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Article

Evaluating the Use of Intelligent Irrigation Systems Based on the IoT in Grain Corn Irrigation

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Abstract: This study was conducted to evaluate the management of smart irrigation in grain maize production (KSC 715 cultivar) at the Seed and Plant Improvement Institute (SPII) located in Karaj, Iran, in the year 2020. Irrigation was performed based on 40% moisture discharge farm capacity and was compared with irrigation based on long-term meteorological statistics that have become common in the field (drip irrigation system, type strip, and determining the irrigation time based on the apparent reaction of the plant). The experimental results showed that under the conditions of smart irrigation management, sensitive phenological stages of the plant occur earlier, and the field is ready to be harvested approximately one month earlier; moreover, 35% of irrigation water consumption can be saved. Water consumption decreased from 8839.5 to 5675.67 m^3/ha; in addition, grain yield and water productivity decreased. Although the moisture stress applied in the intelligent irrigation system completed the plant phenology period faster and due to earlier harvest, irrigation water consumption was decreased by 35%, water productivity was reduced. Finally, it seems that by adjusting the drought stress application time in more tolerant stages of maize growth in future studies and experiments, it will be possible to decrease irrigation water consumption while increasing the physical productivity of water.

Keywords: smart irrigation system; moisture of soil; sustainable agriculture; corn; internet of things

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1. Introduction

There is a growing concern regarding a lack of fresh water, especially in Mediterranean and Middle Eastern countries, such as Iran [1]. Currently, one third of the world's population lives in water-stressed regions, particularly in semi-arid and arid regions of Asia, the Middle East and North Africa, as well as Mediterranean countries [2]. Climate policies and water management are interconnected. Accordingly, numerous variables can influence water management, including water demand from different sectors and the effects of global warming on hydrological resources [3]. Climate change and its impacts are one of the most frequent topics in water resource and agricultural research. The possible consequences of global warming have led to the development of water adaptation measures to ensure the availability of water for food security and for humans as well as for preserving ecosystems [4]. Furthermore, it is important to ensure the safety of water that is consumed by humans and that is returned to the environment. There are many risks associated with climate change, including water shortage, decreased water quality, increased salinity, loss of biodiversity, higher irrigation needs, as well as the possible cost of emergency and corrective measures.

Irrigation is highly dependent on three main factors, including crop type, weather, and soil, which significantly affect the irrigation scheduling criteria [5]. Irrigation and fertilizer rates are determined by crop type and soil type; in turn, weather, soil moisture, moisture level, and temperature determine irrigation schedules [6,7]. Finally, the irrigation demand for crops changes dynamically every year [8].

Smart irrigation is emerging as a new scientific discipline that uses data-intensive methods to increase agricultural productivity while reducing its environmental impact. Smart irrigation automates irrigation systems, decreases water consumption and increases performance. Therefore, improving agriculture systems has become a necessity, and countries are now looking to implement effective frameworks where systems can be adequately run [9]. Moreover, it is necessary to develop a crop irrigation strategy based on these real-time parameters to ensure smart water management and high-quality crop production [10].

According to the Food and Agriculture Organization of the United Nations (FAO), food production must increase by 70% by 2050 to meet the needs of the global population of 9.6 billion people [11]. Several technologies have been adapted for the internet of things (IoT) to meet this demand. This system refers to a network of objects that communicate with each other over the internet without human intervention. IoT-based smart agriculture can reduce losses, optimize fertilizer use, and increase product yields, thereby preventing pollution. In addition, this technology can decrease agricultural costs, increase agricultural productivity, and help conserve water considerably [12,13].

Generally, the IoT is associated with the objects and devices that are connected to the internet and can be controlled as well as managed through the software on smartphones and tablets. In other words, the IoT is the connection of sensors and devices to a network through which they can interact with each other and with their users [13].

Managing water is an important and effective way to meet the ever-increasing demands of the world. Precision irrigation (PI) as an advanced concept in agriculture promises to improve water use efficiency while preserving or improving crop performance. IoT, wireless sensor networks (WSN), and cloud computing are all required for precise irrigation [14]. Thus, emerging technologies such as the IoT have the potential to provide significant benefits to smart agriculture (SF) and precision agriculture (PA) applications, as well as to provide access to environmental data at any time [15]. The adoption of these technologies is expected to revolutionize the agriculture and irrigation sectors, shortening management decisions from a few months or weeks to a few days or hours, while considerably reducing costs and increasing performance. The use of such technologies enables the efficient use of agricultural inputs and supports four pillars of precision agriculture, i.e., apply the right practice at the right place at the right time and with the right quantity. PA is applying the right thing at the right time in the right amount in the right place [16].

