

Agrivoltaics and Weather Risk: a Diversification Strategy for Landowners

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Abstract

Farms are facing increasing pressure from shrinking margins, extreme weather, and increased competition for land use, including from energy producers. There is evidence to suggest that co-locating solar power production and agriculture, known as agrivoltaic systems, may be a means to reduce concern over the latter. A model is developed to test whether co-location can reduce weather-related financial risk for a landowner, a largely unexplored question, while improving profitability. Stochastically generated weather variables and commodity prices are used to simulate net revenues for a solar only plot, a farm only plot, and an agrivoltaic plot. Application to four test cases (alfalfa/soybeans in Oregon and soybeans/strawberries in North Carolina) illustrate the potential impact of agrivoltaics.

Results from the scenarios evaluated indicate that co-location can increase annual net revenues relative to a farm-only scenario by 300-5,000%. For crops subject to considerable risk via weather and market conditions, such as strawberries, co-location diversifies income streams, reducing revenue volatility and lifting worst case net revenues by 48-53%. In this sense, agrivoltaics may also be a partial substitute for federal crop insurance. While the locations and cases considered here were limited, this framework is applicable to any location or crop and

results suggest that agrivoltaics have the potential to increase farmers' revenues and improve financial stability during volatile weather and market conditions.

Keywords: agrivoltaic systems; solar power production; agriculture; hydrometeorological uncertainty; financial risk

1. Introduction

Since 1982, the midpoint farm size in the United States has roughly doubled [1] as tight margins and economies of scale make large-scale farming more financially attractive. This global trend [2] reflects the financial challenges of farming: volatile commodity prices paired with high fixed costs [3] and varying crop yield resulting from environmental factors [4]. Simultaneously, renewable energy production has increased as a result of falling prices and government initiatives, with solar energy generated via photovoltaic panels (PVPs) growing fastest [5].

While PVP energy production is often located on marginal land [6], there are cases in which productive agricultural plots are more suitable for development because of high levels of insolation, proximity to a demand center or transmission connection, or favorable land attributes [7]. As a consequence there are substantial tensions between solar developers and the agricultural community over land use [8–10] and questions regarding trade-offs in land use choices [11].

A growing body of research has begun to quantify these trade-offs, but the majority has considered it a zero-sum game. Rathmann et al. [12] reviews the literature for changes in land use from agriculture to biofuel production globally, finding new pressure on agriculture from biofuels. Rajcaniova et al. [13] attempt to identify and quantify the changes econometrically and find varying impacts by crop grown and region while Calvert and Mabee [14] compare competition between biofuel crops and solar farms. These studies, and others, neglect the possibility of the coexistence of food and energy production on the same land. Co-location with PVPs has drawn the most attention since its initial proposal in 1982, as “agrivoltaic systems” (AVS) [15]. In an AVS, panels are arranged in a manner permitting crops to grow underneath and/or between them (see Figure 1). Such a structure can lead to lower crop yields as a natural

consequence of decreased sunlight, as well as the reduced area available for planting, while similarly reducing the number of solar panels in order to accommodate crops.



Figure 1: Sample agrivoltaic design. Panel spacing allows farming equipment to pass between rows, with the potential to plant shade-tolerant crops underneath the panels as well as a variety of crops between the rows.

There are, however, advantages to co-location. Experimental data suggest that crops shaded by PVPs improve their ability to intercept sunlight [16,17], reduce evapotranspiration levels [18], and increase crop water use efficiency and productivity [19,20]. Co-location can also create a cooler microclimate more favorable for PVP efficiency and plants [21]; in Arizona, Barron-Gafford et al. [22] found co-location increased both power generation and fruit production per plant. Productivity in an AVS, measured as the sum of the ratios of crop yield and solar power production in an AVS to that of the farm only and solar only plot, has been found to increase by 35%-200% [23,24].

Financial analyses of AVS, however, have been limited. Existing studies have highlighted the potential of AVS to increase annual revenues for a pre-existing vineyard [25], improve net present value (NPV) of land relative to farming or power generation individually [20], calculate the levelized cost of energy in an AVS [26], or evaluate an upper bound cost for

meeting solar energy production targets with AVS [27]. Co-location may also increase revenue stability, a critical consideration for agricultural activities, which are vulnerable to fluctuating weather conditions and volatile crop prices. Solar power generation is relatively stable when averaged over an annual time scale [28], and electricity is often sold via power purchase agreements (PPAs) at fixed prices. The revenue streams from solar power production thus tend to be more stable than those of farms. Furthermore, variability in revenue streams from each activity may be uncorrelated, providing an opportunity to reduce the volatility of farm net revenues. This article seeks to address this unanswered question.

With specific regards to weather variability, co-location may afford the opportunity to offset the different financial risks each activity faces. For example, solar panels can reduce evaporation and increase soil moisture, thereby increasing crop water use efficiency and insulating farmers from drought-related losses [24,29]. In addition, the types of weather conditions that are favorable for agricultural production and solar generation activities may not only be uncorrelated but also negatively correlated. This offers an opportunity to further reduce financial risk. For example, solar power production is positively correlated with solar irradiance, which correlates with temperature [30], while in agriculture, warm temperatures are beneficial, but extreme heat is negatively correlated with yield [31,32]. Conversely, wet years reduce the need for expensive irrigation and tend to result in higher yields, while PVPs generate up to 90% less energy on overcast days [33] and their efficiency is reduced by dust and humidity as well [34]. In a scenario where power generation and agricultural yield are negatively correlated, revenues from power generation would increase during a year when agricultural revenues fell, offsetting a drop in revenues.

Any two activities with uncorrelated (or negatively correlated) net revenues can be combined in a manner that increases financial stability and reduces risk [35,36], yet the potential lack of correlation between solar power production and agriculture has not been studied in an agrivoltaic context. The degree to which such an effect is evident is partially dependent on the characteristics of the crops grown under the PVPs, including crop shade tolerance and value. Existing experimental AVS plots have been restricted to a limited set of crops – such as lettuce [16,37,38], corn [39], cucumbers [16,18], tomatoes [22], wheat [16], and peppers [22] – and exclusively identify changes in plant physiology. The few studies that begin to assess financial benefits do not consider the additional effect of reducing financial risk, in terms of diversifying revenues or lifting worst case net revenues, nor isolate weather-related risk.

This analysis seeks to fill this gap and address several related questions, using two different regions (North Carolina and Oregon) and three crops (alfalfa, soybeans, and strawberries) to compare the profitability and risk mitigation potential of AVS, with an additional comparison of the latter vis-à-vis federal crop insurance. A stochastic weather generation model paired with models of PVP power production and growth probabilistically characterizes annual net revenues and financial risk. Results provide insights into how AVS can stabilize net revenues of a land parcel while also improving overall profitability, as well as broader lessons on interactions between food-energy systems.

2. Methods

Initially, a general framework is developed to analyze various crop and location combinations, which is then used to conduct more detailed investigation via four case studies. Locations for the model farms are chosen for their contrasting regulatory environments and insolation levels. North Carolina (NC) has been a leading state in solar power development,

largely due to a friendly regulatory environment, incentives [40], and high insolation, while in Oregon's (OR) agricultural hub, the Willamette River Basin, there is less solar potential and a new regulation restricting solar installations based on soil quality [41]. In addition, electricity generation in OR is heavily weather dependent, due to its reliance on hydropower. Crops were similarly chosen based on their prevalence, profitability and for their potential to contrast different crop values and shade tolerance (See Supplemental Information (SI) Section A.1 for further information). The analysis takes the perspective of a land owning farmer seeking to increase net revenues, without attempting to maximize the net revenues or to optimize the AVS layout. The hypothetical farm size for each case study is 218 acres, the approximate area of a 50 megawatt (MW) solar farm. This size is used to capture economies of scale in capital costs [42]. It is also a farm size between the US average of 434 acres, and a county average for the locations chosen, about 110 acres [43].

The Methods section elaborates on the models used to stochastically simulate weather conditions, which are then used as inputs into the solar energy generation and crop yield models (see Figure 2 for a visual representation of the methodology). It ends with a detailed examination of the financial model. All data used in this study are publicly available. Daily weather data collected between 1950 and 2018 were obtained from the National Oceanic and Atmospheric Administration's (NOAA) Global Historical Climatological Network [44], with the exception of irradiance and "clear sky" data, which were collected from the National Renewable Energy Laboratory's (NREL) National Solar Irradiation Database [45]. Crop yield and price data were taken from the US Department of Agriculture's (USDA) National Agriculture Statistics Service (NASS) [43]. Natural gas price data were taken from the Energy Information Administration, from 2008 onwards [46].

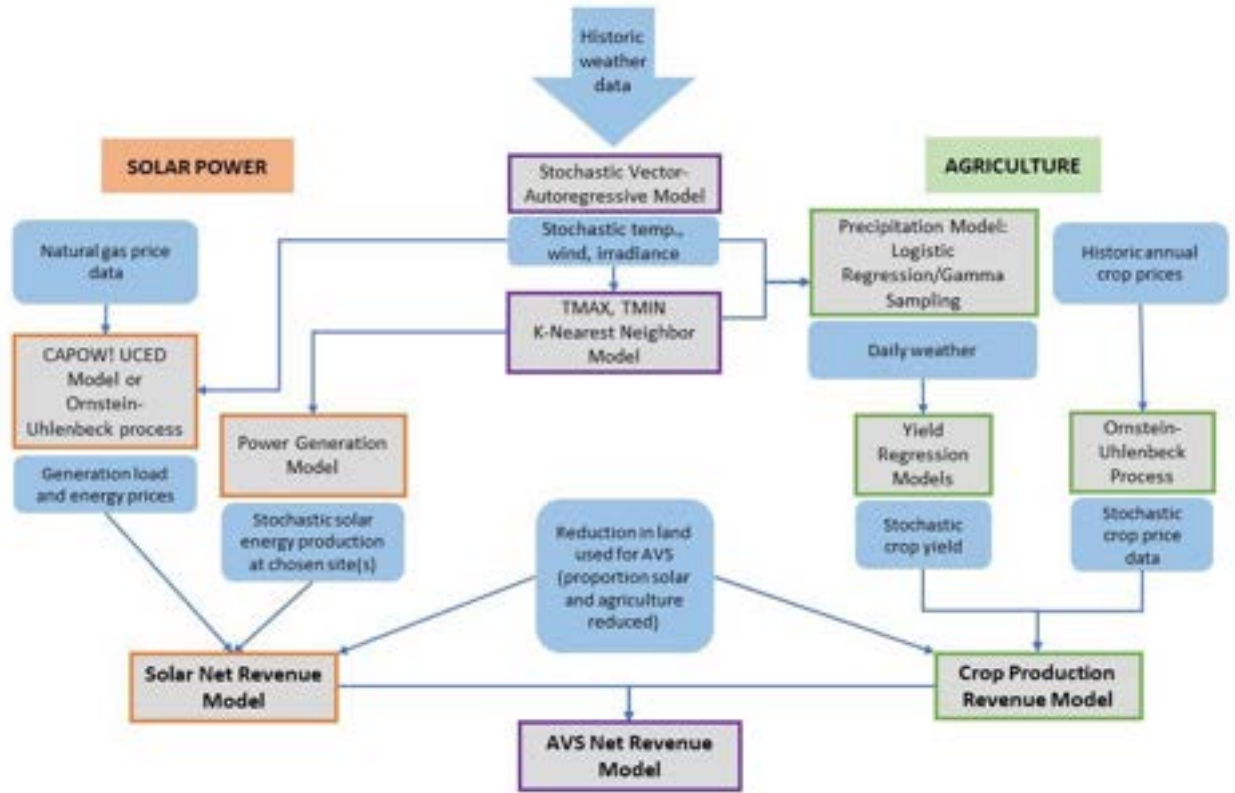


Figure 2. Flow diagram of component models used to generate stochastic inputs to net revenue models for a solar only, farm only, and AVS plot. Blue boxes represent inputs while orange boxes represent models used for the solar power components, green boxes represent models used for the agricultural production components, and purple boxes represent models used for the AVS components.

2.1 Hydrometereological Variables

2.1.1 Temperature, Irradiance, Wind Speeds

A vector auto-regressive (VAR) model is used to simulate average temperature (TAVG), average wind speed (AWND), and irradiance (GHI) for all locations and crops. For OR weather, this study utilizes the existing CAPOW systems model [47], which includes a VAR model to stochastically generate weather conditions, which are then used to simulate energy prices across the West Coast, including the Mid-Columbia market spanning much of the US Pacific Northwest. The stochastic generator in CAPOW simultaneously generates weather timeseries for sites across the West Coast (See SI, Table A.2) which contribute to electricity demand and

generation. Use of the VAR model accounts for both the statistical moments of the historical data and spatial and temporal auto- and cross-correlations between different weather variables and sites. In NC, the same VAR model is applied to a single location.

Daily data for TAVG, AWND, and GHI, jointly available from 1998 to 2017, are used to create daily profiles of statistical moments for each variable. Seasonal patterns are removed from observations, leaving a residual, which is mean-shifted and log-transformed to approximate a Gaussian distribution. As irradiance does not follow a standard distribution, the difference between the mean “clear sky” for a given month and the actual irradiation (“cloud cover”), is used in its stead [48]. The VAR model generates a synthetic record of auto-correlated “whitened” residuals for TAVG, AWND, and GHI. The final value is a combination of the whitened residual and a random error sampled from a multivariate Gaussian distribution. Residuals are then back-transformed, incorporating seasonal patterns.

The correlations between the historical and simulated mean weather conditions on a monthly basis are very high, as indicated in Figure 3. In both NC and OR, the agreement between historical and simulated statistical moments across all weather variables modelled, is very good ($r^2 = 0.98-0.99$). See SI, Figure A.1 for additional validation.

