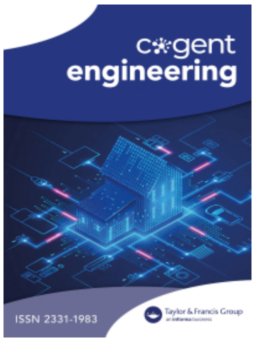

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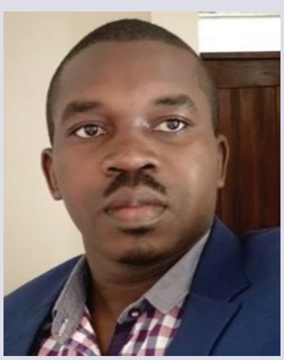
SYSTEMS & CONTROL ENGINEERING | RESEARCH ARTICLE

Model-based smart irrigation control strategy and its effect on water use efficiency in tomato production

Erion Bwambale[1,2,3]*, Felix K. Abagale[1,2] and Geophrey K. Anornu[4]

Abstract: Drip irrigation's potential to conserve irrigation water by around 25% compared to conventional methods is widely acknowledged. Nevertheless, the influence of varied irrigation control strategies on drip irrigation's impact remains uncertain, particularly regarding crop growth parameters and water use efficiency. In this study, we examine the effects of three distinct irrigation control approaches manual, model-based, and open-loop on drip-irrigated tomato plants within an open field agricultural context. Employing a completely randomized design, we cultivated 160 tomato plants and administered irrigation water according to each strategy's water requirements. Comprehensive data on key crop growth indicators, including plant height, stem diameter, leaf chlorophyll content, clusters per plant, flower and fruit counts, yield, and



Erion Bwambale

ABOUT THE AUTHOR

Erion Bwambale is a PhD Candidate at the West African Centre for Water, Irrigation and Sustainable Agriculture (WACWISA) hosted at the University for Development Studies in Ghana. Erion is an early-career researcher passionate about developing data-driven machine learning models for precision irrigation to improved water use efficiency. He holds a masters degree in Civil Engineering with a specialization in irrigation and drainage from Jomo Kenyatta University of Agriculture and Technology, Kenya and a B.Sc in Agricultural Mechanization and Irrigation Engineering of Busitema University, Uganda. He is a member of the American Society of Agricultural and Biological Engineers (ASABE), International Society of Precision Agriculture (ISPA), American Society of Civil Engineers (ASCE), International Water Association (IWA), Pan African Society for Agricultural Engineering (PASAE), International Commission of Agricultural and Biosystems Engineering and a Young Water Professional of International Commission on Irrigation and Drainage. He is presently an assistant lecturer of Water and Irrigation Engineering at Makerere University, Uganda. With over 7 years of experience in irrigation research, Erion believes arid and semi-arid lands in Africa can be turned into productive hubs of nutritious food using sustainable irrigation systems.

PUBLIC INTEREST STATEMENT

Discover how smart irrigation can revolutionize tomato cultivation! Our study investigates innovative irrigation strategies for growing juicy and eco-friendly tomatoes. Imagine if we could boost tomato yield while using less water? That's exactly what we explored using cutting-edge technology. We compared three irrigation methods – manual, model-based, and open-loop – to see how they impact tomato growth and water use. The results are exciting: the model-based approach not only increased yield but also saved water, demonstrating its potential to enhance sustainable farming. This research brings us a step closer to farming practices that benefit both our plates and the planet. Get ready to savour better tomatoes while conserving our precious water resources!

water use efficiency were documented. The results emphasize the pivotal role of the model-based irrigation control strategy. Specifically, this approach yielded a substantial tomato yield increase, recording 20 t/ha, in contrast to the 16 t/ha and 14 t/ha achieved by the open-loop and manual strategies, respectively. Noteworthy, the model-based approach exhibited remarkable water savings of 10.4 kg/m^3, surpassing the values of 7.1 kg/m^3 and 5.6 kg/m^3 obtained through the open-loop and manual strategies. These differences proved statistically significant, evidenced by a p-value of 0.05. The model-based irrigation strategy led to a 29% reduction in water consumption compared to manual control. This study establishes the model-based irrigation strategy's superiority, showcasing elevated tomato yield and improved water use efficiency. These findings furnish valuable insights into sustainable agricultural practices, particularly in the realm of drip irrigation systems.

Subjects: Control Engineering; Dynamical Control Systems

Keywords: Irrigation control; Fertigation; Water use efficiency; Model-based irrigation management

1. Introduction

The escalating impacts of climate change have intensified the challenges faced by agricultural systems worldwide, notably manifesting in erratic rainfall patterns and dwindling water use efficiency (Abdoulaye et al., 2019, 2021). As precipitation becomes increasingly unpredictable, the availability of water resources for crop irrigation has become uncertain, posing a significant threat to agricultural sustainability and food security. The need to optimize water use efficiency has gained paramount importance in mitigating these challenges, necessitating innovative approaches to irrigation management (Bwambale et al., 2022; Wanyama et al., 2017). Amid this backdrop, the exploration of advanced irrigation control strategies, such as model-based smart irrigation, emerges as a promising avenue to address the growing concerns surrounding water scarcity and suboptimal agricultural productivity.

Tomato production is a crucial aspect of agriculture, providing an essential source of food and income for many communities around the world. Effective water management is a critical factor in ensuring the sustainability and profitability of tomato production (Maureira et al., 2022). In recent years, advances in technology have led to the development of smart irrigation control systems, which aim to optimize water use efficiency while maintaining plant growth and yield (Bwambale & Abagale, 2023; Bwambale et al., 2023a).

Model-based smart irrigation control systems are becoming increasingly popular due to their ability to make precise water application decisions based on real-time data (Berberich et al., 2021). These systems use mathematical models to predict water requirements and adjust irrigation schedules accordingly (Bwambale et al., 2023b). The benefits of such systems include reduced water waste, improved plant growth and yield, and reduced energy costs (Abioye et al., 2021; Jang et al., 2022; Lozoya et al., 2016; McCarthy et al., 2014). Despite these advantages, there is limited research on the impact of model-based smart irrigation control systems on water use efficiency in tomato production.

Several studies have investigated the impact of model-based smart irrigation control on water use efficiency in agriculture, with a focus on crops such as grapevine, citrus, and almond. These studies have shown that model-based smart irrigation control systems can improve water use efficiency by up to 20–30% compared to traditional irrigation control systems (Abuzanouneh et al., 2022; Quimbita et al., 2022; Sami et al., 2022).

Despite the growing interest in model-based smart irrigation control, there is limited research on its impact on water use efficiency in tomato production. Previous studies on tomato production have mainly focused on traditional irrigation control systems and have not fully explored the potential benefits of model-based smart irrigation control. The advantages of model-based smart irrigation control in tomato production include improved water use efficiency, reduced water waste, and increased plant growth and yield. Limitations of such systems include the need for reliable data and technical expertise to set up and maintain the system (Wanyama & Bwambale, 2023).

