

Food, Energy, and Health Implications of Agrivoltaic Farms

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Abstract

The societal benefits of agrivoltaics are well supported, with ample empirical evidence for their suitability for collocated energy generation, crop cultivation, and water savings, even for staple crops. What is lacking is a holistic modeling framework to design and optimize AV systems for specific crop types, micro-environments, and panel configurations. To this end, a multiphysics model that solves momentum, energy, and mass exchanges among interacting components, and determines the implications of AV on photosynthesis, power generation, and worker thermal comfort, is introduced. The model is tested against field data from California, and Minnesota. Its applications are illustrated for a representative AV scenario using weather data from central New Jersey, showcasing the multifaceted benefits of AV for a tomato farm under photovoltaic panels. In this scenario, the model predicts a 5.6 °C reduction in average daytime panel temperature (compared to a regular PV installation), reducing overheating-related energy losses by 15.2%. Despite a 47% reduction in light for the setup modeled here, net carbon assimilation declined only by 31%. Daytime crop leaf temperature declined by 1.84 degC, and these reductions offset some of the decline in carbon assimilation. Another benefit is the reduction in transpiration losses by 22.4% compared to an open crop field. Finally, the average perceived temperature experienced by workers improves by approximately 5.2 degC during working hours. While these are illustrative results for a particular crop and climate, they demonstrate how the model enables integrated assessment and optimization of agrivoltaic benefits across varying climates, crops, and PV technologies.

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Key Points:

- This paper develops a model that simulates microclimate, crop growth, and is the first to assess worker comfort in agrivoltaic farms.
- In the studied design and conditions, agrivoltaics cooled crops, panels, and workers while saving water and boosting power output
- The model supports design and optimization of agrivoltaics across various climates, crops, panel array designs, and technologies.

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Abstract

The societal benefits of agrivoltaics are well supported, with ample empirical evidence for their suitability for collocated energy generation, crop cultivation, and water savings, even for staple crops. What is lacking is a holistic modeling framework to design and optimize AV systems for specific crop types, micro-environments, and panel configurations. To this end, a multiphysics model that solves momentum, energy, and mass exchanges among interacting components, and determines the implications of AV on photosynthesis, power generation, and worker thermal comfort, is introduced. The model is tested against field data from California and Minnesota. Its applications are illustrated for a representative AV scenario using weather data from central New Jersey, showcasing the multifaceted benefits of AV for a tomato farm under photovoltaic panels. In this scenario, the model predicts a 5.6 °C reduction in average daytime panel temperature (compared to a regular PV installation), reducing overheating-related energy losses by 15.2%. Despite a 47% reduction in light for the setup modeled here, net carbon assimilation declined only by 31%. Daytime crop leaf temperature declined by 1.84 °C, and these reductions offset some of the decline in carbon assimilation. Another benefit is the reduction in transpiration losses by 22.4% compared to an open crop field. Finally, the average perceived temperature experienced by workers improves by approximately 5.2 °C during working hours. While these are illustrative results for a particular crop and climate, they demonstrate how the model enables integrated assessment and optimization of agrivoltaic benefits across varying climates, crops, and PV technologies.

Plain Language Summary

Agrivoltaic farms combine solar energy production with crop cultivation, but real-world experiments often give mixed results because outcomes depend on crop type, panel layout, and local climate. We developed a computer model to simulate the microclimate beneath solar panels by tracking heat and air movement, water losses, crop growth, and worker comfort. Applied to a hot summer day in New Jersey, the model compared AV farming with open cropland and solar panels over bare soil. It showed that AV systems cooled crop leaves by up to 1.84 °C, lowering water loss by 22.4 %. Crop mass gain dropped by only 31 %, despite a 47% drop in light. Panels cooled by 5.6 °C, preventing overheating efficiency losses by 15.2 %. The combined effects of crops and panels reduced heating of the air, limiting local warming. At the same time, worker comfort improved dramatically, with working hours mean perceived temperature falling from 46.76 °C to 41.55 °C. This modeling tool helps farmers, engineers, and policymakers design AV systems that balance energy production, food yields, water conservation, and worker safety across diverse crops, climates, and solar technologies.

1 Introduction

Meeting future energy and food demands presents an escalating challenge that is yet to be resolved. Global electricity demand is projected to increase by 3500 TWh between 2022 and 2027 (International Energy Agency, 2024), with further growth driven by population expansion, elevated lifestyle standards, industrial activity, electrification, data centers, and electric vehicle adoption (U.S. Energy Information Administration, 2021; International Energy Agency, 2024; Xu, Lin, et al., 2025), as well as climate change and extreme events (De Cian & Sue Wing, 2017; Xu et al., 2024; Xu, Zeng, et al., 2025). Clean energy deployment must accelerate to meet net-zero targets with photovoltaics (PV) projected to become the dominant electricity source by 2050 due to an 80% cost decline since 2010 (Luderer et al., 2021; International Energy Agency, 2024; H. Zhang et al., 2025). Food demand is also expected to rise by 56% in 2050 compared to 2010 (van Dijk et al., 2021), or up to 62% under high-emissions scenarios that exacerbate crop stress and food system disruptions (Hameed et al., 2019; Gholinia & Abbaszadeh, 2024). Because min-

imizing transmission and transportation losses is essential, both food and energy must increasingly be produced near cities—yet such plans are constrained by land scarcity, particularly as 68% of the global population is expected to live in urban areas by 2050 (United Nations Department of Economic and Social Affairs, 2018), drastically increasing the demand for space.

One potential approach to overcoming land availability constraints is the implementation of co-production and dual land-use practices. Among these, a particularly promising strategy involves the integration of photovoltaic (PV) panels within existing croplands—a concept known as agrivoltaics (AV). AV integrates a wide range of sustainable development goals (Cuppari, Fernandez-Bou, et al., 2024), aligns with growers’ aspirations (Cuppari, Branscomb, et al., 2024), and provides positive feedback loops on soil carbon (Krasner et al., 2024). Conceived in the early 1980s (Goetzberger & Zastrow, 1982), this strategy promises to de-escalate competition between solar energy generation and crop production for arable land. Such collocation of energy and food production on the same land, however, raises concerns regarding the allocation of sunlight between the respective systems (Ali Abaker Omer et al., 2022, 2025; Zainali et al., 2025; Krasner et al., 2024; Ma Lu et al., 2025). It is then necessary to optimize the design of such systems based on suitable crops and climate. To achieve this goal, a necessary question that must be addressed is: what are the mutual impacts among the components of an AV system, and how do interactions between panels, crops, and workers co-evolve?

Dupraz et al. (2011) introduced the Land Equivalent Ratio (LER) as a metric to compare the benefits of dual land use with those of separate monocultures. An LER exceeding unity indicates improved land use efficiency compared to conventional, single-use crop and photovoltaic (PV) systems. LER is defined as the sum of two ratios: the ratio of agrivoltaic crop yield to monoculture crop yield plus the ratio of agrivoltaic electricity to conventional PV electricity production. From the PV perspective, evaporative cooling from irrigated soil and crops can reduce panel temperatures, thereby mitigating overheating that reduces electric production efficiency, and increasing power generation (Barron-Gafford et al., 2019; Merheb et al., 2025). For crops, the outcomes may vary depending on the plant’s ontogenetic growth (photosynthetic mechanisms/pathways), background climate, and solar array design. Reducing overheating and evaporative losses can provide benefits for food production. In one experiment (Marrou et al., 2013) examining wheat, lettuce, and cucumber cultivated under 4-meter-high PV arrays tilted at 25° in alternating strips, minimal changes in crop yield were observed despite reduced sunlight. This empirical finding demonstrates that it is indeed possible to design such systems to produce a comparable amount of crop to a single agricultural land use.

The literature goes further and indicates that certain crops in specific climates can exhibit increased yields. For instance, wheat and potato in hot/dry climates (Weselek et al., 2021), chiltepin pepper and cherry tomato (Barron-Gafford et al., 2019), tomato (Roy & Ghosh, 2017), basil and beans in hot/dry climates (Barron-Gafford et al., 2025), olive in Mediterranean climate (Gatto et al., 2025), and lettuce (Marrou et al., 2013) are all candidates. Conversely, other conditions may be unsuitable for crop production under PVs, resulting in yield reductions. Celeriac and wheat during a normal growing season (Weselek et al., 2021), grass under severe shading (Armstrong et al., 2016), maize in warm and dry climate (Ramos-Fuentes et al., 2023), radish and radicchio during fall growing season in humid continental climate (New York State) (Sturchio et al., 2025), wheat in a tropical savanna climate (Prakash et al., 2025), and jalapeño peppers (Barron-Gafford et al., 2019) all experienced declines in yield. While shading from solar panels is often cited as a cause of yield reduction, it can also lower soil temperatures (Armstrong et al., 2016; Choi et al., 2023), effectively reducing evaporation and thereby conserving water (Barron-Gafford et al., 2019; McKuin et al., 2021; Scavo et al., 2021; Giudice et al., 2021; Jiang et al., 2022; Zainali et al., 2023; Barron-Gafford et al., 2025). This increased soil moisture retention can enhance yield, particularly during later growth stages

in arid climates (Hassanpour Adeg et al., 2018; Sturchio et al., 2022). Reductions in crop temperature can also reduce autotrophic respiration (when plants use part of their own organic matter to produce energy), which acts to reduce biomass growth. Additionally, PV panels can protect crops from a range of extreme weather events such as droughts and heat waves (Zainali et al., 2023; Pataczek et al., 2023) that are projected to become more frequent over the coming years (Begmohammadi et al., 2024; Madadgar & Moradkhani, 2013; Xu, Lin, et al., 2025), increasingly threatening food security (Hasegawa et al., 2021). Although these empirical studies (Barron-Gafford et al., 2019; Hassanpour Adeg et al., 2018; Marrou et al., 2013; Armstrong et al., 2016; Roy & Ghosh, 2017) provide insights, the findings are mixed and often case-specific and cannot be generalized across different crop types and climates. Given the impracticality of experimentally testing all possible crop–climate combinations under AV systems, broader design guidelines remain elusive.

To optimize design prior to installation, several modeling and simulation studies have been conducted. Some have focused solely on the distribution of radiation beneath PV arrays (Liu et al., 2018; Cascone et al., 2011; Goetzgberger & Zastrow, 1982; Shepard et al., 2022; Abidin et al., 2023; L. Zhang et al., 2025), while others — primarily biological in nature — have explored how manipulated light conditions and modified microclimates influence crop responses (Zhu et al., 2008; Hallik et al., 2009; Talbot et al., 2014; Camporese & Abou Najm, 2022; Prakash et al., 2023; Ma Lu et al., 2025). Although such studies may inform crop yield optimization strategies, they often overlook the impacts on power generation and workers’ comfort, making them unsuitable as design tools for multiobjective optimization. More critically, the reliability of yield predictions is limited, as they typically consider only a single aspect of the microclimate, most commonly light. A separate group of studies has employed high-fidelity Computational Fluid Dynamics (CFD) simulations to provide comprehensive insights into power production and microclimate conditions beneath PV systems (Zainali et al., 2023; Zainali, 2024; Williams et al., 2023). However, these models generally do not incorporate dynamic coupling with plant physiological responses, which can, in turn, influence the microclimate. Moreover, the case-specific nature of these simulations and their significant computational cost limit their broader applicability and render them impractical for large-scale optimization efforts. Despite growing evidence that chronic heat exposure adversely affects workers’ health (Cruz et al., 2025), the health and comfort of individuals working beneath PV panels also remain largely unexplored in the literature (Lepley et al., 2025). Working conditions under these installations may differ significantly from those in open agricultural fields, yet this distinction has received limited attention to date.

The existing literature, while informative, provides fragmented and mono-disciplinary insights into the impacts of AV systems, focusing separately on crop performance or power generation, and ignores thermal comfort implications. Such compartmental approaches are necessary but insufficient to capture the interdependent dynamics between crop growth, energy generation, water savings, and thermal comfort within an AV farm. These limitations underscore the need for an integrated understanding of the mutual interactions among all the key system components. To address this gap, a unified, physically-consistent, and dynamically-coupled model that incorporates exchanges of energy, momentum, and mass, alongside responsive crop physiology and a thermal comfort metric, is proposed. The framework is designed to be generalizable, extendable, and computationally efficient for broader applications across climatic and cropping conditions.

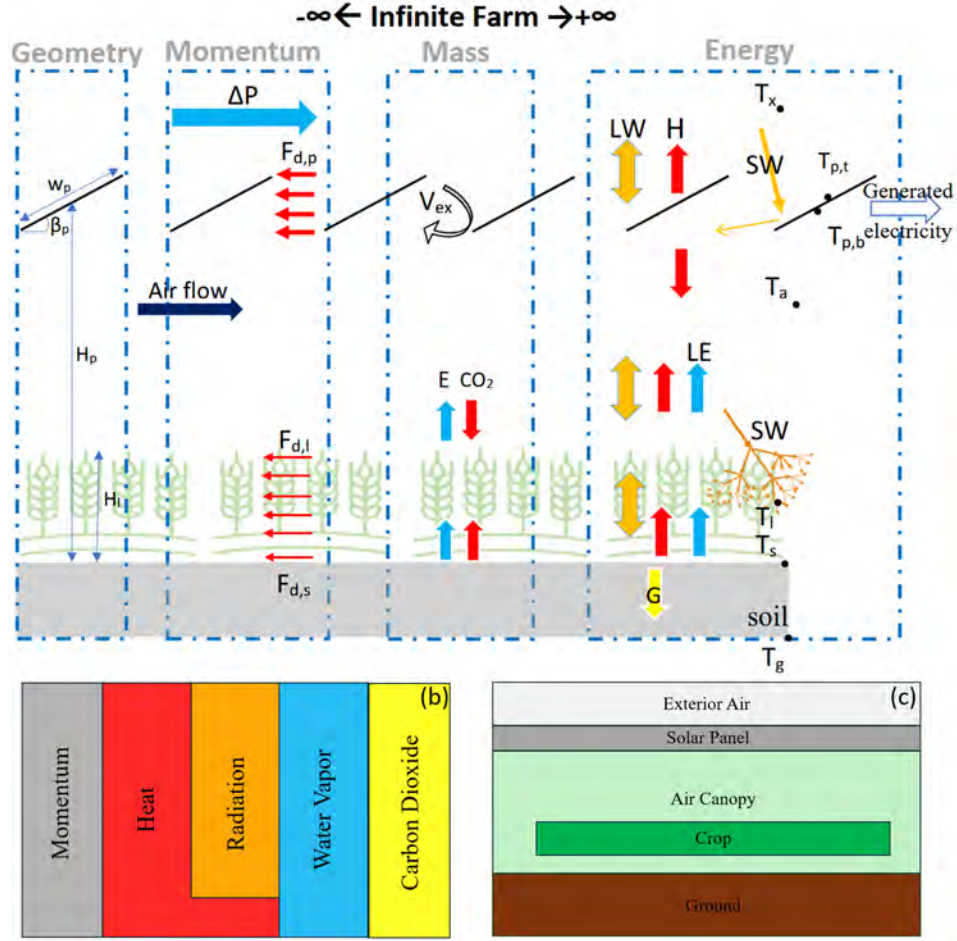


Figure 1. Overview of the key components and processes within the AV system. (top) Representation of the model domain, including all relevant system elements—PV panels, crops, ground surface, and sub-panel air canopy—and associated model parameters and geometrical features. Illustrated fluxes include momentum (pressure-gradient $-\partial P/\partial x$ and drag forces imposed by the panels $F_{d,p}$, the canopy $F_{d,l}$, and the soil $F_{d,s}$), energy (shortwave radiation SW , longwave radiation LW , sensible heat flux H , ground heat flux G , latent heat LE), mass (evaporation and transpiration of water vapor E , soil and crop CO_2 fluxes CO_2), and generated electrical power (P). Black circles denote key surface and air temperatures: ambient exterior (T_x), top and back of panel ($T_{p,t}$, $T_{p,b}$), sub-panel air (T_a), average leaf (T_l), soil surface (T_s), and deep ground (T_g). The $\pm$ symbols indicate that the farm is assumed to be sufficiently large in the horizontal direction, such that variations along the streamwise axis are negligible. As a result, the model can be considered essentially one-dimensional. (bottom left) Conceptual schematic of the principal transport phenomena: momentum exchange, energy exchange, and scalar exchanges of CO_2 and H_2O . (bottom right) Simplified representation of system components, showing the spatial arrangement of exterior air, panel, sub-panel air space, vegetation layer, and soil.

2 Methodology

To represent the AV microclimate, the coupled mean budgets of energy, horizontal momentum, and scalar mass (CO_2 and H_2O), along with crop physiological responses, are considered. The overall structure of the model is presented in Fig. 1 and the param-

eterizations of the associated budgets are described below. Further details, including the modeling of heat perception and additional parameterizations, are available in the SI. A Cartesian coordinate system is used and defines x as along the mean wind direction, y as the lateral direction, and z as the vertical direction, with $z = 0$ being the soil surface.

The farm is presumed to be sufficiently extensive and spatially homogeneous, with negligible horizontal inhomogeneities, aside from those related to radiation. More exactly, this means that the edge zones where the lateral boundaries are felt have a negligible area compared to the whole farm. With minor adjustments (e.g., prescribing surrounding ambient scalar concentrations and wind profiles), the model can also be applied to smaller farms; most modules remain valid except the wind and scalar parameterizations, which would then need modifications. The crop canopy is dense and horizontally uniform, characterized by a crop height H_l and leaf area density $a(z)$ (leaf area per canopy volume) that can vary with z . The $a(z)$ follows the integral property $LAI = \int_{z=0}^{z=H_l} a(z)dz$, where LAI is the leaf area index. The crop radiative, aerodynamic, and physiological properties are assumed to be known a priori for the target crop. The hydraulic and thermal properties of the underlying soil are also externally supplied. The variations in H_l and LAI are presumed to occur on time scales much longer than the simulated period (e.g., a few days), and they are thus kept constant during a given run.

The panel system is characterized by a panel width w_p , a panel inclination angle β_p , and a height of the panel center above the ground H_p . The thermal and radiative properties of the panels are presumed to be known from the manufacturer. The vertical extent of the computational domain is set at $6H_p$. In the x-direction (perpendicular to the panel length), spatial homogeneity can be assumed when averaging over one row, while in the y-direction (along the panel length), the domain is sufficiently long to ensure translational symmetry. Therefore, the equations solved are effectively averaged over a horizontal plane.

2.1 Momentum transfer

The mean wind field determines the panel and leaf convective cooling, and the aerodynamic conductance to the vertical exchanges of heat and mass — particularly carbon dioxide (CO_2) and water vapor (H_2O) — between the soil, vegetation, and overlying atmosphere. These exchanges modulate the overall energy balance of the system and the temperatures of various components, gas concentrations, and crop physiological processes. This subject is occasionally investigated through experiments and high-fidelity CFD simulations (Abiola-Ogedengbe et al., 2015; Baetu et al., 2013; Jubayer & Hangan, 2014, 2016; Williams et al., 2023; Reina & De Stefano, 2017; Aly & Bitsuamlak, 2013). Three-dimensional simulations are required when resolving panel-scale wake dynamics or quantifying aerodynamic parameters such as drag coefficients. However, their computational demands prevent their applicability to high-resolution analyzes of specific configurations and over extended periods, such as a growing season. For broader applications such as microclimate modeling and AV system optimization, where capturing key transport phenomena with reduced computational overhead is needed, a simplified formulation is used. The simplest formulation that we employ here is a one-dimensional simulation of the Reynolds-Averaged Navier-Stokes (RANS) equations. When adapted to represent conditions within the atmospheric boundary layer (ABL) and the system’s geometric layout, this approach can yield a reliable representation of vertical momentum transport and of the drag from the panels, vegetation, and soil — and can thus capture the highly variable wind speed in the system — all while maintaining reasonable computational speed.

To obtain first-order estimates of the wind profile within the AV system, a quasi-steady, horizontally averaged streamwise momentum balance is formulated. For an in-

compressible flow, the mean continuity and mean longitudinal momentum balance can then be expressed as

$$\frac{\partial \overline{\rho_a}}{\partial t} = -\frac{\partial \overline{w}}{\partial z} = 0; \quad \frac{\partial \overline{u}}{\partial t} = -\frac{1}{\overline{\rho_a}} \frac{\partial \overline{P}}{\partial x} - \frac{\partial}{\partial z} \overline{\tau_{zx}} - \frac{1}{\overline{\rho_a}} \overline{f_{d,p}} - \frac{1}{\overline{\rho_a}} \overline{f_{d,l}}, \quad (1)$$

where the overbar denotes Reynolds (time) averaging followed by spatial averaging over a local horizontal plane. No actual averaging is needed in the model since we solve for the mean equations, but conceptually, for RANS, the spatial averaging should be sufficiently large to accommodate many stems and leaves but smaller than the horizontal dimension of the farm. The corresponding time averaging should be over periods much larger than the integral scale of turbulence but much smaller than the time scale associated with diurnal variations. If comparing to observations, it is a common practice to set this time averaging period to 30 min (Charuchittipan et al., 2014), which is deemed as an acceptable compromise between the need to integrate over a large number of eddy turnover times and the need to resolve the diurnal variation of meteorological drivers such as photosynthetically active radiation (PAR) and other radiative loads throughout the day. The u and w represent the streamwise and vertical components of the wind velocity, respectively; t is time. The P denotes the mean pressure field, and $\overline{\rho_a}$ is the mean air density. The mean fluid continuity equation implies that $\overline{w}$ does not vary with z (through the turbulent component of w causes significant vertical mixing), which when combined with the approximation that the soil surface is a rigid impervious wall leads to $\overline{w} = 0$ throughout the domain. In reality, this assumption is an idealization that can be refined in the future by including pressure pumping and gas exchange within the soil-subcanopy system, as reviewed elsewhere (Massman & Frank, 2022). The left hand side of the mean momentum balance equation represents the local acceleration of the mean flow; the first term on the right hand side is the streamwise pressure gradient force; the second combines the turbulent and dispersive forces (the gradient of the total momentum transport τ_{zx}); here, the viscous stress is largely neglected (except in the formulation of the bottom boundary condition, as discussed later) due to the anticipated large Reynolds number of the atmospheric flows even in the first few meters above the surface. The drag forces per unit volume exerted by the panel structures and the crop canopy are denoted by $f_{d,p}$ and $f_{d,l}$, respectively. Before solving the equation, it is normalized by the time-varying velocity boundary condition at the top of the domain, which results in self-similar profiles at all times. The resulting normalized wind profile $\overline{u_n(z)}$ is then in a quasi-steady state, and the local normalized acceleration term is negligible $\partial \overline{u_n} / \partial t \approx 0$.

It is to be noted that density gradients or thermal stratification do not appear explicitly in the mean momentum balance, and thus buoyancy is neglected in the present version. This is reasonable since the various roughness elements generate significant shear turbulence, and the height is limited, which then results in close to neutral conditions within the AV farm. Stability corrections can be introduced for weak wind or strong heat flux conditions, but conventional Monin-Obukhov corrections cannot be used since the hot panels in fact create a stable stratification underneath, and thus more appropriate stability formulations need to be developed.

To close the momentum equation, K-theory (or eddy diffusivity theory) (Boussinesq, 1877) is employed, wherein turbulent+dispersive fluxes are assumed to be proportional to the mean gradient of the corresponding mean quantity, analogous to (very strong) molecular diffusion. While this is usually only used to represent turbulent (not dispersive) fluxes, it will be adopted here for the sum since turbulent fluxes are expected to dominate in dense canopies (Poggi & Katul, 2008) and since there are no practical models to separately parameterize the dispersive component for real AV canopies. Accordingly,

$$\overline{\tau_{zx}} = -K_m \frac{\partial \overline{u}}{\partial z}, \quad (2)$$

where K_m denotes the turbulent eddy viscosity, which may be represented using the Prandtl–von Kármán mixing length formulation (Prandtl, 1925) given by

$$K_m = L_m^2 \left| \frac{\partial \bar{u}}{\partial z} \right|, \quad (3)$$

L_m is the mixing length at a given location in the flow domain (independent of x), often referred to as the ‘master length scale’ (Mellor & Yamada, 1982). Its shape is constrained by the geometric setting and boundary conditions of the AV farm. Inside the canopy, the mixing length L_m is assumed to remain constant (Poggi et al., 2004; Katul et al., 2004). The details of the validation of the L_m model using multiple independent data sources, along with details of the coefficients, are provided in the SI.

Above the canopy, drawing on studies of neutral atmospheric boundary layers (Bou-Zeid et al., 2005), forest canopies (Zahn et al., 2024; Su et al., 1998), and solar power plant (Glick et al., 2020), the following parameterization for L_m is proposed for this study:

$$L_m(z, \beta) = \underbrace{\left(\frac{1}{k_g(\kappa(z - z_d))} + \frac{1}{k_e d_e + L_{e0}} + \frac{1}{L_{inf}} \right)^{-1}}_{\text{Harmonic Base}} + \underbrace{\frac{k_A \tan(\beta_p)}{|z - z_{peak}| + k_W}}_{\text{Panel Peak}}, \quad (4)$$

where κ is the von Kármán constant (≈ 0.41 , Kármán (1930)), and z the height from the ground. The parameter k_g represents the ground influence coefficient, while the zero-plane displacement height z_d is relevant for dense canopies with vertically uniform leaf area distribution and is typically approximated as $0.64 H_l$, following (Stanhill, 1969); a more detailed discussion of this displacement height is provided in the SI. The coefficient k_e , along with the offset L_{e0} , accounts for the influence of the panel edges, where d_e is the vertical distance from the nearest edge of the panel. The constant L_{inf} represents the far-field mixing length contribution, ensuring that the harmonic term asymptotically approaches a lower limit far above the panels. Based on the results from Glick et al. (2020), which we calibrated our mixing length model to match, we added the second term in the equation to capture the panel-induced peak enhancement. Here, k_A and k_W define the amplitude and width of this enhancement, respectively. The vertical height of the peak effect, z_{peak} , is given by $h_p + 0.2 w_p \sin(\beta_p)$, which corresponds approximately to 70% of the vertical projection of the panel width w_p .

The panel drag is parametrized using the quadratic drag law (Shademan et al., 2014):

$$\overline{f_{d,p}} = \frac{1}{2 s_p} c_{d,p} \overline{\rho_a} \overline{u} |\overline{u}| \Delta_{d,p}(z, H_p, \beta_p, w_p), \quad (5)$$

where s_p is the row-to-row spacing between panels; $c_{d,p}$ is a dimensionless drag coefficient (Shademan et al., 2014); and $\Delta_{d,p}$ is a panel drag indicator function to delineate the vertical extent of the panels. It is defined as:

$$\Delta_{d,p}(z, H_p, \beta_p, w_p) = \begin{cases} 1, & \text{if } H_p - \frac{1}{2} w_p \sin(\beta_p) < z < H_p + \frac{1}{2} w_p \sin(\beta_p) \\ 0, & \text{otherwise} \end{cases}. \quad (6)$$

The vegetated drag imposed on the flow is parametrized as:

$$\overline{f_{d,l}} = \frac{1}{2} c_{d,l} \overline{\rho_a} a(z) \overline{u} |\overline{u}| \Delta_{d,p}, \quad (7)$$

where $c_{d,l}$ is the crop canopy drag coefficient set to a mean value 0.4 (or 0.2 when the factor $1/2$ in $f_{d,l}$ is dropped, as conventional in the micro-meteorology literature (Katul et al., 2004)). The corresponding canopy drag indicator function $\Delta_{d,l}$ is defined as

$$\Delta_{d,l}(z, H_l) = \begin{cases} 0, & \text{if } z/H_l > 1 \\ 1, & \text{if } 0 < z/H_l \leq 1. \end{cases} \quad (8)$$

The details of numerical setup is discussed in the SI.

2.2 Energy transfer

This section details how the temperatures of individual elements and facets are determined as outcomes of radiative energy exchanges and heat transfer, and how this is linked to water evaporation and its latent heat. As shown in Fig. 1, the following elements are present within an AV farm: panels are considered to have three principal layers: the topmost glass layer with temperature $T_{p,t}$, the active layer with temperature $T_{p,c}$, and the back surface with temperature $T_{p,b}$. Crops are considered collectively as a single big leaf, behaving thermally as a single facet with temperature T_l . Unlike for momentum (and for carbon in the next section), where we resolve the fine-scale vertical variability, for heat and water vapor, we assume that the sub-panel air canopy is well-mixed with a vertically homogeneous T_a and q_a profiles. This is reasonable since all elements below the panels either emit or receive energy and water from the air at a given time of the day, which renders the profiles much less variable, and this also significantly simplifies the energy and radiative transfer calculations. The soil surface is represented by temperature T_s , and the deep ground by a constant temperature T_g . Each interface/facet is defined as an infinitesimally thin layer of solid with negligible thermal inertia, separating that solid from the surrounding air or from another solid layer. The ground and air are the only parts of the system assumed to have thermal inertia and an ability to store heat, while the panels and leaves are thin enough to be represented as a single interface (leaves) or 3 interfaces (panels) with zero thermal mass. Consequently, the coupled and closed energy budget equations of the system can be solved while ensuring that all elements exchange heat through the relevant modes (conduction, convection, and radiation), to compute the temperature of each facet at each time step and, in turn, the associated fluxes. For each facet, the energy balance is given by

$$\underbrace{[SW_{in} - SW_{out} + LW_{in} - LW_{out}(T)]}_{\text{Net radiative inputs} = R_n} = \underbrace{[H(T) + LE(T) + G(T) + P(T)]}_{\text{Energy partitioning outputs}}, \quad (9)$$

where R_n is the net radiation; T is the target surface temperature; SW_{in} denotes the incoming shortwave radiation incident upon the surface; SW_{out} represents the outgoing shortwave radiation, comprising both reflected and transmitted components; LW_{in} is the incoming longwave radiation originating from the atmosphere as well as from other elements within the surface's field of view; LW_{out} is the outgoing longwave radiation, including both reflection and emission; H is the sensible heat flux exchanged between the surface and the surrounding air; LE denotes the latent heat flux emitted from evaporating surfaces such as soil and crops (panels are assumed dry); G is the conductive heat flux transferred from the surface into the adjacent solid material (which may subsequently be stored as heat or conducted through the material); and P is the electrical power generated, which does not contribute to sensible heating of the panels (applicable only to PV panels).

The incoming shortwave radiation is parametrized as:

$$SW_{in} = VF_{sky} R_{sw,dif} + \cos(\gamma) R_{sw,dir} + \sum_{i=1}^n SW_{ref,i} VF_{i \rightarrow j}. \quad (10)$$

Here, VF_{sky} denotes the sky view factor of the element under consideration, $R_{sw,dif}$ the diffuse shortwave radiation incident upon the surface, γ the angle between the incident direct solar radiation and the surface unit normal vector, $R_{sw,dir}$ the direct beam radiation intensity (perpendicular to the rays), $SW_{ref,i}$ the reflected shortwave radiation from the i^{th} element, and $VF_{i \rightarrow j}$ the view factor from the i^{th} element to the j^{th} element under consideration. The details of the view factor parametrization and the shortwave radiation distribution are derived elsewhere (Hosseini & Bou-Zeid, 2025) and summarized in the Supporting Information (SI) for completeness.

The outgoing shortwave radiation is parametrized as:

$$SW_{out} = (\alpha + \tau) SW_{in}, \quad (11)$$

where α represents the shortwave reflectivity of the surface and τ denotes its transmissivity. For panel tops, panel backs, and soil surfaces, the transmitted and reflected shortwave radiation are determined by the intrinsic surface properties. In contrast, for crop canopies, photosynthesis necessitates a detailed representation of solar exposure, and both reflectivity and transmissivity depend on individual leaf properties, including reflectivity, leaf density, and orientation.

Light attenuation within the crop canopy is parameterized as (Campbell & Norman, 2000; Juang et al., 2008)

$$\tau_l(z) = \exp[-\xi K_{be}(x_o, \varphi) L(z)], \quad (12)$$

where τ_l is the fraction of photosynthetically active radiation (PAR) reaching a level z relative to PAR at $z/H_l = 1$; ξ is the clumping factor; K_{be} is the beam extinction coefficient, which depends on the solar zenith angle φ and the parameter x_o , defined as the ratio of the average projected area of leaves on the horizontal plane to that on the vertical plane (e.g., $x_o = \infty$ for horizontal leaves and $x_o = 0$ for vertical, while $x_o = 1$ for random distributions of leaf orientations (Campbell & Norman, 2000)); $L(z)$ denotes the cumulative leaf area index from the top of the canopy down to height z :

$$L(z) = \int_{H_l}^z a(z) dz. \quad (13)$$

Assuming azimuthal symmetry in the foliage area distribution, the beam extinction coefficient K_{be} for vegetation with an ellipsoidal leaf inclination distribution is given as (Campbell & Norman, 2000):

$$K_{be}(x, \varphi) = \frac{\sqrt{x_o^2 + \tan^2(\varphi)}}{x_o + 1.774(x + 1.182)^{-0.733}}. \quad (14)$$

The components of the longwave exchange for the j^{th} element are parametrized using the Stefan-Boltzmann law

$$LW_{in} = VF_{sky} LW_{sky} + \sum_{i=1}^n \varepsilon_i \sigma T_i^4 VF_{i \rightarrow j} + \sum_{i=1}^n LW_{ref,i} VF_{i \rightarrow j}, \quad (15)$$

$$LW_{out} = \varepsilon_j \sigma T_j^4 + (1 - \varepsilon_j) LW_{in}, \quad (16)$$

where ε_i denotes the longwave emissivity of the i^{th} object; σ is the Stefan-Boltzmann constant equal to $5.67 \times 10^{-8} \text{ (W m}^{-2} \text{ K}^{-4})$; T_i is the temperature of the i^{th} object; $LW_{ref,i}$ is the longwave radiation reflected from the i^{th} object; ε_j and T_j represent the emissivity and temperature of the j^{th} element under consideration, respectively. Note that (1-

ε_j) represents the longwave reflectivity according to Kirchhoff's law of thermal radiation.

The convective heat exchange with the air for each element is parameterized using a bulk heat transfer formulation, and is driven by the difference between the surface temperature (T) and the surrounding air temperature (T_a). Such bulk formulation also requires a heat-transfer coefficient (h) that depends on the surrounding flow regime, as well as the physical and geometrical properties of the element. Mathematically, this sensible heat flux is expressed as

$$H = h(T - T_a). \quad (17)$$

The heat transfer coefficient for panels (h_p), in configurations involving multiple arrays typical of PV plants — rather than a single panel — is parameterized following Smith et al. (2022). Their formulation introduces a PV site characteristic length scale known as the lacunarity length scale (L_l), derived from a fractal lacunarity approach and computed based on the spatial heterogeneity of the solar energy site. Further details on the definition and computation of the heat transfer coefficient, as well as that of the lacunarity length scale, are provided in the SI. This formulation leads to

$$h_p = 10^{0.09 Re_{L_l}^{1/5} Pr^{1/12} + 1.91}, \quad (18)$$

where k_a denotes the thermal conductivity of air ($k_a \approx 0.0263 \text{ W m}^{-1} \text{ K}^{-1}$) and $Pr = 0.71$ is the molecular Prandtl number of air at typical temperatures and pressures (Brutsaert, 1982). The heat transfer coefficient for vegetative surfaces can be expressed as:

$$h_l = \overline{\rho_a} c_p g_{a,h}, \quad (19)$$

where c_p is the specific heat capacity of dry air at constant pressure, and $g_{a,h}$ is the aerodynamic conductance for sensible heat transfer (in units of m s^{-1}), which is the inverse of the atmospheric conductance for sensible heat exchange, $g_{a,h}$, as parameterized in Campbell and Norman (1998) (see 2.3). The modeling of transpiration from the vegetation is described in the following two sub-sections, along with the associated carbon exchange and plant physiology models.

Building on the derivation presented by Bateni and Liang (2012), the sensible and latent heat transport from the soil surface to the sub-panel air canopy are modeled using the bulk aerodynamic formulation:

$$h_s = \overline{\rho_a} c_p C_H U, \quad (20)$$

where C_H is the bulk heat transfer coefficient, and U is the wind speed at the same reference height where the air temperature is taken. This reference height is taken as the mid-point of the below-panel air space, i.e., at $z = H_p/2$. The product $C_H U$ represents the thermal conductance and is defined as

$$C_H U = \left(\int_0^z \frac{1}{K_h} dz \right)^{-1}, \quad (21)$$

where K_h is the turbulent diffusivity for heat transport, given by $K_h = K_m / Pr_t$, where K_m is the turbulent viscosity as derived above in the momentum transfer section, and $Pr_t = 1$ is the turbulent Prandtl number.

Similarly, the latent heat flux from the soil surface is expressed as

$$LE_s = \lambda_v \overline{\rho_a} C_q U [q_s - q_a(z)], \quad (22)$$

where λ_v the latent heat of vaporization, q_s the specific humidity at the soil-air interface (or can alternatively be assumed equal to the saturated value at the soil surface temperature if the soil is fully wet), $q_a(z)$ is the specific humidity at height z above the surface, and C_q is the bulk transfer coefficient for moisture. Both heat and water vapor are scalar quantities transported by turbulent eddies. Under near-neutral atmospheric conditions, this transport is similar (Li & Bou-Zeid, 2011; Li et al., 2011), and it is thus reasonable to assume that $C_q = C_H$.

