



OPEN ACCESS

EDITED BY

Viswanathan Pozhamkandath
Karthiayani,
Amrita Vishwa Vidyapeetham (Amritapuri
Campus), India

REVIEWED BY

Valerio Di Stefano,
Roma Tre University, Italy
Saeed Karimzadeh,
Aalto University, Finland

*CORRESPONDENCE

S. A. Roberts
✉ spencer.roberts@kit.edu

RECEIVED 22 July 2026

REVISED 26 August 2026

ACCEPTED 09 September 2026

PUBLISHED 01 October 2026

CITATION

Roberts SA, Winkler K, Rounsevell MDA,
Saxena A, Marcelis LFM and
Fuchs R (2026) Assessing upper bounds
for solar-powered controlled
environment agriculture on existing
cropland.
Front. Sustain. Food Syst. 10:1945186.
doi: 10.3389/fsufs.2026.1945186

COPYRIGHT

© 2026 Roberts, Winkler, Rounsevell,
Saxena, Marcelis and Fuchs. This is an
open-access article distributed under
the terms of the [Creative Commons
Attribution License \(CC BY\)](https://creativecommons.org/licenses/by/4.0/). The use,
distribution or reproduction in other
forums is permitted, provided the
original author(s) and the copyright
owner(s) are credited and that the
original publication in this journal is
cited, in accordance with accepted
academic practice. No use, distribution
or reproduction is permitted which does
not comply with these terms.

Assessing upper bounds for solar-powered controlled environment agriculture on existing cropland

S. A. Roberts^{1,2*}, K. Winkler¹, M. D. A. Rounsevell^{1,3,4}, A. Saxena¹,
L. F. M. Marcelis⁵ and R. Fuchs¹

¹Land Use Change & Climate Research Group, IMKIFU, Karlsruhe Institute of Technology (KIT),
Karlsruhe, Germany, ²Department of Civil Engineering, Geo and Environmental Sciences, Karlsruhe
Institute of Technology (KIT), Karlsruhe, Germany, ³Institute of Geography & Geo-ecology (IFGG),
Karlsruhe Institute of Technology (KIT), Karlsruhe, Germany, ⁴School of GeoSciences, University of
Edinburgh, Edinburgh, United Kingdom, ⁵Horticulture and Product Physiology, Wageningen University,
Wageningen, Netherlands

Controlled environment agriculture (CEA) has been proposed as a way of limiting cropland expansion and extending growing seasons, but these systems demand substantial amounts of energy, and their associated environmental impacts remain unclear. Here, we developed a framework to compare global crop area and production (reference year 2020) with an idealized, upper-bound scenario consisting of high-tech greenhouses or vertical farms powered by stand-alone photovoltaics (PV) for wheat, soybeans, potatoes, and tomatoes. The CEA energy calculation was combined with land-use, crop mapping, and PV energy datasets to compare CEA capacity with 2020 global crop production values. Of the 420 Mha of cropland area included in this study, hypothetical high-tech greenhouses and vertical farms powered by stand-alone PV arrays could match 2020 production levels on 313 Mha (74.5% aggregated across the four crops on the studied cropland area) and 275 Mha (65.4%), respectively, in the optimistic upper bound scenario. The modelled potential was greatest in parts of North and South America, South Asia, East Asia, West Africa, the Mediterranean, and Central Asia. These results reflect an idealized comparison, and implementing sustainable CEA at scale would face substantial technical, economic, and societal challenges. However, the framework does illustrate the locations where land and PV energy constraints would be least restrictive for CEA implementation.

KEYWORDS

controlled environment agriculture (CEA), geospatial analysis, greenhouse model, land use, solar power and food production

1 Introduction

Agriculture is currently one of the planet's largest land-use activities by area (Foley et al., 2005), a major driver of land-use change (Winkler et al., 2021), and a contributor to 15% of global GHG emissions (Searchinger et al., 2019). The global food system will also need to feed a growing population (Searchinger et al., 2019; Hertel, 2016; Alexander et al., 2015). The current challenges for the global food system are compounded by the need to reduce GHG emissions, mitigate climate change impacts (Hertel, 2016; Ortiz-Bobea et al., 2021) and biodiversity loss (Jaureguiberry et al., 2022); stabilize supplies amidst disruptions from geopolitical conflict

(Alexander et al., 2022) and global trade (Fuchs et al., 2019; Nyström et al., 2019); and adapt to changing societal preferences (Popp et al., 2017). Measures are needed to ensure food security without compromising ecological systems and human wellbeing (Searchinger et al., 2019; Fuchs et al., 2019; Nyström et al., 2019; Meyfroidt, 2018). The features of the last agricultural “Green Revolution” (e.g., widespread fertilizer and pesticide application, irrigation, and mechanization) may not be sufficient to maintain global food production at the levels needed to feed future populations sustainably (Tilman et al., 2011; Gerber et al., 2024). Moreover, changing conditions (Mueller et al., 2012) due to climate change, accompanied by water and fertilizer availability, may impact the ability to realize attainable yields of major crops globally (Gerber et al., 2024; Heino et al., 2023).

An emerging approach for ensuring consistent, increasing yields is through Controlled Environment Agriculture (CEA) (Cowan et al., 2022). CEA aims to reduce seasonal or environmental constraints (e.g., soil properties, water availability, seasonal temperature changes, light availability, and nutrient limitations) by incorporating aspects of the built environment to buffer and to manage indoor environments for consistent crop and food production (Cowan et al., 2022). The goal of homogenizing crop production across geographic and environmental constraints can be accomplished through different levels of infrastructure or technological integration. By increasing the degrees of control, CEA has the potential to optimize indoor crop growing conditions for consistent yields in order to produce multiple harvest cycles that would not be possible in outdoor conditions. CEA in the form of greenhouses (especially with supplemental lighting and advanced environmental controls) and vertical farms (multi-layered fully enclosed plant growing operations) (Weidner et al., 2022; Graamans et al., 2018) can produce large quantities of food while potentially reducing land, water, pesticides and fertilizer use (Cowan et al., 2022; Graamans et al., 2018; Asseng et al., 2020; van Delden et al., 2021). However, this comes at the expense of high costs for infrastructure, and the need for skilled personnel, equipment, artificial nutrients, and energy (e.g. for lighting) (Bomford, 2023; Righini et al., 2023). Improvements in LED lighting efficiency, HVAC (heating, ventilation, and air conditioning), and production mechanization, coupled with decreases in the cost of these components have contributed to recent commercial growth in the sector (Cowan et al., 2022; Asseng et al., 2020; van Delden et al., 2021).

Despite these advances, expanding production beyond high-value crops (e.g., greens, vegetables, medicinal plants) to staple crops (cereals, tubers, legumes) is limited by a variety of factors such as high capital expenditure and operating costs, distinct personnel and expertise compared to other forms of agriculture, and high energy demands (Weidner et al., 2022; Asseng et al., 2020; Kobayashi et al., 2022). Some studies highlight that the high costs and technical shortcomings of current vertical farms undermine their widespread implementation (Bomford, 2023; Righini et al., 2023; Pattison et al., 2018; Stanghellini and Katzin, 2024). It is suggested, therefore, that sustainably developing CEA hinges on using renewable energy sources while lowering energy demands (Bomford, 2023; Pattison et al., 2018; Stanghellini and Katzin, 2024). The prospect of powering CEA with decentralized renewable energy has gained interest as a means of sustainably incorporating CEA into local food systems (Weidner et al., 2022; van

Delden et al., 2021; Bomford, 2023; Kobayashi et al., 2022). However, existing studies have focused on specific locations (Weidner et al., 2022; Righini et al., 2023) or a few nations (Kobayashi et al., 2022), with no global evaluation of indoor farming powered by renewable energy (Bomford, 2023; Stanghellini and Katzin, 2024).

To undertake a global comparison of CEA capacity relative to current production, we developed a model and an analytical framework that integrate spatially explicit CEA energy demand, crop production, and PV potential energy generation. This study does not aim to evaluate whether CEA can replace field agricultural systems, nor does it assess socioeconomic and financial viability, environmental concerns, material constraints, or deployment pathways. Within this framework, we evaluated global land–energy–food trade-offs associated with the partial or complete replacement of natural sunlight and ambient growing conditions with energy-intensive CEA. Our analysis focused exclusively on cropland area, crop production, and CEA–PV equivalent capacity, with particular emphasis on energy constraints. This area-production accounting framework highlights where CEA systems could generate equivalent crop-wise production to current production per grid cell. We then examine potential underlying drivers shaping this equivalent capacity. We present a general, energy-focused framework that uses the available experimental CEA data to explore where idealized CEA–PV systems could theoretically match 2020 production levels within current cropland areas. Results are therefore interpreted as an upper-bound equivalent capacity assessment rather than a forecast. Throughout, we describe a modeled CEA–PV system as able to “match 2020 production levels” when, within a given grid cell, the modeled output equals or exceeds that cell’s actual 2020 crop production without requiring more land than is available for both CEA and PV.

2 Methods

2.1 Analysis framework overview

Here, we calculated the energy demands of vertical farms (VF) and high-tech closed greenhouses (GH) based on published indoor production experiments (Righini et al., 2023; Wheeler et al., 2003; Salisbury and Bugbee, 1988; Volk and Rummel, 1989; Hoff et al., 1982; Hay, 1995) with energy supplied from adjacent PV arrays (Saxena et al., 2023) (Figure 1; Table 1; Supplementary Figure 1; Supplementary Tables 1–4). We simulated PV-powered CEA (CEA–PV) production of four major food crops (wheat, soybeans, potatoes, and tomatoes) and calculated the CEA–PV area footprint (CEA building area and PV array area) required for each crop (ha) (Supplementary Figure 2). There is a lack of experimental data on CEA for staple crops such as wheat, soybeans, and potatoes (Mills, 2025). Hence, we employed this model to explore energy demand as one of the major CEA limitations, and reduced land area requirements as one of the major benefits. However, our simple and straightforward CEA setup and model design can be adapted as more data become available or different questions regarding technical CEA capacity arise. Other aspects such as nutrients, water, CO₂, labor, environmental

