Tipping points in the adoption of agroecological practices

Melissa Chapman[a], Serge Wiltshire[a], Timothy Bowles[a], Liz Carlisle[c], Fredrico Castillo[a], David Gonthier[e], Alastair Iles[a], Daniel Karp[d], Claire Kremen[a,1], Jeff Liebert[f], Elissa Olimpi[d], Amber Sciligo[g], Jennifer Thompson[a], Hannah Waterhouse[a], Kenzo Eszquivel[a], Carl Boettiger[a,]

[a]*Dept. of Environmental Science, Policy, and Management, University of California Berkeley, Berkeley, CA, USA*
[b]*Institute of Resources, Environment and Sustainability, University of British Columbia, Vancouver, BC, Canada*
[c]*Environmental Studies, University of California Santa Barbara, Santa Barbara, CA, USA*
[d]*Wildlife, Fish, and Conservation Biology, University of California Davis, Davis, CA, USA*
[e]*Dept. of Entomology, University of Kentucky, Lexington, KY, USA*
[f]*School of Integrated Plant Science, Cornell University, Cornell, NY, USA*
[g]*The Organic Center, Washington, DC, USA*

Abstract

The emergence and impact of tipping points are of immense interest in both social and ecological research. Yet despite widespread recognition of feedbacks between the two domains, it is often assumed that the underlying forces that lead to nonlinear behaviors rest within either human or natural processes. Our work shows how tipping points can arise in a stylized coupled human and natural systems (CHANS) model representing adoption of agroecological diversification practices. Even when neither system alone has complex dynamics, a farmer's adoption choice, based on their perceived utility over a given time horizon, together with ecological services derived from stochastic environmental change, can drive systems into alternate stable states. Because ecosystem services take years 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 that this tipping point need not be an inherent feature of either ecological or decision dynamics, but can emerge as a general pattern when a simple ecosystem model and a rational decision process are dynamically coupled over time. We suggest that this finding has important implications for agricultural and land use policy design across a range of domains, including land tenure and agroecological subsidies.

