Dynamic Decision Making of Agrivoltaics in California's Central Valley

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Abstract

California's Central Valley (CV) is a crucial agricultural region facing severe water shortages and long-term sustainability challenges. In response to these challenges and the push for renewable energy, agrivoltaics (Ag-PV) – the integration of agriculture and solar energy production – emerges a potential solution. This study develops a regime-switching stochastic dynamic programming model to evaluate land use decisions among purely crop production, solar production and Agrivoltaics under uncertainty. Focusing on two representative crops, processing tomatoes and alfalfa, with various shade tolerance and irrigation need, we conduct simulations to explore the optimal land-use decisions under different scenarios. We also conduct sensitivity analysis that examines variations in shade tolerance, solar intensity, operational expenses, and transition costs etc. Results indicate that agrivoltaics is optimal under high solar lease rates and high irrigation water prices, whereas traditional crop production remains preferable under lower costs. Agrivoltaics is particularly beneficial for crops with lower agricultural margins, high water demand, and better shade tolerance. This study fills a critical gap in the literature by providing an innovative dynamic model that integrates the complexities of the Food- Energy-Water nexus. It offers valuable insights for the policymakers and stakeholders in the agricultural and renewable energy sectors, highlighting the potential of agrivoltaics to enhance sustainability and economic viability in the Central Valley.

1. Introduction

1.1 Background

California’s Central Valley (CV) is a vital agricultural region that covers less than 1% of the U.S. land but contributes significantly to the nation’s agricultural output, providing 8% of the agricultural produce (by value) and 40% of the fruits, nuts, and other table foods. However, the farmers face substantial irrigation challenges. Decades of drought and intensive agricultural pumping have led to chronic groundwater depletion, threatening the sustainability of water resources and increasing irrigation costs for farmers (Liu et al., 2022). In response to these challenges and to ensure water availability for future droughts, California enacted the Sustainable Groundwater Management Act (SGMA). This legislation aims to curb groundwater over-extraction by imposing more stringent regulations on water use, thereby impacting farmers' irrigation practices and agricultural planning (California Department of Water Resources, 2022). From earlier studies, SGMA is estimated to cause 86,000 ha to 200,000 ha of irrigated cropland to retire(Bryant et al., 2020; Hanak et al., 2019).

Additionally, California is ambitious in promoting clean energy through policies like the Renewable Portfolio Standards and SB 100, which aims to achieve 100% zero-carbon energy by 2045. According to These policies have not only underscored California’s commitment to sustainable energy but also influenced land use dynamics across the state. Rich in solar resources, certain areas of California, including Central Valley, are ideal for solar energy production. This has led landowners to consider shifting from traditional farming to establishing utility-scale solar farms (Buckley Biggs et al., 2022).

While transitioning to solar farming could offer a stable income and reduce reliance on increasingly scarce water resources, it also poses potential risks. The conversion to solar power generation in the CV directly competes with the land available for food production. Given that CV is a major source of food for the U.S., reducing the arable land can affect not only local but national food security. Besides, many communities in the CV rely economically on agriculture. Shifting large areas to solar could disrupt these local economies, potentially leading to job losses in traditional farming sectors, which might not be fully offset by the solar industry. Additionally, the CV also serves as a habitat for a variety of plant and animal species, large-scale solar farms can potentially disrupt existing wildlife habitats. Therefore, planning for solar infrastructure must integrate detailed spatial analysis to minimize ecological and social impacts(Wu et al., 2019).

Given the water stress and the considerable potential impact of a full conversion to solar in the Central Valley, innovative solutions are needed to balance renewable energy production with agricultural water sustainability. One such promising approach is agrivoltaics (Ag-PV, or agrisolar, or agriphotovitaics, APV), [1]a joint production configuration that synergistically combines agricultural and solar energy generation on the same unit of land. This approach not only increases land use efficiency, but also enhances water use efficiency for some crops, which is why it has gained significant attention in the CV and other regions.

1.2 Agrivoltaics

The concept of agrivoltaics involves the strategic installation of solar panels above farmlands. There are two types of configurations: 1) for elevated systems, these panels can be elevated to 6 feet and above to allow for routine farmwork underneath, and for sufficient sunlight to reach the

[1] There are four types of agrivoltaics applications, 1) crop and food production, 2) livestock grazing, 3) ecosystem services, and 4) solar greenhouses. In this paper, the scope of agrivoltaics is only combined with crop production.

crops, while providing shade that reduces evaporation from the soil. And 2) inter-row systems usually have wider spacing between the PV arrays to allow for large farming machinery. While it provides less shading, precipitation runoff, or the water used to clean solar panels can also be used to supplement irrigation need. These innovative designs have been tested in various settings to assess their impact on agricultural productivity and water usage.

Pioneering field experiments conducted in Montpellier, France have provided evidence of the impact of agrivoltaics. Studies by Dupraz et al. (2011) and Dinesh & Pearce (2016) have studied the effects of solar panel shading on crops' yield. Elamri et al. (2018) and Marrou et al. (2013) have investigated the microclimate change under the panels, finding that these alterations can lead to significant reductions in water usage. Notably, Elamri et al. (2018) implemented simulation methods showing that agrivoltaics can reduce irrigation needs by up to 20% while tolerating a 10% in crop yield, highlighting the potential of agrivoltaics to address both agricultural and environmental challenges.

There have also been field experiments conducted in Germany (Trommsdorff et al., 2021), Aisa (Ali Abaker Omer et al., 2022; Irie et al., 2019) , and the U.S exploring various configurations for the agrivoltaics systems. In the United States, the InSPIRE (Innovative Solar Practices Integrated with Rural Economies and Ecosystems) project has been particularly instrumental in advancing the application of agrivoltaics. The project has collaborated with universities, local governments and industry partners to develop strategies for low-impact solar development. For the agrivoltaics combined with crop production, they are leading the research on vegetables in Ohio (Quarshie, 2023), tomatoes in Oregon (Al-agele, 2020; Tahir & Butt, 2022), berries in Massachusetts (Mupambi et al., 2021), etc. Macknick et al., 2022 summarizes lessons learned from research across various field experience, and this manuscript provides critical analysis stakeholders considering agrivoltaic systems to reduce environmental impacts while maximizing agricultural and energy production efficiency.

In the Central Valley, landowners are already showing interest in agrivoltaics based on the benefits from shading, including physical protection from inclement weather, increasing water availability and reducing evapotranspiration (Buckley Biggs et al., 2022). Aside from these benefits, farmers can diversify their income streams by generating solar energy while continuing to cultivate crops, which provides a sustainable solution to adapt to climate change and mitigate the impact of droughts and restrictive policies.

However, there remain concerns about the potential reduction of crop yields due to shading, which highlights the importance of an adaptive solar configuration. Furthermore, the conversion to agrivoltaic systems often presents an irreversible commitment for 20-30 years, depending on the duration of the project, which also limits operational flexibility for landowners. The irreversible nature of adopting agrivoltaic systems also raises concerns among landowners regarding future uncertainties, including farming income, the impact of climate change, and changes in agricultural and renewable energy policies. For a risk-averse landowner, these uncertainties may delay the adoption decision until there is more evidence of its impact on their crop production in their region (Macknick et al., 2022).