Among the benefits of IoT in irrigation, smart irrigation systems use IoT-based sensor units to accurately estimate irrigation needs and to prevent plants from becoming stressed by recording product temperature and soil moisture. They provide maximized product (with minimum water consumption) and sustainable development. Therefore, PI is an efficient solution to address the shortage of basic resources such as food, water, land units, and crop yields [17].

The effectiveness of irrigation depends on the monitoring of environmental conditions and the needs of the plant. This is because plant water needs depend on such factors as temperature, moisture, precipitation, and soil moisture. The sensors used in this field should check for parameters such as temperature and moisture [18]. Figure 1 shows an overview of a smart irrigation system based on different sensors. Sensors, microcontroller units, and user units receive environmental information and process it. Then, the farmer is informed through the cell phone communication network.

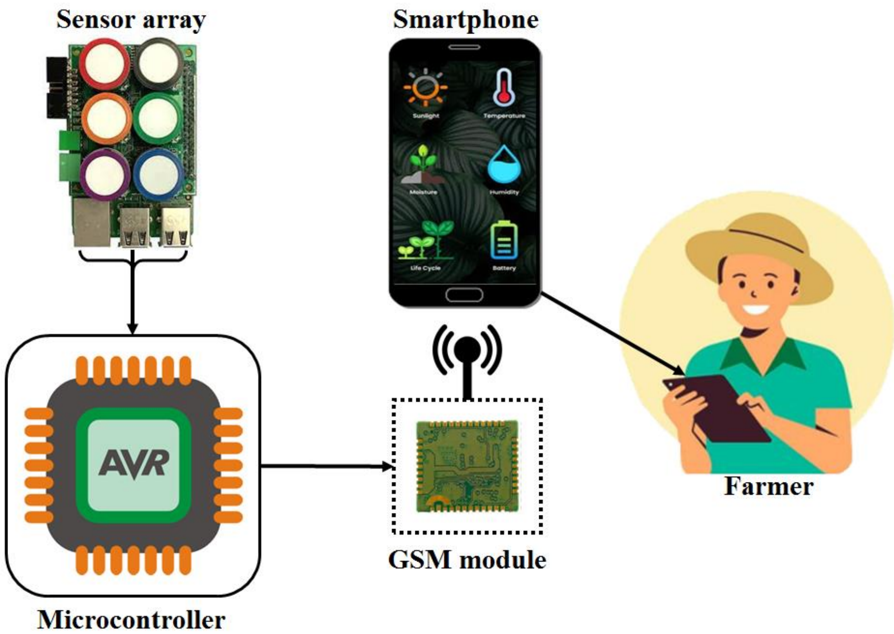

Figure 1. Overview of irrigation systems based on smart sensors.

The availability of real-time weather and in situ soil data has revolutionized agricultural decision making with the advent of the IoT. Monitoring and decision making based on wireless sensor networks and the IoT for irrigation systems has historically accurately predicted irrigation scheduling based on measured data, thereby increasing water productivity [19–22].

There is evidence that in the three methods of irrigation scheduling based on the gypsum block method, water balance, and plant cover temperature, the amount of consumed water is significantly reduced in the plant cover temperature method compared to the other two methods [23]. About 30% of water consumption has been reduced by using tensiometers in irrigation planning [24]. The drip irrigation planning of different plants was carried out using tensiometers, hygrometers, and estimations of evapotranspiration. The results obtained revealed that compared to regular irrigation, these tools could reduce water consumption by 21–40%. Furthermore, the use of soil nutrients decreased by 39–74%, which did not significantly affect plant growth and product quality [25].

A data collection system for monitoring soil moisture and transmitting data remotely was developed using digital sensors and computer software written in Python. To enable remote data access and transfer, the data were automatically collected and uploaded to the internet platform. The data were successfully recorded in real time within a week using this system. The volume content of water ranged from 0.03 to 0.23 m^3, dielectric permittivity from 3.3 to 18.9 (no unit), EC from 0.0 to 0.3 decisiemens per meter (dS/m), and soil temperature from 44.8 to 20.7 °C. The data could be monitored remotely with a free online application [26]. In addition, other researchers have investigated the use of the internet of things in the intelligent irrigation of agricultural fields [27–31].

The literature review showed that irrigation scheduling methods and tools can reduce water use or increase its efficiency compared to traditional irrigation methods. Moreover, the use of intelligent systems will not only increase accuracy but will also facilitate monitoring and control. Although the use of these tools is essential in farming and agricultural management, research is needed in different products and regions, which was investigated in corn in this study. Therefore, the aim of this study was the effect of smart irrigation methods on crop yield in different ripening periods and water consumption efficiency. The results of this study can provide an effective irrigation strategy for the production of maize that can ensure the stable yield of maize, and even increase its yield, while reducing irrigation and successfully saving water.

