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Digital Twin Assisted Optimization of Greenhouse Microclimate for Resource Efficient Crop Production

Svetlana Ivanovna Chudinova
Agrobiotechnology, Agrarian and Technological Institute, RUDN University, Moscow 117198, Russia.
chudinovaiva@rudn.ru

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Corresponding author(s):
Svetlana Ivanovna Chudinova, Agrobiotechnology, Agrarian and Technological Institute, RUDN University, Russia.
Email: chudinovaiva@rudn.ru

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Abstract - The use of digital twin technology has emerged as a promising way for enhancing the management of greenhouses by synchronously monitoring and analyzing the environment, and coordinating the control. Traditional greenhouse management approaches, however, frequently control each environmental factor independently, and do not consider the interactions between the stability of the microclimate, productivity of the crop, water usage, and energy demand. This research proposed a framework called Digital Twin-Guided Resource Optimization (DT-GRO) for resource efficient greenhouse crop production. The suggested framework combined the process of greenhouse state estimation, short-term microclimate prediction, crop suitability assessment, and multi-objective optimization in a closed-loop control system. Digital twin environmental parameters such as temperature, relative humidity, solar radiation, carbon dioxide concentration, and soil moisture were added to describe the greenhouse conditions and direct the irrigation, ventilation, cooling, and shading operations based on these parameters. A tomato growing scenario was chosen to test the framework with different environmental conditions and resource constraints. The optimization mechanism took into account crop growing needs, water use, energy use, and environmental stability, to formulate the optimal control actions. The performance was compared with the conventional threshold-based control, proportional-integral-derivative (PID), model predictive control (MPC), and rule-based irrigation control strategies for microclimate control, resource efficiency, crop productivity, and robustness of operation. The evaluation method also included component-wise ablation and disturbance-based tests to explore the role of individual components. The performance assessment obtained a common framework for the evaluation of digital twin assisted greenhouse management and highlighted the potential of coordinated predictive control for better use of agricultural resources while providing favorable conditions for crop growth.

Keywords - Digital Twin, Greenhouse Microclimate Optimization, Precision Agriculture, Resource-Efficient Crop Production, Predictive Climate Control, Multi-Objective Optimization.

I. INTRODUCTION

Background and Motivation

To cope with climate variability, water scarcity, rising energy expenses, and the demand for good quality food, controlled-environment agriculture has become increasingly relied upon to produce food. Greenhouses offer a viable solution to control the environment and extend the length of the crop production season, when the external environment cannot be controlled. Greenhouse systems have provided better production results, such as improved crop growth, production consistency, and the efficient use of agricultural resources, by controlling temperature, relative humidity, solar radiation, concentration of carbon dioxide, and soil moisture. But it is essential to ensure proper growing condition, which involves constant co-ordinating of ventilation, irrigation, cooling, heating and shading. The interactions between the changing outdoor weather condition, crop growth and the availability of resources are complex and affect the greenhouse

microclimate and performance. These methods have helped basic environmental regulation, but have been effective only in cases of static operating environments as they lack the ability to predict changing conditions. Thus, the integrated and predictive management of greenhouses has become important in order to increase the productivity of the crops and to save water and energy resources.

Digital Twin technology has been recently developed to represent physical agricultural systems by means of virtual models with continuous updates. A digital twin brings together environmental data, mathematical models, modelling results, and operation information to keep a representation of the physical system [1]. This ability is of great value in the greenhouse as a tool for assessing the environment as it is, predicting environmental conditions that are not currently measured, determining potential changes in the microclimate, and assessing the efficacy of greenhouse management techniques. A digital twin differs from static simulation models by continuously monitoring actual greenhouse states and adjusting the digital twin accordingly to inform and guide decision making based on the dynamic operating state. This would allow greenhouse controllers to consider the implications of various actions prior to implementing a control action in the physical environment, when combined with optimization practices [2].

Challenges in Greenhouse Microclimate Management

Greenhouse microclimate management is a combination of interrelated physical and biological processes. Solar radiation affects the temperature of the greenhouse and the transpiration of crops; and ventilation affects the temperature, relative humidity and exchange of carbon dioxide. Irrigation changes the soil moisture and affects the water supply to the plants, while cooling and ventilation equipment will provide extra energy demands. These parameters can thus be independently controlled, resulting in conflicting outcomes. Fixed irrigation schedules often do not consider fluctuations in solar radiation, crop water needs or soil moisture. The interactions show that coordinated control of the whole greenhouse does not involve controlling individual parameters [3].

In addition, environmental disturbances complicate the operation of the greenhouses. Sudden variations in solar radiation, temperature and atmospheric humidity may result in deviations from desired growing conditions. The spatial variability in the greenhouse can also create different temperature and moisture conditions within cultivation areas. These constraints highlight the importance of predictive models which are able to forecast environmental variations, assess the effectiveness of alternative control strategies and tailor the operation to the prevailing greenhouse conditions. In a coordinated optimization strategy, the different factors mentioned above, such as crop suitability, water availability, energy requirement, actuator limitation and environmental stability, should be taken into account simultaneously [4].

Digital Twins for Precision Greenhouse Agriculture

By merging physical measurements with a computational model of greenhouse behaviour, digital twins provide opportunities to address these challenges. The physical greenhouse is used for observations via sensors and equipment interfaces, and the virtual greenhouse is used to depict the environmental states, crop requirements and reactions of control mechanisms. The digital twin can detect any mismatch between the predicted and measured states of the system and adjust the internal model of the system as necessary through continuous synchronization. Mathematical models can then then be used to predict future changes in temperature, humidity and soil moisture for various operating conditions. These predictions enable control decisions to be made that take into consideration the anticipated disturbances in addition to the current measurements [5].

The success of a digital twin in a greenhouse is dependent on the quality of the state representation, the accuracy of the dynamic models and the synchronization of the digital representation with the physical environment. A virtual model which can only simulate sensor measurements is of little use in practice if it is not used to make actionable control decisions. Likewise, predictive control can also minimize the deviation from the environment but may not be optimal for resource efficiency if water and energy usage is not included in the optimization goal. Hence, a comprehensive architecture is required for digital twin-based greenhouse management support, which integrates the four components mentioned above - namely, environmental monitoring, state estimation, microclimate prediction, resource-demand estimation, and control optimization. Such an architecture can assess possible interventions to a crop-growing requirement and/or operational constraint prior to choosing appropriate control actions [6].

Research Gaps and Problem Statement

Although there has been improvement in the greenhouse automation, there are still a number of problems with the application of environmental prediction and resource-efficient control. First, in traditional threshold-based and rule-based controllers, the operating condition is predetermined and the controller can only anticipate limited disturbances in the environment [7]. Second, predictive control methods can focus on the control of climate without properly incorporating water use, energy demand and crop production goals in a common decision-making process [8]. Thirdly, digital twin applications can focus more on visualization, monitoring, or virtual representation, with little consideration of an established feedback loop between environmental prediction and resource allocation [9]. Fourth, greenhouse control performance is frequently measured through single performance indicators, which makes it hard to know if better stability of the environment is achieved using less resources or more crop production. [10] Last but not least, the impact of the

specific DT elements (such as state synchronisation, predictive modelling, and resource-aware optimisation) needs to be evaluated systematically under similar operating conditions.

Proposed Approach and Research Contributions

This study introduced a closed-loop system for coordinating the management of the microclimate environment and the utilization of agricultural resources, called Digital Twin-Guided Resource Optimization (DT-GRO). The framework incorporated environmental sensing, digital twin synchronization, short-term microclimate prediction, crop suitability assessment and multi-objective control optimization. The main environmental variables for representing the greenhouse conditions were: temperature, soil moisture, relative humidity, solar radiation, and concentration of carbon dioxide. The predictive part quantified future environmental changes and the optimization part calculated the irrigation, ventilation, cooling and shading measures based on the crop's needs, resources available, energy consumption and environmental restrictions. The chosen control actions were applied to the greenhouse model and further measurements were used to update the digital twin for the next optimal control cycle.

