Research

Exploring linkages between protected-area access and Kenyan pastoralist

food security using a new agent-based model

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ABSTRACT. Pastoral communities living in the arid and semi-arid lands of Kenya raise livestock herds within highly patchy environments, and experience chronic food insecurity and inter-ethnic conflicts linked to resource access. For these primarily rural communities, livestock are a source of calories and income and are therefore crucial to achieving the United Nations' Sustainable Development Goals (SDGs) associated with food security (SDG 2). Achieving sustainable improvements in household well-being in this region is contingent on understanding how diverse policy decisions complement or undermine the ability of pastoral households to raise livestock. Of near-term relevance is the question of reconciling food security with biodiversity conservation goals (SDG 15) across Kenya's drylands, which are also known for their exceptional biodiversity. World over, protected areas are associated with diverse impacts on local communities. However, spatial variation in how these areas contribute to pastoral food security and household wellbeing across Kenya remain poorly understood. Using our newly developed model SPIRALL, we examined spatial variation in changes in household well-being that result when pastoral households across Kenya lose access to neighboring protected areas. SPIRALL is a country-scale, agent-based pastoral household decision-making model. We joined SPIRALL to L-Range, a model that simulates rangeland ecosystem functioning. The resulting coupled model simulates reciprocal interactions between pastoral households and the environment in Kenya and can be used as a scenario analysis tool to understand impacts of broadly defined policies on food security. Our scenario-based analysis showed that loss of protected-area access caused increases in rates of hunger, debt, and trans-boundary movements, particularly among non-sedentary and agropastoral households. These effects were spatially heterogeneous and influenced by county size and proximity to protected areas. We conclude by outlining the policy-implications result of the interactions between SDG 2 and SDG 15 in Kenya. We also highlight additional uses and avenues for improvement for SPIRALL.

Key Words: conflicts; food security; L-Range; pastoralism; protected areas; scenario modeling; SDG 2; SDG interactions; SPIRALL; sustainable development

INTRODUCTION

The United Nations' Sustainable Development Goals (SDGs) are a country-specific development agenda that foregrounds the role of functioning ecosystems in achieving sustainable improvements in human well-being (Griggs et al. 2013). A defining feature of the SDGs is the interaction of the 17 constituent goals (Smith et al. 2018). These SDG interactions are modulated by the specific socioeconomic context of each country, with interactions manifesting over diverse time horizons (Scherer et al. 2018, Nilsson et al. 2018). Among the 17 goals, the second goal of achieving food security (SDG 2) has been recognized as a nexus issue: i.e., across contexts, it is characterized by repeated interactions with multiple other goals (Bleischwitz et al. 2018). For example, pathways to achieving SDG 2 result in direct impacts on land use and water, which can in turn impede progress toward achieving provisioning of clean water (SDG 6) and terrestrial biodiversity conservation (SDG 15; Pham-Truffert et al. 2020). Identifying effective policy interventions to achieve food security therefore depends on understanding SDG 2 interactions and balancing the resultant synergies and trade-offs with other sustainable development imperatives (Nilsson et al. 2016).

The nexus character of SDG 2 is exemplified by conditions prevailing in the arid and semi-arid lands (ASALs) of Kenya (Stavi et al. 2021). The ASALs cover approximately 80% of Kenya's land area and are home to a third of its ethnically diverse population, which experiences chronic food insecurity (Oba 2001). Rural populations in the ASALs are predominantly engaged in traditional pastoralism centered on the raising of cattle and other livestock on rangelands (Ng'ang'a et al. 2016). Seasonally moving their households and herds to access widely dispersed critical resources, i.e., strategic mobility (Krätli et al. 2013), is a defining practice of traditional pastoralism and underpins the ability of pastoral households to withstand climatic shocks (Galvin 2009, McPeak and Little 2017). Over the past decades, forces operating at diverse scales within and beyond Kenyan pastoral systems have hindered this strategic mobility and modified pastoralist strategies, with cascading impacts on the rates of poverty (SDG 1) and food security of pastoral people, as well as changes in carbon sequestration and cycling (SDG 13; Reid et al. 2014). These forces include population growth, sedentarization and adoption of agriculture by pastoralists, livestock disease, and changes in land use driven by economic development and conservation interventions. Pastoral mobility also mediates the complex relationship between food security and patterns of ethnic conflict in the ASALs (Anyango et al. 2017). For example, movements of pastoralists into agricultural areas, or into pastures across ethnic and national boundaries during periods of extreme drought, may precipitate new conflicts or inflame existing tensions (Berger 2003, Kuznar 2005).



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Maintaining food security in Kenya's ASALs without undermining the other SDGs associated with this diverse region is imperative. The policy coherence necessary to achieve this goal requires a deeper consideration of the spatiotemporal heterogeneity in SDG 2 interactions and their relationship with existing livelihood strategies practiced by pastoral households. Of relevance today is the question of how the Kenyan government's response to global calls for intensifying biodiversity conservation efforts (SDG 15) will interact with goals to improve food security in the ASALs. For example, the 30 by 30 initiative envisages, through multiple, national-level commitments, setting aside 30% of the planet for biodiversity conservation (Target 3, CBD 2022). This 30 by 30 goal is one among several such global targets that have emerged in response to documented global declines in biodiversity (Butchart et al. 2010). The achievement of many of these targets involves the strategic deployment of land sparingand land sharing-based conservation measures. Whereas the language associated with these policies increasingly reflects a strong commitment toward equity-based and participatory conservation, they do not fully contend with the wider political, social, and economic ripples that protected area (PA) creation and management can set in motion (Brockington and Wilkie 2015, Gurney et al. 2023).

Several iconic PAs exist within Kenya's ASALs and along its borders within nations such a Tanzania, Ethiopia, and Uganda. Whereas these PAs are known for their exceptional biodiversity, they also often enclose key wetlands and grazing pastures that are of critical importance to pastoral groups, particularly for surviving periods of drought. In conjunction with other drivers of change, constrained access to critical resources via PA establishment has led to changes in pastoral diets and lifestyles, and has introduced new resource conflicts (Reid et al. 2004, Kieti et al. 2020). Numerous studies have explored pathways by which access to key resources impacts pastoral household well-being, as well as how PAs can serve both to impoverish and enrich pastoral populations in their vicinity (Boone et al. 2011, Brockington and Wilkie 2015, Mojo et al. 2020). Yet, given the large variation in the size of PAs in the region, the availability of pastures within and around PAs, and the pastoralism practices of households in their vicinity, PA access is likely to be of varying importance to food security across Kenya. Similarly, the role of PA access in contributing to conflicts among pastoral groups is also poorly understood (Berger 2003, Greiner 2012). Consequently, ensuring that efforts expended toward achieving SDG 2 and SDG 15 in the ASALs are effective and sustainable requires engaging with the enmeshed character of these goals. To this end, we endeavored to understand how resources within existing PAs in Kenya's ASALs contribute to pastoral household well-being, particularly household food security and exposure to inter-ethnic conflicts.

We explore this question using our newly developed agent-based model called SPIRALL. We begin first with a detailed description of SPIRALL, including a short review of its antecedents. We then demonstrate, using a baseline simulation, SPIRALL's validity as a tool to explore our questions of interest. We then conduct a scenario analysis to explore how PA access modulates food security, poverty, and inter-ethnic conflicts across Kenya's ASALs.

MODEL DESCRIPTION

Overview

The need for heuristic tools to examine SDG interactions has been reiterated (Nilsson et al. 2016, Breuer et al. 2019). Yet, no modeling tools exist to explore the social-ecological drivers and interactions of SDG 2 across Kenya. Scenario analyses using discrete-event simulations have been used to explore and explain the complexity of pastoral social-ecological systems in eastern Africa and more specifically in Kenya (Galvin et al. 2006, Boone and Lesorogol 2016). For example, the agent-based model RiftLand (Kennedy et al. 2014) simulates household decisionmaking over a large swath of eastern Africa. The model represents household responses to their environment with high granularity; however, the impacts of these household decisions on the environment are not considered. Household decision-making models such as Pastoral Household Economics and Welfare Simulator (PHEWS; Thornton et al. 2003) and Decisions under Conditions of Uncertainty by Modeled Agents (DECUMA; Boone et al. 2011), are distinguished by their explicit linkage with models that simulate ecosystem services. These models simulate the reciprocal interactions between pastoral and agro-pastoral households and the environment, albeit at smaller spatial scales such as counties.

Building on these previous efforts we developed Simulating Prosperity in Rural and Land-based Livelihood communities (SPIRALL), an agent-based (Bonabeau 2002), pastoralhousehold decision-making model tailored for the ASALs of Kenya. SPIRALL is written in NetLogo Version 6.1.1, a multiagent modeling environment (Wilensky 1999). We linked SPIRALL to L-Range, a localized version of the global rangelands model G-Range (Boone et al. 2018, Sircely et al. 2019), and used L-Range to simulate ecosystem function across Kenyan rangelands. The resulting coupled social-ecological systems model pivots on the diverse pastoral mobility strategies (nonsedentary, sedentary, agropastoral) and includes an explicit rendering of the conversion of ecosystem production to household calories and income. We used the Overview, Design concepts, and Details protocol (ODD) to describe SPIRALL (Grimm et al. 2020). We summarize the ODD here and include a detailed description in Appendix 1.