We postulate that the implementation of a model-based smart irrigation control strategy in tomato production will result in enhanced water use efficiency, plant growth, and yield compared to traditional irrigation control methods. The mechanistic approach of utilizing real-time data and predictive modelling to tailor irrigation practices based on crop water needs will enable optimal water allocation, minimizing water wastage and promoting targeted nutrient uptake. This will, in turn, foster improved plant health, physiological functioning, and ultimately lead to higher yield production. By examining the intricate interplay between irrigation control strategies and their effects on crop growth parameters and water use efficiency, this study contributes to the advancement of sustainable agricultural practices while shedding light on the potential mechanisms driving these improvements.

The purpose of this research was to evaluate the effect of a model-based smart irrigation control strategy on water use efficiency in tomato production. The study compared the traditional irrigation control system with the model-based system in terms of water use, plant growth, and yield of Mongal F1 tomato variety (Sawadogo et al., 2022). The results of this study provide valuable insights into the potential benefits of model-based smart irrigation control systems for tomato production and contribute to the development of more sustainable and profitable farming practices.

2. Materials and methods

2.1. Study area

The study was conducted at the University for Development Studies, West African Centre for Water Irrigation and Sustainable Agriculture (WACWISA) experimental field located at latitude 0° 58ʹ 53'' W and Longitude 9° 24' 38'' North of the Equator as shown in Figure 1. The study was conducted at the University for Development Studies, West African Centre for Water Irrigation and Sustainable Agriculture (WACWISA) experimental field located at latitude 0° 58ʹ 53'' W and Longitude 9° 24' 38'' North of the Equator as shown in Figure 1.

2.2. Experimental design

The experimental design section of this study describes the methodology used to evaluate the effect of a model-based smart irrigation control strategy on water use efficiency in tomato production. The study employed a one-way Completely Randomized Design (CRD), with three treatments: Model Predictive Control (MPC) control, Open-loop control, and Manual control (Figure 2). Each treatment was replicated four times to increase the robustness of the results. The use of a CRD allows for a fair and balanced comparison of the treatments while controlling for any extraneous factors that may influence the results. By comparing the MPC control, Open-loop control, and manual control, this study provides valuable insights into the effectiveness of a model-based smart irrigation control system for improving water use efficiency in tomato production.

2.3. Irrigation control approaches

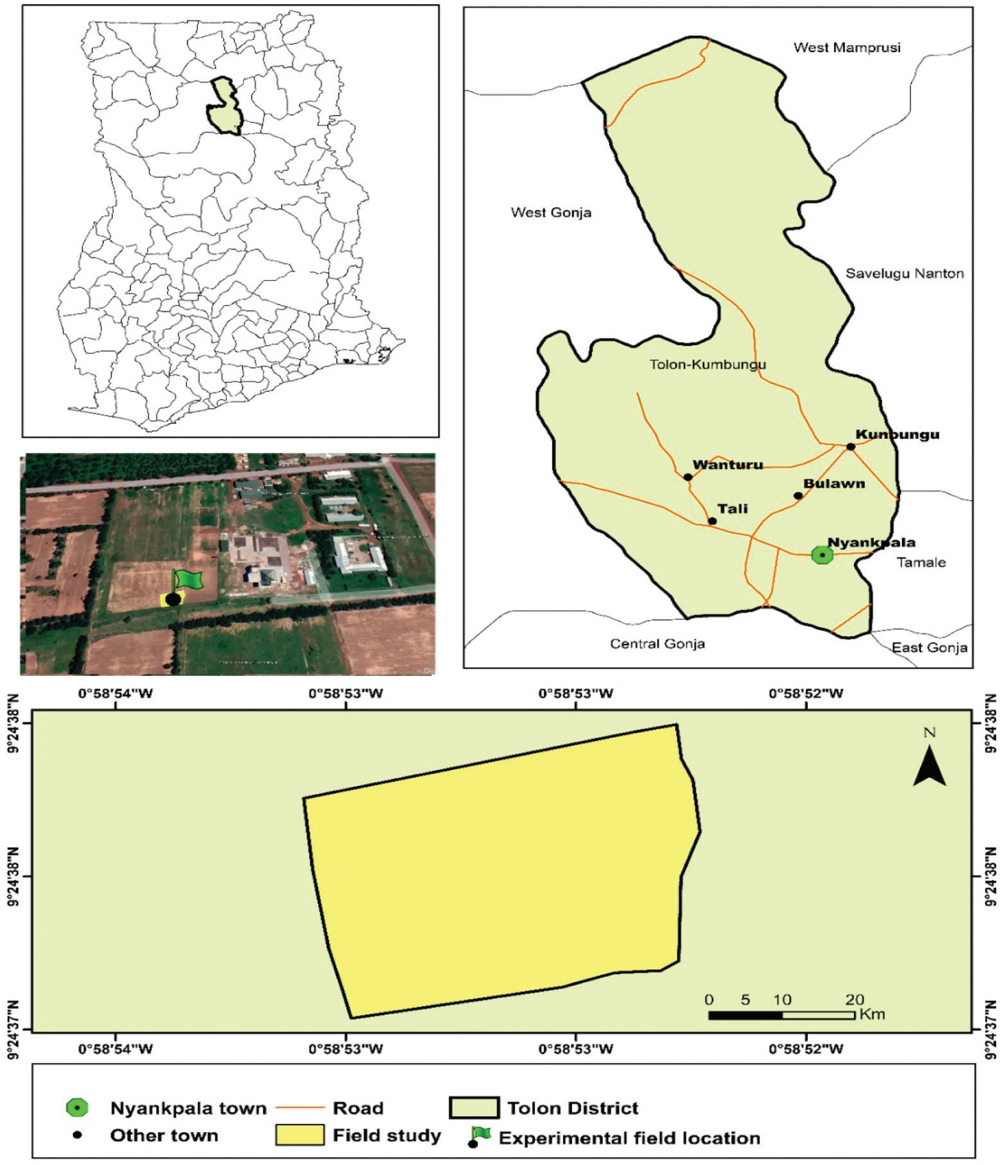
2.3.1. Manual control

Under the manual control approach, irrigation was based on historical data which was run into the CROPWAT software and decadal irrigation water requirements were determined. The climate data were obtained from the CSIR-SARI station.