The major findings of this study were:

- Synchronized greenhouse digital twin: A dynamic greenhouse environmental condition representation was developed, incorporating sensor observations, state estimation and continuous model updating, for better characterization of the environmental condition.
- Predictive multi-objective resource optimization: A co-ordinated control mechanism was developed that balances the suitability of the crop, the stability of the microclimate, water utilization and energy consumption subject to greenhouse operating constraints.
- Comprehensive performance evaluation: A Comparative evaluation framework was created to evaluate environmental regulation, resource efficiency, crop production indicators, control robustness and the individual contributions of the proposed framework elements.

The proposed framework was created for the growing of tomatoes in closed houses, setting up a scenario to study the interactions between microclimate management and resources use. Conventional threshold-based control, proportional-integral-derivative control, model predictive and rule-based irrigation controls were used as reference strategies for the evaluation. Comparative experiments and component-wise analyses were designed to help determine the effectiveness of an integrated prediction and optimization approach compared to the current control approaches.

Organization of the Paper

The rest of this paper is organized as follows. The research published so far related to greenhouse climate control, predictive control, applications of the digital twin model, irrigation system management, and energy efficient agricultural operation is reviewed in this section, revealing the shortcomings to be solved with the proposed framework. The DT-GRO architecture, mathematical formulation, environment prediction mechanism, multi-objective optimization strategy, and closed-loop control procedure are presented in Section 3. Section 4 presents the description of the simulation environment, the environmental inputs, the metrics used to evaluate the simulation, the comparative experiments, and the performance analysis. The paper concludes by summarizing the main findings, research contributions and implications of the use of a digital twin in the domain of greenhouse crop production to optimize resources.

II. RELATED WORKS

Conventional Greenhouse Climate Control

Greenhouse climate control has been typically achieved by using threshold based controllers, PID controllers, and a regimen of operating schedules to keep the greenhouse environment at an appropriate condition. They are widely used in temperature control, air conditioning, irrigation scheduling, humidity control, etc., due to their relatively ease of implementation and low requirement of computation. Threshold-based controllers switch equipment on when the measured value crosses over a threshold, while PID controllers provide a control input that is proportional to the difference between the measured value and desired value of an environmental parameter.

Rule based management of the greenhouse has been extended by predefining relationships between environmental measurements and actions to take. Irrigation, for instance, may be related to soil moisture levels, and ventilation adjusted to temperature and humidity. These strategies have practical benefits of being easily explainable and easy to implement. But they are only effective when the appropriate thresholds and the appropriate operating scenarios are considered. There is a risk that fixed rules are not flexible enough to adapt to changes in the crop-development stage, weather or resource availability. In addition, independently designed rules may not necessarily result in a reduced overall water and energy use for the entire greenhouse. These restrictions have spurred the design of coordinated control schemes that account for interactions with the environment and future operating conditions [11].

Model-Based and Predictive Greenhouse Control

Model-based control techniques have been studied to enhance the greenhouse regulation in order to model the relationship between environmental parameters, greenhouse equipment operation and external disturbances. The mathematical models can describe heat transfer, moisture exchange, ventilation, and the moisture requirements of crops, which can be used to

calculate the effects of different treatments. Among the others, model predictive control (MPC) has been gaining specific interest for its ability to consider sets of candidate control sequences over a certain prediction horizon and choosing the actions that maximize a defined objective, while satisfying the operational constraints.

Model-based control is dependant on the quality of the mathematical model, and the availability of adequate reliable environmental inputs. The uncertainties in the weather, spatial variations, crop characteristics, and omission of physical processes can lead to discrepancies between the predicted and actual greenhouse behavior. Such inconsistencies can decrease the effectiveness of control when the internal model is not kept up to date. In addition, an MPC formulation which focuses mainly on reducing temperature or humidity deviations could not take into consideration the full consequences of its actions on irrigation requirements, energy use and crop yields. Hence, predictive control needs an adequate representation of the environment and an objective function which takes into account the competition between agriculture and operational requirements [12].

Digital Twin Architectures in Agriculture

Digital twin technology is a new addition to the traditional simulation by combining a virtual model of the physical system with data from observation and feedback from operations. The use of digital twins has been explored in agriculture, including crop monitoring, farm management, irrigation planning, equipment management and environmental evaluation. The overall structure of their design incorporates data collection, computational modelling, state estimation, visualization, and decision support. In greenhouse cultivation the digital representation can include measurements of the environment, geometry of the greenhouse, conditions of the growing crop and the operating characteristics of the climate control equipment. This integration can help assess the current conditions and evaluate potential interventions before they are implemented.

Digital model, a digitally connected representation and a decision-oriented digital twin are all key differences. A static digital model is a digital model that doesn't necessarily receive continuous measurements. Data connectivity in a digitally connected representation includes data updates, but might only provide data visualization or monitoring. The decision-oriented digital twin also leverages the synchronized data to forecast system behavior and inform decisions. The latter is more promising for greenhouse management since environmental readings can be used to adjust the virtual state, environmental forecasts can be made using predictive models, and optimal control actions can be calculated using optimization procedures. However, the above implementation needs to be considered for the synchronization frequency, measurement uncertainty, computational complexity and consistency of virtual model with physical greenhouse behaviour [13].

Irrigation Management and Water-Use Optimization

The water needs of crops are dependent on the solar radiation, temperature, humidity, soil properties, and developmental stage of the crop, and efficient management of this water has become an important aspect of sustainable greenhouse production. Standard watering practices such as soil-moisture based watering or watering on a fixed schedule can lead to over or under watering when conditions vary. One of the benefits of sensor-based irrigation is that it can incorporate soil-moisture measurements into irrigation decisions, thereby overcoming some of these limitations. Soil moisture is not always indicative of crop water requirements, however, because transpiration and crop water uptake are also affected by atmospheric factors and crop type.

A possible way to incorporating soil properties, crop needs, and greenhouse environmental dynamics in the same computational framework is digital twin based irrigation management. The virtual representation can simulate evaporation of water, test different irrigation plans, and analyze the impacts of climate-control decisions on future water consumption. The usefulness of this integration would, of course, rely on whether predicted requirements for resources are converted to coordinated operating decisions. The DT-GRO framework meets this requirement by integrating water-demand estimation into the larger optimization process, which considers the irrigation actions in light of environmental stability and energy use [14].

Energy-Efficient Greenhouse Operation

When mechanical ventilation and cooling or heating and supplemental lighting is necessary, energy use is a significant operation factor in greenhouse crop production. These systems require different energy needs, based on the greenhouse structure, covering materials, outdoor weather conditions, greenhouse environmental goals, equipment efficiency and crop needs. Traditional methods of operation might set and hold environmental setpoints without taking into account the cumulative energy impact of each control action. Thus, allowing larger environmental margins can raise operating costs, even if a more conservative, but less resource intensive control combination would yield acceptable growing conditions [15].

A mathematical model of the greenhouse heat and moisture transfer has been used in the study of model-based energy management of the climate-control equipment. In this study, Blasco et al. devised a model-based predictive control (MBPC) strategy that integrates water and energy use in greenhouse climate control and showed its applicability to greenhouse climate control. Later, predictive control and energy-management techniques have been studied from the aspect of efficiency enhancement and lessening reliance on traditional control techniques in greenhouses. However, optimizing

energy use comes with compromises between energy use, environmental stability, and crop performance. A reduction in cooling or ventilation activity will reduce the use of electricity, yet create less desirable temperature or humidity conditions. On the other hand, strict environmental controls could result in higher energy costs, but without a corresponding increase in yield. These relationships must be optimized using methods that consider multiple operational goals and/or constraints. DT-GRO includes an energy-consumption estimation loop in its control formulation, which allows joint considerations of ventilation, cooling, irrigation and shading decisions.

