Coproduction of solar energy on maize farms – experimental validation of recent experiments

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***Abstract*—Developing methods for the sustainable coproduction of food, energy and water resources has recently been recognized as a potentially attractive solution to meeting the needs of a growing population. However, many studies have used models, but have not performed an actual experiment to directly validate all their predictions. Here, we report a recently-constructed test site on the ACRE farm in West Lafayette, Indiana, consisting of single-axis trackers in a novel configuration atop a maize test plot. We present a methodology to measure irradiance therein with 10-minute temporal resolution, which allows us to validate prior PV aglectric farm irradiance models.**

Keywords—aglectric, agrophotovoltaic, agrivoltaic, photovoltaic

I. Introduction

As the world population approaches 9.8 billion people by 2050, food, energy, and water (FEW) requirements are projected to increase exponentially, while the land dedicated to resource production will remain approximately the same [1]. To meet this challenge, design and implementation of novel technologies will be critical to circumvent traditional land constraints for sustainable FEW production without unnecessarily disrupting established farming practices.

Recent work by Miskin *et al.* establishes a viable, utility-scale pathway to renewable energy production while minimizing land constraints that hamstring widespread adoption of traditional PV installations. In 20 states, traditional ground-level PV parks would have power per unit land area requirements in excess of 11 W/m^2, even if 15% and 50% of each state's urban and miscellaneous land were allocated, respectively. Miskin *et al*. propose implementation of aglectric systems on agricultural land to address this concern. Aglectric systems or installations are energy production systems that have neutral or positive impact on agricultural production. Aglectric farms are by definition, technology nonspecific, and in this work we will be examining PV-based aglectric farms. If existing PV parks output and land allocation is assumed to be the same as previously mentioned, each state's remaining energy requirement can be met by implementation of PV aglectric farms on 33% or less of the available agricultural land, with the exception of 3 states. For those states that cannot meet their remaining energy requirement with PV aglectric farms, alternative technology based renewable energy production or energy importation from neighboring states will be required [1].

Recent modeling efforts in literature quantify the degree of irradiance reduction for crop growth below PV aglectric farms. Amaducci *et al.* developed a coupled shading and crop growth model for the patented Agrovoltaico® solar tracking system. The authors then simulated crop response underneath the Agrovoltaico system using climate data from 1976 to 2014 [4]. Work by Dupraz *et al.* use ray tracing algorithms to calculate direct and diffuse components underneath varying density fixed-tilt elevated PV farms. Dupraz *et al.* incorporated photosynthetically active radiation (PAR) capabilities in which the percentage reduction of PAR is calculated per point, and then spatial radiation maps are generated with month and year temporal resolution [2]. Valle *et al.* used a similar ray tracing algorithm and used home-made Photosynthetic Photon Flux Density (PPFD) to verify their model for 10 different locations within their experimental array [3]. For uniform irradiance distributions and less complex PV aglectric farms, this validation methodology is sufficient; however, a comprehensive spatial and temporal model validation has not been conducted in literature, leaving model limitations unestablished.

To the authors' knowledge, no one has examined non-uniform effects or directly validated the developed model both spatially and temporally for any elevated PV system. Additionally, for more complex PV aglectric farms, a more rigorous analysis of the implemented model prior to comparison with crop growth models may yield increased understanding of system behavior and features. Validation is necessary for examination of non-uniform shadow distributions and allows for the study of the impact of varied irradiance levels on crops growth in one growing season. A well validated model will allow for testing and optimization of different PV aglectric systems while minimizing experimental construction.

