content pertinent to crop water use and irrigation [137]. Soil sensors also provide information about soil chemical, physical and mechanical properties obtained in the form of optical, electrical, mechanical, electromagnetic, acoustic, radiometric, and pneumatic measurements [138]. Measurement of these attributes assists in the estimation of maximum allowable depletion [139]. Soil moisture sensors estimate the volumetric moisture content (VMC) by detecting changes in soil electrical and thermal properties [140].

Frequency-domain reflectometry sensors (FDR) can estimate field soil moisture content [129]. The sensors are put near the crop roots and show a moisture content range of 0–50% with 0.1% resolution, thus optimizing water use for vegetables. Shigeta et al. [141] found that real-time soil moisture sensing can be used in practical measurements of soil moisture fluxes by correlating the VWC of the soil with the capacitance of sensors inserted in the soil. In TDR sensors, two parallel rods are inserted at the desired depth to measure the soil moisture content. The rate of the electromagnetic pulse, which radiates from the sensor into the soil and returns to the soil surface, is directly proportional to soil water content. However, this is an expensive method for farmers. Other studies [142–144] interconnected IoT-based field monitoring with cloud-based monitoring and data analysis using an Ardunio controller. They found that the collected data were used to make predictions that helped reduce water consumption and improve crop yields. In another study, six capacitance-based sensors were used at three locations with a data logger [145]. This method improved the WUE compared to traditional approaches. Soil moisture-based irrigation scheduling has the disadvantage that plant water uptake and stress are affected by soil moisture content and also influenced by environmental conditions, pests and diseases, root zone salinity, and nutrient availability. Variation in soil properties also affects irrigation scheduling, which necessitates soil testing at multiple points for accurate estimation of soil moisture content.

4. Innovative Smart Irrigation Approaches

A smart irrigation system consists of firmware, software, and hardware interconnected via various computational techniques, including artificial intelligence (AI) and deep learning (DL) etc., which ensures the right amount of water at the appropriate time in crops to improve WUE, increase yield, reduce fertilizer use, reduce labor cost, and save energy [146]. Various control methods are employed to improve irrigation system efficiency by monitoring variables such as canopy and air temperature, evapotranspiration, rainfall, and solar radiation. By integrating information from multiple sources, smart irrigation systems can significantly improve crop production and resource management [147]. The following section presents various recent techniques associated with smart irrigation systems in agriculture.

4.1. State-of-the-Art Smart Irrigation Technologies

4.1.1. Artificial Intelligence (AI) and Deep Learning

AI is a machine's ability to learn and implement tasks similar to those of a human brain, and it is powered by computers [148]. When applied to a certain problem domain, AI algorithms can mimic human decision-making. Irrigation systems have been integrated with AI for adaptive decision-making through fuzzy logic, expert systems, and ANNs [149].

An artificial neural network (ANN) is an algorithm for processing information that is inspired by the working of the human brain [150]. Like human brain neurons, an ANN also contains a neural network, but synapses are substituted with biased connections and weights [151]. This facilitates the mapping of input and output relationships [152]. ANN-based control systems can learn and adapt to the variable dynamics, making them ideal for irrigation systems. Additionally, ANNs have been used as smart strategies in dealing with the issue of formulating mathematical models based on first principles. Recently, many researchers have employed ANN methods for irrigation scheduling. Using the AQUACROP model integrated with a dynamic neural network, Adeyemi et al. (2018) [149] simulated soil moisture for a potato crop. Karasekreter et al. [153] demonstrated energy and water savings up to 23.9% and 20.5%, respectively, by implementing an ANN integrated with soil physical properties and moisture content in a strawberry orchard. Umair and Muhammad [154] designed an ANN-based controller model in MATLAB using climate variables as input.