The portion of solar energy converted into electricity needs to be accounted for as a sink in the panel's active layers. Conventional silicon-based solar panels exhibit an energy conversion efficiency ranging from approximately 15% to 26% (M. Green et al., 2020; M. A. Green et al., 2024). However, this efficiency is defined under standard test conditions (STC), typically at a panel temperature of $T_{\text{STC}} = 25^\circ\text{C}$. According to data from NREL, panel efficiency decreases by approximately 0.2% to 0.5% per Kelvin of temperature rise above the STC threshold (King et al., 1997). Thus, the electrical power generated per unit area of panel may be described by

$$P = \eta_a SW_{p,\text{inc}} = \eta_n (1 - \delta (T_{p,c} - T_{\text{STC}})) SW_{p,\text{inc}}, \quad (23)$$

where η_a is the temperature adjusted conversion efficiency; $SW_{p,\text{inc}}$ is the incident short-wave radiation on the panel surface; η_n is the nominal efficiency of the panel under STC (provided by the manufacturer); and δ is the temperature coefficient of the PV panel (in K^{-1}).

To parameterize the heat conduction in solids (through panel layers or within the soil), a thermal force-restore model, also known as a resistance-capacitance (RC) model, is applied. In this model, the conductive heat flux is

$$G = \frac{T_1 - T_2}{R_x} + c_x \frac{d}{dt} (T_1 - T_2), \quad (24)$$

where T_1 and T_2 are the temperatures at the two boundaries of the solid layer; R_x is the thermal resistance of the material (e.g., soil or panel), and c_x its thermal capacitance. The resistance is defined as $R_x = d/k_x$, where d is the layer thickness and k_x is the thermal conductivity. The capacitance is defined as $c_x = C d$, where C is the volumetric heat capacity of the material. In cases where direct measurements of soil thermal conductivity and heat capacity are unavailable, they are estimated following the approach by Takebayashi and Moriyama (2007), which is presented in the SI and accounts for their dependence on moisture content. The formulation used to compute the characteristic extinction depth, of the diurnal temperature fluctuations, as proposed by Singh and Sharma (2017), is also detailed in the SI.

2.3 Mass transfer

As described in the previous subsection, the water vapor budget is treated using a lumped approach, as for sensible heat. However, to represent carbon transfer in the AV system, the mean scalar budget equation (i.e., time and planar-averaged) is employed, and resolved vertically using the same resolution as for momentum to capture the strong vertical variability in the carbon profiles (with intermixed sinks and sources) that will impact crop yield. The resulting CO_2 mass balance equation is thus given as

$$\frac{\partial \bar{\xi}}{\partial t} + \bar{u} \frac{\partial \bar{\xi}}{\partial x} + \bar{w} \frac{\partial \bar{\xi}}{\partial z} = -\frac{\partial \overline{w' \xi'}}{\partial z} + S_\xi, \quad (25)$$

where ξ denotes the CO_2 concentration; $\overline{w'\xi'}$ represents the turbulent flux of CO_2 ; primed quantities are, as before, perturbations from their respective means (and as with momentum, the smaller dispersive fluxes are lumped with the turbulent fluxes after applying spatial followed by time averaging); and S_ξ represents biologically controlled source or sink terms. In this version of the model, we will assume that the change in carbon storage in the air layer is negligible compared to the vertical fluxes, which then allows us to neglect the $\partial\bar{\xi}/\partial t$ term (this can be relaxed if needed). For a planar homogeneous flow ($\partial(\cdot)/\partial x = \partial(\cdot)/\partial y = 0$) and in the absence of subsidence, both advective transport terms on the left-hand side of the equation can also be ignored (as was the case for the mean momentum). Despite these simplifications, the resulting equation that balances fluxes and source and sinks of carbon remains mathematically unclosed, as it provides one equation with three unknowns: $\overline{w'\xi'}$, S_ξ , and $\bar{\xi}$, necessitating two other equations (or closure models).

The first closure model is based on analogies to how the mean momentum equation was treated, whereby $\overline{w'\xi'}$ can be described using K-theory (or first-order closure) so that

$$\overline{w'\xi'} = -K_\xi \frac{\partial \bar{\xi}}{\partial z}, \quad (26)$$

where K_ξ is the turbulent diffusivity of the scalar ξ and is parameterized directly from the eddy viscosity using

$$K_\xi = \frac{K_m}{Sc_t}, \quad (27)$$

with K_m defined in subsection 2.1, and Sc_t the turbulent Schmidt number. For consistency with the turbulent Prandtl number used for heat (which also applies for humidity), a constant $Sc_t = 1$ is adopted (though the variability of these numbers with atmospheric stability conditions and other variables can be easily accommodated).

The second closure models linking S_ξ to $\bar{\xi}$, which is also used for water transpiration from the plants and the air, require plant physiological processes operating at the leaf scale, and those processes must then be up-scaled to the layer-scale $a(z)$. They are canonically expressed as

$$S_\xi(z) = \frac{a(z)}{r_s(z) + r_{a,\xi}(z)} (\bar{\xi}_s(z) - \bar{\xi}_a(z)), \quad (28)$$

where $r_s(z)$ is the stomatal resistance; $r_a(z)$ is the aerodynamic resistance due to the presence of a laminar boundary layer attached to the leaf surface; and $\bar{\xi}_s$ and $\bar{\xi}_a$ are the mean surface and local atmospheric concentrations of ξ at z , respectively. The working assumption is that the exchange of scalars at any height z between leaves and the surrounding air encounters two resistances in series: an aerodynamic resistance and a stomatal resistance. The aerodynamic resistance is the inverse of the atmospheric conductance ($g_{a,\xi}$) and for leaves is given as (Campbell & Norman, 1998):

$$r_{a,\xi} = g_{a,\xi}^{-1} = A_{b,\xi} \sqrt{\frac{L_t}{u(z)}}, \quad (29)$$

where L_t represents the characteristic leaf length along the flow direction and $u(z)$ denotes the wind speed at z (modeled from the mean momentum balance as before). The coefficient $A_{b,\xi}$ depends on the scalar ξ . For carbon dioxide and water vapor, $A_{b,\xi} = 342$ and 255, respectively. Similarly, this equation can be used for aerodynamic resistance for heat transfer, and the coefficient is 307. Models for r_s are still needed to close the mass transfer formulation mathematically, and those closure schemes are considered next in the context of crop physiology, whereby when stomata open to uptake carbon dioxide, they lose water vapor molecules that must be replenished from the soil reservoir.

2.4 Crop physiology

Photosynthesis per unit leaf area is the primary term influencing crop yield. It is tightly coupled to leaf transpiration, which in turn, can modify the energy balance of the entire AV farm, including the cooling of the solar panels. As noted earlier, these carbon and water exchange processes are impacted by stomatal conductance at the leaf scale. To model stomatal conductance, a logical starting point is to consider the balance between the biochemical demand and the atmospheric supply of carbon dioxide. The biochemical demand is given by the Farquhar photosynthesis model (Farquhar et al., 1980; Collatz et al., 1991) for C3 plants. It parametrizes the net rate of CO₂ uptake at the leaf, denoted as A_n , as limited by three factors: the carboxylation capacity of Rubisco (A_{JC}), the regeneration capacity of RuBP (electron transport) (A_{JE}), and the triose phosphate utilization (TPU) rate (A_{JS}). That is,

$$A_n = \min \begin{cases} A_{JC} - R_d = \frac{V_m (C_{ci} - \Gamma^*)}{C_{ci} + K_c \left(1 + \frac{O_a}{K_o}\right)} - R_d, \\ A_{JE} - R_d = \frac{\alpha_p e_m Q_p (C_{ci} - \Gamma^*)}{\sqrt{1 + \frac{(e_m Q_p)^2}{J_{\max}^2}} (C_{ci} + 2\Gamma^*)} - R_d, \\ A_{JS} - R_d = \frac{V_m}{2} - R_d. \end{cases} \quad (30)$$

In this expression, V_m represents the maximum Rubisco carboxylation capacity per unit leaf area with species-specific values available in the literature (Wullshleger, 1993); C_{ci} denotes the intercellular concentration of CO₂; O_a denotes the atmospheric O₂ concentration; K_o and K_c are the Michaelis–Menten constants associated with inhibition by oxygen and CO₂, respectively, with typically values at 300 mmol mol⁻¹ for O₂ and 300 μmol mol⁻¹ for CO₂; Γ^* is the CO₂ compensation point and defines the concentration at which net CO₂ assimilation is zero; α_p denotes the leaf absorptivity in the PAR spectrum; e_m is the maximum quantum efficiency defined as the number of CO₂ molecules fixed per absorbed photon; Q_p is the incident PAR photon flux density (approximated as $Q_p \approx 0.43 \left[\frac{W_{\text{PAR}}}{W_{\text{SW}}} \right] \times 4.56 \left[\frac{\mu\text{mol}_{\text{PAR}}}{\text{J}_{\text{PAR}}} \right] \times SW [\text{W}/\text{m}^2] \approx 1.96 SW \left[\frac{\mu\text{mol}}{\text{m}^2 \cdot \text{s}} \right]$); R_d is the dark respiration and accounts for mitochondrial respiration occurring in the absence of light. Since many of these parameters are sensitive to temperature, modeling the leaf microclimate, which our model is capable of, is necessary. The detailed equations for these thermal responses are available in the SI.

The difference in CO₂ concentration across the leaf–air interface is modeled through a resistive formulation that includes stomatal and boundary layer attached to the leaf surface (as detailed in the previous subsection). The CO₂ mole fraction within the substomatal cavity, C_{ci} , is expressed in terms of the stomatal conductance (g_s) and net assimilation rate (A_n) as

$$C_{ci} = C_l - \frac{A_n}{g_s}, \quad (31)$$

where C_l is the CO₂ mole fraction at the leaf surface that can be derived from the atmospheric mole fraction C_a and boundary layer conductance g_b using

$$C_l = C_a - \frac{A_n}{g_b}. \quad (32)$$

The g_s can be modeled using several approaches. The most popular is the semi-empirical Ball–Berry model (Ball, 1988; Collatz et al., 1991), but modified to include vapor pressure deficit instead of surface relative humidity (Leuning, 1995). In its original form, it

is given as

$$g_s = m \frac{A_n RH_s}{C_s} + g_o \geq g_o. \quad (33)$$

The modification proposed here replaces relative humidity at the leaf surface (RH_s) by $1 - 0.6 \log(\text{VPD})$, with VPD denoting the vapor pressure deficit in the atmosphere near the leaf. This modification has received both empirical support (Oren et al., 1999) and theoretical grounding using stomatal optimality theories (Katul et al., 2009, 2010), whereby g_s was predicted based on the assumption that plants maximize their carbon gain for a given amount of water per unit leaf area in the soil. The constants m and b represent the slope and intercept (cuticular conductance) of the linear relation between g_s and A_n/C_s , respectively. Typical values based on experimental calibration are $m = 5.6$ and $g_o = 0.003 \text{ mol m}^{-2} \text{ s}^{-1}$, derived from gas exchange measurements under controlled conditions (Lai et al., 2000). Notably, cuticular evaporation can still occur in the absence of stomatal conductance. With this formulation for r_s , the scalar sources and sinks for carbon dioxide (S_c) and water vapor (S_v) are given by

$$S_c = \frac{a(z)}{r_s(z) + r_{a,c}} [C_{ci}(z) - C_a(z)]; S_v = \frac{a(z)}{(r_s(z)/1.6) + r_{a,v}} [e_s(z) - e_a(z)], \quad (34)$$

where $C_{ci}/C_a < 1$ and $e_s/e_a > 1$, the coefficient 1.6 normalizing r_s in S_v is due to the difference in molecular diffusion coefficients between carbon dioxide (heavier molecules) versus water vapor (lighter molecules); e_s is the saturation vapor pressure (or concentration) within the sub-stomatal cavity (assumed to be near saturation for well watered crops); e_a is the actual vapor pressure (or concentration) in the atmosphere adjacent to the leaves at height z . A number of approximations are invoked to efficiently determine e_s and e_a . For the purposes of estimating S_v , it is assumed that (i) the sub-stomatal cavity is fully saturated and in thermal equilibrium with the leaf surface so that e_s can be determined from leaf surface temperature T_s using the Clausius-Clayperon formulation (i.e. a closed system approximation), (ii) the air relative humidity variations with z within the canopy volume are, to a leading order, presumed to be small compared to the PAR variations so that relative humidity may be approximated by its value in the atmosphere near the canopy top. The model can be extended and refined to include a prediction of the profiles of air relative humidity, but prior analyses suggest this refinement is not necessary for $LE(z)$ (Juang et al., 2008) (which also validates our lumped treatment of water vapor concentration in the model). With these approximations, the latent heat flux at any z is

$$LE(z) = LE_s + \lambda_v \int_0^z S_v(z) dz. \quad (35)$$

During nocturnal periods when $Q_p = 0$, the vegetation-soil system act as a net CO_2 source. Above-ground respiration is modeled as $S_c = R_d a(z)$ as before. This model assumes that respiration is predominantly from leaves instead of stems. Soils emit CO_2 at all times owing to autotrophic (e.g., roots) and heterotrophic (e.g., microbes) respiration, represented here as a surface flux to the atmosphere, much like soil evaporation. The temperature dependence of the soil respiration rate, denoted as R_{es} , follows an Arrhenius-type exponential relation (Lloyd & Taylor, 1994):

$$R_{es} = R_r Q_r^{\frac{T - T_r}{T_r}}, \quad (36)$$

where R_r represents the respiration rate at a reference temperature T_r , typically taken as 10 (C), and Q_r is a dimensionless coefficient quantifying the sensitivity of microbial respiration to temperature changes. We adopt a widely cited soil $R_{10} = 3.2 \text{ } \mu\text{mol m}^{-2} \text{ s}^{-1}$ and $Q_{10} = 2.3$, which reflect temperate agricultural soil conditions under moderate moisture levels.

3 Model evaluation

The final model evaluation employed temperature data from two field experiments (see also validation of individual components, such as wind profiles, in the SI). While no single experiment was available to test all aspects of the proposed model simultaneously, the two experiments described here enabled the assessment of the skill of the proposed framework in predicting AV environments and outputs. Due to the absence of farm-scale measurements of crop assimilation and transpiration—particularly under agrivoltaic conditions—these components could not be directly validated. Instead, we assessed the plausibility of the results through comparison with reported values in the literature; these comparisons are provided in the SI.

3.1 Leaf temperature

Leaf temperature measurements were collected in Davis, California (latitude: 38.54°N, longitude: 121.74°W, elevation: 16 m above sea level) on September 4, 2024. Leaf temperature was measured using a SI-4H1-SS infrared radiometer (Apogee Instruments), while net radiation was recorded with an SN-500-SS net radiometer (Apogee Instruments). Ambient temperature and humidity were measured using the ATMOS 14 sensor, wind and other additional meteorological variables for an open field were obtained from an ATMOS 41 Gen 2 all-in-one weather station. The measurement setup involved a horizontally mounted PV system consisting of frame-embedded panels with dimensions of 216 cm $\times$ 175 cm. During the experiment, the PV modules were electrically disconnected, thereby operating at zero efficiency, and exhibited an average solar transmissivity of approximately 10%. The underlying crop was *Solanum lycopersicum* (tomato), with an average canopy height of 40 cm. Representative physiological parameters used for modeling included a $V_{c,max25}$ of 87.9 $\mu\text{mol m}^{-2} \text{s}^{-1}$ and a J_{max} of 169 $\mu\text{mol m}^{-2} \text{s}^{-1}$ (Wullshleger, 1993). The soil is assumed to have a reflectivity of 15% (Campbell & Norman, 1998), longwave emissivity of 0.95 (Formetta et al., 2016), thermal conductivity of 0.42 $\text{W m}^{-1} \text{K}^{-1}$ and a volumetric heat capacity of 2.3 $\text{MJ m}^{-3} \text{K}^{-1}$ (Campbell & Norman, 1998). In this validation run, we implemented a small-scale farm option that assumes the microclimate beneath the panels (temperature, humidity, $[\text{CO}_2]$) is equivalent to the external environment, reflecting the limited buffering capacity of small installations (air flowing under the panels does not change in properties over the few meters of AV installation).

The comparison between measured and modeled crop surface temperature is presented in Fig. 2. As indicated by the error metrics box in Fig. 2, the model results demonstrate good agreement with measurements, exhibiting a mean absolute error (MAE) of 0.6 $^{\circ}\text{C}$ over temperature fluctuations of approximately 25 $^{\circ}\text{C}$ during the day. Additionally, the mean bias error (MBE) is 0.09 $^{\circ}\text{C}$, well within the measurement error, indicating that the model is unbiased.

3.2 Panel and soil temperatures

To evaluate model predictions for panel and soil surface temperatures, data collected by Choi et al. (2023) at a 9.5-MW Chisago Solar LLC power plant located in North Branch, Minnesota, USA (latitude: 45.5125°, longitude: -92.9833°, elevation: 276 m) are used. The AV system comprises one-axis tracking arrays that remain at 10 angle during nighttime. In the model, the instantaneous tilt angle is defined as $\beta_p = 90 - \varphi$, where φ is the solar zenith angle. This configuration maximizes the incident irradiance by aligning the panel normal with the solar vector, assuming this is also the protocol for the tracking in the real installation. Each panel has a width of 2 m and is mounted at a hub height of 3 m. The row-to-row spacing (center-to-center) is 6.5 m. The monitored area spans approximately 1.2 ha, where 30 cm high native flora vegetation was planted following construction. Soil temperature was measured at 25 cm depth using CS655 (Campbell Scientific, USA), and PV module temperatures were measured using CS240 sensors (Camp-

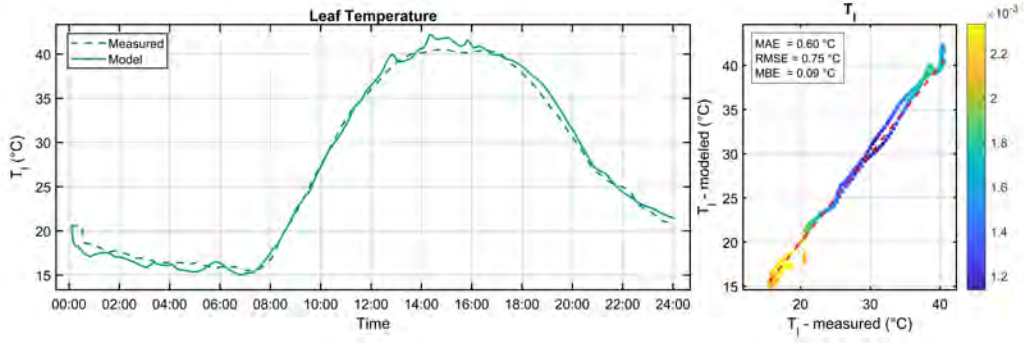


Figure 2. Comparison between modeled and measured leaf temperature (T_l) under horizontal PV panels during an experiment in Davis, California. The left panel shows the temporal evolution of leaf temperature, where the solid line represents the modeled T_l and the dashed line corresponds to observed values. The right panel presents a scatter plot of modeled versus measured T_l values, with the 1:1 line (red dashed) for reference. Color shading indicates the density of point pairs based on kernel density estimation. Summary error metrics include MAE, MBE, and RMSE.

bell Scientific, USA). This is a large installation, and the model is run as described in the previous section (not in its small-farm version). Data were collected using a Campbell Scientific CR6 datalogger, with most variables sampled every 15 seconds and recorded every 15 minutes. The top panel displays the incoming shortwave radiation (SW_{in}), followed by longwave radiation (LW_{in}), wind speed ($\bar{u}$), and exterior air temperature (T_x). Meteorological variables were collected using a Campbell Scientific CR6 datalogger, sampled every 15 seconds and recorded every 15 minutes. Global shortwave radiation was measured with a CS320 thermopile pyranometer, sampled every 10 seconds and averaged hourly. Air temperature and relative humidity were recorded every 15 minutes using EE181 sensors installed 0.5 m above ground across vegetated PV, bare PV, and control plots. Wind speed (min, max, mean, standard deviation) and direction were measured with a 03002 wind sensor. Due to a lack of on-site measurement, longwave radiation data were obtained from the National Aeronautics and Space Administration (NASA) Langley Research Center (LaRC) Prediction of Worldwide Energy Resources (POWER) Project funded through the NASA Earth Science/Applied Science Program.

Vegetation parameters were estimated assuming native flora characteristics reported by Wullshleger (1993), with maximum carboxylation rate at 25 °C ($V_{c,max25}$) of 94 $\mu\text{mol m}^{-2} \text{s}^{-1}$, maximum electron transport rate (J_{max}) of 170 $\mu\text{mol m}^{-2} \text{s}^{-1}$, and a randomly distributed leaf orientation. The soil is characterized by a reflectance of 30% (Campbell & Norman, 1998), a thermal conductivity of 0.21 $\text{W m}^{-1} \text{K}^{-1}$, and a heat capacity of 1.6 $\text{MJ m}^{-3} \text{K}^{-1}$ (Campbell & Norman, 1998). As illustrated in Fig. 3, the modeled panel and soil surface temperatures agree with measurements. The mean absolute errors (MAE) is 1.76 °C for the panel (over a 40 °C range) and 0.21 °C for the soil surface. The soil temperature patterns (wider model diurnal cycle in the left panel and hysteresis in the right panel) indicate that the thermal capacity of the modeled soil is lower than the actual experimental value, with the observations showing a slower thermal response of the soil. While calibration of the soil properties can be done to improve this model-observation match, it is not essential for investigations that follow.

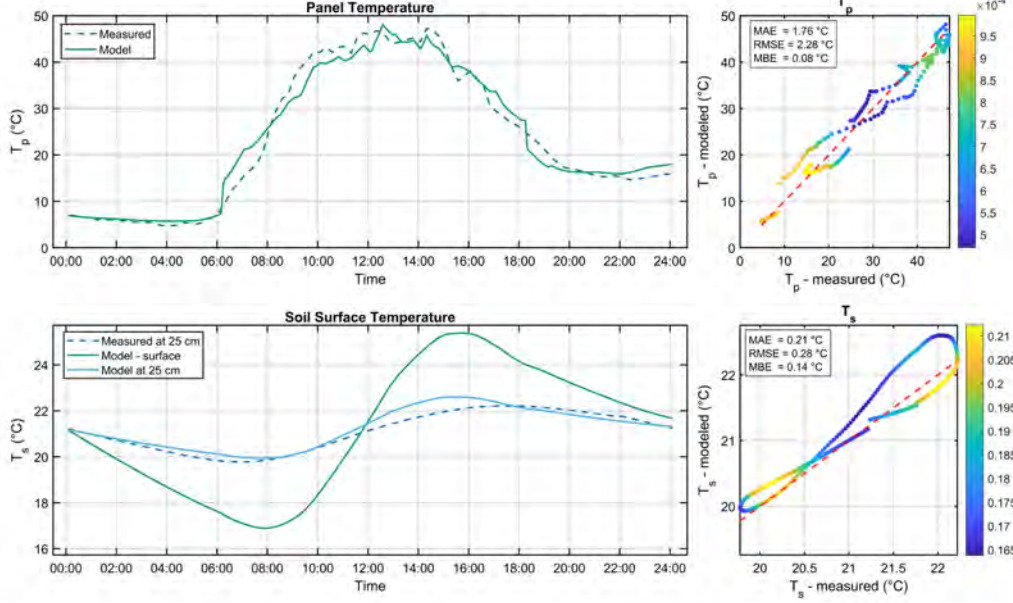


Figure 3. Comparison between modeled and measured temperatures for the solar panel and soil during the experiment in Chisago, Minnesota. **Left panels:** Time series of temperature variations. In the top-left panel, the solid line indicates the modeled panel temperature (T_p) and the dashed line represents the measurements. The bottom-left panel shows soil temperature at different depths: the solid green line shows the modeled surface temperatures (T_s), while the dashed line represents the measurements at 25 cm depth that match the observations at the same depth (solid cyan line) well. **Right panels:** Scatter plot of modeled versus measured values for T_p (top panel) and T_s (bottom panel). The red dashed line in each scatter plot indicates the 1:1 agreement line. Point density is visualized using kernel density estimation. Summary error metrics are included MAE, MBE, and RMSE.

4 Simulation setup

For the model application, meteorological data collected in Princeton, New Jersey (40.3430°N, 74.6514°W; elevation: 45 m above sea level) were used as detailed in the SI. The site experiences a humid subtropical climate (Köppen classification Cfa) during a typical summer day, characterized by clear sky, high temperatures, and elevated humidity. Situated in the middle of the Northeast Corridor, Princeton’s summer environmental conditions are broadly representative of mid-Atlantic urban and suburban settings spanning from Washington, D.C. to New York City, NY. As such, it serves as a relevant proxy for exploring energy fluxes, thermal comfort, and climate-related processes in the most densely populated and urbanized regions in the United States, with high food and energy demand.

Using these meteorological data as input (input for the model is assumed to represent conditions far enough from the PV array and not affected by its presence), the model resolves the transfer of energy, momentum, and mass from the input level (top of the domain) down to depth of the ground, along with the physiological responses of the crop (Fig. 1). The results are interpreted and used for water and agriculture (5.3), energy (5.4), and comfort/health implications (5.5). The photovoltaic (PV) module is summarized in Table 1. The selected crop is, once again, tomato, with an average canopy height of approximately 40 cm (much like the Davis experiment). This choice is moti-

vated by the fact that tomato was used in the model evaluation (Section 3), where its thermal and radiative behavior under panels was evaluated against observational data. Representative physiological parameters used in the modeling include a maximum carboxylation rate at 25 °C ($V_{c,max25}$) of $87.9 \mu\text{mol m}^{-2} \text{s}^{-1}$ and a maximum electron transport rate (J_{max}) of $169 \mu\text{mol m}^{-2} \text{s}^{-1}$ (Wullshleger, 1993). The leaves are assumed to be randomly oriented and distributed, with a maximum leaf area index (LAI) of $2 \text{ m}^2 \text{m}^{-2}$. The underlying soil is assigned a shortwave reflectivity of 25% (Campbell & Norman, 1998), a dry volumetric heat capacity of $2.3 \text{ MJ m}^{-3} \text{K}^{-1}$ (Campbell & Norman, 1998), a longwave emissivity of 0.95 (Formetta et al., 2016), a residual water content of 0.05, and a field capacity of 0.25. Additionally, a solar power plant without any underlying crops (as a reference for energy and heat implications; see Section 5.4) and a cropland without panel coverage (as a reference for agricultural implications; see Section 5.3) are modeled as benchmarks for comparison in each respective aspect. The corresponding characteristics are kept identical to those in the agrivoltaic scenario.

Table 1. Summary of PV module baseline geometry and multilayer material properties (Mertens, 2018; Duffie & Beckman, 2013; Anjana Nair et al., 2025).

layer	thickness	thermal conductivity ($\text{W m}^{-1} \text{K}^{-1}$)	additional properties
glass cover	3 mm	0.8	—
ARC	100 nm	1.2	—
crystalline silicon	225 μm	148	—
EVA encapsulant	800 μm	0.15	—
nanopillar layer	500 nm	1.0	—
rear contact	10 μm	200	—
tedlar backsheet	25 μm	0.15	$\epsilon_{p,b}$: 0.95, $\epsilon_{p,t}$: 0.95
aluminium base	1 cm	205	$\alpha_{p,t}$: 0.12, $\alpha_{p,b}$: 0.70
PV module geometry and orientation			
tilt angle	15	fixed (non-tracking)	south-facing
Mean panel height (H_p)	4 m	—	azimuth 180
width (w_p)	2 m	—	—
row spacing (s_p)	4 m	—	—

5 Results and discussion

The diurnal cycle of the temperatures of the elements of the AV farm (panel layers, leaves, soil, and air) are examined first. Next, an overview of how the environmental conditions (wind speed, and water vapor and carbon dioxide concentrations) are modified in an AV system compared to free air aloft is presented. Then, the agricultural implications for food production are deduced by comparison to a crop field without PV panels, while the power implications are deduced by comparison to a PV site without an underlying crop. Finally, improvements in thermal comfort for workers shaded by the panels, compared to conditions in an open agricultural field, are reported.

5.1 Diurnal cycles of element temperatures

As illustrated in Fig. 4, the model calculations indicate that, due to their low thermal inertia, the solar panels undergo large diurnal temperature variations. Panels heat up rapidly, reaching approximately 25 °C above the ambient air temperature during the day, and cool rapidly to near-ambient levels at night. In this configuration, sub-panel

air temperature (T_a) remains close the exterior air temperature (T_x) at night. Leaves, with minimal stomatal conductance in the absence of light and negligible thermal mass, stay near the canopy air temperature. After sunrise, panels and crops rapidly absorb solar energy and transfer sensible heat to the sub-panel air via convection. Later in the morning, as panel temperatures rise further and crops receive substantial PAR, stomata open to maximize carbon uptake. This leads to transpirative cooling, causing leaf temperatures to drop below T_a , while the shaded soil remains cool. These two factors together keep T_a lower than T_x . As radiation and ambient air temperatures rise, both sub-panel air and leaf temperatures increase. By the afternoon, carbon dioxide in the sub-panel region becomes depleted. These two factors—elevated temperatures, which reduce photosynthetic efficiency and increase vapor pressure deficit, and decreased carbon dioxide—limit stomatal conductance, thereby reducing transpirative cooling. In the absence of transpirative cooling, the leaf temperature (T_l) increases and exceeds the ambient sub-panel air temperature (T_a). This reduction in cooling further elevates temperatures, creating a feedback that exacerbates the process. Toward sunset, as solar radiation and ambient temperatures decline, panel and sub-panel air temperatures decrease as well.

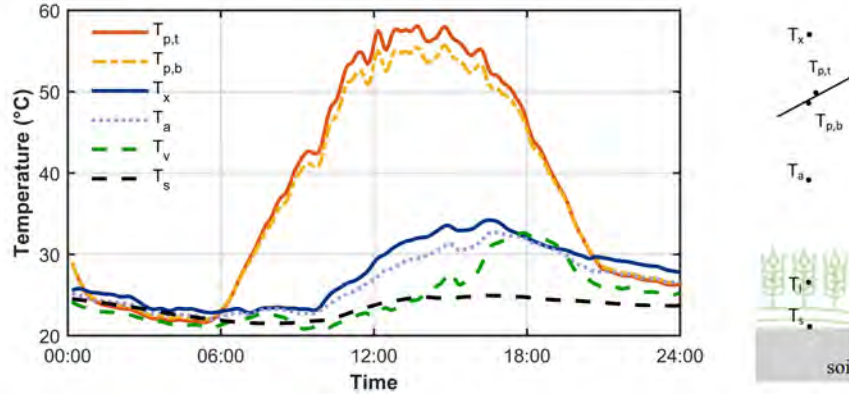


Figure 4. Surface temperature within an AV farm for each component. Left: Diurnal temperature values. Right: Graphical reminder of temperature abbreviations. Variables include: $T_{p,t}$ – top panel surface (glass) temperature, $T_{p,b}$ – back panel surface temperature, T_x – exterior air temperature, T_a – sub-panel air temperature, T_l – leaf temperature, and T_s – soil temperature.

5.2 Diurnal cycles of environmental conditions

As illustrated in Fig. 5, the model determines the microclimate experienced by the crop within the AV system. The primary environmental drivers we examine here include the incident PAR photon density Q_p , the immediate ambient air temperature (T_a) and specific humidity (q) (and the derived relative humidity (RH)). Additional variables that are useful for model verification and physical explanations, such as the mean velocity profile (u) and carbon dioxide concentration (CO_2), are also depicted. Fig. 5.a presents the diurnal variations of PAR for a clear-sky day at the canopy top, and its vertical attenuation through the crop layers. Due to partial penetration of direct light through inter-panel spacing and reflections from the panels, the incoming PAR at the canopy top is lower than that of an open crop field. Given the random orientation and distribution of leaves assumed in the present calculations, Q_p is progressively attenuated with depth through the canopy volume. Since sunlight is a determinant of crop photosynthesis, and since leaves at various heights receive varying levels of irradiance as shown in the lower panel of Fig. 5.a,

the layered representation we adopt, and that resolves the PAR profile, is required for capturing the non-linear effects of PAR on photosynthesis.

Among the primary determinants of leaf temperature is the sensible heat exchange at the leaf surface, which is predominantly influenced by the temperature of the surrounding air (T_a) and mean wind. Additionally, stomatal conductance is significantly modulated by the humidity content of the ambient environment. Figure 5.b (top panel) illustrates the sub-panel air temperature (T_a) in comparison to the external air temperature (T_x). Due to evapotranspirative cooling of crops and soil, the sub-panel region temperature (T_a) remains lower than the exterior air temperature (T_x), specially during the active photosynthesis hours.

The middle and bottom panels of Fig. 5.b show the specific humidity of the sub-panel air (q_a) and that of the exterior environment (q_x). During the day, increased evapotranspiration elevates q_a relative to q_x , contributing to higher absolute humidity beneath the panels. However, during the morning, since the humidity sources are mostly depleted in the absence of significant nocturnal evapotranspiration, the difference between absolute humidity levels across the panels decreases.

Sensible heat exchange from the crop and soil, along with aerodynamic conductance, is directly influenced by wind exposure. Additionally, the presence of panels alters mass exchange with the ambient atmosphere, especially the air space between the canopy and the crop. These effects are accounted for using the mean momentum balance and the resulting mean wind and mixing length profiles. The normalized wind profile is presented in Fig. 5.c, with the upper boundary condition scaled by the measured horizontal wind speed input (u) at a reference height above the farm. As mentioned before, this normalized profile is self-similar and only needs to be computed once at the start of the simulation; the wind profile for a given period is then deduced by scaling the normalized profile with the measured value at the top of the domain.

While soil acts as a source of carbon dioxide via respiration, crops generally function as a net CO₂ sink through photosynthesis during daylight hours. Consequently, individual leaves may encounter varying CO₂ concentrations, and panel structures can further modulate the net gas exchange with the surrounding air. As illustrated in Fig. 5.d, CO₂ levels beneath the panels increase at night due to soil and plant respiration (the eddy diffusivity may also be reduced if the measured wind speed decreases, although stability does not directly enter into our mixing length model). After sunrise, as assimilation commences, the trend reverses and CO₂ concentrations beneath the panels decline. A detailed comparison of the temporal trends of soil respiration versus crop net assimilation/respiration is provided in the SI. The profile of CO₂ concentration is presented in the bottom panel of Fig. 5. As in other components of the AV system, the broader implications depend on the balance between assimilation and respiration. It suffices to note that the model findings indicate that the reduced exchange velocity beneath the panels traps more nighttime-respired CO₂, enriching the leaves and, together with direct light and cooler air temperatures, enhancing early morning photosynthesis. This mechanism is consistent with the experimental observations reported by Sturchio et al. (2024).

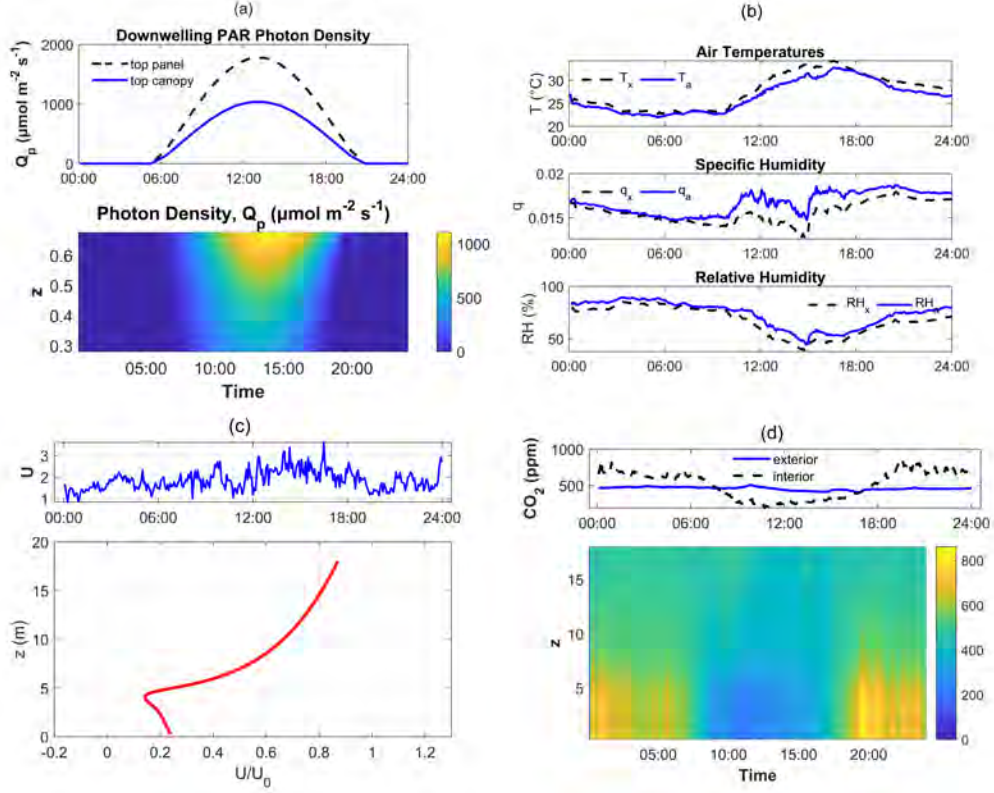


Figure 5. Crop microclimate. (a) Photosynthetically active radiation (PAR) density. (a, top) Incident PAR (Q_p) above the panels and at the top of the crop canopy. (a, bottom) PAR attenuation across the crop canopy (vertical axis) over time (horizontal axis). (b) Temperature and humidity exposure. (b, top) Exterior air temperature (T_s) and sub-panel air temperature (T_a). (b, middle) Exterior specific humidity (q_x) and sub-panel specific humidity (q_a). (b, bottom) Exterior relative humidity (RH_x) and sub-panel relative humidity (RH_a). (c) Wind. (c, top) Horizontal wind speed (u) measured above the panels (Glick et al., 2020). (c, bottom) Normalized wind speed (u_n) profile. (d) CO_2 . (d, top) Measured CO_2 concentration above the panels ($[\text{CO}_2]_x$) and modeled sub-panel concentration ($[\text{CO}_2]_a$). (d, bottom) CO_2 concentration profile with normalized wind speed.

