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Assessment of Photovoltaic-Based Controlled Environment Agriculture as a Viable Solution for Enhancing Energy efficiency, Profitability, and Environmental Sustainability in Major Cities

Guoqing Hu*, Fengqi You

Cornell University, Ithaca, NY 14853 USA
gh429@cornell.edu

Controlled environment agriculture (CEA) offers a promising approach for sustainable food production by mitigating the impacts of climate variability and ensuring consistent yields. This study explores the integration of solar photovoltaic (PV) systems into CEA facilities across the ten most populous cities in the United States. Our comprehensive assessment indicates that, on average, 25.7 % of the energy consumption in these facilities can be offset by solar PV systems, significantly enhancing environmental sustainability. This integration has the potential to reduce carbon emissions by 0.658 CO_2 eq-kg/m², primarily due to decreased transportation needs associated with imports. However, these benefits are accompanied by increased costs, with operational expenses rising by approximately 18% due to the installation of solar panels. Additionally, PV-based CEA facilities contribute to a 5 % increase in light pollution due to the reliance on artificial lighting and result in nitrification, averaging 0.77 NH_3 eq-kg/m². The variation in local energy, environmental, and economic policies across different cities and states leads to significant differences in the benefits and costs associated with PV-based CEA systems. This study aims to inform local policy development to better support the application of PV-based CEA facilities, ultimately advancing environmental sustainability targets in urban agriculture.

1. Introduction

Urban agriculture is increasingly recognized as a key element in sustainable urban development, offering a way to integrate food production within city environments (Orsini et al., 2013). This approach not only shortens the food supply chains, enhancing food security and freshness (Li et al., 2018), but also stimulates the local economy by creating jobs and rejuvenating local businesses (Aubry et al., 2012). Despite its benefits, urban agriculture struggles to remain productive during harsh conditions, posing a significant challenge to maintain year-round food supply (De Bon et al., 2010). Controlled environment agriculture (CEA) emerges as a promising solution in these scenarios (Wang et al., 2020). By providing protection against external weather disturbances, CEA provides the optimal plant growth conditions and guarantees yield throughout the year (Engler and Krarti, 2021). Being a dependable and sustainable method for producing fresh, local food, CEA reinforces the resilience and self-sufficiency of urban food systems (Ajagekar et al., 2024). However, the significant energy and resource consumption of CEA has raised concerns about its sustainability in urban settings (Orsino et al., 2021). Numerous studies have explored the feasibility of adopting CEA in urban agriculture, highlighting worries that the excessive use of non-renewable energy and resources could hinder efforts to achieve carbon neutrality by 2050 (Ajagekar et al., 2023). To address these issues, the concept of photovoltaic-based (PV-based) CEA has been proposed. This approach leverages solar energy, reducing carbon emissions and aligning with sustainability goals. This innovative solution seeks to reduce the reliance on the non-renewable energy and resources while maintaining the benefits of controlled agriculture environments (Hu and You, 2022).
Evaluating the potential of PV-based CEA systems is crucial for maximizing their contribution to sustainable urban food production (Ravilla et al., 2024). Previous research has primarily focused on the viability of replacing traditional CEA systems with those based on photovoltaics, often concentrating on aspects like energy

