Ecological Informatics 98 (2026) 103959

Contents lists available at ScienceDirect

Ecological Informatics

journal homepage: www.elsevier.com/locate/ecolinf

Modeling multifunctional landscape change in southern Kenya: Spatial trade-offs and drivers in an arid and semi-arid landscape

Susan M. Kotikot[a,*], Erica A.H. Smithwick[a,b], Sarah E. Gergel[c], Jedidah Nankaya[d], Romulus Abila[e]

[a] Earth and Environmental Systems Institute, The Pennsylvania State University, 217 Earth-Engineering Sciences Building, University Park 16802, PA, USA
[b] Department of Geography, The Pennsylvania State University, 302 N Burrowes Rd, University Park 16802, PA, USA
[c] Department of Forest and Conservation Sciences, University of British Columbia, 2424 Main Mall, Vancouver, BC V6T 1Z4, Canada
[d] Department of Forestry and Wildlife, Maasai Mara University, Narok, Kenya
[e] Department of Environmental Studies, Geography and Planning, Maasai Mara University, Narok, Kenya

ARTICLE INFO

Keywords:
Land-use change
Drylands
Spatial modeling
Land tenure
Trade-offs
Kenya

ABSTRACT

Arid and Semi-Arid Landscapes (ASALs) support a substantial portion of the world's population and multiple ecological and social functions. However, landcover outcomes in ASALs are determined by competing land uses, which are governed by fine gradients in biophysical conditions, legacy land use policies, and complex socio-economic drivers. Simulating these land use and land cover (LULC) interactions can promote policy that enhances human and ecosystem well-being but capturing dynamics at scales relevant to local livelihoods remains challenging. To explore these interactions, we used the Land Change Modeler (LCM) to simulate spatial patterns of LULC change from 2010 to 2018 in a multifunctional landscape in southern Kenya. Results showed that spatial patterns of LULC transition were associated with biophysical and socio-political factors such as proximity to existing land use types, rainfall and temperature, and land tenure arrangements. Our calibrated model achieved 83% overall correctness, with remaining errors (17%) linked to spatial misallocation. These errors were spatially clustered, suggesting the possible influence of localized socioeconomic factors not included in our parameterization. Notably, transitions in humid–arid ecotones were consistently underestimated, reflecting the challenges of capturing fine-scale heterogeneity in ecologically sensitive landscapes. Our findings demonstrate where conservation objectives, agricultural expansion, and pastoral livelihoods spatially converge, highlighting landscape zones where policy interventions and development investments are most likely to generate trade-offs rather than synergies under increasing climate stress. These results underscore the value of spatially explicit modeling as a diagnostic tool for identifying priority areas where competing land-use demands and socio-ecological vulnerabilities are most tightly coupled.

1. Introduction

Determining how land is utilized and who controls its use is critical in addressing key concerns such as climate change (Pongratz et al., 2021), biodiversity loss (Shah et al., 2023), food and energy insecurity (Zhuang et al., 2022), social conflicts (de Jong et al., 2021), and poverty (Barbier and Hochard, 2016), among others. Even small changes in land use and land cover (LULC) can have pronounced effects on local and regional climate (Cao et al., 2020; Pielke and Avissar, 1990) and ecosystem structure and function (Fu et al., 2025; Turner and Gardner, 2015), with consequences for ecosystems and human wellbeing. On multifunctional landscapes, where land cover outcomes are determined by competing land uses (Mander et al., 2007), it is especially difficult to predict how LULC changes redistribute risks, benefits, and degradation across social-ecological systems (Zhang and Schwärzel, 2017). Even less well characterized, historical land use activities can leave lasting imprints on landscapes, influencing ecosystem structure and function for decades or centuries (Garbarino and Weisberg, 2020; Kotikot et al., 2025a). Understanding the dynamics of land use systems and the factors associated with land use patterns is thus crucial for effective land use planning, facilitating informed decisions and developing strategies for sustainable land use.

* Corresponding author at: Department of Geography, Sustainability, Community, and Urban Studies, University of Connecticut, Storrs, CT 06269, USA.
E-mail address: susan.kotikot@uconn.edu (S.M. Kotikot).

https://doi.org/10.1016/j.ecoinf.2026.103959
Received 9 April 2026; Received in revised form 27 July 2026; Accepted 29 July 2026
Available online 29 July 2026

Modeling approaches are invaluable for exploring system dynamics and understanding the long-term impacts of land use decisions (National Research Council, 2014). By helping to unravel interactions among socio-economic, environmental, and policy factors, land use change models can help discretize spatial patterns of change and their relative drivers. While empirically fitted models such as logistic regression (Estacio et al., 2023), generalized additive models (Brown et al., 2002), and neural networks (Pijanowski et al., 2002) are useful for identifying spatial correlations and causal relationships, they often struggle to capture feedbacks, spatial autocorrelation, and non-stationarity. Process-based models, including cellular automata (CA) and agent-based models (ABMs), offer more flexibility by simulating spatial diffusion and individual decision-making (Parker et al., 2003). ABMs, in particular, are well-suited for Arid and Semi-Arid Landscapes (ASALs) due to their ability to represent decentralized, context-specific land use decisions and complex human-environment interactions (An, 2012; Brown and Robinson, 2006). Further, integrated modeling frameworks combine ABMs with CA models and biophysical simulations to represent complex feedbacks and emergent patterns. For example, the SYPRIA (Southern Yucatán Peninsular Region Integrated Assessment) model (Manson, 2006) integrates household-level decision-making, institutional dynamics, and environmental processes to simulate land use change in Mexico's Yucatán Peninsula.

