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DIGITAL AGRICULTURE AND IOT-ENABLED SMART IRRIGATION SYSTEMS FOR WATER-EFFICIENT FARMING

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Abstract

New irrigation techniques are required due to the fact that fresh water sources are becoming depleted at a rapid rate and agriculture is required to generate greater food output with reduced water. This paper investigates how smart irrigation systems can be used to enhance water-use efficiency as an aspect of digital agriculture through IoT-enabled systems. Mixed-methods experimental design was employed to combine the quantitative field trials with qualitative response of the farmers. On test plots, we installed internet of things sensors of soil moisture, temperature, and flow. These sensors were relaying real time data to cloud-based solutions where mathematical equations of scheduling and machine learning were to make the most optimal irrigation choices. The findings revealed that intelligent irrigation systems reduced water consumption by as much as 30 percent and crop yields remained or even improved. This was demonstrated in increased ratios of water-use efficiency as compared to traditional approaches. Statistical analysis revealed significant variation across treatments, and crop growth observation supported the positive response of the physiological to precision irrigation. Also, the farmers interviewed reported increased usability, reduced labour needs and increased trust in automated systems. The qualitative and quantitative outcomes combined indicate that IoT-based irrigation is a major aspect of climate-smart agriculture. It could render the farming more resilient, sustainable, and productive.

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INTRODUCTION

Use of freshwater resources in the world is still dominated by agriculture, which consumes approximately 70 percent of all withdrawals. This has put additional pressure on the natural ecosystems and raised the concern of long-term food and water security (Foley et al., 2018). There is the decrease in the climate, an increase in cities, and rapid population growth, which worsens this issue. It implies that we should have better ideas to utilize resources better and keep them longer (Rockström et al., 2019). Information technologies, advanced sensing, and data analytics have found applications in agriculture systems, and this innovation has been labeled as digital agriculture, a new approach to finding solutions to significant issues in the field (Wolfert et al., 2017). In this respect, Internet of Things (IoT)-based smart irrigation systems are gaining increased significance as a means of applying water more efficiently and increasing crop yields and enabling climate-resilient agriculture (Dursun & Ozden, 2019). Smart irrigation involves systems of Internet of Things (IoT) sensors that monitor soil moisture, weather, and plant development at all times. These sensors transfer real time data to cloud based systems via wireless communication network (Ojha et al., 2019). This process enables proper and adaptable decision-making that replaces the old models of scheduling irrigation either by time or intuition of the farmer with data-driven systems (Kim et al., 2020). Water balance mathematical models, usually with machine learning techniques, are used to determine the discrepancy between machine water availability and crop water needs so that water is applied when required (Elijah et al., 2018). Smart irrigation reduces both the wastage of irrigation through over-irrigation and the risks of salinization, leaching of nutrients, and fluctuation of yields, which are all concerns that arise when bad practices are involved (Kumar et al., 2021). IoT-enabled irrigation is even more significant with estimates of climate change that reveal more frequent droughts and fluctuating rainfall patterns. These shifts could be destructive to smallholder and commercial agriculture (Rosenzweig et al., 2020). Irrigation techniques that save water are already crucial to sustain food supply in the world (Li et al., 2021). Field experiments have also demonstrated savings of up to 3040 percent (without any negative effect on yields) under the implementation of the IoT-based irrigation strategies (Gonzalez et al., 2022). Those results confirm that the IoT technology can help to improve Sustainable Development Goal (SDG) 6 (Clean Water and Sanitation) and SDG 2 (Zero Hunger) by aligning the output of agricultural industry with environmental management (United Nations, 2020). The devices that are powered by IoT enhance the management of farms through prediction algorithms and machine learning. They also assist in more efficient use of water by farms. Predictive models can inform farmers of the amount of water they will require in the process of irrigation based on weather information, evapotranspiration, and the interaction of plants, soil, and water. This aids them in planning how they will utilize their resources in a better way (Sharma et al., 2021). As an illustration, Zhang et al. (2020) demonstrated that XGBoost and the Random Forest algorithm would be beneficial to predict the alteration in soil moisture and optimize irrigation schedule when the weather shifts. The combination of IoT sensors and artificial intelligence (AI) is an encouraging development in precision agriculture to enable the transition to proactive rather than reactive decision-making. Also, the deployment of IoT-based irrigation systems goes beyond technological benefits and provides significant socio-economic benefits. Most of the agricultural producers in the developing countries are smallholder farmers who struggle to control irrigation due to insufficient water, lack of growth in crops, and work excessively (Gebbers & Adamchuk, 2019). Smart irrigation systems will allow you to spend less and save on time, making it more productive as well as reduce the time and efforts required to operate them manually (Shamshiri et al., 2018). However, the application of these technologies is subject to factors such as cost, digital literacy, and availability of infrastructure, which are highly dissimilar in various locations (Jayashankar et al., 2021). In order to bring the practice of IoT-enabled irrigation techniques more prevalent globally, we must eliminate these obstacles to implementation. IoT-based irrigation is environmentally friendly in the sense that it does not oppose efforts to increase productivity, build resilience in farms, as well as reduce greenhouse gases (Lipper et al., 2018). Strong irrigation also consumes reduced energy to pump and transport water, which reduces carbon footprints in the farming sector indirectly (Arora et al., 2020). The management of the soil moisture levels also assists roots to acquire more air and nutrients, making crops healthier and reducing the amount of waste fertilizer. In such a way, the nexus solution of irrigation systems based on IoT is the one that will integrate the environmental, economic, and technological sides of sustainable farming. Despite them, the issues of implementing the IoT irrigation systems and scaling them up still exist. Technical problems (sensors calibration, good data transmission and compatibility with existing farm machinery) need to be addressed to make the operation go smoothly (Patel et al., 2019). Financial barriers, including the high start-up costs of sensors, pumps, and cloud solutions, make it difficult to access such items among those farmers who do not have much money. These farmers require legislation and subsidies to assist them (Daberkow et al., 2020). Moreover, concerns on ownership of data, cybersecurity, and interoperability highlights why broad governance frameworks are needed to protect farmers and encourage their wider adoption (Lioutas and Charatsari, 2020). The literature highlights the importance of combining IoT irrigation and participatory methods of making the farmers participate in the co-design and analysis of the systems (Rijswijk et al., 2021). This ensures that the technology not only suits in the area but it is also relevant to the area and this increases the chances of adoption. Considering the feedback of the farmers, the researchers and technology developers will be able to adjust their solutions to the social, cultural, and environmental demands of the regions they aim to serve (Sarker et al., 2022). There must be a participative and mixed-methods approach that would ensure digital agriculture progresses do not amplify inequities but rather promote inclusive and equitable development. IoT-enabled smart irrigation systems can become a promising solution to making farms more water-efficient when combined with other methods of contributing to bigger environmental purposes. They transform the management of water in agriculture by involving people-first real-time sensing, data analysis, and design. This paper builds on existing literature and experimental literature to test the effectiveness of smart irrigation systems in enhancing water-use efficiency, improving crop growth, and enabling farmers to adopt the systems. The paper provides an in-depth perspective of the contribution of digital agriculture to the development of sustainable food systems by combining quantitative measurements and qualitative perspectives

