

Tipping points in the adoption of agroecological practices

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Abstract

The emergence and impact of tipping points are of immense interest in both social and ecological systems. Despite widespread recognition and research of feedbacks between these two systems, it is often assumed that underlying nonlinear behaviors of their coupled dynamics rest within either the human or natural processes. Our work presents a novel mechanism of how tipping points can arise in a stylized coupled human and natural systems (CHANS) model. We develop a stylized socio-ecological model representing farmers' sequential decisions to adopt agroecological management practices, and the ecosystem services that result from anthropogenic ecological change. Because ecosystem services take time to accrue, farmers on degraded land or those operating under a shorter time horizon, are disincentivized to invest in agroecology, while others are more likely to bolster ecosystem services further by adopting additional agroecological practices. This path dependency leads to a bifurcation into either a more-simplified (conventional) or more-diversified (agroecological) farming approach, which echoes empirical findings. We show how bistability can emerge purely from the temporal feedbacks between human decisions and their interactions with ecological processes and propose that the mechanisms of these dynamics have important implications for agricultural policy design.

Keywords: agriculture, ecosystem services, tipping points, diversification practices, decision-making

Introduction

Both ecosystems and social systems have been observed to change states abruptly as the result of crossing a critical threshold. Theories of ecological multistability have long described this phenomenon (Scheffer and Carpenter 2003) and explored how ecological management impacts stability landscapes (Horan et al. 2011), with tipping points assumed to stem from complex ecological processes and population dynamics (Mumby, Hastings, and Edwards 2007). Similarly, examples from social science ranging from the collapse of societies (Downey, Haas, and Shennan 2016) to social network dynamics such as the spread of innovations (Kuehn, Martens, and Romero 2014), suggest that tipping points may result from complex features of human systems. Despite widespread interest in the causes and location of tipping points in integrated socio-ecological systems, it has generally been assumed that the underlying nonlinear dynamics can be ascribed to either social processes or natural phenomena.

Empirically exploring tightly coupled dynamic systems presents numerous research challenges (Kline et al. 2017). In such systems, human decisions impact ecological processes, and the resultant changes create feedbacks that alter the scope and efficacy of future decisions (Ostrom 2009; Walker et al. 2004; Liu et al. 2007). For example, agricultural management choices can enhance or degrade ecological services that affect

the long-term productive capacity of the land, impacting future financial returns, and limiting future decision possibilities (Zhang et al. 2007). A complicating factor is that the temporal dynamics of ecological processes do not always align with the temporal scale of human decision-making. For example, land management to promote ecosystem services may require sequential investments over time and/or take years to accrue (Morandin, Long, and Kremen 2016; Blaauw and Isaacs 2014), meaning adoption of these practices requires decisionmakers to be forward looking, adaptive, and cognizant of environmental and economic uncertainty.

Agriculture is a fundamental driver of anthropogenic ecological change (Stoate et al. 2009; Foley et al. 2005, 2011), providing a valuable context to examine how social and ecological systems interact. Agriculture influences both human and ecosystem well-being, while production practices vary in their environmental impacts, long-term sustainability, financial viability, and climate resilience. It is increasingly recognized that effective policies to address environmental issues like the long-term sustainability of agricultural practices require interdisciplinary approaches which consider both human decision-making and ecology as a coupled human-and-natural system (CHANS) (Liu et al. 2007; Alberti et al. 2011). Here we focus on Diversified Farming Systems (DFS), which use agricultural practices that promote beneficial biodiversity and bolster ecosystem services, simultaneously enhancing farm- and landscape-scale productivity (Kremen, Iles, and Bacon 2012). While existing research has increased our understanding of how diversification practices affect ecological and financial outcomes (Rosa-Schleich et al. 2019), an integrated approach requires consideration of the feedback loop between adoption of a given practice, resultant ecological change, and future decision landscapes. Such an approach provides a framework to analyze the potential synergies and tradeoffs inherent to how diversified farming systems affect and are affected by ecosystem processes.

