EMERGENCE, EVOLUTION, AND OUTCOMES OF COMMUNITY-BASED CONSERVATION BEHAVIORS IN COASTAL SYSTEMS

by

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DEDICATION

To my ridiculously, ridiculously supportive partner Isabel and our ridiculously, ridiculously supportive friends and family.

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ABSTRACT

This body of work leverages a variety of quantitative and theoretical approaches to advance our understanding of why individuals adopt community-based conservation behaviors, the impacts those decisions have on natural resources and human wellbeing, and how these insights can be used for practical conservation planning. The first chapter makes a theoretical contribution by fitting data produced from a stylized, agent-based simulation of conservation adoption over time with a set of probabilistic differential equations derived from the theory of diffusion of innovations and cultural evolutionary theory broadly. We use these methods to demonstrate that such a statistical approach can provide accurate inference and prediction around the rates and degree of behavioral adoption within a population even when behavioral uptake is contingent on dynamic feedback processes between human behavior, social learning, and environmental change. The second chapter introduces approximate Bayesian computation as a method for linking hypothesized causal processes in complex land systems with observed changes in the mosaic of land cover. This chapter uses the small-scale agricultural production system in Pemba Island, Tanzania as a case study, identifying that soil degradation is likely the primary driver of agricultural expansion into nearby coral rag forests. The third chapter relies on an extensive data collection campaign in 43 communities across Pemba to measure individuals' perceptions of mangrove cover change and risk of mangrove theft, and to assess their impact on individuals' conservation behaviors and preferences. The results of this study indicate that perceptions of mangrove decline drive individual adoption of conservation behaviors and preferences only if they believe that the resultant gains in mangrove cover will not be stolen by outsiders. Conversely, individuals who believe their community mangrove forests are at high risk of theft actually decrease their support for forest conservation in response to perceived forest decline. Lastly, the fourth chapter explores the alignment and misalignment between individual perceptions of mangrove cover change in Pemba and remotely sensed observations of cover change over the same time period. We qualitatively examine the reasons for mismatches in the two data sources and propose a numerical optimization method for considering both sources of information in systematic conservation planning. Together, these studies contribute to the advancement of both theory and methods in studying human behavior within complex social-ecological systems, primarily in small-scale fishing and agricultural communities. Overall, the research presented underscores the importance of understanding human behavior for effectively implementing conservation strategies, and provides valuable insights for informing future conservation planning and interventions.

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LIST OF ABBREVIATIONS

ABC	Approximate Bayesian Computation
DOI	Diffusion of Innovations
GEE	Google Earth Engine
MAE	Mean Absolute Error
MNDWI	Modified Normalized Difference Water Index
NDVI	Normalized Difference Vegetation Index
NDWI	Normalized Difference Water Index
REDD	Reduced Emissions from Deforestation and Land Degradation
SAR	Synthetic Aperture Radar
SIR	Susceptible, Infected, Recovered
SIRS	Susceptible, Infected, Recovered, Susceptible

CHAPTER ONE: INTRODUCTION

Worldwide, area-based conservation has historically focused disproportionately on preserving lands with unique geologic features and little development value (Joppa & Pfaff 2009). While many of these areas do play critical roles in bolstering ecological connectivity, protecting rare species, and safeguarding natural resources on which human livelihoods depend, such conservation goals have not been systematically planned for on the whole (Naughton-Treves et al. 2005). In recent years, rapid and widely publicized declines in the abundance and diversity of plant and animal species have mobilized a unified global conservation strategy, much of which hinges on the expansion of protected areas in order to explicitly safeguard biodiversity (Seibold et al. 2019, Almond et al. 2022). Specifically, under the 2022 Kunming-Montreal Global Biodiversity Framework set by the United Nations Convention on Biological Diversity, nearly 200 countries have committed to providing hundreds of billions of dollars each year, with a goal of formally protecting 30% of global lands by 2030 (CBD 2022).

If successful, this unified conservation effort will nearly double the amount of Earth’s land surface formally designed for conservation (UNEP-WCMC & IUCN 2023). As the goal of this expansion is expressly to protect biodiversity, this new set of protected areas will ostensibly encapsulate highly biodiverse lands. Protecting these lands, and the species that depend on them, however, poses a fundamentally different challenge than safeguarding areas with unique geologic features and little development value. More than 80% of terrestrial biodiversity exists in human-populated landscapes (Sobrevila 2008).

Further, biodiversity hotspots, the 36 areas most highly prioritized for conservation, strongly overlap with the world's poorest populations of people (Fisher & Christopher 2007). Therefore, it is clear that area-based measures to protect biodiversity must exist alongside, and ideally bolster, human livelihoods and community development.

The success or failure of ambitious global conservation goals will depend, at least in part, on the land use decisions made by people who rely on directly harvesting natural resources in order to meet their daily needs (Friess et al. 2022, Londres et al. 2023). In recognition of this, the general strategy of many modern conservation initiatives is to incentivize individuals to protect, and even restore, natural areas themselves through the close integration of community development and conservation projects (e.g. Skinner et al. 2019). Some institutions, such as the well-known Reducing Emissions from Deforestation and forest Degradation (REDD+) initiative, achieve this by directly paying communities to establish community-based conservation areas and otherwise reduce harvests of natural resources.

However, the social and ecological outcomes of community-based conservation interventions are difficult to predict beforehand and difficult to interpret looking back (Pressey et al. 2021, Borgerhoff Mulder & Coppolillo 2005). Both outcomes are products of multiscalar feedbacks, thresholds, time-lags, and other hallmarks of complexity operating on the coupled social and ecological systems (Mahajan et al. 2019, Liu et al. 2007). For example, interventions to spare forests by increasing the per-hectare productivity of agricultural plots can have profoundly different impacts on farmers' decisions to expand or constrict the geographic extent of their operations depending on the market value of crops and system of land tenure (Meyfroidt et al. 2018). Conservation interventions may also create perverse incentives, such as increasing the demand for land and resources, displacing existing users, or reducing the intrinsic value of nature (Ferraro & Kiss 2002).

It is then a perennial challenge of community-based conservation to understand how and why conservation behaviors emerge and persist within populations and how these meaningfully alter the landscape (Mahajan et al. 2020, Mills et al. 2019, Mascia & Mills 2018, Romero-de-Diego et al. 2021). Moreover, as these decisions alter both the social and ecological contexts of future decisions, it is critical to understand how histories of past behavioral and environmental change precipitate future responses to such conditions (Larrosa et al. 2016). By doing so, we can identify the exact mechanisms by which interventions can simultaneously support sustainable development of local communities while contributing to long-term global conservation targets.

This dissertation contributes to answering these questions in four interrelated chapters. The first makes a theoretical contribution to understanding the patterns by which we expect a conservation behavior, specifically refraining from harvesting from a protected area, to spread between individuals within a population (Clark et al. 2022). This chapter demonstrates that even when behavioral adoption is a product of both social learning and dynamic environmental processes, probabilistic differential equations derived from the theory of diffusion of innovations can accurately predict long-term rates of adoption. Chapter two introduces approximate Bayesian computation as a method for interrogating complex, hypothesized simulations of land system processes with observed changes in the mosaic of land cover derived from remotely sensed data products (Clark et al. 2023A). This chapter uses this emerging method to identify that soil degradation is likely the primary driver of agricultural expansion into coral rag forested areas in Pemba, Tanzania. This chapter shows that we can use this information to project future land cover change scenarios under various conservation interventions to alter the standard scheduling of farm/fallow cycles in agricultural plots in this area.

The third and fourth chapters of this dissertation both rely on an extensive participatory mapping campaign across 43 mangrove-dependent communities in Pemba, Tanzania. This campaign collected individuals' spatially explicit perceptions of mangrove cover change over time, as well as their perceived risk of mangrove theft from outsiders, their preferences for community-based conservation, and their past realized conservation behaviors. The third chapter links this information to show that perceptions of mangrove decline can drive individual support for community-based conservation, only when the benefits of that support are expected to be collected by individuals in that community (Clark et al. 2023B). When individuals expect that outsiders will reap the benefits of their conservation efforts, perceived decline of mangrove forest cover can conversely incentivize individuals to increase their personal harvest and forgo conservation behaviors. Finally, chapter four explores if and how these community perceptions of mangrove change systematically differ from changes observed via the satellite record (Clark et al. 2023C). This chapter demonstrates that the perceptions of mangrove change loss referenced in the previous chapter need not be large-scale clear cuts, but instead may be relatively small changes in the extent of selective cutting of individual trees or branches. Thus, community perceptions of mangrove cover change may significantly differ from what is observable via remote sensing, while still capturing meaningful change, both in an ecological and social sense. This chapter presents a practical workflow to achieve a multi-objective optimization highlighting priority areas for mangrove restoration as identified across both local ecological knowledge and remote sensing.

CHAPTER TWO: A QUANTITATIVE APPLICATION OF DIFFUSION OF INNOVATIONS FOR MODELING THE SPREAD OF CONSERVATION BEHAVIORS

The study of community-based conservation is challenged by a large number of important variables and nonlinear dynamics. This complexity has made quantitative and comparative analyses notoriously difficult. Here, we argue that analyzing the emergence and persistence of community-based conservation institutions as an emergent phenomenon of individual decision-making can yield important quantitative insights. We first review diffusion of innovations theory (DOI) and the broader field of cultural evolution. We then simulate data on community adoption of a conservation institution, contingent on feedbacks between individual behavior and environmental processes. We demonstrate that fitting these data to differential models of disease transmission, on which DOI is founded, can produce reliable estimates of the rates of adoption, dropout, and long-term uptake of an institution. Overall, we explore a new quantitative approach for modeling the spread of conservation behaviors using probabilistic differential equations and argue for further incorporation of cultural evolutionary theory into the field.

1 - Introduction

> “Diffusion study…is something like the use of radioactive tracers in studying the process of plant growth: it helps illuminate the process.”
>
> — Everett M. Rogers, Diffusion of Innovations, 2010

1.1 - Motivation

It is becoming increasingly apparent that humanity will not reach global conservation targets through top-down policies alone (*Dudley et al. 2018*; *Mair et al. 2021*; *Tittensor et al. 2014*; *Brockington 2002*). Conservationists are thus turning to local communities to self-impose and maintain sustainable resource extraction limits and restore degraded natural areas (*Amel et al. 2017*; *Catalano et al. 2019*). Community-based conservation projects aim to incentivize these behaviors in rural, and often very poor, communities with little to no external oversight (*Western and Wright 1994*). While the details of each intervention vary considerably, the general strategy is to closely link community development and conservation goals to promote robust behavioral changes in resource-dependent communities (*Brooks, Waylen, and Borgerhoff Mulder 2013*; *Horwich and Lyon 2007*). While some debate still exists, it is largely accepted that empowering communities to self-run conservation institutions is a viable method for seeding self-sustaining and ethical protections on natural resources (*Turner et al. 2007*; *Berkes 2007*; *Adams et al. 2004*; *Agrawal and Gibson 1999*; *Yates, Clarke, and Thurstan 2019*).

Broadly defined, institutions, like those introduced by community-based conservation interventions, are socially constructed and transmitted prescriptions on behavior that often aim to incentivize collective action (*Lott 1992*; *Currie et al. 2016*; *Richerson and Henrich 2009*). In natural resource management, the desired outcome of any particular institution varies on a case-by-case basis but may include goals like increasing the livelihood benefits produced from a resource or improving the biodiversity of a particular area (*Agrawal 2014*). Regardless of the exact social or ecological outcome of interest, “success” of a conservation institution has become synonymous with the degree to which a population adopts the particular behavioral prescription and whether or not that behavior is sustained over time (*Agrawal 2001*; *Yates, Clarke, and Thurstan 2019*).

Decades of research have identified key contextual factors that support the durability of resource safeguarding behaviors in populations, particularly with regard to common-pool resources (*Agrawal 2001*; *Baland and Platteau 1996*; *Ostrom 1990*). These factors are largely narrative descriptions of the qualities of, and interactions between, resource types, governance structures, and resource users that are most likely to lead to stable and sustainable resource management institutions (*Ostrom 2009*). Scholars have identified at least 40 unique factors as contributing to the success of community-based conservation institutions and some overarching patterns have begun to emerge (*Ostrom 1990*, *2009*; *Agrawal 2001*). Continual monitoring, graduated sanctions for offenses, and well-defined social boundaries particularly stand out as important themes (*Cox, Arnold, and Tomás 2010*; *Baggio et al. 2016*). Research on common property additionally recommends that institutions be matched in scale to the underlying ecological processes of the resources they aim to manage (*McKean 2000*).

Many of the factors that support the long-term viability of conservation institutions are intertwined such that the applicability of one may depend on the level of another and some factors may be inextricably correlated (*Agrawal and Goyal 2001*; *Agrawal 2003*). Predictors and outcomes of interest commonly exhibit threshold effects, time lags, feedbacks, and a variety of other nonlinear dynamics, making causal inference through standard regression practices difficult (*Folke 2007*; *Levin et al. 2013*). And further, which individual factors are most important is highly specific to a given community or location, suggesting that there is not possibly one unifying panacea for common-pool resource management issues (*Brooks, Waylen, and Borgerhoff Mulder 2012*; *Geist and Lambin 2002*; *Agrawal and Gibson 2001*). This complexity of community-based resource management systems and logistical constraints in measuring the sheer number of important variables has made multi-site comparative analyses elusive (*SESMAD 2014*; *Biggs et al. 2021*). Thus, even with decades of productive research on sustainable resource management, all major syntheses remain descriptive in nature, lacking a robust methodology to quantify causal insights (*Cumming et al. 2020*; *Frey 2017*; *McGinnis and Ostrom 2014*; *Gutiérrez, Hilborn, and Defeo 2011*).

We argue here that considering the stability of institutions within a population from the perspective of individuals rather than entire communities may provide valuable insight for implementing community-based conservation projects, both qualitatively and quantitatively. Sustainable resource management institutions are observed at the community level, but in reality, they are an emergent property of individual-level decision making — communities do not adopt behaviors, individuals do (*Currie et al. 2021*). The normative conditions imposed on individuals by their ecological and social environments (i.e. the factors referenced above) affect the likelihood that they will endogenously engage in cooperative resource management practices or adopt them when exogenously introduced by an intervention (*Wilson, Ostrom, and Cox 2013*; *Andrews and Borgerhoff Mulder 2018*).

A major question in implementing these projects is if members of a population will indeed adopt a specific intervention and if so, how quickly (*Radeloff et al. 2013*)?

Predicting the final proportion of a population that will adopt an intervention is critical, as many interventions require buy-in from nearly all community members to be effective (*Mangubhai et al. 2011*; *Visconti et al. 2019*). By examining sustainable resource management institutions as the emergent outcome of individual behavioral changes, we can leverage insights from other areas of social science to further guide theory on why some institutions emerge and persist, and others fail to be adopted long-term (*Berkes 2004*).

In this article, we examine one social science theory specifically focused on individual behavior adoption, diffusion of innovations (DOI), and its previous and potential applications to community-based conservation institutions (*Rogers 2010*; *Mascia and Mills 2018*). Our primary aim is to give a practical demonstration of how insights from DOI can be applied to expand our inference about the spread and persistence of conservation interventions beyond narrative descriptions. We do this by first simulating data on conservation adoption in a resource-dependent population and then statistically fitting a model of diffusion to these data. Adopting resource safeguarding behaviors fundamentally differs from adopting more standard behaviors such as clothing choice. By design, conservation behaviors alter the natural environment and adjust the arena in which individuals make future choices, such as to maintain the behavior. Our simulation highlights this feedback of interest to answer the key question of whether DOI is specifically applicable to community-based conservation, given this unique adoption dynamic. Throughout this article, we situate DOI theory in the broader literature on cultural evolution and argue that this body of work may provide more actionable insight than DOI in isolation, particularly by considering underlying mechanisms of behavioral transmission.

1.2 - Diffusion of innovations

Promoting the widespread adoption of some novel (to the individual) behavior is not an issue unique to community-based conservation; producers of cigarettes and snack foods, as well as public health professionals, have been grappling with these questions for decades. DOI recognizes that this process is primarily governed by the level of uncertainty an individual has about the utility of the novel behavior and their personal threshold for the amount of certainty required to make a decision (*Rogers 2010*). When an individual is introduced to a new behavior, they often have a high degree of uncertainty about the risks and benefits of adopting and will wait to adopt until that uncertainty is reduced to a tolerable level. The primary way individuals reduce uncertainty about the outcome of adopting a particular behavior is through second-hand observation of early adopters. Therefore, at the core of DOI is the observation that individuals imitate those around them when making decisions about adopting a novel behavior, rather than weighing the pros and cons independently (*Rogers 2010*; *Henrich et al. 2001*).

When modifying their beliefs or behaviors, people do not imitate other individuals at random (*Bandura and Walters 1977*). Instead, they preferentially adopt traits by employing a variety of learning biases, such as success-biased learning, where individuals who are perceived as more successful are disproportionately likely to be copied (*Boyd and Richerson 1988a*; *Laland 2004*). As a result, the cumulative culture of a population evolves over time as various beliefs and behaviors are preferentially copied and their frequency within a population changes. While a full review of cultural evolution is beyond the scope of this paper, the general intuition is that populations carry a variable pool of information that is shaped by events in the lives of individuals such as social observation or natural selection (*Mesoudi 2016*). This information affects individuals' behaviors, that in turn may affect their environments, and feedback to further alter which traits are adopted in the future (*Durham 1991*; *Henrich and McElreath 2003*). Observed variation among groups, such as differences in resource management institutions, are produced by such social and environmental histories, then reinforced through conformist-biased learning where the dominant behavioral trait is disproportionately copied (*Henrich and Boyd 1998*). Thus, cultural evolution provides an intuitive way to integrate individual decision-making, population level patterns, and even population level behavior-environment feedbacks.

Diffusion of novel beliefs and behaviors is a specific instance of cultural evolution, where the trait being transmitted is new to the population and outcompetes some previous cultural variant, such as in the classic example of hybrid corn seed adoption in Iowa farmers (*Mesoudi 2016*; *Ryan and Gross 1950*). We observe these patterns using diffusion curves that show the proportion of a population that has adopted a belief or behavior on the Y-axis, as a function of time on the X-axis (*Hoppitt et al. 2010*; *Rogers 2010*; *Ryan and Gross 1950*). The exact shape of these diffusion curves can be highly dependent on the learning mechanism employed by individuals in the population, as well as contextual factors like the population density or ease of trialing the cultural variant (*Smaldino et al. 2017*; *Henrich 2001*; *Rogers 2010*).

In the vast majority of empirical studies, the diffusion of a novel trait produces a sigmoidal "S" shape, where it initially spreads slowly, followed by a period of rapid adoption, then again spreads slowly until it reaches an equilibrium (Rogers 2010). This "S" shaped curve is indicative of biased social learning, in contrast to the relatively rare "R" shaped curves observed when individuals learn through independent trial and error (fig 1) (Henrich 2001). The curvilinear "R" shape produced by individual, or environmental learning is a result of the fact that late adopters represent the tail of the distribution, having not discovered (and thus adopted) the novel behavior even after many trials (Henrich 2001). These two curve shapes however are not completely distinct. As the proportion of learning strategies employed by individuals in a population shifts more toward individual or social learning, we expect to see a shift toward an "R" shape or "S" shape respectively (Henrich 2001).

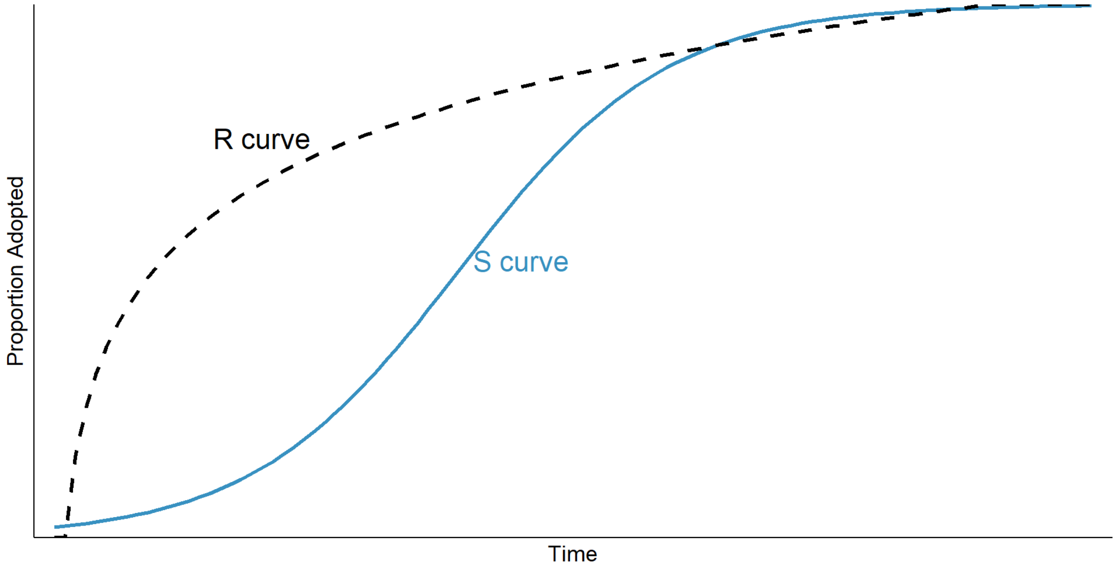


Figure 1 Canonical "S" and "R" diffusion curves. "R" curves are generally indicative of a higher proportion of individuals employing individual learning. "S" curves are generally indicative of a higher proportion of individuals employing social learning.

1.3 - Diffusion of innovations in community-based conservation

Just as the sigmoidal pattern indicative of social learning is seen in the majority of cases on behavioral adoption broadly, scholars have also noticed this pattern in over 80% of case studies on the uptake of community-based conservation interventions worldwide (*Mascia and Mills 2018*; *Mills et al. 2019*). Fittingly, high-level studies have begun identifying DOI as potentially useful for diagnosing why some community-based conservation interventions spread and persist, while others fizzle out. For example, in a review of 22 conservation interventions referenced above, the majority of initiatives were adopted by less than 30% of potential adopters at the sigmoidal equilibrium. The authors use insights from DOI to suggest that practitioners may actively spread information on interventions (as in Abernethy et al. *2014*), or facilitate communication to increase adoption rates (*Mills et al. 2019*; *Greenhalgh et al. 2004*). Further, a recent framework for understanding the establishment, persistence, and spread of community-based conservation practices identifies qualitative insights, such as intervention observability, from DOI as useful in guiding the development of conservation interventions (*Mahajan et al. 2020*).

As these high-level studies suggest, qualitative insights from DOI have been productively applied to understand the rate and success of spread of conservation behaviors in single case studies around the world. In Kenya for example, Mbaru and Barnes (*2017*) showed that identifying socially well-connected individuals can facilitate the rapid diffusion of information on conservation objectives. Similarly, in Fort Collins, CO, researchers demonstrated that both the speed and extent of diffusion of information on native plant gardening likely increase when community members are offered incentives to increase communication (*Niemiec et al. 2021*). Romero-de-Diego et al. (*2021*) used expert interviews to identify that observability of benefits was a key driver of the rapid adoption of a voluntary wildlife management program among landholders in Mexico. Conversely, in contexts where observability and thus imitation are limited, such as across neighboring islands, the rate and degree of spread of community-based conservation interventions is considerably attenuated (*Pietri et al. 2009*). This finding mirrors those of studies which look at more general cultural adoption between islands, further suggesting that conservation behaviors may spread similarly to technological or ideological innovations (*Kline and Boyd 2010*; *Beheim and Bell 2011*).

These studies are compelling in their conclusion that DOI can be productively applied to the spread of community-based conservation, but have been critiqued as general, narrative suggestions from DOI that may miss important contextual factors unique to each intervention (*Steenbergen, Song, and Andrew 2021*; *Lam et al. 2020*; Lund and Bluwstein *2018*). Below, we make a quantitative argument for using DOI to understand the spread of community-based conservation interventions. We envision a practitioner who is monitoring the weekly, monthly, or even yearly uptake rates of an intervention and is hoping to predict if and when it will "take off" in the population, what the final proportion of adopters will be, and what they can do to promote its spread. In this review, we therefore explicitly demonstrate how DOI can be used to generate predictions about the patterns of uptake of conservation behaviors given behavior-environment feedbacks and diagnose how an intervention may be best improved.