II. ACRE Solar Array Overview

In spring 2019, an experimental aglectric system was constructed at the Purdue University Agronomy Center for Research and Education (ACRE) farm, shown in figure 1. This experiment, commonly referred to as the ACRE Solar Array, comprises of 4 single-axis solar trackers implemented in east-west tracking mode. The solar trackers are raised 20 ft above ground level and welded to steel I-beams for compatibility with current high-yield agricultural practices such as mechanized farming. Two different module types were loaded on each tracker and will be referred to as treatments 1 and 2. Treatments 1 and 2 consist of 72-cell 300 W and 36-cell 100 W polysilicon

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modules, respectively. This configuration was implemented to allow for agricultural replications within the field. Loading each tracker identically instead of having 2 trackers dedicated to each treatment creates non-uniform shadow distributions below the array. This results in a range of shadow reduction percentages, referred here on out as shadow depth (SD), enabling future studies into optimal shading regimes.

This configuration creates non-uniform shadow distributions below the array, allowing for study of a range of shadow depths as quantification of edge effects. The entire experimental area covers 0.265 acres and all components are commercially available.

A)

B)

Fig. 1 (a) Image of the ACRE Solar Array taken on 7/8/19 at 9:01PM EST. The planted crop below the array is Maize. Soybeans in the foreground are not a part of this experiment (b) Side view of the ACRE Solar Array taken on 7/8/19 at 9:06 PM showing Maize growth. Size needed adjusting

III. 3D Modeling and Validation

This work modifies and leverages a previously developed ray-tracing model that calculates irradiance reaching the ground. Using the open-source library PVLib, spatial maps of intensity variation are calculated for direct and diffuse light [5]. Solar input was based on astronomical data calculated in PVLib and historical weather data from West Lafayette [1]. The percentage reduction in irradiance for a simulated structure in comparison with an open field is calculated and referred to as shadow depth (SD). The model is capable of simplistic systems as well as custom array layouts such as the ACRE Solar Array shown in figure 1.

Direct irradiance underneath the ACRE Solar Array was modeled at specific dates and times throughout the growing season corresponding to when RGB drone imagery was collected. Each drone image mosaic consists of over a thousand individual images compiled using ENVI image analysis software. For each location imaged, 5 different bands of the spectrum were targeted. These bands include blue, green, red, NIR, and the edge between red and NIR.

The model was used to generate a direct irradiance spatial distribution map corresponding to the time and date of the drone images as well as the duration of imaging. This is to account for possible tracker position changes during data collection as well as any algorithmic differences between PVLib's tracking model and the one implemented by the physical trackers. In this work, only direct light snapshots are analyzed.

Model validation was conducted by comparison of the drone images taken significantly above the array and the simulated direct irradiance snapshots. Significant post processing was required in order to reformat the drone mosaic into a comparable image. Cropping and resizing were implemented without changing aspect ratios or altering the integrity of the original drone mosaic. Significant features or landmarks of the drone mosaic, such as the center of each tracker's torque tube, were manually identified and marked. Drone images were then cropped to include the desired features using a calculated ratio of elements per known distance for each axis, without changing feature aspect ratios. The cropped drone mosaics were resized to match the array dimensions of the simulation and converted to grayscale. Both the mosaic and simulation were normalized to the same value. An element by element comparison was then conducted and the RMSE values were computed according to the following equation:

$$\boldsymbol{RMSE} = \sqrt{\frac{\sum_{1}^{N}(x_i - x_o)^2}{N}}$$

Each drone mosaic has a varying number of images and overall image shape varies at the edge of the mosaic. Additionally, the mosaics are limited by the compilation software, weather conditions during imaging, and if the trackers are stationary, and the overlay quality can vary due to these factors. Occasionally the images of the trackers can be blurred or not completely line up which affects the accuracy of the landmarking and subsequent cropping. While automated landmarking is of significant interest to the authors, its implementation proves nontrivial Also the authors acknowledge that a portion of the reflected light and incident light from the drone images is diffuse which is not included in the simulation snapshot.