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consumption and crop yield. However, a more comprehensive quantitative analysis is necessary to fully understand the scope of renewable energy utilization and the broader environmental impacts associated with these systems. This includes examining the effects on nitrification, light pollution, and carbon footprints. The economic impacts of implementing PV-based CEA systems also require detailed study. These include analysing cost efficiency in terms of initial investment, operational expenses, and profitability. These factors are crucial as they directly influence the viability and sustainability of PV-based CEA systems and are essential to determining whether such systems offer a practical, beneficial solution for urban agriculture. Considering the environmental and economic impacts alongside energy efficiency will provide a holistic view of the potential and challenges of PV-based CEA, guiding more informed decisions in urban agricultural development. To address the existing knowledge gap in the comprehensive evaluation of PV-based indoor farming systems, we conducted a thorough assessment of these systems' performance from various angles, including energy consumption, resource use, renewable energy integration, environmental impact, and carbon footprint. This analysis involved a detailed comparison with traditional CEA facilities across the ten most populous cities in the United States. Our goal was to assess how effectively PV-based CEA systems can enhance sustainability metrics within urban agricultural frameworks, particularly in densely populated areas. By utilizing data on regional energy patterns, local climate conditions, and urban infrastructure, this study offers a nuanced understanding of the benefits and challenges of implementing PV-based CEA systems in different urban environments. We also examined the potential of these systems to reduce urban areas' reliance on non-renewable energy sources and lower their overall environmental impact. The insights gained from this research are intended to guide the development of targeted energy, economic, and environmental policies that support the expansion of sustainable food production methods in urban settings. Our findings aim to help policymakers and urban planners make informed decisions that align with sustainability objectives, promoting urban agriculture as a key component of city planning and development. This approach not only bolsters local food security but also contributes to broader environmental and economic goals by optimizing resource use and minimizing negative environmental effects.

2. CEA model setup and control algorithms

In this section, we detail the components utilized to obtain the results of our study. Initially, we applied the computational model of the PV-based CEA facility, which is anchored in the growth model developed by Vanthoor (2011), complemented by standard mass and energy balance equations. This model has been validated and widely adopted by researchers to enhance our comprehension of the micro-dynamics within the CEA environment (Choab et al., 2019). Subsequently, we discuss the control system which leverages the model predictive control (MPC) methods for controlling the state variables within the PV-based CEA systems. Each of these components plays a crucial role in our study, collectively contributing to a comprehensive understanding of the technological advancements in CEA systems.

2.1 Optimal growth conditions in CEA facility

The models account for various states, including temperatures of the cover, interior, vegetation, mat, tray, floor, and four soil layers; the 24 h average and cumulative temperatures of vegetation; as well as the densities of water vapor and carbon dioxide. Additionally, they measure the carbohydrate mass in fruits, leaves, and stems, alongside the relative growth rates of these plant parts. As demonstrated in Table 1, the operational constraints for the CEA system are set as follows: During daytime hours, from 7:00 AM to 7:00 PM, the temperature is maintained between 24 °C and 29 °C (Ramírez-Arias et al., 2012), while the relative humidity ranges from 80 % to 90%. For night time hours, from 7:00 PM to 7:00 AM the following day, the temperature should range from 16 °C to 24 °C, with relative humidity kept between 65 % and 75 % (Shamshiri et al., 2018). On the other hand, the CO_2 concentration is set between 800 – 1,200 ppm (Nilsen et al., 1983). These parameters, established based on existing research, are critical for optimizing growth conditions within the CEA facility.

Table 1: Control constraints for the control framework

Variable [unit]	Constraints
Temperature [˚C]	Daytime: 24 – 29 Nighttime: 16 – 24
Relative humidity [%]	Daytime: 80 – 90 Nighttime: 65 -75
CO_2 concentration [ppm]	800 – 1200

2.2 MPC and PID methods in PV-based CEA system

Following this, an MPC strategy is employed to calculate optimal control approaches (Hamidane et al., 2023). These strategies are designed to minimize energy and resource consumption while maintaining ideal conditions for crop growth (Chen et al., 2022). Within each control interval, the linear state-space model is calculated for the control system to compute the optimal control decisions as following:

$$x_{t+1}=A_t x_t+B_{u,t}u_t+B_{w,t}w_t \tag{1}$$

The state matrix, A_t, linearly correlates all the states within the PV-based CEA facility at time t. The input matrix, $B_{u,t}$, accounts for the coefficients of all the control actuators managing the states at that same time t, while the disturbance matrix, $B_{w,t}$, describes how the ambient weather and its disturbances impacting the facility at time t. Concurrently, x_t denotes the states within the CEA at time t, u_t represents the quantity of inputs to these states at time t, and w_t captures the weather disturbances affecting the facility at that time t (Van Ooteghem et al., 2004). Subsequently, with the specification of the prediction horizon length, H, the dynamic greenhouse climate model is reformulated into a more concise version as follows:

$$x_H=A_T x_t+B_{u,T}u+B_{v,T}v \tag{2}$$

where system matrices A_T, $B_{u,T}$ and $B_{v,T}$ are formulated as following:

$$A=\begin{bmatrix} A_t \\ A_t^2 \\ \vdots \\ A_t^H \end{bmatrix},\ B_{u,T}=\begin{bmatrix} B_{u,t} & 0 & \cdots & 0 \\ A_tB_{u,t} & B_{u,t} & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ A_t^{H-1}B_{u,t} & A_{u,t}^{H-2}B_{u,t} & \cdots & B_{u,t} \end{bmatrix},\ B_{v,T}=\begin{bmatrix} B_{v,t} & 0 & \cdots & 0 \\ A_tB_{v,t} & B_{v,t} & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ A_t^{H-1}B_{v,t} & A_{v,t}^{H-2}B_{v,t} & \cdots & B_{v,t} \end{bmatrix} \tag{3}$$

And the system states x, u, v are defined as:

$$x_H=\left[x_t^T, x_{t+1}^T, \cdots, x_{t+H}^T\right]^T,\ u=\left[u_t^T, u_{t+1}^T, \cdots, u_{t+H}^T\right]^T,\ v=\left[v_t^T, u_{t+1}^T, \cdots, u_{t+H}^T\right]^T \tag{4}$$

Then the optimization framework can be formed as following (Hu and You, 2023):

$$\begin{aligned} \min \quad & cu + \epsilon^T S \epsilon \\ \text{s.t.} \quad & F_x x_H \leq f_x + \epsilon \\ & F_u x_H \leq f_u + \epsilon \end{aligned} \tag{5}$$

In this model, c represents the coefficients associated with cost, ϵ includes the soft constraints that maintain the feasibility of the optimization framework, and S denotes the penalties applied for any violations of the constraints. These constraints are defined by the state constraints f_x and input constraints f_u. Additionally, F_x and F_u are vectors that help keep the states and inputs within their predefined ranges.

The baseline method employed in this study utilizes predefined rules based on the traditional PID control method (Su et al., 2020). This approach is currently recognized as the state of the art in greenhouse control systems and serves as a solid foundation for assessing potential performance enhancements achievable through the integration of AI technology. Actuator strategies within this method are dictated by the proportional control technique.

$$u_t=K_p e_t+K_i(e_t+e_{t-1})\frac{t}{2}+\frac{K_d(e_t-e_{t-1})}{t} \tag{6}$$

Where K_p, K_i and K_d are the proportional coefficient, integral time coefficient and derivative time coefficient of PID controller, and e_t are the errors between desired states and the current states at time t.

3. Quantitative evaluation of PV-based CEA systems' performances in major cities

Figure 1 provides a quantitative assessment of PV-based CEA systems across various urban areas in the United States in a growth cycle, which is a 10-week period. The climate data of these cities in 2022 are collected (Chen et al., 2024). The weather disturbances considered in this study include ambient temperature, humidity, solar radiation from different directions. The assessment covers key performance indicators: energy consumption, profitability, resource costs, renewable energy investment, and the environmental aspects quantified through light pollution percentage, water pollution, and transportation emissions. In this study, tomatoes were selected as the crop of focus, with their price data sourced from the local market. The costs evaluated include energy expenses and resource consumption, such as CO_2, fertilizers, and water. Energy expenses were calculated using the local monthly average electricity rates, while resource costs were based on local market prices. Additionally, the land surface area required for renewable energy production was factored into the analysis. The reduced transportation data is collected by (Urbano et al., 2022). Energy consumption varies significantly across cities, with San Jose experiencing the highest usage among the surveyed locations. This increased energy consumption in San Jose is largely driven by California's proactive local government policies, which not only offer economic incentives for solar energy use but also promote sustainable energy practices. The favorable sunny weather conditions prevalent in California enhance the suitability for solar energy applications, making it an ideal region for leveraging solar power in urban agriculture. In the control systems of these urban agriculture setups, there is a distinct preference for solar energy, which contributes to greater energy consumption overall. This trend is also evident in the increased utilization of renewable energy sources across these systems.