Computational approaches to explore structural attributes of human-environment systems can illuminate core dynamics, suggest levers of change, and highlight important assumptions to explore empirically. Previous research in this area has shown that distinct stable states of farm management systems often exist (i.e., Andow and Hidaka (1989); Vandermeer (1997)) and that a shift to an alternative syndrome can occur from small changes in conditions when tipping points are reached (Vandermeer and Perfecto 2012). However, techniques that investigate dynamic processes and responsive decision-making do not generally allow for forward looking agents (Lippe et al. 2019), and may misrepresent the complex coupling of these systems.

This paper presents a stylized model of agroecological diversification practice adoption to explore the complex dynamical properties that result specifically from interactions between adaptive decision-making and an ever-changing environment. We find a novel mechanism for bistability that is the result not of complex structural assumptions within either the human or natural system, but simply the rates at which the two systems interact over time. While our model necessarily simplifies both decision-making and environmental processes, it provides a platform to integrate empirical findings and explore emergent properties of CHANS. Additionally, we suggest important implications of such tipping point dynamics for agroecological policy design.

Conceptual model description

We explore the transition to and from diversified farming systems using a Markov Decision Process (MDP) in which a fruit/vegetable farmer makes a series of agroecological choices over time (1). Each year the agent chooses an “action” of 0% to 100% investment in adopting or maintaining diversification practices. The “system state” corresponds to the level of benefit derived from the ecosystem services that result from those adoption decisions, and can include financial, social, ideological, and aesthetic considerations. More investment corresponds to a greater probability of transitioning to a higher (more beneficial) ecological state the next year. While higher ecological states benefit the agent, higher investment actions also come with a greater associated cost. By defining parameter values for cost, benefit, transition stochasticity, ecological change rate, and temporal discounting (values given in Methods, Tab 1), we can calculate the optimal action strategy based on the agent’s expected rewards over a defined time horizon.

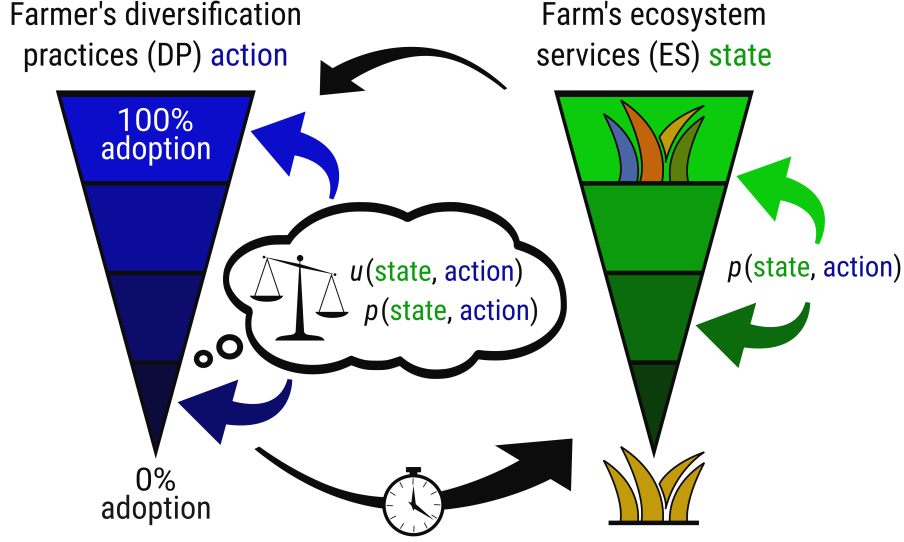


Figure 1: Conceptual diagram of the MDP model. The farmer’s choice of how much to invest (time and/or money) into diversification practices (DP) adoption is shown in blue, and the resulting ecosystem services (ES) state in green, with a more diversified state at the top, and a more simplified state at bottom. Each year, the farmer chooses the optimal action for their current ES state based on the perceived utility function (u) and the state transition probability function (p). (p) describes how, for a given ES state and action at year t , the ecosystem responds stochastically at $t + 1$. The updated ES state then feeds back to influence the farmer’s future choices, leading to complex tradeoffs arising from the coupling of ecological processes with consecutive DP adoption decisions over time.

