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Research

Indigenous climate adaptation sovereignty in a Zimbabwean agro-pastoral system: exploring definitions of sustainability success using a participatory agent-based model

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ABSTRACT. Indigenous peoples are experiencing a wide range of negative impacts due to climate change and should have the right to determine for themselves how to adapt to these changes and define successful adaptation. These adaptations can then be culturally appropriate and grounded in Indigenous knowledge systems; however, the accelerating rate of change in social-ecological systems can be a challenge for traditional knowledge. Appropriate participatory modeling tools such as agent-based models (ABMs) may be of assistance to Indigenous groups in thinking through how systems may change in the future. Using the Zimbabwe Agro-Pastoral Management Model (a community-based ABM cocreated with farmer-researchers in Mazvihwa Communal Area), we explored how different definitions of sustainability affected the conclusions from the model, including average annual harvest and the persistence of resources (livestock, harvest, and woodland biomass) in the modeled system above minimum thresholds. For very low persistence thresholds, these two measures of success traded off against each other (with higher cropland proportions favoring harvest success and lower cropland proportions favoring persistence success); and different combinations of management interventions favored one or the other definition of sustainability. New insights came from community suggestions of higher persistence thresholds for livestock, crops, and woodland, whereby the model suggested that an intermediate proportion of cropland could be most successful. In all cases, higher year-to-year rainfall variation reduced sustainability success, regardless of the definition or thresholds used. Cocreating, cotesting, and coadaptation of the model and the use of multiple definitions rendered the findings more relevant for local application. The community in Mazvihwa has many ways to adapt to challenging circumstances, and local nongovernmental organization The Muonde Trust has used the model to work with local leaders to support collective action on land use planning to protect woodland from deforestation.

Key Words: *community-based research; Indigenous climate sovereignty; Indigenous knowledge systems; local ecological knowledge; participatory modeling; traditional ecological knowledge; Zimbabwe Agro-Pastoral Management Model*

INTRODUCTION

Indigenous peoples have contributed disproportionately little to recent climate change through their typically low-carbon lifeways, and yet many Indigenous peoples are currently experiencing disproportionately large impacts on their ecosystems and cultures (Raygorodetsky 2017). These impacts include the potential loss of culturally essential species (Grah and Beaulieu 2013), higher health risks (Doyle et al. 2014), infrastructure damage (Cochran et al. 2014), lessened availability of traditional foods (Lynn et al. 2014), declining water quantity (Cozzetto et al. 2014) and quality (Patrick 2018), and higher economic vulnerability (Gautam et al. 2014). Indigenous groups are typically highly aware of the complex impacts of climate change, and some have been since precolonial times (Aryal et al. 2016, Nursey-Bray et al. 2019, Simonetti 2019).

In the face of these disproportionate impacts, some Indigenous communities are crafting their own strategies to adapt (Gautam et al. 2014, Patrick 2018, Mashizha 2019, Nyahunda and Tirivangasi 2019), in some cases even shaping the policies that constrain them in developing their own adaptation strategies (Maldonado et al. 2014, Voggesser et al. 2014). For climate adaptation plans to be effective and appropriate, Indigenous people need to be deeply involved in their development at all scales: regionally, nationally, and globally (Cochran et al. 2014). Ideally, the state and other stakeholders then play a supportive role for communities engaging in their own culturally grounded adaptation actions (Richards et al. 2019). We refer to this strategy as "climate adaptation sovereignty," an elaboration of "climate sovereignty" (Smith 2017), which is intended to emphasize self-determination in identifying, adapting to, and rectifying climate impacts, all in ways appropriate to Indigenous territories and cultures. In the context of this paper, we focus on the idea that Indigenous peoples have the right to develop their own solutions and practices for climate change adaptation, and as part of this sovereignty, they have the right to define what success and sustainability look like for themselves.

These community-based climate adaptation plans are best grounded in the community's own knowledge of their system (Davidson-Hunt et al. 2012, Turner and Spalding 2013); however, assessing successful climate adaptation using traditional Indigenous knowledge systems (IKS) may be difficult. Within Indigenous communities there may be a range of levels of awareness of the potential impacts of climate variability (Herman-Mercer et al. 2016, Hossain and Paul 2019) and differences in understanding its causes (Boillat and Berkes 2013, Ahmed and Atiqul Haq 2019). Nevertheless, Indigenous groups

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are observing rapid transformations in the last few decades in the form of changing weather and timing of seasonal plant and animal behaviors (Cochran et al. 2014, Raygorodetsky 2017, Shaibu et al. 2019). Some Indigenous people are finding that their traditional climate indicators no longer work to predict, for example, when to plant, as climate change shifts systems away from historical patterns (Roncoli et al. 2002); this can erode faith in Indigenous knowledge systems to predict weather (Nyahunda and Tirivangasi 2019). There is therefore concern that the typically long-term accumulation methods of IKS may be impaired by the accelerating pace of climate change (Ebhuoma and Simatele 2019).

Many Indigenous groups have become interested in combining traditional knowledge with Western scientific knowledge, when this is done appropriately (Roncoli et al. 2002) and builds on existing Indigenous knowledge (Mapfumo et al. 2016). IKS may benefit from contemporary techniques such as community-based modeling, particularly when exploring the uncertain potential future behavior of social-ecological systems (d'Aquino and Bah 2014). Integrating participatory research with climate models can therefore help enhance adaptive capacity, potentially connecting traditional knowledge with a new generation of Indigenous practitioners as well as outsider climate modeling researchers to develop appropriate adaptation strategies (Valdivia et al. 2010). Modeling potential system impacts with communities can produce knowledge that has the richness of place-based knowledge, but also the advantages of the potential to scale up results (Ford et al. 2019). Agent-based models (ABMs) created using a participatory process (Voinov and Bousquet 2010, Étienne 2013, Barreteau et al. 2017) can be used to respectfully combine local knowledge with Western scientific knowledge and thereby better represent social-ecological systems (Müller et al. 2007, Castellani et al. 2019). ABMs can integrate knowledge with widely varying quantification and can be used to explore how systems may respond to interventions and changes in underlying system drivers (Spies et al. 2017), including possible behaviors under novel conditions. Community-based ABMs can therefore be useful tools for the development of Indigenous-led climate adaptation strategies.

The Zimbabwe Agro-Pastoral Management Model (ZAPMM; Eitzel et al. 2018) is an ABM originally developed in partnership between Zimbabwean nongovernmental organization The Muonde Trust and allied outsider researchers. Muonde is engaged in developing, supporting, and spreading Indigenous innovations in their part of rural Zimbabwe (and beyond), and ZAPMM was intended to facilitate community discussions regarding management interventions and climate change. Initial academic research on ZAPMM focused on quantitative and qualitative validation of the model (Eitzel et al. 2020) and though it was useful to the community, the original version used only a single set of definitions of system sustainability (out of necessity because of the complexity of the model and scope of evaluating and validating it). In the spirit of Indigenous climate adaptation sovereignty, with this study we extend the analysis of ZAPMM to investigate a wider range of sustainability definitions inspired by further conversation with Muonde. We ask, via the model, how definitions of sustainability affect the assessment of Muonde's Indigenous climate adaptations.

METHODS

Mazvihwa Communal Area, Zimbabwe, and The Muonde Trust

ZAPMM was intended to represent the agro-pastoral system in Mazvihwa Communal Area, Midlands Province, south-central Zimbabwe. Mazvihwa is classified in the lowest-potential agricultural zone of the country, and has a semiarid climate with highly variable within-year and between-year rainfall. Farmer-pastoralists living in the Communal Area have survived despite these conditions using a variety of strategies to manage livestock, crops, and woodland grazing areas. They have historically been able to maintain large livestock herds in this grazing area, which also holds importance as a source of medicines, wild foods, and spiritual significance. Over time, however, local land use choices have decreased the amount of woodland grazing area in favor of increasing agricultural production (Fig. 1).

Fig. 1. Study system: Mazvihwa Communal Area, Zimbabwe. Agro-pastoralists have survived in the driest regions of Zimbabwe by innovating in both the past and present; however current concerns include declining woodland grazing area (green region near the top of the image) as agricultural production has increased over time (bottom half of image). The Zimbabwe Agro-Pastoral Management Model was created to explore potential system behavior under a variety of rainfall variation scenarios and combinations of management interventions. See Appendix 1 for additional images representing the study system and recent Indigenous innovations. (Photo credit: Moses Ndlovu)

The Muonde Trust is a local nongovernmental organization governed and staffed by people from around Mazvihwa. The community-based research team currently includes approximately 30 individuals from a range of clans and backgrounds, with more women members than men. This team has been developing and promoting a variety of Indigenous innovations that use agro-ecological principles to increase agricultural productivity (Appendix 1). Through community-based research, Muonde seeks to answer questions regarding the consequences of both existing management techniques as well as newly developed interventions on the sustainability of their agro-ecosystem.

Data sources and modeling process

The Muonde research team has been recording data on a variety of aspects of their agro-pastoral system, including many of these management interventions, over multiple decades. From the 1980s through the 2010s, the team has conducted a variety of semistructured and open-ended interviews and surveys to collect information on farming, animal husbandry, and ecological restoration practices (Wilson 1990). The team has also measured growth rates of woodland trees after clear-cutting and coppicing, fencing consumption rates by termites, amounts of fencing material used, and other factors influencing the sustainability of different system elements. In addition, outsider researchers have partnered with the community-based research team to assist with field measurements and interviews, as well as analysis of aerial imagery. The team has also archived rainfall data. See Eitzel et al. (2020) for a detailed description of these data sources.

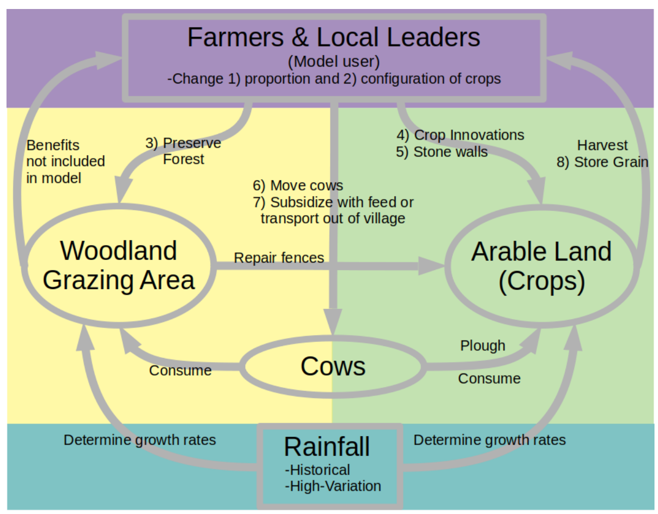
ZAPMM is the result of a modeling process intended to provide discussion support for Muonde and the local community to determine how much land should be allocated to arable production and how much land to leave as woodland grazing area. Initial stages of model construction involved Muonde's cofounders and a team of outsider researchers, with outsider-driven technical implementation but collaborative model design and calibration using Muonde's archive of community-based data. We then held workshops with the whole Muonde research team in small and large groups to collaboratively verify and discuss the model. Ultimately the model was adapted and structurally validated through this process: it contained all the important aspects of the system with appropriate causal mechanisms (Qudrat-Ullah 2012). In addition, the model was practically validated as a useful tool for Muonde to discuss land use planning with local leaders (Saam 2019). We also attempted to behaviorally validate the model by directly comparing the harvests and livestock numbers with Muonde's data (Barlas 1989), and found that while harvests matched relatively well, livestock numbers tended to be much lower than in the actual system (Eitzel et al. 2020). We take this difference into account in the below analyses.

Description of Zimbabwe Agro-Pastoral Management Model (ZAPMM)

ZAPMM was written in NetLogo (Wilensky 1999), representing the scale of Mudhomori village in Mazvihwa (600 hectares in size), broken down into a 50 x 50 grid of NetLogo patches; each patch is therefore 0.24 ha. Model runs lasted at most 60 calendar years (the length of our rainfall data time-series), with a discrete 8-hour time step to allow for management actions to happen several times within a day. The Indigenous innovations of interest to Muonde most directly impact three system components, which we represented in our model as "cows" (NetLogo agents, including both male and female animals and representing livestock in general), "crops" (NetLogo patches, including any type of crop), and "woodland" (namely savannah; also NetLogo patches). In the model, these entities interact in the following ways: cows plough crops, woodland provides fencing material for crops, and cows eat crops and woodland (Fig. 2). Cows also reproduce according to a simple two-stage population model (adults and calves) with a constant probability of reproduction for each adult cow agent in a single model time step.