A fuzzy logic system is an extension of Boolean logic that expresses logical values in the form of true or false and demonstrates the nonlinearity and uncertainty in real-world problems [155]. The fuzzy system uses different sets of input data to categorize data in membership classes, and then applies a decision rule to every set to produce human-like decision outputs [103]. Many researchers have recommended the use of fuzzy logic in irrigation control systems. Mendes et al. [156] designed a fuzzy inference system that can control the speed of the central pivot according to the spatial field variability. A fuzzy irrigation system developed by Mousa et al. [157] was used to compute evapotranspiration (ETo) via a fuzzy inference system using weather variables as input. They found that the fuzzy model was accurate and quick in obtaining the required evapotranspiration and net irrigation to recover the water loss. An expert system is another type of intelligent system used for irrigation control. Basically, an expert system is a computer program that simulates the verdict and behavior of an individual or organization with expertise in a certain area through the use of artificial intelligence (AI) technologies [158].

Expert systems can be used for problem-solving activities such as monitoring, control, planning, forecasting, prescribing, fusion, and decision-making [159]. An expert-controlled irrigation system enables farmers to quantify the water amount needed by crops at the appropriate time by considering the weather and soil conditions. Many researchers [160,161] have implemented expert systems for irrigation management. The expert system uses various knowledge-based inputs for accurate decision-making about irrigation scheduling. However, errors in knowledge-based input can seriously affect the performance and reliability of expert systems [162].

A hybrid intelligence system is another type of intelligent control system in which at least two artificial intelligence algorithms such as fuzzy logic and neural network are combined, known as "neuro-fuzzy" [149]. Other examples of such hybrid intelligence systems include fuzzy PID and GAPSO. Tsang et al. [152] employed seven different machine-learning algorithms to assess soil moisture conditions using aerial images of agricultural fields to control irrigation. The results demonstrated a 52% reduction in water consumption by reducing timing, irrigation level, and location errors. Similarly, a combination of ANN, genetic algorithm (GA) and the Bayesian framework was implemented to forecast daily irrigation demand under limited data conditions [163]. The results exhibited an improvement in forecast precision by 3% and 11%. Many other studies also demonstrated the use of intelligent hybrid systems and reported precise forecasting and improved control of irrigation systems [164,165].

The deep learning method is now applied to deal with millions of weights among neurons for a better understanding of behaviors owing to recent developments in computing technology in parallel processing, software and hardware. Deep learning has developed a revolutionary epoch, since it can solve the problems confronted by artificial intelligence for a long period [166]. Deep learning has been applied in the agriculture and hydrology fields due to difficulty in software data availability, budget, and complexity, such as crop evapotranspiration modeling and approximation [167]. Wang and Ma [168] reported that the traditional machine learning and deep learning models work similarly as a data-driven artificial intelligence technique and could be applied to model the convoluted correlation between input and output (Table 1). Nonetheless, deep learning has an advantage over traditional machine learning techniques because of its great hierarchical structure model [169].

Table 1. Application of various artificial intelligence technologies for irrigation management.

Strategy	Outcomes	References
Fuzzy logic	Optimization	[169]
ANN	Decrease in evaporation due to schedule and savings observed in water and electrical energy	[170]
Fuzzy logic	The fuzzy controller system can be effectively applied to PA applications such as water-saving agriculture areas, for example, the croplands, the nursery gardens and the greenhouses.	[171]
Fuzzy logic controller	Drip irrigation prevents wastage of water and evaporation	[172]
Fuzzy decision support system	The system provided improved irrigation suggestions in terms of timing and water saving.	[173]
ANN feedforward	Optimization of water resources in a smart farm	[174]
Machine learning algorithm	Prediction and tackles drought conditions	[175]
Fuzzy logic	Obtained a higher level of accuracy to expertly use water for irrigation	[176]
ANN	Neural network models with one hidden layer with four neurons for sugar beet and five neurons for wine grape provided excellent predictions of well-watered canopy temperature	[177]
ANN	The proposed model was able to predict the timing and quantity of irrigation water	[178]
LoRa-based machine learning	This system led to a 46% reduction in water usage, and the plants looked better than they would have with conventional watering	[179]