1.3 Literature Review

There is a growing literature focused on the potential design of agrivoltaic systems and its benefits and costs in the Food-Energy-Water nexus (Barron-Gafford et al., 2019; Mamun et al., 2022). There are also qualitative studies about land-owner decisions on solar adoption. For example, Buckley Biggs et al. (2022) conducted interviews with farmers, ranchers, solar developers and government organizations in California and identified the key factors affecting landowner decisions including profit maximization, water availability, visual and ecological landscape values, and an agricultural land preservation ethic. Besides, Ketzer et al. (2020) uses Causal Loop Diagrams (CLDs) to analyze the driving and restraining forces for the adoption of agrivoltaics based on data from citizen workshops, literature reviews, and expert discussions.

More recent research has used quantitative modeling to explore optimal agrivoltaic system design and harvesting cycle. Sarr et al. (2024) develops a model that determines the configuration of agrivoltaic systems which optimizes energy production efficiency and crop yield. Yajima et al. (2023) establishes a model incorporating the amount of electricity generated by solar irradiation to estimate the correct start date to remediate the potential loss of late harvest due to shading.

While qualitative analyses provide insights into the social and economic factors influencing landowner decisions, and recent quantitative models address specific design and operational efficiencies, there remains a significant gap in comprehensive dynamic modeling that accounts for the uncertainties inherent in long-term land use decisions at the intensive and extensive production margins. This gap is particularly critical in light of the complex interdependencies within the Food-Energy-Water nexus and the unpredictable nature of climate conditions, markets, policy developments.

To address these key knowledge gaps, we adopt a real options framework, building on (Dixit & Pindyck, 1994; Insley, 2002) as well as more recent applications in agricultural economics such as Bangjun et al., (2022). Our contribution extends this literature by focusing on both intensive land management and extensive land management options.

We develop a regime-switching model to assess the land use decisions among purely crop production, solar production, and agrivoltaics under uncertainty. We also develop scenarios that account for potential external conditions that affect uncertainty of long-term economic returns to different land management options, including market volatility, climatic changes, and policy shifts, to identify the conditions under which the adoption of intensive solar and/or crop production would be strictly preferred to agrivoltaics.

2. Theoretical Model

As discussed in the last section, the adoption decision of agrivoltaics or purely utility scale solar is subject to a number of uncertain factors, including the profitability of crop production, weather conditions, water management policies, and renewable energy policies, etc., therefore, we adopt a dynamic programming framework that incorporates stochastic elements. By dynamically simulating the economic outcomes under uncertainty, the model offers insights into the optimal land use strategies under unknown environmental and market conditions over time.

2.1 Regime Switching Framework

We consider current agricultural landowners in the CV, and they will consider three land management regimes: purely agricultural production (AO), purely solar production (SO), and agrivoltaic production (AV). Each regime represents a different land use strategy with a different income stream and resource requirements. In the first regime AO, the land is used exclusively for agricultural production, which is the current state and the initial state in the model. Under this regime, the land manager maximizes returns to agricultural production and is typically preferred when the farming yields high economic returns relative to solar or agrivoltaics, or in cases where solar installation is not viable due to various constraints such as grid infrastructure, high site preparation cost, policy constraints or community preferences. The SO regime focuses exclusively on generating income from solar energy production. Landowners lease their land for solar installations, prioritizing energy revenue over agricultural output. This regime is most beneficial in areas with higher solar compatibility and may be preferred due to low agricultural profitability, high irrigation cost, or high solar incentives. Finally, the AV regime integrates solar with crop production on the same land, which means that the solar and agricultural activities will have an impact on each other. The shade from solar panels helps reduce irrigation usage, protects the crop from heat stress, but at the same time may decrease crop yield. The crop underneath solar panels helps lower the temperature which benefits the solar productivity, while routine farmwork may cause dust accumulation on the solar panels which can affect the performance of solar panels.

Due to the irreversibility nature of solar installations, switching is restricted to be one-way, see Figure 1. The starting regime is always AO, a representative agricultural landowner can choose to either switch to AV or SO or stay in only agricultural production. And starting from AV, the landowner may choose to stop agriculture production and switch to SO, or stay in AV, but they do not have the option to remove solar panels and switch back to AO. Finally, the SO regime is the absorbing regime, once achieved, the land will be committed to solar production.

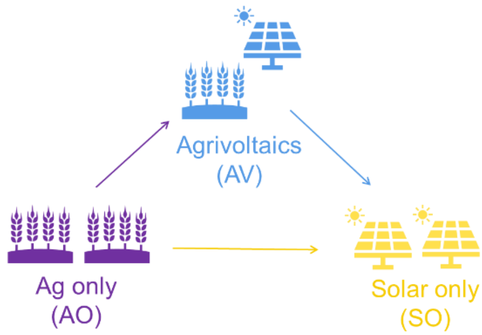

Figure 1 Illustration of the Regime Switching Model

Our approach is grounded in stochastic dynamic programming, a method well-suited for problems where decisions must be made sequentially and where outcomes are uncertain. In a deterministic framework, switching from regime X to Y would occur when the net present value (NPV) of Y is higher than the NPV of regime X plus the switching cost $K^{X \to Y}$. However, by introducing uncertainty, our approach offers a more nuanced method for evaluating land management transitions. Additionally, since the transition is irreversible, the adoption decisions must account for the uncertainty of future states, ensuring that landowners can dynamically adjust their strategies in responses to fluctuations in market conditions, climate change impact, and policy environments.

We employ a discrete-time setup that is aligned with the agricultural cycles and standard (annualized) solar lease rates. To minimize crop disruption, and to allow for specific site preparation adjustment, the installations are usually scheduled during the off-season, which depends on the crop. In California, the standard off-season is considered winter (Dec -Feb), so we assume the adoption decision will be made annually. The model's time horizon is defined to be 30 years, corresponding to the typical lifespan of solar panels.

2.2 Reward Functions

As mentioned earlier, the income stream in different regimes is different. In the SO regime, the landowner's net income can take two forms depending on the ownership of the solar panels. 1) if the landowner installs the solar panels on their own, namely a sole-ownership, the net benefit of solar at each period can be written as: $p_t^e\ E_t - m_t$ where p_t^e represents the electricity price at time t and E_t represents the electricity generated, and m_t is the maintenance cost of solar. 2) The alternative is a third-party ownership, which means the solar panels are owned, installed and maintained by a third-party. The solar developer usually will reach out to the landowners who are willing to lease their land for solar development. The common contracts can be between 20 -30 years with a lease rate R_t^{solar} and a yearly increase rate r, and the net income can be written as:

$$\Pi_t^{SO} = R_t^{solar}(1+r)^t \quad (1)$$

In the AO regime, the representative landowner's net income is their crop revenue R_t^{ag} subtracted by the cost, which includes irrigation cost C_t^{irr}, and other operational costs C^{oth} like labor, machinery, fertilizers, pesticides, etc, which varies across crops. We write the reward from AO regime as follows:

$$\Pi_t^{AO}(\boldsymbol{S}_t) = R_t^{ag} - C_t^{irr} - C^{oth} \quad (2)$$

The main uncertainties we consider in this model come from the crop income and weather, which affects water need for irrigation, thus we define the state space $\boldsymbol{S}_t \equiv \left(R_t^{ag}, C_t^{irr}\right)$. The stochastic nature of these variables is captured through a first-order vector autoregression (VAR (1)) model. $\boldsymbol{S_t} = \mu + \Phi\ \mathbf{S_{t-1}} + \epsilon_t$ where $\epsilon_t \sim N(0, \Sigma)$. This approach allows us to model the temporal dependencies and fluctuations in agricultural income and irrigation costs, providing a realistic simulation of how these variables might evolve over time under different scenarios.