Both outsider researchers and the Muonde team were concerned with possible impacts of climate change on Mazvihwa's agro-pastoral system, so we modeled two rainfall scenarios: one using the historical yearly rainfall data time-series ("historical"), and one drawing from a zero-truncated normal distribution with the same mean as the historical rainfall data and 1.5 times the standard deviation ("high-variation"), representing the potential for increased year-to-year variation in rainfall predicted by climate models downscaled for Southern Africa (Shongwe et al. 2009, Jury 2013).

Fig. 2. Diagram showing the key components of the Zimbabwe Agro-Pastoral Management Model. Cows are modeled explicitly as agents in the model, while crops and woodland grazing area are NetLogo patches. Arrows show ways in which one component affects another component: crops depend on cows through ploughing, crops depend on woodland for fencing material, cows depend on woodland or crops for food intake, and cows reproduce periodically. Rainfall determines many modeling behaviors in a bottom-up fashion by influencing how much biomass is available in the system: we simulate a historical rainfall scenario as well as a high-variation scenario (representing potential increased rainfall variation due to climate change). Farmers and local leaders, role-played by the model user through the model interface, control a variety of aspects of the system in a top-down fashion via a variety of management interventions. (Modified from Eitzel et al. 2018, 2020.)



The Indigenous innovations included in the model are listed in Table 1 and numbered in Figure 2. They are implemented in the model through an interface designed as a computer-mediated roleplay, whereby the user explores the impacts of possible management decisions made by farmers and local leaders in the real system. Intervention 1, "proportion crops," was the central question driving the creation of the model, while interventions 3-5 ("preserve forest," "crop innovations," and "stone walls") represent recent innovations promoted by Muonde, and interventions 6-8 ("move cows," "subsidize cows," and "store grain") are management strategies historically employed by farmers in Mazvihwa. (See Eitzel et al. 2020 for analysis of intervention 2, "spatial configuration," which we do not address here.)

Table 1. Management interventions represented in the Zimbabwe Agro-Pastoral Management Model.

Management Intervention	Model Values	Description
(1) Proportion Crops	1–99% of land area (continuous)	Proportion of land used for arable production (the remainder is left as woodland grazing area)
(2) Spatial Configuration[†]	Moran's I of -0.6 - 0.95 (continuous)	How clumped together crops are, ranging from one large group of crop patches to a chess-board-like pattern scattered throughout the woodland
(3) Preserve Forest	Yes (10% of patches)/No	Increase the number of woodland patches that grow faster (including sacred forest or *rambotemwa*)
(4) Crop Innovations	Yes (10% of patches)/No	Increase the growth rate of crops on some patches through water harvesting techniques or by planting drought-tolerant small grains
(5) Stone Walls	Yes/No	Make field borders stone in order to prevent livestock from breaking in to eat the crops, and avoid cutting down forest biomass in the process
(6) Move Cows	Yes (1/day)/No	Drive cows from one part of the woodland to another where there is more biomass for grazing
(7) Subsidize Cows[‡]	Feed, Transport, or None	Either provide supplemental feed for 70% or 100% of livestock or move them to grazing areas outside the village
(8) Store Grain	Yes (3 years)/No	Store harvest for multiple years, allowing a bumper crop surplus in one year to even out a drought in the next year

[†]We do not address spatial configuration in this paper and average over all possible crop configurations; see Eitzel et al. (2020) for results regarding spatial configuration.
[‡]Subsidy is only applied in years of low rainfall, or less than 400 mm. This results in subsidy during 27% of model years for historical rainfall, and about 34% of model years for high-variation rainfall. Simulations with subsidized cows are still vulnerable to boom-and-bust population cycles during years when cows are not subsidized.

The model also conserves biomass and energy across trophic levels, with metabolic efficiency losses from producer to consumer, energy densities of different kinds of biomass, and a required minimal biological maintenance energy for cows (Molden 2013). We use a linear relationship between rainfall and plant growth (as observed in these Southern African ecosystems; Rutherford 1978) for both crops and woodland with a nonzero intercept for crops. After an initialization period for the simulation to move past any transient behavior dependent on initial conditions, we track several metrics during each model calendar year: number of cows, amount of crop harvested (in metric tons), and amount of woodland biomass (in metric tons).

Definitions of model sustainability: persistence and annualized average harvest

We used NetLogo's BehaviorSpace functionality to explore a range of combinations of management choices; see Eitzel et al. (2020) for the details and results of these parameter sweeps. To explore how definitions of sustainability change the way we view ZAPMM's results, we analyzed two specific outcomes for a given model run: (1) system persistence for all 60 years and (2) average annualized harvest. Average annual harvest is included as a measure of sustainability at the suggestion of one of Muonde's founders, who pointed out that food sovereignty in the context of a weak national economy is central for this community, while their challenge is to achieve this without compromising the long-term persistence of their system. We defined persistence as a set minimum amount of cows, woodland, and harvest at the end of every model year; we calculated average annualized harvest by dividing total accumulated harvest by the number of years before the modeled system dropped below any of the persistence thresholds (if it did so).

Average annualized harvest was therefore a shorter term measure of sustainability: a particular run could maximize harvest at the expense of livestock numbers or woodland biomass and only last a few years but with potentially excellent harvest, resulting in a value of "not persistent" and a high annual harvest for that run. In contrast, persistence was a longer term measure of sustainability: a model run might last all 60 calendar years with cows, crops, and woodland above the persistence thresholds, while the average harvest over that time might be correspondingly lower (representing a classic resilience trade-off).

From a climate adaptation sovereignty perspective, the people of Mazvihwa should define their own persistence thresholds: what constitutes "enough" harvest, cows, or woodland for a village the size of Mudhomori (approximately 100 households in 2013). Through interviews with the Muonde research team, we established minimum thresholds of 50 cows, 48 metric tons of harvest, and enough woodland biomass to replace Mudhomori's current amount of brushwood fencing (280 metric tons of woodland biomass). However, we know from the team's historical data that in recent decades the system has had years of zero harvest and years with as few as five cows in Mudhomori village. In the interest of exploring the sensitivity of our model's results to the definition of these persistence thresholds, we allowed the minima to range from the Muonde team's thresholds down to "biologically-based" minima: two cows (in order to reproduce), one adult woodland tree as a seed source (0.02 metric tons), and enough crop harvest to reseed a field (0.06 metric tons). Eitzel et al. (2020) used these biologically minimal thresholds and give details on the calculations of these minima. Both the average annual harvest and the persistence model outcomes depend on these threshold definitions: for example, if the thresholds are high, then the model will not persist very long, and the harvest will not have enough time to accumulate.

Sensitivity, graphical, and tabular analysis

We illustrate the practical importance of Indigenous climate adaptation sovereignty by comparing the results when preferring maximum harvest versus maximum persistence, or for different persistence threshold definitions. For the biologically minimal persistence thresholds, we test the sensitivity of the average annual harvest variable to all the same model parameters we examined for persistence in Eitzel et al. (2020), using the same methods (see Appendix 2 for details of the generalized additive model used to test sensitivity). Also for biologically minimal thresholds, to assess how the two outcomes (persistence and average annual harvest) traded off for different proportions of crops, we averaged over other interventions and divided the model runs into bins of proportion-crops, graphically representing them for both historical (as a baseline) and high-variation rainfall scenarios.

We can order each combination of the six categorical management interventions (numbered 3–8 in Table 1) by their degree of success based on either definition (harvest or persistence). We assessed the practical importance of using the community's definitions by examining how different the two rankings are, i.e., how much the definition matters in suggesting which intervention combinations are "best." We calculated the average persistence and annual harvest for all simulations in each of the 64 possible combinations of these interventions and ranked each combination in terms of highest to lowest persistence, and highest to lowest average annual harvest. We compared the "best" combinations to each other, and also calculated Kendall's Tau for the two lists. Tau is typically used as a nonparametric test of correlation (ranging from 1 for two identical lists to -1 for reversed lists), so a significant Tau means that the two lists are more similarly ordered than a random ordering. We know that our two outcomes are correlated (because the way they are constructed depends on each other), so we expect Tau to be significantly different than 0. We also use Tau to understand how different the lists are from each other by examining the effect size, asking how our Tau value compares with lists that are only slightly different from each other, e.g., a list with each consecutive pair of items swapped. These analyses were performed in R (R Core Team 2018).

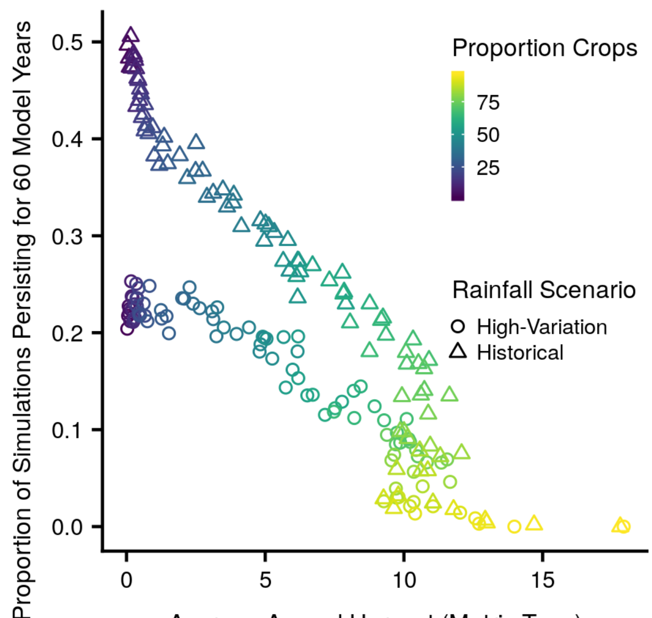
To explore the sensitivity of both outcomes (persistence and average harvest) to different definitions of persistence varying between the biological minima up to Muonde's minima, we used a script in Python (Python Software Foundation 2018) to post-process the model outputs of our parameter sweep. No new NetLogo code was created for this analysis, but rather we randomly selected a persistence threshold independently for cows, crops, and woodland for each of our model runs, and used them to determine whether each model run had persisted all 60 calendar years and what the average annual harvest was for the duration it persisted. We did this 10 times and aggregated the results to average over possible variation in the procedure. We then graphically examined how the evaluation of the most sustainable crop proportion depended on each threshold.

RESULTS

Annual harvest and system persistence suggest different optimal crop proportions

For biologically minimal thresholds (as in Eitzel et al. 2020), the relationship between model persistence and average annual harvest is largely inverse (Fig. 3). Using only the persistence definition, the system is more sustainable for very low proportions of crops and produces very low average harvest, while the harvest definition points to success at very high crop proportions, which result in zero models persisting all 60 model years. There is a compromise at a threshold around 10 metric tons of annual harvest, where persistence can range from hardly any models persisting up to almost 20% of models persisting; this corresponds to around 50–60% proportion-crops. Thus choosing to use either or both measures of sustainability would suggest a different optimal crop proportion.

Fig. 3. Proportion of models that persisted for 60 model-years versus the average annual harvest for those models (using biologically minimal persistence threshold definitions). Each point is a bin of proportion crops (95 bins), with average annual harvest averaged within that bin and proportion of models persistent calculated for those in that bin. Proportion-crops is shown using the color scale: lighter is higher. The inverse trend in the points implies a trade-off between persistence and average yield, and the generally direct relationship between proportion-crops and average annual harvest is reflected in the lightening color as points move to the right. This analysis averages over all other management interventions.