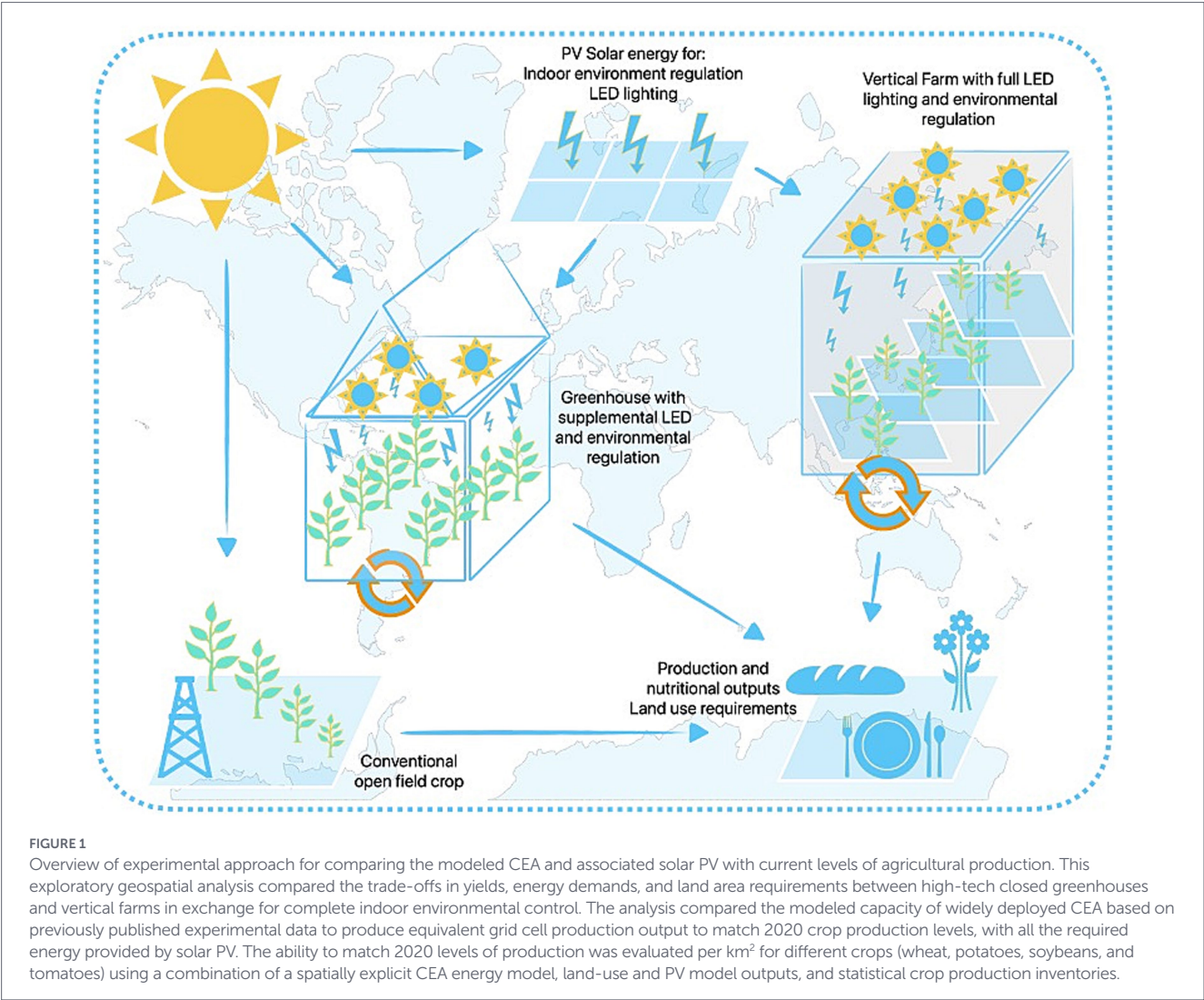


FIGURE 1
Overview of experimental approach for comparing the modeled CEA and associated solar PV with current levels of agricultural production. This exploratory geospatial analysis compared the trade-offs in yields, energy demands, and land area requirements between high-tech closed greenhouses and vertical farms in exchange for complete indoor environmental control. The analysis compared the modeled capacity of widely deployed CEA based on previously published experimental data to produce equivalent grid cell production output to match 2020 crop production levels, with all the required energy provided by solar PV. The ability to match 2020 levels of production was evaluated per km² for different crops (wheat, potatoes, soybeans, and tomatoes) using a combination of a spatially explicit CEA energy model, land-use and PV model outputs, and statistical crop production inventories.

TABLE 1 CEA energy model input parameters for daily light integral (DLI), harvest index, yield, and the resulting average energy demand per unit of harvested crop biomass produced and energy use per unit of growing area.

Crops	Wheat	Soybean	Potato	Tomato
Daily light integral (mol m ⁻² day ⁻¹)	67.0	23.4	39.6	35.1
Harvest index	0.17	0.5	0.63	0.73
Yield (t ha ⁻¹)	45	38	327	365
MJ kg ⁻¹ (GH/VF)	265–1,449/1588–1,607	303–709/690–705	35–119/131–134	32–97/104–106
MJ m ⁻² (GH/VF)	1,153–3,905/4287–4,374	1,153–2,695/2591–2,678	1,153–3,539/3807–6,521	1,194–6,521/7146–7,233

The harvest index is the ratio of harvested biomass to total crop biomass. Yield (t ha⁻¹) is shown for continuous annual production. CEA energy requirements (per unit of harvested biomass and growing area) are shown as the minimum and maximum range for continuous annual production. DLI (mol m⁻² day⁻¹) is derived from the photosynthetic photon flux density (PPFD) (μmol m⁻² s⁻¹) and photoperiod (h).

impacts, and capital were not included in this analysis as the focus was on the factors that most contribute to the CEA energy demands such as lighting, heating, ventilation, and air conditioning (HVAC). These factors can play a major role in CEA design and need to be considered when building site-specific CEA installations.

The CEA–PV area footprint for each crop was compared to the corresponding 2020 production output and area (hereafter

“2020 production”). We used this area–production accounting to determine where modeled CEA–PV demonstrates the area- and energy-constrained capacity to match the 2020 production levels on a regular grid globally (hereafter “CEA–PV equivalent capacity”). To conduct this analysis, we utilized high-resolution geospatial data for land use from the Historic Land Dynamics Assessment+ (HILDA+)[²], crop area and yields from GAEZ v4 (Fischer et al., 2021) and CROPGRIDS (Tang et al., 2023), and

global PV potential (Saxena et al., 2023) (Supplementary Figures 2, 3).

2.2 CEA energy demand model setup

To compare CEA powered by PV with equivalent crop-specific production globally, we derived the spatially explicit energy demand per CEA facility. This type of comparison has been conducted in localized contexts (Weidner et al., 2022), but is lacking at a global scope, as indicated by Bomford (2023), Righini et al. (2023, 2024), and Stanghellini and Katzin (2024). While there are many different greenhouse production models available (Katzin et al., 2022) the specific aim of this study was to examine CEA systems and energy use on a global scale; this led to the construction of a model to address this objective. We developed a general mechanistic model similar to the Van Henten (1994, 2003) model as a way of incorporating experimental CEA crop production values and parameters (Righini et al., 2023) across a global spatial array (Supplementary Figure 1). To make the model globally applicable, we generalized certain parameters more generalized, such as building design, crop growing parameters, and production system, and building interactions with ambient and indoor environment control systems.

The CEA yields, harvest metrics, and light requirements were taken directly from Righini et al. (2023). In that study, the authors compiled and analyzed CEA metrics across multiple studies as well as their own experiments for wheat (Wheeler et al., 2003; Salisbury and Bugbee, 1988; Volk and Rummel, 1989), soybeans (Righini et al., 2023), potatoes (Wheeler et al., 2003; Hoff et al., 1982; Hay, 1995), and tomatoes (Righini et al., 2023). CEA aims to homogenize crop outputs and yields regardless of geographic location, season, and local growing conditions. We applied this assumption to our model and kept CEA yields constant for each crop across the global spatial array. The yields from individual studies in Righini et al. (2023) were analyzed for parameters such as light requirements [photoperiod and photosynthetic photon flux density (PPFD)], the growing cycle length (days), and the resulting yields in terms of plant density, harvest index (ratio of harvested biomass to total plant biomass), fresh harvest yield per growing cycle, dry harvest yield per cycle, and annual fresh weight yield (as the sum of multiple growing cycles possible per year). The values from Righini et al. (2023) used in the CEA energy model presented here are listed in Supplementary Table 2. Long-term and continuous datasets on CEA for the different crops such as those included in this study were not available. Hence, we extrapolated from the experimental results that were available to derive values for multiple yields per year (Searchinger et al., 2019; Hertel, 2016) that would be possible given the reported growing production durations and days to harvest. The reference experimental studies all used soilless growing setups (e.g., hydroponic), so the same was assumed in our modeled CEA. Mills (2025) also compared energy demands across CEA studies and found differences between and across crop types. Mills (2025) acknowledged that for crops such as wheat, few studies are available and, in some cases, there is a reliance on modeled crop simulations. Given the discrepancies and potentially large ranges between crops and individual studies, we chose to directly apply the Righini et al. (2023). CEA data compilation as the primary source of crop-specific parameters.

Two types of CEA were evaluated, a high-tech closed greenhouse (GH) and a vertical farm (VF), to model the energy required for each setup to achieve the target yields as compiled in Righini et al. (2023). The mechanistic greenhouse model assumed uniform internal conditions, also known as a “perfectly stirred tank” (Van Henten, 1994), and considered water vapor and energy balances in a similar way to the Van Henten (1994, 2003) model (Katzin et al., 2022) (Supplementary Tables 1, 3).

We adapted the basic greenhouse balance equations for energy and water vapor from the Van Henten (1994, 2003) model to run the simplified model at a global scale and calculate the CEA energy demand:

$$dE/dt = Q_{\text{Sun}} + Q_{\text{heat}} + Q_{\text{Lamp}} - Q_{\text{Vent}} - Q_{\text{Latent}} - Q_{\text{Con}} - Q_{\text{FIR}} - Q_{\text{cool}} \left(\text{J m}^{-2} \text{ s}^{-1} = \text{W m}^{-2} \right)$$

$$dMW/dt = W_{\text{ET}} + W_{\text{Hum}} - W_{\text{Cond}} - W_{\text{Vent}} - W_{\text{Dehum}} \left(\text{kg \{water vapor\} m}^{-2} \text{ s}^{-1} \right)$$

dE/dt = net change of energy

Q = rate of heat transfer from the various factors, inside and outside the growing space

dMW/dt = net change of water mass

W = rate of water vapor change over time from inside and outside factors

Here, dE/dt is net change in energy within the growing space. Q_{Sun} is the solar heat input, Q_{Heat} is the supplemental heating, Q_{Lamp} is the heat input associated with artificial lighting, Q_{Vent} is the sensible heat loss through ventilation, Q_{Latent} is the latent heat loss associated with evapotranspiration, Q_{Con} is the conductive heat loss through the CEA structure, Q_{FIR} is the far-infrared heat loss, and Q_{cool} is the heat removed by active cooling. dMW/dt is the net change in water vapor within the growing space. W_{ET} is the water vapor added through crop evapotranspiration, W_{Hum} is the water vapor added by humidification, W_{Cond} is the water vapor removed through condensation, W_{Vent} is water vapor removed through ventilation, and W_{Dehum} is water vapor removed through active dehumidification. More detailed processes can be captured in Van Henten (1994, 2003) or other greenhouse models (Katzin et al., 2022); however, to represent the major drivers of energy use, we focused solely on these specific aspects. The process for calculating the influence of solar radiation was the same for both GH and VF and was adapted from the following equation (Righini et al., 2023):

$$\text{Energy Use}_{\text{lights}} = \text{PPFD} * \text{photoperiod} * 3600 * \eta_{\text{lights}} * 10^{-6} \left(\text{MJ m}^{-2} \text{ day}^{-1} \right)$$

η_{lights} = electrical efficacy

The walls in the VF allowed no light transmission, whereas the GH permitted 82% of incident solar radiation to enter the growing space (van Delden et al., 2021). For incoming solar radiation, the daily total values averaged monthly to obtain an average daily solar radiation ($\text{J m}^{-2} \text{ day}^{-1}$). This incoming average daily solar radiation load

was converted to PPFD ($\mu\text{mol m}^{-2} \text{s}^{-1}$) as the total daily PPFD, or daily light integral (DLI), expressed in as $\text{mol m}^{-2} \text{day}^{-1}$.

$$\text{DLI} \left(\text{mol m}^{-2} \text{day}^{-1} \right) = \text{PPFD} \left(\mu\text{mol m}^{-2} \text{s}^{-1} \right) * \text{photoperiod} (\text{hours}) * 0.0036$$

The PPFD and photoperiod for each crop from Righini et al. (2023) were converted into a daily DLI requirement per day. The difference between the actual DLI and this required DLI indicated the lighting ($\text{J m}^{-2} \text{day}^{-1}$) shortfall. Dividing this shortfall by the electrical efficacy*1⁶ of the lights yielded the average daily supplemental lighting demand ($\text{MJ m}^{-2} \text{day}^{-1}$) for each month of 2020.

While there are other potential processes or factors that could contribute to CEA energy demand, such as water pumps and irrigation, mechanized automation, and computer and sensor controls, these are relatively minor compared to major energy drivers, such as supplemental lighting, growing-space heating and cooling, and ventilation (Righini et al., 2023).

