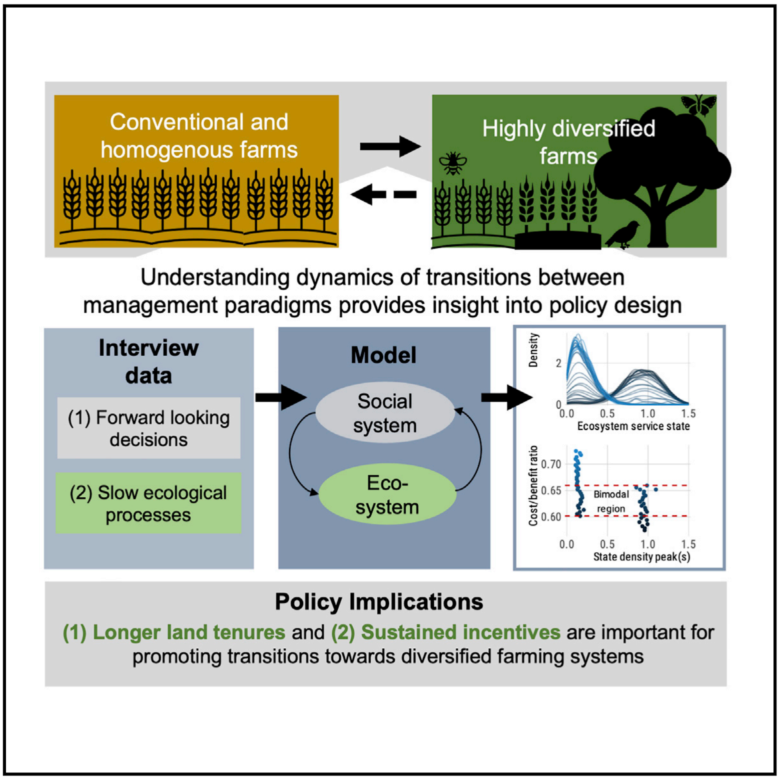
One Earth

Article

Social-ecological feedbacks drive tipping points in farming system diversification

Graphical abstract



Highlights

- Understanding barriers to farming system diversification is critical
- Temporal feedbacks can drive complex dynamics in farm-management patterns
- Decision horizons impact management patterns, suggesting land tenure policy is important
- Sustained incentives can be effective at promoting farm diversification

Authors

Melissa Chapman, Serge Wiltshire, Patrick Baur, ..., Jennifer Thompson, Hannah Waterhouse, Carl Boettiger

Correspondence

mchapman@berkeley.edu

In brief

Understanding what drives the adoption of sustainable land management practices is critical to designing effective policy interventions. Using a stylized model informed by interview data, we show how tipping points in the farming system diversification can emerge from the feedbacks between a farmer's forward-looking management decisions and slow ecological responses to those decisions. We explore why land-tenure policy and the durability of incentive programs are critical to promoting farmers' transitions toward sustainable agriculture.

Chapman et al., 2022, One Earth 5, 1–10
March 18, 2022 © 2022 Elsevier Inc.
https://doi.org/10.1016/j.oneear.2022.02.007

Please cite this article in press as: Chapman et al., Social-ecological feedbacks drive tipping points in farming system diversification, One Earth (2022), https://doi.org/10.1016/j.oneear.2022.02.007

One Earth

CellPress

Article

Social-ecological feedbacks drive tipping points in farming system diversification

Melissa Chapman,[1,10,*] Serge Wiltshire,[1] Patrick Baur,[2] Timothy Bowles,[1] Liz Carlisle,[3] Federico Castillo,[1] Kenzo Esquivel,[1] Sasha Gennet,[4] Alastair Iles,[1] Daniel Karp,[5] Claire Kremen,[1,6] Jeffrey Liebert,[7] Elissa M. Olimpi,[8] Joanna Ory,[1] Matthew Ryan,[7] Amber Sciligo,[9] Jennifer Thompson,[1] Hannah Waterhouse,[1] and Carl Boettiger[1]
[1]Department of Environmental Science, Policy, and Management, University of California, Berkeley, Berkeley, CA, USA
[2]Department of Fisheries, Animal and Veterinary Sciences, University of Rhode Island, Kingston, RI, USA
[3]Environmental Studies, University of California, Santa Barbara, Santa Barbara, CA, USA
[4]The Nature Conservancy, Arlington, VA, USA
[5]Wildlife, Fish, and Conservation Biology, University of California, Davis, Davis, CA, USA
[6]Institute of Resources, Environment and Sustainability, Department of Zoology and Biodiversity Research Centre, University of British Columbia, Vancouver, BC, Canada
[7]School of Integrative Plant Science, Cornell University, Ithaca, NY, USA
[8]Fish and Wildlife Conservation, Virginia Tech, Blacksburg, VA, USA
[9]The Organic Center, Washington, DC, USA
[10]Lead contact
*Correspondence: mchapman@berkeley.edu
https://doi.org/10.1016/j.oneear.2022.02.007

SCIENCE FOR SOCIETY Understanding what drives the adoption of sustainable land management practices is critical to designing effective policy interventions. Using a stylized model informed by interview data, we show how tipping points in the adoption patterns of diversified farming practices can emerge from the feedbacks between a farmer's forward-looking management decisions and slow ecological responses to those decisions. We use our model of this system to explore why land tenure policy and the durability of incentive programs are critical to promoting farmers' transitions toward sustainable agriculture.

SUMMARY

The emergence and impact of tipping points have garnered significant interest in both the social and natural sciences. Despite widespread recognition of the importance of feedbacks between human and natural systems, it is often assumed that the observed nonlinear dynamics in these coupled systems rests within either the underlying human or natural processes rather than the rates at which they interact. Using adoption of agricultural diversification practices as a case study, we show how two stable management paradigms (one dominated by conventional, homogeneous practices and the other by diversified practices) can emerge purely from temporal feedback between human decisions and ecological responses. We explore how this temporal mechanism of tipping points provides insight into designing more effective interventions that promote farmers' transitions toward sustainable agriculture. Moreover, we present a flexible modeling framework that could be applied to other cases as well as questions in social-ecological systems research and environmental policy design.

INTRODUCTION

Both ecosystems and social systems can change states abruptly as the result of crossing critical thresholds. These critical thresholds ("tipping points," or states of a system where small perturbations can trigger large responses) have garnered extensive academic and public attention.[1,2] However, mechanisms of tipping points in social-ecological systems (SESs) remain largely explained by complex assumptions about either the ecological or social system dynamics[3–6] rather than the ways in which these systems interact.

In social-ecological systems, human actions impact ecological processes, and the resultant ecological changes create feedbacks that alter future management actions.[7–9] These systems become challenging to model when the temporal dynamics of ecological processes and their feedback to human systems (i.e., benefits from ecosystems services) do not align with the temporal scale of human decision making.[10] Techniques previously used to investigate both dynamic ecological processes and decision making in SESs have mostly overlooked the temporal complexity of decision making.[11] For instance, agent-based models are commonly used to explore complex emergent phenomena in SESs. However, these models often use single time-step, or user-defined, decision rules rather than allowing for emergent decision strategies that maximize expected rewards over longer time horizons.[11] Similarly, economic models, which typically explicitly consider the time horizons of decisions, often overlook ecological lags.[12] While temporal dynamics are central to understanding both ecological and decision-making processes (e.g., land tenure affects decision making by creating long-term incentives for management),[13–16] new modeling approaches that can integrate temporal attributes of both ecological processes and human decision making are needed.