2. Materials and Methods

2.1. Study Area

This study was carried out in the research farm of Karaj Seedling and Seed Breeding Research Institute (35°48′ N, 51°E, 1321 m above sea level) in 2020. The area is categorized as a semiarid climate with an average annual precipitation of 251 mm, an annual average temperature of 13.5 °C, and a total annual class "A" pan evaporation of 2184 mm. Precipitation in the region averages 275 mm, which makes it one of the coldest and least rainy regions in Iran.

Preparation of the seedbed included plowing with an iron plow, rotavator, disk, and leveling in spring. Before sowing, urea and ammonium phosphate fertilizers were applied based on the soil test (Table 1) and mixed into the soil with a disk. Finally, two plots of 3000 m^2 each were established. To prevent the spread of weeds, the Aradikan herbicide (6 L/ha) was applied before planting and the herbicide 2,4-D was applied after planting (1.5 L/ha) when the plants were at the 4–6 leaf stage. This herbicide was used to control broadleaf weeds. The diazinon insecticide was applied at a rate of two liters per hectare to control corn pests. At the 4–6 leaf stage, 200 kg of urea fertilizer per hectare was used as a top dressing, along with irrigation water in the tank strips and the water filtration system. The plants were cultivated in furrows and stacks and immediately irrigated with the micro-irrigation system. In the smart farm, irrigation was based on intelligent control, while in the control farm, it was based on conventional plant needs and appearance, as well as morphological characteristics. The distance between stacks was 75 cm, and the distance between plants was 18 cm (with a cultivation density of 7.5 plants/m^2).

Table 1. Physicochemical characteristics of the soil test.

Total Nitrogen (%)	Absorbable Phosphorus Mg/Kg	Absorbable Potassium Mg/Kg	Field Capacity (%)	Permanent Wilting Point (%)	Apparent Specific Gravity (g/cm)	Electrical Conductivity (dS/m)	pH
0.06	37	290	25.85	11.07	1.36	0.7	7.5

2.2. Product Application Panel and Intelligent System

In general, the design and implementation of the intelligent irrigation system was divided into two parts: the design of the central controller as well as the design and selection of the network of operators and sensors (Figure 2). Implementation of this project in the field involved using a temperature and moisture sensor (model AM2305) and a soil moisture sensor (model WaterMark200-S), along with two 5-inch flow meters (manufactured by Abban Company in Iran) to measure the amount of water. An operator was also used to interrupt and connect the water flow.

2.3. Determination of Irrigation Timing

The irrigation timing in the smart farm was determined by soil moisture drainage from field capacity using a moisture sensor in the field. Accordingly, the plants were irrigated from planting to before corolla emergence (0–800° growing degree-days (GDD)) based on 40% of field capacity moisture drainage. In addition, before the appearance to the milking stage (800–1200 GDD), the plants were irrigated based on 30% of field capacity moisture drainage, and from seed milking to physiological maturity (1200–1400 GDD), the plants were irrigated based on 40% of field capacity moisture drainage [32].

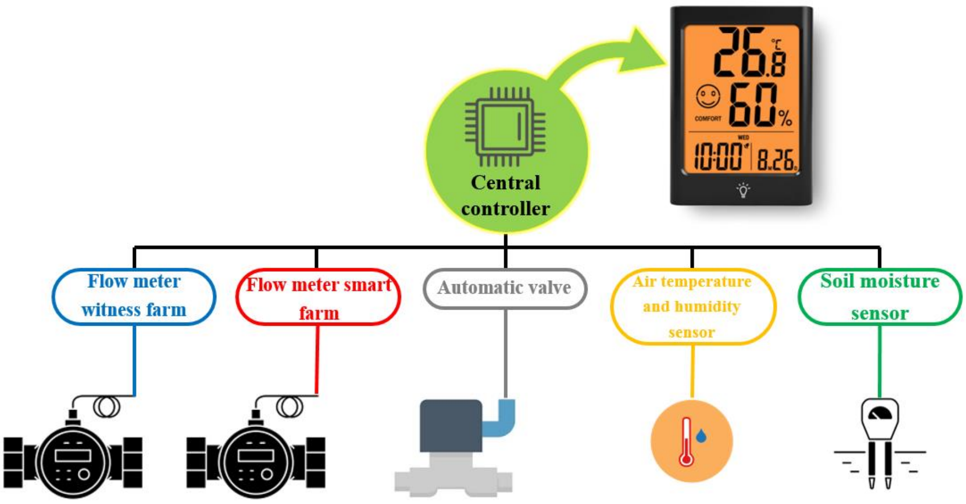

Figure 2. Overview of the intelligent system components.

Growth degree day was calculated based on Equation (1):

$$\mathrm{GDD} = \frac{\mathrm{T_{max}} + \mathrm{T_{min}}}{2} - \mathrm{T_b}. \tag{1}$$

where GDD is the growing degree day in °C, T_{max} is the maximum daily temperature in °C, T_{min} is the minimum daily temperature in °C, and T_b is the base temperature, which is considered to be 10 °C. In this equation, the minimum and maximum daily temperatures for corn growth were considered between 10 and 30 °C, and temperatures higher and lower than 30 and 10 °C were considered as 30 and 10 °C, respectively.