Rankings of intervention combinations differ for persistence and harvest definitions

Like crop proportion, the most sustainable combinations of management interventions were different according to the two different outcome variables (for biologically minimal thresholds). For both rainfall scenarios, the top-ranked intervention for one sustainability definition was lower-ranked for the other definition (Table 2; see Appendix 3 for full tables with all 64 possible combinations, ranked in order by either harvest or persistence.) These results align with a comparison of the single-variable sensitivity analysis results for annual harvest (Appendix 2) and persistence (Eitzel et al. 2020): storing grain had the biggest positive effect on sustainability regardless of the definition of sustainability, but crop innovations and stone walls were

Table 2. Top management intervention combinations as determined by either persistence or average annual harvest definitions, for both rainfall scenarios. This analysis averages over proportion crops.

Stone Walls	Move Cows	Subsidize Cows	Crop Innovations	Preserve Forest	Store Grain	Percentage Persistent Value (Rank)	Average Harvest Value (Rank)
Historical Rainfall Scenario							
	X	X		X	X	81.58 (1st)	3.76 (34th)
X		X	X		X	30.13 (28th)	14.84 (1st)
High-Variation Rainfall Scenario							
X	X	X		X	X	41.04 (1st)	3.65 (32nd)
X		X	X		X	24.25 (16th)	14.67 (1st)

unhelpful for persistence and helpful for average annual harvest, while preserving forest and moving cows to better grazing were helpful for persistence and unhelpful for harvest.

Comparing the full ranked lists, the Kendall's Tau value was 0.43 for the historical rainfall scenario and 0.47 for the high-variation rainfall scenario, which is an intermediate level of correlation (that is, the two lists are still quite different from each other). For comparison, our lists' Kendall's Tau is smaller than Tau for lists with consecutive items swapped relative to the original (0.97) and for lists with each element swapped 16 positions away (0.49; see Appendix 3 Table A3.5 for more examples). The rankings of intervention combinations from our two measures of sustainability success are more different than these examples, though they are significantly more similar than two random ranked lists ($p < 0.001$), as expected.

Different persistence threshold definitions suggest different optimal crop proportions

As requirements for persistence became more stringent, fewer and fewer models were able to meet these criteria; at Muonde's desired persistence thresholds, few if any models persist (see Appendix 4 for additional discussion of which thresholds are most responsible for this effect). This is likely due to ZAPMM's omission of many additional Indigenous adaptations, and the fact that quantitative validation indicated that it produced cow counts much lower than the real system. For model runs that do persist, those with proportion-crops set to intermediate values tend to have higher persistence, with largest values in the range of 30–50%. Proportion-crops otherwise has little interdependence with cow or woodland thresholds in terms of their collective effect on persistence, though there is slightly higher persistence for lower proportion-crops as the cow threshold is raised (more woodland is needed to sustain a larger cow population). The harvest threshold does have a predictable effect: as the threshold becomes higher, models with lower proportion-crops will not be able to generate enough harvest and these become automatically not persistent (Fig. 4).

Effect of higher variation rainfall

Across all results, higher variation rainfall results in worse outcomes, regardless of the definition of sustainability. The patterns described above hold for both historical and higher variation rainfall (Figs. 3-4, Table 2).

DISCUSSION

We examined two different ways to expand sustainability definitions in ZAPMM: comparing persistence with average annual harvest, and altering minimum persistence threshold values. We asked what the model has to say about ideal crop proportions and combinations of other management interventions. The spirit of ZAPMM was always to generate discussion and create connections between what the model is able to represent and what is locally understood to be happening in the real agro-pastoral system in Mazvihwa. We therefore offer first a discussion of the model's outcomes, and then offer historical context for our sustainability definitions and discuss a wider range of adaptations employed in Mazvihwa.

Insights from ZAPMM on definitions of sustainability

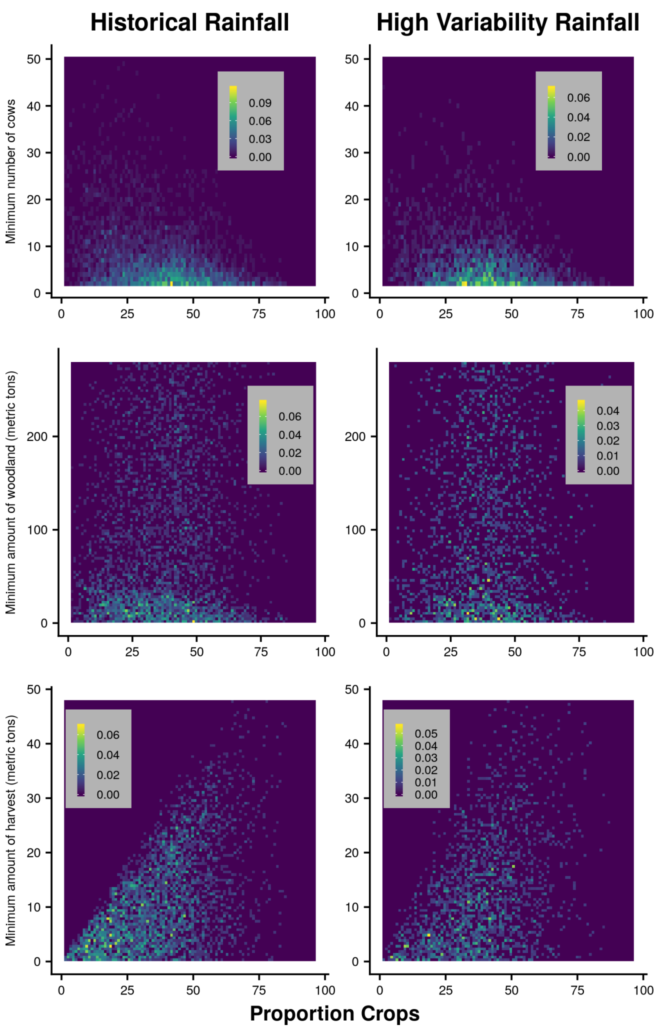
One clear finding from the model is that intermediate crop proportions enhance persistence while balancing the need for adequate harvest (visible in both Figs. 3 and 4). This is a key point for Muonde, addressing their initial concern regarding community land use planning to constrain ongoing conversion of woodland to fields. Notably, only examining the behavior of the model for biologically minimal persistence thresholds (as we did in Eitzel et al. 2020) did not reveal this pattern. And even for biologically minimal thresholds, using different definitions of sustainability (persistence and harvest) highlight different combinations of categorical management interventions as successful. Agriculture-focused interventions like crop innovations contribute to higher harvest, and a wider variety of interventions including preserving forest contribute to higher persistence.

High-variability scenarios are systematically worse in both outcomes (see Appendix 4 Fig. A4.1), reinforcing concerns that climate change will worsen the difficulty of choosing between different definitions of sustainability: the only way to get similar persistence in the high-variability scenario is to be willing to accept lower average annual harvest (Fig. 3). The model also indicates that more interventions may be necessary to achieve a persistence level similar to the historical case (See Appendix 3, Tables A3.1 and A3.3: the best persistence, 41.04%, corresponds to five interventions in the high-variation case, and for a similar persistence level in the historical case, 41.00%, only three interventions are needed). Because higher rainfall variability due to climate change worsens outcomes, it becomes increasingly critical to consider multiple ways of assessing and enhancing sustainability.

Historical context for sustainability definitions in Mazvihwa

The actual minima in the community's dataset indicate that there have historically been many fewer livestock than Muonde's desired threshold (the minimum was 5; Muonde's desired minimum threshold was 50), and that the lowest harvest was lower

Fig. 4. Trade-off between desired persistence thresholds and proportion of land allocated to crops. Historical rainfall scenarios are shown on the left, and high-variability rainfall scenarios shown on the right. Each cell represents the percentage of models persistent within a small range of proportion crops and a small range of one of the persistence thresholds: minimum number of cows (top), minimum amount of woodland (middle), and minimum harvest (bottom); each cell is colored by the proportion of simulations that persisted for all 60 model-years (see each key for appropriate color scale). The percentage of models persistent is much lower than in Figure 3 because we have randomly selected persistence thresholds for each simulation (96,000 model runs) and repeated this process 10 times, and for higher persistence thresholds, dramatically fewer models persist all 60 years. This analysis averages over all other management interventions.



than their desired threshold (there were drought years with no harvest; Muonde's threshold was 48 metric tons), so in reality, the community in Mazvihwa has been obliged to sustain their system with lower thresholds than their stated model goals (by drawing on external resources). During this time period, the agro-ecosystem' resources have been drawn down as well, which the research team and local farmers have observed in a variety of ways (for example, the amount of land set aside for woodland grazing has been steadily declining). There have been extremely difficult times for the community as well (long droughts, need for outside aid, high mortality due to the AIDS epidemic, and political and economic instability). So, though Muonde's persistence thresholds are higher than the system's historical minima, these thresholds reflect the community defining for itself what they need to thrive, not just to survive, setting their goals for their future higher than the way they have functioned in the past.

We must also recognize how colonial history relates to our definitions of sustainability. Requiring a certain amount of grazing area to be sustainable (part of our persistence definition) is related to the idea of a system's livestock carrying capacity, which has potential negative connotations in Mazvihwa. Farmers have historically managed to maintain livestock populations well above what has been thought of by scientists as the carrying capacity of the system, and in fact numbers have continued to increase over time despite apparent system degradation, e.g., in soil, vegetation biomass, and wetlands. After evaluating the system to be above its carrying capacity, the Rhodesian government required farmers to sell animals at low prices while allowing white ranchers to buy the animals at a profit (Scoones 1990), a practice that is painfully remembered by the people of Mazvihwa.

In addition to this top-down and potentially inaccurate assessment of carrying capacity and unjust method of adjustment, the Rhodesian government was also responsible in the first place for the concentration of people into "Native Reserves" with low agricultural potential. Overcrowding in these areas put heavy pressure on the agricultural productivity of the ecosystem, which led in turn to top-down government land use planning, an intervention that eroded Indigenous governance systems around balancing individual and community needs for woodland and stymied Indigenous agricultural innovations and adaptation. This legacy explains Muonde's focus on reclaiming community agency in pushing the system toward greater harvest while moderating the risk of collapse. This trade-off between persistence and harvest is therefore of great interest, as is the insight that an intermediate proportion of cropland may strike a balance between the two.

Indigenous climate adaptation and resilience in Mazvihwa

Several of the historical and recent management strategies employed in Mazvihwa help to smooth over year-to-year variation, potentially increasing resilience of the system to shocks. First, farmers have historically stored harvests, allowing one good year's bumper crop to get the community through multiple years of little harvest. Muonde is also encouraging local farmers to cultivate drought-adapted Indigenous small grains (sorghum, millet) that allow greater harvest in dry years and store better than other crops. And Muonde's water harvesting techniques can help to buffer the community against both within-year and between-year variation in rainfall (see Appendix 1 for more detail). These strategies reflect a classic definition of resilience: that the system can recover to a given state after a shock, for example, a drought. Sustainability, from this perspective, is about defining what state is desirable and then ensuring that the system will recover from shocks and return to that state (Carpenter et al. 2001). And resilience can be defined as more than simply the tendency of a system to return to its initial state after a shock: it can be conceptualized as including human and system agency to adapt and even transform in the face of ongoing disturbance (Galappaththi et al. 2019). Resilience as transformation is a core purpose of Muonde's work.

Because models are necessarily incomplete representations of systems, and our work is intended to support the Indigenous adaptation in Mazvihwa, we complement the model by sharing some of the additional strategies the community has used both traditionally and recently. Traditionally, after harvest is complete, animals are allowed to graze on the crop remnants (e.g., Müller et al. 2007), relieving some of the pressure on woodland vegetation and provisioning livestock in the off-harvest season. Muonde's recent woodland restoration projects, which include grazing areas, sacred forests or *rambotemwa*, and "key resources" like vegetated ditches that grow faster in dry years (Scoones 1989), can provide more grazing for livestock but also yield wild food as well as spiritual and medicinal benefits (Lunga and Musarurwa 2016, Woittiez et al. 2013). As the postindependence government opens up some of the land formerly held by commercial ranches and mining companies for resettlement, some farmers have moved into these nearby areas to take advantage of new resources. Families may take on small jobs ("piece-work"), pan for gold, or find other sources of income like burning wood for charcoal. In addition, there are many groups and local institutions that support community members in difficult times, including women's garden associations, churches, and nongovernmental organizations in addition to Muonde (Eitzel et al. 2016). People in Mazvihwa have also engaged in labor migration, with family members moving to big cities in Zimbabwe and neighboring countries to find work and send funds home. Some of these strategies are seen as undesirable "coping" within this society but they reflect the ingenuity and flexibility of the community.

