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Original article

A simplified approach to energy-water modeling for controlled environment agriculture☆

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A R T I C L E I N F O

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A B S T R A C T

An increasingly implemented alternative to outdoor farming, controlled environment agriculture (CEA) ensures reliable food production despite volatile growing conditions such as drought, flooding, and extreme temperatures. CEA can bolster local food production and revenue, promoting food resilience; however, the high energy and, in some cases, water demand required to optimize indoor environments for crop growth is a notable barrier to adoption. Understanding the resource consumption of CEA facilities is crucial to the sustainable growth of this sector, but existing models tend to be proprietary, limited in scope, or require detailed design data. To address this issue, we propose a simplified, flexible model (CEAEstA) that integrates fundamental lighting, heating, cooling, and evapotranspiration principles to estimate energy and water demand. The model is designed to be accessible for early-stage feasibility assessments, allowing stakeholders to evaluate sustainability trade-offs before committing to more detailed analyses. Leveraging both empirical and modeled datasets from peer-reviewed literature for validation, this study demonstrates the model's effectiveness in estimating order-of-magnitude energy and water consumption across different facility types, crops, and climate zones. The results highlight the key drivers of resource demand in CEA and provide insights into designing efficient facilities and developing sustainable operational strategies.

1. Introduction

Controlled environment agriculture (CEA), generally defined as the practice of growing crops inside structures with varying levels of technological support, is a rapidly expanding part of the agricultural sector. Between 2009 and 2019, the number of CEA facilities more than doubled, and the mass of food produced increased by 56% in the United States [1]. CEA facilities can range from simple, plastic-covered hoop houses, also referred to as high tunnels, to highly automated plant factories, also referred to as vertical farms. They offer varying degrees of protection from environmental conditions that threaten the productivity of conventional open-air farms (e.g., extreme temperature, drought, flooding, pests, soil degradation), in addition to the well-being of employees who work there [2,3]. However, operating CEA facilities in a sustainable and cost-effective manner has proven challenging due to the energy needed for lighting and climate control, in addition to high upfront capital expenditure and other operating costs [4]. Though high-performing facilities have achieved significant water savings (90%) compared to field farms [5], high water demands, particularly for evaporative cooling walls in arid and semi-arid regions [6], also pose a challenge to growers.

Estimating the energy and water demands of these facilities is crucial for promoting the sustainable growth of the sector and enabling smaller growers to establish themselves in a competitive industry. This is of particular importance to burgeoning markets like that of the United States, which has experienced increased private and public investment in recent years [1]. However, traditional modeling approaches such as computational fluid dynamics (CFD) or detailed building energy

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simulation software like EnergyPlus [7] tend to require design data and expertise not always accessible for early-stage feasibility studies. Additionally, many of the energy-water modeling approaches developed in previous studies [7–25] are applicable to a small subset of facilities, but cannot be applied across the full spectrum of structure types, technology implementation levels, and climate zones that CEA facilities span in the real world. A comprehensive review of existing models and software for estimating resource consumption of CEA facilities is found in Section 1 of the Supplementary Information (SI).

This research aims to bridge this gap by developing a simplified, open-source model that provides reasonable estimates of both energy and water consumption, as well as greenhouse gas (GHG) emissions from energy use, while maintaining usability outside the modeling community. This model, abbreviated CEAEstA (CEA Estimation Algorithm), couples a first-principles approach for estimating lighting, heating, and cooling loads with an established evapotranspiration (ET; the combined water loss from evaporation and transpiration) model, and is validated using a mix of real-world and simulated data from other studies. By providing order-of-magnitude estimates specific to facility location, type, crop, and level of technological advancement, this tool can be used by a wide variety of stakeholders to gauge energy-water consumption of individual sites and compare across different scenarios before investing in more detailed estimates, encouraging more data-driven and sustainable development.

2. Methods

2.1. Model structure

CEAEstA can estimate energy and water demand for a variety of CEA scenarios and, therefore, requires several inputs from users (Fig. 1). The published model, available online at the project's public GitHub repository, allows users to simulate 73 locations throughout the United States (Table S1, Fig. S1) representative of the country's different climate zones. Users can model other locations if hourly meteorological data are available. Similarly, though we provide the option of modeling eight commonly grown food crops in the United States, plus roses as a proxy for floriculture operations, users can model different crops if data on crop-specific photoperiod, daily light integral (DLI), suitable temperature ranges, and crop coefficients are available. Mushrooms, while a high-value crop and a significant portion of the CEA sector in regions like Pennsylvania [26], are not included because their growing conditions are notably different from other food crops.

Based on the input parameters, the model infers growing environment specifications suitable for crop production, then estimates the energy loads needed to maintain those conditions throughout the year. Though fogging equipment, water recycling technology, carbon dioxide (CO_2) enrichment systems, and advanced climate controls (e.g., microprocessors, Proportional-Integral-Derivative controllers, and weather stations) can contribute to overall energy demand, energy requirements in greenhouses are typically dominated by heating and cooling systems (65–85% of primary energy consumption [27]) and, for plant factories, lighting and HVAC systems (87–96% of total energy consumption [28]); therefore, we exclude these sources from our model. ET is assumed to comprise the total water consumption for hoop houses and low-tech greenhouses, but 50 and 80% of total water consumption in high-tech greenhouses and plant factories, respectively [29]; the remainder is assumed to be primarily used for climate control and processing.

GHG emissions associated with energy use are also estimated in the model. Electricity consumption emissions are estimated based on balancing area-specific carbon intensity of the electricity supply from the National Laboratory of the Rockies' 2024 Cambium dataset for the contiguous United States [30]. For Alaska and Hawaii, GHG emissions from electricity consumption are estimated based on state-level averages of carbon intensity [31]. GHG emissions from natural gas consumption, relevant for boilers in high-tech greenhouses, are estimated based on carbon intensity for residual heating fuel from the Energy Information Administration (EIA) [32]. Initial versions of this model included crop production estimates, but this output was ultimately excluded due to significant uncertainty associated with crop yield coefficients.