5.3 Agricultural implications

As a result of the microclimate created within the crop canopy, individual leaves respond differently depending on their exposure to environmental conditions, leading to variations in assimilation and transpiration as illustrated in Fig. 6. Across the canopy, as PAR penetration decreases closer to the soil surface, A_n also declines (Fig. 6.a). However, other factors—such as increased canopy temperature or carbon depletion in the late afternoon also contribute to reduced photosynthetic activity. The multi-layer treatment of the canopy here can distinguish between the various limitations on A_n . During high PAR periods (e.g., solar noon), the upper layers of the canopy are likely restricted by A_{JC} , whereas the lower layers are controlled by A_{JE} .

In terms of transpiration, which is influenced by both stomatal conductance and vapor pressure deficit, a similar reduction is observed within the canopy. Yet, over the course of the day, as panels and leaves warm and raise the temperature of the surround-

ing air, the resulting increase in VPD enhances the driving force for transpiration while reducing g_s ($\propto 1 - 0.6 \log(\text{VPD})$). There is a certain 'critical' VPD that, when exceeded, causes transpiration to drop with further increases in VPD, and conversely, below which transpiration continues to increase with VPD. This critical VPD, which signals the onset of an apparent 'feedforward' mechanism, can be computed by setting

$$\frac{\partial}{\partial \text{VPD}} \text{VPD} [1 - 0.6 \log(\text{VPD})] = 0. \quad (37)$$

Solving this expression yields a critical $\text{VPD} = 1.95 \text{ kPa}$. This value is of significance because the relation between transpiration and increasing VPD is fundamentally different below or above this critical value (Nakad et al., 2023; Monteith, 1995), and panels do substantially alter the actual VPD above the canopy compared to their open field counterparts.

Water use efficiency (WUE), expressed as milligrams of carbon assimilated per gram of water transpired (Fig. 6. c), tends to remain relatively constant with canopy height because photosynthesis and transpiration scale together. However, as the day progresses and transpiration begins to outpace photosynthesis, particularly in the late afternoon, WUE declines. Roughly, the leaf-level WUE scales as (Katul et al., 2009, 2010)

$$\text{WUE} = \frac{A_n}{1.6(g_s)\text{VPD}} = \frac{g_s C_a (1 - C_i/C_a)}{1.6 g_s \text{VPD}} = m_{so} \frac{C_a}{1.6 \text{VPD}} (\sqrt{\text{VPD}}), \quad (38)$$

where m_{so} increases with reduced soil moisture. This leading order estimate suggests that WUE is independent from g_s . It is clear that, as VPD increases (e.g., late afternoon), WUE declines, and as atmospheric carbon dioxide concentration increases (high in the early morning), WUE increases.

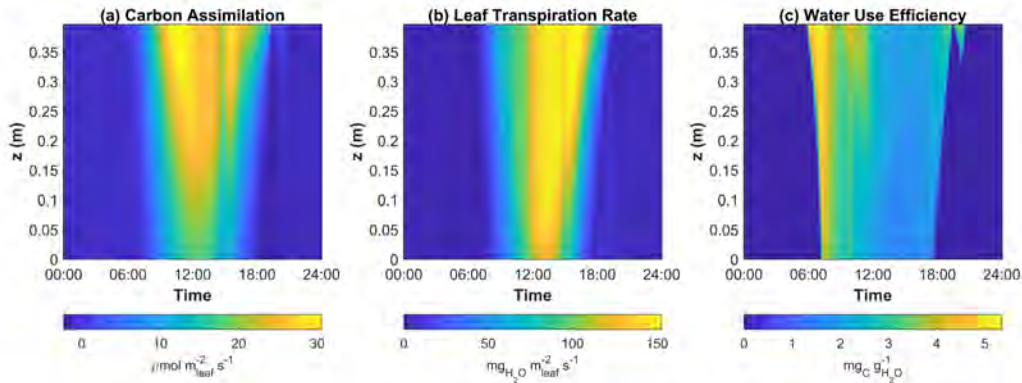


Figure 6. Spatiotemporal profiles across the crop canopy over time: (left, a) net carbon assimilation rate (A_n) per unit leaf area, (middle, b) transpiration rate per unit leaf area, and (right, c) water use efficiency (WUE).

After analyzing the dynamics of the individual components in the AV system, the AV farm's agricultural performance is compared against a monoculture case consisting of an open cropland without panels (Fig. 7) to evaluate the land equivalent ratio and explore potential synergistic gains. The reference cropland has the same crop type (tomato) and identical aerodynamic, physiological, and radiative properties, but it is exposed to full sunlight and ambient environmental conditions. It is also assumed that the reference crop has identical structural properties (i.e. $a(z)$ and H_l) so that only the micro-environment is altered by the presence of PV. The atmospheric states well above the PV are also identical.

Although the primary goal of AV systems is to optimize dual land use by harvesting sunlight for both crops and electricity, model calculations show notable advantages beyond simple resource sharing. For the conditions explored here, crop leaves in the AV farm remain considerably cooler than in the open field during the day, with an average leaf temperature $0.74\text{ }^{\circ}\text{C}$ lower over 24 hours and $1.84\text{ }^{\circ}\text{C}$ lower over daytime; the maximum cooling reaches $7.56\text{ }^{\circ}\text{C}$ around 2:05 pm. Despite a 47 % reduction in incoming PAR photon density at the top of the canopy, the time-averaged total carbon assimilation per unit land area is only 31 % lower than the open cropland, suggesting that carbon assimilation—and hence yield—is not linearly proportional to PAR. This outcome reflects the benefits of moderated canopy and leaf temperatures and reduced vapor pressure deficit due to the modified microclimate under the panels.

The total daily transpiration rate from crops decreases from $7.2\text{ mm day}^{-1}\text{ m}^{-2}$ in open cropland to $5.59\text{ mm day}^{-1}\text{ m}^{-2}$ in the AV system, indicating a water saving of 22.4 % . These estimates are also consistent with the FAO estimates of maximum mid-season for tomato plants under ideal conditions ($6\text{--}10\text{ mm day}^{-1}$). The AV benefit is expected to be even more pronounced in arid environments with intense solar radiation. Repeating the model calculations over a 92-day period (June 1 to August 31) to span a range of meteorological summer conditions, average water conservation, without the confounding influence of a specific day’s radiation–temperature–humidity correlations, appears to be in the range of 18%.

5.4 Energy and heat implications

For energy and heat assessment, we compare the AV installation to PV-only system installed over bare, non-irrigated soil with a volumetric water content of 0.05. The reference solar power plant is identical in panel configuration. Comparing the two systems (Fig. 8), the evapotranspirative cooling from crops and soil significantly lowers panel temperatures. The PV active layer’s peak temperature drops from $67.3\text{ }^{\circ}\text{C}$ in the PV site to $57.1\text{ }^{\circ}\text{C}$ in the AV system ($10.1\text{ }^{\circ}\text{C}$ cooling). During the day, the average panel temperature is reduced from 48.9 to $43.3\text{ }^{\circ}\text{C}$. As a result, daytime power generation per unit panel area increases from 111.31 to 114.39 W m^{-2} , representing approximately 3 % improvement and recovering approximately 15.2 % of the performance losses due to overheating. Moreover, through evapotranspirative cooling and the reduction of both panel and ground surface temperatures, the whole-day average sensible heat fluxes drop from 259.77 W m^{-2} for PV installations to 39.59 W m^{-2} for AV systems; as another reference, they were -62.5 W m^{-2} for cropland-only simulations. For the daytime average, the corresponding values were 413.92 W m^{-2} for PV installations, 114.03 W m^{-2} for AV systems, and -49.2 W m^{-2} for cropland. At peak sensible heat release, the fluxes reached 753.98 W m^{-2} , 268 W m^{-2} , and 63.9 W m^{-2} , respectively. These results indicate that agrivoltaic systems can potentially mitigate the PV heat island effect to a significant extent and throughout the day (Barron-Gafford et al., 2016; Chen et al., 2025).

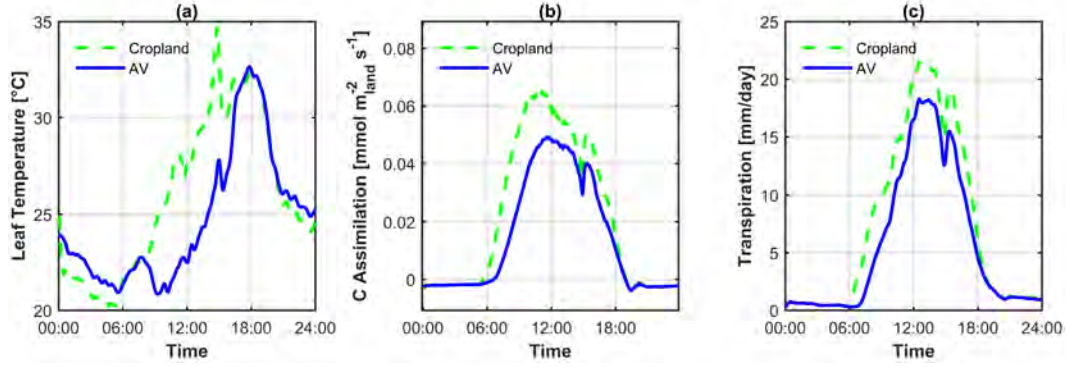


Figure 7. Comparison of agrivoltaic (AV) system and open cropland performance. Shown are (left, a) leaf temperature (T_l), (middle, b) net carbon assimilation rate (A_n), and (right, c) leaf transpiration, all expressed per unit ground area.

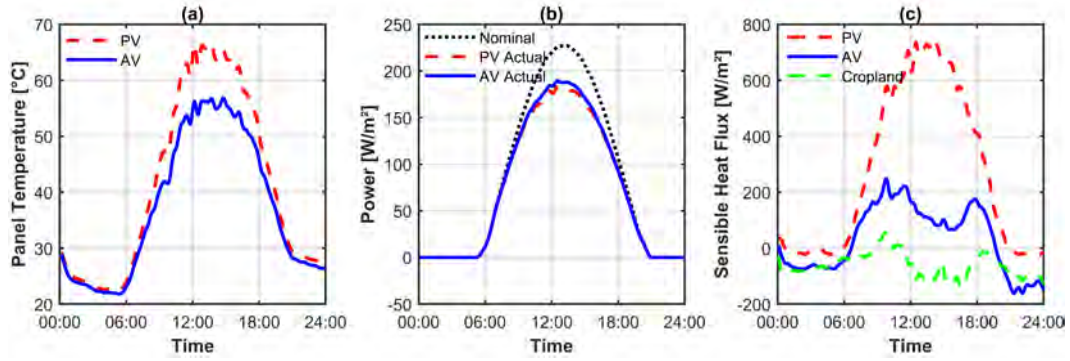


Figure 8. Comparison between agrivoltaic (AV) system and conventional solar power plant: (left, a) panel temperature ($T_{p,c}$), (middle, b) generated power per unit area of PV panel, and (right, c) sensible heat flux (H).

5.5 Health and comfort implications

According to a comprehensive literature review by Lepley et al. (2025), this study is the first to comprehensively investigate thermal comfort and heat perception of workers under AV systems. To address the scientific question concerning the implications of AV installation on worker thermal comfort, the model outputs are used to compute perceived heat stress experienced by a worker (Physical Equivalent Temperature) within the AV farm (for details of parametrization, see SI.). Within an AV environment, three primary working scenarios are considered: exclusively in shaded areas beneath panels; solely in sunlit row spacings; and moving intermittently between shaded and sunlit zones. Each scenario entails exposure to distinct thermal and radiative conditions—including air temperature, humidity, wind speed, and both shortwave and longwave radiation—relative to open cropland. The details of radiative exchange modeling are provided in the SI.

To integrate these environmental factors into a single indicator, the Physical Equivalent Temperature (PET) (Höppe, 1999; Walther & Goestchel, 2018) is applied, which is suitable for outdoor settings. The worker is modeled as a 1.7 m tall, 60 kg male, with a clothing insulation level of 0.5 clo (appropriate for summer labor), a clothing emissiv-

ity of 0.95, skin emissivity of 0.99, and a metabolic rate of 300 W, representative of typical agricultural work. The PET was calculated using MATLABTM codes that were modified by Qinqin Kong and Xinjie Huang based on an existing Python repository developed by Walther and Goestchel (2018). The PET parameterization details are presented in the SI.

As illustrated in Fig. 9 (left, a), throughout the typical working period (07:00–15:00), operating under the shade of PV panels substantially alleviates heat stress compared to exposure in an open cropland. The mean PET during working hours in cropland reaches 46.76 °C, whereas it decreases to 41.55 °C in the AV setting. Although the cooling advantage under the panels diminishes later in the day due to heat and humidity accumulation, the overall reduction remains significant. Working in open cropland (fully exposed to sunlight) provides conditions comparable to intermittent activity between shaded and sunlit zones. In contrast, continuous work under direct sunlight beneath the panels, where humidity accumulates, can be less comfortable than in open cropland. However, working in shaded panel areas, even with increased humidity, remains more comfortable than fully sunlit cropland.

Figure 9 (right, b) presents the contribution of individual environmental forcing by isolating their effects relative to cropland. Among these, reduced radiative exposure is the primary driver of improved comfort, and increased humidity is the most effective worsening factor; changes in wind speed have comparatively minor effects. Air temperature under the panels is slightly lower in the early hours; in our simulations, it never becomes detrimental even as the panel surfaces heat up. Notably, due to the specific AV farm design, wind speed at height of human’s center of mass (1 m) happened to match that of the open cropland reference, which explains the negligible effect observed for wind.

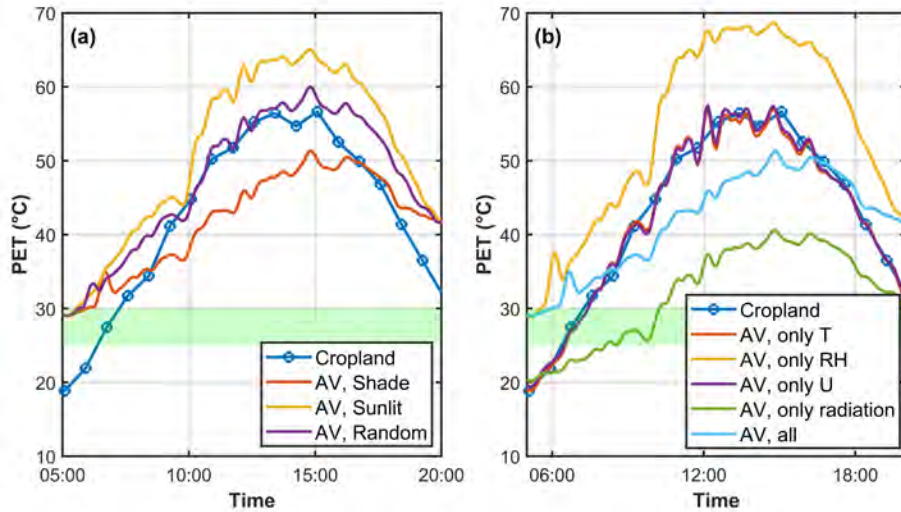


Figure 9. Comparison of PET in agrivoltaic versus cropland scenarios and the isolated contributions of each environmental factor. (left, a) Physical Equivalent Temperature (PET) in various scenarios: **cropland**: open cropland; **AV, Shade**: within the AV farm under panel shade; **AV, Sunlit**: within AV farm, working only in sunlit row spacing; **AV, Random**: moving randomly with 50% exposure to shade and 50% to sunlit areas. (right, b) PET decomposition by environmental factor: **cropland**: reference PET in open cropland; **AV, only T**: temperature is the only differing factor; **AV, only RH**: only humidity differs; **AV, only U**: only wind speed differs; **AV, only radiation**: only radiation differs; **AV, all**: all factors from the AV farm are applied simultaneously. The comfort region is between 25–30 °C.

6 Surmountable and insurmountable model limitations

The aim of this work was to develop a simplified but complete model of AV systems to inform design and optimization of AV farms. Complete in that it captures all the primary processes and components, and simplified in that it aims for maximum simplicity in the representation for each component. The analysis focused on a large, spatially uniform AV farm to eliminate edge effects and geometry-specific complexities, enabling broader conclusions. This approach is also more relevant for large-scale farms, where financial stakes are higher and accurate modeling is especially valuable. Despite this simplification, the primary spatial (above versus below panels) and temporal (diurnal cycle) variabilities are captured. Another goal was to have a modular scheme where individual representations can be updated or advanced within the overall model framework. Here, the main assumptions that impose limitations on the model applications, and whether they can be overcome by future refinements, are reviewed. The methods start with the treatment of momentum, then discuss energy, and finally, scalar exchanges.

Momentum: The flow is represented as a horizontal average (integrated at least over a single row and over the full cross-stream direction) of the streamwise (x -direction) momentum budget, but all vertical variations are considered assuming a near-neutral atmosphere. Thus, the model framework adopts a quasi-one-dimensional RANS approach that assumes planar homogeneity of the averaged quantities. This assumption requires that the agrivoltaic farm be sufficiently large (5MW or larger) so that edge effects have a negligible impact on the overall system behavior. Prior studies (Belcher et al., 2003) have shown that when the flow encountered a vegetated edge, the momentum adjustment distance is about $3 C_d(LAI/H_i)$ (it may be larger for scalars). Beyond this adjustment distance, the effects of the upstream conditions are minimal, and the flow equilibrates with the underlying surface. The steady state assumption for the normalized profiles is also very reasonable since the pressure gradient is the main flow driver, and it propagates very quickly (at the speed of sound) across the AV layer.

As with any RANS, the skill of the model depends on the mixing length (eddy diffusivity) parameterization, which is based on the geometrical features of the soil, plants, and panels. The closure also ignores buoyancy effects, the particular dynamics of dispersive fluxes, and the effect of wind direction (we assume the flow is perpendicular to the rows). All these effects can be included in the current model structure, but they would require some modification to the mixing length parametrization, as well as high-fidelity 3D large eddy simulations (LES) to provide the data for such refinements. In addition, including buoyancy influences would require a coupled thermal model that provides the necessary surface heat fluxes as input, which may then require a version of the current model that is embedded in an LES code to generate the realistic simulations that can then be used to improve our current, simple model. LES can also inform other key parameters in the model (e.g., drag coefficients, thermal and mass exchange coefficients, etc.), as well as the two-dimensional model version that captures entrance zones. A key challenge that may not be surmountable is that the resulting closure would depend on a large set of parameters, making a fully general model expensive to develop (given the LES computing cost required, and the complexity of deriving closures with many inputs). This may be overcome by a non-dimensionalization approach to reduce the parameter space, or machine learning that could help in improving the interpolation of parameters, or in creating surrogate models for the flow, based on a limited set of LES.

Energy: The 2D treatment of radiative transfer across the panels is sufficient for most practical AV farms, given their homogeneity along the y -direction (as long as the cross-stream length of the farm is $\gg$ inter-row spacing). For crops, the radiative field is horizontally averaged with vertical attenuation considered; so in effect, it is one-dimensional. For crops that are grown in very discrete rows, this assumption may miss important effects of crop heterogeneity, but the model can be extended to 2D (either geometrically or through parametrizations based on ray tracing simulations). A key influence on model

skill is the characterization of all the radiative properties of the panels and crops. Another set of key parameters in modeling heat transfer are the thermal transfer coefficients, which are imposed here based on available literature, but which could be improved based on LES studies as described above. Additionally, the subpanel air temperature is assumed to be well mixed (uniform). While a layered approach, similar to the treatment of scalars described earlier, could be applied to sub-panel temperature as well, it would significantly increase computational cost; an assessment of its benefit to model skill is warranted. While PAR photon density and wind are modeled using a layered structure, the surface energy budget of the crop is not layered for individual leaf temperatures. Notably, due to the influence of wind and the low thermal mass of leaves, their temperatures remain closely coupled to the ambient air temperature. Since the model is designed for assessment purposes, the exact temperature of each leaf is not critical. Accounting for individual leaf temperatures would require tracking complex view factors between leaves and surrounding elements, substantially increasing computational cost.

Mass: The model neglects horizontal variations in CO_2 and H_2O , which may pose limitations for smaller to medium farms with important entrance zones. The adjustment lengths for these scalars, which are always exchanged by molecular diffusion at the interfaces, is much longer than for momentum, which can adjust more rapidly due to pressure drag dominance over viscous drag. For such farms, the mass balance might be controlled by advection in the inflow rather than vertical exchange across the PV layer. This would require a 2D model as discussed above. The steady state assumption in the CO_2 model also overlooks the storage capacity of CO_2 in the air, but that assumption can be readily relaxed to examine its impact. Another main limitation of the current model is that soil moisture is assumed constant over the course of a day, representing intelligent irrigation that avoids dry conditions. Dynamic soil water modeling is excluded to prevent moisture retention effects from dominating the results, and to avoid added complexity from irrigation scheduling. However, a soil moisture mass balance model would be needed to optimize AV farm operations, where irrigation is a key control.

Agriculture: This study focuses on carbon assimilation rather than carbon allocation into leaves, stems, roots, and reproductive organs. The total biomass can be assumed to be proportional to the time integration of carbon assimilation over the growing period. Adding a model for dynamic biomass allocation models (Jones et al., 1991) to capture such adaptive responses would enable a detailed assessment of crop growth and yield under different agrivoltaic configurations. Additionally, while crop physiology output could ideally be evaluated against measurements, such evaluation is currently limited by the lack of large-scale physiological data at the AV farm level; most reported values pertain to the leaf scale. In the absence of such data, a model plausibility analysis was conducted (see SI). Should farm-scale datasets become available in the future, they could enable direct model evaluation.

As a concluding remark, although certain aspects of the model could be further refined, the evaluation and plausibility analyses indicate a reasonable agreement with observational data and reported values. Therefore, the current level of detail is deemed sufficient for most intended applications, a range that can expand as the model is further developed and tested.

7 Conclusion

A comprehensive multiphysics numerical model is developed to simulate the microclimate under solar panels in agrivoltaic (AV) systems. The model resolves the coupled exchanges of energy, momentum, and mass, as well as the physiological responses of crops and humans. The modular framework treats the budgets of momentum, energy, water vapor, and carbon, representing the soil, crops, photovoltaic panels, and the air volume under the panels. Evaluation against two field experiments demonstrates the model's

ability to reproduce panel, leaf, and soil temperatures — the key prognostic variables of the surface energy balance — as well as to yield realistic estimates of crop physiological responses. After solving for the unique temperature that satisfies these coupled exchanges, the resulting fluxes are extracted and analyzed to interpret the microclimate beneath the panels.

The model was applied to a representative summer hot and humid day in Princeton, NJ, comparing an AV farm with tomato cultivation, an open tomato cropland, and a conventional PV installation over bare soil. The model computed component-level diurnal variations, including surface temperatures, crop physiological responses, and human thermal comfort. Results indicate that, under AV conditions, average tomato leaf temperature over the whole 24-hour day decreased by 0.74 °C (with daytime reduction of 1.84 °C and a peak reduction of 7.56 °C in the afternoon), leading to a 42.6% reduction in total daily evapotranspiration from soil and crops. Despite a 47% decrease in incident light, net carbon assimilation declined only by 31%, suggesting that improved microclimatic conditions can partially offset light limitation.

From an energy perspective, panel temperatures in the AV farm were on average 5.6°C cooler during the day (and 10.2 °C cooler peak temperature) compared to panels over bare soil, resulting in a $\approx 3\%$ increase in daily solar energy yield and recovery of $\approx 15\%$ of temperature-induced power losses. Furthermore, combined crop and soil evapotranspiration reduced net sensible heat flux from 259.77 to 39.59 W m⁻², potentially mitigating the PV heat island effect.

For worker well-being, the average Physiological Equivalent Temperature (PET) within working hours was reduced from 46.76°C in open cropland to 41.55°C under AV conditions, indicating significant improvements to thermal comfort and occupational health. However, potential drawbacks include elevated humidity when there is poor ventilation under dense panel configurations, but these can be addressed through low-energy interventions such as ventilation fans during daytime, especially given the availability of on-site power infrastructure.

While numerous studies in the literature have confirmed that agrivoltaic systems can deliver substantial benefits under specific configurations, crop types, and environmental settings, the proposed model extends beyond these case-specific findings to provide a generalized evaluation framework. Decisions that maximize a single outcome, such as power generation, may conflict with agricultural productivity due to competition for solar resources. High panel density can increase energy yield but may overshadow crops, alter wind and mass exchanges, and ultimately affect both crop and power outputs in complex, site-specific ways. Moreover, crop species differ in their light requirements, and environmental conditions vary considerably across locations and seasons. By integrating these factors, the model enables feasibility assessments and optimization of AV designs under a wide range of environmental conditions, panel configurations, PV technologies and materials, and crop types—supporting evaluations from local to global scales and helping to identify configurations that balance, and potentially reconcile, the competing objectives of maximizing power generation, agricultural yield, water conservation, and worker comfort. Moreover, this model can be used to explore opportunities to expand agriculture into new areas by creating and managing a microclimate.

Open Research Section

The model code used in this study is currently available in the supplementary material for reviewers only. Upon acceptance in the journal, the code and all necessary requirements will be made publicly available on GitHub and archived with a DOI via Zenodo. A link will be provided in the final version.

Author Contributions

Erfan Hosseini: Conceptualization, Formal analysis, Investigation, Methodology, Software, Data Curation, Visualization, Validation, Writing – original manuscript.
Gabriel G. Katul: Conceptualization, Formal analysis, Investigation, Methodology, Software, Writing – original manuscript.
Majdi Abou Najm: Conceptualization, Investigation, Writing – review and editing.
Andre Daccache: Investigation, Writing – review and editing.
Sujith Ravi: Investigation, Writing – review and editing.
Kelly Mae Heroux: Investigation, Writing – review and editing.
Gavin Chaboya: Investigation, Writing – review and editing.
Chong Seok Choi: Investigation, Writing – review and editing.
Elie Bou-Zeid: Conceptualization, Formal analysis, Funding acquisition, Investigation, Methodology, Project administration, Resources, Visualization, Supervision, Writing – original manuscript.

Declaration of Interests

The authors declare that they have no competing interests.

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Appendix A Parameters**Table A1.** Geometrical and Structural Parameters

Parameter	Description
H_p	Height of panel center above ground
H_l	Height of crop above ground
w_p	Panel width
s_p	Row spacing between panels
β_p	Panel inclination angle
LAI	Leaf Area Index
$a(z)$	Leaf area density at height z
x_o	Leaf orientation parameter (projected area ratio)
L_t	Characteristic leaf length along flow direction

Table A2. Radiation Parameters

Parameter	Description
SW_{in}	Incoming shortwave radiation
SW_{out}	Outgoing shortwave radiation
$SW_{p,inc}$	Incident shortwave radiation on the panel surface
LW_{in}	Incoming longwave radiation
LW_{out}	Outgoing longwave radiation
LW_{sky}	Atmospheric longwave radiation from the sky
α	Shortwave reflectivity of the surface
α_p	Leaf absorptivity in the PAR spectrum
τ	Shortwave transmissivity of the surface
$\tau_l(z)$	Fraction of PAR reaching level z in the canopy
$K_{be}(x_o, \varphi)$	Beam extinction coefficient
$VF_{i \rightarrow j}$	View factor from surface i to j
ϵ_i	Emissivity of surface i
σ	Stefan-Boltzmann constant
$L(z)$	Cumulative leaf area index from top to height z
η_a	Temperature-adjusted conversion efficiency of PV panels
η_n	Nominal PV efficiency under standard test conditions
δ	Temperature coefficient of PV efficiency (K^{-1})

Table A3. Energy and Heat Transfer Parameters

Parameter	Description
H	Sensible heat flux
LE	Latent heat flux
G	Ground or conduction heat flux
h_p, h_s, h_l	Heat transfer coefficients for panels, soil, and leaves
C_H	The bulk heat transfer coefficient
C_q	The bulk moisture transfer coefficient
L_Λ	Lacunarity length scale for panel heterogeneity
c_p	Specific heat capacity of air at constant pressure
R_x	Thermal resistance of the layer
c_x	Thermal capacitance of the layer

Table A4. Aerodynamic and Momentum Parameters

Parameter	Description
$\bar{u}$	Mean streamwise wind speed
$\bar{w}$	Mean vertical wind speed
$u(z)$	Wind speed at height z
$u_n(z)$	Wind speed at height z normalize by the wind at the domain top
Re_{L_l}	Reynolds number based on lacunarity length scale
Pr	Molecular Prandtl number of air
Pr_t	Turbulent Prandtl number of air
Sc_t	Turbulent Schmidt number
C_d	Drag coefficient
$f_{d,p}$	Drag force from panels
$f_{d,l}$	Drag force from vegetation
$f_{d,s}$	Drag force from soil
$g_{a,h}$	Aerodynamic conductance for sensible heat transfer
$\bar{\rho}_a$	Mean air density
P	Mean pressure field
t	Time variable
x	Streamwise coordinate
z	Vertical coordinate
τ_{zx}	Momentum flux (turbulent + dispersive)
K_ξ	Turbulent diffusivity of a scalar ξ
K_m	Turbulent eddy viscosity
$w'\xi'$	Turbulent flux of scalar ξ
S_ξ	Source or sink term for scalar ξ
ξ	Concentration of scalar quantity (e.g., water vapor or CO ₂)
$A_{b,\xi}$	Coefficient depending on scalar ξ for boundary layer transport
R_r	Respiration rate at reference temperature T_r
Q_r	Temperature sensitivity coefficient for respiration

Table A5. Vegetation and Crop Physiology Parameters

Parameter	Description
A_n	Net photosynthetic rate
V_m	Maximum Rubisco carboxylation capacity per unit leaf area
$V_m(T_l)$	Temperature-dependent maximum carboxylation rate
J_{max}	Maximum electron transport rate
Γ^*	CO ₂ compensation point
$R_d(T_l)$	Temperature-dependent dark respiration rate
R_d	Dark respiration rate
g_s	Stomatal conductance
$r_s(z)$	Stomatal resistance at height z
$r_a(z)$	Aerodynamic resistance at height z
C_{ci}	Intercellular CO ₂ concentration
C_a	Atmospheric CO ₂ concentration
C_l	CO ₂ mole fraction at leaf surface
O_a	Atmospheric O ₂ concentration
K_o	Michaelis–Menten constant for O ₂ inhibition
K_c	Michaelis–Menten constant for CO ₂
$\bar{\xi}_s$	Mean scalar concentration at surface
$\bar{\xi}_a$	Mean scalar concentration at atmosphere
e_s	Saturation vapor pressure near leaf surface
e_a	Actual vapor pressure near leaf surface
RH	Relative humidity
RH_s	Relative humidity at soil surface
RH_x	Relative humidity of exterior air
RH_a	Relative humidity of sub-panel air
q_s	Saturation vapor pressure at the soil surface
q_x	Specific humidity of exterior air
q_a	Specific humidity of sub-panel air
m	Slope of linear g_s-A_n/C_s relation
b	Intercept of g_s-A_n/C_s relation
g_o	Cuticular conductance in the absence of stomatal control
S_c	Source/sink term for CO ₂
S_v	Source/sink term for water vapor
WUE	Water use efficiency
$[CO_2]_x$	CO ₂ concentration above panels
$[CO_2]_a$	CO ₂ concentration sub-panel
e_m	Maximum quantum efficiency of photosynthesis
Q_p	Incident PAR photon flux density
PAR	Photosynthetically Active Radiation

Table A6. Temperature Variables

Parameter	Description
T	Generic object temperature
T_x	Exterior (ambient) air temperature
$T_{p,t}$	Panel top surface temperature
$T_{p,b}$	Panel back surface temperature
T_a	Sub-panel air temperature
T_l	Leaf temperature
T_s	Soil surface temperature
T_g	Deep ground temperature

Table A7. Thermal Comfort and Human Parameters

Parameter	Description
PET	Physiological Equivalent Temperature
T_{core}	Human core body temperature
T_{skin}	Human skin temperature
$T_{clothing}$	Human clothing surface temperature
M	External metabolic rate due to physical activity
M_{base}	Basal metabolic rate
m	Body mass of individual
h	Body height of individual
age	Age of individual (reference: 30 years)
A_{Du}	Dubois body surface area
H	Metabolic heat production
E_{res}	Respiratory heat loss
R_n	Net radiation exchange
C	Convective heat loss
E	Evaporative heat loss from skin
$A_{eff,r}$	Effective radiative area of the body
f_{acl}	Fraction of clothed body surface
ε_{sk}	Emissivity of skin (0.99)
ε_{cl}	Emissivity of clothing (0.95)
T_{mrt}	Mean radiant temperature
h_e^{diff}	Diffusion coefficient of air boundary layer
L_w	Lewis number constant (0.167 K/hPa)
f_{ecl}	Burton efficiency factor for evaporation
P_{vs}	Saturation vapor pressure at skin temperature
e_a	Ambient vapor pressure
w	Skin-wetness factor (E_{sw}/E_{max})
r_{cl}	Clothing thermal resistance (clo/6.45)
i_m	Woodcock's ratio (0.38)

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Food, Energy, and Health Implications of Agrivoltaic Farms

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Key Points:

- This paper develops a model that simulates microclimate, crop growth, and is the first to assess worker comfort in agrivoltaic farms.
- In the studied design and conditions, agrivoltaics cooled crops, panels, and workers while saving water and boosting power output
- The model supports design and optimization of agrivoltaics across various climates, crops, panel array designs, and technologies.

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Abstract

The societal benefits of agrivoltaics are well supported, with ample empirical evidence for their suitability for collocated energy generation, crop cultivation, and water savings, even for staple crops. What is lacking is a holistic modeling framework to design and optimize AV systems for specific crop types, micro-environments, and panel configurations. To this end, a multiphysics model that solves momentum, energy, and mass exchanges among interacting components, and determines the implications of AV on photosynthesis, power generation, and worker thermal comfort, is introduced. The model is tested against field data from California and Minnesota. Its applications are illustrated for a representative AV scenario using weather data from central New Jersey, showcasing the multifaceted benefits of AV for a tomato farm under photovoltaic panels. In this scenario, the model predicts a 5.6 °C reduction in average daytime panel temperature (compared to a regular PV installation), reducing overheating-related energy losses by 15.2%. Despite a 47% reduction in light for the setup modeled here, net carbon assimilation declined only by 31%. Daytime crop leaf temperature declined by 1.84 °C, and these reductions offset some of the decline in carbon assimilation. Another benefit is the reduction in transpiration losses by 22.4% compared to an open crop field. Finally, the average perceived temperature experienced by workers improves by approximately 5.2 °C during working hours. While these are illustrative results for a particular crop and climate, they demonstrate how the model enables integrated assessment and optimization of agrivoltaic benefits across varying climates, crops, and PV technologies.

Plain Language Summary

Agrivoltaic farms combine solar energy production with crop cultivation, but real-world experiments often give mixed results because outcomes depend on crop type, panel layout, and local climate. We developed a computer model to simulate the microclimate beneath solar panels by tracking heat and air movement, water losses, crop growth, and worker comfort. Applied to a hot summer day in New Jersey, the model compared AV farming with open cropland and solar panels over bare soil. It showed that AV systems cooled crop leaves by up to 1.84 °C, lowering water loss by 22.4 %. Crop mass gain dropped by only 31 %, despite a 47% drop in light. Panels cooled by 5.6 °C, preventing overheating efficiency losses by 15.2 %. The combined effects of crops and panels reduced heating of the air, limiting local warming. At the same time, worker comfort improved dramatically, with working hours mean perceived temperature falling from 46.76 °C to 41.55 °C. This modeling tool helps farmers, engineers, and policymakers design AV systems that balance energy production, food yields, water conservation, and worker safety across diverse crops, climates, and solar technologies.

1 Introduction

Meeting future energy and food demands presents an escalating challenge that is yet to be resolved. Global electricity demand is projected to increase by 3500 TWh between 2022 and 2027 (International Energy Agency, 2024), with further growth driven by population expansion, elevated lifestyle standards, industrial activity, electrification, data centers, and electric vehicle adoption (U.S. Energy Information Administration, 2021; International Energy Agency, 2024; Xu, Lin, et al., 2025), as well as climate change and extreme events (De Cian & Sue Wing, 2017; Xu et al., 2024; Xu, Zeng, et al., 2025). Clean energy deployment must accelerate to meet net-zero targets with photovoltaics (PV) projected to become the dominant electricity source by 2050 due to an 80% cost decline since 2010 (Luderer et al., 2021; International Energy Agency, 2024; H. Zhang et al., 2025). Food demand is also expected to rise by 56% in 2050 compared to 2010 (van Dijk et al., 2021), or up to 62% under high-emissions scenarios that exacerbate crop stress and food system disruptions (Hameed et al., 2019; Gholinia & Abbaszadeh, 2024). Because min-

imizing transmission and transportation losses is essential, both food and energy must increasingly be produced near cities—yet such plans are constrained by land scarcity, particularly as 68% of the global population is expected to live in urban areas by 2050 (United Nations Department of Economic and Social Affairs, 2018), drastically increasing the demand for space.