2.3.2. Open-loop control

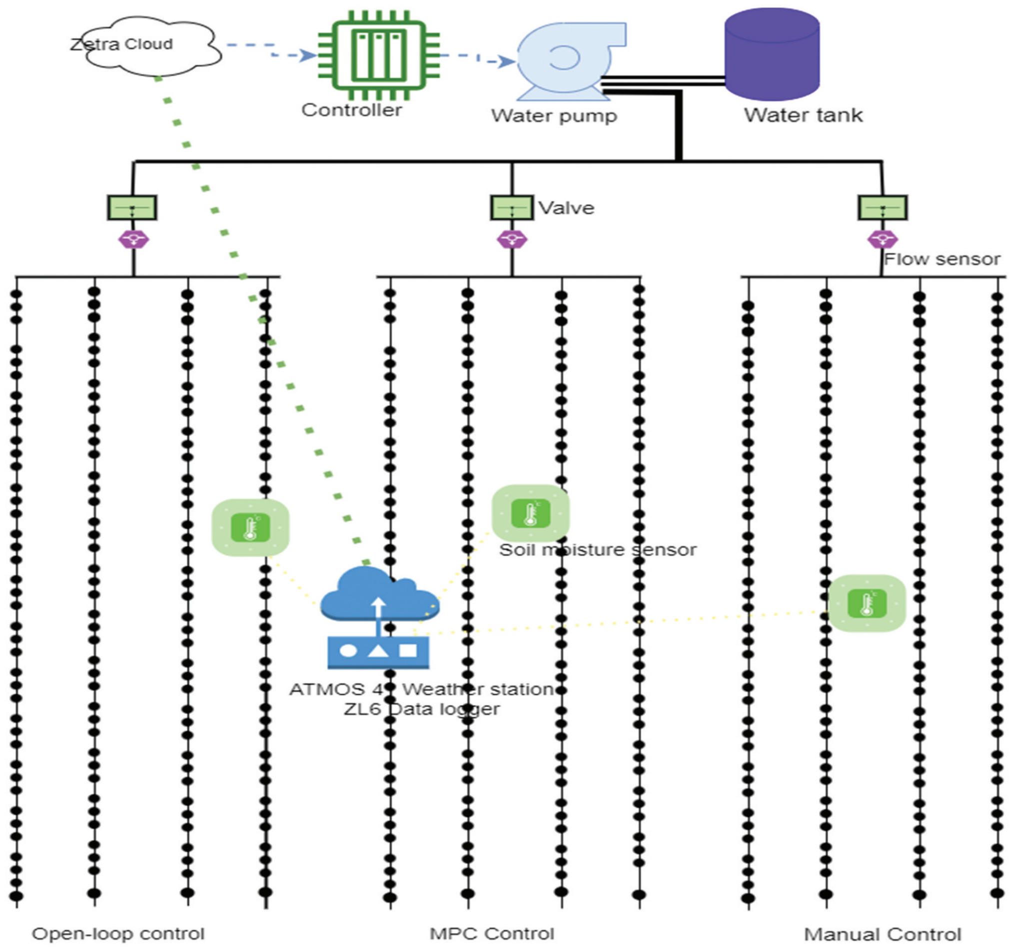
Irrigation scheduling using soil moisture sensors was used to optimize irrigation by measuring the soil moisture content and applying water when necessary. This method involved installing

Figure 1. Experimental site at WACWISA, UDS.



soil moisture sensors at different depths in the soil to continuously monitor the moisture content. The sensors were connected to an irrigation controller that used the data collected to determine when to turn on or off the irrigation system. The goal was to avoid over-watering, which could lead to the leaching of nutrients and wasted water, and under-watering, which can reduce crop yields. Soil moisture sensors installed at a depth of 25 and 40 cm respectively were used under the open loop irrigation approach. Open-loop irrigation control approach refers to a traditional irrigation strategy where water is applied to crops based on a predetermined schedule or fixed interval, without taking real-time feedback or environmental factors into consideration. In this approach, irrigation is not adjusted based on the actual moisture levels of the soil or the water needs of the plants. Instead, a fixed amount of water is supplied at regular intervals, regardless of whether the plants actually require that amount of water. This method relies on assumptions about water needs and does not actively respond to changing conditions such as rainfall, temperature, or soil moisture.

Figure 2. Experimental layout.



The soil moisture content was maintained between field capacity and permanent wilting point. A Management Allowable Depletion (MAD) of 0.6 was used to ensure plant roots have enough moisture for plant growth at every point in time.

2.3.3. Model predictive control

Irrigation scheduling using model predictive control is a technique that used mathematical model of the plant to predict the water requirements of crops and optimize irrigation scheduling. MPC algorithms use real-time data from soil moisture sensors, weather data, to predict future crop water demand and adjust irrigation scheduling accordingly. Table 1 presents the algorithm used in the MPC plot.

2.4. Crop growth parameters

Five plants were selected from each replicate and data on crop growth parameters taken.

2.4.1. Plant height

A tape measure was utilized to measure the height of the plants. The height of the plants was measured at two-week intervals, beginning two weeks after the plants were transplanted, and continued until they reached 12 weeks after transplanting. The measurement was taken by determining the distance from the stem's base to the plant's top. An average height was calculated for five plants sampled in each experimental plot, and this procedure was repeated for each replicate plot.

Table 1. MPC algorithm for smart irrigation

Algorithm 1

Required: Input $IR[k_i - 1], ETc[k_i - 1], P[k_i - 1]$
Output $\theta[k_i - 1]$
Use the previous input and output data to identify a predictive model
Loop
Read $\theta[k_i]$ #Current process output
Predict the process output $\theta_p[k_i]$ over a horizon
Estimate the error e$[k_i]$ and minimize $[J]$
If $\theta_p[k_i] - \theta[k_i] > 0$ ***or*** $ETc \geq ETc_{max}$
Generate $u(k), k = 1, \ldots\ldots, m$
else
wait for the next sampling time $k = k + 1$
End

2.4.2. Stem diameter

To measure the stem diameter of the plants, a vernier calliper was employed. The stem diameter was measured four weeks after transplanting and then again, every two weeks until the plants reached 12 weeks after transplanting. The measurement involved using the vernier calliper to determine the average stem diameter 10 cm from the base of the plant. For each experimental plot, the average stem diameter of the sampled plants was calculated, and this procedure was repeated for each replicate.

2.4.3. Leaf chlorophyll content

A SPAD chlorophyll metre was used to measure the leaf chlorophyll content of the tomato leaves at 2 weeks intervals start at 3-weeks after transplanting until 12 weeks after transplanting.

2.4.4. Number of clusters per plant

To determine the number of clusters per plant, the average number of clusters on five sampled plants within each treatment was calculated. This was done two weeks after transplanting and then repeated every two weeks until the plants reached 12 weeks after transplanting.

2.4.5. Number of flowers per plant

To determine the number of flowers per plant, the average number of flowers on five sampled plants within each treatment was calculated. This was done four weeks after transplanting and repeated every two weeks until the plants reached 12 weeks after transplanting.

2.4.6. Number of fruits

To determine the number of fruits per plant, the average number of fruits for the five sampled plants within each treatment was calculated, relative to the total number of plants.

2.4.7. Total yield (t/ha)

A weighing scale was used to measure the weight of tomatoes harvested from each of the plants and the average weight was calculated.

2.5. Water use efficiency

The water use efficiency (WUE) was calculated using Equation 4.39

$$WUE = \frac{Y}{TWU} \tag{1}$$

Where;

WUE is water use efficiency (kg/m^3), *Y* is the harvested yield in (kg/ha) and *TWU* is the total water used in (m^3/ha)

2.6. Data analysis

The data collected from the study was analysed using the statistical software GENSTAT 12th edition. The analysis of variance (ANOVA) was used to compare the yield and water use efficiency of the two irrigation management practices. The results of the ANOVA were considered statistically significant at $p < 0.05$.

3. Results and discussion

3.1. Weather parameters during the experimental period

During the period of observation, the weather conditions, including monthly rainfall, temperature, and humidity were monitored (Figure 3). The data was collected from an ATMOS 41 weather station located within the experimental field. The weather was characterized by a total rainfall of 0.06 mm. The average solar radiation received during the experimental period was 405 (W/m^2) with maximum values received in March. The average monthly temperature was 32.9 °C, with variations between 27.0 to 35.6 °C. The peak reference evapotranspiration during the experimental period was 77 mm/day with an average ET_0 of 5.01 mm/day.