Because there is considerable variation in how CEA facilities are constructed and operated, we define common scenarios herein to limit the number of input parameters required from the user, prioritizing usability over personalization. We assume that low-tech hoop houses rely on passive lighting, heating, cooling, and ventilation systems and, therefore, do not require any energy to operate. We assume high-tech hoop houses and low-tech greenhouses use two-speed, direct-drive exhaust fans to control temperature and humidity. We assume that high-tech greenhouses use a combination of natural and artificial light from light-emitting diodes (LEDs), depending on the DLI required by the crop and naturally available sunlight at the modeled location, as well as boilers for heating and exhaust fans/evaporative walls for cooling and ventilation. Plant factories are opaque structures that we assume rely entirely on LEDs for lighting and utilize heating, ventilation, and air conditioning (HVAC) systems for climate control. Users have the option of specifying the number of growing levels in plant factories, but the

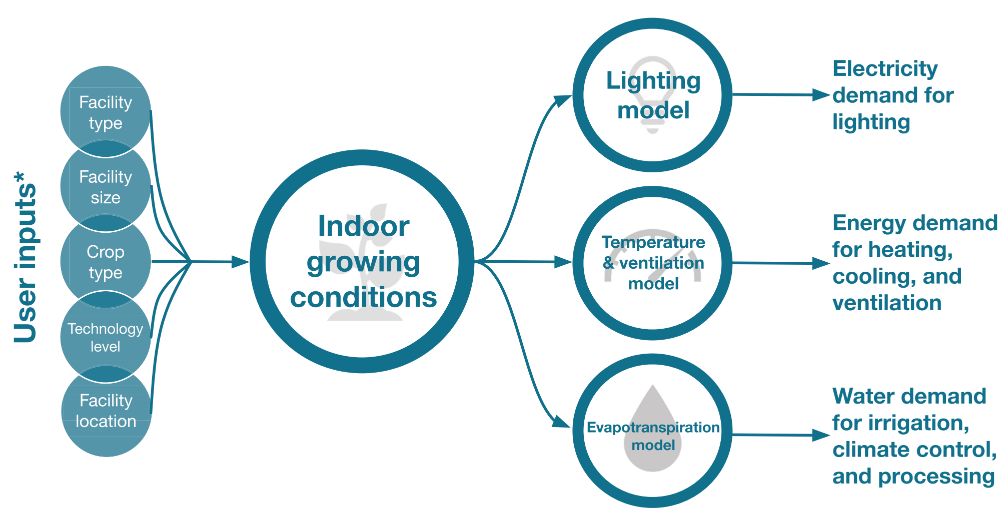

Fig. 1. Overview of energy-water model for controlled environment agriculture (CEA) facilities. *User input selections are as follows: facility type (hoop house, greenhouse, or plant factory); facility location; floor area [m^2]; for plant factories, number of growing levels; crop type (roses, lettuce, spinach, broccoli, basil, tomatoes, bell peppers, zucchini, or strawberries); and technology implementation level (low-tech or high-tech).

default assumption is four; all plant factories are considered high-tech in our model.

2.2. Defining the growing environment

Using the total facility footprint and, if relevant, the number of growing layers specified by the user, facility dimensions and growing area are back-calculated assuming a length-to-width ratio of 3:1 and fraction of productive area specific to facility type (Table S2). Building cover material, structural shading, solar transmissivity, and heat transfer rate are also inferred based on facility type (Table S2). More specifically, we assume that hoop houses use polyethylene, plant factories use uninsulated concrete, and greenhouses use polyethylene, polycarbonate, or corrugated polycarbonate depending on technology level and local temperature. Based on the photosynthetically active radiation (PAR, 400–700 nm) transmitted through the cover material and the crop-specific lighting requirements, the model determines the ideal strength of whitewash and whether the use of a refraction lens, an optical device used to control and optimize sunlight for plant growth, is favorable for greenhouses, then calculates thermal transmittance of the building ($U_{effective}$) (Eq. S1). Temperature and lighting set points within the facility are ultimately derived from the crop-specific growing conditions detailed in Table S3.

2.3. Estimating energy consumption

2.3.1. Estimating energy demand for lighting

Our strategy for estimating the energy demand of LEDs, largely based on previous work by [25], uses location-specific meteorological data in combination with building specifications to estimate the amount of solar radiation entering a facility and whether the crops inside require additional artificial lighting on an hourly basis. Our model assumes that hoop houses and low-tech greenhouses do not use supplemental lighting, but high-tech greenhouses and plant factories do. However, the main distinction between high-tech greenhouses and plant factories in this case is that we assume greenhouses use a combination of natural and artificial lighting, whereas plant factories rely entirely on artificial lighting, as outlined in Table S2.

Using monthly maximum, minimum, and average global horizontal irradiance (GHI) data for a given location from the National Solar Radiation Database (NSRDB) [33], our model first constructs an hourly solar radiation profile for a typical day in each month of the year. For each hour of the day, the solar radiation profile is augmented by the transmissivity of the structure and structural shading, if relevant, to estimate the solar radiation entering the facility and whether additional PAR from LEDs is required to meet the specified crop's required DLI. This is similar to work performed by [34], who estimate average DLI on a monthly basis using the same NSRDB dataset. If any supplemental PAR is required by the crops, electricity consumption by the LEDs is estimated on an hourly basis using an assumed efficiency of 0.59 and a coefficient of performance (COP) for LED cooling that is a function of the temperature outside the facility [25]. Because plant factories are opaque, the energy demand for lighting in these facilities is calculated independently of location and based solely on the photoperiod and optimal DLI of the user-specified crop.

2.3.2. Estimating energy demand for heating, cooling, and ventilation

For facilities that utilize mechanical heating and cooling strategies (i.e., high-tech greenhouses and plant factories), the model constructs an hourly profile of temperature outside of the facility for a typical day in each month of the year using data from the NSRDB. To circumvent the need for CFD, our model makes several simplifying assumptions based on climate zone and the preferred temperature bounds of the crop to estimate the average temperature inside the facility at the hourly timescale. More specifically, if the simulated facility is located in a hot climate zone, we assume the temperature inside the facility is the upper bound of the tolerable temperature range for the crop, and if the simulated facility is located in a cold climate zone, we assume the temperature inside the facility is the lower bound of the tolerable temperature range. For simulated facilities in mixed or temperate climates, we assume the temperature inside the facility is the middle of the tolerable temperature range.