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 or "tipping point". 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 like population dynamics. Similarly, examples from social science—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 dynamical complexity 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 possibilites (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. However, much of the existing literature in this area focuses either on human decision-making (with ecological processes being exogenous to the model), or explores the complexity of ecological processes without sufficiently considering the role of adaptive human agents (Vandermeer and Perfecto 2012). Further, those techniques that do investigate dynamic processes and responsive decision-making don't generally allow for forward looking agents (Lippe et al. 2019), ultimately misrepresenting 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 produce 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. A "system state" represents the degree of beneficial ecosystem services derived from those decisions. 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 stochastiticity, ecological change rate, and 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.
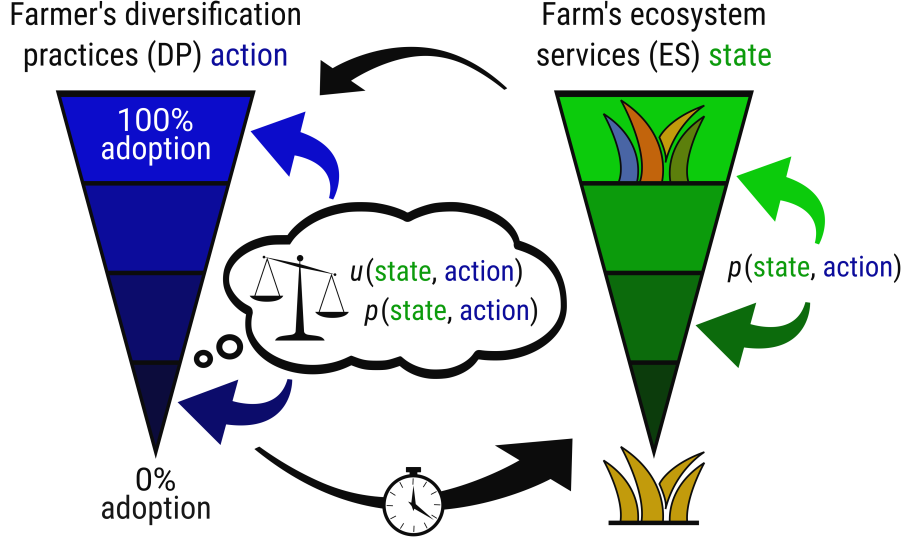
Figure 1: Conceptual diagram of the DFS-MDP model. The farmer's choice of how much to invest (time and/or money) into diversification practices (DP) adoption is shown in blue, and the resulting ecosystem services (ES) state in green, with a more diversified state at the top, and a more simplified state 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. For each experiment, we conduct 500 runs, with agents' initial ecosystem states distributed normally around a mean of $\bar{s} = 0.5$. Fig 2 shows that, after having followed the optimal decision strategy for 19 years, at $t = 20$ agents have largely settled into two groups, with some farms transitioning to more simplfied (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 critical bifurcation, or 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), and with widely-varying rental agreements, the impact of land tenure on best management practice adoption has been increasingly scrutinized. For example, a study of U.S. corn producers 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). A study conducted in British Columbia found that tenant farmers planted fewer perennial crops than land owners (Fraser 2004). Our own ongoing research with produce farmers in California's Salinas Valley suggests
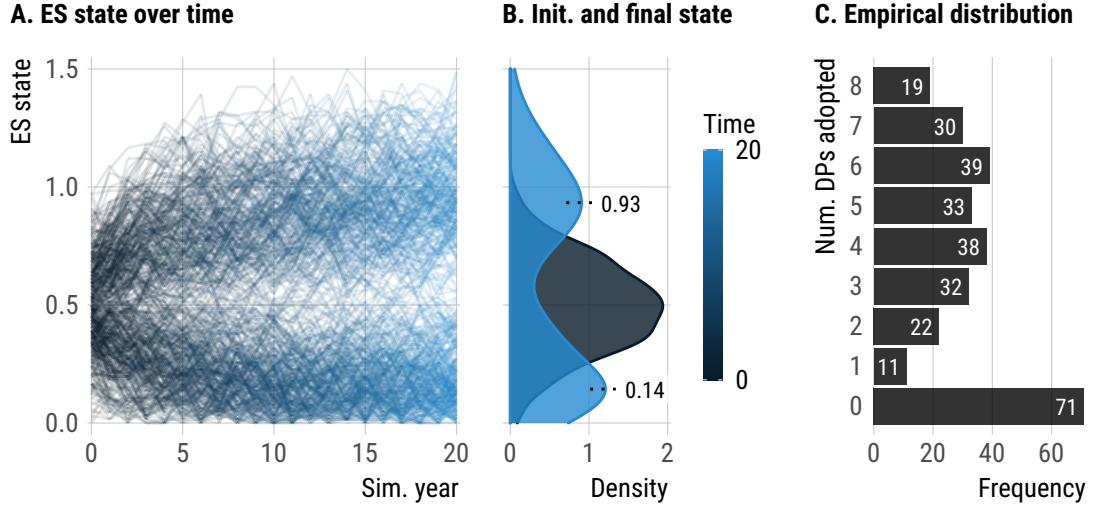
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Figure 2: Replicate simulations of 500 model agents. Initial ES states are distributed normally (mean = 0.5; S.D. = 0.2; truncated at [0,1]). Agents follow decision strategy π as shown in Fig 3 until $t = 20$. (A) ES state of each agent over time. (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.
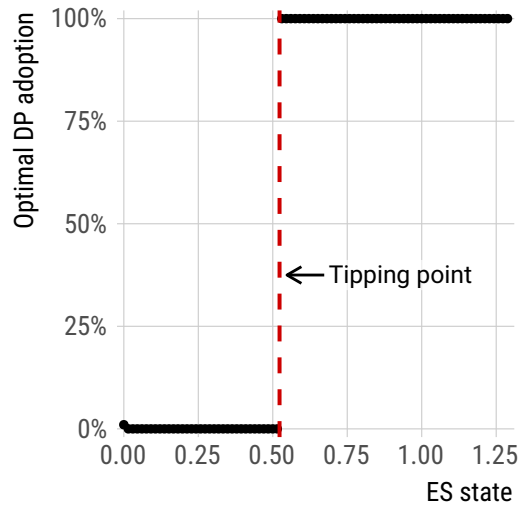

Figure 3: Optimal decision strategy π as a function of ES state, showing a tipping point at $s \approx 0.52$. The upper x axis limit is the 99th percentile of observed states in our simulation results ($s \approx 1.3$).