Agriculture is a particularly interesting case for exploring time lags in social-ecological systems, because many ecological responses to management actions in these systems (such as planting hedgerows or building up organic matter in soils) happen slowly, often taking years to return ecological and/or financial benefits, which can exceed the time frame of investment planning. Further, the duration of land tenure varies considerably among farmers, which creates variation in, and constraints on, horizons over which decisions strategies are optimized.[16] Farmers on owned land may be able to plan for payoffs that occur over the course of multiple decades or generations. Tenant farmers who lease their farmland, by contrast, may be constrained to the decisions that pay off during the length of lease agreements. In the United States, leases are most often short-term, single-year contracts but can extend up to 10 years.[17] Finally, while agriculture is regularly cited as a key driver of anthropogenic ecological change,[18–20] different types of agriculture have radically different effects on ecosystems. Some forms of agriculture rely on promoting ecological processes that regenerate ecosystem services for their productivity and are less input intensive (diversified farming systems), while others rely primarily on external inputs, such as chemical fertilizers and pesticides that often degrade the surrounding water, soil, and air quality.[21] In the context of diversified farming systems, diversification practices include hedgerows, crop rotation, intercrops, the use of compost, growing multiple crop types, reduced tillage, and cover crops. This type of diversification is distinct from the concept of operational diversification (i.e., increasing the range of revenue streams produced on a given farm, such as tourism or value-added products) and has been shown to promote ecosystem services that benefit farmers, including soil fertility and water-holding capacity, pest and disease control, pollination, and productivity, thus providing an economically viable alternative to chemically intensive methods of crop production.[22–25]

While adoption of diversified farm management practices encompasses a continuum of actions and outcomes, suites of practices are often used together in a package, coalescing around distinct stable states or "syndromes."[26–28] The mechanisms used to explain and explore these patterns in agricultural systems mathematically have relied on the assumption that both ecological (or production) and decision (or economic) dynamics are non-monotonic (a function that both increases and decreases).[12,28] In coupled dynamic equations, if either of these systems is approximated as monotonic (a function that only increases or only decreases), the larger social-ecological system is characterized by a single stable point (or no stable point), making multiple syndromes of production impossible to explain with dynamic equations.[12,28] In other words, the existence of distinct stable states in agriculture—defined by high levels of biodiversity and associated ecosystem services on one hand and low levels of biodiversity and comparatively high synthetic inputs on the other—cannot be explained in conventional models without assuming complex structural dynamics. While non-monotonic assumptions are often reasonable, equilibrium explanations overlook the temporal component of both the ecological and decision processes central to agricultural SESs.

Markov decision processes (MDPs) provide a convenient mathematical framework for modeling decision making[29] in SESs because they allow for (1) formulation of situations in which environments (in this case, agroecosystems) change slowly and stochastically and (2) land-management decisions that are forward looking and based on predictions about how those decisions will impact a farmer's productivity and vitality in the future. While MDPs have been widely used in a variety of environmental control problems,[30] they are rarely applied to modeling and exploring the dynamics of social-ecological systems. In addition, like other modeling approaches, these methods are scarcely informed by, or ground truthed with, social science data. Leveraging social science data, such as interviews or surveys, can help inform critical features of social-ecological models.

This paper presents a stylized MDP model of the adoption of agricultural diversification practices to explore the ecosystem service patterns that result specifically from interactions between forward-looking decision making and a slowly changing environment (see experimental procedures for further details). Our modeling work is inspired by patterns and system characteristics (e.g., the concept of forward-looking decision making) that emerged from the extensive empirical fieldwork with farmers that our research team has conducted on commercial farms in California (see experimental procedures for further details)[31–33] and through an iterative, collaborative process with an interdisciplinary team comprising plant and soil scientists, agricultural economists, ecologists, agricultural sociologists, modelers, policy analysts, and farmers. Using this model, we explore a mechanism leading to the two prevailing management paradigms (i.e., relying primarily on ecosystem services versus external chemical inputs) that is the result not of complex structural assumptions within either the human or ecological system but rather the rates at which the two systems interact. While our model necessarily simplifies both decision-making and environmental processes, it provides a useful framework to explore emergent properties in social-ecological systems. We show that our findings have important implications, both for agricultural policy implementation such as incentive design and social-ecological systems theory.

RESULTS

We observe the behavior of farmers' sequential choices and the resultant environmental outcomes through time. The decision strategy, π^*, describes the emergent optimal course of action for a given ecosystem service state (the stationary optimal

Please cite this article in press as: Chapman et al., Social-ecological feedbacks drive tipping points in farming system diversification, One Earth (2022), https://doi.org/10.1016/j.oneear.2022.02.007

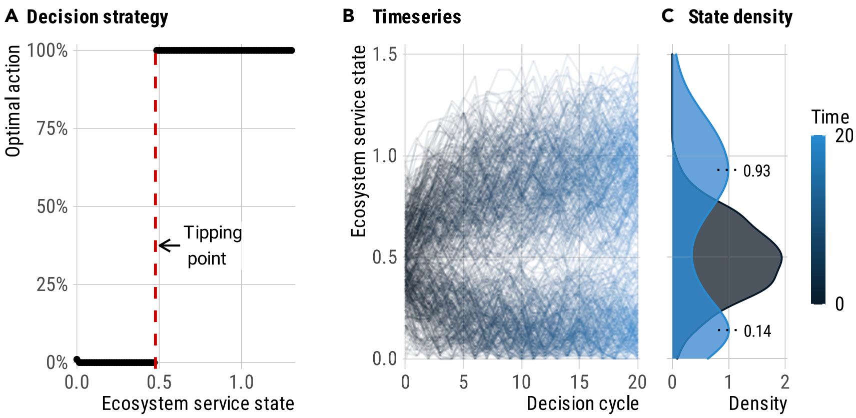


Figure 1. Tipping points in emergent decision strategies drive bistability in ecosystem service states

Initial ecosystem states (dark blue) are distributed normally (mean = 0.5; SD = 0.2; truncated at [0,1]).

(A) Optimal decision strategy π^* for discounted infinite-decision horizon.

(B) Ecosystem state of each agent following decision strategy from (A) over 20 decision cycles (500 simulations).

(C) Initial ecosystem state density (dark blue) and final bimodal ecosystem state density at $t = 20$ (light blue). Density represents the probability density of a given ecosystem service state at a given time step.

state-dependent decision strategy; see experimental procedures for further details). Figure 1A shows this optimal strategy when the farmer plans over a discounted infinite time horizon. Notably, it shows that, at some ecosystem service state, the optimal decision strategy displays a tipping point in which it becomes advantageous to adopt diversification practices (Figure 1A).

We find that, following the optimal decision strategy from Figure 1A, farms have largely settled into two stable ecosystem service states, with some farms transitioning to more simplified (lower levels of ecosystem services) farming systems and others to more diversified (higher levels of ecosystem services) systems (Figures 1B and 1C).

Importance of temporal dynamics in coupled systems

Our baseline model shows how a simple coupling of human choices and ecological responses can result in bistable landscapes of high and low diversification practice adoption and, as a result, high and low levels of ecosystem services (Figure 1). By varying the time horizon of the decision process, the rate of ecological response, and the cost-benefit ratio, we find that this tipping point in decision strategy disappears when the speed of response of either the ecological system or decision-making process overwhelms the coupling (we use this as a proxy for decoupling; Figure 2A).