Results

Using this model, we observe the behavior of agents’ sequential choices and resultant environmental outcomes over time. Agents’ initial ecosystem states distributed normally around a mean of $\bar{s} = 0.5$. Fig 2 showing that, after following the optimal decision strategy for 20 years, agents have largely settled into two groups, with some farms transitioning to more simplified (conventional) farming systems, and others to more diversified (agroecological) systems. Further, we find strong path dependency, with only 17% of agents who started in a simplified ($s < 0.5$) state concluding in a diversified ($s > 0.5$) state, and only 7% initially in the diversified state transitioning to simplified.

Optimal decision strategy

The decision strategy π describes the optimal course of action for a given state and is the same for all agents in the simulation. Fig 3 reveals that there is a tipping point, at a specific ecosystem state, below which the highest expected value is derived by investing little to nothing into diversified farming systems, and above which the optimum action becomes near-full investment. Over time, this results in the bimodal distribution of ecosystem states in Fig 2.

Land tenure

With 39% of U.S. farmland under lease (Service 2016), the impact of land tenure on best management practice adoption has been increasingly scrutinized. For example, a study of U.S. corn farmers found that cash renters were less likely than land owners to implement grassed waterways, strip cropping, contour farming, or conservation tillage (Soule, Tegene, and Wiebe 2000). Similarly, a study conducted in British Columbia found that tenant farmers planted fewer perennial crops than land owners (Fraser 2004). In addition, investments in agroecology may require access to credit, which often also hinges on secure land tenure as collateral (Richardson Jr 2015).

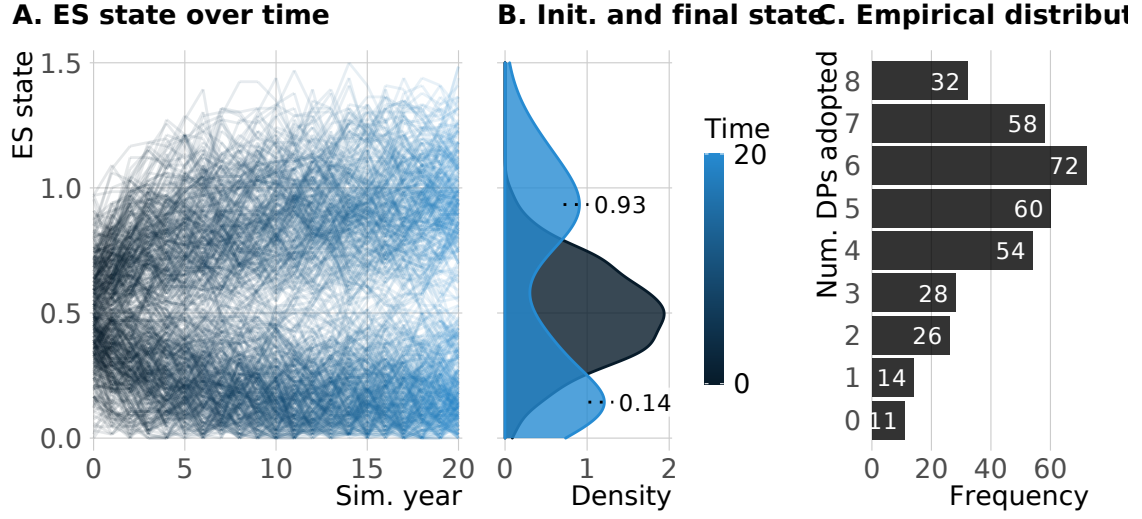


Figure 2: Initial ecosystem states are distributed normally (mean = 0.5; S.D. = 0.2; truncated at $[0,1]$). Agents follow decision strategy π as shown in Fig 3 until $t = 20$. (A) Ecosystem state of each agent over time (500 simulations). (B) Initial ES distribution (dark blue) and final bimodal distribution at $t = 20$ (light blue). (C) Empirical bimodal DP adoption distribution from our survey data.