3.2. Soil moisture, soil temperature and soil EC

The experimental plot was closely monitored for soil water content, soil temperature, and soil electrical conductivity using the Terros 12 soil moisture sensor. The Terros 12 soil moisture sensor was noted to be highly accurate and reliable sensor that provides continuous measurements of soil moisture content at different depths. Soil water content was measured at a depth of 25 cm using the Terros 12 sensor. The results showed that the soil had an average water content of 20% throughout the experiment (Figure 4). The soil water content fluctuated due to changes in rainfall patterns and irrigation practices, but the sensor data allowed for more precise management of water inputs. Soil temperature was also monitored using the Terros 12 sensor, which has an integrated temperature probe. The sensor was installed at a depth of 25 cm and recorded soil temperature every 10 minutes. The results showed that the soil temperature varied from 29 °C to 34 °C throughout the experiment, with the highest temperatures recorded during the day and the lowest at night. Soil electrical conductivity was measured using a portable conductivity meter at a depth of 25 cm. The results showed that the soil electrical conductivity ranged from 0.0 to 0.283 mS/cm (Figure 5), which is within the normal range for most agricultural soils. The data allowed for more precise management of fertilizers and other soil inputs to maintain optimal soil health.

Figure 3. Weather parameters during the experimental period.

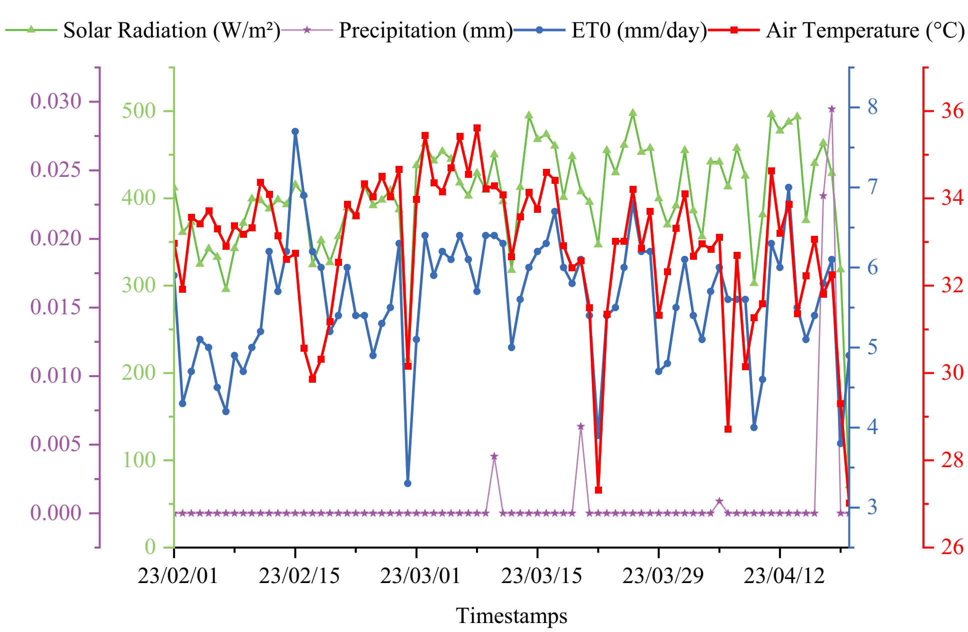
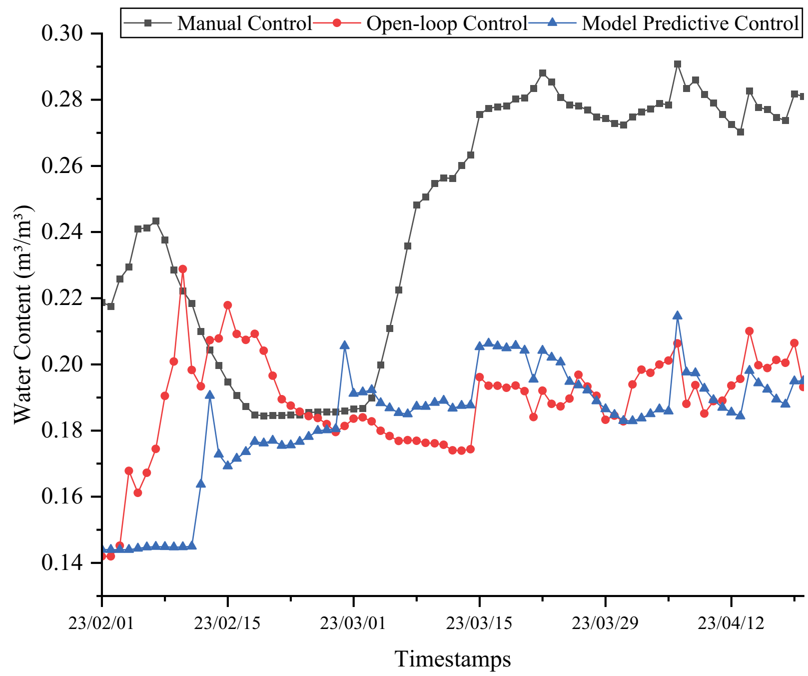


Figure 4. Soil moisture measurements under each treatment.



3.3. Plant growth parameters during the experimental period

3.3.1. Plant height

The results showed that the mean plant height in the Manual Control treatment was 68 cm. In the Open-loop Control treatment, the mean plant height was 73 cm, and in the Model Predictive Control treatment, it was 75 cm (Figure 6). The LSD test revealed that there was a significant difference between the Manual Control treatment and the Model Predictive Control treatment ($p < 0.05$), with the Model Predictive Control treatment resulting in taller plants. However, there was no significant difference between the Open-loop Control treatment and the other two treatments. The results suggest that the model-based smart irrigation control strategy, specifically the Model Predictive Control treatment, can improve plant growth compared to manual control. The use of predictive models can optimize water usage and ensure that plants receive the optimal amount of water needed for growth. The Open-loop Control treatment, which does not use a model to predict water needs, did not show a significant improvement over manual control.

3.3.2. Stem diameter

The results of the study indicate that the model predictive control strategy had the highest impact on stem diameter, with a mean value of 15.6 mm (Figure 7). However, an analysis of variance reveals that there is no significant difference between the stem girth under the three treatments. The model predictive control strategy was found to be the most effective method for optimizing water use in Mongal F1 Tomato plants, resulting in a significant increase in stem diameter compared to the other control strategies. These results are consistent with previous studies that have shown that model-based control strategies can improve water use efficiency and crop yields. Model-based control strategies use mathematical models to predict plant water requirements based on environmental factors, plant growth stage, and other variables. This allows for precise control of irrigation and can reduce water use without compromising crop productivity. In contrast, manual and open-loop control strategies rely on less precise methods for determining irrigation requirements. Manual control requires the grower to visually assess the plant's water needs and adjust irrigation accordingly, while open-loop control uses pre-determined schedules that do not take into account the plant's current water requirements.

Figure 5. Soil temperature and soil electrical conductivity under each treatment.

