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Modeling the Agrivoltaic Potential for Land-Intensive Commodity Crops

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Abstract. Corn and soybean farming use about two-thirds of the agricultural land in the US. To accelerate the large-scale adoption of agrivoltaics, best practices that are compatible with traditional farming operations for corn and soybeans need to be developed. In this presentation, we present the development of a modeling framework to explore the benefits and trade-offs between crop growth and photovoltaic (PV) electricity generation for common commodity crops at the county level. Our model couples a crop growth model, a soil water balance model, and a PV model in one integrated scheme. As an example, we consider corn growth in Renville County, MN. The model suggests that there is a ~0.55% loss in crop yield upon 1% shading because the crop-diminishing effect of reduced radiation is partially offset by increased water retention in the ground.

Keywords: Crop Modeling, Maize, Agrivoltaic System

1. Introduction

Multiple studies have suggested that dual-use of agricultural land can lead to diversification and risk reduction for farmers [1], [2], and to the creation of more than 100,000 jobs in rural communities [3]. However, the vast amount work on agricultural systems has mostly focused on pollinator habitat and the growth of specialty crops including vegetables, lettuce, and berries. Comparatively little work, however, has focused on the agrivoltaic potential of commodity crops such as corn and soybeans.

A potential challenge for integrating agrivoltaics with corn-soybean farming is that corn, a shade-intolerant crop, could be negatively affected by shading from solar panels. A meta-analysis of 10 different experimental studies suggested that the corn crop yield decreases roughly linearly with the degree of shading, with 50% shade leading to a ~50% reduction of crop yield [4]. However, the individual studies used in the meta-analysis addressed widely varying experimental approaches and were conducted in very diverse climatic conditions. It should be noted that none of the 10 studies were performed in the US, but rather in China, Japan, Korea, and Germany, where farming practices may be different from the US. There were also notable exceptions that did not follow the general trend of the meta-analysis. Sekiyama and Nagashima studied corn growth under solar arrays that provided 20% and 49% shading [5]. The arrays were mounted on stilts at a fixed angle and shaded the crop only for part of the day. They reported a 4.9% increase of crop yield for light shading, and only 3.6% decrease of crop yield under heavy shading. Hyon Jo et al. found minimal reduction of corn forage yield under an array with 30% shading over a two year period [6]. The significant spread of crop yields with different amounts of shading reported in the meta-analysis [4], as well as the lack of data under US farming practices, reinforces the urgent need for our proposed study.

It is generally accepted that biomass development in commodity crops like corn is proportional to the solar radiation received. However, the loss of radiation in agrivoltaics systems may be ameliorated by a number of factors. Shading provided by solar panels may reduce evaporation and lead to increased plant available water, particularly during dry spells. Moreover, corn growth slows when the daily maximum temperatures exceed a threshold value during extreme heat events, which occur more frequently with global warming. Depending on shading levels, the microclimate under a solar array may reduce maximum daily temperatures, thus alleviating heat stress during heat spells. Hence, it is important to evaluate these competing effects and study how the yield of corn is affected by light shading in agrivoltaics environments.

Here we present a modeling framework that allows for study of the the yield of a variety of commodity crops under light shading conditions in agrivoltaics system. As an example, we apply this framework to corn yields in Renville County, MN. However, the model can be applied to any county for which agricultural statistical data are available.

2. Modeling Framework

A schematic of the modeling framework used here is shown in Figure 1. The model has three coupled modules that interact with each other: a plant growth model, a soil water balance, and a photovoltaic model. The model retrieves environmental data such as total and diffuse irradiance onto a horizontal surface, daily precipitation, and daily high, low, and medium temperatures from the NASA POWER Database [7]. Crop data at the county level are retrieved from survey data from the USDA National Agricultural Statistical Service. Estimates for annual planting dates are derived from the USDA crop report.