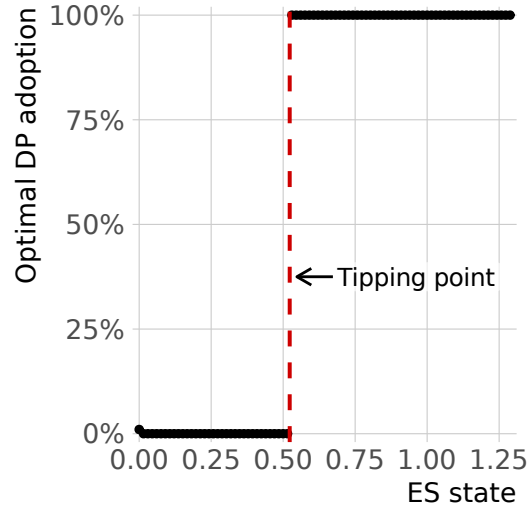


Figure 3: Optimal decision strategy π as a function of ES state, showing a tipping point at $s \approx 0.52$. The upper x axis limit is the 99th percentile of observed states in our simulation results ($s \approx 1.3$).

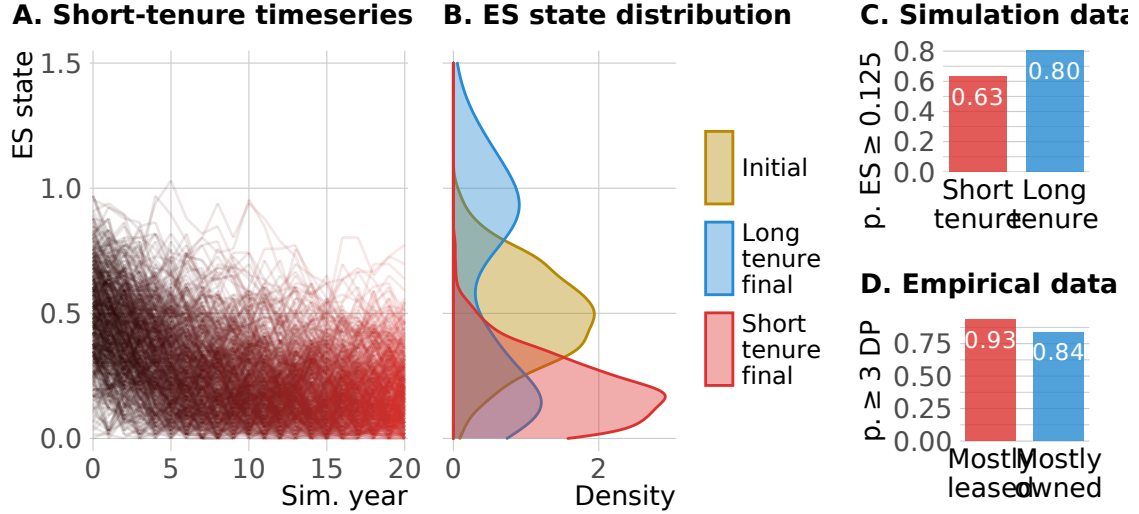


Figure 4: The simulation is identical to that in Fig 2, but the MDP is solved under a finite, two-year time horizon. (A) Result of short land tenure on ES state over time. (B) Comparison between final state distribution of short- vs. long-tenure model runs. (C) Probability of ecosystem services state being ≥ 0.125 at $t = 20$ for the short- vs. long-tenure simulations. (D) Impact of land tenure on the probability of a farmer in our survey dataset adopting at least one DP.