1.4 - Quantitative applications

In this section we explain how we can fit an observed pattern of diffusion mathematically to estimate rates of adoption and dropout, as well as to predict the speed and degree to which a population will adopt an intervention. The "S" shaped diffusion pattern of behavioral spread over time mirrors that of community disease transmission (*Smaldino and Jones 2020*). This parallel implies that the well-established mathematics used to describe disease transmission patterns can be applied to fitting models of behavioral spread (*Cavalli-Sforza and Feldman 1981*; *Strang 1991*). Specifically, the canonical susceptible-infectious-recovered (SIR) model and SIRS variation where individuals are added back to the pool of susceptibles after recovery (eq 1), have been demonstrated to be well suited to fitting the diffusion process (*Famil-Rohani et al. 2019*; *Smaldino and Jones 2020*). These compartmental differential equations assign every member of a population to a category (S, I, or R), depending on the proportion of individuals in the other categories and parameter values for the natural history characteristics of a given disease (*Tolles and Luong 2020*). In this instantiation, the natural history parameter β represents the rate of infection in the population, γ represents the rate of recovery, and χ is the rate that recovered individuals are added back into the pool of susceptibles.

$$\frac{dS}{dt} = -\beta \cdot S_t \cdot I_t + \chi \cdot R_t$$

$$\frac{dI}{dt} = \beta \cdot S_t \cdot I_t - \gamma \cdot I_t$$

$$\frac{dR}{dt} = \gamma \cdot I_t - \chi \cdot R_t$$

(1)

When the natural history characteristics of some pathogen are known, the SI, SIR, SIS, & SIRS suite of models reliably give accurate, deterministic predictions about the number of individuals in a population who will become infected and for how long a disease will persist within a population (*Huppert and Katriel 2013*). For a specific conservation intervention however, there is no way to precisely know the natural history features, such as the rate or duration of adoption, ahead of time. Instead, the qualitative insights from DOI and the study of sustainable resource management institutions referenced above aim to increase the rate of spread and reduce the rate of dropout so that the intervention persists in the population and may even spread to new communities. While we cannot know exactly what the rates of spread and dropout will be ahead of time, we can use Bayesian inference to probabilistically estimate them once the project has been implemented (*Margossian 2019*; *Margossian and Gillespie 2017*; *Carpenter 2018*). Knowing these parameters may allow us to predict the final rate of uptake from early in the project, identify whether adoption or dropout are limiting the overall rate of uptake, and apply the qualitative insights from DOI and natural resource management institutions in a more targeted fashion.

The uptake of community-based conservation is subject to behavior-environment feedbacks, a fundamental difference from behavioral adoption generally (*Liu et al. 2007*). In the case of marine protected areas for example, success in conserving fish populations may actually disincentivize individuals to continue supporting conservation programs (*Christie 2004*). A key question then is whether the diffusion models explained above will still reliably fit the spread of conservation behaviors when those behaviors alter the environment, and changes in the environment alter the payoff structure of various behavioral choices.

To answer this question, we use an agent-based simulation to generate data on the spread of a conservation behavior via social learning, contingent on feedbacks with the environment. Then, using the five run average of just the first 30% of the data, we probabilistically estimate the average rates of intervention spread, dropout, readoption using a Bayesian instantiation of the SIRS model shown in equation 1. We use these estimated parameters to predict the long-term average adoption pattern for the remaining 70% of time steps and compare our predicted values to those observed in the simulations. While the purpose of this example is to test whether the SIRS model can capture our core dynamics of interest, it also explicitly demonstrates how a practitioner or other researchers can directly apply the quantitative process described above. We first briefly describe the simulation below.

2 - Modeling

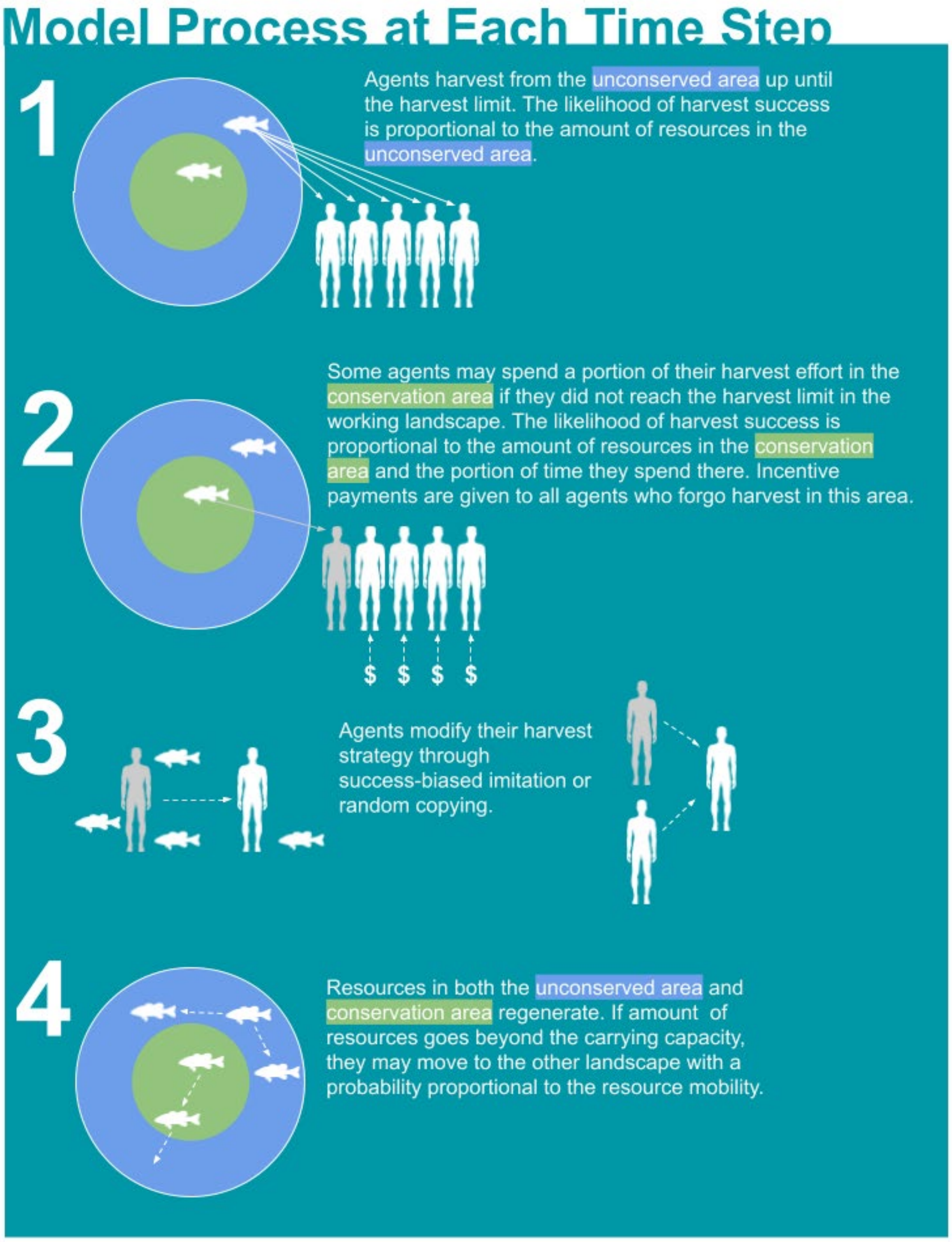
2.1 - Agent-based simulation

We seek to test whether the SIRS model shown in equation 1 can produce reliable insights about community uptake of a conservation behavior, especially given behavior-environment feedbacks common in natural resource management institutions. To answer this question, we first need complete time series data in-hand that are a product of our dynamics of interest. To obtain these data, we develop a minimal agent-based model that we use to simulate data on the spread of a resource safeguarding behavior within a population (*Müller et al. 2013*; *Smajgl et al. 2011*). In order to assess the impact of feedbacks between behavior and the environment, we simulate data using two different social learning strategies, only one of which involves a behavior-environment feedback (*Le, Seidl, and Scholz 2012*; *Kendal et al. 2018*). The first is random copying where agents are paired with another agent at random and have a 25% chance of adopting the strategy of the agent they are paired with, independent of the harvest benefit provided by adopting the behavior or not (*McElreath et al. 2008*; *Barrett 2019*). This strategy does not involve a direct feedback between behavior and the environment. We include it as a baseline to compare against our second strategy, which does. The second mechanism is success-biased learning, under which agents disproportionately copy the behaviors of other agents with the greatest harvesting success (*Baldini 2013*). This mechanism is formally demonstrated in equation 2, for two behaviors: A & B, where the probability that an individual adopts behavior A is a function of the mean harvest, $\bar{P}$, from each behavior at each time step and the strength of the bias, β (*Barrett 2019*). Under biased social learning, the strength of the learning biases (e.g. β) control how disproportionately agents copy others based on a given condition (e.g. success); a β = 1 in this formulation would thus mean that the probability that one agent copies another is directly proportional to the ratio of their harvests. Behavioral change given success-biased learning is therefore dependent on feedbacks with the environment as harvest success results from agent behaviors in previous time steps.

$$\Pr(A|A,B)_{t+1} = \frac{\exp\beta\overline{P_{A,t}}}{\exp\beta\overline{P_{A,t}} + \exp\beta\overline{P_{B,t}}}$$

(2)

Our simulated system is conceptualized as a fishery where agents are directly compensated for forgoing resource extraction from a particular area if they choose (*Rakotonarivo et al. 2021*). We establish a fishery, loosely based on a global average stock integrity, at 20% of its potential carrying capacity (*FAO 2020*). In the first time step, we introduce an intervention that delineates 20% of the fishery as a conservation area and just 2% of agents initially change their behavior to forgo harvesting there. Fish reproduce proportionally to the population in each time period, and move freely between the conservation area and unconserved area. In each subsequent time step, agents who adopted the resource safeguarding behavior (enrolled) receive a reward, and continue to harvest just from the remaining 80% of the unconserved fishery. Agents not enrolled in the intervention harvest from the entire fishery and forgo the reward. After each harvest period, agents are randomly paired, and employ either random copying or success-biased learning to decide whether or not to adopt the behavior of their partner in the next time step (*Baldini 2012*). The conserved and unconserved resource pools are reduced according to agents' harvesting behavior, regenerate, and move from one area to the other if the carrying capacity is reached in any respective area. A visual description of this minimal model is shown in figure 2 and the full Overview, Design concepts, and Details protocol can be found in the supplemental material of the peer-reviewed, published version of this manuscript (*Grimm et al. 2006*; *Grimm et al. 2020*).



1 Agents harvest from the unconserved area up until the harvest limit. The likelihood of harvest success is proportional to the amount of resources in the unconserved area.

2 Some agents may spend a portion of their harvest effort in the conservation area if they did not reach the harvest limit in the working landscape. The likelihood of harvest success is proportional to the amount of resources in the conservation area and the portion of time they spend there. Incentive payments are given to all agents who forgo harvest in this area.

3 Agents modify their harvest strategy through success-biased imitation or random copying.

4 Resources in both the unconserved area and conservation area regenerate. If amount of resources goes beyond the carrying capacity, they may move to the other landscape with a probability proportional to the resource mobility.

Figure 2 Conceptual diagram showing process at each time step in the agnt-based simulation. This simulation was used to produce data on the adoption of conservation behaviors as a function of social learning and environmental outcomes.

We use this model to simulate data on the adoption and persistence of a conservation institution given two different learning mechanisms, random copying and success-biased imitation. Aside from the learning mechanism employed by the population, all model conditions are identical for these two scenarios. Random copying is used as a reference as it reliably produces the standard sigmoidal “S” curve of behavioral adoption and does not incorporate any feedbacks between adoption and the environment. Under the success-biased learning scenario, agents compare their harvests to others in each time step and disproportionately copy more successful agents. In this instantiation then, adoption is dependent on harvest success and harvest success is determined largely by the amount of available resources in each area. As the amount of available resources in an area is determined by the number of agents who harvest there, this learning mechanism incorporates behavior-environment feedbacks typical of natural resource management institutions. Having independently sampled from one or both environments, agents then compare their harvests to those of others in each time step. In this way, the success-biased learning scenario actually represents a mix of individual and social learning, rather than a scenario where individuals make decisions purely from social information. The adoption pattern observed in this simulation results in a mix between an “R” and “S” type curve, reinforcing the interpretation of this scenario as a mix of individual and social learning (*Henrich 2001*). Figure 3 shows the full output for five runs of the later simulation where adoption (enrollment) spikes initially, but drops off dramatically as the resources in the unconserved area are reduced following increased harvest pressure there as a result of the conservation intervention. This exact dynamic is however highly flexible given the specific parameter combinations as described in section (2.3).

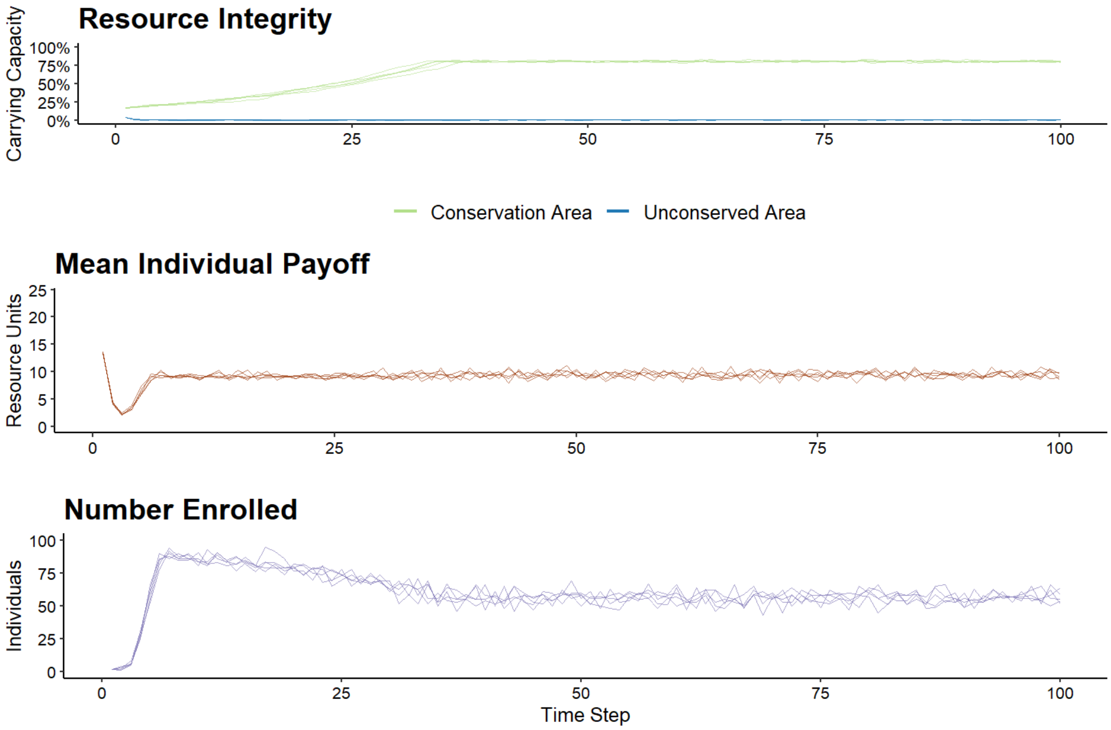


Figure 3 Five runs of the agent-based simulation used to produce data for analysis with the SIRS model of behavioral adoption under the success-biased learning scenario. The top figure shows the number of resources in both the conservation and unconserved areas over time, as a percent of the carrying capacity in those areas. The middle figure shows the average number of resources harvested (payoff) by each agent at each time step. The bottom figure shows the number of agents who have adopted the conservation behavior (enrolled) at every time step.

2.2 - Fitting data with probabilistic differential equations

With data on adoption of conservation behavior for both learning mechanisms in-hand, we fit the SIRS model described in equation 1 to the first 30% of observations, averaged across five model runs. We use multiple model runs to avoid spurious results stemming from model stochasticity alone. Five model runs are used as opposed to 100 or 1000, as this leaves some residual stochasticity in the adoption data that is more representative of what might be realistically observed. Duplicate analyses to those presented below, but instead run on the average of 100 simulation runs can be found in appendix A1. Given these data, we use probabilistic sampling to infer the parameters β,

γ, and χ, for the full Bayesian equation (3) below where Y_t represents the total number of individuals who are enrolled in the community-based intervention at any given time. Here, "infected" individuals are those that are enrolled in the conservation intervention.

$$\mathrm{Y}_t \sim Binomial(\mathrm{N}, \mathrm{I}_t)$$

$$\frac{dS}{dt} = -\beta \cdot \mathrm{S}_t \cdot \mathrm{I}_t + \chi \cdot \mathrm{R}_t$$

$$\frac{dI}{dt} = \beta \cdot \mathrm{S}_t \cdot \mathrm{I}_t - \gamma \cdot \mathrm{I}_t$$

$$\frac{\mathrm{dR}}{\mathrm{dt}} = \gamma \cdot \mathrm{I}_\mathrm{t} - \chi \cdot \mathrm{R}_\mathrm{t}$$

$$\beta, \gamma, \chi \sim Normal(0,0.5)$$

(3)

For both learning mechanisms the SIRS model exhibited Markon chain convergence (fig 4) and resulted in an $\hat{R}$ of 1 for all estimated parameters. As the parameters β, γ, and χ are directly interpretable as the rates of adoption, dropout, and willingness to retry a previously abandoned intervention, accurate estimation of these values, especially in the early stages of an intervention, provides practical and straightforward intuition to diagnose areas for improvement in community-based conservation interventions. For example, a practitioner might fit this model to real-world participation rates during the early weeks of an intervention in order to estimate the rates of adoption and dropout. If both rates are low, the practitioner should focus on increasing initial adoption. Conversely, if both rates are high, they should instead focus efforts on retention of enrolled participants. In addition, these insights may help practitioners better decide which factors from the institutional design literature may be most impactful for their specific system. This might take the form of increasing communication and observability of benefits to boost initial adoption, or investing in conflict resolution mechanisms to reduce dropout.

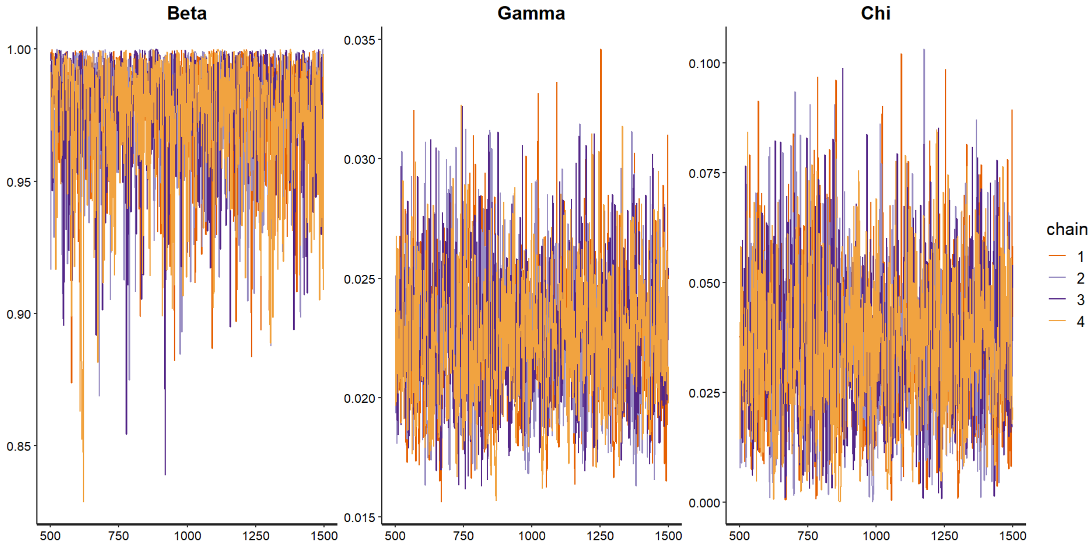


Figure 4 Markov chains for each of the three parameters of interest from the SIRS model fit to simulated data (average of five runs). Beta is interpretable as the rate of adoption of the behavior (enrollment). Gamma is an estimate of the rate of dropout. Chi represents the rate at which individuals who previously dropped out are added back into the susceptible category. The agent-based simulation used to produce the data employed environmentally mediated, success-biased learning.

We can also use these parameter values, estimated from the first 30% of the time series, to predict the long-term patterns of adoption for a community-based conservation initiative. In figures 5 & 6, the translucent black lines show 1000 draws from the posterior predicting the proportion of the population who will be enrolled in the intervention at every time step, averaged across the five model runs. Gray and blue points show the initial 30% of the data that was used to estimate the three parameters of interest and the remaining 70% of data, respectively. These figures show that the SIRS model accurately captures and predicts the pattern of behavioral adoption for both random copying and environmentally mediated success-biased learning. Further, the mean absolute error (MAE) between the simulated “test” data (later 70%) and the median model predictions for those data are 2.98% and 4.52% of the population for the random copying and success-biased learning scenarios respectively, indicating good model fit.

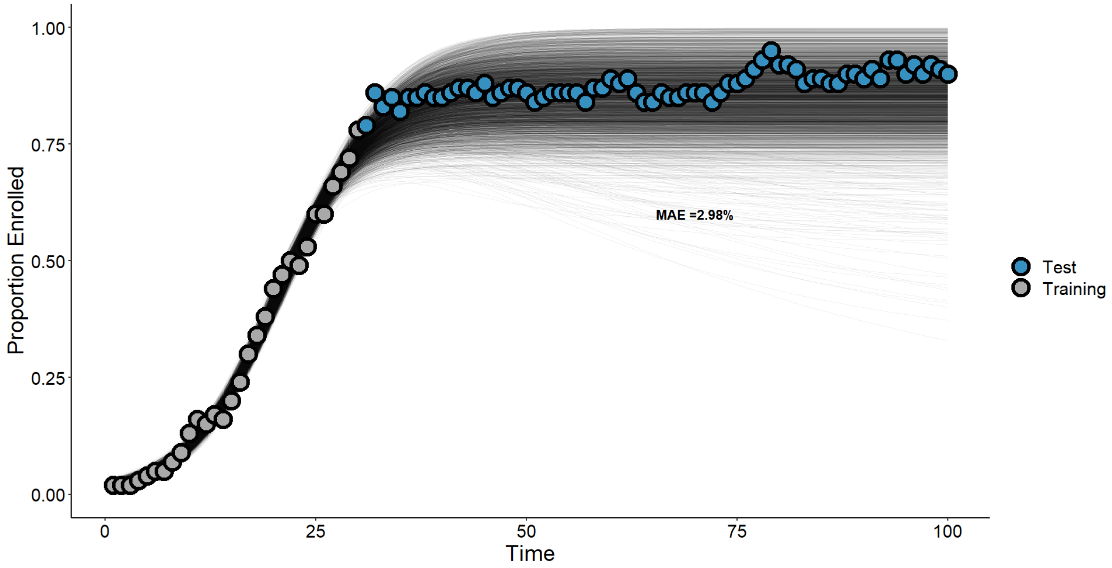


Figure 5 SIRS model fit to the average of five runs of the agent-based simulation data under random copying shown as translucent black lines representing 1000 draws from the posterior. Simulated data are overlaid with gray points signifying training data (first 30%) and blue points signifying test (later 70%) data.

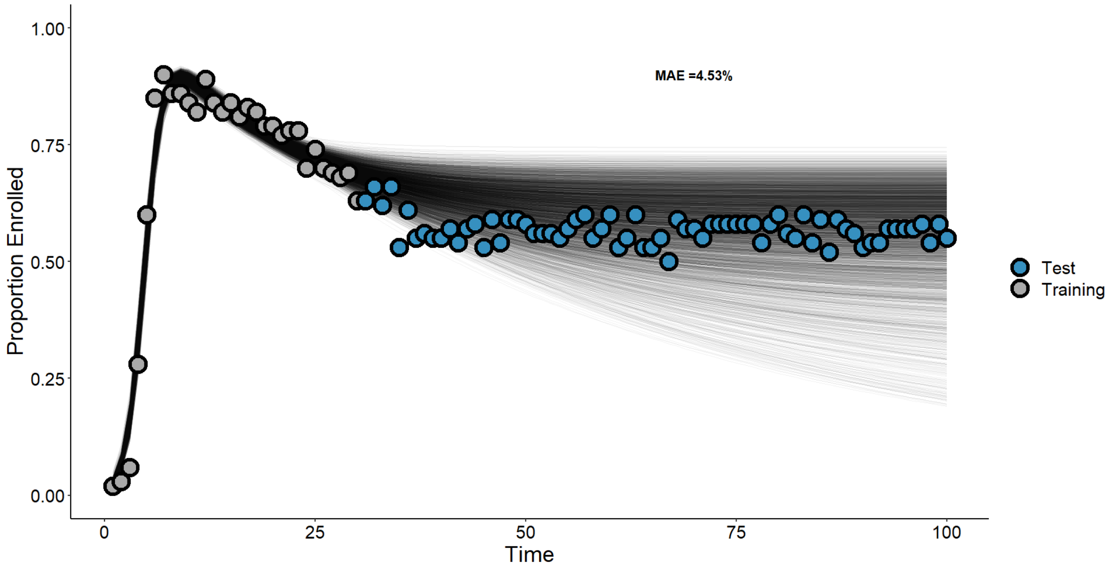


Figure 6 SIRS model fit to the average of five runs of the agent-based simulation data under success-biased social learning contingent on behavior-environment feedbacks shown as translucent black lines representing 1000 draws from the posterior. Simulated data are overlaid with gray points signifying training data (first 30%) and blue points signifying test (later 70%) data.

Figures 5 & 6 also demonstrate that different scenarios and respective learning mechanisms, while both producing a stable adoption rate, can result in different overall rates in adoption of an intervention, even under identical starting conditions. In the simulation of a population employing random copying, the population equilibrates at nearly 90% adoption of the intervention behavior. For success-biased learning on the other hand, resource scarcity in the unconserved area caused the population to adopt the intervention at approximately 60% in the long-term. Lastly, the mix of social and independent learning employed by agents in the success-biased learning scenario produces a somewhat “R” shaped curve as explained in the section above. These results show that the SIRS model of diffusion can reliably fit the pattern of behavioral adoption even when the pattern does not follow a strict sigmoidal “S” shape.