A. Short-tenure timeseries   **B. ES state distribution**   **C. Simulation data**
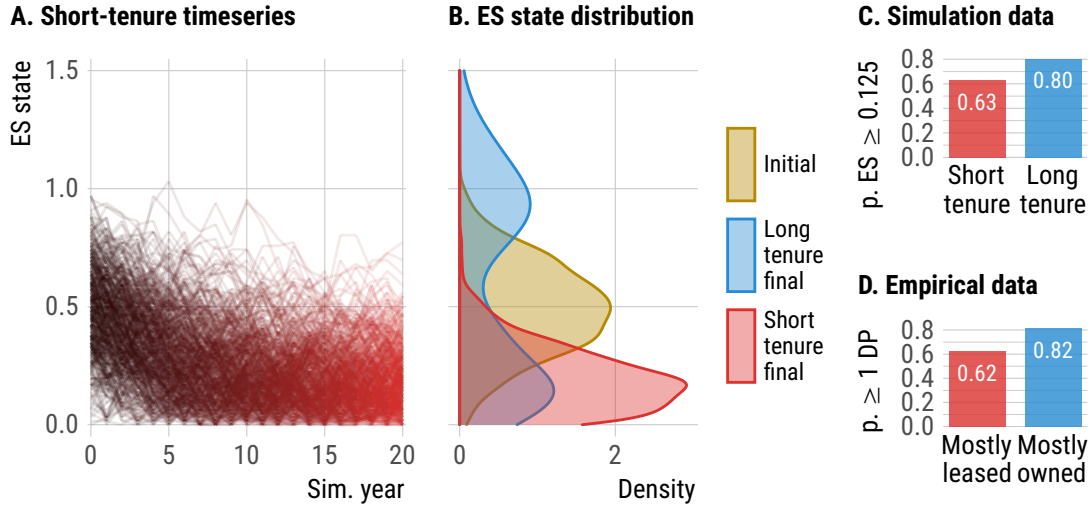
D. Empirical data

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.

that land tenure is an important factor in decisions about cover cropping and crop rotation. In addition, investments in agroecology may require access to credit, which often also hinges on secure land tenure as collateral (Richardson Jr 2015).

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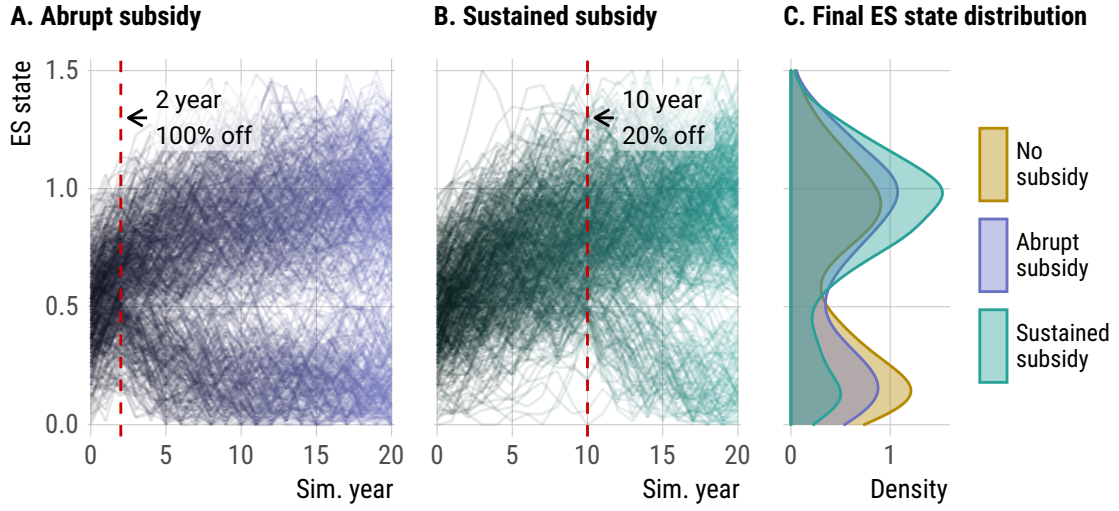
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Figure 5: Starting from the same initial states as Fig 2, ES state timeseries are shown for (A) a large, abrupt subsidy (100% of adoption expenses are covered for two years) vs. (B) a smaller, more sustained subsidy (adoption cost is 80% of baseline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

