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Minimizing climate change adaptation trade-offs in African rangelands

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Check for updates

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Climate change is intensifying precipitation variability in southern African rangelands, challenging existing systems of pastoral management. 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 that buffer livestock losses during poor rainfall years. Given empirical and projected conditions across seven southern African countries, we show that precipitation variability can reduce average economic well-being and worsen inequality among pastoralists; that, when 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 that 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.

Pastoralism is a vital component of livelihoods and cultures for hundreds of millions of people across Africa, practised on 43% of lands and involving the majority of the population in some countries[1]. 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[2–4]. Despite their adaptation to variability, climate change is expected to challenge African pastoral livelihoods by increasing the intensity, extent and duration of extreme events beyond levels experienced over the past centuries[5]. Increasing variability will be accompanied by changes in average temperatures, rainfall and the timing of seasonal onsets, all directly affecting the production of livestock[6,7]. 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 towards a more desirable state[8,9].

African pastoralists have a narrowing set of strategies for adapting to changing climatic conditions[10,11]. Traditional strategies include adjusting herd size, stockpiling or buying supplemental fodder, moving

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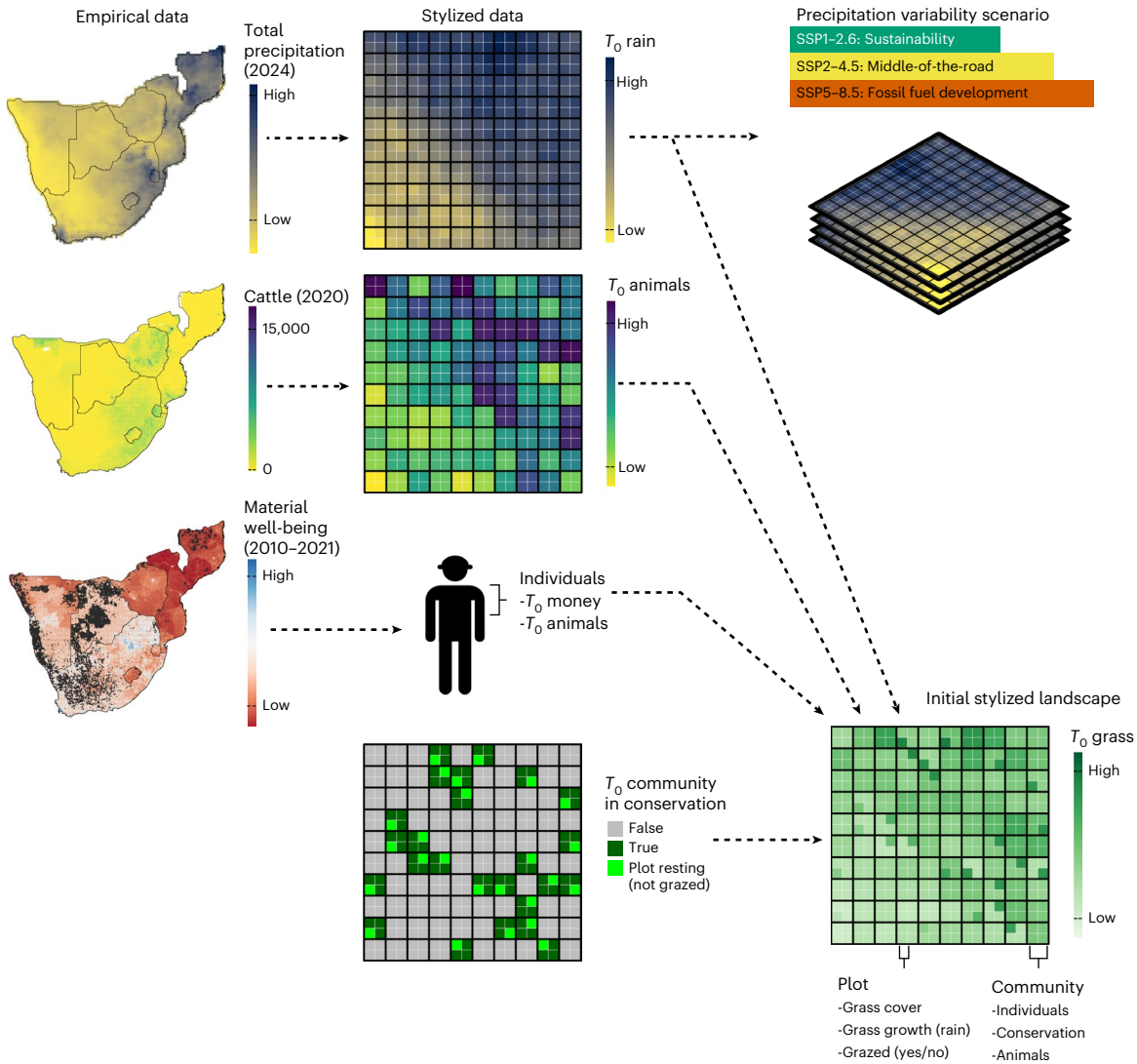


Fig. 1 | Overview of the relationships between the empirical data, stylized landscape and stylized precipitation scenarios underpinning the agent-based model used in this analysis. The empirical distributions of precipitation, cattle populations and community economic well-being across Botswana, Eswatini, Lesotho, Mozambique, Namibia, South Africa and Zimbabwe were used to create the stylized distributions (note that dark-grey pixels show areas without permanent human settlements or areas without adequate data). 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. T_0 values represent the values at model initialization. Credit: farmer icon, A. Oleynik, Noun Project under a Creative Commons licence CC BY 3.0.

animals across the landscape, or income diversification[12]. Although theory and some empirical cases suggest that further increasing mobility could help cope with increased variability and declining rainfall[13,14], roads and fencing greatly restrict movement in practice, especially in southern Africa, where drought risk is the greatest[15,16]. Climate change also undermines historical knowledge about the location and timing of water and pasture availability[17]. This increases risks of conflict with people and wildlife, making mobility a less viable adaptive strategy[18].