TABLE I. Model Error Calculation for 6/27/19

Tracker	**Root Mean Square Error (RMSE)**	**Standard Deviation**
	Drone Data and Simulated Values	***Drone Data Distribution***
1	0.0751	0.0627
2	0.0702	0.0604
3	0.0780	0.0744
4	0.0974	0.0956

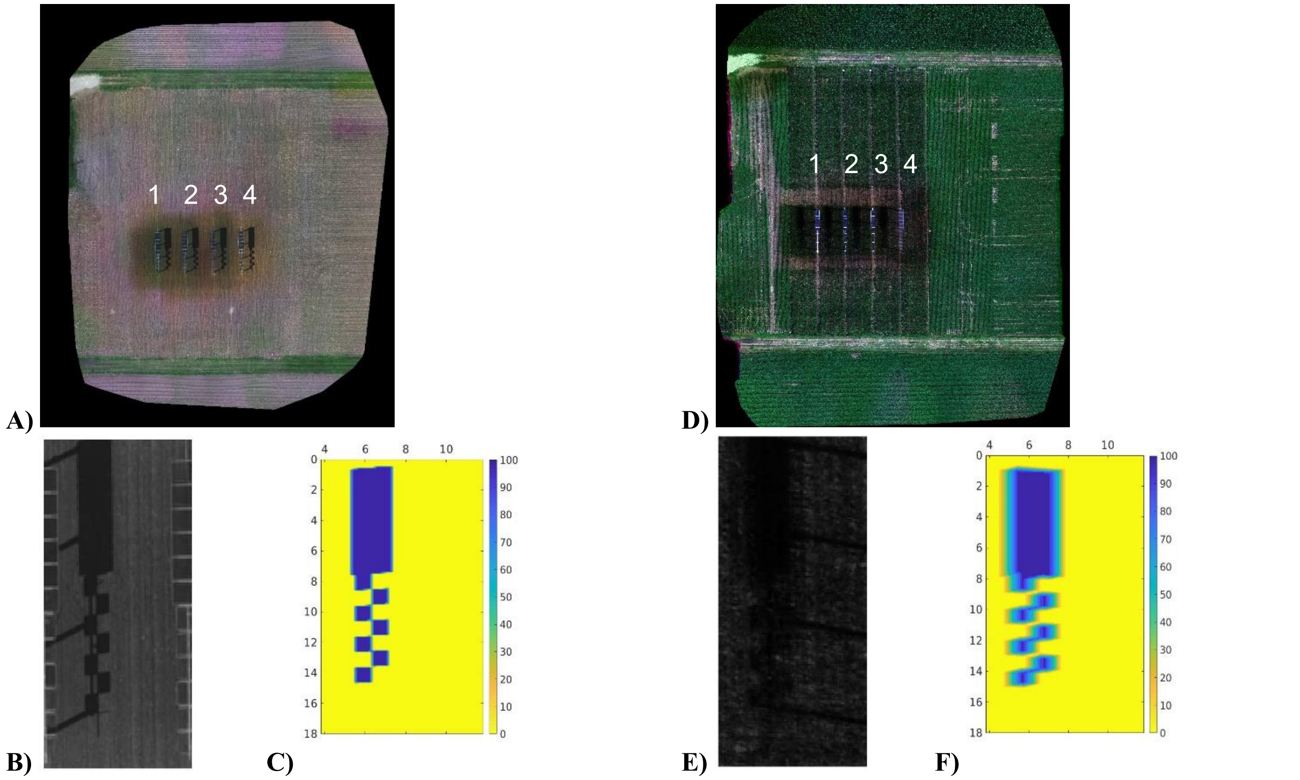

Figure 2 (a) Raw drone image taken on 6/27/19 from 3:55 PM to 4:02 PM (b) processed image of tracker 1 (c) shadow depth percentage simulation snapshot for tracker 1 (d) Raw drone image taken on 7/23/19 from 10:22 AM to 10:42 AM (e) processed image of tracker 2 (f) shadow depth percentage simulation snapshot for tracker 2.