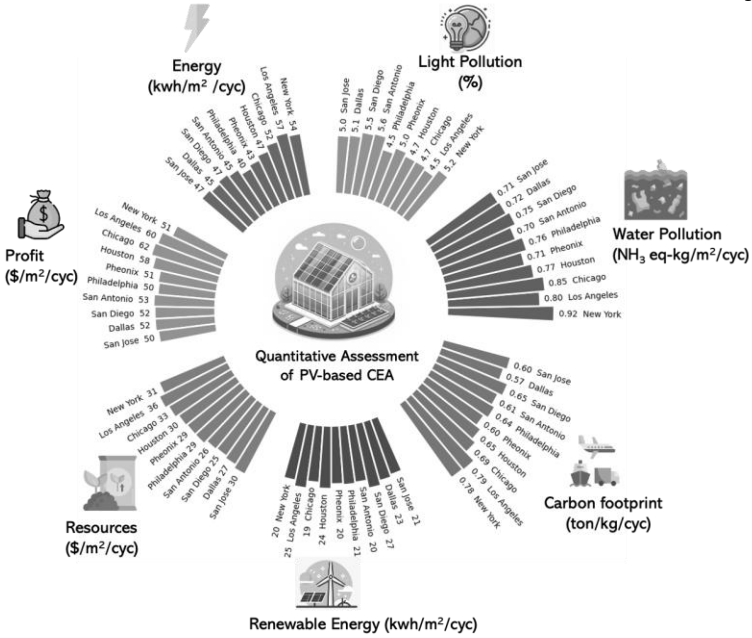

Figure 1: Quantitative assessment of the performance of PV-based CEA in ten populous cities in US, examining various factors such as energy consumption, use of renewable energy, resource costs, profitability, and environmental impacts. These impacts include reduced carbon footprints from food transportation, water pollution from nitrification processes, and light pollution

When it comes to profitability, cities like New York, Los Angeles, San Diego, and San Jose report higher profits compared to other locations. These higher profits are largely due to increased local greenhouse production, which is influenced by the local robust market. Additionally, these cities exhibit higher resource consumption, which correlates directly with their higher yields. Such increased resource usage is necessary to support the extensive agricultural activities that these urban centers undertake. This includes not only water and energy but also nutrients and other inputs essential for high-volume production. Reduced carbon footprints result from local production which decreases the need for imports from other areas, cutting carbon emissions associated with food transportation. From this analysis, it is evident that cities like California, New York, and Chicago, which already have higher production levels, can further diminish their reliance on imports from other cities. This reduction in imports leads to decreased CO_2 emissions from transportation. These cities' ability to localize food production plays a crucial role in mitigating their overall carbon footprints and enhances their sustainability measures. It has been observed that cities in California and those in southern regions tend to experience lower nitrification processes. In California, a decade-long drought has led to significant water scarcity, constraining water usage. Additionally, high water costs discourage excessive use, prompting systems to operate with minimal water to maintain optimal growth conditions. Similarly, cities in southern areas also face challenges with limited water availability, making water recycling a preferred practice. Thus, cities with restricted water supplies often encounter fewer nitrification issues, as water-saving policies are implemented to minimize water pollution. Figure 2 outlines a cost comparison between proportional-integral-derivative (PID) control and model predictive control (MPC) system for PV-based CEA and conventional CEA facilities in a selection of cities. It details capital and operational expenses, with accompanying percentages illustrating the cost variance of different PV-based control systems relative to their conventional counterparts. From the results, the PID is observed to have higher operational cost across all the cities. This is because the PID is the setpoint control which could result in excessive energy for maintaining the state at the certain desired setpoint. Additionally, capital costs for PV-based setups are universally higher across all cities, reflecting the initial investment in solar infrastructure. In more populous cities, such as New York and Los Angeles, capital costs are further elevated due to limited land availability. Although these initial costs are higher, the potential operational savings and the environmental benefits of using renewable energy may offset these initial expenditures over time, making them a worthwhile investment for sustainable urban development.