CONCLUSION

ZAPMM was built to support Indigenous innovation and knowledge in Mazvihwa. It was designed to spark discussion rather than to prescribe particular management strategies, a fortunate aspect of the process, given that different definitions would have yielded different prescriptions. We discovered that broadening our definitions of sustainability was also instrumental in enabling the model to answer the principal community question (what proportion of land to allocate to agriculture) as well as the ancillary question of what other interventions were most effective. Although a typical view of sustainability would emphasize overall long-term persistence, key for the community are questions of how much they need in each aspect of their system in order to thrive. When we can build the model with attention to these local definitions (especially harvest), the relevant trade-offs with persistence actually become clearer. This means that the model can help the community to debate what proportion of their land area should be dedicated to crops, regaining responsibility for something that has grown uncontrollably without community coordination and planning since the retreat of local government from land use planning.

Along those lines, the Muonde Trust has run community workshops with local farmers and leaders using the model as a discussion tool to generate new thinking about collective action in making local land use decisions. Based on these workshops, Muonde's leaders have proposed to local decision makers a plan to negotiate land use rights more flexibly, allowing farmers to recultivate currently fallow land rather than cutting down woodland to create more crop fields, and they have already begun piloting this policy. In addition, they are writing a biocultural protocol protecting the sacred forests (*rambotemwa*) and have formed a Rambotemwa Protection Committee. They have begun hosting restoration festivals in which community members and leaders plant seedlings from Muonde's nursery in parts of the *rambotemwa* that have been degraded. Future work could explore how the model was used to support these community discussions with decision makers to coordinate land use decisions in order to balance harvests with other values in the system.

Collective action such as these discussions about land use planning and local forest protection, when based on traditional norms in local and Indigenous groups, can be key to coping with the impacts of climate change (Nyima and Hopping 2019) and restoring the resilience of degraded social-ecological systems (Lansing 2007). Farming adaptations to climate change can be derived from traditional Indigenous knowledge, and a key part of sustainability at the local level is the exchange of this knowledge among smallholder farmers (Aniah et al. 2019), making Muonde's farmer-to-farmer training programs particularly important. Work like Muonde's is essential in a place like Mazvihwa, where scarce resources and authority made disjointed by colonialism have meant that collective planning has been difficult. Integrating Indigenous values, governance, and knowledge into policies may allow systems that have become maladapted in the face of climate change to escape the historically dependent trajectory they are on (Parsons et al. 2019). Our modeling process and exploration of sustainability definitions has helped Muonde to reach out to local leaders and community members and to generate discussion about how best to plan for land use, reinforcing Indigenous climate adaptation sovereignty through new creation of knowledge and collective self-determination.

Responses to this article can be read online at:
http://www.ecologyandsociety.org/issues/responses.php/11946

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Data Availability:

The data/code that support the findings of this study are openly available in CoMSES.net at https://doi.org/10.25937/ta23-sn46.

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Appendix 1. Additional images of study system showing recent Indigenous innovations. (Photo credits: Moses Ndlovu and Jon Solera)

Images of Indigenous management interventions

Figure 1 from the main paper also demonstrates one possible crop spatial configuration, in which the crops are largely grouped together, with remnant woodland area in the foreground and in the upper half of the image.

Figure A1.1 Maize production near Mudhomori village ("Crops" in our model)

Figure A1.2 A Muonde Trust project meant to enhance crop growth through water harvesting: a "Phiri pit" designed to increase infiltration of runoff into groundwater ("Crop Innovations" in our model)

Figure A1.3 Ploughing crops using livestock for draft power – necessary for planting

Figure A1.4 A hungry cow which may try to eat crops

Figure A1.5 Cutting down woodland biomass in order to make brushwood fences to keep hungry livestock out of crops.

Figure A1.6 A brushwood fence meant to keep hungry livestock out of crops

Figure A1.7 A stone wall which will not need to be replaced, in contrast with a brushwood fence ("Stone Walls" in our model)

Figure A1.8 Some parts of the woodland grow faster than others, referred to as 'key resources' in Scoones (1989) (“Preserve Forest” in our model).

A note on increased rainfall variability in the model and in Mazvihwa

Higher year-to-year rainfall variability in our model results in lower persistence and lower annual harvest, regardless of the number of interventions or the definitions of persistence thresholds. Because the high-variability rainfall scenario had the same mean as the historical rainfall distribution, this result indicates that the management strategies depicted in the model are not enough to average good years across bad. However, there is an important subtlety in the system's ecology that we did not represent: the real system thrives on variable rainfall, with plants germinating in times of abundant water and then persisting through times of drought. That said, the kind of increasing year-to-year variability triggered by climate change could still harm the ecosystem as well as the people, as it does in the model, if droughts become longer than they have been historically. In the real system, too, within-year rainfall variation is likely to be even more important in impacting sustainability success by any measure (this level of complexity was unfortunately beyond the scope of our modeling). Increasing within-year variation in rainfall has already pushed the system towards erosive events followed by dry periods in which nothing can be planted.

Muonde's Indigenous agricultural innovations (which we have implemented in the model simply as increased crop growth regardless of rainfall) include building water harvesting structures designed to retain precipitation on the landscape and improve groundwater infiltration. Vegetated contour ridges interrupt flashy runoff from large storms, reducing erosion and extending the growing season, and "Phiri pits" (named after renowned water harvester Zephaniah Phiri Maseko, Witoshynsky 2002) are deep reservoirs which help to recharge groundwater and potentially retain moisture for longer than a single growing season, a strategy for reducing the impacts of drought years. Muonde's water harvesting projects could therefore become critical for buffering the community against both within-year and between-year variation in rainfall.

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Appendix 2. Summary of dataset in Eitzel et al. (2020) and description of statistical models used in sensitivity analysis of average annual harvest.

Summary of model parameter sweep dataset

In our parameter sweeps conducted in Eitzel et al. (2020), we ran a total of 499,200 simulations. Below are the distributions of both response variables (average annual harvest and persistence) and the predictor variables (categorical management interventions and rainfall scenarios, continuous management interventions, and continuous underlying variables that had been perturbed by 5% above and below their stated values). For results in this paper that use more than one set of simulations with persistence thresholds chosen randomly between biological and Muonde-determined minima, the predictor variables are distributed in the same way (just multiplied 10 times in frequency), so only one version is reported. For the response variables, see below for both versions.

Persistence (response variable)

Of the 499,200 runs in our analysis, 136,548 (27%) of runs persisted for 60 model years (using the biologically minimal thresholds, as in Eitzel et al. 2020).

When we allow thresholds to vary randomly between biological and Muonde-determined minima randomly in each of the 499,200 runs (a global sensitivity test of the thresholds), and then follow this procedure 10 times (creating 10 different versions of the model outputs), only 26,468 of the 4,992,000 runs persisted all 60 years (0.5%).

Average annual harvest (response variable)

Figure A2.1: Average annual harvest distribution (for biologically minimal persistence thresholds), all data (left) and data from only models which lasted for at least a year, making an average harvest more meaningful (left).

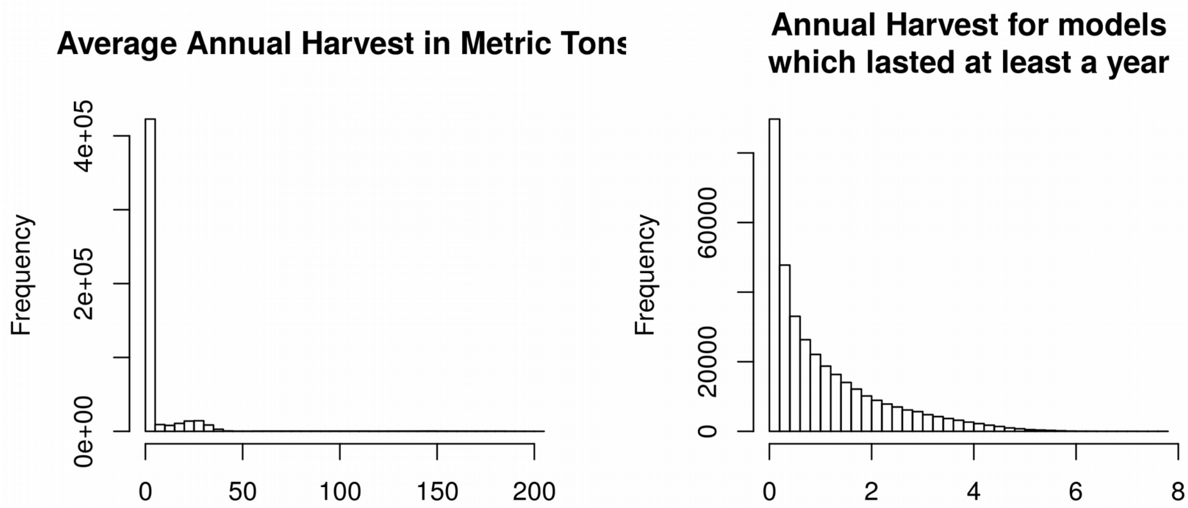
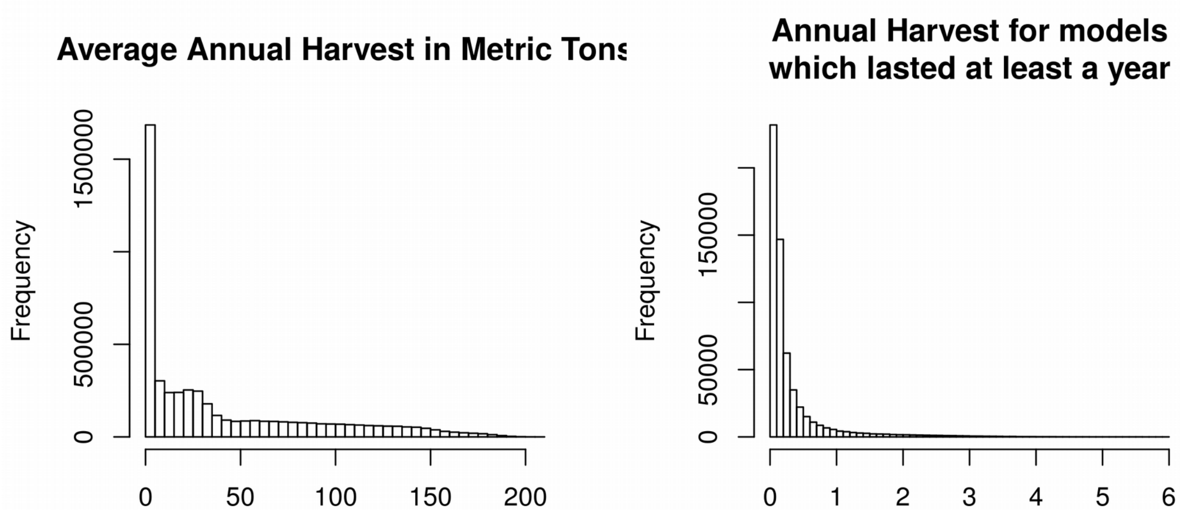


Figure A2.2: Average annual harvest distribution (for the 10 different model datasets with randomly selected persistence thresholds), all data (left) and data from only models which lasted for at least a year, making an average harvest more meaningful (left).



Categorical rainfall scenarios (predictor variables)

Out of all the simulations, the rainfall scenarios were distributed as follows:

Table A2.1: Runs were evenly distributed between different rainfall scenarios using NetLogo's BehaviorSpace tool. "Constant" has fewer runs because subsidy interventions are never used.

Constant	Extreme	Historical	Random	Statistical-extreme	Statistical-random
19200	96000	96000	96000	96000	96000

(Note that the present paper only uses results from the "Historical" and "Statistical-extreme" (high-variation) rainfall scenarios.)