Research Gap and Comparative Positioning

Prior research has laid solid ground for the automation of greenhouses, predictive control of climate, building of digital twins and efficient use of resources in agriculture. However, the inclusion of these functionalities in a single and closed-loop resource optimisation framework is a research challenge. In GH, digital twins identified an abundance of monitoring and control applications, and more advanced predictive and prescriptive applications were yet to emerge. The conclusions they draw emphasize the importance of going beyond the visualization of the environment and to coordinated operational decision making with digital representations. Then, Wang summarized the latest progress and unsolved challenges of agricultural digital twin applications, noting the importance of virtual representation in the monitoring, prediction and optimization of agricultural processes. Slob and Hurst also investigated the use of digital twins and related technologies in the context of agricultural greenhouses, where they can facilitate more effective management and operation of the system.

DT-GRO aims to fill the gap in research related to simultaneous integration of greenhouse state synchronization, short-term greenhouse microclimate prediction, greenhouse suitability evaluation of crops, and multi-objective resource optimization. The suggested framework does not focus on only one of the processes, environmental monitoring, irrigation scheduling or energy reduction, but rather looks at them as part of the whole greenhouse. The assessment of its performance also takes into account comparative performance, the individual contributions of its components and resilience to varying environmental conditions. The proposed framework is summarized in **Table 1** in comparison to the other components.

Table 1. Comparative Positioning of Greenhouse Management Approaches

Approach	Environmental feedback	Predictive capability	Joint water–energy optimization	Crop suitability integration	Closed-loop resource coordination
Threshold-based control	Yes	No	Limited	Setpoint-based	Limited
PID control	Yes	No	Limited	Indirect	Limited
Rule-based irrigation	Soil-moisture dependent	Limited	No	Indirect	Irrigation-focused
Model predictive control	Yes	Yes	Possible, depending on objective	Possible, depending on formulation	Yes, within the modeled control scope
Monitoring-oriented digital twin	Yes	Variable	Not inherent	Variable	Not inherent
Proposed DT-GRO	Yes	Yes	Explicitly integrated	Explicitly integrated	Integrated across irrigation and climate control

III. PROPOSED DT-GRO MODEL

Overview of the Proposed Framework

To coordinate greenhouse microclimate regulation and resource use, the Digital Twin-Guided Resource Optimization (DT-GRO) framework is developed to link the greenhouse environmental modeling and predictive analysis with constrained optimization of greenhouse control. The proposed framework depicted the greenhouse as a physical system, whose environment would change with the outside weather conditions, the water needs of the crop, and the working of the control equipment. A digital twin was developed to keep a current visualization of the greenhouse with the help of sensor observations and the estimated environmental state. The synchronized representation was then used to assist with short term forecasting and decision making on alternative control actions.

The framework consisted of five interdependent modules: environmental data collection, digital twin state synchronization, microclimate prediction, crop suitability estimation and resource-demand estimation, and multi-objective control optimization. Environmental parameters were air temperature, relative humidity, concentration of CO_2, solar radiation, and soil moisture in root-zone. These variables were used as main inputs in the characterization of the greenhouse atmosphere and determining the needs of the plant under cultivation. The prediction module was used to estimate the

subsequent environmental states, and the optimization module was used to evaluate irrigation, ventilation, cooling and shading operations under specific equipment and resource constraints.

DT-GRO made sure to take environmental suitability, water usage, energy consumption and crop production goals into account, whereas independently operated climate controllers did not. Based on the simulated greenhouse state, the optimization process generated control actions and provided the environmental measurements returned to the digital twin. This feedback mechanism enabled to update the state repeatedly and for subsequent optimization cycles. The whole framework was developed for tomato cultivation in a controlled greenhouse and the control strategy aimed to maintain the optimal growing conditions and to optimize the use of resources.

Greenhouse State Representation

The first stage of DT-GRO represented the greenhouse environment using a multivariable state vector. The state incorporated environmental parameters that influenced crop development, irrigation demand, and climate-control requirements. At discrete time step (t), the greenhouse state was defined as follows.

Equation (1): Greenhouse state vector

$$x_t = [T_t, H_t, C_t, R_t, M_t]^T \tag{1}$$

Here, T_t represented greenhouse air temperature, H_t represented relative humidity, C_t represented carbon dioxide concentration, R_t represented solar radiation, and M_t represented root-zone soil moisture. The control vector was defined as $u_t = [I_t, V_t, K_t, S_t]^T$, where I_t, V_t, K_t, and S_t represented irrigation, ventilation, cooling, and shading commands, respectively.

The greenhouse state evolved in response to weather disturbances, crop-related processes, and equipment operations. A discrete-time state-transition function was therefore used to describe the environmental dynamics.

Equation (2): Greenhouse state-transition model

$$x_{t+1} = f(x_t, u_t, d_t, \theta) + w_t \tag{2}$$

In this formulation, $f(.)$ represented the greenhouse dynamics model. The transition function incorporated the principal thermal, moisture, and environmental responses associated with greenhouse operation. This representation enabled the digital twin to estimate the effects of alternative control actions on subsequent environmental conditions.

Digital Twin Synchronization

The digital twin maintained a virtual environmental state corresponding to the physical greenhouse. Sensor measurements were incorporated at each update interval to correct discrepancies between the estimated state and the observed state. Let $\hat{x_t}$ represent the estimated state and y_t represent the available sensor measurements. The observation relationship was expressed as follows.

Equation (3): Digital twin synchronization error

$$e_t = y_t - h(\hat{x_t}) \tag{3}$$

In this case, the observation model h(.) was the one that projected the estimated state to the sensor-measurement space. The error vector measured the difference between the reality of the environment and the virtual environment. This mismatch was exploited by the synchronisation mechanism for updating the state of the digital twin, enabling the model to correct for deviations resulting from disturbances, measurement variation and imperfect dynamic representation. The synchronized state was used to start the prediction and optimization stages. If the environmental measurements were missing or incomplete, the state-estimation procedure could be used to estimate the corresponding variables by using the observations and the dynamic model. This mechanism allowed a uniform link between the physical measurements of the greenhouse and virtual environmental analysis.

Short-Term Microclimate Prediction

The prediction module predicted the future greenhouse conditions based on the synchronized state, historical greenhouse environmental observation, and forecasted control action. To find out about changes in the environment before they led to significant deviations from desired environmental conditions, a finite prediction horizon (FPH) was used. The prediction procedure included the time-lag effects between the temperature, relative humidity, solar radiation, carbon dioxide concentration and soil moisture.

Equation (4): Short-term environmental prediction

$$\hat{x}_{(t+j|t)} = f_j(\hat{x}_t, u_{t:t+j-1}, \hat{d}_{(t:t+j-1)}, \theta) \tag{4}$$

Here, $\hat{x}_{(t+j|t)}$ represented the predicted greenhouse state at future time $(t+j)$, based on information available at time (t). The function $f_j(.)$ represented the repeated application of the greenhouse state-transition model over the prediction horizon. The sequence $u_{t:t+j-1}$ represented candidate control actions, while $\hat{d}_{(t:t+j-1)}$ represented estimated external disturbances. The predicted states provided the environmental information required for assessing crop suitability and determining appropriate control interventions.

Crop Suitability Assessment

The suitability of the crops was assessed using the difference between expected environmental conditions and the respective target ranges for tomato growing. The criteria which were included were temperature, relative humidity, carbon dioxide concentration and soil moisture in the root zone. The target ranges were assigned to each variable according to the desired cultivation scenario and the crop. The deviations were normalized to ensure that the parameters with a higher number were not more influential in the assessment.