One potential approach to overcoming land availability constraints is the implementation of co-production and dual land-use practices. Among these, a particularly promising strategy involves the integration of photovoltaic (PV) panels within existing croplands—a concept known as agrivoltaics (AV). AV integrates a wide range of sustainable development goals (Cuppari, Fernandez-Bou, et al., 2024), aligns with growers’ aspirations (Cuppari, Branscomb, et al., 2024), and provides positive feedback loops on soil carbon (Krasner et al., 2024). Conceived in the early 1980s (Goetzgberger & Zastrow, 1982), this strategy promises to de-escalate competition between solar energy generation and crop production for arable land. Such collocation of energy and food production on the same land, however, raises concerns regarding the allocation of sunlight between the respective systems (Ali Abaker Omer et al., 2022, 2025; Zainali et al., 2025; Krasner et al., 2024; Ma Lu et al., 2025). It is then necessary to optimize the design of such systems based on suitable crops and climate. To achieve this goal, a necessary question that must be addressed is: what are the mutual impacts among the components of an AV system, and how do interactions between panels, crops, and workers co-evolve?

Dupraz et al. (2011) introduced the Land Equivalent Ratio (LER) as a metric to compare the benefits of dual land use with those of separate monocultures. An LER exceeding unity indicates improved land use efficiency compared to conventional, single-use crop and photovoltaic (PV) systems. LER is defined as the sum of two ratios: the ratio of agrivoltaic crop yield to monoculture crop yield plus the ratio of agrivoltaic electricity to conventional PV electricity production. From the PV perspective, evaporative cooling from irrigated soil and crops can reduce panel temperatures, thereby mitigating overheating that reduces electric production efficiency, and increasing power generation (Barron-Gafford et al., 2019; Merheb et al., 2025). For crops, the outcomes may vary depending on the plant’s ontogenetic growth (photosynthetic mechanisms/pathways), background climate, and solar array design. Reducing overheating and evaporative losses can provide benefits for food production. In one experiment (Marrou et al., 2013) examining wheat, lettuce, and cucumber cultivated under 4-meter-high PV arrays tilted at 25° in alternating strips, minimal changes in crop yield were observed despite reduced sunlight. This empirical finding demonstrates that it is indeed possible to design such systems to produce a comparable amount of crop to a single agricultural land use.

The literature goes further and indicates that certain crops in specific climates can exhibit increased yields. For instance, wheat and potato in hot/dry climates (Weselek et al., 2021), chiltepin pepper and cherry tomato (Barron-Gafford et al., 2019), tomato (Roy & Ghosh, 2017), basil and beans in hot/dry climates (Barron-Gafford et al., 2025), olive in Mediterranean climate (Gatto et al., 2025), and lettuce (Marrou et al., 2013) are all candidates. Conversely, other conditions may be unsuitable for crop production under PVs, resulting in yield reductions. Celeriac and wheat during a normal growing season (Weselek et al., 2021), grass under severe shading (Armstrong et al., 2016), maize in warm and dry climate (Ramos-Fuentes et al., 2023), radish and radicchio during fall growing season in humid continental climate (New York State) (Sturchio et al., 2025), wheat in a tropical savanna climate (Prakash et al., 2025), and jalapeño peppers (Barron-Gafford et al., 2019) all experienced declines in yield. While shading from solar panels is often cited as a cause of yield reduction, it can also lower soil temperatures (Armstrong et al., 2016; Choi et al., 2023), effectively reducing evaporation and thereby conserving water (Barron-Gafford et al., 2019; McKuin et al., 2021; Scavo et al., 2021; Giudice et al., 2021; Jiang et al., 2022; Zainali et al., 2023; Barron-Gafford et al., 2025). This increased soil moisture retention can enhance yield, particularly during later growth stages

in arid climates (Hassanpour Adeg et al., 2018; Sturchio et al., 2022). Reductions in crop temperature can also reduce autotrophic respiration (when plants use part of their own organic matter to produce energy), which acts to reduce biomass growth. Additionally, PV panels can protect crops from a range of extreme weather events such as droughts and heat waves (Zainali et al., 2023; Pataczek et al., 2023) that are projected to become more frequent over the coming years (Begmohammadi et al., 2024; Madadgar & Moradkhani, 2013; Xu, Lin, et al., 2025), increasingly threatening food security (Hasegawa et al., 2021). Although these empirical studies (Barron-Gafford et al., 2019; Hassanpour Adeg et al., 2018; Marrou et al., 2013; Armstrong et al., 2016; Roy & Ghosh, 2017) provide insights, the findings are mixed and often case-specific and cannot be generalized across different crop types and climates. Given the impracticality of experimentally testing all possible crop–climate combinations under AV systems, broader design guidelines remain elusive.

To optimize design prior to installation, several modeling and simulation studies have been conducted. Some have focused solely on the distribution of radiation beneath PV arrays (Liu et al., 2018; Cascone et al., 2011; Goetzgberger & Zastrow, 1982; Shepard et al., 2022; Abidin et al., 2023; L. Zhang et al., 2025), while others — primarily biological in nature — have explored how manipulated light conditions and modified microclimates influence crop responses (Zhu et al., 2008; Hallik et al., 2009; Talbot et al., 2014; Camporese & Abou Najm, 2022; Prakash et al., 2023; Ma Lu et al., 2025). Although such studies may inform crop yield optimization strategies, they often overlook the impacts on power generation and workers’ comfort, making them unsuitable as design tools for multiobjective optimization. More critically, the reliability of yield predictions is limited, as they typically consider only a single aspect of the microclimate, most commonly light. A separate group of studies has employed high-fidelity Computational Fluid Dynamics (CFD) simulations to provide comprehensive insights into power production and microclimate conditions beneath PV systems (Zainali et al., 2023; Zainali, 2024; Williams et al., 2023). However, these models generally do not incorporate dynamic coupling with plant physiological responses, which can, in turn, influence the microclimate. Moreover, the case-specific nature of these simulations and their significant computational cost limit their broader applicability and render them impractical for large-scale optimization efforts. Despite growing evidence that chronic heat exposure adversely affects workers’ health (Cruz et al., 2025), the health and comfort of individuals working beneath PV panels also remain largely unexplored in the literature (Lepley et al., 2025). Working conditions under these installations may differ significantly from those in open agricultural fields, yet this distinction has received limited attention to date.

The existing literature, while informative, provides fragmented and mono-disciplinary insights into the impacts of AV systems, focusing separately on crop performance or power generation, and ignores thermal comfort implications. Such compartmental approaches are necessary but insufficient to capture the interdependent dynamics between crop growth, energy generation, water savings, and thermal comfort within an AV farm. These limitations underscore the need for an integrated understanding of the mutual interactions among all the key system components. To address this gap, a unified, physically-consistent, and dynamically-coupled model that incorporates exchanges of energy, momentum, and mass, alongside responsive crop physiology and a thermal comfort metric, is proposed. The framework is designed to be generalizable, extendable, and computationally efficient for broader applications across climatic and cropping conditions.

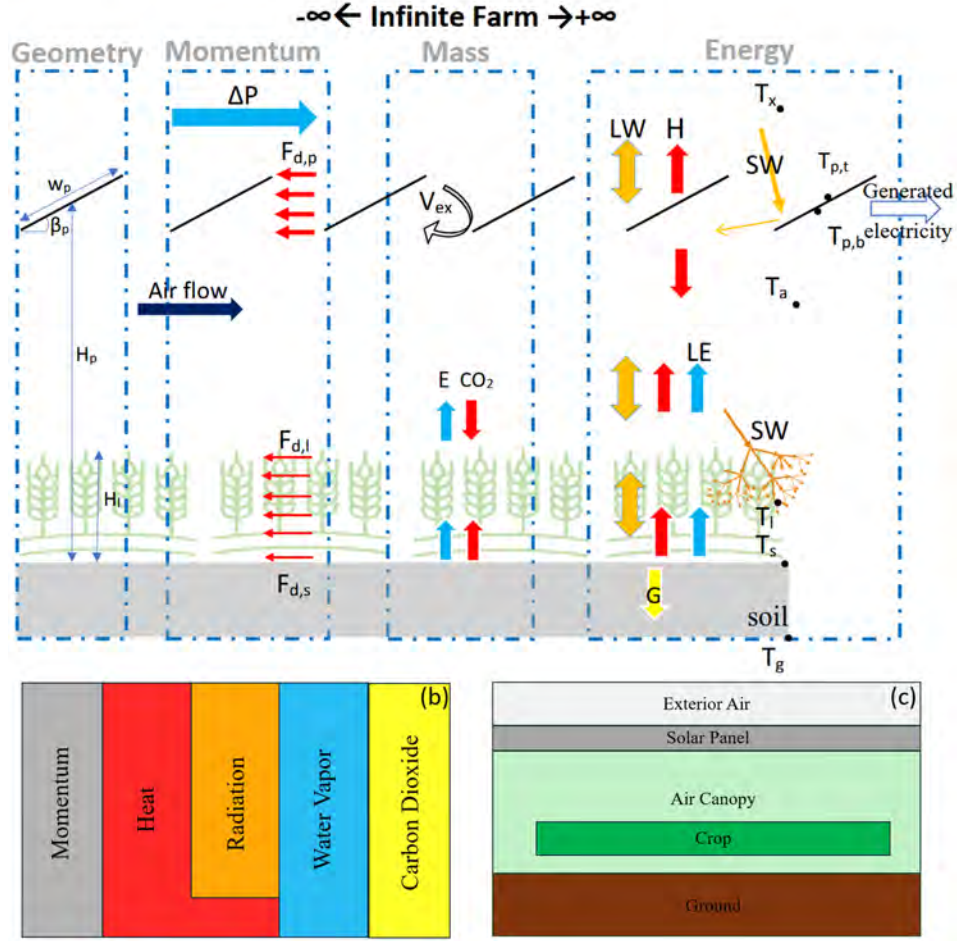


Figure 1. Overview of the key components and processes within the AV system. (top) Representation of the model domain, including all relevant system elements—PV panels, crops, ground surface, and sub-panel air canopy—and associated model parameters and geometrical features. Illustrated fluxes include momentum (pressure-gradient $-\partial P/\partial x$ and drag forces imposed by the panels $F_{d,p}$, the canopy $F_{d,l}$, and the soil $F_{d,s}$), energy (shortwave radiation SW, longwave radiation LW, sensible heat flux H, ground heat flux G, latent heat LE), mass (evaporation and transpiration of water vapor E, soil and crop CO_2 fluxes CO_2), and generated electrical power (P). Black circles denote key surface and air temperatures: ambient exterior (T_x), top and back of panel ($T_{p,t}$, $T_{p,b}$), sub-panel air (T_a), average leaf (T_l), soil surface (T_s), and deep ground (T_g). The $\pm$ symbols indicate that the farm is assumed to be sufficiently large in the horizontal direction, such that variations along the streamwise axis are negligible. As a result, the model can be considered essentially one-dimensional. (bottom left) Conceptual schematic of the principal transport phenomena: momentum exchange, energy exchange, and scalar exchanges of CO_2 and H_2O . (bottom right) Simplified representation of system components, showing the spatial arrangement of exterior air, panel, sub-panel air space, vegetation layer, and soil.

2 Methodology

To represent the AV microclimate, the coupled mean budgets of energy, horizontal momentum, and scalar mass (CO_2 and H_2O), along with crop physiological responses, are considered. The overall structure of the model is presented in Fig. 1 and the param-

eterizations of the associated budgets are described below. Further details, including the modeling of heat perception and additional parameterizations, are available in the SI. A Cartesian coordinate system is used and defines x as along the mean wind direction, y as the lateral direction, and z as the vertical direction, with $z = 0$ being the soil surface.

The farm is presumed to be sufficiently extensive and spatially homogeneous, with negligible horizontal inhomogeneities, aside from those related to radiation. More exactly, this means that the edge zones where the lateral boundaries are felt have a negligible area compared to the whole farm. With minor adjustments (e.g., prescribing surrounding ambient scalar concentrations and wind profiles), the model can also be applied to smaller farms; most modules remain valid except the wind and scalar parameterizations, which would then need modifications. The crop canopy is dense and horizontally uniform, characterized by a crop height H_l and leaf area density $a(z)$ (leaf area per canopy volume) that can vary with z . The $a(z)$ follows the integral property $LAI = \int_{z=0}^{z=H_l} a(z)dz$, where LAI is the leaf area index. The crop radiative, aerodynamic, and physiological properties are assumed to be known a priori for the target crop. The hydraulic and thermal properties of the underlying soil are also externally supplied. The variations in H_l and LAI are presumed to occur on time scales much longer than the simulated period (e.g., a few days), and they are thus kept constant during a given run.

The panel system is characterized by a panel width w_p , a panel inclination angle β_p , and a height of the panel center above the ground H_p . The thermal and radiative properties of the panels are presumed to be known from the manufacturer. The vertical extent of the computational domain is set at $6H_p$. In the x-direction (perpendicular to the panel length), spatial homogeneity can be assumed when averaging over one row, while in the y-direction (along the panel length), the domain is sufficiently long to ensure translational symmetry. Therefore, the equations solved are effectively averaged over a horizontal plane.

2.1 Momentum transfer

The mean wind field determines the panel and leaf convective cooling, and the aerodynamic conductance to the vertical exchanges of heat and mass — particularly carbon dioxide (CO_2) and water vapor (H_2O) — between the soil, vegetation, and overlying atmosphere. These exchanges modulate the overall energy balance of the system and the temperatures of various components, gas concentrations, and crop physiological processes. This subject is occasionally investigated through experiments and high-fidelity CFD simulations (Abiola-Ogedengbe et al., 2015; Baetu et al., 2013; Jubayer & Hangan, 2014, 2016; Williams et al., 2023; Reina & De Stefano, 2017; Aly & Bitsuamlak, 2013). Three-dimensional simulations are required when resolving panel-scale wake dynamics or quantifying aerodynamic parameters such as drag coefficients. However, their computational demands prevent their applicability to high-resolution analyzes of specific configurations and over extended periods, such as a growing season. For broader applications such as microclimate modeling and AV system optimization, where capturing key transport phenomena with reduced computational overhead is needed, a simplified formulation is used. The simplest formulation that we employ here is a one-dimensional simulation of the Reynolds-Averaged Navier-Stokes (RANS) equations. When adapted to represent conditions within the atmospheric boundary layer (ABL) and the system’s geometric layout, this approach can yield a reliable representation of vertical momentum transport and of the drag from the panels, vegetation, and soil — and can thus capture the highly variable wind speed in the system — all while maintaining reasonable computational speed.

To obtain first-order estimates of the wind profile within the AV system, a quasi-steady, horizontally averaged streamwise momentum balance is formulated. For an in-

compressible flow, the mean continuity and mean longitudinal momentum balance can then be expressed as

$$\frac{\partial \overline{\rho_a}}{\partial t} = -\frac{\partial \overline{w}}{\partial z} = 0; \quad \frac{\partial \overline{u}}{\partial t} = -\frac{1}{\overline{\rho_a}} \frac{\partial \overline{P}}{\partial x} - \frac{\partial}{\partial z} \overline{\tau_{zx}} - \frac{1}{\overline{\rho_a}} \overline{f_{d,p}} - \frac{1}{\overline{\rho_a}} \overline{f_{d,l}}, \quad (1)$$

where the overbar denotes Reynolds (time) averaging followed by spatial averaging over a local horizontal plane. No actual averaging is needed in the model since we solve for the mean equations, but conceptually, for RANS, the spatial averaging should be sufficiently large to accommodate many stems and leaves but smaller than the horizontal dimension of the farm. The corresponding time averaging should be over periods much larger than the integral scale of turbulence but much smaller than the time scale associated with diurnal variations. If comparing to observations, it is a common practice to set this time averaging period to 30 min (Charuchittipan et al., 2014), which is deemed as an acceptable compromise between the need to integrate over a large number of eddy turnover times and the need to resolve the diurnal variation of meteorological drivers such as photosynthetically active radiation (PAR) and other radiative loads throughout the day. The u and w represent the streamwise and vertical components of the wind velocity, respectively; t is time. The P denotes the mean pressure field, and $\overline{\rho_a}$ is the mean air density. The mean fluid continuity equation implies that $\overline{w}$ does not vary with z (through the turbulent component of w causes significant vertical mixing), which when combined with the approximation that the soil surface is a rigid impervious wall leads to $\overline{w} = 0$ throughout the domain. In reality, this assumption is an idealization that can be refined in the future by including pressure pumping and gas exchange within the soil-subcanopy system, as reviewed elsewhere (Massman & Frank, 2022). The left hand side of the mean momentum balance equation represents the local acceleration of the mean flow; the first term on the right hand side is the streamwise pressure gradient force; the second combines the turbulent and dispersive forces (the gradient of the total momentum transport τ_{zx}); here, the viscous stress is largely neglected (except in the formulation of the bottom boundary condition, as discussed later) due to the anticipated large Reynolds number of the atmospheric flows even in the first few meters above the surface. The drag forces per unit volume exerted by the panel structures and the crop canopy are denoted by $f_{d,p}$ and $f_{d,l}$, respectively. Before solving the equation, it is normalized by the time-varying velocity boundary condition at the top of the domain, which results in self-similar profiles at all times. The resulting normalized wind profile $\overline{u_n(z)}$ is then in a quasi-steady state, and the local normalized acceleration term is negligible $\partial \overline{u_n} / \partial t \approx 0$.

It is to be noted that density gradients or thermal stratification do not appear explicitly in the mean momentum balance, and thus buoyancy is neglected in the present version. This is reasonable since the various roughness elements generate significant shear turbulence, and the height is limited, which then results in close to neutral conditions within the AV farm. Stability corrections can be introduced for weak wind or strong heat flux conditions, but conventional Monin-Obukhov corrections cannot be used since the hot panels in fact create a stable stratification underneath, and thus more appropriate stability formulations need to be developed.

To close the momentum equation, K-theory (or eddy diffusivity theory) (Boussinesq, 1877) is employed, wherein turbulent+dispersive fluxes are assumed to be proportional to the mean gradient of the corresponding mean quantity, analogous to (very strong) molecular diffusion. While this is usually only used to represent turbulent (not dispersive) fluxes, it will be adopted here for the sum since turbulent fluxes are expected to dominate in dense canopies (Poggi & Katul, 2008) and since there are no practical models to separately parameterize the dispersive component for real AV canopies. Accordingly,

$$\overline{\tau_{zx}} = -K_m \frac{\partial \overline{u}}{\partial z}, \quad (2)$$

where K_m denotes the turbulent eddy viscosity, which may be represented using the Prandtl–von Kármán mixing length formulation (Prandtl, 1925) given by

$$K_m = L_m^2 \left| \frac{\partial \bar{u}}{\partial z} \right|, \quad (3)$$

L_m is the mixing length at a given location in the flow domain (independent of x), often referred to as the ‘master length scale’ (Mellor & Yamada, 1982). Its shape is constrained by the geometric setting and boundary conditions of the AV farm. Inside the canopy, the mixing length L_m is assumed to remain constant (Poggi et al., 2004; Katul et al., 2004). The details of the validation of the L_m model using multiple independent data sources, along with details of the coefficients, are provided in the SI.

Above the canopy, drawing on studies of neutral atmospheric boundary layers (Bou-Zeid et al., 2005), forest canopies (Zahn et al., 2024; Su et al., 1998), and solar power plant (Glick et al., 2020), the following parameterization for L_m is proposed for this study:

$$L_m(z, \beta) = \underbrace{\left(\frac{1}{k_g(\kappa(z - z_d))} + \frac{1}{k_e d_e + L_{e0}} + \frac{1}{L_{inf}} \right)^{-1}}_{\text{Harmonic Base}} + \underbrace{\frac{k_A \tan(\beta_p)}{|z - z_{peak}| + k_W}}_{\text{Panel Peak}}, \quad (4)$$

where κ is the von Kármán constant (≈ 0.41 , Kármán (1930)), and z the height from the ground. The parameter k_g represents the ground influence coefficient, while the zero-plane displacement height z_d is relevant for dense canopies with vertically uniform leaf area distribution and is typically approximated as $0.64 H_l$, following (Stanhill, 1969); a more detailed discussion of this displacement height is provided in the SI. The coefficient k_e , along with the offset L_{e0} , accounts for the influence of the panel edges, where d_e is the vertical distance from the nearest edge of the panel. The constant L_{inf} represents the far-field mixing length contribution, ensuring that the harmonic term asymptotically approaches a lower limit far above the panels. Based on the results from Glick et al. (2020), which we calibrated our mixing length model to match, we added the second term in the equation to capture the panel-induced peak enhancement. Here, k_A and k_W define the amplitude and width of this enhancement, respectively. The vertical height of the peak effect, z_{peak} , is given by $h_p + 0.2 w_p \sin(\beta_p)$, which corresponds approximately to 70% of the vertical projection of the panel width w_p .

The panel drag is parametrized using the quadratic drag law (Shademan et al., 2014):

$$\overline{f_{d,p}} = \frac{1}{2 s_p} c_{d,p} \overline{\rho_a} \overline{u} |\overline{u}| \Delta_{d,p}(z, H_p, \beta_p, w_p), \quad (5)$$

where s_p is the row-to-row spacing between panels; $c_{d,p}$ is a dimensionless drag coefficient (Shademan et al., 2014); and $\Delta_{d,p}$ is a panel drag indicator function to delineate the vertical extent of the panels. It is defined as:

$$\Delta_{d,p}(z, H_p, \beta_p, w_p) = \begin{cases} 1, & \text{if } H_p - \frac{1}{2} w_p \sin(\beta_p) < z < H_p + \frac{1}{2} w_p \sin(\beta_p) \\ 0, & \text{otherwise} \end{cases}. \quad (6)$$

The vegetated drag imposed on the flow is parametrized as:

$$\overline{f_{d,l}} = \frac{1}{2} c_{d,l} \overline{\rho_a} a(z) \overline{u} |\overline{u}| \Delta_{d,p}, \quad (7)$$

where $c_{d,l}$ is the crop canopy drag coefficient set to a mean value 0.4 (or 0.2 when the factor 1/2 in $f_{d,l}$ is dropped, as conventional in the micro-meteorology literature (Katul et al., 2004)). The corresponding canopy drag indicator function $\Delta_{d,l}$ is defined as

$$\Delta_{d,l}(z, H_l) = \begin{cases} 0, & \text{if } z/H_l > 1 \\ 1, & \text{if } 0 < z/H_l \leq 1. \end{cases} \quad (8)$$

The details of numerical setup is discussed in the SI.

2.2 Energy transfer

This section details how the temperatures of individual elements and facets are determined as outcomes of radiative energy exchanges and heat transfer, and how this is linked to water evaporation and its latent heat. As shown in Fig. 1, the following elements are present within an AV farm: panels are considered to have three principal layers: the topmost glass layer with temperature $T_{p,t}$, the active layer with temperature $T_{p,c}$, and the back surface with temperature $T_{p,b}$. Crops are considered collectively as a single big leaf, behaving thermally as a single facet with temperature T_l . Unlike for momentum (and for carbon in the next section), where we resolve the fine-scale vertical variability, for heat and water vapor, we assume that the sub-panel air canopy is well-mixed with a vertically homogeneous T_a and q_a profiles. This is reasonable since all elements below the panels either emit or receive energy and water from the air at a given time of the day, which renders the profiles much less variable, and this also significantly simplifies the energy and radiative transfer calculations. The soil surface is represented by temperature T_s , and the deep ground by a constant temperature T_g . Each interface/facet is defined as an infinitesimally thin layer of solid with negligible thermal inertia, separating that solid from the surrounding air or from another solid layer. The ground and air are the only parts of the system assumed to have thermal inertia and an ability to store heat, while the panels and leaves are thin enough to be represented as a single interface (leaves) or 3 interfaces (panels) with zero thermal mass. Consequently, the coupled and closed energy budget equations of the system can be solved while ensuring that all elements exchange heat through the relevant modes (conduction, convection, and radiation), to compute the temperature of each facet at each time step and, in turn, the associated fluxes. For each facet, the energy balance is given by

$$\underbrace{[SW_{in} - SW_{out} + LW_{in} - LW_{out}(T)]}_{\text{Net radiative inputs} = R_n} = \underbrace{[H(T) + LE(T) + G(T) + P(T)]}_{\text{Energy partitioning outputs}}, \quad (9)$$

where R_n is the net radiation; T is the target surface temperature; SW_{in} denotes the incoming shortwave radiation incident upon the surface; SW_{out} represents the outgoing shortwave radiation, comprising both reflected and transmitted components; LW_{in} is the incoming longwave radiation originating from the atmosphere as well as from other elements within the surface's field of view; LW_{out} is the outgoing longwave radiation, including both reflection and emission; H is the sensible heat flux exchanged between the surface and the surrounding air; LE denotes the latent heat flux emitted from evaporating surfaces such as soil and crops (panels are assumed dry); G is the conductive heat flux transferred from the surface into the adjacent solid material (which may subsequently be stored as heat or conducted through the material); and P is the electrical power generated, which does not contribute to sensible heating of the panels (applicable only to PV panels).

The incoming shortwave radiation is parametrized as:

$$SW_{in} = VF_{sky} R_{sw,dif} + \cos(\gamma) R_{sw,dir} + \sum_{i=1}^n SW_{ref,i} VF_{i \rightarrow j}. \quad (10)$$

Here, VF_{sky} denotes the sky view factor of the element under consideration, $R_{sw,dif}$ the diffuse shortwave radiation incident upon the surface, γ the angle between the incident direct solar radiation and the surface unit normal vector, $R_{sw,dir}$ the direct beam radiation intensity (perpendicular to the rays), $SW_{ref,i}$ the reflected shortwave radiation from the i^{th} element, and $VF_{i \rightarrow j}$ the view factor from the i^{th} element to the j^{th} element under consideration. The details of the view factor parametrization and the shortwave radiation distribution are derived elsewhere (Hosseini & Bou-Zeid, 2025) and summarized in the Supporting Information (SI) for completeness.

The outgoing shortwave radiation is parametrized as:

$$SW_{out} = (\alpha + \tau) SW_{in}, \quad (11)$$

where α represents the shortwave reflectivity of the surface and τ denotes its transmissivity. For panel tops, panel backs, and soil surfaces, the transmitted and reflected shortwave radiation are determined by the intrinsic surface properties. In contrast, for crop canopies, photosynthesis necessitates a detailed representation of solar exposure, and both reflectivity and transmissivity depend on individual leaf properties, including reflectivity, leaf density, and orientation.

Light attenuation within the crop canopy is parameterized as (Campbell & Norman, 2000; Juang et al., 2008)

$$\tau_l(z) = \exp[-\xi K_{be}(x_o, \varphi) L(z)], \quad (12)$$

where τ_l is the fraction of photosynthetically active radiation (PAR) reaching a level z relative to PAR at $z/H_l = 1$; ξ is the clumping factor; K_{be} is the beam extinction coefficient, which depends on the solar zenith angle φ and the parameter x_o , defined as the ratio of the average projected area of leaves on the horizontal plane to that on the vertical plane (e.g., $x_o = \infty$ for horizontal leaves and $x_o = 0$ for vertical, while $x_o = 1$ for random distributions of leaf orientations (Campbell & Norman, 2000)); $L(z)$ denotes the cumulative leaf area index from the top of the canopy down to height z :

$$L(z) = \int_{H_l}^z a(z) dz. \quad (13)$$

Assuming azimuthal symmetry in the foliage area distribution, the beam extinction coefficient K_{be} for vegetation with an ellipsoidal leaf inclination distribution is given as (Campbell & Norman, 2000):

$$K_{be}(x, \varphi) = \frac{\sqrt{x_o^2 + \tan^2(\varphi)}}{x_o + 1.774(x + 1.182)^{-0.733}}. \quad (14)$$

The components of the longwave exchange for the j^{th} element are parametrized using the Stefan-Boltzmann law

$$LW_{in} = VF_{sky} LW_{sky} + \sum_{i=1}^n \varepsilon_i \sigma T_i^4 VF_{i \rightarrow j} + \sum_{i=1}^n LW_{ref,i} VF_{i \rightarrow j}, \quad (15)$$

$$LW_{out} = \varepsilon_j \sigma T_j^4 + (1 - \varepsilon_j) LW_{in}, \quad (16)$$

where ε_i denotes the longwave emissivity of the i^{th} object; σ is the Stefan-Boltzmann constant equal to $5.67 \times 10^{-8} \text{ (W m}^{-2} \text{ K}^{-4}\text{)}$; T_i is the temperature of the i^{th} object; $LW_{ref,i}$ is the longwave radiation reflected from the i^{th} object; ε_j and T_j represent the emissivity and temperature of the j^{th} element under consideration, respectively. Note that (1-

ε_j) represents the longwave reflectivity according to Kirchhoff's law of thermal radiation.

The convective heat exchange with the air for each element is parameterized using a bulk heat transfer formulation, and is driven by the difference between the surface temperature (T) and the surrounding air temperature (T_a). Such bulk formulation also requires a heat-transfer coefficient (h) that depends on the surrounding flow regime, as well as the physical and geometrical properties of the element. Mathematically, this sensible heat flux is expressed as

$$H = h(T - T_a). \quad (17)$$

The heat transfer coefficient for panels (h_p), in configurations involving multiple arrays typical of PV plants — rather than a single panel — is parameterized following Smith et al. (2022). Their formulation introduces a PV site characteristic length scale known as the lacunarity length scale (L_l), derived from a fractal lacunarity approach and computed based on the spatial heterogeneity of the solar energy site. Further details on the definition and computation of the heat transfer coefficient, as well as that of the lacunarity length scale, are provided in the SI. This formulation leads to

$$h_p = 10^{0.09 Re_{L_l}^{1/5} Pr^{1/12} + 1.91}, \quad (18)$$

where k_a denotes the thermal conductivity of air ($k_a \approx 0.0263 \text{ W m}^{-1} \text{ K}^{-1}$) and $Pr = 0.71$ is the molecular Prandtl number of air at typical temperatures and pressures (Brutsaert, 1982). The heat transfer coefficient for vegetative surfaces can be expressed as:

$$h_l = \overline{\rho_a} c_p g_{a,h}, \quad (19)$$

where c_p is the specific heat capacity of dry air at constant pressure, and $g_{a,h}$ is the aerodynamic conductance for sensible heat transfer (in units of m s^{-1}), which is the inverse of the atmospheric conductance for sensible heat exchange, $g_{a,h}$, as parameterized in Campbell and Norman (1998) (see 2.3). The modeling of transpiration from the vegetation is described in the following two sub-sections, along with the associated carbon exchange and plant physiology models.

Building on the derivation presented by Bateni and Liang (2012), the sensible and latent heat transport from the soil surface to the sub-panel air canopy are modeled using the bulk aerodynamic formulation:

$$h_s = \overline{\rho_a} c_p C_H U, \quad (20)$$

where C_H is the bulk heat transfer coefficient, and U is the wind speed at the same reference height where the air temperature is taken. This reference height is taken as the mid-point of the below-panel air space, i.e., at $z = H_p/2$. The product $C_H U$ represents the thermal conductance and is defined as

$$C_H U = \left(\int_0^z \frac{1}{K_h} dz \right)^{-1}, \quad (21)$$

where K_h is the turbulent diffusivity for heat transport, given by $K_h = K_m / Pr_t$, where K_m is the turbulent viscosity as derived above in the momentum transfer section, and $Pr_t = 1$ is the turbulent Prandtl number.

Similarly, the latent heat flux from the soil surface is expressed as

$$LE_s = \lambda_v \overline{\rho_a} C_q U [q_s - q_a(z)], \quad (22)$$

where λ_v the latent heat of vaporization, q_s the specific humidity at the soil-air interface (or can alternatively be assumed equal to the saturated value at the soil surface temperature if the soil is fully wet), $q_a(z)$ is the specific humidity at height z above the surface, and C_q is the bulk transfer coefficient for moisture. Both heat and water vapor are scalar quantities transported by turbulent eddies. Under near-neutral atmospheric conditions, this transport is similar (Li & Bou-Zeid, 2011; Li et al., 2011), and it is thus reasonable to assume that $C_q = C_H$.

The portion of solar energy converted into electricity needs to be accounted for as a sink in the panel's active layers. Conventional silicon-based solar panels exhibit an energy conversion efficiency ranging from approximately 15% to 26% (M. Green et al., 2020; M. A. Green et al., 2024). However, this efficiency is defined under standard test conditions (STC), typically at a panel temperature of $T_{\text{STC}} = 25^\circ\text{C}$. According to data from NREL, panel efficiency decreases by approximately 0.2% to 0.5% per Kelvin of temperature rise above the STC threshold (King et al., 1997). Thus, the electrical power generated per unit area of panel may be described by

$$P = \eta_a SW_{p,\text{inc}} = \eta_n (1 - \delta (T_{p,c} - T_{\text{STC}})) SW_{p,\text{inc}}, \quad (23)$$

where η_a is the temperature adjusted conversion efficiency; $SW_{p,\text{inc}}$ is the incident short-wave radiation on the panel surface; η_n is the nominal efficiency of the panel under STC (provided by the manufacturer); and δ is the temperature coefficient of the PV panel (in K^{-1}).

To parameterize the heat conduction in solids (through panel layers or within the soil), a thermal force-restore model, also known as a resistance-capacitance (RC) model, is applied. In this model, the conductive heat flux is

$$G = \frac{T_1 - T_2}{R_x} + c_x \frac{d}{dt} (T_1 - T_2), \quad (24)$$

where T_1 and T_2 are the temperatures at the two boundaries of the solid layer; R_x is the thermal resistance of the material (e.g., soil or panel), and c_x its thermal capacitance. The resistance is defined as $R_x = d/k_x$, where d is the layer thickness and k_x is the thermal conductivity. The capacitance is defined as $c_x = C d$, where C is the volumetric heat capacity of the material. In cases where direct measurements of soil thermal conductivity and heat capacity are unavailable, they are estimated following the approach by Takebayashi and Moriyama (2007), which is presented in the SI and accounts for their dependence on moisture content. The formulation used to compute the characteristic extinction depth, of the diurnal temperature fluctuations, as proposed by Singh and Sharma (2017), is also detailed in the SI.

2.3 Mass transfer

As described in the previous subsection, the water vapor budget is treated using a lumped approach, as for sensible heat. However, to represent carbon transfer in the AV system, the mean scalar budget equation (i.e., time and planar-averaged) is employed, and resolved vertically using the same resolution as for momentum to capture the strong vertical variability in the carbon profiles (with intermixed sinks and sources) that will impact crop yield. The resulting CO_2 mass balance equation is thus given as

$$\frac{\partial \bar{\xi}}{\partial t} + \bar{u} \frac{\partial \bar{\xi}}{\partial x} + \bar{w} \frac{\partial \bar{\xi}}{\partial z} = -\frac{\partial \overline{w' \xi'}}{\partial z} + S_\xi, \quad (25)$$

where ξ denotes the CO_2 concentration; $\overline{w'\xi'}$ represents the turbulent flux of CO_2 ; primed quantities are, as before, perturbations from their respective means (and as with momentum, the smaller dispersive fluxes are lumped with the turbulent fluxes after applying spatial followed by time averaging); and S_ξ represents biologically controlled source or sink terms. In this version of the model, we will assume that the change in carbon storage in the air layer is negligible compared to the vertical fluxes, which then allows us to neglect the $\partial\bar{\xi}/\partial t$ term (this can be relaxed if needed). For a planar homogeneous flow ($\partial(\cdot)/\partial x = \partial(\cdot)/\partial y = 0$) and in the absence of subsidence, both advective transport terms on the left-hand side of the equation can also be ignored (as was the case for the mean momentum). Despite these simplifications, the resulting equation that balances fluxes and source and sinks of carbon remains mathematically unclosed, as it provides one equation with three unknowns: $\overline{w'\xi'}$, S_ξ , and $\bar{\xi}$, necessitating two other equations (or closure models).

The first closure model is based on analogies to how the mean momentum equation was treated, whereby $\overline{w'\xi'}$ can be described using K-theory (or first-order closure) so that

$$\overline{w'\xi'} = -K_\xi \frac{\partial \bar{\xi}}{\partial z}, \quad (26)$$

where K_ξ is the turbulent diffusivity of the scalar ξ and is parameterized directly from the eddy viscosity using

$$K_\xi = \frac{K_m}{Sc_t}, \quad (27)$$

with K_m defined in subsection 2.1, and Sc_t the turbulent Schmidt number. For consistency with the turbulent Prandtl number used for heat (which also applies for humidity), a constant $Sc_t = 1$ is adopted (though the variability of these numbers with atmospheric stability conditions and other variables can be easily accommodated).