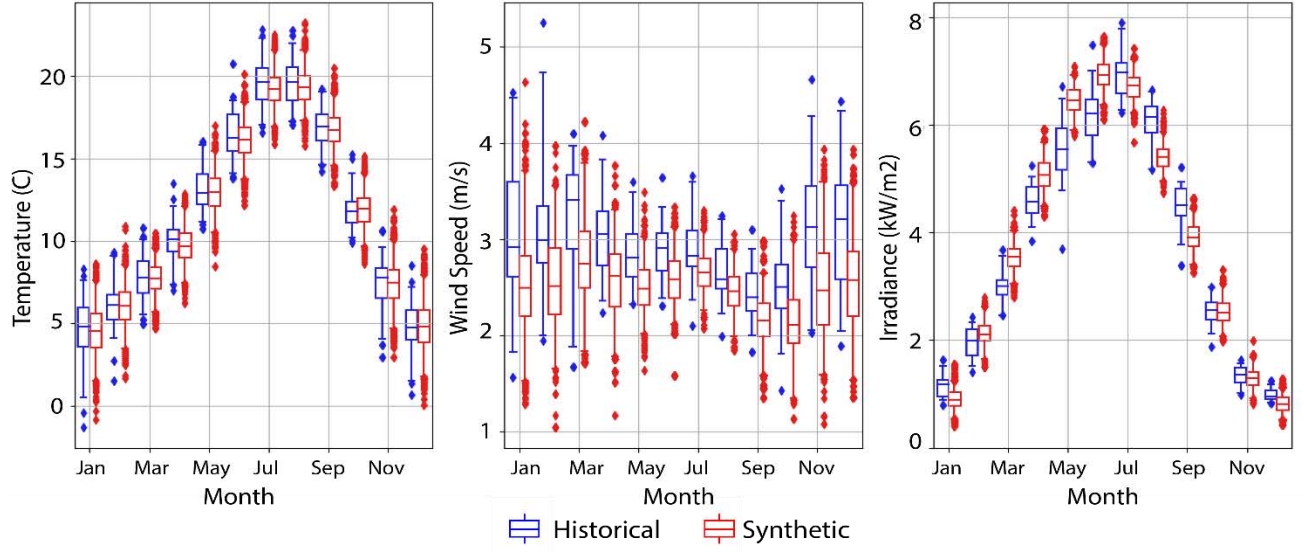


Figure 3: Temperature (left), wind speed (middle), and irradiance (right) validation for OR. Whiskers show range between 2nd and 98th percentile, and the box shows the 25th, 50th, and 75th percentiles.

2.1.2 Maximum/Minimum Temperature

Maximum and minimum temperatures (TMAX/TMIN) are predicted using the K-Nearest Neighbor (K-NN) resampling method as presented by Rajagopalan and Lall [49]. Neighbors are identified using the weighted Euclidean distance [49] to the detrended residuals of TAVG, AWND, and GHI. Trained and validated on the historical dataset, the model is applied to the synthetically generated residuals to produce synthetic TMAX/TMIN residuals which are “re-trended” using daily statistical profiles. Synthetic daily temperatures closely match observations ($r^2 = 0.92$ for TMAX and 0.91 for TMIN), as seen in Figures 4 and 5.

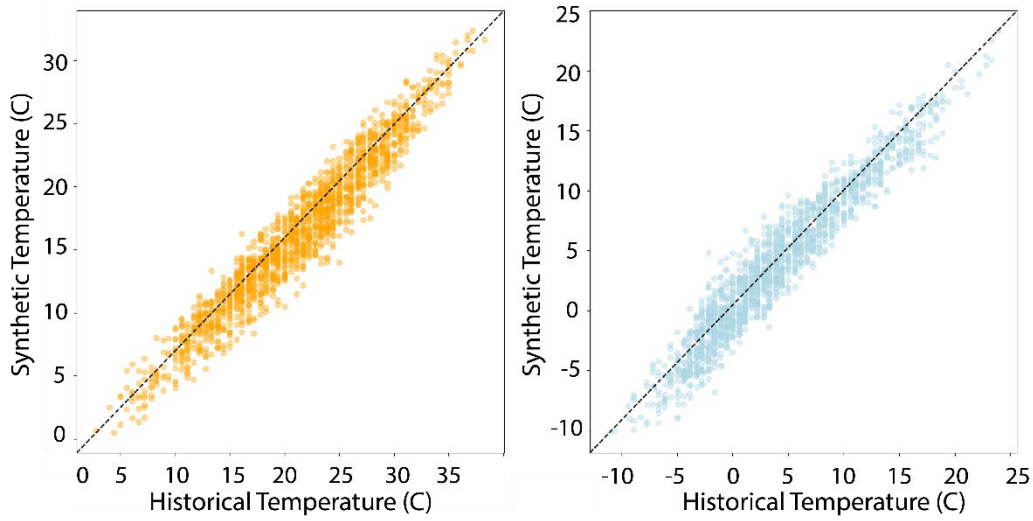


Figure 4: Maximum (left) and minimum (right) temperature model

2.1.3 Precipitation Modelling

Precipitation is typically simulated using a Markov Chain to predict the occurrence of precipitation [50,51], followed by randomly sampling a distribution fitted to historical precipitation amounts, often a gamma or exponential distribution [52,53]. Adding a third state to account for extreme precipitation (i.e. “dry”, “wet”, “very wet”) can more accurately reproduce extreme rainfall [54]. This study inverts the order of operations, as the CAPOW model synthetically generated TAVG, AWND, and GHI prior to precipitation, and identifies three states.

First, a binary logistic regression is used identify days with any level of precipitation based on TMAX, month, AWND, and cloud cover. The probability of transitioning to a wet or very wet state during a given month is then calculated (see SI, Table A.3), as in a traditional Markov Chain model [53], and used to classify days with precipitation as wet or very wet:

$$\text{If } P(S_t = w | S_{t-1}, M_t) > \text{random}(0,1), \text{ then } S_t = w \quad (1)$$

where S is the state at time t , M is the month and w is the “wet”, as opposed to “very wet”, state.

The amount of precipitation on a given day is assumed to be conditionally independent of the previous day's precipitation [50,53] and simulated by sampling a truncated gamma distribution fit to the historical data for each month. Precipitation moments aggregated at the monthly time step show substantial agreement with the historical moments ($r^2=0.92$), as can be seen in Figure 5.

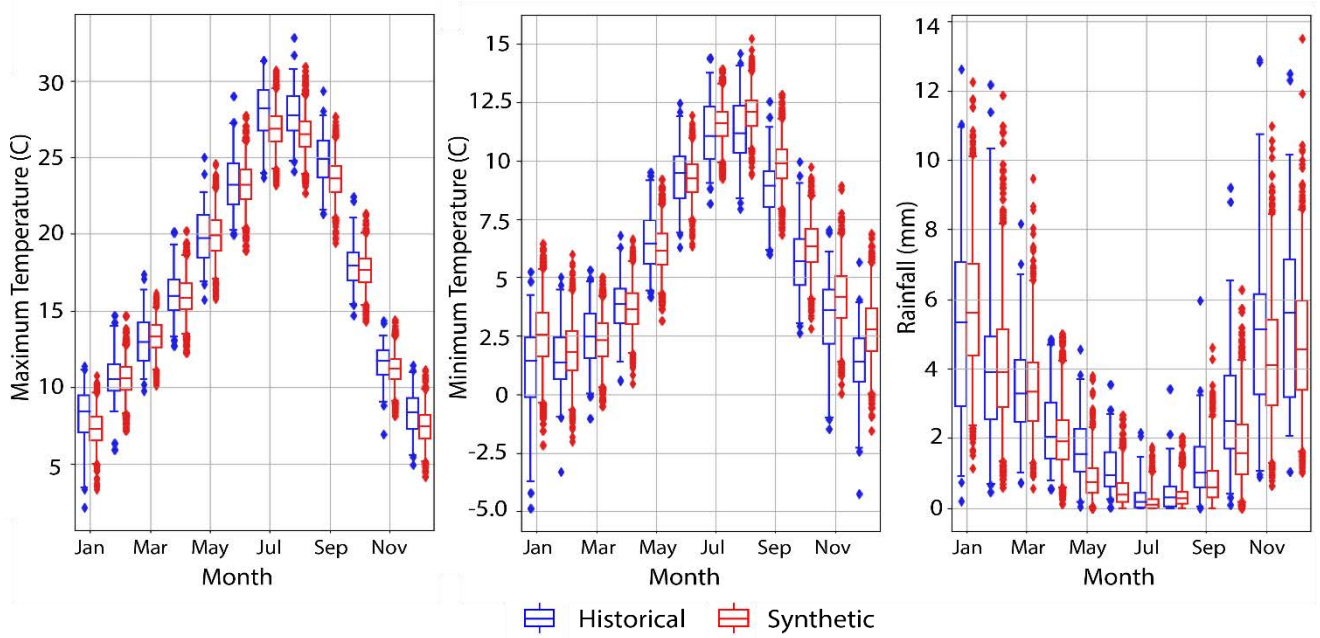


Figure 5: Maximum temperature (left), minimum temperature (middle), and precipitation amount (right) validation for OR. Whiskers show range between 2nd and 98th percentile, and the box shows the 25th, 50th, and 75th percentiles.

2.2 Solar Power Generation Model

Solar power generation is simulated via a thermodynamic model using GHI, TAVG, AWND, and dew point [7] to predict panel efficiency. Generation is the product of efficiency, irradiation, and degradation, an erosion of the physical integrity of the panels that reduces performance by 0.7% annually [55]. Overall average efficiency of a new panel in the simulation is approximately 14%, in line with the model validation on a test site in Oregon from Adeh et al. [21].

The analysis assumes that power production in the AVS is proportionate to the amount of land covered by panels (see SI, Figure A.2 for original spacing). Spacing that allows machinery to pass between rows is assumed to reduce acreage available for PVPs by 25% relative to a farm only situation for alfalfa and soybeans, while it remains constant for the strawberry scenarios. Although research suggests that changes in the microclimate in AVS might slightly positively impact panel efficiencies [22], an exploratory analysis modifying temperatures in the simulated data for the selected locations did not yield noticeable improvements in power production.

2.3 Crop Yield Model

This analysis uses statistical models, which can be generalized to any location and crop and which more accurately reflected historical yields than crop models, to simulate crop yields using local weather conditions. Yields, prices, and weather conditions are assumed to be stationary over all simulations to evaluate the impact of co-location with solar energy generation under historical conditions. Alfalfa demonstrated non-stationary yields, likely due to changes in field management and technology, so historical observations were detrended following the approach used in the literature [56,57] in order to better isolate the relationship between weather variables and annual yields.

Results of crop regression models (see Table 1 below and section A.2.3 in SI) suggest that modelling accuracy is similar to previous studies, which achieve adjusted r^2 values of 0.47-0.96 [56,58]. The addition of an error term, randomly sampled from a Gaussian distribution parameterized with the regression residuals, enables the model to capture the mean crop yield in addition to lower minimums and higher maximums in the synthetic timeseries. Data resolution limited accuracy for the strawberry and soybean models, as yield data was statewide instead of

site specific and aggregated irrigated and non-irrigated yields, which may have reduced the impact of precipitation on yields.

Table 1: Crop yield regression models. 80% of the full dataset was used to train the model, with the remaining 20% used as the validation set. Units of common measurement for each crop are used. For alfalfa, only historical data after 1998 was used in order to consider the influence of irradiance, for which data was only available from 1998.

Crop	Explanatory variables	Test Set Adjusted R^2	Full Set Adjusted R^2	RMSE as percentage of mean yield	Historical Data points
Soybeans (NC)	August/September mean TMAX, summer mean TMAX	.84	.69	11.4%	21
Strawberries (NC)	May/June GHI, February/March TAVG	.63	.47	6%	23
Alfalfa (OR)	August/September mean AWND, October/November 1 period lag precipitation, February/March TMIN	.82	.57	4.7%	17
Strawberries (OR)	Season TAVG, February/March cloud cover	.82	.68	7.2%	20

Previous research suggests that changes in microclimate under AVS can improve crop yields [17,21,22], although when sunlight is the limiting factor for plant growth this may not be the case. Potential changes in the crops considered in this work have not been studied, so yield changes due to variability in microclimate are not considered.

Of the crops considered, only strawberries can be grown directly beneath PVPs without significant changes to panel design. The AVS layout used, however, assumes no strawberries grown underneath the panels, as research largely indicates that yields decrease under full shade conditions [59,60]. This results in a reduction of 33% of yield. In the case of alfalfa and

soybeans, harvesting equipment tends to be at least 3 meters wide [61,62], so both crops are considered planted in 4 meter rows, and this results in a 50% reduction in planted acreage.

2.4 Price Models

2.4.1 Electricity Price Models

Two electricity price models are utilized, including (i) an integrated unit commitment/economic dispatch model of the Mid-Columbia electricity market, which includes Oregon and is a sub-system within the broader CAPOW model and; (ii) a stochastic price simulation via the Ornstein-Uhlenbeck (OU) process for NC, where no detailed electric power systems model has been developed.

Approximately half of the Pacific Northwest's electricity supply and generation capacity comes from hydropower [63], which is heavily influenced by precipitation and streamflow, with hydrologic conditions having a strong influence on electricity prices. Low hydropower generation periods often correlate with periods of high energy demand (summer droughts), causing price spikes. The CAPOW model uses weather conditions across the linked electricity markets of the West Coast (which includes both the mid-Columbian and California Independent System Operator (CAISO) markets) to predict electricity prices based on the marginal cost of generation. Validation efforts suggest CAPOW has the ability to accurately simulate prices ($r^2=0.75$) [47].

