The Viability of Photovoltaics on Agricultural Land: Can PV Solve the Food vs Fuel Debate?

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Abstract

Policies aiding biofuels have supported farm income and rural communities but have also put pressure on food security with questionable benefits related to carbon emissions. Photovoltaics (PV) are poised to become central to the overall energy decarbonization strategy, but because of land requirements they are likely to be developed on farmland, reigniting concerns related to food security. In this work, we study strategies for co-producing food and energy from corn croplands. We find that while traditional PV displaces crops, they can harvest orders of magnitude more energy per unit of land than biofuels. Additionally, systems with elevated PV panels (called PV Aglectric, Agrivoltaics, or Agrophotovoltaics) that allow for crop production underneath them can increase energy production and reduce carbon emissions with minimal impact on crop production. This technology can ease the trade-off between farm income, energy production, crop production, and energy decarbonization. Adoption of PV Aglectric systems may be hindered by high capital costs, but this barrier could be overcome with policy support, especially when crop prices are highly volatile.

1. Introduction

To combat climate change, there has been an increase in government support for renewable energy sources. In 2019, biofuels comprised 43% of renewable energy in the United States, with corn ethanol as the predominant source (U.S. Energy Information Administration, 2020). Demand for corn ethanol was created by the Renewable Fuels Standard (RFS), which mandated the addition of bioethanol to gasoline in hopes of enhancing domestic energy production and reducing greenhouse gas (GHG) emissions. Many studies found that the expansion of biofuel production has increased crop prices and farm incomes (Fatal and Thurman, 2014; Grashuis, 2019; Jung et al., 2020; McNew and Griffith, 2005; Wang et al., 2020). However, biofuels have become a controversial form of renewable energy for three reasons. First, they divert crops from food and animal feed to energy, possibly exacerbating problems of food security and prompting the so called food versus fuel debate (Kumar and Singh, 2019; Tomei and Helliwell, 2016). Second, biofuels have been criticized for only leading to small reductions in carbon emissions, or even increases if indirect land use changes are considered (Searchinger et al., 2008). Third, a key limitation for biofuel production is the low efficiency (< 1%) with which plants harness sunlight, making it a land intensive source of energy (Blankenship et al., 2011; Mallapragada et al., 2013). These features of biofuels create a trade-off along three key dimensions of sustainability as defined by the United Nations (UN) Sustainable Development Goals (SDGs): energy decarbonization, sustainable food production, and farmers' well-being (Sachs et al., 2019). And while this food versus fuel debate sprang up in the United States, similar debates are arising in developing nations that are still growing their agricultural and energy infrastructure (Das and Gundimeda, 2022). New technologies that ease these trade-offs are key to attaining the SDGs and finding a solution to the food versus fuel debate. In this paper, we study the extent to which installing photovoltaics (PV) on farmland can ease these trade-offs.

PV Technology has seen remarkable improvements in recent decades and can now operate with solar conversion efficiencies exceeding 20% (Wilson et al., 2020). Moreover, the cost of PV has fallen dramatically, making this a commercially viable energy source in many parts of the country, including the state of Indiana, our study area (Sesmero et al., 2016; Wilson et al., 2020). Solar energy production is particularly attractive when panels can be

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installed in parcels of land that are cleared (non-forest), flat, and extensive. But precisely because of these characteristics, these parcels of land are often allocated to crop production, especially in highly fertile regions of the country like the US Corn Belt (Adeh et al., 2019; Miskin et al., 2019). Therefore, expansion of solar energy production is likely to create a conflict with crop production, reigniting the food versus fuel issues that limit its sustainability (Gençer et al., 2017).

But while PV panels may displace crops, they may also deliver a larger energy output in exchange for that forgone crop production vis-à-vis biofuel production. Additionally, there have been several suggested methods for integrating photovoltaic systems into agricultural areas (Hoffacker et al., 2017). One way to both minimize crop displacement and increase energy production relative to biofuels is to install elevated PV panels that allow for cropping underneath them (called PV Aglectric, Agrivoltaic, or Agrophotovoltaic systems) (Gomez-Casanovas et al., 2023; Miskin et al., 2019). Yet the potential performance of these systems in the US Corn Belt remains largely unexamined. In this analysis we examine the performance of conventional PV systems and PV Aglectric (PVA) systems under typical conditions in the US Corn Belt. Motivated by the aforementioned dimensions of sustainability we evaluate these systems based on: (1) the amount of crop produced for food/feed, (2) energy generation, (3) GHG emissions, and (4) and economic profitability. We do so by conducting a systematic comparison of conventional corn cropping (treatment 1) with different configurations of PV systems (treatments 2 through 5). Our analysis quantifies the extent to which different configurations of PV systems can ease the tradeoff between these sustainability dimensions. Our findings highlight that PV Aglectic systems are a potential solution to the food versus fuel debate by enabling greater energy production and more available corn as a food/feed resource compared to a system where corn in used for bioethanol production.

2. Methods

For this analysis, five systems will be compared (see Figure 1). All treatments are based on conditions in the Midwest region of the United States, one of the most productive agricultural areas in the world. For each system, it is assumed that the area analysed is representative of the larger Corn Belt. Treatment 1 (T1) is our baseline scenario, with corn being grown over the whole agricultural area. Treatment 2 (T2) will represent a traditional PV system being installed on some fraction of land, replacing the corn crop. While the amount of land dedicated to each could be tuned (see Supplementary Discussion 1), for this analysis we have assumed 25% of the area will be dedicated to traditional photovoltaics. Treatments 3-5 will utilize PVA systems with corn grown below them, with an estimated 5.5% of the land occupied by the PVA support structures and unavailable for crop growth. In treatment 3 (T3) a full PV panel density is used, meaning the row spacing between panels matches that of the traditional PV array in T2. Treatment 4 (T4) and treatment 5 (T5) will have half and quarter PV panel density, respectively.

We compare these five treatments on the basis of four metrics related to the SDGs. First, the production of corn for use as food or animal feed. Second, the production of energy in the form of bioethanol or electricity. Third, the reduction of GHG emissions. And finally, the profitability of the system for the farmer. The details of these calculations are found below. Additionally, a variety of values obtained from literature are used in these calculations. A summary of the specific values used and the typical range from the literature is listed in Table S1.