With temporal human/environment interactions, there exists a region of cost-benefit ratio within which various decision tipping points and bimodal ecosystem service state distributions exist, as in Figures 1 and 2A. Intuitively, at low-enough cost-benefit ratios, bimodality disappears because farmers are expected to always invest (Figure 2A, bottom panel). Similarly, at high-enough cost-benefit ratios, bimodality disappears because farmers are expected to always divest (Figure 2A, bottom panel). However, within a range of cost-benefit ratios, decision strategies are found to drive bimodal ecosystem patterns (Figure 2A, bottom panel between red dotted lines). Shortening the time horizon of decisions (Figure 2B) or increasing the rate of ecological processes (Figure 2C) necessarily changes the ratio of benefits to costs required to make investing in practices worthwhile. However, when decisions become temporally myopic (in this case, with a time horizon of two decision cycles), the potential for bistability in adoption trajectories disappears (Figure 2B, bottom panel). Unlike Figure 1A, there does not exist a region of cost-benefit space for this case, in which bistable patterns of ecosystem states exist (Figure 2B, bottom panel). Similarly, when ecological processes become fast enough that the ecosystem responds almost immediately to farmer actions ($r = 0.95$), alternate stable states fail to emerge, regardless of cost-benefit ratios (Figure 2C, bottom panel). Only when both a gradually changing environment and a forward-looking decision maker (i.e., a farmer who takes into account potential benefits over the long term) are coupled do tipping point phenomena emerge in the decision strategy, leading to two predominant ecosystem service states (Figures 1 and 2A). This bimodal pattern matches farmers' experiences based on quotes from our interview data (see experimental procedures for further details), as well as other real-world agricultural systems.[12]

Influence of land tenure on ecosystem service states

Given that temporal factors emerged as central themes from our interview data on diversified farming adoption patterns (see experimental procedures for further details) and that such factors are more broadly relevant to understanding decision-making patterns on rented land,[16] we investigated the impact of land tenure policy on farmer decision making.

We solved the MDP from Figure 1 on a constrained time horizon (10 decision cycles, in comparison to an infinite time horizon in Figure 1), representing the shorter horizon on which tenant farmers might make decisions.

Comparing the final state distribution of the long-tenure (baseline) versus the short-tenure model shows that, as a farmer's expected land-tenure duration decreases, it becomes optimal to reduce diversification adoption across a wider range of ecosystem states (Figure 3). This results in ecosystem-state degradation even among farm sites with an initially high ecosystem service value after 20 decision cycles (which might represent two separate 10-year leases; Figure 3C). However, the duration of land tenure may not be the sole factor defining decision horizons. Numerous economic and cultural factors—for example, whether farmers are highly motivated to seek sustainability as a goal in itself rather than solely for individual economic reasons—might also impact the time frame over which a farmer is willing to wait for ecological benefit.

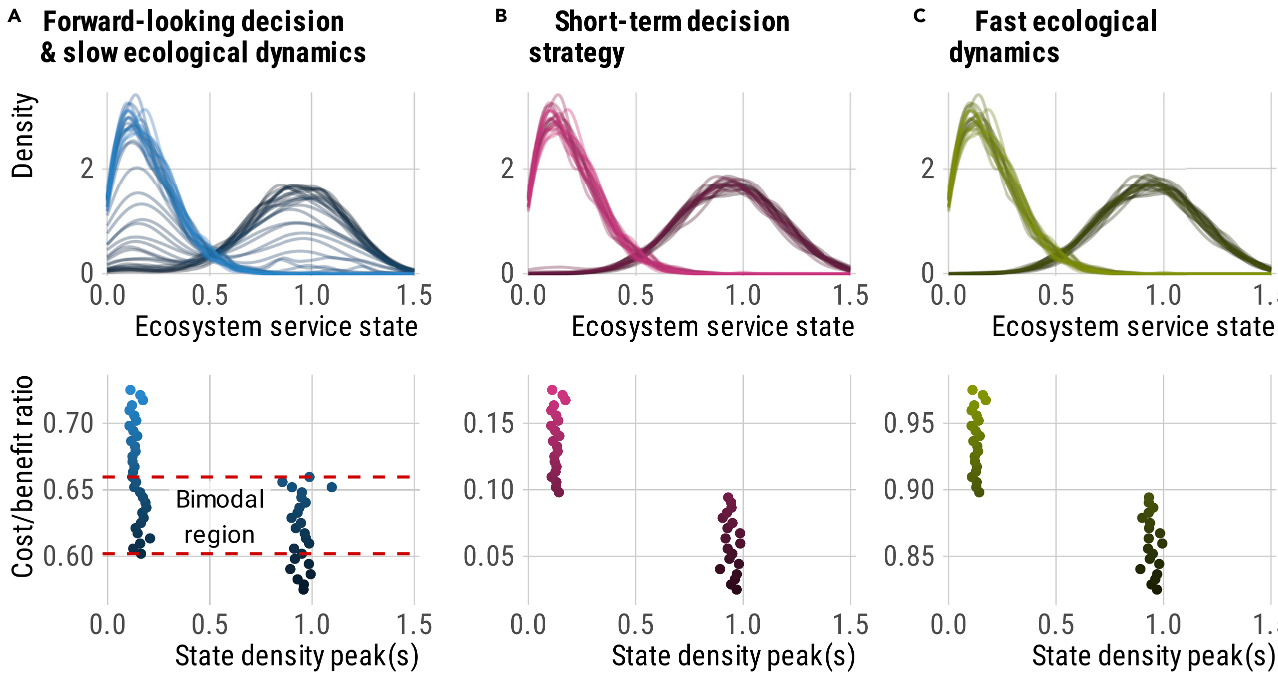


Figure 2. Decision horizons and ecological rates together influence emergent patterns in SESs

For three scenarios (coupled human and 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 Figure 1. Upper plots show distribution of final (t = 20) ecosystem service state for each *c:b*. Lower plots show density curve peak(s). Where overlap is observed in the lower graphs indicates the *c:b* ratios associated with bistability.

(A–C) By coupling (A) a forward-looking decision maker (e.g., a farmer who takes into account potential benefits over the long term) and a slowly adapting environment, complex dynamics like alternate stable states can emerge (seen in cost-benefit ratios between the red dotted lines). Bistable states do not exist at all cost-benefit ratios in this case (i.e., at a high-enough cost-benefit ratio, no adoption will occur, leading to a single low-adoption state). Further, 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. In the cases of (B) and (C), the shift from no adoption to all-in adoption exists at some cost-benefit ratio, removing the possibility of bistability in (A).

Temporal dynamics and incentive structures

Our coupled social-ecological system model also allows for exploration of how incentives that shift cost-benefit structures influence management practices. Based on feedback from the farmers we interviewed (see experimental procedures for further details), we explore the impact of incentive duration on the efficacy of policies to promote adoption of diversification practices by comparing two different publicly funded incentive scheme designs: a short-term (two time step) incentive that fully covers the cost of adoption versus a longer term (10 time step) incentive that only partially offsets the adoption cost. Both schemes offer the same total amount of financial support. Within the model, farmers adapt their optimal decision strategies for the given cost-benefit ratio during the incentive period, and at its conclusion, they revert to the baseline strategy (i.e., without payments).