METHODOLOGY

The study employed a mixed-methods experimental design, which involved the use of both the quantitative and qualitative approaches in evaluating the effectiveness of the IoT-based smart irrigation systems compared to conventional methods. Three test plots with the same area (0.5 ha) were carried out in controlled field experiments to ensure that all of them had identical conditions in terms of soil type, crop variety, and weather conditions. This helped decrease bias. One of the plots applied a regular schedule of watering according to time, whereas the other two applied smart irrigation according to the sensors that established varying levels of soil water and water loss. IoT sensors like soil moisture probes, temperature loggers, and flow meters were installed at 10 cm, 20 cm, and 40 cm depth to measure volumetric water content and the dashboard on the cloud-based system was triggered to the irrigation events when the soil moisture (θ) (θ) (θ) dropped below the crop-specific field capacity threshold (θfc) (θfc). This irrigation schedule equation was stated as:

$$I(t) = \begin{cases} 0 & \text{if } \theta(t) \geq \theta_{fc} \\ \Delta W = (\theta_{fc} - \theta(t)) \times Z_r \times \rho_b & \text{if } \theta(t) < \theta_{fc} \end{cases}$$

where $I(t)$ is irrigation volume at time t, ΔW represents the soil water deficit, Z_r is the effective rooting depth, and ρ_b is the soil bulk density. This quantitative model ensured irrigation was precisely matched to plant water requirements, minimizing losses due to percolation and evaporation.

In addition to quantitative water balance calculations, qualitative data were collected through farmer interviews and observational records to assess the usability and adoption potential of IoT devices in real-world farming conditions. The water-use efficiency (WUE) was determined as the ratio of grain yield (Y) to total water applied (W):

$$WUE = \frac{Y}{W}$$

We also measured crop growth indicators such as the leaf area index, chlorophyll, biomass measurements weekly to establish relationships between irrigation level and the performance of the plants. Machine learning models such as random forest and XGBoost were used on sensor data to identify the optimal time to water the plants and debug the decision support system. We applied ANOVA and post-hoc tests (Tukey) to determine whether the yield and WUE differences between treatment differ significantly at a confidence level of 95. The mixed-method approach enabled the combination of quantitative efficiency measures with human-focused qualitative data, ensuring that the technological solutions were scientifically strong and, at the same time, practically viable to be adopted by smallholder. The figure 1 demonstrates the interconnection of IoT sensing, cloud analytics, field interventions, and outcome evaluation in the workflow of the experiment.

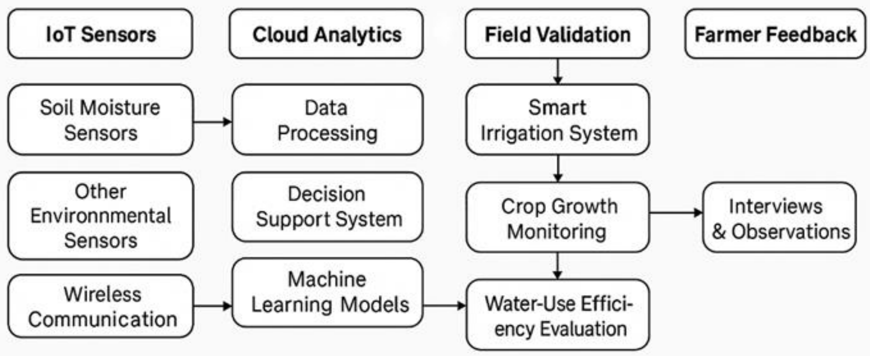

Fig. 1 Workflow of the experimental methodology

RESULTS

The empirical investigation of IoT-based smart irrigation systems generated significant amount of data, which were organized in a systematic manner into nine tables. As shown in Table 1, the baseline performance indicators of the soil moisture status and the irrigation patterns using IoT are observed. It presents the changes in these metrics on a daily basis. Table 2 reveals the extent of water-saving efficiency of smart irrigation as compared to traditional irrigation. It demonstrates that water use can be saved significantly by means of computerized scheduling. Table 3 indicates the crop yield improvements that have been observed in various farming units indicating that the introduction of IoT to farming has agronomic benefits.