Equation (5): Crop suitability penalty

$$J_{crop(t)} = \sum_{i=1}^{n} \omega_i \left[\max\left(0, \frac{x_{i(t)}-U_i}{s_i}\right)^2 + \max\left(0, \frac{L_i-x_{i(t)}}{s_i}\right)^2\right] \quad (5)$$

If an environmental parameter went outside the acceptable range, the penalty got bigger, but if the environmental parameter was in the environmental parameter range, the penalty was still zero. The formulation allowed for the optimization procedure to focus on correcting the unfavourable conditions affecting crop development. This evaluation of the suitability assessment was done over the prediction horizon, not just at the current time step. This enabled DT-GRO to think ahead about the environmental implications of control actions and prevent taking decision to produce a short-term benefit which would lead to a long-term environmental downside.

Water-Demand Estimation

Irrigation demand was calculated as a function of the change in water in the root zone of the soils, the effective water capacity of the root zone, and the expected crop-water requirement. The formulation included environmental factors affecting moisture loss and plant water uptake. Irrigation amounts were estimated to meet the demand while maintaining the moisture level within the specified range of the root zone.

Equation (6): Irrigation demand estimation

$$I_{req(t)} = \max\left(0, ET_{c(t)} - P_{eff(t)} + K_m \max(0, M_{tar} - M_t)\right) \quad (6)$$

The irrigation-caps and water available for the current control interval were taken into account in the estimated requirement. Hence, the final irrigation command was not based on the estimated requirement but rather on the optimization module. This separation allowed for the coordination of irrigation with anticipated climate-control activities and water budget.

Energy-Consumption Modeling

The amount of energy needed was estimated based on the number of operating units and the power rating of the climate control equipment in the greenhouses. Apart from ventilation and active cooling, other electricity consuming devices were involved in the total energy use. This formulation allowed optimization to be performed on candidate control sequences based on the expected electrical demand.

Equation (7): Greenhouse energy consumption

$$E(t) = \Delta t \left[P_v V_t + P_k K_t + P_i I_t + P_s S_t\right] \quad (7)$$

The coefficient for the control variables was normalized equipment commands or duty cycles. The corresponding electrical coefficient could be zero or limited to the energy used by the shading actuator in the case of passive shading systems. A common frame of reference for assessing various control choices was provided by the energy model. To account for the greenhouse scenario selected, the simulation configuration was modified to include the power ratings, operating limits, and actuator characteristics of the equipment.

Multi-Objective Resource Optimization

The central optimization stage assessed suitability of the crop, water usage, energy needs, and deviations from the desirable environmental conditions, all together. The goal function is used to minimize the overall operational penalty for a finite prediction horizon. The different measurement units and the relative operational importance were considered in normalizing or weighting each of the objective components.

Equation (8): Multi-objective optimization function

$$J = \sum_{j=1}^{N}\left[\lambda_c J_{crop(t+j)} + \frac{\lambda_w W(t+j)}{W_{ref}} + \frac{\lambda_e E(t+j)}{E_{ref}} + \lambda_s J_{stab(t+j)}\right] + \lambda_u \sum_{j=0}^{N-1}\left|\left|u_{t+j} - u_{t+j-1}\right|\right|^2 \quad (8)$$

The control-smoothness term unnecessarily penalized too large of a change for the next control command. This minimized equipment switch and allowed for stable operation. Optimization coefficients were chosen based on the priorities of the cultivation scenario and normalization was used to make the objective components comparable in the same scale. The formulation enabled the controller to incorporate multiple objectives. For instance, further cooling may decrease a crop loss due to temperature conditions and increase the energy usage. Likewise, more watering may benefit water levels in the root zone and increase water consumption. These conflicting consequences were evaluated by the optimizer given the predicted state of the greenhouse and it picked the control sequence that had the minimal possible objective value within the feasible range.

Constrained Control Policy

Optimized control sequence was subjected to environmental, equipment and resource constraints. The amount of water for irrigation was limited due to equipment capacity and water available, and ventilation and/or cooling commands were limited to their allowed operating ranges. The predicted environmental states were also compared to the operating limits of the crop.

Equation (9): Constrained control optimization

$$u*_t = \arg\min_{u_{t:t+N-1}} J \; subject\; to\; x_{t+j+1} = f\left(x_{t+j}, u_{t+j}, d_{t+j}, \theta\right) \quad (9)$$
$$u_{\min} \le u_{t+j} \le u_{max_}(t:t+N) \le W_max, E_(t:t+N) \le E_max$$

The state transition constraint that was imposed on the predicted environmental trajectory guaranteed that it was consistent with the greenhouse model. The first action in the optimized control sequence was performed in each control interval. Subsequent sensor observations were then used to update the greenhouse state, which was then used in the optimization again. The receding-horizon procedure helped DT-GRO adapt to the varying conditions without having to rely on a predetermined sequence of control commands across the whole duration of the simulation.

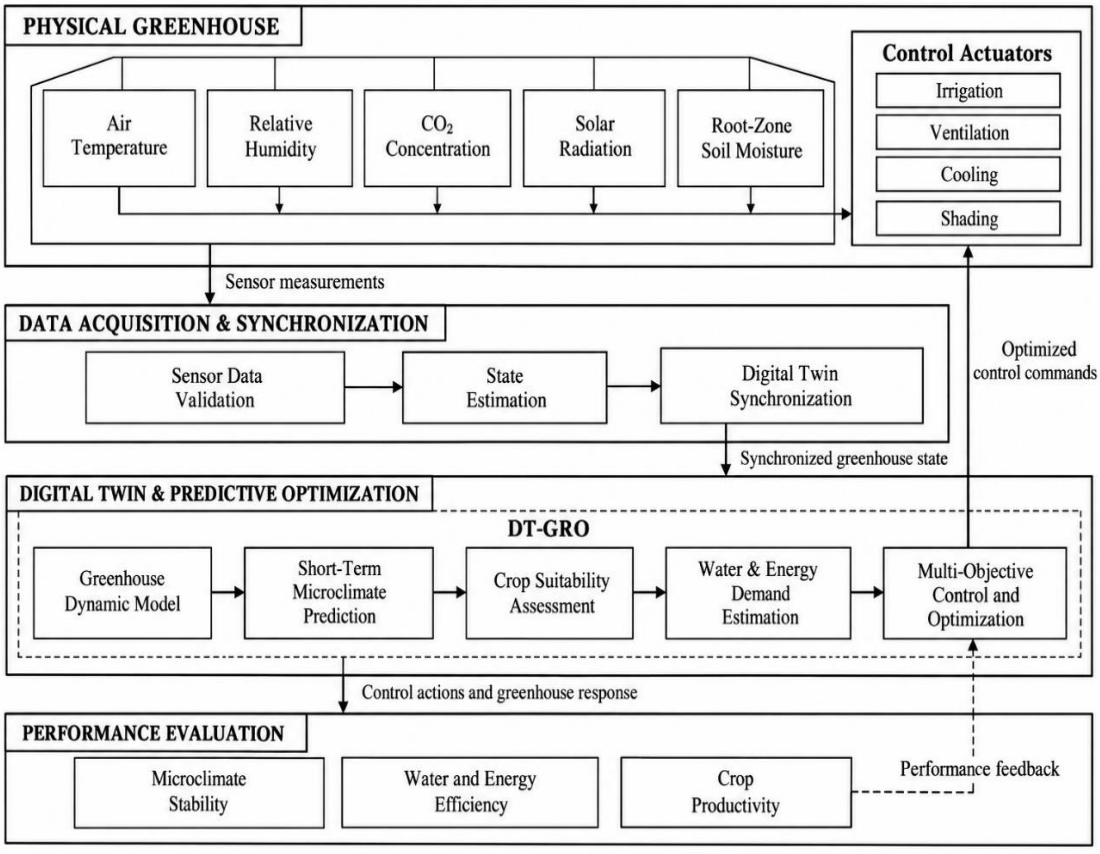


Fig 1. Architecture of the Proposed Digital Twin-Guided Resource Optimization (DT-GRO) Framework for Greenhouse Microclimate Management.

