Eliminating climate change mitigation trade-offs in African rangelands

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Abstract

Climate change is intensifying precipitation variability in southern African rangelands, driving dynamics that pastoral systems are unprepared to cope with. Simultaneously, developments in weather forecast accuracy and access may enable pastoralists to effectively adapt to these conditions. Here, we use a spatial agent-based model to study the benefits of weather forecasting for adaptive rangeland management with and without concurrent risk-smoothing interventions. Given empirical and projected conditions across seven southern African countries, we show that: 1) precipitation variability can reduce average economic wellbeing and worsen inequality amongst pastoralists; 2) if paired with the adaptive use of weather forecasting, risk smoothing interventions such as the provision of supplemental fodder can buffer these effects without overstocking; and 3) risk smoothing is critical for scaling adaptive management practices. Overall, we show how pairing forecasts and risk smoothing can reduce trade-offs inherent to each intervention alone, supporting climate change adaptation at scale.

Main

Pastoralism is a vital component of livelihoods and cultures for hundreds of millions of people across Africa, practiced on 43% of lands and involving the majority of the population in some countries[1,2]. These rangeland systems are characterized by high spatiotemporal variability in weather, which has been widely demonstrated to drive the emergence and stability of cooperative, sustainable resource use[3–7]. Despite their adaptation to variability, climate change is expected to disrupt African pastoral livelihoods by increasing the intensity, extent, and duration of extreme events beyond levels experienced over the past centuries[8]. Increasing variability will be accompanied by changes in average temperatures, rainfall, and the timing of seasonal onsets; all directly affecting the production of livestock[9–12]. Such disruptions are likely to have complex cascading effects throughout the system, necessitating a clearer depiction of the mechanisms through which climate variability affects pastoralist decision-making, how these decisions affect social and ecological outcomes, and how interventions can push the system toward a more desirable state[13,14].

African pastoralists have a narrowing set of strategies for adapting to changing climatic conditions[15,16]. Traditional strategies include adjusting herd size, stockpiling or buying supplemental fodder, moving animals across the landscape, or income diversification[17,18].

Although theory and some empirical cases suggest that further increasing mobility could help cope with increased variability and declining rainfall[19,20], roads and fencing greatly restrict movement in practice, especially in southern Africa, where drought risk is the greatest[21–23]. Climate change also undermines historical knowledge about the location and timing of water and pasture availability[24,25]. This increases risks of conflict with people and wildlife, making mobility a less viable adaptive strategy[26,27].

Traditional decision-making heuristics are also poorly equipped to handle the dramatic changes in weather caused by climate change across Africa. For example, a survey of 500 Kenyan smallholders found nearly one-third rely on the prior season to predict rainfall, despite no scientific evidence supporting this approach[28]. When the reliability of socially learned information declines, it is generally expected that people will turn to alternative, independent sources of information for making livelihood decisions, such as livestock management[29,30].

In response, “conservation grazing” or “regenerative rangeland management” initiatives are attempting to complement cultural decision-making with advanced earth observation and weather forecasting across large swaths of Africa. These initiatives encourage more dynamic management of herd sizes in response to climate, while improving pastoralists’ adaptive capacity through access to livestock markets and supplemental fodder programs, and by supporting collective local governance of rangelands through rotational grazing. Together, these efforts aim to improve rangeland condition and vegetation, carbon storage, and community resilience to climate change, as well as reduce human-wildlife conflict[31,32]. One example is the Herding for Health initiative by Conservation International and Peace Parks Foundation. To date, this initiative has raised nearly $200 million to engage 20,000 pastoralists, with the goal of bringing 10 million hectares of African rangeland under management within a decade. While promising, the outcomes of such initiatives are rarely tested at scale, and evidence from other environments shows that assumed impact pathways require careful interrogation[33].

For example, the distribution of supplemental fodder is controversial; critics argue it inflates livestock numbers, harming natural vegetation and other large mammals[34]. While modeling suggests that better ecological alignment can mitigate negative impacts, these dynamics remain largely untested in small-scale contexts, where drought, degradation legacies, competition, and restrictive trade policies interact to limit adaptive capacity[35]. Moreover, it is unclear how these interventions aimed at stabilizing livelihoods over space and time (i.e., risk smoothing) will interact with the social and ecological impacts of increasing precipitation variability under climate change.

The advances in weather forecasting underpinning emerging adaptive approaches to livestock management are one of the greatest achievements in the physical sciences over the past several decades[36–38]. Recent developments in artificial intelligence show prospects for greater accuracy in the future, with Africa specifically targeted for improved weather services[39–42]. Most relevant to livestock management, seasonal precipitation forecasts are becoming more reliable[43] and allowing for accurate prediction of forage quantity and quality up to three months in advance, enabling the precise management of herd sizes[44,45]. While these advances could revolutionize stock planning, it remains unclear to what extent and under what conditions they can buffer pastoralists against climate change, given constraints on adaptation, social learning, and decision-making[46].

This study uses three progressive simulation experiments to develop formal intuition about how climate change may influence vegetation cover, community economic wellbeing, average herd sizes, and the distribution of wealth (i.e., Gini index), and further explores how interventions can influence these impacts. We begin with a stylized landscape that replicates the current empirical distributions of cattle populations, community economic wellbeing, and rainfall across Botswana, Eswatini, Lesotho, Mozambique, Namibia, South Africa, and Zimbabwe (Fig. 1). We develop a general agent-based model in which precipitation follows the patterns of spatial and temporal variability projected for the empirical landscape under the combined Shared Socioeconomic Pathways (SSP) and Representative Concentration Pathways SSP1-2.6, SSP2-4.5, and SSP5-8.5 up to 2060. These pathways reflect projected changes in climate following the immediate lowering of greenhouse gas emissions, continuation of current trends, and increasing development of fossil fuel production, respectively. In our general model, precipitation affects vegetation growth, which in turn feeds livestock populations. Each animal is assigned to an individual pastoralist, who must make decisions about buying or selling livestock. Individuals are nested within communities, which collectively make decisions to engage or disengage with a conservation initiative in some experimental conditions. The baseline conservation initiative involves rotational grazing of community plots and increased access to livestock markets. In some experimental conditions the initiative is bolstered by the provision of supplemental fodder and/or the adaptive use of weather forecasting.

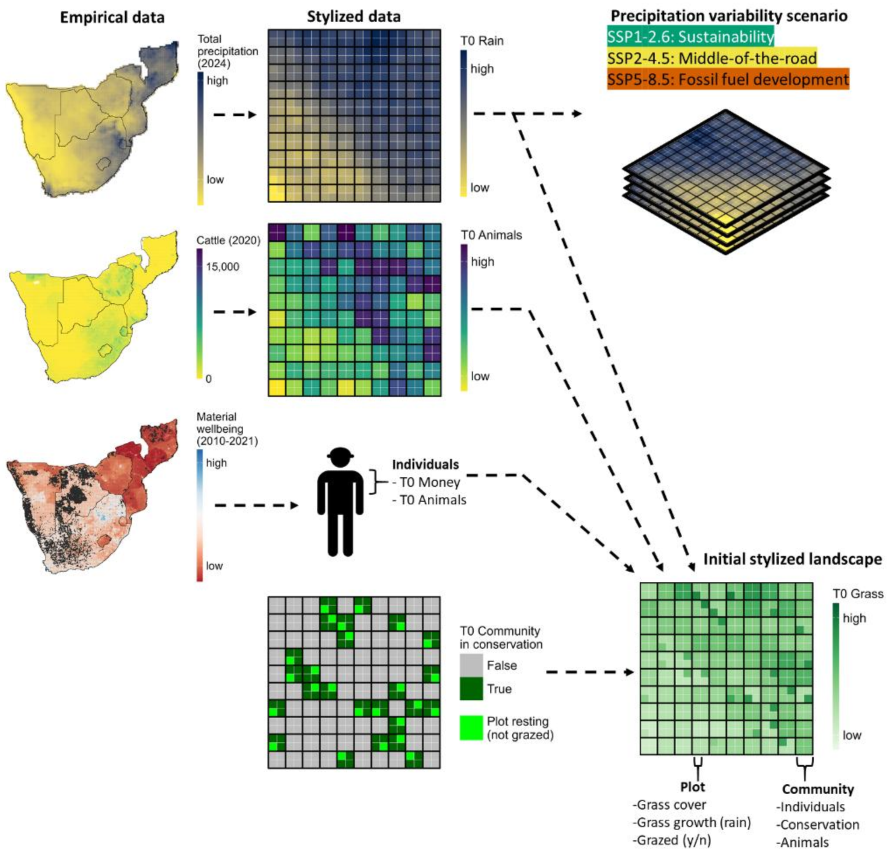

Figure 1: Overview of the relationships between the empirical data, stylized landscape, and stylized precipitation scenarios underpinning the agent-based model used in this analysis. *The empirical distributions of precipitation, cattle populations, and community economic wellbeing across Botswana, Eswatini, Lesotho, Mozambique, Namibia, South Africa, and Zimbabwe were used to create the stylized distributions (note that dark grey pixels show NA values for material wellbeing). The prevalence of the conservation initiative is varied across experimental conditions. In producing precipitation scenarios, we summarized the changes in spatial and temporal variability in precipitation expected under the three SSP scenarios, applying those to the initial stylized precipitation layer to create a timeseries of precipitation. All stylized layers interact in space and time (across iterations) to create the complete stylized landscape. T0 values represent the values at model initialization.*

In each experiment, we measure the expected changes in vegetation cover, non-livestock capital (i.e., money; from here on referred to as “economic wellbeing”), livestock numbers (i.e., herd size), and wealth inequality resulting from differing sets of model conditions. Experiment one demonstrates these outcomes under each precipitation scenario in the absence of widespread conservation initiative implementation. Experiment two then imposes varying levels of conservation initiative implementation, in combination with distribution of supplemental fodder and/or weather forecast use (i.e., different programmatic configurations). This step isolates the potential benefits of these constituent interventions if they were implemented at scale, without yet considering the behavioral dynamics that affect their uptake. Experiment three builds on this by allowing communities to iteratively adopt or abandon the conservation initiative over time through payoff-biased social learning, also measuring how programmatic configurations influence community engagement under the different precipitation scenarios. Together, these three experiments provide insights into the unmitigated impacts of climate change, the mitigation potential of alternative interventions at scale, and the social processes that drive their adoption and persistence at the population level.