Between the two CEA setups, there were minor adjustments to the building dimensions, crop growing area, and wall insulation properties. The simplified building designs, similar to those of Weidner et al. (2021, 2022) as well as previous CEA study parameters (Graamans et al., 2018; van Delden et al., 2021; Tsafaras et al., 2022) were intended to capture the basic parameters of the indoor growing space and its interactions with the outdoor environment. In this way, the major drivers of CEA energy demand could be compared while avoiding specific building designs that vary by location and application. In this simulation, the vertical farm and closed greenhouse each had supplemental lighting, temperature, and humidity controls to maintain the same light requirements, indoor conditions, and annual yields depending on the crop requirements.

The model considered a 1-ha GH (75% of the building footprint is considered usable as growing area) and a 0.25-ha VF (with four stacked layers that utilize 75% of the building footprint for growing area). The VF yield was assumed to be four times greater per hectare of building footprint than the GH to capture the increased production capacity for the VF. In addition, the VF was assumed to be 8 m in height, and the GH was assumed to be 4 m in height. The same indoor environment was assumed for both systems, and in turn, the capacity to maintain that growing space environment is what drives the energy demand (Supplementary Tables 1, 3).

We used the average daily light (PPFD) requirements, photoperiod, and annual yields according to Righini et al. (2023) and included updated lighting and indoor environmental parameters to meet the best available standards for LEDs and heat pumps (Supplementary Table 4). The values presented by Righini et al. (2023) include their own data for tomato and soybean experiments as well as a compilation of previous experiments for wheat (Wheeler et al., 2003; Salisbury and Bugbee, 1988; Volk and Rummel, 1989) and potato (Wheeler et al., 2003; Hoff et al., 1982; Hay, 1995) trials. Each of the selected experiments may have differed in specific CEA designs; however, all were soilless systems that relied entirely on supplemental lighting for crop growth. The mechanistic greenhouse model had a timestep of 1 day for all indoor processes. The outdoor climate conditions were averaged for each month and recorded as the average daily temperature, relative humidity, and solar radiation flux for each grid cell per month. The model received the daily averages (for each

month) as input data and first calculated the influence of outside factors on the indoor growing parameters (temperature, relative humidity, and light) for both the VF and GH. Then, for each growing-space parameter, the corresponding CEA component was forced to correct the factor and bring it back into the target range. For heating and cooling, this was done with a heat pump; for relative humidity, with a humidifier or ventilation; and for supplemental lighting with LEDs.

The energy requirement for each component to maintain the target growing conditions was summed for each average day per month. These daily energy totals were multiplied by the number of days per month to calculate a monthly energy demand based on the average day in that month. These monthly values were then summed to determine an annual energy demand. This annual energy demand was divided by the annual CEA yield per building to obtain energy-use efficiency (MJ kg^{-1}) for each crop and CEA system.

The resulting energy demand reflects the energy needed to maintain these constant internal conditions within the target ranges. By standardizing these conditions, we could compare the plant-specific growing parameters and yields from Righini et al. (2023) between VF and GH systems.

2.3 CEA energy demand simulation inputs

The selected crops for the study were wheat, potato, soybean, and tomato, representing grain, legume, tuber, and vegetable crop types. The temperature range ($15\text{--}23^\circ\text{C}$) and relative humidity range (60–85%) were set at levels similar to those of Weidner et al. (2021, 2022) (Supplementary Table 3). We assumed fixed biomass production per growing cycle and year, using yield biomass per m^2 and harvest index adapted from Righini et al. (2023), rather than simulating crop growth over time and across phenological stages. Because evapotranspiration is a complex process that varies between crops and developmental stages, we applied a single generalized evapotranspiration rate of 4.5 mm day^{-1} for all crops (Arcasi et al., 2022; Pamungkas et al., 2014; Nikolaou et al., 2019). In addition, the energy to power water pumps and recirculation is relatively insignificant compared to other CEA processes, and water use itself can be over 90% lower (for both closed greenhouses and vertical farms) than comparable that of field systems (Graamans et al., 2018; Righini et al., 2023; Tsafaras et al., 2022). For this reason, water use and the associated energy used for irrigation, pumping, and recirculation were not included.

A heat pump was used to maintain the internal temperature within the target range, with a coefficient of performance (COP) of 4.0 for heating and an Energy Efficiency Ratio (EER) of 13.0 for cooling (Shoukas et al., 2022). These COP and EER are general values to reflect that these efficiencies could be influenced by local conditions and product designs. The building wall insulation R -value was kept at 3 for the GH (Sanford, 2011) and 15 for the VF (Graamans et al., 2020). Supplemental lighting from LEDs was set to $3.5 \mu\text{mol J}^{-1}$ to represent the current best available standard (van Delden et al., 2021; Stanghellini and Katzin, 2024) (Supplementary Table 4).

ERA5 agrometeorological environmental data (Boogaard et al., 2020) ($0.1^\circ \times 0.1^\circ$ resolution) were used for daily measurements of solar radiation flux (J m^{-2}), temperature (K at 2 m height), and relative humidity (% at 2 m height at 12 h) for the year 2020. The daily values for each grid cell were averaged for each month in the year 2020. These averaged daily values per month for the climate parameters (solar radiation, temperature, and relative humidity) were input into the CEA energy demand model at 1-day time steps. The use of a monthly

averaged value for each climate factor was a trade-off to run the model efficiently on a global array while still capturing site and seasonal variations. The model outputs were calculated as total energy demand (MJ) per day and then summed into monthly and annual totals. The ratio of annual energy demand to crop yield (MJ kg^{-1}), or energy use efficiency, for each CEA system was then calculated per grid cell. Both monthly energy demand and annual energy use efficiency were down-scaled to a 1 km grid to compare to the higher-resolution land-use and solar PV potential model outputs. The resulting energy use efficiency as MJ kg^{-1} for each crop calculated by region for both CEA systems is shown in Figure 2.

2.4 Global crop area, yield, and production

We used a data-harmonization approach based on the HILDA+ land-use reconstruction model (Winkler et al., 2021) to allocate 2020 crop production (t km^{-2}) and crop harvest area (ha km^{-2}) for the target crops to a 1 km global grid array. This approach allowed us to harmonize the outputs of multiple crop models, datasets, and statistical inventories to produce crop area, yield, and production maps for each target crop. All datasets included in the study were resampled to align with the HILDA+ 1 km spatial resolution. In HILDA+, the cropland areas were isolated and used to mask the CROPGRIDS crop-specific crop area data (reference year 2020, 35). GAEZ v4 (reference year 2015, 34) along with the statistical data for FAO country-level harvest area and production quantity totals (reference year 2020, 50) were used to assign the pixel-level harvest area (ha) and yields (t/ha) for the target crops.

This was achieved by first normalizing the GAEZ v4 crop yield values, i.e., dividing them by their national and cropland-wide mean, as well as normalizing the CROPGRIDS crop area values by their national and cropland-wide sum (all constrained by HILDA+ cropland and at least 5% CROPGRIDS crop coverage). This normalization was done to align each input dataset with a single consistent spatial array and projection. The normalized values, crop yield, and area were then multiplied by the corresponding FAO crop yield and harvested area in 2020, respectively. The crop production (t) was subsequently derived by a pixel-level multiplication of country- and crop-specific yield (t ha^{-1}) and harvested areas (ha). Each crop then had a specific

harvest area (ha), yield (t ha^{-1}), and production (t) per grid cell for the year 2020. To harmonize these different datasets, steps were taken to minimize inter-dataset variability. FAO statistics only report crop area harvested, which can include multiple harvests on the same area, so the CROPGRIDS crop cultivation area layer was used to define a fraction of crop area per grid cell prior to allocating the FAO area harvested within each country's grid cells. Upper thresholds for crop area were established to prevent instances where the area from multiple harvests was applied to the same grid cell. In this way, we were able to remove inconsistencies or data artifacts that would otherwise inflate the crop area beyond what was available in the grid cell (i.e., more than 100 ha crop area for a 100-ha grid cell). The data-harmonization process for crop area, yield, and production is illustrated in Supplementary Figure 3.

2.5 PV-powered CEA comparison with 2020 crop area, yield, and production

The CEA crop yields (Righini et al., 2023) were kept constant across the global array to test the area and PV energy capacity required to scale these experimental values globally. The multiple datasets (Fischer et al., 2021; Tang et al., 2023; FAO, 2022) used across the analysis reported the reference yields and production in harvested biomass. For this reason, we used CEA production and yield values for harvested biomass. For different research questions, this metric could be changed to dry harvest weight, calories, or other specific nutritional or agronomic units. The first step in calculating the comparison against 2020 crop production was to determine the CEA building area needed to generate equivalent yields to 2020 production (t km^{-2}) per grid cell. The annual CEA yields were calculated per growing area and were scaled per grid cell to reflect the CEA systems (0.75 ha growing area per 1 ha GH building area and 0.75 ha growing area per 0.25 ha VF building area). The 2020 production array was divided by the annual CEA yield (per growing area) per crop to yield the CEA building area needed for year-round CEA production in each grid cell. This CEA footprint requirement was summed per hectare for GH or per 0.25 hectare for VF per grid cell.

To calculate the solar PV area needed for CEA, the monthly solar PV potential (kWh m^{-2}) was derived from Saxena et al. (2023). The

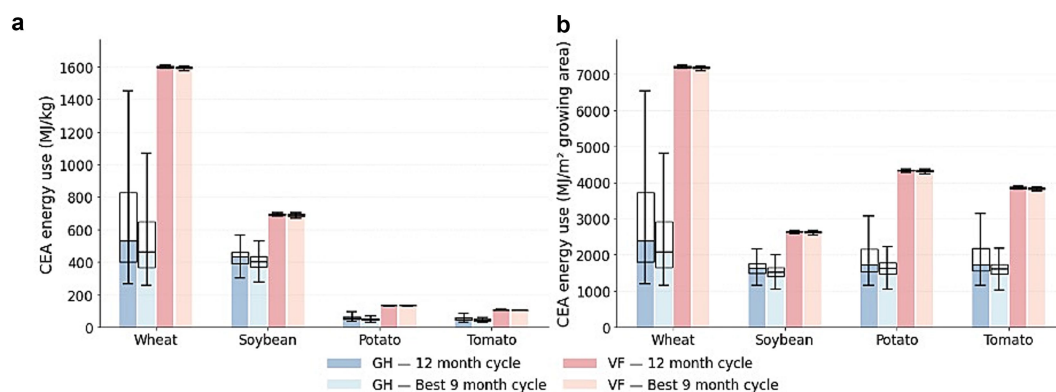


FIGURE 2

CEA average energy demand per unit of harvested crop biomass produced and per unit of growing area. The energy required per (a) fresh biomass and (b) growing area for each crop under both full-year and 9-month growing cycles for wheat, soybeans, potatoes, and tomatoes. Boxplots for each bar indicate the median, interquartile range, minimum, and maximum values for each crop, system, and cycle. This considers the building footprint of 1 ha for the high-tech closed greenhouse ("GH") and 0.25 ha for the vertical farm ("VF"). The 9-month growing cycle was calculated per grid cell as the continuous 9 months required for the smallest PV area to maintain growing conditions.

area available for PV per grid cell was calculated by subtracting the CEA building area from the harvest area. The surface area coverage of the solar PV was assumed to be 75% of a given area (van Delden et al., 2021), therefore, the potential energy available to the CEA was reduced by this factor. This PV potential was then multiplied by an efficiency factor (51, 26.8%) for conversion to usable electricity. The total CEA energy demand per building (1 ha for GH and 0.25 ha for VF) per grid cell was multiplied by the total CEA building area requirement to calculate the total CEA energy demand per grid cell. The monthly PV area requirement to directly power the CEA was calculated by multiplying the potential PV energy by the CEA energy demand per grid cell. The process is summarized visually in [Supplementary Figure 2](#), and all CEA component inputs are summarized in [Supplementary Tables 1–4](#).