2.3 - Example limitations

Parallel to the examples above, we can use our agent-based simulation to explore parameter combinations that expose limitations for the application of the SIRS diffusion model for capturing and predicting conservation adoption dynamics under behavior-environment feedbacks. Specifically, as the parameters in the SIRS model only directly account for social processes, adoption dynamics resulting from abrupt environmental change are not well predicted. For example in figure 7, we consider a resource pool that is relatively intact at the start of the simulation (80% of carrying capacity), paired with an unsustainable harvest rate. In this simulation, all agents initially rapidly enroll in the conservation intervention as there is no cost to doing so (resources in the unconserved area are plentiful). However, when the resource pool in the unconserved area is depleted, agents quickly drop out of the conservation institution in favor of harvesting from the conservation area. Figure 8 shows the result of fitting these data with the SIRS diffusion model described above. The MAE of this model is 43.07%, indicating poor model fit.

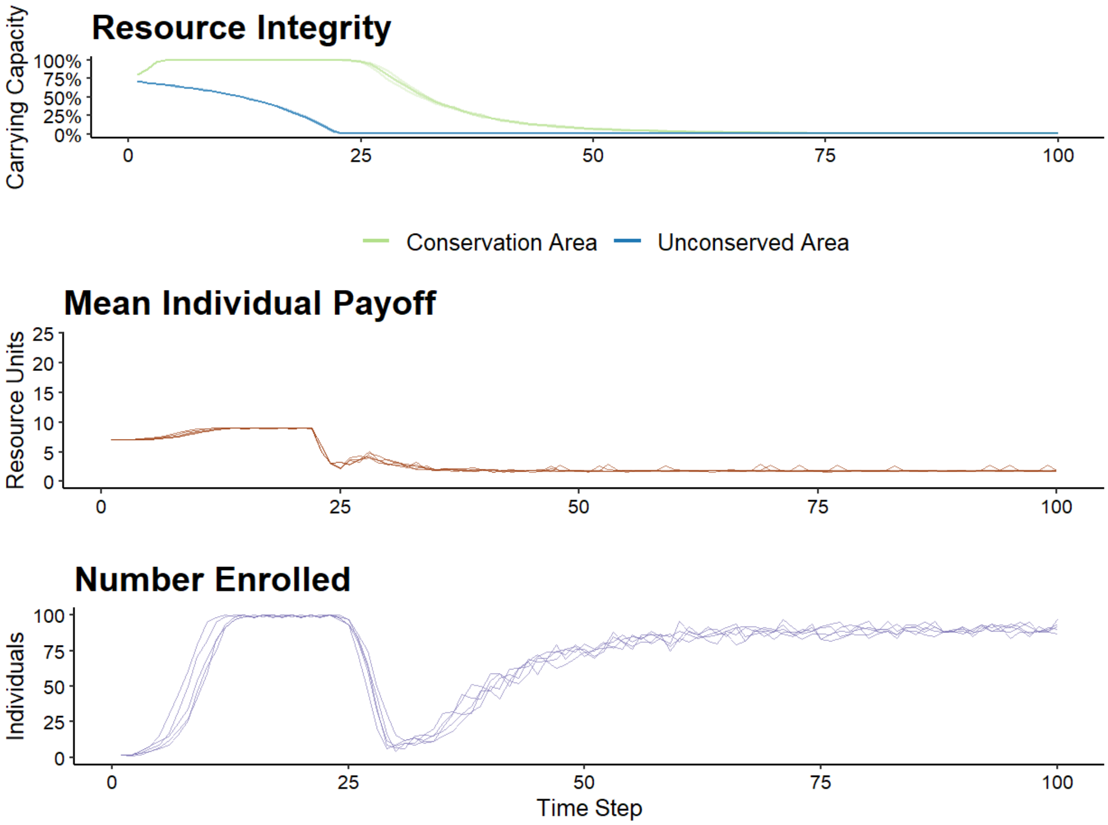


Figure 7 Five runs of the agent-based simulation used to produce data for analysis with the SIRS model of behavioral adoption under the success-biased learning scenario. The top figure shows the number of resources in both the conservation and unconserved areas over time, as a percent of the carrying capacity in those areas. The middle figure shows the average number of resources harvested (payoff) by each agent at each time step. The bottom figure shows the number of agents who have adopted the conservation behavior (enrolled) at every time step.

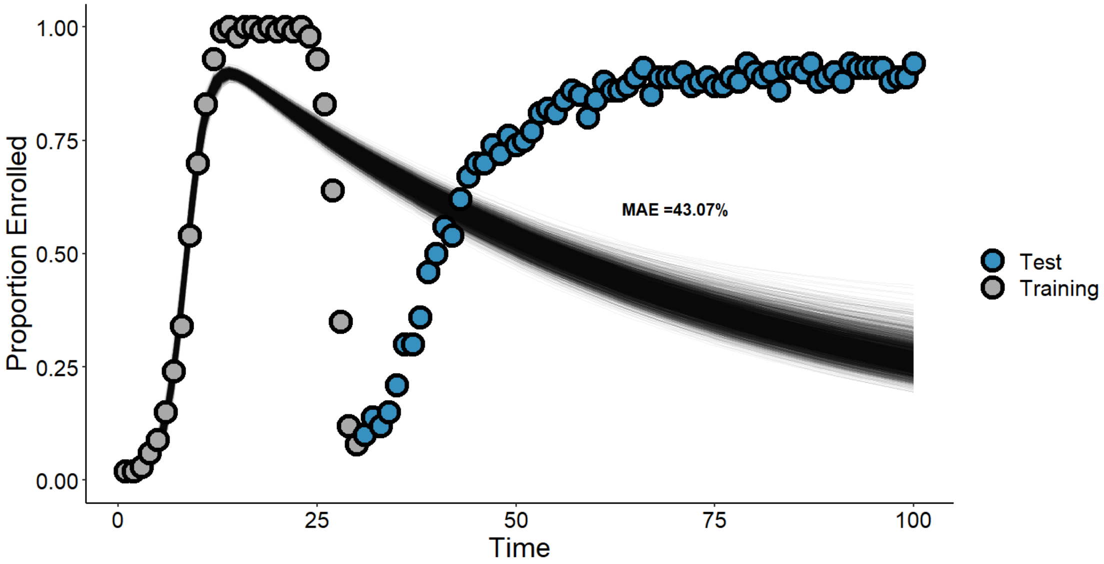


Figure 8 SIRS model fit to the average of five runs of the agent-based simulation data under success-biased social learning contingent on behavior-environment feedbacks shown as translucent black lines representing 1000 draws from the posterior. Simulated data are overlaid with gray points signifying training data (first 30%) and blue points signifying test (later 70%) data. Dynamics in this figure exemplify poor model fit (MAE = 43.07%) under primarily environmentally driven adoption.

To ensure that our modeling approach is generally robust against these types of ecologically-driven dynamics, we again ran five iterations of the agent-based model and assessed SIRS model fit for a wide range of parameter combinations. As shown in figure 9 and in appendix A (figure A2), our approach yields reliable model fit, as assessed through MAE, across the spectrum of realistic parameter values. It is worth noting however that the SIRS model fails to capture trends in conservation adoption in boundary cases, such as when 80-90% of resources are designated for conservation (figure 9). This indicates that the method presented in this paper may not be appropriate for real-world application where adoption dynamics are expected to be heavily driven by ecological change rather than social dynamics.

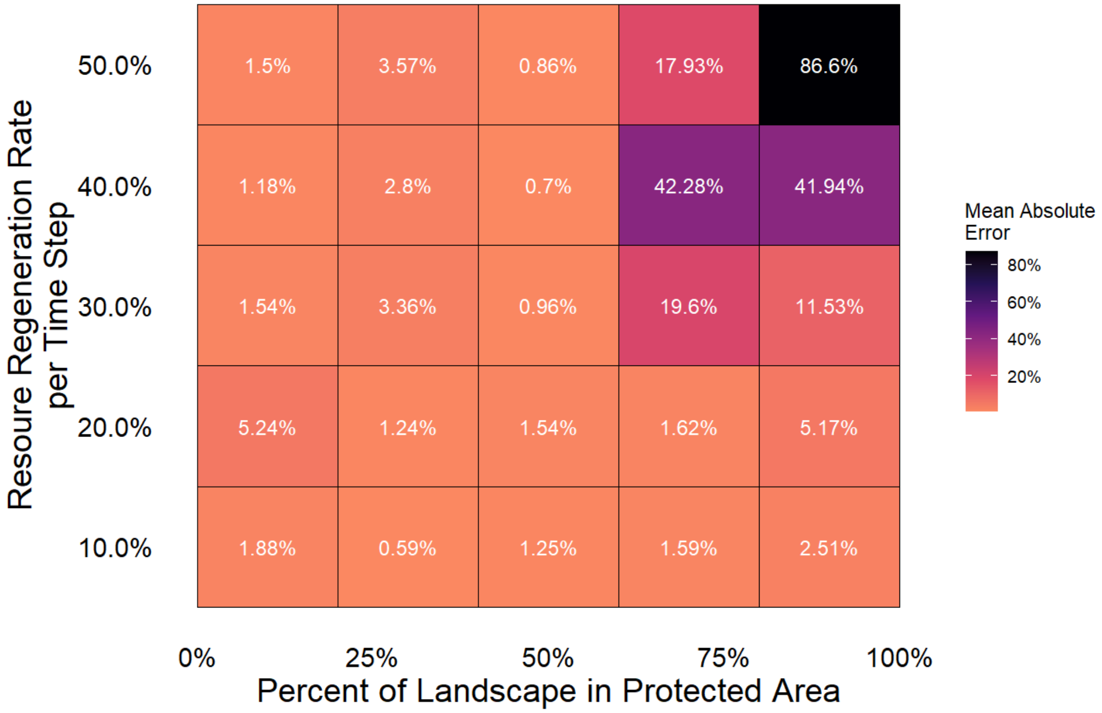


Figure 9 **Sensitivity analysis for the ability of the SIRS model to capture adoption dynamics under a variety of parameter combinations across a range of values for the resource regeneration rate and the percent of the resource designated for conservation.**

3 - Discussion

3.1 - Shortcomings of diffusion of innovations in community-based conservation

As demonstrated in figures 5 & 6, the standard SIRS diffusion model can reliably capture the long-term patterns of behavioral adoption for community-based conservation interventions, even when adoption is contingent on feedbacks with ecological processes. Fitting this model to observed data on the uptake of a behavior can provide us with estimates of the rates of adoption, dropout, and willingness to retry a specific intervention and allow us to predict the final stable rate of adoption in the population from early in the project. These insights, while useful, are somewhat limited in their ability to prescribe improvements for an intervention. As highlighted by the quote in the beginning of this article, diffusion study can explain *what* is happening in a system, but gives little intuition as to the mechanisms behind *why* it is happening (*Rogers 2010*).

As first described by Henrich (*2001*) and demonstrated in figures 5 & 6, we see clear changes in the population patterns of adoption when individuals employ differing levels of social or independent learning. But when comparing many biased social learning mechanisms, the pattern of adoption may exhibit equifinality, where many different underlying mechanisms may produce similar or even identical patterns over time (*Barrett 2019*). Critically, this makes it virtually impossible to infer the specific biased social learning mechanism(s) used by a population from the pattern of adoption over time alone. This information is however important for researchers and practitioners, as the social transmission mechanism, or mix of mechanisms, employed by a population can dramatically affect the overall rates of adoption for a given behavior (*Smaldino et al. 2017*; *Andrews and Borgerhoff Mulder 2018*; *Tam et al. 2021*). Plainly, DOI can tell us if an intervention is being robustly adopted or not, but we need to understand the actual transmission mechanism to effectively act on this information. Thankfully, this information is possible to collect. For example, Tam et al. (*2021*) and Kline et al. (*2018*) give practical examples of how to measure social learning strategies in the context of conservation, and tools (game/survey instrument, code, etc.) with which to collect and analyze the data.

With information on the patterns and mechanisms of uptake of community-based conservation behaviors we can more selectively apply the many narrative insights from DOI and the study of natural resource management institutions. In populations primarily employing prestige-biased learning (where prestigious individuals are disproportionately copied) for instance, the identification of and collaboration with community change agents may be particularly effective (*Jiménez and Mesoudi 2019*; *Henrich and Gil-White 2001*; *Dietz et al. 2002*). Conversely, the observability of both resources and the benefits of conservation are likely of increased importance when the population primarily employs content-biased learning (where some characteristic of the trait itself makes it more desirable than a previous trait) (*Ostrom 1990*; *Rogers 2010*; *Boyd and Richerson 1988b*).

3.2 - Future work

Understanding the causal mechanisms behind the patterns of behavioral transmission is necessary to better delineate and predict how conservation will affect both people and the environment (*Cheng et al. 2020*). Researchers increasingly recognize that models of human-caused environmental change must explicitly incorporate dynamic social processes based on realistic human cognitions that allow actors to modify their behaviors in response to new information (*Meyfroidt 2013*; *B. L. Turner, Lambin, and Verburg 2021*; *Polain de Waroux et al. 2021*). Behavioral adoption is not truly binary, as implied by DOI. Rather, individuals modify behaviors they adopt in response to their personal experiences and needs (*Enquist, Ghirlanda, and Eriksson 2011*). Research on cultural evolution has accordingly begun to incorporate these cognitive processes into formal models (*Gabora and Steel 2017*, *2020*). Hence, modeling human behavior in the context of community-based conservation is in its infancy. Going forward, it will require a complex dynamic systems approach in which behaviors and the biophysical environment coevolve (*Schill et al. 2019*).

Mechanistic or process models allow for us to formally describe these complex interactions while testing the logical consequences of our assumptions and the relation of our hypothesized processes to observed data (*Epstein 2008*). The practice of applying statistical frameworks for parameter estimation to analytical process models, particularly ordinary differential equations, is still relatively new and has been embraced mostly in ecology (*Hefley et al. 2017*; *Laubmeier et al. 2020*; *Morales and Morán López 2021*). This emerging methodology allows for estimating interesting and directly interpretable process parameters, which is not possible with linear regression. We believe this is an exciting new avenue for conservation science as the direct interpretability and applicability of process parameters lend themselves well to tight integration with applied research, as is common in the field. Future research could extend the SIRS diffusion model to include an exposure term (i.e. SEIRS) to allow for individual variation in the exposure to an intervention required before adoption, possibly dependent on individual characteristics.

An additional line of research aimed at better capturing the trends shown in figures 7 & 8 might include a term that represents change in the environment over time and the effect of resource levels on adoption rates to more accurately reflect the social-ecological coupling. As exemplified in figures 7 through 9, any model that predicts human behavior due to past behavioral dynamics will fail to capture trends driven primarily by environmental conditions. An example of such an extension is presented below, where we include another equation for the change in a resource pool over time $\frac{dE}{dt}$. We also must include three additional parameters: ϕ, ρ, and θ, which represent the effect of resource level on enrollment (infection), the effect of harvest on the resource level, and the regeneration rate of the resource, respectively.

$$\frac{dS}{dt} = -\beta \cdot \mathrm{S}_t \cdot \mathrm{I}_t + \chi \cdot \mathrm{R}_t$$

$$\frac{dI}{dt} = \beta \cdot \mathrm{S}_t \cdot \mathrm{I}_t - \gamma \cdot \mathrm{I}_t - \phi \cdot \mathrm{E}_t$$

$$\frac{dR}{dt} = \gamma \cdot \mathrm{I}_t - \chi \cdot \mathrm{R}_t + \phi \cdot \mathrm{E}_t$$

$$\frac{dE}{dt} = -\rho \cdot (\mathrm{S}_t + \mathrm{R}_t) + \theta \cdot \mathrm{E}_t$$

(4)

While process models may be preferable to simulation and linear regression approaches for predicting adoption outcomes of conservation interventions, they might not always be possible. In complex systems, these models can quickly require many parameters in order to account for all moving parts accurately and thus are prone to issues of identifiability in parameter estimation and may even become mathematically intractable (*Laubmeier et al. 2020*). Further, as has been demonstrated in coastal fisheries, these systems can exhibit mathematical chaos, where our inability to measure the parameters of interest at a fine enough resolution results in seemingly stochastic, unpredictable outcomes (*Wilson et al. 1994*).

Coupled human and natural systems commonly exhibit dynamics with thresholds, time lags, and heterogeneity not present in social or natural systems in isolation and therefore are difficult to model analytically (*Liu et al. 2007*). In very complex cases such as these, we argue that agent-based simulations are the preferred approach as they allow for these features of complex systems that are difficult or even impossible to account for with analytical process models such the SIRS or SIRS extension model presented in equation 4 (*Reyers et al. 2018*; *Railsback and Grimm 2012*; *Wilensky and Rand 2015*). Agent-based simulations allow modelers to impose a realism in the governance or institutional dynamics that are largely intractable in closed-form mathematical equations (*Kaiser, Flores, and Hillis 2020*; *Bravo 2011*; *Joffre et al. 2015*). Further, agent-based simulations uniquely allow researchers to hypothesize and test causal processes in complex social-ecological systems (*Baggio and Hillis 2018*; *Schlüter et al. 2019*). As the number of purely subsistence communities shrinks each year worldwide, and multiple levels of institutions are increasingly involved in natural resource management, incorporating these features into our models is paramount for reliable inference (*McKean 2000*; *Armitage et al. 2009*).

4 - Conclusions

Overall, we argue that fitting process models of behavioral diffusion to data on the spread of conservation behaviors is a practical way for researchers and practitioners to apply DOI to community-based conservation. We test the utility of the SIRS diffusion model on simulated data that highlight the feedback between behavioral adoption and environmental change commonly seen in community-based conservation interventions. We show that this model can be a powerful tool for estimating the natural history characteristics of a particular intervention, such as the rate of spread, and for predicting the long-term patterns of adoption, even under reciprocal behavior-environment interactions. We also introduce the broader field of cultural evolution as a more comprehensive body of theory for understanding the underlying mechanisms of behavioral adoption than DOI alone. We hope that this review provides a model for how practitioners might practically apply insights from DOI to community-based conservation interventions, while also clarifying the position of DOI in the current literature on the adoption of sustainable resource management practices.

5 - Software and data availability

The agent-based model used to simulate data for this paper was produced using the R programming language for statistical computing; R version 4.1.2 (*R Core Team 2021*). These simulated data were analyzed by running the probabilistic programming language STAN within the Rstudio environment; STAN version 2.21.3 (*Team 2021*; *RStudio Team 2020*). All R and STAN code used in this project can be found at the Github repository here: *https://github.com/matthewclark1223/A-Quantitative-Application-of-Diffusion-of-Innovations-for-Modeling-the-Spread-of-Conservation-Behav*.

CHAPTER THREE: CAUSAL ATTRIBUTION OF AGRICULTURAL EXPANSION IN A SMALL ISLAND SYSTEM USING APPROXIMATE BAYESIAN COMPUTATION

The extent and arrangement of land cover types on our planet directly affects biodiversity, carbon storage, water quality, and many other critical social and ecological conditions at virtually all scales. Given the fundamental importance of land cover, a key mandate for land system scientists is to describe the mechanisms by which pertinent cover types spread and shrink. Identifying causal drivers of change is challenging however, because land systems, such as small-scale agricultural communities, do not lend themselves well to controlled experimentation for logistical and ethical reasons. Even natural experiments in these systems can produce only limited causal inference as they often contain unobserved confounding drivers of land cover change and complex feedbacks between drivers and outcomes. Land system scientists commonly grapple with this complexity by using computer simulations to explicitly delineate hypothesized causal pathways that could have resulted in observed land cover change. Yet, land system science lacks a systematic method for comparing multiple hypothesized pathways and quantifying the probability that a given simulated causal process was in fact responsible for the patterns observed. Here we use a case study of agricultural expansion in Pemba, Tanzania to demonstrate how approximate Bayesian computation (ABC) provides a straightforward solution to this methodological gap. Specifically, we pair an individual-based simulation of land cover change in Pemba with ABC to probabilistically estimate the likelihood that observed deforestation from 2018 to 2021 was driven by soil degradation rather than external market forces. Using this approach, we can show not only how well a specific hypothesized mechanism fits with empirical data on land cover change, but we can also quantify the range of other mechanisms that could have reasonably produced the same outcome (i.e. equifinality). While ABC was developed for use in population genetics, we argue that it is particularly promising as a tool for causal inference for land system science given the wealth of data available in the satellite record. Thus, this paper demonstrates a robust process for identifying the emergent landscape-level signatures of complex social-ecological mechanisms.

1 - Introduction

The mosaic of land cover on the surface of our planet is a product of complex social-ecological dynamics that make up the complete land system (Turner, Lambin, and Reenberg 2007; Turner, Lambin, and Verburg 2021). Changes in Earth's terrestrial surface have profound implications for ecosystem functioning and human wellbeing, and as such, are of critical importance to understand and predict (Steffen et al. 2006). A key challenge in understanding land cover change and designing effective policies is that there are often multiple plausible, and even interacting mechanisms that can cause a switch in land cover from one state to another (Lambin and Meyfroidt 2010). For example, in the case of agricultural frontier expansion, depletion of soil fertility in existing plots often promotes the conversion of nearby natural vegetation to new cropland, thus pushing the frontier outward (Casetti and Gauthier 1977). Agricultural frontier expansion into forested lands is also observed however, as a result of increased market value for crops and increased population pressure (Meyfroidt et al. 2018).

When designing policies to limit the conversion of natural areas into more intensive land use types such as rotational agriculture, it is important to determine the drivers of conversion, because the impact of a given policy will depend on the dominant driver. The introduction of new agricultural technologies, for instance, can have drastically different effects on the landscape depending on the primary driver of frontier expansion in a given system (see Kaimowitz and Angelsen 1998 for a foundational review). If loss of soil fertility is the primary driver, new technologies can limit forest conversion as they allow existing plots to be farmed for longer periods of time, minimizing the need for agricultural operations to change location. However, if market forces are the primary driver of frontier expansion, this same intervention is likely to incentivize further forest conversion by increasing the returns from any given agricultural plot (Meyfroidt et al. 2018). Despite the importance of identifying causal processes in land cover change, actually doing so in any particular case has often proven difficult given the inherent social-ecological complexity of land systems (Meyfroidt 2016; Turner et al. 2020).

Land systems are complex adaptive systems characterized by feedbacks between the human and ecological subsystems, where a change in the state of one affects ongoing processes in the other and vice versa (Berkes, Folke, and Colding 2000; Le, Seidl, and Scholz 2012; Folke 2007). The possible distribution of land cover types in any one area is also highly path dependent, or constrained by past states and trajectories, sometimes further muddying the relationship between actual drivers and outcomes (Liu et al. 2007). Standard statistical tests fail to produce reliable inference in complex systems exhibiting feedbacks and path dependence, given that it is generally impossible to specify likelihood functions for such processes (Levin et al. 2013). Thus, while critical, identifying causal processes in land systems and social-ecological systems generally has proven difficult.

To begin to build causal theory in complex land systems, researchers commonly use computer simulations to abstract key phenomena and produce 'what-if' scenarios (Ahimbisibwe et al. 2021; An et al. 2021). Simulations allow researchers to code complexities such as feedbacks and path dependence directly into a model of the processes under examination, in order to formally define a hypothesized causal mechanism and check the logical implications and internal validity of their assumptions (Epstein 2008; Verburg 2006). While simulations like this are important for theorizing about social-ecological systems, it can be difficult to relate them back to empirical data and tell where exactly the real-world sits in the multidimensional parameter space of the model (Ren et al. 2019). Without this information, we are limited in our knowledge of how well a given simulation accurately distills the processes we are hoping to examine, and how we might use such a model to infer important things about the real-world.

The biological sciences have largely led the development of methods for comparing simulated, theoretical causal processes to observed data. Ecological research in particular has made considerable use of simulation modeling to theorize about how complex interactions among individuals lead to observed patterns at the population level (i.e. individual-based modeling) (Grimm 1999; DeAngelis and Grimm 2014; Grimm and Railsback 2013). Relatively early on in the use of individual-based modeling in ecology, researchers developed the general process of pattern-oriented modeling in which a given hypothesis is evaluated on its ability to recreate an observed biological pattern at an appropriate temporal and spatial scale (Wiegand et al. 2003; Grimm et al. 2005). This method allowed researchers to match observed trends in population change with plausible rates for various demographic parameters such as pre-breeding survival in woodpeckers, road mortality in lynx, and annual male survival in amphibians, among many others (Wiegand et al. 2003; Kramer-Schadt et al. 2004; Swanack et al. 2009). While pattern-oriented modeling provides a general structure for interrogating causal hypotheses of complex phenomena with empirical data, it does not adequately account for stochasticity in the outcomes of hypothesized mechanisms. In particular, this method fails to quantify the complete range of model parameters that may reasonably reproduce observed patterns and the frequency in which they do so.