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 subsidy packages have a higher chance of nudging behavior beyond the critical threshold, ultimately resulting in more agroecological practice 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 DPs, and conversely, a sufficiently low ratio will result in no DP 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
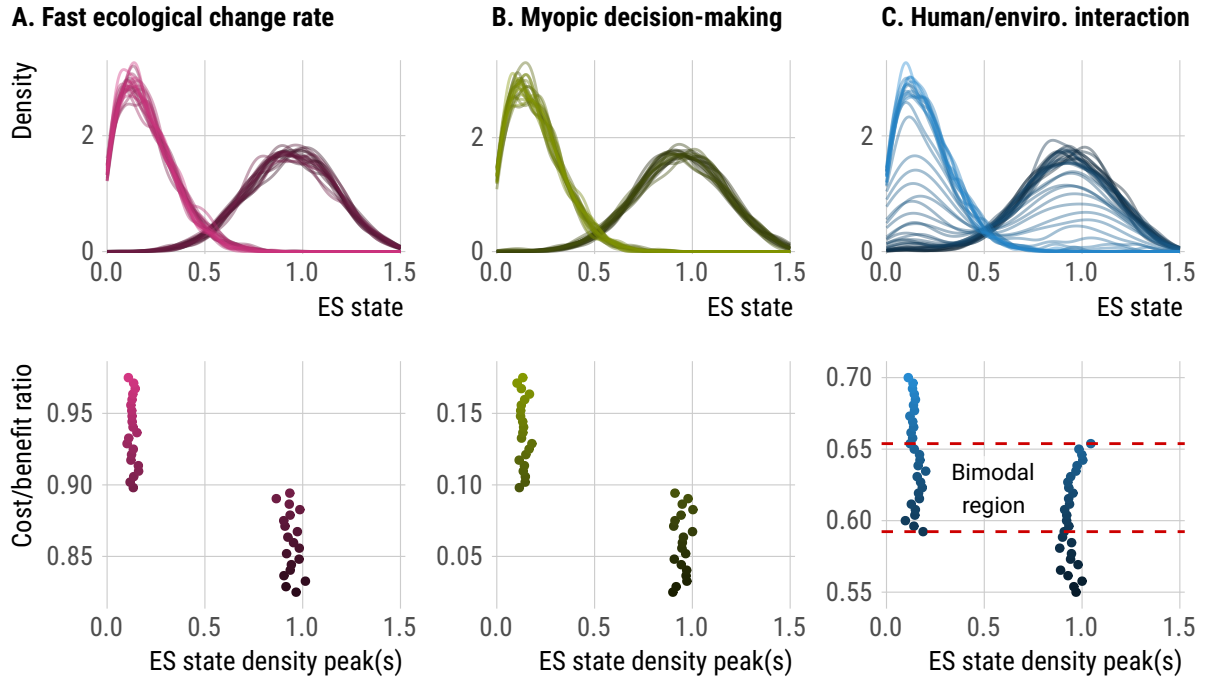
Figure 6: For three scenarios (fast ecological process, temporally-myopic decisions, and coupled system), cost/benefit ratio was varied incrementally over 40 values, indicated by color shade, across a $c:b$ range of width 0.15, encompassing the transition between a "never invest" to an "always invest" 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 values of density curve peak(s) for each $c:b$. With (A) a fast ecological change rate ($r = 0.95$) or (B) a short-term decision strategy (solving the MDP over a 2-year time horizon) no bimodality is seen. (C) Only by coupling a forward-looking decision-maker and a slowly-adapting environment do complex dynamics like bimodality emerge.

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.

By representing diversified agroecological adoption as a coupled system, we find that the empirically-observed bistability may be the result of tipping points in the optimal sequence of decisions regarding 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. Offering incentives and encourage the adoption of agroecological diversification practices is important for increasing food system resilience to global change [CITE]. Existing case studies emphasize that policy mechanisms designed to promote agricultural sustainability have complex ramifications (IPES-Food 2018). Policy design must take into account the likely case of thresholds at which particular farming practices become more or less viable. We suggest that the temporal component of decision-making and feedbacks is an important consideration for incentive and land tenure agricultural policies aiming to promote more resilient food systems. Compared to short-term subsidies, longer-term incentives were found to be more successful in moving farmers who started in the simplified ecological states to diversified states. A ramification of this finding is that the perceived stability of subsidy programs over time may be an important driver of their efficacy. Since the transitional barrier between the two stable states represents a precarious economic position, if a subsidy is not guaranteed for a long enough period to get significant benefits from the ecological feedbacks, the farmer may be incentivized to simply continue in their initial state. With U.S. Farm Bills being overhauled every five years, a farmer may have limited confidence that a critical subsidy program will be sufficiently long-lived, suggesting that a policy lever may be to extend the sunsetting of agroecological policy bills (Jackson 2009).

Land tenure is known to affect sustainable agricultural practice adoption (Soule, Tegene, and Wiebe 2000; Fraser 2004; Richardson Jr 2015; Long et al. 2017). For example, landowners or long-term lease holders have a larger stake in the productive quality of their soil ecology. By coupling the rate of ecological change with the time horizon of decision-making under different tenure situations 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.