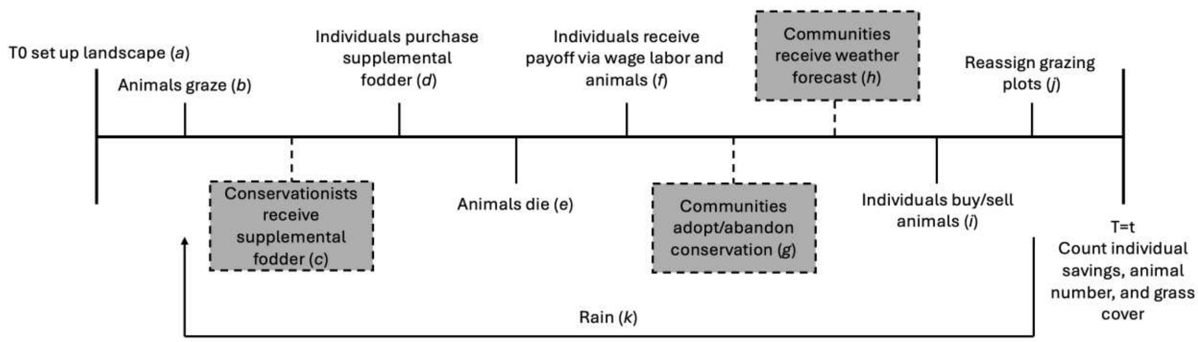

Figure 2: Overview of the 10 modules run for each iteration in the agent-based model. *Grey boxes highlight modules that vary across experimental conditions: supplemental fodder for individuals in conservation communities, group-level social learning of conservation adoption, and access to weather forecasts. Details of each module are: (a) initialization includes the starting proportion of conservation communities, within and between community inequality, spatial autocorrelation in grass cover; (b) animals graze the community plots (N=3 or 4; conservation or not) evenly and split forage evenly; (c) some configurations include free supplemental fodder for individuals in conservation communities when needed; (d) otherwise, if they are able, individuals buy supplemental fodder using savings if needed; (e) animals still without food die; (f) individuals receive income on current savings; (g) some configurations include payoff-biased imitation of conservation engagement in neighbour communities, where payoff is the community mean of individual savings and animals, with animals weighted more than monetary value i.e., total observed wealth; (h) some configurations provide weather forecasts to a subset of the population; (i) without forecasts, individuals manage herd size through payoff-biased imitation within their community where animals are weighted more than their monetary value and market access increased in conservation communities; (j) conservation communities allocate plot with lowest forage cover for protection from grazing in the next iteration; and, (k) forage grows based on rain received in each plot following a logistic growth function and rain following the specified spatiotemporal variability for each precipitation scenario.*

Results

In all three experiments, we tracked long-term, system-wide changes in livestock numbers, vegetation cover, average economic wellbeing, and wealth inequality given the precipitation variability and conservation initiative programmatic configurations of interest. We examined future precipitation scenarios derived from three potential socioeconomic trends: immediate lowering of greenhouse gas emissions (SSP1-2.6), continuation of current trends (SSP2-4.5), and increasing development of fossil fuel production (SSP5-8.5).

Experiment one: The consequences of increasing precipitation variability

Experiment one sets the benchmarks against which the impacts of all other experimental conditions are compared. In this experiment, we isolated the effects of increasing precipitation variability under the three SSP scenarios. We impose these scenarios on a landscape approximating current management conditions, where 10% of communities are engaged in the baseline conservation initiative (i.e., practice rotational grazing and have increased market access) without receiving supplemental fodder or adaptive use of weather forecasts.

This experiment shows that without adaptive measures, higher precipitation variability is expected to negatively affect all four outcomes (Fig. 3). In this system, average livestock numbers and average economic wellbeing were tightly coupled, with both outcomes showing strong declines and little overlap in uncertainty as precipitation variability increases from the least (SSP1-2.6) to most variable precipitation scenarios (SSP5-8.5). In parallel, we show that under these conditions, the distribution of wealth was also expected to become more unequal (higher Gini coefficient). The increase in wealth inequality reflects the inability of poorer individuals to afford supplemental fodder during droughts, leading to stock losses and, in some cases, exit from livestock rearing altogether. Vegetation cover showed the most modest expected impacts of increasing precipitation variability, with no difference across the SSP1-2.6 and SSP2-4.5 scenarios, and relatively small declines under SSP5-8.5. The impacts on vegetation cover are buffered by the ability of individuals to predict and respond to upturns in forage production, meaning that following seasons with poor precipitation and die-offs of livestock, spikes in vegetation growth are not matched by livestock numbers, buffering the average vegetation cover across time (Supplementary Fig. 1).

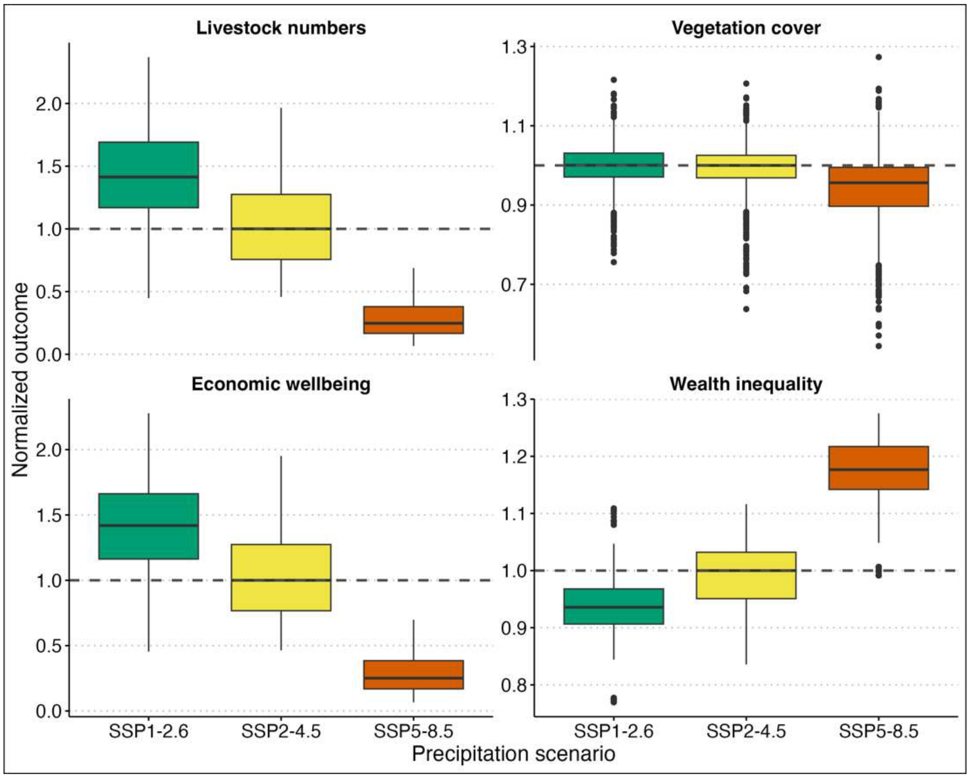

Figure 3: Results of experiment one. *Boxplots show the outcomes resulting from the last 30 iterations for each of 50 repetitions for the agent-based model run on each precipitation scenario. Outcome values are normalized by the median values of the SSP2-4.5 scenario, so the SSP2-4.5 median is 1 and others are shown relative to it.*

Experiment two: The potential of adaptive practices at scale

Experiment two tested how the four outcomes were expected to change along with the scale of conservation initiative implementation under each precipitation scenario, varying participation from 10% to 90% of communities engaged. Across these scales, we compared four programmatic configurations: rotational grazing and increased market access alone, just paired with supplemental fodder, just paired with adaptive use of weather forecasts, and paired with both. This design isolates the role of the baseline conservation initiative and each complementary intervention in shaping livestock numbers, vegetation cover, economic wellbeing, and wealth inequality.

In our model, without supplemental fodder or forecast use, increasing the scale of the baseline initiative had little effect across all outcomes for all precipitation scenarios, averaged across space and time (Fig. 4). Across all precipitation scenarios, adding supplemental fodder linearly increased the number of livestock on the landscape, the economic wellbeing of individuals, and the wealth equality as the initiative was implemented at scale. This configuration, however, resulted in the lowest vegetation cover, with cover in SSP5-8.5 and 90% implementation expected to be well below the same scenario at 10% implementation (Fig. 4). This reflects the long-term consequences of partially decoupling the number of livestock on the landscape from natural vegetation cover, allowing for overstocking (Supplementary Fig. 1).

Conversely, across all outcomes and all scenarios, introducing just the adaptive use of weather forecasting showed little difference from the expected impacts of the baseline initiative alone. This programmatic configuration only meaningfully deviates from the baseline initiative in the expected number of livestock on the landscape and average economic wellbeing for scenarios SSP1-2.6 and SSP2-4.5. This trend is notable, however, in that this configuration shows that under current trends in emissions and climate (SSP2-4.5), implementing the adaptive use of weather forecasting at scale can logically deliver (albeit unequal) economic benefits to communities while simultaneously maintaining high levels of vegetation cover (Fig. 4). This result highlights that better weather prediction alone cannot be widely expected to mitigate the effects of climate change on pastoral communities, given current constraints on the capacities of individuals to independently buy, sell, and provide supplemental nutrition for their animals.