Other simulation models such as the Land Change Modeler (LCM) (Eastman and Toledano, 2018), Dyna-CLUE (Verburg and Overmars, 2009), and LUCAS (Sleeter et al., 2019) each offer distinct advantages and are well-suited in different ways to address the complexities of multifunctional ASALs. These models combine spatially explicit simulation with scenario-based analysis, enabling the capture of nonlinear land dynamics and interactions between environmental and socioeconomic drivers across both space and time. Recent studies in African drylands highlight the growing use of machine learning (e.g., PLUS, random forest) and scenario-based approaches to capture spatial heterogeneity and climate sensitivity in land-use dynamics (Mogonong et al., 2024; Mutale and Qiang, 2024), while broader syntheses emphasize persistent gaps in integrating socioeconomic processes into LULC models across the continent (Assede et al., 2023). LCM, in particular, offers built-in machine learning, probabilistic transition modeling, and a user-friendly interface, making it accessible and effective in data-scarce regions. While, arguably, ABMs offer deeper mechanistic realism, they require extensive data and calibration. In contrast, spatially explicit scenario-based models (e.g., LCM) offer a practical balance between complexity and usability, making them a valuable tool for environmental planning, policy analysis, and sustainable land use strategy development (e.g., Qacami et al., 2023).

Modeling ASALs is particularly challenging for several reasons. First, these landscapes are characterized by extreme and unpredictable weather patterns, increased sensitivity to climate and land use, and complex social-ecological interactions that are difficult to predict (Tajbakhsh et al., 2018). Second, historical legacies of land governance; especially those rooted in colonial land policies have left enduring imprints on the spatial organization and tenure systems of ASALs globally and continue to influence LULC change trajectories. In many parts of post-colonial ASALs, the spatial organization of land use has evolved, driven by a series of new policies and subsequent reforms (Kotikot et al., 2025a). Third, in recent decades, climate change and variability of precipitation (from more frequent and severe droughts to increasingly patchy rainfall) have exacerbated the vulnerability of ASALs to climate and associated stressors (Kotikot et al., 2024; Kotikot et al., 2025b). These climatic shifts are altering the suitability of key crops and expanding the range of crop disease vectors, pests, and pathogens (Ramirez-Villegas and Thornton, 2015; Rippke et al., 2016) potentially leading to further decline in productivity of both cropping and pastoral systems. Moreover, these environmental stressors interact with socioeconomic factors in feedback loops that create complex adaptive systems (Lambin and Geist, 2006). Such systems are characterized by diverse, evolving agents, non-linear interactions, and emergent behaviors (Preiser et al., 2018) that make them particularly difficult to represent in conventional land use models. While the interplay between land policies and other social and environmental stressors have had measurable cumulative impacts on contemporary patterns of land use, their relative influence remains poorly understood.

In this study, we define socio-economic drivers as the social, institutional, governance, and economic conditions that influence land-use decisions and landscape outcomes. Within the Narok social-ecological system, these drivers encompass indigenous pastoral land-use practices, historical colonial and post-colonial land governance structures, land tenure arrangements, demographic pressures, market accessibility, conservation initiatives, and processes of agricultural commercialization. We therefore conceptualize socio-economic factors as the interacting influences of historical institutions, contemporary governance systems, and livelihood strategies that shape how land users access, manage, and transform landscape resources. To represent these processes within the modeling framework, we included land tenure, population density, distance to roads, and distance to markets as spatially explicit indicators of socio-economic conditions. Population density can impact land use through increased resource demand, often contributing to agricultural expansion and forest loss (Misra et al., 2014). Proximity to roads and markets affects accessibility, transportation costs, and economic opportunities, which in turn affects how land is used and developed (Verburg et al., 2004; Kaczan and David, 2020; Laurance et al., 2009). Land tenure, which refers to the rights and arrangements that individuals or groups possess with respect to the ownership and use of land can determine the way land is used, managed, and developed, which in turn affects social, economic, and environmental outcomes (FAO, 2002). For instance, secure land tenure gives landowners the assurance to invest in and enhance their land through sustainable practices and development projects (Chrispus, 2022; Place and Otsuka, 2002). Furthermore, some tenure types can have stipulations that restrict specific land uses.

Finally, the spatial arrangement and spatial context of land cover units can determine land use. For example, fragmented forests are more vulnerable to edge effects, and are more susceptible to external disturbances through logging, agriculture, and urban development (Laurance et al., 2011; Numata and Cochrane, 2012; Sun et al., 2025). On the other hand, fragmentation opens up core forests and increases accessibility to forest resources. For example, forest fragments have been shown to be a key source of food and nutrient resources within ASALs and can support traditional livelihoods (Gergel et al., 2020). Understanding the causes and consequences of spatial patterns on LULC may be critical for understanding resultant landscape services such as biodiversity (Bradfer-Lawrence et al., 2025).

The objective of this study was to model the spatial patterns and drivers of LULC change within multifunctional ASALs. Previously, Kotikot et al. (2025a) showed that land use legacies influenced spatial patterns of land use through a geospatial analysis of LULC maps but did not explore the relative influence of these other factors. To do so, we calibrated a land use model using the Land Change Modeler (LCM) (Eastman and Toledano, 2018) to predict observed LULC changes between 2010 and 2018 using an exemplar ASAL in southern Kenya. We then assessed model performance and showed the nature of agreement (correctness) and disagreement (error) between the predicted and reference map. Finally, we quantified model skill along gradients of explanatory variables. We hypothesized that areas under different historical policy/tenure categories would exhibit different patterns of association with observed transitions, reflecting the legacy context within which land use change occurred. Further, we hypothesized that spatial context, particularly adjacency to similar land cover types, fragmentation, or distance metrics to markets and rivers would determine LULC outcomes. Resultant products include a newly calibrated LULC model for an ASAL in sub-Saharan Africa, maps of spatial patterns of these simulated changes relative to observed patterns, and evidence supporting the relative drivers of simulated land use changes.

