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Ai-driven innovations in greenhouse agriculture: Reanalysis of sustainability and energy efficiency impacts

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A B S T R A C T

In the context of greenhouse agriculture, the integration of Artificial Intelligence (AI) is evaluated for its potential to enhance sustainability and crop production efficiency. This study reanalyzes publicly available datasets, using advanced time series analysis and noise reduction techniques through seasonality detection and removal. This novel approach reveals trends more clearly, providing a detailed comparison between AI-driven methods and traditional agricultural practices. An extensive review of literature on AI applications in agriculture is conducted to establish a broad understanding of its current state and future prospects. The core focus is the Autonomous Greenhouses Challenge, an initiative where research teams apply AI technologies in real-world greenhouse settings. This challenge offers crucial data for a thorough assessment of AI's practical impact. The analysis reveals that AI significantly reduces heating energy consumption, indicating a notable improvement in energy efficiency. However, reductions in CO_2 emissions, along with improvements in electricity and water usage, are only marginal when compared to traditional farming methods. Similarly, enhancements in crop quality and profitability achieved through AI are found to be on par with conventional techniques. These findings highlight the dual nature of AI's impact in greenhouse agriculture: it shows significant promise in some areas, while its effectiveness in other key sustainability aspects remains limited. The study emphasizes the need for further research and investment in technological advancements, as well as the importance of a robust data infrastructure. It also highlights the necessity of education and training in AI technologies for effective implementation in the agricultural sector. The results of this research aim to inform policymakers, researchers, and industry stakeholders about the mixed impacts of AI on sustainable greenhouse farming. By offering a comprehensive evaluation of the benefits and challenges of AI integration, this study contributes to the ongoing discussion on sustainable agricultural practices and provides insights into the future direction of AI in this field.

1. Introduction

Meeting the growing food demands of an increasing global population requires ramping up agricultural production, which often leads to excessive use of natural resources [1–3]. This problem is worsened by the widespread use of agricultural chemicals, which places additional stress on the environment [4,5]. The agriculture sector's reliance on non-renewable energy sources further contributes to environmental degradation [6,7]. Nevertheless, there is substantial potential for agriculture to improve its energy efficiency. Worldwide, issues such as food safety, climate change, carbon emissions, and supply chain waste are linked to a lack of ecological consideration [8,9]. As the push for sustainability strengthens, renewable energy becomes essential in lowering carbon emissions and reducing dependence on fossil fuels, thus helping to mitigate climate change [10,11]. Greenhouse farming plays a crucial role in addressing sustainability challenges by offering a viable solution to enhance agricultural practices. Sustainable greenhouse farming practices have been shown to bridge the gap between food supply and demand [12]. Greenhouse farming plays a crucial role in addressing sustainability challenges by offering a viable solution to enhance agricultural practices. Sustainable greenhouse farming practices have been shown to bridge the gap between food supply and demand [13]. Within this framework, managing energy consumption in greenhouses offers a practical solution [14], as greenhouse farming significantly influences energy and water usage [15].

The European Union, encompassing 405,000 ha of greenhouses, recognizes the critical role of greenhouse farming in optimizing energy efficiency [16,17] and reducing reliance on non-renewable energy

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sources[18]. A study reviewing energy consumption in Spain, Greece, Italy, The Netherlands, and Germany highlights the significant energy demands of irrigation and fertilizer in tomato production, accounting for 1–19 % and 1–27 % of total energy use, respectively [16]. Technological advancements, notably in Artificial Intelligence (AI), are reshaping agriculture to meet changing consumer demands, with AI applications in greenhouse farming reducing energy consumption and increasing yields [8,19]. Technologies such as AI, data-driven approaches, machine learning, and robotics are enhancing the optimization of greenhouse operations [20,21]. AI is particularly effective in environmental control, crop monitoring, product prediction, resource optimization, and process automation [22], which can lead to a comprehensive action plan for agri-food sector [23–26]. such a system that have been a matter of studies [20,27] has the potential to revolutionize greenhouse farming is significant, as it can enhance efficiency, minimize waste, increase crop yields, and ultimately lead to more sustainable and productive food systems [2,28,29].

This paper, drawing on publicly available data [30] and previously published official papers as its baseline information [31], presents an in-depth analysis of the 2019 Autonomous Greenhouses International Challenge (AGIC), hosted by Wageningen University & Research (WUR). The core objective of the Challenge was to implement a data-driven approach and utilize a data management platform to realize the concept of autonomous greenhouses. Participating teams were tasked with remotely cultivating a cherry tomato crop within a set period. To support this effort, WUR provided each interdisciplinary team with a dedicated controlled greenhouse space, fully equipped, at their agricultural research facility in Bleiswijk, Netherlands. This initiative served as both a test of remote agricultural management and an exploration of advanced machine learning techniques in greenhouse farming, focusing on their potential to revolutionize crop cultivation. Over six months, this challenge aimed to demonstrate the effective control of greenhouse environments using AI. The comprehensive data collected from the performance of all teams—including their integration of AI methods, software testing, and sensor deployment in the greenhouse environment—forms the basis of the analysis presented in this paper. The previous version of this challenge had a similar framework [32], which could be subject to comparative analysis in future studies.

It is important to note that this study does not aim to scrutinize how different teams implemented AI or whether their systems could be further optimized. Instead, the focus is on understanding the general impact of AI technologies by averaging the performance data from various AI-assisted teams and comparing it to a baseline of traditional greenhouse management practices. This approach allows for the evaluation of overarching benefits and limitations of AI in a more holistic manner [33] which includes control strategies [34,35]. By focusing on aggregated performance data, the overall improvements that AI can achieve across different implementations and settings can be highlighted [36]. This method helps to mitigate the variability and noise introduced by the individual nuances of each team's specific AI approach [37]. Rather than delving into the specifics of various algorithms and strategies, a clearer picture of the tangible benefits AI can bring to greenhouse farming as a whole is presented.

This study provides valuable insights into the practical applications of AI, emphasizing its potential for enhancing efficiency and productivity in agricultural practices. By examining the broader trends and impacts, the realistic benefits of AI technologies are clarified, addressing common misconceptions and moving beyond often-exaggerated expectations. The analysis aims to bridge the gap between theoretical AI capabilities and real-world agricultural performance, offering a more grounded understanding of how AI can be effectively integrated into greenhouse farming. This comprehensive perspective is crucial for stakeholders, policymakers, and researchers considering the adoption of AI in agriculture, as it provides a balanced view of both the potential and the current limitations of these technologies. The importance of viewing AI's impact in agriculture from a broader lens is underscored, focusing on general trends and aggregate data rather than the specifics of individual implementations. This approach aids in creating a more realistic and practical understanding of AI's role in advancing sustainable and efficient greenhouse farming practices.

2. Materials and methods

This study delves into the application of Artificial Intelligence (AI) in seven key areas of greenhouse farming. It includes an extensive case study where multiple research teams engage in a real-world experiment, utilizing innovative technologies like AI for plant cultivation in greenhouses. The experiment's data serves as a basis for assessing the impact of various technologies. To analyze performance, extensive data processing stages were undertaken. The study then conducts a detailed comparative analysis, exploring AI technology's effectiveness in enhancing greenhouse farming from diverse perspectives, illustrated in Fig. 1. This comprehensive approach offers insights into AI's role in optimizing various aspects of greenhouse agriculture.

- Case study: autonomous greenhouse challenge

The primary material of this study is raw data from "Autonomous Greenhouse Challenge," a real-world experiment where various research teams implemented distinct AI algorithms and control systems in greenhouse settings [30]. Each team developed their own AI models, utilizing a range of machine learning techniques such as Dynamic Regression, Deep Reinforcement Learning (DRL), Deep Deterministic Policy Gradient (DDPG), Generative Adversarial Networks (GAN), Convolutional Neural Networks (CNN), and Recurrent Neural Networks (RNN). These models were trained using an artificial dataset created from the dynamic greenhouse climate model KASPRO and the cucumber crop model INTKAM, which was modified for high-wire cucumber crops. This artificial dataset provided a rich and varied source of training data that was essential for the development and refinement of the AI algorithms. Adequate basic information of the boundary condition of the experiment also has been mentioned in published materials of the challenge [30–32] which briefly re-stated.