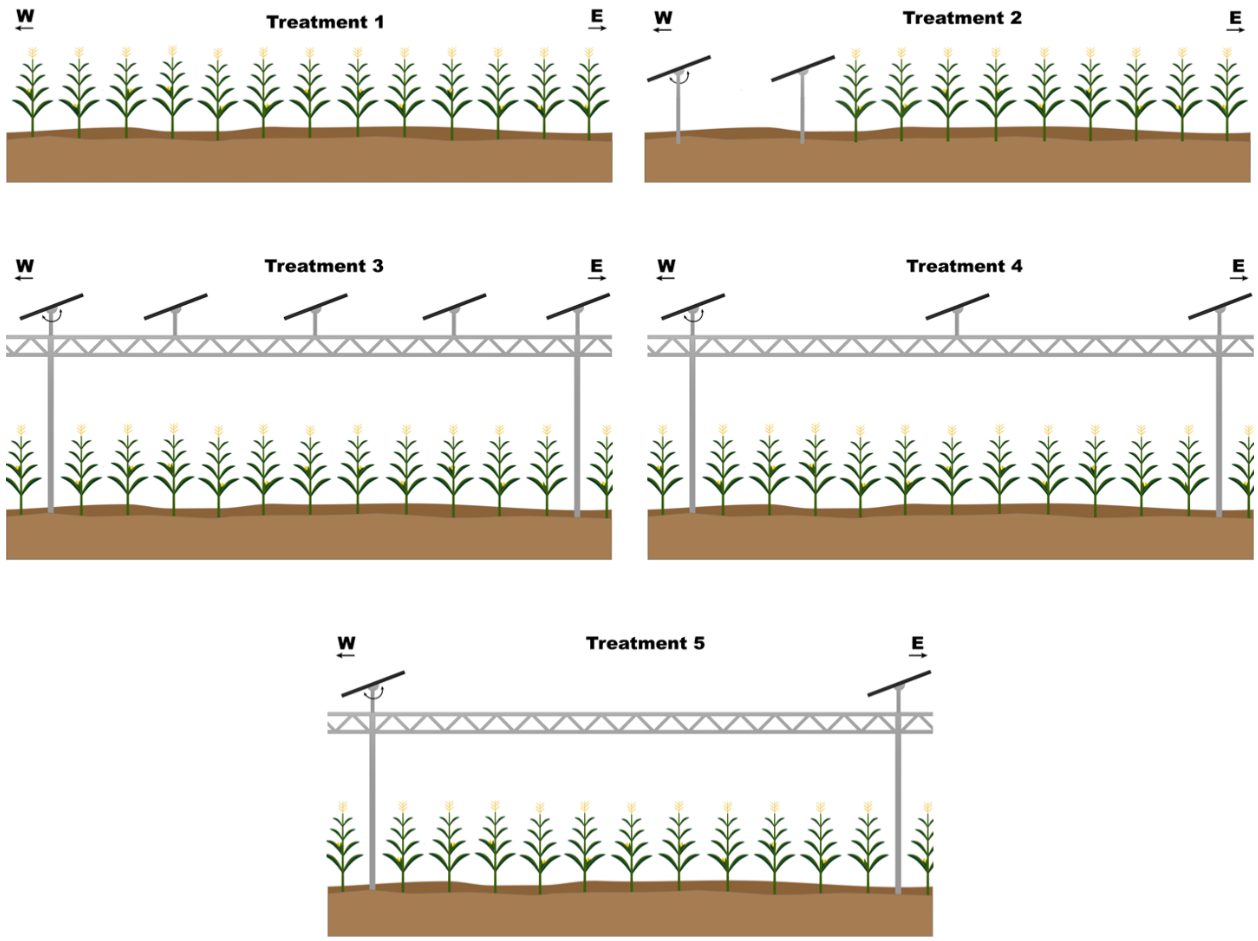

Figure 1. Schematic showing systems for co-producing food and energy. Treatment 1 with corn grown over the whole area, treatment 2 with a traditional PV array occupying 25% of the land, treatment 3 with a full-density PVA system over the whole area, treatment 4 with a half-density PVA system over the whole area, and treatment 5 with a quarter density PVA system over the whole area.

2.1. Light distribution calculations

To model crop growth and solar energy generation via photovoltaics, the amount of light each one receives is needed. Total daily horizontal irradiance per unit area (I_T) data was obtained for Tippecanoe County, Indiana from the NASA POWER database (Sparks, 2018). The total horizontal irradiance per unit of the land area was then divided into the part that fell on the solar panels (I_{PV}) and the part that fell on the corn (I_{corn}). To determine the light that falls on tracking PV we can first consider that the proportion of the total irradiance that would fall on stationary horizontal panels is simply determined by their ground coverage, γ. The ground coverage is a ratio of the total PV panel area divided by the total land area occupied by the PV system. The part of the irradiance that falls on tracking PV is then estimated by multiplying the light that falls on stationary horizontal panels by an enhanced light collection factor, Φ, which typically has a value between 1.3 and 1.4 (Mousazadeh et al., 2009). For this study we have assumed an enhanced light collection factor of 1.35. Note that this is an assumption, and the actual enhanced light collection factor would change day-to-day based on the ratio of direct and diffuse light. With these assumptions, a simple equation estimates the amount of light falling on the PV panels.

$$I_{PV} = I_T * \gamma * \Phi$$

The PV is assumed to be in rows that run north-to-south, so the ground coverage can be determined by taking the PV panel width divided by the row spacing. A typical panel width is 0.5 m. The row spacing for the full panel density needed in treatments 2 and 3 was chosen to match the power output per unit land area that is expected for typical stand-alone PV installations in the USA. In 2013, the twenty-four hour daily-averaged power output for one-axis tracking stand-alone PV systems was 8.5 W/m^2 (Ong et al., 2013). However, since that time the average efficiency of panels has risen from 15.5% to the value of 19.1% used in these calculations so we would expect a new stand-alone PV installation to have an average power efficiency of 10.5 W/m^2 (Fu et al., 2018). Utilizing the irradiance data for Tippecanoe County, Indiana and the energy systems calculations listed below, the ground coverage for full panel density was back calculated to be 0.263 in order to obtain the expected 10.5 W/ m^2. The ground coverage for half-density (treatment 4) and quarter-density (treatment 5) were determined by dividing the full density ground coverage by 2 and 4, respectively.

In treatment 1, there are no PV panels, so all the incident radiation is available to the corn. In treatment 2, the corn and PV panels are separate so for the fraction of land used by the corn all light is available to the corn and for the fraction of land used for solar energy the light available to the PV is governed by the above equation. For treatments 3 through 5 the corn and PV share the same land area. In order to be self-consistent, the amount of light falling on the corn in these treatments must satisfy the following equation, where I_{corn} is the light falling on the corn and I_T is to total light irradiance:

$$I_{corn} = I_T - I_{PV} = I_T\,(1 - \gamma * \Phi)$$

2.2. Crop production modeling

In order to model the corn yield, the Agricultural Production Systems Simulator (APSIM) version 7.10 was used (Holzworth et al., 2014). The Maize module was calibrated based on average corn yields for Tippecanoe County, Indiana and median planting, silking, and flowering dates for the state of Indiana (see Supplementary Tables 2-5) ("Indiana County Estimates," n.d., "Indiana Crop Progress & Condition Report," n.d.). The crop specific cultivars obtained upon calibration and a comparison of the calibrated model to the historical data are listed in Supplementary Table 3. For the Soil module, a Brenton-type silty-loam file was developed using data from the Natural Resources Conservation Service (NRCS) Soil Survey Geographic database (SSURGO) and the APssurgo application for R Studio (Martinez-Feria and Archontoulis, 2018) for a representative site at the Agronomy Center for Research & Education at Purdue University. Using a single representative soil type and maize hybrid enables a clearer analysis of climate effects without additional soil type and genotype interactions (Cammarano et al., 2016). Meteorological data was obtained from the NASA POWER database and the daily irradiance was modified as described above (Sparks, 2018). Simulated yields were obtained from the years 2012 through 2019. Soil water and nitrogen at time of sowing parameters were reset each year, as has been done with crop models used to evaluate weather impacts on crop yield (Cammarano and Tian, 2018). Reported yields are an average of the 2012 through 2019 simulations. For treatment 1, corn is grown over the entire area. For treatment 2, corn is assumed to grow on 75% of the area. For treatments 3 through 5, corn is assumed to grow on 94.5% of the area as 5.5% of the land is occupied by the PVA support structures. Note that in this version of APSIM, crop simulations take place in daily time steps. Therefore, this model only considers the total light received by a plant over the course of a day and would be unable to capture affects caused by shading at specific times during the day.

In treatments where ethanol demand is present, the fraction of corn used for ethanol production was based on average values in the US. While approximately 40% of corn is used in ethanol production in the US, one third of that is converted to dried distillers grain as a biproduct and used as animal feed (Kumar and Singh, 2019). For this analysis we therefore used a value of 26.8% as the net corn that is actually consumed in the production of ethanol, with the remaining being used as a food or animal feed resource. In all cases where ethanol demand is present, we attributed 26.8% of the total corn yield as being consumed to generate ethanol. In cases with no ethanol demand, 0% of the corn was used for ethanol production. It is important to recognize that the amount of ethanol generated is 0.433 liters per kilogram of corn that goes through ethanol processing (40% of the total corn yield) (Rosentrater, 2011).

2.3. Energy production calculations

When comparing bioethanol and solar energy, it is important to consider the end use-energy rather than using a metric for generated energy. This is because different sources of energy are used at different efficiencies. To compare the energy output of bioethanol to PV-generated electricity, we assumed the ethanol is used in vehicular combustion engines and the electricity is fed to the grid.

To determine the end-use energy from ethanol ($E_{ethanol}$), the volume of ethanol ($V_{ethanol}$) is multiplied by the lower heating value of ethanol ($LHV_{ethanol}$) and the efficiency of a combustion engine (η_{CE}).

$$E_{ethanol} = V_{ethanol} * LHV_{ethanol} * \eta_{CE}$$

The lower heating value of ethanol was taken as 5.825x10^{-3} MWh/L and the efficiency of the combustion engine was assumed to be 14.8% (Engineering ToolBox, 2003; Miskin et al., 2019).