Using the same parameters outlined above, we solve the MDP on a finite two-year time horizon, representing the shorter window within which tenant farmers often make decisions (Fig 4). Comparing the final state distribution of the baseline versus the short tenure model shows that, as expected land tenure duration decreases, it becomes optimal to reduce agroecological adoption in a wider number of ecosystem states. This results in ecosystem state degradation even among farm sites with an initially high value, with 92% of farmers ending up in the simplified state. These results echo empirical findings from a recent large-scale survey of U.S. west coast produce farmers, which show that farmers who lease land are roughly 20% less likely to invest in at least one diversification practice.

Agroecological incentives

While land tenure is intertwined with land use decisions, agricultural incentives have also become an integral part of farming over the past half-century. Policymakers are continually called upon to weigh farm viability against food affordability and environmental sustainability to design effective incentive packages (Graddy-Lovelace and Diamond 2017). Agricultural incentives, such as cost-sharing and reimbursement programs have a range of goals, one of which is to promote sustainable management practices. We explore the impact of incentive duration on policy efficacy by implementing two competing incentive structures: a short-term (two-year) incentive which completely covers the cost of diversification practice adoption, versus a longer-term (ten-year) incentive which only partially offsets the transition cost. Within the model, agents adapt their decision strategy during the incentive period, and at its conclusion they revert to the baseline strategy. Formally, the cost of each incentive package to the taxpayer is equal, and in fact the short-term package is technically more valuable if economic discounting is applied.

Fig 5 shows that longer, more sustained incentive programs may be more effective at nudging behavior over the critical threshold toward more sustainable practice adoption. Comparing the incentive simulations to the base case, incentive-free results, we find that, while both incentive packages worked to some extent, the sustained incentive was much more effective at moving the needle. Due to the tipping point dynamic, once an agent has crossed the threshold to the diversified state, it becomes much less likely that they will fall back toward the simplified state. Since ecosystem state change in the model is somewhat stochastic, as it is in real-world ecosystems, it may take a series of investment actions before the ecosystem reacts. Due to this time delay, longer-term incentives have a higher chance of nudging behavior beyond the critical threshold, ultimately resulting in more agroecological practice adoption.

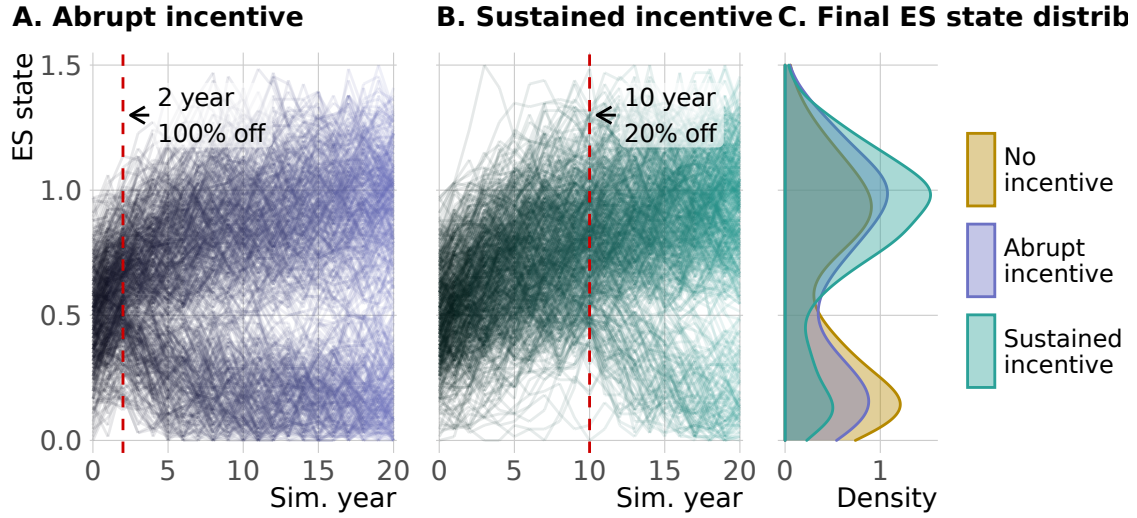


Figure 5: Starting from the same initial states as Fig 2, ES state timeseries are shown for (A) a large, abrupt incentive (100% of adoption expenses are covered for two years) vs. (B) a smaller, more sustained incentive (adoption cost is 80% of baseline for 10 years). Ignoring discounting, both packages have the same total cost to the funder (the equivalent of 2 years' worth of full adoption cost offsets). After the incentive period, agents adjust their decision rules to that of the base case (i.e. no incentive) until $t = 20$. (C) Shows that the sustained incentive ultimately drove more DP adoption.