With respect to modelling electricity price in NC, the mean-reverting, OU process is often used to model commodity price fluctuations under conditions of stationarity [64,65]. In NC, natural gas prices largely determine electricity prices [66,67], making the OU process suitable for stochastically simulating prices. Although NC access point (Citygate) prices are only available at the monthly time step, the relationship between prices at the Henry Hub, a primary

US natural gas hub with a lengthy historical record of daily prices, and Citygate is strong ($r^2=0.86$) and is used to predict historical daily Citygate prices. The OU process is parameterized using historical daily prices post-2008, as the price regime for natural gas changed in 2008 with the advent of hydraulic fracturing [68].

Electricity prices in OR are typically lower than those in NC [69], thanks to abundant, low cost hydropower. The synthetic dataset reflects this, with average prices of \$21.61 and \$38.57 per megawatt-hour (MWh) in the Mid-Columbia market and NC, respectively.

2.4.2 Crop Price Model

Synthetic crop prices are also generated using the OU model. Historical crop prices from the USDA NASS are adjusted to 2015 dollars using the Bureau of Labor Statistics' Producer Price Index for individual crops [70]. Strawberry prices exhibit an increasing trend throughout the historical timeseries and were thus detrended to produce a stationary distribution. The distribution of historical and synthetic soybean prices is shown in Figure 6 below and suggests good agreement. For a comparison of the range of historical and synthetic data for other crops, see SI, Table A.5.

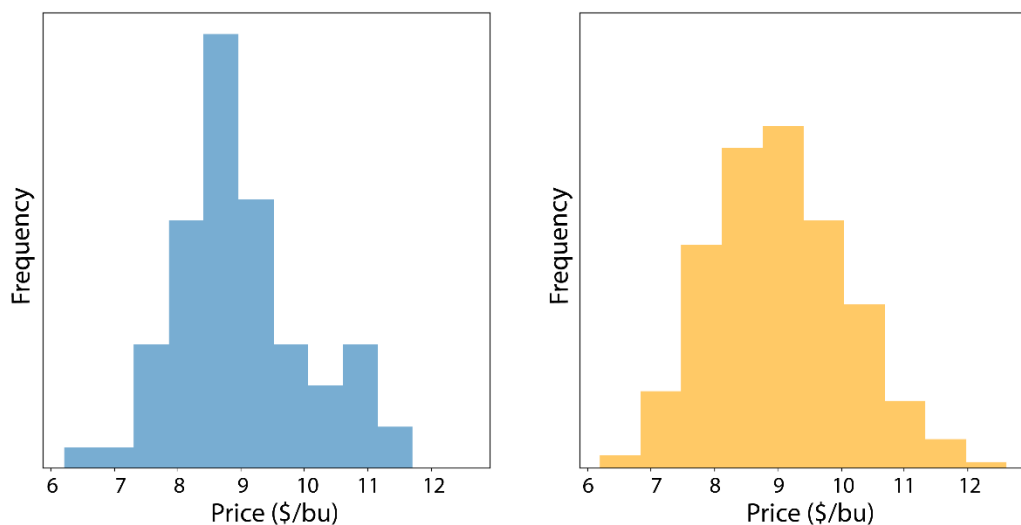


Figure 6: Comparison of distribution of historical (left) and synthetic (right) soybean prices (NC).

2.5 Financial Model

Annual net revenues, the primary metric used to compare the financial impact of AVS, are calculated as:

$$Net\ Revenues = Revenue - OPEX - CAPEX - Taxes \quad (2)$$

where *Revenue* is income from sales of crop yield or power generation; *OPEX* is operational expenditures; *CAPEX* is capital expenditures; and *Taxes* are based on a combined federal and state level taxes, as well as tax deductions and tax credits. Tax deductions are based on crop cost and are included for farm and AVS net revenues, while tax credits in the form of the Investment Tax Credit (ITC) are considered to be evenly distributed across the solar project's lifetime. The NPV of each solar investment over many 30-year ensembles is also calculated, using a 10% discount rate as in Ravi et al. [20]. No salvage value is assumed.

Given the capital cost of a 50 MW, utility-scale project (\$52-62.5 million), this analysis assumes that financing will include third parties, as in cases when a solar developer leases land [71] without landowner capital. However, the developer is presumed to operate the solar facilities for the landowner; the landowner is not paid a lease but instead owns the solar farm. While leasing is the typical ownership arrangement, considering a single owner for all revenue flows (farm or solar) allows this research to more clearly identify how financial risk from variable weather conditions changes with or without co-location.

2.5.1 Solar Power Business Models

Project financing can be split into three components: equity investment repaid in dividends (or other benefits), debt financing, and self-financing. Federal and local regulations have shaped these financing strategies; the ITC provided solar installation owners with a tax credit worth 30% of the initial installation value, although it is in process of being lowered to

10% in 2022. In addition, investments in solar installations are subject to Modified Accelerated Cost Recovery, which means that the full value of the installation is considered to depreciate within its first five years for tax purposes instead of throughout its lifetime. This increases profitability in the early years of an investment relative to a standard depreciation schedule by reducing taxable income.

Given the tax-related benefits involved in solar power projects, a common form of financing involves tax-equity [72]. In tax-equity financing, equity investors provide initial capital in exchange for tax credits or deductions, in addition to the typical project ownership and/or dividends, thereby “monetizing” the tax benefits which a developer may not have sufficient liability to use [73]. Many investors remain involved in the project only long enough to claim tax and depreciation benefits, five years, and are then bought out in a tax-equity flip [73]. Debt financing can involve a construction loan in addition to an operational loan in order to reduce interest rates, which are lower for a loan on an existing project. Self-investment by the developer, without interest rates or dividends, can also lower the cost of capital.

Financing is dependent on project risk though, which is often linked to the volatility of electricity prices. To combat this, most solar projects have hitherto included a long-term PPA that eliminates price risk by guaranteeing the purchase of energy at a fixed price for as long as 25-30 years. Federal and state level regulations have pushed utilities to buy renewable power, specifically through renewable energy standards, often implemented as state-level renewable portfolio standards, and the Public Utilities Regulatory Policies Act. The Public Utilities Regulatory Policies Act obligated utilities to purchase power from facilities up to a certain size – deemed “Qualifying Facilities” (QF) – for a minimum contract period and price. Prices for QFs are based on the “avoided cost” of generating replacement electricity. Today, many utilities have

met their requirements and QF contracts have become less favorable in terms of price and contract length [74]. PPAs have followed that trend, hitting lows of \$20/MWh (or less) from peaks of over \$100/MWh in 2011 [42,75]. In combination with the reduction of federal incentives like the ITC, this has resulted in slower growth in the solar power sector.

The solar market of today has changed significantly from that of just five years ago. Developers are seeking new business models, including signing PPAs directly with corporations, and exploring price hedging strategies other than PPAs such as proxy revenue swaps [75,76]. Insofar as AVS may provide a viable, alternative business model, they too may become more attractive to solar developers as a way to improve a solar installation's profitability.

2.5.2 Solar Net Revenues

Net revenues from solar generation are largely a function of electricity price, as GHI (irradiance) tends to be less volatile than prices at monthly or annual time scales. This leads to the choice of four price scenarios, including those with low and high installation costs:

- Wholesale Price Scenario, in which electricity is sold directly into the day ahead market, a scenario possible should PPAs fully fall out of favor with solar customers;
- PPA Schedule Scenario, based on public QF rates for OR and NC and a 15-year agreement, after which power generated is sold at wholesale prices and which illustrates the impact of changing price regimes;
- Low PPA Scenario, set to the average market price and lasting for the project lifetime, which evaluates profitability at the lower levels of PPAs being seen today for newer projects; and
- High PPA Scenario, set to the amount necessary for the probability of a positive annual net revenue to exceed 90%, lasting for the project lifetime. The High PPA represents historical

PPA prices, which are higher than average electricity rates in most places across the country.

While a 50 MW solar farm does not fall under the QF size, and utilities are therefore not obligated to purchase its energy at the QF rate, the price schedule is used to identify realistic prices that a developer might negotiate.

The project is assumed to be financed with a mixture of 50/50 debt and equity financing [20,77]. Equity investors are largely repaid through tax deductions but additionally receive dividends equal to 2.5% of any profits (revenues minus costs, including debt service and taxes) during the same time period. At year six, investors are paid a “buyback” equal to the value of 5% of their original investment, which combines with their tax credits to generate a favorable return, and at this point their involvement in the project ends.

The remainder of the value of the solar installation is paid for via debt with a lifetime of 30 years and an interest rate of 4.5%, consistent with national trends in project financing [42,55]. Net revenues for the solar and AVS plots are the total revenues after paying all expenses, taxes, debt service, and dividends. See Table 2 for a list of key financing parameters in the solar model and Section A.3 in SI for additional detail. As the sensitivity of a solar farm’s profitability to these financial and technical parameters is not the focus of this paper, these are assumed to be fixed. However, it is natural that increasing interest rates, de-accelerating depreciation, and increasing degradation rates would all have the effect of increasing the costs of the solar power system, thereby reducing its attractiveness. See Table A.6 in the SI for a comparison of the solar only and AVS plot net revenues using different interest rates.

Table 2: Key solar net revenue parameters.

Parameter	Values	Parameter	Values
Electricity Price	Wholesale market prices, qualifying facility PPA price schedule, low PPA, high PPA (\$/MWh)	Lifetime	30 years [78]
CAPEX (low / high)	\$1.25 / \$1.50 per watt-ac [42]	Degradation	0.7% annually [55]
OPEX	\$13/kilowatt-hour [55]	Salvage value	0% [78]
NC High PPA	\$69/MWh	NC low PPA	\$24/MWh
OR High PPA	\$81/MWh	OR low PPA	\$21/MWh
Investment Tax Credit	0%, 10%, 26% of installation cost	Tax-Equity Structure	Dividends of 2.5% of profits for the first five years, plus 5% buyback, and full value of accelerated depreciation
Debt interest rate	4.5% [55]	Federal/state taxes	28% of net revenues
		Type of panel	~70% of PVPs in use are fixed tilt [79], including PVPs thermodynamic model is calibrated with [7]

2.5.3 Federal Crop Insurance

An additional sub-scenario includes the purchase of federal crop insurance, one that is considered so as to explore the risk management potential of AVS compared to a traditional risk management tool. The Federal Crop Insurance Corporation, a body within the USDA, offers US farmers a number of crop insurance programs, ranging from crop specific (e.g., for soybeans or corn) to generic (e.g., Whole Farm Revenue Protection). On average, the government subsidizes 60% of the total insurance premium for any given program [80]. This analysis applies a general insurance program for which most farms are eligible, the Whole Farm Revenue Protection (WFRP) program [81], which insures the revenue of the entire farm operation, protecting against low prices and low yields. Losses are computed relative to a moving average of historical revenue. If revenues are lower than the coverage level, a payout is triggered, such that:

$$r_p = c * r_h \quad (3)$$

$$payout = (r_p - r_a), \text{ if } r_a < r_p \quad (4)$$

$$payout = 0, \text{ if } r_a > r_p$$

where the revenue protection level (r_p) is the product of the percentage of coverage (c) and the historical expected revenues (r_h). The payout, the difference between the revenue protection level and the actual revenue, is triggered when actual revenue (r_a) is lower than the protection level. Insurance premiums are based on the USDA Cost Estimator Tool, which provides county-level premium and subsidy information for a given year and location [82]. An average coverage of 70% is assumed, such that payouts are triggered when revenue falls below 70% of expected revenue, with both measured on a per acre basis. See Table 3 for historical revenues used to calculate premiums and coverage.

2.5.4 Farm Net Revenues

Farm net revenues are a function of planting/harvesting costs, crop prices, crop yields, and, in cases where insurance is considered, premiums and payouts. Planting/harvesting costs are based on costs listed in enterprise budgets for each crop, and have been adjusted to 2015 dollars using the Consumer Price Index [83] (see Table 3 for all parameters, including costs). Although costs may vary year-on-year and contribute an additional source of uncertainty for farmers, they are assumed to be constant, and it should be noted that up to 85% of annual farm costs are fixed and long-term [84]. Annual operating expenses also include taxes, which are lower for farms than other commercial activities and property types.

Table 3: Agricultural Assumptions. Prices adjusted to 2015 dollars.

Parameter	Value	Comment
Farm size	217.7 acres [85]	50 MW is the minimum size to capture economies of scale for solar, and occupies ~217 acres. Average farm size in the US is 444 acres, but in Marion County, OR and Wake County, NC, the average is 111 acres. Average farm size in OR is 434 acres, while in NC it is 181 acres.
OR alfalfa costs	\$220/acre [86]	Includes labor, fertilizer, insurance, repairs, less the assumed land lease, and non-cash costs
OR strawberry costs	\$13,052/acre [87]	Includes labor, fertilizer, insurance, repairs, less the assumed land lease, and non-cash costs
NC soybean costs	\$252/acre [88]	Includes labor, fertilizer, insurance, repairs, less the assumed land lease, and non-cash costs
NC strawberry costs	\$13,310/acre [89]	Includes labor, fertilizer, insurance, repairs, less the assumed land lease, U-Pick, row covers, and non-cash costs
Crop insurance coverage	70% of expected revenues [90]	Average insurance coverage level chosen by farmers in the US
Soybean insurance premium (NC)	\$25.60/acre [82]	Farmer paid premium to cover 70% of average historic soybean revenue
Soybean expected net revenue (NC)	\$65,650 [43]	Average of observed 2009-2014 revenues
Alfalfa insurance premium (OR)	\$19.32/acre [82]	Farmer paid premium to cover 70% of average historical alfalfa revenues
Alfalfa expected revenue (OR)	\$185,449 [43]	Average of observed 2009-2014 revenues
Federal tax rate (agriculture only)	16.8% [91]	
Property tax rate (NC)	\$0.72/\$100 of specially assessed property value [92,93]	Farm values are assessed using the “present use value” method
Property tax rate (OR)	0.0104% of specially assessed property value [94]	Farm values are assessed using the “present use value” method

2.5.5 AVS Net Revenues

In the AVS scenario, net revenues from the farm only and solar only scenarios combined based on the proportion of land which is planted and has panels installed:

$$NR_{AVS} = L_F * NR_F + L_S * NR_S \quad (5)$$

where the net revenue for an AVS (NR_{AVS}) is equal to the proportion of land that is planted (L_F) multiplied by the net revenues of the farm (NR_F) plus the proportion of land with solar panels (L_S) multiplied by the net revenues of the solar installation (NR_S). The costs of producing the crops and installing and operating the smaller area of PVPs are likewise reduced, as are tax deductions and tax credits. While some research suggests that there are synergies inherent to AVS, such as yield or generation increases or a reduction in costs associated with land preparation, or increases in costs due to modifications in existing operations or the PVP layout, this analysis excludes these differences because of a lack of data with which to make reasonable assumptions.