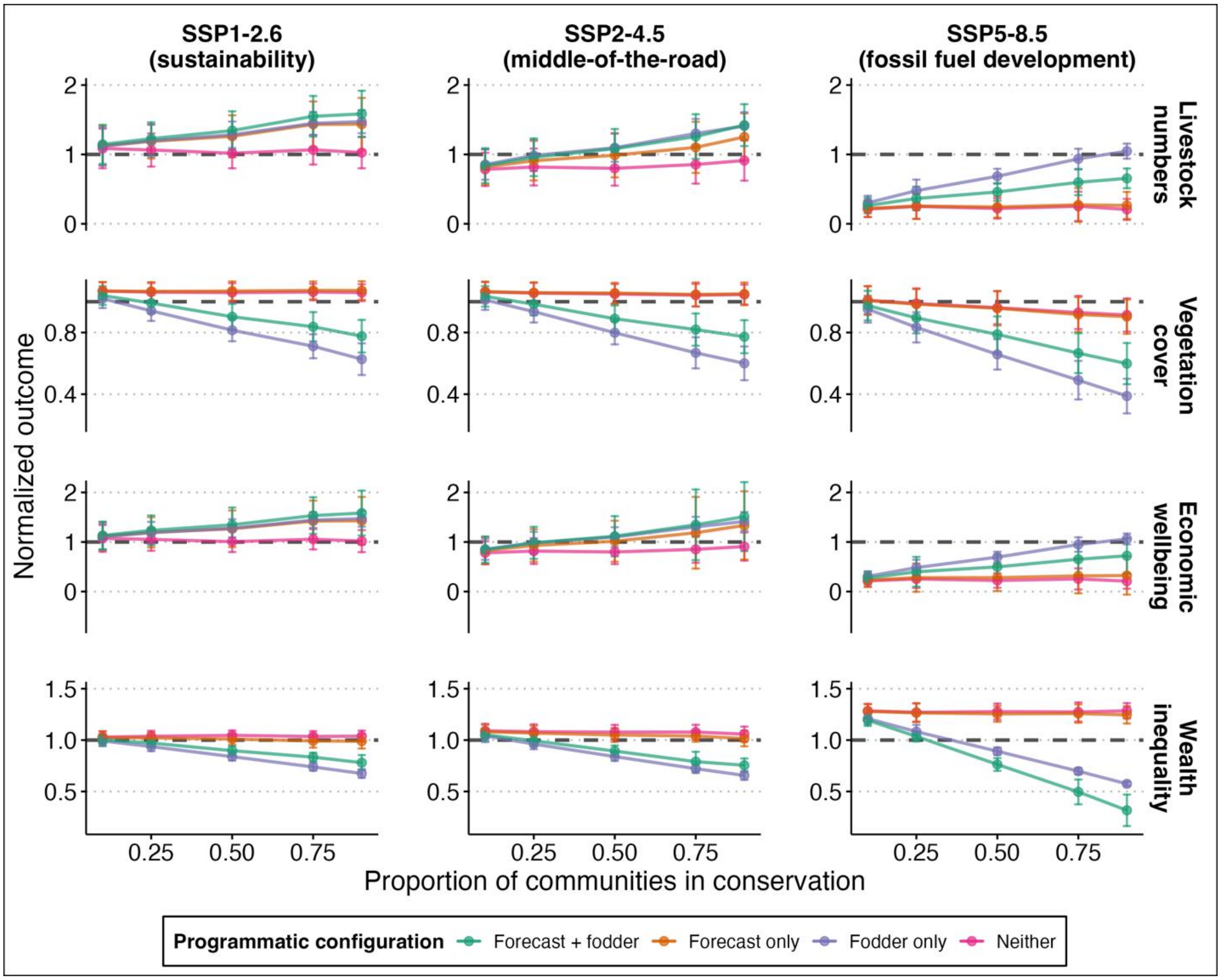

Figure 4: Results of experiment two. Points and error bars show the mean and standard deviation of each outcome across the last 30 iterations and across 50 repetitions for each conservation initiative configuration and for each precipitation scenario. Outcomes are normalized by the median value of the 'Neither' configuration (baseline initiative) across proportions of communities in conservation for the SSP2-4.5 scenario. Lines show the linear interpolation of the average outcome between conservation implementation levels for each precipitation scenario and each programmatic configuration.

Pairing supplemental fodder with the adaptive use of weather forecasting mitigated loss in vegetation cover while maintaining meaningful gains in livestock numbers, economic wellbeing, and wealth equality. Under the most variable precipitation scenario (SSP5-8.5), pairing forecasting and supplemental fodder resulted in the most equal distribution of wealth (Fig. 4). All impacts of paired supplemental fodder and adaptive weather forecasting increased with the scale of implementation across all precipitation scenarios (Fig. 4). By implementing both interventions simultaneously, stock numbers remained tightly tied to ecological conditions, with supplemental fodder simply filling gaps in individuals' capacity to adapt to variable conditions (Supplementary Fig.1). As shown in greater detail for just the most likely SSP scenario (SSP2-4.5) in Fig. 5, the paired implementation of both the adaptive use of weather forecasts and supplemental fodder can effectively eliminate tradeoffs expected under climate change and inherent to the implementation of each intervention alone.

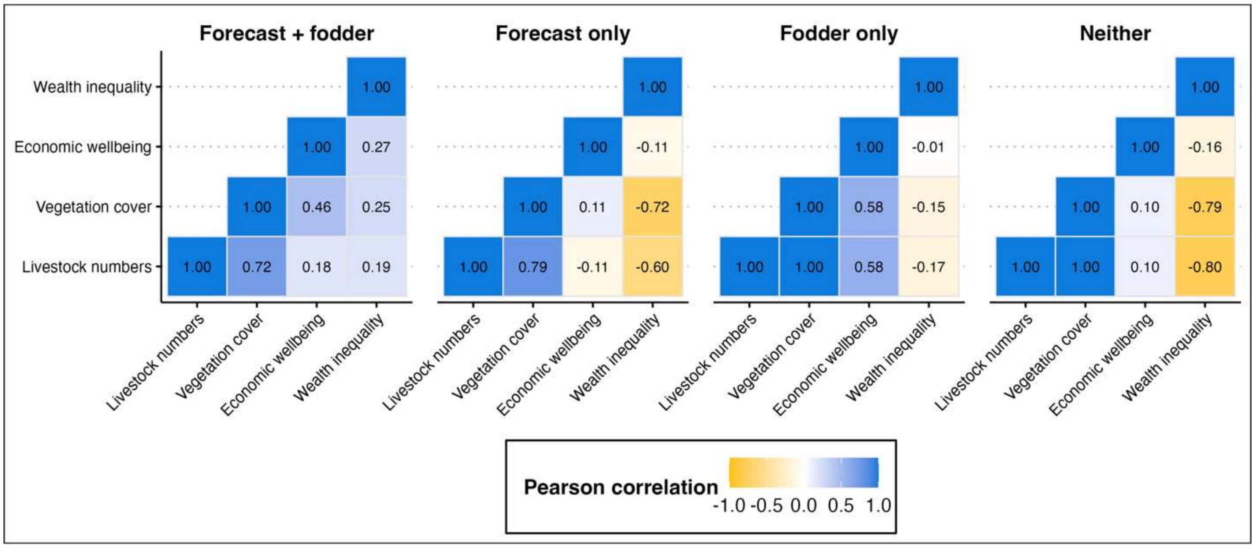

Figure 5: Trade-offs among outcomes under each programmatic condition. *Model outcomes when 50% of communities engaged in the conservation initiative in the SSP2-4.5 scenario. Yellow fill indicates a tradeoff (negative association) between outcomes. Blue fill indicates complementary outcomes (positive association). 'Neither' configuration shows the baseline conservation initiative with just rotational grazing and increased access to livestock markets.*

Experiment three: The drivers of program uptake and persistence

In the final experiment, we allowed communities to observe their neighbors' total wealth and decisions about whether to engage in the conservation initiative. They then used payoff-biased social learning to iteratively make decisions about their own adoption or abandonment of the initiative, consistent with cultural evolutionary theory and evidence within other systems[47–50]. Here, we examined the long-term spread and persistence of the conservation initiative under the three precipitation scenarios, and when paired with the adaptive use of weather forecasting and/or supplemental fodder. Engagement is measured relative to the expected outcomes of the baseline conservation initiative alone, allowing us to isolate which programmatic configurations encouraged or discouraged persistent engagement at scale (Fig. 6). Throughout this experiment, the stylized landscape is initialized with 25% of communities engaging in the conservation initiative at random.

Our model showed that the provision of adaptive weather forecasting alone increased engagement with the conservation initiative relative to the baseline configuration under the low-variability scenario (SSP1-2.6) (Fig. 6). However, this benefit declined steadily as precipitation variability increased, disappearing entirely under the highest-variability scenario (SSP5-8.5). The decline is explained by the behavioral dynamics of success-biased social learning. Forecast-informed communities sell large numbers of livestock before anticipated droughts, temporarily reducing herd sizes (Supplementary Fig. 1). Because neighboring communities place greater weight on visible livestock numbers than on less visible indicators (e.g., monetary wealth), these forecast-using communities appear less successful and are, therefore, less likely to be copied.

Across precipitation scenarios, the inclusion of supplemental fodder, with or without adaptive forecast use, consistently increased engagement relative to the baseline conservation initiative (Fig. 6). In the absence of adaptive forecast use, supplemental fodder buffered livestock losses from drought. When paired with forecasts, supplemental fodder dampened the extent to which communities sold animals. In both cases, including supplemental fodder increased the visible success of communities engaged in the initiative, leading to more widespread and persistent engagement. The effect intensified with greater precipitation variability from SSP1-2.6 to SSP5-8.5, indicating its importance as an intervention under climate change. Under the highest variability scenario (SSP5-8.5), the inclusion of just supplemental fodder without adaptive forecast use resulted in the highest overall engagement. As shown in Fig. 4 and Supplementary Fig. 2, however, this configuration is not expected to result in the most optimal outcomes for wealth equality or vegetation cover, highlighting that programmatic engagement and overall outcomes are not equivocal.