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 that nearly one-third rely on the prior season to predict rainfall, despite no scientific evidence supporting this approach[19]. 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[20,21].

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 conservation 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 programmes, 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[22]. One example is the Herding for Health initiative by Conservation International and Peace Parks Foundation. So far, this initiative has raised nearly US$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 conservation initiatives are rarely tested at scale, and evidence from other environments shows that assumed impact pathways require careful interrogation[23].

For example, the distribution of supplemental fodder is controversial; critics argue it inflates livestock numbers, harming natural

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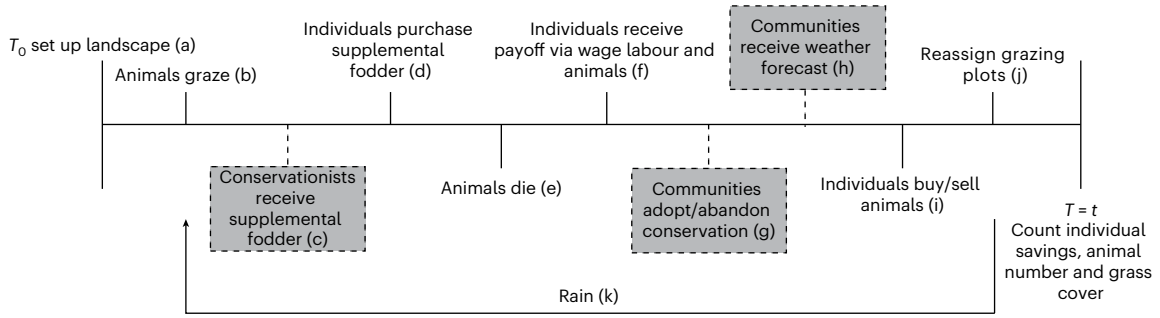


Fig. 2 | Overview of the ten modules run for each iteration in the agent-based model. Grey boxes highlight modules that vary across experimental conditions: supplemental fodder for individuals in conservation communities, group-level social learning of conservation adoption, and access to weather forecasts. 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 ($N = 3$ or4; 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 that is, 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 the plot with the lowest forage cover for protection from grazing in the next iteration; and (k) forage grows on the basis of rain received in each plot following a logistic growth function and rain following the specified spatiotemporal variability for each precipitation scenario.

vegetation and other large mammals[24]. While modelling 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[25]. Moreover, it is unclear how these interventions aimed at stabilizing livelihoods over space and time (that is, 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[26]. Recent developments in artificial intelligence show prospects for greater accuracy in the future, with Africa specifically targeted for improved weather services[27,28]. Most relevant to livestock management, precipitation forecasts are becoming more reliable[29] and allowing for accurate prediction of forage quantity and quality up to 3 months in advance, enabling the precise management of herd sizes[30]. 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.

This study uses three progressive simulation experiments to develop formal intuition (that is, reveal general dynamics and principles) about how climate change may influence vegetation cover, community economic well-being, average herd sizes and the distribution of wealth (that is, 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 well-being 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 (Fig. 2), 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.

In each experiment, we measure the expected changes in vegetation cover, non-livestock capital (that is, money; from here on referred to as 'economic well-being'), livestock numbers (that is, herd size) and wealth inequality resulting from differing sets of model conditions. Experiment 1 demonstrates these outcomes under each precipitation scenario in the absence of widespread conservation initiative implementation. Experiment 2 then imposes increasing proportions of conservation initiative implementation across the landscape, in combination with distribution of supplemental fodder and/or weather forecast use (that is, different programmatic configurations). This step isolates the potential benefits of these constituent interventions if they were implemented at scale, without yet considering the behavioural dynamics that affect their uptake. Experiment 3 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.

Results

In all three experiments, we tracked long-term, system-wide changes in livestock numbers, vegetation cover, average economic well-being 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). We emphasize that this modelling approach is designed to illustrate a small number of key dynamics rather than provide strict predictions across space and time.

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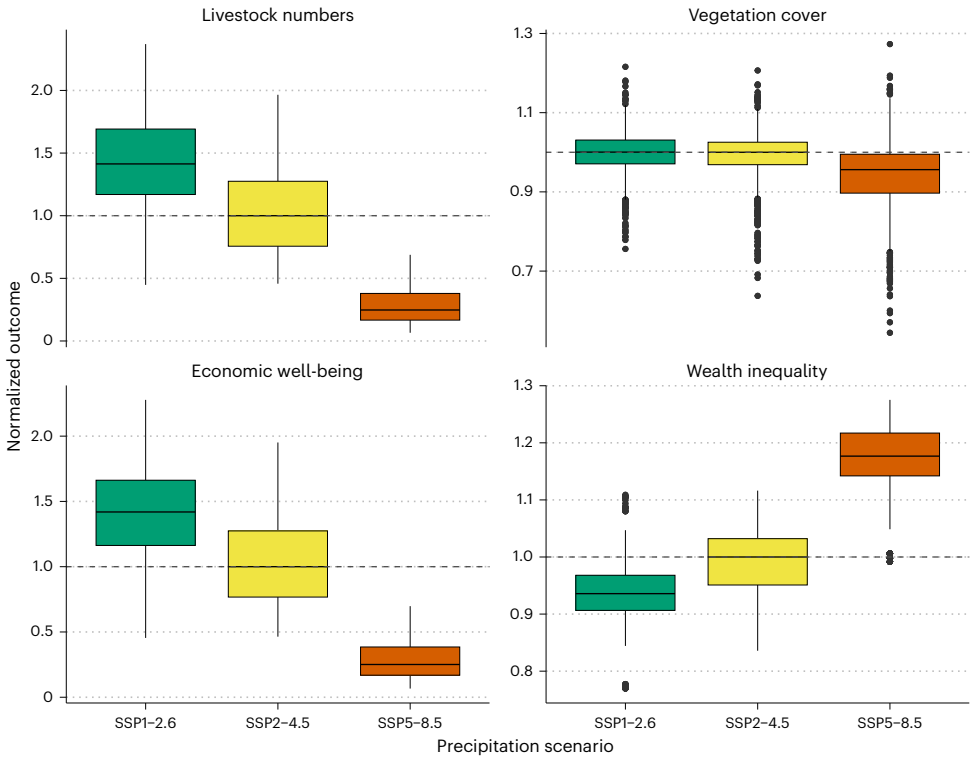