2.6 Limitations

This work intends to contribute to the small, but growing, body of research on AVS by developing a framework for assessing how co-locating solar and agricultural production might reduce revenue variability related to extreme weather. In its specifics, however, it does face limitations. First, lack of access to data on crop behavior in each specific location, specifically in scenarios involving AVS, prevented accounting for the full benefits of AVS (e.g., favorable microclimate changes, changes in plant physiology). This research also assumes no crops are grown directly underneath PVPs, which might be beneficial in some cases, and thus potentially underestimates AVS benefits by reducing the planted area on any farm with AVS. Finally, this work does not account for the necessary trust between the two parties, farmer and solar

developer, crucial to the success of an AVS, Although the trust that each will not interfere in the other's operations cannot be modelled, it is a legitimate concern. For example, solar operators may prefer crops that are manually harvested without bulky equipment and farmers may avoid planting lucrative, but sensitive, crops in an AVS.

3. Results

The Results section only describes scenarios involving “low” costs of installation for solar energy facilities, as high cost scenarios were shown to be unprofitable in all cases. The four crop/location combinations considered are soybeans and strawberries in NC, as well as alfalfa and strawberries in OR. Finally, the NC soybean and OR alfalfa scenarios are also considered for cases involving federal crop insurance.

3.1 Profitability Analysis

In scenarios involving farm only and AVS, returns are very crop dependent; high-value crops like strawberries are much more profitable than alfalfa or soybeans but exhibit higher volatility in terms of net revenues. In AVS scenarios with PPAs, electricity revenues are very stable and it is crop net revenues that drive changes in profitability and variability. Strawberries present opportunities for extremely profitable years when weather conditions and crop prices are favorable, but with a corresponding potential for large negative net revenues when conditions are less favorable. Alfalfa net revenues are consistently positive, but low; the maximum is \$950/acre, quite small when compared to the maximum of OR strawberries, about \$18,043/acre.

As for solar only, in the price scenarios considered, PVP development is only profitable with low installation costs and a long-term, high price PPA (see Figure 7). A scenario with a 15-year PPA schedule using QF rates is profitable during the 15 years with the fixed prices, but revenues become very negative when electricity is sold on the wholesale market over the

remaining 15 years of the project's assumed 30-year lifetime. This analysis assumes that a solar project would only be built if it were projected to be profitable, thus this analysis hereafter only addresses the impact of adopting AVS with a high price, long term PPA.



Figure 7: Distribution of net revenues across NC, low-cost solar scenarios. Only low-cost scenarios with a 26% ITC are shown. Those with a lower ITC and higher costs have very negative net revenues. These values include both annual degradation and the equity buyback in year six

Figure 7 also highlights the shape of the distribution of solar power net revenues. Physical degradation of the PVPs ultimately reduces generation capacity by approximately 20% of original capacity by year 30, and the equity buyback predictably reduces negative net revenues in year six. This buyback gives rise to a second, smaller, and more negative peak in the distribution of net revenues for each scenario. In the 15-year PPA scenario, there are three distinct peaks: the most positive one representing the distribution of net revenues under the first 15 years with a PPA, the middle peak representing the remaining years of the panels' lifetime selling power at market prices, and the most negative, and smallest, peak representing the equity buyback. Without these factors, the overall distribution of solar net revenues is relatively narrow

and depends on the size of the PPA. As net revenues more than double in the high PPA scenario, the variability is correspondingly larger; one standard deviation of net revenues in the NC, low PPA scenario is \$276/acre, while in the NC, high PPA scenario it is \$493/acre (without degradation or buyback).

3.2 Scenario Comparisons

All AVS combinations result in an increase in expected annual net revenues compared to a farm only scenario, as solar net revenues are significantly higher than farm only net revenues for each crop. The additional effects of AVS depend on whether a crop has relatively stable prices and the magnitude of price volatility. Figure 8 illustrates the differences in the distributions of net revenues for each combination of crop, solar installation and location, at different points in the solar installation's lifetime to highlight the impact of panel degradation.

Soybeans exhibit an extraordinarily narrow net revenue distribution compared to solar only net revenues, largely due to low prices and yields in absolute terms as well as a low price volatility, measured as the coefficient of variation. When paired with AVS, a farm growing soybeans finds that expected net revenues increase from -\$26/acre to \$1,281/acre, although the distribution of net revenues widens, translating to increased variability. Particularly in later years, when PVP performance degrades, there is a greater potential for negative net revenues. Similarly, total net revenues in the alfalfa case increase from \$383/acre for the farm only to \$1,580/acre for the AVS, although co-location results in some negative net revenue years as the panels degrade and accounting for the large equity buyback.

On the other hand, strawberries are lucrative, but financially volatile, primarily due to price fluctuations. In both NC and OR, adding PVPs to a strawberry farm raises expected net revenues and reduces the variability thereof, providing revenue support and some measure of risk

management. Although strawberry farms can have net revenues up to \$18,043/acre, they can face very large negative net revenues as a result of poor growth and market conditions, paired with high planting costs. Even as an AVS mitigates the risk of negative net revenues, it also results in higher expected net revenues which increase from \$656/acre to \$2,162/acre in NC and from \$149/acre to \$1,884/acre in OR.

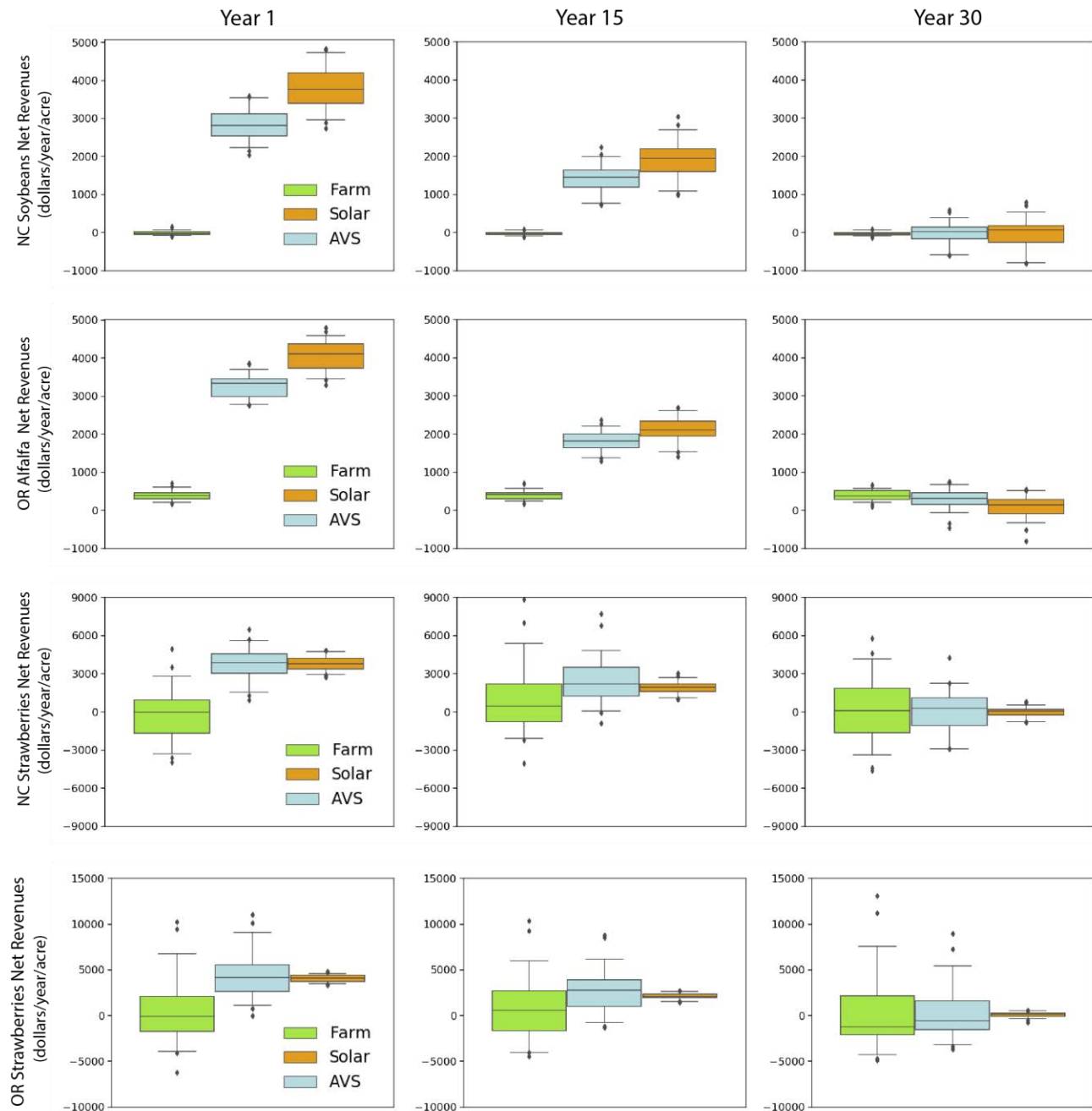


Figure 8: Boxplot comparing quartiles of annual net revenues across crops and scenarios. Distributions of net revenues are shown on a per acre basis for year 1 (left column), year 15 (middle column), and year 30 (right column) for soybeans (top row), alfalfa (second row), NC strawberries (third row), and OR strawberries (fourth row). Solar and AVS scenarios assume a high PPA, low cost, and the 26% ITC. Whiskers extend to the 5th and 95th percentiles, and boxes show the 25th, 50th, and 75th percentiles.

While this analysis has largely focused on a farmer choosing to invest in PVPs, a solar developer may benefit from investing in AVS with high-value crops that do not reduce the number of panels, such as leaf lettuce. The addition of such a crop can increase expected net revenues, as in the case of NC strawberries (Figure 8), for which adding the crop to a solar only investment to create an AVS increases annual expected net revenues from \$1,726/acre to \$2,162/acre while reducing net revenue variability.

The impact of adding solar to a pure farm varies by crop as well as by year, with a negative impact on net revenues during the latter part of the solar investment's lifetime due to panel degradation. Solar net revenues, and therefore the contribution of the solar installation to the AVS net revenues, are highest in year one and progressively fall as the solar panels degrade. By the end of the project lifetime, the solar plots are earning as much or less than their farm only counterparts. Without degradation, the only major source of variability in the solar PPA scenario is irradiance, which is relatively stable at an annual time scale; excluding panel degradation and the buyback, one standard deviation in solar net revenues is only \$493/acre in NC and \$379/acre in OR (one standard deviation rises to \$1,474/acre and \$1,453/acre, respectively, including degradation and buyback). A standard deviation for strawberry net revenues is much larger: \$2,497/acre in NC and \$3,414/acre in OR. However, one standard deviation for low-value soybeans and alfalfa is low relative to solar: \$48 and \$127/acre, respectively.

While annual net revenues are of significant interest, so is the total value of investment, and a comparison of the annual and cumulative net present value in each scenario provides a more holistic understanding of the profitability of each scenario over time throughout the 30 year investment horizon. Figure 9 depicts the annual and cumulative NPVs of OR scenarios. Strawberries (top panel) exhibit a higher annual NPV in AVS than in the farm only or solar only

scenarios in almost all runs. These values represent averages for each year of the planning cycle (calculated from forty 30 year ensembles), and while the trajectories are mostly smooth, in some years, a large negative outlier (e.g., for year “three”) or combination of low value years skews the average annual NPV a noticeable amount. This inconsistency is relatively small and can be attributed to the volatility of strawberry net revenues. The alfalfa scenario (lower panel), exhibits much less variability, while also describing the solar only plot as the most profitable. The very narrow, but positive distribution of alfalfa net revenues is such that the alfalfa NPV is higher than the strawberry NPV.

The NPV is calculated using a discount rate of 10%, consistent with a private sector venture, and this significantly lowers the NPV in the latter years of the investment cycle for all three scenarios (farm only, solar only and AVS). This rate provides a conservative estimate of the lifetime benefits of solar and AVS installations, which have high initial capital costs. In the case of infrastructure projects that benefit future generations, some governments use lower discount rates or declining rate schedules to account for the long-term value of projects [96]. These same considerations can apply to the AVS; a less conservative discount rate of 7% adds \$1-\$1.2 million to the cumulative NPV of an AVS in OR (\$4,630-\$5,622/acre over the project lifetime), and a discount rate of 4% adds \$2.5-\$3 million (\$11,566-\$13,970/acre). The range of discount ranges from 4-10% all yield positive NPVs.