The second closure models linking S_ξ to $\bar{\xi}$, which is also used for water transpiration from the plants and the air, require plant physiological processes operating at the leaf scale, and those processes must then be up-scaled to the layer-scale $a(z)$. They are canonically expressed as

$$S_\xi(z) = \frac{a(z)}{r_s(z) + r_{a,\xi}(z)} (\bar{\xi}_s(z) - \bar{\xi}_a(z)), \quad (28)$$

where $r_s(z)$ is the stomatal resistance; $r_a(z)$ is the aerodynamic resistance due to the presence of a laminar boundary layer attached to the leaf surface; and $\bar{\xi}_s$ and $\bar{\xi}_a$ are the mean surface and local atmospheric concentrations of ξ at z , respectively. The working assumption is that the exchange of scalars at any height z between leaves and the surrounding air encounters two resistances in series: an aerodynamic resistance and a stomatal resistance. The aerodynamic resistance is the inverse of the atmospheric conductance ($g_{a,\xi}$) and for leaves is given as (Campbell & Norman, 1998):

$$r_{a,\xi} = g_{a,\xi}^{-1} = A_{b,\xi} \sqrt{\frac{L_t}{u(z)}}, \quad (29)$$

where L_t represents the characteristic leaf length along the flow direction and $u(z)$ denotes the wind speed at z (modeled from the mean momentum balance as before). The coefficient $A_{b,\xi}$ depends on the scalar ξ . For carbon dioxide and water vapor, $A_{b,\xi} = 342$ and 255, respectively. Similarly, this equation can be used for aerodynamic resistance for heat transfer, and the coefficient is 307. Models for r_s are still needed to close the mass transfer formulation mathematically, and those closure schemes are considered next in the context of crop physiology, whereby when stomata open to uptake carbon dioxide, they lose water vapor molecules that must be replenished from the soil reservoir.

2.4 Crop physiology

Photosynthesis per unit leaf area is the primary term influencing crop yield. It is tightly coupled to leaf transpiration, which in turn, can modify the energy balance of the entire AV farm, including the cooling of the solar panels. As noted earlier, these carbon and water exchange processes are impacted by stomatal conductance at the leaf scale. To model stomatal conductance, a logical starting point is to consider the balance between the biochemical demand and the atmospheric supply of carbon dioxide. The biochemical demand is given by the Farquhar photosynthesis model (Farquhar et al., 1980; Collatz et al., 1991) for C3 plants. It parametrizes the net rate of CO₂ uptake at the leaf, denoted as A_n , as limited by three factors: the carboxylation capacity of Rubisco (A_{JC}), the regeneration capacity of RuBP (electron transport) (A_{JE}), and the triose phosphate utilization (TPU) rate (A_{JS}). That is,

$$A_n = \min \begin{cases} A_{JC} - R_d = \frac{V_m (C_{ci} - \Gamma^*)}{C_{ci} + K_c \left(1 + \frac{O_a}{K_o}\right)} - R_d, \\ A_{JE} - R_d = \frac{\alpha_p e_m Q_p (C_{ci} - \Gamma^*)}{\sqrt{1 + \frac{(e_m Q_p)^2}{J_{\max}^2}} (C_{ci} + 2\Gamma^*)} - R_d, \\ A_{JS} - R_d = \frac{V_m}{2} - R_d. \end{cases} \quad (30)$$

In this expression, V_m represents the maximum Rubisco carboxylation capacity per unit leaf area with species-specific values available in the literature (Wullshleger, 1993); C_{ci} denotes the intercellular concentration of CO₂; O_a denotes the atmospheric O₂ concentration; K_o and K_c are the Michaelis–Menten constants associated with inhibition by oxygen and CO₂, respectively, with typically values at 300 mmol mol⁻¹ for O₂ and 300 μmol mol⁻¹ for CO₂; Γ^* is the CO₂ compensation point and defines the concentration at which net CO₂ assimilation is zero; α_p denotes the leaf absorptivity in the PAR spectrum; e_m is the maximum quantum efficiency defined as the number of CO₂ molecules fixed per absorbed photon; Q_p is the incident PAR photon flux density (approximated as $Q_p \approx 0.43 \left[\frac{W_{\text{PAR}}}{W_{\text{SW}}} \right] \times 4.56 \left[\frac{\mu\text{mol}_{\text{PAR}}}{\text{J}_{\text{PAR}}} \right] \times SW [\text{W}/\text{m}^2] \approx 1.96 SW \left[\frac{\mu\text{mol}}{\text{m}^2 \cdot \text{s}} \right]$); R_d is the dark respiration and accounts for mitochondrial respiration occurring in the absence of light. Since many of these parameters are sensitive to temperature, modeling the leaf microclimate, which our model is capable of, is necessary. The detailed equations for these thermal responses are available in the SI.

The difference in CO₂ concentration across the leaf–air interface is modeled through a resistive formulation that includes stomatal and boundary layer attached to the leaf surface (as detailed in the previous subsection). The CO₂ mole fraction within the substomatal cavity, C_{ci} , is expressed in terms of the stomatal conductance (g_s) and net assimilation rate (A_n) as

$$C_{ci} = C_l - \frac{A_n}{g_s}, \quad (31)$$

where C_l is the CO₂ mole fraction at the leaf surface that can be derived from the atmospheric mole fraction C_a and boundary layer conductance g_b using

$$C_l = C_a - \frac{A_n}{g_b}. \quad (32)$$

The g_s can be modeled using several approaches. The most popular is the semi-empirical Ball–Berry model (Ball, 1988; Collatz et al., 1991), but modified to include vapor pressure deficit instead of surface relative humidity (Leuning, 1995). In its original form, it

is given as

$$g_s = m \frac{A_n RH_s}{C_s} + g_o \geq g_o. \quad (33)$$

The modification proposed here replaces relative humidity at the leaf surface (RH_s) by $1 - 0.6 \log(\text{VPD})$, with VPD denoting the vapor pressure deficit in the atmosphere near the leaf. This modification has received both empirical support (Oren et al., 1999) and theoretical grounding using stomatal optimality theories (Katul et al., 2009, 2010), whereby g_s was predicted based on the assumption that plants maximize their carbon gain for a given amount of water per unit leaf area in the soil. The constants m and b represent the slope and intercept (cuticular conductance) of the linear relation between g_s and A_n/C_s , respectively. Typical values based on experimental calibration are $m = 5.6$ and $g_o = 0.003 \text{ mol m}^{-2} \text{ s}^{-1}$, derived from gas exchange measurements under controlled conditions (Lai et al., 2000). Notably, cuticular evaporation can still occur in the absence of stomatal conductance. With this formulation for r_s , the scalar sources and sinks for carbon dioxide (S_c) and water vapor (S_v) are given by

$$S_c = \frac{a(z)}{r_s(z) + r_{a,c}} [C_{ci}(z) - C_a(z)]; S_v = \frac{a(z)}{(r_s(z)/1.6) + r_{a,v}} [e_s(z) - e_a(z)], \quad (34)$$

where $C_{ci}/C_a < 1$ and $e_s/e_a > 1$, the coefficient 1.6 normalizing r_s in S_v is due to the difference in molecular diffusion coefficients between carbon dioxide (heavier molecules) versus water vapor (lighter molecules); e_s is the saturation vapor pressure (or concentration) within the sub-stomatal cavity (assumed to be near saturation for well watered crops); e_a is the actual vapor pressure (or concentration) in the atmosphere adjacent to the leaves at height z . A number of approximations are invoked to efficiently determine e_s and e_a . For the purposes of estimating S_v , it is assumed that (i) the sub-stomatal cavity is fully saturated and in thermal equilibrium with the leaf surface so that e_s can be determined from leaf surface temperature T_s using the Clausius-Clayperon formulation (i.e. a closed system approximation), (ii) the air relative humidity variations with z within the canopy volume are, to a leading order, presumed to be small compared to the PAR variations so that relative humidity may be approximated by its value in the atmosphere near the canopy top. The model can be extended and refined to include a prediction of the profiles of air relative humidity, but prior analyses suggest this refinement is not necessary for $LE(z)$ (Juang et al., 2008) (which also validates our lumped treatment of water vapor concentration in the model). With these approximations, the latent heat flux at any z is

$$LE(z) = LE_s + \lambda_v \int_0^z S_v(z) dz. \quad (35)$$

During nocturnal periods when $Q_p = 0$, the vegetation-soil system act as a net CO_2 source. Above-ground respiration is modeled as $S_c = R_d a(z)$ as before. This model assumes that respiration is predominantly from leaves instead of stems. Soils emit CO_2 at all times owing to autotrophic (e.g., roots) and heterotrophic (e.g., microbes) respiration, represented here as a surface flux to the atmosphere, much like soil evaporation. The temperature dependence of the soil respiration rate, denoted as R_{es} , follows an Arrhenius-type exponential relation (Lloyd & Taylor, 1994):

$$R_{es} = R_r Q_r^{\frac{T - T_r}{T_r}}, \quad (36)$$

where R_r represents the respiration rate at a reference temperature T_r , typically taken as 10 (C), and Q_r is a dimensionless coefficient quantifying the sensitivity of microbial respiration to temperature changes. We adopt a widely cited soil $R_{10} = 3.2 \text{ } \mu\text{mol m}^{-2} \text{ s}^{-1}$ and $Q_{10} = 2.3$, which reflect temperate agricultural soil conditions under moderate moisture levels.

3 Model evaluation

The final model evaluation employed temperature data from two field experiments (see also validation of individual components, such as wind profiles, in the SI). While no single experiment was available to test all aspects of the proposed model simultaneously, the two experiments described here enabled the assessment of the skill of the proposed framework in predicting AV environments and outputs. Due to the absence of farm-scale measurements of crop assimilation and transpiration—particularly under agrivoltaic conditions—these components could not be directly validated. Instead, we assessed the plausibility of the results through comparison with reported values in the literature; these comparisons are provided in the SI.

3.1 Leaf temperature

Leaf temperature measurements were collected in Davis, California (latitude: 38.54°N, longitude: 121.74°W, elevation: 16 m above sea level) on September 4, 2024. Leaf temperature was measured using a SI-4H1-SS infrared radiometer (Apogee Instruments), while net radiation was recorded with an SN-500-SS net radiometer (Apogee Instruments). Ambient temperature and humidity were measured using the ATMOS 14 sensor, wind and other additional meteorological variables for an open field were obtained from an ATMOS 41 Gen 2 all-in-one weather station. The measurement setup involved a horizontally mounted PV system consisting of frame-embedded panels with dimensions of 216 cm $\times$ 175 cm. During the experiment, the PV modules were electrically disconnected, thereby operating at zero efficiency, and exhibited an average solar transmissivity of approximately 10%. The underlying crop was *Solanum lycopersicum* (tomato), with an average canopy height of 40 cm. Representative physiological parameters used for modeling included a $V_{c,max25}$ of 87.9 $\mu\text{mol m}^{-2} \text{s}^{-1}$ and a J_{max} of 169 $\mu\text{mol m}^{-2} \text{s}^{-1}$ (Wullshleger, 1993). The soil is assumed to have a reflectivity of 15% (Campbell & Norman, 1998), longwave emissivity of 0.95 (Formetta et al., 2016), thermal conductivity of 0.42 $\text{W m}^{-1} \text{K}^{-1}$ and a volumetric heat capacity of 2.3 $\text{MJ m}^{-3} \text{K}^{-1}$ (Campbell & Norman, 1998). In this validation run, we implemented a small-scale farm option that assumes the microclimate beneath the panels (temperature, humidity, $[\text{CO}_2]$) is equivalent to the external environment, reflecting the limited buffering capacity of small installations (air flowing under the panels does not change in properties over the few meters of AV installation).

The comparison between measured and modeled crop surface temperature is presented in Fig. 2. As indicated by the error metrics box in Fig. 2, the model results demonstrate good agreement with measurements, exhibiting a mean absolute error (MAE) of 0.6 °C over temperature fluctuations of approximately 25 °C during the day. Additionally, the mean bias error (MBE) is 0.09 °C, well within the measurement error, indicating that the model is unbiased.

3.2 Panel and soil temperatures

To evaluate model predictions for panel and soil surface temperatures, data collected by Choi et al. (2023) at a 9.5-MW Chisago Solar LLC power plant located in North Branch, Minnesota, USA (latitude: 45.5125°, longitude: -92.9833°, elevation: 276 m) are used. The AV system comprises one-axis tracking arrays that remain at 10 angle during nighttime. In the model, the instantaneous tilt angle is defined as $\beta_p = 90 - \varphi$, where φ is the solar zenith angle. This configuration maximizes the incident irradiance by aligning the panel normal with the solar vector, assuming this is also the protocol for the tracking in the real installation. Each panel has a width of 2 m and is mounted at a hub height of 3 m. The row-to-row spacing (center-to-center) is 6.5 m. The monitored area spans approximately 1.2 ha, where 30 cm high native flora vegetation was planted following construction. Soil temperature was measured at 25 cm depth using CS655 (Campbell Scientific, USA), and PV module temperatures were measured using CS240 sensors (Camp-

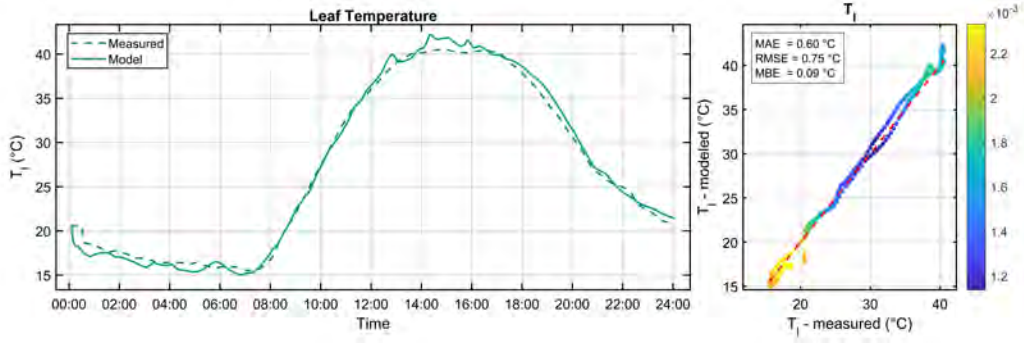


Figure 2. Comparison between modeled and measured leaf temperature (T_l) under horizontal PV panels during an experiment in Davis, California. The left panel shows the temporal evolution of leaf temperature, where the solid line represents the modeled T_l and the dashed line corresponds to observed values. The right panel presents a scatter plot of modeled versus measured T_l values, with the 1:1 line (red dashed) for reference. Color shading indicates the density of point pairs based on kernel density estimation. Summary error metrics include MAE, MBE, and RMSE.

bell Scientific, USA). This is a large installation, and the model is run as described in the previous section (not in its small-farm version). Data were collected using a Campbell Scientific CR6 datalogger, with most variables sampled every 15 seconds and recorded every 15 minutes. The top panel displays the incoming shortwave radiation (SW_{in}), followed by longwave radiation (LW_{in}), wind speed ($\bar{u}$), and exterior air temperature (T_x). Meteorological variables were collected using a Campbell Scientific CR6 datalogger, sampled every 15 seconds and recorded every 15 minutes. Global shortwave radiation was measured with a CS320 thermopile pyranometer, sampled every 10 seconds and averaged hourly. Air temperature and relative humidity were recorded every 15 minutes using EE181 sensors installed 0.5 m above ground across vegetated PV, bare PV, and control plots. Wind speed (min, max, mean, standard deviation) and direction were measured with a 03002 wind sensor. Due to a lack of on-site measurement, longwave radiation data were obtained from the National Aeronautics and Space Administration (NASA) Langley Research Center (LaRC) Prediction of Worldwide Energy Resources (POWER) Project funded through the NASA Earth Science/Applied Science Program.

Vegetation parameters were estimated assuming native flora characteristics reported by Wullshleger (1993), with maximum carboxylation rate at 25 °C ($V_{c,max25}$) of 94 $\mu\text{mol m}^{-2} \text{s}^{-1}$, maximum electron transport rate (J_{max}) of 170 $\mu\text{mol m}^{-2} \text{s}^{-1}$, and a randomly distributed leaf orientation. The soil is characterized by a reflectance of 30% (Campbell & Norman, 1998), a thermal conductivity of 0.21 $\text{W m}^{-1} \text{K}^{-1}$, and a heat capacity of 1.6 $\text{MJ m}^{-3} \text{K}^{-1}$ (Campbell & Norman, 1998). As illustrated in Fig. 3, the modeled panel and soil surface temperatures agree with measurements. The mean absolute errors (MAE) is 1.76 °C for the panel (over a 40 °C range) and 0.21 °C for the soil surface. The soil temperature patterns (wider model diurnal cycle in the left panel and hysteresis in the right panel) indicate that the thermal capacity of the modeled soil is lower than the actual experimental value, with the observations showing a slower thermal response of the soil. While calibration of the soil properties can be done to improve this model-observation match, it is not essential for investigations that follow.

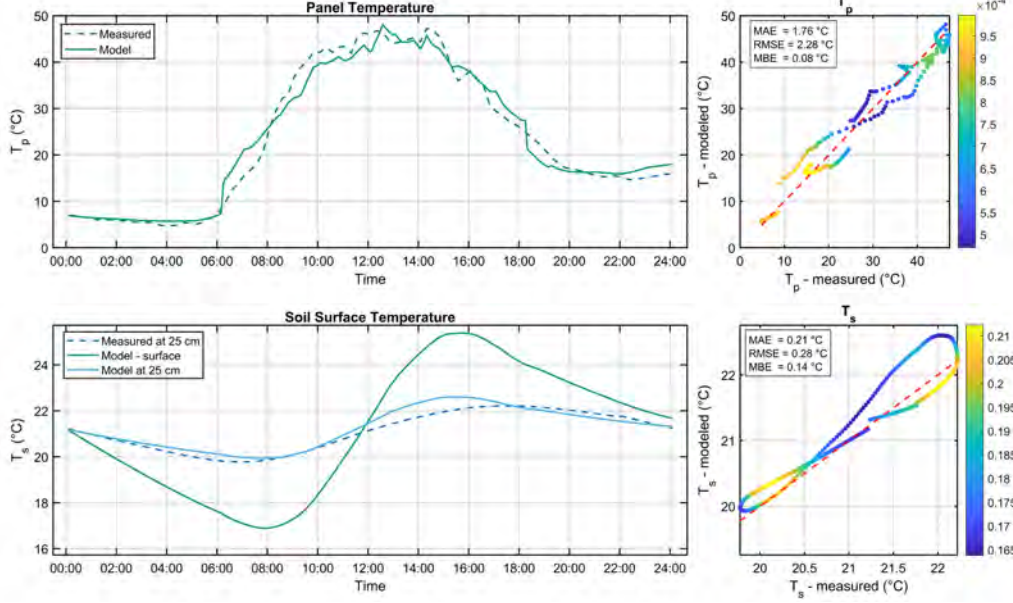


Figure 3. Comparison between modeled and measured temperatures for the solar panel and soil during the experiment in Chisago, Minnesota. **Left panels:** Time series of temperature variations. In the top-left panel, the solid line indicates the modeled panel temperature (T_p) and the dashed line represents the measurements. The bottom-left panel shows soil temperature at different depths: the solid green line shows the modeled surface temperatures (T_s), while the dashed line represents the measurements at 25 cm depth that match the observations at the same depth (solid cyan line) well. **Right panels:** Scatter plot of modeled versus measured values for T_p (top panel) and T_s (bottom panel). The red dashed line in each scatter plot indicates the 1:1 agreement line. Point density is visualized using kernel density estimation. Summary error metrics are included MAE, MBE, and RMSE.

4 Simulation setup

For the model application, meteorological data collected in Princeton, New Jersey (40.3430°N, 74.6514°W; elevation: 45 m above sea level) were used as detailed in the SI. The site experiences a humid subtropical climate (Köppen classification Cfa) during a typical summer day, characterized by clear sky, high temperatures, and elevated humidity. Situated in the middle of the Northeast Corridor, Princeton’s summer environmental conditions are broadly representative of mid-Atlantic urban and suburban settings spanning from Washington, D.C. to New York City, NY. As such, it serves as a relevant proxy for exploring energy fluxes, thermal comfort, and climate-related processes in the most densely populated and urbanized regions in the United States, with high food and energy demand.

Using these meteorological data as input (input for the model is assumed to represent conditions far enough from the PV array and not affected by its presence), the model resolves the transfer of energy, momentum, and mass from the input level (top of the domain) down to depth of the ground, along with the physiological responses of the crop (Fig. 1). The results are interpreted and used for water and agriculture (5.3), energy (5.4), and comfort/health implications (5.5). The photovoltaic (PV) module is summarized in Table 1. The selected crop is, once again, tomato, with an average canopy height of approximately 40 cm (much like the Davis experiment). This choice is moti-

vated by the fact that tomato was used in the model evaluation (Section 3), where its thermal and radiative behavior under panels was evaluated against observational data. Representative physiological parameters used in the modeling include a maximum carboxylation rate at 25 °C ($V_{c,max25}$) of $87.9 \mu\text{mol m}^{-2} \text{s}^{-1}$ and a maximum electron transport rate (J_{max}) of $169 \mu\text{mol m}^{-2} \text{s}^{-1}$ (Wullshleger, 1993). The leaves are assumed to be randomly oriented and distributed, with a maximum leaf area index (LAI) of $2 \text{ m}^2 \text{m}^{-2}$. The underlying soil is assigned a shortwave reflectivity of 25% (Campbell & Norman, 1998), a dry volumetric heat capacity of $2.3 \text{ MJ m}^{-3} \text{K}^{-1}$ (Campbell & Norman, 1998), a longwave emissivity of 0.95 (Formetta et al., 2016), a residual water content of 0.05, and a field capacity of 0.25. Additionally, a solar power plant without any underlying crops (as a reference for energy and heat implications; see Section 5.4) and a cropland without panel coverage (as a reference for agricultural implications; see Section 5.3) are modeled as benchmarks for comparison in each respective aspect. The corresponding characteristics are kept identical to those in the agrivoltaic scenario.

Table 1. Summary of PV module baseline geometry and multilayer material properties (Mertens, 2018; Duffie & Beckman, 2013; Anjana Nair et al., 2025).

layer	thickness	thermal conductivity ($\text{W m}^{-1} \text{K}^{-1}$)	additional properties
glass cover	3 mm	0.8	—
ARC	100 nm	1.2	—
crystalline silicon	225 μm	148	—
EVA encapsulant	800 μm	0.15	—
nanopillar layer	500 nm	1.0	—
rear contact	10 μm	200	—
tedlar backsheets	25 μm	0.15	$\epsilon_{p,b}$: 0.95, $\epsilon_{p,t}$: 0.95
aluminium base	1 cm	205	$\alpha_{p,t}$: 0.12, $\alpha_{p,b}$: 0.70
PV module geometry and orientation			
tilt angle	15	fixed (non-tracking)	south-facing
Mean panel height (H_p)	4 m	—	azimuth 180
width (w_p)	2 m	—	—
row spacing (s_p)	4 m	—	—

5 Results and discussion

The diurnal cycle of the temperatures of the elements of the AV farm (panel layers, leaves, soil, and air) are examined first. Next, an overview of how the environmental conditions (wind speed, and water vapor and carbon dioxide concentrations) are modified in an AV system compared to free air aloft is presented. Then, the agricultural implications for food production are deduced by comparison to a crop field without PV panels, while the power implications are deduced by comparison to a PV site without an underlying crop. Finally, improvements in thermal comfort for workers shaded by the panels, compared to conditions in an open agricultural field, are reported.

5.1 Diurnal cycles of element temperatures

As illustrated in Fig. 4, the model calculations indicate that, due to their low thermal inertia, the solar panels undergo large diurnal temperature variations. Panels heat up rapidly, reaching approximately 25 °C above the ambient air temperature during the day, and cool rapidly to near-ambient levels at night. In this configuration, sub-panel

air temperature (T_a) remains close the exterior air temperature (T_x) at night. Leaves, with minimal stomatal conductance in the absence of light and negligible thermal mass, stay near the canopy air temperature. After sunrise, panels and crops rapidly absorb solar energy and transfer sensible heat to the sub-panel air via convection. Later in the morning, as panel temperatures rise further and crops receive substantial PAR, stomata open to maximize carbon uptake. This leads to transpirative cooling, causing leaf temperatures to drop below T_a , while the shaded soil remains cool. These two factors together keep T_a lower than T_x . As radiation and ambient air temperatures rise, both sub-panel air and leaf temperatures increase. By the afternoon, carbon dioxide in the sub-panel region becomes depleted. These two factors—elevated temperatures, which reduce photosynthetic efficiency and increase vapor pressure deficit, and decreased carbon dioxide—limit stomatal conductance, thereby reducing transpirative cooling. In the absence of transpirative cooling, the leaf temperature (T_l) increases and exceeds the ambient sub-panel air temperature (T_a). This reduction in cooling further elevates temperatures, creating a feedback that exacerbates the process. Toward sunset, as solar radiation and ambient temperatures decline, panel and sub-panel air temperatures decrease as well.

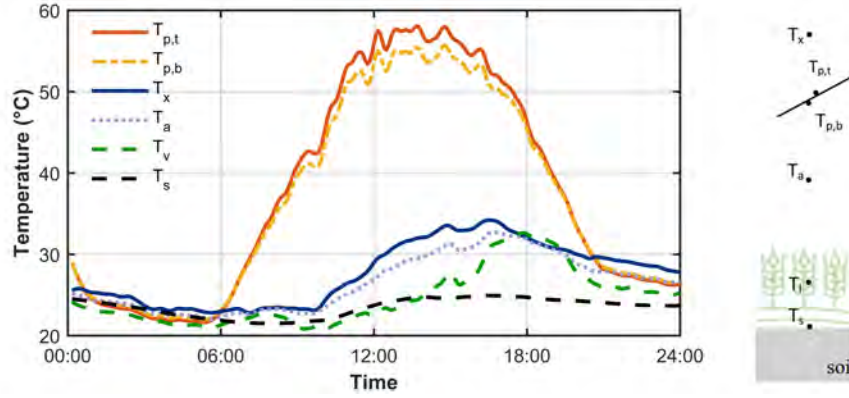


Figure 4. Surface temperature within an AV farm for each component. Left: Diurnal temperature values. Right: Graphical reminder of temperature abbreviations. Variables include: $T_{p,t}$ – top panel surface (glass) temperature, $T_{p,b}$ – back panel surface temperature, T_x – exterior air temperature, T_a – sub-panel air temperature, T_l – leaf temperature, and T_s – soil temperature.

5.2 Diurnal cycles of environmental conditions

As illustrated in Fig. 5, the model determines the microclimate experienced by the crop within the AV system. The primary environmental drivers we examine here include the incident PAR photon density Q_p , the immediate ambient air temperature (T_a) and specific humidity (q) (and the derived relative humidity (RH)). Additional variables that are useful for model verification and physical explanations, such as the mean velocity profile (u) and carbon dioxide concentration (CO_2), are also depicted. Fig. 5.a presents the diurnal variations of PAR for a clear-sky day at the canopy top, and its vertical attenuation through the crop layers. Due to partial penetration of direct light through inter-panel spacing and reflections from the panels, the incoming PAR at the canopy top is lower than that of an open crop field. Given the random orientation and distribution of leaves assumed in the present calculations, Q_p is progressively attenuated with depth through the canopy volume. Since sunlight is a determinant of crop photosynthesis, and since leaves at various heights receive varying levels of irradiance as shown in the lower panel of Fig. 5.a,

the layered representation we adopt, and that resolves the PAR profile, is required for capturing the non-linear effects of PAR on photosynthesis.

Among the primary determinants of leaf temperature is the sensible heat exchange at the leaf surface, which is predominantly influenced by the temperature of the surrounding air (T_a) and mean wind. Additionally, stomatal conductance is significantly modulated by the humidity content of the ambient environment. Figure 5.b (top panel) illustrates the sub-panel air temperature (T_a) in comparison to the external air temperature (T_x). Due to evapotranspirative cooling of crops and soil, the sub-panel region temperature (T_a) remains lower than the exterior air temperature (T_x), specially during the active photosynthesis hours.

The middle and bottom panels of Fig. 5.b show the specific humidity of the sub-panel air (q_a) and that of the exterior environment (q_x). During the day, increased evapotranspiration elevates q_a relative to q_x , contributing to higher absolute humidity beneath the panels. However, during the morning, since the humidity sources are mostly depleted in the absence of significant nocturnal evapotranspiration, the difference between absolute humidity levels across the panels decreases.

Sensible heat exchange from the crop and soil, along with aerodynamic conductance, is directly influenced by wind exposure. Additionally, the presence of panels alters mass exchange with the ambient atmosphere, especially the air space between the canopy and the crop. These effects are accounted for using the mean momentum balance and the resulting mean wind and mixing length profiles. The normalized wind profile is presented in Fig. 5.c, with the upper boundary condition scaled by the measured horizontal wind speed input (u) at a reference height above the farm. As mentioned before, this normalized profile is self-similar and only needs to be computed once at the start of the simulation; the wind profile for a given period is then deduced by scaling the normalized profile with the measured value at the top of the domain.

While soil acts as a source of carbon dioxide via respiration, crops generally function as a net CO₂ sink through photosynthesis during daylight hours. Consequently, individual leaves may encounter varying CO₂ concentrations, and panel structures can further modulate the net gas exchange with the surrounding air. As illustrated in Fig. 5.d, CO₂ levels beneath the panels increase at night due to soil and plant respiration (the eddy diffusivity may also be reduced if the measured wind speed decreases, although stability does not directly enter into our mixing length model). After sunrise, as assimilation commences, the trend reverses and CO₂ concentrations beneath the panels decline. A detailed comparison of the temporal trends of soil respiration versus crop net assimilation/respiration is provided in the SI. The profile of CO₂ concentration is presented in the bottom panel of Fig. 5. As in other components of the AV system, the broader implications depend on the balance between assimilation and respiration. It suffices to note that the model findings indicate that the reduced exchange velocity beneath the panels traps more nighttime-respired CO₂, enriching the leaves and, together with direct light and cooler air temperatures, enhancing early morning photosynthesis. This mechanism is consistent with the experimental observations reported by Sturchio et al. (2024).

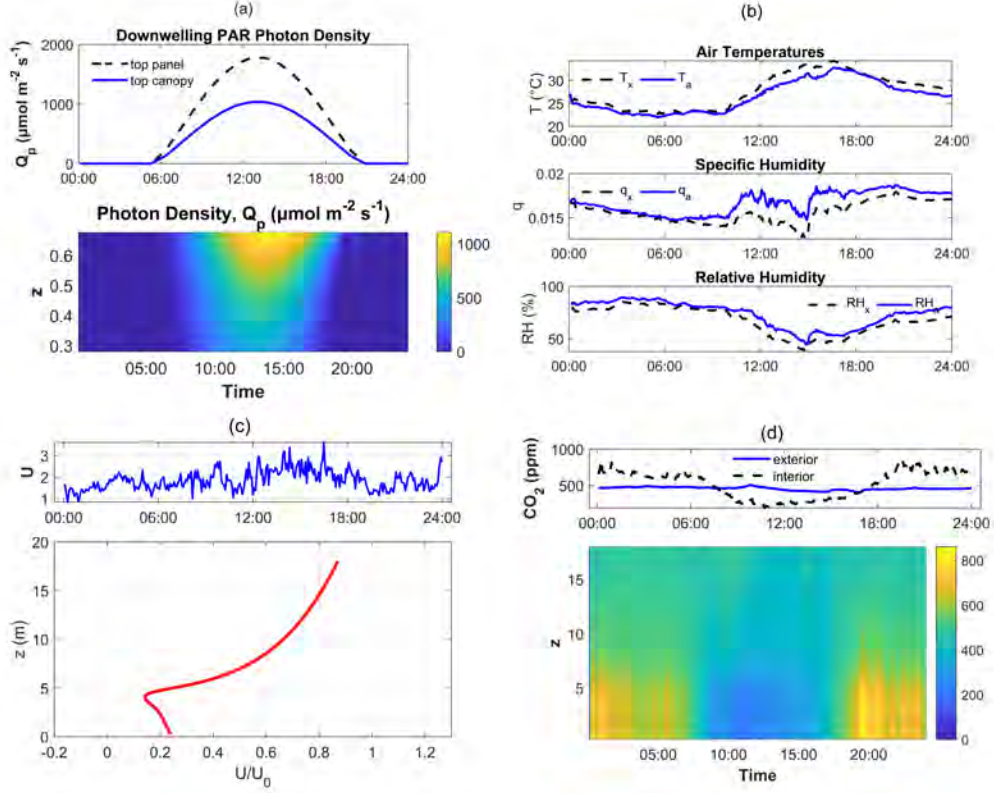


Figure 5. Crop microclimate. (a) Photosynthetically active radiation (PAR) density. (a, top) Incident PAR (Q_p) above the panels and at the top of the crop canopy. (a, bottom) PAR attenuation across the crop canopy (vertical axis) over time (horizontal axis). (b) Temperature and humidity exposure. (b, top) Exterior air temperature (T_s) and sub-panel air temperature (T_a). (b, middle) Exterior specific humidity (q_x) and sub-panel specific humidity (q_a). (b, bottom) Exterior relative humidity (RH_x) and sub-panel relative humidity (RH_a). (c) Wind. (c, top) Horizontal wind speed (u) measured above the panels (Glick et al., 2020). (c, bottom) Normalized wind speed (u_n) profile. (d) CO_2 . (d, top) Measured CO_2 concentration above the panels ($[\text{CO}_2]_x$) and modeled sub-panel concentration ($[\text{CO}_2]_a$). (d, bottom) CO_2 concentration profile with normalized wind speed.

5.3 Agricultural implications

As a result of the microclimate created within the crop canopy, individual leaves respond differently depending on their exposure to environmental conditions, leading to variations in assimilation and transpiration as illustrated in Fig. 6. Across the canopy, as PAR penetration decreases closer to the soil surface, A_n also declines (Fig. 6.a). However, other factors—such as increased canopy temperature or carbon depletion in the late afternoon also contribute to reduced photosynthetic activity. The multi-layer treatment of the canopy here can distinguish between the various limitations on A_n . During high PAR periods (e.g., solar noon), the upper layers of the canopy are likely restricted by A_{JC} , whereas the lower layers are controlled by A_{JE} .

In terms of transpiration, which is influenced by both stomatal conductance and vapor pressure deficit, a similar reduction is observed within the canopy. Yet, over the course of the day, as panels and leaves warm and raise the temperature of the surround-

ing air, the resulting increase in VPD enhances the driving force for transpiration while reducing g_s ($\propto 1 - 0.6 \log(\text{VPD})$). There is a certain 'critical' VPD that, when exceeded, causes transpiration to drop with further increases in VPD, and conversely, below which transpiration continues to increase with VPD. This critical VPD, which signals the onset of an apparent 'feedforward' mechanism, can be computed by setting

$$\frac{\partial}{\partial \text{VPD}} \text{VPD} [1 - 0.6 \log(\text{VPD})] = 0. \quad (37)$$

Solving this expression yields a critical $\text{VPD} = 1.95 \text{ kPa}$. This value is of significance because the relation between transpiration and increasing VPD is fundamentally different below or above this critical value (Nakad et al., 2023; Monteith, 1995), and panels do substantially alter the actual VPD above the canopy compared to their open field counterparts.

Water use efficiency (WUE), expressed as milligrams of carbon assimilated per gram of water transpired (Fig. 6. c), tends to remain relatively constant with canopy height because photosynthesis and transpiration scale together. However, as the day progresses and transpiration begins to outpace photosynthesis, particularly in the late afternoon, WUE declines. Roughly, the leaf-level WUE scales as (Katul et al., 2009, 2010)

$$\text{WUE} = \frac{A_n}{1.6(g_s)\text{VPD}} = \frac{g_s C_a (1 - C_i/C_a)}{1.6 g_s \text{VPD}} = m_{so} \frac{C_a}{1.6 \text{VPD}} (\sqrt{\text{VPD}}), \quad (38)$$

where m_{so} increases with reduced soil moisture. This leading order estimate suggests that WUE is independent from g_s . It is clear that, as VPD increases (e.g., late afternoon), WUE declines, and as atmospheric carbon dioxide concentration increases (high in the early morning), WUE increases.

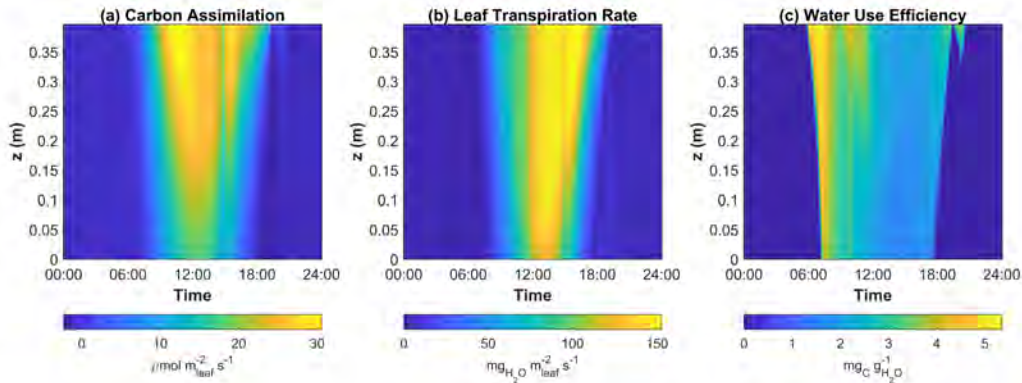


Figure 6. Spatiotemporal profiles across the crop canopy over time: (left, a) net carbon assimilation rate (A_n) per unit leaf area, (middle, b) transpiration rate per unit leaf area, and (right, c) water use efficiency (WUE).

After analyzing the dynamics of the individual components in the AV system, the AV farm's agricultural performance is compared against a monoculture case consisting of an open cropland without panels (Fig. 7) to evaluate the land equivalent ratio and explore potential synergistic gains. The reference cropland has the same crop type (tomato) and identical aerodynamic, physiological, and radiative properties, but it is exposed to full sunlight and ambient environmental conditions. It is also assumed that the reference crop has identical structural properties (i.e. $a(z)$ and H_l) so that only the micro-environment is altered by the presence of PV. The atmospheric states well above the PV are also identical.

