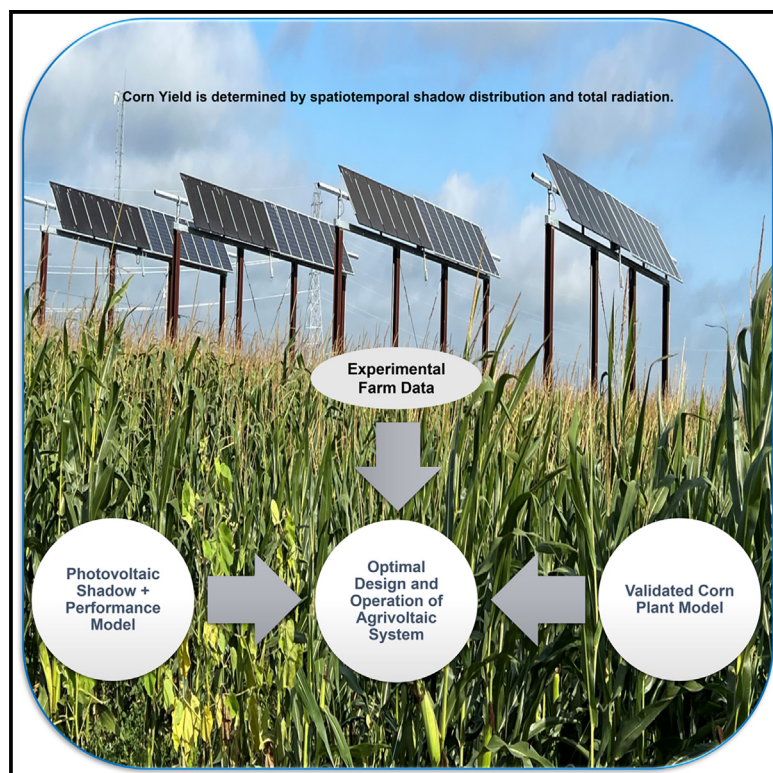


Optimizing corn agrivoltaic farming through farm-scale experimentation and modeling

Graphical abstract



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In brief

The authors present the findings of an integrated agrivoltaic model. The model consists of an analytical shadow model and a crop model calibrated and validated in close agreement using shaded and unshaded experimental corn plant data. The dependence of yield on spatiotemporal shadow distribution, in addition to total radiation, opens up the possibility of agrivoltaic optimization.

Highlights

- Extensive experimental data for corn growth for PV-shaded and full Sun regions
- Calibrated crop model using full Sun region data to predict unshaded region yield
- The calibrated model with analytical shadow model predicts PV-shaded region yield
- The spatiotemporal shadow distribution, in addition to total radiation, determines yield



Article

Optimizing corn agrivoltaic farming through farm-scale experimentation and modeling

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<https://doi.org/10.1016/j.crsus.2024.100148>

SCIENCE FOR SOCIETY By the end of the current century, Earth's population will rise to over 9 billion people. Meeting the food and energy demands of the global population during adverse climate conditions will require sustainable food and energy solutions given the limited land availability. One such solution is agrivoltaics, a practice of co-producing food and energy by installing photovoltaics on agricultural farmland. Through extensive corn growth data, we present a calibrated and validated crop model integrated with an analytical shadow model. Using this model, we observe that the corn yield is determined by spatiotemporal shadow distribution in addition to total radiation. Moreover, we demonstrate that the full Sun data-calibrated crop model predicts crop growth for the PV-shaded region given the shadow profile from the analytical shadow model.

SUMMARY

To address the limited agrivoltaic research with photovoltaics (PVs) collocated with major row crops, such as corn (*Zea mays*), we collected extensive corn growth data from neighboring “without-PV” (unshaded) and “with east-west Sun-tracking-PV” regions. The Agricultural Production Systems Simulator (APSIM) plant model calibrated with unshaded region data provided excellent agreement with the experimental PV region corn yield when using hourly light intensity for each plant row computed using spatiotemporal shadow distribution (SSD) between PV panels from our shadow model. The validated APSIM and PV shadow models are then simulated for insights on plant performance and power generation at various PV panel heights, distances between the adjacent PV rows, tracking angles, tracking and anti-tracking during different times of the day and different periods of plant growth, etc. We observed that corn yield is governed by SSD and total radiation, highlighting active control of shadow distribution to optimize crop yield and power production in agrivoltaic farming.

INTRODUCTION

In the face of an escalating global population, economic standards, and worsening climate conditions,¹ ensuring the long-term food^{2,3} and energy security^{4,5} of our planet necessitates sustainable solutions.⁶ One such solution is to transition from the use of fossil fuels to clean energy alternatives such as solar energy.⁷ Solar energy is quite abundantly available in many regions on Earth and can be harnessed through photovoltaic (PV) systems.⁸ Despite its numerous advantages, there are some inherent challenges with the installation of these systems. Specifically, the application of feasible sustainable energy alter-

natives, such as PV, will likely be hampered by land availability constraints.^{9,10} A potential strategy to circumvent this predicament is through the co-production of food and solar electricity on agricultural land via PV installations, known interchangeably as PV agriculture (PVA), agrophotovoltaic, or PVA systems.^{10–13} PVA farming mitigates the impact of greenhouse gas emissions over burning fossil fuels and has been shown to improve the climate resilience of crops.^{14–16}

PVA farms shown in Figure 1, a photo taken by Dr. Rakesh Agrawal, employ PV panels whose layout and geometry, combined with the Sun's position, yield a spatiotemporal shadow distribution (SSD)^{10,12,17} that diminishes the total radiation (TR)





Figure 1. Experimental agrivoltaic farm

The experimental PVA farm at Purdue Agronomy Center of Research and Education (ACRE). The with-PV region is under the PV panels while without-PV regions are on far north and south sides. In the figure, h represents the height of the tracker from the ground while d shows the distance between adjacent PV rows. Photo courtesy: Dr. Rakesh Agrawal.

available to plants over the growing season. The design of PV structures can also influence microclimatic conditions.^{18,19} Given that PVA farming utilizes fertile agricultural land, it is critical to mitigate any potential negative effects on food yield, necessitating an in-depth understanding of the interaction between SSD and the plants grown beneath.

Extensive research on shade-tolerant vegetables such as lettuce, cucumbers, peppers, and tomatoes has demonstrated their successful growth under PV panels.^{14,19–24} However, a decrease in yield for potatoes, winter wheat, and some types of beans under PVA farming has been reported.^{25,26} Unfortunately, PVA studies on major row crops such as corn, soybean, and wheat under real farming conditions are almost nonexistent.

According to the U.N. Food and Agriculture Organization's 2020 FAOSTAT database, these crops account for a large fraction of the farmland. For instance, in the US, maize and soybean are cultivated on 33 and 36 million ha, respectively, while vegetables such as lettuce only occupy 0.022 million ha. Therefore, the global-scale sustainability and implementation of PVA farming necessitate a detailed analysis of solar photon sharing between PV arrays and agronomic row crops.¹⁰

Major row crops such as corn pose challenges for PVA farming due to their incompatibility with existing PV structural layouts used for other crops. These crops are typically cultivated using tall and wide combine harvesters, which are incompatible with

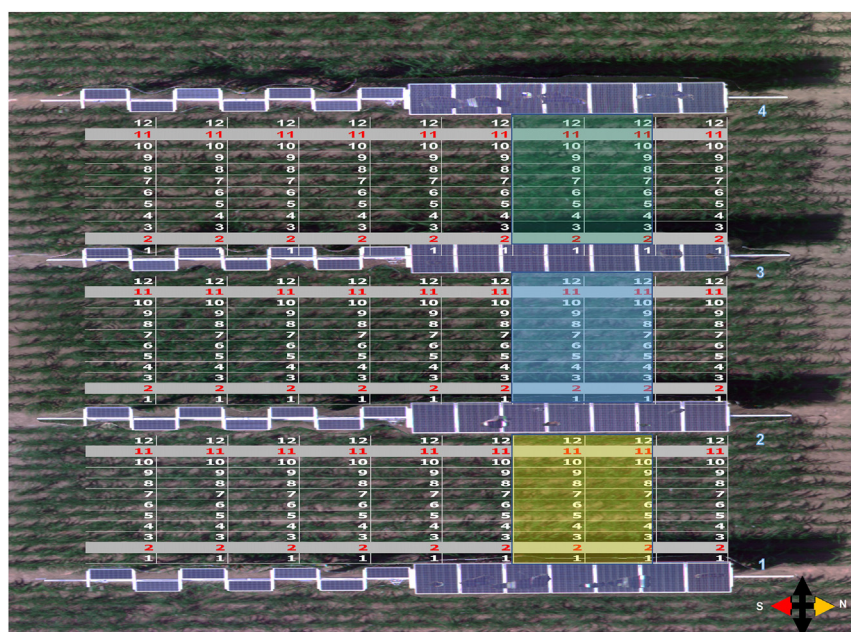


Figure 2. Farm layout

The field layout shows 12 rows of crops between adjacent panel rows in with-PV region. The panels and the rows are numbered in increasing order from east to west. Different colors represent different areas between different panel rows.