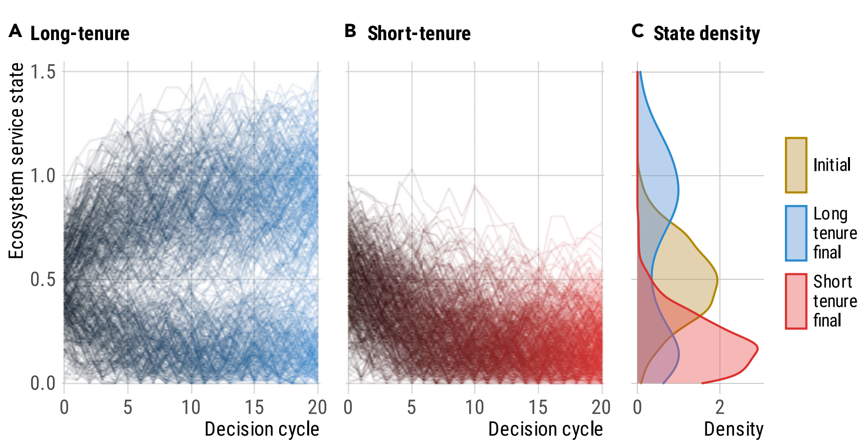


Figure 3. Shortened decision horizons decrease adoption of diversified farming practices

(A) The simulation is identical to that in Figure 1B and represents long, stable land tenure.

(B) The model from (A) is solved under a finite, 10 decision time horizon (rather than an infinite time horizon) to represent short tenure.

(C) Comparison between final state distribution of short- versus long-tenure model runs.

Please cite this article in press as: Chapman et al., Social-ecological feedbacks drive tipping points in farming system diversification, One Earth (2022), https://doi.org/10.1016/j.oneear.2022.02.007

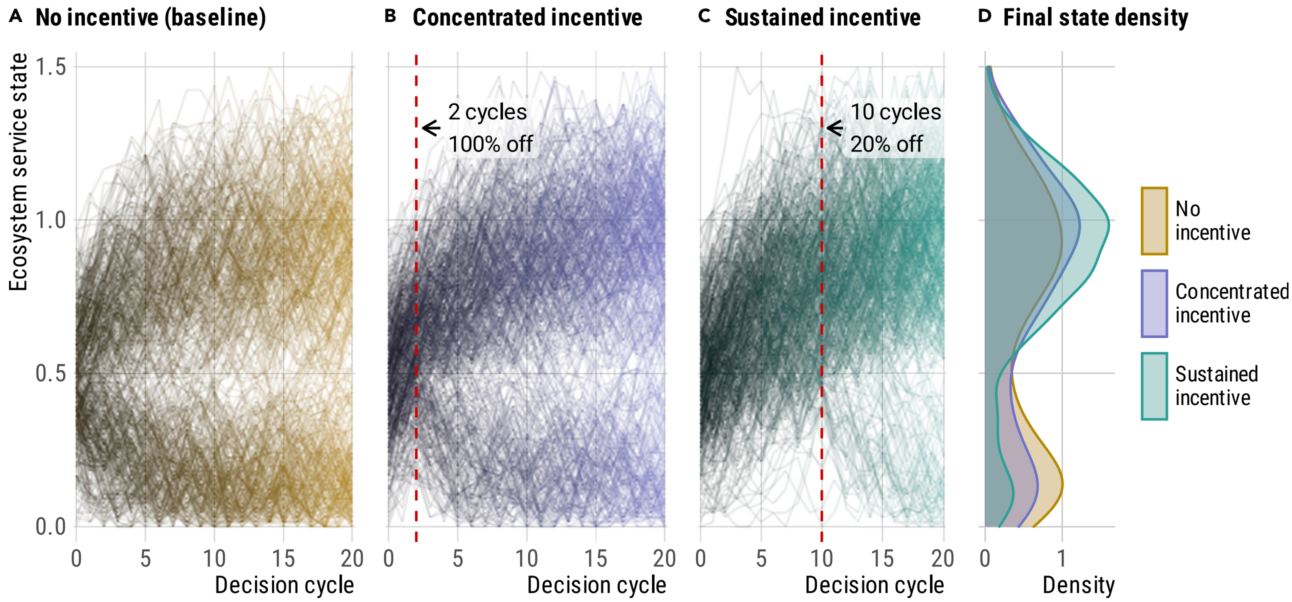


Figure 4. Exploring incentive design with MDP models

(A–C) Starting from the same initial states as Figure 1, ecosystem service state time series are shown for (A) a large, abrupt incentive (100% of adoption expenses are covered for 2 years) versus (B) a smaller, more sustained incentive (i.e., adoption cost is 80% of baseline for 10 years). Before discounting, both packages have the same total cost to the funder (the equivalent of 2 years' worth of full-adoption-cost offsets). With discounting, (C) scenario is cheaper. After the incentive period, farmers (agents) adjust their decision rules to that of the base case (i.e., no incentive) until $t = 20$.

(D) The sustained incentive ultimately drove more diversification practice adoption.

We find longer, more sustained incentive programs to be more effective at pushing the farmer over the critical threshold toward diversified farming (Figure 4). Once a farmer has crossed the viable ecosystem service state threshold (or optimal decision strategy tipping point), it becomes less likely that they will return to simplified systems, even after incentives are removed. Because it takes a series of investment actions for the ecosystem service state to cross this threshold, longer term incentives ultimately result in more adoption of diversification practices. In addition, because the agent is forward looking, they are able to assess the entire expected reward of a long-term incentive.

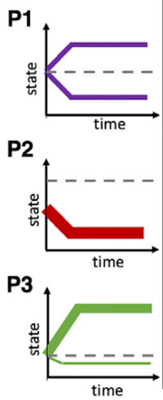
DISCUSSION

Our analysis suggests a mechanism for tipping points in social-ecological systems that does not rely on complex assumptions about the structure of the social or ecological systems alone. Instead, these tipping points emerge from the temporal interactions between forward-looking decisions (i.e., a farmer who considers potential benefits over the long term) and slowly emerging ecological outcomes. While alternate stable states within social-ecological systems, including farming systems, have been previously explored and observed,[6,12,28] our results shed light specifically on temporal feedback that might contribute to this pattern (Figure 2). We also show how path dependence can result in self-perpetuating low ecosystem states and low adoption of diversification practices (Figure 1) and why this provides novel insights not only for social-ecological research (Figure 2) but also for agricultural policy (Figures 3 and 4).

In contrast to equilibrium models,[12] our model assumes (Figure 6; experimental procedures) that ecological and environmental processes take time to respond to the adoption of a diversified practice. For example, soil organic matter and its benefits (such as improved water retention and storage of essential nutrients) take years to build after starting practices like cover cropping and compost additions.[34] Our interviews with farmers support this reality (Figure 7; experimental procedures). One farmer explains:

> "I'll use five years, which seems like a long time, but I mean, that's only potentially 5 or 10 crop cycles depending how heavy you crop … There's probably some very good soils that can be turned around relatively quickly if everything works right. Somebody might see some pretty dramatic benefits in a year or two, depending how bold they wanted to do things. But I think the changes in soil in my mind, they're not immediate. You don't make grand changes right away. So I mean, if you get started doing some reduced tillage using more cover crops, if you have a good source of compost and start incorporating those practices, I would hope that you would see something in five years."