For year-round production, the month with the greatest PV area requirement for each grid cell defined the fixed PV area needed to power the required CEA area for that grid cell. No energy storage was assumed from 1 day to the next; therefore, each day relied solely on the monthly 1-day average to fulfill the CEA demand. We also analyzed continuous 9-month CEA production capacity to evaluate the potential reduction in the energy demand and the required PV area to power the CEA. The reduction in yield capacity was accounted for, and the CEA area needed to match 2020 production per grid cell was recalculated. For the shortened 9-month production cycle, the 9-month period with the lowest PV area requirements to satisfy indoor energy demands was identified. Similar to year-round production, the month with the greatest PV area requirement within this 9-month cycle determined the PV area needed for that grid cell. The resulting area (ha) of PV needed to power a year-round or 9-month CEA system is displayed spatially in [Supplementary Figure 7](#).

This combined CEA building area plus PV footprint was the total area that was then compared to the crop harvest area per grid cell. The land-area requirement balance (ha) was calculated by subtracting the sum of the CEA building footprint and PV area from the crop area per grid cell. If the area balance was negative, insufficient land was available for the CEA–PV system to match equivalent yields to 2020 production in that grid cell. If the balance was zero or positive, the CEA–PV matched 2020 production; any positive value could be considered a lower required land area than the 2020 production area in ha.

Only the grid cells with a positive area balance were used to calculate the potential extra or surplus production by allowing the model to allocate all available crop area to CEA production above 2020 production values. This extra production was calculated by incrementally adding CEA units (1 ha for GH and 0.25 ha for VF) along with the required PV area per building. This process was performed iteratively until the remaining crop harvest area in that grid cell reached zero. The sum of this extra production, according to the CEA building area added, was then added to the total production quantity of that grid cell. The spatial distribution of areas where CEA matched 2020 production is shown in [Figure 3](#). The global totals and comparisons between CEA systems for harvest area (ha) where CEA matched 2020 production, production quantity (t) matched by CEA, lower CEA–PV land-area requirements compared to 2020 production (ha), and extra production (t) by CEA are given in [Figure 4](#). The regional breakdowns relative to the global totals as well as the breakdowns within each region are given in [Supplementary Figures 7, 8](#).

2.6 Electricity grid constraints

The [Arderne et al. \(2020\)](#) electrical grid dataset was used to evaluate current electrical grid coverage in areas that overlap with those that generate grid cell production equivalent to 2020 production (CEA–PV equivalent capacity areas). Where at least medium-voltage electricity was present, a 2 km buffer was established as the maximum distance for connection to these distribution networks. The grid cells where there was overlap of this transmission network and buffer with these CEA–PV grid cells that matched equivalent production to 2020 production were summed, alongside those that were outside of this 2-km buffer. The grid cells were then multiplied by the crop harvest area (ha) in that grid cell and then summed by crop at the country and regional levels. The proportion of harvest area (ha) where CEA matched 2020 production within the 2 km electricity grid was then calculated for country and region, as seen in [Figure 5](#). The spatial overlap of areas where CEA matched 2020 production and the electricity grid can be seen in [Supplementary Figure 9](#).

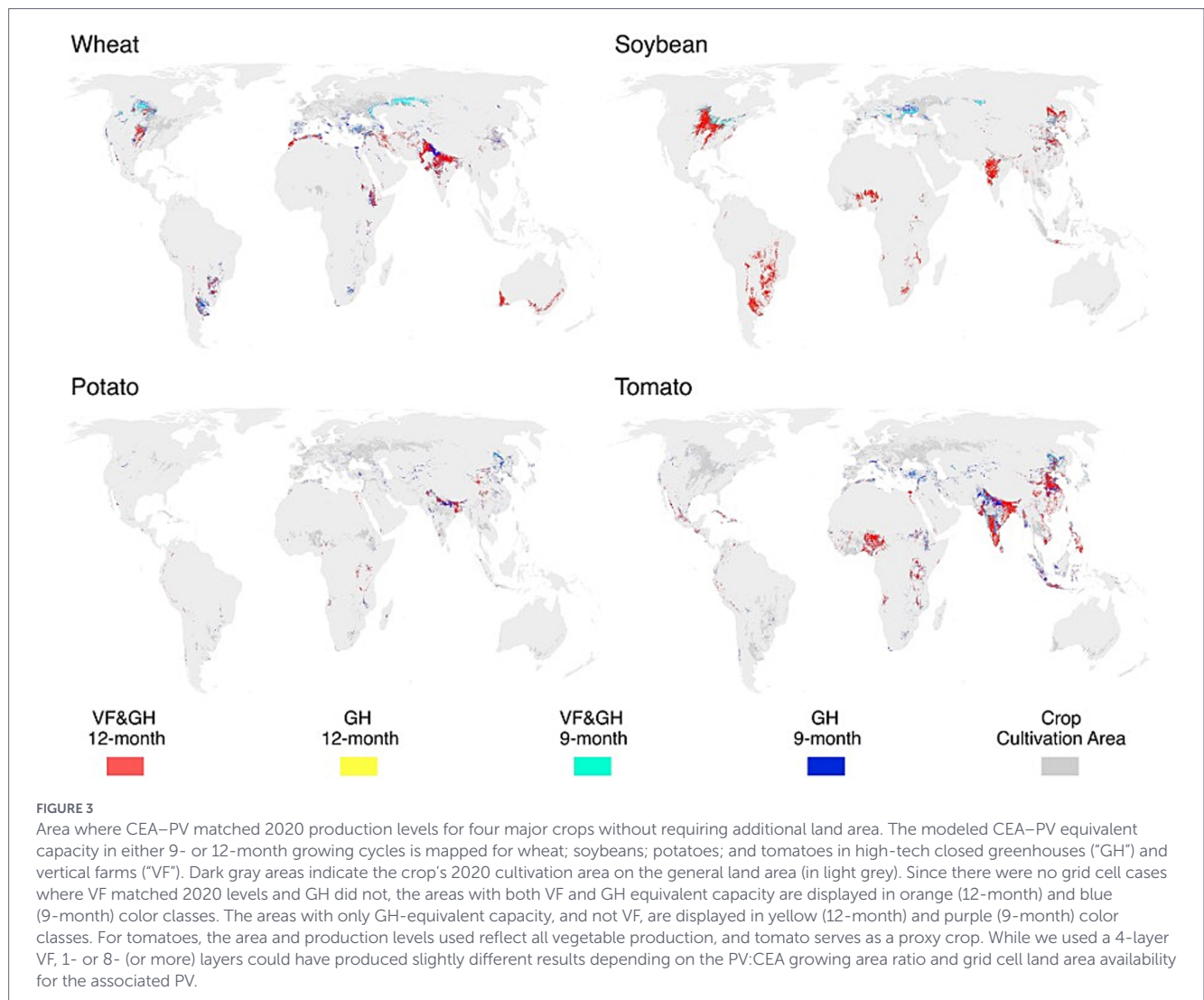
2.7 Aridity index

The Global Aridity Index Database, as described by [Zomer et al. \(2022\)](#), was used to compare areas where CEA matched 2020 production across aridity zones. The aridity index was categorized into bins according to the index value. These index bins were then overlaid on the grid cells where CEA matched 2020 production. The harvest area (ha) was then multiplied by the number of grid cells within each index bin. The harvest area (ha) where CEA matched 2020 production was plotted according to aridity index bin, and the results are presented in [Supplementary Figure 11](#).

2.8 Model assumption sensitivity

A deterministic sensitivity analysis was conducted to evaluate the response of CEA–PV equivalent capacity to changes in model assumptions. The sensitivity analysis evaluated alternative assumptions around three parameters directly influencing CEA–PV area requirements and subsequent equivalent-capacity calculations: CEA crop yield, CEA energy demand, and PV conversion efficiency. Changes to each assumption were evaluated individually and for their combined effects on CEA–PV equivalent capacity. The “baseline” analysis for GH and VF applied the experimental CEA yields described above and calculated the CEA building area required to match 2020 crop production in each grid cell, while the PV area requirement was determined from the corresponding CEA energy demand and a baseline PV conversion efficiency of 26.8%.

For the yield sensitivity analysis, the annual CEA yield for each crop was reduced by 10, 25, and 50%. The required CEA building area was then recalculated directly from 2020 crop production using the reduced yields while retaining the same GH- or VF-specific growing areas and corresponding year-round or 9-month growing cycles. The greater CEA area required under lower yields also increased the growing area and associated PV area requirements to match 2020 crop production. For the energy-demand sensitivity, CEA energy-demand per unit growing area was increased by 10, 25, and 50%, while CEA yields and building area requirements were maintained at baseline input values. In turn, the corresponding PV area requirement increased to meet the higher energy demand. For the PV efficiency sensitivity analysis, conversion efficiency was reduced from the



baseline input value of 26.8–22%, while CEA crop yields and energy demands were kept constant. The PV area requirements were then recalculated to provide the same amount of energy to meet CEA energy demands.

In addition, the joint effects of combining CEA yield reductions, energy demand increases, and PV conversion efficiency reductions were evaluated. For each joint-effect scenario, the revised CEA building area and PV requirements were compared to the available crop-specific harvested area in each grid cell using the same approach as the baseline analysis to calculate equivalent capacity. The sensitivity analysis tested the change in absolute area (ha), production (t), and less crop area required (ha) and their corresponding global percentages for the CEA systems, year-round and 9-month growing cycles, and four crops. The sensitivity analysis therefore assessed how these CEA systems performed under less favorable model assumptions rather than representing probabilistic uncertainty ranges.

3 Results

Energy demand per unit of harvested biomass produced (MJ kg^{-1}) varied by crop, system, and region (Figure 2; Table 1; Supplementary Figure 4). Here we focused on harvested biomass to

remain consistent with FAO reporting units for direct comparison with 2020 production levels and area statistics (FAO, 2022). From the CEA energy model (using monthly averages at a one-day timestep), we found that the GH consistently exhibited lower annual energy demands than the VF. This energy difference is primarily attributable to the VF’s sole reliance on LEDs and consequent higher additional lighting needs. For the GH, outside temperature, solar radiation, and humidity substantially influence the energy needed to maintain consistent growing conditions. Crops such as tomatoes (GH: $40\text{--}70 \text{ MJ kg}^{-1}$, VF: $\sim 105 \text{ MJ kg}^{-1}$) or potatoes (GH: $44\text{--}92 \text{ MJ kg}^{-1}$, VF: $132\text{--}133 \text{ MJ kg}^{-1}$) require less energy per kg of harvested biomass than soybeans (GH: $372\text{--}569 \text{ MJ kg}^{-1}$, VF: $690\text{--}701 \text{ MJ kg}^{-1}$), and wheat (GH: $375\text{--}1,097 \text{ MJ kg}^{-1}$, VF: $1595\text{--}1,604 \text{ MJ kg}^{-1}$) (Figure 2; Table 1). Tomatoes and potatoes had lower lighting requirements than wheat, while having much higher yields per CEA building than both wheat and soybeans (Table 1; Supplementary Table 2). GH had lower MJ kg^{-1} for all crops and in all regions, but with greater variability driven by geographic and seasonal climatic influences. Energy demand per m^2 growing area and per CEA-building follow similar full-year versus 9-month trends, but vary across crops. Soybeans required the least energy per m^2 of growing area and per CEA-building (GH: $2\text{--}4 \text{ GWh}$, VF: $4\text{--}5 \text{ GWh}$), followed by tomatoes (GH: $2\text{--}5 \text{ GWh}$, VF: $6\text{--}8 \text{ GWh}$), potatoes (GH: $2\text{--}6 \text{ GWh}$, VF: $6\text{--}9 \text{ GWh}$), and wheat (GH: $3\text{--}9 \text{ GWh}$,