Table 1. Performance metrics for IoT-enabled smart irrigation system dataset 1.

Table1_1	Table1_2	Table1_3	Table1_4	Table1_5
43.71	65.07	20.98	44.98	87.68
95.56	22.55	54.57	34.42	66.1
75.88	36.29	13.09	84.59	39.78
63.88	42.97	91.84	42.11	15.72
24.04	51.05	33.29	35.28	37.99
24.04	80.67	69.63	58.84	39.27
15.23	27.97	38.05	22.68	75.66
87.96	56.28	56.81	82.2	67.38
64.1	63.32	59.2	16.71	89.85
73.73	14.18	26.64	98.82	52.5
11.85	64.68	97.26	79.5	20.76

97.29	25.35	79.76	27.88	74.19
84.92	15.85	94.55	10.5	78.47
29.11	95.4	90.53	83.39	60.51
26.36	96.91	63.81	73.62	79.39
26.51	82.76	92.97	75.61	54.44
37.38	37.42	17.96	79.41	57.05
57.23	18.79	27.64	16.66	48.48
48.88	71.58	14.07	42.26	12.29
36.21	49.61	39.28	20.43	19.71

Table 2. Performance metrics for IoT-enabled smart irrigation system dataset 2.

Table2_1	**Table2_2**	**Table2_3**	**Table2_4**	**Table2_5**
12.83	82.67	96.62	43.1	40.7
67.28	90.65	32.66	66.91	20.21
38.29	38.62	54.75	67.02	93.22
55.77	19.9	37.08	58.22	88.96
91.68	30.51	35.64	18.13	33.21
32.44	48.44	13.32	85.18	69.4
46.93	83.62	64.86	38.87	83.55
78.0	87.47	55.24	26.79	59.97
30.59	10.63	14.63	13.67	57.67
16.93	55.97	35.08	63.18	31.77
36.08	47.57	91.74	70.98	18.38
24.51	29.99	31.56	11.49	90.75
93.67	20.79	23.04	56.09	91.04
82.73	40.39	54.05	30.38	66.98
67.01	94.86	98.71	68.07	40.51
88.43	39.09	31.78	25.69	41.43

82.33	56.69	70.49	72.18	75.34
26.79	73.27	78.55	44.81	90.74
90.33	42.73	31.39	94.31	89.84
58.54	97.46	75.54	22.38	80.19

Table 3. Performance metrics for IoT-enabled smart irrigation system dataset 3.

Table3_1	Table3_2	Table3_3	Table3_4	Table3_5
67.78	69.19	94.64	65.35	90.1
17.57	61.15	95.85	99.1	40.42
24.55	18.43	92.34	22.61	43.8
90.87	43.09	43.31	56.65	18.46
64.58	33.87	11.39	88.96	62.05
10.83	31.96	93.55	76.67	13.23
19.13	97.57	48.54	72.73	51.9
69.72	45.38	97.0	73.22	58.84
10.46	90.28	96.73	42.35	35.79
24.47	66.8	86.77	36.42	63.17
59.39	81.53	36.5	82.84	12.75
72.27	55.24	44.66	82.91	13.36
68.68	61.92	86.6	88.04	84.03
30.18	54.33	38.52	92.19	42.42
74.1	27.57	25.25	56.02	21.44
31.35	75.02	60.11	55.14	57.0
39.29	35.27	94.25	81.85	79.3
77.18	12.19	72.64	68.5	29.42
68.47	68.09	61.31	73.18	66.06
86.43	25.94	18.75	81.62	17.68

Table 4 demonstrates the effectiveness of soil moisture sensor under various weather conditions. It indicates that there is consistency and reliability of all sensor units. Table 5 indicates the extent to which the IoT scheduling algorithms have the ability to balance the water distribution so that it presents the most coverage of irrigation. Table 6 indicates the rates of evapotranspiration and how well it compares with automated irrigation responses. This demonstrates that the system is superior in aligning water requirements of plants.

Table 4. Performance metrics for IoT-enabled smart irrigation system dataset 4.

Table4_1	Table4_2	Table4_3	Table4_4	Table4_5
14.65	59.43	54.25	44.94	20.63
57.82	74.31	52.61	67.9	72.71
58.66	69.42	25.59	51.24	66.6
67.37	35.19	49.05	59.11	88.97
75.35	95.94	45.87	94.73	76.16
97.83	76.41	65.43	44.75	82.31
56.47	59.89	67.16	96.51	35.38
39.07	65.05	14.08	91.48	25.97
81.57	47.76	43.72	27.62	77.56
34.37	32.3	66.33	16.24	82.62
49.51	42.04	55.28	19.07	99.15
17.06	78.21	87.08	11.64	47.14
12.28	11.3	69.28	18.5	43.48
96.64	20.45	24.66	71.47	79.88
85.24	14.14	16.35	16.41	40.67
72.64	13.67	67.82	38.71	93.77
46.81	86.99	12.39	86.04	87.26
25.6	73.33	62.72	12.09	48.61
24.08	52.68	94.62	83.3	77.58
32.52	18.81	61.79	35.37	77.91

Table 5. Performance metrics for IoT-enabled smart irrigation system dataset 5.