We show how time delays in ecosystem responses to management decisions, as exemplified above, can explain patterns of multiple stable ecosystem service states (Figure 5, P1). While existing explanations of multiple stable states in SESs provided by equilibrium models[12] are not necessarily wrong, temporal explanations for this pattern reflect key system attributes described by farmers and allow for the exploration of intervention strategies that are temporally constrained (e.g., land tenure, incentives, etc.). While not addressed in this analysis, the interaction of non-monotonic (or generally more complex) subsystem dynamics and the



	Model prediction	Evidence in support of patterns	Value of MDP method
P1	Multiple stable ecosystem (or ecosystem service) states can emerge without assumptions of non-monotonic cost structures and nonlinear ecological dynamics (Figure 1)	Syndromes of production, or bistable patterns in adoption of agricultural practices, have been both empirically documented and theoretically described (Vandermeer and Perfecto, 2012).	The temporal mechanism for multiple stable ecosystem service states allows for exploration of intervention strategies that might be implemented over constrained time horizons.
P2	Decision making over short time horizons decreases investment in ecosystem promoting activities (Figure 3) and removes bistability as decision horizons become infinitely short (Figure 2)	U.S. corn farmers who rent land are less likely than landowners to implement grassed waterways, strip cropping, contour farming, and conservation tillage (Soule et al., 2000)	Decision horizons are less intuitive to explore in equilibrium models. Including these attributes of decision making is important for understanding the impact of tenure systems and policies.
P3	Longer, more sustained incentive programs are more effective than short term policies at encouraging adoption of practices for which benefits accrue slowly (Figure 4)	Little research has focused on the role of time in inventive programs or on whether changes in farmer behavior persists once conservation or ecosystem service payments end.	Tradeoffs between incentive duration and magnitude remain unresolved. MDPs allow us to explore these policy scenarios more readily than equilibrium models.

Figure 5. Summary of results
The main model predictions (P1–P3), evidence in support of emergent patterns, and value added of the temporal complexity and minimal assumptions.

temporal interactions of those subsystems will be an important path for future research.

Our results also have important implications for understanding farmer decision making and agricultural policy design. Our model explains why the land-tenure status of a farmer can significantly influence their willingness and ability to adopt diversification practices (Figures 3 and 5, P2). This finding accords with a large body of sociological research documenting how security and length of land tenure affect the adoption of sustainable agricultural practices,[13–16] suggesting that our model captures emergent socio-ecological dynamics of farming systems. As another farmer explains, "We do have hedgerows on several of the ranches, more where we have long-term leases." Growers who hold shorter leases are more likely to decide that adopting diversification practices will not benefit them. They may lose their investment if their lease ends forcibly or may have insufficient time to learn how to use practices in the particular ecological and geographical conditions of their farm.[35,36] Immigrant farmers and farmers of color, especially those new or beginning, often struggle to achieve stable land tenure due to racial discrimination, poverty, or language barriers in farmer networks, policy, and finance.[37] Thus, policies that specifically aim to increase land tenure, for example, by supporting ownership and generational succession, may be powerful levers to effect positive change in this area.

Finally, our model suggests that existing incentive programs to promote agricultural sustainability and ecosystem services by reducing the costs of practice adoption may need significant redesign (Figures 4 and 5, P3). Such policies have become an integral part of farming over the past half-century.[38,39] They are particularly interesting to explore with a MDP due to their often sequential but time-limited nature. Incentive policies rolled out over a given time frame are challenging to study with equilibrium analyses or simple decision rules.

Our results suggest that long-term *sustained* incentives, even when only partially covering the cost of adoption, may be more effective in shifting farmers from simplified ecological states to diversified states than more concentrated short-term incentives. We show that the cost of interventions and the social-environmental benefit of those interventions are not necessarily equivalent. Rather, the perceived stability of incentive programs may be an important driver of adoption. This dynamic can be overlooked when the temporal rates of coupled dynamics in social-environmental systems are not considered. If farmers expect a stable source of support over a known time period, they may decide it is worthwhile to experiment and persist with a new practice that may not provide observable benefits for many years.[40] Unstable support, by contrast, may lead to farmers abandoning practices after a short time or may prevent farmers from trying new conservation practices.[41] Moreover, the reduced transaction costs that come with farmers making a longer term commitment, while not captured in our model, would only further suggest the higher efficacy of sustained incentives compared with concentrated incentives.

This finding is particularly relevant to the design of government payment programs and suggests that smaller payments can be highly effective in encouraging the adoption of diversification practices (or other ecosystem-service-promoting practices) when distributed over long time horizons. Small payments over a longer time frame also constitute a lower total cost to the government when considering even modest discount rates. Yet the relationship between the length of incentive programs and the persistence of changes in land-manager behavior once payments end remains unclear. One study found that, when landowners were unable to re-enroll in a waterbird habitat program in northern California due to 3-year-period limits, participant numbers declined and farmers persisted less with their practices.[41] Other studies have found that growers tend to switch back land that is left unused in return for payments via the federal conservation reserve program to "more valuable" productive uses (e.g., corn ethanol).[42] It is possible, as our model suggests, that steady, if somewhat lower, conservation payments might result in more favorable outcomes when compared with fluctuating or short-term payments.

Several federal government programs provide incentives to farmers over long time periods. For example, the US Department

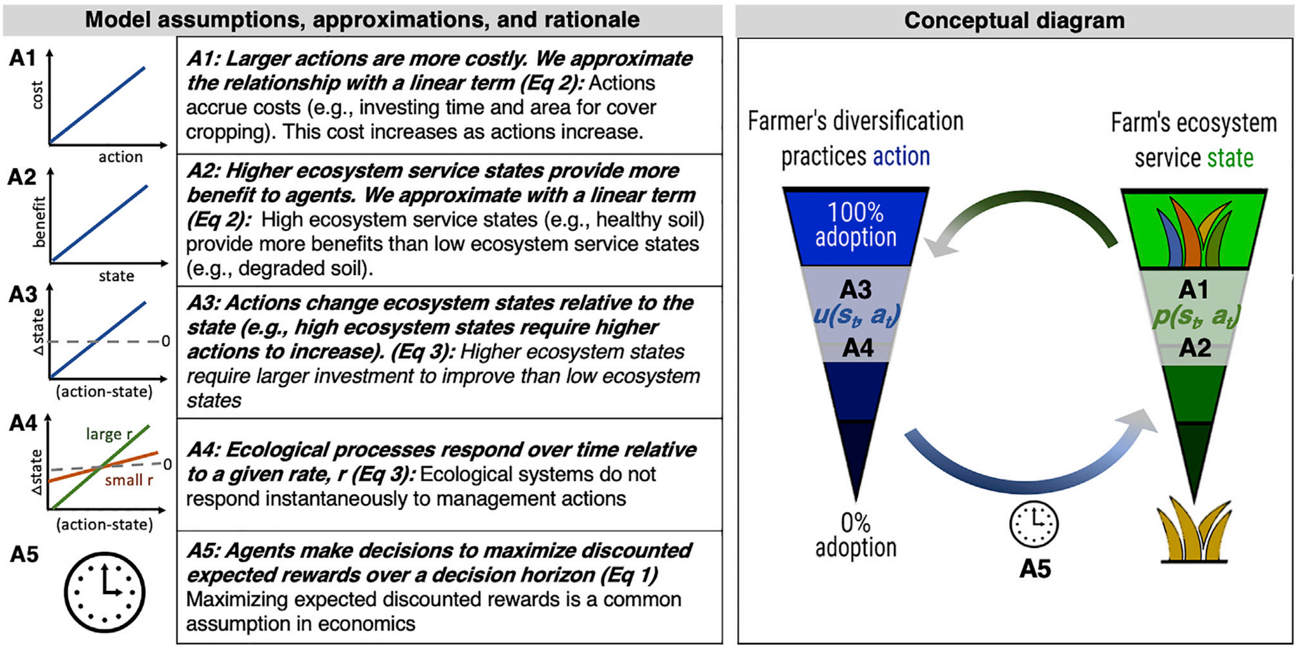


Figure 6. Conceptual diagram and model assumptions

The farmer's choice of how much to invest (time and money) into the adoption of diversification practices is shown in blue, and the resulting ecosystem services state in green, with a more diversified ecosystem state at the top and a more simplified ecosystem state at bottom. Each time step, the farmer chooses the optimal action for their current ecosystem service state based on the perceived utility function, u, and state transition probability function, p. For a given ecosystem service state and action at time t, p describes how the ecosystem responds stochastically to result in an updated state at $t + 1$. The updated ecosystem service state then feeds back to influence the farmer's future choices, leading to tradeoffs arising from the coupling of ecological processes with consecutive diversification-practice-adoption decisions over time. Main model assumptions (A1–A5) are outlined along with a brief rationale for each approximation.