Toward this aim, approximate Bayesian computation (ABC) has emerged as a formal method of pattern-oriented modeling in which researchers run simulation models across many parameter values and systematically accept or reject the outputs of each run as consistent with observed data. All accepted parameter values are then aggregated into a probability distribution of parameter values that are likely to produce the observed data (Hartig et al. 2011; Troost et al. 2022). ABC has proven effective for identifying the range of simulation model parameters consistent with observed data across a wide breadth of biological fields from ecology to epidemiology (Scranton, Knape, and Valpine 2014; Kosmala et al. 2016; Vaart, Johnston, and Sibly 2016; Boult et al. 2018; Martínez et al. 2011; Cipriotti et al. 2012). When different simulation parameters represent specific hypothesized causal processes, ABC can then be used to estimate the probability that a given causal process produced a given set of observed data. Importantly, ABC enables researchers to statistically estimate model parameters even for generative models containing complex processes such as the feedbacks and path dependence characteristic of social-ecological systems (Gallagher et al. 2021).

In this paper we demonstrate the utility of ABC for generative inference in complex land systems and social-ecological systems generally. Specifically, we simulate hypothesized patterns of agricultural expansion in a small island system given two possible drivers, declining soil fertility and external market forces. We then filter the range of possible model parameters to just the inputs that produce land use patterns consistent with the observed time-series of agricultural frontier expansion. We show that this method allows us to determine the proportion of each of these drivers in causing the observed agricultural expansion in our study system, Pemba Island, Tanzania. In this way, we provide a straightforward demonstration for linking land system simulations with empirical data to draw causal inference in even very complex systems involving feedbacks and path dependence.

2 - Study system

2.1 - Pemba

The Indian Ocean archipelago of Zanzibar is a semi-autonomous jurisdiction lying off the coast of Tanzania. Pemba, the northernmost island, is densely populated with 428 people per square kilometer. While the island has a few main population centers (Wete, Chake Chake, and Mkoani), the vast majority of the island's 400,000 people live in small villages scattered across some 120 wards (*shehia*), all of which are connected by a dense, relatively modern road network (fig 10). Based on the 2022 census, we estimate the average growth rate between 2012 and 2022 to be about 2.1%, more than double the world average of 0.9% per year.

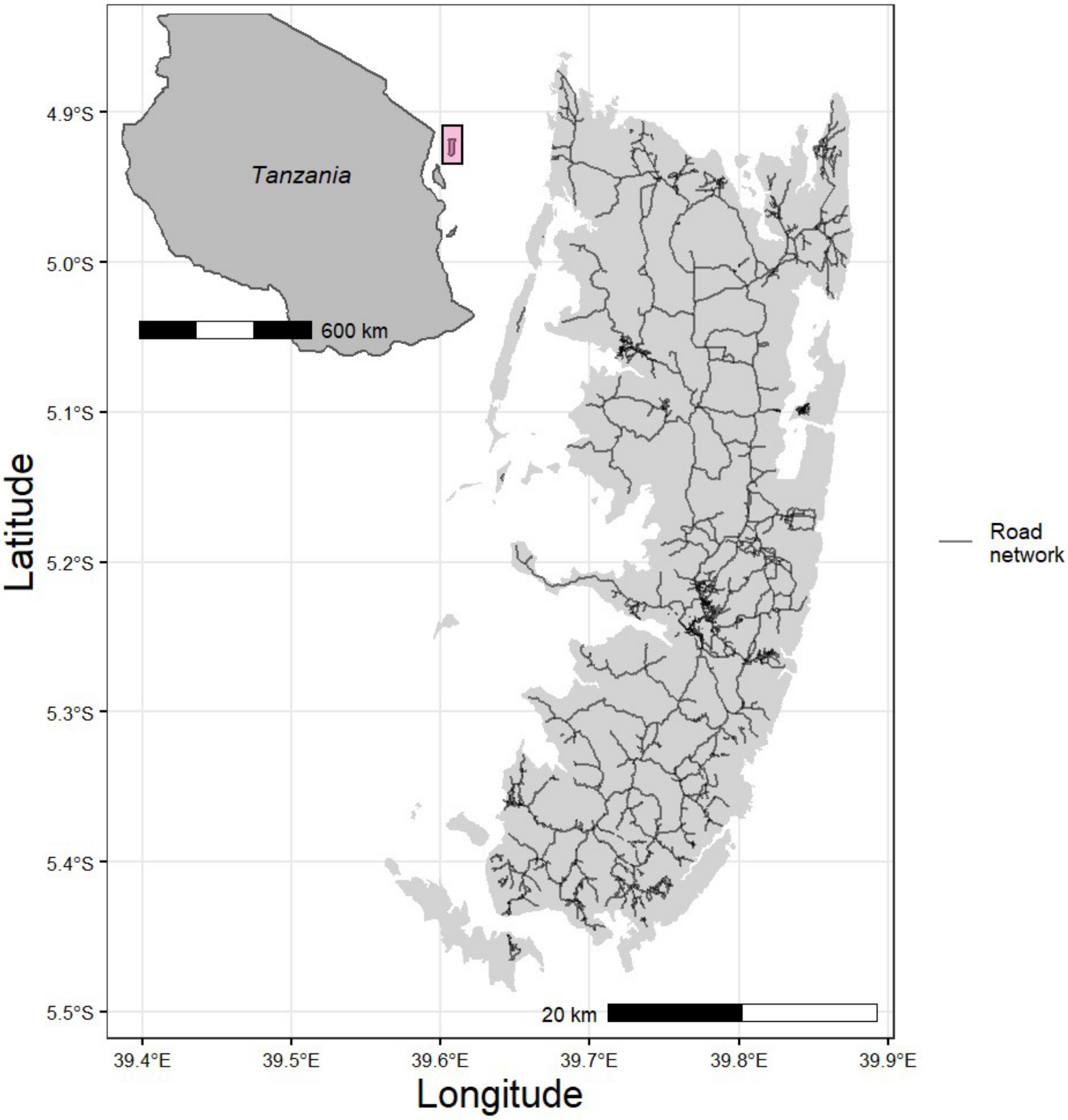


Figure 10 Inset map showing the location of Pemba Island relative to the Tanzanian mainland (upper left) and the dense Pemban road network (main figure).

The rural economy of Pemba is primarily subsistence (farming, fishing, and livestock), with a single important cash crop, cloves. Cloves were introduced to the island in the early 19th century and have come to dominate the economy of the island's western half due to the region's highly productive soils (see below). In contrast, the island's eastern side, characterized by poor, shallow soil, has lower human population density, is less developed, and is generally less economically productive. For example, in an extensive household survey focused on economic production carried out in 2017, we find that the average household income from the sale of crops (excluding cloves) in the east is approximately $25, compared with an estimated $80 in the highly productive western half.

Nevertheless, there is considerable pressure in the east for new farmland. Some 30% of All eastern households surveyed stated that they had cleared forested land to expand their farming operations in the past 7 years. On average, households report clearing approximately 0.91 acres, primarily to plant staple crops such as cassava. And while cassava is almost exclusively a subsistence crop in Pemba, there has been considerable pressure to develop the Pemban economy in the past decade, as it has lagged behind the rest of Tanzania and Zanzibar. New development initiatives, particularly in agriculture, are a constant of government programming, and new crops such as watermelon and tomatoes are being experimented with on the once underutilized eastern soils. However, Pemba has historically struggled to develop its own internal market for agricultural goods, and the impact that these new cash crops are having on the eastern landscape is unknown.

2.2 - Coral rag vegetation and rotational agriculture

Pemba is a narrow island, in many places just 15 kilometers wide, yet most of the environmental variation exists across the narrow east/west span. This is owed to three distinct soil types that run the length of the island and can generally be thought of as going from deep and fertile in the west, to shallow and nutrient poor in the east (Stockley 1928). The easternmost topography is characterized by jagged, fossilized coral beds covered with a shallow soil layer and scrubby vegetation ranging from approximately 1 to 5 meters in height (i.e. coral rag forest) (Burgess and Clarke 2000; Burrows et al. 2018). This forest type has traditionally been overlooked by conservation efforts in Pemba, and Zanzibar generally, yet it is critical habitat for a variety of plant and animal species such as the endemic Pemba flying fox (*Pteropus voeltzkowi*) (Kingdon 1988).

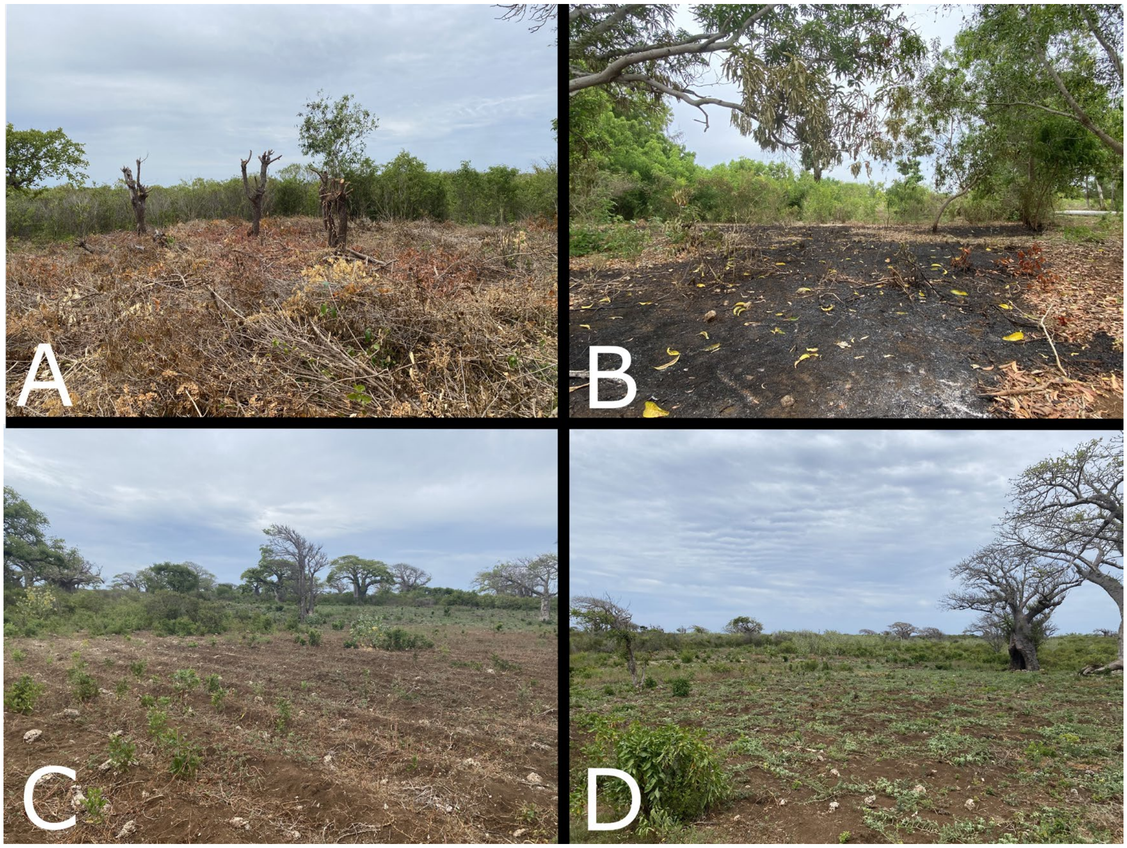


Figure 11 Panels A, B, C, and D show the process of coral rag forest conversion to agriculture in Pemba in four distinct stages. Panel A shows the cutting of coral rag vegetation, which is then left to dry before burning. Panel B shows a freshly burned plot before planting. Panel C shows a productive agricultural field. Panel D shows a fallow agricultural field.

The shallow soils atop porous coral rag geology characteristic to eastern Pemba cannot be productively farmed for long, continuous periods. Farmers in this region thus typically rely on rotational swidden agriculture where primary forest is cleared and the land is farmed for a short period, then left to recharge for a number of years (fig 11).

While this process could potentially be interrupted by regenerative agricultural practices or the introduction of rainwater catchment systems, currently farmers in this region lack resources to escape the cycle of ecologically costly, short-term resource extraction (Wild et al. 2020; Biazin et al. 2012; Garrity et al. 2010). Thus, in this system, there are considerable feedbacks between the condition of the environment, decisions made by farmers to clear and farm a forested area, and the state of the environment in future time periods. Further, as any one forested area is cleared, it opens new patches to potential clearing through frontier expansion. Hence, specific patches available in any one time period are highly dependent on social-ecological events in previous time steps. Thus, this system displays both the feedbacks and path dependence characteristic of complex social-ecological systems.

3 - Methods

3.1 - Data

3.1.1 - Land cover classification

We produced 20 m land cover maps using top of atmosphere Sentinel-2 time series imagery and ancillary datasets in a data fusion approach using Google Earth Engine (GEE) (Gorelick et al. 2017; Mondal et al. 2019). GEE is an open-access cloud computing platform that hosts petabytes of freely available earth observation data, and is ideal for creating land cover maps with built-in classification functions. For this study, we created annual median composite images for conversion into thematic land cover maps. We filtered the time series by date, and used the image metadata to further filter by estimated cloud cover, using a threshold of <20%. We then used the ‘QA60’ quality band to remove any remaining clouds prior to creating the composites of median values.

Beyond the native Sentinel-2 spectral bands, we calculated common normalized difference indices useful for distinguishing common land cover types such as the Normalized Difference Vegetation Index (and red edge adaptations) and the Normalized Difference Water Index (NDWI), as well as its modified version (MNDWI) (DeFries and Townshend 1994; Schuster, Förster, and Kleinschmit 2012; Xu 2006; Gao 1996). We also used synthetic aperture radar (SAR) backscatter from the corresponding Sentinel-1 ground range detected time series available in GEE. We used SAR scenes from ascending paths only and incorporated both vertical-vertical and vertical-horizontal polarizations in our analysis. SAR data are known to be influenced by varying incidence angles, so we normalized these images by multiplying the backscatter by the incidence angle with the understanding that greater incidence angles result in less backscatter returned to the instrument (Banks et al. 2019; Kaplan et al. 2021). To reduce inherent speckle in the SAR images, we opted for a time for space substitution by using a mean composite of all images for the given year to maintain a 10 m spatial resolution. Lastly, we considered topographic covariates for classification (elevation, slope, and aspect derived from the NASA Shuttle Radar Topography Mission digital elevation model) that dictate locations of land covers of interest relative to sea level and topography (Appendix B) (Farr et al. 2007).

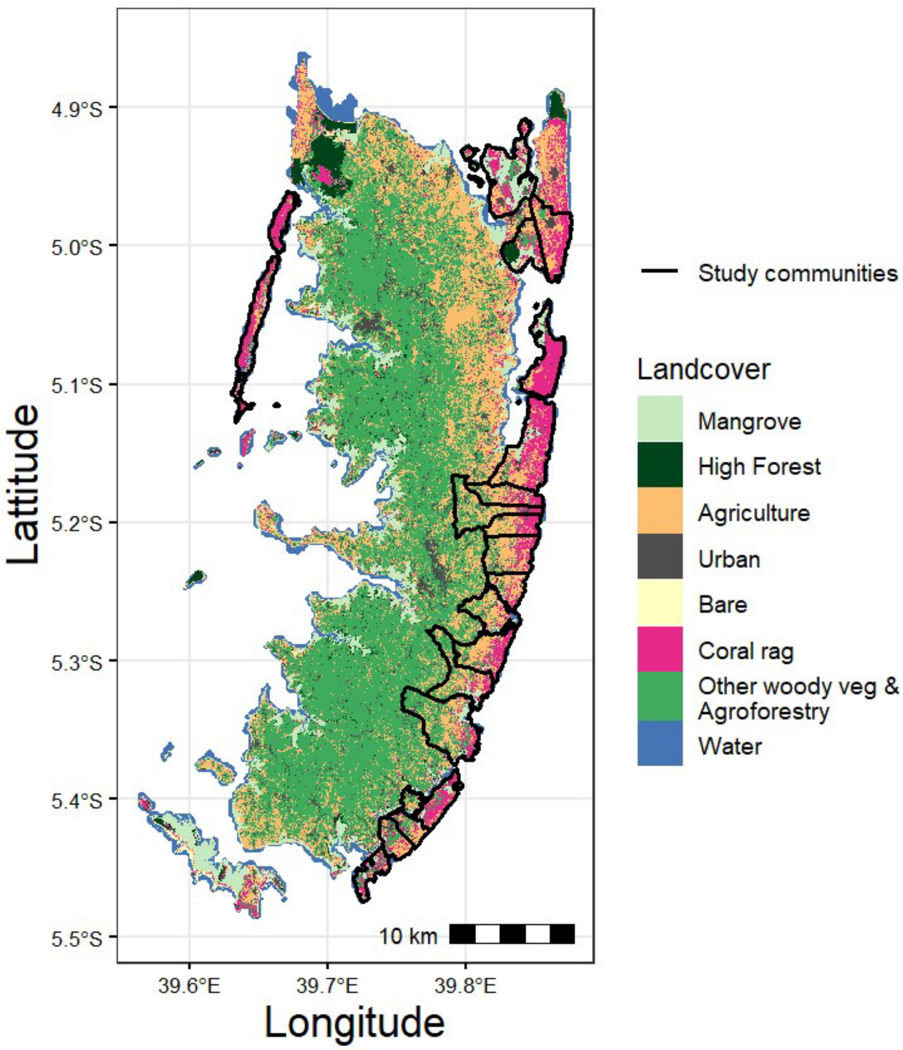


Figure 12 Land cover estimates for the year 2018 in Pemba. The classification for each 20m pixel is distinguished by color, with the class of interest, coral rag vegetation, highlighted in pink. Black lines show each of the 19 shehia included in this study.

From each composite image, we collected representative training samples for all classes of interest (mangrove, high forest, agriculture, urban, bare, coral rag, other woody vegetation, and water). We trained a random forest classifier using training samples from 2018, 2019, & 2021 to account for potentially varying atmospheric and illumination conditions among images (Breiman 2001). The random forest we used for classification had 100 trees, and utilized four variables per split (the square root of the number of covariates), consistent with other remote sensing applications (Belgiu and Drăguţ 2016). Due to relative class imbalances, we chose to use a stratified random sampling design to assess the accuracy of our outputs, and computed area adjusted accuracy metrics (Olofsson et al. 2013; Stehman and Foody 2019). An expert hand labeled these stratified points based on high resolution median composite PlanetScope images with 20 points from each mapped class. Results show estimated overall accuracies of 92.86% (+/- 4.21%) and 95.93% (+/- 2.95%) for 2018 and 2021, respectively (Appendix B). Much of the confusion and sources of error in the maps is found among upland woody vegetation classes (high forest, mangrove, and other woody vegetation) that share similar spectral and physical characteristics. Other mentionable errors occur among urban and agriculture in 2018, and bare and agriculture in 2021, leading to relatively high uncertainty for area estimates and producer's accuracies in the rare urban and bare classes in 2018 and 2021, respectively (Appendix B).

3.1.1 - Interview data

In July 2021, we conducted informal interviews with staff of Community Forests Pemba, a nonprofit aimed at building conservation capacity on the island, and farmers in four *shehia* with coral rag forests in the east of the island. Researchers asked farmers about how they make decisions regarding when and how long to farm and fallow agricultural plots, as well as how they decide to clear forest vegetation to establish new cropland. There was broad consensus among non-profit staff and farmers that agricultural plots in these areas are typically farmed for two years and then left fallow for three years. Clearing forested land is labor intensive and thus, forested land is only cleared when nearby productive plots reach their two-year limit and no other previously-cleared adjacent plots are available.

3.2 - Individual-based simulation

Our individual-based model incorporates two mechanisms of land conversion from coral rag vegetation to productive agricultural land. The first follows the decision rules described during the farmer interviews where coral rag vegetation is converted in response to soil degradation and space limitations following the fallowing of cropland. Under this mechanism, each pixel (20m area) is autonomous and follows the following basic set of decision rules also described visually in figure 13. Each pixel classified as agriculture in the study *shehia* is initialized randomly as either productive or fallow. Each productive agricultural pixel is then randomly assigned to either the first or second year of agricultural production. Each fallow agricultural pixel is randomly assigned as in the first, second, or third year of fallow time. When transitioning to the next year, agricultural pixels in their second year of production go fallow and the lost agricultural production is relocated as follows. If there is an adjacent (8 directional) fallow pixel in the final (third) year, the crop production moves there. If there is no adjacent third year fallow pixel available and there is adjacent coral rag vegetation, that coral rag pixel is converted to first year productive agriculture for the next year. All other land cover types (e.g. water, urban, mangrove, etc.) are left alone.

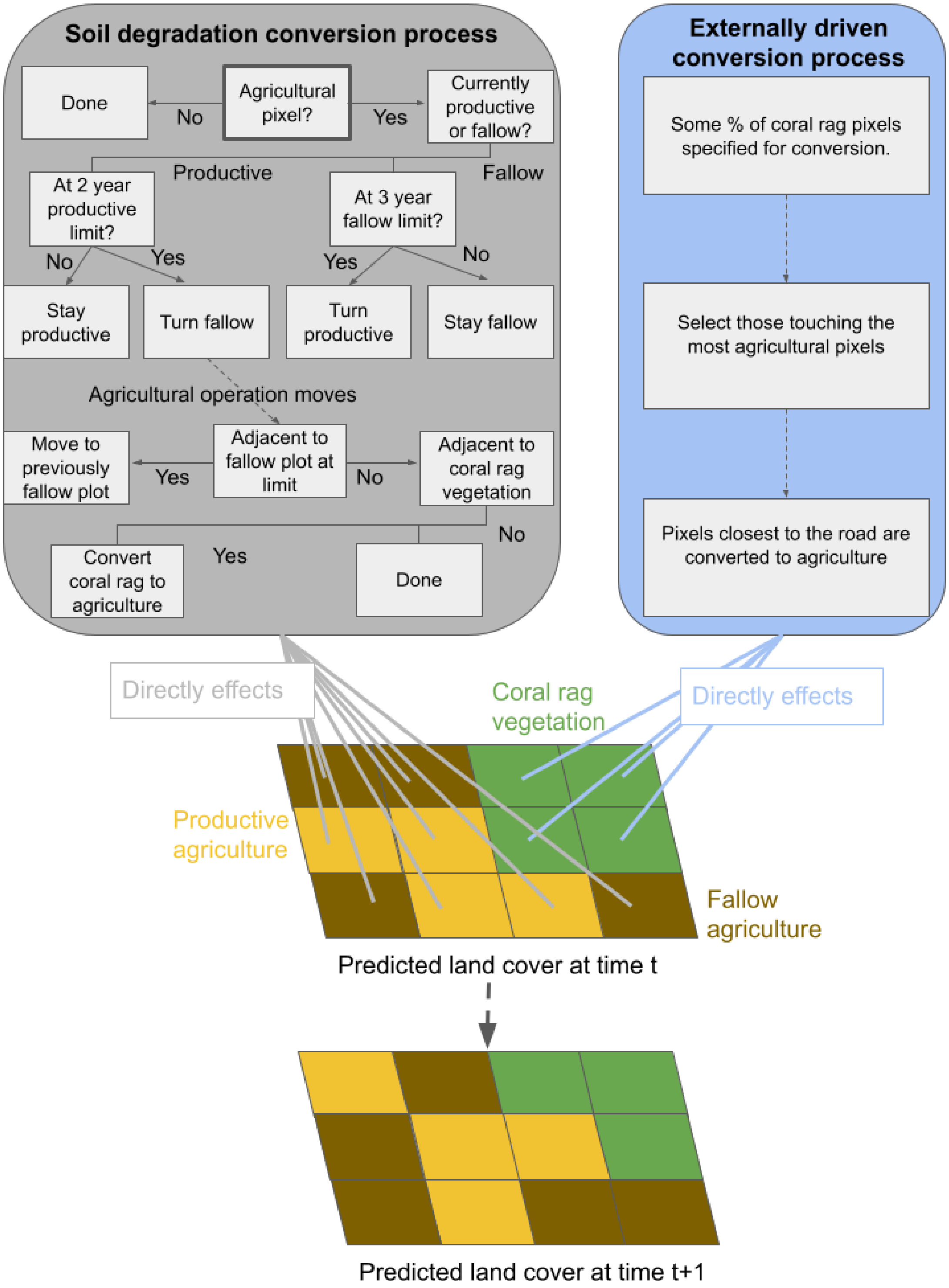


Figure 13 Visual representation of the individual-based simulation used to model coral rag vegetation conversion to agriculture in each of the 19 shehia included in this study. The top two boxes show the competing causal forces driving land conversion. The bottom portion of the figure shows how those forces affect the pixel-based land cover in each time step.

The second mechanism of land conversion from coral rag vegetation to productive agricultural land represents all other factors driving land conversion outside of the soil degradation process. In our system, the most prominent other factors include a rapidly growing population and the increasing market value for crops. Under this mechanism, some additional percentage of coral rag vegetation is converted to first year agriculture each year, representing a yearly rate of forest loss caused by factors other than soil degradation. Coral rag pixels allocated to conversion are those that are adjacent to the greatest number of agricultural pixels. When coral rag pixels are adjacent to an equal number of agricultural pixels, then the coral rag pixels closest to a road are selected for conversion to first year agricultural land. A visual representation of this simulation can be found in figure 13.

For each run of this simulation, the observed land cover on Pemba Island in 2018 (fig 12) is used as the starting year and the model is run for three time steps to yield a predicted land cover for 2021, given a set rate of externally driven agricultural expansion. By then comparing this predicted land cover in 2021 to the observed land cover in 2018, we can produce a predicted number of coral rag pixels to be converted to agriculture under different rates of externally driven land conversion.