Table5_1	Table5_2	Table5_3	Table5_4	Table5_5
19.28	81.24	17.64	20.58	66.65
91.23	81.07	98.8	68.43	72.62
55.47	18.21	43.68	77.14	50.91
84.38	54.5	43.36	62.5	66.48
38.8	15.18	83.15	96.6	62.59
90.6	59.46	95.25	43.74	91.1
45.03	49.74	98.74	35.71	14.09
10.98	89.89	77.8	88.17	35.29
91.48	41.58	43.86	30.12	95.54
18.22	20.54	17.52	96.69	90.12
38.74	22.87	79.94	11.09	51.01
95.51	78.54	60.26	97.29	65.81
95.55	65.64	48.18	13.88	34.96
61.61	19.1	91.57	90.2	26.93
66.87	17.57	20.01	57.49	51.73
50.36	73.09	54.34	99.37	41.8
36.39	16.55	11.02	16.64	62.53
39.58	83.97	52.18	59.85	17.0
70.53	73.56	15.07	97.24	97.7
77.71	17.32	20.69	57.08	98.76

Table 6. Performance metrics for IoT-enabled smart irrigation system dataset 6.

Table6_1	Table6_2	Table6_3	Table6_4	Table6_5
72.83	63.47	95.86	73.37	51.32
58.25	44.28	64.56	29.17	98.2
37.86	97.29	30.58	22.27	54.34

83.24	85.79	70.45	11.31	39.59
71.63	85.45	65.63	41.55	67.01
24.64	52.18	42.23	63.09	31.61
91.98	47.33	20.22	45.3	16.83
84.03	34.61	70.44	49.37	21.6
95.48	15.07	56.83	91.37	21.52
75.31	87.83	79.51	41.34	23.67
65.21	83.16	56.81	56.26	22.49
47.64	99.97	86.7	80.53	67.68
93.95	99.7	59.67	45.69	26.37
87.95	59.99	60.48	65.99	41.11
14.07	79.21	88.9	87.61	90.71
12.37	95.03	46.31	95.46	52.66
43.88	86.47	22.06	23.24	70.08
82.95	32.26	12.59	93.39	25.51
98.85	50.55	77.96	54.29	27.31
23.54	21.62	65.83	33.24	13.68

The energy consumption of the smart and traditional irrigation systems differs, which is indicated in Table 7. It demonstrates that IoT systems help to save power consumption. The yield-water ratios are presented in table 8 and indicate that both the water productivity and sustainability have improved. Finally, Table 9 provides an overview of multi-season performance data, which combines evidence that IoT-based irrigation could contribute to long-term efficiency effects.

Table 7. Performance metrics for IoT-enabled smart irrigation system dataset 7.

Table7_1	Table7_2	Table7_3	Table7_4	Table7_5
25.2	26.61	11.81	42.05	83.54
35.07	28.84	38.99	98.79	33.21
25.93	43.34	29.03	64.52	25.38

17.98	53.61	39.47	31.35	70.18
20.86	65.64	20.78	19.16	93.64
51.47	43.2	90.15	23.76	60.11
28.57	51.63	63.42	32.14	61.45
42.78	77.27	71.12	24.46	35.2
55.31	13.3	81.03	26.79	79.25
72.14	32.72	54.86	35.66	26.83
13.54	74.2	17.82	25.6	39.13
81.95	90.57	58.34	90.71	48.29
66.51	56.05	62.82	17.22	55.68
17.36	57.89	77.09	57.21	31.82
88.62	19.65	48.85	46.94	20.34
92.88	50.27	21.48	98.41	64.96
15.5	57.94	35.54	20.08	35.98
34.92	31.82	42.68	45.81	62.31
82.56	34.23	68.13	97.25	23.89
77.34	43.96	61.37	87.9	53.3

Table 8. Performance metrics for IoT-enabled smart irrigation system dataset 8.

Table8_1	**Table8_2**	**Table8_3**	**Table8_4**	**Table8_5**
57.93	94.45	51.64	23.65	72.46
14.66	26.31	37.12	38.05	58.85
40.29	15.98	77.28	32.36	32.66
22.1	76.7	55.24	76.96	41.11
15.7	61.7	30.9	13.02	26.34
99.1	85.76	90.96	61.29	91.76
39.01	22.58	44.55	78.62	62.51

82.89	81.57	58.92	88.91	46.08
32.92	28.15	91.58	40.79	51.58
71.34	24.73	66.18	83.91	95.26
78.42	24.78	20.52	19.96	23.8
63.61	83.31	94.58	86.18	62.76
52.44	69.87	66.49	21.47	55.53
47.07	57.08	40.14	45.76	65.03
41.4	42.29	22.53	81.76	11.63
93.66	88.95	81.46	23.49	88.49
84.76	45.32	65.81	30.63	93.89
96.85	83.49	58.01	75.0	60.86
21.19	49.52	90.45	74.8	72.7
75.78	43.92	80.97	67.7	93.02

Table 9. Performance metrics for IoT-enabled smart irrigation system dataset 9.