Even 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 some 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 grower'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 (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 ($T \to \infty$ 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

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

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 mangement, 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

The model was developed in the R programming language (R Core Team 2019). The *MDPtoolbox* library was leveraged 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.

Table 1: Baseline parameter values

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

Table 2: Diversification practices and adoption rates in the survey data

DP Name	Adoption rate
Crop Rotation (3 or more)	63%
Cover Cropping	68%
Intercropping	52%
Insectary Plantings	61%
Riparian Buffers	84%
Border Plantings	45%
Compost or Manure	75%
Reduced Tillage	69%

Empirical dataset

To groud-truth our modeling work, we examine farmers' sustainable management practice adoption distributions using a dataset of survey responses from 295 vegetable growers in Washington, Oregon, and California *CITE DATA SOURCE*. Table 2 gives the set of diversification practices queried in the survey, with their adoption rates across the entire sample. A histogram plotting the number of DPs used by each grower (Fig 2C) shows a bimodal distribution, with growers generally tending to either adopt zero DPs—the most likely case—or else to adopt many, with six practices being the next-most-likely. To investigate the effect of land tenure on DP adoption, we partition the dataset into growers who primarily own their land versus those who primarily lease. Figure 4D shows that owners in our sample are about 20% more likely than leasers to invest in at least one diversification practice.

References

Alberti, Marina, Heidi Asbjornsen, Lawrence A Baker, Nicholas Brozovic, Laurie E Drinkwater, Scott A Drzyzga, Claire A Jantz, et al. 2011. "Research on Coupled Human and Natural Systems (Chans): Approach, Challenges, and Strategies." *The Bulletin of the Ecological Society of America* 92 (2): 218–28.

Blaauw, Brett R, and Rufus Isaacs. 2014. "Flower Plantings Increase Wild Bee Abundance and the Pollination Services Provided to a Pollination-Dependent Crop." *Journal of Applied Ecology* 51 (4): 890–98.

Chades, Iadine, Guillaume Chapron, Marie-Josee Cros, Frederick Garcia, and Regis Sabbadin. 2017. *MDPtoolbox: Markov Decision Processes Toolbox.* https://CRAN.R-project.org/package=MDPtoolbox.

Downey, Sean S, W Randall Haas, and Stephen J Shennan. 2016. "European Neolithic Societies Showed Early Warning Signals of Population Collapse." *Proceedings of the National Academy of Sciences* 113 (35): 9751–6.

Foley, Jonathan A, Ruth DeFries, Gregory P Asner, Carol Barford, Gordon Bonan, Stephen R Carpenter, F Stuart Chapin, et al. 2005. "Global Consequences of Land Use." *Science* 309 (5734): 570–74.

Foley, Jonathan A, Navin Ramankutty, Kate A Brauman, Emily S Cassidy, James S Gerber, Matt Johnston, Nathaniel D Mueller, et al. 2011. "Solutions for a Cultivated Planet." *Nature* 478 (7369): 337–42.

Fraser, Evan DG. 2004. "Land Tenure and Agricultural Management: Soil Conservation on Rented and Owned Fields in Southwest British Columbia." *Agriculture and Human Values* 21 (1): 73–79.

Graddy-Lovelace, Garrett, and Adam Diamond. 2017. "From Supply Management to Agricultural Subsidies—and Back Again? The Us Farm Bill & Agrarian (in) Viability." *Journal of Rural Studies* 50: 70–83.

Horan, Richard D., Eli P. Fenichel, Kevin L. S. Drury, and David M. Lodge. 2011. "Managing Ecological Thresholds in Coupled Environmentalhuman Systems." *Proceedings of the National Academy of Sciences* 108 (18): 7333–8. https://doi.org/10.1073/pnas.1005431108.

IPES-Food. 2018. "Breaking Away from Industrial Food and Farming Systems: Seven Case Studies of Agroecological Transition."

Jackson, Wes. 2009. "The 50-Year Farm Bill-a Long-Term Plan for Sustainable Land Use Across America."

Kline, Jeffrey D, Eric M White, A Paige Fischer, Michelle M Steen-Adams, Susan Charnley, Christine S Olsen, Thomas A Spies, and John D Bailey. 2017. "Integrating Social Science into Empirical Models of Coupled Human and Natural Systems." *Ecology and Society* 22 (3).