The hourly difference in temperature between the inside and outside of the facility, coupled with the heat loss rate based on the insulation of the building, is then used to estimate the hourly sensible heating and cooling loads. The energy required for heating is calculated by subtracting internal gains from solar radiation, lighting, and other equipment from the sensible heating load and dividing by the heating efficiency (0.99 for condensing boilers in high-tech greenhouses [35]) or heating COP (3 for HVACs in plant factories [36,37]). To estimate the energy required for cooling, the moisture production rate is first estimated based on the hourly ET rate in the facility, then multiplied by an assumed latent heat of vaporization at 14°C to obtain the latent heat within the facility. Latent heat, sensible cooling load, and internal gains from solar radiation and heat-producing equipment are summed and divided by a cooling COP (10 for evaporative pads in high-tech greenhouses [38] and 3 for HVACs in plant factories [36,37]) to obtain the total energy required for cooling. Hoop houses and low-tech greenhouses are assumed to use passive temperature control techniques and, therefore, have an energy demand of zero for heating and cooling.

Ventilation requirements for greenhouses vary based on growing season, where hot and cool seasons generally require a ventilation rate of 0.04 and 0.01 $m^3 \cdot s^{-1} \cdot m^{-2}$ of growing area, respectively [39]. Assuming that exhaust fans turn on at a relative humidity greater than 80% within greenhouses and high-tech hoop houses, our model first determines the required ventilation rate at the hourly scale based on the relative humidity setpoints and growing area, then estimates the size and number of exhaust fans needed to meet that ventilation requirement. Small facilities (less than or equal to 929 m^2), medium facilities (greater than 929 and less than 2,322 m^2), and large facilities (greater than or equal to 2,322 m^2) are assumed to use 16-, 18-, and 24-inch diameter fans, respectively. To meet variable ventilation requirements based on season, we assume that high-tech greenhouses use two-speed, direct-drive exhaust fans with the power requirements listed in Table S4 [39].

2.4. Estimating water consumption

ET is a core component of water consumption in CEA facilities. Fogging systems, evaporative cooling walls, and water recycling, as well as the loss of water through air exchange for climate control, can also contribute to the overall water demand of a facility. However, given the complexity of modeling these additional components, we assume water consumption is a function of ET in our model. Similar to average facility temperature, hourly relative humidity needs to be simplified to circumvent dynamic modeling. We assume that the average hourly relative humidity within the facility is equal to a setpoint, generally between 65% and 85%, that is determined based on the daily average temperature outside the facility and the photoperiod of the crop. Using the relative humidity and average temperature within the facility, the hourly reference ET is calculated using the Food and Agriculture Organization of the United Nations' (FAO) Penman-Monteith equation (Eq. (1) [40]), a variation on the original Penman-Monteith equation adapted for agricultural settings. Crop-specific ET is then calculated by multiplying the reference ET, a baseline value for the amount of water evaporated and transpired from a well-watered grass, with the time-averaged crop coefficient (k_c) for the user-specified crop, assuming non-stressed, well-managed crops in subhumid climates (Table S3). Note that soil heat flux is considered negligible for daily ET calculations, and the wind speed term (u_2) is a function of time of year, where we assume an ideal air exchange rate of 0.04 and 0.01 $m^3 \cdot s^{-1} \cdot m^{-2}$ of growing area in the summer and winter, respectively, for hoop houses and greenhouses [39], and a u_2 of 1 $m \cdot s^{-1}$ for plant factories year-round [41].

$$ET = k_c*(0.408\Delta(R_n - G) + \gamma(900/(T+273))u_2(e_s - e_a))/(\Delta + \gamma(1 + 0.34u_2)) \quad (1)$$

where

k_c = crop coefficient [dimensionless].
Δ = slope vapour pressure curve [$kPa \cdot {}^{\circ}C^{-1}$].
R_n = net radiation at the crop surface [$MJ \cdot m^{-2} \cdot hr^{-1}$].
G = soil heat flux density [$MJ \cdot m^{-2} \cdot hr^{-1}$].
γ = psychrometric constant [$kPa \cdot {}^{\circ}C^{-1}$] (Eq. S2).
T = air temperature within facility [°C].
u_2 = wind speed [$m \cdot s^{-1}$].
e_s = saturation vapour pressure [kPa].
e_a = actual vapour pressure [kPa].

Total water consumption in CEA facilities generally consists of water applied to plants, water used to regulate the growing environment, and process water (e.g., domestic use by employees). Because the partitioning of total water consumption varies by facility type, design, and climate, there is, to the best of our knowledge, not yet a peer-reviewed, standardized method of scaling ET to obtain total water consumption in CEA facilities. Therefore, we rely on generalized water use ratios for a hypothetical high-tech greenhouse with evaporative cooling and no water recycling, as well as a plant factory with HVAC and recycled irrigation water, developed based on guidance from industry experts [29]. According to this best practices guide, for soil-based greenhouses, the majority of irrigation water is lost through transpiration, and a relatively small fraction is retained in the plants themselves as fresh weight or lost through the substrate as leachate. In plant factories, the majority of water consumed is for irrigation, but a portion of this water is often captured and recycled. High-tech greenhouses and plant factories also require water for climate control and processing, but climate control and processing water needs are proportionally higher in greenhouses than in plant factories. For high-tech greenhouses and plant factories, we estimate total water consumption by assuming ET is 50% and 80% of total water consumption, respectively [29]. For hoop houses and low-tech greenhouses, we assume that total water consumption is equivalent to ET, as these facilities are less likely to require large amounts of water for climate control via boilers, evaporative cooling pads, and HVAC systems. Water lost during air exchange, in addition to water retained in crops themselves and water used for processing, is therefore neglected for these facilities in our model.