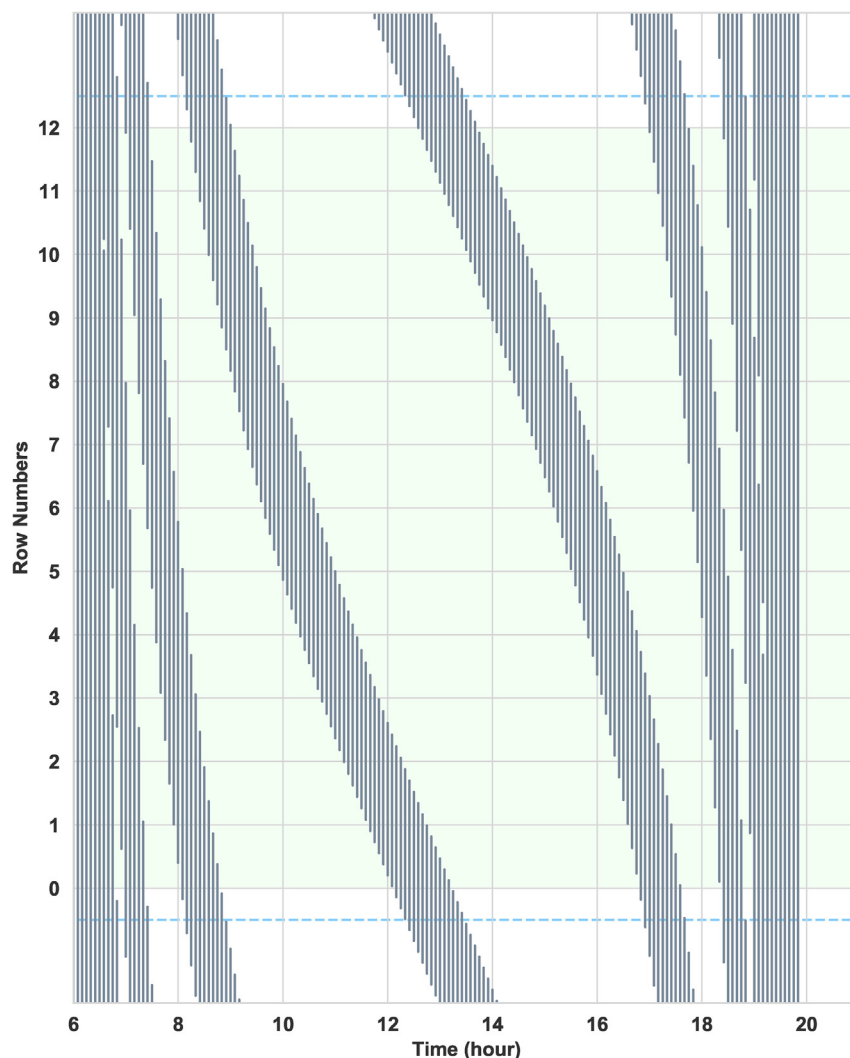


Figure 3. Reference shadow profile

Base case shadow profile for unrestricted movement of panels. The shadow profile is generated for the PV structure shown in Figure 2 when we only take the contiguous PV panels and extend infinitely in the north-south direction. Specifications: tracker height: 6.1 m, offset angle: 90°, unrestricted tracking with no AT, ground pitch: 9.91 m. The blue-colored dashed line represents the center line of panel rows. Each shadow continuum above represents the movement of shadow due to individual PV rows in spatial dimension as a function of time.

the current short and narrow PV arrays in the existing literature.^{20,22,25,28,29} Unlike non-tracking fixed PV panels, like those installed at the Fraunhofer Institute in Germany,³⁰ east-west Sun-tracking PV panels offer economic incentives for power generation and cast a dynamic shadow that shifts throughout the day. This dynamic shadow mitigates the impact of daylong shadow at a given location. The Montpellier group in France manipulated ground shadow to increase photosynthetic active radiation (PAR) on growing lettuces by anti-tracking (AT) the Sun-tracking panels during morning and evening times.²⁰ The space between the PV rows was insufficient for the operation of a farm-scale combine harvester. To facilitate large-scale implementation of PVA farming, it is essential to generate plant data for major crops under actual farming conditions and develop validated plant and PV models. These models will elucidate the impact of PV panel design, installation, and operation on plant growth and crop yield.

Existing literature on shadow profiles and PAR intensity modeling at the plant level and their usage with crop models to predict PVA farm crop yields is limited.^{28,31,32} Although the avail-

able models work well for PAR intensity and PV power generation, their ability to predict plant performance when combined with crop models is limited. The Montpellier group was the first to use a shadow model with a crop model for durum wheat but found contradictory results with respect to experimental observations.²⁸ The Fraunhofer group used idealized plant models to understand relative plant yields for different distances between PV arrays but did not compare their calculations with experimental yields.³⁰ A study by Amaducci et al. simulated crop model performance for biogas maize and found that the average yield for rainfed maize in PVA farms was higher than fields without-PV.³¹ However, they did not validate their model with experimental results, and our experimental findings described later contrast with theirs. Grubbs et al.³³ proposed a critical-time anti-tracking algorithm intended to improve yield preservation during specific growth periods.

Moreover, the current modeling literature lacks crop models calibrated and validated with real PVA farm data and primarily operates on coarser timescales, such as daily or seasonal. This approach fails to account for the impact of incremental

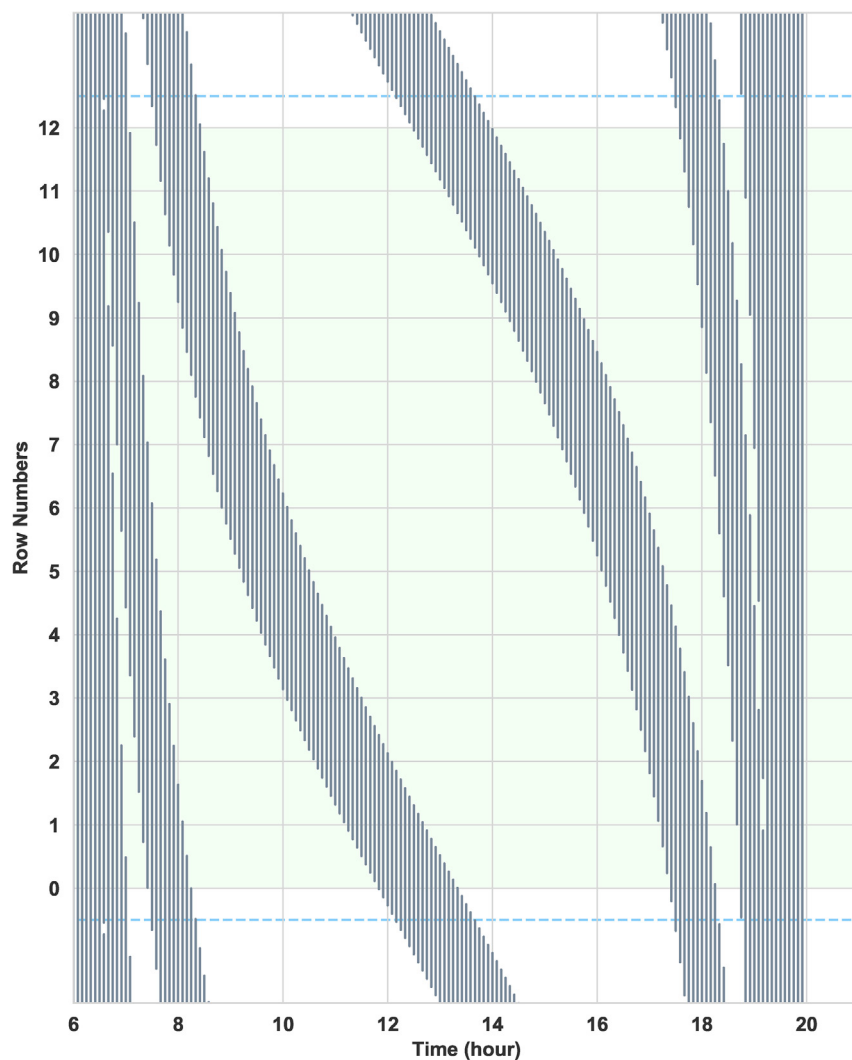


Figure 4. Shadow profile for 4.572 m height
Shadow profile for unrestricted tracking with tracker height of 4.57 m. The shadow profile is generated by varying the height of the PV structure shown in Figure 1 when we only take the contiguous PV panels and extend infinitely in the north-south direction. The blue-colored dashed line represents the center line of panel rows. Each shadow continuum above represents the movement of shadow due to individual PV rows in spatial dimension as a function of time.

dynamic shadow variation caused by tracking PV panels, which is observable on finer timescales like hourly variations.