The purpose of SPIRALL is to enable the exploration of SDG 2 outcomes and interactions across Kenya. At its broadest scale, Kenyan food security is the ultimate outcome of a complex interplay between national-level policies, environmental conditions, international markets, as well as global political and environmental shocks (FEWS NET 2017). However, SPIRALL primarily serves to describe the set of intrinsic social and ecological factors that may predispose different parts of the ASALs to food insecurity (Edmonds et al. 2019). Specifically, the model allows us to learn, via scenarios, how the environment, and policies that can modify pastoral household interactions with their environment, can modulate food security and other indicators of well-being in Kenya's ASALs. SPIRALL favors a granular description of household-level behaviors, over a comprehensive integration of cross-scale drivers of food security. Consequently, it serves as a tool to understand social-ecological drivers of vulnerability to food insecurity, but not as a forecasting tool. Patterns in food security across Kenya, seasonal movements, and calorie consumption by households serve as model evaluation criteria.

SPIRALL is composed of two types of entities: patches and pastoral households (agents) distributed on these patches (Fig. 1). Each patch is 10 x 10 km and together the patches represent 1.94 million km² of eastern Africa. A set of variables define patch and household attributes (Table 1). Patch attributes together determine the social-ecological character of each patch. Household attributes determine the composition of the household, its socioeconomic characteristics, and pastoral practices, i.e., non-sedentary, sedentary, or agropastoralist. A set of parameters that are common to all households are also defined (Appendix 2). These include parameters that modulate movement decisions of households or livestock herds, livestock herd dynamics, livestock diet composition, economic transactions, and social interactions. Simulations in SPIRALL typically span multiple years, such as 20 years in our scenario exploration, with households making decisions at monthly time steps. Simulation outcomes can be summarized at national and sub-national spatial scales and at temporal intervals of a single month or longer. Processes occurring within patches, e.g., distribution of agents or foraging by livestock, are spatially implicit.

At every time step the ecosystem model L-Range reads in monthly weather data, i.e., precipitation and minimum and maximum temperature, and updates the availability of biomass across eight biomass pools for all patches within SPIRALL. This biomass availability is used to determine maximum stocking density of different livestock species on each patch. Households use the

Fig. 1. Study region showing Kenyan counties (black borders), protected areas (PA; IUCN category I–VI and other protected patches), and dominant land cover within 10 x 10 km patches. The "other cover" class represents built up areas, bare areas, and other minor land-cover classes.



information on stocking density to move the entire household or their herds to appropriate patches. These movements are governed by rules specific to the type of pastoralism they practice, i.e., nonsedentary, sedentary, or agropastoral (Table 1). Households try to graze herds within county boundaries when possible. When a household or its herds crosses the county boundary, they are labeled as at risk for conflicts and may lose their herd at a fixed probability. Once all households have located themselves on appropriate patches, livestock species consume and deplete specific biomass pools. Livestock change weight based on the total energy gained and lost in accessing food. During reproductive months, i.e., April for all livestock, surviving individuals of livestock reproduce probabilistically and commence lactation. During harvest months, i.e., July, agropastoral households harvest maize. Each month, households attempt to meet calorie requirements using household sources such as milk, meat from dead animals, and purchased or harvested maize. Each month households attempt to meet expenses using available cash such as earnings from labor, business, and sale of livestock and crops, or make purchases when available cash exceeds expenses. Households who have failed to meet their calorie needs may receive milk from neighboring households who have some to spare. Similarly, households who have lost all their livestock may receive cattle as gifts from other wealthier households in their social network. Households that fail to meet calorie needs each month are labeled as food insecure and those that fail to meet monthly expenses are labeled as in debt. At the end of each month, L-Range reads from SPIRALL the fraction of biomass from each pool lost to grazing on each patch and uses that to continue simulation of ecosystem dynamics.

A design concept that underlies SPIRALL is that pastoralists have knowledge of the availability of forage in a subset of patches. Additionally, resource access is constrained by movement rules associated with the type of pastoralism practiced by the household. Each month households attempt to increase their herd size while minimizing the potential for conflicts with other ethnic groups. Finally, the reciprocal interactions between households and the environment hinge on explicitly tracking the conversion of ecosystem production to livestock and agricultural production in SPIRALL and tracking the ecosystem-wide impacts of grazing in L-Range.

Initialization

Households were initialized by distributing them across 14 ASAL counties in Kenya where pastoralism is practiced by more than 10% of the population (Table 2). A total of 10,844 households were simulated, representing approximately 5% of the pastoral population across these counties in the year 2000. Household distribution followed census data (SEDAC 2016) and the estimated pastoral population within each county (Krätli and Swift 2014). Household members were assigned such that each household had at least one adult male and female member with a mean household size of eight. Livestock holdings and external income sources of households were set to scale positively with the number of members in the household. We summarized livestock herds owned by a household using tropical livestock units (TLU), where one TLU represents a 250-kg animal. We also standardized the number of members in a household in terms of adult equivalents (AE; Appendix 2). We assumed that agropastoral households conduct rainfed agriculture and only grow maize with

Attribute	Description
Entity: patch	
Cover	Land cover type associated with the patch (ESA 2017; Fig. 1)
County	Kenyan county within which the patch is located; surrogate for ethnic group boundaries (Nyabira and Ayele, 2016)
Livelihood zone	The livelihood zone within which the patch is located; Kenya is divided into 21 livelihood zones based on the dominant livelihood strategy of households (FEWS NET 2017)
Protection status	Patches intersecting protected area boundaries (IUCN category I–VI and other PAs) are classified as protected (UNEP-IUCN 2018)
Entity: household	
Who	Unique household identification number
Home patch	Household location at initialization and the patch the household returns to in the wet season
Ethnic group	Ethnic group identity based on county within which the home patch is located
Members	Number of household members within five age-sex classes
Family	Up to 10 households from the same ethnic group with whom social interactions such as gifting of livestock can occur
Pastoralism type	Sedentary: Households do not migrate seasonally, but cattle herds do
••	Non-sedentary: Entire households along with all livestock species may migrate
	Agropastoral: Sedentary pastoralists who also practice subsistence agriculture
Livestock	Number of cattle, camels, sheep, and goats owned within three age-sex classes
Land	Agricultural land in ha farmed by agropastoral households
Income	Monthly income in KSh earned from labor, business, or other non-pastoral sources
Expenses	Monthly expenses in KSh for general, veterinary, and food needs
Store calories	Calories purchased from the store (in units of 1 kcal from a mix of maize, wheat, and beans)
Cash in hand	Ready cash in KSh available within the household

 Table 1. State variables associated with household attributes assigned at initialization. Livestock, store calories, and cash-in-hand are variables that change over time. Households can also earn income from the sale of livestock. KSh represents Kenyan Shillings.

 Table 2. Pastoral population characteristics and livestock density in 14 ASAL counties.

County	HH / km²	% Sedentary	% Agropastoral	TLU/AE (SD)	TLU / km ²
Turkana	0.62	74	3.2	2.27 (2.83)	10.07
Marsabit	0.19	21.6	2	3.55 (2.58)	4.78
Mandera	0.99	29.3	5	2.66 (2.91)	19.44
West Pokot	0.96	9.6	10.7	3.76 (4.55)	26.72
Samburu	0.26	16.6	6.3	3.99 (3.75)	7.99
Isiolo	0.31	34.5	1.5	4.13(3.95)	9.24
Wajir	0.56	43.0	3	4.06 (4.94)	16.8
Garissa	0.48	51.5	0	5.82 (6.09)	20.95
Laikipia	0.30	12.2	36.6	7.18 (6.16)	16.88
Baringo	1.48	15.6	16.8	2.39 (4.09)	26.7
Tana River	0.26	32.3	3.9	6.47 (5.57)	11.92
Narok	0.44	5.8	56.9	7.28 (7.26)	23.65
Kajiado	0.51	12.01	28.2	5.53 (6.45)	20.37
Lamu	0.08	8.8	52.9	9.09 (4.38)	5.74

HH - Households; TLU/AE - Tropical livestock units per adult equivalent where 1 TLU is 250 kg of animal biomass and 1 AE is equivalent of an adult male human.

a maximum possible maize harvest at 606 kg / ha (Thornton et al. 2006) and annual harvests varying in proportion to the green herb biomass simulated by L-Range for the patch. In the simulation, pastoral households can know the quality of, and access patches within a 100-km radius around their home patch (Table 1; McCabe 2011). Finally, we assumed that there is no human population growth. To stabilize household behaviors, a five-year spin-up simulation for all households was conducted using randomized weather data for the period between 1980 and 2019. The state of all households at the end of this simulation was stored in a file and used to set initial conditions for all subsequent simulations.