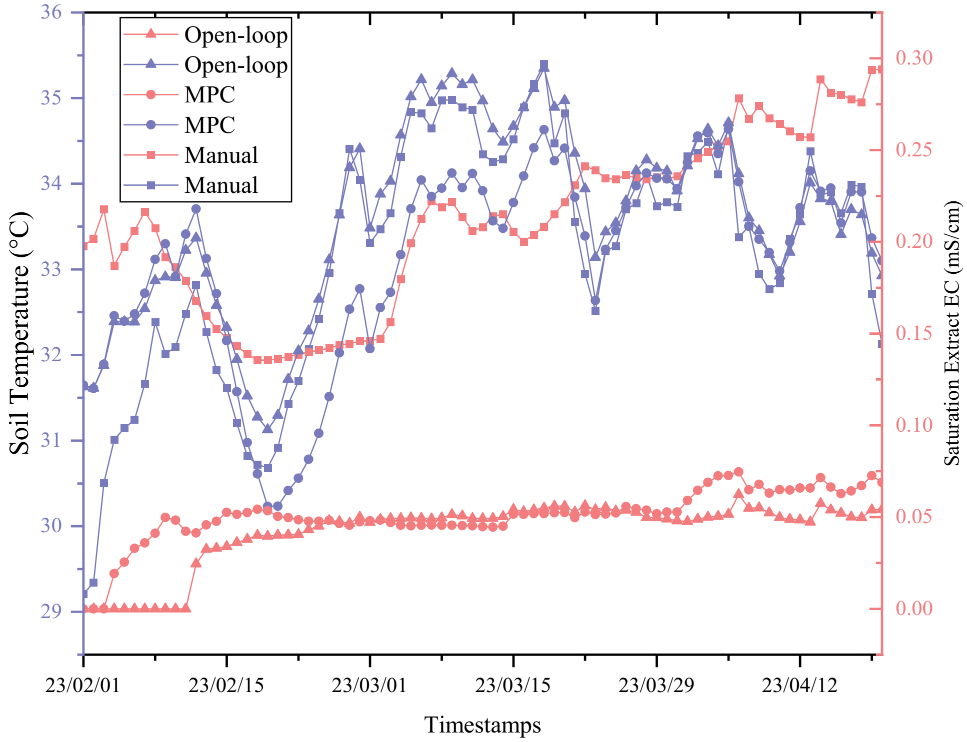
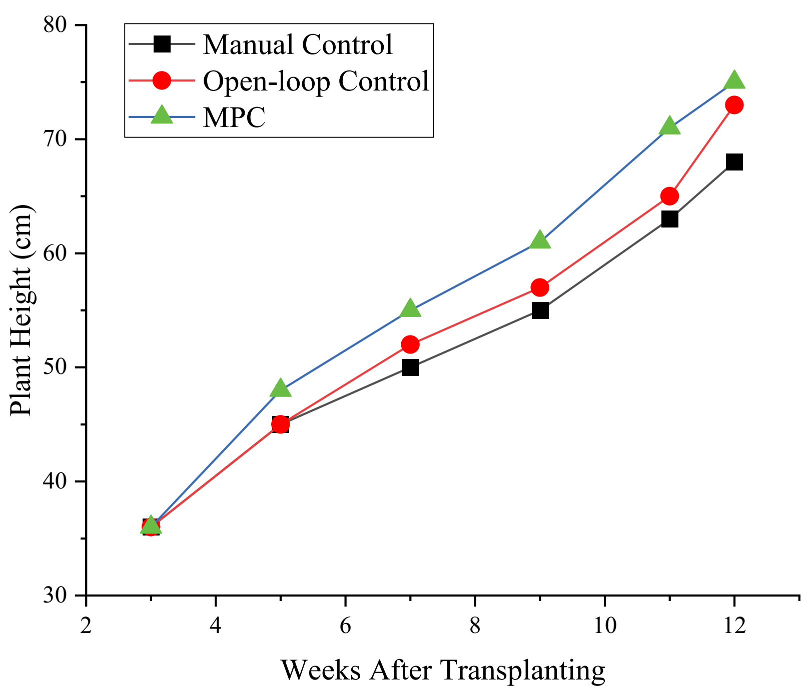


Figure 6. Weekly development of plant height under each treatment.



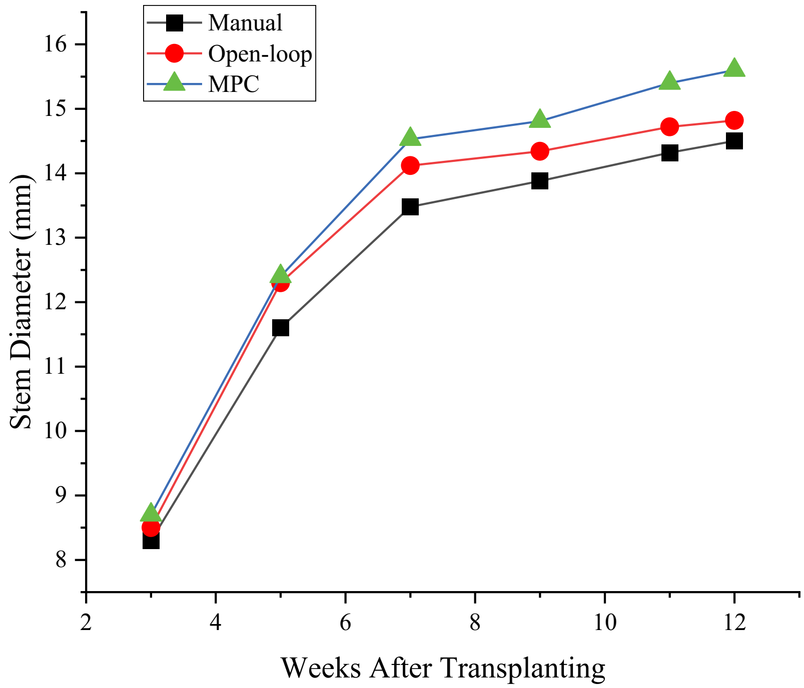


Figure 7. Weekly development of stem diameter under each treatment.

3.3.3. Number of clusters per plant

The results of the study indicate that the model predictive control strategy had the highest impact on the number of clusters per plant, with a mean value of 49 (Figure 8). This was significantly higher than the values obtained for the manual control (45) and open-loop control (47) strategies. The results of this study suggest that a model-based smart irrigation control strategy can significantly improve the number of clusters per Mongal F1 Tomato plant. The model predictive control strategy was found to be the most effective method for optimizing water use in this crop, resulting in a significant increase in the number of clusters compared to the other control strategies.