2. Materials and methods

2.1. Study area characteristics

The LCM was simulated across Narok county, Kenya, a highly multifunctional, yet increasingly vulnerable landscape representative of ASALs in sub-Saharan Africa more broadly. The region provides an ideal setting for exploring the spatial and temporal patterns of landscape change under multiple environmental stressors, for at least three foundational reasons. First, the region comprises a diversity of landcover types in a relatively small area, including forest lands, croplands, grasslands; and transhumance is traditionally practiced locally within county borders. Second, the region has a long history of land use and governance changes and a recent history of rapid agricultural expansion (Kotikot et al., 2025a), making it a good setting to explore the influence of land use legacies on contemporary LULC. Third, changes in precipitation, including evidence of a drying trend for the main growing season (March–May) (Nicholson, 2017) and increasing rainfall variability (Kotikot et al., 2024), are challenging agricultural and transhumance practices across the landscape (Kotikot et al., 2025b). Collectively, these factors allow for the exploration of the relative influence of social and environmental dynamics on LULC.

2.2. Data sources and preprocessing workflow

This study follows a reproducible geospatial workflow involving the integration and harmonization of multiple spatial data sources and aligned with FAIR data principles (Findable, Accessible, Interoperable, and Reusable), ensuring transparency in data use, processing, and model implementation. We assembled a suite of spatial datasets representing historical land use and land cover, biophysical conditions, and socioeconomic context from publicly available and institutional sources. Because datasets differed in resolution, extent, and format, they were harmonized through a standardized preprocessing workflow (Fig. 1). The workflow included projection to a common coordinate system (WGS84 UTM Zone 37S), resampling to a unified spatial resolution (90 m) using bilinear (continuous variables) or nearest-neighbor (categorical variables) methods, derivation of explanatory variables (e.g., slope, distance rasters, EVI metrics), and aggregation of LULC classes. The final dataset consisted of spatially aligned 90 m GeoTIFF layers (compatible with open GIS platforms e.g., QGIS and R) representing biophysical, socio-economic, and spatial-context drivers (see Supplementary Table 3 for full variable definitions and units). All candidate variables were subsequently screened for multicollinearity (correlation filtering where Spearman $\rho > 0.6$), redundancy, and temporal misalignment prior to inclusion.

Correlation among environmental variables is expected in coupled social-ecological systems. Correlation filtering was therefore not intended to eliminate ecological relationships, but rather to reduce redundancy among highly similar predictors and improve interpretability within the selected modeling framework. Alternative approaches may retain correlated predictors and evaluate their collective influence through different modeling strategies.

2.2.1. Historical land use and land cover maps

LULC data for 1990, 2000, 2010, and 2018 were obtained from the Kenya Department of Resource Surveys and Remote Sensing (DRSRS). The original maps contained ten land-cover classes (dense forest, moderate forest, sparse forest, woodlands, closed grasslands, open grasslands, perennial croplands, annual croplands, wetlands, and water). Several of these subclasses were difficult to distinguish reliably due to mixed pixels, interpreter inconsistency, and lack of temporal coherence across years. Further, preliminary modeling using the full ten-class dataset produced substantial classification noise and unstable

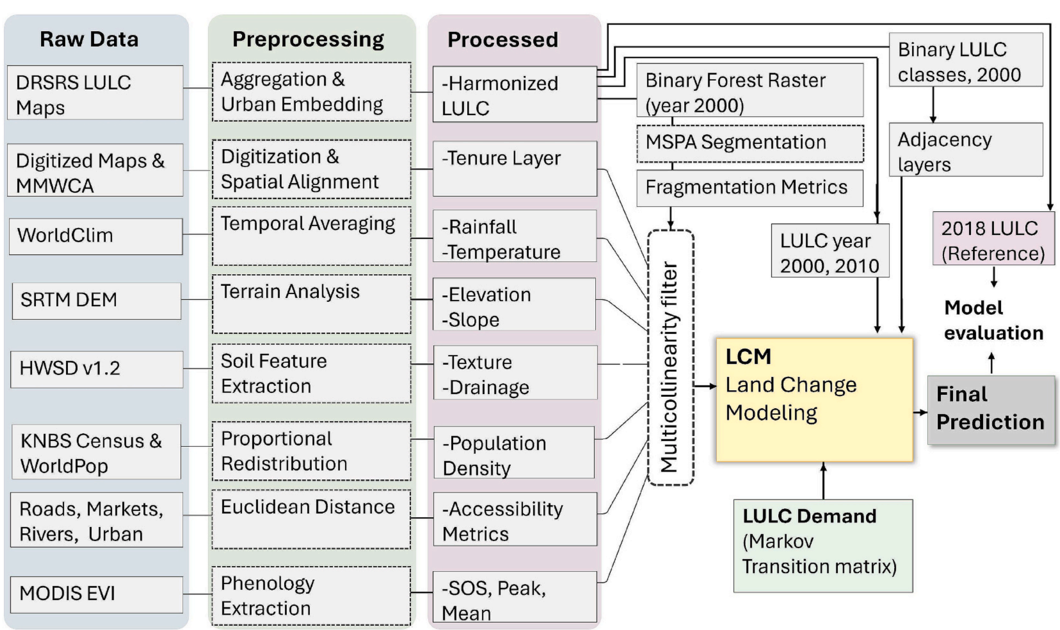

Fig. 1. Data preprocessing and modeling workflow. The workflow illustrates the transformation of heterogeneous raw spatial datasets into harmonized predictor variables used for land-use and land-cover (LULC) modeling. Raw inputs, including LULC maps, climate data, topography, soils, population, infrastructure, and vegetation indices, were systematically processed through aggregation, spatial alignment, temporal averaging, variable derivation, and distance calculations. Derived layers (e.g., climate variables, terrain metrics, accessibility, vegetation phenology, and land tenure) were harmonized to a common spatial framework and screened for multicollinearity prior to model input. Additional spatial context layers, including adjacency metrics and fragmentation indices derived from MSPA, were incorporated alongside LULC demand estimates (Markov transition matrix). These inputs were then used within the Land Change Modeler (LCM) to simulate land-use transitions and generate final predictions. **Acronyms:** MSPA (Morphological Spatial Pattern Analysis); DRSRS (Department of Resource Surveys and Remote Sensing); MMWCA (Maasai Mara Wildlife Conservancies Association); SRTM (Shuttle Radar Topography Mission); HWSD (Harmonized World Soil Database); MODIS EVI (Moderate Resolution Imaging Spectroradiometer Enhanced Vegetation Index); KNBS (Kenya National Bureau of Statistics); SOS (Start of Season).