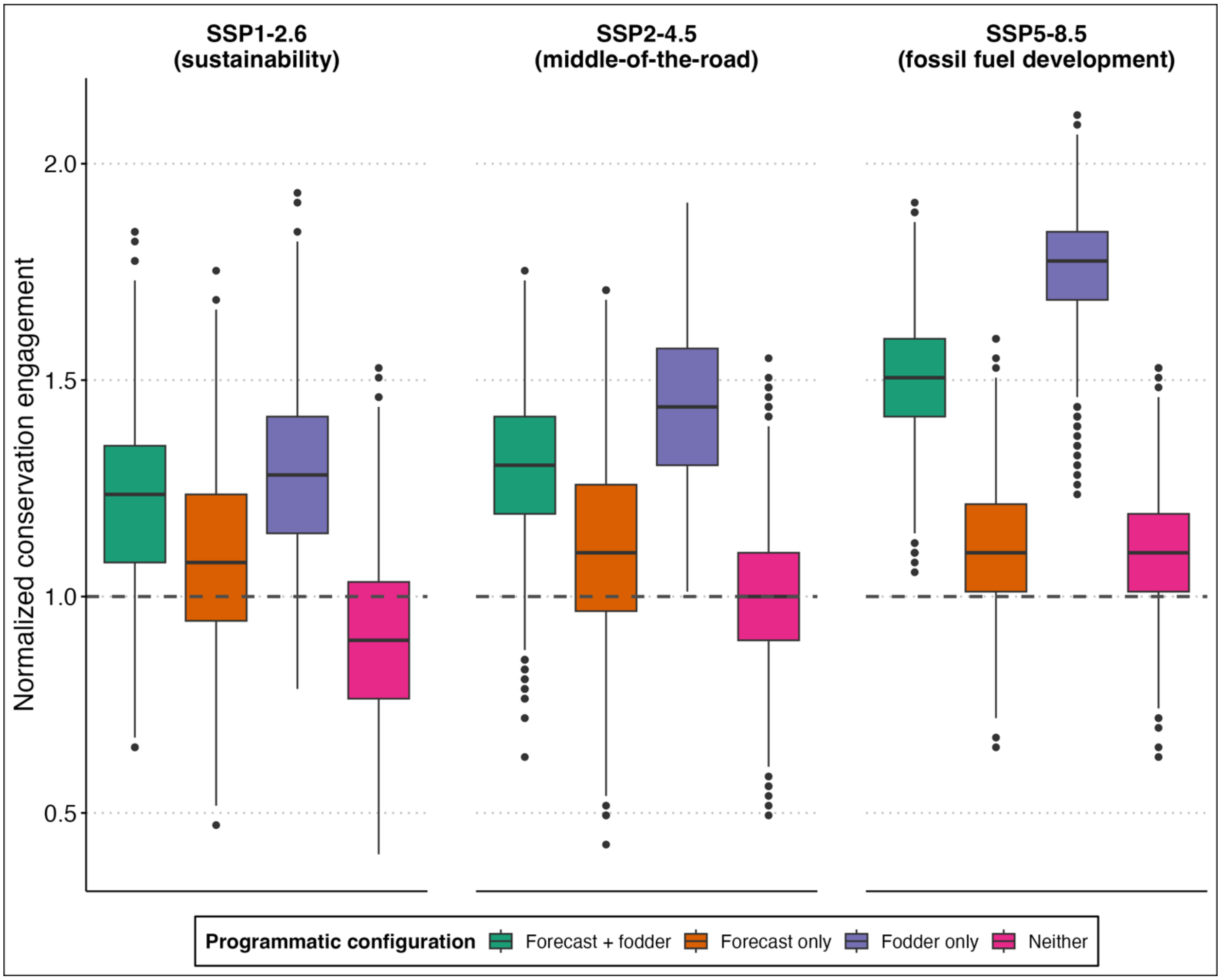

Figure 6: Results of experiment three. *Boxplots show the level of community engagement with the conservation initiative resulting from the last 30 iterations for each of 50 repetitions for the agent-based model run on each precipitation scenario and for each programmatic configuration. Outcome values are normalized by the median value of the 'Neither' configuration (baseline initiative) for the SSP2-4.5 scenario. Livestock numbers, economic wellbeing, vegetation cover, and wealth inequality outcomes for this experiment can be found in Supplementary Fig. 2.*

We conducted supplemental analyses to test the sensitivity of the results to the precision of forecasts and subset of the population targeted for forecast access. Forecast precision was reduced such that observed values varied normally around the true value. Additionally, adaptive forecast use was applied to the richest quartile of communities, just the poorest quartile, and all communities, comparing these to forecasts tied to the conservation initiative and configurations without forecasting. Across all precipitation scenarios, we found no strong effects of either forecast targeting strategy (Supplementary Fig. 3) or reduced forecast precision (Supplementary Fig. 4). These null effects indicate that, within the modelled system, neither the distribution strategy nor the precision of forecasting information substantially influenced outcomes, and that other factors—such as paired distribution with supplemental fodder—are likely to play a more critical role in driving system-wide change.

Discussion

Our results show that, under current distributions of livestock and community economic wellbeing, projected increases in precipitation variability are expected to dramatically reduce overall wealth and increase wealth inequality of pastoralists in southern Africa (Fig. 3). There are, however, existing interventions that may offset these impacts. Adaptive herd management using weather forecasts and risk-smoothing measures such as the provision of supplemental fodder can help prepare-for and buffer the effects of intensifying dry periods, respectively. Yet, when examined in detail, each intervention alone appears limited in effectiveness and prone to generating trade-offs among ecological outcomes, community wealth, and equity (Figs. 4 and 5). When implemented together, however, these interventions effectively mitigated both the direct impacts of climate change and the trade-offs associated with each intervention in isolation. Supplemental fodder, in particular, appears crucial for ensuring widespread adoption and long-term persistence of adaptive management strategies (Fig. 6).

While our model emphasizes supplemental fodder as a key form of risk smoothing, similar benefits may be achieved through direct monetary payments during drought. Such initiatives, including proposals for a "conservation basic income," highlight the disproportionate potential gains of targeted financial support[51]. Evidence suggests that these measures are especially cost-effective when aligned with predictable seasonal shifts in weather and associated fluctuations in income for resource-dependent economies[52]. However, our results emphasize that for risk-smoothing to be effective when implemented at scale, it must be aligned with local ecologies such as resting rangelands after drought[35].

Prior research on African agricultural systems has shown that the capacity for farmers to beneficially align their practices with local ecology increases with forecast accuracy[13]. In a set of robustness checks, our model indicates that—somewhat to the contrary—in pastoral systems, the scale of forecast use (Fig. 4) matters more than the precision (Supplementary Fig. 4). It is important to note, however, that we varied precision around the mean, meaning that forecasts were always directionally accurate. Moreover, while the scale of implementation matters substantially (Fig. 4), varying exactly who received forecasts—whether only conservation adopters, wealthier or poorer communities, or all communities—did not shift aggregate outcomes. This does not mean that distribution strategies are irrelevant in practice. Governments and international organizations may still shape equity and cooperation through the ways forecasts are shared, for example by distributing information via mobile apps. More deliberate engineering of these information architectures could influence how forecasts are interpreted and used, potentially supporting cooperative decision-making beyond what is captured in our model[53]. In reality, communities will almost certainly use a combination of social learning and forecast information to make decisions, which evolutionary models suggest may be more effective when forecast information is difficult to interpret or incomplete[54].

Our research illustrates that in human-modified landscapes such as rangelands, the effects of human decision-making often outweighs direct climatic effects. In Australian rangelands, for example, mean precipitation is the primary determinant of standing vegetation, yet inter- and intra-annual precipitation variability are more determinative of stocking rates, ultimately determining final vegetation cover in some areas[55]. In southern Africa, poorer and smaller-scale pastoralists are less able to adaptively respond to dry periods, amplifying cascading impacts beyond changes in weather alone[15]. Identifying how human responses to climate change ripple through ecosystems and economies to amplify or dampen climate pressures remains a critical frontier for research in social-ecological systems.

Study simplifications and limitations

In our model, rotational grazing and increased market access alone did not improve vegetation cover (Fig. 4), likely due to tightly coupling to livestock numbers. Studies similarly show that higher livestock density and increased grazing pressure negatively impact vegetation cover, condition, and diversity in shrublands[56,57], while the vegetation responses in grassier biomes vary with management and climate[58]. Rotational grazing also offers additional ecological benefits beyond conserving standing vegetation. Namely, it enhances carbon storage and soil resilience by allowing vegetation to recover, which promotes deeper root systems and greater organic content, potentially allowing pastoralists to seek funding in the form of carbon payments[59].

Adaptive management decisions typically do not only account for rainfall and standing vegetation biomass, but also vegetation type, for example arid shrubland versus mesic grassland or savanna. The grazing capacity of an area is determined by species composition and species cover[60]. While our model provides some indication of vegetation outcomes, it is limited in its ability to consider biome-specific vegetation and biodiversity responses, as well as site-level grazing capacity and condition.

In developing a parsimonious model that allowed us to isolate the dynamics of interest, we have also not considered a number of important social dynamics in southern African rangeland systems. Specifically, we assume that conflict among individuals[26], including increased stock theft during droughts[61], changes in policy[62,63], and categorical variation in household livelihood strategies[64] all do not systematically bias our findings. Similarly, we do not account for differences among livestock types (i.e., cattle, sheep, and goats), spillover effects between livestock and wildlife populations[65], nor do we model the dynamics of inter-community leakage following the implementation of the conservation initiative[66]. More broadly, we assume that pastoralists and their livestock do not move between communities. Previous modeling work has shown that differences in adaptive mobility of richer versus poorer pastoralists can result in more distributed and equitable grazing patterns, potentially buffering some of the impacts on equity shown here[67].

Our analytical strategy relies on finding a stable state, or "solution," for all outcomes given each set of model conditions (Supplementary Fig. 5). This framework allows us to compare the impacts of different conditions and interventions, but it should not be interpreted as implying that rangeland systems are themselves stable or should be managed toward equilibrium, especially under climate change[68]. In particular, our experiments adjust the variance of precipitation while holding mean levels constant and introducing this variability as stationary over time[69]. This design isolates the role of variability, but it does not capture expected directional changes in mean precipitation or the fact that variability itself will increase over time. Given these simplifications, we emphasize that the modelling work presented here is intended to build intuition about how different sets of conditions may logically affect important system dynamics, rather than present formal predictions of real-world outcomes.

Future research directions

While the section above lists simplifications of our stylized rangeland system, we do not recommend that future research simply builds on our model by adding additional modules. It is a perennial challenge in modeling complex systems to not simply replicate our difficult-to-understand world with a difficult-to-understand model[70]. Instead, we suggest that researchers modify our model (using the available code; see 'Code and Data Availability' in Supplementary Information) to isolate specific dynamics of interest, trimming away as much superfluous detail as possible[71]. These lines of research may usefully evaluate the impacts of carbon payments on system-wide outcomes, cross-community conflict, or identify the causes or consequences of social-ecological tipping points[72,73].

Alongside forecasting technology, gains are being made in direct observation of vegetation[74] and grasses in particular[75]. Continued private sector investment in image processing[76] and earth observation satellites[77] will soon enable highly informed, independent decision-making about where to move animals. The implications of this real-time earth observation technology for complex pastoralist systems could be similarly detailed with formal models.

Rather than studying future implications of novel conditions and interventions, researchers may build on our modeling framework to understand past phenomena. Shifting mosaics of land cover result from interacting social and biophysical processes and hence, leave a signature of those processes. Using emerging methods for simulation-based inference, such as approximate Bayesian computation, researchers can theorize about mechanisms that result in spatiotemporal patterns consistent with observed data[78,79]. A key challenge in this line of research will that individuals' perceptions of environmental change, and hence their resulting behaviours[80], may not necessarily match landcover changes observed in the satellite record[81].

Conclusions

In southern Africa, variability in rainfall, vegetation cover, and human wellbeing are increasing, along with our capacity to monitor and respond to these dynamics. In the coming years, it is likely that anyone with internet access will know precisely where and when adverse weather will occur months in advance, yet our results show that information alone is largely insufficient to buffer pastoralist communities from climate change under all possible future scenarios. Forecasts must be paired with interventions that enable households to act on these insights, reduce inequality, and sustain adoption of adaptive practices. The challenge, therefore, is not simply to expand the reach and precision of forecasts, but to formally articulate the pathways through which they can affect change and use these tools to better target more direct interventions.

Methods

We describe the dynamics of interest using an agent-based model. The system contains several stochastic processes and complex hierarchical dynamics among the social and ecological components, making closed-form mathematical exploration intractable and providing justification for our computational simulation-based approach[70,82–84]. We model all social dynamics as cognitively realistic, cultural evolutionary processes[14,85]. These evolutionary dynamics affect two distinct traits: a community-level trait of engagement in the conservation initiative and an individual-level trait determining individuals' strategy for changing their herd size. By building our analytical framework on evolutionary theory, we can explore, across three progressive experiments, how changes in selective forces drive emergent outcomes at the population level and across the integrated social-ecological system[86–88]. Our general approach consists of simulating a stylized starting landscape and set of precipitation scenarios based on empirical data across southern Africa and three potential socioeconomic trends (i.e., SSPs), respectively (Fig. 1). We then apply a set of conditions associated with each experiment and iteratively run the model until a stationary set of outcomes is reached (Supplementary Fig. 5), repeating this process for 50 repetitions for each set of conditions (Fig. 2). Iterations loosely represent the system behavior in response to one annual growing season. The reported outcomes are the summarized outcomes across the stationary iterations and across all repetitions.