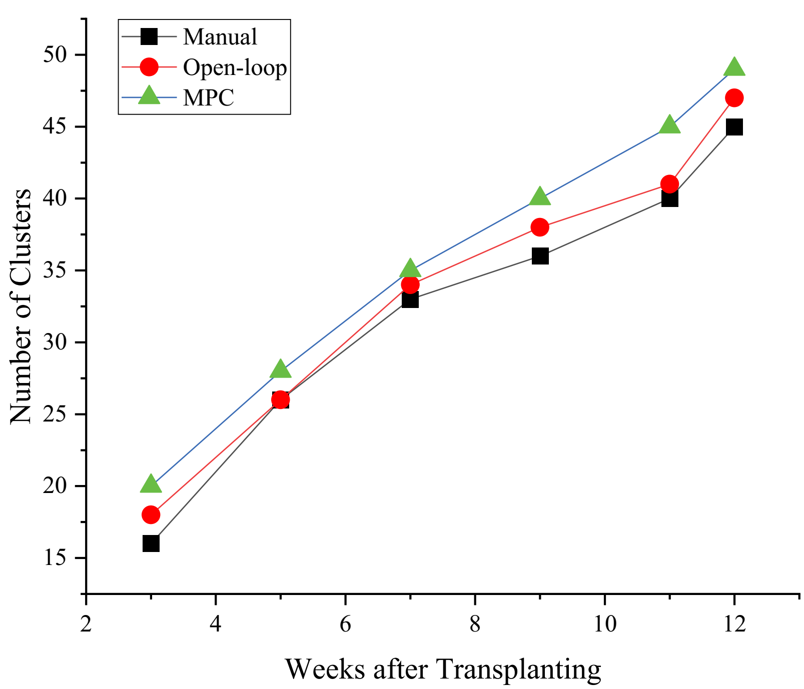


Figure 8. Weekly development of number of clusters under each treatment.

3.3.4. Leaf chlorophyll content

The results of the study indicate that the model predictive control strategy had the highest impact on the leaf chlorophyll content, with a mean value of 68.1 (Figure 9). This was significantly higher than the values obtained for the manual control (66.1) and open-loop control (67) strategies despite the ANOVA showing no significance among the treatments. The results of this study suggest that a model-based smart irrigation control strategy can significantly improve the leaf chlorophyll content of Mongal F1 Tomato plants. The model predictive control strategy was found to be the most effective method for optimizing water use in this crop, resulting in a significant increase in the leaf chlorophyll content compared to the other control strategies.

3.3.5. Number of flowers

The mean number of flowers per plant for manual control, open-loop control, and model predictive control were 17, 27, and 37, respectively (Figure 10). A statistical analysis using the least significant difference (LSD) test at a significance level of 5% revealed significant differences between all three treatments ($p < 0.05$).

Model predictive control resulted in the highest number of flowers per plant, followed by open-loop control and manual control. The results of this study demonstrate the efficacy of a model-based smart irrigation control strategy in improving water use efficiency in tomato plants. The significant increase in the number of flowers per plant under model predictive control compared to manual control suggests that the use of real-time data and predictive models can lead to more efficient water use and improved plant growth. The higher number of flowers observed under open-loop control compared to manual control indicates that the use of a pre-determined irrigation schedule based on environmental conditions can also lead to improved plant growth. However, the superior performance of model predictive control suggests that incorporating real-time data and predictive models into the control strategy can further optimize water use and plant growth. The results of this study have important implications for agricultural practices, particularly in regions with limited water resources. By implementing a model-based smart irrigation control strategy, farmers can optimize water use and increase crop yields while reducing environmental impact. Additionally, the use of predictive models can provide valuable insights into plant growth and development, allowing for more informed decision-making regarding irrigation and fertilization.

Figure 9. Weekly development of leaf chlorophyll content under each treatment.

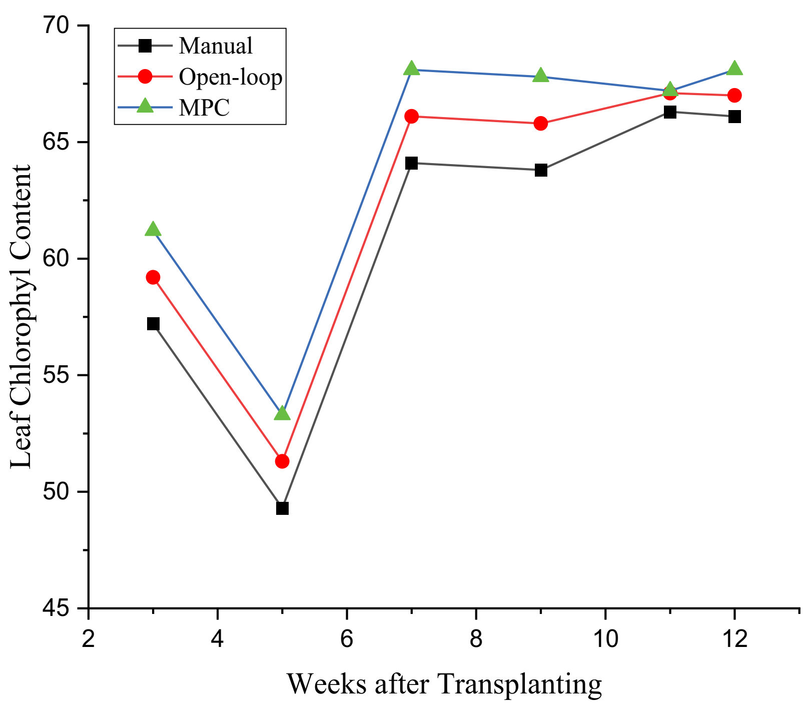
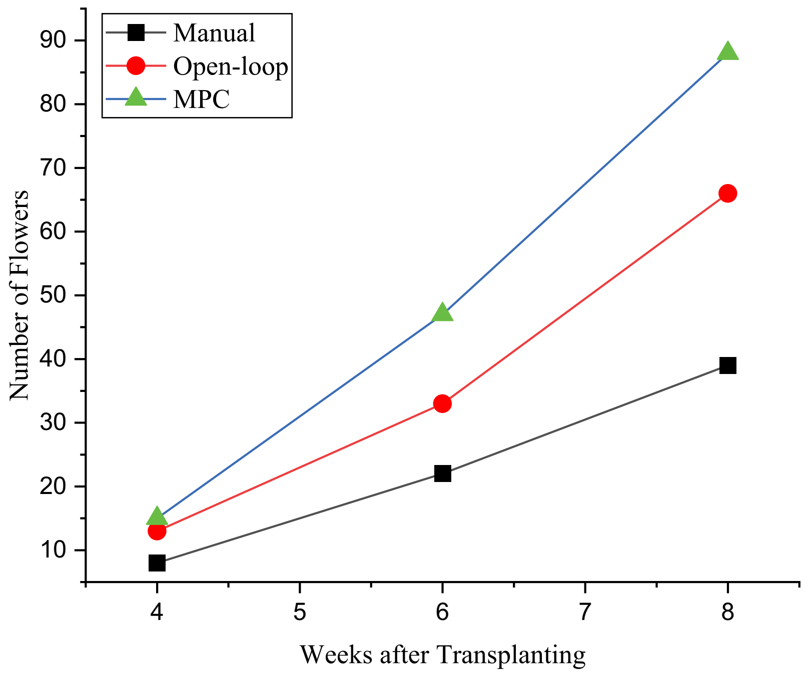


Figure 10. Weekly development of number of flowers under each treatment.



3.3.6. Number of fruits

The mean number of fruits per plant for manual control, open-loop control, and model predictive control were 56.2, 66.2, and 76.2, respectively (Figure 11). A statistical analysis using the least significant difference (LSD) test at a significance level of 5% revealed significant differences between all three treatments ($p < 0.05$).