Fig. 3 | Results of experiment 1. Boxplots show the outcomes resulting from the last 30 iterations for each of 50 repetitions for the agent-based model run on each precipitation scenario; green, yellow and orange colouring indicate the SSP1–2.8, SSP2–4.5 and SSP5–8.5 scenarios, respectively. Horizontal black lines show median values. Boxes contain the inner 50% of the data, that is second and third quartiles. Whiskers show data within 1.5 times the interquartile range. Points show data outside 1.5 times the interquartile range. 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 1

Experiment 1 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 (that is, 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 well-being 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 inability of individuals to predict and respond to future increases in forage production. This manifests in a dynamic where, following seasons with poor precipitation and die-offs of livestock, spikes in vegetation growth are not matched by increased livestock numbers, buffering the average vegetation cover across time (Supplementary Fig. 1).

Experiment 2

Experiment 2 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 (that is, baseline conservation initiative), 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 well-being 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 well-being 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 conservation initiative alone. This programmatic configuration only meaningfully deviates from the baseline conservation initiative in the expected number of livestock on the landscape and average economic well-being for scenarios SSP1–2.6

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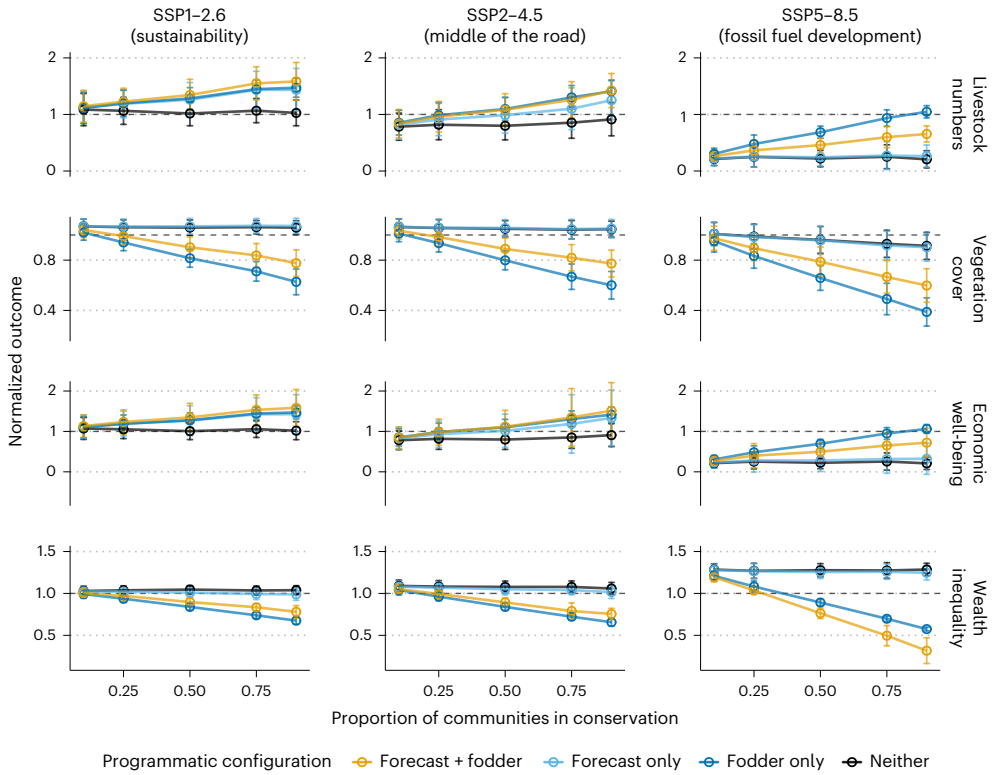


Fig. 4 | Results of experiment 2. Points and error bars show the mean and standard deviation of each outcome across the last 30 iterations and across 50 repetitions for each conservation initiative configuration and for each precipitation scenario. Outcomes are normalized by the median value of the 'Neither' configuration (baseline conservation 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.

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.

Pairing supplemental fodder with the adaptive use of weather forecasting mitigated loss in vegetation cover while maintaining meaningful gains in livestock numbers, economic well-being 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 trade-offs expected under climate change and inherent to the implementation of each intervention alone.