The amount of electricity generated by the photovoltaics per unit of total land area (ε_{PV}) is determined by the fraction of the total land occupied by the PV system (χ), the irradiance that falls on the PV panels (I_{PV}), the PV panel efficiency (η_{PV}), and the system and transmission efficiency (η_{System}).

$$\varepsilon_{PV} = \chi * I_{PV} * \eta_{PV} * \eta_{System} = \chi * I_T * \gamma * \Phi * \eta_{PV} * \eta_{System}$$

Note that χ is not the area of the panels themselves, rather it includes the PV panels and the spaces between panels. For treatment 2, the PV system occupies 25% of the land. For treatments 3, 4, and 5 the PV systems occupy 100% of the land as they are PV Aglectric systems. The PV efficiency is assumed to be 19.1% and the system/transmission efficiency is assumed to be 95.3% (Fu et al., 2018; Miskin et al., 2019). The PV systems were assumed to have a 25-year lifetime with efficiency degradation at 0.5% per year.

To determine the amount of end-use energy from PV when sent to the grid (E_{PV}), the amount of electricity is multiplied by the grid-averaged end-use efficiency (η_{grid}).

$$E_{PV} = \varepsilon_{PV} * \eta_{grid}$$

The grid-averaged end-use efficiency is taken to be 65% (Schwartz et al., 2017). No battery storage is considered in this analysis.

For treatments where it was calculated the number of vehicles that the systems could support per hectare per year, it was assumed an average passenger vehicle drives 11,443 miles per year and gets 25 miles per gallon when using a fuel that is 90% gasoline and 10% ethanol (Sivak and Schoettle, 2018). While ethanol and gasoline have different lower heating values, the efficiency of the internal combustion engine when using gasoline or ethanol was assumed to be the same at 14.8%. The grid to wheels efficiency of an electric vehicle was taken to be 75% (Miskin et al., 2019).

2.4. Greenhouse gas (GHG) reduction calculations

GHG reductions for each treatment were calculated by using the renewable energy source to replace its current alternative. For ethanol, this means it is used as a replacement for gasoline. For the PV generated electricity, this means it is used to replace the current grid-averaged electricity generation for the state of Indiana. For each treatment the GHG emissions from each energy source were based on lifecycle assessments.

For the grid-averaged electricity in Indiana, a GHG emission equal to 0.916 metric tonnes of CO_2-equivalent per megawatt-hour is generated (Office of Energy Policy and Systems Analysis, 2016). For electricity from photovoltaics 0.025 metric tonnes of CO_2-equivalent per megawatt hour is generated (Louwen et al., 2016). This means that each megawatt-hour of solar electricity saves 0.891 metric tonnes of CO_2-equivalent emissions.

Lifecycle assessments of gasoline indicate emissions of 0.3312 metric tonnes of CO_2-equivalent per megawatt-hour, with the energy content being based off of the lower heating value of gasoline (Liska et al., 2009). Ethanol on the other hand has emissions of 0.152 metric tonnes of CO_2-equivalent per megawatt-hour (Liska et al., 2009). Because we will assume that a combustion engine has equal efficiency for both gasoline and ethanol, the emissions saved per liter of ethanol is equal to the difference in emissions for gasoline and ethanol mentioned above multiplied by the lower heating value of ethanol. This means that each liter of ethanol produced saves 1.04x10^{-3} metric tonnes of CO_2-equivalent emissions.

2.5. Economic viability calculations

To economically compare the treatments from the perspective of the farmers, changes in Net Present Value (NPV) were calculated with respect to T1. We assume that the price the farmer gets for corn is the same irrespective of if the corn is used for ethanol or as a food resource, therefore there is no difference in the calculations from the farmer's perspective between situations with and without ethanol production. Because we are using a change in net present value, any costs that are the same between the treatments need not be considered. The time for the evaluation is 25 years as this is often considered the lifetime of a PV system (Wilson et al., 2020). For treatments with a PV system, installation costs were accounted for in year zero. For each treatment with a PV system, the PV installation cost needed to break-even with treatment 1 was calculated for various year-1 corn prices to determine the break-even line. Each of the year one cost values and price values was assumed to grow at a yearly rate of 2.44% based on inflation. Corn yields were assumed to be consistent over the 25-year period. The PV efficiency is assumed to decrease at a rate of 0.5% per year (step-wise) over the 25-year period (Jordan et al., 2016). An electricity price of $42.99 per megawatt-hour was used in year one. Operation and Maintenance costs were taken to be $18 per kilowatt in year one (Bolinger et al., 2019). Treatments involving PV systems had areas that weren't used to grow corn, which led to savings due to lower agricultural costs. This savings value was based on the cost of growing corn in Indiana at $1623 per hectare in year one (Langemeier et al., 2019). These economic calculations assume that these systems implemented locally as to not impact commodity prices. Further work is needed to understand how implementation at a national scale would impact the cost of corn and electricity.

3. Theory

Agricultural land offers immense potential for solar energy generation. Researchers have predicted that globally, croplands offer more potential for solar energy generation than any other classification of land (Adeh et al., 2019). With photovoltaics becoming increasingly viable economically, farmers are already looking to install them on their land. Between 2012 and 2017, the number of farms in the USA with photovoltaics increased by nearly 150% (United States Department of Agriculture - National Agricultural statistics Service, 2017).

The most straightforward use of photovoltaics on agricultural land would be to simply replace the crops on a portion of the land with a traditional PV array. However, replacing crops with photovoltaics sacrifices the potential production of a food or animal feed resource for an energy resource, which is one of the major criticisms of corn-based ethanol (the food versus fuel debate). While it seems inevitable that agricultural lands will contribute to energy production, a true solution to the food versus fuel debate requires that energy be produced synergistically with food rather than replacing food.

Researchers have been developing solutions to this problem in the form of PV Aglectric (PVA) systems (Miskin et al., 2019). Also referred to as agrivoltaics, agrophotovoltaics, or solar sharing, these systems utilize structures that elevate PV panels above crops (Dupraz et al., 2011; Sekiyama and Nagashima, 2019; Weselek et al., 2019). This allows for normal farm operations below, with the crops using the light that falls between the panels. Research suggests that careful optimization in the system design is needed to balance the light distribution between the PV panels and the crop (Amaducci et al., 2018; Perna et al., 2019). Early results have shown that PVA systems can lead to uniform and low cumulative shading over the course of the day by increasing the spacing between panels and utilizing rows of east-west one-axis tracking PV (Perna et al., 2019; Valle et al., 2017). To date, most of the PV Aglectric research has focused on shade tolerant crops like lettuce, potatoes, and peppers (Barron-Gafford et al., 2019; Elamri et al., 2018; Marrou et al., 2013; Weselek et al., 2019). Other researchers have focused on using elevated panels above grazing pastures for sheep (Andrew et al., 2024; Sturchio et al., 2024). What is only beginning to be addressed in the literature are methods for integrating PV Aglectric systems with major crops like corn, soybean, and rice, which are not usually considered shade tolerant but do occupy more of the world's agricultural land (Amaducci et al., 2018; Ramos-Fuentes et al., 2023; Sekiyama and Nagashima, 2019). In particular, the use of PVA systems with corn is intriguing because large amounts of corn are already used for energy production in the form of bioethanol. The demand for bioethanol in the US is due to the policy environment of the RFS. Understanding the outcomes for PVA systems with corn, both with and without ethanol demand, could guide future policy on energy generation from agricultural land and lead to a solution to the food versus fuel debate. Early experimental work suggests corn can be grown beneath PV Aglectric systems, but more work is needed to understand how the system design impacts the system outputs like corn and electricity production (Grubbs et al., 2024).

To begin to understand if PVA systems could be beneficial when utilized with widely produced crops that are not shade tolerant, we utilize a series of questions and thought experiments which can be evaluated through simple modeling and back-of-the-envelope calculations. In the following section, we will elaborate on these finding and how these results can guide future research into the hybrid use of land for food and energy production.