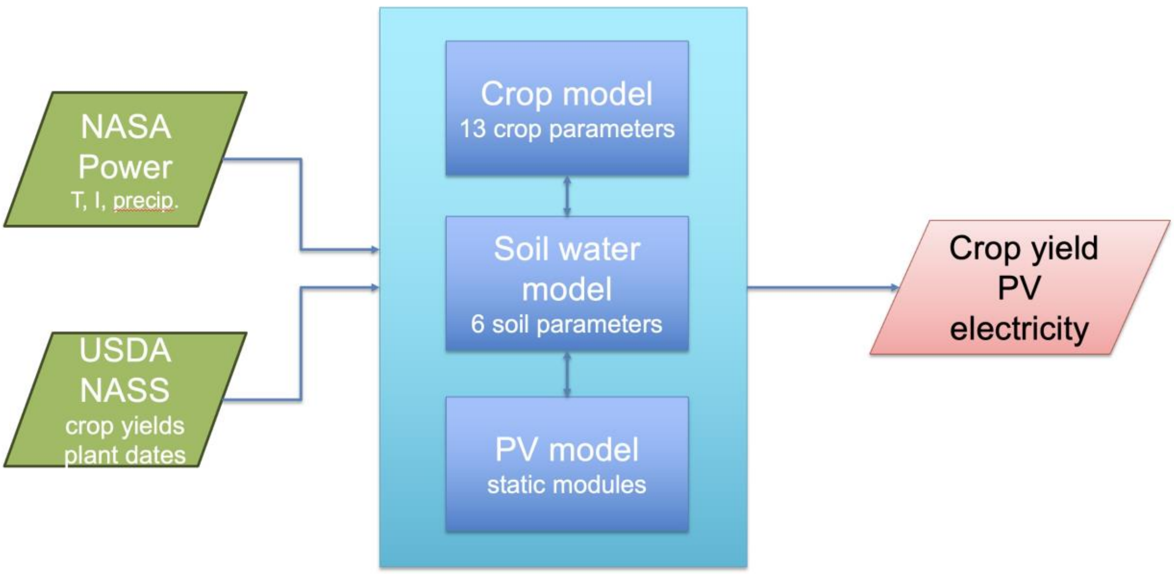

Figure 1. *Schematic of agrivoltaic modeling framework for commodity crops.*

A number of sophisticated crop models are available to describe crop growth based on local environmental data and crop management practices [8], [9]. Based on their experience with these models, Zhao et al. developed a simple, generic model for crop development and yield (SIMPLE) that can be adapted to various target crops [10]. The model describes each crop by a set of 13 crop parameters, 4 of them cultivar specific. The SIMPLE model assumes that the daily increase in biomass is proportional to the daily radiation received, and modified by factors that account for the development of leaf area and stressors such as excessive daily high temperature, low plant available water, and low daily mean temperatures.

The growth of any crop is strongly affected by plant available water. Hence, the SIMPLE crop growth model draws on a soil water balance according to work by Woli et al. [11] that balances water received by precipitation and irrigation and water lost through plant transpiration, evaporation, run-off and deep drainage. The ratio of actual evapotranspiration to potential evapotranspiration, according to Priestley and Taylor [12], is expressed as the agricultural reference index for drought (ARID), which ranges from 0 to 1, with 0 corresponding to saturated soil, and 1 corresponding to no evapotranspiration due to extreme drought.

The photovolatic performance is evaluated using daily direct and diffuse irradiation data from the NASA Power database. These data account for daily variations of the irradiation due to cloud cover and other environmental factors. We currently model static, south-facing panels at a tilt angle that is chosen by the latitude of the location considered. The total daily radiation received by the panels is evaluated based on the model by Liu and Jordan [13], and converted to photovoltaic power assuming a power conversion efficiency of 19% and system losses of 14%. The current version of our framework does not assume a specific configuration of the solar array because our emphasis is on understanding the impact of shading on crop yield. In practice, solar panels would be mounted at a height that is compatible with the use of farming equipment, which is about 14 ft. We currently assume that the solar array causes a certain amount of average crop shading, irrespective of a particular array configuration. Since we have found crop yield to decrease linearly with the degree of shading, this appears to be a reasonable simplification. However, future versions of our framework will include more details of the solar array configuration, such as shading caused and PV electricity produced by static and tracking mounts for various installation heights and row spacings.

Model calibration of crop and soil parameters is essential. The SIMPLE model features only one set of crop parameters for corn, for the cultivar McCurdy 84aa, which has been studied since the 1980s. However, in recent years, the introduction of new corn varieties has led to remarkable improvements in drought and disease resistance, which are not reflected in the crop parameters for McCurdy 84aa. Hence, we performed a sensitivity analysis of the 13 crop and 6 soil parameters and identified the 4 most important parameters. These parameters were subsequently optimized using the Broyden-Fletcher-Goldfarb-Shanno (BFGS) algorithm using 20 years of crop yield data for Renville County, MN. The "Renville County" cultivar represents an average over the many varieties planted in the county. Compared to crop yields obtained with McCurdy 84aa parameters, Figure 2a, significantly better agreement with USDA reported crop yields are obtained after calibration, as seen in Figure 2b.