Experiment 3

In the final experiment, we allowed communities to observe their neighbours' 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 engagement or abandonment of the initiative, consistent with cultural evolutionary theory and evidence within other systems[31–33]. 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 behavioural 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 neighbouring communities place greater weight on visible livestock numbers than on less visible indicators (for example, 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 conservation initiative,

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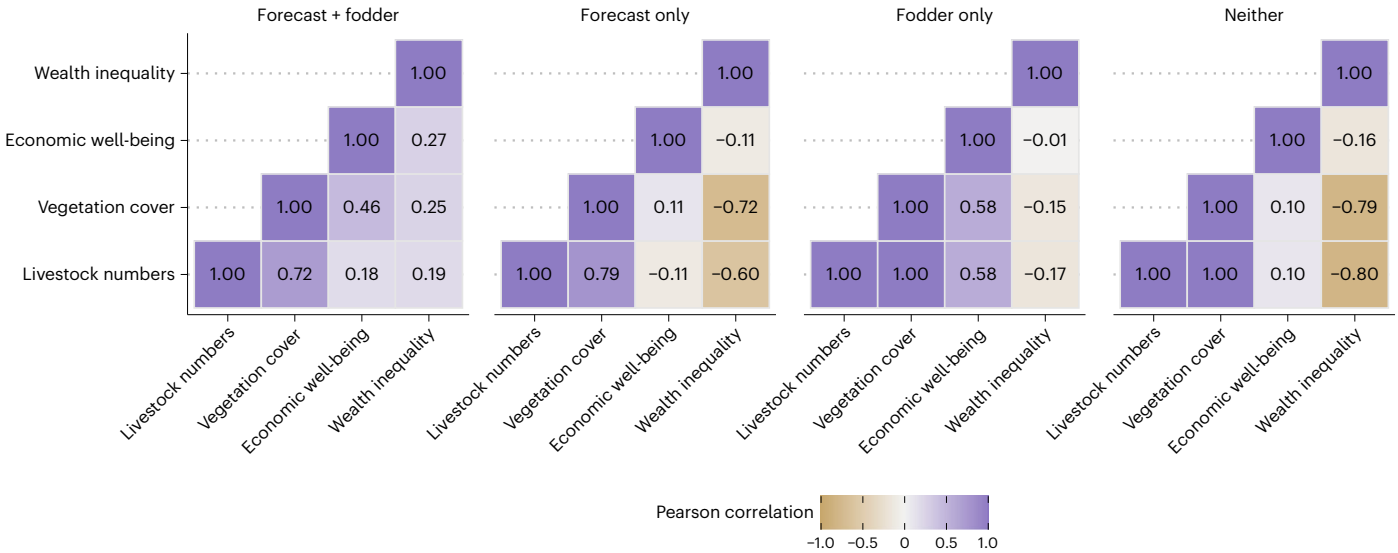


Fig. 5 | Trade-offs among outcomes under each programmatic configuration. Model outcomes when 50% of communities engaged in the conservation initiative in the SSP2–4.5 scenario. Yellow fill indicates a trade-off (negative association) between outcomes. Blue fill indicates complementary outcomes (positive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

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 initiative engagement and overall outcomes are not equivocal.

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. In addition, adaptive forecast use was applied to the richest quartile of communities, just the poorest quartile, and all communities, comparing these with 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 well-being, 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[34]. 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[35]. 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[25].

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[8]. 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[36]. 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[37].

Our research illustrates that, in human-modified landscapes such as rangelands, the effects of human decision-making can outweigh direct climatic effects. In Australian rangelands, for example, mean precipitation is the primary determinant of standing vegetation, yet

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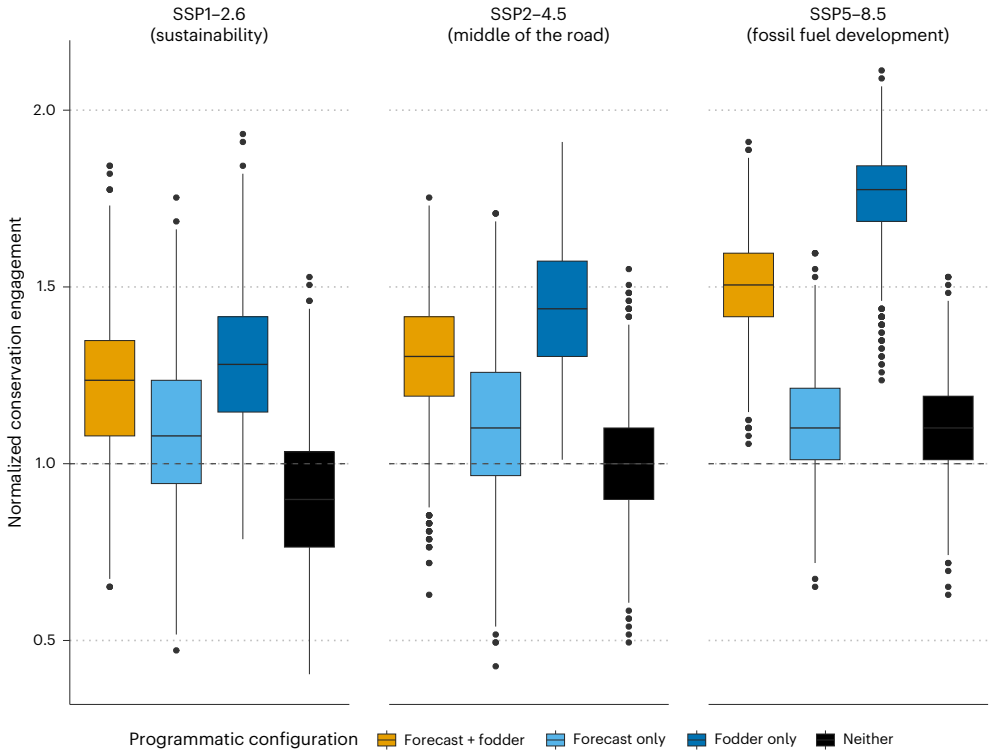


Fig. 6 | Results of experiment 3. Boxplots show the level of community engagement with the conservation initiative resulting from the last 30 iterations for each of 50 repetitions for the agent-based model run on each precipitation scenario and for each programmatic configuration. Horizontal black lines show median values. Boxes contain the inner 50% of the data, that is second and third quartiles. Whiskers show data within 1.5 times the interquartile range. Points show data outside 1.5 times the interquartile range. Outcome values are normalized by the median value of the 'neither' configuration (baseline conservation initiative) for the SSP2–4.5 scenario. Livestock numbers, economic well-being, vegetation cover and wealth inequality outcomes for this experiment can be found in Supplementary Fig. 2.

intra- and interannual precipitation variability are more determinative of stocking rates, ultimately determining final vegetation cover in some areas[38]. 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[10]. 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 outcomes (that is, the 'neither' scenario in Fig. 4), probably due to the tight coupling of livestock numbers and vegetation cover imposed by our framework. Studies similarly show that higher livestock density and increased grazing pressure negatively impact vegetation cover, condition and diversity in shrublands[39]; however, the vegetation responses in grassier biomes vary with management and climate[40]. 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[41].