Although the primary goal of AV systems is to optimize dual land use by harvesting sunlight for both crops and electricity, model calculations show notable advantages beyond simple resource sharing. For the conditions explored here, crop leaves in the AV farm remain considerably cooler than in the open field during the day, with an average leaf temperature $0.74\text{ }^{\circ}\text{C}$ lower over 24 hours and $1.84\text{ }^{\circ}\text{C}$ lower over daytime; the maximum cooling reaches $7.56\text{ }^{\circ}\text{C}$ around 2:05 pm. Despite a 47 % reduction in incoming PAR photon density at the top of the canopy, the time-averaged total carbon assimilation per unit land area is only 31 % lower than the open cropland, suggesting that carbon assimilation—and hence yield—is not linearly proportional to PAR. This outcome reflects the benefits of moderated canopy and leaf temperatures and reduced vapor pressure deficit due to the modified microclimate under the panels.

The total daily transpiration rate from crops decreases from $7.2\text{ mm day}^{-1}\text{ m}^{-2}$ in open cropland to $5.59\text{ mm day}^{-1}\text{ m}^{-2}$ in the AV system, indicating a water saving of 22.4 % . These estimates are also consistent with the FAO estimates of maximum mid-season for tomato plants under ideal conditions ($6\text{--}10\text{ mm day}^{-1}$). The AV benefit is expected to be even more pronounced in arid environments with intense solar radiation. Repeating the model calculations over a 92-day period (June 1 to August 31) to span a range of meteorological summer conditions, average water conservation, without the confounding influence of a specific day’s radiation–temperature–humidity correlations, appears to be in the range of 18%.

5.4 Energy and heat implications

For energy and heat assessment, we compare the AV installation to PV-only system installed over bare, non-irrigated soil with a volumetric water content of 0.05. The reference solar power plant is identical in panel configuration. Comparing the two systems (Fig. 8), the evapotranspirative cooling from crops and soil significantly lowers panel temperatures. The PV active layer’s peak temperature drops from $67.3\text{ }^{\circ}\text{C}$ in the PV site to $57.1\text{ }^{\circ}\text{C}$ in the AV system ($10.1\text{ }^{\circ}\text{C}$ cooling). During the day, the average panel temperature is reduced from 48.9 to $43.3\text{ }^{\circ}\text{C}$. As a result, daytime power generation per unit panel area increases from 111.31 to 114.39 W m^{-2} , representing approximately 3 % improvement and recovering approximately 15.2 % of the performance losses due to overheating. Moreover, through evapotranspirative cooling and the reduction of both panel and ground surface temperatures, the whole-day average sensible heat fluxes drop from 259.77 W m^{-2} for PV installations to 39.59 W m^{-2} for AV systems; as another reference, they were -62.5 W m^{-2} for cropland-only simulations. For the daytime average, the corresponding values were 413.92 W m^{-2} for PV installations, 114.03 W m^{-2} for AV systems, and -49.2 W m^{-2} for cropland. At peak sensible heat release, the fluxes reached 753.98 W m^{-2} , 268 W m^{-2} , and 63.9 W m^{-2} , respectively. These results indicate that agrivoltaic systems can potentially mitigate the PV heat island effect to a significant extent and throughout the day (Barron-Gafford et al., 2016; Chen et al., 2025).

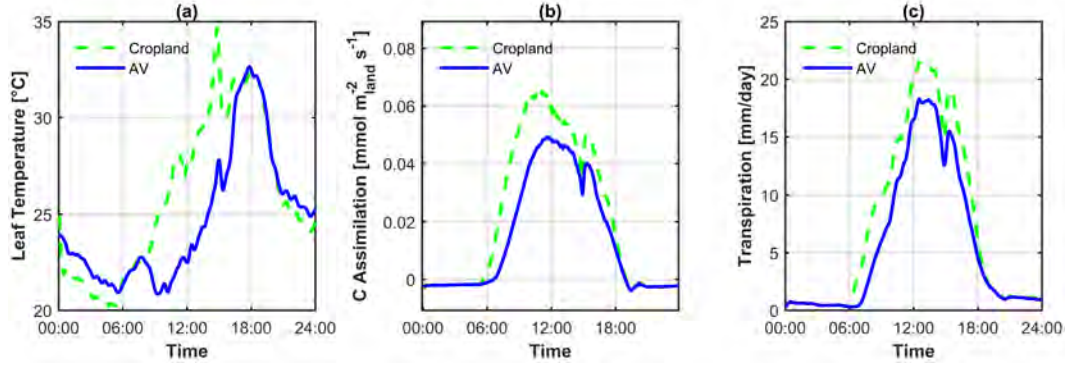


Figure 7. Comparison of agrivoltaic (AV) system and open cropland performance. Shown are (left, a) leaf temperature (T_l), (middle, b) net carbon assimilation rate (A_n), and (right, c) leaf transpiration, all expressed per unit ground area.

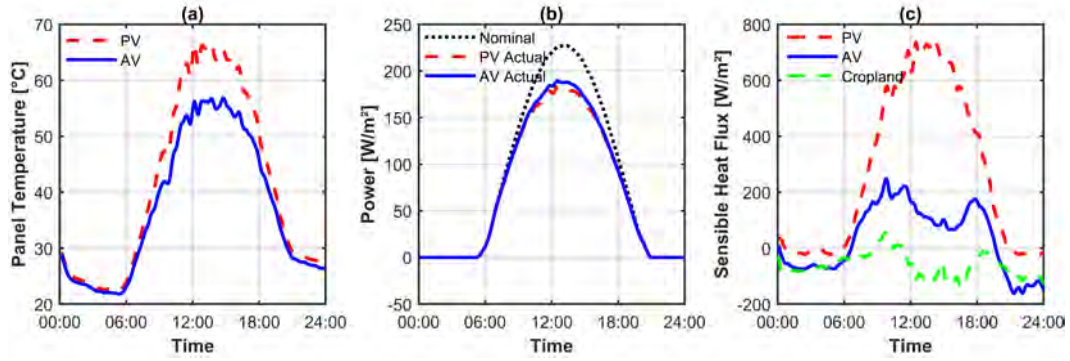


Figure 8. Comparison between agrivoltaic (AV) system and conventional solar power plant: (left, a) panel temperature ($T_{p,c}$), (middle, b) generated power per unit area of PV panel, and (right, c) sensible heat flux (H).

5.5 Health and comfort implications

According to a comprehensive literature review by Lepley et al. (2025), this study is the first to comprehensively investigate thermal comfort and heat perception of workers under AV systems. To address the scientific question concerning the implications of AV installation on worker thermal comfort, the model outputs are used to compute perceived heat stress experienced by a worker (Physical Equivalent Temperature) within the AV farm (for details of parametrization, see SI.). Within an AV environment, three primary working scenarios are considered: exclusively in shaded areas beneath panels; solely in sunlit row spacings; and moving intermittently between shaded and sunlit zones. Each scenario entails exposure to distinct thermal and radiative conditions—including air temperature, humidity, wind speed, and both shortwave and longwave radiation—relative to open cropland. The details of radiative exchange modeling are provided in the SI.

To integrate these environmental factors into a single indicator, the Physical Equivalent Temperature (PET) (Höppe, 1999; Walther & Goestchel, 2018) is applied, which is suitable for outdoor settings. The worker is modeled as a 1.7 m tall, 60 kg male, with a clothing insulation level of 0.5 clo (appropriate for summer labor), a clothing emissiv-

ity of 0.95, skin emissivity of 0.99, and a metabolic rate of 300 W, representative of typical agricultural work. The PET was calculated using MATLABTM codes that were modified by Qinqin Kong and Xinjie Huang based on an existing Python repository developed by Walther and Goestchel (2018). The PET parameterization details are presented in the SI.

As illustrated in Fig. 9 (left, a), throughout the typical working period (07:00–15:00), operating under the shade of PV panels substantially alleviates heat stress compared to exposure in an open cropland. The mean PET during working hours in cropland reaches 46.76 °C, whereas it decreases to 41.55 °C in the AV setting. Although the cooling advantage under the panels diminishes later in the day due to heat and humidity accumulation, the overall reduction remains significant. Working in open cropland (fully exposed to sunlight) provides conditions comparable to intermittent activity between shaded and sunlit zones. In contrast, continuous work under direct sunlight beneath the panels, where humidity accumulates, can be less comfortable than in open cropland. However, working in shaded panel areas, even with increased humidity, remains more comfortable than fully sunlit cropland.

Figure 9 (right, b) presents the contribution of individual environmental forcing by isolating their effects relative to cropland. Among these, reduced radiative exposure is the primary driver of improved comfort, and increased humidity is the most effective worsening factor; changes in wind speed have comparatively minor effects. Air temperature under the panels is slightly lower in the early hours; in our simulations, it never becomes detrimental even as the panel surfaces heat up. Notably, due to the specific AV farm design, wind speed at height of human’s center of mass (1 m) happened to match that of the open cropland reference, which explains the negligible effect observed for wind.

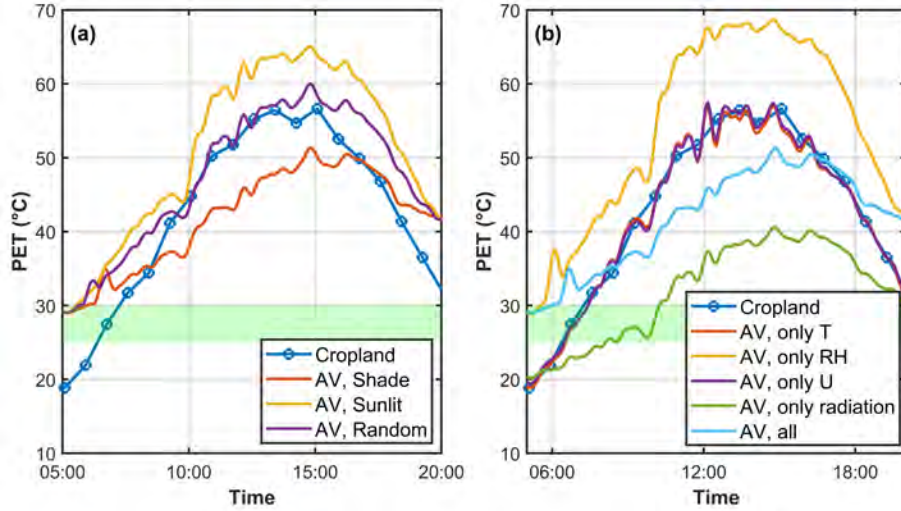


Figure 9. Comparison of PET in agrivoltaic versus cropland scenarios and the isolated contributions of each environmental factor. (left, a) Physical Equivalent Temperature (PET) in various scenarios: **cropland**: open cropland; **AV, Shade**: within the AV farm under panel shade; **AV, Sunlit**: within AV farm, working only in sunlit row spacing; **AV, Random**: moving randomly with 50% exposure to shade and 50% to sunlit areas. (right, b) PET decomposition by environmental factor: **cropland**: reference PET in open cropland; **AV, only T**: temperature is the only differing factor; **AV, only RH**: only humidity differs; **AV, only U**: only wind speed differs; **AV, only radiation**: only radiation differs; **AV, all**: all factors from the AV farm are applied simultaneously. The comfort region is between 25–30 °C.

6 Surmountable and insurmountable model limitations

The aim of this work was to develop a simplified but complete model of AV systems to inform design and optimization of AV farms. Complete in that it captures all the primary processes and components, and simplified in that it aims for maximum simplicity in the representation for each component. The analysis focused on a large, spatially uniform AV farm to eliminate edge effects and geometry-specific complexities, enabling broader conclusions. This approach is also more relevant for large-scale farms, where financial stakes are higher and accurate modeling is especially valuable. Despite this simplification, the primary spatial (above versus below panels) and temporal (diurnal cycle) variabilities are captured. Another goal was to have a modular scheme where individual representations can be updated or advanced within the overall model framework. Here, the main assumptions that impose limitations on the model applications, and whether they can be overcome by future refinements, are reviewed. The methods start with the treatment of momentum, then discuss energy, and finally, scalar exchanges.

Momentum: The flow is represented as a horizontal average (integrated at least over a single row and over the full cross-stream direction) of the streamwise (x -direction) momentum budget, but all vertical variations are considered assuming a near-neutral atmosphere. Thus, the model framework adopts a quasi-one-dimensional RANS approach that assumes planar homogeneity of the averaged quantities. This assumption requires that the agrivoltaic farm be sufficiently large (5MW or larger) so that edge effects have a negligible impact on the overall system behavior. Prior studies (Belcher et al., 2003) have shown that when the flow encountered a vegetated edge, the momentum adjustment distance is about $3 C_d(LAI/H_i)$ (it may be larger for scalars). Beyond this adjustment distance, the effects of the upstream conditions are minimal, and the flow equilibrates with the underlying surface. The steady state assumption for the normalized profiles is also very reasonable since the pressure gradient is the main flow driver, and it propagates very quickly (at the speed of sound) across the AV layer.

As with any RANS, the skill of the model depends on the mixing length (eddy diffusivity) parameterization, which is based on the geometrical features of the soil, plants, and panels. The closure also ignores buoyancy effects, the particular dynamics of dispersive fluxes, and the effect of wind direction (we assume the flow is perpendicular to the rows). All these effects can be included in the current model structure, but they would require some modification to the mixing length parametrization, as well as high-fidelity 3D large eddy simulations (LES) to provide the data for such refinements. In addition, including buoyancy influences would require a coupled thermal model that provides the necessary surface heat fluxes as input, which may then require a version of the current model that is embedded in an LES code to generate the realistic simulations that can then be used to improve our current, simple model. LES can also inform other key parameters in the model (e.g., drag coefficients, thermal and mass exchange coefficients, etc.), as well as the two-dimensional model version that captures entrance zones. A key challenge that may not be surmountable is that the resulting closure would depend on a large set of parameters, making a fully general model expensive to develop (given the LES computing cost required, and the complexity of deriving closures with many inputs). This may be overcome by a non-dimensionalization approach to reduce the parameter space, or machine learning that could help in improving the interpolation of parameters, or in creating surrogate models for the flow, based on a limited set of LES.

Energy: The 2D treatment of radiative transfer across the panels is sufficient for most practical AV farms, given their homogeneity along the y -direction (as long as the cross-stream length of the farm is $\gg$ inter-row spacing). For crops, the radiative field is horizontally averaged with vertical attenuation considered; so in effect, it is one-dimensional. For crops that are grown in very discrete rows, this assumption may miss important effects of crop heterogeneity, but the model can be extended to 2D (either geometrically or through parametrizations based on ray tracing simulations). A key influence on model

skill is the characterization of all the radiative properties of the panels and crops. Another set of key parameters in modeling heat transfer are the thermal transfer coefficients, which are imposed here based on available literature, but which could be improved based on LES studies as described above. Additionally, the subpanel air temperature is assumed to be well mixed (uniform). While a layered approach, similar to the treatment of scalars described earlier, could be applied to sub-panel temperature as well, it would significantly increase computational cost; an assessment of its benefit to model skill is warranted. While PAR photon density and wind are modeled using a layered structure, the surface energy budget of the crop is not layered for individual leaf temperatures. Notably, due to the influence of wind and the low thermal mass of leaves, their temperatures remain closely coupled to the ambient air temperature. Since the model is designed for assessment purposes, the exact temperature of each leaf is not critical. Accounting for individual leaf temperatures would require tracking complex view factors between leaves and surrounding elements, substantially increasing computational cost.

Mass: The model neglects horizontal variations in CO_2 and H_2O , which may pose limitations for smaller to medium farms with important entrance zones. The adjustment lengths for these scalars, which are always exchanged by molecular diffusion at the interfaces, is much longer than for momentum, which can adjust more rapidly due to pressure drag dominance over viscous drag. For such farms, the mass balance might be controlled by advection in the inflow rather than vertical exchange across the PV layer. This would require a 2D model as discussed above. The steady state assumption in the CO_2 model also overlooks the storage capacity of CO_2 in the air, but that assumption can be readily relaxed to examine its impact. Another main limitation of the current model is that soil moisture is assumed constant over the course of a day, representing intelligent irrigation that avoids dry conditions. Dynamic soil water modeling is excluded to prevent moisture retention effects from dominating the results, and to avoid added complexity from irrigation scheduling. However, a soil moisture mass balance model would be needed to optimize AV farm operations, where irrigation is a key control.

Agriculture: This study focuses on carbon assimilation rather than carbon allocation into leaves, stems, roots, and reproductive organs. The total biomass can be assumed to be proportional to the time integration of carbon assimilation over the growing period. Adding a model for dynamic biomass allocation models (Jones et al., 1991) to capture such adaptive responses would enable a detailed assessment of crop growth and yield under different agrivoltaic configurations. Additionally, while crop physiology output could ideally be evaluated against measurements, such evaluation is currently limited by the lack of large-scale physiological data at the AV farm level; most reported values pertain to the leaf scale. In the absence of such data, a model plausibility analysis was conducted (see SI). Should farm-scale datasets become available in the future, they could enable direct model evaluation.

As a concluding remark, although certain aspects of the model could be further refined, the evaluation and plausibility analyses indicate a reasonable agreement with observational data and reported values. Therefore, the current level of detail is deemed sufficient for most intended applications, a range that can expand as the model is further developed and tested.

7 Conclusion

A comprehensive multiphysics numerical model is developed to simulate the microclimate under solar panels in agrivoltaic (AV) systems. The model resolves the coupled exchanges of energy, momentum, and mass, as well as the physiological responses of crops and humans. The modular framework treats the budgets of momentum, energy, water vapor, and carbon, representing the soil, crops, photovoltaic panels, and the air volume under the panels. Evaluation against two field experiments demonstrates the model's

ability to reproduce panel, leaf, and soil temperatures — the key prognostic variables of the surface energy balance — as well as to yield realistic estimates of crop physiological responses. After solving for the unique temperature that satisfies these coupled exchanges, the resulting fluxes are extracted and analyzed to interpret the microclimate beneath the panels.

The model was applied to a representative summer hot and humid day in Princeton, NJ, comparing an AV farm with tomato cultivation, an open tomato cropland, and a conventional PV installation over bare soil. The model computed component-level diurnal variations, including surface temperatures, crop physiological responses, and human thermal comfort. Results indicate that, under AV conditions, average tomato leaf temperature over the whole 24-hour day decreased by 0.74 °C (with daytime reduction of 1.84 °C and a peak reduction of 7.56 °C in the afternoon), leading to a 42.6% reduction in total daily evapotranspiration from soil and crops. Despite a 47% decrease in incident light, net carbon assimilation declined only by 31%, suggesting that improved microclimatic conditions can partially offset light limitation.

From an energy perspective, panel temperatures in the AV farm were on average 5.6°C cooler during the day (and 10.2 °C cooler peak temperature) compared to panels over bare soil, resulting in a $\approx 3\%$ increase in daily solar energy yield and recovery of $\approx 15\%$ of temperature-induced power losses. Furthermore, combined crop and soil evapotranspiration reduced net sensible heat flux from 259.77 to 39.59 W m⁻², potentially mitigating the PV heat island effect.

For worker well-being, the average Physiological Equivalent Temperature (PET) within working hours was reduced from 46.76°C in open cropland to 41.55°C under AV conditions, indicating significant improvements to thermal comfort and occupational health. However, potential drawbacks include elevated humidity when there is poor ventilation under dense panel configurations, but these can be addressed through low-energy interventions such as ventilation fans during daytime, especially given the availability of on-site power infrastructure.

While numerous studies in the literature have confirmed that agrivoltaic systems can deliver substantial benefits under specific configurations, crop types, and environmental settings, the proposed model extends beyond these case-specific findings to provide a generalized evaluation framework. Decisions that maximize a single outcome, such as power generation, may conflict with agricultural productivity due to competition for solar resources. High panel density can increase energy yield but may overshadow crops, alter wind and mass exchanges, and ultimately affect both crop and power outputs in complex, site-specific ways. Moreover, crop species differ in their light requirements, and environmental conditions vary considerably across locations and seasons. By integrating these factors, the model enables feasibility assessments and optimization of AV designs under a wide range of environmental conditions, panel configurations, PV technologies and materials, and crop types—supporting evaluations from local to global scales and helping to identify configurations that balance, and potentially reconcile, the competing objectives of maximizing power generation, agricultural yield, water conservation, and worker comfort. Moreover, this model can be used to explore opportunities to expand agriculture into new areas by creating and managing a microclimate.

Open Research Section

The model code used in this study is currently available in the supplementary material for reviewers only. Upon acceptance in the journal, the code and all necessary requirements will be made publicly available on GitHub and archived with a DOI via Zenodo. A link will be provided in the final version.

Author Contributions

Erfan Hosseini: Conceptualization, Formal analysis, Investigation, Methodology, Software, Data Curation, Visualization, Validation, Writing – original manuscript.
Gabriel G. Katul: Conceptualization, Formal analysis, Investigation, Methodology, Software, Writing – original manuscript.
Majdi Abou Najm: Conceptualization, Investigation, Writing – review and editing.
Andre Daccache: Investigation, Writing – review and editing.
Sujith Ravi: Investigation, Writing – review and editing.
Kelly Mae Heroux: Investigation, Writing – review and editing.
Gavin Chaboya: Investigation, Writing – review and editing.
Chong Seok Choi: Investigation, Writing – review and editing.
Elie Bou-Zeid: Conceptualization, Formal analysis, Funding acquisition, Investigation, Methodology, Project administration, Resources, Visualization, Supervision, Writing – original manuscript.

Declaration of Interests

The authors declare that they have no competing interests.

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Appendix A Parameters**Table A1.** Geometrical and Structural Parameters

Parameter	Description
H_p	Height of panel center above ground
H_l	Height of crop above ground
w_p	Panel width
s_p	Row spacing between panels
β_p	Panel inclination angle
LAI	Leaf Area Index
$a(z)$	Leaf area density at height z
x_o	Leaf orientation parameter (projected area ratio)
L_t	Characteristic leaf length along flow direction

Table A2. Radiation Parameters

Parameter	Description
SW_{in}	Incoming shortwave radiation
SW_{out}	Outgoing shortwave radiation
$SW_{p,inc}$	Incident shortwave radiation on the panel surface
LW_{in}	Incoming longwave radiation
LW_{out}	Outgoing longwave radiation
LW_{sky}	Atmospheric longwave radiation from the sky
α	Shortwave reflectivity of the surface
α_p	Leaf absorptivity in the PAR spectrum
τ	Shortwave transmissivity of the surface
$\tau_l(z)$	Fraction of PAR reaching level z in the canopy
$K_{be}(x_o, \varphi)$	Beam extinction coefficient
$VF_{i \rightarrow j}$	View factor from surface i to j
ϵ_i	Emissivity of surface i
σ	Stefan-Boltzmann constant
$L(z)$	Cumulative leaf area index from top to height z
η_a	Temperature-adjusted conversion efficiency of PV panels
η_n	Nominal PV efficiency under standard test conditions
δ	Temperature coefficient of PV efficiency (K^{-1})

Table A3. Energy and Heat Transfer Parameters

Parameter	Description
H	Sensible heat flux
LE	Latent heat flux
G	Ground or conduction heat flux
h_p, h_s, h_l	Heat transfer coefficients for panels, soil, and leaves
C_H	The bulk heat transfer coefficient
C_q	The bulk moisture transfer coefficient
L_Λ	Lacunarity length scale for panel heterogeneity
c_p	Specific heat capacity of air at constant pressure
R_x	Thermal resistance of the layer
c_x	Thermal capacitance of the layer

Table A4. Aerodynamic and Momentum Parameters

Parameter	Description
$\bar{u}$	Mean streamwise wind speed
$\bar{w}$	Mean vertical wind speed
$u(z)$	Wind speed at height z
$u_n(z)$	Wind speed at height z normalize by the wind at the domain top
Re_{L_l}	Reynolds number based on lacunarity length scale
Pr	Molecular Prandtl number of air
Pr_t	Turbulent Prandtl number of air
Sc_t	Turbulent Schmidt number
C_d	Drag coefficient
$f_{d,p}$	Drag force from panels
$f_{d,l}$	Drag force from vegetation
$f_{d,s}$	Drag force from soil
$g_{a,h}$	Aerodynamic conductance for sensible heat transfer
$\bar{\rho}_a$	Mean air density
P	Mean pressure field
t	Time variable
x	Streamwise coordinate
z	Vertical coordinate
τ_{zx}	Momentum flux (turbulent + dispersive)
K_ξ	Turbulent diffusivity of a scalar ξ
K_m	Turbulent eddy viscosity
$w'\xi'$	Turbulent flux of scalar ξ
S_ξ	Source or sink term for scalar ξ
ξ	Concentration of scalar quantity (e.g., water vapor or CO ₂)
$A_{b,\xi}$	Coefficient depending on scalar ξ for boundary layer transport
R_r	Respiration rate at reference temperature T_r
Q_r	Temperature sensitivity coefficient for respiration

Table A5. Vegetation and Crop Physiology Parameters

Parameter	Description
A_n	Net photosynthetic rate
V_m	Maximum Rubisco carboxylation capacity per unit leaf area
$V_m(T_l)$	Temperature-dependent maximum carboxylation rate
J_{max}	Maximum electron transport rate
Γ^*	CO ₂ compensation point
$R_d(T_l)$	Temperature-dependent dark respiration rate
R_d	Dark respiration rate
g_s	Stomatal conductance
$r_s(z)$	Stomatal resistance at height z
$r_a(z)$	Aerodynamic resistance at height z
C_{ci}	Intercellular CO ₂ concentration
C_a	Atmospheric CO ₂ concentration
C_l	CO ₂ mole fraction at leaf surface
O_a	Atmospheric O ₂ concentration
K_o	Michaelis–Menten constant for O ₂ inhibition
K_c	Michaelis–Menten constant for CO ₂
$\bar{\xi}_s$	Mean scalar concentration at surface
$\bar{\xi}_a$	Mean scalar concentration at atmosphere
e_s	Saturation vapor pressure near leaf surface
e_a	Actual vapor pressure near leaf surface
RH	Relative humidity
RH_s	Relative humidity at soil surface
RH_x	Relative humidity of exterior air
RH_a	Relative humidity of sub-panel air
q_s	Saturation vapor pressure at the soil surface
q_x	Specific humidity of exterior air
q_a	Specific humidity of sub-panel air
m	Slope of linear g_s-A_n/C_s relation
b	Intercept of g_s-A_n/C_s relation
g_o	Cuticular conductance in the absence of stomatal control
S_c	Source/sink term for CO ₂
S_v	Source/sink term for water vapor
WUE	Water use efficiency
$[CO_2]_x$	CO ₂ concentration above panels
$[CO_2]_a$	CO ₂ concentration sub-panel
e_m	Maximum quantum efficiency of photosynthesis
Q_p	Incident PAR photon flux density
PAR	Photosynthetically Active Radiation

Table A6. Temperature Variables

Parameter	Description
T	Generic object temperature
T_x	Exterior (ambient) air temperature
$T_{p,t}$	Panel top surface temperature
$T_{p,b}$	Panel back surface temperature
T_a	Sub-panel air temperature
T_l	Leaf temperature
T_s	Soil surface temperature
T_g	Deep ground temperature

Table A7. Thermal Comfort and Human Parameters

Parameter	Description
PET	Physiological Equivalent Temperature
T_{core}	Human core body temperature
T_{skin}	Human skin temperature
$T_{clothing}$	Human clothing surface temperature
M	External metabolic rate due to physical activity
M_{base}	Basal metabolic rate
m	Body mass of individual
h	Body height of individual
age	Age of individual (reference: 30 years)
A_{Du}	Dubois body surface area
H	Metabolic heat production
E_{res}	Respiratory heat loss
R_n	Net radiation exchange
C	Convective heat loss
E	Evaporative heat loss from skin
$A_{eff,r}$	Effective radiative area of the body
f_{acl}	Fraction of clothed body surface
ε_{sk}	Emissivity of skin (0.99)
ε_{cl}	Emissivity of clothing (0.95)
T_{mrt}	Mean radiant temperature
h_e^{diff}	Diffusion coefficient of air boundary layer
L_w	Lewis number constant (0.167 K/hPa)
f_{ecl}	Burton efficiency factor for evaporation
P_{vs}	Saturation vapor pressure at skin temperature
e_a	Ambient vapor pressure
w	Skin-wetness factor (E_{sw}/E_{max})
r_{cl}	Clothing thermal resistance (clo/6.45)
i_m	Woodcock's ratio (0.38)

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Supporting Information for "Food, Energy, and Health Implications of Agrivoltaic Farms"

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Introduction

This Supporting Information (SI) contains supplementary materials that provide additional context, methods, and data supporting the results presented in the main manuscript. It includes parameter tables used in the simulations, meteorological input data, and extended model evaluation outputs.

Several sections detail the parameterizations and assumptions used in the model, such as representations of thermal comfort (PET), soil and vegetation heat exchange, biochemical temperature responses, radiation transfer under varying solar array geometries, the concept of lacunarity length scale, displacement height calculations, soil respiration, and meteorological forcings.

The data and results presented here were either generated through numerical simulations or compiled from previously published literature for model evaluation. All processing steps are described to allow for reproducibility. Some figures show modeled wind and CO₂ exchange profiles under different conditions, as well as sensitivity analyses at the leaf scale results.

This SI aims to enhance transparency and enable further use or adaptation of the modeling framework by the broader research community.

1. Evaluation of modeled crop assimilation and transpiration

In this study, the accuracy of the thermal model was evaluated using measured panel, crop, and soil temperatures. However, due to the absence of farm-scale measurements of crop carbon assimilation and transpiration—particularly under agrivoltaic (AV) conditions—direct validation of the physiological model was not feasible. Existing datasets are typically limited to leaf-level measurements and do not reflect spatially averaged behavior across AV systems. While this limitation is acknowledged and may be addressed in future work if suitable datasets become available, a plausibility assessment has been conducted by comparing model outputs with values reported in the literature, as presented in this SI section.

Data from a controlled pot study conducted by Li et al. (2020) investigating the effects of two planting densities (single vs. competing plants) and two nitrogen levels on tomato

plants is used. These data included leaf gas exchange measurements conducted between 9:00 and 13:00 on fully expanded tomato leaves grown in a controlled pot experiment involving two planting densities (single vs. four competing plants) and two nitrogen levels (1 and 15 mmol L⁻¹). Reported net photosynthetic rates (A_n) ranged from approximately 6.5 to 14.0 $\mu\text{mol CO}_2 \text{ m}^{-2} \text{ s}^{-1}$, while transpiration rates (T_r) ranged from about 1.5 to 4.5 mmol H₂O m⁻² s⁻¹ (corresponding to 27.0 to 81.1 mg H₂O m⁻² s⁻¹ or 2.33 to 7.00 mm day⁻¹). Measurements were taken using a LI-6400XT system under a controlled photosynthetically active radiation (PAR) level of 400 $\mu\text{mol m}^{-2} \text{ s}^{-1}$, consistent with ambient light conditions at the time of measurement. Moreover, in a study conducted by Liu et al. (Liu et al., 2023), with radiation of $225.35 \pm 72.11 \text{ W m}^{-2}$, air temperature $T_a = 27.36 \pm 2.18^\circ\text{C}$, relative humidity $69.36 \pm 16.48\%$, and wind velocity $1.49 \pm 0.98 \text{ m s}^{-1}$, transpiration rates between 4–14 mmol m⁻² s⁻¹ (equivalent to 6.2–21.8 mm day⁻¹) and instantaneous net assimilation rates between 0–14 $\mu\text{mol m}^{-2} \text{ s}^{-1}$ were reported.

To assess model plausibility, results from our model (as illustrated in Figures 6 of the main text) are compared against reported values in Fig. S1. Within the same time window (9:00 AM to 1:00 PM), the average modeled PAR photon density per unit leaf area ranges from 420 $\mu\text{mol m}^{-2} \text{ s}^{-1}$ for lower leaves receiving less light, to 650 $\mu\text{mol m}^{-2} \text{ s}^{-1}$ for uppermost leaves with higher exposure. Notably, the middle canopy layer receives an average of 477.5 $\mu\text{mol m}^{-2} \text{ s}^{-1}$ PAR. Corresponding carbon assimilation rates range from 8.3 to 21.8 $\mu\text{mol CO}_2 \text{ m}_{\text{leaf}}^{-2} \text{ s}^{-1}$. Similarly, modeled transpiration rates per unit leaf area range from 4 mm H₂O day⁻¹ to 12 mm H₂O day⁻¹. The agreement between model results supports the realism of the model predictions for tomato under the specified light conditions and time window.

2. Parametrization of zero-plane displacement height, z_d

z_d is the zero-plane displacement that can be estimated from the centroid of the drag exerted by the canopy on the flow given as (Jackson, 1981)

$$z_d = \frac{\int_0^{H_l} z \overline{f_{d,i}} dz}{\int_0^{H_l} \overline{f_{d,i}} dz}. \quad (1)$$

For dense canopies and uniform leaf area, it can be estimated as (Stanhill, 1969):

$$z_d/H_l = 0.64. \quad (2)$$

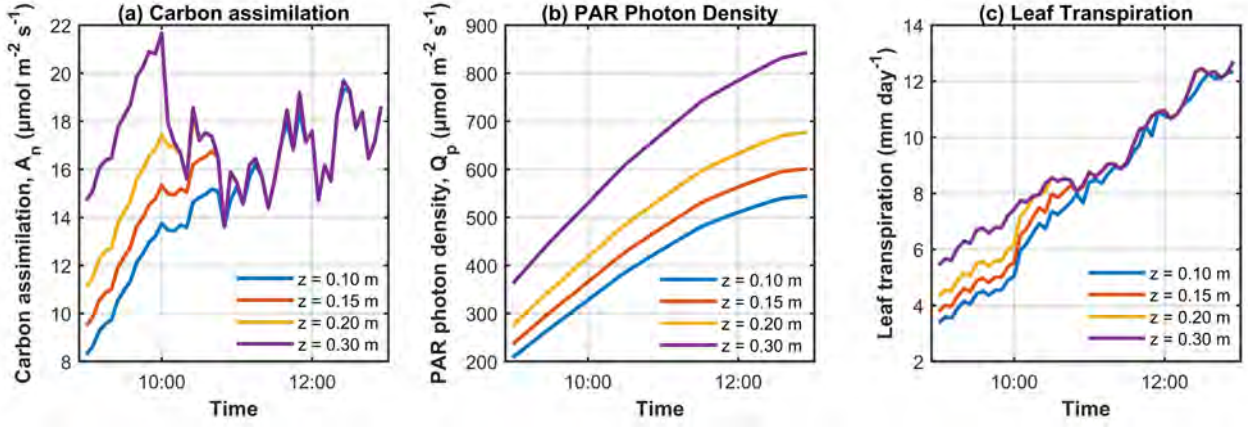


Figure S1. Time series (9:00–13:00) of (a) net assimilation, (b) photon density, and (c) transpiration at different heights (10, 15, 20, and 30 cm). Each subplot shows model predictions, highlighting diurnal variations across canopy profiles.

In the present study, following the model execution, the results indicate that, depending on the crop height to panel height ratio, for $H_l = 0.02 H_p$, the displacement height is $z_d = 0.3 H_l$, whereas for $H_l = 0.1 H_p$, z_d can reach up to $0.685 H_l$. As the current focus is on mature crops, which are typically on the order of $H_l = 0.1 H_p$, the estimation provided by Stanhill (1969) is considered appropriate.

3. Temperature dependencies of key biochemical parameters

The explicit temperature dependence of key biochemical parameters highlights the role of modeling microclimate conditions within the AV farm, particularly leaf temperature. The temperature dependence of these biochemical parameters is based on standard formulations reviewed elsewhere (Lai et al., 2000). The CO_2 compensation point in the absence of mitochondrial respiration, Γ^* , is expressed as a quadratic function of leaf temperature (T_l):

$$\Gamma^* = 36.9 + 1.88(T_l - 25) + 0.036(T_l - 25)^2, \quad (3)$$

where T_l is the leaf temperature ($^{\circ}\text{C}$). The V_m is adjusted from its standard value at 25°C ($V_{m,25\text{C}}$) using an exponential temperature response, dampened by a sigmoidal limitation at high temperatures:

$$\frac{V_m(T_l)}{V_{m,25\text{C}}} = \frac{\exp[0.088(T_l - 25)]}{1 + \exp[0.29(T_l - 41)]}. \quad (4)$$

The dark respiration rate, R_d , similarly exhibits a temperature response given by

$$\frac{R_d(T_l)}{R_{d,25\text{C}}} = \frac{\exp(0.069(T_l - 25))}{1 + \exp(1.3(T_l - 55))}, \quad (5)$$

where $R_{d,25\text{C}}$ is defined as a fraction of $V_{m,25\text{C}}$:

$$R_{d,25\text{C}} = 0.015 V_{m,25\text{C}}. \quad (6)$$

The generic temperature dependency of other kinetic parameters is given by:

$$K = k_{25\text{C}} \exp(T_l - 25), \quad (7)$$

where $k_{25\text{C}}$ denotes the baseline parameter value at 25°C .

4. Thermal comfort

The assessment of human thermal comfort is based on the Munich Energy Balance Model for Individuals (MEMI), as introduced by Höppe (1999), which defines a Physiological Equivalent Temperature (PET). PET represents the air temperature in a standardized indoor reference environment (with fixed radiation, wind speed, humidity, metabolic activity, and clothing insulation) that would result in the same physiological response—specifically, the same internal thermal state of the human body—as that observed under the actual environmental conditions. PET is also extensively used for assessing outdoor thermal comfort (Spagnolo & de Dear, 2003; Ali-Toudert & Mayer, 2006; Sharmin et al., 2019; Heng & Chow, 2019; Farzaneh, 2020; Ribeiro et al., 2022) and for this reason, it is adopted in the analysis here. Notably, in this study, the PET was calculated using MATLAB™ codes that were modified by Qinqin Kong and Xinjie Huang based on an existing Python repository developed by Walther and Goestchel (2018).