of Agriculture (USDA) manages a conservation stewardship program (CSP), which is a 5-year contract—potentially renewed for 5 more years—that pays farmers an annual sum in return for agreeing to implement a customized conservation plan co-created with a USDA agent. The plan allows growers to build on their existing conservation practices by implementing practices that improve a wide range of on-farm conditions, from soils to biodiversity. USDA also manages the environmental quality improvement program (EQIP), which similarly supports on-farm diversification practices with contracts that typically last 1–3 years but may extend to 10 years. Payment rates are reviewed and changed annually; certain practices may receive sizable assistance, but rates can be unstable over time.[43] While both CSP and EQIP are heavily in demand by farmers in many states, including California, researchers have not yet examined whether the differing longevity of the incentives provided via these programs could impact the durability of diversification practice implementation.

In conclusion, by combining semi-structured interview data with a modeling approach that captures complex temporal dynamics in a stylized social-ecological system model, we offer insights into important agricultural management patterns and their implications for ecological outcomes and public policy. While tipping points have been extensively studied throughout the social-ecological systems literature, including agriculture, we suggest a novel mechanism for these tipping points that makes minimal assumptions about system-specific behavior. Further, we present a flexible model framework that can be built on to address critical questions in social-ecological systems research and policy design.

EXPERIMENTAL PROCEDURES

Resource availability

Lead contact

Further information and requests should be directed to and will be fulfilled by the lead contact, Melissa Chapman (mchapman@berkeley.edu).

Materials availability

This study did not generate new materials.

Data and code availability

All code underlying the models and figures is available at https://github.com/boettiger-lab/dfs-mdp.

Conceptual model description

We explore the transition to and from diversified farming systems (low and high ecosystem service provisioning states) using an MDP in which a farmer makes a series of decisions about whether or not to employ agricultural-diversification practices over time (Figure 6). Modeling the adoption of diversification practices and the resultant ecosystem services as a MDP requires that we first define a set of available "actions" (or decisions) and a set of possible system states. In our model, at each time step, the farmer takes an action of 0%–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. While higher ecological states are beneficial, investments in diversification practices also come with higher associated costs (Figure 6, A1). Costs and benefits may be financial, social, ideological, and/or aesthetic, and we approximate that relationship as linear (Figure 6, A2). A greater percent investment in diversification practices corresponds to a greater probability of transitioning to a higher (more beneficial) ecological state within

Please cite this article in press as: Chapman et al., Social-ecological feedbacks drive tipping points in farming system diversification, One Earth (2022), https://doi.org/10.1016/j.oneear.2022.02.007

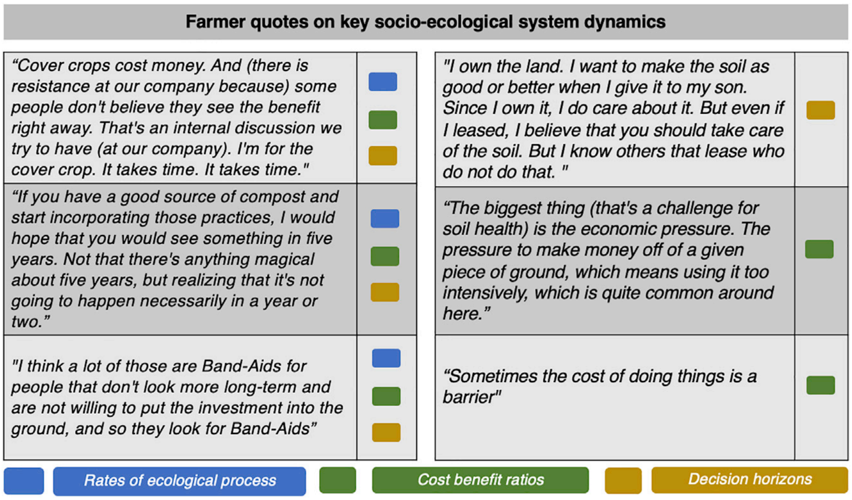


Figure 7. Key quotes from interviews

Key quotes from farmers interviewed suggest that the temporal horizon of decision making and the rate at which farmers receive ecosystem benefits as a result of those decisions are important factors in the adoption of diversification practices.

the next decision cycle (Figure 6, A3). Our model makes minimal assumptions about the relationships between actions and costs (Figure 6, A1), states and benefits (Figure 6, A2), and actions and state changes (Figure 6, A3). While additional assumptions could be integrated into this MDP framework (e.g., nonlinear functions for Figure 6, A1–A3), we focus our study on the impact of the interactions between ecological rates and time horizons of decisions by minimizing assumptions around the functional forms of these subsystems.

The rate at which that ecological response occurs depends on parameter r but importantly is not instantaneous (Figure 6, A4). By defining parameter values for cost, benefit, transition stochasticity, ecological change rate, and future discounting, an MDP allows the optimal action strategy for the farmer (agent) to emerge based on expected rewards (benefits minus costs) over either a finite (to represent short-tenure leased farms) or infinite (to represent longer term leases and land ownership) time horizon (Figure 6, A5). We use a 10-year time horizon to represent shorter term decision making, essentially the longest frame of reference that tenant farmers tend to work within and a conservative way of looking at the impact of lease length for tenant farmers.[17] This frame of reference is suggested not only in the agrarian sociology literature but in the farmer interviews we conducted. Discounted infinite decision horizons are meant to represent landowners and other farmers with the capacity to account for the economic viability of an action over the long run.

Interview data

As part of the larger project that our modeling work contributes to, between February 2018 and August 2020, the agricultural sociologists in our team interviewed 25 lettuce growers and 17 almond growers from California using a snowball sampling method. We developed an interview guide with questions that focused on the barriers and motivations for using diversification practices, such as cover cropping, planting hedgerows, and diverse crop rotations. We focused on almonds and leafy greens and lettuce because these are among the most economically valuable and regionally prevalent crops in California, represent different farming systems and environmental conditions, and their increased diversification could have major impacts (for almonds, a very large acreage could benefit; for leafy greens, their requirements for fertilizer and pesticide applications could be reduced greatly). We selected interviewees to represent a range of growers (small to large scale, organic to conventional, early adopters of diversification practices to late adopters, family run to corporate management, and direct-to-consumer marketing to wholesale). Interviews were conducted in person or over the phone when in-person interviews were not possible due to farmer schedules or the need to social distance during coronavirus disease 2019 (COVID-19) restrictions. Most interviews were audio recorded and transcribed. If recording was not possible, careful notes were taken to create a transcript.

We performed deductive coding for central themes and keywords of the transcripts to inform structural attributes of our model. Specifically, our interview coding informed the relationships among costs, benefits and actions in diversified farming systems, the integration of time horizons into decision strategies, and the gradual rate of ecological change in response to management actions (Figure 7). In addition, interviews provided quotes to contextualize model findings.