Adaptive management decisions typically do not only account for rainfall and standing vegetation biomass, but also vegetation type, such as arid shrubland versus mesic grassland or savanna. The grazing capacity of an area is determined by species composition and species cover. 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[18], including increased stock theft during droughts[42], changes in policy, and categorical variation in household livelihood strategies[43] all do not systematically bias our findings. Similarly, we do not account for differences among livestock types (that is, cattle, sheep and goats), or spillover effects between livestock and wildlife populations, nor do we model the dynamics of leakage, as individuals move livestock to forage in neighbouring areas following the implementation of the conservation initiative[44]. More broadly, we assume that pastoralists and their livestock do not move between communities. Previous modelling 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[45].

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 suggesting that rangeland systems are themselves stable or should be managed towards equilibrium, especially under climate change. In particular, our experiments adjust the variance of precipitation while holding mean levels constant and introducing this variability as stationary over time. 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 modelling complex systems to avoid replicating our difficult-to-understand world with a difficult-to-understand model[46]. Instead, we suggest that researchers modify our model (using the available code; see 'Code availability' section) to isolate specific dynamics of interest, trimming away as much superfluous detail as possible. 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.

Alongside forecasting technology, gains are being made in direct observation of grasslands[47]. Continued private sector investment in image processing and Earth observation satellites 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 modelling 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[48,49]. A key challenge in this line of research will that individuals' perceptions of environmental change, and hence their resulting behaviours[50], may not necessarily match land cover changes observed in the satellite record[51].

In conclusion, variability in rainfall, vegetation cover and human well-being are increasing in southern Africa, 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 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[46,52–54]. We model all social dynamics as cognitively realistic, cultural evolutionary processes[9,55]. 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[56,57]. 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 (that is, 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 system behaviour in response to one annual wet season (that is, growing season). The reported outcomes are then summarized across the stationary iterations and 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 well-being distributions that approximate the highly unequal, exponential distributions found in southern Africa, as identified from the United Nations Food and Agricultural Organization's livestock of the world dataset and the NASA Deprivation Index, respectively[58,59]. 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 access only three of the four plots (rotational grazing).

Each plot receives an initial amount of precipitation that translates to a pregrazing 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[60] (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[61].

In the empirical data, community economic well-being and the number of livestock are uncorrelated at the landscape level but are highly associated within communities (see 'Code availability' and 'Data availability' sections). We approximate these patterns by randomly assigning the exponentially distributed values of average material well-being 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 (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 well-being (that is, 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

$$W_i = E_i + L_i. \tag{1}$$

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 well-being than wealth held elsewhere (for example, in a bank account; equation (2)). The total observed wealth for each individual is then defined as

$$P_i = W_i + 0.10 \times L_i. \tag{2}$$

To initialize a standing stock of behavioural 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 1 January 2050 to 31 December 2059, produced by the Max Planck Institute Earth System Model (MPI-ESM1.2-LR)[62]. We selected this model because it is tailored for comparison of outputs across SSP scenarios and has been shown to reflect mean precipitation estimates for our study region from the entire 'Phase Six of the Coupled Model Intercomparison Project' (CMIP6) ensemble[63]. 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, monthly precipitation data were resampled to a 0.25° grid and aggregated into austral summer totals (December, January and February), the primary wet period and period most sensitive to projected climate shifts in our study region[64]. For each SSP scenario, we calculated the year-to-year variance of the austral summer total precipitation for each grid cell. Cells with mean austral summer total precipitation below 3 mm were excluded to avoid artificially large variance arising from small absolute fluctuations in near-zero precipitation regimes. 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 interannual wet season precipitation variance projected for the empirical landscape under climate change. The projected SSP1–2.6 precipitation variance is comparable to pre-industrial levels (1850–1900)[64]. 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 wet 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 availability' and 'Data availability' sections).

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

$$F_c = \sum G_c. \tag{3}$$

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

$$F'_c = F_c - V_c \tag{4}$$

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

$$G' = \frac{F'_c}{\{3|4\}}. \tag{5}$$

We show in Supplementary Fig. 8 that following the first iteration, and thus, the first instance of grazing, the distribution of G' approximately matches the empirical distribution of natural and semi-natural grass height across the study region[47,65].

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 (that is, 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.

Under some experimental conditions, the conservation initiative includes the distribution of supplemental fodder (Figs. 4–6). In these cases, individuals with ten 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 (more than ten 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.

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 well-being (E_i). The price of supplemental fodder for one animal for one iteration is 20% of the price of an animal. This approximates the real cost to feed an animal for an entire year, inclusive of feed and supplement licking blocks.

All animals that did not get enough forage from the community plots did not receive supplemental fodder as part of the conservation initiative, and those 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

$$W_i = E_i + L_i - L'_i \tag{6}$$

and

$$P_i = W_i + 0.10 \times \left(L_i - L'_i\right), \tag{7}$$

respectively.

In each iteration, individuals receive 2% returns on both their economic well-being 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. The return on economic well-being represents gains made through wage labour 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.