Stylized landscape and precipitation scenarios

For each repetition, we simulate a landscape divided into 100 communities, each with four grazing plots (Fig. 1). Communities have livestock numbers and economic wellbeing distributions that approximate the highly unequal, exponential distributions found in southern Africa, as identified from the FOA livestock of the world dataset and the NASA Deprivation Index, respectively[89,90]. An initial proportion of communities is randomly assigned to engage in the conservation initiative. In communities that do not engage, animals can access all four plots (representing continuous grazing); for communities engaged in the conservation initiative, animals can only access three of the four plots (rotational grazing).

Each plot receives an initial amount of precipitation that translates to a pre-grazing amount of vegetation cover normalized between 20 and 100, with a spatial autocorrelation (Moran's I) of 0.98 as observed in the empirical precipitation data[91] (see Supplementary Fig. 6). The animals in each community then graze the three or four available plots evenly with a set rate per animal, resulting in an initial vegetation cover for each plot (Fig. 1). While exact values vary stochastically across repetitions, the initial number of animals in each community ranges from approximately 15 to 75 with a median value of 40, and is correlated with the initial precipitation, as is observed in the empirical landscape. Each community has an associated number of individual pastoralists, each with their own characteristics. The number of individuals in each community is randomly assigned, with a mean and standard deviation that approximate the distribution of individuals engaged in the Herding for Health initiative[92].

In the empirical data, community economic wellbeing and the number of livestock are uncorrelated at the landscape level but are highly associated within communities (see 'Code and Data Availability' in Supplementary Information). We approximate these patterns by randomly assigning the exponentially distributed values of average material wellbeing to communities across the landscape, then assigning each individual a value of wealth around that community average. The number of animals in each community is then allocated between individuals, proportional to their wealth (see Supplementary Fig. 7). Again, while the exact values vary stochastically, the number of animals assigned to each individual at initialization ranges from approximately 2 to 200 with a median value of 10. Each individual then has a resulting economic wellbeing (i.e., cash on hand; E_i) and a value of the livestock in their herd (L_i). These are summed together to yield their total wealth (W_i) as,

$$W_i = E_i + L_i$$

Equation 1

However, we assign each individual a total *observed* wealth value (or payoff; P_i) which weights the value of animals by an additional 10%, representing the fact that animals are a more observable signal of economic wellbeing than wealth held elsewhere (e.g., in a bank account; Equation 2). The total observed wealth for each individual is then defined as

$$P_i = W_i + 0.10 \cdot L_i$$

Equation 2

To initialize a standing stock of behavioral variation, each individual is randomly assigned a past buying or selling strategy (S_i) for managing their herd size; this is represented as a positive or negative proportion of their herd that was previously bought or sold, respectively.

After the described initialization in precipitation across the landscape, precipitation varies across iterations according to SSP scenario-specific variability. Variability is defined using estimates derived from monthly rainfall projections for the study area from January 1, 2050, to December 31, 2059, produced by Phase Six of the Coupled Model Intercomparison Project (CMIP6; Copernicus Climate Change Service, 2021). Three SSP scenarios are considered: SSP1-2.6, SSP2-4.5, and SSP5-8.5, with each simulation using one of these three consistently. To calculate estimates, precipitation data were resampled to a 0.25° grid and aggregated into austral summer totals (December, January, February), the primary wet period and period most sensitive to projected climate shifts[94]. For each SSP scenario, we calculate the variance of the seasonal change in precipitation for each grid cell, relative to the mean seasonal precipitation of that grid cell. Cells with mean seasonal precipitation below 3 mm were excluded to avoid inflated measures of relative changes. For each SSP scenario, the highest variance observed across all grid cells was scaled to match the scale of precipitation on the stylized landscape and used as the precipitation variance in the agent-based model. The scenarios in the model therefore represent an upper bound on seasonal precipitation variance projected for the empirical landscape under climate change. In the CMIP6 data, the projected SSP1-2.6 precipitation variance is comparable to pre-industrial levels (1850–1900; Engelbrecht et al., 2024). Under SSP2-4.5, maximum variability rises by a factor of 1.3 relative to SSP1-2.6 and the pre-industrial climate, while under SSP5-8.5 it increases by a factor of 3.3.

Model processes

The model processes are best described as 10 sequential modules each run for 100 iterations, or growing seasons, following the initialization of the stylized landscape (Fig. 2), described in detail below. Many alternative model specifications are possible; we encourage readers to build on our work by downloading and adjusting the provided code for new research questions (see ‘Code and Data Availability’ in Supplementary Information).

Grazing

In each iteration, the total available forage (F) in each community (c) is calculated by summing the vegetation cover across the three or four plots (G) available under the presence or absence of rotational grazing, respectively, as

$$F_c = \sum G_c \quad .$$

Equation 3

We then calculated the total amount of forage required to feed all livestock in each community (V_c). If the required forage is less than the available forage, the available forage is reduced by the required amount to yield F_c' as

$$F_c' = F_c - V_c \quad .$$

Equation 4

This total forage is distributed evenly across all grazed plots in the community, reducing their vegetation cover to G'as

$$G' = \frac{F_c'}{\{3|4\}}.$$

Equation 5

If the required forage is greater than the amount available, the available forage across the grazed plots is set to 1% of the maximum initial value (i.e., rather than 0, to allow for multiplicative growth) and the difference between available and required forage is recorded proportionally and assigned to each individual pastoralist as a proportion of their herd that must be fed with supplemental fodder, or else will die.

Supplemental fodder distribution in the conservation initiative

Under some experimental conditions, the conservation initiative includes the distribution of supplemental fodder (Figs. 4, 5, & 6). In these cases, individuals with 10 animals (the median at initialization) or fewer are given supplemental feed for their animals if they are in a community currently engaged in conservation, as decided in the previous iteration or in the landscape initialization for the first iteration (Fig. 2). Individuals with large herds (greater than 10 animals) and those in communities not engaged in conservation do not receive any supplemental fodder, as in reality, conservation organizations rarely subsidize operations of unaffiliated or large commercial operations.

Supplemental fodder purchasing

Individuals who do not receive supplemental fodder as a programmatic condition of the conservation initiative buy supplemental fodder (if required) if they have the required economic wellbeing (E_i). The price of supplemental fodder for one animal for the entire season is 20% of the price of an animal. This approximates the real cost to feed an animal for an entire season, inclusive of feed and supplement licking blocks (Conservation South Africa unpublished data).

Animal mortality

All animals that did not get enough forage from the community plots, did not receive supplemental fodder as part of the conservation initiative, and whose owners were unable to purchase supplemental fodder, die. The total wealth of the individuals is reduced by the value of the lost animals (L_i') and the total observed wealth of the individuals is reduced by the value of the animals plus their associated 10% additional weighting, calculated as

$$W_i = E_i + L_i - L_i'$$

Equation 6

and

$$P_i = W_i + 0.10 \cdot (L_i - L_i'),$$

Equation 7

respectively.

Payoffs from wage labor and animals

In each iteration, individuals receive 2% returns on both their economic wellbeing and on livestock-associated wealth. Livestock returns approximate the expected revenue from the reproduction and sale of calves on average across cattle and across years (Conservation South Africa unpublished data). The return on economic wellbeing represents gains made through wage labor and/or through remittances or investments, scaled proportionately assuming that richer individuals received proportionately higher regular incomes. The returns on both capital and livestock are equal (2%) as to give no inherent preference for the accumulation of money versus livestock.

Adoption and abandonment of conservation

In experiments one and two, conservation behaviors are fixed exogenously. In experiment three, communities choose to engage or disengage in the conservation initiative in every iteration. They make this decision by observing the communities around them and using payoff-biased social learning based on the average total observed wealth of each community, as defined by Barrett (2019). Specifically, the probability that a community adopts or continues engaging in conservation (A) in the next iteration is defined as

$$\Pr(A|A,B) = \frac{\exp(\beta \cdot \bar{P}_{A,t-1})}{\exp(\beta \cdot \bar{P}_{A,t-1}) + \exp(\beta \cdot \bar{P}_{B,t-1})},$$

Equation 8

where β is the strength of the payoff bias and $\bar{P}_{A,t-1}$ is the sum of the total observed wealth of all neighboring communities engaged in conservation in the current iteration. The sum of the total observed wealth of all neighboring communities not engaged in conservation is $\bar{P}_{B,t-1}$. We set β to 0.1 for all simulations, although we show in a set of sensitivity tests that model results are not sensitive to this value (Supplementary Fig. 8).

Distribution of weather forecasts

In some experimental conditions, a subset of communities receive forecasts of vegetation cover for their three or four grazed plots in the upcoming iterations. Using this forecast, the total number of animals that the expected forage can support is calculated at the community level, while maintaining a 15% reserve. This target stocking level is expressed as a proportion of the community's current total number of livestock. Each individual in the community then adjusts their own strategy (i.e., proportion of their herd they try to buy or sell; S_i) to match this proportion, conditional on their economic capacity to buy or sell animals. In experiments one, two, and three, the forecast predicts the vegetation cover in the next iteration with complete precision. In Supplementary Fig. 4, we vary the precision of the forecasts by allowing the forecasted value to vary normally around the true value with a standard deviation of 10%, 20%, and 30% of the true value. In Supplementary Fig. 3, we vary the forecast targeting strategy to distribute forecasts selectively to different groups, including 'poor' communities only (communities in the lower 25% quantile of economic wealth) and 'rich' communities only (communities in the upper 75% quantile of economic wealth).

Livestock sales

The number of animals each individual actually buys or sells in each iteration is determined by their chosen strategy (S_i) and their capacity to achieve that strategy. As described above, in communities using forecasts, the strategy of each individual results directly from the vegetation cover projected for the next iteration. In communities not using forecasts, individuals use payoff-biased social learning to adjust their strategy in each iteration, such that the probability that a given individual (i) changes their strategy to that of another individual (j) is defined as

$$\Pr(i \rightarrow j) = \frac{P_{j,t-1}}{\sum_{k=1}^{10} P_{k,t-1}}, \{\text{ only if } P_{j,t-1} > P_{i,t-1}$$

.

Equation 9

This implementation results in sigmoidal payoff bias based on the total observed wealth values (i.e., relative payoffs; P) of ten randomly sampled peers (k) from within their community. Individuals i will only adopt the strategy of their chosen peer (j) if the peer's payoff was greater than their own in the previous iteration ($t - 1$).