Categorical management variables (predictor variables)

Out of all the simulations, the categorical management variables were distributed as follows:

Table A2.2: Runs were evenly distributed between different management interventions

Subsidize Cows	Move Cows	Stone Walls	Preserve Forest	Crop Innovations	Store Grain
Feed 70%: 96000 Feed all: 96000 Transport 70%: 96000 Transport all: 96000 No Subsidy: 115200	Yes: 249600 No: 249600	Yes: 249600 No: 249600	Yes: 249600 No: 249600	Yes: 249600 No: 249600	Yes: 249600 No: 249600

Continuous management variables (predictor variables)

Figure A2.3: Distribution of proportion-crops variable; this variable ranged up to 97%, hence the short bar at 100.

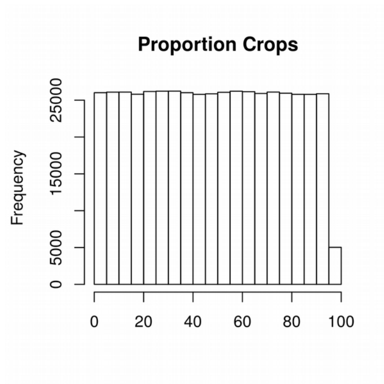
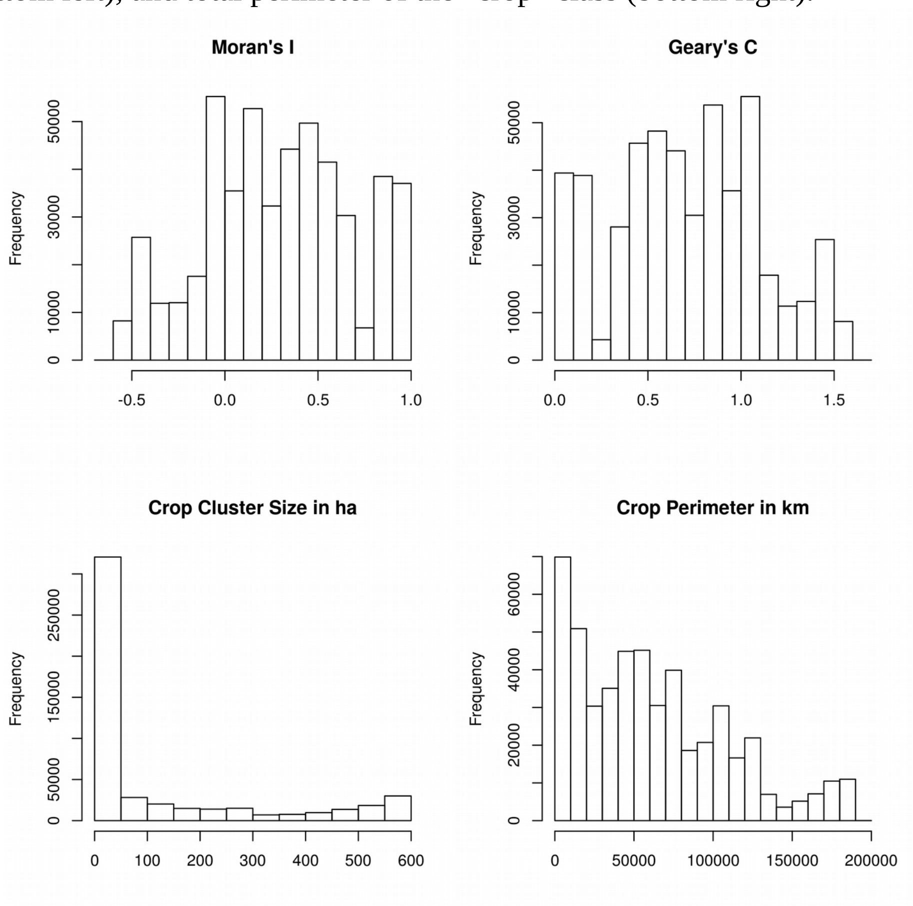
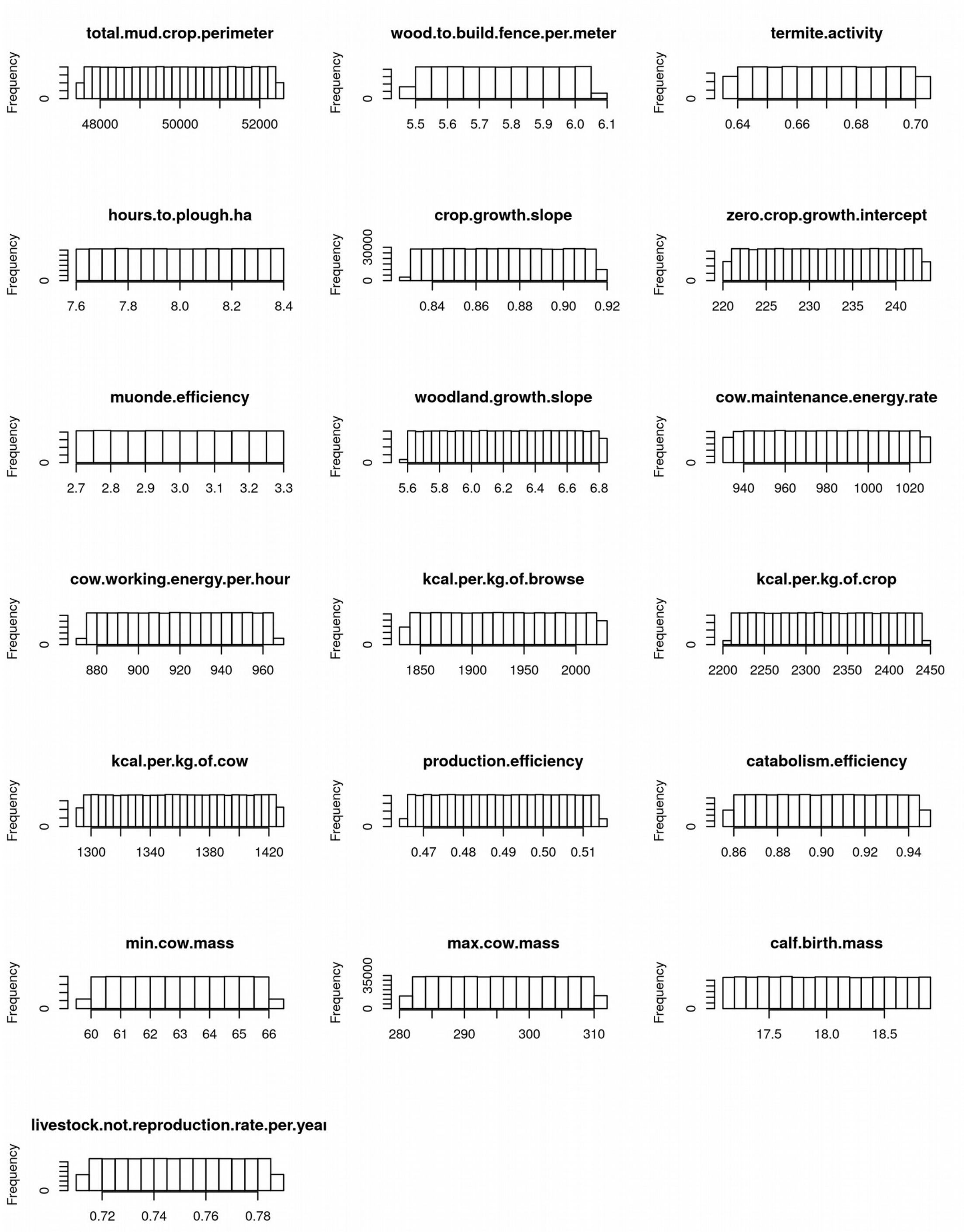


Figure A2.4: Distribution of Moran's I (top left), Geary's C (top right), Crop cluster size in hectares (bottom left), and total perimeter of the "crop" class (bottom right).



Underlying variables (predictor variables)

Figure A2.5: Distributions of underlying parameters, which were perturbed by 5% above and below their stated values.



Statistical sensitivity analysis: Generalized Additive Models (GAMs) of average annual harvest

We used statistical models to compare the relative impacts of different variables while controlling for the others, focusing on effect size rather than exclusively on significance. With a simulation model, the sample size (number of model runs) can be increased to an arbitrarily large number so statistical significance has less meaning. We assume statistical distributions only for the response variables. Many of our simulations had cows, woodland, or harvest below one of the thresholds after the five-year intitialization period (31% of our runs), leading to runs that lasted zero years. The distribution of average annual harvest was therefore zero-inflated, and we used a Tweedie distribution in the GAM estimation process. These distributions are appropriate for zero-inflated, semi-continuous distribution like our harvest variable (Tweedie 1984, Jorgensen 1997). The Tweedie power parameter p was estimated to be 1.788 (between 1 and 2, as expected for a distribution with a point mass at zero and continuous positive values otherwise).

We used GAMs in the "mgcv" package (Wood 2017) in R to test the sensitivity of persistence and average annual harvest to underlying parameters, rainfall scenarios, and management variables. We chose generalized statistical models because the outcome variables are not normally distributed and additive models using smoothing splines because our proportion-crops and spatial configuration variable varied over a wide range of values and a local linear assumption was not appropriate. To represent spatial configuration, we used Moran's I (Moran 1950) because it is a classic landscape ecology indicator used to represent spatial diversity, and was least correlated with the proportion-crops of the variables we calculated (see above in Figure A2.4 for distributions of other spatial configuration variables).

For sensitivity testing of underlying variables, we used a local linear approximation. We also centered and scaled each of the continuous variables to enhance comparability of parameter estimates and interpretability of the overall model intercept. For the discrete management variables and rainfall scenarios, we used categorical factors. For our outcome variables, we report untransformed parameter estimates in order to compare the magnitude of different model parameters' influence on model results, but also discuss transformed parameters using the log link. Note that all parameters significant at the $p<0.05$ level are highlighted in bold text. The above analysis is the same as was used in Eitzel et al. (2020) for persistence, with the exception of the Tweedie distribution (for annual harvest) as opposed to a binomial/Bernoulli distribution (for persistence).

Average annualized harvest response variable GAMs

Transformed estimates have had the model intercept added to the estimate before transformation, so annual harvest for that management intervention, rainfall scenario, or underlying variable can be compared with the intercept for the base case with constant rainfall, no management interventions, and average values of all continuous variables (0.776, an annual harvest of 2.173 metric tons, p<<0.01).

Note that this appendix uses the names for variables from the NetLogo code; see Eitzel et al. (2018) for definitions.

Table A2.3: Rainfall Scenario parameter estimates for the average annual harvest model (t statistic = 320.22, df = 5, **p<<0.01**).

Rainfall Scenario	Estimate	Transformed Estimate (metric tons)
historical	-0.236	1.716
statistical-random	-0.287	1.632
random	-0.289	1.627
extreme	-0.355	1.524
statistical-extreme	-0.418	1.431

Table A2.4: Management Intervention parameter estimates for the average annual harvest model. See Figure A2.6 for the functional forms for proportion crops and Moran's I.

Management Intervention	Estimate	Transformed Estimate (metric tons)	Degrees of Freedom	t Statistic	p-value
s(proportion.crops)		(Fig A2.1)	8.990†	36376‡	**0.00**
s(morans.i)		(Fig A2.1)	8.993†	1369‡	**0.00**
how.long.to.store.grain3	1.207	7.268	1	80131	**0.00**
muonde.projects10	0.2055	2.669	1	2360.5	**0.00**
subsidy.proportiontransport-0.7	0.07572	2.344	4	62.571	**0.00**
subsidy.proportiontransport-1	0.05584	2.298	4	62.571	**0.00**
invincible.fencestrue	0.055	2.296	1	169.08	**0.00**
subsidy.proportionfeed-0.7	0.02644	2.232	4	62.571	**0.00**
subsidy.proportionfeed-1	-0.01664	2.138	4	62.571	**0.00**
key.resources10	-0.2007	1.778	1	2251.5	**0.00**
times.per.day.farmers.move.cows1	-0.7359	1.042	1	30012	**0.00**

†df is 'effective df', reference df 9.000
‡F-statistic

Figure A2.6: Smooth functions of proportion-crops and Moran's I from the average annual harvest model.