Importance of temporal dynamics in coupled system trajectories

Our model shows how a simple coupling of human choices and ecological response can result in bistable landscapes of high and low diversification practice adoption. Importantly, this tipping point disappears when human and natural systems are decoupled. To explore this, we incrementally sweep through cost/benefit ratios and examine the effect on final ecosystem state distributions. As the ratio grows, at some point the decision strategy favors full investment into diversification practices, and conversely, a sufficiently low ratio will result in no diversification practices adoption.

Fig 6 shows that, with human/environment interaction, there exists a region of cost/benefit space within which various bimodal ecosystem state distributions emerge. However, when ecological processes become fast enough that the ecosystem responds almost-immediately to farmer actions ($r = 0.95$), it becomes impossible to parameterize the model's cost-benefit ratio to result in alternate stable states. Similarly, as decisions become temporally-myopic (time horizon = 2 yrs.), the potential for bistability also disappears. Only when both a gradually-changing environment and a forward-looking decision-maker are coupled do tipping point phenomena emerge in decision strategy, leading to alternate stable diversification states.

Discussion

Our analysis suggests a mechanism for bistability in coupled human and natural systems that is not the result of complex structural assumptions about either system alone, but rather the temporal interactions between forward-looking decisions and ecological processes. While the concepts of regime shifts and tipping points within coupled human and natural systems (???) have been previously explored, our results cast light on temporal mechanisms that might help to explain this phenomenon. We suggest this knowledge provides novel considerations not only for coupled human and natural systems research but also agricultural policy.

While we present a novel mechanism for bistability in diversified practice adoption, other mechanisms have been presented to explain bistability in agroecological practice adoption. For example, research on production syndromes shows that structure of agricultural systems is based on numerous drivers and components of social-ecological systems (e.g., market opportunities, regulations, etc.) which can create alternative stable states characterized as production syndromes (Vandermeer and Perfecto 2012). Although such external sociological drivers were not integrated into this analysis, our results provide insights into tipping points for

A. Forward-looking decision-maker and adaptive ecological system decision strategy **B. Unrealistically short-term ecological change** **C. Unrealistically fast ecological change $r = 0.95$**