Finally, in the AV regime, solar and crops are jointly produced, but at different levels of intensity than in the AO and SO regimes. The agricultural revenue in this regime is reduced by a factor α due to partial shading by the solar panels, or due to spacing for solar arrays, while irrigation cost is reduced by a factor ρ due to decreased evapotranspiration. Note that the factors vary across crops due to the different crop shading tolerance and compatibility for different agrivoltaic designs. In this regime, the landowner also gains additional income from solar leasing, whereas the lease rate is usually a proportion (γ) of a purely solar farm rent. The reward function in the AV regime can then be written as:

$$\Pi_{\mathrm{t}}^{\mathrm{AV}}(\boldsymbol{S}_t) = (1-\alpha)R_t^{ag} - (1-\rho)C_t^{irr} - C^{oth} + \gamma R_t^{solar} \tag{3}$$

2.3 Bellman Equations

We further utilize Bellman Equations to solve the optimal switching decision recursively. For the SO regime, if we consider the stochasticity in solar income, the value function is expressed as: $V^{SO}\left(R_t^{solar}\right) = \Pi_t^{SO} + \beta\mathbb{E}[V^{SO}(R_{t+1}^{solar})|\, R_t^{solar}]$ (and if the stochasticity is not considered, it is simply the NPV of the solar rent in 30 years, V^{SO}).

Based on the reward functions of agrivoltaics, the value function for the AV regime is:

$$V^{AV}(\boldsymbol{S}_t) = \max\{\underbrace{\Pi_{\mathrm{t}}^{\mathrm{AV}}(\boldsymbol{S}_t) + \delta\mathbb{E}[V^{AV}(\boldsymbol{S}_{t+1})|\boldsymbol{S}_t]}_{\text{stay in AV}}, \underbrace{V^{SO} - K_{AV\to SO}}_{\text{switch to SO}}\} \tag{4}$$

This function captures the decision to either stay in the AV regime, earning the immediate reward from AV and the discounted expected net present value (ENPV) of staying in the AV regime in the next period conditional on the current state $\boldsymbol{S}_t$; or to switch to the SO regime, which the value equals to the value of SO regime subtracted by the switching cost $K_{AV\to SO}$.

Finally, in the AO regime, the landowner faces three options: option to continue with purely agricultural operations, switch to solar production, or to joint agrivoltaic production. The value function is given by:

$$V^{AO}(\boldsymbol{S}_t) = \max\{\underbrace{\Pi_t^{AO}(\boldsymbol{S}_t) + \delta\mathbb{E}[V^{AO}(\boldsymbol{S}_{t+1})|\boldsymbol{S}_t]}_{\text{stay in AO}}, \underbrace{V^{SO} - K_{AO\to SO}}_{\text{switch to SO}}, \underbrace{V^{AV}(\boldsymbol{S}_t) - K_{AO\to AV}}_{\text{switch to AV}}\} \quad (5)$$

In each period, the landowner evaluates the value of the three options, and if the immediate reward from AO and the ENPV of AO is the highest, then it is optional to stay in AO. If the value of SO subtracted by the switching cost $K_{AO\to SO}$ is the highest, then the landowner's optimal decision is to sink the cost and switch to SO. If it is optimal to switch to AV, the value function is determined by the value function from equation (4).

3. Data and Empirical Analysis

3.1 Data Source

The agricultural data employed in this study, including crop yields and prices for California, are sourced from the USDA National Agricultural Statistics Service (NASS) yearly survey data. Operational cost data are derived from sample cost and return studies conducted by the University of California Agriculture and Natural Resources Cooperative Extension. This study categorizes the crops into four main types based on their value and irrigation needs:

1) High value and high irrigation need crops, such as almonds and pistachios.
2) High value and relatively low irrigation need crops, such as grapes and tomatoes.

3) Low value and high irrigation need crops, such as rice.

4) Low value and relatively low irrigation need crops, such as cycle alfalfa.

Weather-related data are collected from the California Irrigation Management Information System (CIMIS). This includes station-level monthly reference evapotranspiration (ETo) and precipitation data specific to the Central Valley. Crop coefficients (Kc) are adopted from the Food and Agriculture Organization (FAO) to compute crop-specific evapotranspiration (ETc) and effective rainfall annually, [2]which are essential for estimating the irrigation requirements of each crop type. Additionally, irrigation water price data are obtained from the Central Valley Project (CVP) water report.

We calculated crop revenues and irrigation costs for various types of crops grown in California's Central Valley, reflecting the income and water related cost for the landowners. Utilizing this data, we will further estimate the coefficients for a first-order vector autoregression (VAR (1)) model to analyze the dynamics of these two stochastic variables. The descriptive statistics presented in Table 1 offer an overview of the revenue and irrigation costs associated with each crop type over time, illustrating temporal financial fluctuations and water use efficiencies. Notably, our analysis includes county-level data for tomatoes and rice, which provides a more detailed view of economic and irrigation trends. For other crops, the data is aggregated at the state level, offering broader insights but with less local specificity. More information about the source data distribution, including price, yield, and evapotranspiration can be found in the Appendix.

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[2] $\text{Irrigation need}_y^c = \Sigma_m \text{ETo}_{m,y} * \text{Kc}_m - \Sigma_m \text{effective\_rainfall}_{m,y} * \text{I}(\text{Kc}_m > 0)$

	Tomatoes		Rice		Grapes Table		Alfalfa Cycle		Almond	
	Revenue	Irr_cost	Revenue	Irr_cost	Revenue	Irr_cost	Revenue	Irr_cost	Revenue	Irr_cost
mean	3862.64	612.76	1285.22	791.32	11328.61	849.82	981.77	298.93	4994.78	954.04
std	763.44	48.12	679.70	56.81	2609.07	33.29	347.09	9.89	1460.28	46.61
min	2061.23	498.19	317.13	628.38	7594.55	763.48	513.36	276.89	2674.00	860.07
max	6089.46	726.68	3371.52	939.52	15453.00	892.72	1864.94	312.43	8040.00	1022.06
count	143	143	125	125	16	16	23	23	17	17

Table 1Descriptive Statistics of Crop Revenue and Irrigation Cost in California's Central Valley

In this study, a key assumption for solar development is that the solar company will design agrivoltaic systems to optimally suit the specific condition of each representative landowner. This includes the consideration of spacing, height and tracking system that suit the crop type, installation method for the soil type, and geographic location, among other factors. To reflect the varying degrees of compatibility between different crops and solar installations, we have incorporated various switching costs into our model. We also conduct sensitivity analysis concerning these switching costs to understand their impact on land use decisions. It is worth noting that the optimization of system configurations, although crucial, is beyond the scope of this study. The site preparation cost and lease rate data are sourced from the InSPIRE projects.