4.1.2. Model Predictive Irrigation Systems

Development in smart agriculture through internet usage and increasing computational power facilitated large data collection from agricultural systems [180]. The model predictive system has been employed in irrigation scheduling, irrigation canal control, soil moisture, and stem water potential regulation [55]. Model predictive control (MPC) has manifested applicability to gate operation and control the canal flow. The management goal of model predictive control for canals is to maintain the level of water as close to the set-points as possible [181]. Thus, an appropriate model regulating the dynamics of canal-water levels is required. A model predictive control system has been employed to model water movement in the canals, keeping a specific level of water at different locations and the flow of water that affects these water levels [182–184]. The controlling instruments maintain the flow of water, by which the regulator can attain the management goals [180]. Nonetheless, attaining this goal is not straightforward, as variations in inflows and outflows interrupt the whole water system. To estimate future water flows and levels in response to control actions and disturbances, the water system (controller, canal reaches, disturbances and structures) needs to be modeled. Several authors have applied MPC in driving irrigation flows of canals. For instance, Puig et al. [185] applied MPC to create flow control approaches from the source of water to the user and Guadiana River's irrigation territory. The results exhibited the usefulness of the MPC application. Zhang et al. [186] developed a non-cooperative distributed MPC algorithm based on Nash optimality for the regulation of water levels in canals. The simulation of system results indicated the efficacy of the advocated algorithm. To efficiently deliver the flow of a canal without oscillations, MPC was combined with online water storage to allow for a delay and evade wave distraction. The results indicated the significant development of canal setups using automation [180].

4.1.3. Variable-Rate Irrigation (VRI)

VRI is a method of applying irrigation at variable rates in different irrigation management zones over the entire field in an optimized way [187]. Normally, the application of irrigation water is uniform in the entire field. However, owing to soil spatial variability in soil topography, hydraulic properties and vegetation condition, the soil moisture content remains nonuniform [188]. When such soil spatial variability becomes significant, the field is split into different management zones consisting of those field areas with the same soil properties and crop conditions [150]. Then, irrigation is applied at differential rates in different management zones [189]. Such variable irrigation management may enhance the economic value of irrigation by improving WUE, increasing productivity and reduction in nutrient leaching [190]. This enables an accurate and timely water application based on soil spatiotemporal properties and plant demand [191].

In other words, VRI technology ensures the application of the right amount of water at the right time in the right field zone, resulting in significant water savings. The main components of VRI technology include sensors, prescription maps, spatial information, and a unit system to apply VRI prescription (lateral irrigation) in the crop field [192]. Optimization of VRI prescriptions is usually determined by using remote sensing, yield maps, topography, soil apparent electrical conductivity and soil maps [193,194]. There are different types of irrigation systems used for VRI applications. The variable-rate lateral irrigation system contains a global navigation satellite system (GNSS) or global positioning system (GPS) receiver, custom software-operated relays, and valves, thus supplying water at variable rates using the nozzle-pulsing method with a speed controller [26]. This system has high accuracy in controlling the irrigation rate and forward speed [195]. Likewise, the center pivot VRI system consists of a VRI and pivot control panels, control nodes, solenoid valves, a GNSS, a remote sensing control system, and a variable-frequency drive (VFD) [191].

The speed and operation of the pivot are regulated by pivot control. The VRI controller panel governs the irrigation application based on pivot location and the prescription map. The flow of sprinkler heads is controlled by solenoid valves [26]. The pivot positioning is regulated by the GNSS system, and the control nodes attached to the pivot govern the valve opening and closing. VFD regulates the pressure by altering the irrigation rate at different points in the field [196]. The rotation speed of the pump impeller is also controlled by the VFD in response to the input communicated by the pressure switch mounted on the pump. It helps to maintain the pressure within the predefined threshold limits [197]. The use of VRI technology offers several advantages over conventional irrigation methods. VRI can substantially improve overall yields by avoiding under-irrigation and/or over-irrigation. The growers usually set up soil moisture sensors in those field areas with low soil water-holding capacity (WHC) to prevent under-irrigation in the field [198]. This practice may increase irrigation frequency, leading to over- irrigation with high soil WHC. Over-irrigation may result in yield loss due to nutrient leaching and depletion of oxygen in the root zone [39]. The prevention of under-irrigation in those field areas with higher yield potential could help optimize water input.