3. Results

3.1. Model validation

Though many studies have modeled resource consumption at CEA facilities, ample empirical data from real-world operations are not readily available for model validation. Therefore, we compiled both modeled energy and water consumption data from peer-reviewed studies [13,42–48], as well as empirical data from growers collaborating with the Resource Innovation Institute (RII) through their proprietary PowerScore tool [49], to assess the accuracy of CEAEstA. This validation set (Table S5) consists of 50 annual energy consumption points, 11 of which are measurements reported directly by growers and the remaining 39 are estimates from the published literature. The validation set also includes 19 annual water consumption values, split roughly evenly between measurements and modeled values. To preserve the anonymity of the growers who shared their data with RII, empirical water and energy use data sourced from these farms are not included in Table S5. Because the validation set skews heavily towards high-tech facilities that grow lettuce, tomatoes, or herbs, we were unable to validate the estimates for low-tech greenhouses, hoop houses, and less common crops.

We assessed the accuracy of CEAEstA by comparing the estimated annual energy and water consumption to that of the validation set and calculating root mean squared error (RMSE) (Eq. S3), mean percent error (MPE) (Eq. S4), and mean absolute percent error (MAPE) (Eq. S5) (Table S6). To better understand the mix of over- and underestimation, we also visualized the MPE distribution as a kernel density estimate (KDE) plot (Fig. 2).

As shown in Table S6 and Fig. 2, the accuracy of the model varies depending on which point in the validation set is used for comparison. The average MPE for energy consumption is approximately −27%, meaning the model tends to underestimate energy consumption; this makes sense considering we ignore several factors that can contribute to energy consumption (e.g., water recycling, fogging, CO_2 enrichment equipment, etc.). However, the percent error for 18% of the validation set (9 facilities) is greater than 0%, meaning energy use can still be overestimated by our model. Water consumption estimates also vary in accuracy depending on the facility used for validation but display a stronger trend towards underestimation, as indicated by an average MPE of −34%. While there are fewer validation points available for water consumption, clustering around −75% MPE suggests that scaling ET to estimate total water consumption is a valid assumption for some facilities, but leads to substantial underestimation for others. For CEAEstA's error statistics disaggregated by validation point, see Table S7 of the SI.

To investigate potential trends in model accuracy, we also calculated MPE for energy and water consumption estimates based on facility type, location, and crop (Table 1). MPE is slightly lower for plant factories than high-tech greenhouses, and exhibits larger variations for certain climate zones and crop types. More specifically, energy consumption estimates are more accurate for hot-humid, hot-dry, and marine climates ($n = 24$) but less accurate for very cold, cold, and mixed-humid climates ($n = 26$). Similarly, energy estimates are more accurate for facilities growing lettuce ($n = 44$) than those growing tomatoes and herbs ($n = 6$). Because there are fewer points available to validate water consumption estimates ($n = 19$), it is more difficult to identify trends in accuracy based on facility characteristics. With this in mind, water consumption estimates were most accurate for marine climates and facilities growing lettuce, but struggled to accurately capture water use in other scenarios, particularly cold and mixed-humid climates and facilities growing tomatoes. Interestingly, CEAEstA underestimates water consumption more when validated using real-world grower data (MPE of −82%, $n = 9$) than when validated using modeled estimates from other published studies (MPE of −9%, $n = 10$) (Table S6). This discrepancy may originate from differences in how water consumption is defined for growers versus academics. Because growers who reported their water consumption data to RII most likely used utility bills to estimate water consumption, the empirical portion of the validation set likely includes water use for non-crop production applications (e.g., domestic use by employees), whereas modeled water consumption estimates from literature typically only include water applied to plants and sometimes water used for climate control. These results highlight the uncertainty in how water consumption is defined across industry stakeholders.

3.2. Analyzing energy footprint

To analyze trends in energy use by facility type, location, and technology implementation level, we applied CEAEstA to a portfolio of hypothetical CEA facilities in 73 locations across the United States (Table S1, Fig. S1). As illustrated in Fig. 3, average national energy consumption is lowest for high-tech hoop houses and low-tech greenhouses, but highest for plant factories. Note that, because they are assumed to use passive climate control strategies, low-tech hoop houses are not analyzed in this discussion. In high-tech greenhouses, energy use is dominated by heating, cooling, and ventilation requirements, whereas in plant factories, energy use is dominated by lighting requirements.

Meteorological conditions outside of CEA facilities have varying

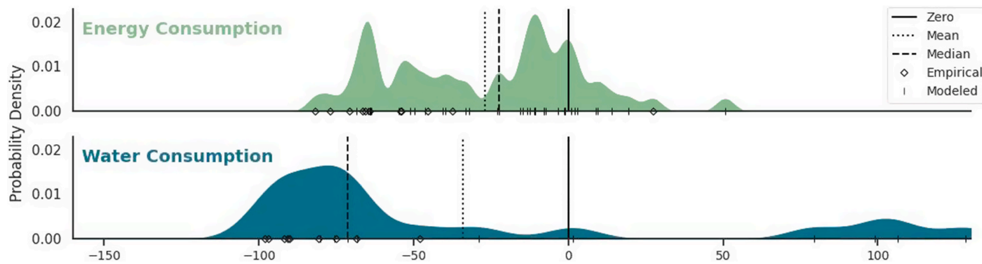

Fig. 2. Kernel density estimation (KDE) plots for controlled environment agriculture energy-water model. Each marker on the x-axis represents the mean percent error (MPE) in estimating annual energy (n = 50) or water consumption (n = 19) for a facility in the validation set, where diamonds represent empirical validation points and short, vertical lines represent modeled validation points from other studies. The solid black line represents no error, the dashed black line represents the median percent error, and the dotted line represents the average MPE for the full validation set.

Table 1
Mean percent error (MPE) of the energy-water model by facility characteristics.