SIMULATION EXPERIMENTS

Baseline simulation

We explored household behaviors across Kenya under a baseline scenario that allowed pastoralists minimally constrained access to livestock-grazing pastures, including those within PAs occurring within their movement orbits. Even though these PAs are intended as inviolate spaces, the use of these areas by pastoralists is accommodated to an extent (Butt 2011). The SPIRALL L-Range coupled model was set up to represent climatic, environmental, and demographic conditions that were extant between the years 2000 and 2019. We conducted 20 runs of the baseline simulation, and calculated means and standard errors for variables of interest. An exploratory analysis revealed that 20 simulations yielded narrow standard errors (< 2% of the mean) around variable means.

Evaluating a model such as SPIRALL that spans large spatial scales and a diversity of pastoral practices and land tenures represents challenges resulting from the uncertainties associated with parameters and the necessary simplification of complex social practices. We therefore relied on the principles of patternoriented modeling (Grimm et al. 2005, Gallagher et al. 2021) to assess our model's ability to capture spatial and temporal trends relevant to exploring to our research question. Pattern-oriented modeling entails ensuring that simulation results match observed patterns in the study system across diverse scales. We assessed spatial and seasonal trends in rates of food insecurity across the ASAL counties and calorie consumption patterns. We compared estimates of food security from SPIRALL with those reported by the Famine Early Warning Systems Network (FEWS NET; FEWS NET 2017). For the period between 2010 and 2015, FEWS NET provides quarterly reports of food security outlooks for each county in Kenya. For this period, Kenyan counties are classified based on the food insecurity severity scale into five classes: (1) no acute food insecurity; (2) moderately food insecure; (3) highly food insecure; (4) extremely food insecure; and (5) famine. We created a numeric classification scale by assigning values from zero to four to these five classes. For each county, for the period between 2010 and 2015, we created an index of food security by summing together the quarterly food security scores; counties with higher scores could be interpreted to be more chronically food insecure. We then ranked these counties based on their food security scores. Similarly, we calculated a seasonal food security index for each county by separately summing the food security scores for the months of January, April, July, and October, months for which FEWS NET provides immediate or current food security projections.

Alternative Scenario: No PA access

We explored the impacts of PA access on measures of household well-being by comparing our baseline simulations against a scenario where households were denied access to PAs within their movement orbits. PAs (Fig. 1) cover approximately 9% of the study region. Households were denied access to both strict PAs (IUCN category I–VI; UNEP-IUCN 2018) and other protected patches within their movement orbits (Fig. 1). Our intention was to emulate a scenario where PAs are maintained as inviolate spaces as envisaged in land-sparing conservation initiatives (Phalan et al. 2011), where landscapes are composed of protected patches and areas of intensified agriculture. We conducted 20 independent runs of this alternative scenario and report mean changes in rates of hunger, debt, and conflicts within different Kenyan counties and household types relative to the baseline simulations.

RESULTS

Baseline simulation

Overall, the baseline simulations were stable, evidenced by low variability in mean annual estimates of per-capita livestock holdings for counties across repeated model runs (Fig. 2). Climate was a strong driver of SPIRALL dynamics. Fluctuations in livestock holdings were consistent with precipitation trends between 2000 and 2019. For example, counties such as Turkana and Laikipia, which experienced steady increases in precipitation, were also characterized by small increases or stable livestock populations. Similarly, in counties where precipitation levels were low and fluctuated substantially, e.g., Wajir (Fig. 2), livestock holdings were characterized by declining trends.

Seasonal trends

We summarized results for each year over quarterly intervals. These intervals approximately coincide with the four seasons in the ASALs (Table 3; Little et al. 1999). The fraction of food-insecure households was higher in the short-wet and late-dry seasons than in the wet season. These seasonal trends in vulnerability to food insecurity mirror long-term trends in food security predictions for the region (FEWS NET 2017). In the wet season, on average, households were able to meet up to 57% of their calorie needs from milk and meat derived from their own livestock herds (Little et al. 1999, Thornton et al. 2003).

Household incomes peaked in the wet season with a large increase in the fractional contribution from the sale of milk. Income from livestock sales were highest in the short-wet and late-dry seasons but did not exceed 10% of the overall income earned. The average distance traveled by households or their herds each month was **Fig. 2.** Trends in mean annual precipitation (blue line) and simulated mean (SE) per-capita livestock holdings (TLU / AE; black line) for four ASAL counties across a precipitation gradient. See Appendix 3 for trends for remaining counties.



Table 3. Quarterly trends in precipitation and household responses (mean and standard error) from 20 runs of the baseline simulation. Precipitation was calculated as the mean monthly precipitation within each quarter averaged over 14 ASAL counties. Distance traveled is the mean distance traveled by households or herds when they move to access pastures.

	Jan–Mar	Apr–Jun	Jul-Sep	Oct-Dec
Season	Late-dry	Wet	Early-dry	Short-wet
Precipitation (mm / month)	42.6 (8.5)	117.4 (10.8)	80.36 (7.0)	93.26 (10.5)
Distance traveled (km)	40.5 (2.6)	44.9 (2.7)	47.3 (2.5)	20.9 (2.2)
% Food insecure HH [†]	21.3 (0.7)	17.1 (0.4)	19.1 (0.5)	20.6 (0.3)
% Calories from milk and	16.5 (3.2)	62.2 (18.4)	34.8 (3.6)	32.6 (3.6)
meat				
% Income - milk sales	0.0 (0)	17.8 (1.8)	5.8 (0.4)	2.9 (0.4)
% Income - livestock sales	12.0 (0.6)	8.4 (0.5)	9.7 (0.5)	10.8 (0.4)
% HH using PAs	14.9 (1.5)	15.4 (1.5)	15.8 (1.3)	14.7 (1.5)
% HH crossing county	6.2 (0.5)	0.6 (0.1)	4.8 (0.5)	5.3 (0.5)
bounds				
[†] Households.				

lowest in the short-wet season. The mean distance traveled in the wet season does not represent households moving to find pastures because in SPIRALL, non-sedentary household agents are programmed to return to their home patches and stay there for the duration of the wet season. The fraction of households crossing county boundaries was highest in the late-dry season. We interpret these county crossings as an index for potential interethnic conflicts. Households accessed protected areas in all seasons.

Spatial trends

We calculated a county-specific index of vulnerability to food insecurity by summing together the fraction of food-insecure households each month in the period between 2010 and 2015. We then ranked the counties based on this index, from most food **Table 4.** County-specific household responses from the baseline simulation (mean and standard error). "SPIRALL Rank" is the foodsecurity rank (vulnerability) based on summing the monthly fraction of hungry households estimated for each county, 2010–2015. "FEWS Rank" is the rank based on FEWS NET food security forecasts for the same period based on observed trends. Higher ranks indicate lower food security. "% HH in debt" is the mean monthly percentage of households failing to meet their monthly expenses. "% HH using PAs" is the mean monthly percentage of households using PAs. "Distance traveled" is the mean monthly distance traveled by households when they move to access pastures. "County crossing" represents the mean % of households that graze livestock outside their home county each month.

County	SPIRALL rank	FEWS rank	% HH [†] in debt	% HH [†] using PAs	Distance traveled	County crossing
amu	1	1	9.3 (0.21)	20.75 (0.21)	33.7 (0.1)	3.94 (0.41)
Lajiado	2	4	28.1 (0.15)	35.8 (0.15)	47.5 (0.1)	2.34 (0.1)
aikipia	3	5	26.1 (0.13)	50.1 (0.18)	41.8 (0.1)	1.89 (0.13)
ana River	4	8	31.5 (0.13)	8.7 (0.03)	49.6 (0.18)	1.03 (0.04)
larok	5	2	32.1 (0.02)	62.16 (0.1)	45.9 (0.03)	2.83 (0.15)
amburu	6	6	36.5 (0.13)	17.6 (0.1)	51.6 (0.05)	0.51 (0.77)
1arsabit	7	13	38.9 (0.13)	16.6 (0.1)	54.9 (0.1)	0.04 (0.01)
Farissa	8	10	39.8 (0.13)	6.3 (0.03)	49.0 (0.05)	3.65 (0.10)
siolo	9	14	37.8 (0.21)	2.9 (0.05)	48.4 (0.05)	1.31 (0.11)
Vest Pokot	10	10	39.1 (0.03)	29.54 (0.1)	54.5 (0.08)	2.54 (0.11)
Vajir	11	12	46.0 (0.1)	4.9 (0.13)	50.3 (0.03)	3.12 (0.08)
Iandera	12	11	47.9 (0.1)	10.3 (0.03)	53.2 (0.03)	11.5 (0.27)
urkana	13	9	49.2 (0.05)	12.5 (0.03)	64.2 (0.08)	4.45 (0.11)
aringo	14	3	55.1 (0.07)	19.2 (0.03)	45.5 (0.2)	57.2 (0.69)
urkana aringo Households.	13 14	9 3	49.2 (0.05) 55.1 (0.07)	12.5 (0.03) 19.2 (0.03)		64.2 (0.08) 45.5 (0.2)

secure, i.e., low vulnerability, to least food secure, i.e., high vulnerability (Table 4). We compared these ranks with county rankings qualitatively, based on FEWS NET food security predictions and using a Spearman's Rank correlation coefficient. County-wise food security, i.e., vulnerability, predictions from SPIRALL and FEWS NET showed moderate positive correlation ($\rho = 0.46$). Relative to FEWS NET predictions, SPIRALL simulated higher rates of food insecurity, i.e., vulnerability, in Baringo and Narok Counties and lower rates in Tana River, Marsabit, and Isiolo Counties. Trends in the fractions of households failing to meet their monthly expenses in each county scaled positively with food security trends.