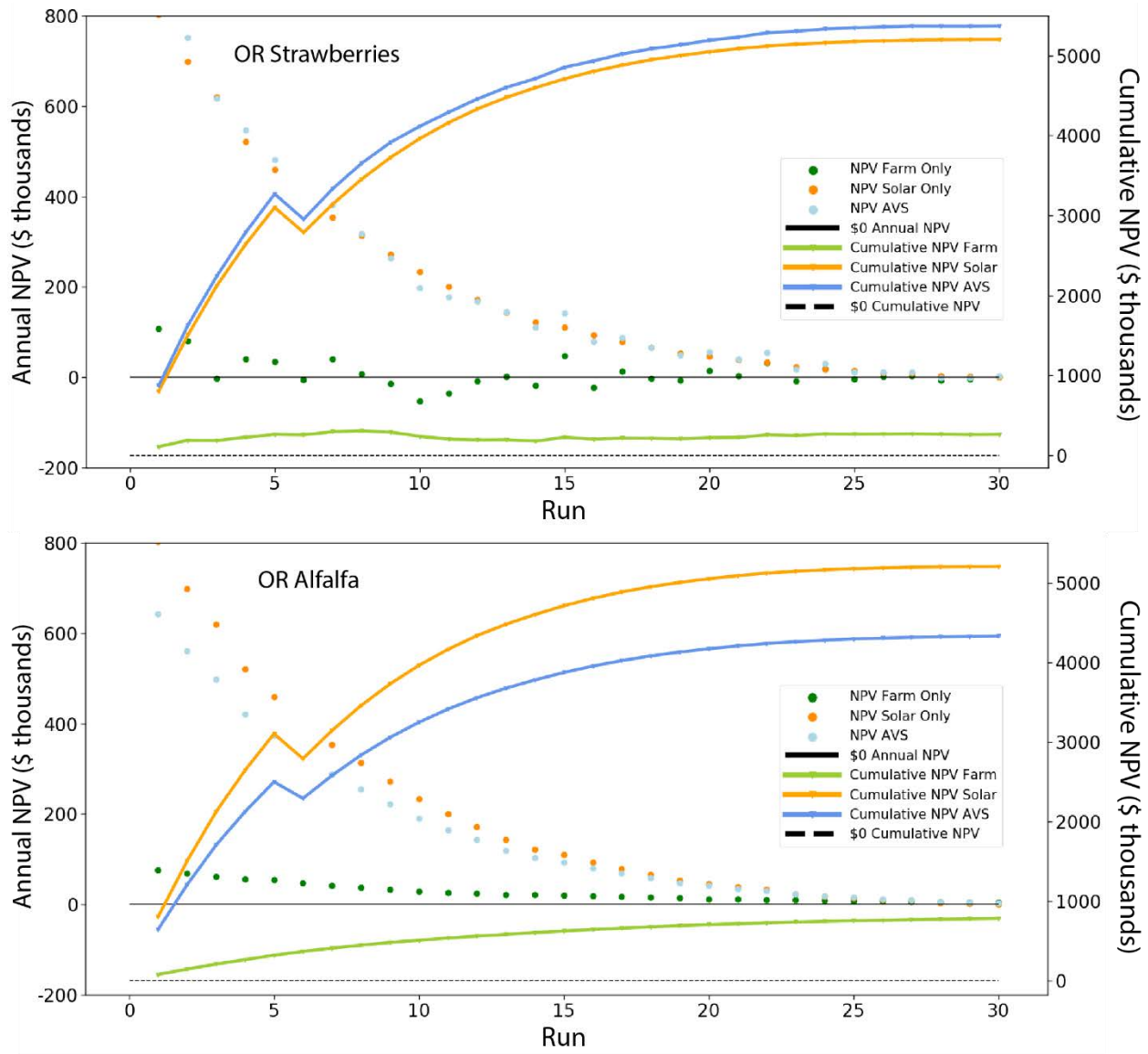


Figure 9: Comparison of solar, farm, and AVS NPVs for OR strawberries (top) and OR alfalfa (bottom). Annual NPV (left axis) is shown with points while lifetime (cumulative) NPV is shown with lines (right axis), both calculated with a 10% discount rate.

3.3 Financial Risk

Results suggest that in addition to improving profitability relative to a farm only scenario, AVS may additionally provide risk management benefits to landowners, measured by the ability to increase the lowest 5th percentile of net revenues (lower whiskers on Figure 8). In the initial years of its installation, AVS increases the 5th percentile of net revenues relative to the farm only

scenario for all crops, although for soybeans and alfalfa this effect does not hold for the lifetime of the AVS. For NC and OR strawberries, however, AVS improves the lifetime 5th percentile of net revenues by \$1,642/acre (53%) and \$2,237 (48%), respectively, including the buyback. Conversely, AVS with a low-value crop improves the 5th percentile of net revenues compared to the solar only plot by \$81/acre (24%) with NC soybeans and \$206/acre (192%) with OR alfalfa, suggesting that AVS might also have risk mitigation benefits when the solar developer is the landowner.

From the perspective of a farming landowner with a highly profitable, but highly financially volatile (in prices and yields), crop, AVS stabilizes net revenues. In cases of low-value crops (soybeans and alfalfa), AVS may make net revenues more variable relative to a farm only scenario. Nonetheless, when viewed from the perspective of a solar energy developer, AVS could provide a risk management function when compared to a solar only scenario, one that many developers are likely to pursue, and the option to grow a relatively stable, low lying and low maintenance crop could have advantages in some settings. These might include the reduced volatility of net revenues, as well as a way to defuse concerns by local communities and state regulators regarding land use competition. The absence of a correlation between farm only and solar only plots underpins these impacts, suggesting that the activities' net revenues can offset each other. This is a more important effect when the magnitude of farm only and solar only net revenues are similar. Annual net revenues for the solar only and farm only scenarios are essentially uncorrelated ($r = -0.03$ to 0.04) considering the crops selected for this analysis, but correlation between electricity and agricultural output may be much higher (or lower) if crops that depend on high levels of sunlight are chosen compared to those that prefer shaded conditions.

3.4 Risk Management Potential of AVS vs Federal Crop Insurance

Financial outcomes with USDA's Whole Farm Revenue Protection, which covers total farm revenues, are considered for the farm only ("Insured Farm") and AVS ("Insured AVS") scenarios with soybeans and alfalfa, with these values then compared in terms of risk management potential against the uninsured scenarios. Insurance premiums for strawberries are quite high, as determined through the USDA Risk Management Agency's Cost Estimator Tool, and for the two locations explored here, it was deemed unlikely that farmers would purchase these contracts.

Crop insurance through the WFRP program would be anticipated to raise expected crop net revenues relative to uninsured farm only scenarios, largely due to the premium subsidy from the federal government. So, while it is not surprising that results indicate that the insured farms have higher expected net revenues than non-insured farms (see Figure 10), it is interesting to note that the non-insured AVS plots have substantially higher expected net revenues than even the insured farms as a result of the profitability of solar generation. Purchasing insurance for an AVS parcel has the same effect as purchasing insurance for the farm only parcel, but scaled down to account for the reduction in planted area. The ultimate impact of insuring crop yield in an AVS is negligible, as adding solar power generation to a farm already raises expected net revenues far more than insurance without the annual premium costs.

Two metrics are used to evaluate the impact of crop insurance on reducing financial risk: the 5th percentile of net revenues and the coefficient of variation for net revenues. For alfalfa, insurance raises the 5th percentile of net revenues from \$201/acre without insurance to \$332/acre. For soybeans, this effect is larger, raising the 5th percentile of net revenues from -\$97/acre without insurance to \$24/acre. These improvements are negligible compared to those in a typical

first year with AVS: the 5th percentile increases to \$2,824/acre (a \$2,623 per acre improvement) for OR alfalfa and to \$2,375/acre (a \$2,473 per acre improvement) for NC soybeans. This effect shrinks with annual degradation (excluding the buyback): the 5th percentile of net revenues from the farm only scenario to the AVS scenario increase by \$87/acre (43%) for OR alfalfa and by \$77/acre (79%) for NC soybeans.

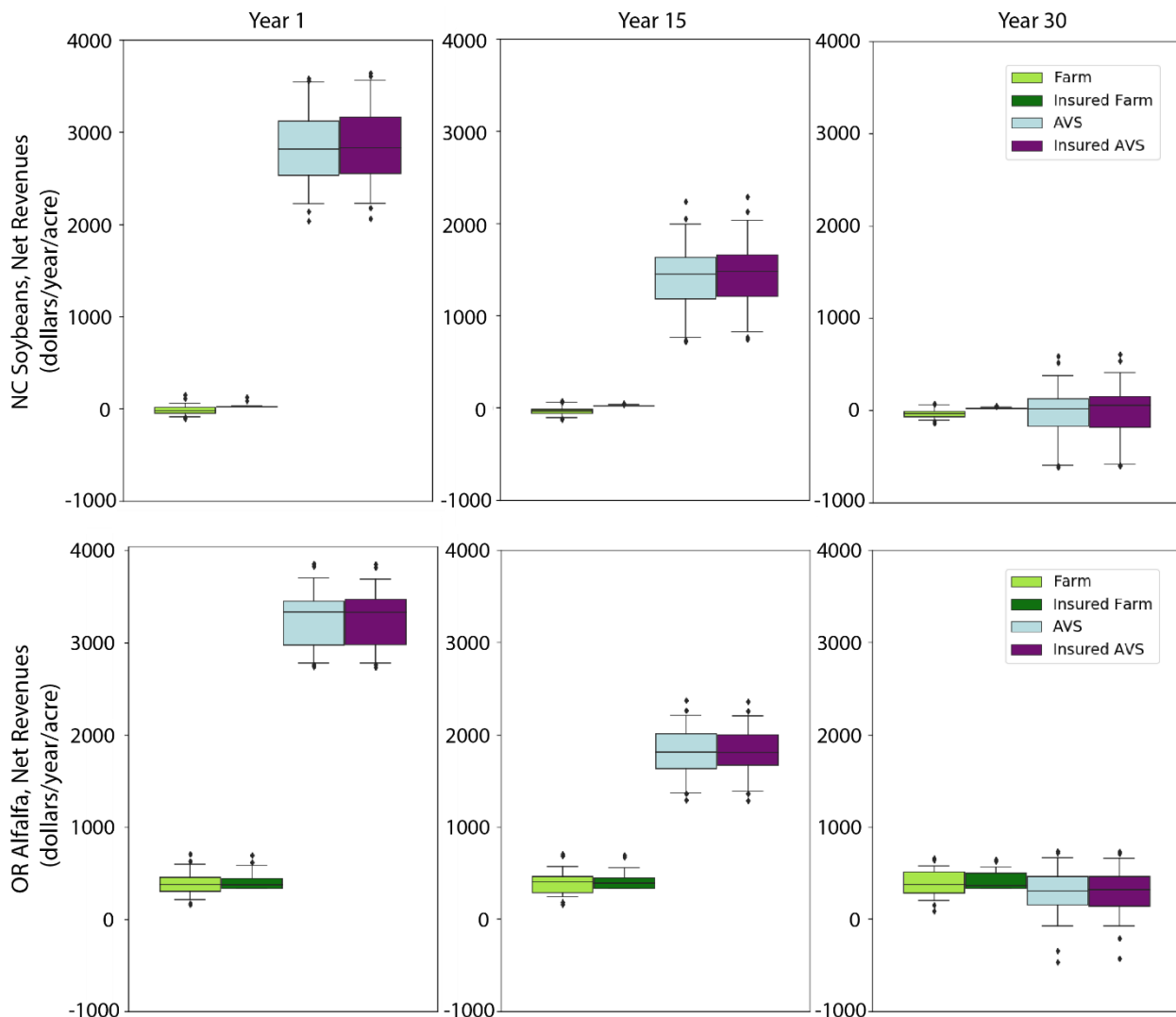


Figure 10: Comparison of annual net revenues with and without federal crop insurance. Expected net revenues are shown on a per acre basis for year 1 (left column), year 15 (middle column), and year 30 (right column) for soybeans (top row) and alfalfa (bottom row). “Insured” scenarios include Whole Farm Revenue Protection.

Revenue variability in absolute terms increases in AVS, but the coefficient of variation falls in certain AVS scenarios, depending on the crop. Insurance is more effective than AVS at reducing variability in net revenues across the case studies, but in the case of soybeans relative variability falls between the farm only scenario and the AVS scenario (see Table 4).

Table 4: Coefficients of variation of non-insured and insured scenarios.

	Farm	Insured Farm	AVS	Insured AVS
Soybeans	1.82	0.36	0.86	0.85
Alfalfa	0.33	0.24	0.69	0.68

Premium prices play a significant role in determining the value of insurance. In none of the scenarios examined here do farmers pay the full premiums charged by insurers, as the federal government subsidizes approximately 60% of the premium (\$36.80/acre for soybeans and \$26.28/acre for alfalfa in this analysis). The increases in expected annual net revenues with and without insurance is significant: \$52/acre for soybeans and \$38/acre for alfalfa where the original expected annual net revenues are -\$26/acre and \$383/acre, respectively. This means that farmers are benefitting more from insurance than they are paying for the service; were insurance less subsidized, expected payouts from the WFRP would be equal to or less than the premium, to account for the insurer's loading, the amount above expected value of payouts that an insurer typically charges, which compensates them for reducing the farmer's exposure to yield and price risk. On the other hand, with AVS, the same objectives of crop insurance can be met – to reduce relative revenue variability and increased expected net revenues – without a premium. The spread of AVS could therefore play a role in reducing the demand and need for crop insurance.

3.5 Sensitivity Analysis

A first-order Delta Moment sensitivity analysis [97,98] is used to evaluate the effects of variation in crop price, crop yield, and power generation on variation in the distribution of annual

net revenues. Power price variability is not considered as all solar generation is assumed to be sold at a fixed price via a PPA. In the farm only scenario, net revenues are computed using only crop price and crop yield, as power generation does not influence farm net revenues directly. Weather variability – which influences both power generation and crop yield – may initially seem to be the largest financial risk affecting both activities, especially because solar developers manage price risk with PPAs. Yet, Figure 11 demonstrates the degree to which crop price presents a major risk to farmers. This means that the main benefit of co-location is in diversifying revenue streams; only in a scenario without a PPA and with negatively correlated electricity and crop prices would changes in one activity be offset by changes in the other. Solar power generation is relatively stable (if aggregated to a monthly or annual time step), compared to crop prices and yields, but its contribution to AVS net revenues depends on its relative magnitude. In scenarios with low-value crops, net revenues for solar power are relatively more variable and so contribute more to variation in AVS net revenues than in scenarios with high-value crops. In NC, the sensitivity analysis showed similar results, although crop yields contributed more to variance in the case of soybeans (see Section A.4 in SI).