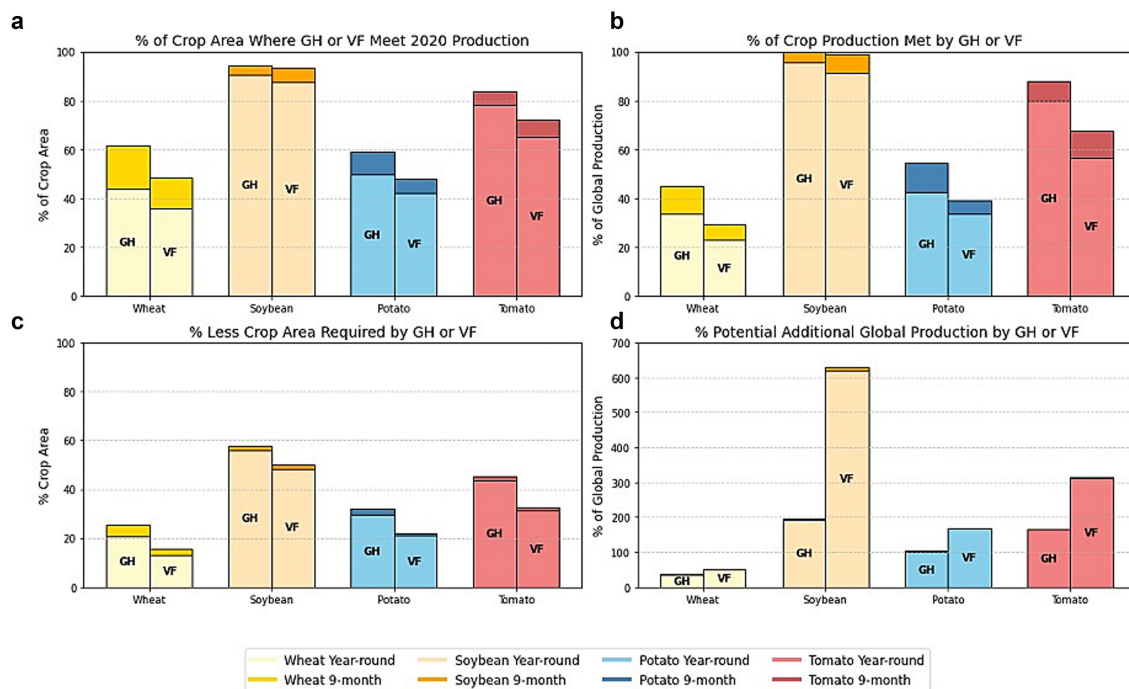


FIGURE 4

Modeled high-tech closed greenhouse ("GH") or vertical farm ("VF") ability to match 2020 production levels aggregated globally. The areas or production levels (% of global area or production) are plotted by crop and system (GH or VF), with both the year-round (12-month) and 9-month cycles included in each. (a) the percent of global crop area where CEA systems match 2020 production levels, (b) the percent of global crop production matched by CEA-PV, (c) how much less crop area required by the CEA-PV systems as a percent of global crop, and (d) the percent of global production that could be added by forgoing land savings and developing CEA and PV on these savings.

VF:11–15 GWh) (Figure 2; Table 1; Supplementary Figure 4). Among the study crops, soybeans had the lowest lighting requirements, which led to lower overall growing space energy needs. The VF energy used varied little between 12- and 9-month utilization, but the PV area required to fully power either CEA can vary greatly and thus, we included a 9-month production period for both. From a production perspective, this reduction would be counterintuitive to the full utilization of a high-cost VF; however, but here it provided a means of evaluating the seasonal challenges of off-grid CEA-PV systems.

The 2020 production output ($t\ km^{-2}$) was calculated per grid cell within the harvest area (ha) for each crop globally, followed by the calculation of the equivalent CEA building area needed to match that production (Supplementary Figure 2). Within each grid cell, the required CEA building area and energy demand determined the PV area (ha) needed and, thus, the resulting total CEA-PV area requirements (as the sum of PV area and CEA building area). The PV area needed to power the CEA ranged from less than 1 ha PV area per 1 ha CEA to a ratio of well over 100:1 (i.e., more area than the entire grid cell) (Supplementary Figure 6). The difference between the CEA-PV and 2020 production areas resulted in an area balance, which was either negative (CEA-PV needed more area than the available 2020 production area in that cell) or positive (CEA-PV matched 2020 production output within this area). In our assessment, both the VF and GH were technically able to match simulated equivalent levels of 2020 production output at varying capacities depending on the crop, area, and system. The GH consistently matched 2020 production levels on more cropland area than the VF (Figures 3, 4).

For wheat, the most energy-demanding crop, GH and VF equivalent capacities corresponded to 62 and 49% of global crop harvest

area, respectively. These areas represent up to 45 and 30% of global wheat production quantity (t). GH and VF demonstrated equivalent capacity on up to 59 and 48% of potato harvest area, with hotspots in South and East Asia, North and East Africa, and South America. This area corresponded to 54 and 39% of potato production, respectively. For tomatoes, GH and VF demonstrated equivalent capacity for up to 89 and 68% of production on 83 and 73% of harvest area, respectively, notably in S, E, and SE Asia and W Africa. Soybean had the highest modeled potential to match current production, with both GH and VF equivalent capacities accounting for up to 99% of production on 94% of the harvest area.

The GH demonstrated more widespread simulated equivalent capacity and lower land-area requirements compared to VF. For wheat, where GH and VF both demonstrated simulated capacity to match 2020 production levels, GH and VF required 26 and 16% less area globally compared to 2020 production. For soybeans, potatoes, and tomatoes, GH required 57, 32, and 45% less crop area than 2020 production, versus 50, 22, and 33% with VF. These lower land-area requirements are primarily in South and East Asia, North and South America, and North, West, and East Africa. (Supplementary Figures 7, 8).

However, the model was subsequently run to utilize all available cropland to maximize CEA-PV output and increase production beyond 2020 production levels in each grid cell. In this case of "surplus production," VF (4x yields per hectare compared to GH) produced more than GH at the global level, but not always regionally. For wheat, the VF produced up to an additional 51% of the global production quantity compared to 37% from the GH. For soybeans, potatoes, and tomatoes, both systems contributed additional production quantities exceeding current global

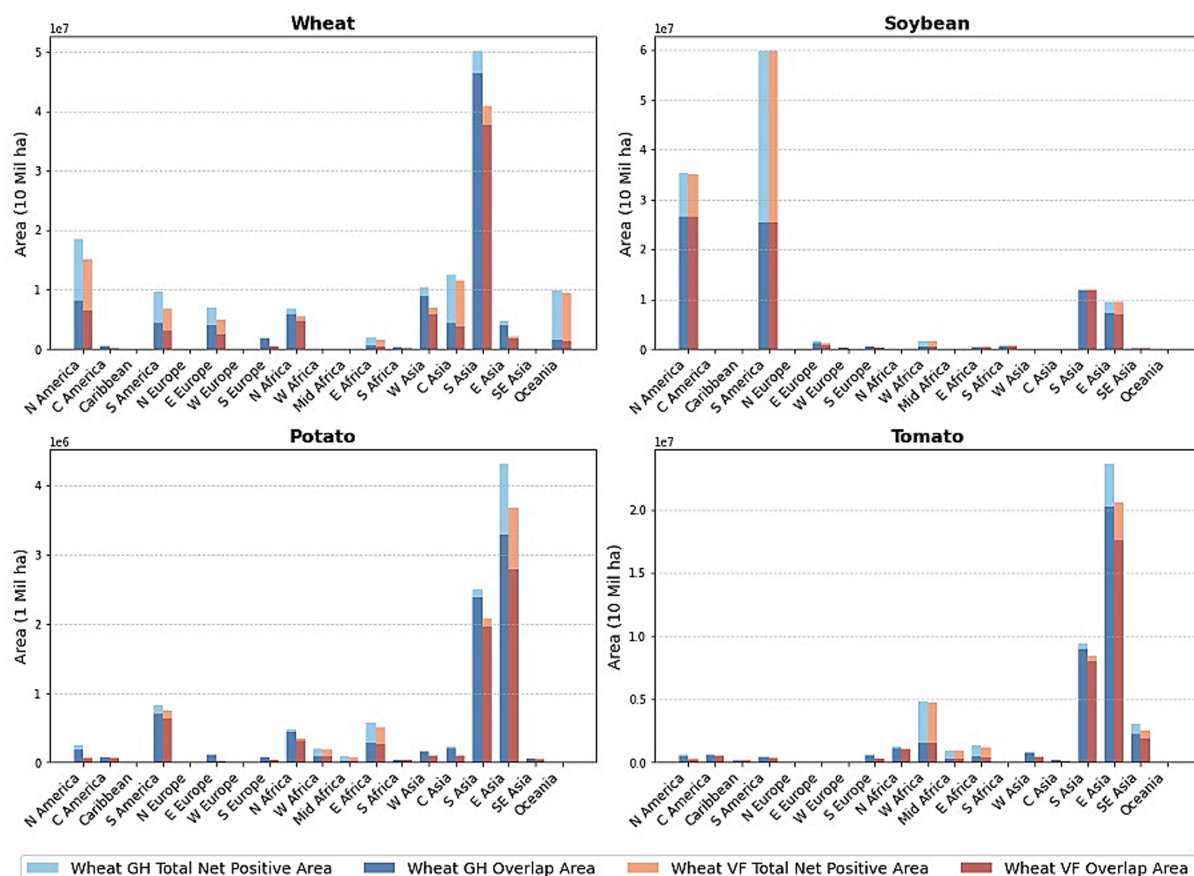


FIGURE 5

Regional electrical grid coverage in areas where modeled CEA–PV matched 2020 production levels. The spatial extent of the existing electrical grid (at least medium voltage) and a 2-km buffer were overlaid onto the output map of areas where the high-technology closed greenhouses (“GH”) and vertical farms (“VF”) match 2020 production levels. In these grid cells, the harvest area per crop was scaled and summed across each region. In the plots, light blue and red indicate the total area where CEA systems match 2020 production levels, while the darker colors indicate how much of that area falls within 2 km of these electrical grids.

totals, with the VF yielding higher surpluses (614, 164, and 298%) compared to the GH (190, 102, and 157%) (Supplementary Figures 7, 8).

While these CEA–PV systems were assumed to be self-reliant, a connection to electricity grids with at least medium voltage can indicate an immediate capacity for electrification (Figure 5; Supplementary Figure 9). The presence of electrical grids (Arderne et al., 2020) (within 2 km) on areas of CEA equivalent capacity varied both between and within crops and regions (Figure 5). For wheat, some areas with high CEA potential had lower grid presence, such as North and South America (44 and 46%), Eastern Europe (57%), Central Asia (35%), Oceania (15%), compared to higher coverage in Eastern, Western, and Southern Asia (85%, 86, and 93%), North Africa (88%), and Southern Europe (86%). For soybeans, South America (44%) showed lower grid presence than North America (75%), Eastern Asia (75%), and Southern Asia (98%). Potatoes and tomatoes followed similar regional trends with lower grid coverage in Eastern and Western Africa (37–51% and 32–47%) compared to North and South America (76–77% and 77–83%), Eastern and Southern Asia (76–86 and 95%), and Southern Europe (96%).

CEA–PV equivalent capacity decreased progressively under less favorable assumptions for CEA crop yields, energy demand, and PV conversion efficiency. The VF was generally more sensitive to changes compared to the GH (Figure 6, Supplementary Tables 5, 6,

Supplementary Figure 12). Across the four study crops, increasing CEA energy demand by 10, 25%, or 50% resulted in decreases in global crop equivalent area (year-round/9-month cycles) from 265/312 Mha for GH by 7/6 Mha, 18/15 Mha, and 37/31 Mha, respectively, compared to decreases in VF crop equivalent area from 234/270 Mha by 19/14 Mha, 42/39 Mha, and 68/82 Mha for VF (Supplementary Table 5). Reducing CEA crop yields by 10, 25%, or 50% resulted in decreases in GH global crop equivalent area (year-round/9-month cycles) by 7/6 Mha, 21/19 Mha, and 78/87 Mha, respectively, compared to decreases of 17/13 Mha, 44/44 Mha, and 96/116 Mha for VF. Decreasing PV conversion efficiency from 26.8 to 22% led to decreases in GH global crop equivalent area (year-round/9-month cycles) by 16/13 Mha and 37/32 Mha for VF.