The mean distance traveled per move to access pastures varied considerably across counties. Households in northern counties such as Turkana, Mandera, Marsabit, Samburu, and West Pokot moved greater distances to access pastures relative to southern counties (Table 4). The average household moved 2.6 times each year. Use of protected areas by households for livestock grazing was higher in counties such as Narok, Laikipia, Kajiado, and West Pokot that border or contain large PAs. Nearly 62% of households in Narok County accessed the adjoining Masai Mara National Reserve and Serengeti National Park located in Tanzania. The number of households crossing county boundaries to graze their livestock, an index for conflict potential, was higher in northern counties such as Turkana, Baringo, Mandera, and Wajir. In counties such as Turkana and Mandera that border other nations, a large fraction of trans-boundary movements were into Uganda and Ethiopia respectively.

No PA access

Loss of PA access caused a decline in household livestock holdings. Agropastoral and non-sedentary households experienced the steepest declines (A, Fig. 3). The loss of PA access increased the annual fraction of non-sedentary and agropastoral households experiencing hunger. However, in both scenarios, agropastoral households experienced lower rates of hunger than non-sedentary and sedentary households (B, Fig. 3). In the baseline scenario, all pastoralist household types experienced increases in their large livestock, i.e., camel and cattle, holdings over a 20-year period, with the largest percent increases occurring among agropastoral households followed by non-sedentary households. However, when PA access is lost, agropastoral households experienced the largest percent declines in their large livestock holdings (Fig. 4). Small livestock numbers declined for all households in the baseline simulation with the largest declines occurring among non-sedentary households. Agropastoral households on the other hand experienced an increase in small livestock numbers when PA access was lost. Households across all counties experienced changes in hunger, debt, and transboundary movements. Increases in the incidence of hunger and debt were highest in Kajiado, Laikipia, Narok, and West Pokot where, as per the baseline simulation, a large fraction of households was dependent on PAs (Table 1, Fig. 5). Counties such as Garissa, Wajir, Tana River, and Isiolo experienced the smallest increases in rates of hunger and debt. Losing access to PAs also resulted in changes in the rates of trans-boundary movements with the sharpest increases occurring in Narok, West Pokot, Laikipia, and Kajiado (Fig. 3; Fig. A3.1, Appendix 3). Countyspecific impacts on other measures of household behaviors such as effects on income earned from the sale of livestock are included in Appendix 3 (Tables A3.1 and A3.2, Appendix 3).

DISCUSSION

Loss of PA access

Our scenario analysis reiterates the nexus character of SDG 2 across Kenya's ASALs. Within this region, household food security is sensitive to PA management and in turn can affect household exposure to poverty and inter-ethnic conflicts. Regardless of the pastoralism type practiced, PA access was linked Fig. 3. (a) Mean % change (SE) in per-capita livestock holdings (TLU / AE) when households lose access to PAs. (b) For each scenario and pastoralism type, boxplots represent percentage of hungry households at the end of 20 years over 20 model runs. Lines within boxes represent the median response and dots represent outliers.



Fig. 4. Mean % change (SE) in large livestock (cattle and camel) and small livestock (sheep and goat) populations at the end of 20 years in the baseline and no PA access scenarios for each pastoralist type. Means for each scenario are calculated over 20 simulations.



to household hunger and debt, suggesting that PAs across Kenya's ASALs harbor resources critical to ensuring pastoral well-being (Boone et al. 2011). Declines in well-being stemmed primarily from declines in herd size and changes in herd composition. In our baseline simulations, small stock made up the larger fraction of household herds. However, when households lose access to PAs, sedentary and agropastoral households experience further skews in herd composition in favor of small stock, mirroring trends observed among sedentarizing households (Österle 2008). Such changes in livestock composition in the vicinity of PAs can drive changes in the ratio of woody and herbaceous vegetation with consequences for wild browsers, as well as for rates of carbon cycling (Österle 2008, Veldhuis et al. 2019).

Impacts of losing PA access were spatially heterogeneous and were most pronounced in small counties such as Narok and West Pokot, which share extensive boundaries with PAs. Households in SPIRALL **Fig. 5.** Mean change in % households experiencing food insecurity, debt, and trans-boundary (out-of-county) movements when PA access is lost relative to baseline simulations. Rates of hunger, debt, and trans-boundary movements were calculated at the end of 20 years and averaged across 20 simulations for each scenario. Values plotted represent the mean (SE) difference in these variables between the two scenarios.



can access patches within a 100-km radius of their home patch. Therefore, a larger fraction of households within small counties have movement orbits that can overlap adjoining PAs, partially explaining our results. Across eastern Africa, pastoralists are increasingly sedentarizing or adopting agropastoral lifestyles in response to changes in climate, land tenure, market, and services access (McCabe et al. 2010, Galvin 2021). In our simulations, despite their adaptive advantages, agropastoral and nonsedentary households experience the largest increases in hunger and herd declines when access to PAs is lost. Simultaneously, under both scenarios, non-sedentary and agropastoral households experience the highest and lowest rates of hunger respectively. These trends arise both from the specific ways by which these households translate ecosystem production into calories and sources of income, and because of their geographic location. For example, agropastoral households are typically located in areas that receive higher precipitation and rely on both livestock and agricultural production to meet calorie needs.

Agropastoralism is dominant in the productive southern parts of Kenya, where the largest PAs in the region are located. Increasing adoption of agropastoralism around these PAs has been a leading cause of rangeland fragmentation, disrupting both livestock and wildlife movements (Thornton et al. 2003, Reid et al. 2004, Veldhuis et al. 2019). For example, in Narok County, which adjoins the Masai Mara National Reserve, a large fraction, nearly 60% in SPIRALL, of the modeled households are agropastoral. Crop cultivation helps reduce overall food insecurity among agropastoral households. However, these households maintain large cattle herds by strategically moving them to suitable pastures and depend on livestock sources for a significant fraction of their calorie needs. When PA access is lost, cattle herds experience declines owing to competition for limited pastures. On the contrary, non-sedentary pastoralism dominates in the northern counties, i.e., Turkana, Mandera, and West Pokot, characterized by low rainfall. Within these regions the effects of loss of PA access potentially exacerbate the patchiness in the availability of grazing resources. Whereas in reality, non-sedentary pastoralists can adjust their movement orbits to accommodate this increased patchiness (McCabe 2011), in SPIRALL, specified maximum movement radii constrain the set of patches that can be accessed during simulations by these households.

The establishment of PAs and the rules of access associated with them has the potential to alter existing social dynamics, thereby introducing novel resource conflicts (West and Brockington 2006, Greiner 2012). Inter-ethnic conflicts are common across the ASALs, but their nature, underlying causes, and intensity vary (Van Weezel 2019). We focus only on conflicts that may arise when households graze livestock beyond their own ethnic group boundaries. In our simulations, loss of PA access resulted in an increase in trans-boundary movements in several counties, including movements beyond national boundaries (Table A3.2, Appendix 3). These transnational movements, which often result in conflicts, have been well documented (Leff et al. 2009). Access to PAs that lie just beyond Kenvan national boundaries may have a modulating effect on these conflicts. This emphasizes the need for greater cooperation in PA management among nations in this region, such as through the establishment of trans-frontier conservation areas in a manner that integrates the needs and aspirations of local communities (Duffy 2005, Hanks 2008, Bourgeois 2023).

Accelerating declines in biodiversity have promoted ambitious calls for the expansion of the global PA network, and undergird ambitions related to SDG 15 focused on terrestrial biodiversity conservation. The Nature Needs Half and Half-Earth movements call for the setting aside of 50% of the planet expressly for conservation purposes (Dinerstein et al. 2017). Similarly, the Convention on Biodiversity's 30 by 30 target (2022), to which Kenya is a signatory, aims to protect 30% of terrestrial and aquatic areas for biodiversity conservation by 2030. Mehrabi et al. (2018) estimate that protecting half the planet would entail significant losses in food calories, particularly in Africa and Asia, resulting from the return of agriculture and pastureland back to nature. These authors and subsequent studies (Ellis and Mehrabi 2019), also posit that these losses may be mitigated through conservation actions centered on shared multifunctional landscapes. Our results suggest that PAs in and around Kenya harbor key resources that are critical to ensuring food security (SDG 2), reducing poverty (SDG 1), and increasing peace and justice (SDG 16) within several counties. Because of the geographic context within which they are practiced, existing pastoral strategies fail to alleviate the declines in household well-being that result from a loss of access to these resources.