- Data analysis:

Initial data validation checks were performed to identify and correct any anomalies or errors in the raw data. The data was tested for stationarity to ensure that it met the requirements for further time-series analysis. Seasonal components were removed from the data through decomposition analysis, allowing for the extraction of underlying trends. Advanced data science algorithms were used to identify and extract significant trends from the cleaned and processed data.

- Comparative analysis

The study employs a detailed comparative analysis to evaluate the effectiveness of AI in enhancing greenhouse farming. This involves comparing a reference case (traditional greenhouse management without AI) against several AI-assisted scenarios. The AI-assisted scenarios included AI-based climate control, energy and water management, and growth monitoring systems.

Key performance indicators (KPIs) such as resource consumption efficiency, environmental impact reduction, crop yield, and product quality were analyzed. Relative changes, rather than absolute values, were used to provide a clearer picture of the improvements brought about by AI. This approach helps to highlight the broader impacts of AI technologies, moving beyond the comparison of individual strategies to assess their overall potential in sustainable agriculture.

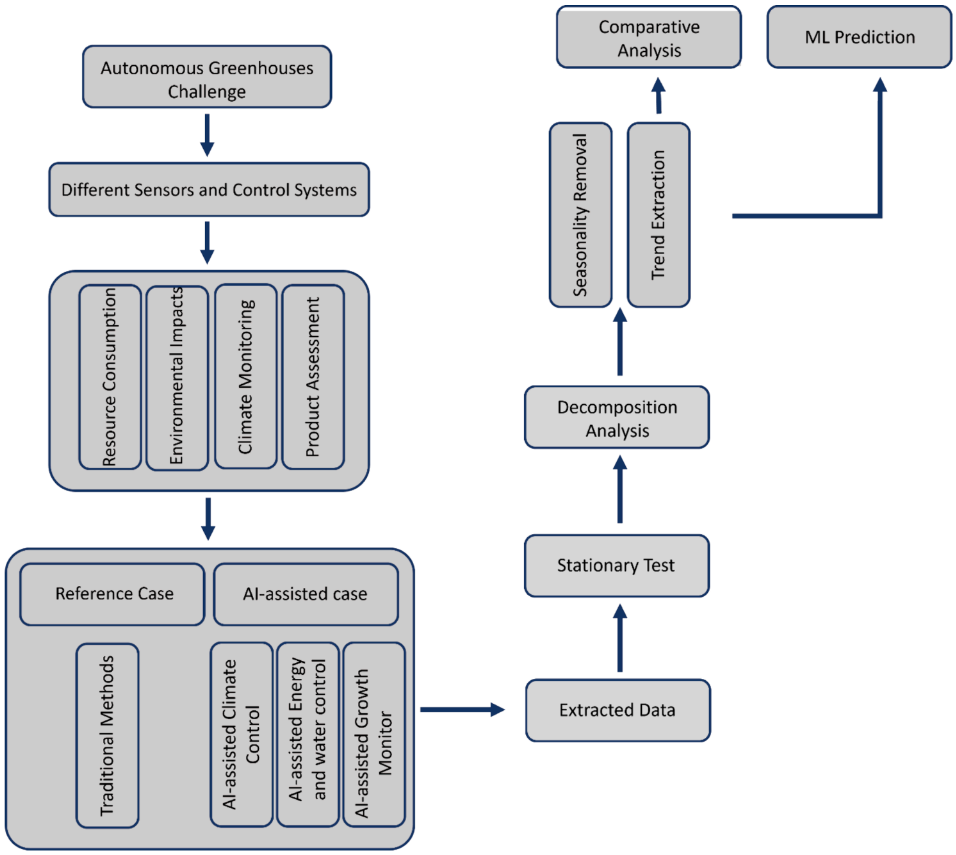


Fig. 1. Research workflow.

2.1. Contribution

In this paper, a re-analysis of publicly available data from the Autonomous Greenhouses Challenge is presented, following a standard practice in the scientific community. The re-analysis of existing datasets is crucial for extracting new insights, validating previous findings, and applying different analytical techniques that may reveal additional dimensions of the data. This ensures the robustness of scientific conclusions and fosters continuous improvement in research methodologies. This study diverges from the original published materials of the Autonomous Greenhouses Challenge [28–32] in several key ways. Originally, the focus was primarily on comparing various data-driven strategies to identify the optimal one. In contrast, a different sampling strategy is employed here by averaging the data of AI-aided strategies and comparing this aggregated data to the baseline (non-AI) case. This shift in focus is significant: instead of seeking to identify the best individual strategy, the aim is to understand the overall potential impact of AI-assisted methods in greenhouse farming. This broader perspective is essential for policymakers and stakeholders who are interested in the general effectiveness of AI technologies in enhancing sustainability and productivity in agriculture, rather than the performance of specific strategies.

The analytical techniques employed in this study also differ significantly from those used in the original challenge publications. Emphasis is placed on uncovering trends and patterns hidden in the raw data through advanced data science algorithms. Specifically, time-series analysis, white noise detection and removal, and seasonality adjustment are utilized to refine the dataset and extract meaningful insights. These methods help to eliminate extraneous variations and focus on the underlying trends attributable to AI interventions. Additionally, relative changes compared to the baseline case, rather than absolute values, are focused upon. This method allows for a more nuanced understanding of the performance improvements attributable to AI, considering the inherent variability and seasonality present in agricultural data. By applying these advanced analytical techniques, the study provides a deeper and more detailed examination of the data, revealing insights that might not be apparent through traditional analysis methods. For instance, while the original analysis found that AI significantly reduces heating energy consumption, this study further examines the relative improvements in CO_2 emissions, electricity usage, and water consumption. Although these improvements are marginal compared to traditional methods, they highlight the nuanced impact of AI technologies in greenhouse farming.

Thus, a significant contribution is made by re-analyzing publicly available data with a fresh perspective and advanced analytical methods. This approach not only validates and complements the original findings but also expands the understanding of AI's potential in greenhouse farming by providing a comprehensive and nuanced analysis. These contributions are crucial for guiding future research, policy decisions, and the practical implementation of AI technologies in sustainable agriculture.

2.2. Experiment setup details

This section contains the official information about the experiment setup from the challenge organizers. In the Autonomous Greenhouses Challenge, the monitoring involved five distinct greenhouse compartments. Each compartment, with areas of 96 m^2 and a growing space of 76.8 m^2, was scrutinized for the experiment.

General information: Initiated in mid-December 2019, the focus was on cultivating a single tomato variety. Grodan's slabs were utilized as the chosen substrate due to their uniform quality and high absorbency, which are key factors in promoting root health and plant growth. These slabs facilitated precise regulation of water content and Electrical

Conductivity (EC) levels in the root zone. Moreover, their dirt-free nature contributed to maintaining a pristine greenhouse environment, underlining the importance of substrate choice in controlled agricultural settings.

Sensors: GroSens sensors, utilizing Frequency Domain Reflectometry (FDR) technology, were installed to gather data from the slabs and monitor crop growth. These sensors measure the electrical properties and moisture levels within the slabs. Additionally, the greenhouse environment—factors like temperature and humidity—was closely monitored. Detailed plant profiles were also recorded, including height, leaf count, fruit per truss, and stem thickness. To optimize plant growth, various other sensors, including those for measuring leaf temperature, were employed in the greenhouse.

Advanced monitoring and data analysis: Advanced sensors were utilized to measure the temperature, Electrical Conductivity (EC), and weight of the slab. Monitoring the weight is crucial for evaluating the water content and, consequently, the health of the plants, including their foliage and fruits. GroSens sensors were pivotal in this process, providing additional vital data. Integrating the slab's weight data with the information from GroSens allowed for a more detailed and comprehensive understanding of the plants' conditions. This approach highlighted the significance of gathering data that is not only plentiful but also rich in insights, leading to a deeper understanding of the plants' health and needs. The collected data, comprising sensor and webcam inputs, was consistently sent to servers, where it undergoes a detailed daily review each morning. This process involves verifying the volume of water used for irrigation and analyzing the drainage to calculate its percentage. The data, particularly regarding slab water content measured by Grodan sensors and slab weight from ioCrops sensors, is graphically analyzed. This analysis helps assess fluctuations in water content, informing critical adjustments to the irrigation strategy, including decisions on when to start or stop irrigation, and determining optimal irrigation amounts, durations, and intervals.