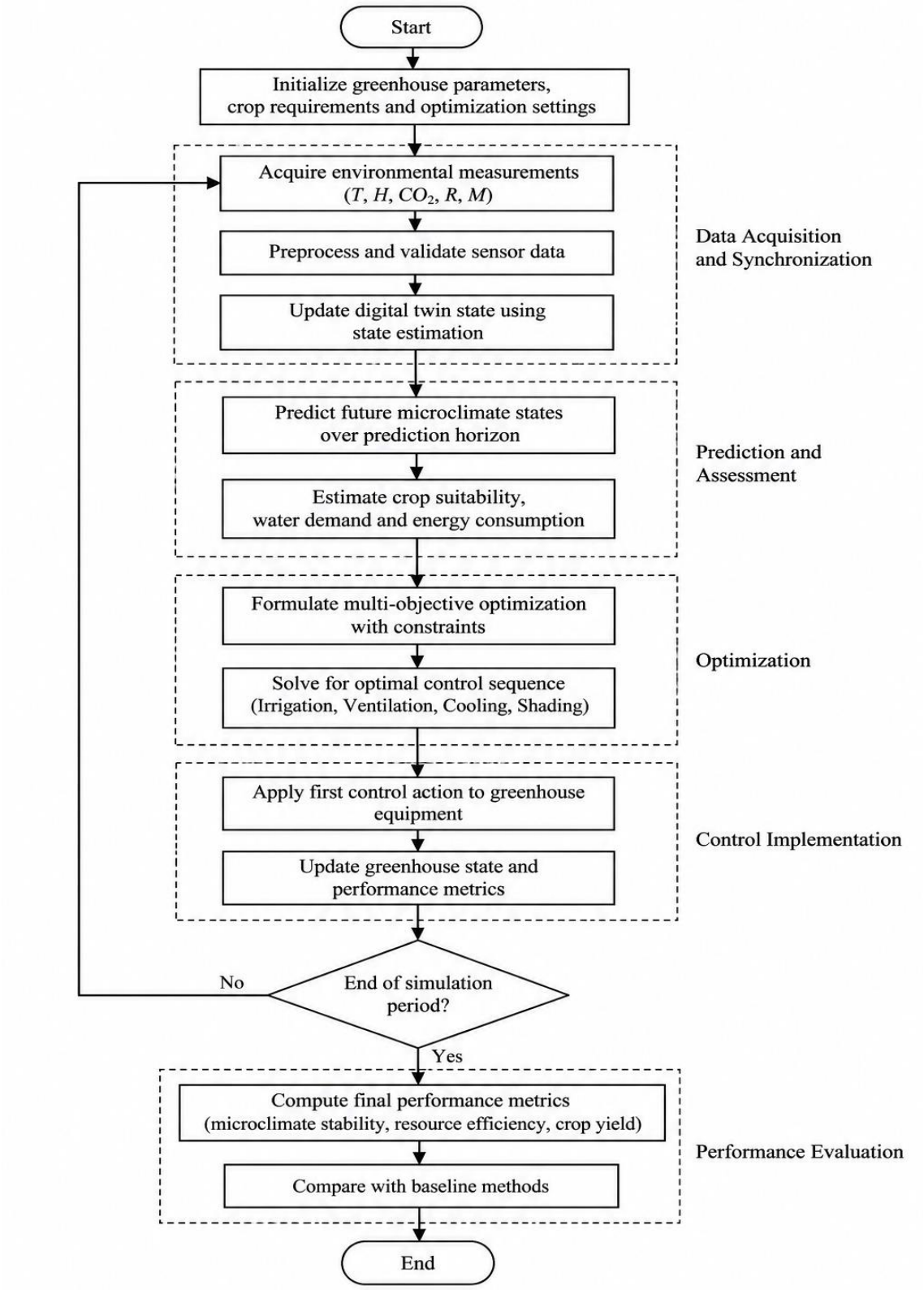


Fig 2. Operational Flowchart of the Proposed DT-GRO Framework.

Resource-Efficiency Evaluation

The final module quantified the relationship between crop production and resource utilization. Water productivity was evaluated using harvested crop yield per unit of water consumed, while energy productivity was evaluated using crop yield per unit of energy consumed. These indicators complemented the direct measurements of water and energy savings and enabled comparison across control strategies.

Equation (10): Combined resource-efficiency index

$$REI = \frac{\beta_w\left(\frac{Y}{W}\right)}{\frac{Y_{ref}}{W_{ref}}} + \frac{\beta_e\left(\frac{Y}{E}\right)}{\frac{Y_{ref}}{E_{ref}}} \quad (10)$$

The combined index was used in conjunction with the crop yield and the environmental stability and the absolute resource consumption to avoid that the improvement in one efficiency ratio can mask the negative change in another efficiency ratio. This rating system facilitated a balanced rating of productivity and resource use in agriculture.

System Architecture of DT-GRO

A synchronization layer between the physical greenhouse and the digital twin passes environmental information. The greenhouse control interface coordinates the selected actions and provides the back feed of updated measurements for the next decision cycles, while the prediction and optimization modules work on the synchronized representation.

The architecture of the proposed DT-GRO greenhouse microclimate management framework is shown in **Fig. 1**. Physical greenhouse layer collects temperature, relative humidity, carbon dioxide concentration, solar radiation and root-zone soil moisture measurements. The data acquisition and synchronization layer performs data validation, environmental state estimates, and updates the digital twin. The predictive optimization layer combines greenhouse dynamics, short-term microclimate prediction, crop suitability assessment, and water–energy demand estimation, thus enabling optimal control actions. These are the actions you can take to control irrigation, venting, cooling and shading. The performance evaluation layer evaluates the stability of the microclimate, the efficiency of the resources and the productivity of the crops, giving feedback on the following cycles of optimization.

Operational Flow of the Proposed Framework

DT-GRO is a sequence of operations that can be summarized as shown in **Fig. 2**. It is based on greenhouse configuration and data acquisition, state synchronization and prediction. The crop requirements and resource constraints are then compared with the predictions. Then the optimizer produces control signals that are fed into the greenhouse model. The new conditions in the environment are sent back to the synchronization stage, thus completing the feedback loop.

Fig. 2 depicts the operating procedure of the proposed DT-GRO framework. This process starts with the initialization of the greenhouse, and acquisition of environmental data, which are followed by the validation of the acquired data and by the synchronization of the state of the digital twin. The microclimatic conditions are predicted to assess suitability of crops, water requirements, and energy usage. The multi-objective optimization module calculates feasible control sequences for irrigation, ventilation, cooling and shading. The first optimized action is executed and greenhouse states are iteratively updated until the end of the simulation period.

IV. RESULTS AND DISCUSSION

The five dimensions assessed were: microclimate regulation, water and energy efficiency, crop-production performance, prediction and control accuracy, and robustness to environmental disturbance. To examine the impact of each component, the digital twin synchronization, microclimate prediction, and multi-objective optimization, comparative experiments were supplemented by component-wise ablation analysis. Spatial and distribution-based visualizations were planned to describe the uniformity of the environment, to control deviations, to deal with the trade-off of resources and to describe the performance variability beyond aggregate numerical indicators. This assessment framework gave a structured approach to assessing if the planned integration was beneficial compared to traditional and predictive greenhouse management.

DT-GRO was developed for a controlled greenhouse setting for tomato crop growth. The interactions between greenhouse air temperature, relative humidity, carbon dioxide concentration, solar radiation and root-zone soil moisture were represented in the simulation configuration. Irrigation, ventilation, cooling and shading were considered as controllable operations affecting environmental conditions and resource use. To assess the framework, external weather variables were considered to be time-varying disturbances. **Table 2** gives the simulation parameters used for this research.