Mathematical description

The MDP is composed of two coupled models: a model of the ecological processes, $s_{t+1} = f(s_t,a_t)$, and a model of how the farmer views those processes, expressed as the utility function of the biological state and the cost of the farming actions and decisions $u(s_t,a_t)$. Both models incorporate temporal dynamics. The biological model has a notion of time that says that actions do not immediately change the biological environment but instead change it over time at rate r. Meanwhile, the farmer pays the cost of action a_t as soon as that action is taken. However, unlike common alternative frameworks, such as most agent-based ("individual-based simulation") models, the farmer does not choose actions one at a time. Instead, the farmer plans ahead over the future by considering actions that may be costly now but pay off in years to come, given the utility of a strategy (i.e., a sequence of actions, the discounted sum of the utility of all the individual actions in the strategy). This decision model can be formulated as

$$\max_{\{a_t \in A\}} \mathbb{E}\left[\sum_t^T u(s_t,a_t)\gamma^t\right], \quad (1)$$

where $\{a_t\}$ is chosen from the set of available actions, $\mathbb{E}$ the expected utility operator, $u(s_t,a_t)$ the utility that the farmer associates with being in state s_t and taking action a_t at time t, γ the myopic discount factor, and T the time horizon of the decision, which in this case represents the land tenure of the farm. In our study, we set $T = 10$ to represent tenant farms and $T \rightarrow \infty$ to represent a farmer who owns the land or has a long lease. The farmer takes action a_t to get the highest expected return over either an infinite decision horizon or a given finite decision horizon (methods to solve for the action policy are outlined in Marescot et al.[30]).

We assume a simple model of the farmer's perceived utility $u(s_t,a_t)$ as a function of the difference between the cost c_a associated with diversification practice action a_t versus expected benefits b_s derived from ecosystem state s_t, at time t, such that

$$u(s_t,a_t) = b_s s_t - c_a a_t, \quad (2)$$

where farmers' initial ecosystem states were distributed normally around a mean of $s_0 = 0.5$. The ecosystem state is also dynamic, evolving according to the transition probability function $p(s_t,a_t)$, such that

$$s_{t+1} = p(s_t,a_t) := s_t + r(a_t - s_t) + \epsilon, \quad (3)$$

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 width 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 functions for both the ecosystem state transition and perceived utility could be substituted into this framework.

Model implementation

The model was developed in the *R* programming language.[44] The *MDPtoolbox* library was used to set up and solve the MDP.[45]

ACKNOWLEDGMENTS

Funding for this research was provided from the National Science Foundation grant number CNH-1824871.

AUTHOR CONTRIBUTIONS

Conceptualization, C.B., M.C., S.W., P.B., T.B., L.C., F.C., K.E., S.G., A.I., D.K., C.K., J.L., E.M.O., J.O., M.R., A.S., J.T., and H.W.; data curation, M.C., S.W., and C.B.; formal analysis, M.C., S.W., and C.B.; funding acquisition, T.B., A.I., C.K., D.K., and C.B.; methodology, C.B., M.C., S.W., P.B., T.B., L.C., F.C., K.E., A.I., D.K., C.K., E.M.O., J.T., and H.W.; code, M.C., S.W., and C.B.; visualization, M.C., S.W., and C.B.; writing – original draft, M.C., S.W., C.B., L.C., and A.I.; writing – review & editing, C.B., M.C., S.W., P.B., T.B., L.C., F.C., K.E., S.G., A.I., D.K., C.K., J.L., E.M.O., J.O., M.R., A.S., J.T., and H.W.

DECLARATION OF INTERESTS

The authors declare no competing interests.

INCLUSION AND DIVERSITY

We worked to ensure ethnic or other types of diversity in the recruitment of human subjects. We worked to ensure that the study questionnaires were prepared in an inclusive way. One or more of the authors of this paper self-identifies as an underrepresented ethnic minority in science. One or more of the authors of this paper self-identifies as a member of the LGBTQ+ community. One or more of the authors of this paper self-identifies as living with a disability.

Received: September 24, 2021
Revised: January 26, 2022
Accepted: February 22, 2022
Published: March 11, 2022

REFERENCES

1. Gladwell, M. (2006). The Tipping Point: How Little Things Can Make a Big Difference (Little, Brown).
2. Rockström, J., Steffen, W., Noone, K., Persson, Å., Chapin, F.S., Lambin, E.F., Lenton, T.M., Scheffer, M., Folke, C., Schellnhuber, H.J., and Nykvist, B. (2009). A safe operating space for humanity. Nature *461*, 472–475.
3. Dai, L., Vorselen, D., Korolev, K.S., and Gore, J. (2012). Generic indicators for loss of resilience before a tipping point leading to population collapse. Science *336*, 1175–1177. https://doi.org/10.1126/science.1219805.
4. Mumby, P.J., Hastings, A., and Edwards, H.J. (2007). Thresholds and the resilience of Caribbean coral reefs. Nature *450*, 98–101. https://doi.org/10.1038/nature06252.
5. Scheffer, M. (2010). Foreseeing tipping points. Nature *467*, 411–412. https://doi.org/10.1038/467411a.
6. Horan, R.D., Fenichel, E.P., Drury, K.L.S., and Lodge, D.M. (2011). Managing ecological thresholds in coupled environmental human systems. Proc. Natl. Acad. Sci. *108*, 7333–7338. https://doi.org/10.1073/pnas.1005431108.
7. Liu, J., Dietz, T., Carpenter, S.R., Alberti, M., Folke, C., Moran, E., Pell, A.N., Deadman, P., Kratz, T., Lubchenco, J., and Ostrom, E. (2007). Complexity of coupled human and natural systems. Science *317*, 1513–1516. https://doi.org/10.1126/science.1144004.
8. Ostrom, E. (2009). A general framework for analyzing sustainability of social-ecological systems. Science *325*, 419–422. https://doi.org/10.1126/science.1172133.
9. Walker, B., Holling, C.S., Carpenter, S.R., and Kinzig, A. (2004). Resilience, adaptability and transformability in social-ecological systems. Ecol. Soc. *9*, 5. https://doi.org/10.5751/ES-00650-090205.
10. Cumming, G.S., Cumming, D.H.M., and Redman, C.L. (2006). Scale mismatches in social-ecological systems: causes, consequences, and solutions. Ecol. Soc. *11*, 14. https://doi.org/10.5751/ES-01569-110114.
11. Lippe, M., Bithell, M., Gotts, N., Natalini, D., Barbrook-Johnson, P., Giupponi, C., Hallier, M., Hofstede, G.J., Le Page, C., Matthews, R.B., and Schlüter, M. (2019). Using agent-based modelling to simulate social-ecological systems across scales. GeoInformatica *23*, 269–298. https://doi.org/10.1007/s10707-018-00337-8.
12. Vandermeer, J.H., and Perfecto, I. (2012). Syndromes of production in agriculture: prospects for social-ecological regime change. Ecol. Soc. *17*, 39. https://doi.org/10.5751/ES-04813-170439.
13. Fraser, E.D. (2004). Land tenure and agricultural management: soil conservation on rented and owned fields in southwest british columbia. Agric. Hum. Values *21*, 73–79. https://doi.org/10.1023/B:AHUM.0000014020.96820.a1.
14. Long, R.F., Garbach, K., and Morandin, L.A. (2017). Hedgerow benefits align with food production and sustainability goals. Calif. Agric. *71*, 117–119. https://doi.org/10.3733/ca.2017a0020.
15. Richardson, J.J., Jr. (2015). Land tenure and sustainable agriculture. Tex. A&M L. Rev. *3*, 799.
16. Soule, M.J., Tegene, A., and Wiebe, K.D. (2000). Land tenure and the adoption of conservation practices. Am. J. Agric. Econ. *82*, 993–1005. https://doi.org/10.1111/0002-9092.00097.
17. Bigelow, D., Borchers, A., and Hubbs, T. (2016). US Farmland Ownership, Tenure, and Transfer. U.S. Department of Agriculture, Economic Research Service EIB-161. www.ers.usda.gov/publications/eib-economic-information-bulletin/eib161.
18. Foley, J.A., DeFries, R., Asner, G.P., Barford, C., Bonan, G., Carpenter, S.R., Chapin, F.S., Coe, M.T., Daily, G.C., Gibbs, H.K., and Helkowski, J.H. (2005). Global consequences of land use. Science *309*, 570–574. https://doi.org/10.1126/science.1111772.
19. Foley, J.A., Ramankutty, N., Brauman, K.A., Cassidy, E.S., Gerber, J.S., Johnston, M., Mueller, N.D., O'Connell, C., Ray, D.K., West, P.C., and Balzer, C. (2011). Solutions for a cultivated planet. Nature *478*, 337–342. https://doi.org/10.1038/nature10452.
20. Stoate, C., Baldi, A., Beja, P., Boatman, N.D., Herzon, I., Van Doorn, A., De Snoo, G.R., Rakosy, L., and Ramwell, C. (2009). Ecological impacts of early 21st century agricultural change in europe–a review. J. Environ. Manag. *91*, 22–46. https://doi.org/10.1016/j.jenvman.2009.07.005.
21. Kremen, C., Iles, A., and Bacon, C. (2012). Diversified farming systems: an agroecological, systems-based alternative to modern industrial agriculture. Ecol. Soc. *17*, 44. https://doi.org/10.5751/ES-05103-170444.
22. Tamburini, G., Bommarco, R., Wanger, T.C., Kremen, C., van der Heijden, M.G., Liebman, M., and Hallin, S. (2020). Agricultural diversification promotes multiple ecosystem services without compromising yield. Sci. Adv. *6*, eaba1715. https://doi.org/10.1126/sciadv.aba1715.
23. Kremen, C., and Miles, A. (2012). Ecosystem services in biologically diversified versus conventional farming systems: benefits, externalities, and trade-offs. Ecol. Soc. *17*.
24. Rosa-Schleich, J., Loos, J., Mußhoff, O., and Tscharntke, T. (2019). Ecological-economic trade-offs of diversified farming systems–a review. Ecol. Econ. *160*, 251–263.
25. Beillouin, D., Ben-Ari, T., Malezieux, E., Seufert, V., and Makowski, D. (2021). Positive but variable effects of crop diversification on biodiversity and ecosystem services. Glob. Change Biol. *27*, 4697–4710. https://doi.org/10.1111/gcb.15747.
26. Andow, D.A., and Hidaka, K. (1989). Experimental natural history of sustainable agriculture: syndromes of production. Agric. Ecosyst. Environ. *27*, 447–462. https://doi.org/10.1016/0167-8809(89)90105-9.
27. Ong, T.W.Y., and Liao, W. (2020). Agroecological transitions: a mathematical perspective on a transdisciplinary problem. Front. Sustain. Food Syst. *4*, 91. https://doi.org/10.3389/fsufs.2020.00091.
28. Vandermeer, J. (1997). Syndromes of production: an emergent property of simple agroecosystem dynamics. J. Environ. Manag. *51*, 59–72. https://doi.org/10.1006/jema.1997.0128.
29. Bellman, R. (1957). A Markovian decision process. J. Math. Mech. *6*, 679–684. http://www.jstor.org/stable/24900506.