transition estimates. To improve thematic accuracy and reduce misclassification errors, we therefore aggregated these classes into three dominant categories (forest, rangeland, cropland). This decision was supported by two considerations: (1) the aggregated classes exhibited greater agreement across years, reducing error propagation within LCM, and (2) they map more directly onto the functionally meaningful major livelihood strategies shaping land-use decisions in Narok (pastoral grazing, crop agriculture, and forest resource use). While this aggregation inevitably masks finer ecological distinctions (e.g., shrubland vs. grassland, sparse vs. dense forest), it provides the most reliable basis for modeling dominant land-use reallocations in this data-scarce landscape.

An urban class was then embedded on the reclassified maps as an additional class. Urban areas were extracted from multiple sources including supervised classification of Landsat satellite imagery, and the Global Land Cover and Land Use Change dataset (Potapov et al., 2022). The accuracy of the extracted urban class was assessed for each year through manual comparison with Google Earth imagery before harmonizing the different sources and embedding on the aggregated LULC maps. Thus, the final maps used in this study had four LULC classes including forest, rangeland, cropland, and urban. These were then spatially aggregated to 90 m spatial resolution to reduce data complexity while capturing dominant LULC patterns. Spatial aggregation has been shown to reduce errors due to co-registration and noise in imagery, potentially improving the accuracy of model outputs (Hogland and Affleck, 2019; Turner et al., 1989).

2.2.2. Land tenure and the spatial policy map

We assembled a harmonized spatial policy map to represent tenure-linked governance environments relevant to land-use decisions. Tenure categories included private land (PR), group ranch (GR), historically group ranch (HGR), conservancies (CON), and protected areas (PA, PA_CA). Historical group ranch (GR) boundaries were digitized from a georeferenced 1970s map (Wales and Chabari, 1979). Contemporary conservancy (CON) boundaries were obtained from the Maasai Mara Wildlife Conservancies Association (MMWCA), and colonial era private (PR) lands were identified from secondary literature as parcels allocated as freehold during the colonial/early post-colonial period that either never entered the group ranch system or privatized rapidly in the first wave of subdivisions in the early 1980s. We further distinguished historical group ranch (HGR) areas as those that had already privatized by the start of calibration (circa 2000), versus current GR areas that remained under communal title or were actively subdividing after 2000. Protected areas were separated into PA (Mau Forest) and PA_CA (Maasai Mara Game Reserve) because their governance regimes impose distinct