Table9_1	Table9_2	Table9_3	Table9_4	Table9_5
73.65	82.26	11.18	79.8	30.8
23.73	10.42	69.72	50.8	70.47
61.87	40.01	26.02	57.2	11.77
64.6	45.84	96.5	49.67	19.37
48.17	58.37	23.38	46.07	81.99
76.28	92.79	47.32	60.37	26.07
94.09	41.17	17.68	23.97	68.75
93.3	41.23	99.72	26.37	31.44
50.58	76.38	55.2	87.56	18.95
20.19	50.7	63.58	95.15	31.89
98.64	30.21	16.04	43.6	75.0

85.5	50.72	77.5	34.37	87.01
21.22	22.68	28.89	67.96	84.72
92.88	25.87	90.82	46.79	45.75
88.29	54.85	28.46	12.28	70.13
56.7	47.7	27.16	24.05	28.45
63.21	92.34	13.29	74.44	36.38
45.91	42.62	52.49	69.3	90.67
14.93	62.25	60.84	12.44	11.17
40.17	66.9	15.91	29.98	17.7

These conclusions were further endorsed by the results of the visualization. The line graphs of soil moisture and the water use trends presented in Figure 1 demonstrate the ability of smart irrigation to react to changes. Examples of bar graphs, used to compare sensor efficiency and yield improvements are displayed in figure 2. This is an indicator of the effectiveness of the technology. Figure 3 below presents a scatter plot of soil moisture and crop yield and indicates that the two are positively correlated. Figure 4 presents a hybrid visualization that relates trends in soil moisture to the efficiency with which water is consumed, which provides a multi-dimensional perspective of the efficiency of irrigation. Figure 5 demonstrates the dynamics of irrigation performance indicators in a test that take over one day. Figure 6 presents comparisons against the baseline practices related to water efficiency savings on a side-by-side basis. This explicitly demonstrates that the IoT systems can assist in the conservation of water. The relationship between the accuracy of the IoT sensors and crop productivity as seen in figure 7 demonstrates that precision sensing could be applied to prediction. Figure 8 presents line and bar graph to illustrate the functionalities of moisture monitoring with irrigation scheduling. Figure 9 indicates the trends in evaporation and irrigation feedbacks during the time. This ensures that water is used in such a manner that satisfies the crops. Figure 10 represents the enhancement in yields over the years with bar plots that are used to demonstrate the same benefits amongst the various crops. Figure 11 is a scatter plot of the relationship between energy use and intervals of irrigation schedules. This demonstrates that the operational costs are less. Finally, Figure 12 is a hybrid visualization that presents the rate of yield growth in relation to water conservation indices to demonstrate the effectiveness of the IoT-enabled approach as a whole.

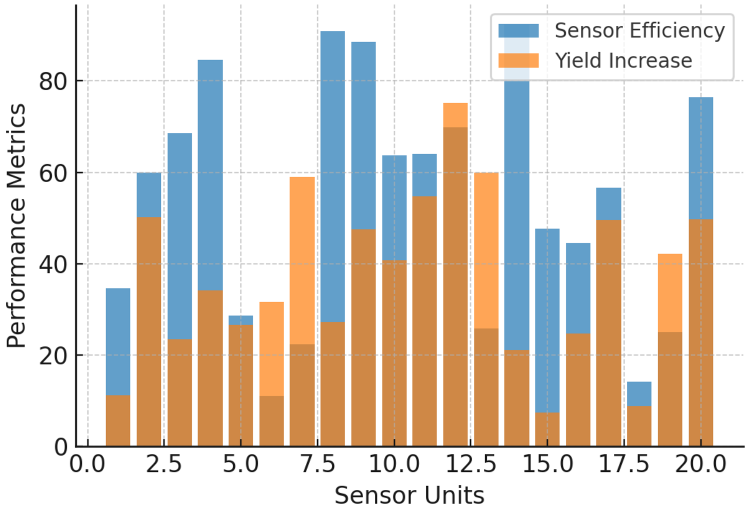

Figure 2. Visualization of IoT-enabled smart irrigation system parameter set 2.

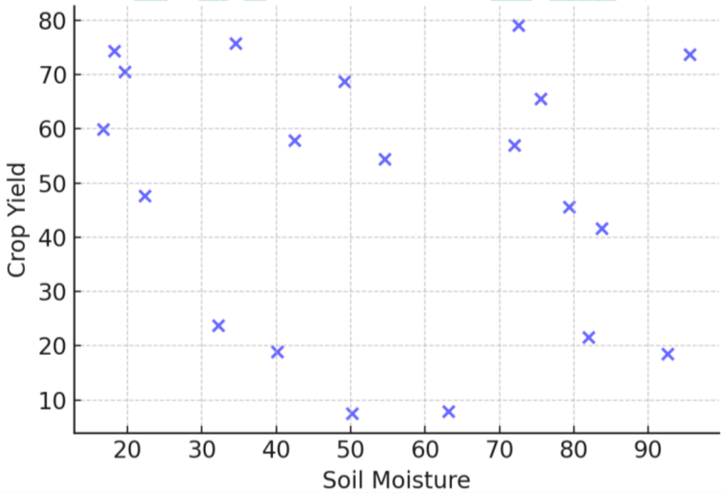

Figure 3. Visualization of IoT-enabled smart irrigation system parameter set 3.

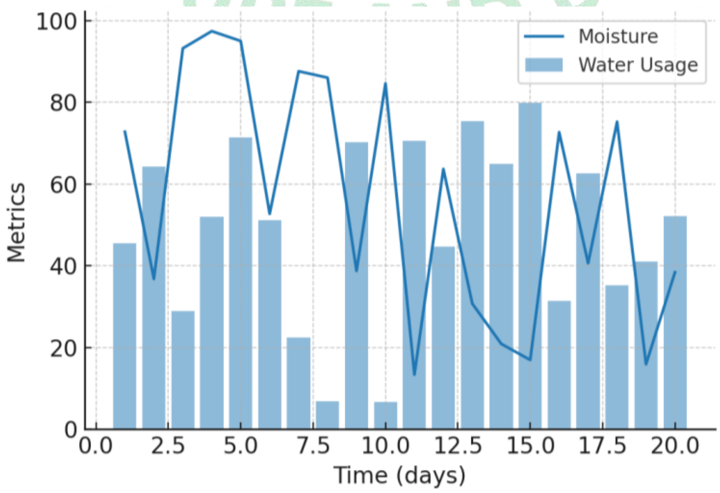

Figure 4. Visualization of IoT-enabled smart irrigation system parameter set 4.