Output	MPE (%)										
	Facility Type		Climate Zone						Crop		
	Green house	*Plant Factory*	*Very Cold*	*Cold*	*Mixed-Humid*	*Hot-Humid*	*Hot-Dry*	*Marine*	*Lettuce*	*Tomato*	*Herbs*
Energy Consumption	−30.7 (n = 24)	−23.6 (n = 26)	−50.8 (n = 2)*	−39.7 (n = 21)	−58.8 (n = 3)	−11.6 (n = 3)	−6.11 (n = 14)	−16.8 (n = 7)	−24.7 (n = 44)	−36.0 (n = 5)	−81.7 (n = 1)*
Water Consumption	−48.8 (n = 11)	−14.0 (n = 8)	NaN (n = 0)	−59.5 (n = 12)	−80.6 (n = 1)*	NaN (n = 0)	92.9 (n = 2)*	−10.0 (n = 4)	−11.8 (n = 13)	−79.4 (n = 5)	−98.1 (n = 1)*

* Note that error statistics associated with small sample sizes have limited interpretability.

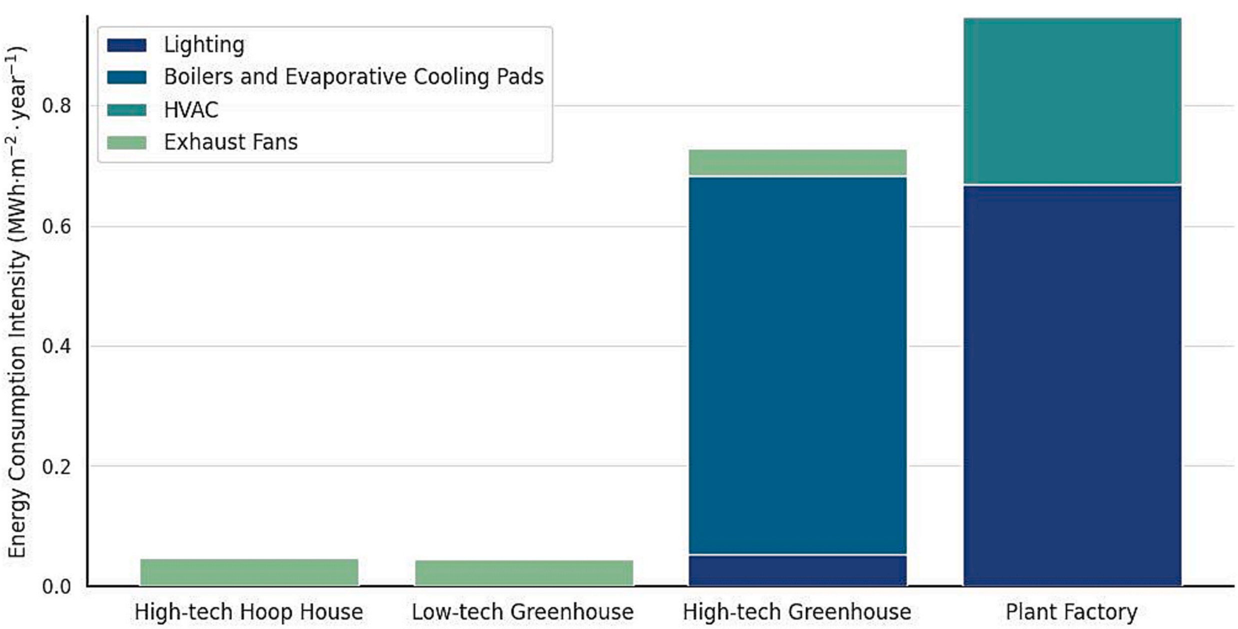

Fig. 3. Bar chart of national average energy consumption intensity ($MWh \cdot m^{-2} \cdot year^{-1}$) for controlled environment agriculture facilities in a hypothetical portfolio of 73 locations throughout the United States. Energy consumption is separated into energy required for lighting, temperature control, and ventilation. Note that HVAC = heating, ventilation, and air conditioning.

degrees of influence over energy consumption. For instance, hoop houses and greenhouses leverage natural light for crop growth, but are more susceptible to temperature swings outside the growing environment due to their high transmissivity. Conversely, plant factories require additional energy for lighting because they do not take advantage of natural sunlight to meet crop DLI requirements. To investigate geospatial trends in resource consumption driven by meteorological conditions, we mapped energy use intensity by climate zone for high-tech hoop houses and low-tech greenhouses, high-tech greenhouses, and plant factories (Fig. 4). Note that high-tech hoop houses and low-tech greenhouses are grouped in these figures because our model assumes their energy consumption intensity, based solely on energy consumed by exhaust fans, is equivalent for the same location.

As illustrated above, high-tech greenhouses exhibit a wider range of modeled energy intensities across climates than plant factories. We estimate that energy consumption intensity is lowest in hot-humid and very cold climate zones for high-tech greenhouses and plant factories, respectively, and that intensity is highest in very cold climate zones for

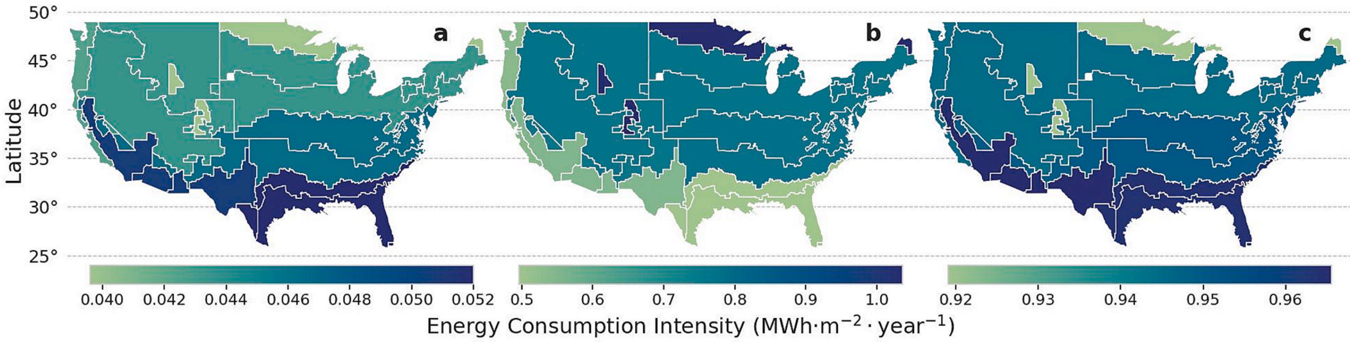

Fig. 4. Average energy consumption intensity (MWh·m^{-2}·year^{-1}) by climate zone for controlled environment agriculture facilities in a hypothetical portfolio of locations throughout the contiguous United States. Panel a) high-tech hoop houses/low-tech greenhouses; b) high-tech greenhouses; and c) plant factories. Note that high-tech hoop houses and low-tech greenhouses are modeled as having equivalent energy intensities.