3.2 Scenarios

In order to comprehensively assess the viability and impact of solar and agrivoltaic systems under varying conditions, we conduct simulations under several scenarios considering fluctuations in the environmental economic, and policy-related factors. Each scenario is carefully constructed with specific assumptions that influence the adoption of different land-use types in the CV.

For economic variability, the analysis includes scenarios of stable market conditions (S0), as well as conditions of high market volatility (S1) to explore the effects of market uncertainties on landowner's adoption decision. Aside from a baseline of normal weather patterns with historical data, we also construct a scenario of increased climate variability (S2), thereby assessing the resilience of adoption decisions. Additionally, in response to the ongoing discussions around the SGMA, we consider scenarios where aggressive groundwater policy measures might increase irrigation water price (S3). We also include potential government incentives that could increase solar rents (S4), as well as a scenario that contemplates the implications of reduced solar rent (S5), potentially due to policy changes or market saturation.

3.3 Sensitivity Analysis

To evaluate the model's robustness and to understand how various factors affect the adoption decisions, a series of sensitivity analysis are conducted on key parameters. The yield impact coefficient α was varied from -0.2 to 0.9 in increments of 0.1 to assess various shade tolerances. For shade-tolerant crops that benefit from protection against heat and inclement weather, a negative α value indicates an increase in yield under shade. Similarly, the shade evapotranspiration impact parameter (ρ) is also allowed to vary from -0.2 to 0.9, in 0.1 increments, to explore its effects on irrigation needs. Additionally, the solar intensity parameter in agrivoltaics, γ, which reflects the proportion of solar income in agrivoltaics compared to purely solar, is also tested across a range from 0.1 to 1.0 in 0.1 increments.

Further analyses extend to operational costs (C^{oth}), which contributes to the overall cost effectiveness of agricultural production in AO and AV regimes; switching costs associated with moving one regime to another, including ($K_{AO\rightarrow AV}, K_{AO\rightarrow SO}, K_{AV\rightarrow SO}$) that affects the flexibility of the irreversible switching decision; and base solar rents, to test a higher range of solar profitability scenarios. These parameters are tested from 50% to 150% of their baseline values in increments of 10%. By adjusting these parameters, we were able to compare the optimal steady-state regime (AO, AV, or SO) under each sensitivity scenario to assess how sensitive our model is to changes in both parameters and assumptions regarding future uncertainty.

4. Simulation Results

In this section, we present the simulation results for two types of crop, processing tomatoes, and alfalfa, which are widely grown in the Central Valley. Tomatoes are chosen for this analysis because they represent a high-value crop with low shade-tolerance, and relatively low irrigation needs, which makes agrivoltaics adoption controversial and is of special interest to this studied area. And alfalfa is chosen because it represents low-value low irrigation crop that is widely suited for an inter-row configuration. Simulation results for other crops are included in the supplemental appendix.

This narrower focus two crop types allows us to explore in detail the impacts of agrivoltaics on a crop that is widely cultivated in the region and is potentially very responsive to the dual use of land for both agriculture and solar power generation.

4.1 Baseline Scenario Results (S0) – Processing tomatoes

In the baseline scenario, we analyze the optimal regime-switching decisions under stable market conditions and weather patterns using historical data. For processing tomatoes, we assume that shade decreases crop yield by 25% and saves 20% of irrigation water. The solar rent in the baseline scenario is $1000 per acre per year. More information about the parameter values can be found in the supplemental appendix. The baseline scenario provides a reference for understanding the impact of economic, climatic, and policy variations on the adoption of different land-use types.

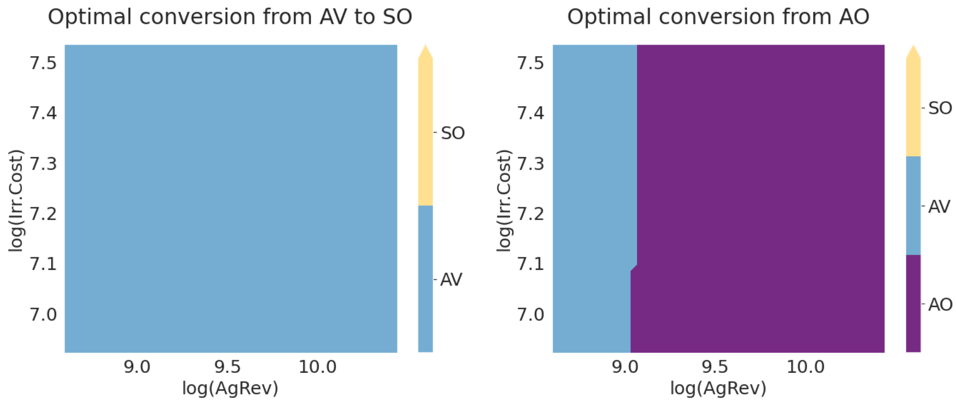

Figure 2: Optimal Conversion Surface for Processing Tomatoes (S0)

We visualize the optimal conversion surfaces for switching between regimes in Figure 2. The left panel of Figure 2 illustrates the optimal conversion decision from agrivoltaics (AV) to solar-only (SO). The horizontal axis represents the logarithm of agricultural revenue, and the vertical axis represents the logarithm of irrigation costs. The plot indicates that, in the state space, if the land is already used for agrivoltaics purposes, it is optimal to stay in agrivoltaic production rather than switch to purely solar.

The right panel of Figure 2 shows the optimal conversion decisions from traditional agriculture (AO) to either AV or SO. At low agricultural revenue levels, it is optimal to switch to agrivoltaics. However, if agricultural revenue is higher, it is optimal to stay in traditional agriculture, regardless of the irrigation costs. This suggests that revenue is the primary factor influencing the decision to integrate solar panels into crop production, especially for a crop like tomatoes that has relatively low irrigation needs. Additionally, in the state space, we do not find it optimal to switch to purely solar.

We simulate the regime switching decisions over 30 years for 1000 simulations. The results in Figure 3 show the distribution of regimes over time.