Irrigation time was determined in the control field (drip irrigation system) with an irrigation cycle of three days after planting and plant establishment based on their apparent response. At harvesting time, 40 plants were randomly harvested, and several parameters were measured. The plant height was determined after the appearance of silk (in cm) on each experimental plot using a wooden ruler (from the ground (stack height) to the base of the corolla). In addition, the stem diameter was measured at the internode above the highest bud. The cob length and diameter of each plant were determined in centimeters at the post-emergence silk stage. Moreover, the number of leaves remaining at the post-silking stage was counted.

2.4. Statistical Analysis

The data were analyzed using SAS software version 9.1. In addition, experimental factors were compared using Student's *t* test.

3. Results and Discussion

The results indicate that the number of days until maturity in the control and the smart farms was 171 and 141 days after planting (DAP), respectively (Table 2). With the one-month reduction in the growing season under smart irrigation conditions, it seems possible to cultivate corn in seed form in areas with a limited growing season by controlling the field moisture.

Plants can mature one month earlier as a result of moisture stress caused by smart irrigation treatments, because plants have to complete their life cycle earlier and survive under these conditions [33]. According to the national water document, the net requirement for irrigation of grain maize in Karaj is 7000 m^3/ha [34]. Therefore, at least 20% less irrigation was applied in the smart farm. The results of the experiment showed that the moisture stress applied in the intelligent irrigation system completed the phenological period of the plant faster, and due to the earlier harvest of the field, irrigation water consumption was reduced by 35%, but water productivity decreased. As a result, it can be argued that by applying drought stress at more tolerant stages of corn growth, in future studies and experiments, irrigation water consumption will be reduced, while physical productivity will be increased.

Table 2. Different experimental factors under the influence of different forms of irrigation management in the control and smart fields (based on whole field harvest or estimation).

Experimental Parameters	Control Farm	Smart Farm
Days to corolla appearance	64	63
Days to pollination	64	65
Days to the silk emergence	71	69
The interval between pollination and silk emergence	5	4
Days to harvest	171	141
Seed moisture (%)	40.15	33.8
Hectoliter (g/cm^3)	722	717
Water consumption (m^3/ha)	8839.50	5676.67
Water efficiency (kg/m^3)	0.86	0.66

3.1. Morphological Features

The difference in morphological traits in the smart and control fields was significant for plant height and comb diameter ($p < 0.01$) as well as the number of leaves ($p < 0.05$) (Table 3). By contrast, no significant difference was observed in stem diameter and comb length (Table 3).

Table 3. Different experimental factors under the influence of different forms of irrigation management in control and smart farms using *t* test.

Experimental Parameters	Control Farm	Smart Farm	Standard Error	Probability Level
Height (cm)	163.22	183.30	7.06	**
Stem diameter (cm)	1.44	1.56	0.07	ns
Leaf number	13.97	14.55	0.27	*
Comb length (cm)	18.53	18.51	0.63	ns
Comb diameter (cm)	4.71	4.42	0.10	**
Number of seed rows	17.7	17.45	0.39	ns
The number of seeds in the row	40.15	33.8	1.38	**

Note: **, *, and ns indicate significance at the probability level of 0.01 and 0.05 and non-significance, respectively.

Plant height increased by 12.30% in the smart farm, from 163.22 to 183.30 cm (Table 3). Since there is a slight lack of irrigation in the vegetative growth stage, the corn plant tolerates relative water stress at this stage. In other words, a reduction in irrigation interval based on 40% field capacity drainage compared to irrigation under normal conditions improves moisture availability for cell division and plant height increase [35]. Under these conditions, the comb diameter decreased from 4.71 to 4.42 cm (Table 3). According to the potential of comb diameter after pollination, it seems that the moisture conditions after pollination were better in the control field than in the smart field.

Furthermore, the average number of leaves in the smart field was 14.55 and in the control field, 13.97 (Table 3). The higher number of leaves in the smart farm conditions might indicate that the moisture conditions in the vegetative growth stage were better in the smart farm.