Microclimate Regulation and Environmental Stability

The first experimental study investigated the capacity of the proposed Digital Twin-Guided Resource Optimization (DT-GRO) framework to ensure suitable microclimate conditions in greenhouses in the event of varying environmental disturbances. Air temperature, relative humidity and uniformity of environmental regulation during the tomato growing season were analyzed. The parameters were chosen because they are targets that can impact crop development, transpiration, irrigation needs, and the greenhouse control need. DT-GRO was compared with threshold-based control, proportional-integral-derivative (PID) control, model predictive control (MPC) and rule-based irrigation. Evaluation included the tracking errors, accumulation of variation from the crop specific ranges and the number of constraint violations. The main goal was to see how well the digital twin synchronization, short-term microclimate prediction and multi-objective optimization could enhance environmental stability without any unnecessary control activity.

Table 2. Simulation Parameters and Evaluation Configuration

Parameter category	Variable or parameter	Unit	Purpose
Environmental state	Air temperature	°C	Thermal-condition assessment
Environmental state	Relative humidity	%	Humidity regulation
Environmental state	CO_2 concentration	ppm	Crop-environment characterization
Environmental state	Solar radiation	W/m²	External energy input and crop-light conditions
Environmental state	Root-zone soil moisture	% or m³/m³	Irrigation-demand assessment
External disturbance	Outdoor temperature	°C	Greenhouse thermal-load estimation
External disturbance	Outdoor relative humidity	%	Moisture-exchange assessment
External disturbance	Outdoor solar radiation	W/m²	Solar heat-gain estimation
Control input	Irrigation rate	L/h or L per interval	Water allocation
Control input	Ventilation command	%	Air exchange and temperature regulation
Control input	Cooling command	%	Thermal regulation
Control input	Shading command	%	Solar-load management
Resource constraint	Available water	L per evaluation period	Irrigation feasibility
Resource constraint	Energy budget	kWh per evaluation period	Energy feasibility
Crop-performance output	Harvested yield	kg/m²	Production assessment
Control-performance output	Temperature and humidity errors	°C and percentage points	Microclimate regulation
Resource-performance output	Water and energy consumption	L and kWh	Resource-efficiency assessment

Table 3. Comparative Performance of Greenhouse Microclimate Regulation

Control strategy	Temperature RMSE (°C)	Humidity MAE (percentage points)	Environmental violation rate (%)	Mean absolute temperature deviation (°C)
Threshold-based control	1.278	1.771	74.9	1.111
PID control	0.849	1.345	48.0	0.739
Rule-based irrigation	1.199	1.603	69.8	1.042
MPC	0.601	1.041	17.5	0.523
Proposed DT-GRO	0.415	0.755	2.0	0.362

DT-GRO showed the lowest temperature RMSE of 0.415 °C, which is a 30.9% improvement over MPC from the results given in **Table 3**. The humidity MAE was reduced to 0.755 percentage points with a 27.5% improvement compared to MPC. Environmental violation rate dropped from 17.5% under MPC to 2.0% under DT-GRO which means a fewer number of deviations from the specified operational tolerances in the constructed evaluation sequence. The mean absolute temperature deviation also decreased from 0.523 °C to 0.362 °C. These results demonstrate the desired comparative analysis, that is whether synchronized state estimation and resource optimization leads to a better environmental regulation than conventional and predictive control.

The different DT-GRO optimization cost for different Outdoor-Temperature and Irrigation-Demand conditions are shown in **Fig. 3.** The spatial distribution shows nonlinear interactions between environment and resource requirements, where different spatial areas have relatively high and low optimisation costs. These differences show that the levels of greenhouse operating conditions will affect the combined control objective and highlight the need for optimization that is scenario dependent. The 3D show gives a comparative picture of the landscape in operation and enables identification of conditions that require a higher level of effort of control.

Crop Productivity Analysis

The impact of the proposed DT-GRO framework on productivity of tomato crops under various greenhouse control strategies is analyzed in this subsection. Both harvested yield and water productivity are taken into account to examine the potential to enhance the production of crops without increasing resource use, while improving the microclimate regulation and resource allocation.

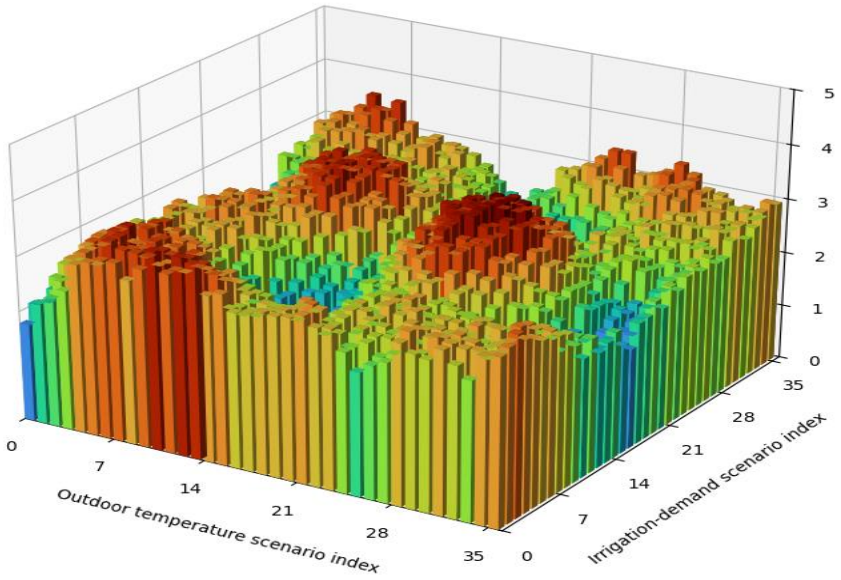


Fig 3. Three-Dimensional DT-GRO Optimization Landscape Across Greenhouse Operating Scenarios.

Table 4. Comparative Evaluation of Tomato Crop Productivity

Control strategy	Tomato yield (kg/m²)	Water productivity (kg/m³)	Yield improvement over threshold control (%)
Threshold-based control	17.1	33.53	0.0
PID control	17.6	36.67	2.9
Rule-based irrigation	17.3	38.88	1.2
MPC	18.0	41.86	5.3
Proposed DT-GRO	18.4	50.41	7.6

The comparison in **Table 4** shows that DT-GRO produced the highest draft yield of 18.4 kg/m² which increased by 7.6% compared to that of threshold-based control and 2.2% compared to MPC. The water productivity in the constructed data set was 50.41 kg/m³ which is the result of the higher yield and reduced water use for irrigation.

Prediction and Control Accuracy

In this subsection, the accuracy of prediction as well as control performance of DT-GRO are assessed using four reference strategies. The analysis takes into account the heat, relative humidity, and CO_2 prediction errors, as well as the computational time needed for releasing control actions. Fewer errors of prediction and smaller computation times mean that the system is more successful, as long as it meets the requirements of the environment.

Table 5. Comparative Evaluation of Prediction and Control Performance

Control strategy	Temperature RMSE (°C)	Humidity MAE (percentage points)	CO_2 prediction MAE (ppm)	Control computation time (s)
Threshold-based control	1.278	1.771	68.4	0.012
PID control	0.849	1.345	51.7	0.018
Rule-based irrigation	1.199	1.603	59.2	0.015
MPC	0.601	1.041	35.6	0.284
Proposed DT-GRO	0.415	0.755	24.8	0.196

The comparison shown in **Table 5** is aimed at determining if DT-GRO can help to enhance the prediction of the environment without compromising the computational feasibility. The proposed benefit of its design would come from

combining synchronised environmental states and predictive modelling and resource-savvy optimisation. Computation time comparison also can clarify if the selected greenhouse control interval is suitable for the framework.