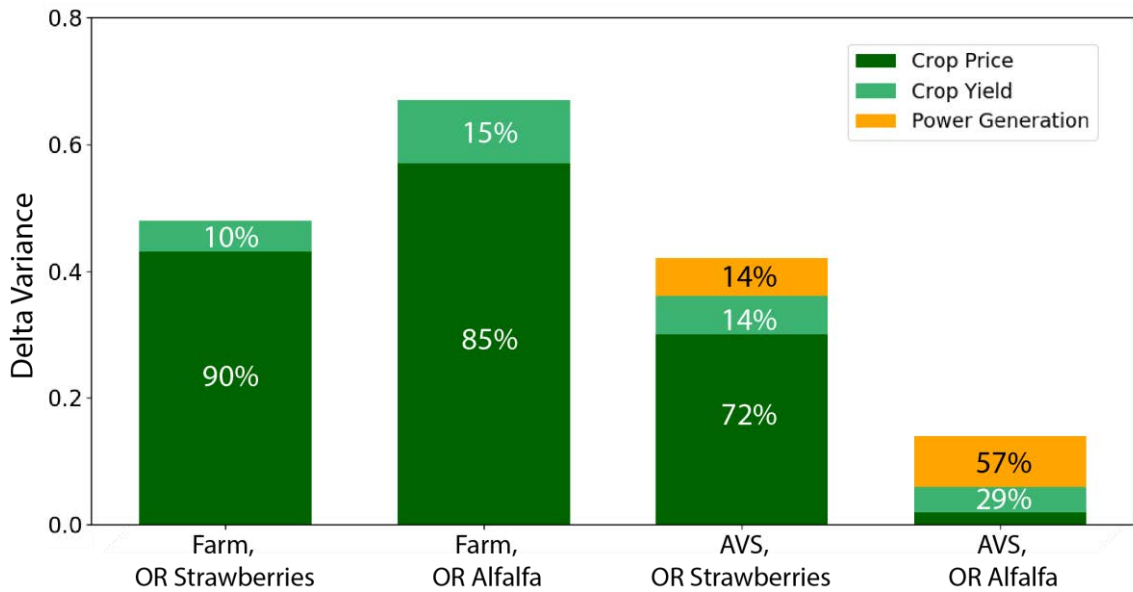


Figure 11. First-order Delta Moment sensitivity analysis for OR crops.

4. Discussion

This analysis holds several lessons for the solar and agricultural industries. First, results indicate that there are crop and location combinations for which the potential benefits of AVS can involve not only boosting expected revenues, but also stabilizing net revenues for farmers. This builds on previous research which also found increased revenues in an AVS, while establishing a more comprehensive framework that farmers and solar developers can use for decision-making. Especially if solar projects are able to obtain long-term PPAs with reasonably high prices (despite current downward trends), or able to reduce installation costs (more likely given present trends), agricultural landowners stand to benefit significantly from installing PVPs on their land. That said, solar does not seem poised to displace significant portions of agricultural acreage, and by installing an AVS, farmers can increase the profitability of their land in some situations. As such, AVS could be advantageous to farms seeking alternative revenue streams.

One of finding of this analysis is that scenarios involving solar generation using current PPA prices in the US (\$20-\$60/MWh) do not appear profitable, especially as government incentives decline. Falling PPA prices reduce the financial viability of projects even in areas with high irradiance levels and are likely driving small projects (<5 MW) out of the market. For solar developers, this may increase the future attractiveness of AVS. Should developers begin to build projects without PPAs, they may consider planting low-maintenance and low-volatility crops around their PVPs, like alfalfa, to establish a secondary source of revenue which can both supplement revenues from power generation and offset the revenue variability due to fluctuating electricity prices.

While AVS raised expected net revenues in all case studies evaluated, it also reduce financial risk for three of the four. Solar installations exhibit a narrower range of net revenues than farms with high value crops, which means that AVS have less financial variability compared to a farm. This combination can be beneficial to a solar developer when AVS does not result in a reduction in total PVP area, as in the strawberry scenarios presented here; in that case, adding a crop to an existing installation under such circumstances will always raise expected net revenues, another novel finding with respect to the existing literature.

This potential provides an ability to compare the risk management potential of AVS and crop insurance, which is intended to protect against extreme revenue declines for many crops. The US subsidizes an average of 60% of crop insurance premiums, a subsidy that amounted to over \$6 billion nationwide in 2019 [99], and which has frequently come under fire by policymakers pushing budget cuts [100,101]. Incentivizing AVS, rather than subsidizing insurance, might provide a way to increase crop revenues and reduce the need for crop insurance, while increasing renewable energy generation. For crops without specific, federally subsidized

insurance programs, AVS can act to reduce net revenue variability. In the case of the low-value crops modelled here, the AVS scenario has a much higher variance than the farm only scenario, although this also results in overall higher expected net revenues than the farm only scenario. Compared to the solar only scenario, however, AVS with low-value crops offer the promise of lower revenue variability. This suggests that adding crops with stable prices (mostly low value) to an existing solar installation may provide risk mitigation from the perspective of a solar developer.

Agrivoltaic systems can also offer intangible benefits. Planting pollinator habitat below PVPs, for example, is a simple form of co-location and can improve pollination, thereby increasing yields or reducing the costs of renting pollinator bees [29,102]. Pollinator habitat may also have broader ecosystem benefits, such as helping to maintain or increase biodiversity [103]. Co-location with food crops may offer broader societal benefits and synergies, like powering carbon-free farms and reducing emissions associated with farming. A premium might someday be placed on “carbon-free food”, and in places with carbon taxes, the advantages of AVS as a means to generate carbon free energy will also increase as, for example, in the US under a Green New Deal framework [27]. As farmers seek to decouple their agricultural production from their emissions [104], agrivoltaics may provide both a solution and an uncorrelated source of additional income. Already, countries around the world have expressed interest in AVS [105], with the US state of Massachusetts launching an initiative to incentivize dual use solar [106], and discussion in India to permit dual use systems [107]. Water-scarce areas may also benefit from the reduced water demand as PVP shading reduces evapotranspiration, and PVPs with crops planted below them may require less water for cleaning [29]. Finally, co-location may reduce the combined area of agricultural and solar land development, preserving wildlife habitat [29].

Future work on AVS more broadly would benefit from field scale experiments in which both the broader benefits and logistical challenges of AVS can be explored, namely the compatibility of PVPs with different types of harvesting equipment and agricultural practices. Additional work to improve results on financial risk could target non-irrigated crops and explore how potential water savings from solar panels could reduce the risk of low yields in low-precipitation years. Finally, conducting larger scale simulations with a selection of common crops across different climate regions around the world would provide more comprehensive results on the range of impacts co-location might have, and the most-well suited crops.

5. Conclusion

Farms and solar power developers both find themselves in a period of tremendous change. Agriculture is continuing to consolidate and the risk hedging strategies and regulatory incentives that long made solar profitable are becoming less common. In the face of such change, agriculture and solar power may become unlikely bedfellows; the co-location of agriculture and power production has received more attention as a means of increasing the productivity of land. Field research has begun to explore the physical changes agricultural and solar power operations may face in an agrivoltaic system, and this research builds on that foundation by exploring the financial benefits of co-location.

In addition, the comparison of agrivoltaics to crop insurance suggests that co-location can increase the net revenues of the landowner by up to 3,000% while also providing some of the same risk management benefits as crop insurance, lifting 5th percentile net revenues by 48-53% in case studies presented here. For solar developers, co-location could also provide a form of risk management, presuming they were interested in becoming more involved in land ownership and/or farming. Incentivizing agrivoltaics could offer farmers and solar developers with risk

management tools whilst also contributing to renewable energy generation capacity, providing dual benefits to a world seeking to shift away from fossil fuels.

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Author Contributions

R.I.C. prepared computer models aside from CAPOW and the solar power production model, which C.W.H. contributed, conducted the simulations and performed the data analysis. G.W.C supervised the project. G.W.C. and C.W.H. secured funding. R.I.C. wrote the manuscript, with editing and feedback from G.W.C. and C.W.H.

Competing Interests

The authors declare no competing interests.

Supplemental Information

Supplemental information is available for this paper.

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Code Availability

Code is available upon request to the author.

Data Availability

All data is publically available.

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Supplemental Information

Cuppari et al., “Agrivoltaics and Weather Risk: a Diversification Strategy for Landowners”

A.1 Crop Choice

Initial research on AVS has limited itself to a select number of crops, but there are many that could be grown underneath of PVPs (in terms of size and shade tolerance), and others that could actually benefit from the shade provided by PVPs. Table A.1 provides five criteria that can be used to identify crops suitable for PVPs. This analysis chose three as exemplars to establish the generalizable framework for assessing financial risk.

Table A.1: Crop Selection Criteria. Crops that would likely do well in AVS tend to be shade-tolerant, low to the ground and, ideally, handpicked. This makes many berries well suited to co-location, with some vegetables like lettuce and peppers also performing well. In terms of maximizing the solar component and reaping potential additional benefits of AVS, like water savings, crops that grow in water-stressed, high sun regions are optimal.

Crop	Some Shade Tolerance	Potential to Benefit from Shade	Less than 2 ft. height	Manually Harvested	Literature on agrivoltaic impact
Alfalfa	X				
Blueberries		X	X	X	
Corn					
Cucumbers					X
Hay	X				X
Lettuce		X	X	X	X
Jalapeño	X		X	X	X
Peppers (chili)	X		X		X
Soybeans	X				
Spinach		X	X		
Strawberries			X	X	
Sweet Potatoes	X		X		
Tobacco	X		X		
Tomatoes				X	X

A.2 Weather, Yield, and Price Simulation

The models used in this paper can be broken down into six classes: the weather simulation models, the thermodynamic solar power generation model, the crop models, the price models, the agrivoltaic model (a combination of the solar and crop models), and the financial model. The temperature/wind/irradiance model for Oregon, thermodynamic model, and the electricity price model for the Mid-Columbia market are the only externally produced and validated models. All other models were built for the purposes of this analysis. The following sections (A.2.1-A.2.4) provide further detail and validation about the weather simulation, power generation, crop yield, and crop price models.

A.2.1 Weather Simulation Models

The simulation of average temperature (TAVG), wind speed (AWND), and irradiance (GHI) were the basis for simulation of the remaining weather variables. The CAPOW model [50] simultaneously simulates TAVG and AWND across seventeen sites within the Western Electricity Coordinating Council jurisdiction, along with GHI at seven sites. For the purposes of this analysis, irradiance at an eighth site (Salem, OR) was simulated as well. Table A.2 lists the sites modelled using CAPOW, including Salem. Concurrent modelling of these sites maintains the spatial and temporal cross-correlation of weather necessary to accurately simulate energy demand, and therefore prices, in the interconnected system.

Table A.2: Sites modelled in the CAPOW model. The original CAPOW model included seventeen sites modelled for wind and temperature in addition to seven sites modelled for irradiance. Modifications to CAPOW for this analysis only involved adding a solar site at Salem, OR (Site #8), which was already represented in the wind and temperature modelling. Table modified from Su et al. [50]

Station ID	Name		Latitude	Longitude
USW0002432	SALEM AIRPORT MCNARY FIELD, OR	Wind/Temp	44.90° N	123° W
USW00024221	EUGENE MAHLON SWEET FIELD, OR	Wind/Temp	44.12° N	123.21° W
USW00024233	SEATTLE TACOMA INTERNATIONAL AIRPORT, WA	Wind/Temp	47.45° N	122.30° W
USW00024131	BOISE AIR TERMINAL, ID	Wind/Temp	43.56° N	116.22° W
USW00024242	PORTLAND TROUTDALE AIRPORT, OR	Wind/Temp	45.54° N	122.39° W
USW00024157	SPOKANE INTERNATIONAL AIRPORT, WA	Wind/Temp	47.62° N	117.53° W
USW00024163	PASCO TRI CITIES AIRPORT, WA	Wind/Temp	46.26° N	119.11° W
USW00093193	FRESNO YOSEMITE INTERNATIONAL, CA	Wind/Temp	36.77° N	119.71° W
USW00023230	OAKLAND METRO INTERNATIONAL AIRPORT, CA	Wind/Temp	37.71° N	122.21° W
USW00023174	LOS ANGELES INTERNATIONAL AIRPORT, CA	Wind/Temp	33.94° N	118.40° W
USW00023188	SAN DIEGO INTERNATIONAL AIRPORT, CA	Wind/Temp	32.73° N	117.19° W
USW00023232	SACRAMENTO EXECUTIVE AIRPORT, CA	Wind/Temp	38.51° N	121.49° W
USW00023293	SAN JOSE, CA	Wind/Temp	37.33° N	121.88° W
USW00023234	SAN FRANCISCO INTERNATIONAL AIRPORT, CA	Wind/Temp	37.62° N	122.37° W
USW00023160	TUCSON INTERNATIONAL AIRPORT, AZ	Wind/Temp	32.11° N	110.93° W
USW00023183	PHOENIX AIRPORT, AZ	Wind/Temp	33.43° N	112.00° W
USW00053123	LAS VEGAS AIR TERMINAL, NV	Wind/Temp	36.21° N	115.19° W
NSRDB 154166	NATIONAL SOLAR RESOURCE DATABASE #1	Irradiance	40.45° N	121.66° W
NSRDB 13631	NATIONAL SOLAR RESOURCE DATABASE #2	Irradiance	38.57° N	121.7° W

NSRDB 111895	NATIONAL SOLAR RESOURCE DATABASE #3	Irradiance	36.81° N	119.38° W
NSRDB 93873	NATIONAL SOLAR RESOURCE DATABASE #4	Irradiance	35.09° N	117.3° W
NSRDB 83553	NATIONAL SOLAR RESOURCE DATABASE #5	Irradiance	34.05° N	118.38° W
NSRDB 82442	NATIONAL SOLAR RESOURCE DATABASE #6	Irradiance	33.93° N	115.9° W
NSRDB 77068	NATIONAL SOLAR RESOURCE DATABASE #7	Irradiance	33.33° N	114.7° W
NSRDB 209204	NATIONAL SOLAR RESOURCE DATABASE #8	Irradiance	44.97° N	123.06° W

As in OR, the synthetically generated weather timeseries for NC accurately reproduced historical, monthly statistical moments for weather conditions simulated, as seen in Figure A.1.