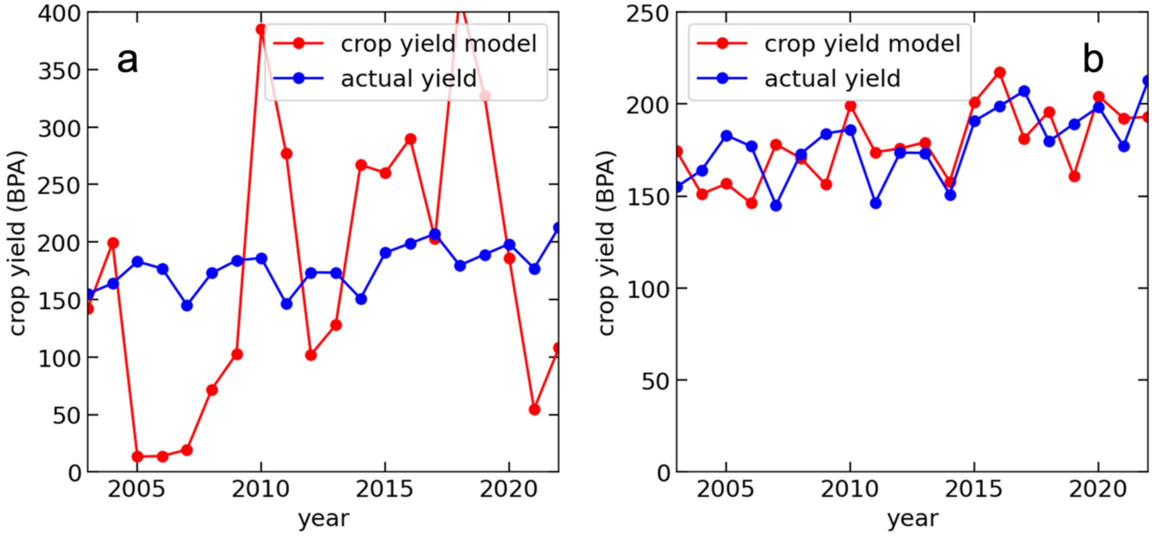

Figure 2. *Actual vs. predicted corn crop yields in bushel per acre (BPA) for Renville County, MN, from 2003-2022. (a) original McCurdy 84aa crop parameters, (b) optimized crop parameters for Renville County, MN.*

3. Results

After model calibration, we tested the crop yield at various levels of shading from the solar array. Figure 3a shows results for the biomass generation at shading levels from 0-20%. For 2021 in Renville County, our model predicted a continuous reduction in biomass, and thus crop yield, with increased shading level. At 20% shading, the yield decreased by about 11%. The less than 1:1 reduction in crop yield upon increased shading is caused by the increased moisture retention in the soil due to partial shading. This is demonstrated by Figure 3b, which shows that the ARID index is reduced with increased shading and remains lower for increased shading particularly after precipitation events.