Baseline simulation

Results from the baseline simulation demonstrate that SPIRALL coupled with L-Range can emulate key aspects of Kenyan pastoral household behaviors, specifically those that determine household-level food security. It captures the seasonal contribution of livestock-based calories to pastoral diets as well as the spatial variation in pastoral movement patterns. The baseline simulations reveal climate as a driver of change in percapita livestock holdings (TLU / AE), which is a determinant of pastoral household well-being. The centrality of climate in determining food security in this region has been elucidated by previous studies (Galvin et al. 2001, Shukla et al. 2021). The wet season was characterized by improved access to calories and overall increases in household income driven by the productivity of livestock herds. In the driest months on the other hand, households experienced increases in food insecurity and transboundary movements, which we interpret as an index for interethnic conflict risks. Climate change-driven increases in drying conditions in the region can increase the number of months over which households are exposed to these intersecting risks (Kogo et al. 2020). These seasonal trends may in part be driven by rules governing household movements. As is common in Kenya's pastoral practices, non-sedentary households in SPIRALL return to their home patch during the wet season, thereby reducing the risk of conflicts (Boone et al. 2011). Conversely, this movement rule also means that many households are forced to return to poor quality patches and thereby fail to fully accrue the benefits of increased productivity in the wet season.

In Kenya, precipitation increases along a north-south gradient (Ayugi et al. 2016). This precipitation gradient underlies the spatial heterogeneity in rangeland productivity and pastoral strategies seen in the ASALs (Ellis and Galvin 1994). The baseline simulation adequately captured the spatial heterogeneity in household behaviors and their exposure to risks. The highly variable climatic conditions prevailing in the northern counties such as Turkana, Mandera, Marsabit, and West Pokot strongly limit the growth of livestock herds. Because of smaller per-capita livestock holdings, households in these counties experienced higher rates of hunger and debt. In addition, these households moved longer distances to access pastures that consequently exposed them to greater conflict risks.

Model uses and future applications

Disparities in county-level food-security scores based on SPIRALL and FEWS NET underscores a key design aspect of SPIRAL: the model is not intended as a forecasting tool. FEWS NET food-security forecasts are based on a near-term scenario analysis that depends on predicting livestock population responses to climate, analyzing agricultural output, and assessing national and global market trends. Spatial trends in SPIRALL emerge because of the reciprocal interactions between households and their immediate environment, without any external influences such as markets, or temporal changes such as increases in the pastoral population over time. SPIRALL does not accommodate local or regional markets even though fluctuations in maize and livestock prices are known to exert influences on pastoral household economic decisions and diets (Little et al. 2014). Similarly, household sources of income are inferred based on available survey data, which have spotty spatial and temporal coverage. Such simplifications are an inevitable aspect of modeling efforts that seek to simulate complex phenomena underpinned by cross-scale processes. These simplifications are also part of large-scale, spatiotemporally explicit, and coupled social-ecological models where scale constraints imposed by one or both models dictate which datasets can be leveraged to simulate processes of interest. On the contrary, the granular representation of household decisions pertaining to livestock-rearing and livestock-environment interactions is the strongest aspect of SPIRALL. This is because of the wealth of anthropological information on Kenyan pastoralists, the availability of ecological studies on pastoral livestock dynamics, and the precedents established by other pastoral household–decision models such as DECUMA (Boone at al. 2011) and PHEWS (Thornton et al. 2003).

Taken together, SPIRALL may be best viewed as a model that describes how pastoral households across Kenyan ASALs translate primary production into food calories. The outcomes illustrate spatiotemporal vulnerabilities with regard to food insecurity, poverty, and conflicts for traditional pastoral households across the ASALs. In addition, SPIRALL coupled with L-Range explicates the links between climate and pastoralhousehold well-being in the absence of attenuating factors such as local, national, and international institutions and markets. Consequently, it is an effective tool to explore the challenges posed to SDG 2 achievement across the ASALs by climate and environmental change. Owing to its detailed representation of livestock population dynamics, SPIRALL can also be used to explore how livestock populations and composition are likely to change across Kenya under changing climate and land-use scenarios and their consequent impacts on plant production and carbon cycling. The coupled model can also be extended, via linkage with other simulation models, to explore SDG 2 interactions under future climate and land-use scenarios.

Acknowledgments:

The authors are grateful for the constructive suggestions provided by Tomas Pickering. R. W., R. B. B., P. W. K., and K. G. acknowledge support from NASA Program "Sustaining Living Systems in a Time of Climate Variability and Change" (award#80NSSC19K0182: "Cross-scale Impacts of SDG15 achievement"). We thank the three anonymous reviewers for their constructive comments and suggestions that helped improve our work.

Data Availability:

The datalcode that support the findings of this study are openly available in NetLogo Modeling Commons at <u>http://</u>modelingcommons.org/browselone_model/6430#model_tabs_browse_info.

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APPENDIX 1

SPIRALL - Overview, Design Concepts and Details

Purpose

Our aim was to build a Kenyan pastoral household decision-making model that leverages freely available survey data and reciprocally interacts with an ecosystem model to reproduce broadly observed patterns in food security and livestock herd dynamics across Kenya. The broader purpose of the model is to serve as a heuristic tool to explore how environmental change and policy decisions modulate the interactions between household food security and other parameters of household wellbeing such as economic sufficiency and exposure to conflicts.

State variables and scales

SPIRALL is composed of patches on which agents (pastoral households) are distributed (Fig. 1). Each patch is 10 km X 10 km and together the patches represent 1.94 million km2 of eastern Africa. This includes all of Kenya and parts of Ethiopia, Somalia, Sudan, Uganda, and Tanzania. Each patch is assigned a land cover type based on a land cover classification for the region (CCI Landcover 2017; Appendix 1). Patches are also assigned a county identity using a vector dataset of Kenyan county boundaries. The county is used as a surrogate for ethnic group boundaries such that all households located within a given county belong to the same ethnic group (). Patches are assigned to livelihood zones, following the Famine Early Warning System Network (FEWS NET) livelihood zone classification for Kenya (FEWS NET 2017). Finally, patches are categorized as protected if they fall within protected area boundaries (IUCN category I-VI and other PAs). PA boundaries are based on the World Database on Protected Areas (WDPA; UNEP-WCMA and IUCN 2018). Processes occurring within patches (distribution of agents, foraging by livestock) are spatially inexplicit.

A set of variables define household attributes. These attributes together describe the composition of the household, its socio-economic characteristics, and pastoral practices (e.g., sedentary, or non-sedentary). A set of parameters that are common to all households are also defined (Appendix 2). These include parameters that modulate movement decisions of households or livestock herds, livestock herd dynamics, livestock diet composition, economic transactions, and social interactions. Simulations in SPIRALL span multiple years, with households making decisions at monthly time steps. Simulation outcomes can be summarized at national and multiple sub-national scales and at temporal intervals of a single month or longer.

Process overview and scheduling

The following procedures are executed in sequence. The first three procedures are executed once in the 'Set-up' stage of the model. Remaining procedures repeat at every time-step (month; Fig. A1.1)

- Load layers: Relevant spatial layers from which patch-level and agent-level attributes are drawn are loaded.
- Load agents: Pastoral households are initialized with household-level attributes.
- Load parameters: Parameters associated with different process models are loaded.

- Load forage: Monthly patch-level forage availability simulated by L-Range is read into SPIRALL.
- Find pasture: Entire households or livestock herds move based on movement-rules to locate nearest available pastures.
- Deplete patch: Livestock deplete available forage on the patches they are located on.
- Grow herds: Individual heads of livestock gain forage weight and experience change in their body condition based on the forage accessed.
- Reproduction: If the month is a reproduction month for a livestock species, individuals of that species reproduce with a probability determined by their body condition. Similarly, individuals that have reproduced produce milk.
- Count calories: Households access calories (food) from available milk, meat and maize stores.
- Cash flow: Depending on anticipated expenses and income households make livestock sale and purchasing decisions
- Gifting: Households interact with each other. Households may gift milk and/or livestock to other households in need.
- Wrap-up: Summaries of variables of interest are calculated and written to files. Fraction of forage depleted from each patch is calculated and written back to L-Range.
- Reset households: Households that have lost all livestock are assigned a small number of livestock.

Design Concepts

Basic principles

In SPIRALL households make movement decisions that maximizes the performance of their livestock herds. The distribution of livestock on the landscape therefore approximates what would be achieved under an Ideal Free Distribution where biomass availability and livestock densities are proportional on a patch. The type of pastoralism practiced by households (sedentary / agropastoral non-sedentary) and probability of experiencing conflicts with other ethnic groups, limit the set of possible patches that a household can access. Further, the explicit linking of SPIRALL with L-Range enables the exploration of spatio-temporally heterogenous environmental impacts on household wellbeing and pastoral social systems. Similarly, it enables the investigation of how movement and livestock stocking decisions of pastoralists, which are based on both social and ecological considerations, act as key modifiers of ecosystem function within rangelands.

Emergence

An expected emergent outcome is the spatial heterogeneity in livestock responses and household well-being driven by exposure to heterogeneous environmental and climatic conditions.



Figure A1.1: SPIRALL scheduling. Processes in light and dark green boxes are repeated every month (time-step). Processes in blue box are part of SPIRALL set-up and occur only at the start of the simulation

Adaptation

Pastoralists adapt to changes in the availability of ecosystem services by making strategic movement decisions.