4. Results and Discussion

4.1. Can corn grow under partial shading?

Understanding the effect of shading on crop yields is vital in predicting outcomes for PVA systems, but due to numerous environmental conditions it is complicated and often difficult to do so. Research on PVA systems suggests some plants increase leaf growth when shaded, which could maintain or increase yields in crops like lettuce and spinach (Marrou et al., 2013). Other crops, like potatoes, prefer partial shading which protects them from intense radiation. Researchers at Fraunhofer ISE observed that potato yields increased slightly under PVA systems during an especially hot growing season (Schneider and Schindele, 2019). While not all crops prefer these conditions under normal circumstances, PVA systems could offer protection for many crops during droughts and heat waves (Barron-Gafford et al., 2019; Schlenker and Roberts, 2009).

This effect can be particularly complex in the case of PVA systems that create transient shading, where the crops are in full sun part of the day and in shade part of the day. In general, it might be expected that less light would lead to lower yields in non-shade-tolerant crops, like corn. However, studies have suggested that radiation use efficiency (RUE) increases as light intensity decreases, which may minimize harmful effects of shading (Sinclair et al., 1992). Additionally, in their initial experimental work on PVA systems with corn, Sekiyama and Nagashima did not see yield losses when the PV panels were spaced farther to reduce shading (Sekiyama and Nagashima, 2019).

With limited experimental work studying the effect of transient shading on corn, it becomes difficult to precisely predict the corn output for each scenario. Therefore, we evaluated a range of possible corn yields (see Figure 2). The Agricultural Production Systems Simulator (APSIM) (Holzworth et al., 2014) was implemented for this evaluation, calibrated based on average corn yields for Tippecanoe County, Indiana for the years 2012 through 2019 (see Methods and SI). Then APSIM was used to determine the lower bound for the corn yield under various light conditions while assuming a constant RUE (Low Shaded Yield, LSY). However, research suggests that for low levels of shading, corn yields may not see any negative effects from PVA systems (Sekiyama and Nagashima, 2019). Therefore, the upper bound was assumed to be the same yield as the full light condition (High Shaded Yield, HSY). The amount of light received by the crops can be expressed based on the shadow depth, which refers to the percentage of incident solar energy that is lost relative to full irradiation. In Figure 2, the green shaded region shows the estimated range for corn yields at any given shadow depth. For the treatment conditions used in the following scenarios, the corn in T1 and T2 are grown under full light conditions. However, the corn in T3, T4, and T5 is partially shaded by the PVA systems. The shadow depth in T3, T4, and T5 was calculated as 35.5%, 17.8%, and 8.9%, respectively, leading to LSYs of approximately 63%, 86%, and 94%. Though corn is not considered a shade tolerant crop (Schindele et al., 2012), APSIM predicts that at low shadow depths, the loss in corn yield is small, even without a potential increase in RUE.

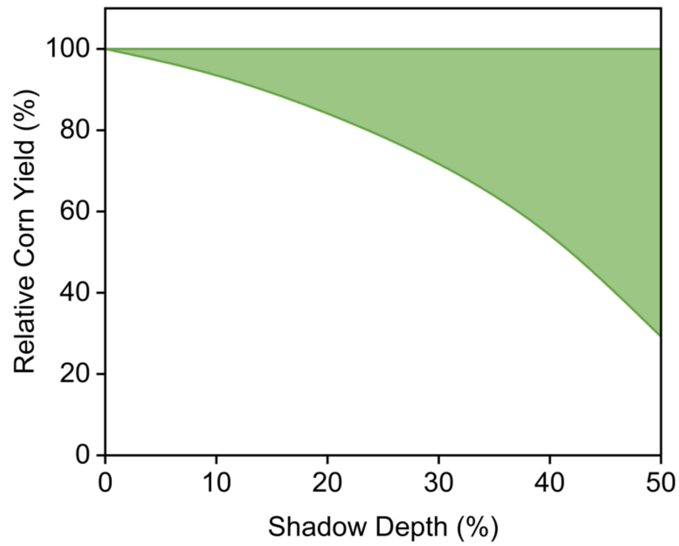

Figure 2. Corn yields at various shadow depths are expected to fall within an upper bound set by the yield under full light conditions and a lower bound determined by crop simulations with a constant RUE.

4.2. What are the system outputs from different co-production strategies when there is ethanol demand?

Quantifying potential tradeoffs between energy and crop-for-food (i.e., including direct uses for processed foods and indirect uses like animal feed) production is crucial to understand the implications of producing energy on croplands. The corresponding extent of GHG reduction depending on the type and quantity of the energy production can further guide decision making. Additionally, the economic profitability for farmers and other stakeholders influences the likelihood of adoption of any of these systems.

In the context of corn, the amount of corn available as a food and animal feed resource is not the same as total crop production when a portion of the corn crop is dedicated to bioethanol production. This is precisely the situation in the United States under the RFS, which prompted approximately 40% of corn to be used in the production of ethanol. However, because byproducts of ethanol production can be used as an animal feed resource, ethanol production consumes around 27% of all corn grown in the US.

To evaluate the various co-production systems shown in Figure 1 under the economic conditions produced by the RFS, the system outputs were first determined assuming this same fraction (~27%) of corn is consumed in ethanol production. This distinction is vital for understanding tradeoffs between energy and food production. Against the backdrop of the RFS, displacing one kilogram of crop production with photovoltaics does not equate to displacing 1 kilogram of corn for food and feed; it displaces 0.73 kilograms for food and feed and 0.27 kilograms for energy. Moreover, and importantly, the energy produced from 0.27 kilograms of corn as ethanol is significantly lower than that achievable with photovoltaics displacing the same amount of corn. Consequently, when the RFS diverts corn away from food and feed and towards a relatively inefficient source of energy such as bioethanol, it mitigates the tradeoff between photovoltaic energy and food, making photovoltaics a more attractive alternative. Our analysis explicitly accounts for this important feature of corn markets.

In Figure 3.a the amount of corn available as a food and animal feed resource is shown for treatments 1 through 5 assuming the same fraction of corn is dedicated to ethanol production (~27% of corn yield) in all treatments. Naturally, the highest food/feed production was achieved in T1, where no photovoltaics are incorporated. When traditional photovoltaics were incorporated (T2) the amount of corn as a food/feed resource dropped by 25%, in proportion to the reduction in available land for corn growth. The output for the PVA treatments (treatments 3-5) varied based on the LSY and HSY boundaries. At the HSY limit, the impact on corn as a food/feed resource is minimal, with losses of 5.5% attributed to the reduction in corn growing area caused by support structures. Conversely, at the LSY limit, losses in corn as a food/feed resource increase with higher panel density and reduced light for crops. However, the penalty is relatively modest under low density; even at the LSY boundary of T5, there's only an 11% reduction in corn available for food/feed compared to T1.

Corn as a food/feed resource is not the only relevant outcome to evaluate the performance of alternative technologies against the conventional crop production baseline; energy production and GHG emissions are also crucial outcomes to consider. Two sources of energy generation are present in this analysis, bioethanol produced with corn and electricity produced with photovoltaics. To compare these dissimilar energy sources, we determined the quantity of end-use energy by considering the efficiency of a vehicle engine that uses ethanol as a fuel and the grid-averaged efficiency of electricity consumption.

The end-use energy obtained in each treatment is shown in Figure 3.b. Considering outputs per unit area per year, photovoltaics generated much more energy than bioethanol. In T1, which only has bioethanol from corn as an energy source, the output is less than 2 MWh/ha/year. On the other hand, the systems with photovoltaics had larger end-use energy values by two orders of magnitude. So, while the amount of ethanol generated in each of the treatments changed, the ethanol had a minimal impact on the total energy production in treatments 2 through 5. Therefore, there was no significant difference on overall energy outputs when considering the low shaded yield and high shaded yield boundaries of corn production. Between the treatments with photovoltaics, the energy generation trends with the number of PV panels that are incorporated over the whole treatment area. T2, with traditional PV at full density on one quarter of the land, had the same number of panels as treatment 5, with PVA at quarter density over all of the land. Hence, treatments 2 and 5 had nearly identical energy outputs, separated by less than 1 MWh/ha/year due to differences in ethanol production. Considering these results as a whole shows the major advantage of photovoltaics over bioethanol. While a liquid fuel could be useful in some cases, the amount of energy that can be generated from photovoltaics compared to bioethanol is staggering.