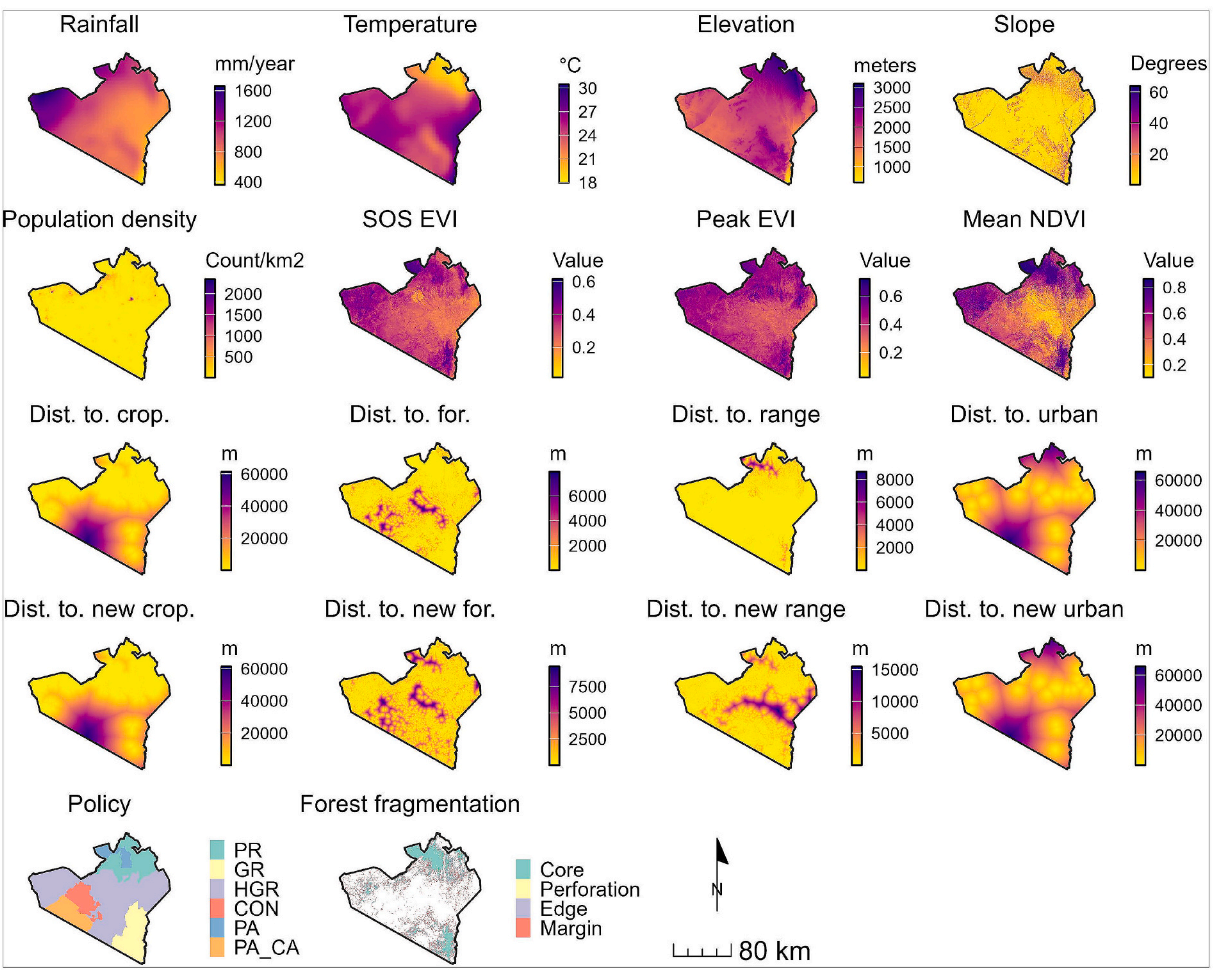

Fig. 2. Spatial maps of all the predictor variables used in the study. The spatial patterns of environmental variables show variations that potentially influence heterogeneous land use across the landscape. We included adjacency variables that represent distances to each land use class that existed in 2000 which is the beginning of the calibration period; crops (Dist. to. crop), forest (Dist. to. for), rangeland (Dist. to. range), and urban areas (Dist. to. urban). We also included additional adjacency variables that represent distances to areas that had transitioned to a different class between 1990 and 2000; crops (Dist. to new. crop), forest (Dist. to new. for), rangeland (Dist. to new. range), and urban areas (Dist. to new. urban). We hypothesized that these new transition areas represent areas of actively shifting land use. Policy and forest fragmentation are categorical variables. Policy categories include private (PR), group ranch (GR), historically group ranch (HGR), conservancies (CON), protected areas of Mau Forest (PA), and protected areas of the Maasai Mara game reserve (PA_CA).

land use constraints. For example, Mau Forest has experienced recurrent encroachment and conversion for cultivation and timber extraction, whereas the Maasai Mara, though historically permitting limited livestock grazing, now enforces strict prohibitions. The tenure layer represents baseline conditions (best available) circa 2000 for calibration (2000−2010) and was held constant during modeling (2010–2018 prediction). Accordingly, tenure is treated as a contextual variable, and model outputs are interpreted as spatial associations rather than causal effects. Further details on tenure classification, historical evolution, and governance characteristics are provided in Supplementary Section S1.

2.2.3. Potential drivers of land use change

We adopted a theory-driven, parsimonious variable selection strategy to balance explanatory power, interpretability, and model stability. Predictor variables were selected based on their established relevance to land-use change in agropastoral arid and semi-arid systems, data quality, and temporal alignment with the model calibration period. Variables that were highly correlated, static administrative descriptors, or weakly connected to land-use decision processes at the pixel scale were not included to reduce redundancy and limit overfitting. As a result, the model captures associations with a core set of biophysical, socioeconomic, and governance-related drivers (Fig. 2).

We initially considered a broad range of potential factors. Biophysical drivers included local climate (average rainfall in millimeters, temperature in degree Celsius), topography (slope as a percentage, elevation in meters above sea level), and soil characteristics (texture, drainage). Monthly rainfall and temperature data for the years 2000–2009 were obtained from WorldClim at ~4.5 km spatial resolution (Fick and Hijmans, 2017). Elevation data was obtained from the Shuttle Radar Topography Mission (SRTM) at 30 m spatial resolution (NASA JPL, 2013). The slope was calculated as a measure of topographic gradient from the elevation data. Soil texture and drainage data were obtained from the Harmonized World Soil Database v 1.2. (Fischer et al., 2008).

Socioeconomic factors included land tenure, population density, distance to roads, and distance to markets which may be spatially associated with land use transitions. Socio-economic predictors in this study represent measurable proxies of governance, demographic, and accessibility-related processes that influence household and community land-use decisions. We obtained population data from the Kenya National Bureau of Statistics (KNBS) 2009 Census at the ward administrative level, and calculated population density as persons per square kilometer. To introduce greater spatial variability into the population surface, we redistributed the ward-level KNBS counts using the spatial distribution of the WorldPop gridded population dataset (WorldPop (www.worldpop.org - School of Geography and Environmental Science, U. of S. D. of G. and G. U. of L. D. de G. U. de N, and Center for International Earth Science Information Network (CIESIN), 2018). The rescaling procedure involved several steps. First, for each administrative ward, we calculated the proportion of the WorldPop population contained within each 100 m WorldPop grid cell. We then used these proportions to redistribute the total KNBS ward level population across a coregistered 100 m grid. This produced a population surface whose total population matched the KNBS census counts but whose spatial pattern followed the finer resolution WorldPop distribution.

Road data were obtained from the world resources institute (WRI) and integrated with additional data from Open Street Map (OpenStreetMap contributors, 2025), to incorporate newer and minor roads that did not exist in the WRI dataset. Comparison with Google Earth imagery indicated that most newer roads existed as access tracks in 2000 and were subsequently upgraded, and that no new roads emerged or were developed between 2010 and 2018. Market locations were manually digitized from Google Earth imagery. We calculated distances to roads, markets, and urban areas as Euclidean distances from the edge of the feature to any location on the landscape represented in a 90 m spatial resolution grid surface. The Euclidean distances were generated using distance accumulation tools in ArcGIS Pro 3.2.0.

We included forest fragmentation metrics as indicators of potential for conversion to other land uses. Using the Morphological Spatial Pattern Analysis (MSPA) approach (Soille and Vogt, 2022), we extracted forest pattern attributes consistent with fragmentation categories (ranging from a patch forest to a large core forest). MSPA is a morphology-based technique that classifies binary raster features into distinct spatial pattern classes. We used the MSPA implementation available in the Guidos Toolbox (Vogt and Riitters, 2017), a software developed by the European Commission's Joint Research Centre (JRC).