AI models and performance analysis: In the 2019 vol of the challenge, detailed information regarding the AI models used by the teams is limited. The published material highlights that teams operated different greenhouse compartments using their own AI algorithms, resulting in varied management strategies for climate, irrigation, and crop. These strategies affected crop yields, product qualities, resource use efficiencies, income, costs, and net profit. A performance analysis compared the results of real greenhouse crop production in different compartments with a virtual greenhouse crop production model, or digital twin, to better understand the roles of various growth factors such as light, temperature, and CO_2 [29]. Based on information from previous volumes of the challenge, it is known that each competing team developed their own AI algorithms, employing a range of techniques including supervised, unsupervised, and reinforcement machine learning. These included Dynamic Regression, Deep Reinforcement Learning (DRL), Deep Deterministic Policy Gradient (DDPG), Generative Adversarial Networks (GAN), Convolutional Neural Networks (CNN), and Recurrent Neural Networks (RNN). The use of AI techniques necessitates training data, which is often scarce. To address this, an artificial training dataset was created using the validated dynamic greenhouse climate model KASPRO and the cucumber crop model INTKAM, modified for high-wire cucumber crops. This artificial dataset was provided to the teams before the experiment commenced [30].

However, the main focus of this study is not on the types of AI algorithms and their comparative performance. Instead, it aims to address the broader question of the potential impacts of AI on greenhouse agriculture. By averaging the data from various AI-aided strategies and comparing it to a base case, this work seeks to provide insights into the overall potential impacts of AI in greenhouse farming. Moreover, the type of analysis and methods employed in this paper differ significantly from those in the challenge's published materials. This study focuses on uncovering trend patterns hidden in the raw data using advanced data science algorithms, time-series analysis,

Analytical techniques and experiment details: The study employs advanced analytical techniques, including white noise detection and removal, and seasonality removal. Another key difference is that this paper uses relative changes compared to the base case, instead of working with absolute values. By concentrating on these aspects, this study aims to provide a comprehensive understanding of the broader potential impacts of AI in greenhouse agriculture, rather than merely comparing the performance of different AI algorithms. This approach offers valuable insights into how AI can enhance sustainability and efficiency in greenhouse farming. An extensive experiment was conducted with a cherry tomato crop, specifically the cv. "Axiany" variety provided by Axia Seeds, The Netherlands. Seedlings were sown on October 19, 2019, and grafted onto Maxifort rootstock. Initially planted in rock wool cubes, the seedlings were later transferred to greenhouse compartments on December 16, 2019. Teams began remotely controlling the experiment on December 20, 2019. Throughout the experiment, various growth parameters, such as stem growth rate, stem thickness, number of new trusses, stem density, and plant density, were monitored on a weekly basis.

In the experiment, energy resource consumption for tomatoes was meticulously quantified. This included measuring heat energy (MJ/m^2), electricity usage (kWh/kg) for artificial lighting during peak hours (7:00–23:00), and electricity for lighting during off-peak hours (kWh/m^2). Additionally, CO2 emissions (kg/m^2), drainage water (L/m^2), and irrigation water (L/m^2) were recorded. Wageningen University & Research (WUR) validated these measurements post-challenge using specific resource metrics, ensuring the accuracy and reliability of the data collected during the experiment.

3. Results and discussion

During the course of the experiment, several teams experimented with diverse methods, algorithms, and control systems to optimize greenhouse performance. This was in an effort to achieve better results than a reference greenhouse, which applied more conventional methods. The findings detailed in this section compare the collective performance of the teams using AI assistance with that of the reference case. The critical aspect under examination is whether the incorporation of these sophisticated technologies, including various machine learning algorithms, actually translates to enhanced outcomes. The initial phase of this analysis involved comparing the production quality of the AI-assisted greenhouses, represented by all five teams, against the benchmark set by the reference case.

Fig. 2 presents the changes in various growth metrics of tomato plants, comparing AI-assisted greenhouses to the reference case over a 16-week period. The metrics include stem growth, stem thickness, number of new trusses, and number of tomatoes per square meter. Below is a detailed analysis and discussion of the results shown in the figure.

The first graph shows the changes in stem growth (length) compared to the reference case. The AI-assisted greenhouses exhibit fluctuations, with both positive and negative deviations from the reference case. Initially, the AI-assisted growth lags behind the reference, with the most significant drop around week 6, showing nearly a 20 % decrease. However, around week 10, there is a notable improvement, with the AI-assisted growth surpassing the reference case before stabilizing towards the end.

The second graph displays changes in stem thickness. Here, the AI-assisted greenhouses demonstrate a consistent positive performance compared to the reference case. The stem thickness in AI-assisted environments generally remains above the reference line, with a significant peak nearing a 20 % increase by week 16. This indicates that while the AI methods may not have consistently increased stem length, they have positively impacted stem robustness.

The third graph shows the changes in the number of new trusses. The AI-assisted greenhouses do not show a significant improvement over the reference case. The number of new trusses remains relatively close to the

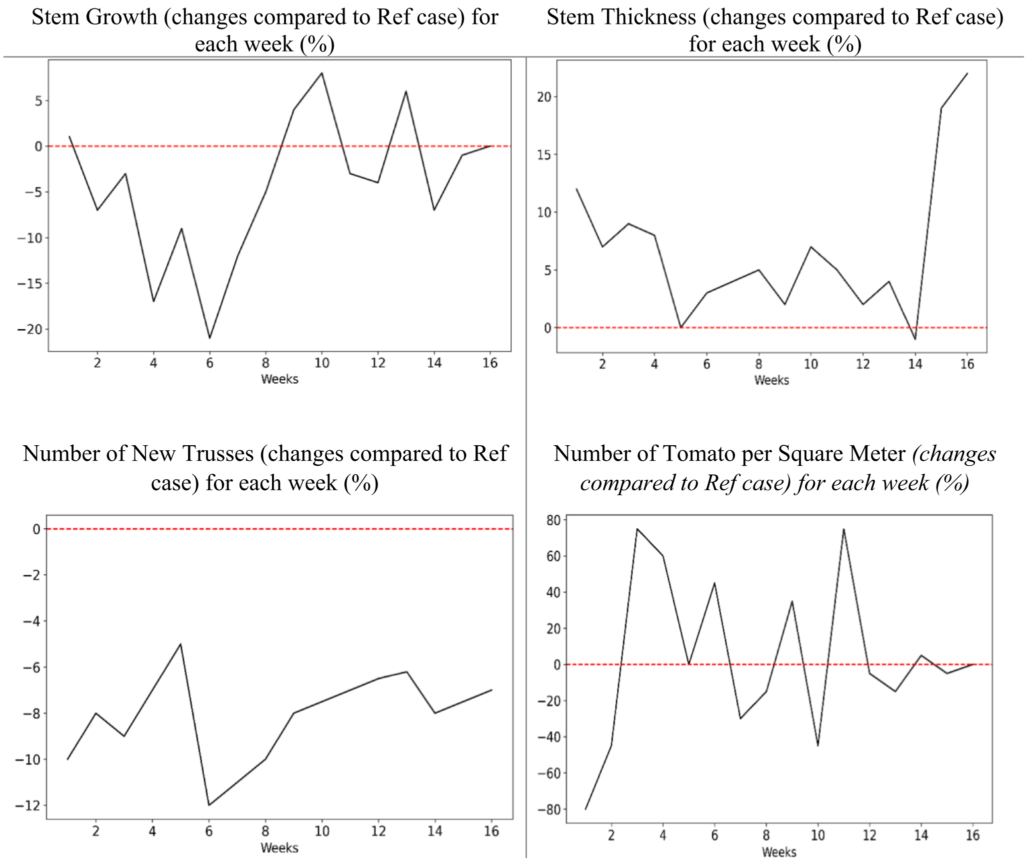


Fig. 2. Average AI-assisted greenhouse performance compared to the reference case.

reference throughout the experiment, with minor fluctuations. This suggests that AI methods did not substantially influence the formation of new trusses compared to traditional methods.