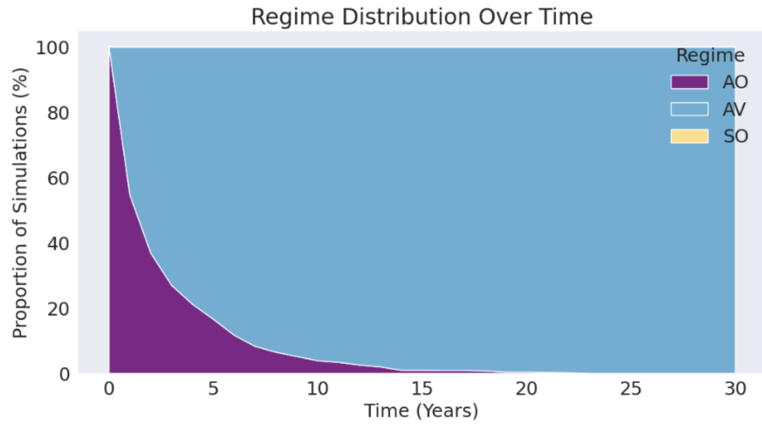

Figure 3: Regime Distribution for Processing Tomatoes (S0)

The plot presents the proportion of simulations(%) that results in each regime(AO, AV, SO) over a 30- year period. Initially, the majority of land remains in traditional agriculture (AO), as indicated by the purple area at the beginning of the timeline. However, within the first 5-10 years, there is a significant transition to AV, shown by the rapid increase in the blue area. As time progress, the proportion of land in agrivoltaic stabilizes, accounting for the majority of the simulations. This trend suggests that, under stable market conditions and historical weather patterns, agrivoltaics becomes the dominant land-use type for processing tomatoes. The stable solar rent and irrigation water savings make AV a more attractive option compared to traditional agriculture. Consistent with our optimal conversion results, the transition to solar-only (SO) , represented by the yellow area do not appear in our simulation. This outcome indicates that, given the assumptions of the baseline scenario, switching entirely to solar is not a common or optimal decision for landowners focused on processing tomatoes.

4.2 Scenario Analysis (S1-S5) – Processing tomatoes

As mentioned earlier, in addition to the baseline scenario, we examine several alternative scenarios to assess the impact of economic variability, climate conditions, and policy measures on regime-switching decisions for processing tomatoes. These scenarios include high market volatility (S1), increased climate variability (S2), aggressive groundwater policy measures (S3), increased solar rents (S4), and reduced solar rents (S5).

High Market Volatility Scenario (S1)

In the high market volatility scenario, we introduce increased economic uncertainty (Σ) to assess its impact on regime-switching decisions. The results indicate that it is still not optimal to switch from AV to SO. The result shows a higher propensity to remain in AO due to increased revenue uncertainty, resulting in a less frequent switch to AV. This suggests that under high revenue volatility, landowners prefer to wait and see, which delays the adoption decision. Compared to the baseline, there is a slower and less pronounced transition from AO to AV, with a higher proportion of land remaining in AO throughout the simulation period. The preference for AO persists longer, highlighting the impact of high market volatility on regime-switching decisions. The proportion of land transitioning to SO remains negligible.

Increased Climate Variability Scenario (S2)

This scenario examines the impact of greater fluctuations in weather patterns on regime-switching decisions. The results show a similar pattern to the baseline, indicating that it is still not optimal to switch from AV to SO. The decisions from AO to AV are influenced by agricultural revenue and irrigation costs, but overall, the model is less sensitive to climate variability, with landowners making similar decisions as in the baseline scenario.

Aggressive Groundwater Policy Measures Scenario (S3)

This scenario simulates the effects of aggressive groundwater policy measures that increase irrigation water prices. The results still do not reflect it to be optimal to switch to SO. From AO, there is a higher propensity to switch to AV at elevated irrigation costs, driven by the increased burden of water expenses.

Increased Solar Rents Scenario (S4) and Decreased Solar Rents Scenario (S5)

These two scenarios explore the impact of potential government incentive about boosting solar rents, or the reduction in support. In the high solar scenario S4, the results show an expanded region favoring agrivoltaics, and it is optimal to switch earlier. And in the low solar scenario S5, any solar adoption will be delayed. And there will be a much higher percentage of the landowners to remain in traditional agricultural production by the end of the 30 year period.

4.3 Baseline Scenario Results (S0) – Alfalfa

For alfalfa, we assume similar conditions for the water saving benefit of shade as for processing tomatoes. However, since alfalfa is more shade-tolerant, we assume that the shade impact on yield to be 10%. Figure 4 shows the regime distribution over time for alfalfa. Initially, most land remains in AO, and the transition starts to happen within the next 5 years. Compared to processing tomatoes, the switch happens slower and it is more likely for the landowner to stay in traditional agricultural production despite its shade-tolerance nature. The transition to SO does not appear in our simulations, indicating that switching entirely to solar is not a common or optimal decision under the baseline scenario.

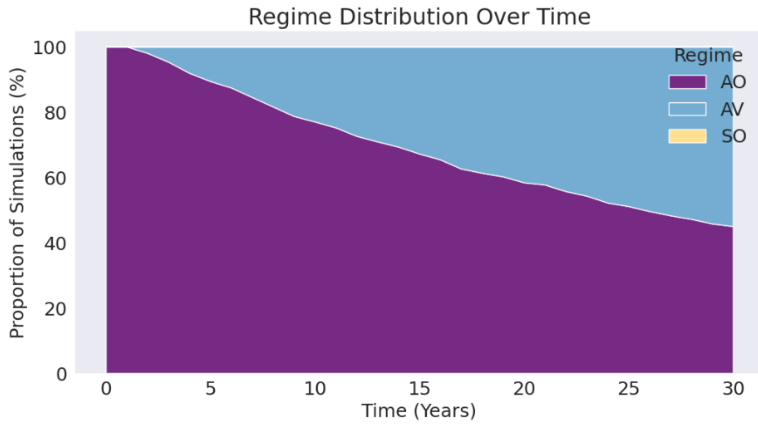

Figure 4 Regime Distribution for Alfalfa (S0)

4.4 Scenario Analysis (S1-S5) – Alfalfa

Similar to tomatoes, we examine the impact of various scenarios on regime-switching decisions for alfalfa. The detailed figures are provided in the appendix, and the results are summarized below.

High Market Volatility Scenario (S1) and Increased Climate Variability Scenario (S2)

Change in S1 and S2 present similar results as tomatoes. However, alfalfa is more sensitive to climate variability. Under high irrigation cost and lower revenue states, it is preferable to switch to AV.

Aggressive Groundwater Policy Measures Scenario (S3)

Higher irrigation costs due to aggressive groundwater policies lead to a stronger inclination to switch from AO to AV. Compared with tomatoes, adoption decision for alfalfa land is more sensitive to irrigation cost change. While both crops have low irrigation costs, tomatoes are a high-value crop, making irrigation costs a smaller proportion of the overall revenue. In contrast, alfalfa is a low-value crop, so even relatively low irrigation costs represent a higher proportion of the revenue, significantly impacting the decision-making process.