IV. 1D Modeling and Validation

The collected drone data from 6/27/19 was also compared to a previously constructed 1D model shown in figure 3. An infinitely periodic array was modeled using the geometry of the ACRE solar array for treatment 1. A horizontal transect from the center of tracker 1 to the center of tracker 2 was marked in the drone data. The drone data was then averaged for a small range of vertical elements along that transect and compared to the ground irradiance. Comparison of the 1D simulation and the averaged drone transect data resulted in a calculated RMSE of 0.174. The 1D simulation follows the same normalization process as the 3D simulation.

V. Discussion

Following the methodology outlined previously, several raw drone mosaics were processed and compared element by element with the direct irradiance at ground level calculated by the PVLib-based model. This was done for early and late season drone images, with raw drone mosaics shown in figure 2(a,d). Processed images, showing a single example tracker shadow map and corresponding shadow maps are also shown in figure 2. RMSE values for the trackers on 6/27/19 are shown in Table 1. Early season simulations are more accurate than later season due to significant scattering from the canopy. The RMSE value for the tracker shown in figure 2(e) is approximately 0.0.2025 with the drone data standard deviation of 0.1912. Additionally, drone mosaics may have minor imperfections, not line up perfectly, or have blurring that may drive down RMSE error as shown in figure 2(b).

The absolute value of the difference between the processed grayscale image and corresponding shadow depth snapshot is shown in figure 3. This indicates that the largest contribution of error between the drone images and simulated snapshots is due to a minor rotational mismatch, structural elements, and the reflection from the trackers. The experimental array is rotated 1° from true north, which is not currently reflected in the 3D simulation and explains the rotational and slight translational mismatch shown in figure 3. Landmarking and cropping was performed without consideration for this deviation. Additional modeling of structural elements such as the I-beams and support steel will increase model accuracy. The largest difference between simulation and experiment is due to the reflection of light from the trackers, as the simulation calculates SD at ground level, while the drone image is taken above ground looking downwards. RMSE can be reduced further by cropping the trackers from the grayscale drone image; however, it was needed for initial landmarking.

For simulations with strict computational requirements, the 1D simulation can also be substituted for the 3D simulation with a minor increase in error.

The RMSE values indicate that both the 1D and 3D simulations agree within value close to the standard deviation of the drone data, for small regions of the field, as expected.

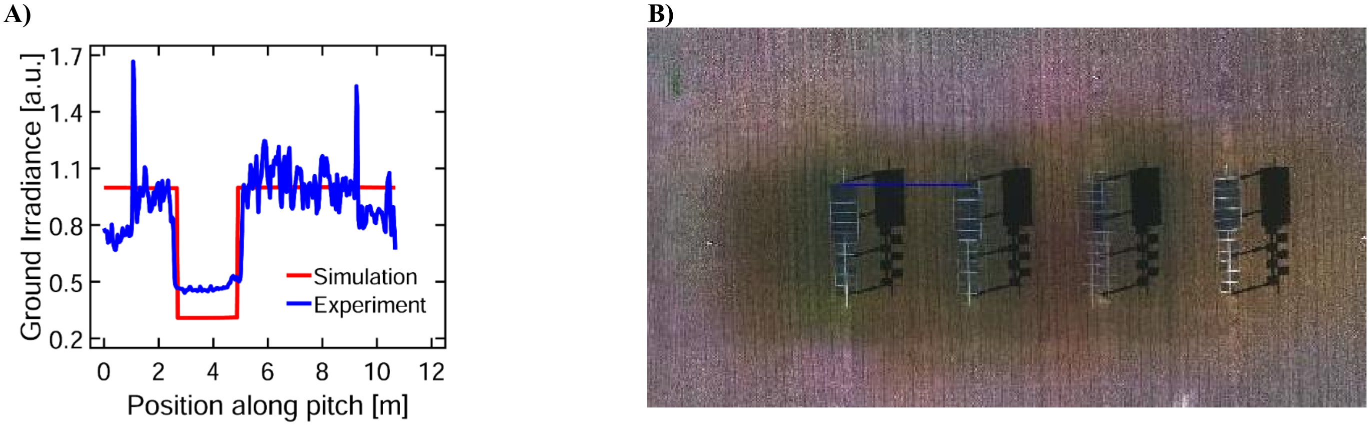

Figure 3 (a) 1D model of simulated irradiance versus drone image transect data (b) location of transect data selected on drone image, shown in blue.