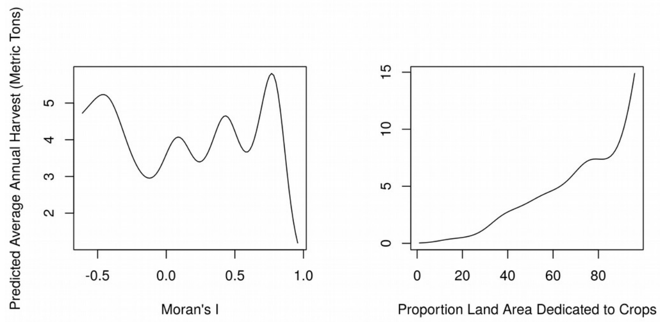


Table A2.5: Underlying variable parameter estimates for average annual harvest model.

Underlying variable	Estimate	Transformed Estimate (metric tons)	Degrees of Freedom	t Statistic	p-value
crop.growth.slope	0.034	1.069	1	251.18	**0.00**
livestock.not.reproduction.rate.per.year	0.025	1.061	1	144.33	**0.00**
muonde.efficiency	0.018	1.053	1	71.25	**0.00**
cow.maintenance.energy.rate	0.009	1.044	1	19.305	**0.00**
cow.working.energy.per.hour	0.005	1.040	1	6.5545	**0.01**
total.mud.crop.perimeter	0.005	1.039	1	5.9519	**0.01**
termite.activity	0.003	1.038	1	2.4822	0.12
kcal.per.kg.of.cow	0.003	1.038	1	2.4752	0.12
hours.to.plough.ha	0.002	1.037	1	1.3486	0.25
min.cow.mass	0.002	1.037	1	1.2402	0.27
max.cow.mass	0.002	1.036	1	0.66224	0.42
production.efficiency	0.001	1.035	1	0.33075	0.57
catabolism.efficiency	-0.001	1.033	1	0.081553	0.78
wood.to.build.fence.per.meter	-0.002	1.032	1	0.55755	0.46
calf.birth.mass	-0.003	1.031	1	1.6416	0.20
kcal.per.kg.of.crop	-0.003	1.031	1	1.9649	0.16
kcal.per.kg.of.browse	-0.006	1.028	1	6.8944	**0.01**
woodland.growth.slope	-0.019	1.015	1	81.558	**0.00**
zero.crop.growth.intercept	-0.021	1.012	1	102.12	**0.00**

We note that for the biologically minimal persistence thresholds, sensitivity analysis of the average annual harvest had different significant underlying biomass-related variables than the persistence variable did (compare with Eitzel et al. 2020), and more of them (12 were significant as opposed to 10 for the sustainability model), but were still mostly smaller in magnitude than the rainfall scenarios and management interventions (except storing grain).

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Appendix 3. Tables of model system persistence and average annual harvest for different combinations of categorical management interventions, examples of Kendall's Tau for various paired lists, and analysis of optimal numbers of interventions.

Tables showing all combinations of interventions, sorted by percentage persistent or average annual harvest (for both rainfall models)

Table A3.1: Percentage of runs that lasted all 60 years sorted by ***percentage persistent***. Points which are Pareto optima are shown in bold text (see last section of Appendix 3 for explanation of Pareto optimization of intervention combinations). (***Historical rainfall***)

Stone Walls	Move Cows	Subsidize Cows	Crop Innovations	Preserve Forest	Store Grain	count	N	Percentage Persistent
	X	**X**		**X**	**X**	**4**	**2400**	**81.58**
	X	**X**	**X**	**X**	**X**	**5**	**2400**	**79.83**
X	X	X		X	X	5	2400	76.63
X	**X**	**X**	**X**	**X**	**X**	**6**	**2400**	**75.50**
	X			X	X	3	600	61.17
	X		X	X	X	4	600	60.67
	X	**X**			**X**	**3**	**2400**	**58.38**
X	X		X	X	X	5	600	58.33
	X	**X**	**X**		**X**	**4**	**2400**	**57.75**
X	X			X	X	4	600	57.67
X	X	X			X	4	2400	55.21
		X		**X**	**X**	**3**	**2400**	**54.58**
		X	**X**	**X**	**X**	**4**	**2400**	**51.96**
X	X	X	X		X	5	2400	50.71
X		X		X	X	4	2400	49.71
		X			X	2	2400	48.29
		X	**X**		**X**	**3**	**2400**	**46.42**
				X	X	2	600	43.17
X		**X**	**X**	**X**	**X**	**5**	**2400**	**42.88**
			X	X	X	3	600	41.00
X		X			X	3	2400	40.50
X				X	X	3	600	38.50
X			X	X	X	4	600	38.00
X	X				X	3	600	31.50
					X	1	600	31.33
X	X		X		X	4	600	31.00

			X		X	2	600	31.00
X		**X**	**X**		**X**	**4**	**2400**	**30.13**
X					X	2	600	28.17
	X				X	2	600	27.50
X			X		X	3	600	27.33
	X		X		X	3	600	24.00
	X	X	X	X		4	2400	8.38
X	X	X	X	X		5	2400	5.21
	X	X	X			3	2400	4.13
	X	X		X		3	2400	2.67
X	X	X	X			4	2400	2.33
		X	X	X		3	2400	1.88
X		X	X	X		4	2400	1.67
X	X	X		X		4	2400	1.33
		X	X			2	2400	0.79
	X	X				2	2400	0.63
X		X		X		3	2400	0.54
X	X	X				3	2400	0.46
		X		X		2	2400	0.33
X		X	X			3	2400	0.25
X		X				2	2400	0.13
		X				1	2400	0.08
X	X		X	X		4	600	0.00
	X		X	X		3	600	0.00
X			X	X		3	600	0.00
X	X			X		3	600	0.00
X	X		X			3	600	0.00
			X	X		2	600	0.00
	X			X		2	600	0.00
	X		X			2	600	0.00
X				X		2	600	0.00
X			X			2	600	0.00
X	X					2	600	0.00
				X		1	600	0.00
			X			1	600	0.00
	X					1	600	0.00

X						1	600	0.00
						0	600	0.00

Table A3.2: Percentage of runs that lasted all 60 years sorted by ***average annual harvest***. Points which are Pareto optima are shown in bold text. (***Historical rainfall***)

Stone Walls	Move Cows	Subsidize Cows	Crop Innovations	Preserve Forest	Store Grain	count	N	Average Annual Harvest (metric tons)
X		**X**	**X**		**X**	**4**	**2400**	**14.84**
X		**X**	**X**	**X**	**X**	**5**	**2400**	**14.36**
		X	**X**		**X**	**3**	**2400**	**14.09**
X			X		X	3	600	13.91
		X	**X**	**X**	**X**	**4**	**2400**	**13.90**
			X	X	X	3	600	13.70
			X		X	2	600	13.67
X			X	X	X	4	600	13.42
X				X	X	3	600	12.46
					X	1	600	12.14
X		X			X	3	2400	11.60
X					X	2	600	11.34
		X			X	2	2400	11.34
X		X		X	X	4	2400	11.10
				X	X	2	600	11.03
		X		**X**	**X**	**3**	**2400**	**11.00**
	X		X		X	3	600	8.92
	X	**X**	**X**		**X**	**4**	**2400**	**8.80**
	X				X	2	600	8.02
	X	**X**			**X**	**3**	**2400**	**7.08**
X	X	X	X		X	5	2400	6.59
X	X		X		X	4	600	6.30
X	**X**	**X**	**X**	**X**	**X**	**6**	**2400**	**5.25**
X	X				X	3	600	5.11
X	X		X	X	X	5	600	5.01
X	X	X			X	4	2400	4.71
	X		X	X	X	4	600	4.62
	X	X				2	2400	4.56
	X			X	X	3	600	4.47

	X					1	600	4.21
	X	**X**	**X**	**X**	**X**	**5**	**2400**	**4.20**
	X	X	X			3	2400	4.08
	X		X			2	600	3.84
	X	**X**		**X**	**X**	**4**	**2400**	**3.76**
			X	X		2	600	3.75
X	X	X		X	X	5	2400	3.51
X	X			X	X	4	600	3.47
X			X			2	600	2.82
X	X	X	X	X		5	2400	2.68
		X	X	X		3	2400	2.66
X	X		X	X		4	600	2.63
	X	X	X	X		4	2400	2.57
X	X	X	X			4	2400	2.55
X		X	X	X		4	2400	2.54
X			X	X		3	600	2.53
X		X	X			3	2400	2.43
X	X		X			3	600	2.33
		X	X			2	2400	2.31
		X				1	2400	2.31
						0	600	2.22
X				X		2	600	2.20
X		X		X		3	2400	2.15
X	X	X		X		4	2400	2.11
X		X				2	2400	1.92
	X		X	X		3	600	1.82
			X			1	600	1.81
X	X	X				3	2400	1.79
	X			X		2	600	1.77
		X		X		2	2400	1.76
X	X					2	600	1.73
X						1	600	1.66
				X		1	600	1.48
	X	X		X		3	2400	1.24
X	X			X		3	600	0.95

Table A3.3: Percentage of runs that lasted all 60 years sorted by ***percentage persistent***. Points which are Pareto optima are shown in bold text. (***High-variability rainfall***)

Stone Walls	Move Cows	Subsidize Cows	Crop Innovations	Preserve Forest	Store Grain	count	N	Percentage Persistent
X	**X**	**X**		**X**	**X**	**5**	**2400**	**41.04**
X	**X**	**X**	**X**	**X**	**X**	**6**	**2400**	**40.25**
X		**X**		**X**	**X**	**4**	**2400**	**39.25**
	X	X	X	X	X	5	2400	39.00
	X	X		X	X	4	2400	38.92
		X	**X**	**X**	**X**	**4**	**2400**	**38.67**
		X		X	X	3	2400	38.29
	X	X			X	3	2400	36.46
	X	X	X		X	4	2400	36.00
X	X	X			X	4	2400	34.33
		X			X	2	2400	33.46
X		**X**	**X**	**X**	**X**	**5**	**2400**	**33.21**
		X	X		X	3	2400	32.25
X	X	X	X		X	5	2400	31.38
X		X			X	3	2400	29.21
X		**X**	**X**		**X**	**4**	**2400**	**24.25**
X				X	X	3	600	16.00
X			X	X	X	4	600	13.67
			X	X	X	3	600	12.50
				X	X	2	600	11.17
X					X	2	600	11.00
X	X			X	X	4	600	9.50
	X			X	X	3	600	8.83
X			X		X	3	600	8.67
	X		X	X	X	4	600	8.00
			X		X	2	600	8.00
					X	1	600	7.50
X	X		X	X	X	5	600	7.33
X	X				X	3	600	4.50
X	X		X		X	4	600	4.00
	X		X		X	3	600	4.00
	X				X	2	600	2.50
	X	X	X	X		4	2400	1.83

X	X	X	X	X		5	2400	1.25
	X	X	X			3	2400	1.17
X	X	X	X			4	2400	0.92
		X	X	X		3	2400	0.79
	X	X		X		3	2400	0.71
X	X	X		X		4	2400	0.58
		X		X		2	2400	0.58
		X	X			2	2400	0.54
X		X		X		3	2400	0.50
X	X	X				3	2400	0.46
		X				1	2400	0.42
	X	X				2	2400	0.38
X		X				2	2400	0.38
X		X	X	X		4	2400	0.33
X		X	X			3	2400	0.25
X	X		X	X		4	600	0.17
	X		X	X		3	600	0.17
X			X	X		3	600	0.17
X	X			X		3	600	0.17
X	X					2	600	0.17
			X			1	600	0.17
X	X		X			3	600	0.00
			X	X		2	600	0.00
	X			X		2	600	0.00
	X		X			2	600	0.00
X				X		2	600	0.00
X			X			2	600	0.00
				X		1	600	0.00
	X					1	600	0.00
X						1	600	0.00
						0	600	0.00

Table A3.4: Percentage of runs that lasted all 60 years sorted by ***average annual harvest***. Points which are Pareto optima are shown in bold text. (***High-variability rainfall***)

Stone Walls	Move Cows	Subsidize Cows	Crop Innovations	Preserve Forest	Store Grain	count	N	Average Annual Harvest (metric tons)
X		**X**	**X**		**X**	**4**	**2400**	**14.67**