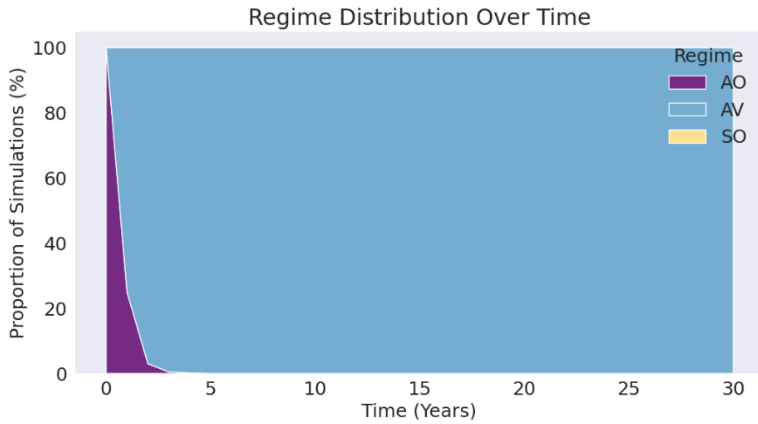

Figure 5 Regime Distribution for Alfalfa (S3)

Increased Solar Rents Scenario (S4) and Decreased Solar Rents Scenario (S5)

The adoption decision for alfalfa landowners is more sensitive to changes in solar rents. Under high solar rents (S4), SO becomes the dominant regime. As shown in Figure 6, at low agricultural revenue levels, it is optimal for landowners to switch directly to SO rather than AV.

In contrast, under low solar rents (S5), it is optimal to stay in traditional agricultural production (AO). We do not observe any significant transitions to other regimes, indicating that landowners prefer to remain in AO when solar rents are low.

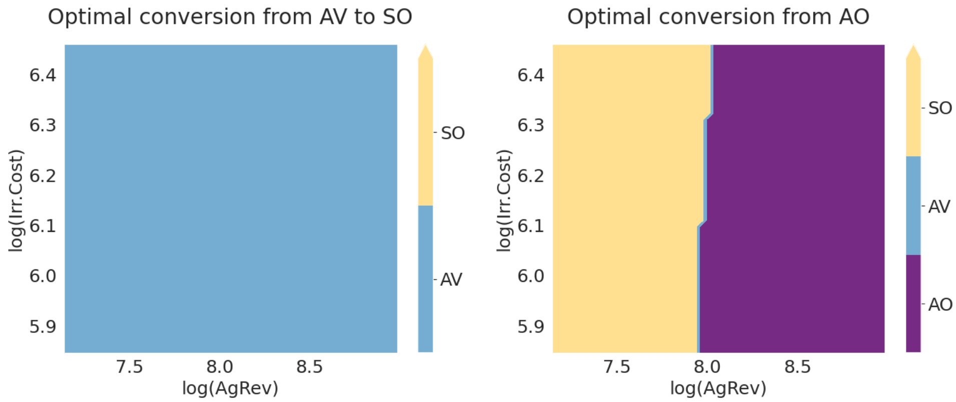

Figure 6 Optimal Conversion for alfalfa (S4)

5. Sensitivity Analysis

5.1 Processing tomatoes

To evaluate the model's robustness and understand how various factors affect adoption decisions, we conducted a series of sensitivity analyses on key parameters. These parameters include the yield impact coefficient (α), the shade evapotranspiration impact parameter (ρ), the solar intensity parameter in agrivoltaics (γ), operational costs (C^{oth}), switching costs between regimes ($K_{AO\to AV}$, $K_{AO\to SO}$, $K_{AV\to SO}$), and base solar rents (R_t^{solar}). Each parameter was varied within a specified range to observe its effect on the optimal steady-state regime (AO, AV, or SO).

The results for processing tomatoes are summarized in Appendix B1. The table presents the steady-state regime (SS regime) under each sensitivity scenario.

From the results, we observe that the decision to switch regimes is not sensitive to changes in ρ and γ. Only when the solar intensity parameter (γ) is lower than 0.1 do landowners stay in traditional agricultural production AO. However, the decision is highly sensitive to the yield impact coefficient (α). If the yield impact is higher than 40%, it is optimal to remain in traditional agriculture (AO). This indicates that significant yield losses due to shading make agrivoltaics less attractive, highlighting the importance of compatibility when considering agrivoltaics integration.

The model is not sensitive to switching costs, except when the cost of switching from AV to SO ($K_{AV\rightarrow SO}$) exceeds $26,000, which results in a preference to stay in AO. Operational costs also play a crucial role; if other expenses are lower than $3,040, the profit margin increases, making it more preferable to stay in AO. The model shows minimal sensitivity to changes in solar rent within the tested range, indicating that solar rent variations do not significantly impact the regime-switching decisions for processing tomatoes.

5.2 Alfalfa

The sensitivity analysis results table for alfalfa can be found in Table 2. Similar to tomatoes, the sensitivity analysis for alfalfa shows that the adoption decision is highly sensitive to the yield impact coefficient (α). When shading decreases yield by more than 40%, it is optimal to stay in traditional agriculture (AO). The decision is also sensitive to the solar intensity parameter (γ); if the solar intensity is 0.5 or lower, it is optimal for landowners to remain in AO. Additionally, if other operational costs are lower than $1500, it becomes more profitable to stay in AO.

$\boldsymbol{\alpha}$	SS Regime	ρ	SS Regime	γ	SS Regime	$K_{AO\rightarrow SO}$	SS Regime	$K_{AO\rightarrow AV}$	SS Regime	$K_{AV\rightarrow SO}$	SS Regime	C^{oth}	SS Regime	R_t^{solar}	SS Regime
-0.2	AV	-0.2	AV	0.9	AV	10000	AV	12500	AV	2500	AV	1250	AO	800	AO
-0.1	AV	-0.1	AV	0.8	AV	12000	AV	15000	AV	3000	AV	1500	AO	900	AO
0	AV	0	AV	0.7	AV	14000	AV	17500	AV	3500	AV	1750	AV	**1000**	**AV**
0.1	**AV**	0.1	AV	**0.6**	**AV**	16000	AV	20000	AV	4000	AV	**2000**	**AV**	1100	AV
0.2	AV	**0.2**	**AV**	0.5	AO	18000	AV	22500	AV	4500	AV	2250	AV	1200	AV
0.3	AV	0.3	AV	0.4	AO	**20000**	**AV**	**25000**	**AV**	**5000**	**AV**	2500	AV	1300	AV
0.4	AO	0.4	AV	0.3	AO	22000	AV	27500	AV	5500	AV	2750	AV	1400	AV
0.5	AO	0.5	AV	0.2	AO	24000	AV	30000	AV	6000	AV	3000	AV	1500	AV
0.6	AO	0.6	AV	0.1	AO	26000	AO	32500	AV	6500	AV	3250	AV	1600	SO
0.7	AO	0.7	AV			28000	AO	35000	AV	7000	AV	3500	AV	1700	SO

Table 2 Sensitivity analysis results for Alfalfa

However, the model for alfalfa is not sensitive to switching costs or the shade evapotranspiration impact parameter (ρ), but it is sensitive to solar rent. When solar rent is below $1000 per acre per year, it is optimal to stay in AO. Conversely, if solar rent exceeds $1500 per acre per year, landowners are more likely to switch directly to the solar-only (SO) regime. This highlights the importance of solar rent in influencing land-use decisions for alfalfa, making it a critical factor in the adoption of solar energy systems.