Model predictive control resulted in the highest number of fruits per plant, followed by open-loop control and manual control. The results of this study demonstrate the potential of a model-based smart irrigation control strategy in improving water use efficiency and fruit yield in tomato plants. The significant increase in the number of fruits per plant under model predictive control compared to manual control suggests that the use of real-time data and predictive models can lead to more efficient water use and improved plant growth. The higher number of fruits observed under open-loop control compared to manual control indicates that the use of a pre-determined irrigation schedule based on environmental conditions can also lead to improved plant growth and yield. However, the superior performance of model predictive control suggests that incorporating real-time data and predictive models into the control strategy can further optimize water use and fruit yield.

3.4. Effect of irrigation control strategy on yield

Figure 12 presents the average yield under each control strategy.

The results of the analysis of manual control, open-loop control, and model predictive control strategies on the average yield of 14, 16, and 20 t/ha, respectively, have been statistically significant with an ANOVA p-value of 0.003. This indicates that the control strategy employed has a significant impact on the yield of the crop. Manual control is a basic method where the farmer decides on the timing and number of inputs to be given to the crop. The average yield obtained in this case was 14 t/ha. Open-loop control is a more advanced method where the inputs are pre-determined based on the conditions of the crop. The average yield obtained in this case was 16 t/ha. Model predictive control is the most advanced method where inputs are calculated based on a mathematical model of the crop, and the environmental conditions affecting it. The average yield obtained in this case was 20 t/ha. The results obtained suggest that the model predictive control strategy is the most effective in terms of yield. This is expected as it takes into

Figure 11. Weekly development of number of fruits under each treatment.

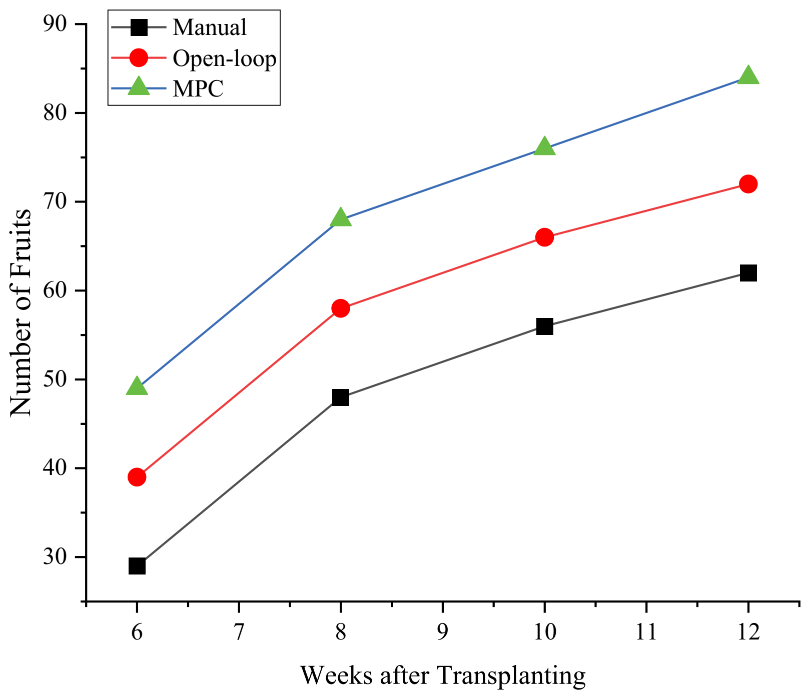
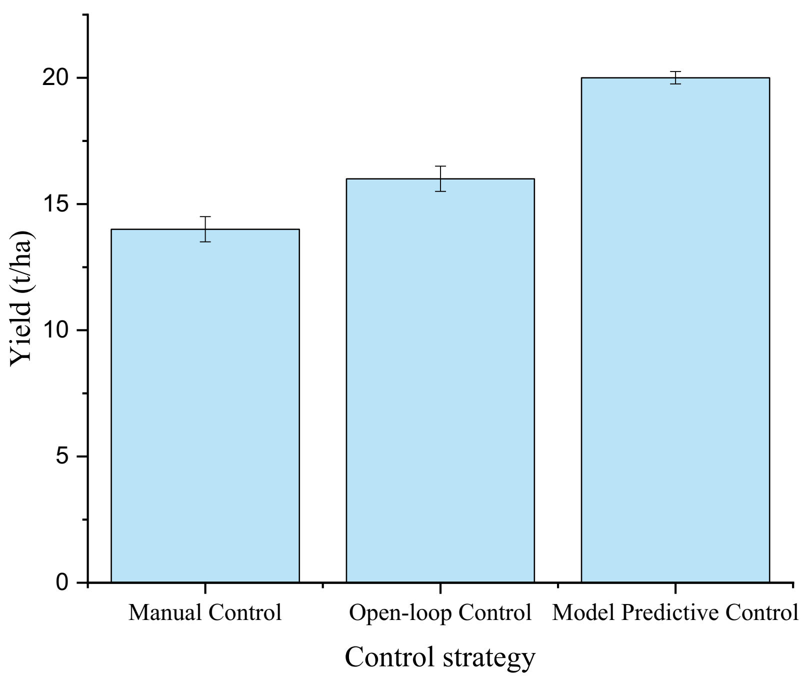


Figure 12. Effect of irrigation control strategy on yield.



account more parameters such as environmental conditions, crop growth stage, and the characteristics of the crop. This allows for more accurate predictions of the required inputs, resulting in optimal yield. On the other hand, manual control is the least effective in terms of yield. This is because it relies solely on the farmer's judgment, which may not always be accurate or based on scientific knowledge. Open-loop control, although more advanced than manual control, is limited by its inability to adjust to changing conditions and only considers pre-determined inputs. In accordance with the present results, previous studies have demonstrated Mongal F1 tomato variety can attain up to a productive capacity of 13.46 t/ha under full irrigation (Kah, 2021).

3.5. Effect of irrigation control strategy on water use efficiency

Figure 13 presents the average water use efficiency under each control strategy.

The analysis of the water use efficiency of manual control, open-loop control, and model predictive control strategies with average values of 5.6, 7.1, and 10.4 kg/m^3, respectively, revealed a statistically significant difference with an ANOVA p-value of 0.05. This suggests that the choice of control strategy has a significant impact on the water use efficiency of the crop. Manual control is a basic method where the farmer decides on the amount and timing of water inputs to the crop. The average water use efficiency obtained in this case was 5.6 Kg/m^3. Open-loop control is a more advanced method where the amount of water input is pre-determined based on the conditions of the crop. The average water use efficiency obtained in this case was 7.1 kg/m^3. Model predictive control is the most advanced method where the amount of water input is calculated based on a mathematical model of the crop and the environmental conditions affecting it. The average water use efficiency obtained in this case was 10.4 kg/m^3. The results obtained indicate that model predictive control is the most effective strategy for improving water use efficiency. This is because it takes into account more parameters such as environmental conditions, crop growth stage, and the characteristics of the crop. This allows for more accurate predictions of the required water inputs, resulting in optimal water use efficiency. On the other hand, manual control is the least effective in terms of water use efficiency. This is expected as it relies solely on the farmer's judgment, which may not always be accurate or based on scientific knowledge. Open-loop control, although more advanced than manual control, is limited by its inability to adjust to changing conditions and only considers pre-determined inputs.