3.3 - Approximate Bayesian computation (ABC)

As described in the introduction, simulation modeling allows researchers to formally express complex, hypothesized causal mechanisms in land system science. The primary limitation for the use of simulation modeling to enhance our understanding of real-world causality, however, is the absence of a straightforward statistical process for relating simulations to empirical data. Approximate Bayesian computation is one way to produce such generative inference (Kandler and Powell 2018). In this framework, researchers run a simulation model under a wide range of parameter combinations, representing alternative hypotheses, to produce many simulated datasets for which all parameters and outcomes of interest are known. All simulated datasets are then systematically accepted or rejected as consistent with the observed data, and the combination of model parameters that provides the best fit is estimated probabilistically (Vaart et al. 2015; Beaumont, Zhang, and Balding 2002). Hence, ABC allows researchers to quantitatively compare the likelihoods of competing hypothesized causal mechanisms in complex land systems.

In this study we vary just one model parameter, the externally driven rate of coral rag vegetation conversion to rotational agriculture. We first specify a prior distribution that we believe will capture all possible values of this parameter of interest (fig 14). This prior is based on a combination of calibration with earlier models, and *a priori* understanding of the system from working with local conservation organizations and farmers.

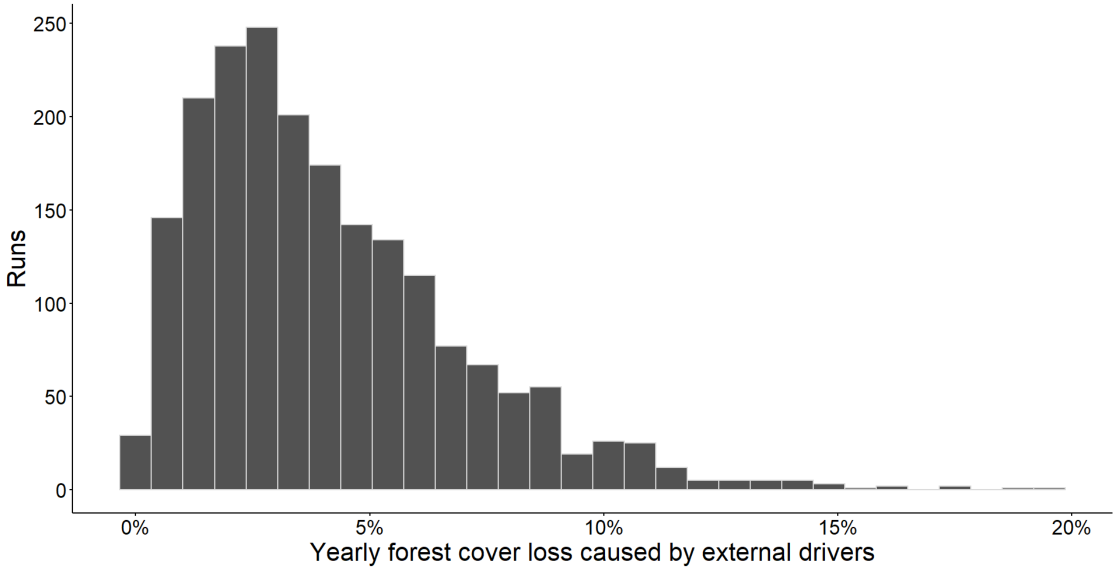


Figure 14 Two thousand draws from the prior distribution of the rate of externally driven coral rag vegetation conversion to agriculture. These draws were used to produce the prior distribution of the expected number of coral rag vegetation pixels to be converted to agriculture from 2018 - 2021 for each shehia.

We then run our simulation model 2,000 times using draws from this prior distribution as the parameter of interest — the externally driven rate of coral rag forest conversion. For each run, the model then produces a synthetic dataset including the number of expected agricultural conversions for each *shehia* in our study. Each of these synthetic datasets is then accepted or rejected as consistent with the observed changes in land cover as measured through our 20m land cover classification map for 2021. We use an acceptance criteria of predicted agricultural conversions within 10% of the observed conversions. Finally, the parameter value for the extrinsic growth rate in each synthetic dataset that is accepted as consistent with the observed data is saved as one “draw” from the posterior for the estimated real-world parameter value.

4 - Results

4.1 - Parameter estimation

As described in the methods, for each *shehia* we ran 2,000 simulations, using each draw from the prior distribution of externally driven coral rag forest conversion for each simulation (fig 14). Each of these simulations converted some number of coral rag vegetation pixels to agriculture in each of the 19 *shehia* from 2018 to 2021 (fig 15). An average of 231 of these estimates per *shehia* were within 10% of the observed number of converted coral rag vegetation pixels (Sunnåker et al. 2013). Keeping only these synthetic datasets consistent within the 10% error bound, we observe the distribution of externally driven growth parameter values that, based on our model, are likely to have produced the observed 2021 land cover (fig 16). The median parameter values consistent with the observed data (parameter estimates) for each *shehia* range from 0.0% to 3.9% for yearly coral rag forest cover loss due to external forces (fig 16). For four of the study *shehia*, the observed number of coral rag forest pixels converted to agriculture was fewer than predicted by the cycles of soil degradation built into our model alone. These four *shehia* all generally exhibited overall low rates of observed coral rag forest conversion to agriculture observed through the satellite imagery. We discuss contextual factors that may be influencing these trends in the discussion.

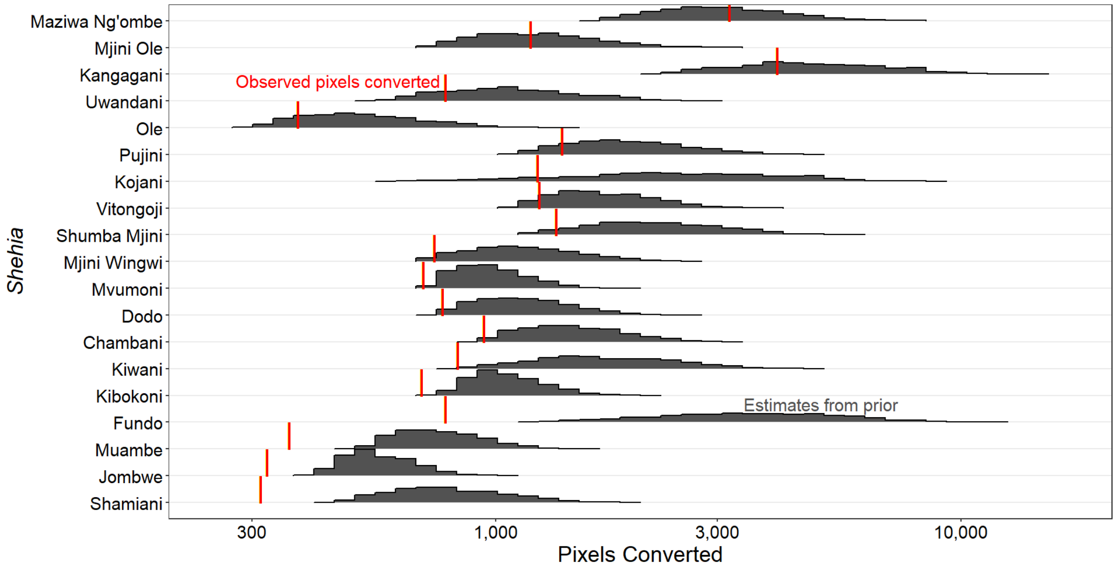


Figure 15 Black histograms represent the expected number of coral rag vegetation pixels to be converted to agriculture for each draw from the prior for each shehia from 2018 to 2021. Red lines show the observed number of conversions for each shehia from 2018 to 2021.

The width of the posterior parameter estimates shown in figure 16 are indicative of how much information about causal processes we can infer from the observed land cover change from 2018 to 2021. Wider estimates indicate a greater degree of equifinality, where a wide range of externally driven deforestation rates could have produced the observed data. Conversely, narrow parameter estimates indicate that only a small range of externally driven deforestation rates could have produced the observed number of coral rag vegetation pixels converted to agriculture from 2018 to 2021. Thus, when parameter estimates are more narrow, the data carry a stronger underlying causal signature. The width of the posterior parameter estimates can then be thought of as the range of processes that could have reasonably produced the observed data (Kandler and Powell 2018). Across *shehia*, we observe relatively narrow parameter estimates, with an average range of 1.47%; the most narrow being 0.46% and the widest being 2.24% (fig 16). We can conclude then that based on our model, on average, less than a 1%

increase or decrease in the externally driven deforestation rate from the median model estimate is likely is result in the observed land cover change in each *shehia*.

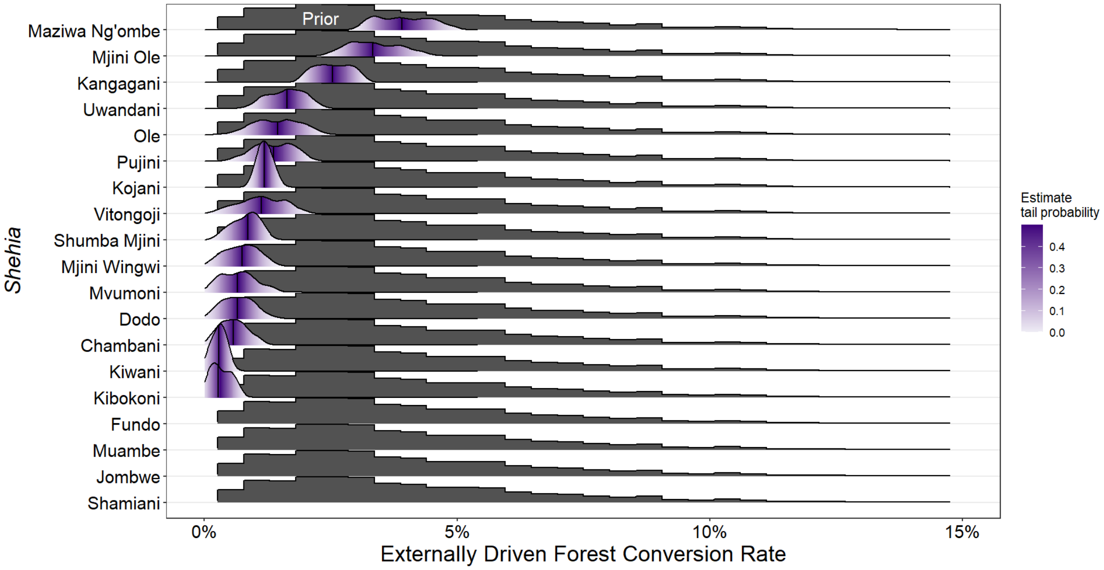


Figure 16 Black histograms show the prior distribution of externally driven deforestation rates for coral rag vegetation in Pemba. The prior values are identical for each shehia. Purple density plots show the density of draws from the prior in which the prior value resulted in a deforestation rate within 10% of the observed rate for that shehia. Shading in the density plots shows the tail probability that a particular value from the prior will result in the observed land cover based on our model.

4.2 - Estimating the contribution of each process

With the observed rates of coral rag vegetation conversion from 2018 to 2021 and estimates for the externally driven agricultural expansion (deforestation) rate for each *shehia* in hand, we can assess the proportion of total loss driven by soil degradation versus external influences such as market integration and population growth. We subtract the median estimate of the contribution of external forces from the total satellite-observed rates of conversion to yield the point estimates shown in figure 17.

On average, we observe a 5.1% yearly rate of total coral rag forest conversion to agriculture from 2018 to 2021. Between study *shehia* this rate of total conversion ranges from 1.1% to 9.8%. We estimate that the percent of coral rag vegetation converted to agriculture in each *shehia* driven by soil degradation was between 1.0% and 7.6% per year, with an average rate of 4.0%. By comparison, a relatively small proportion of coral rag vegetation in each *shehia* is converted to agriculture each year as a result of external forces. We estimate that the average rate of externally driven conversion is 1.1% of total coral rag forest cover, ranging from 0.0% to 3.9% between *shehia*.

While there is considerable variability in both the total rate of coral rag vegetation loss and in the contribution from external drivers between *shehia*, a general and intuitive trend is that *shehia* with a greater proportion of loss caused by external drivers show greater coral rag vegetation loss overall. The four *shehia* that showed a total number of observed coral rag pixels lost below that which is expected from soil degradation alone in figure 15, also show relatively little vegetation loss as a percentage of total coral rag cover from 2018 to 2021.

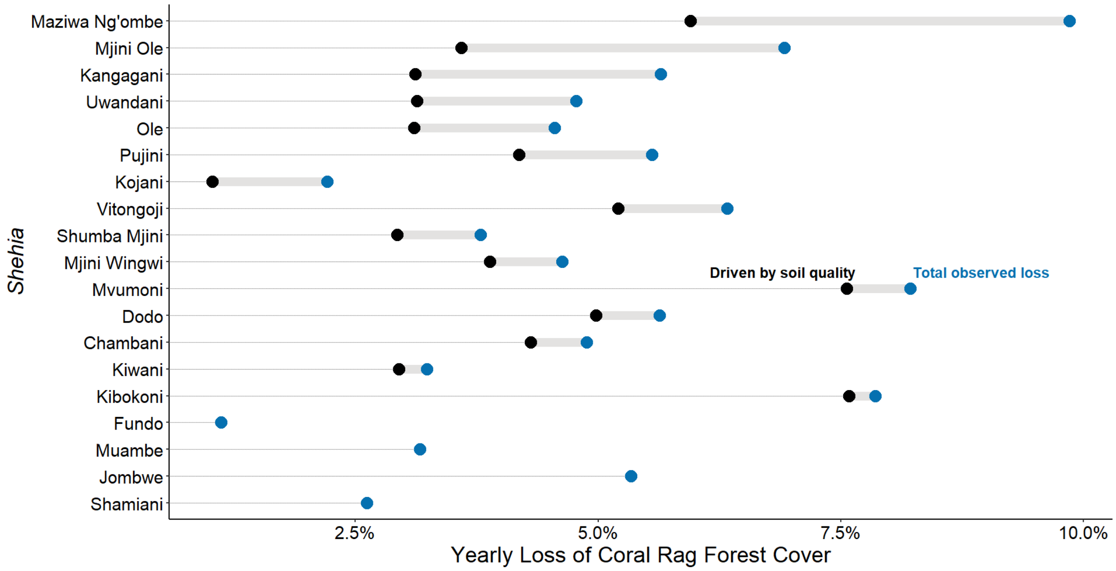


Figure 17 Barbell plot showing the median estimates of the influence of soil degradation on the observed coral rag vegetation loss in each shehia. Blue points show the total loss of coral rag vegetation as measured using satellite imagery. Black points show the median model estimates for the contribution of soil fertility loss to the observed deforestation.

5 - Discussion

5.1 - Pemba specific implications

Across the *shehia* in our study, we observe a 5.1% yearly rate of coral rag vegetation conversion to agriculture. We show here that reported farmer behavior in response to soil degradation, paired with the topography of the study *shehia*, should account for an estimated 4.0% yearly rate of conversion on average. Thus, while variable, we can conclude that on average a relatively small proportion of the observed coral rag vegetation conversion to agriculture in the study *shehia* is driven by external forces such as increasing demand driven by increasing subsistence needs or market forces. This finding matches our theoretical expectations given that farmers in this region generally clear land in order to plant low value staple crops such as cassava (Meyfroidt et al. 2018). This suggests that regenerative agriculture programs, along with rainwater catchment systems may considerably reduce the long-term loss of coral rag forest in Pemba, Tanzania. These programs will also ease the strain that clearing forested land puts on farmers, and may potentially help farmers break free of the cycle of environmentally damaging agricultural practices in pursuit of short-term gains.

While the 1.1% average estimated yearly conversion rate of coral rag vegetation to agriculture in the study *shehia* driven by external forces is relatively small compared to the rate of loss driven by soil degradation, it is not negligible. Further, this value could reasonably increase as a result of continued market integration and population growth in Pemba. As the impact of external forces on land conversion increases, theory tells us that the effect of improved agricultural technologies on mitigating forest loss may be reduced or even reversed (Kaimowitz and Angelsen 1998). Top-down interventions such as designating one or more coral rag forest reserves on the island may help to slow the conversion of primary forest in some areas, but may also be subject to leakage, attenuating their overall efficacy (P. Meyfroidt et al. 2020; Bastos Lima, Persson, and Meyfroidt 2019). Instead, interventions focused on the introduction and establishment of value chains for alternative income sources, aside from rotational agriculture, may have greater success (Akyoo and Lazaro 2007).

5.2 - Implications for land system science and social-ecological systems

Social-ecological systems, and therefore land systems, are inherently very complex. They commonly exhibit feedbacks between system components and past and future states. Because of this complexity, researchers generally describe phenomena of interest qualitatively, or they break the components of a given causal pathway down into many sub components (Meyfroidt 2016; Turner et al. 2020). Nevertheless, inference from limited time series data is difficult due to issues of equifinality, simultaneous causation, and unobserved complexity(Barrett 2021; Cumming et al. 2020). We echo the argument of Schlüter and others (2019) that agent/individual-based modeling can allow inference about causality in social-ecological systems and emphasize that this approach is especially powerful when combined with empirical data, as presented here, in order to increase validity and interpretability.

We argue here that individual-based models will be of the greatest utility for land system science when they are combined with a standard, systematic framework for comparing synthetic data to real-world observations. Approximate Bayesian computation may fill this niche as it is relatively straightforward and allows for parameter estimation given even very complex generative models. A key advantage of this method is that it allows modelers to explicitly confront equifinality in a given simulation and to some extent a given empirical system. By explicitly quantifying the range of causal processes that are likely to produce an outcome of interest, researchers will greatly increase the applicability of simulation models to real-world policy decisions (Williams et al. 2020).

5.3 - Limitations and future work

A limitation of any process model is that they assume that researchers know and can accurately represent causal processes in silico. In the case of models like the individual-based simulation presented here, researchers must abstract down to only key phenomena of interest, eliminating much contextual nuance and again, assuming that we know what matters and what does not. This is a big assumption in social-ecological systems considering that emergent and often unexpected phenomena are a defining feature of the field. This limitation is exemplified by the four *shehia* (Fundo, Muambe, Jombwe, and Shamiani) that showed fewer coral rag forest pixels converted to agriculture than expected by the model even under no externally driven forest conversion pressure. We know through our in-person observations and interviews with Community Forests Pemba staff that these four *shehia* have been the focus of considerable tree planting, particularly of *Casuarina spp.* in woodlots. We are likely observing both some confusion between native coral rag vegetation and woodlot vegetation in our satellite observations, as well as a reduction in coral rag deforestation for fuelwood. Approximately 95% of Pemban households rely on cutting fuelwood for daily cooking activities. Hence, the introduction of woodlots, which we do not account for in our simulation, likely reduces the overall rates of coral rag deforestation and conversion to rotational agriculture. Further, Fundo and Shamiani are both islets of Pemba and are both home to luxury resorts. The limited connection between these islets and the main population centers of Pemba likely limits the effect of market forces driving agricultural expansion in these two areas. Also, our anecdotal experience is that the resort operators intentionally limit local development nearby the properties, possibly reducing the rate of agricultural development below what we expect as a result of soil degradation.

Another contextual limitation of our specific model for drawing inference about agricultural expansion in Pemba Island is that we do not account for the long-term processes of soil degradation that lead to complete land abandonment and eventually the recovery of coral rag vegetation. While the two year farm and three year fallow cycle is standard in the coral rag geological areas of Pemba, some agricultural areas are completely abandoned when crop yields are consistently low even after a fallow period. Additionally, the agricultural units themselves are independent 20m pixels which is considerably smaller than many agricultural operations. Clumping these pixels to better match realistic farm sizes may produce different and more accurate inference than presented here.

Lastly, our model does not allow for heterogeneity or evolution in human behavior. All agricultural pixels follow the same scheduling process. While this scheduling process is standard in the study *shehia*, an interesting exercise would be to allow for the diffusion of regenerative agricultural practices across farm units to examine direct feedbacks between environmental and cultural change.

6 - Conclusion

Computer simulations are critical to theoretical development in land system science as they allow us to formally define and scrutinize hypothesized mechanisms driving phenomena of interest. When we develop competing plausible mechanisms however, it can be difficult to identify the contribution of each hypothesized mechanism in the real world. Recent advances in ABC, primarily in population genetics, but also cultural evolution, have provided a structured process to begin to overcome this challenge in other fields (Hartig et al. 2011; Kandler and Powell 2018). Until now however, ABC has yet to be applied to land system science. In this paper we show how ABC can be used to better leverage the wealth of available satellite data in combination with individual-based models of land system change in order to assess the importance of competing mechanisms.

In particular, we develop an individual-based simulation of agricultural expansion in Pemba, Tanzania under two different mechanisms: soil degradation and external forces such as population growth and increasing market integration. We use ABC to systematically compare runs from this model with observed land cover change in 19 *shehia* in Pemba from 2018 to 2021. This process allows us to estimate the likelihood that various rates of externally driven agricultural expansion are responsible for the observed land cover change in each *shehia*. Importantly, this process also allows us to directly estimate the range of externally driven expansion rates that could have also reasonably resulted in the observed data, or the degree to which the system is equifinal.

7- Acknowledgements

We thank the entire Community Forests Pemba staff for continued support on research in Pemba. We also thank the Hazards and Climate Resilience Institute at Boise State University for funding this research. We thank Dr. Monique Borgerhoff Mulder and Dr. Tim Caro their help in conceptualizing the project and with all things related to fieldwork in Pemba. Lastly, we thank the Max Planck Institute for Evolutionary Anthropology, department of Human Behavior, Ecology and Culture for providing the computing resources necessary for this project and Dr. Anne Kandler for her support with the ABC and for providing an initial review of the paper.

8 - Open data and software

All data, R code, and GEE code used in this project are available at this github: https://github.com/matthewclark1223/CPR_ABM/tree/master/HCRI_Grant and this GEE link: https://code.earthengine.google.com/3774c9546268839fcbf43176e4d2eb46. An open source web app that displays the runs from the agent-based model for specific *shehia* can be found here: https://matthewclark.shinyapps.io/LandUsePredictionsApp/.

CHAPTER FOUR: QUANTIFYING LOCAL PERCEPTIONS OF ENVIRONMENTAL CHANGE AND LINKS TO COMMUNITY-BASED CONSERVATION PRACTICES

Approximately two billion people — a quarter of the earth's population — directly harvest forest products to meet their daily needs. These individuals disproportionately experience the impacts of increasing climatic variability and global biodiversity loss, and must disproportionately alter their behaviors in response to these impacts. Much of the increasingly ambitious global conservation agenda relies on voluntary uptake of conservation behaviors in such populations. Thus, it is critical to understand how individuals in these communities perceive environmental change and use conservation practices as a tool to protect their well-being. To date however, there have been no quantitative studies of how individual perceptions of forest change and its causes shape real-world conservation behaviors in forest dependent populations. Here we use a novel participatory mapping activity to elicit spatially explicit perceptions of forest change and its drivers across 43 mangrove-dependent communities in Pemba, Tanzania. We show that perceptions of mangrove decline drive individuals to propose stricter limits on fuelwood harvests from community forests only if they believe that the resultant gains in mangrove cover will not be stolen by outsiders. Conversely, individuals who believe their community mangrove forests are at high risk of theft actually decrease their support for forest conservation in response to perceived forest decline. High rates of inter-group competition and mangrove loss are thus driving a 'race to the bottom' phenomenon in community forests in this system. This finding demonstrates a mechanism by which increasing environmental decline may cause communities to forgo conservation practices, rather than adopt them, as is often assumed in much community-based conservation planning. However, we also show that when effective boundaries are present, individuals are willing to limit their own harvests to stem such perceived decline.

1 - Introduction

1.1 - Problem statement

Diverse and healthy ecosystems are unequivocally our best insurance against the worsening impacts of climate change (Isbell et al. 2015; Loreau et al. 2001; Oliver et al. 2015; Lloret et al. 2012). Yet, increasingly intensive resource extraction from ecosystems over the last 150 years has greatly attenuated their ability to buffer human communities against impacts such as fires and flooding (Parks et al. 2016; Alongi 2008). Simultaneously, this switch from low to high intensity resource use has diminished global biodiversity on a magnitude only seen five other times in our planet's history, further accelerating climate change (Caro et al. 2022).

Recent land use intensification strongly reflects the displacement of local communities and traditional practices by large-scale producers and outside economies (Stephens et al. 2019; Ellis et al. 2021; Bird et al. 2019). It is then largely recognized that effective and equitable conservation efforts must to empower local communities to set resource management priorities and design strategies to achieve them (Fernández-Llamazares et al. 2020; Garnett et al. 2018). Thus, achieving global conservation goals hinges, at least in part, on local community engagement and the decisions that individuals in those communities make in the environment (Gatiso et al. 2018).

Numerous studies have shown that resource users can reliably detect long-term changes in their local environments (Lauer and Aswani 2010; Early-Capistrán et al. 2022; Tengö and Belfrage 2004). However, it is still unclear how individuals perceptions' of environmental change affect their choices to limit resource use, restore ecosystems, or otherwise change their behaviors (Paloniemi et al. 2018). In particular, as pointed out by Meyfroidt (2013), few studies have linked individual perceptions of threats and change in natural resources with observed conservation behaviors and preferences (although see Nyangoko et al. 2022). Further, a recent systematic review of 128 studies of voluntary adoption of conservation behaviors showed a dearth of research on the subject in non-Western populations (Thomas-Walters et al. 2022).