In addition, we included MODIS Enhanced Vegetation Index (Didan, 2015; Huete et al., 1999) (EVI)-derived metrics including start of season (SOS), mean season (MN), and peak season (PK) EVI as predictors in the LCM. To calculate the metrics, seasonal values (March–May) for each year were first calculated through EVI differencing and thresholding, then averaged over the 2003–2009 period to derive long-term means. Different combinations of our derived metrics appeared to correspond to known LULC classes. For example, very low values of SOS EVI and very high values of PK EVI corresponded to agricultural land, while consistently high MN EVI corresponded to forested land. Furthermore, existing studies show that vegetation indices derived from satellite imagery, such as NDVI, can distinguish vegetated from non-vegetated areas and can also inform classification of land cover types, including cropland, rangeland, and degraded forests (Huang et al., 2019; Huang et al., 2021).

2.3. Methodology

The modeling workflow integrates both open-source and proprietary components. Spatial data preparation, harmonization, and exploratory analyses were conducted using standard Geographic Information System (GIS) tools (ArcGIS Pro version 3.2, R version 4.4.1) and open data formats (GeoTIFF, shapefiles). Land-use change simulation was implemented using the Land Change Modeler (LCM) within TerrSet, selected for its established implementation of spatially explicit transition modeling and suitability for data-scarce landscapes. All intermediate and final raster outputs were exported in open formats to ensure interoperability and reuse across GIS platforms.

2.3.1. Model parametrization

We calibrated a land use model in LCM using historical land use data for the years 2000 (initial) and 2010 (final) and associated drivers (Fig. 3). The LCM predicts transition based on specified drivers using one of several available modeling approaches (e.g., multilayer perceptron, logistic, etc.) (Eastman and Toledano, 2018). The transitions may be grouped into sub-models based on similarity of driving factors or modeled separately if it is determined that each transition is driven by a separate set of factors. For example, forest-to-crop and forest-to-rangeland are not driven by the same set of factors, and would thus be defined as separate sub-models. For each modeled transition, a transition potential map is produced that shows for each pixel, the likelihood (on a scale of 0 to 1) of transitioning from one class to another.

Here, we used the Multi-Layer Perceptron (MLP) neural network approach to model transitions as it has been shown to be extremely powerful for modeling complex non-linear relationships (Eastman and Toledano, 2018). First, all categorical variables were transformed using the Evidence Likelihood transformation utility within LCM so that they were linearly related to the potential for transition and therefore easier to interpret. Evidence Likelihood transforms categories of a variable into numeric values based on the relative frequency of each category being in the changing group. Values in the transformed variable represent the likelihood that a pixel with that category is likely to change land uses. Then, to train and test the MLP model, a sample of 10,000 pixels were selected that had undergone a specific land use transition and 10,000 pixels that persisted (i.e., they were eligible to undergo the transition but did not) between the two dates of land cover information (2000–2010). Half (50%) of the selected samples were used

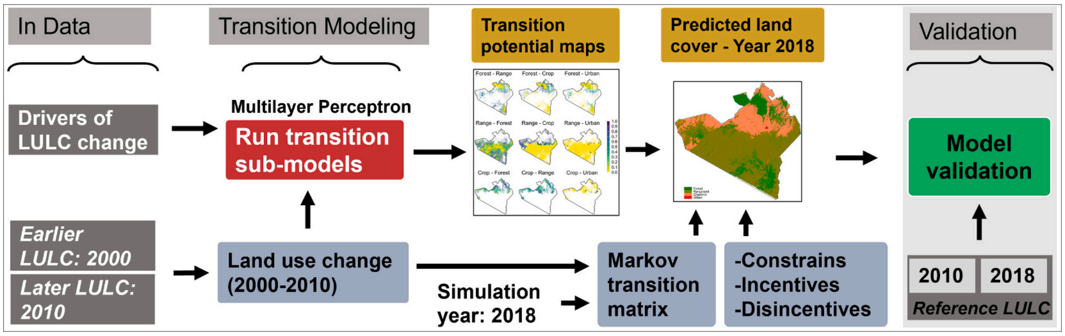

Fig. 3. Modeling workflow using the Land Change Modeler. Land use transitions were modeled based on historical changes in land use and specified drivers of change. The multilayer perceptron approach was used to model transitions and generate transition potential maps for each land use transition. Future land allocation (2018 prediction) is guided by these maps and the Markov transition matrix derived from past land cover data. We adjusted the matrix to reflect observed amounts of land cover classes in 2018 and applied a spatial constraint to restrict transitions to cropland in protected areas. We then validated the predicted LULC based on the reference 2018 map to assess prediction accuracy.

for training and the other half (50%) for testing. The default MLP parameters (e.g., number of hidden layer nodes and the learning rate) were adopted after determining that changing them did not improve the model skill measure. Moreover, MLP automatically adjusts the learning rate to achieve the highest model skill measure (see supplementary Section S3 for additional details on MLP configuration). The MLP was implemented for each transition as we determined that each was driven by a different set of factors, and generated transition potential maps (supplementary fig. 1). Transition potentials derived from the MLP process represent relative suitability indices based on observed spatial associations rather than formal probabilities derived from parametric statistical assumptions.

To determine the amount of change that is likely to occur to some point in the future, LCM employs a Markov chain process. Generally, LCM calculates these amounts by projecting the modeled transition potentials into the future (in our case, 2010–2018). Often, the estimated amount does not match the actual observed changes, and this results in errors in the model predictions (errors due to quantity). To minimize these errors and focus our analysis on spatial allocation, we adjusted the estimated amounts of expected change for each category of land use transition to approximate the observed proportions in the 2018 LULC map. This involved calculating the proportions of each LULC class that transitioned to every other class between 2010 and 2018 and creating an alternative transition matrix (supplementary table 1).