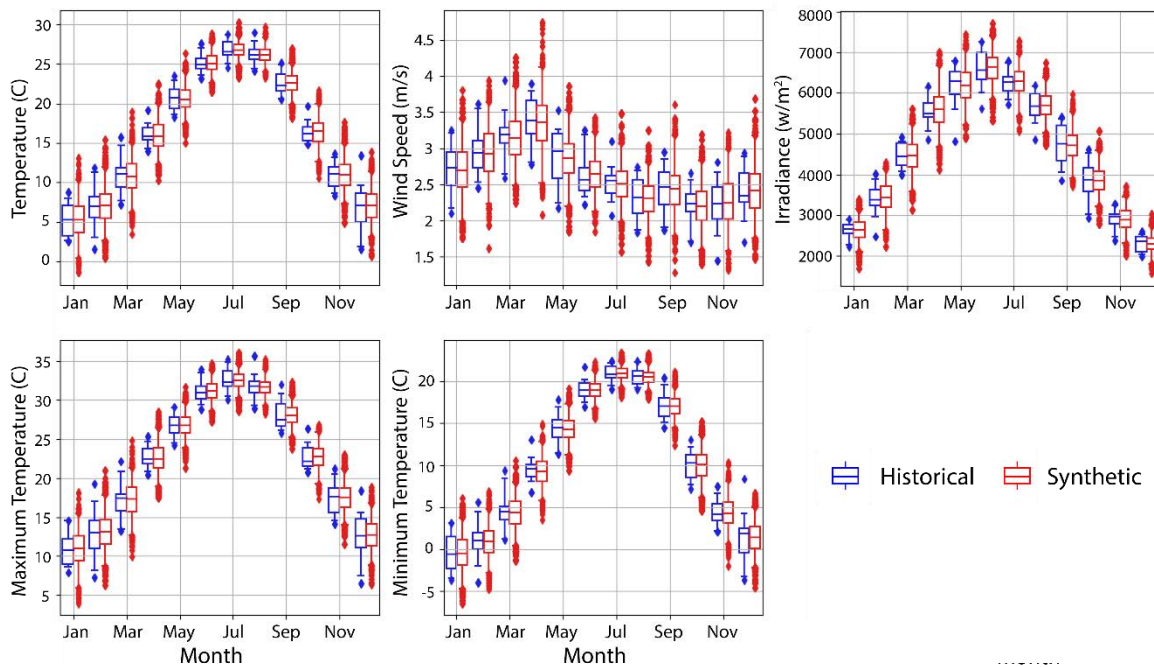


Figure A.1: Weather validation for NC. Whiskers show range between 2nd and 98th percentile, and the box shows the 25th, 50th, and 75th percentiles.

The simulation of precipitation relies on inputs of AWND, TMAX, cloud cover, and month, along with the historical transition probabilities listed in Table A.3. Transition probabilities are used to classify a day as dry (d), wet (w), or very wet (vw). First-order Markov

models are used to simulate the occurrence of precipitation based on the previous day's classification. For the purposes of this three state model, a day is first classified as rainy or dry based using a logistic regression. Once a day has been classified as rainy, transition probabilities are used to sub-classify each rainy day as wet or very wet, by randomly sampling a uniform distribution. The probability of a transition is calculated as the ratio of the total count of transitions between two states in a given month (e.g., transitions from wet to very wet days) to the total count of transitions from the initial state considered in the numerator (i.e. transitions from a wet day to any state).

Table A.3: Empirical transition probabilities for North Carolina (top) and Oregon (bottom).

North Carolina

Month	P_{dw}	P_{dv}	P_{ww}	P_{wv}	P_{vw}	P_{vv}
1	0.87	0.13	0.83	0.17	0.87	0.13
2	0.91	0.09	0.86	0.14	0.83	0.17
3	0.83	0.17	0.82	0.18	0.82	0.18
4	0.87	0.13	0.81	0.19	0.79	0.21
5	0.89	0.11	0.86	0.14	0.96	0.04
6	0.84	0.16	0.92	0.08	0.85	0.15
7	0.84	0.16	0.79	0.21	0.85	0.15
8	0.85	0.15	0.83	0.17	0.79	0.21
9	0.78	0.22	0.74	0.26	0.70	0.30
10	0.83	0.17	0.83	0.17	0.74	0.26
11	0.84	0.16	0.78	0.22	0.81	0.19
12	0.89	0.11	0.84	0.16	0.89	0.11

Oregon

Month	P_{dw}	P_{dv}	P_{ww}	P_{wv}	P_{vw}	P_{vv}
1	0.88	0.12	0.80	0.20	0.64	0.36
2	0.93	0.07	0.84	0.16	0.69	0.31
3	0.94	0.06	0.89	0.11	0.72	0.28
4	0.97	0.03	0.93	0.07	0.86	0.14
5	0.96	0.04	0.95	0.05	0.88	0.12
6	0.96	0.04	0.92	0.08	0.95	0.05
7	0.97	0.03	0.93	0.07	1	0
8	0.98	0.02	0.96	0.04	0.67	0.33
9	0.94	0.06	0.86	0.14	0.88	0.12
10	0.91	0.09	0.83	0.17	0.78	0.22
11	0.87	0.13	0.81	0.19	0.73	0.27
12	0.90	0.10	0.78	0.22	0.64	0.36

A.2.2 Thermodynamic Solar Model

The thermodynamic solar model is based on an Oregon State University solar plot. The model predicts panel efficiency, in order to simulate watts/m². Panels are spaced as seen in Figure A.2 below, with each row of 3 meter panels set 3 meters apart from the remaining rows.

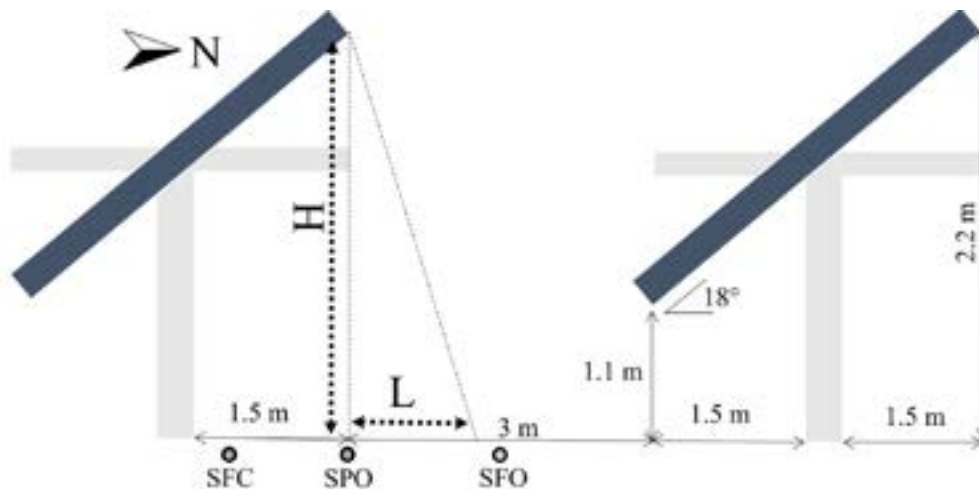


Figure A.2: Schematic of solar array at Oregon State University with shade zones [22], where the zones are solar fully covered (SFC), or full shade, solar partially open (SPO), or partial shade, and sky fully open (SFO), or no shade.

A.2.3 Crop Yield Models

All four crops – soybeans (NC), strawberries (NC), alfalfa (OR), and strawberries (OR) – were modelled using regressions between local weather variables, averaged over two-month periods, and annual crop yields. Where possible, county level crop yield data was used (i.e. alfalfa, soybeans), otherwise state-level data was used. R^2 values range from 0.47 to 0.69. Regressions were able to predict yields reasonably well for all four crops, as can be seen in Figure A.3.

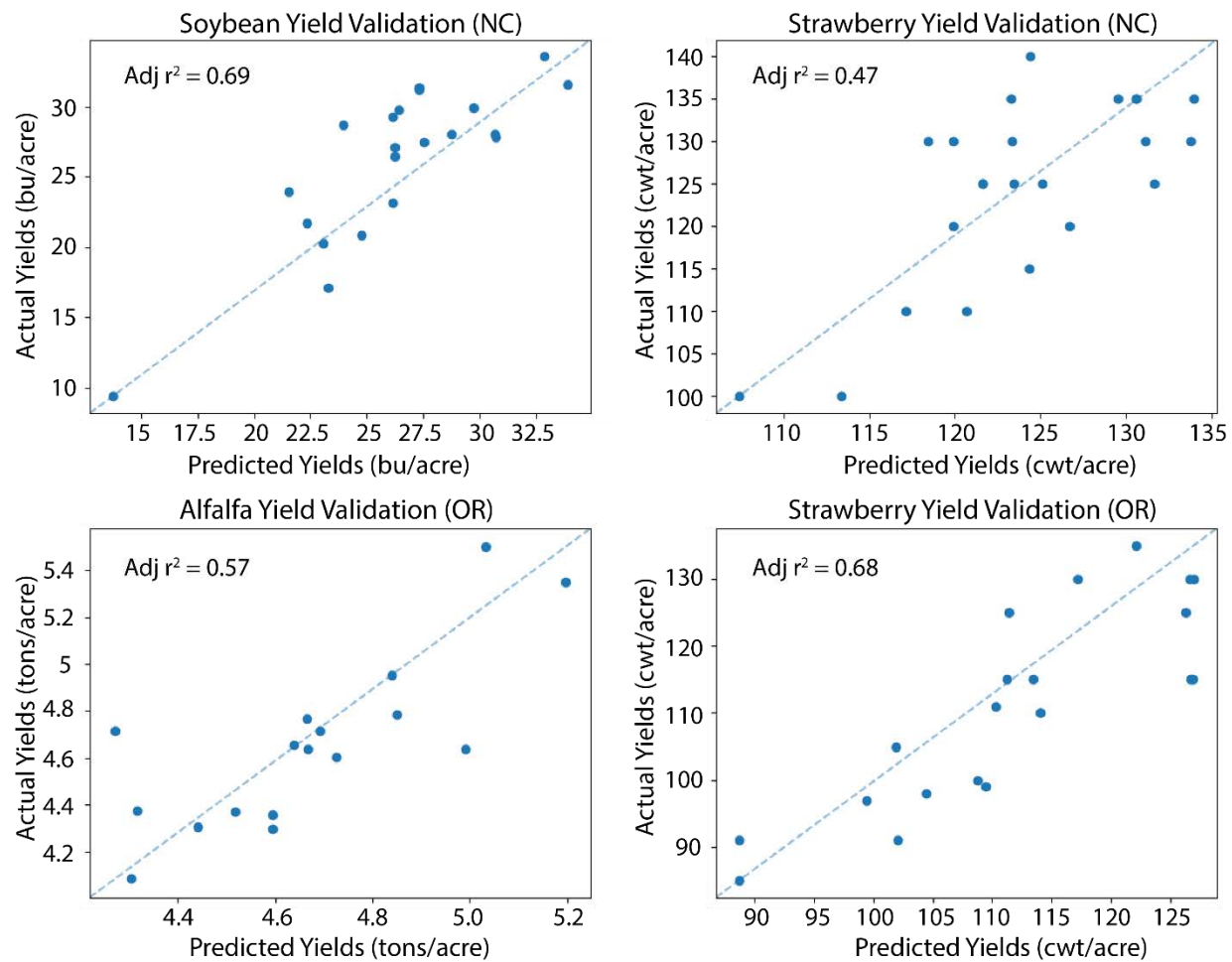


Figure A.3: Crop yield regression validation. Row 1: NC soybeans (left), NC strawberries (right). Row 2: OR alfalfa (left), OR strawberries (right).

Yield regressions include a random error term in the synthetically generated dataset to account for variability not linked to the regression inputs and thereby enabling the model to capture

examples of more extreme yields. The statistical moments of the synthetically generated crop yields align well with those of historical crop yields, as can be seen in Table A.4 and Figure A.4.

Table A.4: Percent difference between historical and synthetically generated crop yield moments.