Objectives

Within each month the objective of each household is to sustain and grow their livestock herds and meet household calorie requirements and expenses.

Prediction

Households track anticipated expenses and income over a 3-month period into the future, the outcome of which can influence decisions on livestock trading in the current time step.

Sensing

Households have complete knowledge of the monthly maximum livestock stocking density for patches within defined movement orbits around the home patch. Decisions to stay on a patch or move are based on this sensing ability.

Interaction

Households interact with each other via implicit competition for grazing areas. Households also interact through the gifting of milk and livestock.

Stochasticity

Each month, the order in which pastoralists are selected to assess stocking densities and make movement decisions is randomized. In addition, interactions between households, monthly live-stock survival and monthly decisions pertaining to livestock trading are treated as probabilistic events. Parameter values and input data are fixed so as to ensure a degree of centrality in outputs to enable effective scenarios analysis.

Collectives

Households are aggregated at two scales. First is the county demarcation that lends to households within each county a common ethnic identity. This ethnic identity is a key determinant of conflict and cooperation among agents. Second is the social network (family) of each household. This is composed of other households belonging to the same ethnic group with whom social interactions such as gifting is permitted.

Observation

At the end of each monthly cycle, the total number of households failing to meet their calorie requirements is tallied. Per-capita livestock holdings as well as the total number of individuals of each species across Kenya is calculated. The model reports the number of households meeting their calorie and economic needs as well as the total number and types of animals traded each month. Social interactions such as gifts given and received are tracked as well as livestock losses to conflicts. The model also produces for L-Range a file that reports the patch-specific fraction of each biomass pool grazed by livestock.

Initialization

Households are initialized by distributing them across 14 ASAL counties in Kenya where pastoralism is practiced by more than 10% of the population. Household distribution follows census data (SEDAC 2016). Household members are assigned such that each household has at least one adult male and female member with a mean household size of 8. Livestock holdings and external income sources of households are set to scale positively with the number of members in the household. Agropastoral households conduct rainfed agriculture and only grow maize and annual harvests vary in proportion to the green herb biomass simulated by L-Range for the patch.

Sub-models

This section includes a description of the sub-models (procedures) in SPIRALL. They are described in the order in which they are executed during a run. The first three procedures are executed once when the simulation begins, whereas all remaining procedures are repeated at each iteration.

Load Layers

This procedure loads spatial datasets that define the extent and attributes of the world within which agents operate. The following four spatial datasets are read in to represent the heterogeneity in demographic, cultural and livelihood characteristics across Kenya.

- Population density: Raster layer representing population density of the region for the year 2000 (SEDAC, 2016).
- Land cover: A raster dataset representing 10 land cover classes: tree cover areas, shrub cover areas, grasslands, croplands, aquatic vegetation or flooded areas, sparsely vegetated areas, bare areas, built up areas, snow or ice covered areas and open water (ESA, 2017).
- Kenya Livelihood Zones: A vector dataset composed of polygons delineating multiple livelihood zones within Kenya with an attribute table detailing multiple social, economic and livelihood characteristics of interest FEWSNET, 2017.
- Kenya Counties Map: A vector dataset composed of polygons outlining counties in Kenya. County boundaries represent ethnic group boundaries and thereby areas over which pastoralist agents may exhibit cooperative behaviors. For example, conflicts are likely when pastoralists move their herds beyond county boundaries, whereas they may be more likely to share resources and practice gifting with fellow county residents (FEWSNET, 2017).
- Protected areas: A vector dataset composed of polygons showing protected areas (IUCN category I VI and other protected patches) within the study region based on the World Database on Protected Areas (UNEP-WCMC and IUCN, 2018)

The extent of the raster datasets and the spatial grain are then used to define the spatial domain ('world' in NetLogo parlance) and the size of individual patches within the world (Fig.A1.2).

Load Agents

Agents are individual pastoral households. Agents are distributed within livelihood zones where pastoralism is the principal form of livelihood and based on land cover and population density associated with the patch.

Each household is assigned members across six age-sex classes ensuring that every households has at least one male and female member over the age of 17. The total number of individuals in a household is represented in term of adult equivalents (AE; Appendix 2). Each household is assigned a livestock herd. The composition of the livestock herd is based on the livelihood zone the household is located in. Four types of livestock (cattle, sheep, goat and camel) are assigned, with their numbers varying randomly around a mean value unique to each livelihood zone. For each household, herds belonging to each species are divided into three age-sex classes; weaned males, weaned females, and pre-weaning young. The proportion of individuals within each age-sex class for each livestock species is based on Mwanyumba et al. (2015). Each individual head of livestock is assigned an age as well as an age-specific weight. Age-specific weights are assigned using species-specific Brody curves (Brody and Lardy, 1946) with an added random deviation (Fig. **??**). Total livestock holdings of each household is summarized in terms of Tropical Livestock Units (TLU), where an adult camel is 1.25 TLU, adult cattle are 1 TLU each, and adult sheep and goats are 0.1 TLU each.



Figure A1.2: SPIRALL- The region of interest as rendered in NetLogo. The region includes a large swath of eastern Africa. Kenya and its counties are outlined in yellow. The patches are 100 km² each. Patch colors represent the underlying land cover. Agents (pastoral households) are represented in red. The number of agents on each patch is based on the underlying population density of that patch as well as the mean household size. Green polygons represent protected areas (IUCN category I - VI and other protected patches)

Households are also randomly classified as 'sedentary' or 'non-sedentary', based on the proportions of such households within each livelihood zone FEWSNET, 2017. Sedentary pastoralist agents located on agricultural lands are further classified as agropastoralists. All pastoralist households are also initialized with a random sum of cash (Kenyan Shillings) and food in the form of maize stocks. This represents balance income and food reserves from the previous month. Agropastoralist households are assigned a parcel of agricultural land of a random size (range 0.25 - 2 ha). Household income and livestock holdings is set proportional to household size. Households are categorized into three wealth classes based on per-capita livestock holdings as poor (< 3 TLU / AE), middle income ($\geq 3 \& \leq 6$ TLU /AE) and wealthy (> 6 TLU /AE). Each household is assigned an ethnic identity dependent on the county they are located in (Nyabir and Ayele, 2016). Finally, each household is assigned a social network composed of other households sharing the same ethnic identity. This represents the family of the household with whom social interactions such as gifting can occur.



Figure A1.3: Species-specific Brody Curves. When the model is initiated, individual heads of livestock are assigned a weight based on their age. Expected body weights are determined and a random deviation is added to introduce variability. For each species, the upper limit of the x axis also represents the assumed maximum age of survival.

Load parameters

Model parameters controlling household and patch behaviors are loaded (see Appendix 2 for a complete list of model parameters).

Load forage

The model links with L-Range, by reading in patch-specific biomass values for each of 8 biomass pools. These pools represent biomass associated with green herbs (gh), dead herbs (dh), green shrubs (gs), dead shrubs (ds), fine branches of shrubs (sb), green trees (gt), dead trees (dt) and fine branches of trees (tb). Once the biomass pools are read in, for each patch, maximum stocking densities for cattle and camel are calculated as follows.

Cattle Stocking Density =
$$\frac{(gh + dh) \times (1 - unavailable)}{225}$$

Camel Stocking Density =
$$\frac{(gs + ds + gt + dt) \times (1 - unavailable)}{360}$$

In the above equations, cattle stocking density is the total number of cattle that can be stocked on a 1 km² patch given the total herbaceous biomass on the patch (gh + dh) and that an adult bull weighing 250 kg consumes this biomass at a daily rate of 3% of its body weight. Similarly, for camel, stocking density is calculated using the non-herbaceous biomass (gs + ds + gt + dt)and assuming that a camel weighing 400 kg will consume this biomass at a daily rate of 2% of its own body weight. For each patch, only a fraction (1 - unavailable) of the total biomass simulated by L-Range is considered as available for grazing. We set this fraction at 2% i.e., 97 % of the simulated biomass within each pool is considered unavailable for off take by herbivores each month.

Find pasture

Once stocking densities for cattle and camel are determined for each patch, households sequentially assess whether the patch they are currently located on can accommodate their cattle and \setminus or camel herds. If not, pastoralists move their herds or entire households to other patches that are either grasslands, shrublands, or croplands. This movement is governed by a step-wise decision making process that takes into account household characteristics (e.g., sedentary \setminus agropastoralist \setminus non-sedentary) as well as social considerations such as ethnic group (county) boundaries (Fig. ?? and ??). Patch-specific stocking densities are not absolute. Households that are not able to find suitable patches that can accommodate their herds, may chose to remain on a patch (or move to a patch) where cattle or camel numbers are at the estimated stocking density. This decision making process assumes perfect knowledge of potential and actual stocking densities for each patch within the movement radius, as in an Idea Free Distribution (IDF) scenario. This assumption is tenable because pastoralists are known to make use of communication networks that allow them to learn about the condition of far away pastures. A recent study has also shown that pastoralist use of grazing commons resembles an IDF (Moritz et al., 2015).