3.2. Irrigation Water

As compared to the control farm, the average irrigation water consumption of the smart farm decreased by 35.78%, from 8839.5 to 5675.67 m^3/ha (Table 2). Under smart irrigation conditions, irrigation water productivity decreased from 0.86 to 0.66 kg/m^3. To save costs, both pilot and control farms directly measured the growth indicators of the crop to monitor plant growth and production levels. Water usage and soil moisture were monitored intelligently, and the notifications indicating the minimum as well as maximum soil moisture points were sent to the user via mobile devices. Moreover, the user could control the soil moisture before and after irrigation according to the notifications received regarding minimum moisture (start of irrigation) and maximum moisture (end of irrigation). On the basis of the superiority of the plant growth indicators in the pilot farm compared to the control, the user did not consider it necessary to control soil moisture through direct measurement (sampling) when starting and stopping irrigation. Hence, there are no control data (it was not necessary). However, sampling was conducted during the reproductive period, and the obtained values were confirmed as a function of soil moisture. Soil moisture monitoring data were displayed in one-hour periods (Figure 3). The amount of water delivered to the farm was also measured by flowmeters and was made available to users. Figure 3 shows soil moisture during the three stages of growth before and after irrigation. This figure exhibits that the moisture sensor worked well; in addition, it controlled the minimum and maximum time of soil moisture according to the moisture changes.

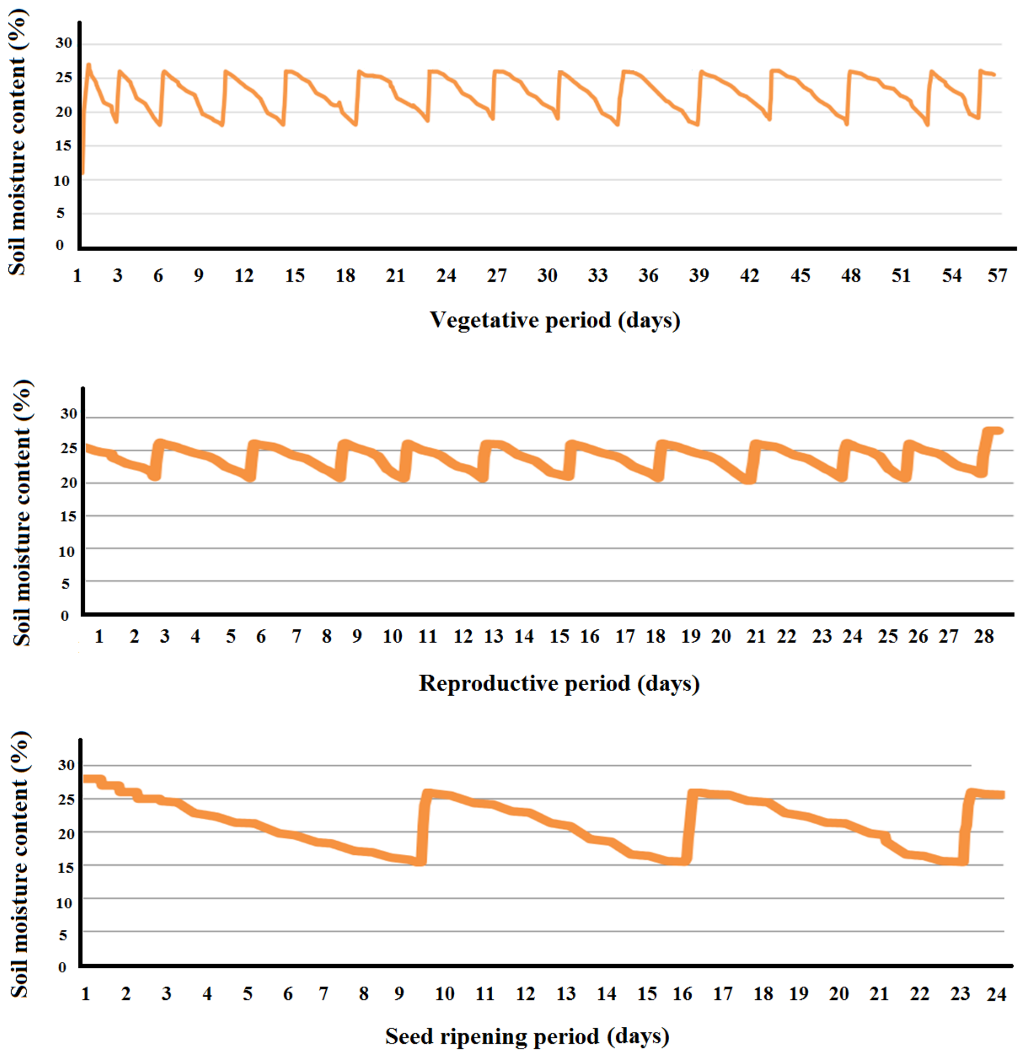

Figure 3. Moisture percentage at different times.

The results of the smart irrigation system in this figure indicates that the smart farm was irrigated about every 3–4 days and 15 times during the growing season, each time for about 4 h and 30 min, for a total of 67 h and 30 min. In contrast, this plot in the reproductive stage was irrigated less than once every 4 days and 11 times, each time for about 3 h for a total of 33 h and 45 min. From the milking stage until physiological maturity, the plot was irrigated once every 7 days and three times, for an average of 4 h and a total of 12 h and 45 min. Figure 4 depicts the status of water delivered to the farm after conversion to the amount of water delivered to the farm per hectare.