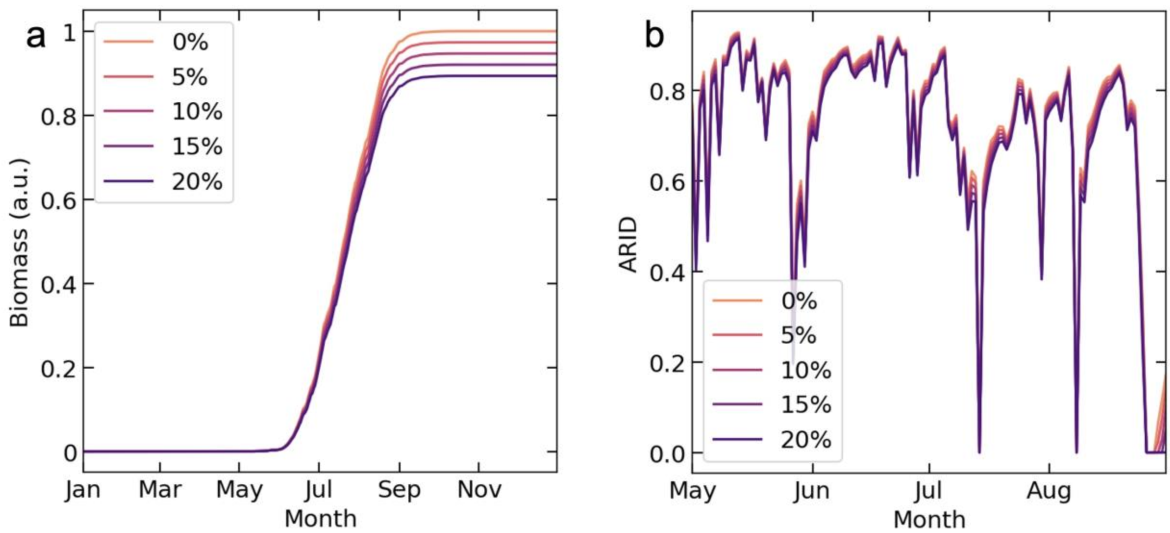

Figure 3. *Crop yield and ARID index for 2021 for Renville County, MN: (a) Predicted level of crop yields for different levels of shading. (b) ARID index for different levels of shading.*

These results are different from predictions using the McCurdy 84aa crop parameters. An important result of the optimization we performed is that the generic "Renville County" crop variety is much less sensitive to drought than the McCurdy 84aa cultivar. Since the McCurdy

84aa cultivar is extremely sensitive to drought, yield increases are sometimes observed with increased shading. This observation amplifies the need to train the crop growth model with actual yield data.

While the results in Figure 3 reflect a single year of crop growth, simulations were performed for the 20-year period from 2003-2022. The crop yield for these 20-year simulations for various levels of shading is shown in Figure 4, which demonstrates that the crop yield decreases linearly with increasing shading. The general guideline that results from our simulations is that **every 1 percent of shading leads to a 0.55 percent loss in crop yield**. The predicted yield loss is less than the 1:1 loss found in ref. [4], which shows that some of the yield loss caused by the loss of radiation can be offset by increased moisture retention in the soil. However, given the drought tolerance of many modern seed varieties, increased soil moisture is unable to fully compensate for the loss in radiation.

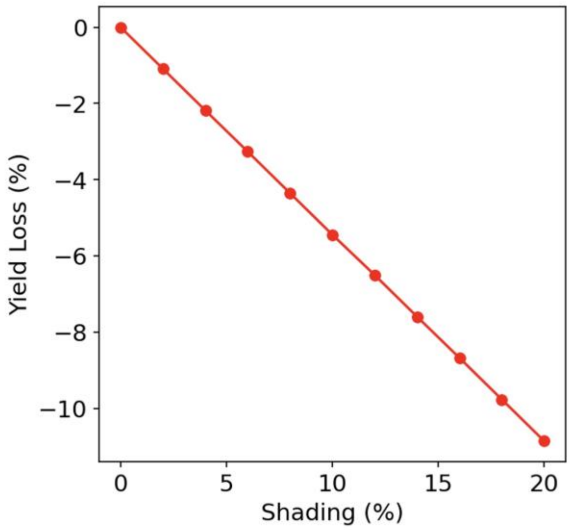

Figure 4. *Simulated corn crop yield loss for various levels of shading for Renville County, MN.*

4. Conclusions

We presented a modeling framework that enables the study of crop yield under agrivoltaic systems of common commodity crops at the county level. We examined the example of corn yields in Renville County, MN, studied over a period from 2003 to 2022.

The developed modeling framework highlights the significant trade-offs involved in agrivoltaic systems for commodity crops. The model predicts for Renville County that a 1% increase in shading results in a 0.55% decrease in corn yield. Given the slim profit margins in corn farming, even a few percent of yield loss may turn a profitable crop year into an unprofitable one. For instance, for 2023, the USDA Economic Research Service reported for each acre of corn harvested an average income of $920, an average cost of $907, for a profit of $13 per acre, before government payments [14]. Even small reductions in income may raise the question whether it is not more profitable to take some land out of production and build a fully dense solar array, possibly with other higher value agrivoltaics crops beneath them. This conclusion underscores the necessity of carefully considering factors such as agricultural incentives and electricity rates to determine the viability of agrivoltaic systems in different scenarios.

Data availability statement

Data will be provided upon reasonable request to the corresponding author.

Underlying and related material

No supplementary materials are provided.

Author contributions

U.R.K: Conceptualization, Methodology, Investigation, Software, Writing – original draft, Writing – review & editing. V.E.F.: Conceptualization, Methodology, Writing – review & editing.

Competing interests

The authors declare no competing interests.

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