In experiments 1 and 2, conservation behaviours are fixed exogenously. In experiment 3, 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 previously[66]. Specifically, the probability that a community adopts or continues engaging in conservation (A) in the next iteration is defined as

$$\Pr(A|A,B) = \frac{\exp(\beta \times \bar{P}_{A,t-1})}{\exp(\beta \times \bar{P}_{A,t-1}) + \exp(\beta \times \bar{P}_{B,t-1})} \tag{8}$$

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 neighbouring communities engaged in conservation in the current iteration. The sum of the total observed wealth of all neighbouring 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. 9).

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 (that is, 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 1, 2 and 3, 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).

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

$$\Pr(i \to j) = \frac{P_{j,t-1}}{\sum_{k=1}^{10} P_{k,t-1}}, \text{only if } P_{j,t-1} > P_{i,t-1}. \quad (9)$$

This implementation results in sigmoidal payoff bias based on the total observed wealth values (that is, 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 well-being (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.

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.

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 nonlinear effects on vegetation growth at the landscape scale[6]. 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

$$G_{t+1} = G' + r \times R \times G' \times \left(1 - \frac{G'}{K}\right) \quad (10)$$

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 (that is, centring 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 (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.

Reporting summary

Further information on research design is available in the Nature Portfolio Reporting Summary linked to this article.

Data availability

All data used in this Article are available via Zenodo at https://doi.org/10.5281/zenodo.21549680 (ref. 67).

Code availability

All analyses were done using R V4.5.1. All code used in this Article is available via Zenodo at https://doi.org/10.5281/zenodo.21549680 (ref. 67).

References

1. FAO. *Pastoralism in Africa's Drylands* (Food and Agriculture Organization of the United Nations, 2018).
2. Chiaravalloti, R. M. & Dyble, M. Limited open access in socioecological systems: how do communities deal with environmental unpredictability? *Conserv. Lett.* **12**, e12616 (2019).
3. Robinson, L. W. Open property and complex mosaics: variants in tenure regimes across pastoralist social–ecological systems. *Int. J. Commons* **13**, 804–826 (2019).
4. Schlüter, M., Tavoni, A. & Levin, S. Robustness of norm-driven cooperation in the commons. *Proc. R. Soc. B* **283**, 20152431 (2016).
5. Masson-Delmotte, V. et al. *IPCC, 2021: Climate Change 2021: The Physical Science Basis. Contribution of Working Group I to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change* (IPCC, 2021).
6. Arena, G., Hoffman, M. T., van der Merwe, H. & O'Connor, T. Expansion of the Grassland Biome in the eastern Karoo corresponds with changes in rainfall and livestock numbers. *Afr. J. Range Forage Sci.* **40**, 1–19 (2023).
7. Thornton, P. K., Ericksen, P. J., Herrero, M. & Challinor, A. J. Climate variability and vulnerability to climate change: a review. *Glob. Chang. Biol.* **20**, 3313–3328 (2014).
8. Alexander, S. & Block, P. Integration of seasonal precipitation forecast information into local-level agricultural decision-making using an agent-based model to support community adaptation. *Clim. Risk Manag.* **36**, 100417 (2022).
9. Schill, C. et al. A more dynamic understanding of human behaviour for the Anthropocene. *Nat. Sustain.* **2**, 1075–1082 (2019).
10. Clark, M. et al. Community wellbeing moderates drought adaptation in South African rangelands. *J. Environ. Manage.* **393**, 127066 (2025).
11. Ntombela, K. P. et al. Pastoral coping and adaptive management strategies to climate change in communal areas in Namibia and South Africa. *Pastor. Res. Policy Pract.* **14**, 13548 (2024).
12. Letsoalo, N. et al. Coping and adapting to drought in semi-arid Karoo rangelands: key lessons from livestock farmers. *J. Arid Environ.* **219**, 105070 (2023).