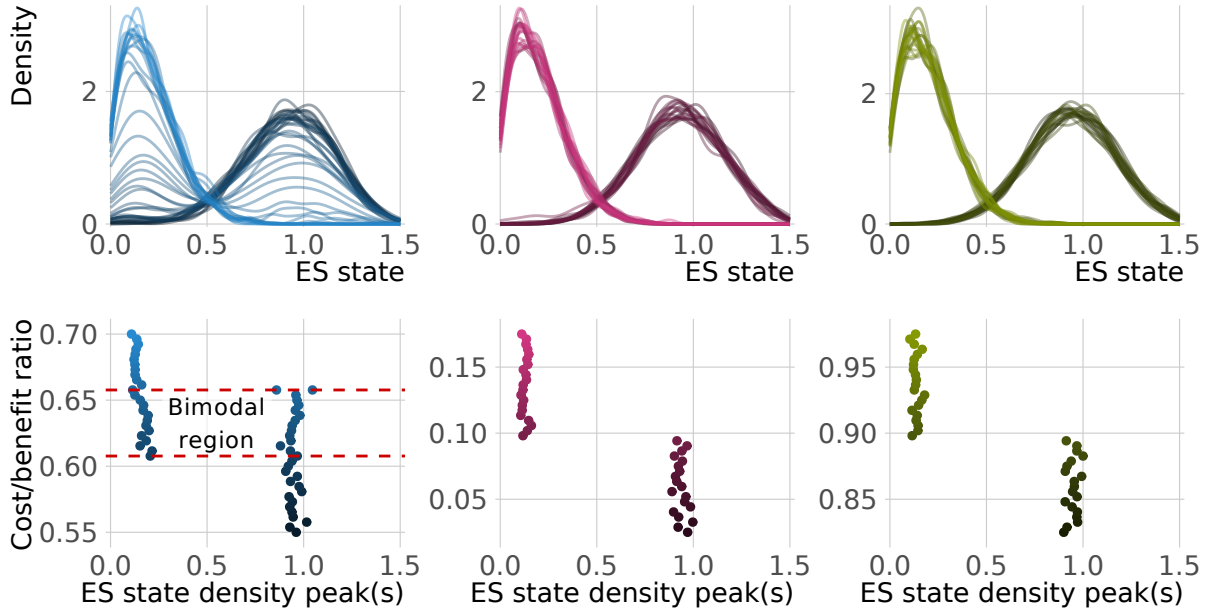


Figure 6: For three scenarios (coupled human/natural system, overly-myopic decision maker, and overly-fast ecological change), cost/benefit ratio was varied incrementally over 40 values, indicated by color shade, across a $c : b$ range of width 0.15, encompassing the transition between a “never invest” to an “always invest” policy. For each $c : b$, 500 replicate simulations were conducted as in Fig 2. Upper plots show distribution of ES state at $t = 20$ for each $c : b$. Lower plots show density curve peak(s). (A) By coupling a forward-looking decision-maker and a slowly-adapting environment, complex dynamics like alternate stable states can emerge. However, with (B) a short-term decision strategy (solving the MDP over a 2-year time horizon), or (C) a fast ecological change rate ($r = 0.95$), no bimodality is observed.

practice adoption, temporal dynamics, and the impacts of land tenure on adoption, and can therefore guide incentive programs inform policy decisions. By representing diversified agroecological adoption as a coupled system, we find that the observed bistability may be the result of tipping points in the optimal sequence of management that effect slow ecological processes, rather than tipping points inherent in the ecological dynamics or the cognitive/social predispositions of human agents alone.

In light of historical agricultural catastrophes like the Dust Bowl, the importance of informed policy action in response to stressors like climate change and soil degradation is imperative. Policy designed to promote agricultural sustainability can have complex ramifications (IPES-Food 2018), and designing effective policy in the light of tipping points is In our model, we find that compared to short-term incentives, longer-term packages were found to be more successful in moving farmers who started in the simplified ecological states to diversified states. Similarly, while land tenure is largely known to affect sustainable agricultural practice adoption (Soule, Tegene, and Wiebe 2000; Fraser 2004; Richardson Jr 2015; Long et al. 2017), we illustrate why secure land tenure is integral to the adoption of diversified agroecological practices. Policies that increase land tenure duration, such as regulating lease agreement terms, providing low interest loans, or promoting stable farm succession plans, may therefore represent a key lever to nudge farmers toward more diversified agroecological systems. Likewise, perceived stability of incentive programs over time may be an important driver of efficacy, which can be overlooked when not considering the temporal components of coupled social-environmental systems. With U.S. Farm Bills being overhauled every five years, a farmer may have limited confidence that a critical incentive program will be sufficiently long-lived, suggesting that a policy lever may be to extend the sunseting of agroecological policy bills (Jackson 2009).

(this paragraph needs to be stronger) With no inherent complexity in the ecological model, and decision-making agents that simply optimize their expected utility based on current conditions, our model generates the bimodal distribution of agroecological practice adoption and ecological outcomes. By conceiving of sustainable agricultural through this lens, we offer new insights into important agricultural policy conundrums.