The fourth graph highlights the number of tomatoes per square meter. The AI-assisted greenhouses exhibit a highly variable performance compared to the reference case. Initial weeks show significant positive deviations, with one instance of nearly 80 % increase. However, this advantage diminishes over time, and fluctuations continue, ending close to the reference by week 16. This variability suggests that while AI methods can lead to higher yields, the results are inconsistent.

The AI-assisted methods seem to favor stem thickness over length. Thicker stems could contribute to a more robust plant structure, potentially supporting larger or more numerous fruits, even if stem length is compromised. Despite the AI-assisted greenhouses not outperforming the reference case in the number of new trusses, the increased number of tomatoes per square meter in certain weeks indicates that AI might improve fruiting efficiency. Thicker stems may support heavier or more tomatoes per truss, compensating for the fewer trusses. The fluctuations observed in all metrics suggest that AI methods still require refinement to achieve consistent improvements over traditional methods. The peaks and troughs indicate sensitivity to environmental factors or the need for further optimization of the AI algorithms. This comprehensive analysis demonstrates that AI-assisted methods in greenhouse farming can significantly impact specific growth metrics, such as stem thickness and tomato yield, but may not consistently outperform traditional methods across all metrics. Further research and refinement of AI techniques are necessary to harness their full potential in agricultural applications.

Fig. 3 indicates the percentage changes in tomato weight per square meter over a 16-week period, comparing AI-assisted greenhouses to the reference case. The results provide insights into the performance of AI-assisted methods in terms of overall production weight. During certain

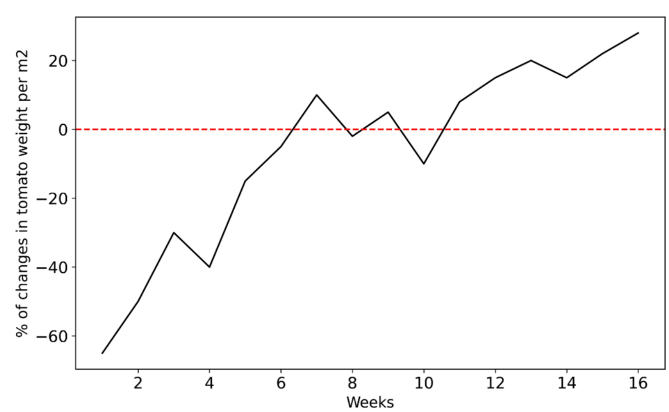


Fig. 3. Production of AI-assisted cases compared to the reference case.

stages of the experiment, AI-assisted greenhouses outperformed the reference case, as evidenced by the positive percentage changes observed from around week 6 onwards. Initially, there is a significant dip, with AI-assisted greenhouses showing up to a 60 % decrease compared to the reference case. This early decline could be attributed to the initial learning phase of the AI systems, where the algorithms were adjusting and optimizing the greenhouse conditions. Such adaptation periods are common in AI implementations, as the systems require time to process data, understand the environmental variables, and fine-tune their control strategies.

However, from week 4 onwards, there is a consistent upward trend, culminating in a positive percentage change of over 20 % by week 16. This consistent improvement suggests that once the AI systems adapted to the greenhouse environment, they were able to optimize the conditions more effectively, leading to better growth outcomes. The steady increase in performance highlights the potential of AI to learn and improve over time, enhancing its effectiveness in managing agricultural environments. This upward trend in AI performance indicates that while the AI-assisted greenhouses produced fewer tomatoes in some weeks, the fruits tended to be larger and heavier. Larger and heavier fruits contribute significantly to the overall production weight, compensating for the lower quantity of tomatoes. This phenomenon can be explained by the AI systems' ability to precisely control factors such as nutrient delivery, watering schedules, and environmental conditions, which can enhance fruit quality and size. The result is an overall production weight that is comparable to the reference case by the end of the experiment. This outcome underscores the varying impacts of AI assistance on different aspects of tomato cultivation. While the AI methods may not always increase the number of tomatoes produced, they can improve the quality and size of the fruits, leading to a higher total weight. This balance between quantity and quality is crucial for agricultural productivity, as market preferences often favor larger, high-quality produce. Moreover, the ability of AI systems to optimize for fruit size and weight, even when the number of fruits is lower, suggests that AI can play a vital role in improving the efficiency of resource use. By producing larger fruits, the plants may utilize water, nutrients, and other inputs more effectively, resulting in a more sustainable agricultural practice. This aspect of AI-driven optimization is particularly important in the context of modern agriculture, where resource efficiency and sustainability are becoming increasingly critical. In the analysis of AI-assisted greenhouses, a notable difference was observed in resource consumption compared to the reference case. The heating load in AI-assisted greenhouses was significantly lower, as indicated by sensor data. However, water and electrical consumption were similar to the reference case. This suggests AI's effectiveness in reducing heating needs, a crucial factor considering the implications of climate change and global warming. Extreme weather events could alter the significance of heating load requirements. Surprisingly, in terms of electrical load and water usage, sophisticated AI methods and control systems didn't significantly enhance efficiency. Longer-term monitoring might provide more insights into the effectiveness of these strategies in improving greenhouse performance. This analysis underscores the complex relationship between AI applications and resource efficiency in greenhouse agriculture.

Since this data is a time series, additional preprocessing and time series analysis may be beneficial in order to enhance comprehension of the data's trend. Decomposition analysis, which breaks down a time series into its constituent elements, is a popular technique for dealing with this kind of data. These components include things like a pattern, a seasonal component, and a residual component. The trend component depicts the time series' long-term movement, whereas the seasonal component captures the time series' recurrent patterns or cycles [38].

For accurate forecasting and anomaly detection, understanding the data structure, removing seasonality, and minimizing noise are crucial. Decomposition analysis is key, requiring deep data comprehension to select the appropriate model—either additive or multiplicative—depending on the time series type. This process enhances the reliability of forecasts and the ease of identifying trends and anomalies [39,40]. In an additive model, the seasonal and trend components are combined to form observed values, assuming consistent amplitude in seasonal swings regardless of the series level. This model is suitable when seasonal fluctuations are independent of the trends or series levels.

In a multiplicative model, the observed values in a time series are understood as the product of its seasonal and trend components. Unlike an additive model where these components are constant, in the multiplicative model, the impact of seasonal variations is directly proportional to the level of the series. This means that as the series level changes, the seasonal fluctuations adjust accordingly, either increasing or decreasing in magnitude. This type of model is particularly effective in scenarios where seasonal changes are believed to scale with the overall trend or magnitude of the data, providing a more dynamic and responsive analysis of time series data.

Choosing between an additive or multiplicative model in time series analysis is crucial and largely depends on the stationarity of the data. Stationary data is characterized by stable statistical properties, such as mean and variance, over time. When data exhibits these stationary characteristics, an additive model is generally more suitable for time series decomposition than a multiplicative model. Ensuring the data's stationarity is a critical step in this analysis. This test's ability to determine the constancy of statistical features over time makes it an indispensable tool in time series analysis, guiding the choice of the appropriate decomposition model [41]. The results of ADF test for the resource data are presented in Table 1.

After choosing appropriate model for each data, the decomposition analysis was performed. In the following figure the results of decomposition analysis for the resource consumption and environmental impact variables are presented (Fig. 4).

The decomposition analysis revealed a significant seasonal influence on the performance of both AI-assisted and reference greenhouses. The resource consumption and environmental impacts displayed a consistent, time-bound pattern, evident in the seasonal segment of Fig. 5. By identifying and removing seasonality and white noise errors from the data, the analysis isolated the actual trends, as shown in Fig. 6. These findings underscore the cyclical nature of greenhouse performance factors and highlight the importance of considering seasonal variations in evaluating greenhouse efficiency.