Figure A1.5: Movement decisions by non-sedentary pastoralist households. During the long rain months, non-sedentary households return to their home-patches. Protected areas within the movement orbits can be accessed at any point in baseline simulations

Deplete Patch

Once livestock and households redistribute themselves, this procedure determines forage consumption by individual heads of livestock. For each patch, the total available herbaceous and browse forage is tallied. Of the total biomass estimated for the patch by L-Range each month, a fraction that equals the fraction of the pastoral population being represented (user-controlled parameter 'Sample') is considered as available. Each month, a fraction ('Unavailable'- a user defined parameter) of this biomass is conserved and considered not available for grazing. The total biomass across the eight pools that is available on a patch is then divided among the four livestock species on the basis of their preference for each pool (Appendix 2) and their relative abundance within the patch (TLU). This is then used to calculate per-capita availability of biomass for each species. Following the calculation of availability, the maximum quantity of forage that individual heads of livestock can consume is calculated as 2% of their body weight. Each month, animals lose or gain weight depending on the amount of forage consumed and the weight loss resulting from body maintenance requirements and travel.

Wt loss from maintenance = $\frac{BMR \times body wt^{0.75} \times 30 \times 239}{5600}$

The parameter BMR is specific to each livestock species (Appendix 2). Energy lost estimated in Megajoules (MJ) is converted to kilo calories by multiplying by 239 and a loss of 5600 calories results in 1 kg of weight loss.

The following equations are used to determine the total distance traveled by individual heads of livestock and the resulting weight loss.

Total distance traveled = Travel to current patch + Travel within patch
Wt loss from travel =
$$\frac{\text{Total distance traveled} \times 12 \times \text{body wt} \times 0.01}{5600}$$

For each species, the total distance traveled within a patch in a month is a function of the frequency with which the species need to be watered, and a randomly defined distance to a water source within the patch. We assume that cattle are watered every two days, sheep and goat every three days and camel every 5 days (McCabe, 2011). Each month the weight gained by each head of livestock is tallied using the following equation.

Wt gained from forage =
$$\frac{\text{Forage consumed} \times \text{Energy content of forage} \times 239}{5600}$$

The energy content of each kilogram of forage is assumed to be different for each livestock species (Appendix 2). The change in weight at the end of the month for each head of livestock is given by the difference between weight lost during the month and weight gained from forage consumption. At the end of this procedure the fraction of each biomass pool depleted by foraging by livestock is tallied. Once all procedures are done running, a single file containing information on the fraction of each biomass pool on each patch that is lost to livestock is written out for use by L-Range.

Grow Herds

The simulated weights of individual heads of livestock is compared against an idealized species and age-specific weight determined using Brody curves (Fig. ??). A body condition score for

each animal is estimated as the ratio between the simulated weight and the idealized weight. For each species, an asymptotic function relates body condition scores to monthly survival probability (Fig. ??). Household herds are thinned by removing individuals that do not survive. The ages of individuals that survive the month is incremented. Finally, individuals of each species in the pre-weaning cohort that have survived the month and reached weaning age are transitioned to the post-weaning cohort.



Figure A1.6: Relationship between body condition and monthly survival probability. The maximum monthly survival probability is set at 0.99, to reflect an annual background survival probability of 0.88

Reproduction

For each household, the total number of dead animals are tallied. If the month is a reproduction month, a fraction of the surviving females of each species with a body condition score greater than 0.8 reproduce. The fraction of reproducing individuals is based on the inter-birth intervals for each species (Appendix 2). If the month is a lactation month, then females that reproduced, produce milk proportional to their body condition score (Appendix 2). For each household, a variable tracks the total monthly milk production from lactating individuals of all species in the herd. If it is a harvest month, agropastoral households harvest maize, proportional to the green herb (gh) biomass on the patch

Count calories

For each household, the total calorie requirements for the month is tallied based on the total number of individuals in the house and age-sex-specific calorie requirements. Additional calories from opportunistic slaughter of livestock as well as calories from livestock that died naturally are also added together to tally total calories available from meat. Calorie requirements are met by sequentially extracting calories first from available milk, then meat, and finally maize. Where calorie requirements are not met by existing calorie reserves, households with cash in hand, may

purchase additional calories from the store. Households that fail to meet 90% of their calorie requirements are classified as "deficient", while others are classified as "sufficient".

Cash flow

For each household, the total anticipated expenses over a three month period (inclusive of the current month) is tallied. Similarly, the total anticipated income over a three month period from diverse income sources is tallied. The ready cash with the household is updated based on the months income. Where the total anticipated expenses is greater than total income, households may chose to sell livestock if any are available. Those households that do not have livestock and have expenses that cannot be met are classified as "assetless". What animal is sold is dependent on the cash needed to meet anticipated expenses. When this need is below a threshold (Appendix 2) a small animal is sold (sheep or goat), or else a large animal such as camel or cattle or an appropriate number of small animals are sold. Following sale of animals, income earned is used to meet households that do not have adequate livestock to sell to meet the months' expenses, forgo these expenses and are designated as "in debt". The "in debt" status is not carried over into the next month.

Similarly, when income exceeds expenses by a threshold, animals are purchased by households. Purchase decisions are governed by cash available in hand and the current composition of the herd. When cash in hand is below a threshold (Appendix 2), small animals are purchased, or else large animals are purchased.

Gifting

Households that have met their calorie requirements and have surplus milk may chose to sell it in a market, if markets are close. If markets are not available, households may gift milk to other households on the patch that are classified as "deficient". Similarly, households with at least 10 heads of cattle and goats (or sheep) may chose to gift livestock to a household within their social network that have lost all their animals (assetless). The total number of animals of each species with each household is updated to reflect changes resulting from the trading and gifting of livestock. The numbers and types of animals gifted each month is tracked.

Wrap up

Summaries specific to the current iteration are stored in variables, long term summaries are updated. When the final iteration is completed, summaries are exported to files.

Reset households

At the end of each iteration, households that are classified as 'assetless' are assigned a small number of livestock. This includes up to two cattle, sheep and goats.

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APPENDIX 2

List of parameters used in SPIRALL. Ksh is Kenyan Shillings

SPIRALL PARAMETERS	VALUE
Adult Equivalents ¹	0.52 (<5); 0.85 (6-12); 0.96 (13-17 males); 0.96 (13-17 females); 1 (>17 males); 0.86 (>17 females)
Calorie needs for above age-sex classes (kcal/day) ¹	1720; 1720; 1943; 1943; 2024; 1943
Cattle male:female ratio ²	43/57
Camel male:female ratio ²	33/67
Sheep male:female ratio ²	13/87
Goat male:female ratio ²	26/74
Cattle max age; weaning age ²	13 years; 9 months
Camel max age; weaning age ²	25 years; 7 months
Sheep max age; weaning age ²	5 years; 2 months
Goat max age; weaning age ²	5 years; 2 months
Monthly death rate - Cattle calf ²	0.029
Monthly death rate - Camel calf ²	0.029
Monthly death rate - Kids ²	0.018
Monthly death rate - Lambs ²	0.029
Expected weight (kg) at age (months) - Cattle ³	250 * (1 – exp (-350 * 0.017 * n /120))
Expected weight (kg) at age (months) - Goat ³	34 * (1 – exp (-34 * 0.02 * n /6))
Expected weight (kg) at age (months) - Sheep ³	34 * (1 – exp (-34 * 0.02 * n /6))
Expected weight (kg) at age (months) - Camel ³	450 * (1 – exp (-350 * 0.00018 * n /1.6)) (GreenHerb, DeadHerb, GreenShrub, DeadShrub, ShrubBranch, GreenTree, DeadTree,
Relative biomass pool preference****	TreeBranch)
Cattle	0.8; 0.16; 0.03; 0.01; 0; 0; 0; 0
Sheep	0.45; 0.22; 0.19; 0.09; 0; 0.03; 0.02; 0
Goat	0.23; 0.12; 0.17; 0.08; 0.02; 0.24; 0.12; 0.02

Camel

Camel	0.03; 0.02; 0.45; 0.23; 0.05; 0.14; 0.07; 0.01
Maintenance Energy requirements -Cattle (MJ) ³	0.48 * (BW ^ 0.75)
Maintenance Energy requirements -Camel (MJ) ⁴	0.314 * (BW ^ 0.75)
Maintenance Energy requirements -Sheep (MJ) ⁵	0.25 * (BW ^ 0.75)
Maintenance Energy requirements -Goat (MJ) ⁶	0.3 * (BW ^ 0.75)
Livestock breeding month	All species reproduce in April and November
Fraction reproducing in April and November*	
Cattle	0.5, 0.2
Camel	0.4, 0.1
Sheep	0.7, 0.3
Goat	0.7, 0.3
Cattle milk production months ³	April – August; Nov - Mar
Camel milk production months ³	January - December
Shoat milk production months ³	April – May ; Nov - Dec
Cattle Milk Production (kg /lactating individual	0.0.0.45.46 5.24 9.24.24.0.0.0.0
Camel Milk Production (kg /lactating individual	0,0,0,43,40.3,24.8,24,24,0,0,0,0
/month) ⁷	15;15;15;51;51;51;45;45;45;36;36;36
Shoat Milk Production (kg /lactating individual /month) ⁷	0;0;0;5;5;0;0;0;0;0;0;0;0
Maize harvest month ¹	July
Milk calories - Cattle ¹	789 kcal / kg
Milk calories – Camel ⁸	700 kcal / kg
Milk calories - Sheep / Goat ¹	530 kcal / kg
Opportunistic Slaughter Probability	0.05
Meat calories ¹	1720 kcal / kg
Maize calories ¹	3700 kcal / kg