The capacity of individuals to achieve their strategy depends on their economic wellbeing (if choosing to buy animals) and their market access (if choosing to sell). Individuals can only buy animals for which they have enough money. Individuals not in communities engaged in the conservation initiative can only sell 25% of their animals in a given iteration. Individuals in engaged communities can sell up to 50% of their animals in a given iteration. Regardless of their chosen strategy, individuals will never sell animals once their herd size reaches two or fewer, representing a strong attachment to livestock rearing as an important component of cultural identity among the pastoralists we study.

Reassignment of grazing plots

For communities engaged in the conservation initiative, the plot with the lowest vegetation cover is identified and allocated for protection (not grazed in the following iteration), representing a rotational grazing scheme. If multiple plots have equally low vegetation cover, one is randomly selected.

Precipitation

Finally, precipitation then replenishes the vegetation cover of the landscape following the precipitation conditions of the specific simulation (Fig. 1) and following a logistic growth pattern for vegetation cover. The growth function is defined such that precipitation (R) has a linear effect on vegetation cover and can be interpreted as precipitation quality, rather than precipitation strictly defined, which often has non-linear effects on vegetation growth at the landscape scale [9]. The effect of precipitation on vegetation growth ($G_{t+1} - G'$) is controlled by the growth rate (r), with vegetation growth also dependent on current vegetation cover of each plot (G') and the carrying capacity (K) to yield the function

$$G_{t+1} = G' + r \cdot R \cdot G' \cdot (1 - G'/K),$$

Equation 10

defining the vegetation cover in each plot in the following iteration (G_{t+1}). Note that we assume a single carrying capacity (K) across the entire simulated landscape.

Estimating outcomes and uncertainty

Using stationary precipitation variability (i.e., centering around a stable mean value) over time allows the model to reach a stable state for each condition set, dependent in part on initial stylized landscape conditions and process stochasticity. We leveraged this stochasticity to produce envelopes of uncertainty regarding the expected outcomes of each combination of modelled conditions. As such, we performed 50 repetitions for each set of model conditions, with each repetition run for 100 iterations, until a stable model state was reached, generally after 50 iterations (see Supplementary Fig. 5). In presenting the outcomes of each combination of conditions, we summarize across all values in the final 30 iterations of each repetition to produce estimates of central tendency and variation.

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Supplementary information:

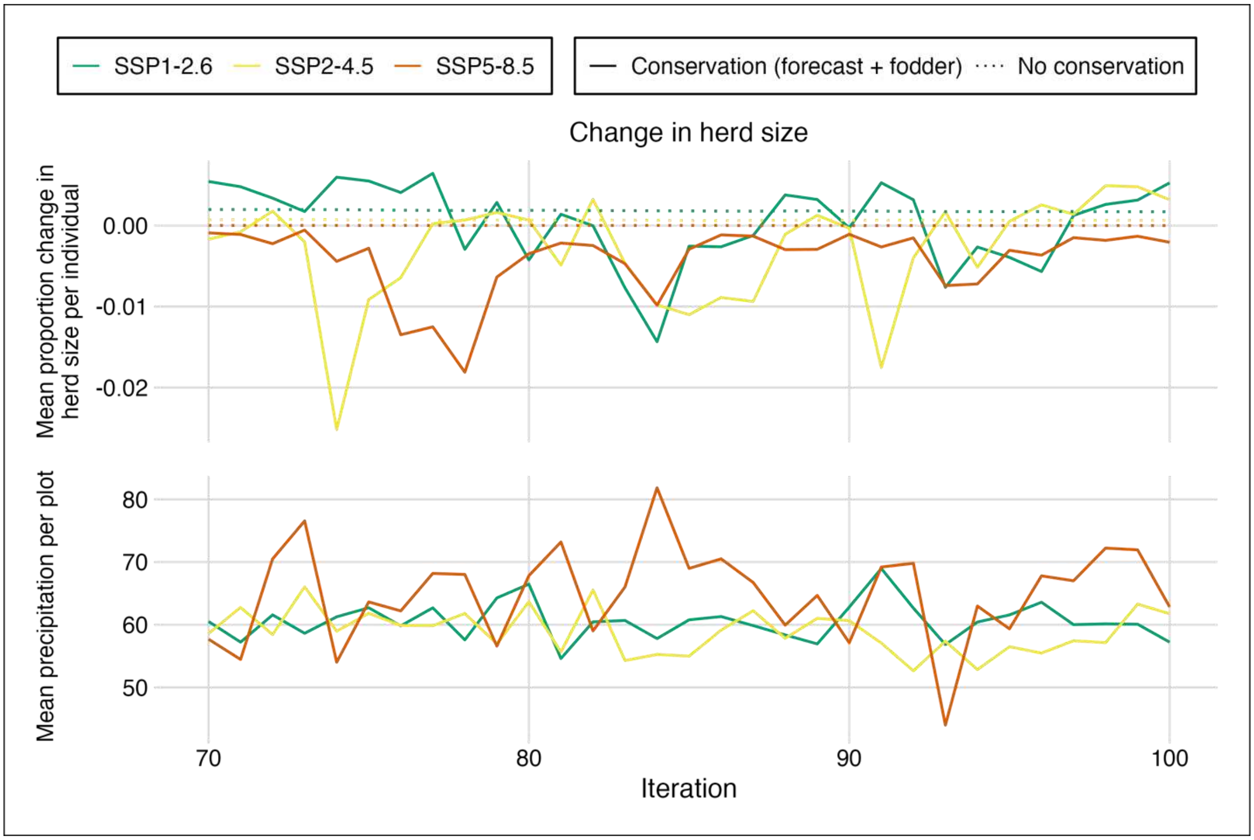

Figure S1: Precipitation and herd size management across iterations. *Lines show mean selling strategy across individuals, averaged over 50 repetitions, for those involved in conservation with fodder and precipitation forecasting, compared with individuals not involved in conservation. Results are shown alongside mean precipitation across the stylized landscape during the final 30 iterations (after burn-in). The figure shows that individuals' selling behavior often aligned with drought conditions. However, selling was not always followed by an immediate "buy-back" (positive y-values) following the drought. individuals not using forecasts exhibited stable buying/selling behavior after burn-in, largely decoupled from precipitation.*

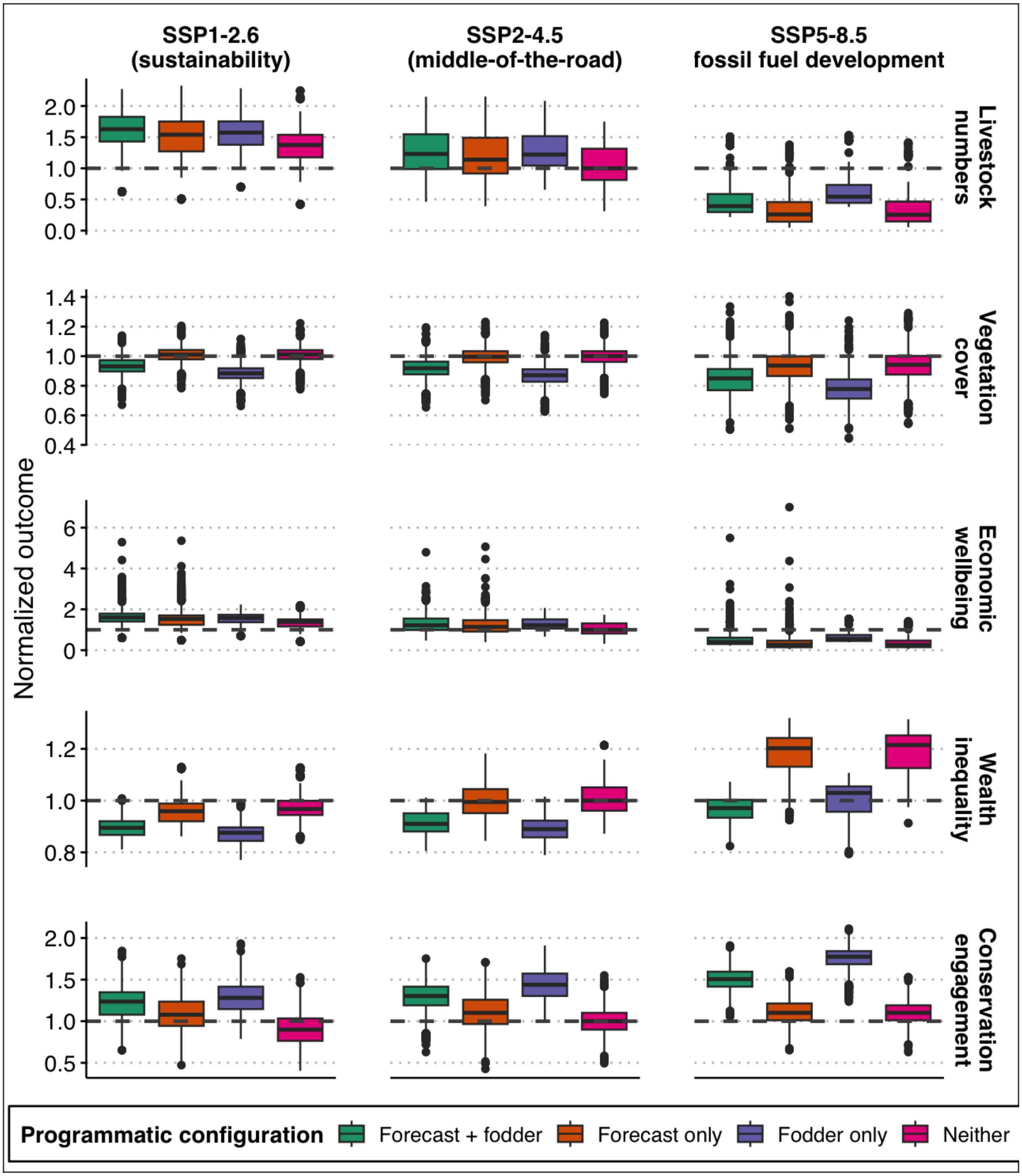

Figure S2*: *Livestock numbers, economic wealth, vegetation cover, and wealth inequality and conservation engagement outcomes for experiment three. *Boxplots show the values for each outcome for resulting from the last 30 iterations for each of 50 repetitions for the agent-based model run on each precipitation scenario and for each programmatic configuration. Outcome values are normalized by the median value of the 'Neither' configuration (baseline initiative) for the SSP2-4.5 scenario.*