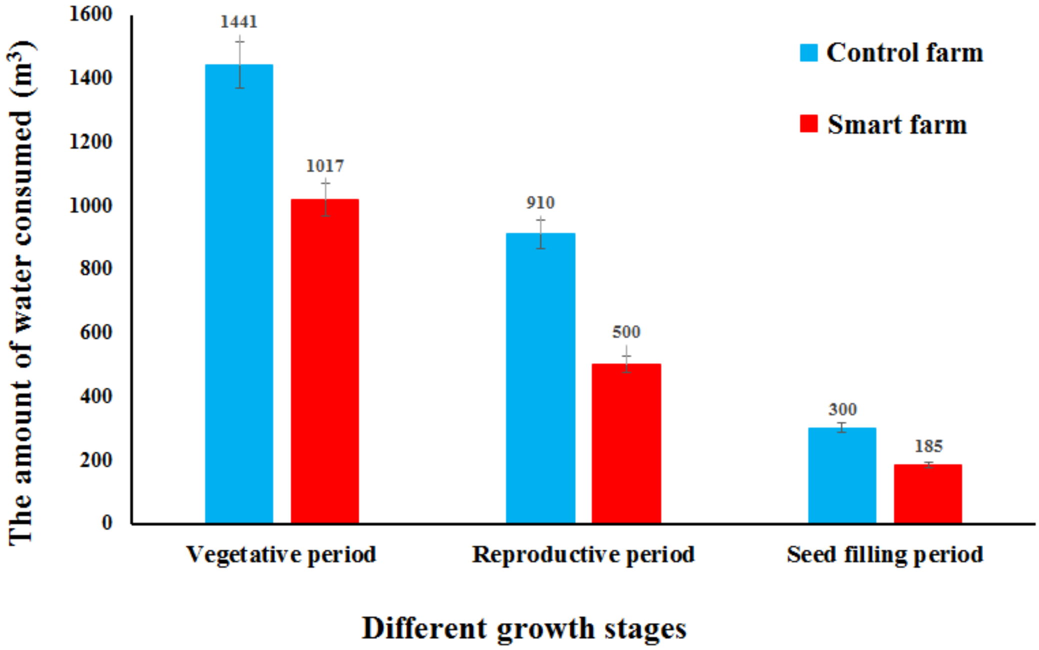

Figure 4. Irrigation water quantity in the three phases of growth, reproduction, and seed maturity.

3.3. Savings in the Water Balance Used

The processed data of the intelligent system and their conversion into units per hectare revealed that in the two-week irrigation period of June, the amount of water delivered to the intelligent farm was 5675 m^3/ha. The same value was 8839 m^3/ha compared to the control farm, where irrigation continued until October. Thus, the savings in irrigation water was 35.8% (according to the soil moisture data, irrigation was stopped when the water reached the limit of field capacity (FC) and the penetration depth was zero). The graph of water delivery to the farm, for each period and per hectare, is shown in Figure 5.

Zia, Rehman, Harris, Fatima and Khurram [10] compared flood irrigation with IoT-based and traditional irrigation in a lime farm and found that the IoT-based irrigation method saved 52,280 L of water in the field. In contrast, this irrigation system increased production by 1680 kg/ha, i.e., it achieved 35% greater production while saving 50% water. Gong et al. [36] used an IoT-based smart irrigation system with data combination and a large self-recharging network. According to the results, they achieved average water savings of 94.74% with the proposed system compared to conventional manual adjustment solutions. Similarly, another study aimed to use cloud IoT solutions to control an advanced subsurface irrigation system to improve the irrigation management of date palms in drylands. The researchers found that sensor-based irrigation scheduling (S-BIS) and time-based irrigation scheduling (T-BIS) of the controlled subsurface irrigation system (CSIS) reduced the amount of irrigation water applied by 64.1 and 61.2%, respectively, compared to traditional surface irrigation (TSI). Water productivity in CSIS using S-BIS methods was significantly higher at 1.783 kg/m and T-BIS at 1.44 kg/m compared to TSI at 0.531 kg/m [27]. Thus, controlled water use increases fruit yield and quality, leading to changes in the stages of vegetative and productive growth as well as in the intensity and duration of water deficit [37]. Cheng et al. [29] investigated the effects of soil water deficiency in different stages of corn growth. They used two irrigation methods, i.e., conventional irrigation (CI) and alternate partial root zone irrigation (APRI). The results showed that APRI and CI reduced total water consumption by 34.7% and 23.8%, respectively, compared to the control treatment. In addition, deficit irrigation at the milking stage produced a longer tip length, resulting in a lower grain yield. Their results are very consistent with the results of this research. In another study that was conducted on the response of summer corn growth and water consumption to different irrigation regimes, researchers reported that when irrigation decreased, grain yield decreased, and water use efficiency increased, whereas water deficit at the tasseling stage had the greatest effect on yield and water use efficiency [30]. Smart irrigation systems were investigated for four crops: wheat, corn, sunflower and rapeseed. Their results showed that average water-use productivity rose from 4.09% to 9.8% for wheat and sunflower. In addition, an increase in yields varied from 5.72% to 13.42% for wheat and corn [31].