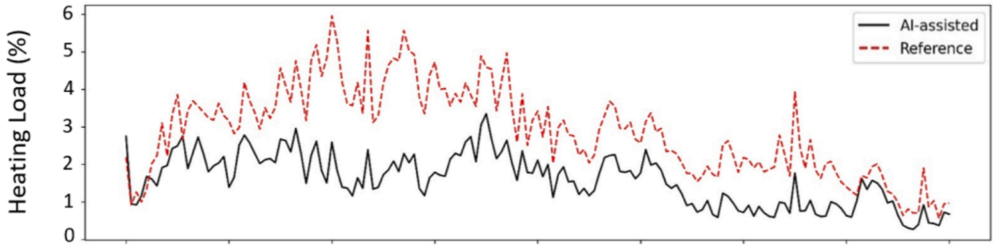
Throughout the experiment, a significant observation was the impact of AI technology on the heating load in AI-assisted greenhouses. These greenhouses consistently recorded lower heating loads compared to the reference case. However, this difference exhibited a dynamic nature; initially, the gap between the heating loads of the AI-assisted and reference cases was substantial, but as the experiment progressed, this gap narrowed. This trend suggests a potential future scenario where the heating load of the reference case could equal or even be lower than that of the AI-assisted greenhouses. While this remains speculative at this point, it underscores the need for more extensive and long-term studies to fully understand and predict these trends.

The heating load trend, as illustrated in the first graph, shows that AI-assisted greenhouses began with a significantly lower heating load, indicating that AI was initially very effective in optimizing the thermal environment. However, the narrowing gap over time could be attributed to various factors, such as seasonal changes or the AI systems reaching a plateau in their optimization capabilities. This decreasing difference highlights the necessity for a closer examination of the AI algorithms to identify potential improvements and adapt to changing conditions over extended periods.

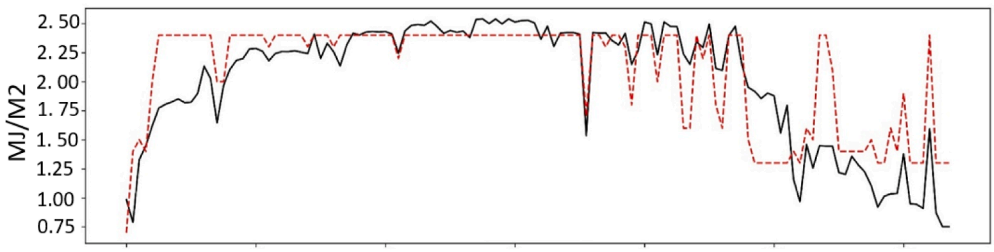
Regarding electricity consumption, the AI-assisted greenhouses demonstrated behavior almost parallel to the reference case, with minor yet noticeable fluctuations. As shown in the second graph, the electrical

Table 1
ADF results of resource data.

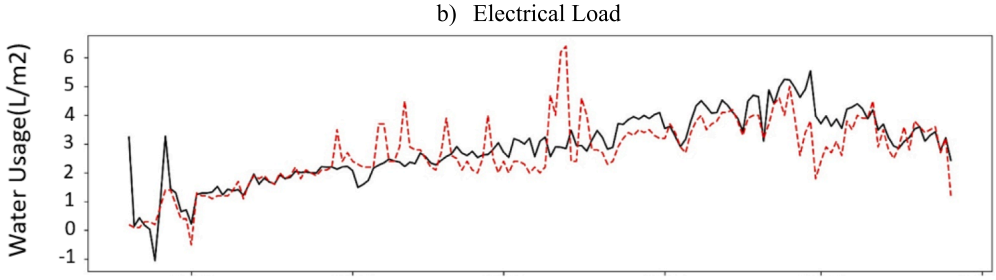
Resource	Type of case	ADF p-value	Stationary data	Not stationary data
Heating load	AI-assisted	0.26068		X
	Reference	0.34892		X
Electrical load	AI-assisted	0.91805		X
	Reference	0.15630		X
Water usage	AI-assisted	0.71840		X
	Reference	0.01908	X	
CO_2 emission	AI-assisted	0.01486	X	
	Reference	0.12259		X



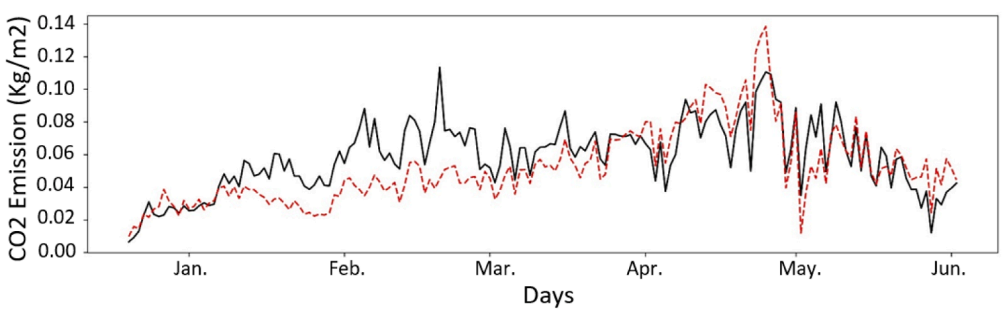
a) Heating load



b) Electrical Load



c) Water Usage



d) CO_2 Emissions

Fig. 4. Resource consumption and environmental impacts of cases.

load for both AI-assisted and reference greenhouses follows a similar pattern, with AI-assisted greenhouses initially exhibiting slightly lower consumption. However, as the experiment progressed, this difference became less pronounced. This parallel trend suggests that while AI can optimize electricity use, the gains might be limited under current conditions and technologies. It also indicates the potential for AI to maintain efficiency comparable to traditional methods but not necessarily exceed it significantly without further advancements.

This similarity was also observed in the water usage data, as depicted in the third graph, where, on most days, the reference case's water consumption was actually lower than that of the AI-assisted greenhouses. This finding challenges the expectation that AI would universally optimize all resource usages more efficiently. The higher water usage in AI-assisted greenhouses might be due to the AI systems prioritizing other growth factors over water efficiency, or it might indicate a need for better calibration of the AI algorithms to manage water resources more effectively. The study highlights both the potential and limitations of AI in optimizing resource management within greenhouse environments. The observed patterns indicate that AI has a significant impact on reducing heating loads but shows mixed results for electricity and water usage. These insights provide a nuanced understanding of the specific areas where AI technology increases efficiency and where its impact aligns closely with traditional greenhouse farming methods. This emphasizes the importance of targeted improvements and customizations in AI algorithms to enhance their effectiveness in all aspects of resource management.

Environmental impacts of AI-assisted greenhouses, as shown in the fourth graph, displayed different behavior. Up to the middle of the experiment, AI-assisted cases were weaker than the reference case in terms of CO2 emissions. However, in the second half of the experiment, the performance of AI-assisted greenhouses improved and became quite close to the reference case. This trend suggests that AI systems may require a certain period to adapt and optimize their strategies for effectively minimizing environmental impacts. The initial higher emissions could be due to the AI's learning phase, where the systems were adjusting their controls. As the systems learned and refined their