Through an allocation procedure, LCM creates a LULC map (hard prediction) for the prediction year. The hard prediction is an LULC map with the same classes as the inputs and represents a single realization of a scenario. It is created through a competitive land allocation model similar to a multi-objective decision process (Eastman et al., 1995). In our 2018 prediction, we included a constraint to limit LULC transitions to cropland within the protected Maasai Mara Game Reserve (MMGR). We specified the constraint through a spatial layer of the same extent as the input layers but with a value of 0 within the MMGR and 1 elsewhere. LCM also provides the option to generate a map of vulnerability to change for the selected set of transitions. The map is known as a soft prediction, and it represents the degree to which the areas (pixels) have the right conditions to bring about change. The soft prediction is particularly valuable because it highlights the uncertainties inherent in the model output, enabling a more nuanced assessment of change rather than enforcing rigid decisions.

2.3.2. The relative influence of predictor variables

For each modeled transition, the MLP provides a skill measure for each variable included in the sub-model. This is a statistic that measures model performance on a scale of -1 to $+1$ where a skill of 0 means the model is no better than chance, a skill of 1 indicates perfect prediction, and a negative skill means the model is doing worse than chance. Unlike the accuracy rate (proportion of validation pixels that are predicted correctly), the skill statistic is favorable as it is not affected by the number of transition/persistence classes. For ease of interpretation, we calculated and present the percent change in model skill associated with each explanatory variable as a measure of variable importance. Variables that result in large reductions in model skill when held constant are considered more important.

In addition, we assessed predicted transitions along gradients of explanatory variables to understand how the variables are associated with observed and predicted changes (Chen and Pontius, 2010). To achieve this, we performed a cross-tabulation between the spatial map of predicted transitions and maps of key explanatory variables that were included in the model. Cross-tabulation is a method of comparing two maps by analyzing how the categories in one map correspond to those in the other. We illustrate our results as a distribution of predicted transitions in percentage of the landscape along the gradient of an explanatory variable. This additional analysis highlights the nature of relationships between key driver variables and land use transitions.

2.3.3. Model evaluation

We performed an evaluation of the predicted land cover map by doing a three-way cross comparison of the “initial map (year 2010)” to “predicted map (year 2018)” to “reference map (year 2018)” and generated a map that shows the spatial distribution of change categories as grouped based on similarities in land cover classes across the three maps. We classified the map into generalizable categories that show the nature of agreement (correctness) or disagreement (error) between the predicted (2018) and reference (2018) class, considering the initial (2010) class. The categories included correct rejections (persistence simulated correctly), false alarms (persistence simulated as change), wrong hits (change simulated as change to wrong category), hits (change simulated correctly), and misses (change simulated as persistence) (Memarian et al., 2012; Varga et al., 2019).

To quantitatively show performance of the model prediction, we used the Figure of Merit (FOM) (Varga et al., 2019). The FOM is a ratio between the intersection of simulated and reference change, and the union of simulated and reference change (Chen and Pontius, 2010; Pontius et al., 2008). It budgets the five general categories of prediction correctness and error as a percentage of the landscape. From these budgeted categories, the error due to quantity disagreement, error due to allocation, and total error of the prediction can be calculated. Error due to quantity is the difference between the observed and predicted amounts of change. This was not calculated as the model was parameterized not to have quantity errors. Error due to allocation is the deviation in spatial allocation of change. We calculated this as the sum of false alarms and misses. Total error was equal to the error due to allocation since error due to quantity was zero in this case.

2.4. Model assumptions and limitations

The modeling framework is based on several simplifying assumptions inherent to spatially explicit land-use change models. First, the modeling framework operates on a raster-based representation of the landscape, where each pixel (90 m resolution) is treated as the fundamental unit of analysis. This resolution reflects a compromise between data availability, computational feasibility, and the need to capture dominant landscape patterns. Because land-use processes in this system are inherently multi-scalar, pixel-level representations approximate aggregated outcomes of finer-scale decision-making (e.g., household or parcel-level processes). We acknowledge that the chosen spatial resolution and modeling approach may limit the representation of fine-scale heterogeneity and localized transitions, a challenge widely noted in dryland and Sub-Saharan African LULC modeling studies where spatial data constraints and scale mismatches remain common (Govender et al., 2022; Nxumalo et al., 2026). Accordingly, model outputs should be interpreted at the landscape scale, and patterns understood as emergent properties of spatial processes rather than discrete management units.

Second, explanatory variables were selected using a theory-driven and parsimonious approach; therefore, the model does not incorporate all potentially relevant drivers (e.g., dynamic socioeconomic processes such as land leasing, short-term market fluctuations, or development interventions). Unexplained spatial patterns may reflect these omitted factors rather than model error. This limitation reflects a broader challenge in African LULC modeling, where integrating dynamic socioeconomic processes into spatially explicit models remains difficult due to limited data availability and representation (Assede et al., 2023). Third, the tenure layer is treated as a static contextual variable and does not capture temporal changes in governance during the prediction period. In addition, preprocessing steps such as spatial aggregation, resampling, and correlation filtering introduce trade-offs between data consistency and information loss. Collectively, these assumptions imply that model outputs should be interpreted as diagnostic representations of spatial patterns and relative associations, rather than precise predictions or causal inferences about land-use dynamics (Govender et al., 2022).

3. Results

3.1. Spatial pattern of the predicted LULC map

We produced LULC predictions for the year 2018 which included a hard (Fig. 4a) and soft (Fig. 4b) prediction. The hard prediction represents a single realization of what LULC would look like given the predetermined driving factors and historical LULC changes between 2000 and 2010. The overall spatial allocation of classes in the predicted map is largely consistent with that of the reference 2018 map (Fig. 4c) except for deviations associated with model error. Landscape-level metrics indicate that the predicted map exhibits a slightly more aggregated spatial pattern than the reference 2018 map, as reflected by higher contagion values (55.1% vs. 53.7%) and lower edge density (23 m ha^{-1} vs. 30 m ha^{-1}). This indicates a smoothing effect in the model. The soft prediction shows for each pixel the susceptibility to transition from one class to another. High values imply that the pixel is susceptible to change to multiple possible classes, while low values imply that a pixel is either unlikely to change or could change to fewer possible classes.