GHG reduction was calculated by assuming ethanol displaced gasoline and the photovoltaic-generated electricity displaced a grid-averaged electricity source. Similar to the observation in energy generation, the GHG reduction of ethanol per unit area per year is orders of magnitude smaller than that of photovoltaics. This result has two causes. First, when considering the lifecycle analysis of each energy source, the GHG emissions for bioethanol are higher than photovoltaics (Liska et al., 2009; Louwen et al., 2016). Second, photovoltaic systems generate more energy per unit area per year and therefore can displace more of the high GHG emitting energy sources.

As shown in Figure 3.c, T1, with only ethanol as an energy source, had a GHG reduction of less than 2 tonnes CO_2-eq/ha/year. Treatments 2-5, which incorporated photovoltaics, reduced GHG emissions by hundreds of tonnes CO_2-eq/ha/year. The quantity of GHG reduction in each of these treatments similarly trended with the number of PV panels that were incorporated into the entire treatment area as the effects of ethanol were negligible by comparison. This also negated any effects of the LSY and HSY boundaries on GHG emissions.

An important comparison can be made between T2 and T5. These treatments utilize the same number of photovoltaics over the entire treatment area, but in a traditional PV array and a PV Aglectric array, respectively. This results in effectively the same energy generation and GHG reduction for both treatments. However, the benefits of a PVA system can be seen when crop production is considered. A higher corn yield was predicted for T5 because the PVA system allowed more area for crop growth and the shading was minimized by the large spacing between PV panels.

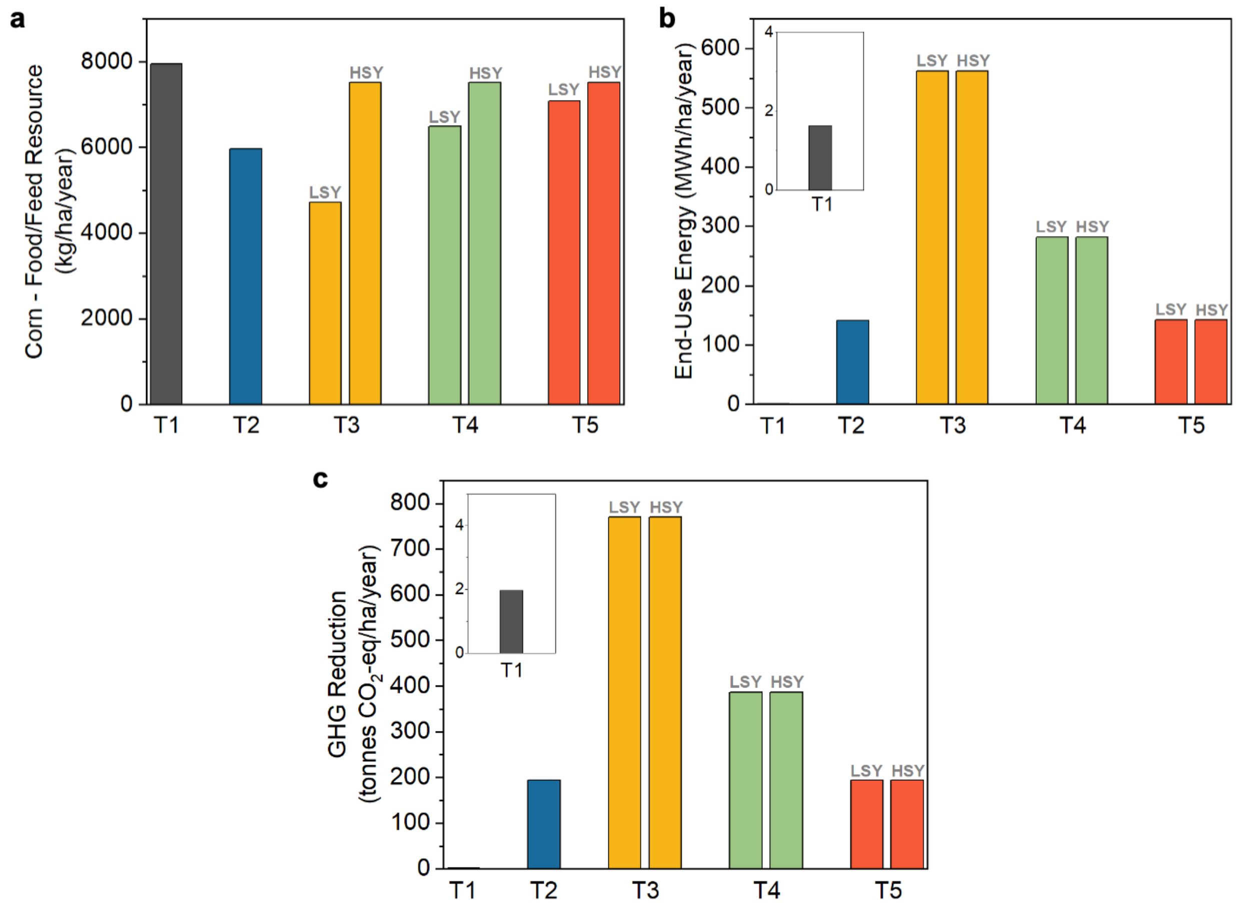

Figure 3. System outputs with ethanol demand. a) Corn available as a food and animal feed resource, b) end-use energy production, and c) greenhouse gas (GHG) reduction for treatments 1 through 5 with ethanol production consuming approximately 27% of corn produced.

4.3. What are the system outputs from different co-production strategies when there is no ethanol demand?

Corn-based ethanol demand in the United States is intricately tied to the RFS. Given that ethanol demand is predominantly policy-driven, alterations in policy can significantly influence ethanol demand. Consequently, we also examined each of these treatments under scenarios where no ethanol demand existed. This consideration is particularly pertinent, given the earlier findings indicating limited advantages to bioethanol production compared to integrating photovoltaics into corn croplands.

The system outputs are given in Figure 4. As was previously shown, the energy production and GHG reduction of ethanol were negligible compared to the photovoltaics. Therefore, there was very little change for treatments 2 through 5 in those metrics. However, without ethanol production, T1 no longer had a source for energy production or GHG reduction.

The largest change occurred in the amount of corn available as a source of food and animal feed. While the trends between all the treatments remained the same, the value of the outcomes increased. T1 with ethanol demand reflected a typical use of corn agricultural land under the RFS. In that scenario it was calculated that the amount of corn available as a source of food/feed was approximately 7,950 kg/ha/year. It is unsurprising that without ethanol production, the corn available as a source of food/feed increased substantially to 10,860 kg/ha/year in T1. Interestingly, even the LSY boundaries for T4 and T5 eclipse the 7,950 kg/ha/year value at approximately 8,860 kg/ha/year and 9,680 kg/ha/year, respectively. Keeping in mind that each of T3, T4, and T5 also increased the total energy output and lead to greater GHG reduction than was possible in T1 with coproduction of ethanol, PVA systems offer numerous advantages in terms of system outputs and are therefore an interesting solution to the food versus fuel debate. For emphasis, we can consider that the ethanol generated under the RFS is primarily used as a fuel for transportation. In T1 with coproduction of ethanol it would take around 1.4 hectares to provide the fuel to operate an ethanol-powered passenger vehicle for a year. In contrast, the yearly solar energy from one hectare of the systems in T2 and T5 could power approximately 73 electric vehicles for a year. A single hectare of the systems in T3 and T4 could power approximately 294 and 147 electric vehicles, respectively.