There has been significant progress in understanding the economic dynamics of agrivoltaics. Ahmed et al. concluded high net profitability of rice production in PVA conditions compared with conventional farming conditions.³⁴ The PVA system is shown to be more beneficial than conventional PV farms for high-value crops and suitable module configurations if special consideration is given to land cost, module density, and feed-in-tariff adjustments.³⁵ A study conducted on Benban Solar Park in Egypt, where the government supports a feed-in-tariff program to encourage investment in PV, has estimated a reasonable payback period and to be economically viable given the investment scale and expected benefits.³⁶ Economies of scale and national policies have been shown to play a key role in the adoption of PVA farming to maintain the land-use efficiency advantage.^{37,38}

However, in the western part of the world, for major row crops such as corn, soybean, and wheat, where tall and wide combine harvesters are used for farming activities, additional constraints emerge. The unimpeded movement of combine

harvesters requires special attention be paid to the design and installation of solar panels. Currently, a proposed solution has been to install PV panels at a height of 6–8 m, adding to the overall cost of the enterprise. Fraunhofer's team has built and performed a techno-economic analysis of such a PVA farm with solar panels installed at a height of 7.8 m.²⁵ The team found that as compared with the conventional PV farms, while the annual operating expenditures (OPEX) for the PVA were lower due to the reduced land, maintenance, and mowing costs, its capital expenditure (CAPEX) was 73% higher, resulting in a levelized cost of electricity (LCOE) for PVA higher by 38%.^{25,32} In terms of increased capital cost due to elevated PV panel height, our experience with the installation shown in Figure 1 is similar to that of Fraunhofer's. As a result, compared with simply elevating the height of the PV panels for the unimpeded movement of the combine harvesters, there is a need for innovative PV panel designs, their installation, and operation to reduce the capital cost while maximizing crop performance and yield. The installation of new panel designs at a PVA farm is expensive, and data collection due to one growing season

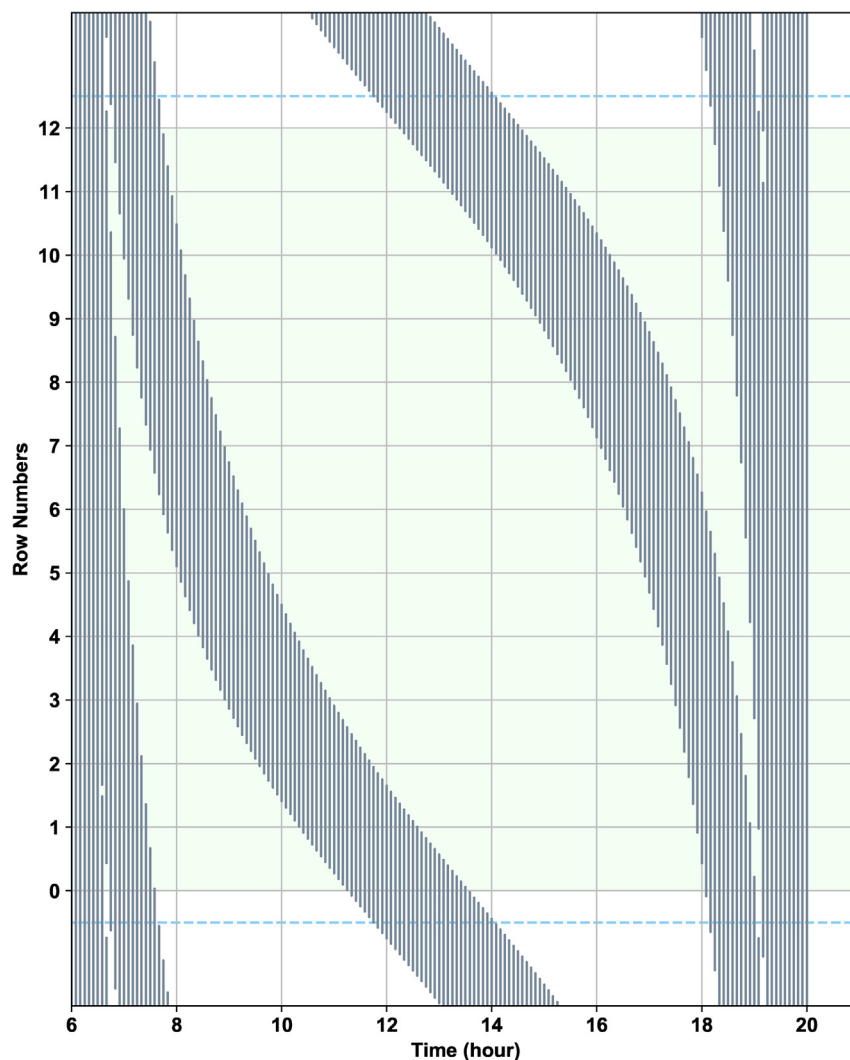


Figure 5. Shadow profile for 3.048 m height
Shadow profile for unrestricted tracking with tracker height of 3.05 m. The shadow profile is generated by varying the height of the PV structure shown in Figure 1 when we only take the contiguous PV panels and extend infinitely in the north-south direction. The blue-colored dashed line represents the center line of panel rows. Each shadow continuum above represents the movement of shadow due to individual PV rows in spatial dimension as a function of time.

per year is slow. To quickly assess various PV panel designs, a validated modeling framework is needed to conduct a systematic study concerning the design and operating variables of the PV panels and to assess their impact on the performance of the PVA farm in terms of power generation and crop performance. This work aims to provide a robust and adaptable integrated modeling approach using experimentally validated models to study the variation in crop yield and power, two primary output variables in PVA, as a function of PV design and operating parameters. This information is crucial to building economic PVA farms on a large scale.

Alongside economic aspects, most studies in the literature focus on land use and policy considerations using existing and known PV structures. The purpose of our study is to develop insights as to how PV design and operation influence row crop growth and yield underneath.¹⁴ Our goal is to provide models and tools needed for the optimal design of PV panels, their installation, and their operation.

This is a comprehensive study developing PV shadow and maize models in tandem with experimental observations from

a modern, mechanized corn PVA farm. The design and installation features of our east-west tracking PV panel PVA farm at Purdue University in West Lafayette, Indiana, USA (Figure 1), extensive data collection strategies, and critical corn yield observations are provided. A crop model, first calibrated with reference field data using full unobstructed hourly solar radiation,³⁹ predicts the yield of the PVA farm in close agreement with experimental data. The effect of different SSDs on yield is demonstrated for a given TR, thereby emphasizing the need for light spatiotemporal distribution optimization. The impact of various tracker heights—the vertical distance between the ground and center of the panels mounted on the tracker—on the SSD and the associated corn plant performance is studied through simulation. In addition, plant growth is analyzed for different tracking and AT algorithms, and results corresponding to various PV array densities in a PVA farm are discussed. Our study offers a systematic framework for PVA system analysis and provides some of the essential understanding needed for the optimized design, installation, and operation of PV arrays. This knowledge allows SSD

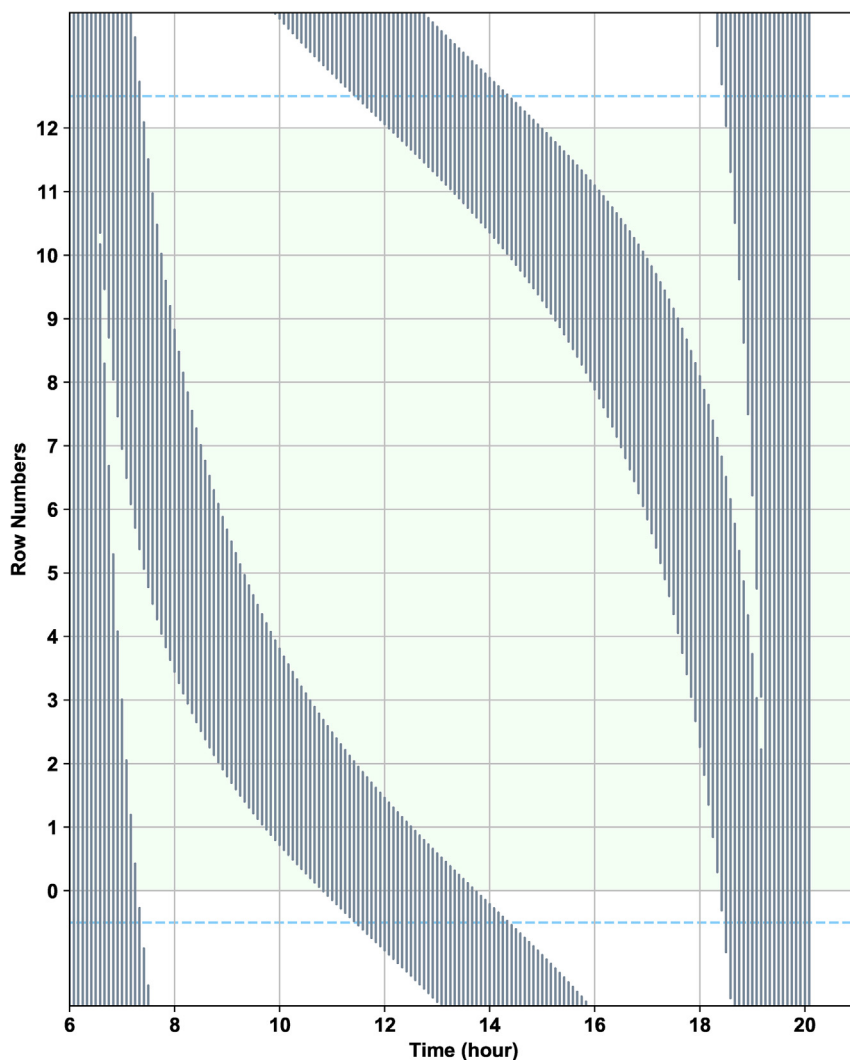


Figure 6. Shadow profile for 2.4384 m height
Shadow profile for unrestricted tracking with tracker height of 2.44 m. The shadow profile is generated by varying the height of the PV structure shown in Figure 1 when we only take the contiguous PV panels and extend infinitely in the north-south direction. The blue-colored dashed line represents the center line of panel rows. Each shadow continuum above represents the movement of shadow due to individual PV rows in spatial dimension as a function of time.

manipulation during various stages of plant growth for optimal power and food production from a PVA farm, especially farms with shade-intolerant crops.