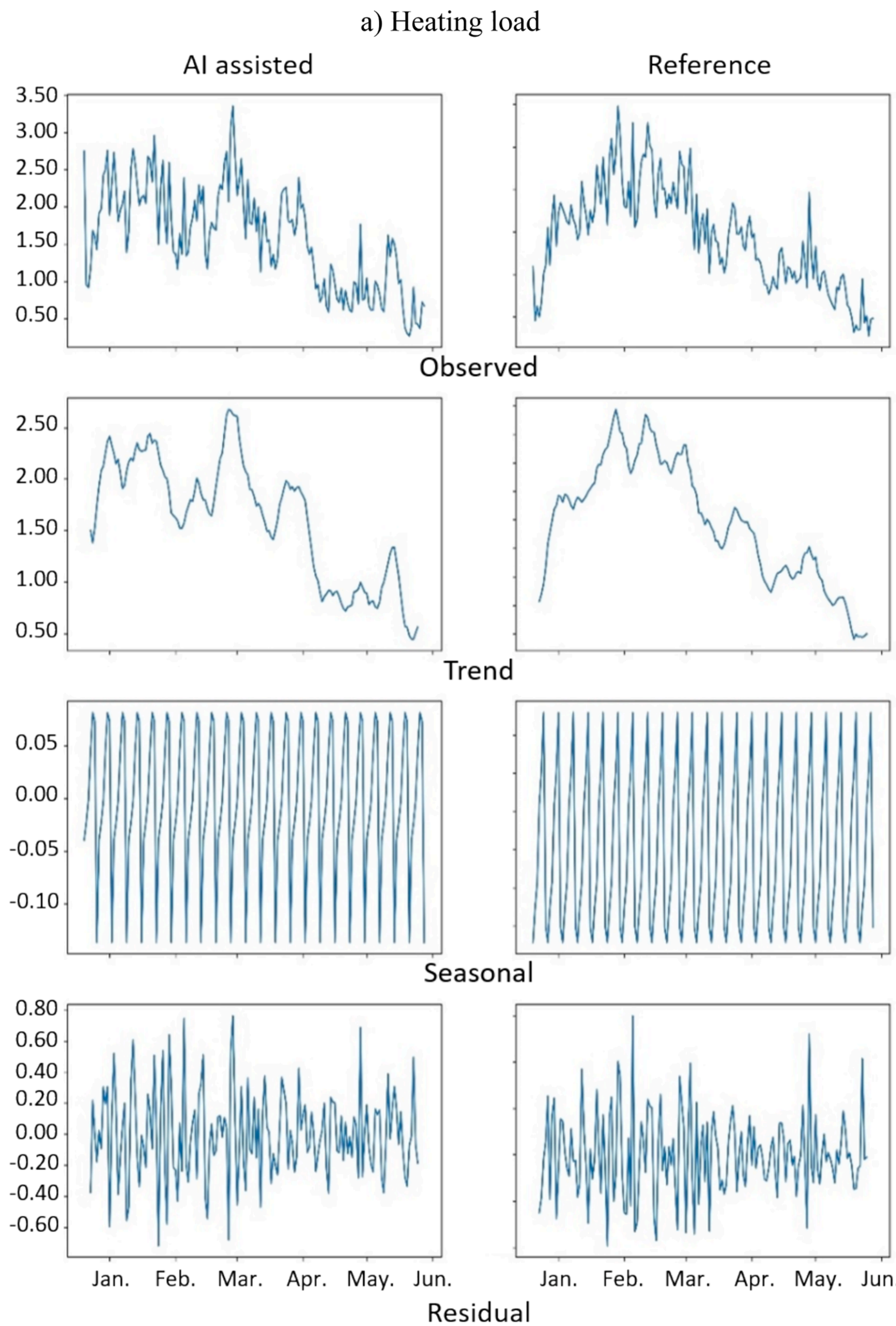


Fig. 5. Decomposition analysis of resource consumption and Environmental Impacts of cases.

approaches, their environmental performance improved, indicating the potential for AI to eventually match or even surpass traditional methods in reducing greenhouse gas emissions.

These observations underscore the complex relationship between AI applications and resource efficiency in greenhouse agriculture. They highlight the need for continuous improvement and adaptation of AI algorithms to achieve holistic benefits across all resource metrics. While the immediate impacts on heating loads are promising, the ultimate goal is to develop AI systems that can simultaneously optimize multiple aspects of greenhouse management, including water and electrical usage, as well as minimize environmental impacts.

4. Evaluation and validation

Evaluation and validation processes are crucial in ensuring that AI applications in agriculture, particularly in sustainable greenhouse farming, are performing effectively and fulfilling user requirements. This study adopted a systematic and rigorous approach to determine the impact of AI technologies in this domain. A comprehensive review of literature on AI applications in agriculture was conducted, which was instrumental in understanding the current state of research, the potential advantages, and the challenges associated with implementing AI in greenhouse farming. Further, the study employed a case study methodology, centering on the Autonomous Greenhouses Challenge (AGIC) organized by Wageningen University & Research (WUR). This challenge

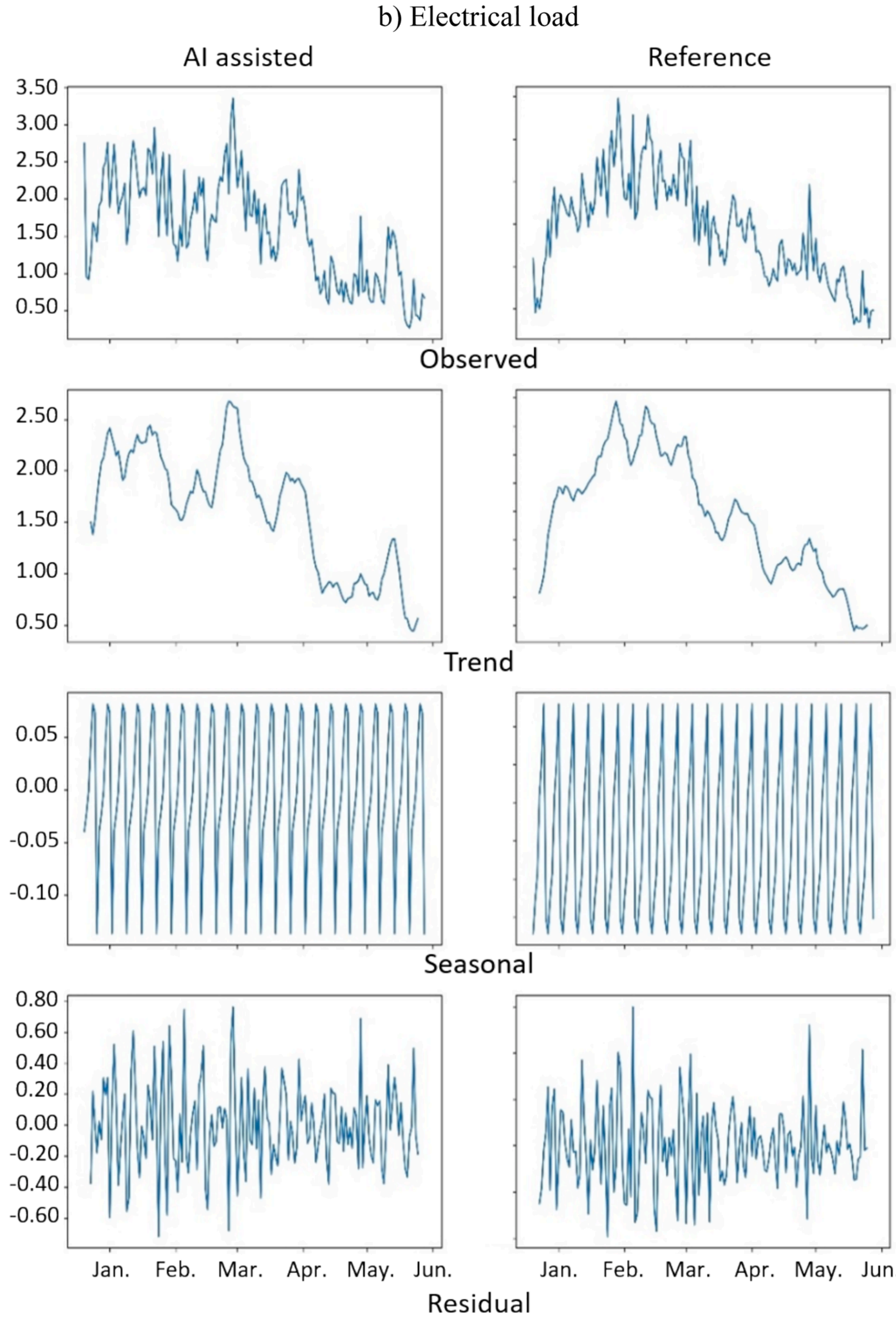
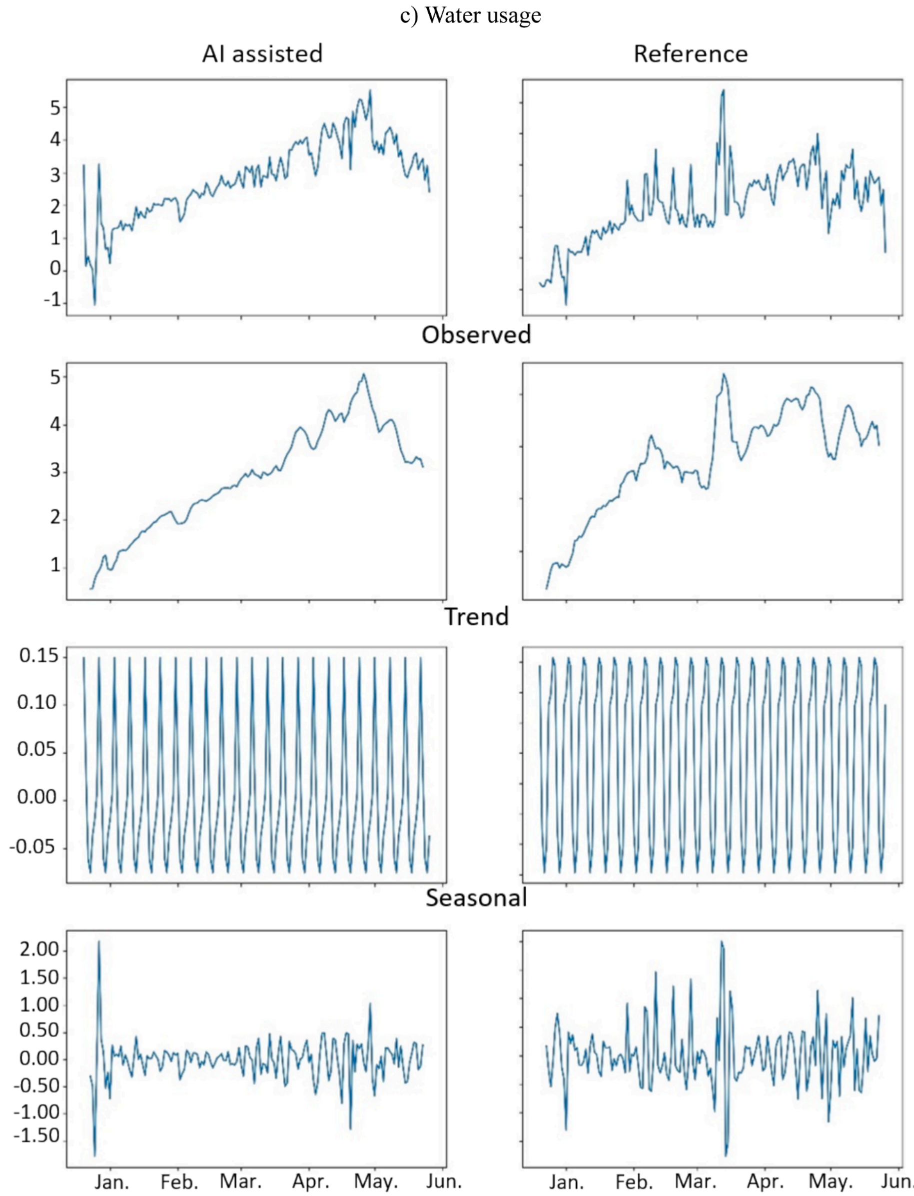