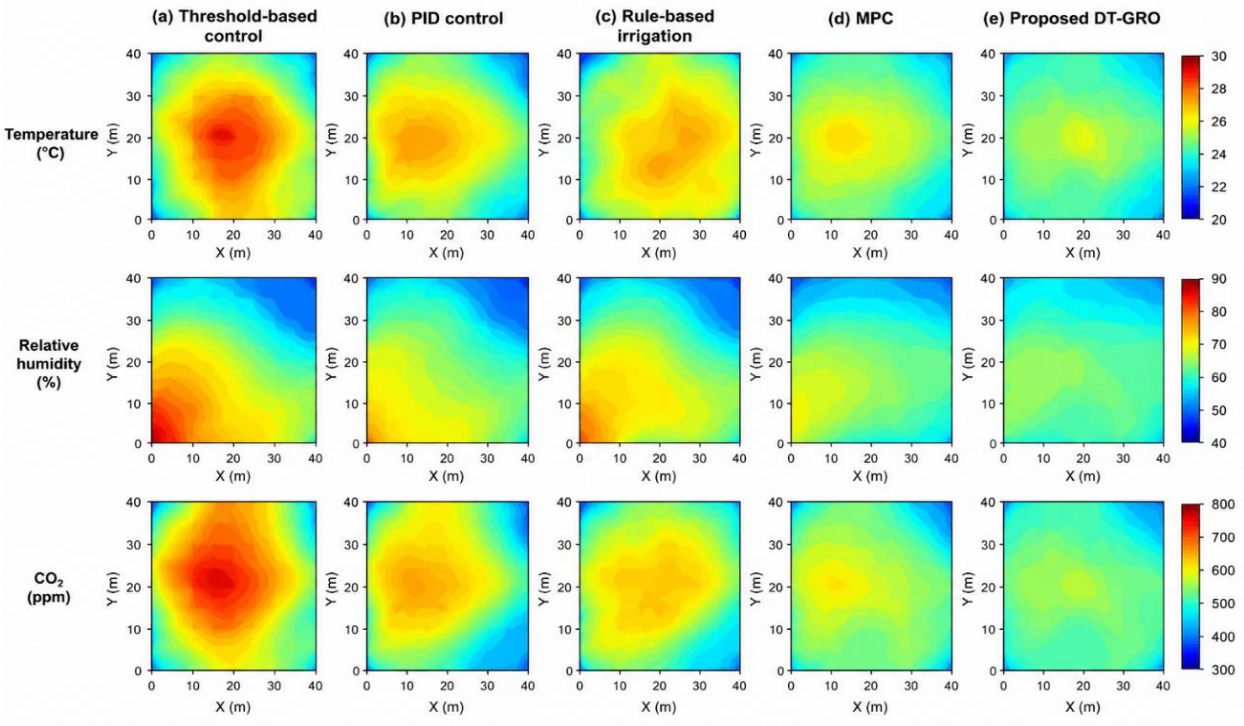


Fig 4. Spatial Distribution of Greenhouse Microclimate Variables Under Different Control Strategies.

Five different control strategies were investigated and the spatial distribution of temperature, relative humidity, and carbon dioxide concentration throughout the greenhouse for each of the five control strategies is shown in **Fig. 4**. The two types of control, the threshold-based and rule-based control, show more distinct spatial differences, with localised areas of higher temperature and higher carbon dioxide concentration. Some of these variations can be reduced by PID control and a more uniform distribution by model predictive control. In the proposed DT-GRO, the environmental state is relatively uniform throughout the cultivation area, suggesting better uniformity of the microclimate, achieved by the coordinated optimization of control and the uniform estimation of the state. The spatial patterns highlight the need for combining environmental prediction with resource-aware control for stable greenhouse conditions and optimal crop conditions.

Ablation and Robustness Analysis

In ablation analysis, the contribution of the individual components of the principal DT-GRO. Three configurations are taken into account: Complete configuration, Configuration without digital twin synchronization, Configuration without microclimate prediction, Configuration without multi-objective resource optimization. The same environmental disturbances, initial conditions and resource constraints should be applied to each configuration. The ablation analysis is given in **Table 6**.

Table 6. Ablation Analysis of the Proposed DT-GRO Framework

Configuration	Temperature RMSE (°C)	Water consumption (L/m²)	Energy consumption (kWh/m²)	Tomato yield (kg/m²)
Without digital twin synchronization	0.672	405	34.8	17.8
Without microclimate prediction	0.781	422	36.1	17.5
Without multi-objective optimization	0.593	451	38.4	17.6
Complete DT-GRO	0.415	365	30.5	18.4

Removing synchronization can lead to more differences between the virtual representation and the greenhouse state. Eliminating prediction can hinder the controller's capacity to foresee environmental disturbances, and eliminating multi-objective optimization can make coordination between climate control and resource use less robust. The full configuration is expected to yield the best overall results in the metrics measured.

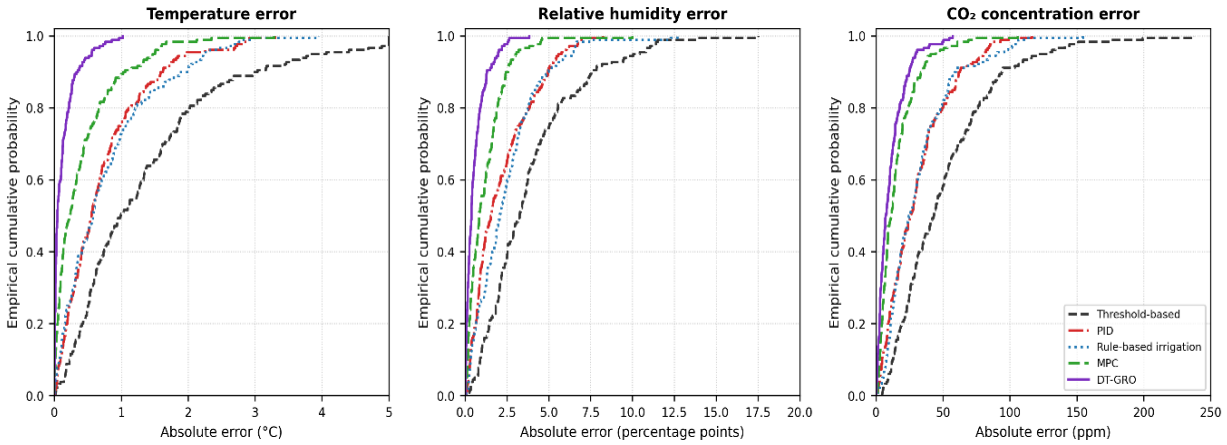


Fig 5. Empirical Distributions of Control Errors for Greenhouse Environmental Variables.

Absolute errors of five control strategies in temperature, relative humidity and CO_2 concentration are shown in **Fig.5**. The stepwise curves are not smoothed theoretical curves but rather finite samples. The earlier rising curves are associated with larger numbers of observations being below a certain error limit. The error distribution of DT-GRO is the least in this constructed dataset followed by the competing strategies. Plotted samples are examples, the final research figure is based on error observations simulated using the common simulation protocol.