Several limitations of this model should be considered. We do not draw distinctions between diversification practices that have different cost structures or ecological outcomes. Additionally, our model does not capture market dynamics resulting from feedbacks between production and consumption, but rather conceives of the system as a commodity market within which an individual farmer’s production does not influence the market price. We also do not consider ecosystem services or deleterious environmental effects that spillover from neighboring farms. However, these can all be integrated into the presented framework and offer potential avenues for future research.

Methods

We developed a Markov Decision Process model to represent a farmer’s agroecological adoption choices over time. The model’s state space is a vector with a lower bound of 0 and a soft upper bound of 1, with the system state s_t representing the degree to which the agent derives ecosystem service benefits b_s from the diversification practices they have implemented on their farm. Actions to increase investments in diversification practices probabilistically increase or decrease the future system state, with r defining the rate at which the ecosystem responds to change. While agents may stochastically transition to $s > 1$, investments into diversification practices do not positively correlate with the probability of upward state transitions beyond $s = 1$.

The action space is a continuous vector from 0 to 1, with $a = 0$ representing no investment of resources into DP adoption or maintenance, and $a = 1$ representing the highest conceivable level of investment. Investment in diversification practices incurs costs c_a , either as a direct result of implementation (e.g. equipment, materials, and labor), opportunity costs (e.g. forgone yields due to reduced cultivated acreage or lost production efficiency), or both.

The time step t corresponds to a single growing season. At each time step, the agent chooses an action based on their current state by following decision strategy π . This strategy is calculated by maximizing expected utility for each state/action pair over the full time horizon using a Stochastic Dynamic Programming

Table 1: Baseline parameter values

Parameter	Value
Benefit b	1.56
Cost c	1.00
Noise σ	0.1
State response rate r	0.1
Discount factor γ	0.97

(SDP) approach (Marescot et al. 2013), with the discount rate γ determining how much the agent values current rewards relative to future rewards.

Mathematical description

The farmer’s decision model can be expressed as

$$\max_{\{a_t\}} \mathbb{E} \left[\sum_t^T u(s_t, a_t) \gamma^t \right]$$

where $\{a_t\}$ is the set of available actions to be taken at each point in time t , \mathbb{E} the expected utility operator, $u(s_t, a_t)$ the utility which the farmer associates with being in state s_t and taking action a_t at time t , and γ the myopic discount factor. T is the land tenure of the farm ($T \rightarrow \infty$ if the farmer owns the land or has a long lease).

We assume a simple model of the farmer’s perceived utility, $u(s_t, a_t)$, as a function of the costs c_a associated with diversification practice investment action a_t at time t , versus benefits b_s derived from ecosystem state s_t at time t

$$u(s_t, a_t) = b_s s_t - c_a a_t$$

The ecosystem state is also dynamic, evolving according to the transition probability function $p(s_t, a_t)$, such that

$$s_{t+1} = p(s_t, a_t) := s_t + r(a_t - s_t) + \epsilon$$

Where $\epsilon \sim N(0, \sigma)$. This provides a minimal state transition model in which the parameter r sets the natural timescale at which the ecosystem can respond to changes in land management decisions, and σ defines the spread of the state transition probability distribution, capturing the noise inherent to ecological system change. While we have assumed very basic transition and utility functions for this stylized model, in general more complicated nonlinear functions for both the ecosystem state transition and derived utility are possible using this framework.

Model implementation

(do we need this??) The model was developed in the *R* programming language (R Core Team 2019). The *MDPtoolbox* library was used to set up and solve the MDP (Chades et al. 2017), *tidyverse* for data analysis (Wickham et al. 2019), and *ggplot2* to generate all figures (Wickham 2016). Code for our model and the experiments conducted in this paper is available freely at <https://github.com/boettiger-lab/dfs-mdp>.

Parameterization

We have parameterized the model to illustrate the emergence of bistability in CHANS resulting from agroecological investment decision-making given stochastic ecological responses over time. Parameter values appear in Table 1.

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