high-tech greenhouses and hot-dry and hot-humid climate zones for plant factories. The energy footprint of high-tech greenhouses is dominated by heating demand, meaning that the reductions in energy use for cooling associated with cooler climates tend to be outweighed by the increased heating demand in the winter. Conversely, the energy footprint of plant factories is dominated by lighting demand, which is largely latitude-agnostic, meaning that differences in cooling demand are the driver of overall differences in energy intensity across climates. This results in an interesting dichotomy for CEA in hot climates of the United States: high-tech greenhouses exhibit relatively low energy intensities, whereas plant factories exhibit relatively high energy intensities. The same inverse relationship exists for very cold climates, where high-tech greenhouses exhibit relatively high energy intensities and plant factories exhibit relatively low energy intensities. However, we suspect that additional energy for dehumidification, due to simplifying assumptions about relative humidity in greenhouses, may not be fully captured by our model, which may therefore be underestimating the energy required for dehumidification in humid climates.

3.3. Analyzing water footprint

We applied CEAEstA to the same portfolio of hypothetical CEA facilities to analyze trends in water consumption by facility type, location, and technology implementation level. As shown in Fig. 5, we estimate that water use is lowest for plant factories and highest for high-tech greenhouses. ET rates are heavily linked to the temperature and relative humidity within the growing environment, as well as the solar radiation entering a facility [40]; therefore, we suspect that ET is lower in plant factories because they are opaque structures in which light is provided exclusively by LEDs and higher in semi-transparent structures like greenhouses and hoop houses that have the potential to transmit more solar radiation than necessary. Additionally, high-tech greenhouses require more water for climate control than other facilities due to their use of boilers and evaporative cooling pads.

Water use, as shown in Fig. 6, also varies based on facility type and climate. High-tech greenhouses located in hot-dry and hot-humid climates are estimated to have the highest ET rates and overall water use. However, plant factories exhibit a different spatial gradient of water use intensity. Though they consume substantially less water than hoop houses and greenhouses, they consume the most water in marine and mixed-humid climates.

3.4. Analyzing GHG footprint

We model the carbon intensity of CEA facilities as a function of both the amount of energy consumed and the GHG footprint of the source of energy (electricity and natural gas) (Fig. 7). Excluding low-tech hoop houses, which are energy neutral, high-tech hoop houses and low-tech

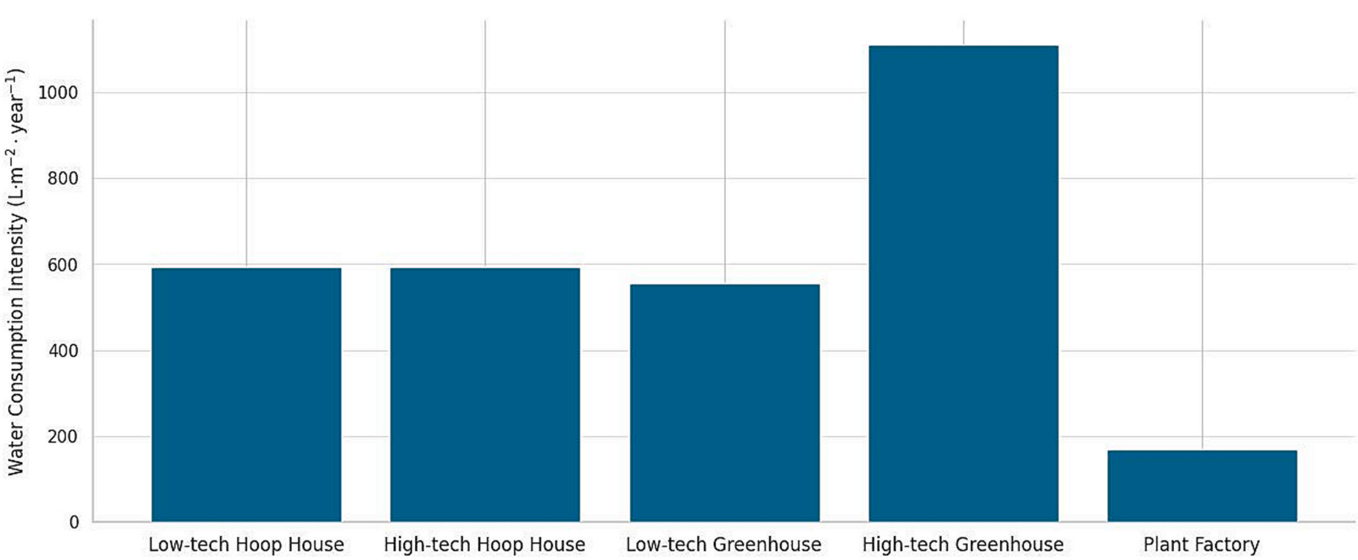

Fig. 5. Bar chart of national average water consumption intensity (L·m^{-2}·year^{-1}) for controlled environment agriculture facilities in a hypothetical portfolio of 73 locations throughout the United States. Water consumption is assumed to be a function of evapotranspiration based on facility type and technology level for the sake of simplicity in this model.