The effects intensified when less favorable assumptions were combined. When CEA crop yield reductions were combined with energy demand increases of 10% each, GH crop equivalent area decreased compared to the baseline analysis by 15/12 Mha, compared to 34/30 Mha decreases for VF. Including PV efficiency reductions in this combination results in CEA–PV crop equivalent area decreases of 35/30 Mha for the GH and 64/77 Mha for VF. These combined reductions equated to decreases in global crop equivalent area of 8/7% for GH and 15/18% for VF compared to the reference 420-Mha total crop area (Supplementary Table 6). The 9-month production cycle generally retained greater equivalent

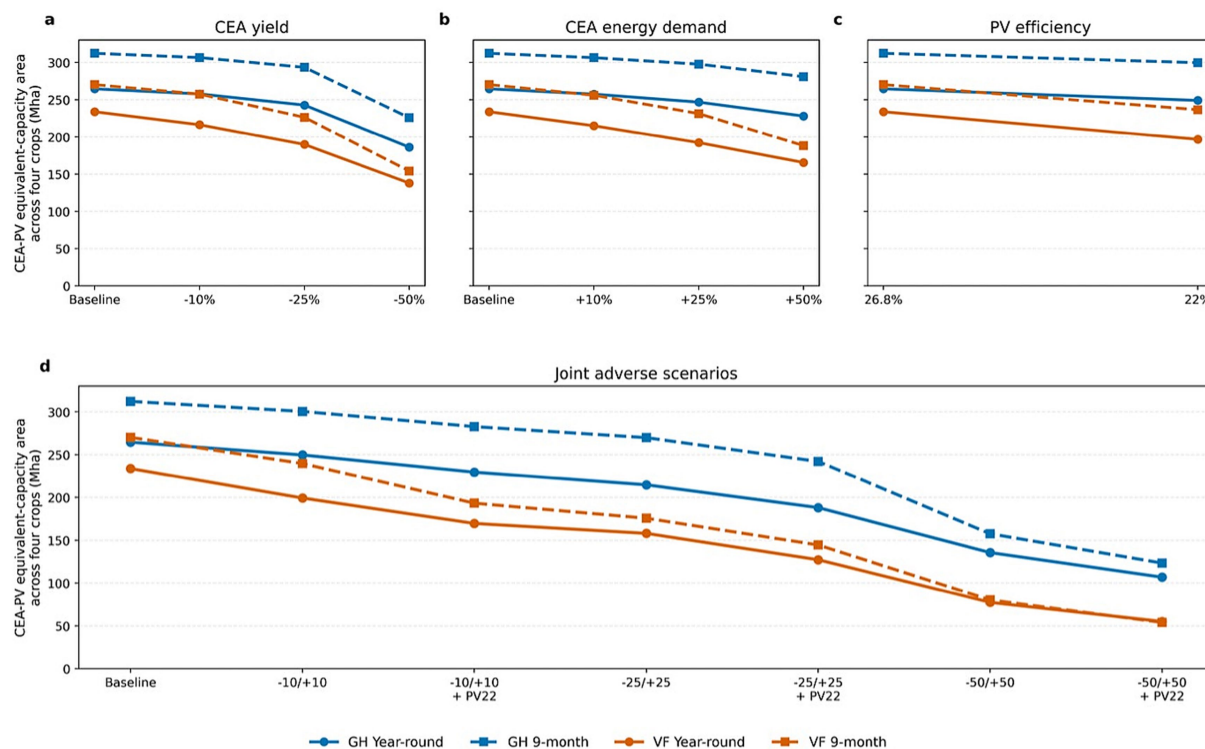


FIGURE 6

Sensitivity of CEA–PV equivalent capacity to model assumption changes. The summed crop harvest area across all four study crops where modeled CEA–PV could matched 2020 production without requiring additional land is shown for VF and GH under year-round and 9-month growing cycles under the main or “baseline” analysis and sensitivity scenarios. Individual sensitivity tests considered (a) CEA crop yield reductions by 10, 25, and 50%, (b) CEA energy demand increases by 10, 25, and 50%, (c) PV conversion efficiency reduction from 26.8 to 22%, and (d) joint adverse effects corresponding to CEA crop yield reductions and energy demand increases (–10%/+10%, –25%/+25%, –50%/+50%), with the baseline PV conversion efficiency and with the reduced 22% efficiency value. CEA–PV equivalent capacity is summed globally across the harvest area of the four crops (Mha).

capacity than year-round production, although this difference was substantially reduced for the VF under the most adverse combined assumptions.

4 Discussion

In this study, we presented a global model and framework for evaluating the widespread energy, land, and food production trade-offs associated with CEA implementation. The modeled CEA systems demonstrated the potential to match 2020 production levels on 313 Mha (GH) and 275 Mha (VF) of the total 420-Mha harvest area for the four crops. The GH consistently required less energy and land for energy production compared to the VF. There were no areas where the VF demonstrated equivalent capacity, and the GH did not. This pattern emerged despite the GH's greater variability in energy demand between regions. While the original CEA experiments used in the model apply directly to VF development, adapting and optimizing the GH to account for local conditions and constraints would likely lead to further gains over the VF, as Weidner et al. (2022) demonstrated. Conversely, VF (with four times the yield and higher energy demand relative to GH), had a higher potential to exceed global 2020 production quantities in areas where land availability and PV energy potential were greater. This concurs with the assertion of Asseng et al. (2020) that a more effective strategy for applying the technology would be to generate additional or complementary crop

production in target areas (e.g., near areas with high population centers or with high energy supplies), instead of directly replacing all croplands.

In both CEA systems, the energy requirements per building highlight the substantial energy demands and material resources associated with maintaining complete control over growing conditions. For perspective, global PV electricity supply in 2024 was estimated at 2,135 TWh (Masson et al., 2024) (1,000 GWh = 1 TWh). In comparison, the total energy demand for year-round soybean-equivalent VF capacity (88% of the harvested area) exceeded 262,777 TWh (Supplementary Figure 4). Global PV capacity grew 20-fold from 2013 to 2024 (Masson et al., 2024), but widespread CEA development would join a competitive pool of activities (transportation, residential, industrial) attempting to rapidly electrify with PV.

Although CEA yields were obtained from experimental research, the associated system components [e.g., building designs (Graamans et al., 2018; Badji et al., 2022), supplemental lighting (van Delden et al., 2021), PV efficiency (NREL, 2024), and air-source heat pumps (Shoukas et al., 2022)] reflect existing commercial technologies. We found that increases in technological efficiencies for LED lighting and heat pumps significantly lowered the energy demand in the VF by up to 25–30% per harvest weight compared to recent estimates by Righini et al. (2023). Heat pumps are often overlooked in greenhouse systems even though they are more efficient than traditional fossil-fuel-based HVAC systems (Shoukas et al., 2022; Badji et al., 2022). However, heat pumps have been included in previous CEA experiments and modeling studies such as those by Weidner et al. (2021, 2022).

Similarly, advances in PV technology (in this study, we applied NREL record silicon-PV efficiency of 26.8% (NREL, 2024)), reduce PV area requirements substantially compared with other studies that used lower efficiencies (20–21% (van Delden et al., 2021; Weidner et al., 2021)). Only silicon PV was included in our study, but other emerging forms of PV (e.g., multijunction or perovskite with 39% efficiency), demonstrate higher energy potential globally (Saxena et al., 2023). PV efficiency gains have led to cost [e.g., LCOE (IRENA, 2023; Way et al., 2022)] drops by over 88% since 2010 that are accompanied by a 26-fold increase in PV deployment (IRENA, 2023; Weinand et al., 2023). This rapid deployment of PV (along with other renewable energy and sustainable transition technologies) follows a pattern described by Wright's Law (Way et al., 2022). For CEA deployment to achieve a similar growth trajectory to PV, widespread energy and economic optimization relative to competing systems would be required (Kaiser et al., 2024).

When considering less favorable conditions for CEA crop yields, energy demands, and PV conversion efficiency, the VF demonstrated higher sensitivity to changes compared to GH. This resulted in the VF matching less of 2020 production across all individual scenarios with compounding reductions when adverse conditions were combined. As the main analysis represented upper-bound production and efficiency assumptions for CEA. Reductions in yield and energy efficiencies would be expected in commercial deployment and highlighting the need for site- and system-specific tailoring to buffer against less favorable conditions.

When evaluating the energy needed for CEA production, crops such as tomatoes (GH: 40–70 MJ kg⁻¹, VF:105 MJ kg⁻¹) and potatoes (GH: 44–92 MJ kg⁻¹, VF:132–133 MJ kg⁻¹) stand out. To maintain consistency when comparing to FAO statistics for crop production, the CEA values were expressed as harvested biomass (FAO, 2022). Other metrics such as dry weight, caloric content, protein, or other specific nutrients could also be applied when comparing different aspects of CEA. Although tomatoes and potatoes have higher water contents, their high biomass yield and high harvest index result in a greater dry weight per unit of yield than soybean and wheat (Righini et al., 2023). However, when considering total CEA building energy demand, soybeans (with relatively low light requirements) had the lowest energy consumption. Combined with the geographic distribution of global soybean cropland, this made soybean the highest performing CEA system in our study.

Commercial potato CEA continues to develop (Tunio et al., 2020; Kusnierek et al., 2023), but no commercial wheat or soybean CEA systems currently exist, with only experimental systems reported to date (Asseng et al., 2020; Righini et al., 2023, 2024). This lack of commercial development for these staple crops is likely the result of high up-front and running costs (e.g., energy) relative to low commodity prices for these crops (Bomford, 2023; Pattison et al., 2018; Stanghellini and Katzin, 2024). Wheat and potato CEA–PV technical capacity is found more in arid or semiarid areas compared to their overall harvest areas (Supplementary Figure 11). Similarly, Tong et al. (2024) found that the greenhouse sector (including all types of greenhouses classified as CEA) is clustering in arid and semi-arid areas. Global greenhouse area cover is currently over 1.3 Mha globally (primarily in China, the Mediterranean, and Mexico). These greenhouses mostly produce a range of fruits, vegetables, and other plant products that supply local and export markets (Tong et al., 2024). In addition, the process of moving tomatoes

and other vegetables into high-tech systems such as CEA is already underway (Costa and Heuvelink, 2018).

In particular, China accounts for 60% of the global greenhouse area. Within China, greenhouse production has focused on connecting peri-urban and rural fruit and vegetable producers with domestic urban markets (Tong et al., 2024). PV development is following a similar trend in China. The country accounts for over 42% of installed global PV capacity (Masson et al., 2024), 60% of additional global capacity under construction (Masson et al., 2024; IEA, 2024) and 80% of the global PV supply chain (IEA, 2024). Although PV and CEA growth are not currently linked, integrating the two could accelerate CEA implementation. Whether or not this could serve as a strategy to meet China's domestic consumption demands, especially for imported crops [e.g., China imports 58% of the global soybean production (FAO, 2022)], requires local socioeconomic and environmental considerations.

The Mediterranean region in particular shows comparable potential for implementing CEA–PV when considering its high PV potential and current crop production systems. Major greenhouse clusters for exporting fresh vegetables have developed in countries such as Spain (with the largest greenhouse land cover in Europe), Morocco, Italy, and Turkey (FAO, 2022; Tong et al., 2024). At the same time, the world's leading wheat importer, Egypt (FAO, 2022), is looking for ways to meet its growing domestic demand (Asseng et al., 2018). In Northern Europe, the Netherlands has become one of the major vegetable producers for Europe through its use of greenhouses (FAO, 2022; Tong et al., 2024). This demonstrates the capacity of nations with limited available cropland area to utilize and scale-up high-tech farmland infrastructure (Fuchs et al., 2020).