Purdue PVA farm and data collection

The current experimental setup, as shown in Figure 2, at Purdue was installed in April 2019.⁴² The setup employs 4 WattSun HZLA single-axis trackers for the Sun tracking within $\pm 45^\circ$ east and west. The panels are oriented at -45° and 45° , respectively, in reference to horizontal, beyond these bounds, i.e., before the beginning and after the end of the tracking during morning and evening, respectively. The dimensions of 300 W modules are $1.78 \times 0.99 \times 0.05$ m, while that of 100 W modules are $0.68 \times 1.01 \times 0.03$ m. The northern half of each tracker, also called contiguous panels, comprises modules placed adjacent to each other, while the southern half of each tracker row, referred to as checkerboard panels, packs modules in an alternate pattern and is 0.051 m away from the center. The elevation of the center of each tracker is 6.1 m from the ground, and the

spacing between centers of adjacent tracker rows is 9.91 m. This distance is also known as the pitch. During tracking, the angle between the plane of the panel and the direct normal irradiance (DNI) will be referred to as offset angle. The offset angle is 90° for the experimental setup.

For the growing season 2020, corn hybrid Pioneer 0825AM seeds were planted on April 27th, and corn ears were harvested on October 7th. This region where the rows of panels cast a shadow on the crops referred to as the “with-PV” region. Parallel to the with-PV region are running two rectangular areas on each side, i.e., north and south, where the crops receive no shadow from these PV panels. These regions are collectively referred to as “without-PV” regions or the reference field as shown in Figure 1.

Commercial PV parks generally deploy contiguous panels running parallel to each other. Therefore, this study only considers the region under contiguous panels as highlighted in (Figure 2) green, blue, and yellow. This area is impacted by the shadow cast due to contiguous panels only. For validation,

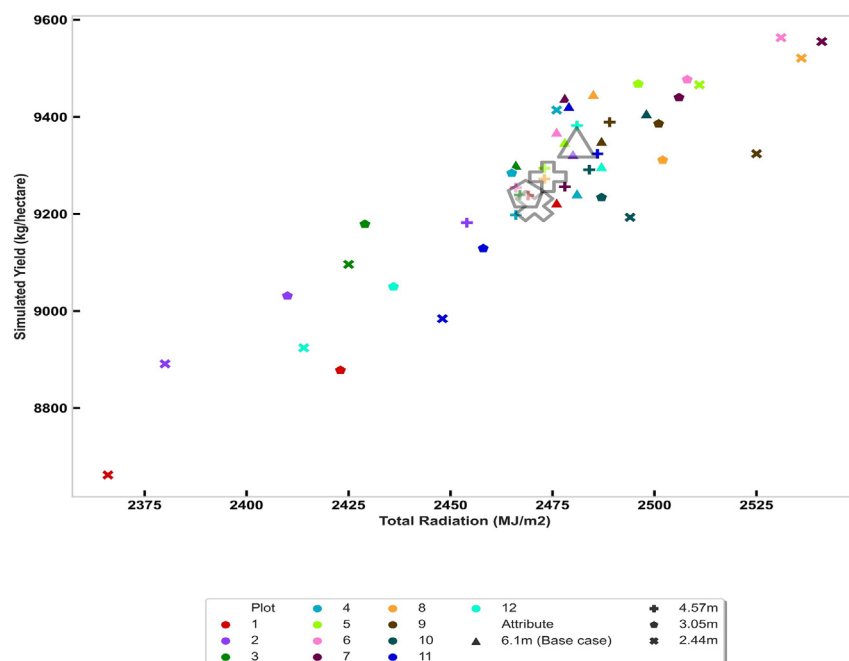


Figure 7. Yield versus radiation curve for different tracker heights

Simulated yield for unrestricted tracking panels of different heights. For a given symbol, different colors represent different plots, and larger gray symbols represent average yield for each set of simulated heights.

the 12 plots highlighted in blue are considered. Corn ears of three representative plants from each of these plots were hand-collected. Overall, 570 corn plants from the without-PV region and 36 corn plants from the with-PV region, respectively, were used in the analysis. The ears were cleaned, imaged, and processed using a DuPont pioneer ear photometer. The system provided approximately 40 parameters, including corn yield, which is used in this study. Grubbs et al.³³ provided a detailed experimental data collection procedure and several statistical correlations between thermal time and yield. Based on the cultivated land area and 15% moisture content, the yield obtained in the without-PV region was observed to be 10,955 kilogram per hectare (kg/ha), while that in the with-PV region was 10,182 kg/ha. Please note that the yield in the “PV region” is reported based on cultivated land area only and does not include 7.7% of the uncultivated area associated with PV rows.

Shadow modeling and plant model validation

Solar radiation data from the National Renewable Energy Laboratory (NREL) database⁴⁰ was collected for the latitude and longitude of our PVA farm. The hourly radiation data was used as an input to the Agricultural Production Systems Simulator (APSIM) plant model.³⁹ The choice of APSIM as a plant model was based on finer temporal resolution and literature supporting the validity of the model. As described in appendix A, the APSIM model was first calibrated and then validated using the without-PV and with-PV region experimental yields, respectively. The calibrated APSIM model simulation result of 10,856 kg/ha is in close agreement with the average experimental yield of 10,955 kg/ha for the without-PV region. Next, as described in the supplementary information, a SSD model

for the PV panels was developed, which is then used in conjunction with NREL radiation data to calculate hourly radiation distribution at the ground level for each plant row in the with-PV region throughout a day for the entire growing season. This hourly radiation data was then used as an input parameter in the calibrated APSIM model, without any further parameter adjustment within the plant model to calculate corn yield for any plant row in the PV region of interest (Figure 2). Interestingly, the calculated average corn yield for the with-PV regions is 10,102 kg/ha, which is in excellent agreement with the corresponding average experimental yield of 10,182 kg/ha. This excellent agreement between the results from the crop and the SSD models and the observed experimental values gives us the confidence to explore various potential interactions between PV panels and plant performance as discussed in the next section.

Shadow profile visualization

A typical PV park consists of a large number of contiguous PV rows located equidistant from each other. Therefore, an array of twenty, unrestricted trackers—free to rotate without any bounds—loaded with contiguous PV rows (i.e., no checkerboard arrangement) with the geometric specification and field layout in our experimental setup were simulated. Here, the PV panel tracking was unrestricted, i.e., it was allowed to track Sun from the sunrise to sunset. The resultant SSD for a randomly selected day, July 18, 2020, between two adjacent panel rows is shown in Figure 3. While the x axis represents the hours of the day, the y axis denotes plot numbers arranged in ascending order from east to west. The area between $y = m$ and $y = m + 1$ represents plot $m + 1$. The plant rows are located at the east-west mid-point of the respective plot. Please note

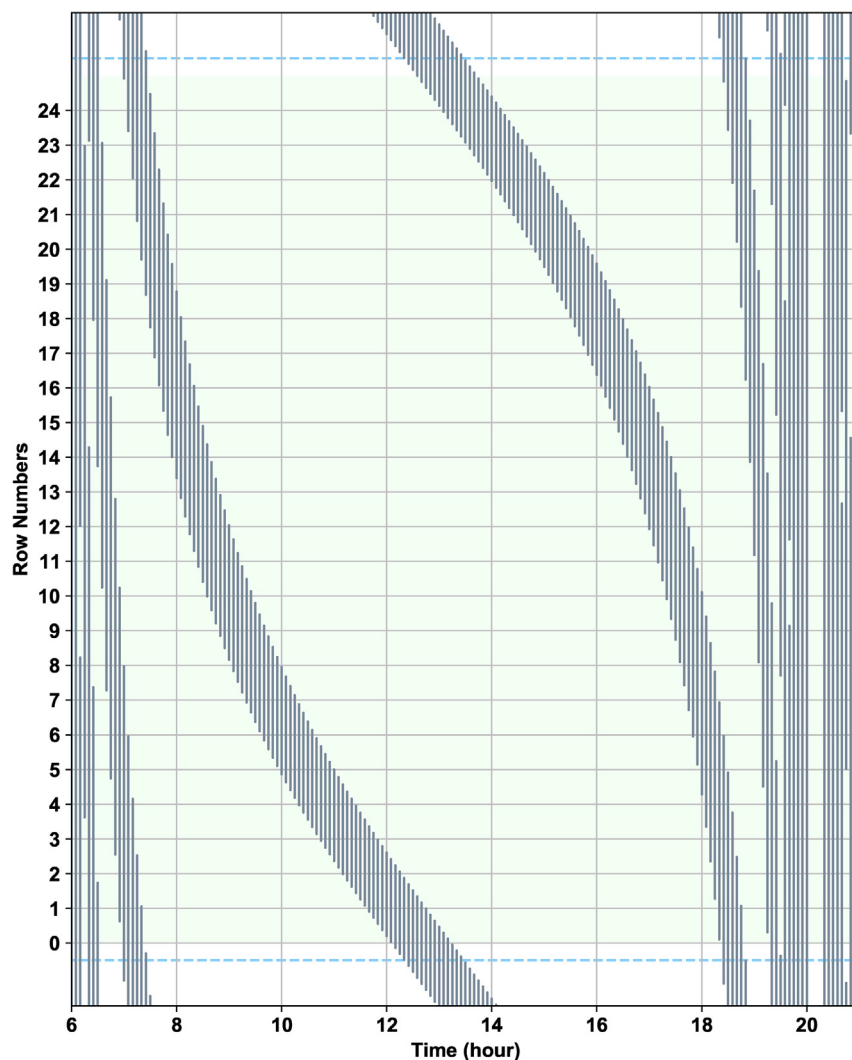


Figure 8. Shadow profile for double pitch
Shadow profile for unrestricted tracking for double pitch. The shadow profile is generated by varying the pitch of the PV structure shown in Figure 1 when we only take the contiguous PV panels and extend infinitely in the north-south direction. The blue-colored dashed line represents the center line of PV rows. Each shadow continuum above represents the movement of shadow due to individual PV rows in spatial dimension as a function of time.

that for one dimension in the east-west direction, rows and plots can be used interchangeably. Each dark gray continuum represents the movement of the shadow due to individual PV panels, while light colors represent unshaded regions. The blue region shown in Figure 2 simulated for these studies shall be referred to as the base case shadow profile shown in Figure 3.