Kremen, Claire, Alastair Iles, and Christopher Bacon. 2012. "Diversified Farming Systems: An Agroecological, Systems-Based Alternative to Modern Industrial Agriculture." *Ecology and Society* 17 (4).

Kuehn, Christian, Erik A Martens, and Daniel M Romero. 2014. "Critical Transitions in Social Network Activity." *Journal of Complex Networks* 2 (2): 141–52.

Lippe, Melvin, Mike Bithell, Nick Gotts, Davide Natalini, Peter Barbrook-Johnson, Carlo Giupponi, Mareen Hallier, et al. 2019. "Using Agent-Based Modelling to Simulate Social-Ecological Systems Across Scales." *GeoInformatica* 23 (2): 269–98.

Liu, Jianguo, Thomas Dietz, Stephen R Carpenter, Marina Alberti, Carl Folke, Emilio Moran, Alice N Pell, et al. 2007. "Complexity of Coupled Human and Natural Systems." *Science* 317 (5844): 1513–6.

Long, R, Kelly Garbach, L Morandin, and others. 2017. "Hedgerow Benefits Align with Food Production and Sustainability Goals." *California Agriculture* 71 (3): 117–19.

Marescot, Lucile, Guillaume Chapron, Iadine Chades, Paul L Fackler, Christophe Duchamp, Eric Marboutin, and Olivier Gimenez. 2013. "Complex Decisions Made Simple: A Primer on Stochastic Dynamic Programming." *Methods in Ecology and Evolution* 4 (9): 872–84.

Morandin, LA, RF Long, and C Kremen. 2016. "Pest Control and Pollination Cost–Benefit Analysis of Hedgerow Restoration in a Simplified Agricultural Landscape." *Journal of Economic Entomology* 109 (3): 1020–7.

Ostrom, Elinor. 2009. "A General Framework for Analyzing Sustainability of Social-Ecological Systems." *Science* 325 (5939): 419–22.

R Core Team. 2019. *R: A Language and Environment for Statistical Computing.* Vienna, Austria: R Foundation for Statistical Computing. https://www.R-project.org/.

Richardson Jr, Jesse J. 2015. "Land Tenure and Sustainable Agriculture." *Tex. A&M L. Rev.* 3: 799.

Rosa-Schleich, Julia, Jacqueline Loos, Oliver Mußhoff, and Teja Tscharntke. 2019. "Ecological-Economic Trade-Offs of Diversified Farming Systems–a Review." *Ecological Economics* 160: 251–63.

Scheffer, Marten, and Stephen R Carpenter. 2003. "Catastrophic Regime Shifts in Ecosystems: Linking Theory to Observation." *Trends in Ecology & Evolution* 18 (12): 648–56.

Service, USDA National Agricultural Statistics. 2016. "2016 Agricultural Statistics." https://data.nal.usda.gov/dataset/nass-quick-stats.

Soule, Meredith J, Abebayehu Tegene, and Keith D Wiebe. 2000. "Land Tenure and the Adoption of Conservation Practices." *American Journal of Agricultural Economics* 82 (4): 993–1005.

Stoate, C, A Báldi, Pl Beja, ND Boatman, I Herzon, A Van Doorn, GR De Snoo, L Rakosy, and C Ramwell. 2009. "Ecological Impacts of Early 21st Century Agricultural Change in Europe–a Review." *Journal of Environmental Management* 91 (1): 22–46.

Vandermeer, John, and Ivette Perfecto. 2012. "Syndromes of Production in Agriculture: Prospects for Social-Ecological Regime Change." *Ecology and Society* 17 (4).

Walker, Brian, Crawford S Holling, Stephen R Carpenter, and Ann Kinzig. 2004. "Resilience, Adaptability and Transformability in Social–Ecological Systems." *Ecology and Society* 9 (2).

Wickham, Hadley. 2016. *Ggplot2: Elegant Graphics for Data Analysis.* Springer-Verlag New York. https://ggplot2.tidyverse.org.

314   Wickham, Hadley, Mara Averick, Jennifer Bryan, Winston Chang, Lucy D'Agostino McGowan, Romain
315 François, Garrett Grolemund, et al. 2019. "Welcome to the tidyverse." *Journal of Open Source Software* 4
316 (43): 1686. https://doi.org/10.21105/joss.01686.
317   Zhang, Wei, Taylor H Ricketts, Claire Kremen, Karen Carney, and Scott M Swinton. 2007. "Ecosystem
318 Services and Dis-Services to Agriculture." *Ecological Economics* 64 (2): 253–60.