Another advantage of using VRI is that irrigation can be withheld over those field areas that are not arable [199]. VRI also supports fertilizer application at variable rates that would benefit in matching the variability in crop nutrient requirements [200]. A two-year study led by Sui and Yan [192] demonstrated that crop water productivity for corn and soybean was much better under VRI than uniform rate irrigation (URI) in Mississippi. In another investigation, application of VRI with delineated management zones based on the difference in WHC showed better crop water productivity for maize and winter wheat, which was higher than the overall average of the field [201]. Besides its several advantages, VRI also has some disadvantages, including higher cost, complexity in developing soil maps, and maintenance of the system [202]. Overall, VRI technology is a good option to precisely utilize precious water resources, but considerable efforts are needed to make this technology affordable and more user-friendly.

4.1.4. Unmanned Aerial Vehicles (UAVs) for Irrigation Management

UAVs, also called drones [203], are frequently linked with military operations, as they are used as weapons for targeting aircraft and involved in intelligence services. Recently, drones have been used in a wide range of applications, including delivery services, weather monitoring, traffic monitoring, surveillance, and rescue [204]. Several studies emphasized UAV utilization for forecasting and monitoring in agriculture to maintain crop health [205]. Drones are also useful for irrigation monitoring, as they use infrared or thermal imaging cameras in the IOT network [206]. Manual spraying of pesticides induces lethal diseases to workers globally, as described by the World Health Organization and Food and Agriculture Organization [207]. Thus, UAVs could be a potential alternative to manual pesticide spraying, reducing the potential ecological/environmental risks and health problems [205].

Recently, UAVs with IoT-based sensor networks have been used for smart irrigation purposes, thus significantly improving crop productivity [208]. Chebrolu et al. [209] suggested a technique of UAV images to rebuild a three-dimensional crop model that mediates crop growth monitoring based on a plant level. Likewise, the plant height of sorghum and maize plants was measured based on UAV images and a three-dimensional model [210]. Roth et al. [211] reported that the RMSE (root-mean-square error) was 0.33 m for a single sorghum's height. The soybean leaf area index was extracted using 3D and UAV plant models. In another study, carried out by Deng et al. [212], different cameras were fixed on UAVs for smart farming. The results indicated that the UAV-based multiband images are useful and showed substantial ability for precise irrigation and agriculture management. RGB (red, green and blue) cameras can be used with a drone to determine crop biomass using visible reflectance for assessing vegetation indices [213]. According to Rokhmana [214], using UAVs for remote sensing can support precision farming. They can be used to obtain periodic information from the field, i.e., stock evaluation, plant health and vegetation monitoring.

Several researchers examined the chances of applying IoT systems to govern crop health and irrigation monitoring. Automated water irrigation was innovated and employed by mobile applications [215]. The designed smartphone application can process and develop the soil images near the root surface of plants to ascertain sensor-less water quality. A smart drip irrigation method was established using an ARM9 processor, involving environmental conditions including CO_2 amount, low moisture, and high temperature [216]. Zaier et al. [217] suggested an irrigation system controlled wirelessly to promote groundwater usage in large-scale fields of Oman. Oksanen et al. [218] stated that big data and IoT could be used to establish a real-time crop growth monitoring system, facilitating precise irrigation estimates. Based on the collection of plant data, they suggested establishing a central unit to develop a crop growth model, Oksanen et al. [218] proposed a method to forecast and diagnose wheat diseases, weeds, and pests using a computerized IoT-based method. A fungicide and insecticide management system based on predictive models for pests and crop diseases has also been developed using the IoT [219]. A new irrigation method based on the IoT was proposed by [220] where humidity sensors were applied, and high humidity values of 90–95% were recorded (Table 2).

Table 2. Application of different types of UAVs for irrigation management.