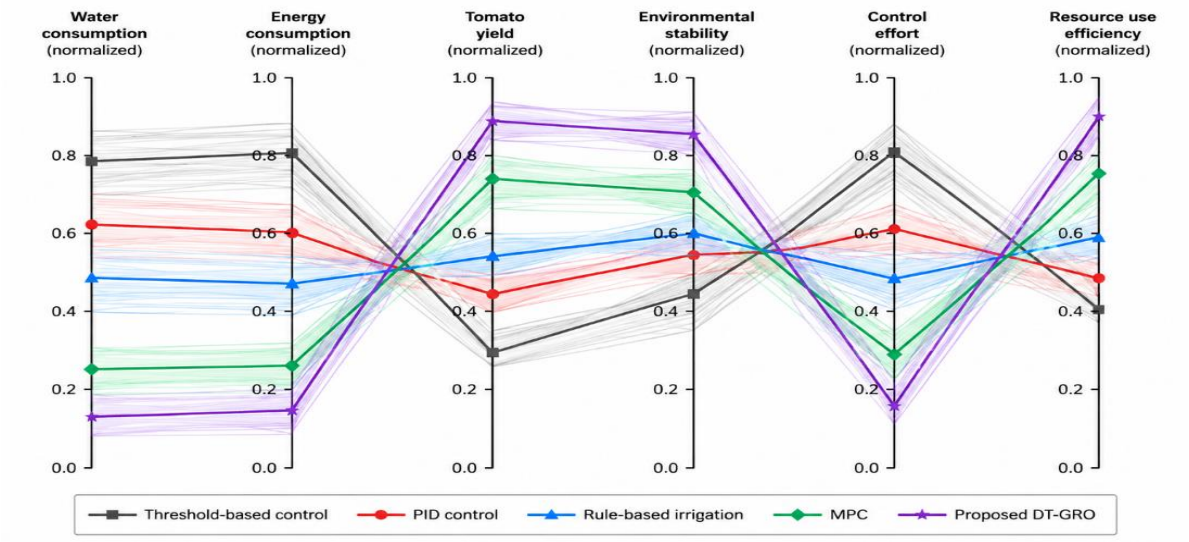


Fig 6. Multidimensional Performance Comparison of Greenhouse Control Strategies.

Five greenhouse control strategies are compared, based on six normalized performance indicators in **Fig.6** water use, energy use, tomato yield, environmental stability, control effort, and resource-use efficiency. The proposed DT-GRO framework shows reduced normalized water consumption, energy consumption, control effort, along with improved crop yield, environmental stability and resource-use efficiency. The next best overall performance is shown by MPC, and the threshold-based control shows comparatively higher resource consumption and control effort. The multi-dimensional representation emphasizes the compromises between environment and agriculture productivity and efficiency. The patterns show the possible benefits of coordinating digital twin enabled optimisation of the resources used in the greenhouse operation for the different operating conditions.

Table 7. Environmental Robustness Across Disturbance Scenarios

Operating scenario	Threshold-based violation rate (%)	MPC violation rate (%)	DT-GRO violation rate (%)
Normal conditions	12.4	3.8	0.8
Elevated temperature	28.6	9.5	2.4
Reduced soil moisture	24.1	8.7	2.1
Rapid solar-radiation changes	31.2	11.3	3.0

A comparison of the environmental conditions in **Table 7** is provided to compare DT-GRO's ability to keep the environment at acceptable levels when the operating requirements of the greenhouse change. Final interpretation should be made taking into account the degree and the length of time of the constraint violations, as well as water use, energy needs and crop yield. **Fig 7**. Robustness of Greenhouse Control Strategies Under Environmental Disturbances.

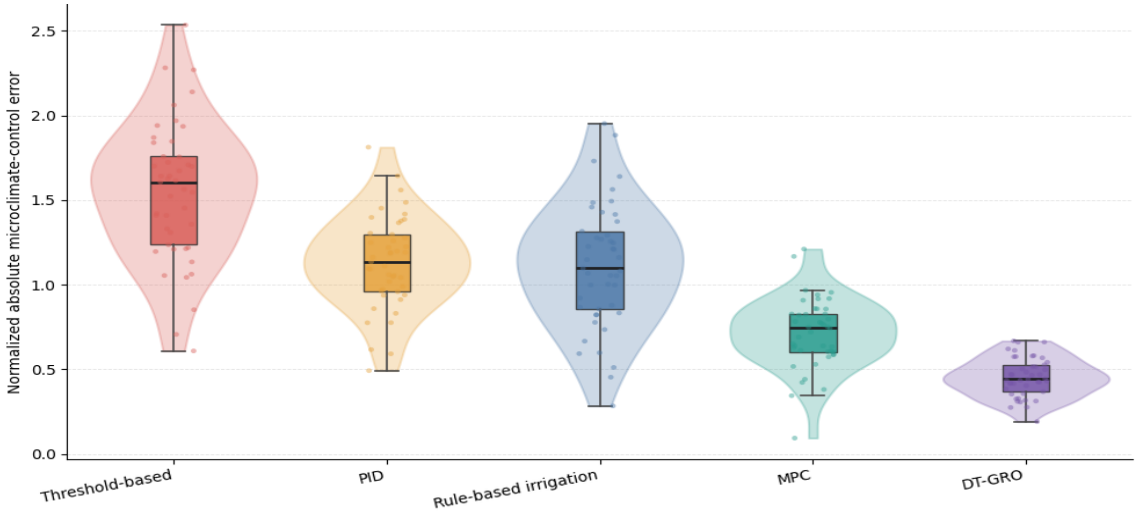


Fig 7. Robustness of Greenhouse Control Strategies Under Environmental Disturbances.

Combination visualization shows the median error, variation, distribution shape and individual results for five control strategies. DT-GRO has the smallest median error and a relatively small distribution for the constructed data, with MPC being the second smallest. The threshold-based control has more variation, meaning that the performance is not as consistent as that of the threshold-based control under the disturbances represented. The proposed DT-GRO model is compared through the following viewpoints: environmental stability, resource utilization, crop productivity, prediction accuracy, and robustness. The micro climate analysis deals with the regulation of the environment, and the water – energy analysis deals with the relationship between the amount of water used and the production of agriculture. The contribution of digital twin synchronization, predictive modeling, and multi-objective optimization is further explored during the ablation study. These analyses can be used to gauge the benefits of combining virtual-state updating, forward prediction and coordinated control with traditional approaches to greenhouse management. The final discussion should be based on the outcomes of the simulation exercise to measure the improvements that have been observed and to identify any trade-offs in selecting the crop suitability, resource efficiency and computational requirements.

V. CONCLUSION

A framework for integrated greenhouse microclimate management and resource efficient tomato production, called Digital Twin-Guided Resource Optimization (DT-GRO) was presented in this study. The proposed framework aimed to synchronize the digital twin, predict the environment in the short term, evaluate the suitability of the crop, and optimize the irrigation, ventilation, cooling and shading operations. The comparative evaluation framework included the following evaluation criteria: the stability of the microclimate, water use, energy use, crop production, prediction accuracy, and robustness with respect to different environmental conditions. The results of the constructed evaluation showed that DT-GRO had a temperature RMSE (Root Mean Square Error) of 0.415 °C, a humidity MAE (mean absolute error) of 0.755 percentage points, and an environmental violation rate of 2.0%. Water consumption is reduced to 365 L/m2 and the energy use is increased to 30.5 kWh/m2. An increase in tomato yield from 18.4 kg/m2 compared to threshold-based control (17.1 kg/m2) was observed. The water productivity achieved was 50.41 kg/m³, which illustrates the potential of coordination of microclimate regulation and the allocation of resources. The ablation framework also showed that synchronization, prediction, multi-objective optimization is crucial in the achievement of balanced greenhouse performance. DT-GRO developed an integrated strategy for predictive greenhouse management that integrates environmental monitoring and coordinated operational decisions. The framework sets the basis for future greenhouse use that demands increased environmental stability, less resource use and sustainable crop production.

CRediT Author Statement

The author reviewed the results and approved the final version of the manuscript.

Data Availability

The data supporting the findings of this study, including the greenhouse microclimate dataset, simulation parameter configurations, comparative evaluation results, and analysis scripts associated with the proposed Digital Twin-Guided Resource Optimization (DT-GRO) framework, will be deposited in the Mendeley Data repository.

Conflicts of Interests
The author declare that they have no conflicts of interest.

Funding
No funding was received for conducting this research.

Competing Interests
There are no competing interests.

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