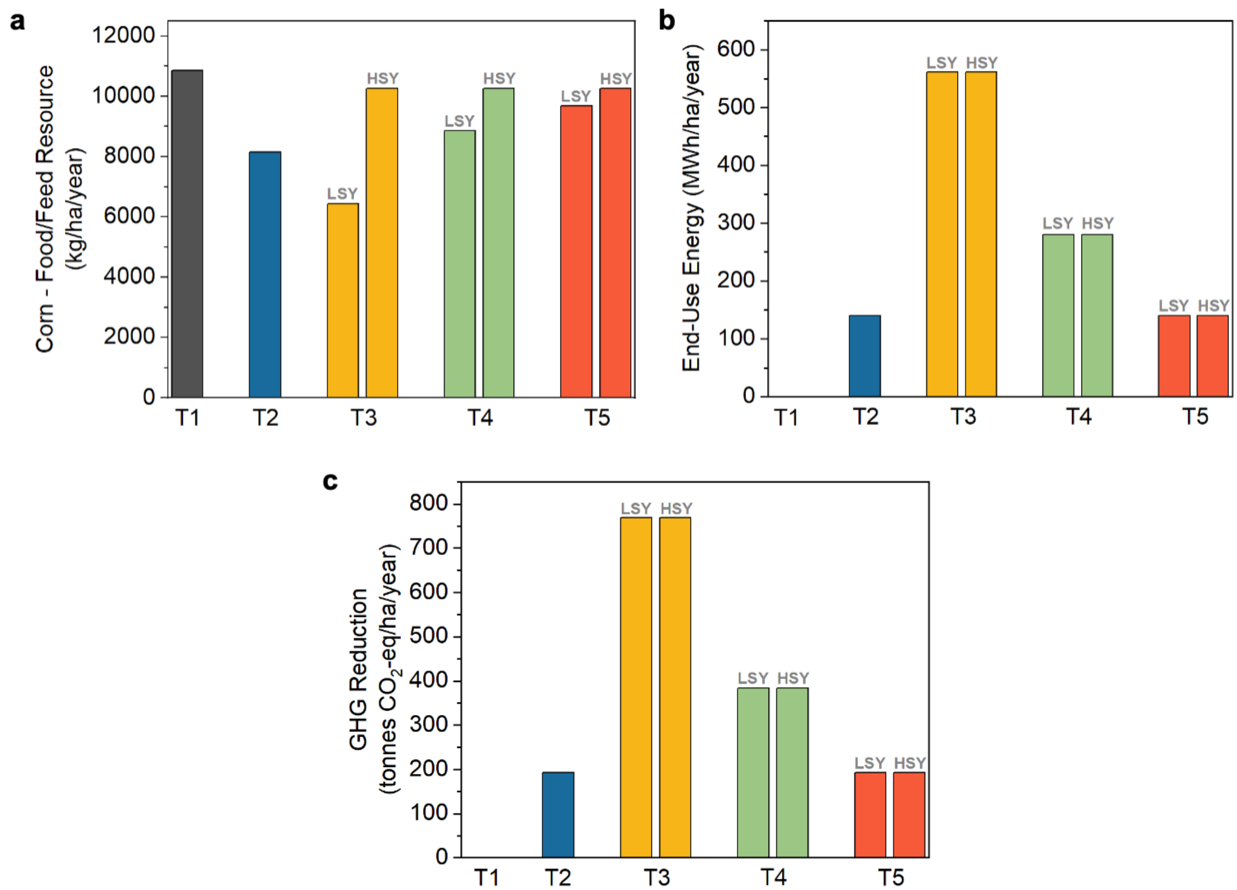

Figure 4. System outputs with no ethanol demand. a) Corn available as a food and animal feed resource, b) end-use energy production, and c) greenhouse gas (GHG) reduction for treatments 1 through 5 with no ethanol demand.

4.4. Under what conditions would different co-production strategies be economically viable?

Economics will ultimately play a major role in farmers adopting systems to generate both food and energy (Yang et al., 2021). While electricity prices remain fairly constant, corn prices have the potential to fluctuate greatly. The relative profitability of treatments 2-5 compared to treatment 1 are considered in Figure 5. Assuming a 25-year lifespan for the PV system, the required upfront costs of the PV system to break even with simple corn farming (T1) are graphed as functions of corn price for the respective configurations in treatments 2-5. This means that if the actual values for cost of PV installation and corn price are below the respective line, the hybrid system in question is more profitable for the farmer than only growing corn. On the other hand, for a given combination of corn price and total installed PV cost that lies above the line, it is more profitable for the farmer to just grow corn with no PV system.

It is important to note that corn prices were relatively low between 2015 and 2020, fluctuating between \$0.12/kg and \$0.16/kg. But before 2013 and again in 2021 corn prices spiked at \$0.30/kg (United States Department of Agriculture - National Agricultural statistics Service, 2021). Meanwhile, the total installed cost for tracking PV at utility scale had dropped to \$1.13/W_p in 2018 (Fu et al., 2018). While the smaller size for a hybrid system incorporated onto farmland might mean the total installed cost is slightly above that of the average utility scale PV system, we can see that when corn prices are relatively low, integrating traditional PV into crop cropland has comparable profitability to traditional corn farming making it an economically viable option on agricultural land.

While there is abundant data on the total installed cost for a traditional PV system, the total installed cost of a PV Aglectric system is unknown. Early analysis on the first PV Aglectric systems indicated they could be twice as expensive to install as traditional PV because of the additional support structures needed to elevate the panels

(Schindele et al., 2020). This would make any of the PVA systems less profitable than T1 along the domain of plausible corn prices (i.e., the combination of corn price and PV installation cost would fall well above the break-even line). But it is important to remember that costs often drop as technologies develop. Still, this points to a major challenge that engineers working on PVA system designs need to address. The system that elevates the PV panels above the crops needs to be very cheap, nearly as cheap as the support structures in traditional PV arrays. Additionally, government support in the form of a subsidy to reduce installation cost may be warranted, in light of the ability of these systems to alleviate sustainability tradeoffs (produce much more energy than T1, while reducing GHG emissions and maintaining crop production for other uses). For a risk-neutral farmer, our results suggest that a 50% reduction in installation cost (essentially approaching the price of traditional PV) would make PVA economically competitive. This cost reduction could be achieved by engineered solutions, policy support, or a mixture of both. However, a key economic benefit of PVA relative to PV is its ability to exploit high crop prices; and a key economic benefit of PVA relative to conventional cropping, is its ability to reduce downside risk in the case of low crop prices by adding revenue from electricity production. This can be noted by the very small slope for the break-even lines of the PVA systems in Figure 4, especially at the HSY boundary. Therefore, the PVA system strikes a balance between downside risk and upside potential that could make it an attractive alternative for risk-averse farmers, especially if installation costs are reduced or subsidized.

Numerous policies influence the relative performance of PVA systems compared to conventional PV systems and traditional agriculture. Energy policies promoting renewable energy, carbon markets, regulations curbing non-point source pollution, and policies supporting agricultural production are among the measures that could favor PV Aglectric systems. Two additional factors can significantly enhance the economic viability of photovoltaics, particularly in favor of PVA. Firstly, the emergence of regulations restricting the widespread adoption of PV on farmland to safeguard crop production is noteworthy. PVA, as opposed to PV, presents a potential solution, allowing landowners to enjoy the economic advantages of energy production while adhering to regulations aimed at preserving food production. Secondly, given that property taxes are generally lower for agricultural land, implementing a PVA system (again, in contrast to a PV system) can assist landowners in maintaining the agricultural classification of their land and benefiting from associated tax incentives.

It is important to note that the break-even lines shown in Figure 5 are not dependent on how the corn is used (food vs animal feed vs bioethanol production), only on its price. That being said, altering the demand for corn by removing ethanol production would likely have a significant impact on corn price, though the magnitude of this impact is difficult to predict and beyond the scope of this analysis. Additionally, any largescale implementation of PVA systems could also reduce the total amount of corn produce, which would also impact the price of corn. This points to a need for future research to investigate the economic impact of the implementation of PVA systems at a national scale.