Each shadow continuum shows the SSD of the individual panels. Before solar noon, the shadows are from the panel rows that are located on the eastern side of the plot, and after the solar noon from the panel rows on the western side of the plot. While the slope of a shadow continuum indicates the speed at which the shadow moves from one location to another, the width of a shadow continuum at any point in space-time shows the residence time of the shadow at that point. At the beginning of the day, the shadow moves faster. However, as the day progresses, it slows down and stays for a longer time at any given location for a significant duration of the day before accelerating again at the end of the day.

The following set of simulations demonstrate the impact of geometrical aspects of PV panels on crop yield. The results of the simulation are applicable for the specific set of parameters mentioned for the set of simulations. Caution must be taken while extrapolating these results due to the complexity of the models involved.

Results and discussion

Impact of the tracker height

Schindel et al.²⁵ have shown that tall trackers contribute significantly to the cost of the PV arrays and impact the overall economics of PVA farming. Therefore, the impact of reducing tracker height on plant yield was investigated. As the tracker height decreases, the shadow tends to spread in the temporal dimension as depicted by comparing Figures 3, 4, 5, and 6. This implies that shadows stay for a longer duration at a location as the height of the tracker is decreased. Three different heights, i.e., 4.57, 3.05, and 2.44 m, were simulated in addition to the base case height of 6.1 m.

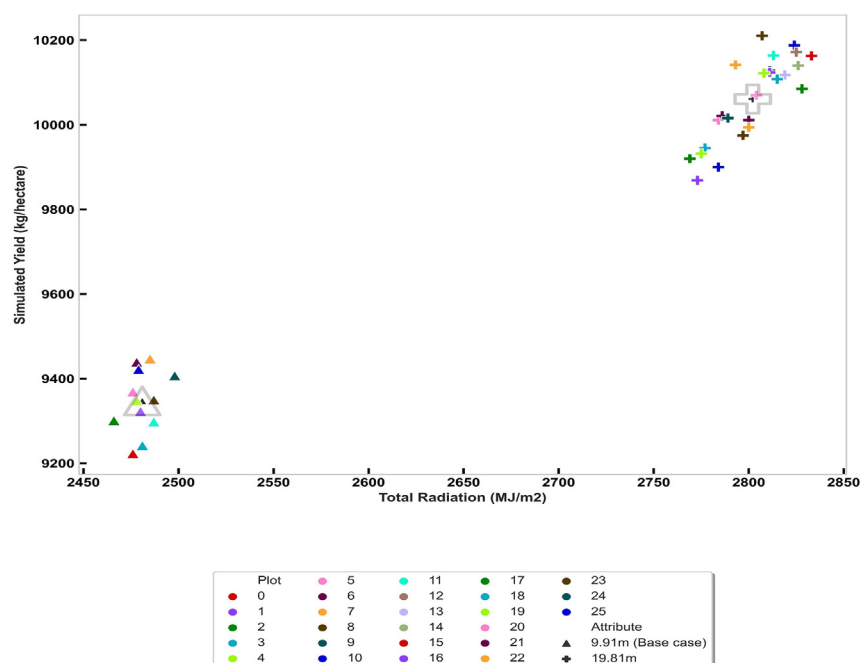


Figure 9. Yield versus radiation curve for different pitches

Simulated yield for unrestricted tracking for base case pitch (9.91 m) and double pitch (19.81 m), respectively.

In this case, from the plot-wise data as shown in Figure 7, for the same TR, the yield values are observed to vary between the plots. Alternately, an increase in TR between the two plots does not necessarily lead to an improvement in yield. This implies that in addition to TR, one must account for the SSD to correctly estimate the yield.

Changing the height of the tracker causes the shadows to rearrange in space-time dimensions such that the change in average cumulative radiation over the entire area between the adjacent PV panel rows is insignificant. The average yield of the plant rows grown under panels mounted on trackers of different heights has no significant difference as shown in Figure 7. Therefore, it is found that in order to reduce the fixed cost for the specific set of heights studied here, one should consider installing panels at the shortest tracker height possible as per the machinery and safety allowance.

Impact of doubling the distance between the PV arrays

The inclusion of a double pitch between two adjacent PV rows, compared with the base case, allows for the spread of shadow spatially. As shown in Figure 8, the shadow profile for each pitch remains continuous.

Introducing more area between adjacent PV rows causes the rows to separate in terms of TR received on the ground. On doubling the distance between the adjacent PV rows, the cumulative radiation on the area between the two adjacent PV rows increases by 11%. This causes an increase in yield by 7% as shown in Figure 9. However, it is interesting to compare this case with a second case where half the land is populated with PV panels at a distance of the base case pitch, and the remaining half is used for regular agricultural farming. Simulating these two scenarios reveals similar corn yield. Because both cases use the same amount of total land and produce the same power

from a cost perspective, the second case is likely preferable and shows an increasing pitch between adjacent PV rows beyond that of the base case, which is likely not advantageous. Increasing the distance between the adjacent PV rows will likely use more copper wires that will need to be run over larger distances, contributing to an increase in cost.

Changing the offset angle

For a given set of design parameters, one can alter the operational strategy to achieve the desired trade-off between yield and solar power by adjusting the sharing of photons between the PV panels and the plants. For this set of simulations, the impact of partial tracking is studied by changing the offset angle. In this case, the shadow profiles received on the ground are compared for four different offset angles, ϕ_{tr} : 90°, 60°, 30°, and 15°. For example, $\phi_{tr} = 60^\circ$ means that direct normal irradiance (DNI) makes an angle of 60° with the plane of the panel during tracking.

For the base case, the offset angle of 90° obstructs the maximum amount of direct light due to interception of light on the maximum allowable panel area, produces maximum power, and results in minimum TR available for the plants. Reducing the offset angle from 90° to 15° allows less light interception area on the panels and more direct light to reach the ground. Consequently, the duration of the shadow decreases gradually, thereby decreasing the thickness of the shadow in the x-direction (i.e., time) as observed on comparing Figures 3, 10, 11, and 12. This implies that at any point in time, the radiation available for biomass fixing is greater under the panels with a lower offset angle compared with that under the panels with a higher offset angle. Please note that although the solar panel efficiency will vary with PV material, the power will scale proportionately.

For different offset angles, the average yield from the validated APSIM model shows (Figure 13) a monotonically increasing

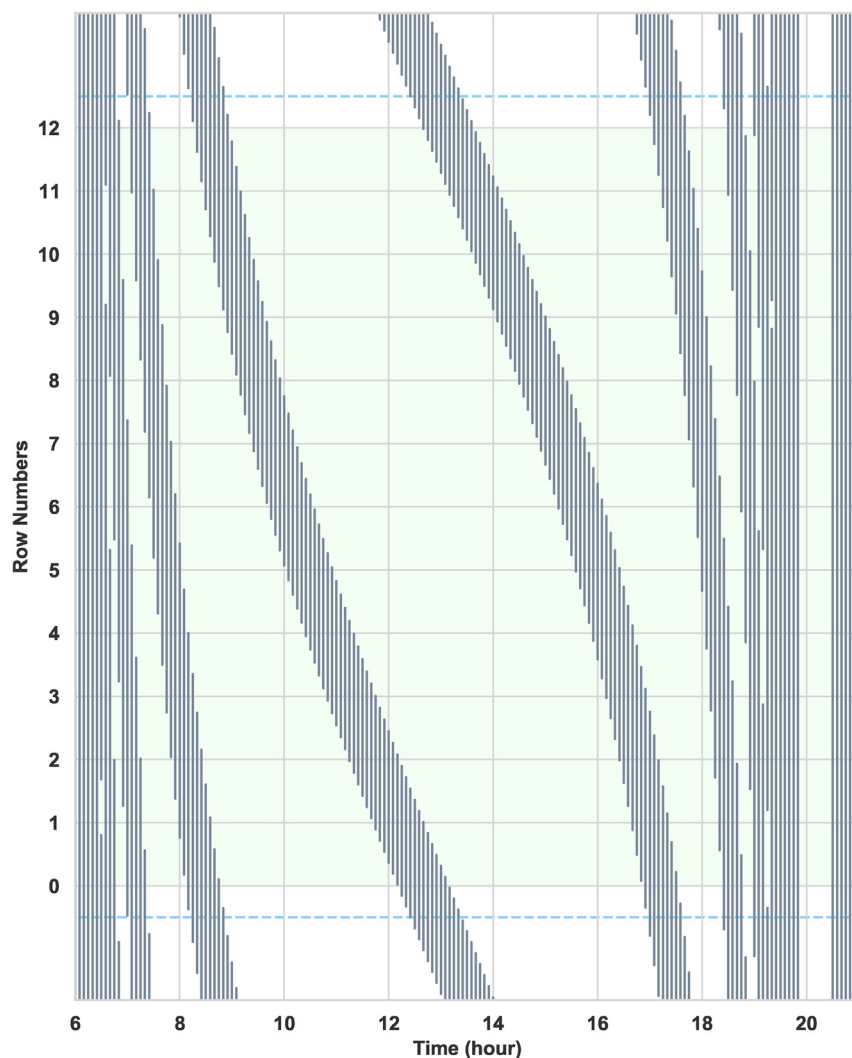


Figure 10. Shadow profile for 60° offset angle
Shadow profiles for unrestricted tracking at an offset angle of 60°. The shadow profile is generated by varying the tracking algorithm of the PV structure shown in Figure 1 when we only take the contiguous PV panels and extend infinitely in the north-south direction. The blue-colored dashed line represents the center line of PV rows. Each shadow continuum above represents the movement of shadow due to individual PV rows in spatial dimension as a function of time.