Fig. 5. (*continued*).

provided a unique opportunity to gather real-life data from multiple research teams. These teams conducted experiments using AI alongside other new technologies in greenhouse farming. The data collected from these experiments was critical in the evaluation and validation of the AI applications used. The review and case study approach allowed for a multi-faceted analysis. It not only evaluated the technical performance of the AI systems but also their practical applicability in real-world agricultural settings. This comprehensive assessment is pivotal for stakeholders in the agricultural sector considering the adoption of AI technologies. It offers insights into the tangible benefits and potential limitations of AI, guiding future research and application in the field of sustainable agriculture.

In order to gather data, cooperation was formed with the research teams that took part in the experiment to gain access to their measurements of environmental factors (like temperature, humidity, and light intensity), crop growth parameters (like growth rate and yield), and resource consumption (like energy, water, and fertilizers). Strict processes were followed during the data collection process to guarantee accuracy and consistency. To learn more about the study teams' algorithms, control schemes, and AI-assisted greenhouse systems, interviews with them were also undertaken. The gathered data was analyzed using a variety of statistical methods. First, descriptive statistics were run in order to provide an overview of the main characteristics of the data, including ranges, means, and standard deviations. This made it possible to fully comprehend both the reference case's and the AI-assisted greenhouses' performance indicators. Next, inferential statistics were conducted to assess the significance of the observed differences between the AI-assisted cases and the reference case. Appropriate statistical tests, such as t-tests or analysis of variance (ANOVA), were used depending on the nature of the data and the research questions being addressed. These



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statistical analyses helped determine if the observed differences in performance metrics were statistically significant or occurred by chance.

To guarantee the authenticity and dependability of the results, quality assurance procedures were put in place in addition to statistical analysis. Data abnormalities and errors were found and fixed through data validation processes. In order to determine how robust the results were, this required cross-referencing data points, confirming data quality, and performing sensitivity studies. Additionally, confounding variables that can affect the results were taken into account. These variables included differences in greenhouse design, crop choice, and weather. While all these factors could not be controlled, they were carefully documented and accounted for in the analysis to minimize their impact on the interpretation of the results.

The cost of implementing AI was not part of the original data and presents a significant limitation in our analysis. Accurately determining these costs would require detailed information on several critical factors, such as the exact computation time, the specifications and efficiency of the machine used, and the energy consumption associated with running the AI algorithms. Unfortunately, this information was not available in the provided dataset. Understanding the computational costs is crucial, as it directly impacts the overall economic feasibility of deploying AI solutions in agricultural settings. High computational demands can lead to increased energy consumption and operational costs, which in turn could affect the decision-making process for stakeholders considering the adoption of AI technologies. Moreover, the type of hardware used—whether it's high-performance servers, specialized AI accelerators, or more conventional computing resources—can significantly influence these costs. Without access to detailed logs of computation time and specific machine configurations, estimating these costs accurately is impossible. This gap in the data highlights a broader issue within the field of AI applications in agriculture: the need for comprehensive datasets that include not only performance metrics but also detailed operational costs.

While our study emphasizes the performance benefits and practical applicability of AI in optimizing greenhouse operations, it is essential to acknowledge this limitation. Future research should aim to include detailed cost analysis to provide a more holistic understanding of the viability of AI technologies in sustainable agriculture. Despite this limitation, we believe our findings still offer valuable insights into the potential benefits of AI, guiding future research and application in the

d) CO_2 Emission

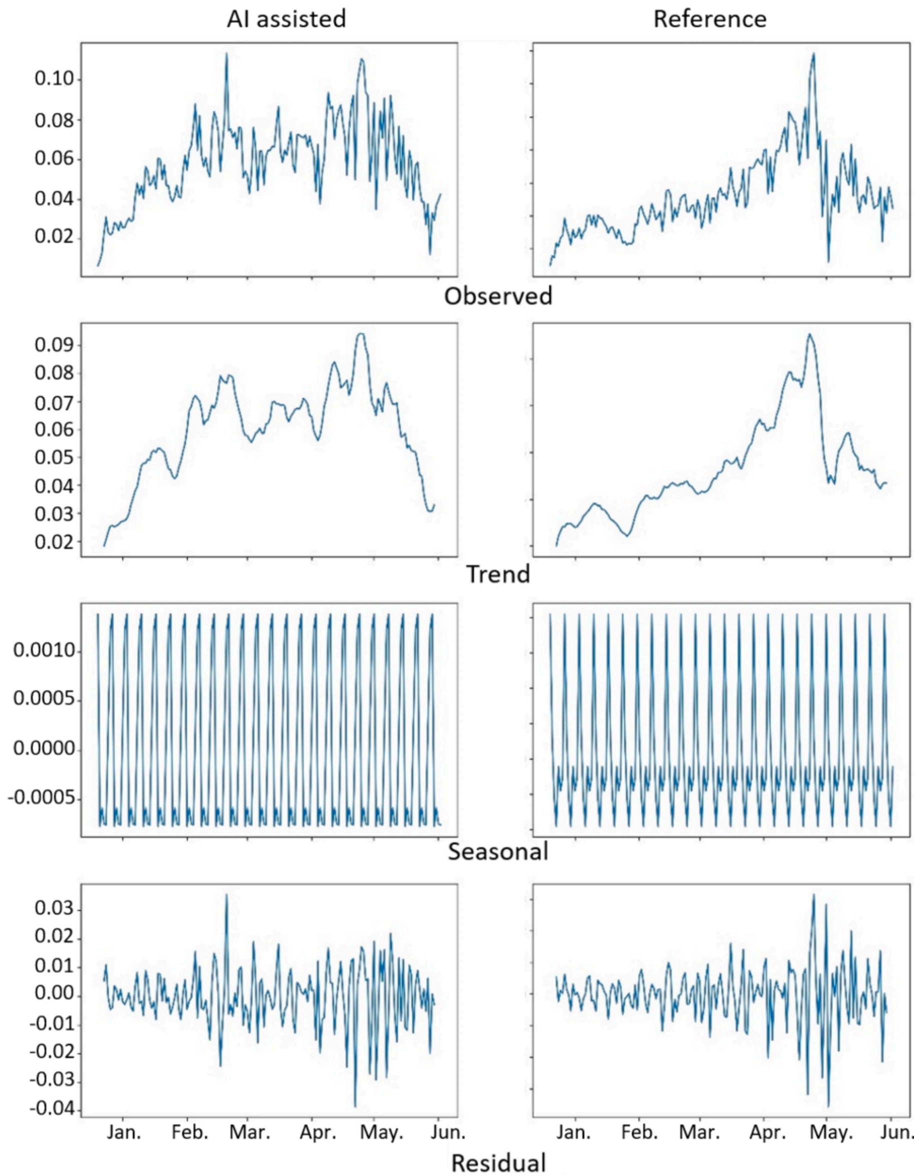

Fig. 5. (*continued*).

field.