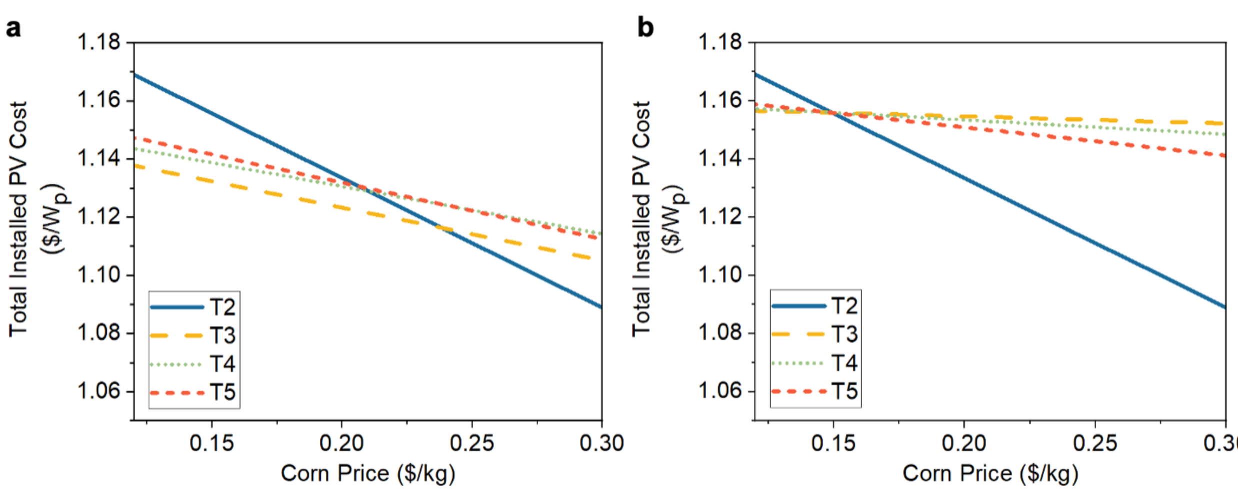

Figure 5. Break-even lines for treatments 2-5 relative to treatment 1. The total installed PV system cost in each treatment needed to break even with treatment 1 is graphed as a function of corn price under a) the LSY boundary and b) the HSY boundary.

5. Conclusion

With increasing pressure for energy production from croplands, we have shown that the integration of photovoltaics with agriculture is a viable option and could alleviate competition between food and energy. Our analysis indicates that both PV and PVA systems can substantially increase energy production per hectare relative to the baseline where around 27% of corn is attributed to ethanol. This is because PV systems are substantially more efficient than plants at converting sunlight into usable forms of energy. The traditional PV system and a quarter-density PVA system raise end-use energy production from less than 2 MWh/ha/year to approximately 140 MWh MWh/ha/year. The half density PVA raises energy production to around 280 MWh/ha/year, and a full density PVA raises energy production to approximately 560 MW/ha/year. As a result, PV systems (and, in particular, PVA systems) reduced GHG emissions substantially relative to the baseline. In contrast to PV systems, PVA systems do so under very little penalty on production of crops for food/feed and, therefore, their economic viability conveniently has little reliance on corn prices. Traditional photovoltaics are economically competitive with growing corn and offer more energy generation and GHG reduction per unit land, helping producers meet key Sustainable Development Goals. However, for PVA systems to be economically competitive they will either need to be supported by subsidies or engineer solutions that reduce the cost of installation and support structures. Given that this is an emerging technology, it seems reasonable to expect the costs of PVA systems to decrease as the technology develops further. Overall, we find that PVA systems can provide a viable strategy to ease the current tradeoff between energy production, GHG emissions, food production, and farm profitability.

Importantly, while the findings in this study support the idea that PVA technologies could play an important role in future systems for the hybrid production of food and energy, more work is needed before these systems can be implemented. This includes developing a better understanding of stakeholder perceptions/needs and improved engineering to drive down costs while maximizing system outputs (Torma and Aschemann-Witzel, 2023). Furthermore, future innovation in solar energy technology could lead to new and creative methods for integrating energy production into agricultural lands.

This work also highlights the need for analysing policy around bioethanol like the RFS. Our finding suggest that PV systems may be able to meet many of the goals of the RFS while addressing the issues that have arisen in the food versus fuel debate. Integrating photovoltaics into agricultural land offers greater potential for the production of renewable energy and reducing GHG emissions. Furthermore, our calculations show that if there is no ethanol demand the amount of corn available as a food and animal feed resource can actually be increased even when solar panels are integrated, relative to the amount available under the conditions of ethanol demand and no PV integration. In this view, PVA technologies provide a viable solution to the food versus fuel debate, allowing large amounts of energy to be produced with minimal impact on corn as a food/feed resource. Finally, with solar energy becoming economically viable, the integration of photovoltaics may be profitable for farmers and have the added benefit of diversifying revenue sources.

CRediT authorship contribution statement

Jonathan W. Turnley: Conceptualization, Methodology, Software, Formal Analysis, Investigation, Data Curation, Writing – Original Draft, Visualization. **Alison Grant:** Conceptualization, Methodology, Formal Analysis, Writing – Review & Editing. **Val. Z. Schull:** Software, Writing – Review & Editing. **Davide Cammarano:** Software, Writing – Review & Editing. **Juan Sesmero:** Conceptualization, Methodology, Writing – Review & Editing, Supervision. **Rakesh Agrawal:** Conceptualization, Methodology, Writing – Review & Editing, Supervision, Funding Acquisition.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available upon request.

Supplementary information

Supplemental discussion, table of relevant data, APSIM calibration, and additional system outputs (PDF)

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Supplementary Information

The Viability of Photovoltaics on Agricultural Land: Can PV Solve the Food vs Fuel Debate?

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Supplementary Discussions

1. Allotment of land between corn and traditional PV

For this analysis, T2 was designed to have traditional photovoltaics on 25% of the total land area. While this provided a convenient comparison, in practice there is no specific reason that farmers would use exactly that amount of their land for traditional photovoltaics.

As policy already plays a role in dictating how energy is generated from corn croplands, it is feasible that policy would determine how photovoltaics are integrated into agricultural land. From this perspective, one option could be to eliminate the mandate for ethanol and install traditional photovoltaics on land in such a way that the current production of corn as a food and animal feed resource is maintained. As approximately 27% of corn consumption can be attributed to ethanol production, replacing the corn on 27% of the land with traditional photovoltaics would achieve this outcome (Kumar and Singh, 2019).

Relevant Literature Data

Supplementary Table 1. Literature Values Used In Calculations

Variable	Value Used for Calculations	Typical Range	Reference
Enhanced light collection factor for tracking PV (Φ)	1.35	1.3 – 1.4	(Mousazadeh et al., 2009)
Efficiency of a PV panel (η_{PV})	19.1 %	16 – 22%	(Benda and Černá, 2020; Fu et al., 2018)
System and transmission efficiency for a PV system (η_{System})	95.3%	94 – 97%	(Miskin et al., 2019; "US Electricity Profile 2022 - U.S. Energy Information Administration (EIA)," n.d.)
Efficiency of a combustion engine (η_{CE})	14.8%	13 – 17%	(Miskin et al., 2019; Weiss et al., 2000)
Fraction of corn in the USA that goes towards ethanol production	40%	35 – 48%	("Alternative Fuels Data Center: Maps and Data," n.d.; Kumar and Singh, 2019)
Fraction of corn used in ethanol production that is recovered as dried distillers grain	33%	30 – 33%	(Kumar and Singh, 2019; Loy and Lundy, 2019)
Volume of ethanol generated per mass of corn	0.433 L/kg	0.40 - 0.44 L/kg	(Lee et al., 2021; Rosentrater, 2011)
Lifespan of a PV system	25 years	25 – 30 years	(Prieto-Castrillo et al., 2020; Wilson et al., 2020)
PV efficiency degradation rate	0.5%	0.35 – 1.15%	(Jordan et al., 2016)
PV system operation and maintenance costs	$18/kW/year	$14 – 20/kW/year	(Bolinger et al., 2019; Boretti and Castelletto, 2020)
Average miles traveled by a passenger vehicle	11,443 miles/year	10,439 – 13,476 miles/year	("Average Annual Miles per Driver by Age Group," n.d.; Sivak and Schoettle, 2018; Tefft, 2022)
Passenger vehicle fuel efficiency	25 miles/gallon	20 – 40 miles/gallon	(Greene et al., 2020; Sivak and Schoettle, 2018)
Grid-averaged GHG emissions for Indiana	0.916 tonnes CO_2-eq/MWh	0.70 – 0.96 tonnes CO_2-eq/MWh	(Office of Energy Policy and Systems Analysis, 2016; "US Power Sector Emissions," n.d.)
GHG emissions for PV	0.025 tonnes CO_2-eq/MWh	0.008 – 0.080 tonnes CO_2-eq/MWh	(Louwen et al., 2016)
GHG emissions for bioethanol	0.152 tonnes CO_2-eq/MWh	0.022 – 0.37 tonnes CO_2-eq/MWh	(Lee et al., 2021; Liska et al., 2009)
GHG emissions for gasoline	0.3312 tonnes CO_2-eq/MWh	0.30 – 0.35 tonnes CO_2-eq/MWh	(Liska et al., 2009; Venkatesh et al., 2011)
Yearly inflation rate	2.44%	1.2 – 6.6%	("Bureau of Labor Statistics Data," n.d.)
Wholesale price of electricity in Indiana (2019)	$42.99/MWh	$27 – 100/MWh	("U.S. Energy Information Administration - EIA - Independent Statistics and Analysis," n.d.)
Cost of growing corn in Indiana	$1623/ha/year	$1400 – 2000/ha/year	(Langemeier et al., 2019)