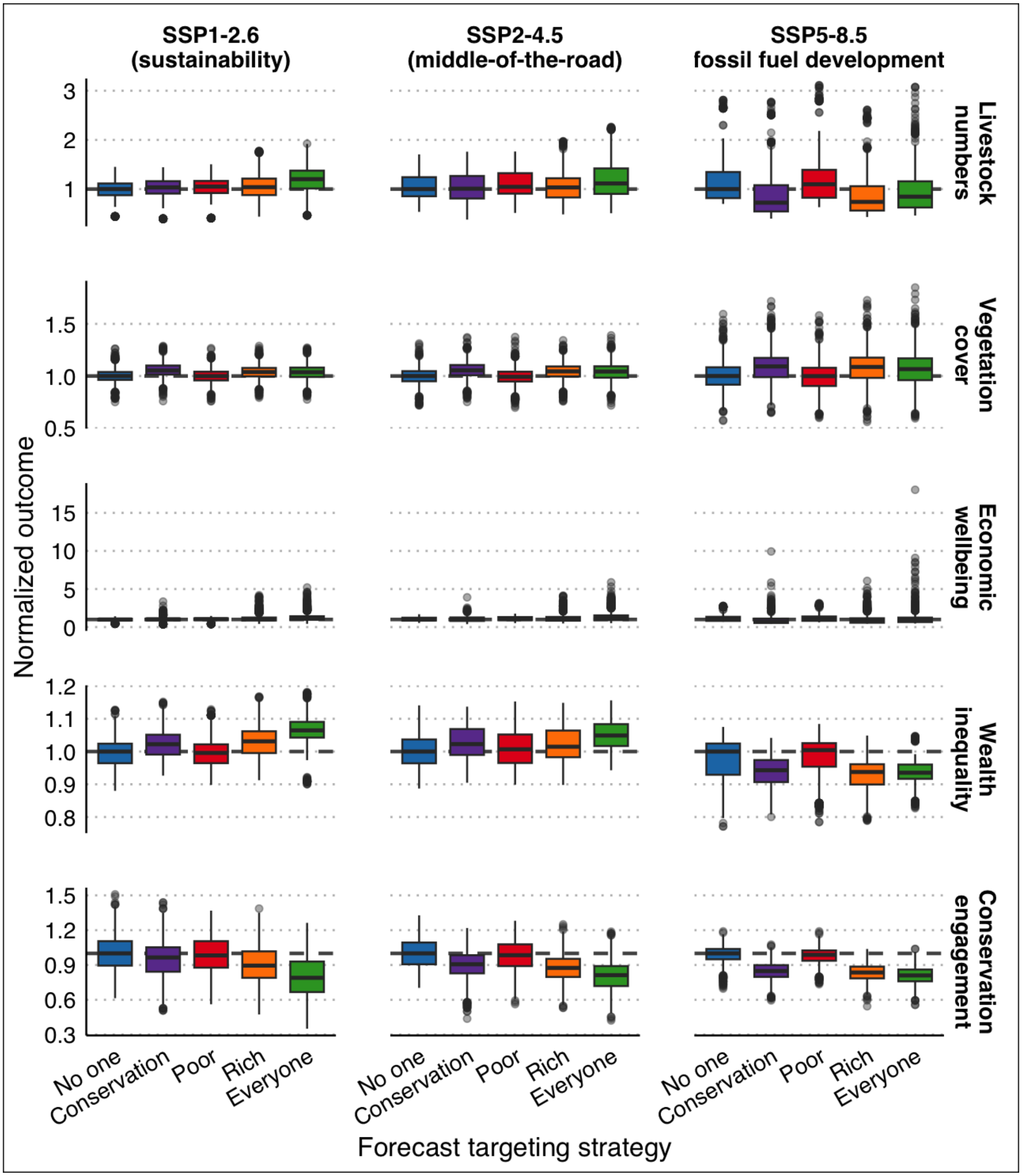

Figure S3: Outcome sensitivity to forecast targeting strategy. *Boxplots show the values for each outcome resulting from the last 30 iterations for each of 50 repetitions for the agent-based model run on each precipitation scenario and for each forecast targeting strategy. 'Poor' refers to a strategy in which forecasts were selectively distributed to communities in the lower 25% quantile of economic wealth; 'Rich' to communities in the upper 25% quantile. Values are normalized by median values of forecast targeting to "No one" for each precipitation scenario and each outcome variable. Model conditions include the distribution of supplemental fodder accompanying the conservation initiative.*

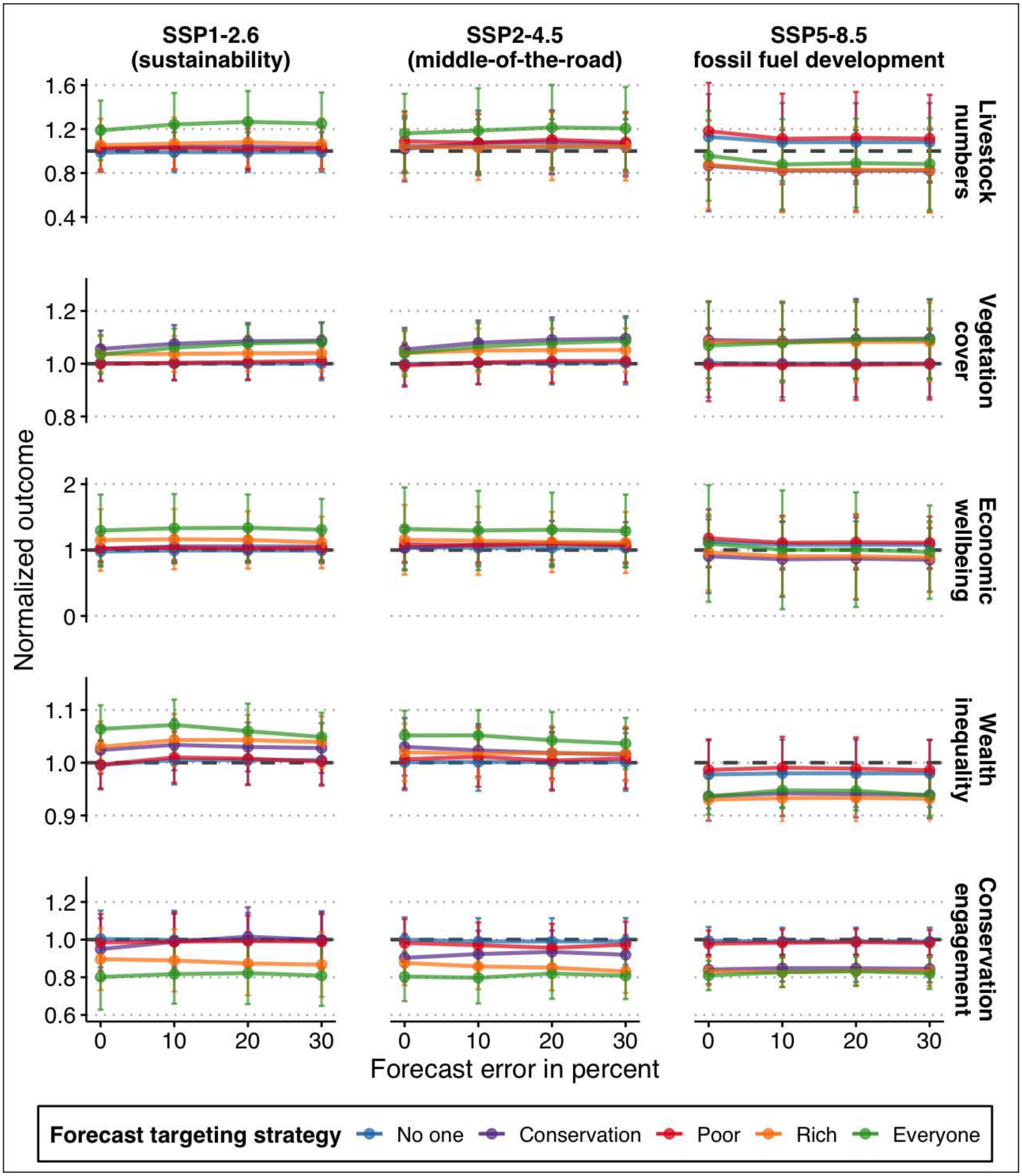

Figure S4: Model sensitivity to forecast precision. *Points and error bars show the mean and standard deviation of each outcome across the last 30 iterations and across 50 repetitions for each conservation initiative configuration and for each precipitation scenario. An initial engagement in the conservation initiative of 25% of communities is used across all scenarios and configurations. Outcomes are normalized by the median value of the 'Neither' configuration (baseline initiative) for the SSP2-4.5 scenario. Lines show the linear interpolation of the average outcome between levels of forecast precision for each scenario and each programmatic configuration.*

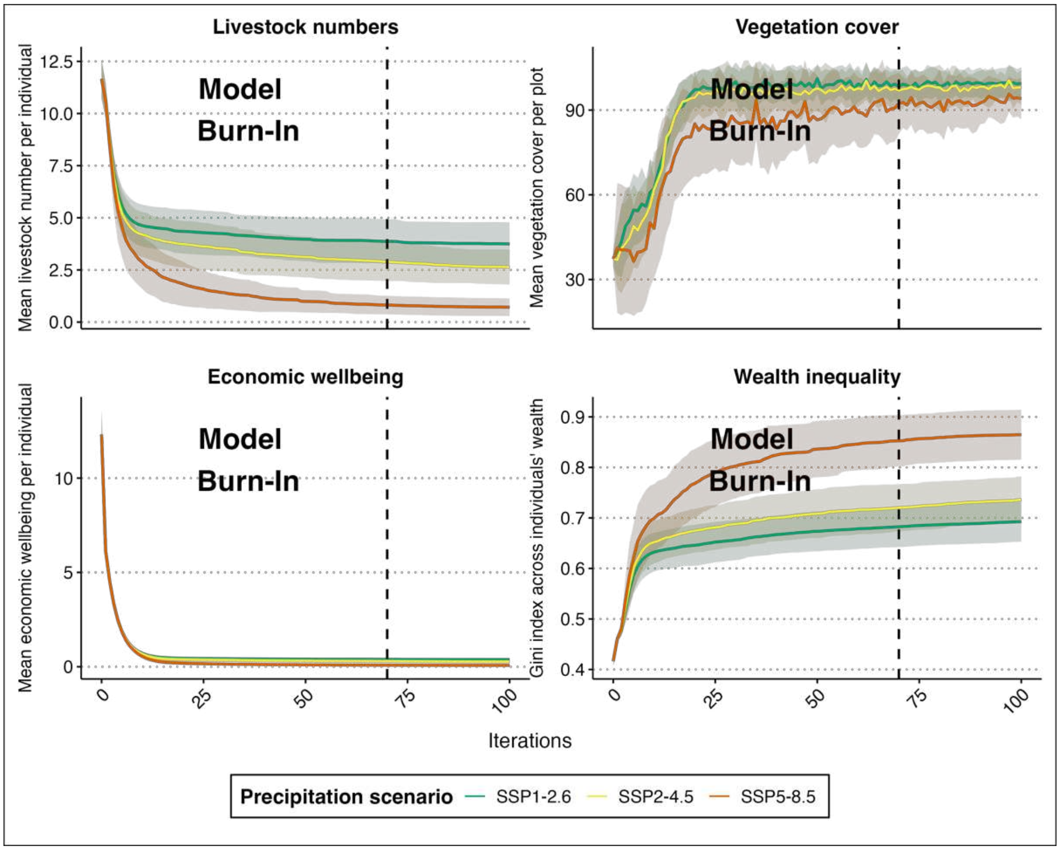

Figure S5: Visualization of model "burn-in" process. *Summarized model outcomes across 100 iterations during experiment one. Iteration 0 shows model summary statistics at initialization (T0). Colored lines and shading show the mean value and standard deviation for each precipitation scenario at each iteration, respectively. Dashed vertical line shows cutoff for values considered to be the "burn-in" period (left of the line) versus the stable outcome reported in the results (right of the line). Experiment one shown illustratively here; all experiments used the same process to identify model outcomes.*