The human body's thermoregulatory response is modeled using a three-node approach, consisting of core, skin, and clothing nodes. Body temperatures under real outdoor conditions—including core temperature (T_{core}), skin temperature (T_{skin}), and clothing surface temperature (T_{clothing})—are first calculated. These serve as boundary conditions for a second energy balance, applied to a reference environment characterized by standardized parameters: a metabolic rate of 80 W (plus basal metabolism), a fixed vapor pressure of 12 hPa, an air velocity of 0.1 m/s, and a clothing insulation value of 0.9 clo.

In this reference environment, radiative equilibrium is assumed by setting the mean radiant temperature equal to the PET value being solved for, ensuring that the body experiences no additional thermal load from surrounding surfaces. The PET is then determined as the air temperature at which the thermal conditions in this standardized environment impose the same heat load on the body as the actual environment. Accordingly, the core principle of the PET model is captured by the fundamental energy balance of the human body, expressed as:

$$H + LE_{\text{res}} + R_n + C + LE = 0 \quad (8)$$

where each term denotes a distinct mode of heat exchange between the human body and its environment, where H is metabolic heat production, LE_{res} is respiratory heat loss;

R_n is net radiation exchange; C is convective heat loss; and LE is evaporative heat loss from skin.

The metabolic heat rate is calculated as:

$$H = \frac{M + M_{\text{base}}}{A_{\text{Du}}} \quad (9)$$

where M is the external metabolic rate due to physical activity, which is set to 350 W for hard activity in the farm, and M_{base} is the basal metabolic rate. For a male subject, M_{base} is estimated using the following empirical formula:

$$M_{\text{base}} = 3.45 m^{0.75} [1 + 0.004 (30 - \text{age}) + 0.01 \left(\frac{100h}{m^{1/3}} - 43.4 \right)] \quad (10)$$

In this formulation, m is the body mass (here assumed to be 60 kg); h is the body height (set to 1.7 m); and age is the age of the subject (taken as 30 years). These values represent a reference individual used for thermal comfort assessment under urban environmental conditions. The denominator, A_{Du} , represents the Dubois body surface area in square meters, calculated from body height and mass as:

$$A_{\text{Du}} = 0.203 m^{0.425} h^{0.725}. \quad (11)$$

This surface area allows normalization of the total metabolic heat load, making it comparable across individuals of different body sizes and physical characteristics.

The respiratory heat loss (LE_{res}) is modeled as:

$$LE_{\text{res}} = LE_{\text{res,sensible}} + LE_{\text{res,latent}} \quad (12)$$

where respiratory sensible heat ($LE_{\text{res,sensible}}$) is modeled as:

$$LE_{\text{res,sensible}} = c_{\text{air}} (T_{\text{ref}} - T_{\text{exp}}) \dot{V}_{\text{pulm}}, \quad (13)$$

and respiratory latent heat ($LE_{\text{res,latent}}$) is modeled as:

$$LE_{\text{res,latent}} = \frac{0.623 \lambda_v}{p} (e_a - e_{\text{exp}}) \dot{V}_{\text{pulm}}, \quad (14)$$

where $c_{\text{air}} = 1010 \text{ J kg}^{-1} \text{ K}^{-1}$ is the specific heat of air, and T_{ref} is the equivalent ambient temperature being solved for. $T_{\text{exp}} = 0.47 T_{\text{ref}} + 21.0$ is the temperature of exhaled air; $\dot{V}_{\text{pulm}} = 1.44 \times 10^{-6} H$ is the pulmonary ventilation rate; and H is the metabolic heat production rate. $\lambda_v = 2.42 \times 10^6 \text{ J/kg}$ is the latent heat of vaporization at typical body temperatures; p is the ambient atmospheric pressure (in hPa); e_a is the ambient vapor pressure in standard conditions (fixed at 12 hPa); and e_{exp} is the saturated vapor pressure at T_{exp} .

The radiative heat balance (R) is:

$$R_{\text{bare}} = A_{\text{eff,r}} (1 - f_{\text{acl}}) \varepsilon_{\text{sk}} \sigma (T_{\text{mrt}} + 273.15)^4 - (T_{\text{skin}} + 273.15)^4 \quad (15)$$

$$R_{\text{clothed}} = f_{\text{eff}} A_{\text{clo}} \varepsilon_{\text{cl}} \sigma (T_{\text{mrt}} + 273.15)^4 - (T_{\text{cl}} + 273.15)^4. \quad (16)$$

The total radiative heat loss is given by:

$$R = \frac{R_{\text{bare}} + R_{\text{clothed}}}{A_{\text{du}}}. \quad (17)$$

Here, $A_{\text{eff,r}}$ is the effective radiative area of the body; f_{acl} is the fraction of the clothed body surface; $\varepsilon_{\text{sk}} = 0.99$ and $\varepsilon_{\text{cl}} = 0.95$ are the emissivities of skin and clothing, respectively; $\sigma = 5.67 \times 10^{-8} \text{ (W m}^{-2} \text{ K}^{-4})$ is the Stefan-Boltzmann constant; and T_{mrt} , T_{skin} , and T_{cl} are the

mean radiant temperature, skin temperature, and clothing surface temperature in Celsius, respectively.

Convective heat loss (C) accounts for the transfer of sensible heat from the human body to the surrounding air due to temperature differences and air movement. Similar to radiation, convection is modeled separately for bare skin and clothed areas:

$$C_{\text{bare}} = h_c (T_{\text{ref}} - T_{\text{skin}}) A_{\text{du}} (1 - f_{\text{acl}}), \quad (18)$$

$$C_{\text{clothed}} = h_c (T_{\text{ref}} - T_{\text{cl}}) A_{\text{clo}}, \quad (19)$$

and the total convective heat loss is given by

$$C = \frac{C_{\text{bare}} + C_{\text{clothed}}}{A_{\text{du}}}. \quad (20)$$

The convective heat transfer coefficient h_c depends on the body posture and wind speed. For example, here in standing posture, it is modeled as $h_c = 2.26 + 7.42 v^{0.67} \text{ W m}^{-2} \text{ K}^{-1}$, and modified by atmospheric pressure. T_{ref} is the PET-equivalent air temperature being solved, and T_{skin} and T_{cl} are the skin and clothing temperatures, respectively. A_{clo} is the heat-exchange area of clothing.

Evaporative heat losses (LE) occur through two mechanisms: diffusion through the skin and active sweating. The total evaporative heat loss is given by

$$LE = -(LE_{\text{diff}} + LE_{\text{sw}}), \quad (21)$$

where E_{sw} is the heat loss due to sweat evaporation and is calculated as

$$LE_{\text{sw}} = \frac{\lambda_v}{1000} \times \frac{q_{\text{sw}}}{3600}, \quad (22)$$

with $\lambda_v = 2.42 \times 10^6 \text{ J/kg}$ being the latent heat of vaporization and q_{sw} the sweat production rate in $\text{g m}^{-2} \text{ h}^{-1}$. The maximum possible evaporation (diffusion capacity) from the skin is:

$$LE_{\text{max}} = h_e^{\text{diff}} f_{\text{ecl}} (P_{\text{vs}} - e_a), \quad (23)$$

where $h_e^{\text{diff}} = h_c L_w$ is the diffusion coefficient of the air boundary layer, with $L_w = 0.167 \text{ K/hPa}$ being the Lewis number, $f_{\text{ecl}} = \frac{1}{1+0.92 h_c r_{\text{cl}}}$ the Burton efficiency factor, P_{vs} the saturation vapor pressure at skin temperature, and e_a is the ambient vapor pressure. If the skin-wetness $w = LE_{\text{sw}}/LE_{\text{max}}$ exceeds 1, the excess sweat is assumed to be ineffective. Finally, diffusion-driven evaporation is calculated as

$$LE_{\text{diff}} = (1 - w) \times \frac{P_{\text{vs}} - e_a}{R_{\text{ecl}}}, \quad (24)$$

where R_{ecl} is the clothing vapor resistance given by

$$R_{\text{ecl}} = \frac{\frac{1}{f_{\text{cl}} h_c} + r_{\text{cl}}}{(L_w i_m)}, \quad (25)$$

with $r_{\text{cl}} = \frac{r_{\text{clo}}}{6.45}$ and $i_m = 0.38$ (Woodcock's ratio (Woodcock, 1962a, 1962b)).

5. Meteorological forcings for the PET model

Having established the parameterization of heat perception through the Physical Equivalent Temperature (PET), the environmental inputs used in its calculation for the four scenarios analyzed in this study are presented.

For the *cropland* scenario, it is assumed—based on the high turbulence and well-mixed nature of the open atmosphere—that both air temperature and humidity are equivalent to the exterior ambient conditions, denoted by

T_x and q_x , respectively. Wind speed is taken at a height of 1 m, derived from the computed mean wind profile typical of open cropland without overhead structures. Radiative inputs are calculated based on contributions from the sky and the underlying vegetated surface, as further detailed:

$$R_{\text{open}} = 0.5 (SW_{\text{sky}} + LW_{\text{sky}} + SW_{l,\text{ref}} + LW_l) \quad (26)$$

where R_{open} is the radiation exposure of the person in an open field (cropland); SW_{sky} and LW_{sky} represent the incoming shortwave (direct and diffuse) and longwave radiation from the sky, respectively. The term $SW_{l,\text{ref}}$ denotes the shortwave radiation reflected from the crop canopy, and LW_l refers to the combined longwave radiation emitted and reflected by the crops, all evaluated over horizontal surfaces. In this formulation, it is assumed that the person is standing in an unobstructed open field and that radiation is distributed isotropically across the upper and lower hemispheres. Under these conditions, the view factors to the sky and ground can be reasonably approximated as 0.5 each for vertical surfaces (the prefactor in the equation), which is a common simplification in thermal perception modeling ((VDI), 2008).

In contrast, for the three AV scenarios, temperature and humidity correspond to conditions underneath the solar panels, denoted as T_a and q_a . Wind speed is again taken at 1 m height, but is now derived from the modeled mean wind profile within the AV farm with panel structures. Radiative exposure varies depending on the position of the worker within the panel array and is computed using contributions from the sky, the panels, and the vegetated ground, weighted by appropriate view factors. The key distinction among the AV scenarios lies in the worker's exposure to the downwelling radiation (sunlight and longwave radiative environments). Notably, the upwelling radiation is calculated using the same method applied to thermal comfort in open cropland:

- In the *shade-AV* scenario, the worker is assumed to be located directly beneath the panels with no direct incident solar radiation. Longwave radiation exposure is determined using view factors to both the sky and the underside of the panels, as seen from the central (hub) point beneath the array.

$$R_{\downarrow, \text{shade-AV}} = 0.5 (VF_{b \rightarrow s}^{x=0, z=1} SW_{\text{sky,diff}} + VF_{b \rightarrow s}^{x=0, z=1} LW_{\text{sky}} + VF_{b \rightarrow p}^{x=0, z=1} LW_p) \quad (27)$$

In this expression, $R_{\downarrow, \text{shade-AV}}$ represents the total downwelling radiative flux received by a vertically oriented human body standing beneath a shaded region of the agrivoltaic system. The term $VF_{b \rightarrow s}^{x=0, z=1}$ denotes the view factor from the body positioned at the center point of the panel hub ($x = 0$) and at a height of 1 m above the ground ($z = 1$, human's center of mass), toward the sky. This factor multiplies both the diffuse shortwave radiation from the sky, $SW_{\text{sky,diff}}$, and the longwave radiation emitted by the sky, LW_{sky} . The remaining terms include $VF_{b \rightarrow p}^{x=0, z=1}$, the view factor from the same body point toward the underside of the panels, which is multiplied by $LW_{p,b}$, the longwave radiation emitted by the bottom surface of the photovoltaic panels.

The view factors are computed based on a horizontal hemispherical configuration. However, in the present analysis, the human body is idealized as a cylindrical form, whose surface is predominantly vertical. To represent the radiative exchange over a full spherical field of view appropriate for a vertical surface, a conversion factor of 0.5 is applied. This coefficient accounts for the transition from the hemispherical calculation of the view factors to the spherical domain of radiative exposure.

- In the *sunlit-AV* scenario, the worker is situated in the gap between rows of panels and is directly exposed to sunlight. Here, longwave exposure to the sky and the panels is computed using view factors from the midpoint between panel rows.

$$R_{\downarrow, \text{sunlit-AV}} = 0.5 \left(SW_{\text{sky,dir}} + VF_{b \rightarrow s}^{x=\frac{w}{2}+\frac{s}{2}, z=1} SW_{\text{sky,diff}} + VF_{b \rightarrow s}^{x=\frac{w}{2}+\frac{s}{2}, z=1} LW_{\text{sky}} + VF_{b \rightarrow p}^{x=\frac{w}{2}+\frac{s}{2}, z=1} LW_p \right) \quad (28)$$

In this equation, $SW_{\text{sky,dir}}$ denotes the direct component of incoming solar shortwave radiation, which is nonzero in the sunlit scenario due to direct exposure to sunlight between panel rows. The view factors $VF_{b \rightarrow s}^{x=\frac{w}{2}+\frac{s}{2}, z=1}$ and $VF_{b \rightarrow p}^{x=\frac{w}{2}+\frac{s}{2}, z=1}$ represent the angular fractions of the sky and panel surfaces, respectively, as seen from a point located at a horizontal position midway between adjacent panels (i.e., $\frac{w}{2} + \frac{s}{2}$) and a vertical height of 1 meter above the ground. These view factors account for the geometric visibility of radiative sources when a person is standing in the open inter-row space of the agrivoltaic system.

- In the *random-AV* scenario, the worker is assumed to move intermittently throughout the array, alternating between shaded and sunlit positions. In this case, both shortwave and longwave radiation inputs are spatially averaged to reflect a representative exposure beneath the panels over time.

$$R_{\downarrow, \text{random-AV}} = 0.5 \left(\overline{SW_{\text{sky,dir}}} + \overline{VF_{b \rightarrow s}} SW_{\text{sky,diff}} + \overline{VF_{b \rightarrow s}} LW_{\text{sky}} + \overline{VF_{b \rightarrow p}} LW_p \right) \quad (29)$$

In this formulation, the overbars on $SW_{\text{sky,dir}}$ and the view factors $\overline{VF_{b \rightarrow s}}$ and $\overline{VF_{b \rightarrow p}}$ indicate spatial averaging over possible positions that a worker might occupy beneath the panel array. This reflects the assumption that the individual moves randomly throughout the agrivoltaic rows, leading to an averaged exposure to both shortwave and longwave radiation from the sky and panel surfaces.

6. Details of heat transfer parametrization

The heat transfer coefficient for panels (h_p) in configurations involving multiple arrays—such as those typical of AV farms, rather than isolated panels—is parameterized following the approach of Smith et al. (2022). Their formulation introduces a characteristic length scale for PV plants, referred to as the lacunarity length scale (L_l), which is derived using a fractal lacunarity method and accounts for the spatial heterogeneity of the array layout. Additional details regarding the definition and computation of L_l are provided in Section 10.

In solar power plants with regularly arranged arrays—where panels are uniformly tilted, mounted at the same height, and spaced evenly— L_l simplifies to the largest characteristic length scale that governs airflow between rows. The Reynolds number is then defined based on this lacunarity length scale and the free-stream wind velocity above the array as:

$$Re_{L_l} = \frac{U_{\infty} L_l}{\nu},$$

where U_∞ is the free-stream velocity and ν is the kinematic viscosity of air.

The Nusselt number is defined using the vertical distance between the mid-point of the photovoltaic array (i.e., the tilt axis) and the underlying ground (H_p):

$$Nu = \frac{h H_p}{k},$$

where k is the thermal conductivity of air. The correlation among these parameters was validated for Reynolds numbers in the range 2.2×10^5 to 2.2×10^6 , yielding the following expression for the panel heat transfer coefficient:

$$h_p = \frac{k_a}{H_p} Nu = 10^{0.09 Re_L^{1/5} Pr^{1/12+1.91}}, \quad (30)$$

where k_a is the thermal conductivity of air ($k_a = 0.0263 \text{ W m}^{-1} \text{ K}^{-1}$ and $Pr = 0.71$ is the molecular Prandtl number for air (Brutsaert, 1982).

The heat transfer coefficient for vegetative surfaces can be expressed as:

$$h_l = \overline{\rho_a} c_p g_{a,h}, \quad (31)$$

where the term $g_{a,h}$ represents the aerodynamic conductance for sensible heat transfer (units in m s^{-1}). This quantity is the inverse of the aerodynamic resistance for sensible heat exchange, $r_{a,h}$, which is parameterized as (Campbell & Norman, 1998)

$$r_{a,h}(z) = g_{a,h}^{-1}(z) = \frac{1.5 L_t}{\alpha_h Re^{1/2} Pr^{1/3}} \approx 307 \sqrt{\frac{L_t}{\bar{u}(z)}}, \quad (32)$$

where α_h is the thermal diffusivity of air, and Re is a leaf-scale Reynolds number defined as:

$$Re = \frac{\bar{u}(z) L_t}{\nu}. \quad (33)$$

with $\bar{u}(z)$ determined from the mean momentum balance.

7. Parameterization of soil thermal properties and effective depth

The soil thermal conductivity (k_s) and volumetric heat capacity (C_s) are parameterized as functions of the actual and saturated volumetric water contents (θ_s and θ_{sat}) using the model in Takebayashi and Moriyama (2007)

$$k_s = k_{s,d} + 0.5 \theta_s^{1/3}, \quad (34)$$

where $k_{s,d}=0.025$ is the thermal conductivity of dry soil representing the overall effect of contact areas between soil grains, and

$$C_s = (1 - \theta_{\text{sat}}) C_{s,d} + \theta_s C_{\text{water}}, \quad (35)$$

where $C_{s,d}$ is the specific heat capacity of dry soil, and C_{water} the specific heat capacity of water. The effective thermal diffusivity is $\kappa_{h,s} = k_s / C_s$. It is customary to define a characteristic depth beyond which diurnal temperature fluctuations become negligible. From dimensional considerations, this depth must exceed the diffusive length scale determined over a 12-hour ($=43200$ s) period as $(43200 \kappa_{h,s})^{0.5}$. Since the diffusive depth is usually set to the damping depth where the amplitude of the sinusoidal temperature fluctuations are damped by $1/e$ (e-folding distance), it is safe to assume that this characteristic depth can be approximated by

$$d_{\text{deep}} = 2.273 (43200 \kappa_{h,s})^{0.5}. \quad (36)$$

This estimate is consistent with other studies on damping depths in soils (Singh & Sharma, 2017).

8. Additional alternative parametrization for soil respiration

Besides the parametrization proposed in the main text, another formulation for soil respiration that collapses wide-ranging data sets is given by (Lloyd & Taylor, 1994)

$$R_{\text{es}} = R_r \exp\left(-\frac{E_o}{T - T_o}\right), \quad (37)$$

where $E_o = 308.56 \text{ K}$ and $T_o = 227.13 \text{ K}$ can be employed as well.

Note on reused material

The following two sections of the Supplementary Information, on radiation exchange across arrays of tilted solar panels (Section 9) and the definition of the lacunarity length scale (Section 10), are almost identical to those included in the Supplementary Information of our earlier publication: Hosseini, Erfan and Bou-Zeid, Elie, The Diverging Indoor, Outdoor, and Power Implications of Different Rooftop Photovoltaic System Designs, Energy and Buildings, 2025 (Hosseini & Bou-Zeid, 2025)

This material is reproduced here with minor modifications to ensure the current work is self-contained and to provide readers with direct access to relevant background, methods, and data that are integral to the understanding of this study. The inclusion of this previously published supplementary content is solely for the convenience of the reader and does not represent newly generated or original material in the context of this publication. Where applicable, citation of the original source should be used when referring to this content. In addition, the top of the vegetation is equivalent to the roof surface in the discussions and equations.

9. Radiation in multiple tilted arrays configurations

The geometric configuration of inclined solar panel arrays over a flat surface is complex, necessitating a detailed geometric analysis to determine the distribution of incident shortwave and longwave radiation on each surface. This appendix presents the methodology for computing the radiative interactions within a system comprising multiple inclined photovoltaic (PV) arrays.

Direction shortwave radiation and shading

As illustrated in Fig. S2, a general configuration of tilted PV deployment is considered. The system consists of PV panel arrays, with an aspect ratio of at least 10:1 (width of panel: length of a single panel array row) and with at least 10 rows. Each panel is characterized by a transmissivity τ_p (in the model runs for this paper, only opaque panels are considered) and a panel width w_p . The panels are installed at a height H_p above the roof surface (here, the top of the vegetation canopy), with a horizontal spacing of s_p between adjacent arrays in their inclined position, and an inclination angle β_p .

We begin by introducing fundamental concepts, including the determination of shade length on the roof (in this study, the top of the vegetation canopy) and the calculation

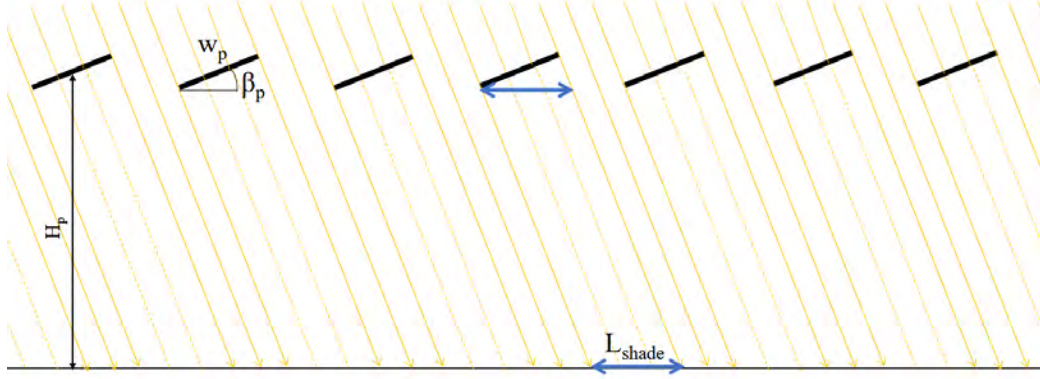


Figure S2. Side view of a solar power plant with inclined PV panels. Each panel has a width w_p , is positioned at a height H_p , and is separated by a distance s_p from adjacent panels. The panels are tilted at an inclination angle of β_p .

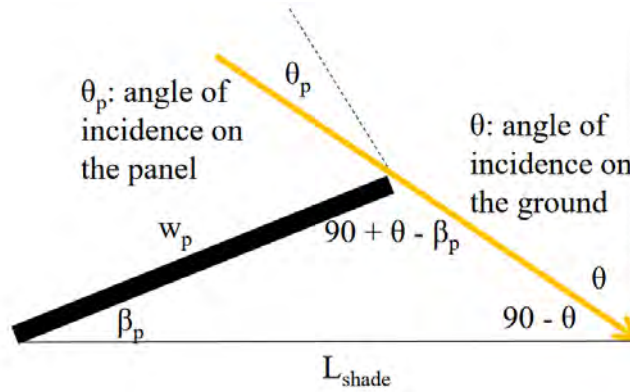


Figure S3. Shade length of one panel.

of view factors between surfaces and the sky. By integrating these components, we systematically evaluate the incident shortwave and longwave radiation on each surface, namely: the top surface of the panels, the back side of the panels, and the underlying surface (the top of the vegetation canopy, in this study).

To determine the width of the shaded region (which, in the case of transparent PV panels, corresponds to the sunlit area receiving only transmitted shortwave radiation), we assume that incoming direct solar rays are parallel (diffuse radiation is treated later). Under this assumption, the two segments indicated by blue arrows in Fig. S2 are of equal length. Consequently, as illustrated in Fig. S3, the shade length can be expressed using the law of sines as:

$$\frac{w_p}{\sin(90 - \theta)} = \frac{L_{shade}}{\sin(90 + \theta - \beta_p)}, \quad (38)$$

which simplifies to:

$$L_{shade} = \frac{\cos(\beta_p - \theta)}{\cos(\theta)} w_p. \quad (39)$$

when L_{shade} exceeds or is equal to the effective spacing ($s_{eff} = w_p \cos(\beta_p) + s_p$), the ground is fully covered by shade (or exclusively transmitted sunlight, in the case of transparent panels), and no direct shortwave radiation reaches the ground.

As illustrated in Fig. S4, adjacent panels may cast shadows on one another when the shade length exceeds the effective spacing ($L_{shade} > s_{eff}$). In such cases, if the incidence angle of sunlight relative to the normal of the panel's top surface (θ_p) is less than 90° , the shadow cast by one panel onto the top surface of another ($l_{s,tp}$) is given by:

$$\frac{\max(L_s - s_{eff}, 0)}{\sin(90 - \beta_p + \theta)} = \frac{l_{s,tp}}{\sin(90 - \theta)}, \quad (40)$$

which simplifies to:

$$l_{s,tp} = \frac{\cos \theta}{\cos(\beta_p - \theta)} \max(L_s - s_{eff}, 0). \quad (41)$$

If the incidence angle of sunlight relative to the panel's top surface (θ_p) exceeds 90° , the shadow falls instead on the back side of the adjacent panel. The corresponding shadow length on the panel's back surface ($l_{s,bp}$) is determined as follows:

$$\frac{\max(L_s - s_{eff}, 0)}{\sin(\beta_p + \theta - 90)} = \frac{l_{s,bp}}{\sin(90 - \theta)}, \quad (42)$$

which simplifies to:

$$l_{s,bp} = \frac{\cos \theta}{-\cos(\beta_p + \theta)} \max(L_s - s_{eff}, 0). \quad (43)$$

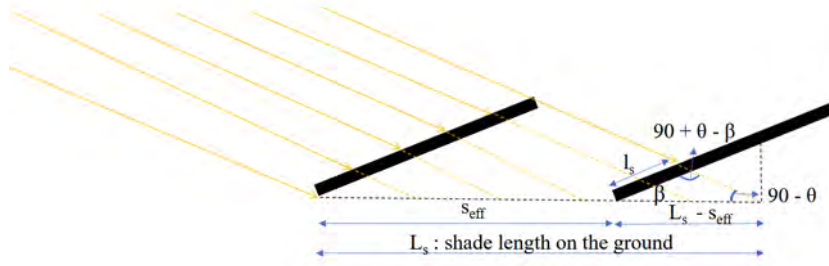


Figure S4. Illustration of mutual shading between panels, where applicable.

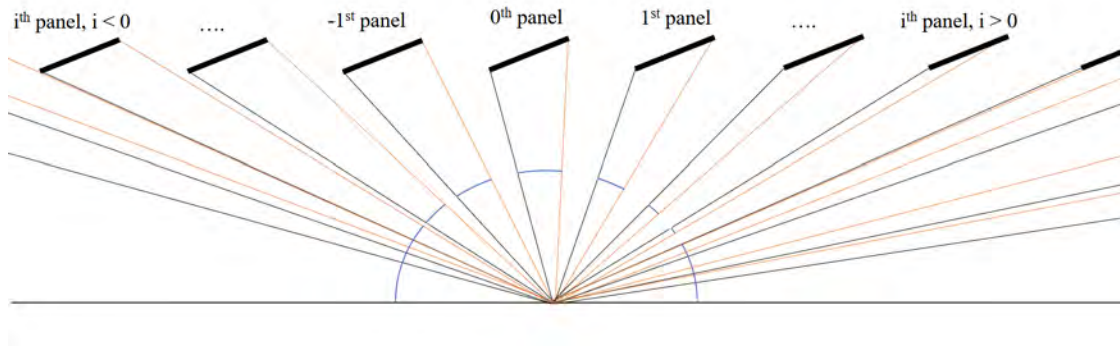


Figure S5. Illustration of panel view factors from a given point on the ground.

View factors

The next aspect to consider is the view factors of each object from a given observation point. These view factors play a crucial role in determining the incident diffuse shortwave radiation and longwave radiation exchanges with the surrounding surfaces and the sky.

We start with the view factors for points on the underlying roof (in this study, the top of the vegetation canopy). By placing the origin of the coordinate system directly beneath the left edge of a reference panel and extending the x-axis to the left edge of the adjacent panel on the right, the coordinate x varies within the range $0 \leq x \leq s_{eff}$. To simplify the analysis, each point on the ground is assumed to have a view in a specific direction that is either obstructed by the panels or open

to the sky, as depicted in Fig. S5. The viewing angle of the i^{th} panel (the panel right above that point has $i=0$) as seen from a point X on the ground, denoted by α_i , is given by:

$$\alpha_i = \left| \tan^{-1} \left(\frac{H_p - \left(\frac{w_p}{2}\right) \sin \beta_p}{i s_{eff} - x - \left(\frac{w_p}{2}\right) \cos \beta_p} \right) - \tan^{-1} \left(\frac{H_p + \left(\frac{w_p}{2}\right) \sin \beta_p}{i s_{eff} - x + \left(\frac{w_p}{2}\right) \cos \beta_p} \right) \right| \quad (44)$$

The panel view factors are then the summation of these angles for all panels:

$$VF_{X \rightarrow \text{panels}} = \frac{\sum \alpha_i}{\pi}; \quad (45)$$

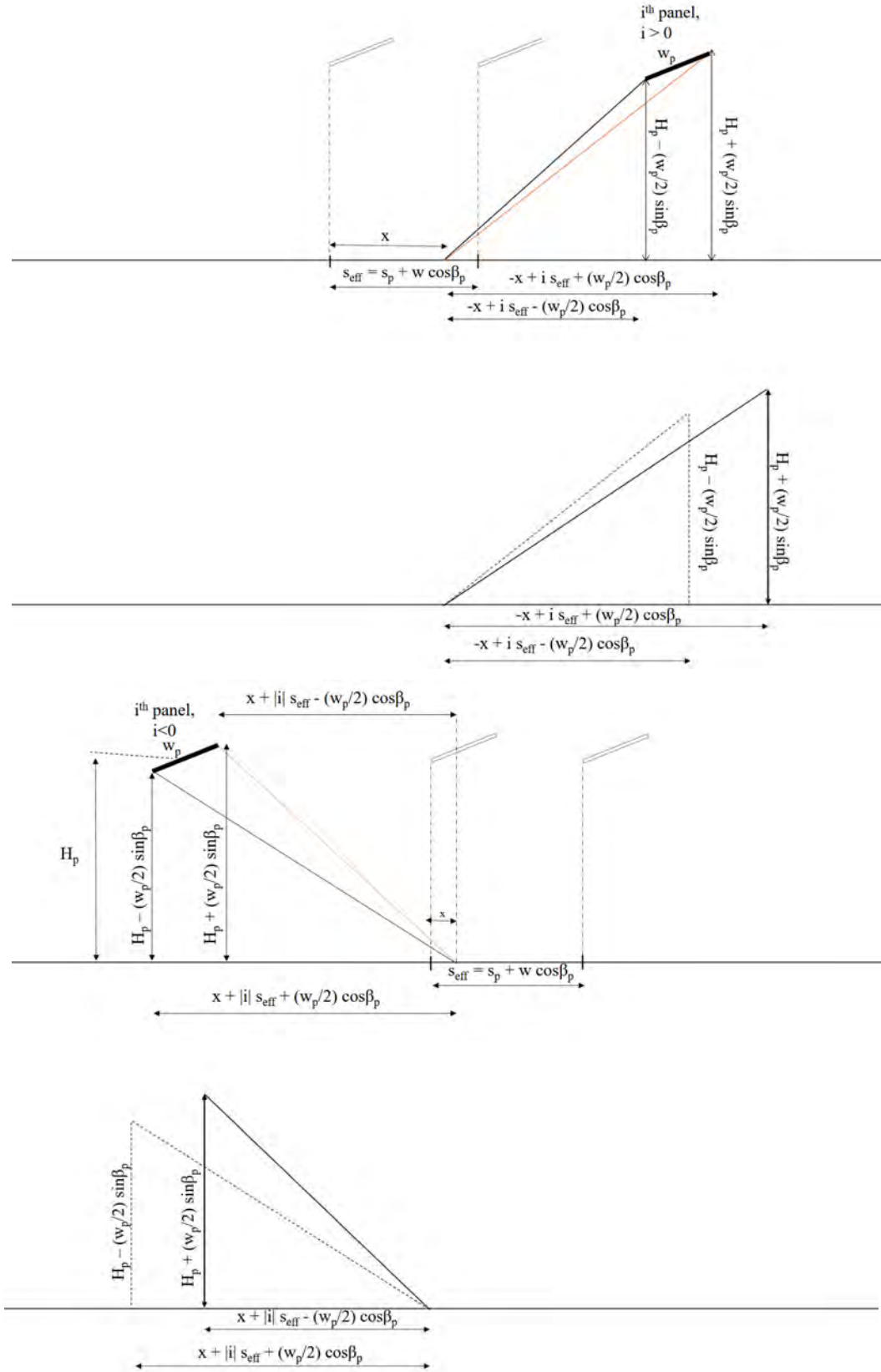


Figure S6. Visualization of the i -th panel geometry. Top two panels represent the i -th panel on the right ($i > 0$), and the bottom two represent the i -th panel on the left ($i < 0$). The second and fourth figures show simplified versions, retaining only the important dimensions.

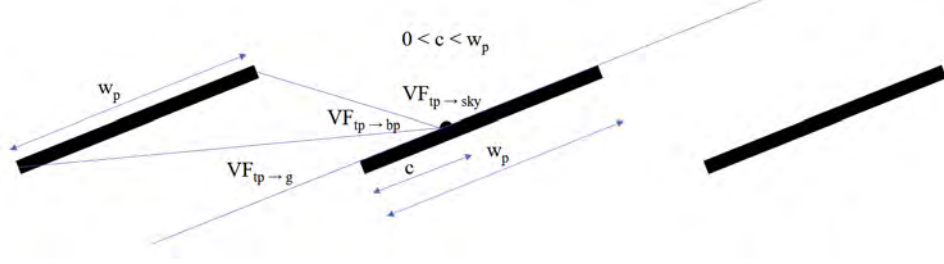


Figure S7. Illustration of panel view factors from a point on the top surface of the PV panel.

the whole surroundings has to be unity:

$$VF_{X \rightarrow \text{sky}} = 1 - \frac{\sum \alpha_i}{\pi}, \quad (46)$$

where $VF_{X \rightarrow \text{panels}}$ is the total view factor of all panels from a given point X , α_i is the view angle of the i^{th} panel from X , and $VF_{X \rightarrow \text{sky}}$ is the sky view factor from X .

We now evaluate the view factors for points on the top surface of the panel. For a point on the panel's top surface, located at a distance c from the lower edge of the panel, the view includes the sky, the back of the adjacent panel, or the ground, as illustrated in Fig. S7.

As shown in Fig. S8, the lines from that point on the top surface to the top and bottom edges of the adjacent panel ($VF_{tp \rightarrow bp}$) form two triangles with the horizontal. The pertinent angle in these triangles can then be

summed to obtain the corresponding view factor:

$$VF_{tp \rightarrow bp} = \frac{1}{\pi} \left[\tan^{-1} \left(\frac{c \sin \beta_p}{c \cos \beta_p + s_{\text{eff}}} \right) + \tan^{-1} \left(\frac{(w_p - c) \sin \beta_p}{s_{\text{eff}} - (w_p - c) \cos \beta_p} \right) \right] \quad (47)$$

The ground view factor ($VF_{tp \rightarrow g}$) from the same point on the panel top at a distance c from the lower edge can be expressed as (illustrated in Fig. S9):

$$VF_{tp \rightarrow g} = \frac{\tan^{-1} \left(\frac{s_{\text{eff}} + c \cos \beta_p}{c \sin \beta_p} \right) - \left(\frac{\pi}{2} - \beta_p \right)}{\pi}. \quad (48)$$

Finally, the sky view factor ($VF_{tp \rightarrow \text{sky}}$) is the remainder:

$$VF_{tp \rightarrow \text{sky}} = 1 - VF_{tp \rightarrow bp} - VF_{tp \rightarrow g}. \quad (49)$$

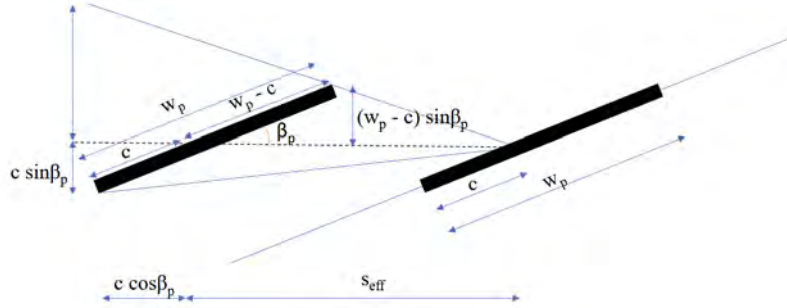


Figure S8. Detailed view of panel view factors from a point on the top surface of the PV panel.

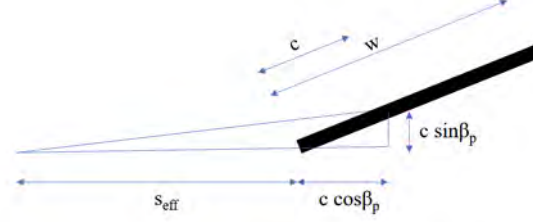


Figure S9. Ground view factor from a point on the top surface of the PV panel.