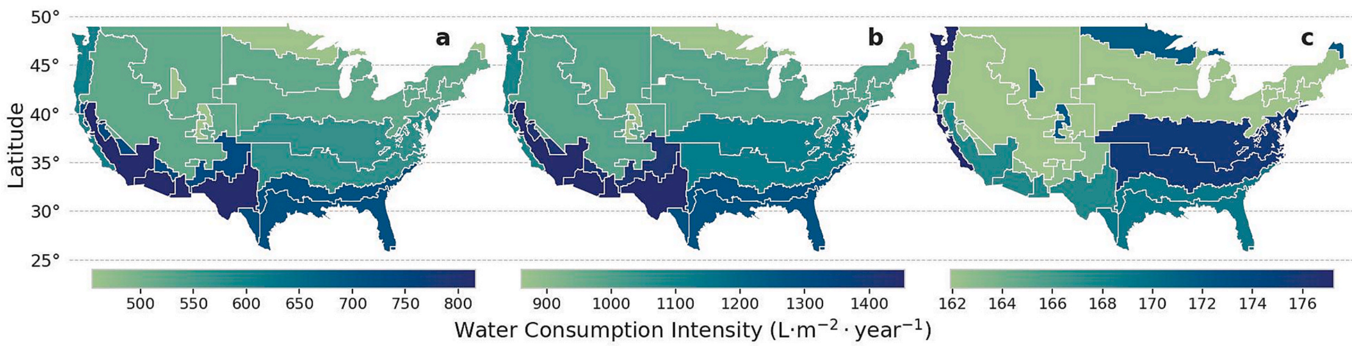

Fig. 6. Average water consumption intensity (L·m^{-2}·year^{-1}) by climate zone for controlled environment agriculture facilities in a hypothetical portfolio of locations throughout the contiguous United States. Panel a) high-tech hoop houses, b) high-tech greenhouses, c) plant factories. Water consumption is assumed to be a function of evapotranspiration based on facility type and technology level for the sake of simplicity in this model.

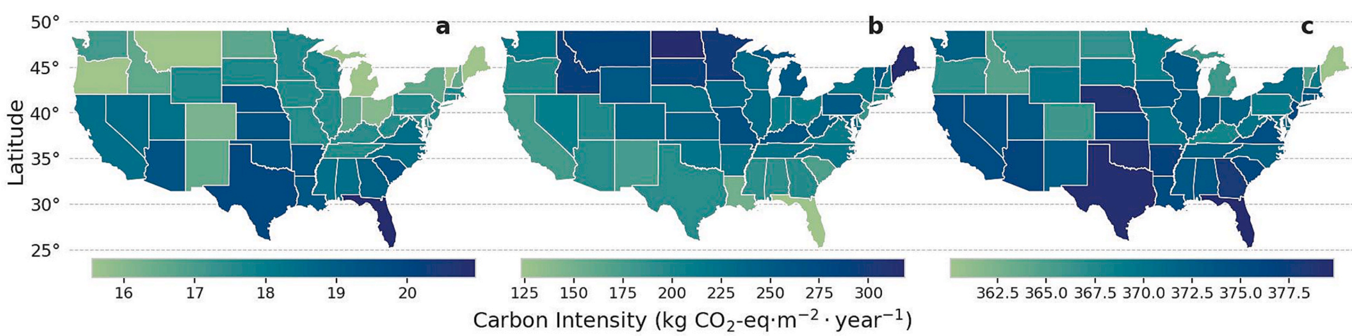

Fig. 7. Average carbon intensity (kg CO_2-eq·m^{-2}·year^{-1}) by state for controlled environment agriculture facilities in a hypothetical portfolio of locations throughout the contiguous United States. Panel a) high-tech hoop houses/low-tech greenhouses; b) high-tech greenhouses; and c) plant factories. Note that high-tech hoop houses and low-tech greenhouses are modeled as having equivalent energy intensities.

greenhouses located in regions that utilize less carbon-intensive forms of power such as solar, wind, and hydroelectric power produce the least GHG emissions, whereas high-tech greenhouses and plant factories, particularly in cold and hot regions, respectively, produce the most CO_2 equivalents.

4. Discussion

4.1. Model limitations

As an open-source and flexible model of energy and water use, CEAEstA enables users to simulate a broad range of scenarios, regardless of modeling expertise or knowledge of the industry. Though we apply the model to a portfolio of locations throughout the United States, it is easily adaptable for other locations and crops. However, this simplicity is only possible by inferring building specifications and climate control setpoints within the facility based on a limited number of user inputs, as summarized in Section 2. If desired, these assumptions could be relatively easily adjusted by directly editing the parameters of the model, specifically the basic_setup function. However, the biggest assumption underpinning this analysis, which would require substantial effort to rework, is that we assumed that the actual temperature and relative humidity within the facility are both uniform and equal to the setpoints derived from tolerable ranges for crops. More specifically, we assume that the temperature inside the facility is the lower, middle, or upper value of the tolerable range for the crop based on average hourly temperatures outside of the facility, and that the relative humidity within the facility is between 65 and 85% based on the photoperiod of the crop and temperature outside the facility. These assumptions, though they enable us to bypass numerically modeling the flow of air, water, and energy throughout the building, are not representative of real-world facilities that experience different temperatures and moisture levels at different locations within the facility throughout the day.

Additionally, our assessment of model performance is limited by the quantity and quality of data available for validation, as well as data regarding partitioning of water use (e.g., irrigation water, ET, climate control, domestic use, etc.). Because many facilities have not published their energy and water consumption data publicly, we used a combination of empirical and modeled data for validation. Consequently, human error in submitting energy and water data to RII, differences in how energy and water use are defined across growers and models, and sources of error from published models may propagate through this analysis. Our validation efforts indicate that model performance varies based on facility characteristics, but without more validation data available, it is difficult to draw definitive conclusions about the reliability of CEAEstA beyond the goal of this research, which was to provide order-of-magnitude estimations for energy and water use.

4.2. Opportunities for improvement

Because CEAEstA only considers energy consumption by LEDs, boilers, evaporative cooling pads, exhaust fans, and HVAC systems, incorporating additional sources of energy consumption, such as fogging, water recycling, and CO_2 enrichment equipment, could improve the model's performance. Thermal screens, a relatively popular form of temperature control sometimes used in greenhouses, could also be incorporated in the model as a method of decreasing heating and cooling loads. Refining the building material choice based on climate zone (e.g., more insulated materials in cold climates) has the potential to improve model performance. Lastly, directly linking CEAEstA to the NSRDB would add functionality by allowing users to automatically access meteorological data for any location rather than just the 73 locations included in this analysis.