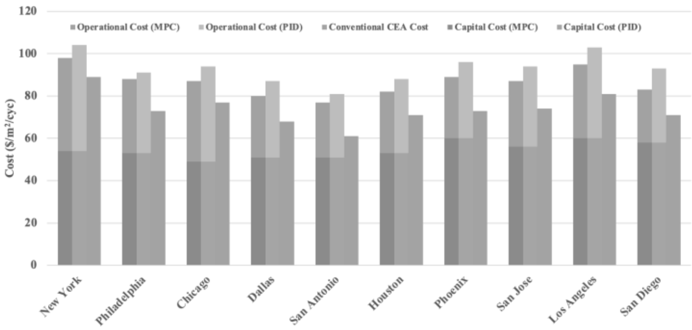

Figure 2: Comparative cost analysis of PV-based vs. conventional CEA operations across major U.S. Cities

4. Conclusions

Controlled Environment Agriculture (CEA) offers a promising solution for sustainable food production by mitigating the impacts of climate variability and ensuring consistent yields. However, the high energy consumption inherent to CEA necessitates a shift towards renewable energy sources to enhance its environmental benefits. Our study focused on the integration of solar photovoltaic (PV) systems in CEA facilities across ten major U.S. cities, assessing both economic and environmental implications. The results revealed that, on average, 25.7 % of the energy consumption in CEA facilities can be offset by solar PV systems, potentially reducing carbon emissions by 0.658 CO_2 eq-kg/m². However, this benefit comes with an approximate 18% increase in operational costs due to the initial investment in solar panels. Additionally, the study found that PV-based CEA facilities could increase light pollution by around 5 % due to reliance on artificial lighting at night. These findings offer significant insights into the formulation of energy, economic, and environmental policies aimed at promoting sustainable urban agriculture. Our research underscores the critical need for energy policies that encourage the adoption of renewable energy sources in CEA facilities. The integration of solar PV systems not only offsets a substantial portion of energy consumption but also reduces the overall carbon footprint of urban agriculture. With current government incentives for solar energy, the proportion of solar energy utilized in PV-based CEA facilities could increase by up to 5 %, enhancing environmental stewardship and promoting eco-friendly agricultural practices. By developing policies that support the installation of solar panels and other renewable energy technologies in CEA, governments can facilitate a broader transition towards sustainable food production systems that are less reliant on fossil fuels and more resilient to energy price fluctuations.

The economic benefits of integrating solar PV systems into CEA facilities are evident from our study, which shows an average energy consumption offset of 25.7 %. Despite an initial increase in operational costs by approximately 18 %, the long-term savings and environmental benefits make this investment compelling. In regions such as the East Coast and southern areas of the United States, where solar irradiance is higher, CEA facilities can leverage these geographical advantages to further decrease electricity costs. This localized use of solar energy not only reduces overall expenses but also provides a more sustainable economic model for urban agriculture. Policies that incentivize the use of solar energy in CEA, such as tax credits, subsidies, and grants, can help mitigate the initial cost barriers and promote wider adoption. Additionally, fostering public-private partnerships can enhance financial support and innovation in renewable energy applications for urban agriculture. The future study should be conducted to include the cost analysis based on the comparison of using artificial light versus only natural light.From an environmental perspective, promoting PV-based CEA in major cities offers substantial sustainability benefits. Our findings indicate that integrating PV systems in CEA facilities can reduce carbon emissions by an average of 0.658 CO_2 eq-kg/m², primarily by decreasing transportation needs from imports. This reduction is critical for cities aiming to meet their carbon reduction targets and combat climate change. Managing light pollution is crucial in urban areas, where dense populations and extensive use of artificial lighting pose significant challenges. Implementing variable lighting schedules at night can reduce light pollution by up to 5 %, making PV-based CEA a more environmentally friendly option. Environmental policies that mandate or encourage such practices can help mitigate the negative impacts of artificial lighting and enhance the overall sustainability of urban agriculture. These measures support broader environmental policy goals, contributing to the development of resilient and sustainable urban food systems.

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