In her foundational work, Elinor Ostrom described a set of conditions that, when met, promote cooperative behaviors in natural resource management settings (Ostrom 1990). Among these conditions, Ostrom identifies the need to clearly demarcate and enforce proprietary access to group resources through physical and/or social boundaries (Ostrom 1990). Three decades of scrutiny via case studies and meta analyses from across the globe further cement this conclusion (Cox, Arnold, and Tomás 2010; Cox 2014; Cumming et al. 2020). In a recent set of theoretical models, Andrews and others (2022, 2023) delineate the social-ecological evolutionary mechanisms by which excluding outsiders promotes sustainable resource management behavior and cooperation in the face of threats to the local environment. However, the reverse is also true. These models show that in the absence of strong social or physical boundaries, perceived degradation of local resources may cause a 'race to the bottom' phenomenon where individuals are incentivized to extract all they can before the resource is gone (Andrews et al. 2023).

This theory explicitly predicts that environmental degradation should promote preferences for limiting resource extraction when theft from outsiders is low. And degradation should conversely promote preferences for increasing resource extraction when theft from outsiders is high, because the gains made by sustainable management may be eroded by outsiders and never realized by the local community (Andrews et al. 2023). This process has however not yet been examined empirically. An empirical test of these mechanisms is critical for building further theory in conservation science and for applying scientific insights to real-world resource management. For example, individuals make resource management decisions under the backdrop of past exposure to external conservation interventions and within a range of acceptable community norms (Hayes et al. 2022; Gómez-Baggethun and Ruiz-Pérez 2011). Thus, we must observe how theorized processes of behavioral change in response to environmental degradation operate in the real-world in order to have confidence in their general importance and applicability.

In this study, we perform an empirical test of how perceived environmental degradation and threat of resource theft from outsiders affect individuals' conservation behaviors and preferences. We achieve this by implementing a novel participatory mapping activity to collect quantitative, spatially explicit perceptions of mangrove cover change in Pemba, Tanzania. We then link these perceptions of mangrove change with a questionnaire of individual perceptions of mangrove theft and self-reports of conservation behaviors and preferences. We specifically look at individuals' self-reported frequency of patrolling behavior to protect community mangrove forests from outsiders and preferences for limits on the amount of fuelwood that community members can harvest from those forests. We assess these dynamics while simultaneously considering the impact that a major conservation initiative on the island (see section below) may have had on individuals' conservation behaviors and preferences in the communities involved. We interpret the results of this analysis in light of their relation to theoretical work on the subject of perceived environmental change and resource boundary efficacy on conservation behaviors, thus increasing their generalizability and decreasing the probability of spurious findings (Smaldino and McElreath 2016).

1.2 - Field site

This study examines community-based mangrove conservation in Pemba Island, Tanzania, the smaller of the two Zanzibari islands, identified as part of the Coastal Forests of Eastern Africa biodiversity hotspot. Like much of the developing world, Pemba has been subject to a series of conservation initiatives that stretch back to the colonial period, with novel initiatives increasing in frequency since the late 1990s. These begin with British colonial afforestation programs and the gazetting of forest reserves by both the British and post-revolutionary governments in the 1960s (Chachage 2000). Following 50 more years of initiatives driven by a number of Scandinavian countries, in 2010 the Reduced Emissions from Deforestation and Land Degradation program (REDD+) identified 18 wards (*shehia*) in Pemba as appropriate for piloting their payments for ecosystem services conservation framework (Burgess et al. 2010; RGZ 1996; Nations 1992). The REDD+ project intended to pay communities to forego harvesting fuelwood and timber and cease farm expansion inside of designated areas in each of the 18 selected shehia. The objective of this intervention was to slow deforestation, reduce greenhouse gas emissions, and reduce poverty. While hope for this project waxed and waned over several years among Pemban communities, these payments were never delivered and the 18 selected shehia ultimately showed no measurable benefit in forest cover (Andrews et al. 2021; Collins et al. 2022).

Alongside the proliferation and succession of these conservation projects, the population on the island has grown by approximately 2.9% each year (estimate from 2012 - 2022; more than triple the global average), increasing the need for the production of timber, fuelwood, and other forest products (URT 2023). Prior research shows that approximately 90% of rural Pemban households rely exclusively on forest products (fuelwood and charcoal) to meet their daily cooking needs (RGZ 2014; Ely et al. 2000). Further, these forest products account for 27% of total household income (Andrews and Borgerhoff Mulder 2022). This local need for forest products is driving a median deforestation rate of 3.4% per year in the forests of the island (Collins et al. 2022).

Many individuals across Pemba recognize that forests provide valuable ecosystem services such as erosion control, among many others. Thus, there is a conflict between the desire to safeguard local community forests, while still meeting daily needs. We find extensive evidence that individuals adapt to this challenge by stealing forest products from the community forests of other shehia; 70% of residents blamed their neighboring shehia for deforestation of their own local forests, and 31% of residents report having whole trees cut and stolen by outsiders (Borgerhoff Mulder, Caro, and Ngwali 2021 and unpublished data 2017).

Widespread cutting of mangroves in particular has caused considerable decline of mangrove cover and resultant flooding and saltwater intrusion in many mangrove adjacent communities (Andrews and Borgerhoff Mulder 2022). In response, many communities and community members therein have taken it upon themselves to prohibit outsiders from harvesting (or “stealing”) from their community mangroves and to reduce the harvests of their own community members. This generally takes the form of the establishment of village and shehia conservation committees, mangrove patrols to exclude outsiders from harvesting from community forests, mangrove planting, and setting specific fuelwood harvest limits. There is nevertheless considerable variability in preferences and practices of these actions on the island, both between and within shehia (Borgerhoff Mulder, Caro, and Ngwali 2021). We use this variability in individual preferences for limiting harvests and patrolling behavior as the outcomes of interest in this analysis.

2 - Methods

2.1 - Data collection

2.1.1 - Participatory mapping activity

We collected data on individual perceptions of environmental change using a participatory mapping methodology in order to elicit fine-scale, spatially explicit perceptions of change. This methodology builds on that of Herrmann et al. (2014) to tangibly link participant responses with specific locations and provide a more accurate measure than would be possible with a simple questionnaire (Emmel 2008; Cadag and Gaillard 2012). Over an eight-month field season in 2022, we were able to implement this methodology in 43 of the 49 shehia on the island which contain mangrove forest (fig 18). The six shehia not included in the study were excluded due to time and funding constraints, rather than for any systematic purpose. In each of these 43 shehia, we randomly selected five men and five women to participate in this activity, which resulted in a final sample size of 423 after dropping seven responses due to incomplete survey information.

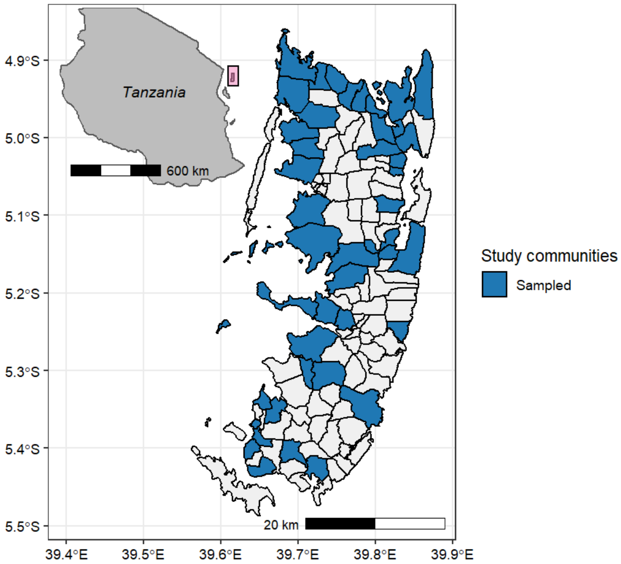


Figure 18 Wards (shehia) surveyed in this study. Large map shows the island of Pemba, Tanzania with each of the shehia where data were collected for this study shaded in blue. Inset map shows the location of Pemba in relation to the Tanzanian mainland.

The participatory mapping activity began with a workshop format where we established a shared understanding of our goals and did a simple mapping orientation, as most of the local population does not regularly use maps to navigate their environment. Each participant was then provided with a gridded basemap of their community, with towns, roads, bodies of water, cultural landmarks (e.g. mosques), and any protected areas labeled to help with orientation. Each grid cell corresponded to 0.5 km2 area. After a further orientation we asked participants to identify their own place of residence and other important locations to verify their basic understanding of the map. The final group task was to mark (initially with buttons until consensus was reached, then with a pen) each grid cell where mangrove forest is present. Thus, the workshop-style component of the participatory mapping activity ended once each participant was adequately oriented to a gridded map of their community, and each grid containing mangrove forest was marked identically across all participant maps (picture 1).

For the remainder of the participatory mapping activity and the questionnaire following, all participants responded individually. With the consensus map of mangrove locations in-hand, each participant was asked to indicate, for each grid cell containing mangrove, whether they felt the tree cover in that area had increased, stayed the same, or decreased in the last year. Participants could also indicate that they were not sure about how mangrove cover had changed. An example of a completed map can be found in figure C1. The total number of grid cells in which a participant indicated that the mangrove cover had declined in the last year was tallied to produce an estimate of the perceived percent decline in community mangrove forest cover for each respondent.

Picture 1 Example of the participatory mapping activity used in this study. Grid squares containing mangrove cover are first identified as a group, then respondents individually record their perceived change in each square. Photo shows H. M. Hamad explaining the individual response portion of the activity.

2.1.2 - Questionnaire

Following the participatory mapping activity all participants completed an individual questionnaire with the help of research staff. The purpose of this questionnaire was to elicit responses regarding conservation behavior and preferences, perceived pressure of theft from outsiders, and general demographic information. Specifically, participants used a binary response to indicate whether or not they ever engage in patrols to protect community mangrove forests from theft from outsiders. If yes, participants listed the number of mangrove patrols that they estimated they had performed in the past month. Participants also indicated their preferences' for harvest limits on themselves and other community members who rely on community mangroves to collect fuelwood. This outcome variable was collected as an integer value corresponding to the number of fuelwood bundles that they would like to limit themselves and their fellow community members to harvesting each month.

To quantify individuals' perceptions of theft from outsiders in their community mangroves, we asked respondents to estimate the number of outsiders they believe come to their shehia to harvest fuelwood each week. We asked participants to provide their best guess of where these individuals generally come from in order to ensure they were describing individuals from outside their shehia, rather than a smaller village-level group. Finally, we recorded the gender and occupation of each participant through multiple choice questions and asked whether they were a member of a village or shehia conservation committee using a binary choice question. The full questionnaire instrument can be found in the supplemental material of the peer-reviewed, published version of this research.

2.2 - Analysis

We performed two separate analyses in this research. The first (model 1; eq 1) was designed to estimate the effects of perceived decline of community mangroves and perceived mangrove theft on preferences for in-group harvest limits on fuelwood. In accordance with current best practices for causal inference, we constructed a directed acyclic graph to determine what parameters needed to be controlled for in order to estimate the direct effects of interest (Table 1) (McElreath 2020; Westreich and Greenland 2013; Pearl 2009). In this process, we explicitly describe the complete hypothesized causal pathway between our predictors and outcome of interest and identify other variables, and associations between them, that may be affecting the outcome through separate causal paths (Pearl 2009). We then control for these alternative causal paths in order to capture accurate effect sizes for our direct effects of interest.

Table 1: List of variables and associated models

Variable	Collected from	Estimand or control	Model used in
PREDICTORS			
Occupation	Questionnaire	Control	Model 1 (equation 1)
Perception of community mangrove change in the past year	Participatory mapping activity	Estimand	Both
Perceived number of outsiders stealing from community mangroves per week	Questionnaire	Estimand	Both
Interaction between perceived mangrove change and perceived mangrove theft	Questionnaire & participatory mapping activity	Estimand	Model 1 (equation 1)
Size of community mangrove area	Participatory mapping activity	Control	Both
Community included in REDD+ initiative	Previous research	Estimand	Both
Member of shehia or village conservation committee	Questionnaire	Estimand	Both
Gender	Questionnaire	Estimand	Model 2 (equation 3)
OUTCOMES			
Preferred community fuelwood harvest limit	Questionnaire	Outcome	Model 1 (equation 1)

Number of mangrove patrols conducted in the past month	Questionnaire	Outcome	Model 2 (equations 2 & 3)

We used a Poisson distributed generalized linear mixed-model operationalized in a Bayesian framework to estimate the direct effects of interest (estimands) (Table 1). We estimated the effect of the interaction between perceived mangrove loss and the theft pressure from outsiders on community mangrove forests. As identified using the directed acyclic graph, we controlled for participant occupation, the size of the community mangrove area, whether or not the participant was a member of a village or shehia conservation committee, and whether the shehia was one of the 18 exposed to the failed REDD+ intervention on the island. Finally, as we used a mixed model, we estimated a varying intercept ($\boldsymbol{\beta 0}_j$) for each of the 43 study shehia. This model is formalized in equation 1.

$$\mathrm{Y}_{ij} \sim Poisson(\mu_{ij})$$

$$\begin{gathered}\mu_{ij} = \exp(\alpha 0 + \boldsymbol{\beta 0}_j + \beta 1 \cdot \mathrm{Theft}_i + \beta 2 \cdot \mathrm{MangDecl}_i + \beta 3 \cdot \mathrm{MangArea}_i + \\ \beta 4 \cdot \mathrm{REDD}_i + \beta 5 \cdot \mathrm{Occupation}_i + \beta 6 \cdot \mathrm{CommitteeMemb}_i)\end{gathered} \tag{1}$$

The secondary analysis for this research (model 2; eq 2 & 3) estimated the effects of perceived mangrove theft from outsiders and forest cover loss on reported respondent engagement in community mangrove patrols. To adequately model the data generating process for participation in community mangrove patrols, we operationalized this research question as a *hurdle* process (Zuur et al. 2009). In this framework, we model the joint outcome of whether or not a respondent is likely to report engaging in mangrove patrols at all (Bernouli distributed with probability θ) and if so, the number of patrols that they report engaging in each month (zero-truncated negative binomial distribution with mean μ and dispersion ϕ). Thus, the probability mass function is shown in equation 2.

$$\mathrm{P}_{HurdleNegBinom}(y|\pi,\mu,\theta) = \begin{cases} \pi, & y = 0 \\ (1-\pi)\cdot \mathrm{P}_{ZeroTruncNegBinom}(y|\mu,\theta), & y > 0 \end{cases} \tag{2}$$

Again, for this analysis, we selected the parameter set necessary to estimate the direct effects of interest using a directed acyclic graph. Through this procedure, we concluded that to estimate the effect of perceived theft and forest loss on patrolling behavior, we must account for the size of the community mangrove area, the gender of the participant, whether or not the participant was a member of a village or shehia conservation committee, and whether the shehia was one of the 18 subjected to the failed REDD+ intervention on the island. In this model we substitute gender for participant occupation because gender affects both occupation and patrolling behavior, thus including both gender and occupation would result in estimating the effect of gender along two separate causal paths. In model 1 we do not assume that participant gender should affect their preferences for in-group harvest limits. We again used a Bayesian mixed-model, where we estimate a varying intercept for each of the 43 shehia in our study ($\boldsymbol{\beta 0}_j^{\eta}$ & $\boldsymbol{\beta 0}_j^{\mu}$). This model is formalized in equation 3.

$$\mathrm{Y}_{ij} \sim HurdleNegBinom(\pi_{ij}, \mu_{ij}, \phi)$$

$$\pi_{ij} = \frac{\exp(\eta_{ij})}{1 + \exp(\eta_{ij})}$$

$$\begin{aligned}\eta_{ij} = \alpha0^{\eta} + \boldsymbol{\beta0}_j^{\eta} + \beta1^{\eta} \cdot \mathrm{Theft}_i + \beta2^{\eta} \cdot \mathrm{MangDecl}_i + \beta3^{\eta} \cdot \mathrm{MangArea}_i + \\ \beta4^{\eta} \cdot \mathrm{REDD}_i + \beta5^{\eta} \cdot \mathrm{Gender}_i + \beta6^{\eta} \cdot \mathrm{CommitteeMemb}_i\end{aligned} \tag{3}$$

$$\begin{aligned}\mu_{ij} = \exp(\alpha0^{\mu} + \boldsymbol{\beta0}_j^{\mu} + \beta1^{\mu} \cdot \mathrm{Theft}_i + \beta2^{\mu} \cdot \mathrm{MangDecl}_i + \beta3^{\mu} \cdot \mathrm{MangArea}_i + \\ \beta4^{\mu} \cdot \mathrm{REDD}_i + \beta5^{\mu} \cdot \mathrm{Gender}_i + \beta6^{\mu} \cdot \mathrm{CommitteeMemb}_i)\end{aligned}$$

$$\boldsymbol{\beta0}_j \sim Norm(0, \sigma)$$

For both models, we used regularizing priors as recommended by Gelman et al. (2008) for producing conservative coefficient estimates. Both models exhibited adequate convergence of Markov chains, adequate posterior predictive capacity, and $\hat{R}$ values equal to 1 for all coefficients (Appendix C2). All data for this project and the R and STAN code used in these models is available in the Open Science section.

3 - Results

As this is a Bayesian analysis, we consider any parameter estimate in which the inner 0.9 quantile of the posterior mass does not overlap zero to be statistically significant. This threshold is standard in the literature as it indicates that 95% or greater of the entire probability mass of sample estimates sit on one side of zero and therefore a 0.95 probability of a true effect given the data (Goodrich et al. 2020).

3.1 - Preferences for fuelwood harvest limits

We find strong evidence that the interaction between individual perceptions of mangrove degradation and perceptions of mangrove theft from outsiders significantly affects preferences for fuelwood harvest limits from community mangroves. Two thousand draws from the posterior distribution indicated a 0.98 probability that the interaction term has a positive effect on the outcome (fig 19). In respondents who reported no perceived theft in their community mangrove forests, an increase in perceived mangrove decline from 0% to 50% of the community mangrove area resulted in an expected decrease in preferred harvest limits from 2.73 to 2.36 bundles of fuelwood. Respondents who reported that 100% of their community mangroves were declining in cover in turn reduced their fuelwood harvest limits to 2.04 bundles.

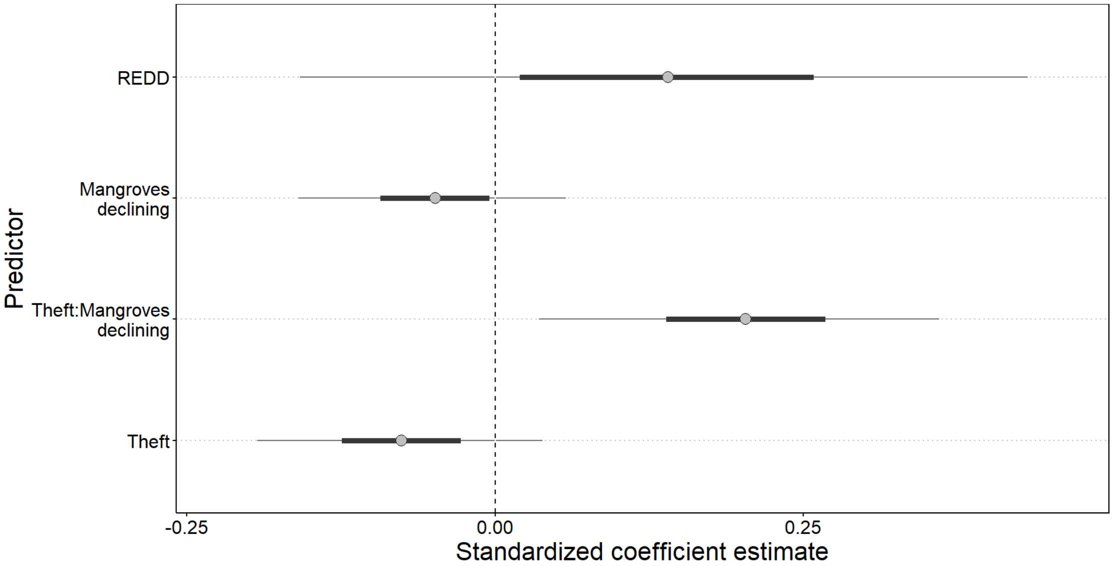


Figure 19 Standardized posterior estimates from the model shown in equation 1 used to estimate the drivers of preferences for limiting fuelwood use. The thick bars show the inner 50% of the posterior distribution and the thin bars show the inner 90% of the posterior distribution (credibility interval).

The interaction term indicates that this trend is reversed in individuals who perceive high levels of mangrove theft from outsiders. In these respondents, an increase in perceived mangrove decline from 0% to 50% of the community mangrove area resulted in a loosening of preferred harvest limits from 1.24 bundles of fuelwood to 2.73. Interestingly, the strength of this trend increased as more of the mangrove area was perceived as being in decline. Respondents who perceive the highest levels of theft and report that 100% of the community mangrove area is declining are expected to report a preference for a harvest limit of 6.07 bundles, a nearly fivefold increase from those who perceive that 0% of the community mangrove area is in decline. The marginal effect of this interaction term, given a mean value of all other predictors, can be seen in figure 20.

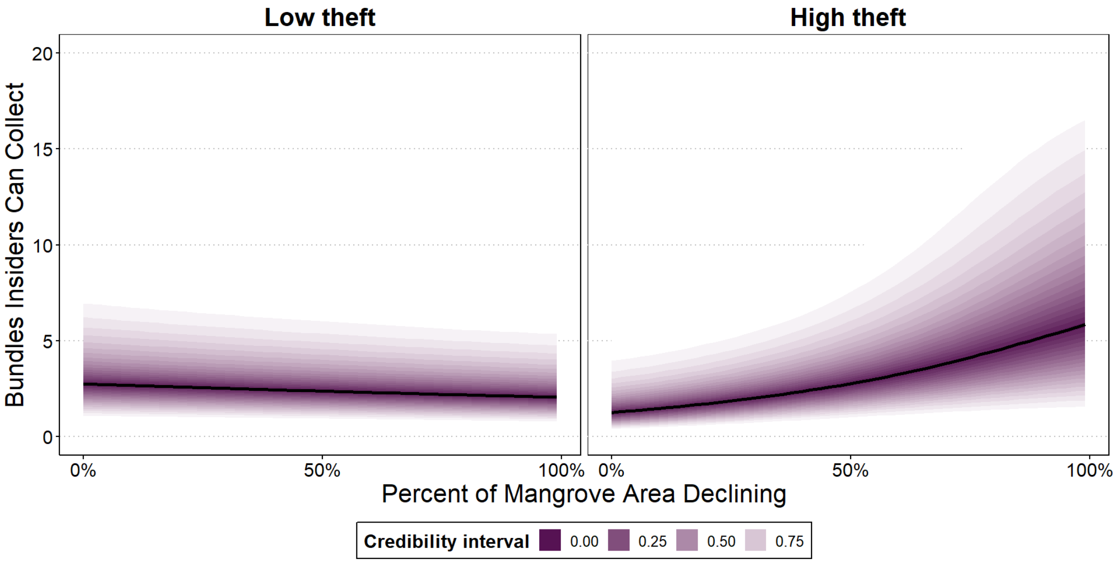


Figure 20 Marginal effect of the interaction of individual perception of mangrove decline and perceived inter-group theft on individual preference for in-group fuel-wood harvest limits. Low theft shows the effect of perceived mangrove decline when perceived theft was near 0 and high theft shows the effect when perceived theft was at the highest recorded value. The marginal effect shows the effect of these predictors at a mean value of all other predictors. Black lines show median model estimates. Shading those the credibility interval.

Finally, shehia who were part of the failed REDD+ initiative on the island showed a slight, although statistically insignificant, increase in preferred harvest limits compared to individuals in shehia where the REDD+ project was never introduced (fig 19). This effect is not statistically significant as the proportion of samples greater than zero is 0.79, representing a 0.79 probability of a true effect given our data.

3.2 - Mangrove patrolling behavior

The coefficient estimates from the regression described in equation 3 show that patrolling behavior is likely driven by different processes than are preferences for restricting fuelwood harvests. The Bernoulli component of the model indicates that neither perceived mangrove theft or perceived mangrove decline significantly affected whether or not individuals reported engaging in mangrove patrols at all. The posterior distribution of the Bernoulli component of the model resulted in a statistically insignificant 0.87 probability that perceived theft increases the likelihood that individuals engage in mangrove patrols. Perceptions of mangrove decline had essentially no effect on likelihood of patrolling behavior (fig 21). Similarly, perceptions of mangrove decline and theft also had essentially no effect on the number of patrols an individual engaged in (fig 22).