Crop	Minimum	Maximum	Mean
NC soybeans	-11%	13.9%	4.5%
NC strawberries	-2.6%	17.6%	2.1%
OR alfalfa	-13.5%	4%	-2.6%
OR strawberries	-11.9%	3.4%	4.9%

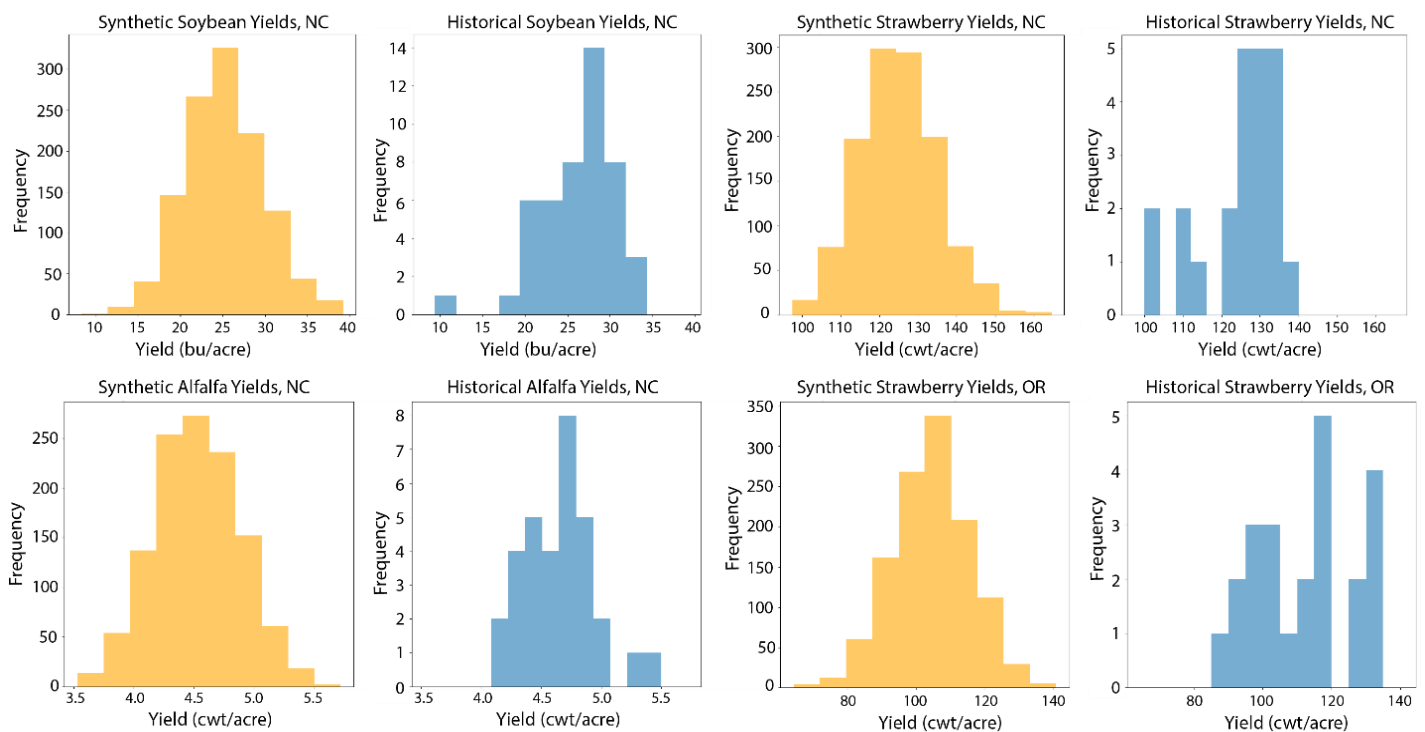


Figure A.4: Histograms of synthetic (orange) and historical (blue) crop yields in NC (top row) and OR (bottom row).

A.2.4 Crop Price Models

Crop prices were synthetically generated using the Ornstein-Uhlenbeck process to expand the historical timeseries of price data. The stochastic and mean-reverting nature of the process translated to a wider range of crop prices than the historical dataset, while staying true to the

mean values, as can be seen in the percent change calculated between historical and synthetic crop price data in Table A.5 below.

Table A.5: Percent change between historical and synthetically generated crop price data.

	Minimum	Mean	Maximum
Soybeans (NC)	1.1%	0.1%	15.5%
Strawberries (NC)	-9.8%	-2.3%	9.5%
Alfalfa (OR)	-28.9%	0.04%	27.5%
Strawberries (OR)	-31.5%	0%	13.6%

A.3 Cash flows

This analysis assumes a tax-equity and debt-financing model with 50% of financing through debt and 50% through equity. As such, initial developer investment is \$0. Initial capital from both the equity and debt provides the upfront funding to construct the solar installation, which produces electricity. Electricity generated can be sold either through wholesale market prices or through a PPA, although only the profitable, high PPA scenario is considered throughout the results section. Revenues earned through the sale of electricity are then used to service debt, pay for ongoing maintenance and taxes (combined state and federal taxes of 28%), and to repay equity investors through dividends equal to 2.5% of profits in the first five years of the solar installation's lifetime. Tax deductions accumulated by the solar installation are attributed to the tax-equity investors as part of their repayment, and in year six, the developer buys back the equity investor's share with a payment equal to 5% of the original equity investment. Remaining cash flow is considered profit, or net revenue. See Figure A.5 for a visual representation of cash flows.

The AVS financial model follows the same cash flows as the solar only financial model while adding the agricultural component. The agricultural financial model is fairly straightforward: annual crop costs go to procuring supplies for planting each year. Crops are sold to generate revenues and, in scenarios with insurance, payouts are triggered when revenues are below the revenue threshold. Revenues are used to pay federal income taxes (16.8%) and property taxes as well as cover the annual cost of planting. Net revenues from both the solar power generation and the agricultural production benefit the landowner. See Figure A.6 for a visual representation.

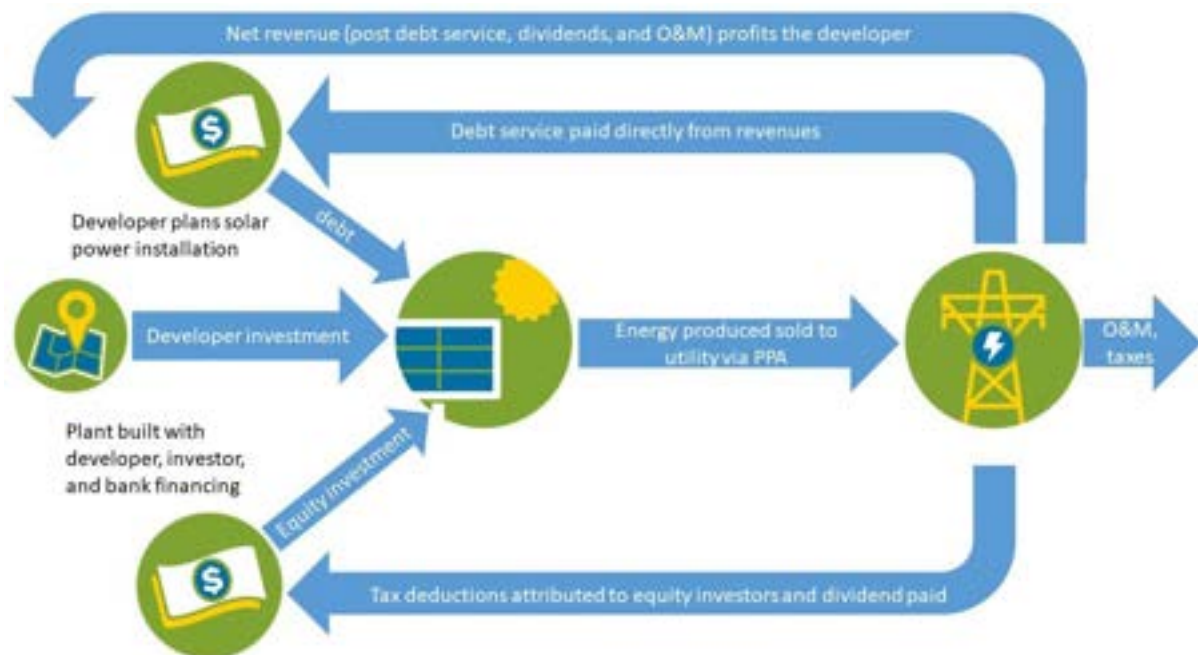


Figure A.5: Schematic of cash flows in solar only financial model.

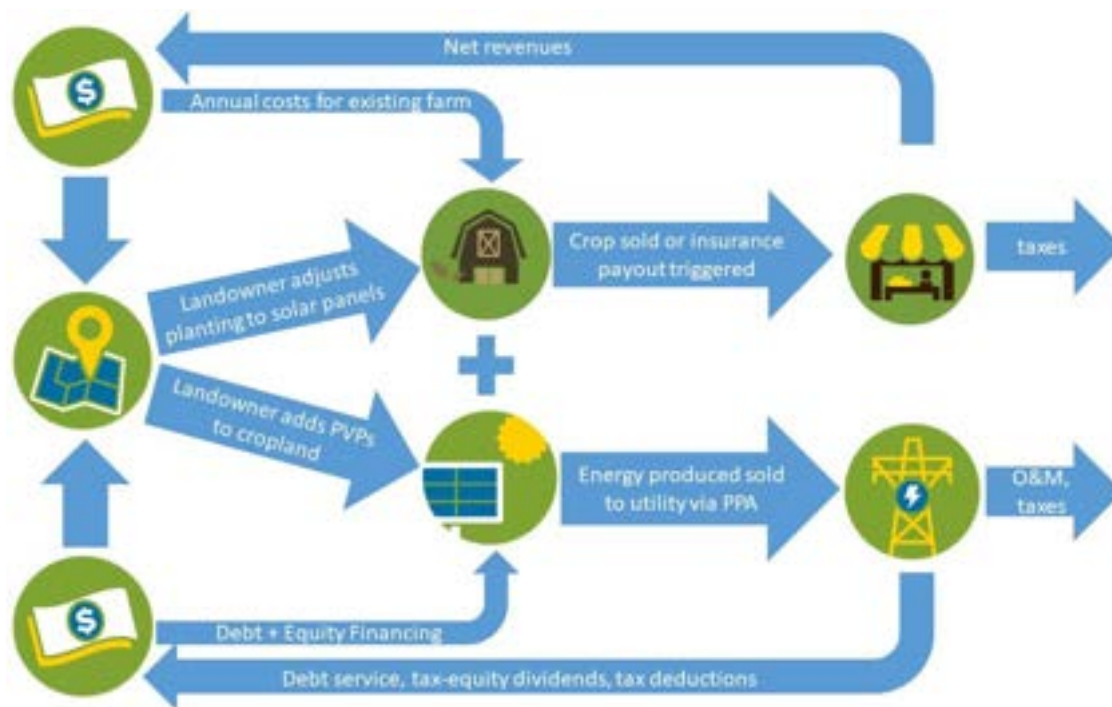


Figure A.6: Schematic of cash flows in AVS financial model.

A.4 Sensitivity Analysis

The results of this analysis might vary due to a range of factors, including the parameters used to assess the returns of a solar farm. A key component is the interest rate on the loan for the installation; while 4.5% is consistent with national trends, using a lower (3.5%) or higher (4.5%) interest rate substantially changes the average per acre revenues for the solar only plot and, consequently, the agrivoltaic plot. Table A.6 below highlights the average net revenues for the four cases studies at three different interest rates. That said, the focus of this article is the ability of co-location to mitigate the impact of weather related risk, for which reason the authors chose to highlight a single interest rate and discuss sensitivity only to weather factors.

Table A.6: Average per acre net revenue for the four case study locations (solar only / AVS) at three different interest rates.

	3.5% interest rate	4.5% interest rate	5.5% interest rate
NC Soybeans	\$3,398 / \$2,535	\$1,725 / \$1,281	-\$40 / -\$43
NC Strawberries	\$3,398 / \$3,834	\$1,725 / \$2,162	-\$40 / \$395
OR Alfalfa	\$3,499 / \$2,834	\$1,826 / \$1,580	\$60 / \$255
OR Strawberries	\$3,499 / \$3,598	\$1,826 / \$1,884	\$60 / \$159

A sensitivity analysis carried out using the first-order Delta Moment method. The trends are similar between OR and NC, when moving from high-value (strawberry) to low-value (alfalfa/soybean) crops. However, in NC, soybean yield contributes more to the variation in net revenues relative to crop yield for strawberries (OR and NC) and alfalfa (see Figure A.7). This is likely because soybeans have a much larger range of yields (14-36 bushels) in absolute terms than alfalfa (3.8-5.3 tons).

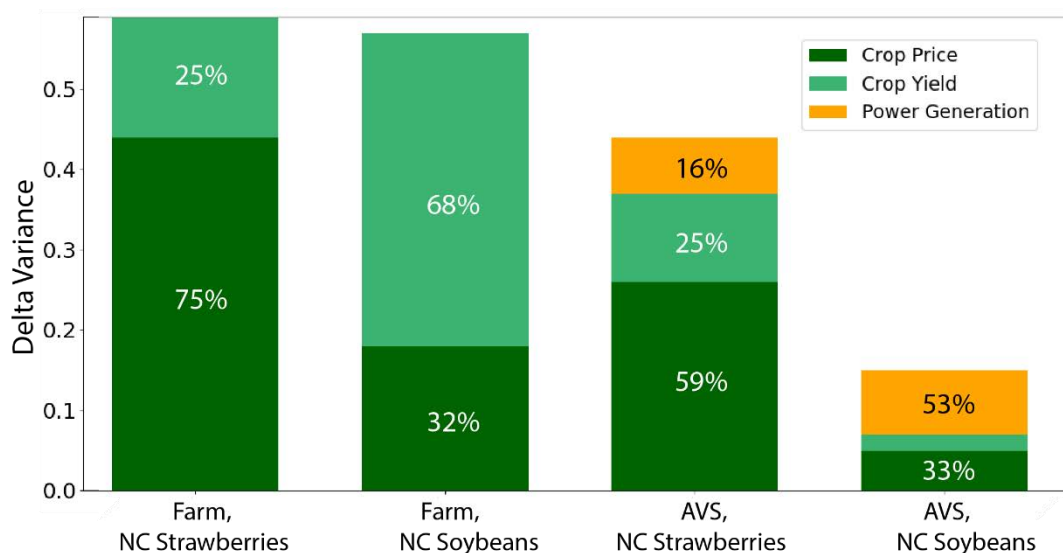


Figure A.7: First-order Delta Moment sensitivity for NC crops.