Farmland electrification can contribute to sustainability in the global food system if powered by renewable energy in addition to reducing other environmental impacts. Electricity infrastructure near cropland may not be needed in all cases (e.g., for off-grid systems), but it serves as an indicator of an area's readiness for farmland electrification and potential CEA development. Some regions where CEA demonstrated equivalent capacity (e.g., wheat in Oceania, soybeans in South America) are characterized by large expanses of continuous cropland with limited electrical grid connectivity. Electrifying these areas for the sole purpose of CEA development may be neither feasible nor desirable for local producers and communities.

Regions with small and medium field sizes adjacent to human settlements (Arderne et al., 2020; Lesiv et al., 2019) (e.g., Southern Asia and North Africa) tended to have more grid coverage and may be more ready for CEA–PV development. However, as noted by Arderne et al. (2020) the presence of electrical grids does not guarantee access to farmers or producers. This aspect of CEA development is one of many factors required to ensure CEA sustainability within agricultural landscapes. Furthermore, the sensitivity analysis demonstrated that even slightly less favorable conditions could diminish the widespread technical feasibility of these CEA–PV systems, highlighting the importance of system design and site selection.

While we simplified CEA design to capture the main processes, CEA could be tailored to local growing conditions, renewable energy sources, and cultural preferences (e.g., Chinese or Dutch greenhouses). For example, we find that at higher latitudes, a 9-month

production cycle optimized seasonal PV potential and CEA energy demands (e.g., 18% of the global wheat area for GH). Furthermore, different designs are emerging, such as vertical farms with transparent facades (Graamans et al., 2020) to reduce reliance on supplemental lighting or greenhouses with integrated semi-transparent PV (Ravishankar et al., 2021) for self-produced energy and shading when needed.

The analysis utilized available experimental and crop production data to compare the modeled CEA capacities to current (2020) FAO production statistics, but this analytical framework could be adapted to different aspects of CEA. Other inputs outside of the scope of this study, such as nutrients, seeds, CO₂, labor, materials, and capital, could all play roles in widespread CEA deployment. CEA as described can use and recirculate inputs such as nutrients and water efficiently, but these systems would not be completely insulated from supply shortages or limitations that affect an area's agricultural system. CEA would then similarly be vulnerable to disruptions to the input supplies (Alexander et al., 2022; Ahvo et al., 2023). The modeled CEA in our study is assumed to use soilless growing media, so these CEA would be completely reliant on external inputs. Relying on a high degree of inputs and building materials would likely increase greenhouse gas emissions depending on the production methods of these components. Assessing CEA's impact on local or landscape emissions and the environment requires analysis of these trade-offs across site- and system-specific contexts.

It should also be noted that yields are not the only consideration for meeting food security goals. CEA may be in a position to address multiple food sustainability goals beyond increasing yields and available calories. In both urban and rural contexts, CEA may be a strategy for bringing diverse and culturally significant food to markets and producing crops (such as medicinal plants) that require consistent quality. In addition, closed CEA systems can reduce waste and minimize environmental impacts related to water, nutrient, and pesticide use.

In conclusion, both greenhouse and vertical farm CEA systems demonstrate widespread global potential capacities when powered only by their own PV arrays. When comparing production-land-energy trade-offs, GH stands out in its ability to match 2020 production levels, reduce land use, and adapt to local conditions better than VF. Many other factors are required to fully determine CEA feasibility (socioeconomic, financial, environmental, or geographic). In addition, CEA development alone cannot solve many pressing challenges in the global food system (nutrient limitations, equipment and labor shortages, supply chain disruptions). For future research, more data sharing and collaborations across research and commercial enterprises could help overcome data bottlenecks currently seen in the relatively few published experiments across crop types and growing systems.

Data availability statement

The data files and code needed to replicate the study and analyses are available in the Zenodo repository at DOI: [10.5281/zenodo.14921975](https://doi.org/10.5281/zenodo.14921975). All other supporting data are included within the article, online methods, and [Supplementary materials](#). Additional data, code, or clarifications are available upon request from the corresponding author, Spencer A. Roberts (spencer.roberts@kit.edu).

Author contributions

SR: Writing – review & editing, Methodology, Software, Data curation, Writing – original draft, Investigation, Visualization, Validation, Formal analysis, Conceptualization, Project administration. KW: Writing – review & editing, Data curation, Methodology, Investigation. MR: Conceptualization, Resources, Project administration, Methodology, Investigation, Funding acquisition, Writing – review & editing, Supervision. AS: Methodology, Investigation, Data curation, Writing – review & editing. LM: Validation, Writing – review & editing, Data curation, Conceptualization, Methodology. RF: Resources, Funding acquisition, Methodology, Writing – review & editing, Conceptualization, Investigation, Supervision, Project administration.

Funding

The author(s) declared that financial support was received for this work and/or its publication. This study was made possible by funding from the Helmholtz Association Excellence Recruiting Initiative and a Karlsruhe Institute of Technology Recognition Grant.

Conflict of interest

The author(s) declared that this work was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Generative AI statement

The author(s) declared that Generative AI was not used in the creation of this manuscript.

Any alternative text (alt text) provided alongside figures in this article has been generated by Frontiers with the support of artificial intelligence and reasonable efforts have been made to ensure accuracy, including review by the authors wherever possible. If you identify any issues, please contact us.

Publisher's note

All claims expressed in this article are solely those of the authors and do not necessarily represent those of their affiliated organizations, or those of the publisher, the editors and the reviewers. Any product that may be evaluated in this article, or claim that may be made by its manufacturer, is not guaranteed or endorsed by the publisher.

Supplementary material

The Supplementary material for this article can be found online at: <https://www.frontiersin.org/articles/10.3389/fsufs.2026.1945186/full#supplementary-material>