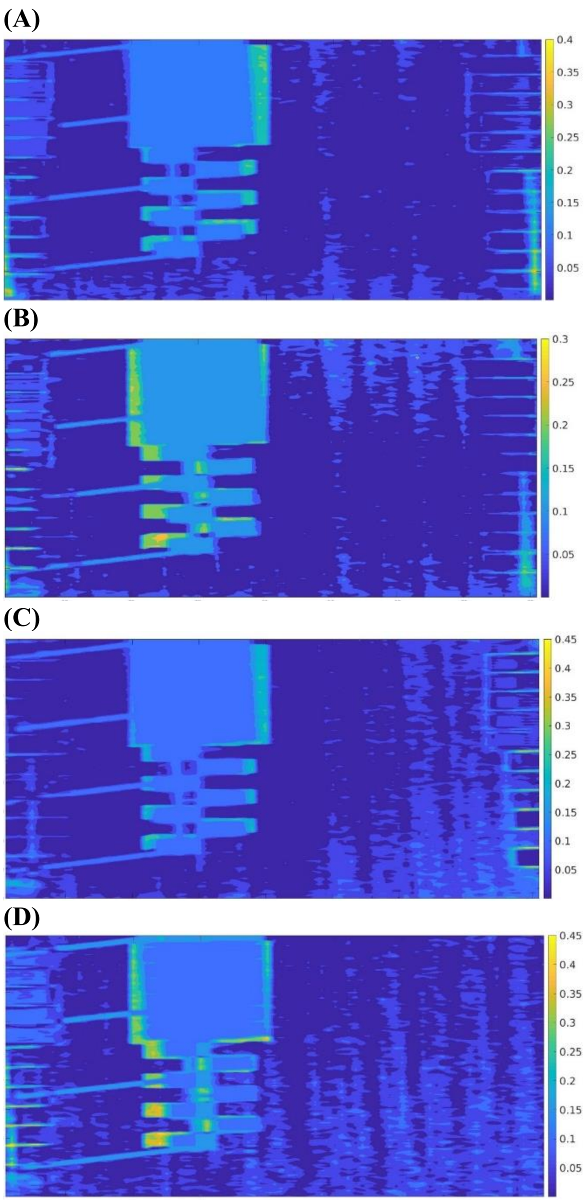

Figure (4): (a-d) contour plots of the absolute value of the difference between the drone data and the simulated snapshot for trackers T1 to T4 on 6/27/19 at 4PM

VI. Conclusions and Future Work

A methodology for validation of spatial and temporal irradiance maps of non-uniform shadow distributions has been evaluated and shows significant agreement. Depending on computational requirements of the application, we propose both a validated 1D and 3D model.

Inclusion of system modifications during construction more commonly known "as-builts" as well as structural components such as the I-beams, torque tubes, and mounting brackets are likely to increase agreement between simulation and experiment. Removal of areas with trackers from the bounds of the regions used for validation, will more fully describe accuracy of both 1D and 3D models. Evaluation of canopy scattering effects seen in late-season drone imagery into model as well as spectral selectivity capabilities are also of significant interest especially for late season simulations. The calculated RMSE value is close to the standard deviation of the drone data, indicating that the accuracy calculation may be limited by the RGB image of the camera. For reduction of model errors below approximately 6%, high resolution measurements of experiments may be needed. The next immediate step is to correlate the validated spatial and temporal shadow depth maps with the observed growth of the 2019 season and relevant growth models. Future work may include implementation of optimized tracking algorithms, as well as global optimization of the installation to maximize annual crop and energy outputs.

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