trend with respect to the TR for the individual rows. Moreover, since this is true for all the plots, the same is also true for average TR and yield values as well. It is observed that the percentage change in TR exceeds the percentage change in yield, implying that a gain in TR on increasing offset angle leads to a higher percentage change (decrease) in power than the corresponding percentage change (increase) in yield.

Impact of the AT

For the base case, solar panels track the Sun during the entire day with an offset angle of 90°. To understand the impact of AT on crop yield, a simulation was performed with the panels AT the Sun for four different periods of time during the day: before 8 AM, between 8 AM and 2 PM, and between 2 PM and 6 PM, and after 6 PM. This results in the corresponding shadow continuum being omitted during these parts of the day when the panels anti-track the Sun as evident from Figures 14, 15, 16, and 17. For example, AT between 8 AM and 2 PM omits the shadow cast due to the east side panels, and similarly, AT between 2 and 6 PM omits the shadow cast by the west side panel.

Introducing the shadow discontinuity by AT during different time periods of each day over the entire growing season can have an impact, albeit modest, on the plant yield as shown in Figure 18. AT during early morning and late evening causes the cumulative radiation for the plants to increase by approximately 5.2% and 3.8%, respectively. This causes the growing season power production to reduce by 7% and 4.9%, respectively. However, the corresponding change in average yield for both cases is 1.1% and 3.4%. AT 6 h before the solar noon and 4 h after the solar noon lead to an increase in cumulative radiation by 9.5% and 7.6%, respectively, whereas the respective growing season power production goes down by 41.1% and 24.5%, respectively. The resultant improvement in average yield is by only 5.4% and 5.6%, respectively.

Instead of AT during the entire growing season, AT was explored over the entire day during juvenile, flowering, or grain-filling seasons. AT during juvenile, flowering, and grain-filling seasons has different effects on yield. While AT during

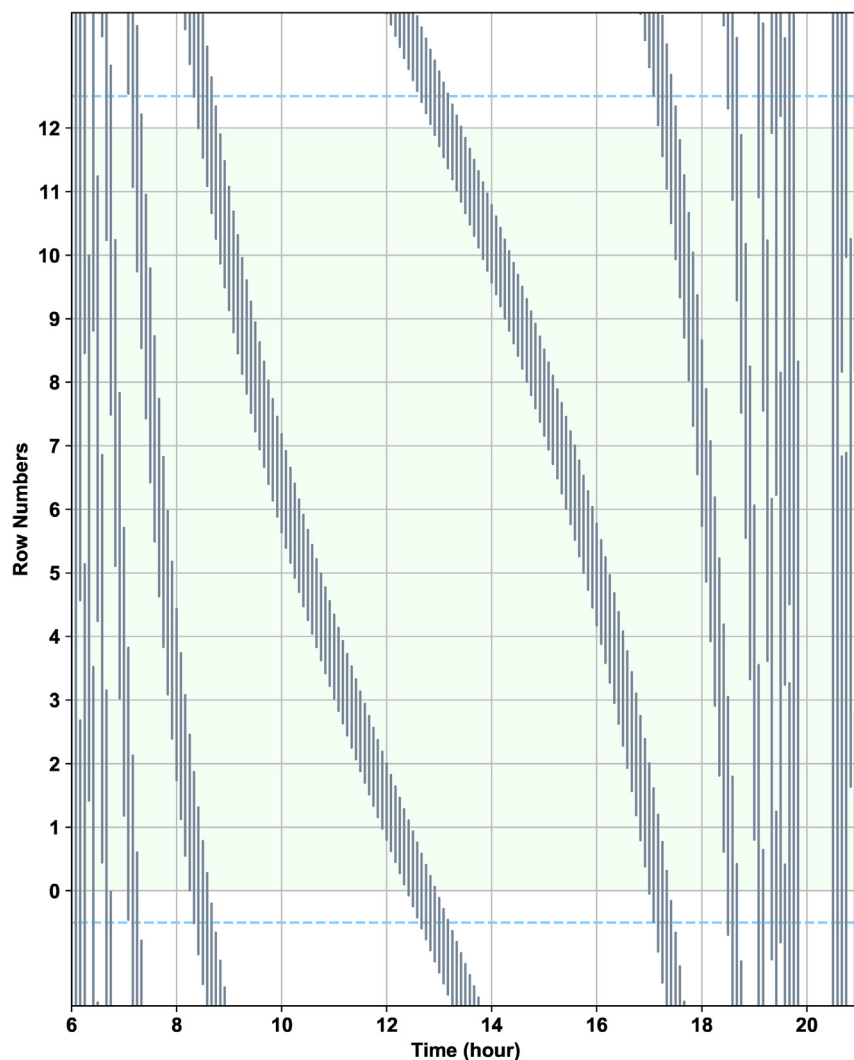


Figure 11. Shadow profile for 30° offset angle

Shadow profiles for unrestricted tracking at an offset angle of 30°. The shadow profile is generated by varying the tracking algorithm of the PV structure shown in Figure 1 when we only take the contiguous PV panels and extend infinitely in the north-south direction. The blue-colored dashed line represents the center line of PV rows. Each shadow continuum above represents the movement of shadow due to individual PV rows in spatial dimension as a function of time.

the juvenile phase does not have pronounced effects on both radiation and yield as shown in Figure 19. AT during flowering and grain-filling causes an increased TR by 13.9% and 5.9%, respectively. The growing season power generation decreases by 45.6% and 16.8%, respectively. The improvement in yield value obtained on AT during flowering and grain-filling stages are 11.8% and 1%, respectively. This implies that AT during flowering may lead to significant improvement in yield and provide an average corn yield that is similar to the one from the without-PV farming region.

Conclusions

Extensive corn yield data under dynamic shadows from east-west Sun-tracking PV panels has been collected herein. The installation of PV panels and crop growth is done at a scale to replicate actual farming practices for corn. The corn yield from the adjoining farming area without-PV was measured to be 10,955 kg/ha, compared with the yield of 10,182 kg/ha of the planted area between the PV panels.

APSIM, a crop model, was calibrated using corn yield data for the adjoining area farming without any PV installation. For this purpose, hourly solar irradiation for each day during the entire growing season was an input parameter. The corn yield of 10,856 kg/ha of the cultivated area from the calibrated APSIM model was in good agreement with the experimental value of 10,955 kg/ha. A shadow model was used in conjunction with the available hourly radiation data to calculate the calculate hourly radiation available for each corn row growing underneath the tracking solar panels. The spatiotemporal radiation distribution was then used as an input parameter to the calibrated APSIM model, and the calculated 10,102 kg/ha corn yield was found to be in remarkable agreement with the experimental yield for the with-PV region of 10,182 kg/ha.