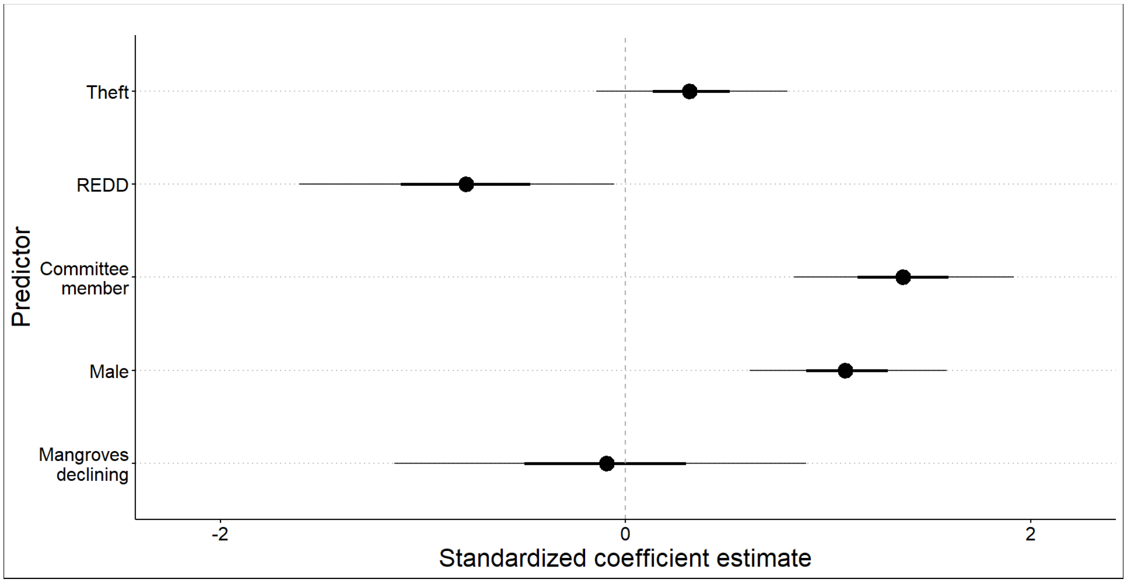


Figure 21 Standardized posterior estimates for the Bernoulli component of the model estimating the effect of these predictors on patrolling behavior (eq. 3). The Bernoulli component estimates the effect that the predictors have on whether or not individuals engage in patrolling behavior at all. The thick bars show the inner 50% of the posterior distribution and the thin bars show the inner 90% of the posterior distribution (credibility interval).

Men were significantly more likely than women to engage in patrols and to engage in a greater number of patrols (fig 21 & 22). Given a mean value for all other predictors, the probability that women reported engaging in patrols at all was 0.17 and the probability that men reported engaging in patrols at all was 0.38. Of men and women who reported patrolling, the median number of patrols performed by each gender in the last month was 6 and 3 respectively. Lastly, membership in a shehia or village conservation committee was significantly associated with individuals reporting going on patrols at all (fig 21), but was not significantly associated with the number of patrols they reported engaging in, as only 91% of model estimates were greater than 0 (fig 22).

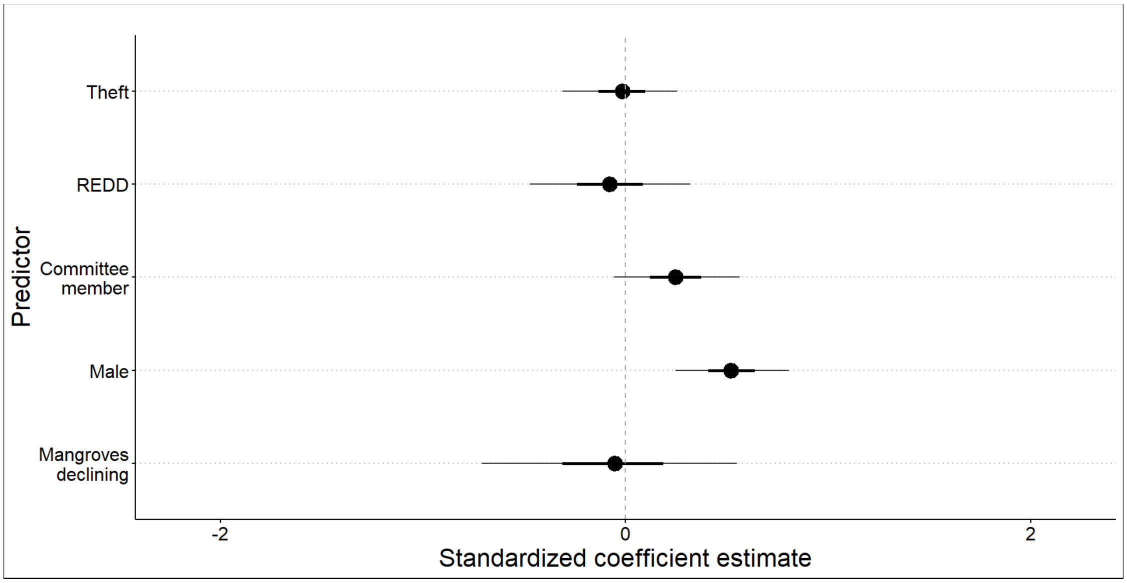


Figure 22 Standardized posterior estimates for the zero-truncated negative binomial component of the model estimating the effect of these predictors on patrolling behavior. The zero-truncated negative binomial component estimates the effect that the predictors have on the number of patrols that individuals engage in. The thick bars show the inner 50% of the posterior distribution and the thin bars show the inner 90% of the posterior distribution (credibility interval).

The outputs of this model also indicate that past community exposure to REDD+ significantly decreased the probability of individual engagement in mangrove patrols. Specifically, there is a 0.96 probability that individuals from shehia selected for the failed REDD+ project were less likely to engage in mangrove patrols at all compared to those from shehia not exposed to the REDD+ project (fig 21). Given a mean value for all other predictors, the probability that individuals in shehia that were part of the REDD+ project reported engaging in patrols at all was 0.17, compared to a 0.32 probability for individuals from shehia not exposed to REDD+. However, this predictor was not significantly associated with the number of patrols that individuals engaged in (fig 22).

4 - Discussion

4.1 - Relation to & deviation from theory

In this research, we sought to test the theory that individual perception of environmental degradation will result in increased participation and support for conservation only if a lack of effective boundaries does not diminish the benefits of such conservation behaviors. Our data strongly support this intuition and furthermore show that perceived environmental degradation can actually decrease support for conservation if the threat of out-group freeriders is high. Thus, this finding, in combination with the theoretical development by Andrews et al. (2022, 2023), helps to detail the mechanisms underlying Ostrom's first tenet that reliable boundaries are critical for sustainable common-pool resource management.

This research begins to fill the gap identified by Meyfroidt (2013), namely that little is known about how individuals use conservation behaviors to respond to perceived environmental change. These analyses reveal that different types of conservation behaviors are likely affected differently by perceived environmental change. While preferences for limiting resource use were greatly affected by perceptions of environmental change and its causes, behaviors to enforce resource boundaries were not. One reason for this result could be that individuals are hesitant to deviate from community norms. For example, women were much less likely to report engaging in mangrove patrols than men, even if they had identical perceptions of mangrove theft and decline, and a similar history with conservation programming. Additionally, patrolling is largely conducted by members of a village or shehia conservation committee; noncommittee members were unlikely to begin engaging in this behavior solely of their own accord.

We speculate that because patrolling behavior is a visible action, pressure to adhere to local norms may operate more strongly on this outcome than on preferences for allowable community harvests which may be privately held. There is a growing body of literature on the adoption of conservation behaviors and scaling up of conservation projects to which this insight might be applicable (e.g. Mahajan et al. 2020; Mills et al. 2019; Clark, Andrews, and Hillis 2022). For example, theoretical models and analyses of empirical data may assume different social and ecological drivers of different classes of conservation actions. This field may then benefit by defining categories of conservation actions such as 'in-group regulatory behaviors' and 'out-group exclusionary behaviors,' or predominantly 'environmentally-driven' versus 'socially-driven' actions, among many other possible categorizations.

One interesting and somewhat unexpected important predictor emerged for both fuelwood harvest limits and mangrove patrolling. Past community exposure to the failed REDD+ project on the island was significantly associated with reduced probability of engagement in mangrove patrols, and showed a non-significant ($p=0.79$), yet interesting positive association with individual preferences for fuelwood harvest limits (these individuals preferred less stringent harvest limits). We hesitate to draw strong conclusions given these data, as this effect was not the primary question of the study (Tredennick et al. 2021). Yet, these trends are well aligned with theories regarding motivational crowding (Rode, Gómez-Baggethun, and Krause 2015; Frey and Jegen 2001). Along these lines, we speculate that past promises of payments for conservation behaviors, such as reducing fuelwood use and community forest patrols, may have crowded out individuals' motivations to engage in such behaviors in the absence of payments (Cinner et al. 2021). Although there are other indications from a larger sample of individuals and broader environmental context (not limited to mangroves) collected in Pemba in 2017 that preferences for conservation did persist in communities exposed to the REDD+ intervention (Andrews and Borgerhoff Mulder 2023). This effect may then be nonlinear or context dependent.

4.2 - Policy implications

As the negative impacts of climate change continue to affect communities of small-scale producers around the world, nature-based solutions, such as mangrove protection and restoration, are increasingly posited to buffer individuals against the worst impacts (E. Cohen-Shacham et al. 2016; Emmanuelle Cohen-Shacham et al. 2019). We show here that the uptake of nature-based solutions may be greatly hindered by a lack of clear social or physical boundaries to protect the benefits accrued by such actions. Yet, actions to exclude out-group members from community resources are costly. Our results show that they are so costly, that in fact, even when individuals perceive them as necessary, they will not perform them without some degree of social license (e.g. membership in a shehia conservation committee). Thus, this study suggests that support in the form of training and funding for community-based conservation initiatives specifically to demarcate and protect resource boundaries may increase their ability to combat the negative impacts of climate change through conservation. Such a policy may have dual benefits, directly stopping harvests from outsiders and supporting the endogenous emergence of sustainable in-group norms.

When gains from conservation behaviors are not eroded by outsiders, we show that individuals respond to perceived environmental degradation by supporting stricter limits on resource harvests. This result is promising for the prospect of meeting global conservation goals through community-based initiatives. The status of many resources are, however, not easily observable to local communities and even observed changes may be forgotten as individuals' baselines for resource condition shift (Papworth et al. 2009). We emphasize then that supporting communities in effectively monitoring both local resources and the social benefits gained from protecting them is critical for the success of community-based conservation (Jones et al. 2013; Salerno et al. 2021).

4.3 - Limitations and future work

The primary limitation in this research was non-random exclusion of the six shehia that we were unable to include due to time and funding constraints. However, our extensive ethnographic experience in Pemba does not lead us to believe that these shehia should fundamentally differ from those sampled in a way that would alter the results of this research. Specifically, these shehia do not greatly differ from those sampled in the importance of mangroves to the community, exposure to REDD+, or rates of environmental change. While we did not foresee the incomplete sampling of the 49 total shehia that contain mangrove forest at the onset of the data collection, the data collection scheme could have been improved by randomizing the order in which the shehia were visited for data collection.

Another key limitation of this work is that we rely on self-reported conservation preferences and behaviors for our outcomes of interest. The insights provided here would be bolstered if the realized conservation behaviors of participants could be observed.

Future work might perform a similar participatory mapping activity with a random sample of a community after researchers host a tree planting activity or other conservation oriented event. Researchers may then record whether or not respondents attended the tree planting activity.

Conservation science would also benefit from a comprehensive examination of the effect that failed or terminated conservation projects, such as the REDD+ initiative on Pemba Island, have on local conservation preferences and behaviors (eg. Chervier, Le Velly, and Ezzine-de-Blas 2019; Massarella et al. 2018). Our results shown here are exploratory as this phenomenon was not the intended subject of study, but they may be an early signal of an important trend. Further, our measure of REDD+ exposure was at the community level, whether or not the shehia was one of the 18 selected for the intervention, and our outcomes were at the individual level. This finding would be strengthened by measuring individual exposure to REDD+ at the individual level as well.

5 - Conclusion

In this paper we uncovered an important interaction between perceptions of environmental degradation and exposure to resource theft on two different types of conservation behaviors (harvest limits and community patrols). Put simply, individuals who are not exposed to theft while simultaneously experiencing resource decline are motivated to protect that dwindling resource. In contrast, individuals who *are* exposed to high levels of theft while simultaneously experiencing resource decline are motivated to actually *weaken* harvest limits, presumably in a race to grab what they can while it's still available.

We also show that perceived mangrove degradation and theft from outsiders do not significantly affect individual engagement in patrols to exclude outsiders from stealing mangroves from community forests. Instead, this behavior is performed only by specific members of the community. Thus, as theft increases between communities, there is little mechanism to reduce it. And as theft is left largely unregulated, the 'race to the bottom' phenomenon causes in-group members to also harvest rapidly from community forests.

This social-ecological mechanism highlights the importance of clearly defined boundaries detailed by Ostrom in her first principle (1990). This research then echoes the importance of clear and effective boundaries and enforcement in community-based conservation efforts, and the positive endogenous changes in self-regulation that can follow in the wake of stronger boundaries.

6 - Open Science

All code and data used in this project can be found at the Github link here: https://github.com/matthewclark1223/ParticipatoryMappingProj

CHAPTER FIVE: A PRODUCTIVE FRICTION: LEVERAGING MISALIGNMENTS BETWEEN LOCAL ECOLOGICAL KNOWLEDGE AND REMOTELY SENSED IMAGERY FOR FOREST CONSERVATION PLANNING

Earth's forests are continually monitored in both the satellite record and the lived experiences of nearly 2 billion forest-proximate peoples. Generally, the satellite record summarizes production estimates and proxies, such as percent tree cover, at regular, relatively coarse scales. Conversely, local perceptions of forest resources tend to capture changes at irregular and very fine scales. While the utility of both of these sources of information has been widely demonstrated in isolation, little work has explored how they might be systematically and quantitatively integrated. Here, we collect gridded information on community perceived and remotely sensed mangrove cover change across 719 unique 0.5-km grid cells in Pemba Island, Tanzania. We reveal variation in the association between these two data sources across different wards (*shehia*) and explore the reasons for this variation using informal interviews and direct observation. We find that shehia with the greatest alignment between the satellite and community derived measures of mangrove change tended to have little planting or natural regeneration of mangrove propagules and large areas of complete tree cover loss. Alternatively, in shehia with the lowest levels of alignment, we find high levels of natural and/or human-assisted mangrove recolonization and selective harvesting of individual trees and branches. Finally, we demonstrate a practical workflow for quantitatively leveraging these misalignments by optimizing across both data sources to identify restoration priority areas.

1 - Introduction

The potential for local ecological knowledge to provide rich information on the status and ecological function of species and ecosystems is widely recognized in conservation science (Reyes-García and Benyei 2019). In fact, for many areas, species, and time periods, local ecological knowledge is the only information available to inform the decisions made by conservation scientists or practitioners (Taylor, Morrison, and Shears 2011). Researchers studying birds, mammals, and fish, in particular, made early advances in methods for using local knowledge to strengthen estimates such as population size and breeding success (Moller et al. 2004; Poizat and Baran 1997). This tradition of productively incorporating local ecological knowledge has continued in wildlife ecology even amidst rapid changes in satellite and computational capacity, and clearly has an important role in increasing the inclusivity of conservation strategies (Early-Capistrán et al. 2022; Salomon et al. 2023).

In the study of conservation and ecology of forests, however, less progress has been made in developing methods for linking local ecological knowledge with Western scientific information. A review of 51 studies that used local ecological knowledge in forest conservation found that while the potential contribution is high, little work has shown any practical application (Joa, Winkel, and Primmer 2018). Further, few studies have attempted to incorporate quantitative forms of local ecological knowledge with research on forest conservation (Rist et al. 2010). Instead, this stream of research has largely focused on describing the cultural significance and connections between plant species, rather than recording location-specific abundance data. There are, however, some notable examples of quantitative applications of local ecological knowledge from the field of ethnobotany, many of which focus on the abundance of individual species (e.g. Fernández-Llamazares et al. 2016).

One possible reason for the relative scarcity of methods for integrating quantitative forms of local ecological knowledge into research on forests compared to wildlife and individual plant species, is that forest cover can be readily observed via the satellite record. Therefore, researchers may see these two sources of information as redundant. Indeed, studies have shown high concordance between local knowledge of the presence of timber and satellite imagery in the Peruvian Amazon, for example (Takasaki et al. 2022; Braga-Pereira et al. 2022).

However, congruence between local knowledge and the satellite record is not always the case. These measurements are generated by disparate underlying processes, and as discussed by Klein et al. (2014), may actually best serve scientific inquiry by revealing points of contradiction. For example, a study of rangelands on the Tibetan Plateau showed that satellite imagery alone provided a poor estimate of locally meaningful plant cover change and its drivers, as it was unable to identify changes in palatable versus unpalatable vegetation (Hopping et al. 2018). Also, a given conservation action may appear optimal based on satellite imagery, but be logistically impossible to execute or unacceptable to local decision-makers. Therefore, local knowledge can also provide critical information about the on-the-ground feasibility of conservation actions (Canessa et al. 2020; Carter et al. 2022). Further, individuals' harvest and conservation decisions are driven by their perceptions of the status of their environment, rather than what is strictly accurate (Fernández-Llamazares et al. 2016; Clark, Hamad, et al. 2023). Thus, systematically integrating local ecological knowledge with satellite imagery may serve to identify a truly optimal set of actions for forest conservation, especially in multi-use social-ecological landscapes.

Local ecological knowledge and satellite derived products both also contain error. This error is itself driven by disparate causal processes. Local ecological knowledge is subject to miscommunications between researchers and local knowledge holders, as well as the litany of biases that affect human cognition, such as shifting baselines or attributing greater importance to more recent events (Kai et al. 2014). Conversely, satellite-derived data products are often coarsely resolved spatially and thematically (e.g. land cover classes), causing misclassifications at local scales (Wyborn and Evans 2021). Researcher misunderstandings of a system may further bias a data product during the training and validation process (Rinaldi and Jonsson 2020; Brandt et al. 2020). Hence, we argue that local ecological knowledge and satellite imagery should be considered as different, yet complementary data sources in forest conservation, rather than as calibration tools or ways of corroborating one another.

Here, we use the mangrove forests of Pemba Island, Tanzania to present a practical example of how priority locations for conservation can be identified by optimizing across quantitative data derived from local ecological knowledge and satellite imagery. Mangrove forests are an archetypal example of a social-ecological system where the causes of cover change and the feasibility of restoration interventions cannot be disentangled from socioeconomic factors (Quinn et al. 2017; Ram, Caughlin, and Roopsind 2021). Worldwide, these ecosystems are in flux due to changing biophysical conditions, such as temperature and atmospheric CO_2 (although see Reich et al. 2018), as well as both widespread deforestation and planting (Jennerjahn et al. 2017; Ferreira, Ganade, and Luiz de Attayde 2015; Lacerda, Borges, and Ferreira 2019). These global trends are paralleled in Pemba, as the cutting of mangroves for firewood and building materials, as well as mangrove loss due to biophysical factors, has caused erosion and saltwater intrusion and resultant widespread mangrove restoration efforts (Mchenga and Ali 2015; Hamad, Mchenga, and Hamisi 2014, 2019; Andrews and Borgerhoff Mulder 2022).

Across Pemba, we collected quantitative, spatially explicit data on local perceptions of mangrove cover change and compared these to satellite-observed changes from the same time period. In this study, we explore the overall alignment of these two data sources and highlight communities where they strongly agree or disagree. We investigated the reasons for differences in agreement by interviewing knowledgeable individuals in these focal communities and interpret these in light of the data generating process for both sources of information. Lastly, we demonstrate an optimization approach (as in Hanson et al. 2019) for identifying restoration priority areas that equally considers observations made by local communities and satellite imagery.

2 - Methods

2.1 - Data collection

2.1.1 - Local perceptions of mangrove cover change

We used participatory mapping to collect fine-scale, spatially explicit perceptions of mangrove cover change in Pemba Island, Tanzania from 2021 to 2022. This methodology is loosely based on that of Herrmann et al. (2014), in which the authors use participatory mapping to measure perceptions of re-greening in the Sahel. In our modified methodology, presented in greater detail in Clark et al. (2023A), participants used gridded basemaps to record their perceptions of forest change in specific areas of their community over the past 12 months. Specifically, for each 0.5-km grid cell where mangrove forest was present in their community, participants indicated whether they felt the tree cover had increased (+1), stayed the same (0), decreased (-1), or were unsure (NA) (picture 2). We implemented this methodology over eight months in 2022, managing to reach 43 of the 49 wards (*shehia*) on the island containing mangrove forests, and using community rosters to randomly select five men and five women to participate in each. Finally, we digitized each map and calculated the mean response for each of the 719 unique 0.5-km grid cells to yield one island-wide map (Fig. 23A).

Picture 2 Example photo showing H. Hamad leading the participatory mapping exercise used to collect information on individual perceptions of environmental change.

2.1.2 - Remotely sensed mangrove cover change

We accessed the Sentinel-2 time series via Google Earth Engine to produce classified maps of mangrove stands in Pemba for 2021 and 2022 at a 20-m resolution. We did so by using median annual composites of all images in the given year with <20% cloud cover and masked remaining clouds using the 'QA60' band prior to generating composites. We used a random forest classifier to distinguish mangroves from other ecologically distinctive land cover types. Beyond optical information, we integrated Sentinel-1 synthetic aperture radar backscatter measurements shown to be effective for quantifying mangrove extents (Chen et al. 2017; Poortinga et al. 2019). We also incorporated pertinent topographic variables derived from the NASA Shuttle Radar

Topography Mission digital elevation model. We validated our data fusion approach using pseudo ground truthing for 2021, which produced mangrove extents with a producer's accuracy of 91.61% (+/- 5.99%) (estimated 2.4 - 14.38% omission rate). User's accuracy (commission rate) was 100% for 2021, indicating that our maps show conservative underestimates of mangrove extents. For more details on this mapping effort, see Clark et al. (2023B). Lastly, we calculated the net change in 20-m pixels within each of the 719 0.5-km grid cells to produce the data shown in figure 24.

2.2 - Alignment and follow-up interviews

To build an understanding of if, how, and why the community- and satellite-derived data differ, we compared the overall relationship between the two sources and identified focal communities to investigate qualitatively. First, we correlated (Pearson) the mean perceived change with the net change in satellite-observed 20-m pixels inside each of the 719 grid cells (fig 25). To identify shehia with the highest and lowest agreement between the two data sources, we removed any shehia with fewer than 15 mangrove grids (n=25), as these shehia showed extreme correlation values driven by a small number of data points. We then identified the two shehia with the highest and lowest (four total) correlation between the community and satellite-derived measures of mangrove cover change.

After identifying the focal shehia, we arranged an informal interview with three members of the conservation committee in each, if one existed, and otherwise knowledgeable individuals if one did not. In these interviews, we asked the participants about mangrove planting and cutting events from 2021 to 2022, the overall trends in tree cover, and how individuals get their information regarding the status of the mangrove forest.

2.3 - Conservation prioritization

We use mangrove restoration as an example conservation action that can be planned for by quantitatively optimizing across community- and satellite-derived measures of environmental change. In this demonstration, we used mixed integer linear programming implemented in the ‘prioritizr’ R package to identify which 0.5-km grid cells showed the greatest decrease in mangrove cover across both data sources and prioritize these for restoration (Hanson et al. 2023). Before running the optimization, we standardized the values from both data sources so that all values were on the scale of standard deviations. Our implementation of this method used these values along with a penalization for isolated grid cells (following the standard assumption that these are inefficient compared to contiguous areas) to identify approximately 10% of the mangrove area as an optimal target for restoration.

3 - Results

3.1 - Participatory mapping data

Across the 719 grid cells, the mean participant response ranged from -1 to 1, indicating that all ten participants in a shehia reported that mangrove cover had decreased or increased, respectively. The mean response across all cells was 0.17, showing an average perception that mangrove cover is increasing in the communities studied. However, the standard deviation across the grid cells is 0.39, showing high variation in mean perception of mangrove change from area to area.