30. Marescot, L., Chapron, G., Chadès, I., Fackler, P.L., Duchamp, C., Marboutin, E., and Gimenez, O. (2013). Complex decisions made simple: a primer on stochastic dynamic programming. Methods Ecol. Evol. *4*, 872–884. https://doi.org/10.1111/2041-210X.12082.

31. Gonthier, D.J., Sciligo, A.R., Karp, D.S., Lu, A., Garcia, K., Juarez, G., Chiba, T., Gennet, S., and Kremen, C. (2019). Bird services and disservices to strawberry farming in Californian agricultural landscapes. J. Appl. Ecol. *56*, 1948–1959. https://doi.org/10.1111/1365-2664.13422.

32. Olimpi, E.M., Garcia, K., Gonthier, D.J., De Master, K.T., Echeverri, A., Kremen, C., Sciligo, A.R., Snyder, W.E., Wilson-Rankin, E.E., and Karp, D.S. (2020). Shifts in species interactions and farming contexts mediate net effects of birds in agroecosystems. Ecol. Appl. *30*, e02115. https://doi.org/10.1002/eap.2115.

33. Olimpi, E.M., Baur, P., Echeverri, A., Gonthier, D., Karp, D.S., Kremen, C., Sciligo, A., and De Master, K.T. (2019). Evolving food safety pressures in California's Central Coast Region. Front. Sustain. Food Syst. *3*, 102. https://doi.org/10.3389/fsufs.2019.00102.

34. Poeplau, C., and Don, A. (2015). Carbon sequestration in agricultural soils via cultivation of cover crops–A meta-analysis. Agric. Ecosyst. Environ. *200*, 33–41. https://doi.org/10.1016/j.agee.2014.10.024.

35. Calo, A., and De Master, K.T. (2016). After the incubator: factors impeding land access along the path from farmworker to proprietor. J. Agric. Food Syst. Community Dev. *6*, 111–127. https://doi.org/10.5304/jafscd.2016.062.018.

36. Calo, A. (2018). How knowledge deficit interventions fail to resolve beginning farmer challenges. Agric. Hum. Values *35*, 367–381. https://doi.org/10.1007/s10460-017-9832-6.

37. Minkoff-Zern, L.A. (2019). The New American Farmer: Immigration, Race, and the Struggle for Sustainability (MIT Press).

38. Batáry, P., Dicks, L.V., Kleijn, D., and Sutherland, W.J. (2015). The role of agri-environment schemes in conservation and environmental management. Conserv. Biol. *29*, 1006–1016. https://doi.org/10.1111/cobi.12536.

39. Graddy-Lovelace, G., and Diamond, A. (2017). From supply management to agricultural subsidies—and back again? The US farm bill & agrarian (in) viability. J. Rural Stud. *50*, 70–83. https://doi.org/10.1016/j.jrurstud.2016.12.007.

40. Claassen, R., Horowitz, J., Duquette, E., and Ueda, K. (2014). Additionality in US Agricultural Conservation and Regulatory Offset Programs (USDA-ERS Economic Research Report), p. 170.

41. Dayer, A.A., Lutter, S.H., Sesser, K.A., Hickey, C.M., and Gardali, T. (2018). Private landowner conservation behavior following participation in voluntary incentive programs: recommendations to facilitate behavioral persistence. Conserv. Lett. *11*, e12394. https://doi.org/10.1111/conl.12394.

42. Roberts, M.J., and Lubowski, R.N. (2007). Enduring impacts of land retirement policies: evidence from the conservation reserve program. Land Econ. *83*, 516–538. https://doi.org/10.3368/le.83.4.516.

43. United States Department of Agriculture (2021). State Payment Schedules (USDA). https://www.nrcs.usda.gov/wps/portal/nrcs/detailfull/national/programs/financial/?cid=nrcseprd1328426.

44. R Core Team (2019). R: A Language and Environment for Statistical Computing (R Foundation for Statistical Computing).

45. Chades, I., Chapron, G., Cros, M.J., Garcia, F., and Sabbadin, R. (2017). MDPtoolbox: Markov decision processes toolbox. R. Package Version *4*.