With the remarkable agreement between the experimental crop yield from the PVA farm and our simulation models, a number of interesting questions associated with the design, installation, and operation of the solar panels could be explored. First, it

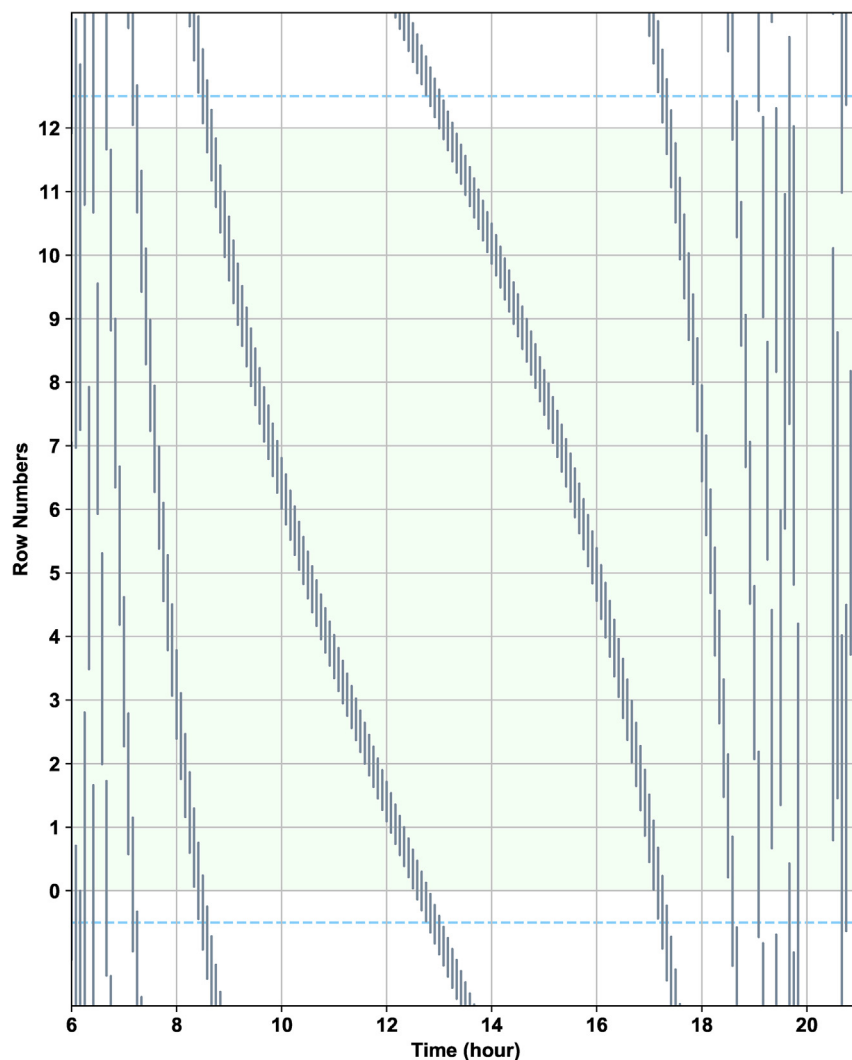


Figure 12. Shadow profile for 15° offset angle
Shadow profiles for unrestricted tracking at an offset angle of 15°. The shadow profile is generated by varying the tracking algorithm of the PV structure shown in Figure 1 when we only take the contiguous PV panels and extend infinitely in the north-south direction. The blue-colored dashed line represents the center line of PV rows. Each shadow continuum above represents the movement of shadow due to individual PV rows in spatial dimension as a function of time.

is found that designs that lower the tracker height without impeding the movement of plant machinery should be envisioned as the overall average corn yield is a weak function of the tracker height up to 2.44 m. However, the variability from one corn row to another increases as the tracker height is reduced. Another interesting finding is that for our PV module sizes, increasing the distance between the adjacent PV rows beyond the 9.1 m, while keeping the total power over the entire land constant, does not lead to an increase in corn yield based on the total land area. AT during certain periods of the day for the entire growing season was considered as a means to increase the radiation available to the plants. It was found that AT around solar noon, i.e., from 2 PM to 6 PM provided the greatest increase in the corn yield; however, this increase in corn yield of 5.6% is quite modest and should be weighed against a substantial decline in solar power. All-day AT during different stages of plant growth was also explored. Among the three stages considered, juvenile flowering and grain-filling, it is found that AT is most effective during the flowering period and provides

an average corn yield that is similar to the one from the without-PV farming region. This corn yield advantage needs to be considered in the context of minimal power from PV panels during the flowering stage of plant growth. In conclusion, the TR received by plants during the growing season does not always exhibit a direct relationship with yield. Instead, in addition to TR, accounting for SSD is critical to discern the exact variation in crop growth dynamics.

Although the PVA farm we study in this work is located in a region that has Dfa classification (humid continental hot summers) as per the Köppen-Geiger Climate Classification system,⁴¹ our methodology can be similarly applied not only to other Dfa climate regions such as eastern and rest of the mid-western US but also to other PVA farms under different climate conditions to conduct a similar analysis.

Moreover, our results show that the crop model validated using the without-PV region can potentially be applied to the with-PV region to simulate plant growth dynamics with reasonable accuracy.

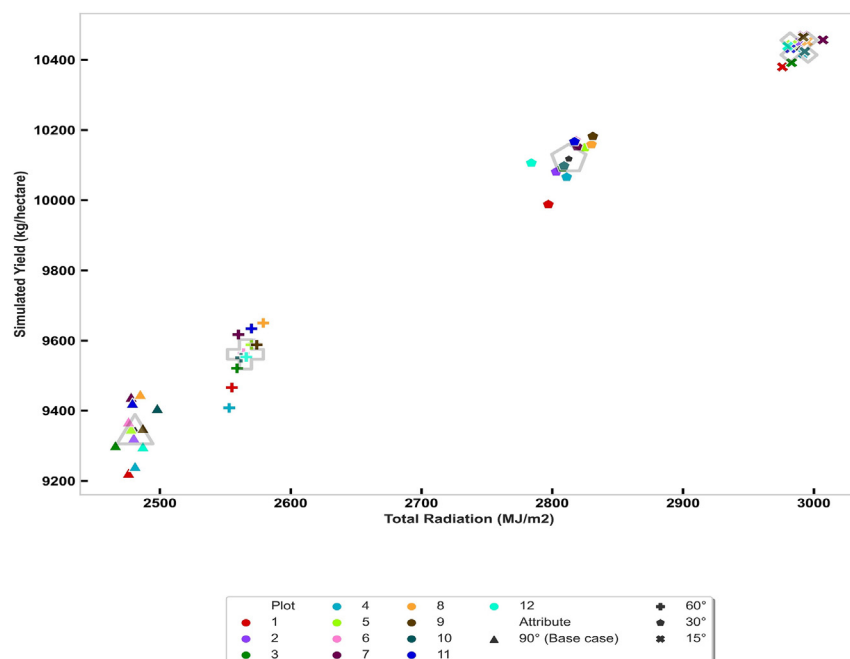


Figure 13. Yield versus radiation curve for different offset angles

Simulated yield for unrestricted tracking panels of different offset angles. For a given symbol, different colors represent different plots, and larger gray symbols represent average yield for each set of simulated heights.

Other crops such as soybean and wheat can be investigated to gain similar insights into PVA system design. Similarly, a detailed economic analysis can offer a more holistic understanding of the feasibility of such systems in both the short and long term. However, given the limitation on time and resources, we leave it as future work. Furthermore, understanding system impacts on soil health and biodiversity requires larger studies of much longer duration as these effects tend to be small in magnitude, highly variable in space and time, and much slower to accrue.

EXPERIMENTAL PROCEDURES

Resource availability

Lead contact

Further information and resource requests should be directed to the lead contact, Rakesh Agrawal (agrawalr@purdue.edu).

Materials availability

No reagents were generated in this study.

Data and code availability

All data and code used in this paper will be shared by the lead contact upon request. In addition, the public repository for the years 2019 and 2020 agrivoltaics dataset has been updated: <https://purr.purdue.edu/publications/4478/versions/2>.

Background

The primary input for this problem is spatial and temporal variations in shadow. The distribution of shadow in spatial and temporal dimensions is referred to as a shadow profile. To reduce the computational complexity, the spatial and temporal state space is discretized such that a single temporal and spatial unit is equivalent to 1 h and 1.3 m, respectively. A single spatial unit is referred to as a plot. In a PVA field, the panel operational strategy governs the shadow profile. Understanding the effect of resultant shadow profiles on crop growth dynamics would require us to conduct numerous experiments by changing the panel operation strategy during

different growing seasons. However, an actual experimental setup has execution limitations due to financial, physical, labor, and time constraints due to one growing season per year. Therefore, in this paper, the ability of simulations to mimic our experimental setup for predicting the yield of the corn plants was utilized. The shadow profiles generated as a result of simulating a particular panel operational strategy are plugged into plant modeling software with other input parameters. To achieve the results with reasonable accuracy and reduced time complexity, the following are the model-simplifying assumptions:

- (1) The PV rows are mounted lengthwise in the north-south direction.
- (2) The thickness of the panels is negligible.
- (3) The length of the PV rows is infinitely long.
- (4) The variation in shadow only happens in the east-west direction.
- (5) The variation in temperature and moisture due to spatial and temporal changes in shadow has a negligible effect on plant growth dynamics.

Crop growth model calibration

As a first step, a plant simulation software called APSIM³⁹ was calibrated using a set of measured data from our experimental field. This is done to ensure that the simulation results closely approximate our experimental setup.