5. Conclusion

A rapidly expanding part of the agricultural sector, CEA has the potential to strengthen food security despite diminishing arable land, intensifying weather, and water scarcity, pressures that increasingly threaten the viability of open-air farming in some regions. Technologically advanced facilities such as greenhouses and plant factories, when operated correctly, can optimize resource use and promote local food production. However, understanding and minimizing the energy and water footprint of these facilities is essential to building a more resilient, sustainable food system capable of meeting the needs of a growing global population. In this study, we present a simplified model (CEAEstA) to estimate energy and water demand in CEA facilities, supporting early-stage site feasibility analysis. By coupling foundational principles of heating, cooling, ventilation, and evapotranspiration with user-specified growing conditions, CEAEstA provides order-of-magnitude estimates of annual energy and water demand (−27% and −34% MPE, respectively) across a wide variety of scenarios.

Applying CEAEstA to a portfolio of facilities across the United States, we found that energy and water impacts vary by climate, facility type, and technological level. The energy intensity of plant factories, driven by lighting and cooling demands, was lowest in very cold climates and highest in hot climates. The energy intensity of high-tech greenhouses, driven by heating demand, was lowest in hot climates and highest in very cold climates. High-tech greenhouses tend to be more water-intensive than plant factories, particularly in hot-dry climates, but plant factories, particularly in hot regions with a carbon-intensive grid mix, have the highest carbon footprint.

These results affirm that sustainable site selection requires the joint evaluation of energy and water impacts rather than the independent optimization of each. This work also highlights the importance of publicly reported, consistently defined data on resource consumption. For example, we observed notable discrepancies between measured and modeled water use, likely attributable to the lack of standardized system boundaries and reporting conventions across industry and academic sources. Greater cross-sector transparency, data sharing, and standardization are therefore essential to research that will facilitate the sustainable diffusion of CEA across the United States, and CEAEstA is designed to be easily updated and improved as additional data becomes available. Although its accuracy is limited by several simplifying assumptions and a paucity of empirical data, this work provides a flexible, intuitive model to assess CEA energy-water impacts across a wide range of facility types, technology levels, crops, and climates and highlights resource consumption tradeoffs.

CRediT authorship contribution statement

Abigayle Rose Hodson: Methodology, Software, Validation, Formal analysis, Data curation, Writing – original draft, Writing – review & editing, Visualization. **Arian Aghajanzadeh:** Writing – review & editing, Writing – original draft, Validation, Methodology, Data curation. **Robert Eddy:** Writing – review & editing, Methodology. **Tyler Tarr Huntington:** Writing – review & editing, Methodology. **Robinson Negron-Juarez:** Writing – review & editing, Methodology. **Jennifer Stokes-Draut:** Writing – review & editing, Supervision, Project administration, Methodology, Funding acquisition, Conceptualization.

Declaration of Generative AI and AI-assisted technologies in the writing process

During the preparation of this work, the authors used ChatGPT to identify relevant sources and summarize key points from other research articles, primarily for the literature review included in the SI, and to generate definitions for the glossary. After using this tool/service, the authors reviewed and edited the content as needed and take full responsibility for the content of the published article.

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.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.seta.2026.105347.

Data availability

Data necessary to reproduce this work are available at our GitHub repository: https://github.com/AbbyHodson/cea-energy-water-model. To preserve the anonymity of growers who provided empirical energy-water data to the Resource Innovation Institute (used in model validation herein), exact locations, facility footprints, and energy-water consumption have been removed from this dataset prior to publication.

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Glossary

Carbon dioxide (CO_2) enrichment system: a system that increases the amount of CO_2 in a greenhouse or indoor grow space to enhance plant growth and productivity.

Controlled environment agriculture (CEA): a method of growing plants indoors, or in structures that provide a controlled environment, where factors like temperature, humidity, light, and nutrient delivery are precisely managed to optimize plant growth and yield.

Computational fluid dynamics (CFD): a branch of fluid mechanics that uses numerical analysis and computer algorithms to simulate and analyze fluid flows and their interaction with surfaces.

Daily light integral (DLI): the total amount of light, specifically photosynthetically active radiation (PAR), that a plant receives over 24 hours.

Evaporative cooling pads: a type of evaporative cooling system used to reduce the temperature inside a greenhouse by drawing in outside air and passing it over water-saturated pads, which cool the air through evaporation.

Evapotranspiration (ET): the process by which water is transferred from land to the atmosphere by evaporation from the soil and other surfaces and by transpiration from plants.

Fogging: a technique to create a fine mist of water in the air within a greenhouse, primarily for temperature and humidity regulation.

Global horizontal irradiance (GHI): the total amount of solar radiation received on a horizontal surface, including both direct and diffuse sunlight.

Greenhouse: a structure, typically made of glass or clear plastic, used to cultivate plants in a controlled environment.

Greenhouse gases (GHG): gases in the Earth's atmosphere that trap heat, contributing to the greenhouse effect and warming the planet.

Heating, ventilation, and air conditioning (HVAC): a system designed to regulate the temperature, humidity, and air quality within a building or space.

Hoop house: also referred to as a high tunnel, an outdoor, covered structure used to extend the growing season of plants.

Hydroponic farming: a method of growing plants without soil, instead using a nutrient-rich water solution.

Microprocessor: a specialized computer, often a microcontroller, that controls and manages various aspects of the greenhouse environment, like temperature, humidity, irrigation, and ventilation.

Photoperiod: the period in a day that an organism is exposed to light.

Photosynthetically active radiation (PAR): the portion of the solar spectrum (roughly 400–700 nm wavelengths) that plants use for photosynthesis.

Plant factory: also referred to as a vertical farm, an agricultural system that cultivates crops in stacked layers or towers within a controlled indoor environment.

Proportional-Integral-Derivative (PID) controllers: a widely used feedback control mechanism that adjusts the output of a process to match a desired setpoint.

Refraction lens: often a Fresnel lens, integrated into the greenhouse roof structure to manage and optimize sunlight for plant growth and energy efficiency.

Transpiration: the process by which plants release water to the atmosphere, primarily through the stomata and other plant surfaces.

Whitewash: often called limewash, a mixture of lime and water used in greenhouses to provide shading and control heat.