5. Conclusion

Greenhouse farming can be a useful strategy to boost agricultural productivity while reducing its negative environmental effects in response to the present crises of food security, energy, and sustainability. In the framework of sustainable greenhouse farming, this research aims to illustrate the potential of artificial intelligence (AI) to enhance the agricultural sector. Through a case study analysis of the Autonomous Greenhouses Challenge, the research shows how artificial intelligence is affecting greenhouse agriculture. The study highlights AI's role in enhancing greenhouse efficiency, especially in reducing heating energy consumption, while maintaining crop yield, quality, and profitability. However, it also points out AI's limitations in greenhouse farming. While AI has shown potential in energy reduction, its effectiveness in lowering CO2 emissions and reducing electricity and water usage is not as pronounced. Additionally, AI's contribution to improving production quality in comparison to traditional methods needs further development. This underlines the need for ongoing research and advancement in AI technology to fully leverage its capabilities in sustainable greenhouse farming.

This study adds to the body of knowledge by emphasizing how artificial intelligence (AI) can revolutionize sustainable greenhouse farming. This study allows policymakers, researchers, and industry stakeholders to gain a deeper understanding of the state-of-the-art AI technologies in greenhouse farming and their impact on promoting sustainable agriculture. It does this by highlighting the potential advantages and limitations of AI technology. Furthermore, by addressing the need for more funding for R&D, instruction and training, and data infrastructure, this study offers a fresh viewpoint on how to improve the efficacy and efficiency of AI technology in greenhouse farming. By recognizing the significance of these factors, stakeholders can make informed decisions to drive progress and innovation in the field.

This research significantly contributes to understanding AI's role in sustainable greenhouse farming. It explores AI's benefits and limitations, providing crucial insights for policymakers, researchers, and industry stakeholders. This study enhances comprehension of state-of-the-

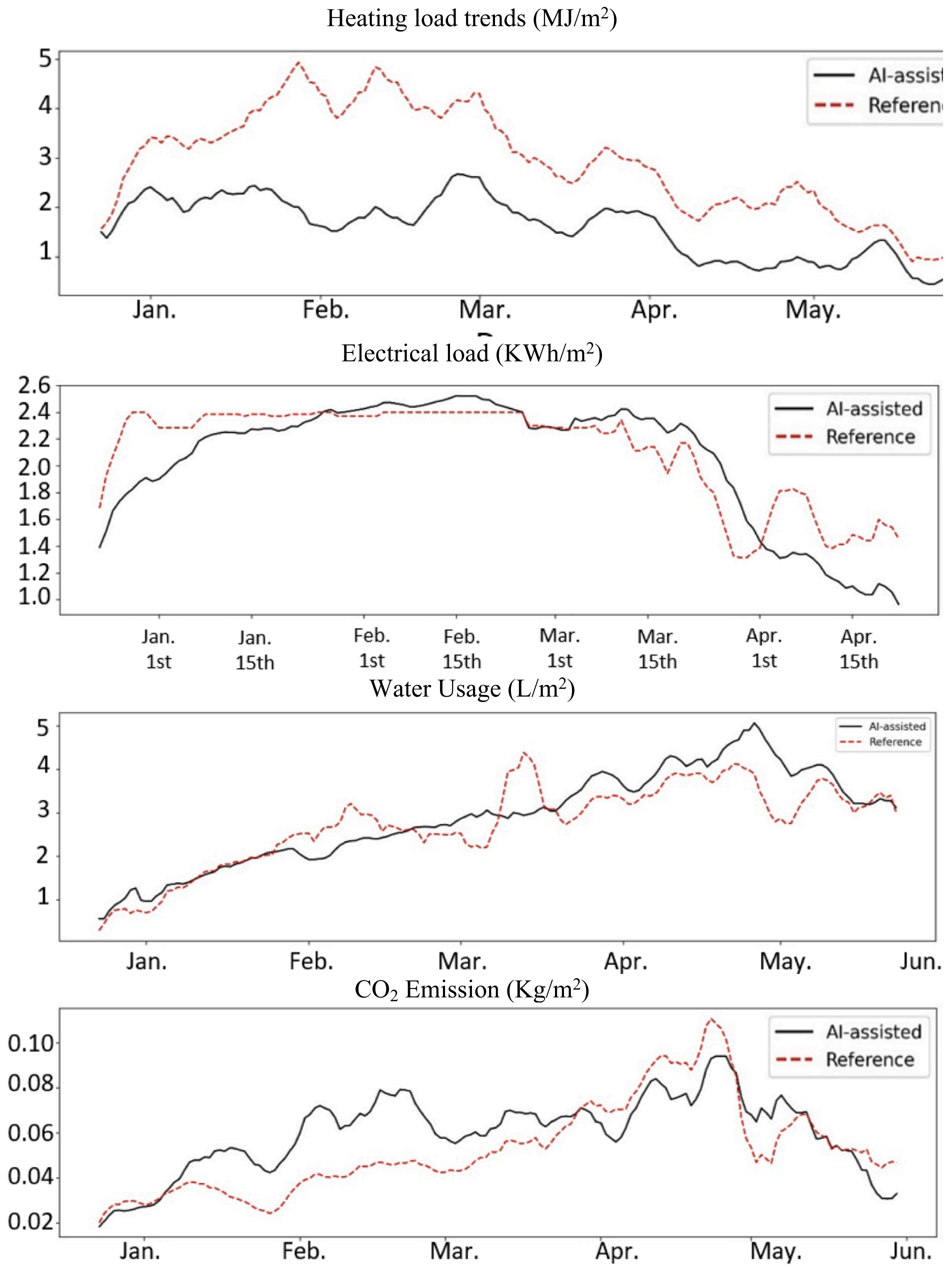

Fig. 6. Trends of resource consumption and environmental impacts of greenhouses after seasonality removal.

art AI technologies in greenhouse farming, focusing on their potential to advance sustainable agricultural practices. The findings are particularly useful for stakeholders aiming to implement AI technologies effectively in greenhouse environments. Future research should consider longer timeframes to thoroughly assess AI's long-term effects on greenhouse farm performance, ensuring a comprehensive evaluation of its impact on sustainability and efficiency.

The following are the key finding of the paper:

- AI significantly reduces heating energy consumption in greenhouse environments.
- AI maintains crop yield, quality, and profitability at levels comparable to traditional methods.
- AI shows promise in reducing overall energy use, but its impact on electricity and water consumption is less significant.
- AI's effectiveness in lowering CO2 emissions remains limited.
- In terms of production quality, further development is needed to enhance AI's role in improving production quality over traditional methods.
- In terms of resource efficiency, AI-assisted greenhouses demonstrate significant heating load reductions, but water and electricity consumption remain similar to traditional methods.
- In terms of environmental impacts, Initially, AI-assisted greenhouses exhibited lower environmental impacts, which equalized with traditional methods over time.

CRediT authorship contribution statement

Siamak Hoseinzadeh: Writing – review & editing, Writing – original draft, Methodology, Investigation, Data curation, Conceptualization. **Davide Astiaso Garcia:** Writing – review & editing, Writing – original draft, Supervision, Data curation, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The data that has been used is confidential.

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