6. Conclusions

This study introduces a novel stochastic dynamic programming model to assess the decision-making processes involved in adopting agrivoltaic or solar systems on agricultural lands in California's Central Valley. Employing a regime-switching framework, akin to a real options approach, our model analyzes how uncertainties in agricultural income and irrigation costs, coupled with the irreversibility of investments, influence landowners' adoption decision between agrivoltaic and purely solar systems. Specifically, the study focuses on two types of crops—processing tomatoes and alfalfa—to illustrate the trade-offs involved. These crops were selected due to their differing water needs and economic values, providing a comprehensive view of the potential impacts on yield reduction, water cost savings, and solar income generation. This approach allows for a nuanced exploration of the economic and environmental benefits and challenges associated with each system under various scenarios.

The findings of this study reveal distinct differences in the economic outcomes for agrivoltaic and solar-only systems, particularly when applied to processing tomatoes and alfalfa. For processing tomatoes, the model suggests that despite the yield reduction due to shading, AV systems could significantly lower water costs and generate stable solar income, making them a potentially more viable option than solar-only systems, especially under scenarios of high water price volatility. This is particularly relevant as the Sustainable Groundwater Management Act (SGMA) may drive up irrigation costs, thereby incentivizing the adoption of AV systems which offer reduced water usage. Conversely, for alfalfa, which is less sensitive to shading, the benefits of agrivoltaics are even more pronounced, providing substantial water savings with minimal impact on yields. The analysis indicates that the optimal adoption strategy for both crops involves a delayed transition to agrivoltaics, allowing landowners to capitalize on advancements in technology and potentially favorable policy changes. This strategic delay enables landowners to manage the risks associated with the irreversibility of investment and the uncertainties related to future market conditions and policy landscapes.

While the model provides insights into the timing flexibility and the potential economic benefits of agrivoltaic systems, it also highlights a key sensitivity: the yield impact coefficient (alpha). This sensitivity underlines the importance of developing agrivoltaic technologies that minimize negative impacts on crop yields to make them economically viable for farmers.

However, the study also acknowledges several limitations that must be addressed in future research. Due to data constraints, our model could not fully incorporate the dynamics of operational costs or the fluctuations in solar rent, which are significant factors that could affect the economic outcomes of agrivoltaics adoption. Moreover, our analysis is based on the scenario of a representative one-acre landowner with no cross-crop choices, and assumes an optimal agrivoltaics configuration without specifying the exact nature of these configurations. These simplifications may limit the generalizability of our results across different agricultural contexts and scales. Finally, we do not consider potential constraints or relative opportunity costs of solar investments that vary spatially across the CV and how these factors might influence solar incentives and adoption decisions.

Moving forward, it is essential to refine the economic models of agrivoltaics adoption to include more detailed and dynamic considerations of operational costs, solar rent variations, groundwater constraints, and specific agrivoltaic configurations. Additionally, expanding the scope to consider different crop types and larger agricultural operations will enhance our understanding of the broader economic impacts and scalability of agrivoltaics.

As California continues to lead in innovative environmental management, the insights from this study contribute to a broader understanding of how integrated solutions like agrivoltaics can play a pivotal role in the sustainable transformation of agriculture, supporting resilience in food production while advancing towards a zero-carbon future.

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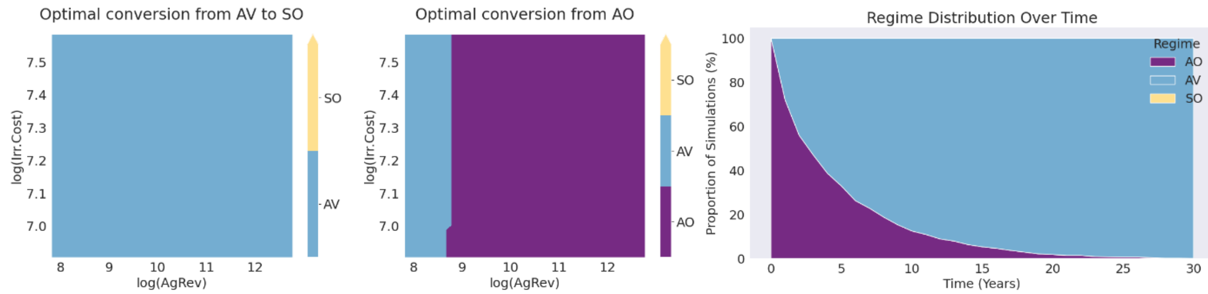
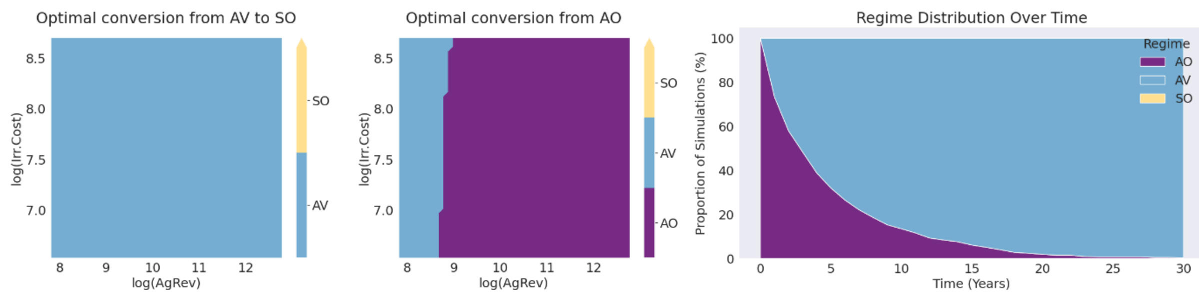
Appendix A1: Scenario Analysis for Processing Tomatoes

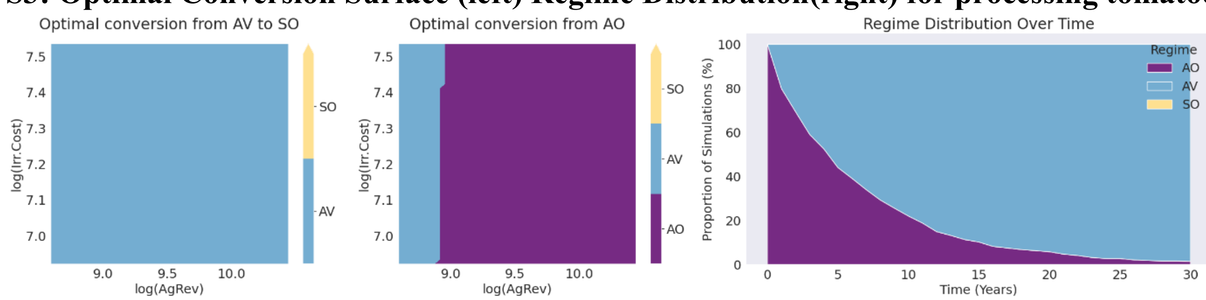
S1: Optimal Conversion Surface (left) Regime Distribution(right) for processing tomatoes