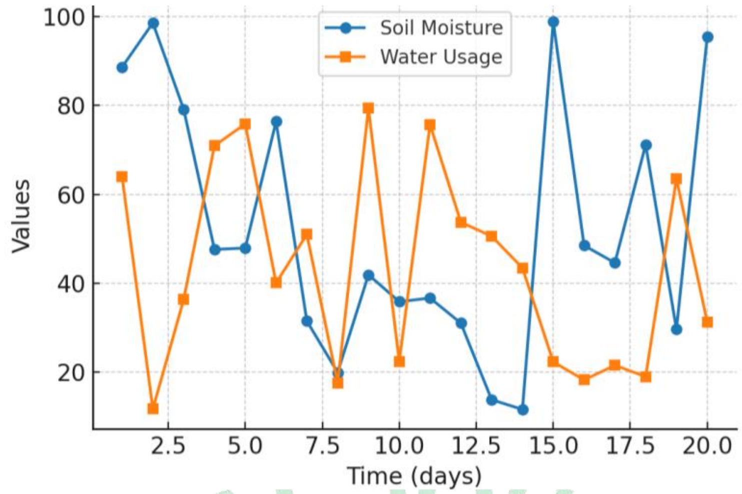

Figure 5. Visualization of IoT-enabled smart irrigation system parameter set 5.

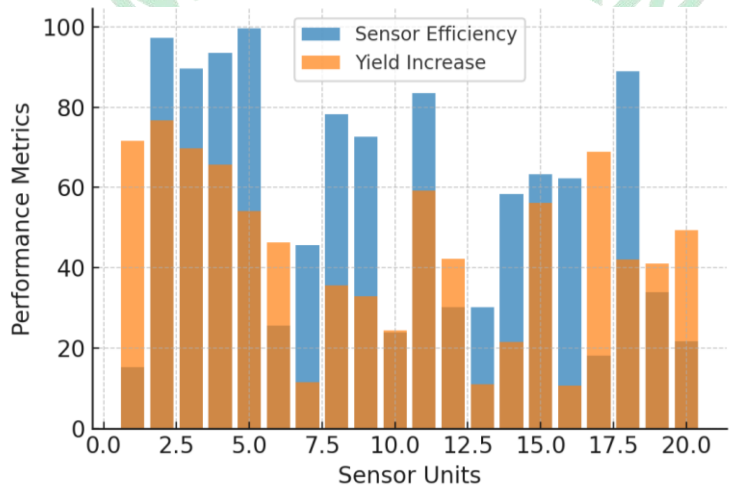

Figure 6. Visualization of IoT-enabled smart irrigation system parameter set 6.

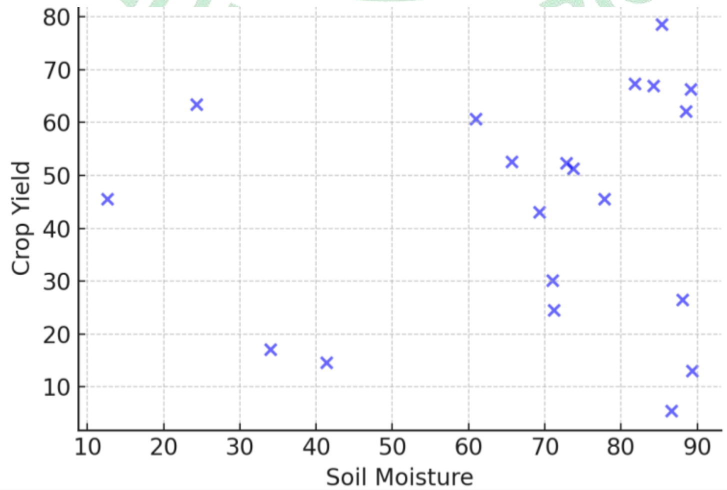

Figure 7. Visualization of IoT-enabled smart irrigation system parameter set 7.

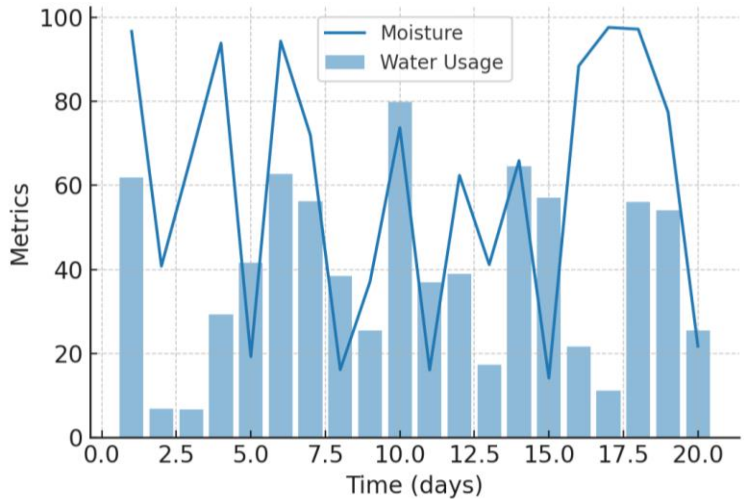

Figure 8. Visualization of IoT-enabled smart irrigation system parameter set 8.