This study confirms the findings obtained by Abioye et al. (2023) who registered high plant yields of Cantaloupe under model predictive control approach in a greenhouse environment. Additionally, Lozoya et al. (2016) demonstrated model predictive control is an effective approach of improving water use efficiency of open-field green pepper crop compared to traditional irrigation approaches. This study also supports experimental evidence by Jang *et al*. (2022) who observed water savings under model predictive control approach compared to the rule-based irrigation approach simulated using the Decision Support System for Agrotechnology Transfer (DSSAT) model.

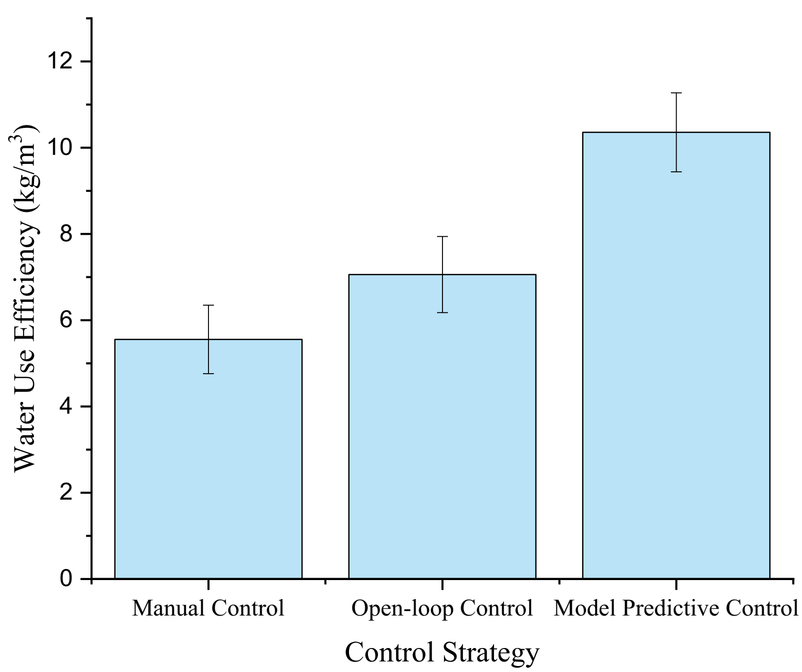


Figure 13. Effect of irrigation control strategy on water use efficiency.

Table 2. Water consumption under each irrigation control strategy

Control Strategy	Water Consumption (litres)	Water Savings (%)
Manual Control	32400	29
Open-loop Control	27200	8
Model Predictive Control	25200	-

3.6. Effect of irrigation control strategy on water savings

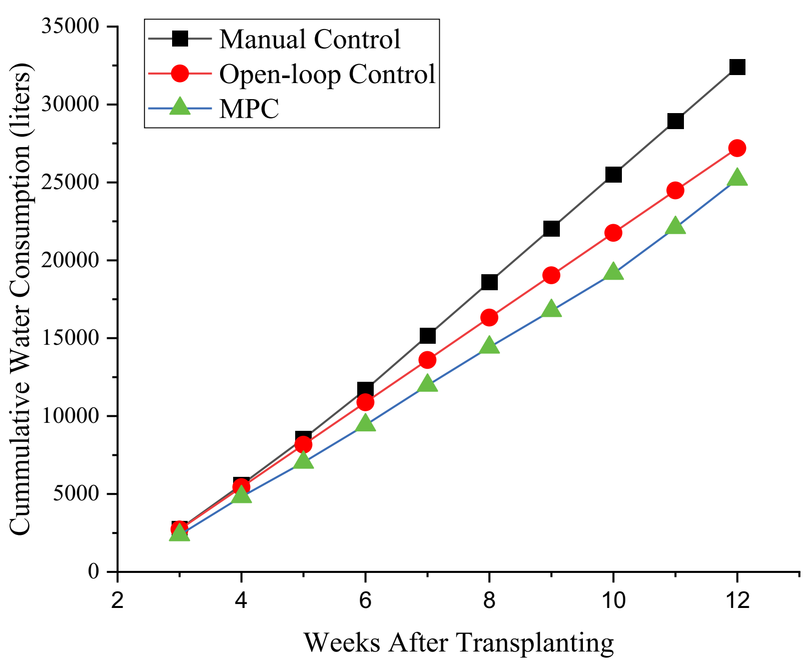
3.6.1. Water consumption for the irrigation strategies

The results of the study show that the MPC control strategy resulted in the highest WUE, with a cumulative weekly water consumption of 25,200 litres. This represents a water savings of 29% compared to manual control and 8% compared to open-loop control. In contrast, the manual control strategy resulted in the highest water consumption, with a cumulative weekly water consumption of 32,400 litres (Table 2).

The differences in water consumption between the control strategies were observed throughout the 12-week experiment (Figure 14). The MPC control strategy consistently resulted in the lowest water consumption, with a decreasing trend over time, whereas the manual control strategy resulted in the highest water consumption, with an increasing trend over time. The open-loop control strategy resulted in a moderate level of water consumption, with a relatively constant trend over time.

The results of this study suggest that the implementation of an MPC control strategy can lead to a significant reduction in water consumption and an increase in WUE in tomato production. The MPC control strategy is designed to adapt to changes in the crop's water requirements over time and adjust the irrigation schedule accordingly, which may explain its superior performance in this study.

Figure 14. Cumulative water consumption over the experimental Period.



In contrast, the manual control strategy resulted in the highest water consumption, which can be attributed to the lack of flexibility in the irrigation schedule. The open-loop control strategy, while offering some level of control, did not result in the same level of water savings as the MPC control strategy. The results of this study support the use of model-based control strategies in smart irrigation systems, such as MPC, to improve WUE and promote sustainable crop production.

4. Conclusion

This investigation scrutinized the efficacy of model-based smart irrigation control strategies in elevating crop yield and enhancing water use efficiency in tomato cultivation, employing the Mongal F1 variety as the test bed. Within this study, three distinct control strategies were subjected to evaluation: manual control, open-loop control, and model predictive control, each assessed through parameters encompassing crop growth, yield, and water use efficiency. The findings of this study underscore the pivotal role of the model predictive control strategy in optimizing both crop yield and water use efficiency. Notably, the average yield achieved through this strategy, standing at 20 t/ha, substantially surpassed the yields attained via manual control (14 t/ha) and open-loop control (16 t/ha). Furthermore, the water use efficiency yielded by the model predictive control strategy reached 10.4 kg/m3, significantly eclipsing the corresponding figures for manual control (5.6 kg/m3) and open-loop control (7.1 kg/m3).

These revelations coalesce to emphasize the potency of the model predictive control strategy, which adeptly integrates a spectrum of environmental and crop growth parameters. The result is a refined orchestration of water and nutrient management, culminating in the augmentation of both crop yield and water use efficiency. In contrast, manual control, reliant solely on the farmer's judgment, emerged as the least effective in optimizing both yield and water use efficiency. Open-loop control, although more sophisticated than manual control, found its efficacy hampered by an inability to adapt to shifting conditions.

Author contributions
E.B. was responsible for the conceptualization, methodology, formal analysis, investigation, and original draft preparation of this research study. F.K.A and G.K.A were responsible for reviewing and editing the manuscript. Additionally, F.K.A. was responsible for visualization and both F.K.A. and G.K.A. provided supervision for the project. Finally, F.K.A. was responsible for project administration. All authors have reviewed and approved the manuscript.

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