13. Martin, R., Müller, B., Linstädter, A. & Frank, K. How much climate change can pastoral livelihoods tolerate? Modelling rangeland use and evaluating risk. *Glob. Environ. Change* **24**, 183–192 (2014).
14. Samuels, M. I., Allsopp, N. & Hoffman, M. T. Traditional mobile pastoralism in a contemporary semiarid rangeland in Namaqualand, South Africa. *Rangel. Ecol. Manag.* **72**, 195–203 (2019).
15. McGahey, D. J. Livestock mobility and animal health policy in southern Africa: the impact of veterinary cordon fences on pastoralists. *Pastor. Res. Policy Pract.* **1**, 14 (2011).
16. Trancoso, R. et al. Significantly wetter or drier future conditions for one to two thirds of the world's population. *Nat. Commun.* **15**, 483 (2024).
17. Tugjamba, N., Walkerden, G. & Miller, F. Adapting nomadic pastoralism to climate change. *Clim. Change* **176**, 28 (2023).
18. Kennedy, W. G. et al. An agent-based model of conflict in East Africa and the effect of watering holes. In *Proc. 19th Conference on Behavior Representation in Modeling and Simulation* 274–281 (BRiMS Committee, 2010).
19. Guido, Z. et al. Farmer forecasts: impacts of seasonal rainfall expectations on agricultural decision-making in Sub-Saharan Africa. *Clim. Risk Manag.* **30**, 100247 (2020).
20. Turner, M. A., Moya, C., Smaldino, P. E. & Jones, J. H. The form of uncertainty affects selection for social learning. *Evol. Hum. Sci.* **5**, e20 (2023).
21. Demps, K., Herzog, N. M. & Clark, M. From mind to matter: patterns of innovation in the archaeological record and the ecology of social learning. *Am. Antiq.* **89**, 19–36 https://doi.org/10.1017/aaq.2023.71 (2023).
22. Arena, G. & Hawkins, H.-J. Nearly six decades of grazing research published by the Grassland Society of Southern Africa: trends, recommendations and gaps. *Afr. J. Range Forage Sci.* **42**, 25–40 (2025).
23. O'Garra, T. et al. National-level evaluation of a community-based marine management initiative. *Nat. Sustain.* **6**, 908–918 https://doi.org/10.1038/s41893-023-01123-7 (2023).
24. Hess, K. & Holechek, J. L. Policy roots of land degradation in the arid region of the United States: an overview. *Environ. Monit. Assess.* **37**, 123–141 (1995).
25. Schulze, J., Frank, K. & Müller, B. Governmental response to climate risk: model-based assessment of livestock supplementation in drylands. *Land Use Policy* **54**, 47–57 (2016).
26. Ritchie, H. & Roser, M. Weather forecasts have become much more accurate; we now need to make them available to everyone. *Our World Data* https://ourworldindata.org/weather-forecasts (2024).
27. Ebert-Uphoff, I. & Hilburn, K. The outlook for AI weather prediction. *Nature* **619**, 473–474 (2023).
28. Lamptey, B. et al. Challenges and ways forward for sustainable weather and climate services in Africa. *Nat. Commun.* **15**, 2664 (2024).
29. Gibson, P. B. et al. Training machine learning models on climate model output yields skillful interpretable seasonal precipitation forecasts. *Commun. Earth Environ.* **2**, 1–13 (2021).
30. Pringle, M. J. et al. Using remote sensing to forecast forage quality for cattle in the dry savannas of northeast Australia. *Ecol. Indic.* **133**, 108426 (2021).
31. Clark, M. et al. Forecasting adoption with epidemiological models can enable adaptively scaling out conservation. *One Earth* https://doi.org/10.1016/j.oneear.2024.08.017 (2024).
32. Pienkowski, T. et al. Conservation abandonment is a policy blind spot. *Nat. Ecol. Evol.* **10**, 14–17 https://doi.org/10.1038/s41559-025-02910-5 (2025).
33. Rivera-Hechem, M. I. et al. Exploring pathways to the persistence of community engagement in co-management across social-ecological conditions. *Conserv. Lett.* **19**, e70050 (2026).
34. de Lange, E. et al. A global conservation basic income to safeguard biodiversity. *Nat. Sustain.* **6**, 1016–1023 (2023).
35. Andrews, J. et al. Seasonality in cash income drives illegal resource extraction: evidence from Zanzibar. *Zenodo* https://doi.org/10.5281/zenodo.13908797 (2024).
36. Smaldino, P. E. et al. Information architectures: a framework for understanding socio-technical systems. *npj Complex* **2**, 13 (2025).
37. Perreault, C., Moya, C. & Boyd, R. A Bayesian approach to the evolution of social learning. *Evol. Hum. Behav.* **33**, 449–459 (2012).
38. Godde, C. et al. Climate change and variability impacts on grazing herds: insights from a system dynamics approach for semi-arid Australian rangelands. *Glob. Chang. Biol.* **25**, 3091–3109 (2019).
39. Nenzhelele, E., Todd, S. W. & Hoffman, M. T. Long-term impacts of livestock grazing and browsing in the Succulent Karoo: a 20-year study of vegetation change under different grazing regimes in Namaqualand§. *Afr. J. Range Forage Sci.* **35**, 277–287 (2018).
40. Oomen, R. J. et al. Effect of management on rangeland phytomass, cover and condition in two biomes in South Africa. *Afr. J. Range Forage Sci.* **33**, 185–198 (2016).
41. Teague, R. & Kreuter, U. Managing grazing to restore soil health, ecosystem function, and ecosystem services. *Front. Sustain. Food Syst.* **4**, 534187 (2020).
42. Bahta, Y. T., Jordaan, A. & Muyambo, F. Communal farmers' perception of drought in South Africa: policy implication for drought risk reduction. *Int. J. Disaster Risk Reduct.* **20**, 39–50 (2016).
43. Dressler, G. et al. Implications of behavioral change for the resilience of pastoral systems—lessons from an agent-based model. *Ecol. Complex.* **40**, 100710 (2019).
44. Andrews, J., Hillis, V., Clark, M. & Mulder, M. B. Adaptive responses to inter-group competition over natural resources: the case of leakage. *Ecol. Soc.* **30**, 16 (2025).
45. Okayasu, T., Okuro, T., Jamsran, U. & Takeuchi, K. An intrinsic mechanism for the co-existence of different survival strategies within mobile pastoralist communities. *Agric. Syst.* **103**, 180–186 (2010).
46. Smaldino, P. *Modeling Social Behavior: Mathematical and Agent-Based Models of Social Dynamics and Cultural Evolution* (Princeton Univ. Press, 2023).
47. Parente, L. et al. Annual 30-m maps of global grassland class and extent (2000–2022) based on spatiotemporal Machine Learning. *Sci. Data* **11**, 1303 (2024).
48. Clark, M., Andrews, J., Kolarik, N., Omar, M. M. & Hillis, V. Causal attribution of agricultural expansion in a small island system using approximate Bayesian computation. *Land Use Policy* **137**, 106992 (2024).
49. Jørgensen, A. C. S. et al. Forecasting the adoption and spread of a community-based marine management initiative using agent-based models. Preprint at *bioRxiv* https://doi.org/10.1101/2024.06.16.599026 (2024).
50. Clark, M., Hamad, H. M., Andrews, J., Hillis, V. & Mulder, M. B. Effects of perceptions of forest change and intergroup competition on community-based conservation behaviors. *Conserv. Biol.* **38**, e14259 (2024).
51. Clark, M. et al. A productive friction: leveraging misalignments between local ecological knowledge and remotely sensed imagery for forest conservation planning. *Conserv. Sci. Pract.* **6**, e13247 (2024).
52. Railsback, S. F. & Grimm, V. *Agent-Based and Individual-Based Modeling: A Practical Introduction* (Princeton Univ. Press, 2012).
53. Schlüter, M. et al. Toward a methodology for explaining and theorizing about social-ecological phenomena. *Curr. Opin. Environ. Sustain.* **39**, 44–53 (2019).