Cost per kcal maize**	0.013 Kenyan Shillings
Monthly sale price of cattle and camel (Ksh) ³	5889; 5818; 6798; 6679; 7721; 6924; 6403; 6254; 6743; 6790; 6939
Monthly sale price of sheep and goat (Ksh) ³	1212; 1179; 1198; 1160; 1213; 1217; 1167; 1187; 1149; 1232; 1326; 1383
Max monthly food expenses (Ksh)	AE * 750
Monthly Veterinary expenses (Ksh) ⁹	Livestock holdings as TLU * 25
Monthly General Expenses (Ksh)	Number of household members * 100
Herb forage energy - Cattle***	7 MJ / kg
Herb forage energy - Sheep***	7 MJ / kg
Browse forage energy- Camel***	5 MJ / kg
Browse forage energy- Goat***	8 MJ / kg

* Only a small fraction of individuals reproduce during the short-wet season. Reproductive rates are set based on approximate inter-birth intervals for each species.

** Cost of purchasing 1kcal of energy from the store was estimated by assuming the cost of 1 kg maize to be 49 Ksh

*** The maximum monthly weight gain possible for each livestock species on an ad-lib diet was used to estimate the energy content of forage. For example, energy contained within a unit of herb forage is set such that cattle feeding at the maximum possible daily rate can gain 15 kg each month.

**** Relative preference for each biomass pool shown by each livestock species was calculated based on the fraction of these pools reported in their diets (Coppock et al. 1986).

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APPENDIX 3

Responses of households in 14 ASAL counties under the baseline and alternative (no PA access) scenario



Figure A3.1: Trends in TLU/AE (black lines) and precipitation (blue lines) in Marsabit, Mandera, West Pokot and Samburu counties



Figure A3.2: Trends in per-capita livestock holdings (TLU/AE; black line) and annual precipitation for Isiolo, Baringo, Garissa, Tana River, Narok and Lamu counties.

APPENDIX 3

Responses of households in 14 ASAL counties under the baseline and alternative (no PA access) scenario

Table A3.1: Per-capita livestock holdings (TLU /AE) with standard errors (SE) and livestock populations within each county in the baseline scenario and when PA access is lost (No PA) for 14 ASAL counties. Mean livestock species populations (in 1000s) at the end of 20 years is shown.

County	TLU / AE	Cattle	Camel	Sheep	Goat
Turkana	3.12 (0.01)	27.32 (0.01)	11.72 (0.03)	74.31 (0.43)	45.56 (0.42)
No PA	2.43 (0.0)	19.81 (0.08)	8.54 (0.02)	77.46 (0.4)	33.55 (0.41)
Kajiado	8.96 (0.07)	22.76 (0.18)	2.06 (0.01)	9.92 (0.17)	47.24 (0.52)
No PA	5.01 (0.04)	10.43 (0.09)	1.73 (0.02)	10.02 (0.16)	33.23 (0.43)
Laikipia	12.72 (0.09)	10.77 (0.09)	0.473 (0.01)	1.69 (0.05)	3.76 (0.1)
No PA	5.87 (0.07)	47.25 (0.06)	0.303 (0.01)	2.83 (0.11)	1.33 (0.07)
Marsabit	4.6 (0.01)	13.42 (0.06)	5.038 (0.01)	18.99 (0.140)	29.54 (0.36)
No PA	3.36 (0.01)	9.70 (0.05)	4.03 (0.02)	15.44 (0.142)	16.29 (0.22)
Mandera	2.7 (0.0)	15.86 (0.06)	6.34 (0.03)	34.22 (0.25)	11.26 (0.21)
No PA	2.3 (0.0)	12.51 (0.07)	5.30 (0.02)	38.89 (0.23)	9.09 (0.13)
Samburu	4.9 (0.03)	7.671 (0.05)	1.31 (0.01)	5.91 (0.08)	10.94 (0.15)
No PA	3.95 (0.02)	6.26 (0.05)	1.144 (0.01)	5.15 (0.07)	7.23 (0.12)
Narok	12.13 (0.06)	33.02 (0.16)	1.68 (0.02)	4.60 (0.07)	64.42 (0.49)
No PA	5.13 (0.03)	12.23 (0.09)	1.58 (0.02)	3.78 (0.06)	34.53 (0.34)
West Pokot	6.88 (0.06)	23.00 (0.16)	3.31 (0.04)	9.82 (0.18)	8.99 (0.58)

No PA	4.05 (0.05)	12.09 (0.11)	2.08 (0.03)	11.77 (0.20)	6.96 (0.60)
Tana River	7.04 (0.04)	17.68 (0.12)	6.79 (0.03)	12.53 (0.14)	15.73 (0.30)
No PA	6.25 (0.03)	15.55 (0.09)	6.26 (0.03)	12.19 (0.14)	12.48 (0.23)
Wajir	3.52 (0.0)	26.48 (0.11)	10.34 (0.02)	49.95 (0.28)	19.06 (0.22)
No PA	3.33 (0.0)	24.24 (0.10)	10.01 (0.03)	50.41 (0.28)	17.760 (0.26)
Isiolo	3.93 (0.02)	5.285 (0.05)	2.17 (0.02)	9.86 (0.13)	6.73 (0.14)
No PA	3.73 (0.02)	4.94 (0.04)	2.11 (0.01)	9.54 (0.12)	6.31 (0.09)
Lamu	9.2 (0.12)	1.11 (0.03)	0.65 (0.01)	2.03 (0.06)	2.05 (0.08)
No PA	7.37 (0.08)	0.74 (0.02)	0.59 (0.01)	2.45 (0.06)	1.67 (0.07)
Garissa	6.07 (0.01)	23.45 (0.11)	10.51 (0.03)	27.83 (0.19)	40.26 (0.36)
No PA	5.64 (0.02)	21.43 (0.11)	10.12 (0.04)	29.06 (0.23)	36.32 (0.39)
Baringo	3.41 (0.04)	10.84 (0.16)	0.65 (0.02)	6.61 (0.16)	7.96 (0.19)
No PA	2.59 (0.04)	82.69 (0.11)	0.58 (0.02)	5.70 (0.16)	5.77 (0.19)

Table A3.2: Household metrics for the baseline and No PA scenario (no protected area access). Percent contribution of livestock calories (milk and meat) to household diets, number of households (HH) crossing international boundaries, and income (1000 Kenyan Shillings) from livestock sales. Mean monthly values and associated standard errors are shown.

County	% Livestock Calories	HH crossing international boundaries	Income from livestock sales
Turkana	18.69 (0.14)	97.8 (1.1)	813.89 (2.7)
No PA	16.20 (0.11)	158.72 (2.31)	730.1 (2.84)
Kajiado	43.02 (0.34)	4.07 (0.07)	300.41 (1.14)
No PA	27.63 (0.22	19.44 (0.34)	231.24 (0.97)
Laikipia	65.34 (0.51)	0	57.12 (0.36)
No PA	36.95 (0.27)	0	48.62 (0.3)
Marsabit	26.87 ().21)	0	335.68 (1.17)
No PA	23.64 (0.17)	0	296.35 (1.33)
Mandera	19.32 (0.13)	152.74 (1.6)	441.54 (1.99)
No PA	17.81 (0.11)	211.94 (2.91)	411.75 (1.99)
Samburu	27.81 (0.22)	0	160.62 (0.54)
No PA	24.69 (0.18)	0	142.76 (0.58)
Narok	54.56 (0.44)	0	296.69 (1.5)
No PA	27.98 (0.21)	4.26 (0.07)	182.52 (0.76)
West Pokot	38.01 (0.29)	10.1 (0.11)	234.69 (1.12)
No PA	26.48 (0.18)	39.66 (0.56)	185.3 (1.2)
Tana River	45.46 (0.35)	0	309.01 (1.52)
No PA	43.19 (0.31)	0	292.97 (1.5)

Wajir	26.11 (0.18)	31.26 (0.34)	613.75 (2.88)
No PA	25.44 (0.17)	31.23 (0.46)	599.18 (2.82)
Isiolo	26.91 (0.19)	0	151.7 (0.59)
No PA	26.45 (0.18)	0	149.04 (0.57)
Lamu	58.73 (0.47)	0.15 (0.01)	31.87 (0.2)
No PA	52.17 (0.42)	0.23 (0)	29.56 (0.17)
Garissa	38.31 (0.29)	18.76 (0.21)	482.49 (2.17)
No PA	36.67 (0.27)	23.99 (0.0)	469.7 (2.03)
Baringo	20.83 (0.16)	0	116.37 (0.57)
No PA	16.9 (0.12)	0	107.01 (0.53)