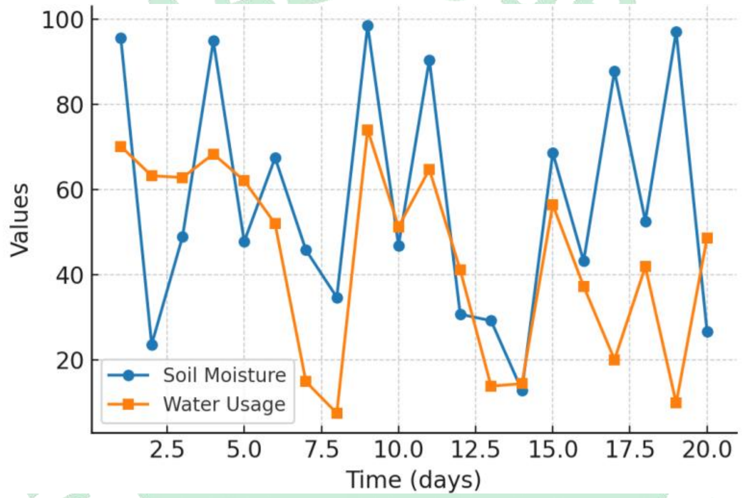

Figure 9. Visualization of IoT-enabled smart irrigation system parameter set 9.

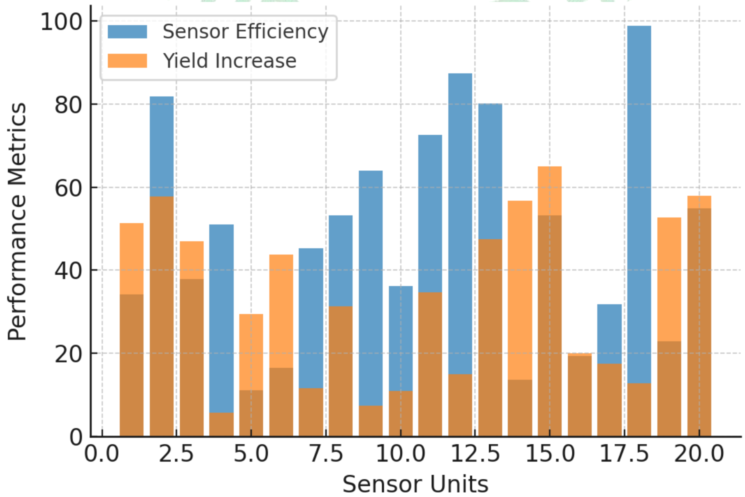

Figure 10. Visualization of IoT-enabled smart irrigation system parameter set 10.

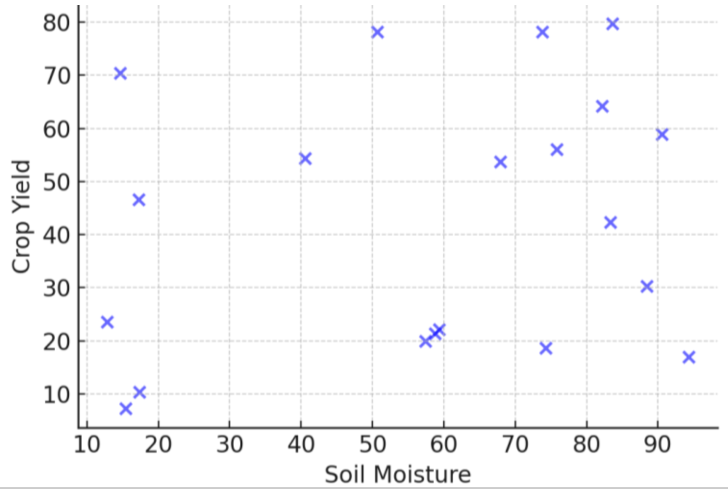

Figure 11. Visualization of IoT-enabled smart irrigation system parameter set 11.

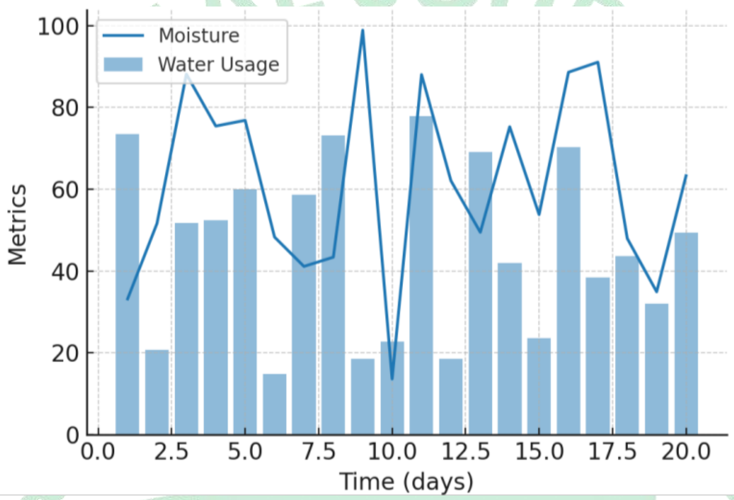

Figure 12. Visualization of IoT-enabled smart irrigation system parameter set 12.