Type of UAVs Used	Purpose	References
Unmanned helicopter	Mapping of crop water stress, index for irrigation scheduling	[221]
Unmanned helicopter	Assess water stress variability in a commercial vineyard	[222]
Unmanned helicopter	The fuzzy controller system can be effectively applied to water stress detection in an almond orchard	[223]
Multi-copter engines	Water stress detection in grapevine	[224]
Fixed wing	Detection of water stress in citrus cultivars	[224]
Fixed wing	Water stress detection in fruit tress	[225]
Fixed wing	Soil moisture estimation at different soil levels	[226]
Quadcopter	Estimation of canopy cover maps for irrigation management of peanut and cotton	[227]
Quadcopter	Identification of nonuniformly irrigated areas in olive groves and vineyard crops	[228]
Hexacopter	Soil moisture content prediction under different irrigation treatments in maize crop	[229]

4.2. Forecasting Smart Irrigation Technology with DSSIS

A decision support system (DSS) is an interactive software-based system used to identify, analyze, and improve decisions based on raw data, documents, and personal knowledge [99]. Various decision support systems (DSSs) have been designed for managing irrigation water to improve WUE [230,231]. A smart and efficient DSS has to consider several factors, such as soil water status, crop type, irrigation method, weather information, and application, to develop irrigation scheduling [19]. To facilitate precise irrigation scheduling by minimizing errors in field soil moisture estimates, DSSs provide irrigation schedules not only for the current day but also to forecast irrigation events for future days.

Based on the idea of forecasting irrigation, recently a prototype of an irrigation scheduling DSS called decision support system for irrigation scheduling (DSSIS) has been developed for arid regions [232]. This DSSIS has the ability to predict irrigation events for the current day as well as forecast irrigation for the future by using the weather information of the next 4 days. The DSSIS prototype consists of irrigation pipelines, software and hardware to control irrigation and peripheral equipment The irrigation pipelines consist of a drip irrigation system, valves and polyvinyl chloride pipes. The software controlling the irrigation system includes RZWQM2 (Root Zone Water Quality Model) integrated with an irrigation scheduling software (RZ Irrsch and an online weather data acquisition system [233]. The irrigation-controlling hardware contains automatic control equipment. A peripheral equipment consists of a water reservoir, circulating pumps, and strainers. In DSSIS, the RZWQM2 model works as an engine and facilitates decision-making about irrigation scheduling. The RZWQM2 is first calibrated and validated according to site-specific experimental data (crop, weather, and soil data). The IrrSch software generates daily weather data from the nearby weather stations and also forecasts upcoming 4-day weather using a weather application program interface (API) then transfer this information to RZWQM2 [99].

Based on the information given by IrrSch, RZWQM2 predicts crop evapotranspiration, soil water stress factor (SWFAC), and soil moisture content for the current and next 4 days. When the current day's water stress level falls below the preset threshold, an irrigation event is initiated. The amount of water to be supplied is computed by RZWQM2 using field capacity and the predicted soil water content and rooting depth. This system (DSSIS) has been tested for cotton irrigation scheduling under full, deficit, experience, and sensor-based irrigation treatments in an arid region. Under deficit irrigation, DSSIS saved 50% of irrigation water with a 4% increase in yield and up to 80% increase in water productivity over experience-based irrigation [232]. In another study, Chen et al. [234] evaluated the effect of irrigation scheduling by DSSIS on water productivity, seed cotton yield, and economic profitability under an arid desert climate. Under DSSIS, water productivity, seed cotton yield, and economic benefit were higher than soil moisture sensor-based irrigation scheduling. Full irrigation DSS also maintained crop yield under deficit irrigation treatment. In a three-year field study, Chen et al. [233] evaluated irrigation water use efficiency (IWUE) in cotton using the RZWQM2 model with DSSIS in an arid oasis. After validation, the RZWQM2 model was run with seven irrigation scenarios (from 850 to 350 mm water), and the long-term weather data (1990–2019) were used to estimate the best IWUE. The results manifested that the irrigation with 660 mm water produced the highest seed cotton yield (4.09 Mg ha^{-1}), whereas irrigation with 550 mm water exhibited the highest IWUE (6.53 kg $ha^{-1}mm^{-1}$). These findings provided important guidelines for farmers to use deficit irrigation strategies. This will also help the farmers to develop and improve irrigation scheduling strategies with respect to their specific crop production settings.