References

- Ahvo, A., Heino, M., Sandström, V., Chrisendo, D., Jalava, M., and Kumm, M. (2023). Agricultural input shocks affect crop yields more in the high-yielding areas of the world. *Nat. Food* 4, 1037–1046. doi: 10.1038/s43016-023-00873-z
- Alexander, P., Arneth, A., Henry, R., Maire, J., Rabin, S., and Rounsevell, M. D. A. (2022). High energy and fertilizer prices are more damaging than food export curtailment from Ukraine and Russia for food prices, health and the environment. *Nat. Food* 4, 84–95. doi: 10.1038/s43016-022-00659-9
- Alexander, P., Rounsevell, M. D. A., Dislich, C., Dodson, J. R., Engström, K., and Moran, D. (2015). Drivers for global agricultural land use change: the nexus of diet, population, yield and bioenergy. *Glob Environ Change* 35, 138–147. doi: 10.1016/j.gloenvcha.2015.08.011
- Arcasi, A., Mastrullo, R., Mauro, A. W., and Pantaleo, A. M. (2022). State of the art of evapotranspiration models for plant cultivation in open fields, greenhouse systems and plant factories. *J. Phys. Conf. Ser.* 2385:012002. doi: 10.1088/1742-6596/2385/1/012002
- Arderne, C., Zorn, C., Nicolas, C., and Koks, E. E. (2020). Predictive mapping of the global power system using open data. *Sci. Data* 7:19. doi: 10.1038/s41597-019-0347-4
- Asseng, S., Guarin, J. R., Raman, M., Monje, O., Kiss, G., Despommier, D. D., et al. (2020). Wheat yield potential in controlled-environment vertical farms. *Proc. Natl. Acad. Sci.* 117, 19131–19135. doi: 10.1073/pnas.2002655117
- Asseng, S., Kheir, A. M. S., Kassie, B. T., Hoogenboom, G., Abdelaal, A. I. N., Haman, D. Z., et al. (2018). Can Egypt become self-sufficient in wheat? *Environ. Res. Lett.* 13:094012. doi: 10.1088/1748-9326/aada50
- Badji, A., Benseddik, A., Bensaha, H., Boukhelifa, A., and Hasrane, I. (2022). Design, technology, and management of greenhouse: a review. *J. Clean. Prod.* 373:133753. doi: 10.1016/j.jclepro.2022.133753
- Bomford, M. (2023). More bytes per acre: do vertical farming's land sparing promises stand on solid ground? *Agric. Hum. Values* 40, 879–895. doi: 10.1007/s10460-023-10472-0
- Boogaard, H., Schubert, J., De Wit, A., Lazebnik, J., Hutjes, R., and Van der Grijn, G. (2020). *Agrometeorological Indicators from 1979 to Present Derived from Reanalysis*. Copernicus Climate Change Service (C3S) Climate Data Store (CDS). doi: 10.24381/cds.6c68c9bb
- Costa, J. M., and Heuvelink, E. (2018) The global tomato industry. In: *Tomatoes*. p. 1–26. (Crop Production Science in Horticulture). Available online at: <https://www.cabidigitallibrary.org/doi/abs/10.1079/9781780641935.0001> (accessed January 31, 2025)
- Cowan, N., Ferrier, L., Spears, B., Drewler, J., Reay, D., and Skiba, U. (2022). CEA systems: the means to achieve future food security and environmental sustainability? *Front. Sustain. Food Syst.* 6:891256. doi: 10.3389/fsufs.2022.891256
- FAO. (2022). FAOSTAT: Crops and livestock products. Available online at: <https://www.fao.org/faostat/en/#data/QCL>. Licence: CC-BY-4.0. (Accessed January 28, 2024).
- Fischer, G., Nachtergaele, F., van Velthuisen, H., Chiozza, F., Franceschini, G., Henry, M., et al. *Global Agro-Ecological Zones (GAEZ v4) Model Documentation*. Rome: FAO & IIASA. (2021). p. 303. Available online at: https://pure.iiasa.ac.at/id/eprint/17175/1/GAEZ4_model_documentation+app_20210415_withFAOstyles_covers.pdf (Accessed January 5, 2024).
- Foley, J. A., DeFries, R., Asner, G. P., Barford, C., Bonan, G., Carpenter, S. R., et al. (2005). Global consequences of land use. *Science* 309, 570–574. doi: 10.1126/science.1111772
- Fuchs, R., Alexander, P., Brown, C., Cossar, F., Henry, R. C., and Rounsevell, M. (2019). Why the US–China trade war spells disaster for the Amazon. *Nature* 567, 451–454. doi: 10.1038/d41586-019-00896-2
- Fuchs, R., Brown, C., and Rounsevell, M. (2020). Europe's green Deal offshores environmental damage to other nations. *Nature* 586, 671–673. doi: 10.1038/d41586-020-02991-1
- Gerber, J. S., Ray, D. K., Makowski, D., Butler, E. E., Mueller, N. D., West, P. C., et al. (2024). Global spatially explicit yield gap time trends reveal regions at risk of future crop yield stagnation. *Nat. Food* 5, 125–135. doi: 10.1038/s43016-023-00913-8
- Graamans, L., Baeza, E., van den Dobbelaert, A., Tsafaras, I., and Stanghellini, C. (2018). Plant factories versus greenhouses: comparison of resource use efficiency. *Agric. Syst.* 160, 31–43. doi: 10.1016/j.agry.2017.11.003
- Graamans, L., Tenpierik, M., Van Den Dobbelaert, A., and Stanghellini, C. (2020). Plant factories: reducing energy demand at high internal heat loads through façade design. *Appl. Energy* 262:114544. doi: 10.1016/j.apenergy.2020.114544
- Hay, R. K. M. (1995). Harvest index: a review of its use in plant breeding and crop physiology. *Ann. Appl. Biol.* 126, 197–216. doi: 10.1111/j.1744-7348.1995.tb05015.x
- Heino, M., Kinnunen, P., Anderson, W., Ray, D. K., Puma, M. J., Varis, O., et al. (2023). Increased probability of hot and dry weather extremes during the growing season threatens global crop yields. *Sci. Rep.* 13:3583. doi: 10.1038/s41598-023-29378-2
- Hertel, T. W. (2016). Food security under climate change. *Nat. Clim. Chang.* 6, 10–13. doi: 10.1038/nclimate2834
- Hoff, J. E., Howe, J. M., and Mitchell, C. A. (1982) Nutritional and cultural aspects of plant species selection for a controlled ecological life support system. Report NASA-CR-166324. Available online at: <https://ntrs.nasa.gov/citations/19820016109> (Accessed September 9, 2025).
- IEA (2024). *Renewables 2023: Analysis and Forecast to 2028*. Paris: International Energy Agency, 143.
- IRENA (2023). *World Energy Transitions Outlook 2023: 1.5 °C Pathway*. Abu Dhabi: International Renewable Energy Agency.
- Jaureguiberry, P., Titeux, N., Wiemers, M., Bowler, D. E., Coscieme, L., Golden, A. S., et al. (2022). The direct drivers of recent global anthropogenic biodiversity loss. *Sci. Adv.* 8:eabm9982. doi: 10.1126/sciadv.abm9982
- Kaiser, E., Kusuma, P., Vialat-Chabrand, S., Folta, K., Liu, Y., Poorter, H., et al. (2024). Vertical farming goes dynamic: optimizing resource use efficiency, product quality, and energy costs. *Front. Sci.* 2:1411259. doi: 10.3389/fsci.2024.1411259
- Katzin, D., Van Henten, E. J., and Van Mourik, S. (2022). Process-based greenhouse climate models: genealogy, current status, and future directions. *Agric. Syst.* 198:103388. doi: 10.1016/j.agry.2022.103388
- Kobayashi, Y., Kotilainen, T., Carmona-Garcia, G., Leip, A., and Tuomisto, H. L. (2022). Vertical farming: a trade-off between land area need for crops and for renewable energy production. *J. Clean. Prod.* 379:134507. doi: 10.1016/j.jclepro.2022.134507
- Kusnerek, K., Heltoft, P., Møllerhagen, P. J., and Woznicki, T. (2023). Hydroponic potato production in wood fiber for food security. *NPJ Sci Food* 7:24. doi: 10.1038/s41538-023-00200-7
- Lesiv, M., Laso Bayas, J. C., See, L., Duerauer, M., Dahlia, D., Durando, N., et al. (2019). Estimating the global distribution of field size using crowdsourcing. *Glob. Change Biol.* 25, 174–186. doi: 10.1111/gcb.14492
- Masson, G., de l'Epine, M., and Kaizuka, I. (2024). *IEA PVPS Trends in Photovoltaic Applications 2024*. International Energy Agency Photovoltaic Power Systems Programme, 104 (Report IEA PVPS T1-43).
- Meyfroidt, P. (2018). Trade-offs between environment and livelihoods: bridging the global land use and food security discussions. *Glob. Food Secur.* 16, 9–16. doi: 10.1016/j.gfs.2017.08.001
- Mills, E. (2025). The emergence of indoor agriculture as a driver of global energy demand. *NPJ Sustain. Agric.* 3:52. doi: 10.1038/s44264-025-00091-z
- Mueller, N. D., Gerber, J. S., Johnston, M., Ray, D. K., Ramankutty, N., and Foley, J. A. (2012). Closing yield gaps through nutrient and water management. *Nature* 490, 254–257. doi: 10.1038/nature11420
- Nikolaou, G., Neocleous, D., Katsoulas, N., and Kittas, C. (2019). Irrigation of greenhouse crops. *Horticulturae* 5:1. doi: 10.3390/horticulturae5010007
- NREL. (2024) Popular NREL cell efficiency chart now better presents tandem photovoltaics. Available online at: <https://www.nrel.gov/news/detail/program/2024/popular-nrel-cell> (Accessed November 25, 2024)
- Nyström, M., Jouffray, J. B., Norström, A. V., Crona, B., Søgaard Jørgensen, P., Carpenter, S. R., et al. (2019). Anatomy and resilience of the global production ecosystem. *Nature* 575, 98–108. doi: 10.1038/s41586-019-1712-3
- Ortiz-Bobea, A., Ault, T. R., Carrillo, C. M., Chambers, R. G., and Lobell, D. B. (2021). Anthropogenic climate change has slowed global agricultural productivity growth. *Nat. Clim. Chang.* 11, 306–312. doi: 10.1038/s41558-021-01000-1
- Pamungkas, A. P., Hatou, K., and Morimoto, T. (2014). Evapotranspiration model analysis of crop water use in plant factory system. *Environ. Control. Biol.* 52, 183–188. doi: 10.2525/ecb.52.183
- Pattison, P. M., Tsao, J. Y., Brainard, G. C., and Bugbee, B. (2018). LEDs for photons, physiology and food. *Nature* 563, 493–500. doi: 10.1038/s41586-018-0706-x
- Popp, A., Calvin, K., Fujimori, S., Havlik, P., Humpenöder, F., Stehfest, E., et al. (2017). Land-use futures in the shared socio-economic pathways. *Glob. Environ. Change* 42, 331–345. doi: 10.1016/j.gloenvcha.2016.10.002
- Ravishanker, E., Charles, M., Xiong, Y., Henry, R., Swift, J., Rech, J., et al. (2021). Balancing crop production and energy harvesting in organic solar-powered greenhouses. *Cell Rep. Phys. Sci.* 2:100381. doi: 10.1016/j.xcrp.2021.100381
- Righini, I., Graamans, L., van Hoogdale, M., Carpineti, C., Hageraats, S., van Munnen, D., et al. (2024). Protein plant factories: production and resource use efficiency of soybean proteins in vertical farming. *J. Sci. Food Agric.* 104, 6252–6261. doi: 10.1002/jsfa.13458
- Righini, I., Stanghellini, C., Hemming, S., Graamans, L., and Marcelis, L. F. M. (2023). Resources for plant-based food: estimating resource use to meet the requirements of urban and peri-urban diets. *Food Energy Secur.* 12:e462. doi: 10.1002/fes3.462
- Salisbury, F. B., and Bugbee, B. (1988). Plant productivity in controlled environments. *HortScience* 23, 293–299
- Sanford, S. (2011). *Reducing Greenhouse Energy Consumption—An Overview*. Madison: Energy Effic Greenh (A3907-01).
- Saxena, A., Brown, C., Arneth, A., and Rounsevell, M. (2023). Modelling the global photovoltaic potential on land and its sensitivity to climate change. *Environ. Res. Lett.* 18:104017. doi: 10.1088/1748-9326/acf86f
- Searchinger, T., Waite, R., Hanson, C., and Ranganathan, J. (2019) Creating a sustainable food future: a menu of solutions to feed nearly 10 billion people by 2050 (Final Report). p. 564. Available online at: https://agritrop.cirad.fr/593176/1/WRP_Food_Full_Report_0.pdf (Accessed November 18, 2024).
- Shoukas, G., Bonnema, E., Paranjothi, G., Faramarzi, R., and Klun, L. (2022). Performance assessment of high efficiency variable speed air-source heat pump in cold climate applications. p. NREL/TP-5500-80802, 1847877, MainId:78580. Report NREL/TP-5500-80802,

1847877, MainId:78580. Available online at: <https://www.osti.gov/servlets/purl/1847877> (Accessed October 15, 2024)

Stanghellini, C., and Katzin, D. (2024). The dark side of lighting: a critical analysis of vertical farms' environmental impact. *J. Clean. Prod.* 458:142359. doi: 10.1016/j.jclepro.2024.142359

Tang, F. H. M., Nguyen, T. H., Conchedda, G., Casse, L., Tubiello, F. N., and Maggi, F. (2023). CROPGRIDS: a global geo-referenced dataset of 173 Crops Circa 2020. Available online at: <https://essd.copernicus.org/preprints/essd-2023-130/> (Accessed October 15, 2024)

Tilman, D., Balzer, C., Hill, J., and Befort, B. L. (2011). Global food demand and the sustainable intensification of agriculture. *Proc. Natl. Acad. Sci.* 108, 20260–20264. doi: 10.1073/pnas.1116437108

Tong, X., Zhang, X., Fensholt, R., Jensen, P. R. D., Li, S., Larsen, M. N., et al. (2024). Global area boom for greenhouse cultivation revealed by satellite mapping. *Nat. Food* 5, 513–523. doi: 10.1038/s43016-024-00985-0

Tsafaras, I., Campen, J. B., de Zwart, H. F., Voogt, W., Harbi, A. A., Assaf, K. A., et al. (2022). Quantifying the trade-off between water and electricity for tomato production in arid environments. *Agric. Water Manag.* 271:107819. doi: 10.1016/j.agwat.2022.107819

Tunio, M. H., Gao, J., Shaikh, S. A., Lakhiar, I. A., Qureshi, W. A., Solangi, K. A., et al. (2020). Potato production in aeroponics: an emerging food growing system in sustainable agriculture for food security. *Chil. J. Agric. Res.* 80, 118–132. doi: 10.4067/S0718-58392020000100118

van Delden, S. H., SharathKumar, M., Butturini, M., Graamans, L. J. A., Heuvelink, E., Kacira, M., et al. (2021). Current status and future challenges in implementing and upscaling vertical farming systems. *Nat. Food* 2, 944–956. doi: 10.1038/s43016-021-00402-w

Van Henten, E. J. (1994). *Greenhouse Climate Management: An Optimal Control Approach* Wageningen: Agricultural University. Available online at: <https://research.wur.nl/en/publications/79507e5f-af20-4b82-a0ec-754b395f5304> (accessed November 26, 2024)

Van Henten, E. J. (2003). Sensitivity analysis of an optimal control problem in greenhouse climate management. *Biosyst. Eng.* 85, 355–364. doi: 10.1016/S1537-5110(03)00068-0

Volk, T., and Rummel, J. D. (1989). Transpiration during life cycle in controlled wheat growth. *Adv. Space Res.* 9, 61–64. doi: 10.1016/0273-1177(89)90029-X

Way, R., Ives, M. C., Mealy, P., and Farmer, J. D. (2022). Empirically grounded technology forecasts and the energy transition. *Joule* 6, 2057–2082. doi: 10.1016/j.joule.2022.08.009

Weidner, T., Yang, A., Forster, F., and Hamm, M. W. (2022). Regional conditions shape the food–energy–land nexus of low-carbon indoor farming. *Nat. Food* 3, 206–216. doi: 10.1038/s43016-022-00461-7

Weidner, T., Yang, A., and Hamm, M. W. (2021). Energy optimisation of plant factories and greenhouses for different climatic conditions. *Energy Convers. Manag.* 243:114336. doi: 10.1016/j.enconman.2021.114336

Weinand, J. M., Hoffmann, M., Göpfert, J., Terlouw, T., Schönauf, J., Kuckertz, P., et al. (2023). Global LCOEs of decentralized off-grid renewable energy systems. *Renew. Sust. Energ. Rev.* 183:113478. doi: 10.1016/j.rser.2023.113478

Wheeler, R. M., Sager, J. C., Prince, R. P., Knott, W. M., Mackowiak, C. L., Stutte, G. W., et al. (2003). *Crop Production for Advanced Life Support Systems—Observations from the Kennedy Space Center Breadboard Project* (NASA/TM–2003-211184) Florida: Kennedy Space Center.

Winkler, K., Fuchs, R., Rounsevell, M., and Herold, M. (2021). Global land use changes are four times greater than previously estimated. *Nat. Commun.* 12:2501. doi: 10.1038/s41467-021-22702-2

Zomer, R. J., Xu, J., and Trabucco, A. (2022). Version 3 of the global aridity index and potential evapotranspiration database. *Sci. Data* 9:409. doi: 10.1038/s41597-022-01493-1