Similarly, for view factors of point on the back of the panel, we consider a point located at distance c from the lower edge on the back surface. The view factors (panel $VF_{bp \rightarrow tp}$, ground $VF_{bp \rightarrow g}$, and sky $VF_{bp \rightarrow sky}$) are then given by (see Figs. S10 and S11):

$$VF_{bp \rightarrow tp} = \frac{1}{\pi} \left[\tan^{-1} \left(\frac{(w_p - c) \sin \beta_p}{s_{eff} + (w_p - c) \cos \beta_p} \right) + \tan^{-1} \left(\frac{c \sin \beta_p}{s_{eff} - c \cos \beta_p} \right) \right], \quad (50)$$

$$VF_{bp \rightarrow g} = \frac{\pi - \beta_p - \tan^{-1} \left(\frac{c \sin \beta_p}{s_{eff} - c \cos \beta_p} \right)}{\pi}, \text{ and} \quad (51)$$

$$VF_{bp \rightarrow sky} = 1 - VF_{bp \rightarrow tp} - VF_{bp \rightarrow g}. \quad (52)$$

The direct shortwave radiation hitting the roof (in this study, the top of the vegetation canopy) is given by:

$$SW_{dir,g} = \left(1 - \min \left(\frac{L_s}{s_{eff}}, 1 \right) (1 - \tau) \right) I_b \cos \theta, \quad (53)$$

where $SW_{dir,g}$ is the direct component of solar shortwave radiation reaching the ground; L_s is the shade length on the ground, s_{eff} is the effective spacing between the panels; τ is the transmissivity of the panels; I_b is the beam radiation; and θ is the incident angle between the beam and the normal to the ground.

Similarly, the direct shortwave radiation on the top surface of the solar panel is:

$$SW_{dir,tp} = \left(1 - \frac{l_{s,tp}}{w_p} (1 - \tau) \right) I_b \max(\cos \theta_p, 0), \quad (54)$$

and the direct shortwave radiation to the back surface of the panel is:

$$SW_{dir,bp} = - \left(1 - \frac{l_{s,bp}}{w_p} (1 - \tau) \right) I_b \min(\cos \theta_p, 0). \quad (55)$$

The total incident shortwave radiation on each surface can then be computed by summing the direct and diffuse components:

$$SW_{in,i} = SW_{dir,i} + VF_{i \rightarrow sky} SW_{dif} + \sum_{j=1}^n (VF_{j \rightarrow i} \alpha_j SW_{in,j}), \quad (56)$$

where $SW_{in,i}$ is the incident radiation on facet i ; $SW_{dir,i}$ is the direct radiation hitting facet i ; $VF_{i \rightarrow sky}$ is the sky view factor of that facet (for varying VFs across the facet, the average is used); SW_{dif} is the diffuse sky shortwave radiation, and $\sum_{j=1}^n (VF_{j \rightarrow i} \alpha_j SW_{in,j})$ accounts for the reflected radiation from other facets j to facet i .

The incident longwave radiation is similarly expressed as:

$$LW_{in,i} = VF_{i \rightarrow sky} LW_{atm} + \sum_{j=1}^n (VF_{j \rightarrow i} \epsilon_j \sigma T_j^4), \quad (57)$$

where $LW_{in,i}$ is the incident longwave radiation on facet i ; LW_{atm} is the atmospheric longwave radiation; $VF_{j \rightarrow i}$ is the view factor from facet j to facet i ; ϵ_j is the emissivity of facet j ; σ is the Stefan-Boltzmann constant; and T_j is the temperature of facet j (in Kelvin).

10. Definition and quantification of the lacunarity length scale

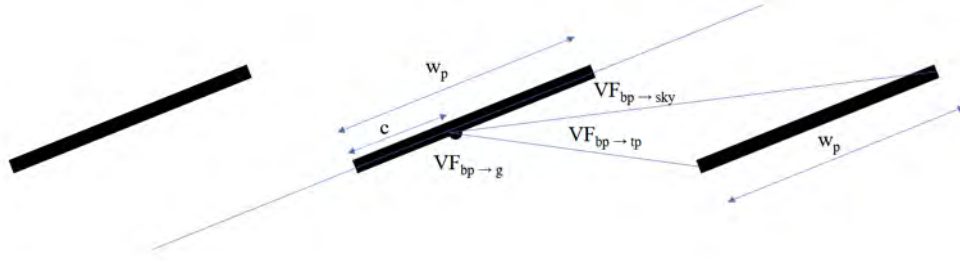


Figure S10. View factors from a point on the back surface of the PV panel.

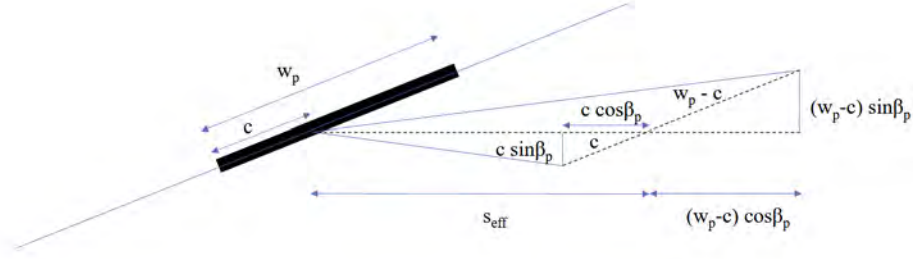


Figure S11. Detailed view of view factors from a point on the back surface of the PV panel.

Smith et al. (2022) introduced a spatial parameter termed the lacunarity length scale (L_Λ), derived from a fractal lacunarity framework that quantifies the heterogeneity or gappiness of spatial PV patterns. This parameter was employed to compute the Reynolds number for characterizing an entire solar power plant (i.e., multiple photovoltaic arrays), as opposed to the conventional approach of parameterizing a single panel based on its individual length. Lacunarity (Λ) is calculated using the gliding box method (GBM), where a box of size (b_i), starting from panel length growing up to the largest scale that can contribute to heterogeneity (typically this larger limit matches the row spacing meaning that the box size does not exceed the row to row spacing between adjacent panels as larger boxes no longer capture new spatial patterns), is moved through a defined space, counting the number of object instances (n , in this case how many panels are at least partially in the box) in each box at each position. The mean ($\bar{n}(b_i)$) and variance ($\sigma_n^2(b_i)$) of these counts per box are then used to define lacunarity as a measure of the spatial heterogeneity of the pattern:

$$\Lambda(b_i) = \frac{\sigma_n^2(b_i)}{\bar{n}^2(b_i)} + 1. \quad (58)$$

By varying the box size b_i and calculating the associated lacunarity (Λ), the lacunarity length scale can be defined as:

$$L_\Lambda = \frac{\sum_{i=1}^{|B|} \Lambda(b_i) B_i}{|B|}, \quad (59)$$

where B_i is the vector containing various b_i , and $|B|$ is the number of iterations (e.g., the size of the vector representing the number of tested box sizes).

In the case of perfectly arranged arrays of solar panels, with uniform height, inclination angle, and spacing across the roof (in this study, the top of the vegetation canopy), the spatial distribution of panels is highly ordered and homogeneous. As a result, the variance for all b_i s ($\sigma^2(b_i)$) is zero, as there is no fluctuation of numbers from box to box. Therefore,

$$\Lambda(b_i) = \frac{0}{\bar{n}^2(b_i)} + 1 = 1, \quad (60)$$

and the lacunarity length scale (L_Λ) is the largest characteristic length scale at which the air can flow.

11. Wind profile results

This section details the evaluation of the simplified momentum exchange model used to estimate the profile of the mean horizontal wind within an agrivoltaic farm. Accurate wind profiles are needed to compute various exchange coefficients and to provide reliable estimates of scalar (mass and heat) exchange between the AV air and the atmosphere aloft. To ensure the robustness and proper functioning of the momentum model, particularly the closure and parameterized mixing length, its performance was tested against various reference datasets.

The model's predictions for the mean horizontal wind profile were compared across three distinct scenarios. First, in figure S12, the model's output was evaluated

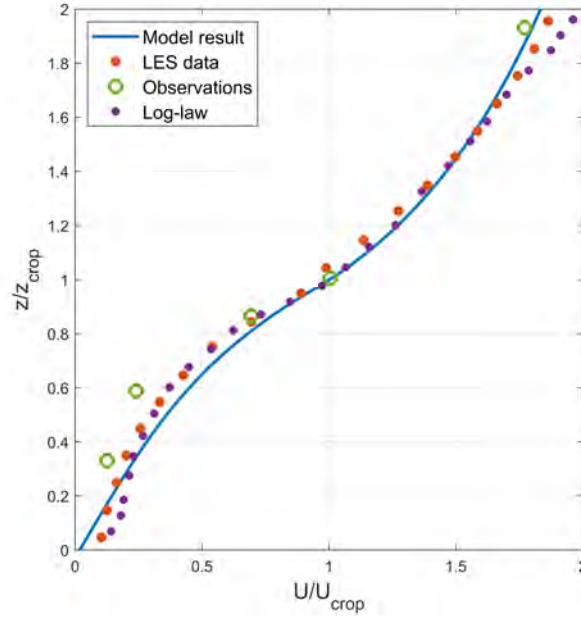


Figure S12. Validation of mean horizontal wind speed profile over cropland (LAI 2.57), compared with observations and LES. Solid lines represent model outputs; circles denote observational data.

against results from conditions representative of vegetated canopies, the model was compared with data from a study by Su, Shaw, Paw, Moeng, and Sullivan (1998), which includes observations and LES data over cropland with a leaf area index (LAI) of 2.57 (comparable to the value for tomato used here) (here, we did not include the panel terms in the mixing length formulation). Lastly, in figure S13, the model's performance was assessed against a wind tunnel experiment using a scaled-down model of a solar power plant by Glick et al. (2020), simulating wind profiles within a solar installation environment (here, we omitted the vegetation terms in the mixing length model). This specific solar deployment configuration featured panels tilted at 15, 30 and 45 degrees, with a spacing-to-bottom-panel-height ratio of 2.3, and a bottom edge of panel-to-panel length ratio of 0.748. In all comparisons, the continuous line represents the results from the first-order closure model proposed here, while the circles denote the reference data from the respective studies. S1 represents the required coefficients for mixing length parametriza-

tion. The momentum model was also successfully tested against large eddy simulation results for a neutral atmospheric boundary layer (ABL) from Bou-Zeid, Meneveau, and Parlange (2005), representing a neutral wall without canopy or panel effects included in the mixing length.

12. Meteorological input

12.1. Princeton, NJ

The input data used for model runs are provided in Fig. S14.

12.2. Davis, CA

The input data used for model evaluation (T_l) are provided in Fig. S15.

12.3. Chisago, MN

The input data used for model evaluation (T_p and T_s) are provided in Fig. S16.

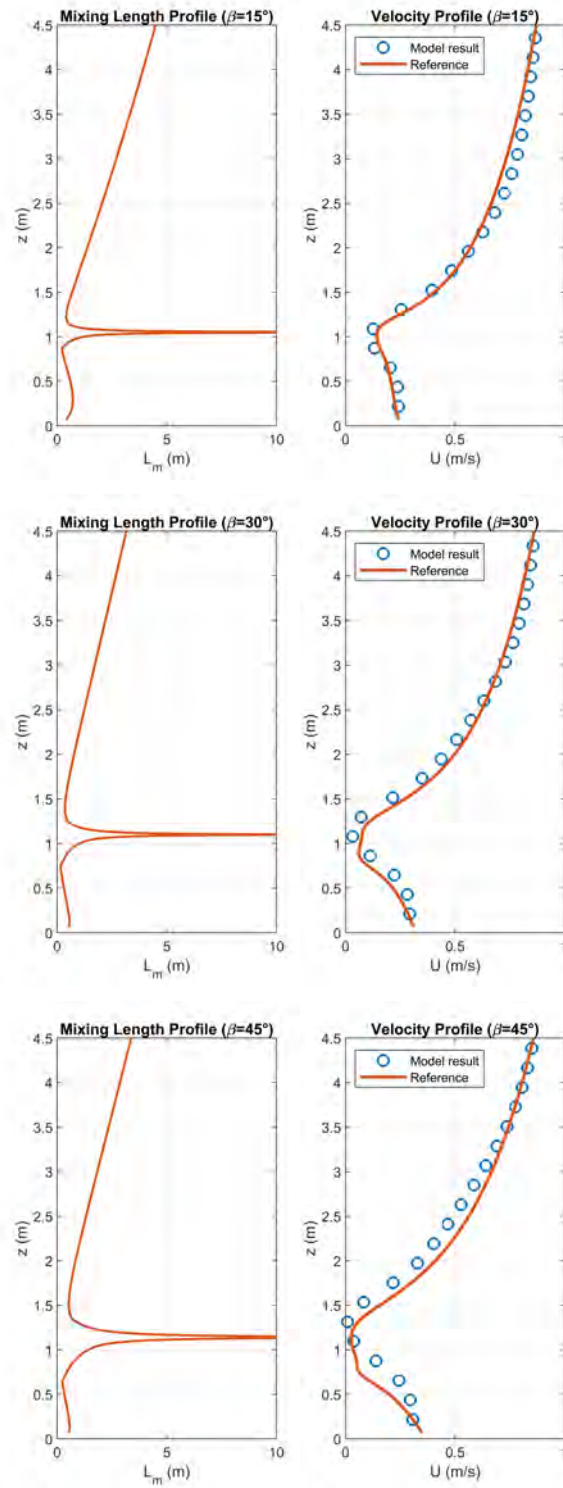


Figure S13. Simulated mean wind speed profiles for solar energy installations with different panel tilt angles. Top to bottom: 15° , 30° , and 45° tilt configurations. Comparisons are made against wind tunnel data from Glick et al. (2020), using identical geometric parameters (spacing/height = 2.3, bottom edge/length = 0.748).

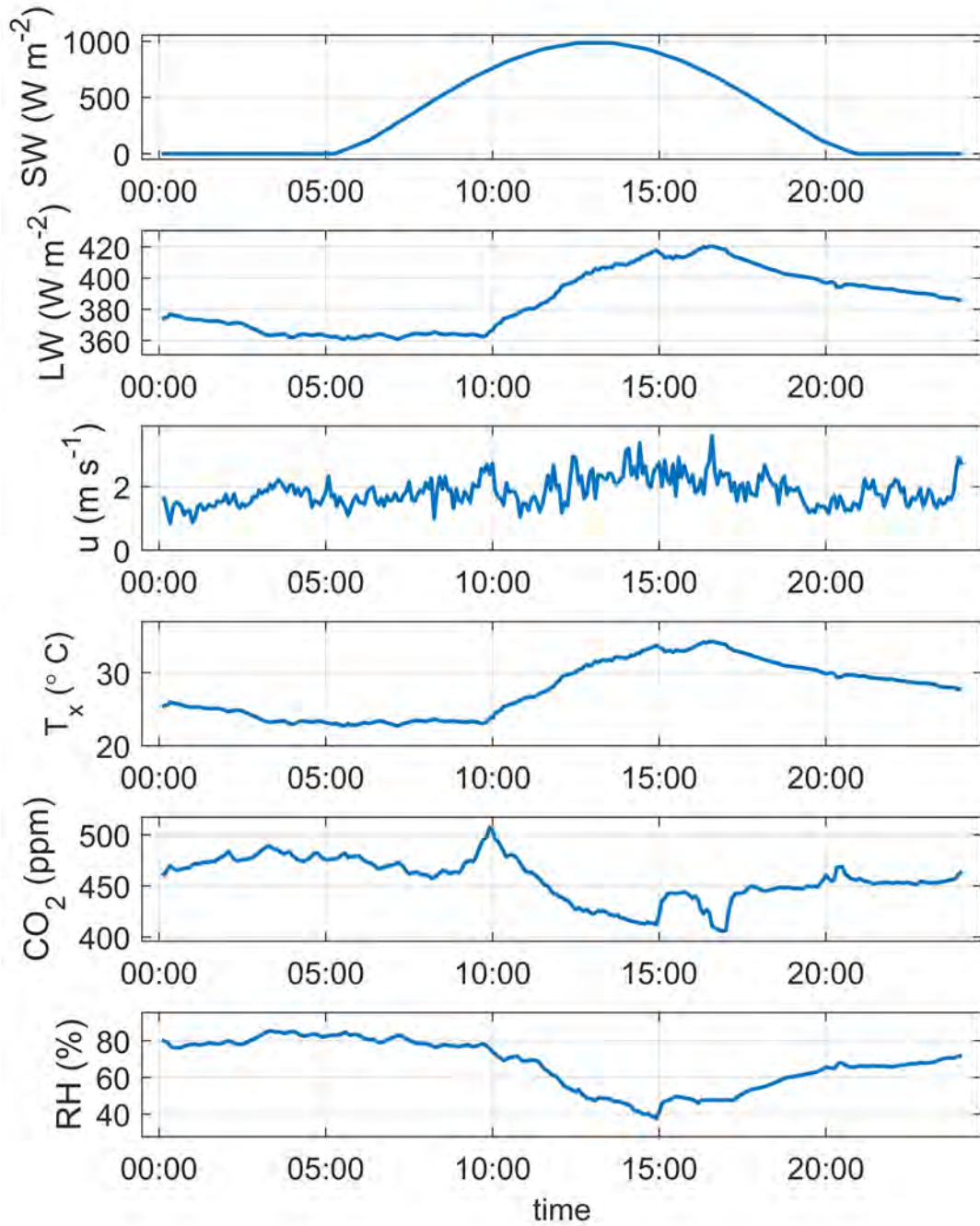


Figure S14. Environmental input forcing for the model application: from top to bottom, shortwave radiation (SW_{in}), longwave radiation (LW_{in}), wind speed ($\bar{u}$), and exterior air temperature (T_x), carbon dioxide concentration ($[\text{CO}_2]$), and relative humidity (RH), all of which are assumed by the model to apply well above the solar panels and not to be influenced by presence of AV farm (the actual Princeton weather station was over a roof (in this study, the top of the vegetation canopy) and did not have an AV farm).

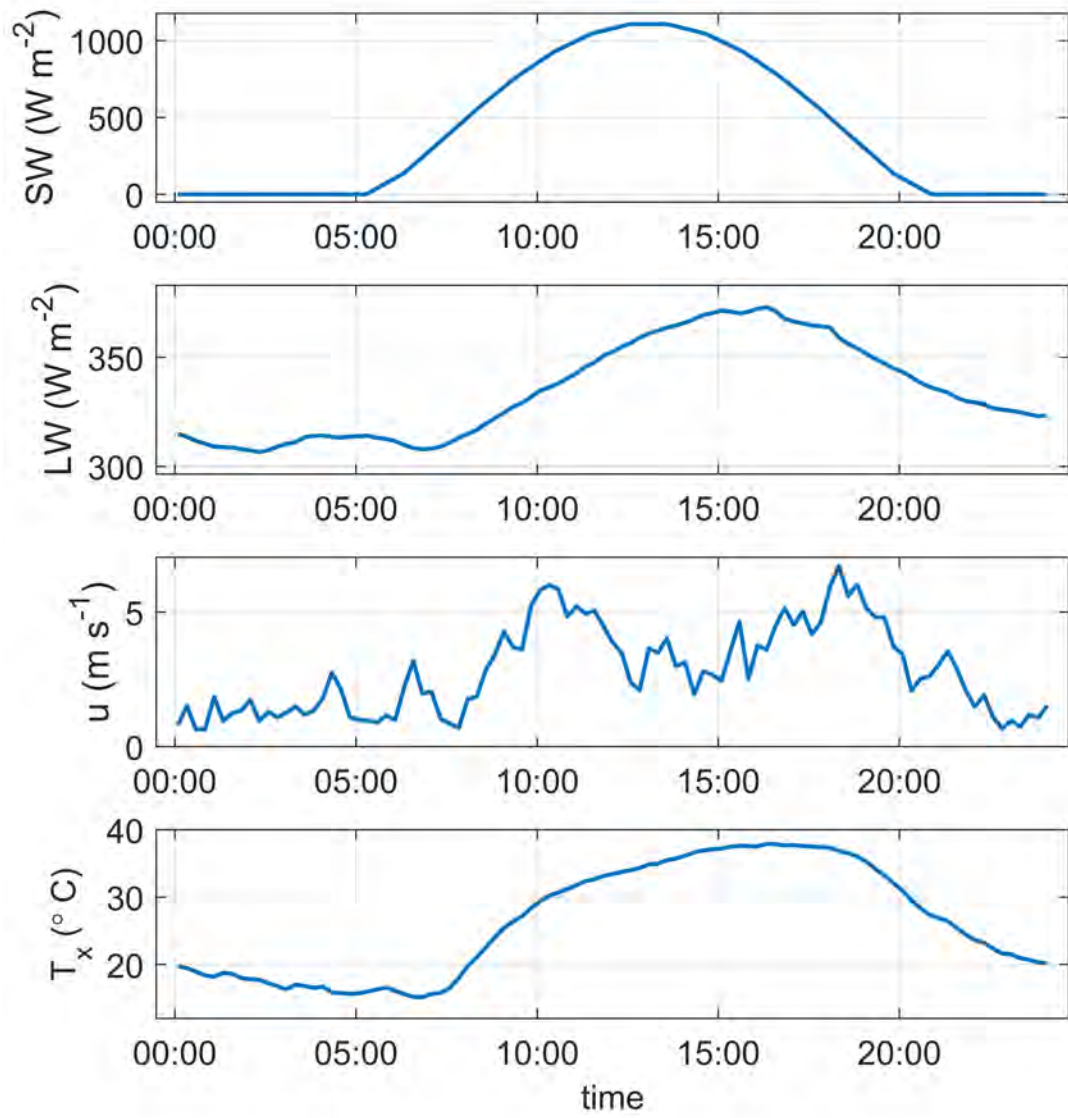


Figure S15. Environmental input forcing used for the model validation described for model evaluation, based on measurements in **Davis, CA** on **Sep 4, 2024**. The top panel displays the incoming shortwave radiation (SW), followed by the incoming longwave radiation (LW), wind speed ($\bar{u}$), and air temperature ($T_x = T_a$ for Davis only).

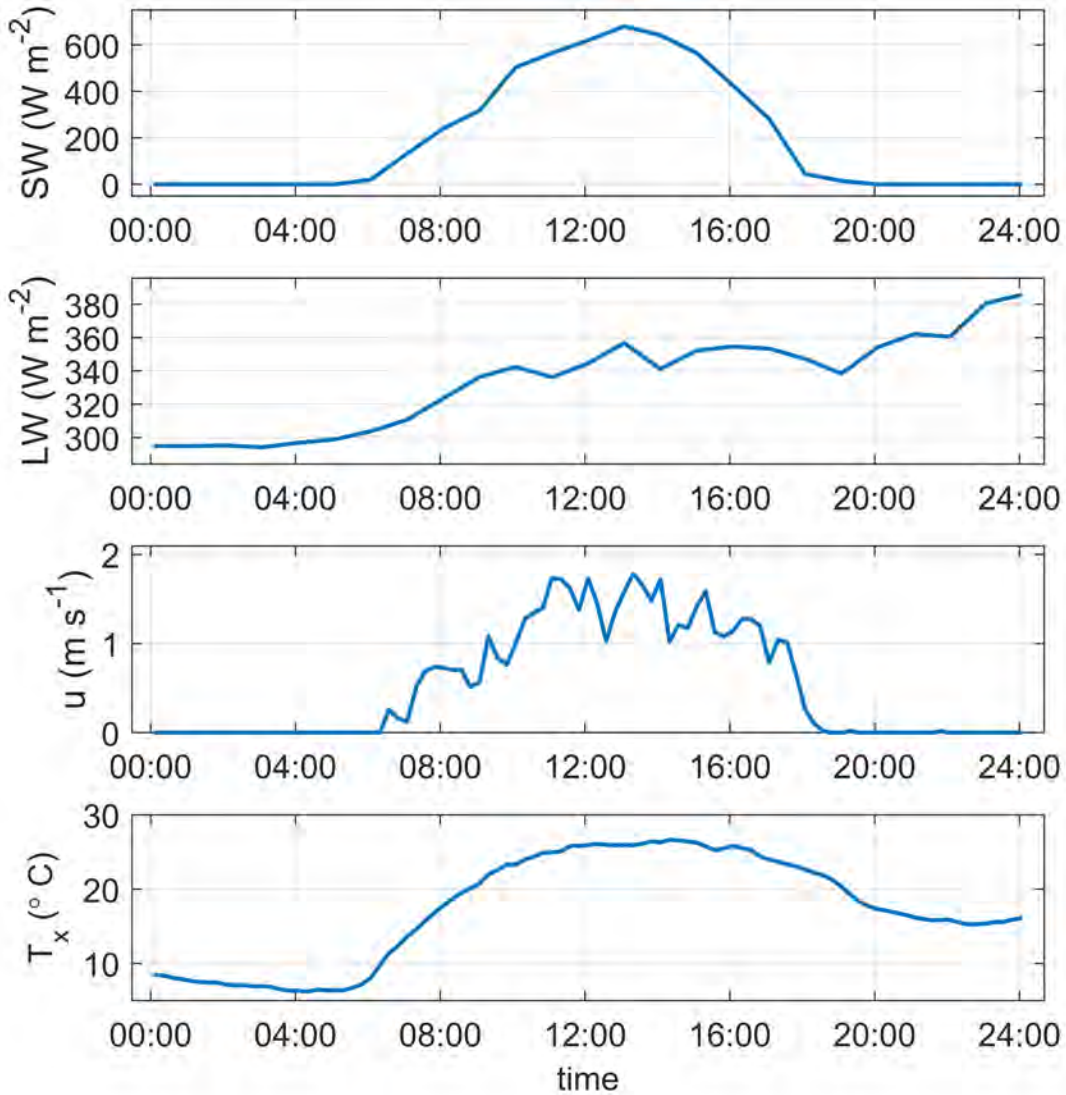


Figure S16. Environmental input forcing used for the model validation described for model evaluation, based on measurements at location **Chisago, MN** on **Aug 9, 2019**. The top panel displays the incoming shortwave radiation (SW_{in}), followed by the incoming longwave radiation (LW_{in}), wind speed ($\bar{u}$), and exterior air temperature (T_x). * Although the panels are tracking and the effect is negligible, a diffuse-to-direct shortwave radiation ratio of 0.25 is assumed (Muneer et al., 2007).

13. Numerical setup

The momentum budget equation was numerically solved using the Newton–Raphson method to handle the system of non-linear equations derived from the Fi-

nite Difference Method. Within each Newton–Raphson iteration, the resulting linear system was solved using the Thomas algorithm. The momentum evaluation was performed assuming solar panel installation heights of 1 m, with the computational domain extending from a lower boundary condition (BC) at 0.07 m to an upper

BC at 4.5 m. A grid size of 0.00225 m was used for these simulations to capture the very fine variability of the velocity. The wind speed and the slope of the profile from the same study were applied at the top of the domain. The iterative solver employed a convergence criterion based on the squared error between two itera-

tions, such that the iterations continued until the sum of squared differences fell below a prescribed tolerance ($1e - 10$). For subsequent applications involving wind profiles and mass exchange in the main model, the panel height was set to $h_p = 4$ m, and the grid size was adjusted to $\Delta z = 0.009$ m.

Table S1. Mixing length parameter values for different tilt angles.

	k_g	k_e	L_{e0}	L_{inf}	k_A	k_W
15°	6.68e+00	1.83e+00	-7.92e-02	3.73+01	2.04e-01	2.39e-05
30°	2.68e+01	1.04e+00	-1.00e-01	1.26e+02	1.61e-01	7.36e-03
45°	1.58e+01	1.17e+00	-9.56e-02	1.22e+02	1.66e-01	7.12e-03

14. Diurnal Patterns of CO₂ Exchange in Crop–Soil Systems

To assess the carbon dioxide dynamics beneath the PV panels, the CO₂ exchange rates from both the crop (weighted by leaf area density) and the soil, per unit area of land, are shown in this SI. At night, leaves respire, but overall CO₂ emissions are dominated by respiration from the soil. During the day, as discussed earlier, assimilation by crops generally follows sunlight availability. However, just before 3 p.m., as canopy pho-

tosynthesis reaches a local peak and CO₂ becomes partially depleted under the PV panels, a local minimum in net CO₂ flux can be observed. These patterns show how the microenvironment beneath the panels and can inform strategies to optimize system design for improved performance and productivity. The values reported by Yang et al. (Yang et al., 2018) indicate soil respiration ranging from 0.2 to 2.5 mol m⁻² day⁻¹ (equivalent to 2.22 to 27.7 $\mu\text{mol m}^{-2} \text{s}^{-1}$). In comparison, the present results suggest a total daily soil carbon respiration of 1.26 mol m⁻² and total canopy carbon uptake (assimilation) of 1.24 mol m⁻².

15. A discussion on a single leaf under various microclimates, the role of AV, crop type, and climate

The cube in Fig. S18 illustrates the average net assimilation rate of tomato plants under varying relative humidity, leaf temperature, and levels of sunlight, assuming no effect of sunlight on leaf temperature. In reality, increasing solar radiation typically raises leaf temperature; however, leaf thermodynamics are complex. Depending on concurrent changes in humidity, radiation, and other factors, stomatal opening and closure can modulate transpirative cooling, thereby influencing leaf thermal behavior. The atmospheric CO₂ concentration near the crop canopy is assumed constant at 400 ppm, as elevated [CO₂] facilitates diffusion into leaves and enhances photosynthesis. Notably, the model presented in the main text accounts for full interactions among all factors, without treating them as independent. The simplification used in this figure serves only for illustrative analysis.

In this analysis, sunlight intensity ranges from 0 to 1200 W m⁻², leaf temperature varies between 10 and 50 °C, and relative humidity spans from 0 to 100 %. At

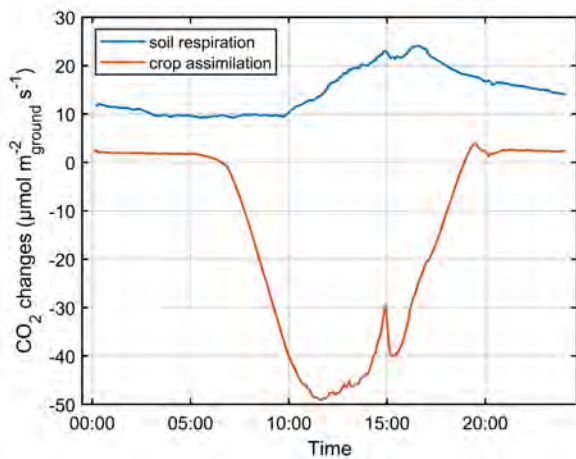


Figure S17. Net CO₂ exchange rates from the entire crop canopy (over ground) and the soil surface. Negative values indicate net CO₂ uptake (sink behavior), typically due to assimilation, while positive values represent net CO₂ release (source behavior), typically from soil respiration or dark respiration from leaves. This convention reflects ecosystem-scale CO₂ dynamics under PV panels.

a fixed leaf temperature and humidity level, increasing shortwave (SW) radiation enhances net assimilation. For a given relative humidity and SW level, photosynthetic activity peaks when leaf temperature is maintained between 25 and 35 °C, where the photosynthetic machinery operates most efficiently. At constant SW radiation and leaf temperature, increasing humidity reduces the vapor pressure gradient between the leaf and the surrounding air, thereby limiting transpirative water loss. This reduction in evaporative demand helps maintain stomatal openness, facilitating CO₂ uptake and, consequently, enhancing the assimilation rate.

While these mentioned trends may appear straightforward, in practice, increasing light intensity typically elevates leaf temperature and reduces relative humidity. Consequently, the system's response is not confined to movement along the positive SW axis, but also involves simultaneous shifts along the T_l axis and in the opposite direction along the RH axis. Depending on the initial conditions, such coupled changes can yield contrasting effects. For instance, starting from cooler leaves, moderate warming may enhance assimilation, and although declining RH tends to reduce assimilation, the overall effect may still be positive. However, if the reference state already lies within an optimal photosynthetic range, further increases in temperature and reductions in RH can become detrimental. In this case, elevated temperatures may impair photosynthetic efficiency and promote stomatal closure (Knapp & Sturchio, 2024), while lower RH exacerbates water stress—both of which contribute to a decline in net assimilation.

In conclusion, the impact of AV systems on photosynthesis and net assimilation is nuanced and context-dependent. Depending on the crop type and climatic conditions serving as the reference case, the observed increase in photosynthesis under reduced sunlight and as a side-effect lower leaf temperatures, may not be negligible, as explained by the thermodynamic and physiological mechanisms discussed earlier.

Regarding the influence of AV systems on net assimilation, outcomes vary with the crop's growth stage, seasonal timing, prevailing climate, and species-specific light requirements. When sunlight levels remain above the saturation threshold, moderate reductions in irradiance may not impair photosynthetic performance. In fact, such conditions can sustain or even enhance assimilation rates. Additionally, the physical presence of PV panels is likely to elevate relative humidity in the microclimate beneath them by limiting vapor exchange with the atmosphere, particularly since both the ground and the plants are primary sources of moisture. During early morning hours, reduced vertical mixing may also lead to elevated carbon dioxide concentrations under the panels due to nocturnal damped soil respiration, thereby enhancing CO₂ diffusion into leaves and supporting photosynthesis. However, this advantage may

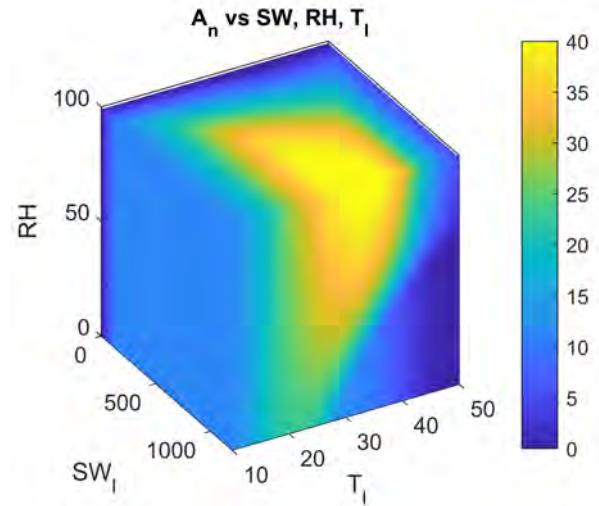


Figure S18. Three-dimensional color plot showing the variation of net assimilation rate ($\mu \text{ mol CO}_2 \text{ m}^{-2} \text{ s}^{-1}$ as color bar) as a function of leaf temperature (°C) and relative humidity (%), across different levels of shortwave irradiance. Shortwave irradiance is included as a third axis but is assumed to have no direct effect on leaf temperature. The color bar represents the net assimilation rate.

reverse in the afternoon, when carbon uptake by crops surpasses CO₂ contributions from soil respiration, potentially leading to reduced assimilation efficiency.

These findings underscore the need for further investigation into crop responses within AV systems—an area this model is designed to support in future research.

16. A discussion on the framework of interest

As often attributed to Einstein, “Everything should be made as simple as possible, but not simpler.” The critical question remains: what constitutes an appropriate level of simplicity for a scientific model, and who defines these boundaries? The degree of simplification depends on the specific scientific questions being addressed. In the present study, the primary focus is on semi-long-term phenomena, typically on seasonal timescales, as further elaborated below.

Within an agrivoltaic (AV) farm system, the primary variables of interest include crop yield (food production), power generation, and human thermal comfort. For crop production, the central outcome is yield, which correlates with the cumulative carbon assimilation integrated over the entire growing season, spanning several months. Spatially, the domain of interest extends horizontally across the entire farmland, rather than focusing on specific rows or strips. Vertically, however, stratification is necessary since crops at different canopy levels may experience distinct environmental conditions. Temporally, while precise instantaneous crop responses

are less critical, capturing diurnal variations remains important. The general daily pattern tends to repeat, and understanding its dynamics allows identification of potential inefficiencies and opportunities for optimization. Therefore, a horizontally averaged model with vertical discretization is appropriate for crops, while temporal resolution should capture diurnal cycles rather than instantaneous fluctuations.

For power generation, the incident radiation on the panel surface and the associated thermal loads are of primary importance, as both temporal and spatial variations can influence system performance. Temporal variations are directly captured within the model framework. Regarding spatial variations, since most panels within the system are uniformly oriented and assuming homogenous atmospheric conditions (which remains a valid assumption for modeling purposes, regardless of minor atmospheric inconsistencies), all panels are exposed to nearly identical incoming radiation. The only significant deviation arises from mutual shading effects, which are explicitly incorporated into the model. From a thermal perspective, both radiative and convective heat fluxes across an individual panel surface exhibit minimal spatial variability. View factors remain essentially consistent across the panel surface,

and all points experience the same ambient air temperature. Although some studies have reported minor differences in convective heat transfer coefficients between the lower and upper edges of panels, these variations are generally negligible in the context of overall thermal modeling. In contrast, variations between panel rows are primarily governed by sub-panel air temperature dynamics, which are not fully captured in the entrance region.

For human thermal comfort, both temporal and spatial variations may play a significant role, as individuals have the ability to select their location and timing for outdoor activities. While ambient temperature, humidity, and wind speed can be reasonably assumed to be horizontally uniform across the site, radiative exposure varies considerably at spatial scales comparable to the dimensions of the human body and typical movement paths. To address this heterogeneity, the model explicitly distinguishes between three representative scenarios, which capture the primary radiative exposure conditions relevant for human comfort assessment. This manual categorization effectively accounts for spatial variability in radiative load. Temporal variations are directly incorporated into the model and are well-resolved.

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