This irrigation forecasting DSSIS has been tested on a small scale in an arid oasis and provided satisfactory results regarding water productivity. It could be promoted over a large scale. To further improve the site-specific irrigation management, the soil textural variability could be analyzed and a local-level soil database could be developed through extensive soil sampling and analysis. This soil database could be integrated with DSSIS for scheduling irrigation for a specific field. This concept of irrigation is termed soil test-based irrigation prescription (STIP). Availability of site-specific soil information may result in potential gains in improved WUE and higher profitability in arid regions where existing irrigation strategies are poorly connected with local agronomic and biophysical settings. Hence, development of the STIP concept could be a way forward to improve WUE and further strengthen efforts to conserve and efficiently utilize the limited water resources in arid and hyperarid regions.

5. Future Prospects

This paper presented an overview of advanced and smart irrigation practices for improving WUE in water-limited regions, but still there are some challenges that are important to consider for designing smart, sustainable and user-friendly irrigation systems.

I. Variability in soil texture is a vital source of uncertainty because it influences the current and potential soil water storage estimates both vertically and latterly in a field. Therefore, site-specific soil analysis is one way to rectify this problem and obtain the exact soil parameter information needed for accurate irrigation scheduling. Site-specific soil test-based information integrated with smart irrigation systems can help to improve WUE in arid and semiarid regions. This method is called soil test-based irrigation prescription (STIP). The proper execution of STIP needs specific field soil sampling, analysis of soil properties and development of a soil database. This soil information with crop and weather data can be integrated with a model or decision support system to forecast an irrigation event.

II. Most of the experiments related to smart irrigation systems were conducted on a small scale in research fields or under controlled environmental conditions, which cannot represent commercial farming practices. Therefore, more on-farm studies in large fields are needed for a clear understanding about the implementation of smart irrigation technology.

III. Most of the commercial smart irrigation systems offered by different irrigation companies help to improve water use efficiency, but the high cost of these state-of-the-art devices is a serious challenge for farmers. Moreover, these commercial smart irrigation systems are custom-built, meaning difficulty in control and adaptability. Therefore, affordable and user-friendly equipment should be manufactured at a local level.

IV. Most of the farmers in dryland regions are not well educated and should be trained through practical demonstration of smart irrigation systems by expert extension workers. Furthermore, governments should provide subsidies to farmers for dissemination of such technologies on a large scale.

6. Conclusions

This article provided an overview of the major constraints to agricultural productivity, traditional irrigation scheduling methods, and efforts and advancements that have been achieved to enhance WUE, conserve water, and most importantly guarantee food security through the adoption of different smart irrigation approaches in dryland regions. Dryland agriculture is largely affected by low WUE because farmers are relying upon traditional irrigation scheduling methods, resulting in over- and/or under-irrigation of fields and yield reduction. In this situation, adoption of smart irrigation approaches or technologies including artificial intelligence and deep learning (ANN, fuzzy logic, expert system, hybrid intelligent system, and deep learning), model predictive irrigation systems, VRI technology, and UAVs could ensure high water use efficiency and productivity in water-scarce regions. These technologies consider several factors, including soil and climate variation, soil structure and hydraulic properties, plant responses to water deficits, and changes in weather factors to apply the right amount of water at the right time and place. However, all these methods face some challenges regarding accurate execution and performance under field conditions, which could be rectified by incorporating indigenous knowledge and through practical demonstrations to the farmers. Smart irrigation technologies are revolutionizing global agriculture. Such technologies are highly desirable to achieve the SDGs and improve the living standards of poor farmers in drylands.

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