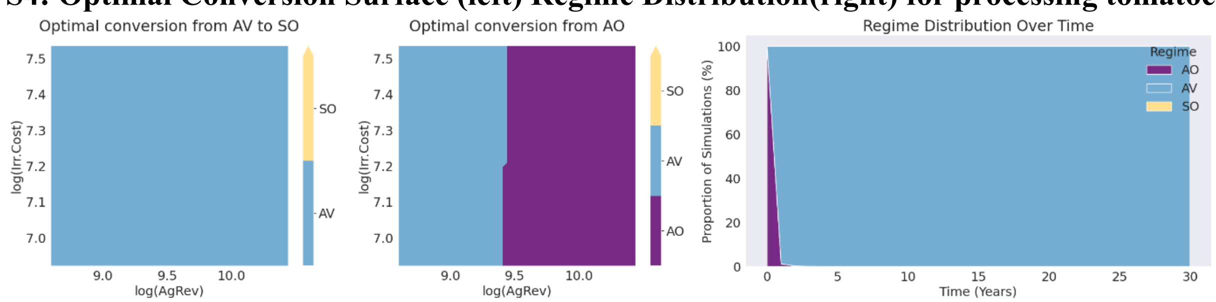
S2: Optimal Conversion Surface (left) Regime Distribution(right) for processing tomatoes



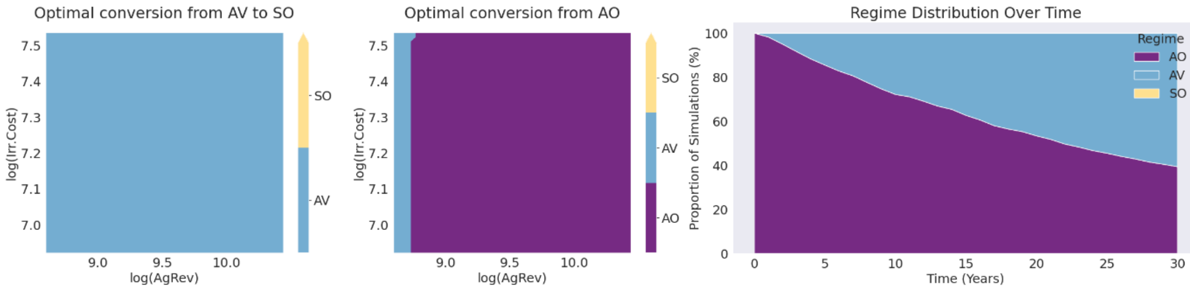
S3: Optimal Conversion Surface (left) Regime Distribution(right) for processing tomatoes



S4: Optimal Conversion Surface (left) Regime Distribution(right) for processing tomatoes



S5: Optimal Conversion Surface (left) Regime Distribution(right) for processing tomatoes



Appendix B1 Sensitivity Analysis Result for Processing Tomatoes

$\boldsymbol{\alpha}$	SS Regime	ρ	SS Regime	γ	SS Regime
-0.2	AV	-0.2	AV	0.9	AV
-0.1	AV	-0.1	AV	0.8	AV
0	AV	0	AV	0.7	AV
0.1	AV	0.1	AV	**0.6**	**AV**
0.2	**AV**	**0.2**	**AV**	0.5	AV
0.3	AV	0.3	AV	0.4	AV
0.4	AO	0.4	AV	0.3	AV
0.5	AO	0.5	AV	0.2	AV
0.6	AO	0.6	AV	0.1	AO
0.7	AO	0.7	AV		
0.8	AO	0.8	AV		

$K_{AO\to SO}$	SS Regime	$K_{AO\to AV}$	SS Regime	$K_{AV\to SO}$	SS Regime	C^{oth}	SS Regime	R_t^{solar}	SS Regime
10000	AV	12500	AV	2500	AV	1900	AO	500	AV
12000	AV	15000	AV	3000	AV	2280	AO	600	AV
14000	AV	17500	AV	3500	AV	2660	AO	700	AV
16000	AV	20000	AV	4000	AV	3040	AO	800	AV
18000	AV	22500	AV	4500	AV	3420	AV	900	AV
20000	**AV**	**25000**	**AV**	**5000**	**AV**	**3800**	**AV**	**1000**	**AV**
22000	AV	27500	AV	5500	AV	4180	AV	1100	AV
24000	AV	30000	AV	6000	AV	4560	AV	1200	AV
26000	AO	32500	AV	6500	AV	4940	AV	1300	AV
28000	AO	35000	AV	7000	AV	5320	AV	1400	AV

Appendix B2 Sensitivity Analysis Result for Alfalfa

$\boldsymbol{\alpha}$	SS Regime	ρ	SS Regime	γ	SS Regime
-0.2	AV	-0.2	AV	0.9	AV
-0.1	AV	-0.1	AV	0.8	AV
0	AV	0	AV	0.7	AV
0.1	**AV**	0.1	AV	**0.6**	**AV**
0.2	AV	**0.2**	**AV**	0.5	AO
0.3	AV	0.3	AV	0.4	AO
0.4	AO	0.4	AV	0.3	AO
0.5	AO	0.5	AV	0.2	AO
0.6	AO	0.6	AV	0.1	AO
0.7	AO	0.7	AV		
0.8	AO	0.8	AV		

$\boldsymbol{\alpha}$	SS Regime	ρ	SS Regime	γ	SS Regime	$K_{AO\to SO}$	SS Regime	$K_{AO\to AV}$	SS Regime	$K_{AV\to SO}$	SS Regime	C^{oth}	SS Regime	R_t^{solar}	SS Regime
-0.2	AV	-0.2	AV	0.9	AV	10000	AV	12500	AV	2500	AV	1250	AO	800	AO
-0.1	AV	-0.1	AV	0.8	AV	12000	AV	15000	AV	3000	AV	1500	AO	900	AO
0	AV	0	AV	0.7	AV	14000	AV	17500	AV	3500	AV	1750	AV	**1000**	**AV**
0.1	**AV**	0.1	AV	**0.6**	**AV**	16000	AV	20000	AV	4000	AV	**2000**	**AV**	1100	AV
0.2	AV	**0.2**	**AV**	0.5	AO	18000	AV	22500	AV	4500	AV	2250	AV	1200	AV
0.3	AV	0.3	AV	0.4	AO	**20000**	**AV**	**25000**	**AV**	**5000**	**AV**	2500	AV	1300	AV
0.4	AO	0.4	AV	0.3	AO	22000	AV	27500	AV	5500	AV	2750	AV	1400	AV
0.5	AO	0.5	AV	0.2	AO	24000	AV	30000	AV	6000	AV	3000	AV	1500	AV
0.6	AO	0.6	AV	0.1	AO	26000	AO	32500	AV	6500	AV	3250	AV	1600	SO
0.7	AO	0.7	AV			28000	AO	35000	AV	7000	AV	3500	AV	1700	SO