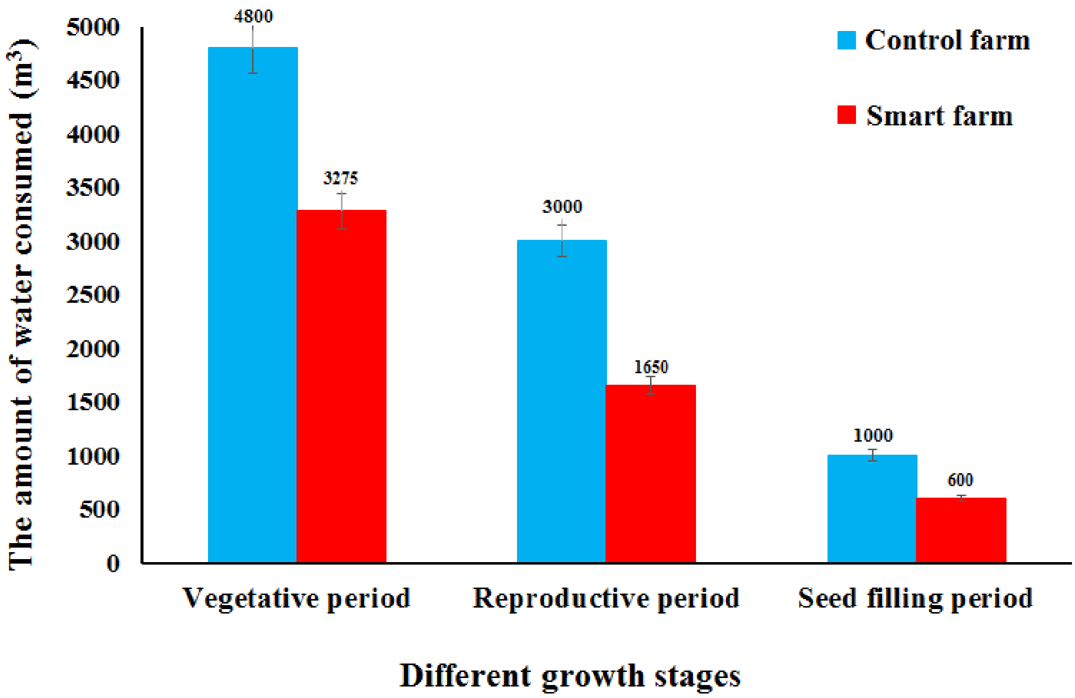

Figure 5. Irrigation status per hectare in three periods of growth, reproduction and seed maturity.

According to the network planner's irrigation schedule and based on long-term data as well as prediction of the plant's water needs, the control farm was irrigated twice per week during the growing season, for a total of 16 times, each time for six hours, for a total of 96 h. In the reproductive phase, this farm was irrigated three times per week, each time for about five hours, for a total of 60 h. Moreover, in the maturity stage, it was irrigated once per week and five times, each time for about four hours, for a total of 20 h (Figure 6).