54. Schwarz, N. et al. Formalising theories of human decision-making for agent-based modelling of social-ecological systems: practical lessons learned and ways forward. *SocioEnviron. Syst. Model.* **2**, 16340 (2020).
55. Boyd, R. & Richerson, P. J. *Culture and the Evolutionary Process* (Univ. Chicago Press, 1985).
56. Andrews, J., Clark, M., Hillis, V. & Borgerhoff Mulder, M. The cultural evolution of collective property rights for sustainable resource governance. *Nat. Sustain.* **7**, 404–412 https://doi.org/10.1038/s41893-024-01290-1 (2024).
57. Mesoudi, A. A Darwinian Theory of Cultural Evolution Can Promote an Evolutionary Synthesis for the Social Sciences. *Biol. Theory* **2**, 263–275 (2007).
58. Center For International Earth Science Information Network-CIESIN-Columbia University. *Global Gridded Relative Deprivation Index (GRDI), version 1* (NASA Socioeconomic Data and Applications Center (SEDAC), 2022).
59. Robinson, T. P. et al. Mapping the global distribution of livestock. *PLoS ONE* **9**, e96084 (2014).
60. Funk, C. et al. The climate hazards infrared precipitation with stations—a new environmental record for monitoring extremes. *Sci. Data* **2**, 150066 (2015).
61. Gardiner, M., Mogane, L. & Mfazwe, P. *Long-term Conservation Stewardship Data for the Namakwa District, the Greater Kruger Region, and the Alfred Nzo District: 2019–2024* (Conservation South Africa, 2024).
62. Gutjahr, O. et al. Max Planck Institute Earth System Model (MPI-ESM1.2) for the High-Resolution Model Intercomparison Project (HighResMIP). *Geosci. Model Dev.* **12**, 3241–3281 (2019).
63. Lim Kam Sian, K. T. C. et al. Projections of precipitation extremes based on bias-corrected Coupled Model Intercomparison Project phase 6 models ensemble over southern Africa. *Int. J. Climatol.* **42**, 8269–8289 (2022).
64. Engelbrecht, F. A., Steinkopf, J., Padavatan, J. & Midgley, G. F. In *Sustainability of Southern African Ecosystems under Global Change. Ecological Studies* (eds. von Maltitz, G. P. et al.) vol 248, 169–190 https://doi.org/10.1007/978-3-031-10948-5_7 (Springer, 2024).
65. Hunter, M. O. et al. Global 30-m annual median vegetation height maps (2000–2022) based on ICESat-2 data and machine learning. *Sci. Data* **12**, 1470 (2025).
66. Barrett, B. J. Equifinality in empirical studies of cultural transmission. *Behav. Processes* **161**, 129–138 (2019).
67. Fröhner, C. & Clark, M. matthewclark1223/Regenerative RangelandManagementABM: PublicationRelease. *Zenodo* https://doi.org/10.5281/zenodo.21549680 (2026).

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Author contributions

M.C. conceived the idea, designed the model, wrote the paper and conducted background field investigation. C.F. designed and conducted the experiments, oversaw scientific reproducibility and edited the paper. M.M. oversaw the project, acquired funding and edited the paper. A.C.S.J., P.E.S. and J.A. advised with model and experimental design, advised on sensitivity analyses and edited the paper. T.P. advised on model conception and implementation and edited the paper. S.Y., A.I., O.C. and G.A. assisted in background field investigations, provided ethnographic insight, provided data for calibrating the model and edited the paper. I.T.G. identified relevant public datasets, performed checks on the reproducibility of the analyses and edited the paper.

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Competing interests

The authors declare no competing interests.

Additional information

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Reporting on sex and gender	We include no data nor modeled representation of sex or gender
Reporting on race, ethnicity, or other socially relevant groupings	We include a peer-reviewed, satellite-derived measure of community material welbeing. This is calculated as a relative index and displayed & summarized in raster format.
Population characteristics	The population relevant to this study includes all individuals engaged in pastoralism practices across Botswana, Eswatini, Lesotho, Mozambique, Namibia, South Africa, and Zimbabwe
Recruitment	We did not recruit subjects for this study
Ethics oversight	This study does not require ethics approval as it uses exclusively publicly-available data

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Study description	We develop a stylized, simulated landscape and population of pastoralists derived from empirical distributions across southern Africa. We then run sequential agent-based experiments on this simulated population, using expected changes in precipitation across the region as a backdrop for the modeled processes.
Research sample	We collected remotely-sensed and other publicly available data from across southern Africa.
Sampling strategy	Our data include full observations across the study region and are not sampled.
Data collection	All data used are open-source.
Timing and spatial scale	Precipitation scenarios are 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. The study area covers all of Botswana, Eswatini, Lesotho, Mozambique, Namibia, South Africa, and Zimbabwe.
Data exclusions	In calculating cell-level precipitation variance, cells with mean austral summer total precipitation below 3 mm were excluded to avoid artificially large variance arising from small absolute fluctuations in near-zero precipitation regimes.
Reproducibility	All analyses can be reproduced using the data and code in the repository here: https://doi.org/10.5281/zenodo.21549680
Randomization	Each repetition of our agent-based model begins with a stochastically-generated distribution of covariates across the simulated landscape. We rely on the pseudo-randomization native to R to implement this.
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