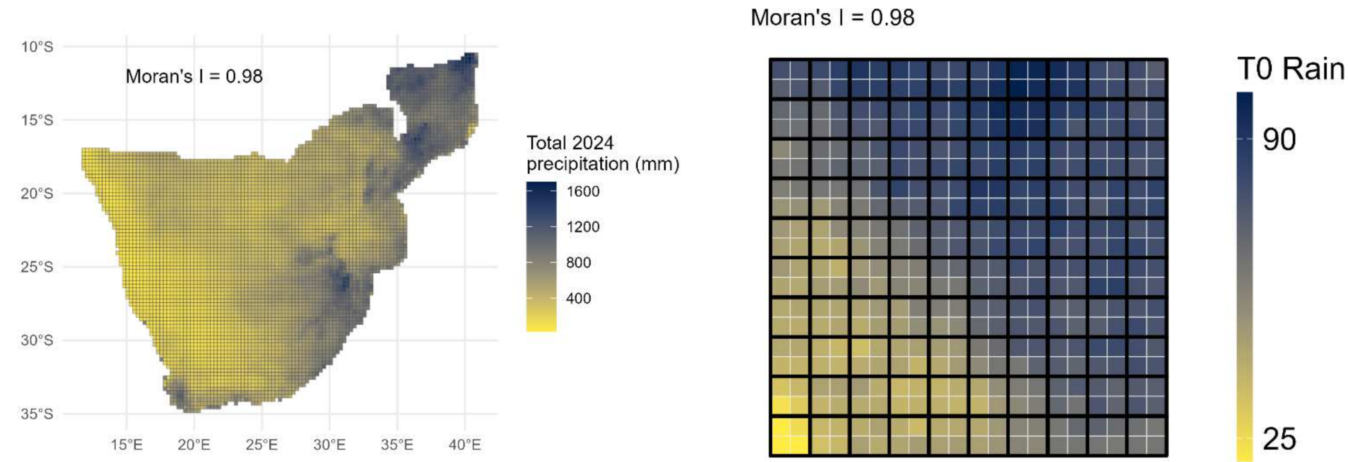

Figure S6: Empirical and stylized precipitation. *Visualization of empirical spatial autocorrelation of precipitation across our study region (2024) and how it is translated to the stylized landscape. To calculate empirical spatial autocorrelation we summarized annual precipitation values across 0.25° grid, then calculated the Moran's I for the entire area. For every repetition of the model, we initialized random precipitation across the stylized landscape with a tolerance of 0.025 around the empirical Moran's I. We use this Moran's I for all precipitation scenarios as the spatial autocorrelation is not expected to change under the various SSP scenarios used in this study.*

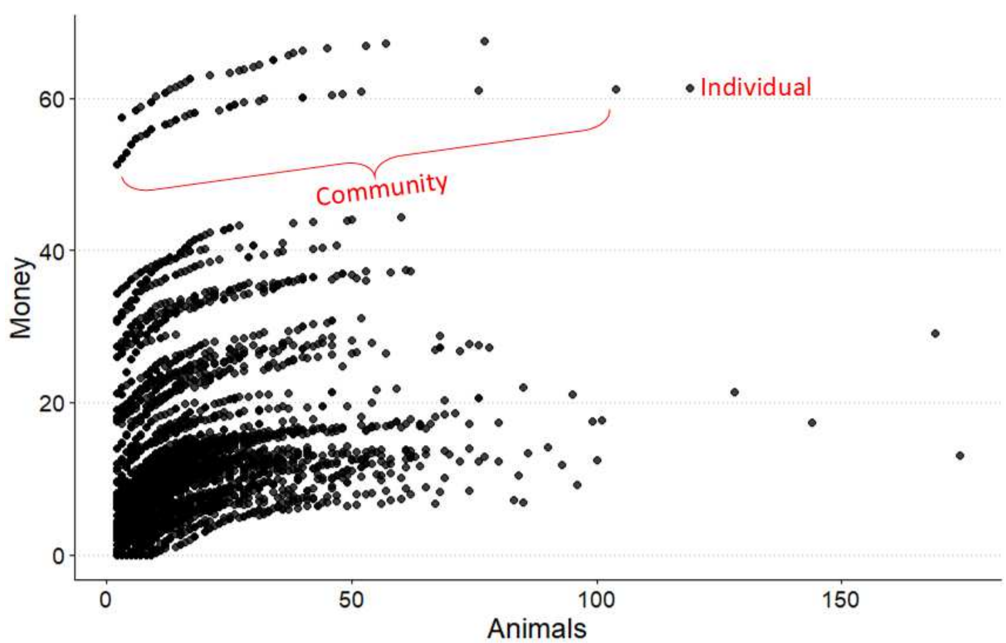

Figure S7: Simulated relationship between economic wellbeing (money) and herd size (animals). *Example distribution across the stylized landscape at initialization T0. Each point shows the values for a single individual. Exact values vary across repetitions as data are produced stochastically. As aligned with the empirical data across the study area, herd size and economic wellbeing are not correlated at the landscape scale but are highly correlated within communities.*

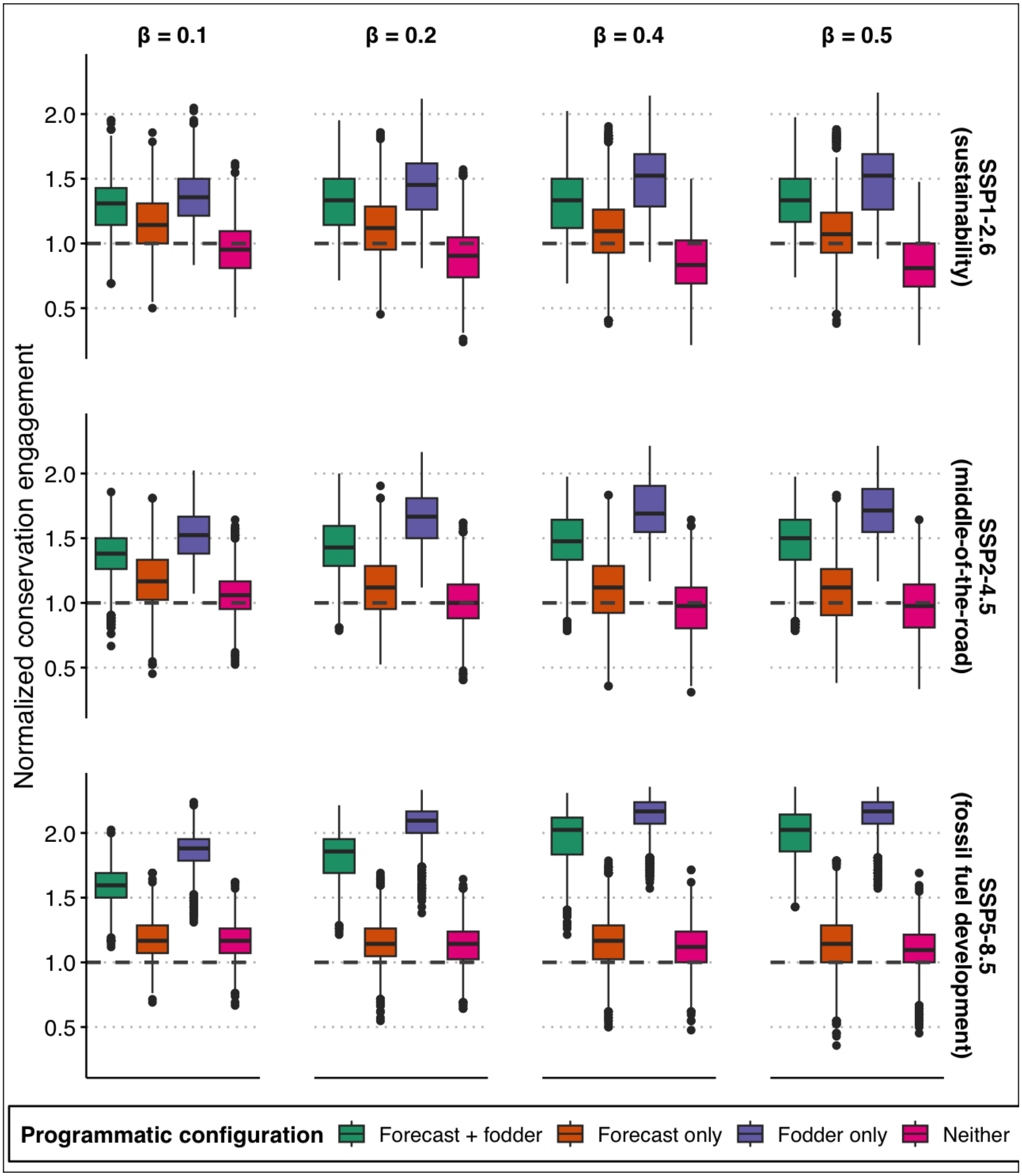

Figure S8: Sensitivity tests of model results in experiment three to different payoff bias values. *Each column shows the level of community engagement for varying payoff bias of beta = 0.1 (left; employed in experiment three) to 0.5 (right). Boxplots within one column show the level of community engagement with the conservation initiative resulting from the last 30 iterations for each of 50 repetitions for the agent-based model run on each precipitation scenario and for each programmatic configuration. Outcome values are normalized by the median value of the 'Neither' configuration (baseline initiative) for the SSP2-4.5 scenario across beta values.*

Supplementary Information 1:

SI 1.1 Code and Data Availability

All code and data used in this manuscript can be found at the repository here: https://github.com/matthewclark1223/RegenerativeRangelandManagementABM