Supplementary Results

1. APSIM Calibration

To simulate crop growth, the Agricultural Production Systems Simulator (APSIM) (Holzworth et al., 2014) was calibrated for average corn development (time to flowering and maturity) and final yield in Tippecanoe County, Indiana for the years 2012 through 2019. This was done by altering the cultivar specific parameters in the Maize module to minimize the errors between observed and simulated phenology and yield. First, development was calibrated by adjusting the thermal time to flowering and then to maturity. Then, growth was calibrated by adjusting the radiation use efficiency and potential kernel weight. The cultivar specific parameters obtained after calibration are shown in Supplementary Table 2. The simulated times to various developmental stages (in terms of days after sowing, DAS) are compared to observed county averages ("Indiana Crop Progress & Condition Report," n.d.) in Supplementary Table 3. The simulated yields (in terms of kilograms of dry matter per hectare, kg/ha) are compared to observed county averages ("Indiana County Estimates," n.d.) in Supplementary Table 4. Statistical analysis (correlation coefficient, R^2; root mean square error, RMSE; relative root mean square error, RRMSE; Willmott's index of agreement, d-index) (Wallach, 2006; Willmott, 1981) comparing observed and simulated values for time to flowering, time to maturity, and yield are shown in Supplementary Table 5. The largest difference in the simulated and observed yields occurred in 2012, a year where a major drought occurred. This may be due to the extreme conditions or other factors that aren't accounted for in these simulations like farmers taking additional agronomic management actions, spatial soil variability, or water table impacts.

Supplementary Table 2. Cultivar specific parameters after calibration of APSIM maize module

Parameter	Explanation (Archontoulis et al., 2014)	Unit	Value
tt_emerg_to_endjuv	Thermal time from emergence to the end of juvenile state	°C*day	220
tt_endjuv_to_init	Thermal time from end of juvenile to floral initiation	°C*day	0
tt_flag_to_flower	Thermal time from flag leaf to silking	°C*day	1
tt_flower_to_start_grain	Thermal time from silking to start of effective grain filling period	°C*day	215
tt_flower_to_maturity	Thermal time from silking to physiological maturity	°C*day	900
tt_maturity_to_ripe	Thermal time from physiological maturity to harvest	°C*day	1
potKernelWt	Potential kernel weight	mg	325
rue	Radiation use efficiency	g/MJ	1.60

Supplementary Table 3. Comparison of simulated and observed developmental times

Year	Sowing Date	Observed Flowering (DAS)	Simulated Flowering (DAS)	Observed Maturity (DAS)	Simulated Maturity (DAS)
2012	4/25	72	68	138	121
2013	5/15	64	64	131	127
2014	5/8	67	67	135	135
2015	5/9	70	70	133	135
2016	5/17	61	63	122	118
2017	5/6	73	68	139	137
2018	5/7	61	61	128	119
2019	6/6	54	60	119	124

Supplementary Table 4. Comparison of simulated and observed corn yields

Year	Observed Yield (kg/ha)	Simulated Yield (kg/ha)
2012	7,030	5,852
2013	11,618	11,439
2014	12,967	11,763
2015	9,283	10,584
2016	Not Available	11,604
2017	11,317	11,584
2018	12,622	12,300
2019	11,310	11,755

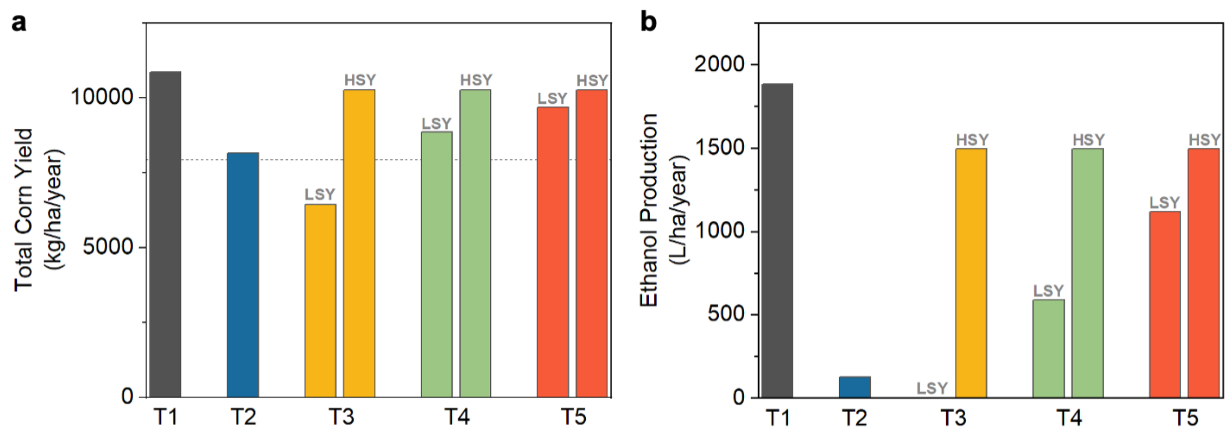
Supplementary Table 5. Statistical analysis of APSIM calibration

	R^2	RMSE	RRMSE	d-Index
Time to Flowering	0.86	3.2 (DAS)	4.9%	0.88
Time to Maturity	0.34	7.4 (DAS)	5.6%	0.68
Yield	0.84	840 (kg/ha)	7.7%	0.95

2. System Outputs with Limited Ethanol Production

Given that ethanol demands are policy driven under the Renewable Fuels Standard (RFS), it stands to reason that changes in policy could alter that demand. In this work we analyzed the system outputs under the ethanol demand observed with the RFS and with no ethanol demand. An additional option is to lower the ethanol demand. One option could be to mandate a certain amount of corn be available as a food and animal feed resource, but all surplus corn be used for ethanol production. The total corn yield for each of the treatments is shown in Supplementary Figure 1.a. In this figure the horizontal line at approximately 7,950 kg/ha/year represents the corn available as a food and animal feed resource in T1 with the ethanol demand created by the RFS. In any of the treatments where the total corn yield falls above that line, there is the possibility of having that amount of corn available for food/feed and using the surplus for ethanol. If each treatment were to meet exactly that amount of corn available for food/feed, the quantity of ethanol that could be produced is shown in Supplementary Figure 1.b.

Only T3 at the LSY boundary would be unable to produce any ethanol. Comparing T2 and T5, which have the same number of total PV panels, we see that the larger total corn yield afforded by the PVA system would allow for much greater ethanol production than when a traditional PV system is used.



Supplementary Figure 1. Ethanol production from surplus corn. **a)** The total corn yields for each treatment with the horizontal line indicating the amount of corn available for food/feed in T1 under the ethanol demand created by the RFS and **b)** the amount of ethanol that could be produced for each treatment if the corn available as a food/feed resource was set to exactly match the value for T1 under ethanol demand from the RFS.

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