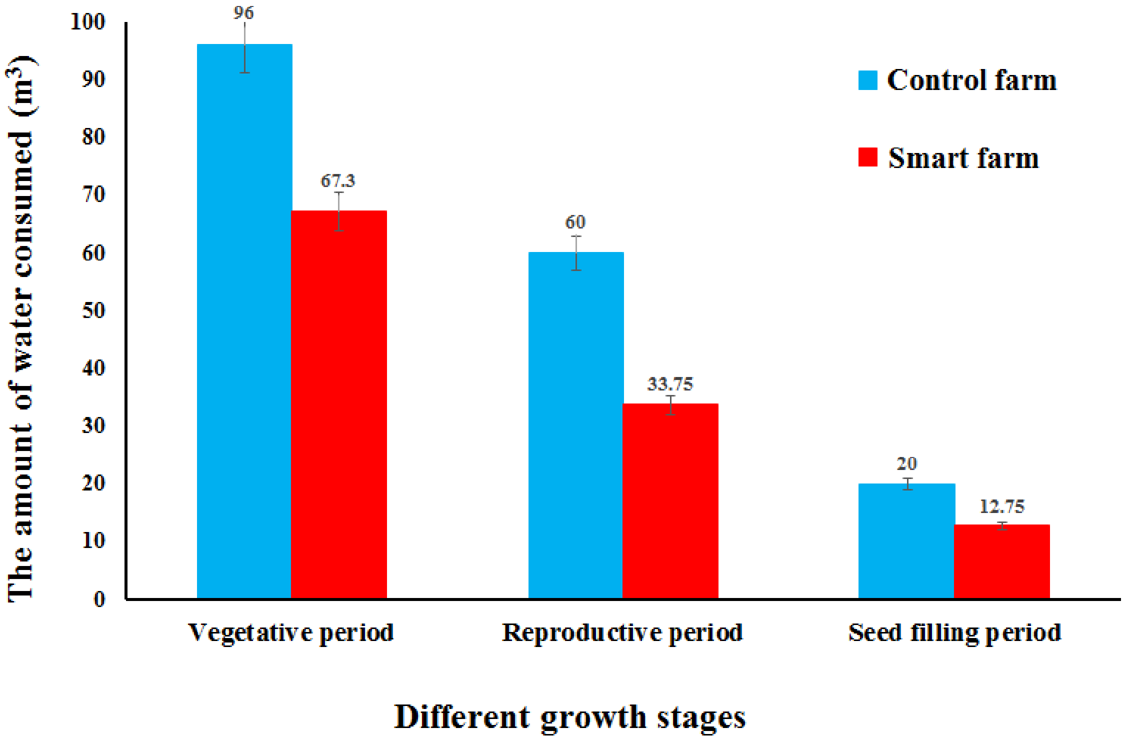

Figure 6. The final condition of the pilot and control farm irrigation hours.

3.4. Time Monitoring of Decision Data

Figure 7 illustrates the final state of the decision data after a given monitoring period. Compared to the plot of the proposed algorithm, this graph stopped growing at 1400 GDD.

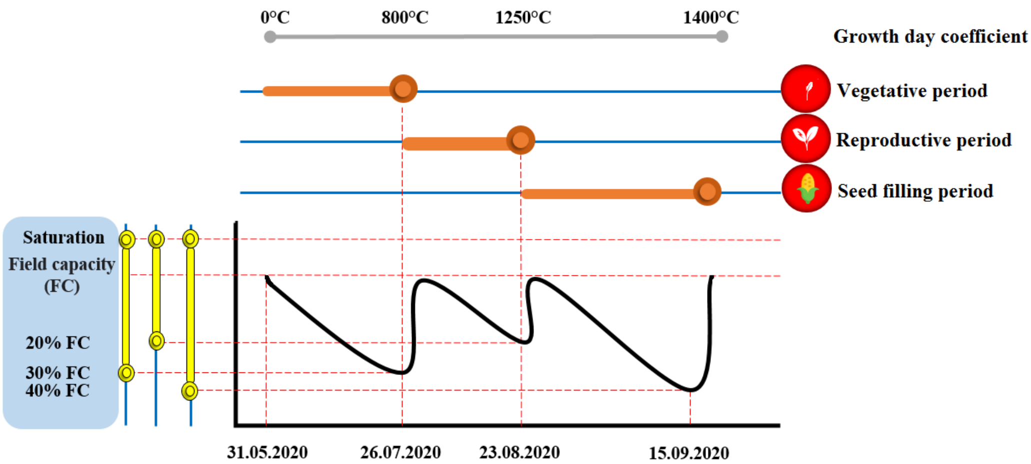

Figure 7. Time monitoring of decision data over time (GDD in three growth periods).

3.5. Analysis of the Number of Moisture Sensors

Smart irrigation systems rely on soil moisture to develop appropriate systems. There are several environmental variables that can affect this parameter, including air temperature, moisture, ultraviolet radiation, soil temperature, etc. [19]. One sensor was sufficient in meeting the needs of the system so that the plant received sufficient moisture. A clear recommendation is to use two sensors (instead of one sensor) to allow for intelligent control of possible errors. In the farms larger than five hectares, the use of at least two sensors is recommended, because soils can be heterogeneous. The intelligence of the proposed system depends on the accuracy of the predicted soil moisture.

4. Conclusions

In this study, the effect of two different irrigation methods on the physiological performance of corn and water consumption was determined. According to the results, the reduction in irrigation water consumption corresponded to the stages of corn plant growth. This can be attributed to the creation of water stress, resulting in a shorter growth period and reduced water consumption through decreased transpiration. Even though the moisture stress applied by the smart irrigation system resulted in faster completion of plant phenology, and owing to earlier harvesting under smart irrigation conditions in this study, the consumption of irrigation water decreased from 8839.5 to 5675.67 m^3/ha; in addition, grain yield and water productivity were reduced. Overall, it can be concluded that adjusting the timing of drought stress application at more tolerant stages of corn growth can reduce irrigation water use while increasing the physical productivity of water in future studies and experiments.

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