X		**X**	**X**	**X**	**X**	**5**	**2400**	**14.49**
		X	**X**	**X**	**X**	**4**	**2400**	**14.14**
			X		X	2	600	13.91
X			X	X	X	4	600	13.90
			X	X	X	3	600	13.71
		X	X		X	3	2400	13.40
X			X		X	3	600	13.00
X				X	X	3	600	11.93
		X		X	X	3	2400	11.76
X		X			X	3	2400	11.43
		X			X	2	2400	11.13
X		**X**		**X**	**X**	**4**	**2400**	**11.00**
				X	X	2	600	10.08
X					X	2	600	10.02
					X	1	600	9.48
	X	X	X		X	4	2400	7.44
	X		X		X	3	600	7.13
	X	X			X	3	2400	6.75
	X				X	2	600	6.41
X	X	X	X		X	5	2400	5.81
X	X	X			X	4	2400	4.90
	X	X	X	X	X	5	2400	4.90
X	X		X		X	4	600	4.60
X	**X**	**X**	**X**	**X**	**X**	**6**	**2400**	**4.38**
	X	X				2	2400	4.31
	X					1	600	4.14
X			X	X		3	600	4.14
X	X				X	3	600	3.99
	X	X	X			3	2400	3.87
	X		X			2	600	3.82
X	**X**	**X**		**X**	**X**	**5**	**2400**	**3.65**
X	X			X	X	4	600	3.58
	X	X		X	X	4	2400	3.37
			X	X		2	600	3.28
X	X		X	X	X	5	600	3.13
	X		X	X	X	4	600	2.98

				X		1	600	2.83
X		X		X		3	2400	2.45
	X			X	X	3	600	2.42
	X	X	X	X		4	2400	2.33
						0	600	2.23
X		X	X	X		4	2400	2.16
		X				1	2400	2.15
X						1	600	2.15
X	X		X			3	600	2.05
		X		X		2	2400	2.02
X		X				2	2400	2.00
X	X					2	600	1.96
X		X	X			3	2400	1.92
X			X			2	600	1.90
X	X	X	X			4	2400	1.86
X				X		2	600	1.83
		X	X			2	2400	1.80
X	X	X	X	X		5	2400	1.80
		X	X	X		3	2400	1.71
			X			1	600	1.59
X	X	X				3	2400	1.47
	X	X		X		3	2400	1.46
	X		X	X		3	600	1.26
	X			X		2	600	1.20
X	X	X		X		4	2400	1.08
X	X			X		3	600	0.89
X	X		X	X		4	600	0.43

Examples of Kendall's Tau for different pairs of ranked lists

Table A3.5: Examples of Kendall's Tau for various pairs of 64-element ranked lists

Example	Tau
Identical lists	1.0
Each item swapped one position away: i.e. 2, 1, 4, 3, 6, 5, 8, 7… †	0.97
Each item swapped two positions away: i.e. 3, 4, 1, 2, 7, 8, 5, 6… †	0.94
Each item swapped four positions away: i.e. 5, 6, 7, 8, 1, 2, 3, 4… †	0.87
Each item swapped eight positions away †	0.75
Each item swapped 16 positions away †	0.49
Our persistence and harvest rankings, high-variation rainfall scenario	***0.47***
Our persistence and harvest rankings, historical rainfall scenario	***0.43***
Two lists of randomly selected items	~0§
Each item swapped 32 positions away †	-0.02
Reversed lists	-1.0

†Compared with another list in ascending order: 1, 2, 3, 4, 5, 6, 7, 8…
§Any two randomly selected lists may not have a Kendall's Tau of 0, but the mean of lists created and compared in this way is zero.

Exploration of the optimal number of management interventions

Because each intervention represents additional financial and opportunity cost for the farmers in Mazvihwa, we summarized model persistence and average annual harvest (for biologically minimal thresholds) by the number of management interventions employed. The number of simulations in each category (e.g. zero interventions, one intervention, etc.) varies for two reasons: 1) combinatorics: there are several different ways to have three interventions, and only one way to have zero or six interventions; and 2) subsidy can be implemented four different ways, as opposed to only one way to implement other interventions, so there are more replications for subsidy. In addition, each of these possible combinations has 100 replications and is being averaged over all rainfall models, proportion crops, and spatial configurations.

We therefore report the total number of simulations used in calculating the overall proportion of models that persisted for all possible ways to have zero, one, two, three, four, five, or six interventions, and also give the average, maximum and minimum probability of persistence. For example for three interventions, there are 20 different combinations of three out of the six interventions, and the proportion of models that persisted 60 years varies a great deal between these, depending on which interventions are included.

For the historical rainfall scenario, average persistence increased monotonically with more interventions (Table A3.6). This was also true for the high-variation rainfall scenario, though the persistence was much less in each set of combinations than in the historical scenario. For average annual harvest, there was a maximum value at four interventions, regardless of rainfall scenario, and nearly all of the combinations had lower average annual harvest in the high-variation scenario. There was a wide range in different intervention combinations, however, especially for those with many possible combinations (e.g. two, three, and four interventions) and for many interventions (five interventions also has a relatively large range within each of the scenarios and variables). The wide range is likely partly due to the averaging over the spatial configurations and proportion-crops. Note that both the persistence and annual harvest averages are similar for the 2-3 intervention categories in the historical rainfall scenario and the 3-4 intervention categories in the high-variation rainfall scenario, implying that more interventions are necessary to achieve the same level of function under higher rainfall variability.

Table A3.6: Number of interventions and impacts on model outcomes (annual average harvest and persistence for all 60 model years), summarizing tables A3.7 and A3.8.

Number of Interventions	Zero	One	Two	Three	Four	Five	Six
Number of combinations†	1	6	15	20	15	6	1
Number of simulations§	600	5400	18000	30000	27000	12600	2400
Persistence over 60 Years, Historical Rainfall Scenario							
Average	0	5.24	12	21.66	35.16	52.26	75.5
Range	NA	0–31.33	0–48.29	0–61.17	0–81.58	5.21–79.83	NA
Persistence over 60 Years, High-Variation Rainfall Scenario							
Average	0	1.35	4.54	9.75	16.69	25.53	40.25
Range	NA	0–7.5	0-33.46	0–38.29	0.17–39.25	1.25–41.04	NA
Average Annual Harvest in Metric Tons, Historical Rainfall Scenario							
Average	2.22	3.93	5.47	6.22	6.49	6.06	5.25
Range	NA	1.48–12.14	1.73–13.67	0.95–14.09	2.11–14.84	2.68–14.36	NA
Average Annual Harvest in Metric Tons, High-Variation Rainfall Scenario							
Average	2.23	3.72	5.04	5.84	5.9	5.63	4.38
Range	NA	1.59–9.48	1.2–13.91	0.89–13.71	0.43–14.67	1.8–14.49	NA

†The number of ways to get each combination of number of interventions, e.g. there is only one way to have all six, but six different ways to only have one. See the tables below for individual numbers for each possible combination.
§Each way of having each combination of interventions had many simulations associated with it (and for subsidy, there were several different ways to subsidize). This is the total number of simulations across all combinations for each number of interventions.

When ranking the individual possible combinations of interventions by the percentage of runs that persisted all 60 years, we found that using all six interventions was ranked 4th out of 64 for historical rainfall and second out of 64 for high-variability rainfall; for average annual harvest, all six interventions ranked 23rd out of 64 for historical rainfall, and 25th out of 64 for high-variability rainfall. For persistence, using no interventions at all ranked last (tied with 15 other models in the historical case and nine other models in the high-variability case), while for average annual harvest, using no interventions ranked 50th out of 64 for the historical rainfall case and 42nd out of 64 in the high-variability case. Comparing the two measures of success, the Pareto set between them (the set of intervention combinations where performing better on one measure requires doing worse on the other; see Figure A3.1 for a graphical representation) includes only cases with 3, 4, 5, and 6 interventions in the case of persistence, and only 4, 5, and 6 interventions in the case of average annual harvest. See above for the full tables of percentage persistent runs ordered by number of interventions (Table A3.1), by percentage persistent (Table A3.2), and by average annual harvest (Table A3.3) for the historical rainfall scenario, and the same for the high-variation rainfall scenario (Tables A3.4-6).

Therefore, though increasing the number of interventions did on the whole improve the persistence and average annual harvest of the model system, it mattered which combinations of interventions were used and how success was measured (short-term annual harvest or long-term persistence). Higher variability in rainfall resulted in lower success, and using no interventions at all was surprisingly beneficial for average annual harvest. For persistence, it was equally bad to use no interventions as to use 3 or 4 interventions depending on the rainfall scenario and combination of interventions. (Note that these results are averaged over all values of proportion crops and spatial configurations.)

Table A3.7: Percentage of runs that lasted all 60 years sorted by number of management interventions (for biologically minimal persistence thresholds and historical rainfall). The averages and ranges appearing in Table A3.6 were derived from this table. Points which are Pareto optima are shown in bold text.

Stone Walls	Move Cows	Subsidize Cows	Crop Innovations	Preserve Forest	Store Grain	count	N	Percentage Persistent	Average Annual Harvest (metric tons)
X	**X**	**X**	**X**	**X**	**X**	**6**	**2400**	**75.50**	**5.25**
X	X	X	X	X		5	2400	5.21	2.68
X		**X**	**X**	**X**	**X**	**5**	**2400**	**42.88**	**14.36**
X	X	X	X		X	5	2400	50.71	6.59
X	X		X	X	X	5	600	58.33	5.01
X	X	X		X	X	5	2400	76.63	3.51
	X	**X**	**X**	**X**	**X**	**5**	**2400**	**79.83**	**4.20**
X	X		X	X		4	600	0.00	2.63
X	X	X		X		4	2400	1.33	2.11

X		X	X	X		4	2400	1.67	2.54
X	X	X	X			4	2400	2.33	2.55
	X	X	X	X		4	2400	8.38	2.57
X		**X**	**X**		**X**	**4**	**2400**	**30.13**	**14.84**
X	X		X		X	4	600	31.00	6.30
X			X	X	X	4	600	38.00	13.42
X		X		X	X	4	2400	49.71	11.10
		X	**X**	**X**	**X**	**4**	**2400**	**51.96**	**13.90**
X	X	X			X	4	2400	55.21	4.71
X	X			X	X	4	600	57.67	3.47
	X	**X**	**X**		**X**	**4**	**2400**	**57.75**	**8.80**
	X		X	X	X	4	600	60.67	4.62
	X	**X**		**X**	**X**	**4**	**2400**	**81.58**	**3.76**
	X		X	X		3	600	0.00	1.82
X			X	X		3	600	0.00	2.53
X	X			X		3	600	0.00	0.95
X	X		X			3	600	0.00	2.33
X		X	X			3	2400	0.25	2.43
X	X	X				3	2400	0.46	1.79
X		X		X		3	2400	0.54	2.15
		X	X	X		3	2400	1.88	2.66
	X	X		X		3	2400	2.67	1.24
	X	X	X			3	2400	4.13	4.08
	X		X		X	3	600	24.00	8.92
X			X		X	3	600	27.33	13.91
X	X				X	3	600	31.50	5.11
X				X	X	3	600	38.50	12.46
X		X			X	3	2400	40.50	11.60
			X	X	X	3	600	41.00	13.70
		X	**X**		**X**	**3**	**2400**	**46.42**	**14.09**
		X		**X**	**X**	**3**	**2400**	**54.58**	**11.00**
	X	**X**			**X**	**3**	**2400**	**58.38**	**7.08**
	X			X	X	3	600	61.17	4.47
			X	X		2	600	0.00	3.75
	X			X		2	600	0.00	1.77
	X		X			2	600	0.00	3.84
X				X		2	600	0.00	2.20

X			X			2	600	0.00	2.82
X	X					2	600	0.00	1.73
X		X				2	2400	0.13	1.92
		X		X		2	2400	0.33	1.76
	X	X				2	2400	0.63	4.56
		X	X			2	2400	0.79	2.31
	X				X	2	600	27.50	8.02
X					X	2	600	28.17	11.34
			X		X	2	600	31.00	13.67
				X	X	2	600	43.17	11.03
		X			X	2	2400	48.29	11.34
				X		1	600	0.00	1.48
			X			1	600	0.00	1.81
	X					1	600	0.00	4.21
X						1	600	0.00	1.66
		X				1	2400	0.08	2.31
					X	1	600	31.33	12.14
						0	600	0.00	2.22