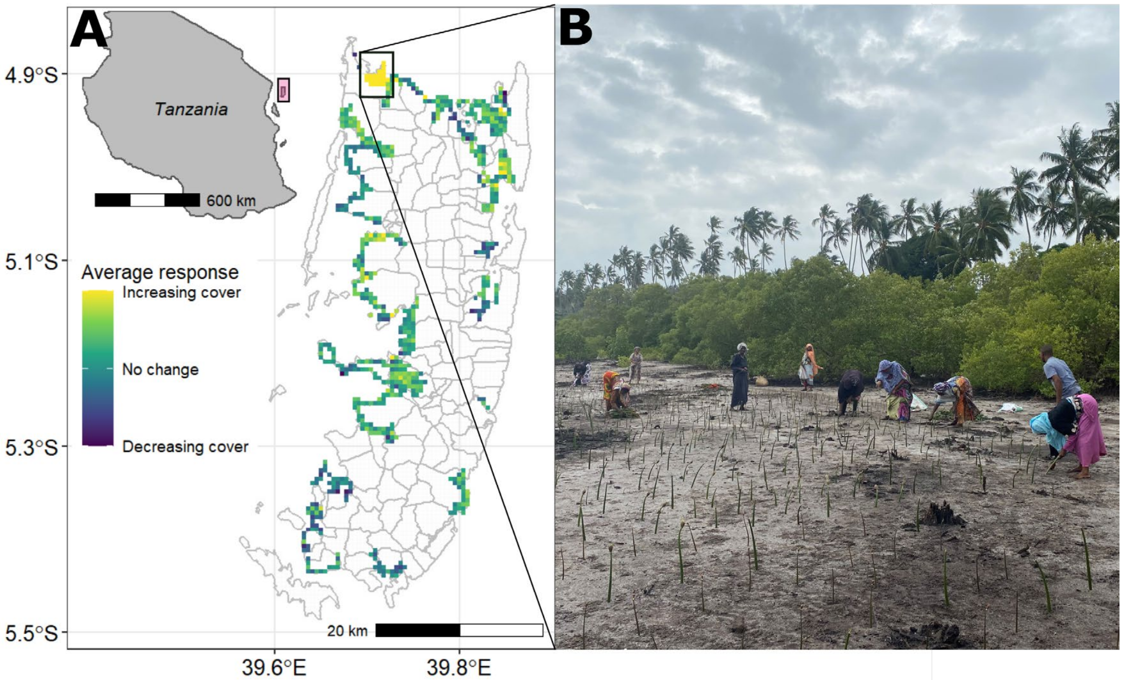


Figure 23 Mean perceived mangrove change from 2021 to 2022. Panel A shows the location of Pemba Island, Tanzania in relation to the mainland of Tanzania (inset), as well as the mean perception of mangrove change inside each of 719 unique 0.5-km grid cells containing mangrove included in this study (main). Panel B shows a photo of ongoing mangrove planting taken during the time of the study in the northwest area perceived by community members as strongly increasing in mangrove cover shown in panel A.

3.2 - Satellite imagery

Our remote sensing analysis showed that the net change in pixels classified as mangrove across each 0.5-km cell from 2021 to 2022 ranged from a loss of 13 20-m pixels to a gain of 29 pixels. On average, the 0.5-km grid cells sampled gained 0.37 20-m pixels in the year studied, with a standard deviation of 4.0 pixels lost or gained. Of the 719 total grid cells, 264 showed an increase in net mangrove pixels, 232 showed a decrease, and 223 showed no change. Thus, overall we do not detect dramatic changes in mangrove cover in our study shehia using satellite imagery alone.

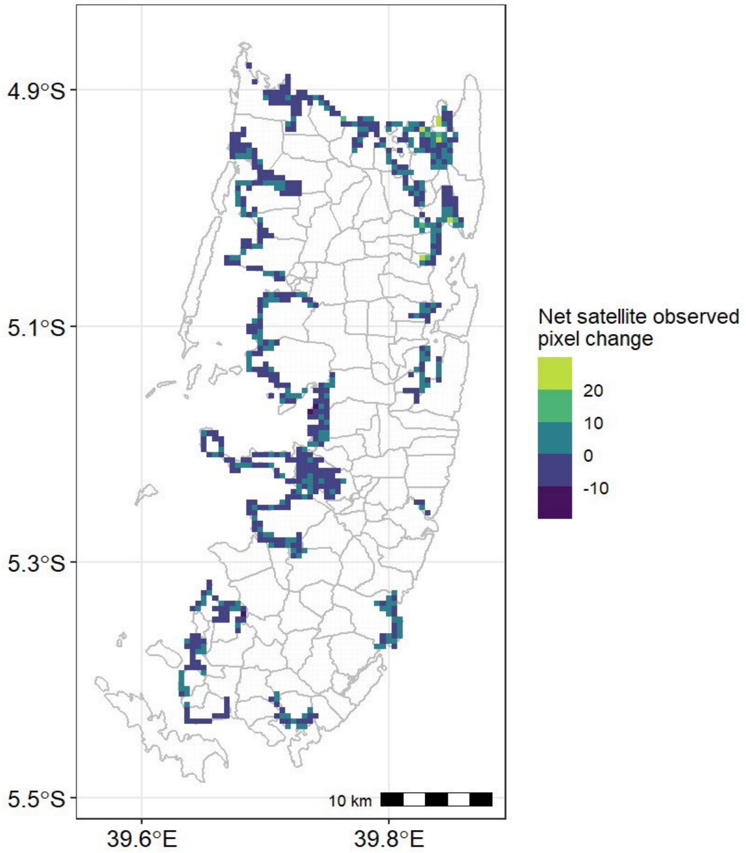


Figure 24 Map of the net change in 20-m pixels identified as mangrove from 2021 to 2022 inside each of the 719 0.5-km grid cells used in this analysis. The color ramp indicates the exact number of pixels lost or gained inside each grid cell during the time period of this study.

3.3 - Alignment and follow-up interviews

Across sampled grid cells, we see virtually no relationship (r = 0.07) between the remotely sensed mangrove change and the mean perception of mangrove change (fig 25). However, there is high variation in the correlation between these two variables among the different shehia. Ziwani and Tibirinzi shehia have the lowest correlation values of -0.49 and -0.37, respectively. Conversely, the two shehia with the highest agreement between the community perception and satellite observed data, Kisiwani and Kengeja, have correlations of 0.58 and 0.39, respectively.

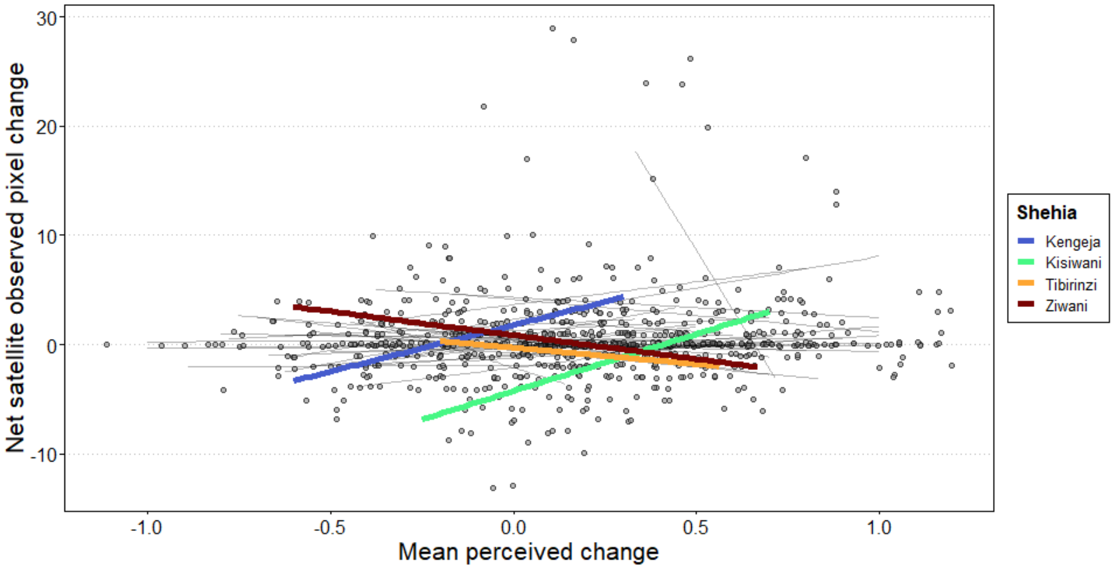


Figure 25 Scatterplot showing the association between the net satellite observed mangrove pixel change and the mean perceived change for each of the 719 0.5-km grid cells containing mangrove in Pemba, Tanzania. A mean perceived change of -1 or 1 indicates that every respondent reported the grid cell as decreasing or increasing in cover, respectively. Each point shows the values for one grid cell. Points have been jittered to reduce overlap. Thin black lines show the association between the two data sources for each of the 43 communities in this study. Thick colored lines highlight the communities (mangrove grid cells >15) with the two highest and two lowest correlation values.

During informal interviews, conservation committee members in Ziwani shehia emphasized that from 2021 to 2022, there were large efforts to replant mangrove propagules (e.g. fig 23B), as well as noticeable natural regeneration. These individuals also emphasized that there had been no mass cutting or death of mangroves, but instead that people selectively cut branches and individual trees when harvesting. These observations were paralleled in Tibirinzi, where community members showed us several areas where people selectively cut individual mangrove trees, resulting in noticeable degradation of the forest, but presumably no detectable change of land cover at the 20-m scale.

Interviewees in the two shehia with the greatest agreement between the two data sources, Kisiwani and Kengeja, described and showed researchers considerably different situations to those in Ziwani and Tibirinzi. In both shehia, there had been mass losses of mangrove cover in 2021 to 2022, no organized planting of mangroves, and little natural recruitment. In Kisiwani, community members showed researchers several large areas where many adult and juvenile trees had died due to unknown biophysical causes, and all subsequently planted propagules had also died. In Kengeja shehia, interviewees showed researchers a large area where community members clearcut all mangroves during 2021 to 2022. This shehia had no conservation committee, and thus there were no organized planting efforts. The lack of fine-scale changes (selective cutting & new propagules), alongside mangrove losses at a scale >20-m are presumably driving the strong correlations between data sources in these shehia.

3.4 - Prioritization

In figure 26, we show restoration priority maps derived by optimizing for both data sources in isolation and together. We identify starkly different priority areas based on the two metrics independently. Namely, just one area was prioritized for restoration in both the independent satellite- and community-derived maps. In addition to this one area where the data sources align well, the integrated map also displays the areas where either the community- or satellite-derived measure of mangrove loss were particularly high. We note that the specific output is also contingent on parameter settings in the optimization package, such as the strength of the penalty for including isolated pixels.

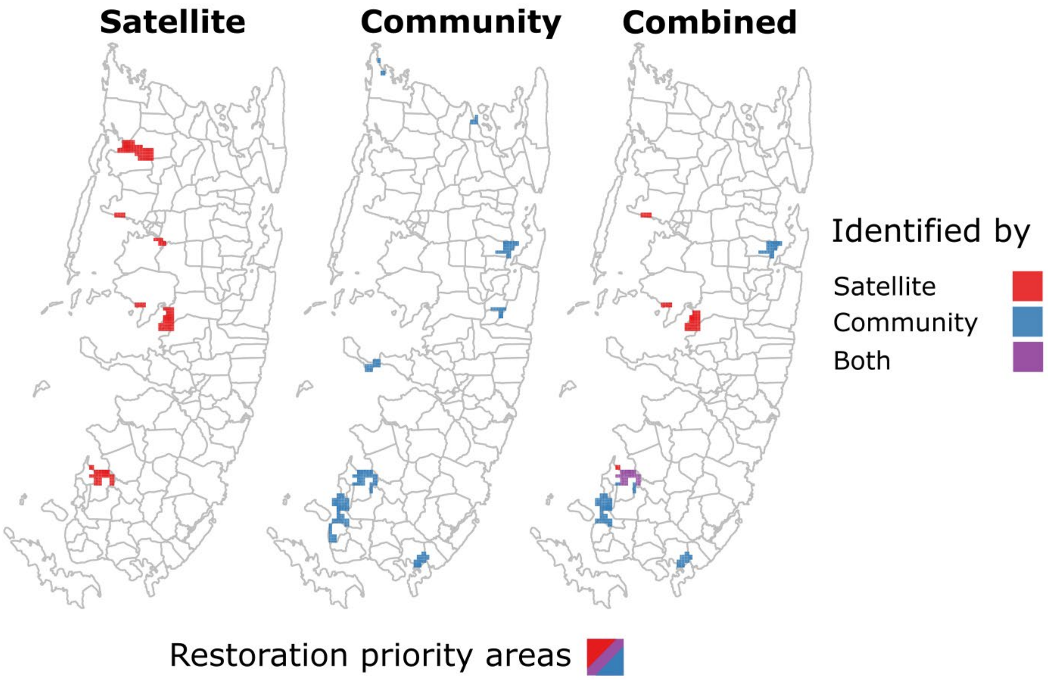


Figure 26 From left to right: restoration priority maps for approximately 10% of the mangrove area in Pemba, Tanzania based on our remote sensing analysis alone, the community perceptions of mangrove change alone, and the optimization across the two data sources. On the right-hand map showing priority areas identified by optimizing across both data sources (combined), red coloring indicates the areas identified by the satellite imagery, blue coloring indicates areas identified by the community, and purple coloring indicates areas identified by both.

4 - Discussion

Our findings suggest that within our study area and within this short timescale, the mechanisms driving misalignments between individual perceptions and satellite observations of mangrove change are the observability and salience of fine-scale changes. Our remotely sensed data product does not accurately reflect changes at fine spatial scales, which may also be overemphasized in our measure of perceived change. Given that much of the data available for conservation science and practice exists at 20-m or greater scales, we argue that systematically incorporating local knowledge of environmental change will provide a more accurate picture of both the true changes in forest cover and also the community preference for conservation actions. Thus, we echo the increasingly-established finding that including community perspectives will both practically and ethically benefit conservation science (e.g. Zinda et al. 2016). Furthermore, quantifying indigenous perceptions, while inevitably simplifying the richness of local ecological knowledge, allows for a systematic comparison between both frameworks. We present this finding alongside an optimization methodology for practically accomplishing such an integration, similar to Nielsen et al. (2023), who suggest this technique to incorporate molecular information into conservation planning.

The optimization approach here serves as a base case demonstration. In this example, we chose to weight both data sources equally and ignore many important real-world factors for conservation planning, such as land price. This weighting, however, may be adjusted to better account for the biases shown in each data source, depending on the goals of a specific project. For example, community members might overemphasize the ecological significance of recent tree planting events or illegal harvesting from socially important areas. Researchers may then consider weighting these data less strongly when estimating changes in, for example, carbon stocks. Conversely, if the goal of a project is to identify socially acceptable targets for conservation efforts or areas with recent increases in selective harvesting, community perceptions of environmental change may be weighted more strongly than remotely sensed data. Further, restoration prioritization can benefit by including community knowledge of where natural and human-assisted regeneration is already occurring, as to avoid redundancy.

4.1 - Limitations and future work

There are important drawbacks to incorporating local ecological knowledge into conservation planning. For one, obtaining this knowledge requires considerable time and effort, and presents a risk of misrepresenting community voices (Laituri et al. 2023). Additionally, while this study only looks at recent changes, the reliability of the data can be limited by a number of cognitive biases, especially if considering longer time periods. As a more general matter, increasing the number of data sources being optimized across will introduce additional uncertainty into conservation decisions, which may not accurately propagate into the final quantitative results. Future work would then make a valuable contribution by developing methods for propagating uncertainty from all data sources into the end result of the mixed linear integer optimization method.

We also see two key limitations to our data collection protocol. First, our protocol condenses individual perceptions of change down to one of four values: -1, 0, 1, or NA. This forces all values of one sign (- or +) to be the same magnitude. Future work might develop a modified implementation to efficiently capture a range of perceptions of environmental change. Second, we do not account for within-community variability in perceptions of environmental change and alignment with satellite imagery. For example, future work might ask what remotely sensed signals tend to be associated with high levels of consensus about how and where the environment is changing? Further, examining variation in perceptions of change within and between genders, ethnic groups, or economic classes might yield productive insights, as members of different groups often play different roles in resource-dependent communities (Hopping, Yangzong, and Klein 2016; Luizza et al. 2013; Diaz-Reviriego et al. 2016; Uisso et al. 2023).

5 - Open science

All data and code used in this project can be found here: https://github.com/matthewclark1223/CPR_ABM/tree/master/ConservationPrioritization

6 - Acknowledgements

This research was made possible through ongoing collaboration with the Zanzibar Department of Forests, Community Forests Pemba, the Boise State Hazards and Climate Resilience Institute, the Max Planck Institute for Evolutionary Anthropology department of Human Behavior, Ecology & Culture, and many community members in Pemba.

CHAPTER SIX: CONCLUSION

This dissertation contributes to our understanding of the social and ecological dynamics that govern the emergence and persistence of community-based conservation behaviors and their outcomes. Specifically, this research shows that individual perceptions of environmental change, even at very fine scales, can strongly encourage or discourage conservation preferences and behaviors, dependent on the system of resource tenure. Further, this research advances theory describing the patterns with which we expect these preferences and behaviors to spread within groups and methods for interrogating such theorized processes with empirical observations, namely satellite imagery.

Collectively, these four chapters reinforce our understanding of social-ecological systems as both complicated and complex. They are complicated in that they contain a large number of important variables that vary in their relevance and interactions from case to case. They are complex in that social, ecological, and coupled phenomena of interest often emerge as a result of independent smaller-scale interactions. Thus, shaping these systems in order to produce desirable outcomes requires clear theoretical models of how the individual components interact in space and over time to produce such outcomes, be them social, ecological, or both. And the effective application of theoretical insights to a given empirical case requires a detailed understanding of local dynamics.

Through the near doubling of the world's conservation efforts by 2030, we are undertaking an experiment in the modification of the global social-ecological system at an unprecedented scale. While this experiment will have global consequences, these outcomes will be driven by nested interventions and outcomes at local to regional scales and ultimately by the decisions made by individuals. This dissertation provides insights as to how policy makers, practitioners, and researchers can better incorporate diverse forms of knowledge with formal theory in order to better plan those interventions considering both social and ecological conditions.

Moving forward, it is crucial to continue building upon this research and expand our understanding of conservation as a dynamic and evolving system. Further investigations into the long-term consequences of area-based conservation measures at nested scales and the development of methods for delineating complex causal processes are areas of particular importance. Moreover, continued collaboration between scientists, policymakers, and local communities is essential for designing interventions that align with local conditions.

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APPENDIX A

Supplementary material for chapter 2

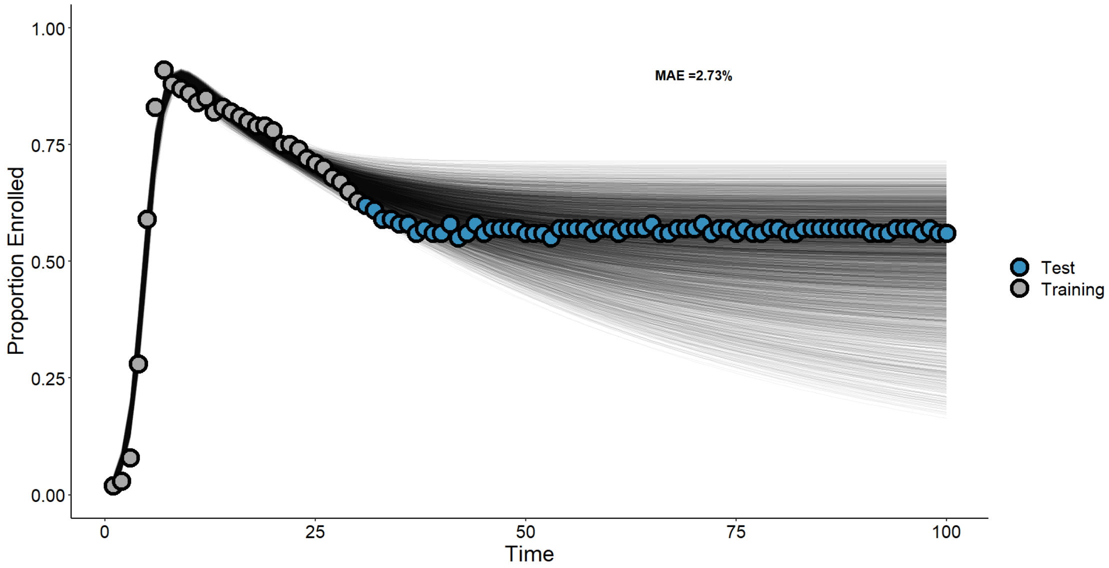

Figure A1 SIRS model fit to the average of 100 runs of the agent-based simulation data under success-biased social learning contingent on behavior-environment feedbacks shown as translucent black lines representing 1000 draws from the posterior. Simulated data are overlaid with gray points signifying training data (first 30%) and blue points signifying test (later 70%) data.

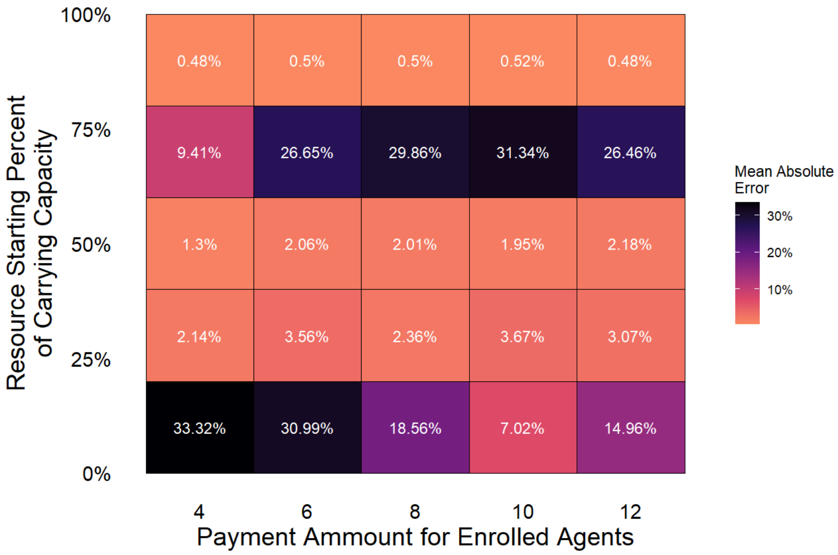

Figure A2 Sensitivity analysis for the ability of the SIRS model to capture adoption dynamics under a variety of parameter combinations across a range of values for the starting resource integrity (percent of carrying capacity) and payment amount for agents.

APPENDIX B

Supplementary material for chapter 3

All supplemental materials can be found in the GoogleSheet here: https://docs.google.com/ spreadsheets/d/18jGNxQl8uVK2m-jHzR6Pq4H-OmEXWMJFTSswoklx1-8/edit?usp=sharing

APPENDIX C

Supplementary material for chapter 4

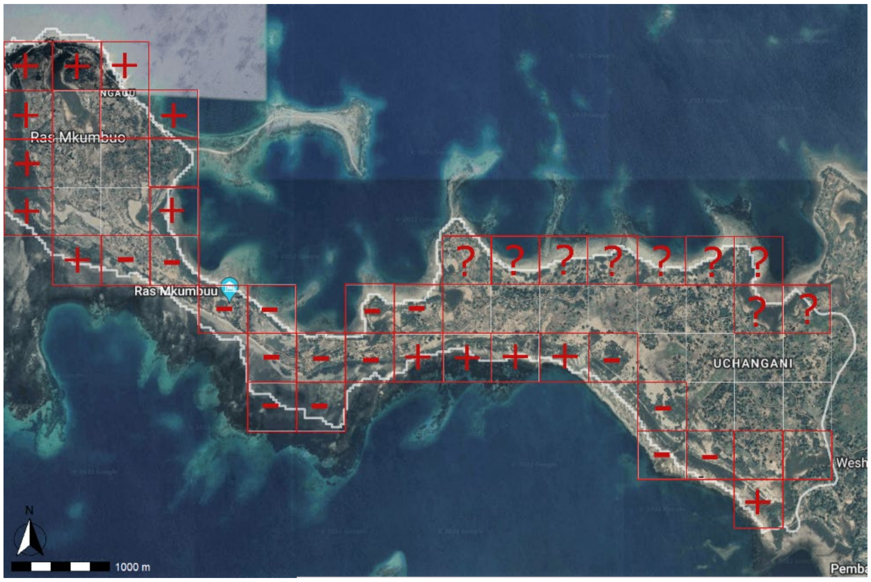

Figure C1 Stylized example of a completed map used in the participatory mapping activity in this research. Grid cells correspond to $0.5km^2$ areas. Outlined grid cells indicate community consensus on the presence of mangrove trees in the area. Plus (+) signs indicate individual perception that mangrove cover has increased in the area in the past year. Minus (-) signs indicate individual perception that mangrove cover has decreased in the area in the past year. Empty squares indicate individual perception of no change in mangrove cover in the past year. Question marks (?) indicate that the respondent does not know how mangrove cover in that specific area has changed in the past year.

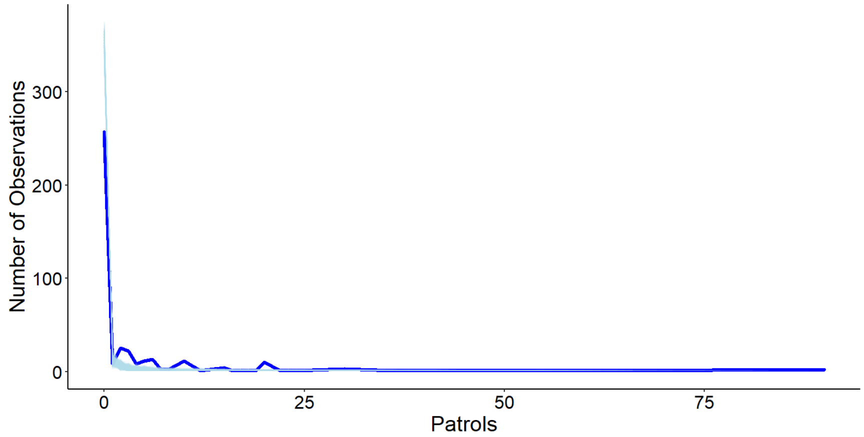

Figure C2 Posterior predictive check for model 2 used in this research. Dark blue line shows the true number of observed patrols. Light blue lines show the 2,000 draws from the model. We show that our model reliably reproduces data that match our observed data, further indicating adequate model fit in addition to adequate mixing of chains, rhat values equal to 1 for all model parameters, and lack of divergent transitions after warmup.