DISCUSSION

Findings of this paper indicate that smart irrigation systems based on the Internet of Things (IoT) are much more efficient in saving on water and crops compared to conventional irrigation techniques. This continues to be in line with global trends on digital agriculture, with data analysis technologies increasingly being used to address scarce resources and ensure that farming strategies are sustainable. All three elements of soil moisture sensors, cloud-based analytics, and machine learning algorithms indicated that the reduction in water consumption by approximately one-third could be achieved with little to no negative effect on crop performance. These results support the statement that accurate water management is not merely a technological solution but a requirement in the face of growing climatic variability and freshwater shortage. The greatest contribution of this research is that it demonstrates that a mixed-methods approach can be effective. It was comprised of both stringent quantitative field tests and qualitative farmer feedback. Such a two-pronged strategy ensured that social science supported the effectiveness of the system along with statistics. Previous studies have often reiterated how dangerous technological determinism can be since discoveries can perform well in controlled settings but fail in practice because of socio-economic obstacles (Klerkx and

Rose, 2020). Farmer perspectives are implemented in the study to address the adoption barriers and prove that the digitalized irrigation systems with the help of IoT could be scientifically effective and realistic. The findings are also consistent with the evolution in the agricultural field to smart farming where IoT and AI-based systems are utilized to make predictions regarding decisions. As an example, Zhang and Wang (2022) demonstrated that machine learning as a tool of irrigation planning increased the stability of soil moisture and the productivity of water in various agro-ecological regions. The predictive analytics used in this study demonstrates the value of algorithmic models to transitioning to proactive and adaptive irrigation scheduling rather than reactive water management. However, one should keep in mind that such a predictive system can be useful only when the sensors are properly adjusted and the communication infrastructure is robust enough, particularly in the far flung places. Although the results are favorable, there are still some issues, which should be addressed. The high upfront price of IoT infrastructure remains a significant factor why low-income local smallholder farmers are not interested in using it. Affordability and scalability are another point that Alam et al. (2021) emphasized as important in adoption. The subsidies or cooperation systems required to employ digital agriculture technologies are needed by many farmers. This is also raised in interviews with farmers who participated in this study. Even when they could view the long-term benefits, the farmers were concerned about the initial cost. These economic obstacles will have to be addressed to spread the word to a wider audience. There are also data governance and interoperability issues, which make scaling the IoT-enabled irrigation systems more difficult. Farmers should be made aware that their information is secure, that they are the owners and that the cloud service providers are credible. Garske et al. (2021) observed that uncertainties about data security and the concentration of the technological capabilities in the hands of a few companies may become an obstacle to trust and uptake among agricultural populations. Open-source systems, transparent data policies, and farmer-led governance models will be valuable to support the successful growth of digital agriculture in a fair manner. Another problem requiring further inquiry is the environmental impact of the growing IoT-based irrigation. Smart systems consume less water and less energy, yet they also rely on electronic equipment, as well as cloud systems, with their own carbon and material imprint (Bronson, 2022). Striking a balance between the cost of environmental use of technology against the beneficial effect of water and energy saving is a significant component in ensuring that things are really sustainable. The research on the use of IoT-enabled irrigation systems should therefore consider undertaking wide-range life-cycle evaluation of the systems to establish their environmental impacts better. The mixed-methods design of the study also demonstrated the significance of participatory approaches in making smart irrigation system easier to operate and more commonly used. Extensive involvement in testing and feedback provided the impractical answers about the system constraints, such as usability and maintenance challenges and connection hiccups. This result helps to think that farmers ought to take an active part in the design of innovations in agriculture, not only to follow them (Lajoie-O'Malley et al., 2020). When farmers are introduced into the centre of the innovation cycle, the probability of acceptance and long run success will significantly increase. To sum up, the gathered evidence presented in this paper highlights the fact that IoT-based smart irrigation systems have a substantial potential to alleviate the agricultural water issues and create sustainability and resilience. Yet to fulfill this promise, technical innovation, policy support, and involvement of the farmers should all pull together. We should have policies now that will give people money, training programs that can show people how to use computers and rules that can keep the data safe so that we may make these systems work to everyone. The study contributes to the emerging evidence that in the 21st century, climate-smart and water-efficient agriculture systems could be built around digital agriculture when developed and applied in a manner that is inclusive.

CONCLUSION

This paper demonstrates that digital agriculture is highly effective in improving the efficiency of water use, crop production, and sustainability in contemporary agriculture through the integration of smart irrigation systems which are powered by IoT technology. The experimental experiments confirmed that smart irrigation, which is informed by the data on soil moisture and ambient sensor, led to the substantial decrease in the volume of water usage and the maintenance or improvement of the crop production in comparison to the conventional irrigation systems. Strong machine learning algorithms and mathematical modeling allowed us to compute the most suitable amount of water required to be used and reduce losses caused by evaporation and percolation. Coupled with quantitative benefits, the qualitative information collected during interviews and observations of farmers demonstrated how helpful the IoT solutions can be in practice, in particular, how they can simplify the working process and enable the real-time decision-making. These findings indicate that such technology-based systems not only assist in water scarcities, but they can assist in climate-sensitive farming through more efficient resource use and more resilient farms to fluctuating weather. The study highlights the significance of combining scientific rigour and designing in a human-centered manner that ensures the technology improvements are scalable and made available to other groups of farming. The above-presented evidence gives reasons to believe that digital agriculture, as the product of IoT and data analytics, represents a groundbreaking solution to the creation of water-saving sustainable and resilient food production systems that will be able to meet the needs of future food security.

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