Calibration method

To calibrate the plant simulation software, a set of measured data is required from experimental field. The measured dataset includes the following parameters:

- (1) Plant flowering and maturity duration
- (2) Soil moisture data
- (3) Soil organic matter data

The weather information is accessed by utilizing the NREL database.⁴⁰ The NREL weather data is available at a frequency of 5-min intervals for the year 2020. APSIM³⁹ requires the input weather data to be provided at a resolution of 1 h. Therefore, the radiation profile obtained using the NREL database is integrated for hourly intervals to simulate the reference

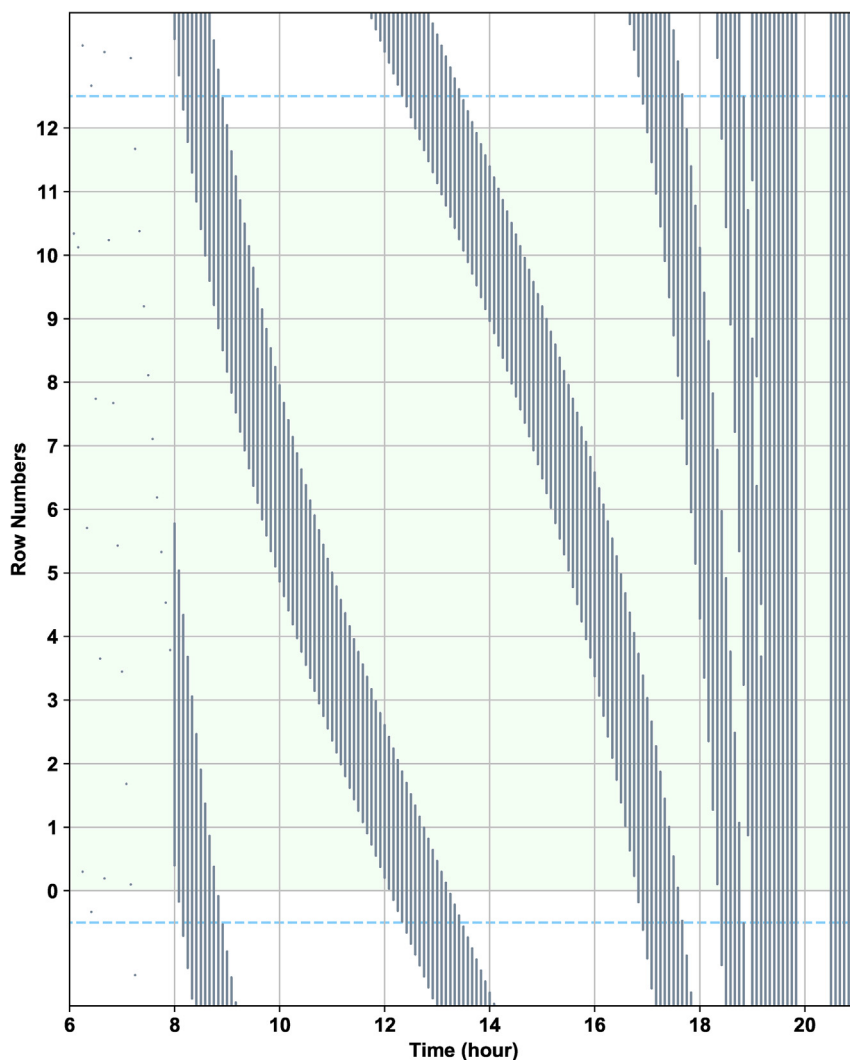


Figure 14. Shadow profile for AT before 8 AM

The shadow profile is generated by varying the tracking algorithm of the PV structure shown in Figure 1 when we only take the contiguous PV panels and extend infinitely in the north-south direction. The blue-colored dashed line represents the center line of PV rows. Each shadow continuum above represents the movement of shadow due to individual PV rows in spatial dimension as a function of time.

region or without-PV region of the experimental setup. The with-PV region includes all the rows except 2 and 11 as data from these rows was not collected.

To simulate the radiation profile in the PV-affected region (with-PV) of the field, the NREL radiation data was modified to account for the shadow information followed by hourly integration of the resultant radiation data.

The radiation data along with other weather information, i.e., temperature, rain, and relative humidity is stored in one file. The weather information, on an hourly basis, is plugged into the plants' simulation model with other data sets such as soil moisture and organic matter data. Using this information, the plant growth timeline is adjusted in APSIM such that it matches closely with the field measured information.

Calibration results

Simulating the reference region in a calibrated APSIM model gives a yield value of 10,856 kg/ha. The simulation results are in close approximation with the average experimental yield of 10,955 kg/ha as shown in Figure 20. The length of the error bars for each plot's experimental yield is a measure of the standard deviation observed in the yield for that plot. These error bars show the variance in yield due to a combination of other factors in the experimental field. The good agreement between the average experimental and simulated yield results shows that the

model approximates the profile of an average plant grown in the whole area.

For validation, radiation profiles for the with-PV were simulated in the calibrated model while keeping the rest of the parameters the same. As shown in Figure 21, the average experimental yield for the with-PV region is 10,182 kg/ha while the average simulated yield for this region, using the irradiation profile for each plant row, is found to be 10,102 kg/ha. Interestingly, the agreement between both simulation and experimental values is within $\pm 1\%$.

Based on the results discussed above for both without-PV and with-PV regions, it is clear that calibrated model predicts the results with a fairly good approximation with respect to the experimental results. This implies that the calibrated model, on average, can mimic the plant growth dynamics for the experimental field. With and without the presence of east-west tracking PV panels, using this calibrated model, various shadow profiles were simulated to study the relationship between shadow profiles and yield.

SUPPLEMENTAL INFORMATION

Supplemental information can be found online at <https://doi.org/10.1016/j.crsus.2024.100148>.

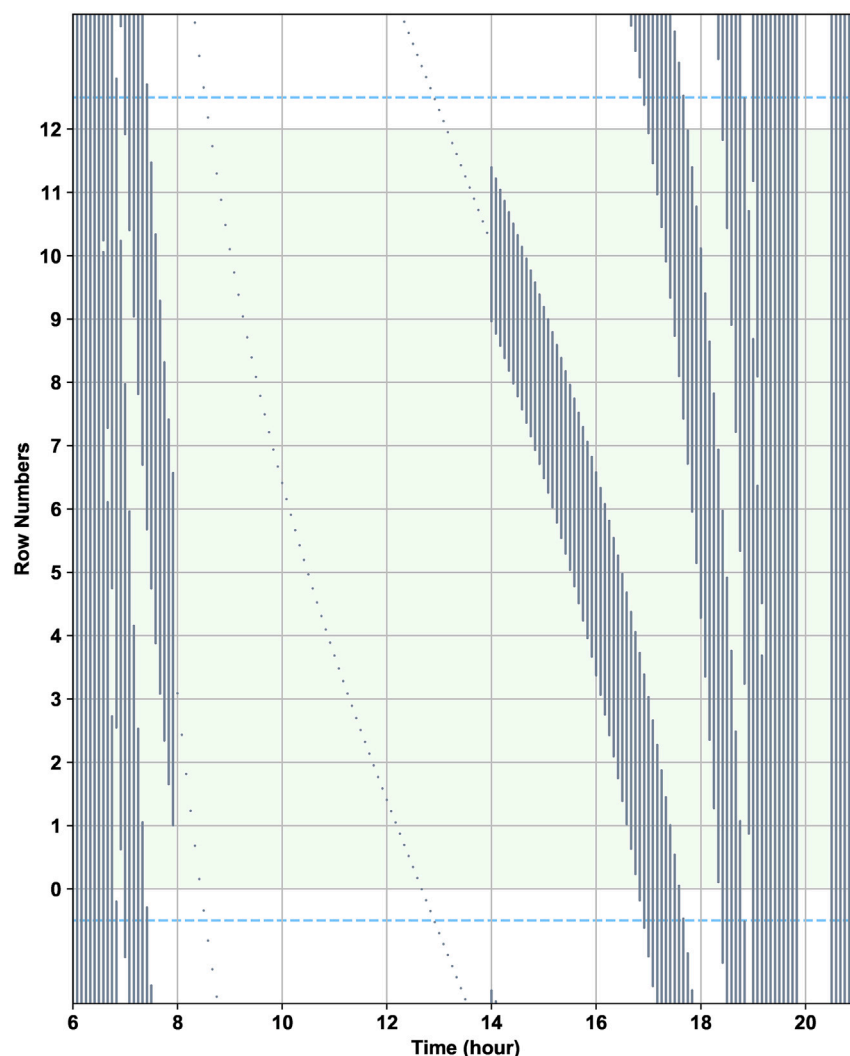


Figure 15. Shadow profile for AT between 8 AM and 2 PM

The shadow profile is generated by varying the tracking algorithm of the PV structure shown in Figure 1 when we only take the contiguous PV panels and extend infinitely in the north-south direction. The blue-colored dashed line represents the center line of PV rows. Each shadow continuum above represents the movement of shadow due to individual PV rows in spatial dimension as a function of time.

ACKNOWLEDGMENTS

The authors would like to thank all the members of the National Science Foundation (NSF) Research Trainee Program (NRT) cohort, Elizabeth K. Grubbs, Daniel Hayes, Anna Murray, Apurva Pradhan, David Rokke, Val Z. Schull, Jonathan Turnley, and Kyle Weideman for their valuable assistance with plot layout, field data collection, and hand harvesting. Financial support from NSF grants 1735282 and 1855882 is gratefully acknowledged.

AUTHOR CONTRIBUTIONS

Conceptualization ideas, R.A. and M.R.T.; methodology, R.A., M.R.T., and V.G.; software development, V.G.; validation, V.G., S.M.G., D.C., S.M.B., P.A.B., M.R.T., M.W.G., and R.A.; formal analysis, V.G., D.C., P.A.B., and R.A.; resources, R.A. and M.R.T.; data curation, S.M.G., V.G., M.R.T., M.W.G., P.A.B., and R.A.; writing—original draft, V.G. and R.A.; writing—review and editing, V.G., M.W.G., S.M.B., P.A.B., D.C., M.R.T., and R.A.; supervision, R.A., M.R.T., and M.W.G.; project administration, R.A. and M.R.T.; funding acquisition, R.A.

DECLARATION OF INTERESTS

The authors declare no competing interests.

Received: November 22, 2023

Revised: May 21, 2024

Accepted: June 27, 2024

Published: July 26, 2024; Corrected online: December 14, 2024

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