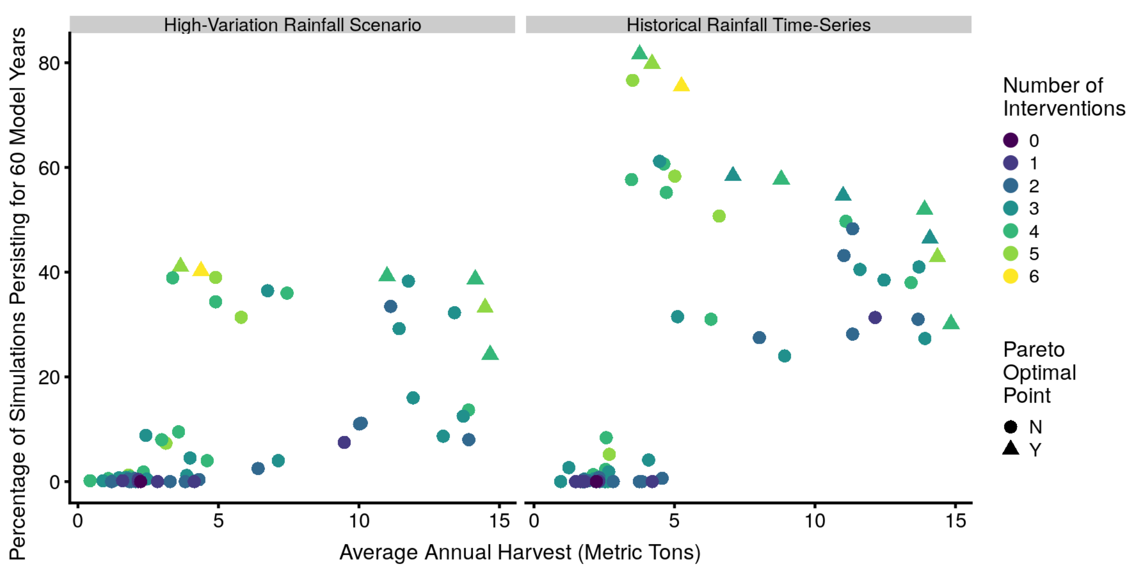
Table A3.8: Percentage of runs that lasted all 60 years sorted by number of management interventions (for biologically minimal persistence thresholds and high-variability rainfall). The averages and ranges appearing in Table A3.6 were derived from this table. Points which are Pareto optima are shown in bold text.

Stone Walls	Move Cows	Subsidize Cows	Crop Innovations	Preserve Forest	Store Grain	count	N	Percentage Persistent	Average Annual Harvest (metric tons)
X	**X**	**X**	**X**	**X**	**X**	**6**	**2400**	**40.25**	**4.38**
X	**X**	**X**		**X**	**X**	**5**	**2400**	**41.04**	**3.65**
	X	X	X	X	X	5	2400	39.00	4.90
X		**X**	**X**	**X**	**X**	**5**	**2400**	**33.21**	**14.49**
X	X	X	X		X	5	2400	31.38	5.81
X	X		X	X	X	5	600	7.33	3.13
X	X	X	X	X		5	2400	1.25	1.80
X		**X**		**X**	**X**	**4**	**2400**	**39.25**	**11.00**
	X	X		X	X	4	2400	38.92	3.37
		X	**X**	**X**	**X**	**4**	**2400**	**38.67**	**14.14**
	X	X	X		X	4	2400	36.00	7.44
X	X	X			X	4	2400	34.33	4.90

X		**X**	**X**		**X**	**4**	**2400**	**24.25**	**14.67**
X			X	X	X	4	600	13.67	13.90
X	X			X	X	4	600	9.50	3.58
	X		X	X	X	4	600	8.00	2.98
X	X		X		X	4	600	4.00	4.60
	X	X	X	X		4	2400	1.83	2.33
X	X	X	X			4	2400	0.92	1.86
X	X	X		X		4	2400	0.58	1.08
X		X	X	X		4	2400	0.33	2.16
X	X		X	X		4	600	0.17	0.43
		X		X	X	3	2400	38.29	11.76
	X	X			X	3	2400	36.46	6.75
		X	X		X	3	2400	32.25	13.40
X		X			X	3	2400	29.21	11.43
X				X	X	3	600	16.00	11.93
			X	X	X	3	600	12.50	13.71
	X			X	X	3	600	8.83	2.42
X			X		X	3	600	8.67	13.00
X	X				X	3	600	4.50	3.99
	X		X		X	3	600	4.00	7.13
	X	X	X			3	2400	1.17	3.87
		X	X	X		3	2400	0.79	1.71
	X	X		X		3	2400	0.71	1.46
X		X		X		3	2400	0.50	2.45
X	X	X				3	2400	0.46	1.47
X		X	X			3	2400	0.25	1.92
	X		X	X		3	600	0.17	1.26
X			X	X		3	600	0.17	4.14
X	X			X		3	600	0.17	0.89
X	X		X			3	600	0.00	2.05
		X			X	2	2400	33.46	11.13
				X	X	2	600	11.17	10.08
X					X	2	600	11.00	10.02
			X		X	2	600	8.00	13.91
	X				X	2	600	2.50	6.41
		X		X		2	2400	0.58	2.02

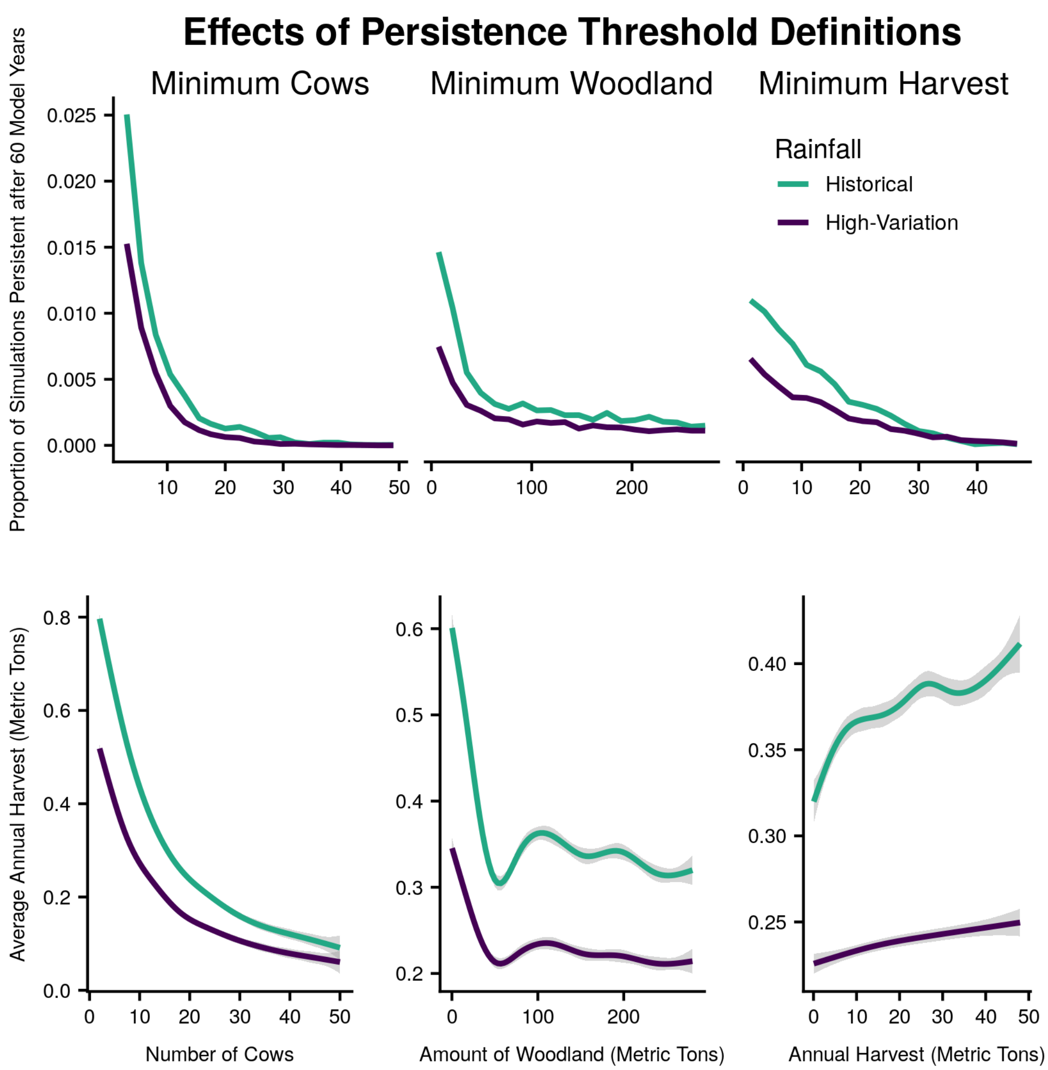
		X	X			2	2400	0.54	1.80
	X	X				2	2400	0.38	4.31
X		X				2	2400	0.38	2.00
X	X					2	600	0.17	1.96
			X	X		2	600	0.00	3.28
	X			X		2	600	0.00	1.20
	X		X			2	600	0.00	3.82
X				X		2	600	0.00	1.83
X			X			2	600	0.00	1.90
					X	1	600	7.50	9.48
		X				1	2400	0.42	2.15
			X			1	600	0.17	1.59
				X		1	600	0.00	2.83
	X					1	600	0.00	4.14
X						1	600	0.00	2.15
						0	600	0.00	2.23

Figure A3.1: Scatterplots showing average annual harvest and percent persistent colored by number of interventions. Optimal Pareto points are shown as triangles, on the upper left edge of the point cloud. All the Pareto optima have 3 interventions or greater for historical rainfall, and 4 interventions or greater for high-variation rainfall.



Appendix 4. Effects of differing persistence thresholds on the two outcome variables (persistence and annual average harvest).

Figure A4.1: Proportions of model runs that successfully lasted 60 years (top) and the average annual harvest of these models (bottom), as influenced by randomly chosen persistence thresholds (ranging from biological minima to community-chosen minima). Proportions are calculated for 20 different bins of each threshold, and a Generalized Additive Model smoothing spline is used to show the trend in average annual harvest (gray bands show 95% credible intervals). Each column shows the effects of the minimum threshold for cows (left), woodland biomass (center), and harvest (right) Models using the historical rainfall time-series are shown in light green, with high rainfall variation scenarios shown in dark blue. High rainfall variation models have consistently worse outcomes.



Note that the persistence rates are much lower for this analysis (which includes ten permutations of the simulation dataset with differently selected random persistence thresholds for each, resulting in 960,000 simulations for each of the two rainfall scenarios) than the previous analyses (which only included the 96,000 runs per rainfall scenario and used biologically minimal persistence thresholds). This analysis also averages over all categorical management interventions.

The thresholds differed in how quickly they caused models to fail: model persistence was highest for low cow minimum thresholds (as high as 2.5%), but this decreased rapidly, as opposed to the definition of the woodland minimum, which had lower initial persistence (1.5%) at the biological minimum, but then models remained persistent over a wider range of woodland thresholds, with persistence never falling to zero. Crop thresholds began the lowest of all (around 1% of models persisted all 60 years, even with a biologically minimal threshold definition), and decreased much more slowly than the other two thresholds, eventually reaching zero at Muonde's desired threshold of 48 metric tons per year. Cows are thus more expensive, ecologically, to maintain at a higher quantity, which is consistent with their position at a higher trophic level (subject to the efficiencies associated with consumption of a resource).

The average annual harvest is less for simulations with higher required amounts of cows and woodland, but this tradeoff is strongest for cows, while increasing the woodland threshold has the greatest impact at low thresholds: above roughly 100 metric tons, requiring more woodland does not drastically change the amount of harvest. As the harvest amount required for persistence increases, the average harvest increases as well because the persistence thresholds eliminate the models with smaller average harvests.