3.2. Model prediction correctness and error

As a proportion of the entire landscape area, our model obtained 83% correct prediction rate including 79% correctly predicted persistence (correct rejections) and 4% correctly predicted change (hits). Errors in modeled land cover transitions (as a function of either misclassified persistence or change) showed clear spatial patterns (Fig. 5a). The error rate was 17% of the entire landscape, including 8% of change simulated as persistence (misses), 8% persistence simulated as change (false alarms), and 1% change simulated as change to the wrong category (wrong hits) (Fig. 5b). Because we adjusted our expected amounts of land use change between 2010 and 2018 to match observed quantities in 2018, we did not have any errors associated with the wrong amount of predicted change. Therefore, all prediction errors in our model are a result of errors due to misallocation.

The spatial distribution of model errors was consistent with specific LULC transitions (Fig. 6). Misses primarily involved predictions of rangeland, forest and cropland persistence in areas where change occurred. Specifically, the model underestimated forest to cropland transitions around the Mau Forest, rangeland to cropland transitions near the central part of the landscape, and cropland to rangeland transitions on the western parts of the landscape. In contrast, false alarms were primarily associated with predicted transitions involving rangeland to cropland, forest to rangeland, and cropland to rangeland in areas where persistence occurred. These were predominant around the central parts of Narok along the cropland-rangeland interface and involved transitions between rangeland and cropland. Wrong hits were minimal and primarily associated with erroneous prediction of forest to cropland transitions in areas where forest to rangeland transitions occurred.

3.3. Drivers of LULC change

Between 2000 and 2010 (the calibration period), the main LULC transitions involved rangeland to cropland (11%), forest to cropland (9.5%), forest to rangeland (7.3%), and cropland to rangeland (7.3%), with percentages representing the proportion of the initial class area on the landscape that changed (Fig. 7a). Fig. 7b shows the relative importance of factors in driving the land use transitions. Rangeland to cropland transitions were widespread but concentrated in the central and western regions (Fig. 7a), most strongly associated with proximity to existing cropland (Fig. 7b). Forest to cropland transitions were most prominent in the northern landscape near the Mau Forest and were more likely in areas classified as private land, and proximity to existing cropland. Forest to rangeland transitions were linked spatially to slope, proximity to rangeland, forest fragmentation, and land policy. Remotely

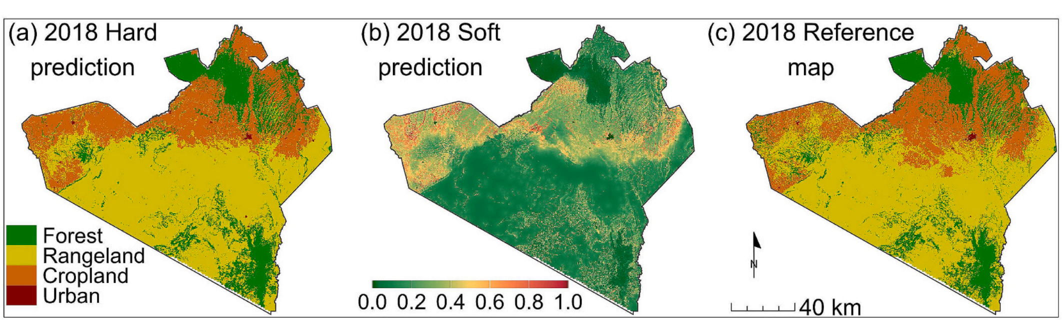

Fig. 4. (a) shows the predicted LULC map for 2018. (b) shows the overall susceptibility of pixels transitioning from one class to another. (c) shows the reference LULC for the year 2018.

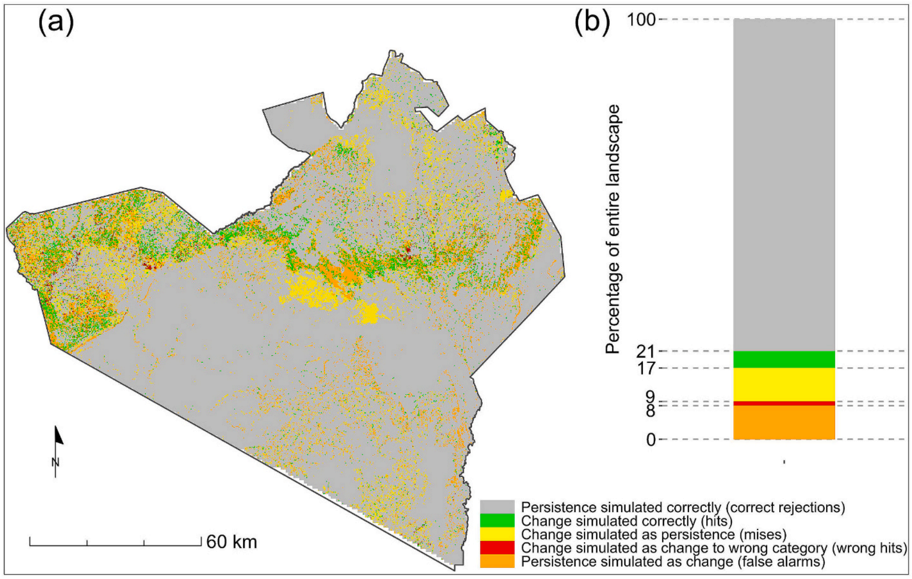

Fig. 5. (a) shows the spatial distribution of model correctness and error based on a three-way cross validation of the 2010 reference map, 2018 reference map and 2018 predicted map. (b) Figure of merit showing a budget of model correctness and error as proportions of the whole landscape.

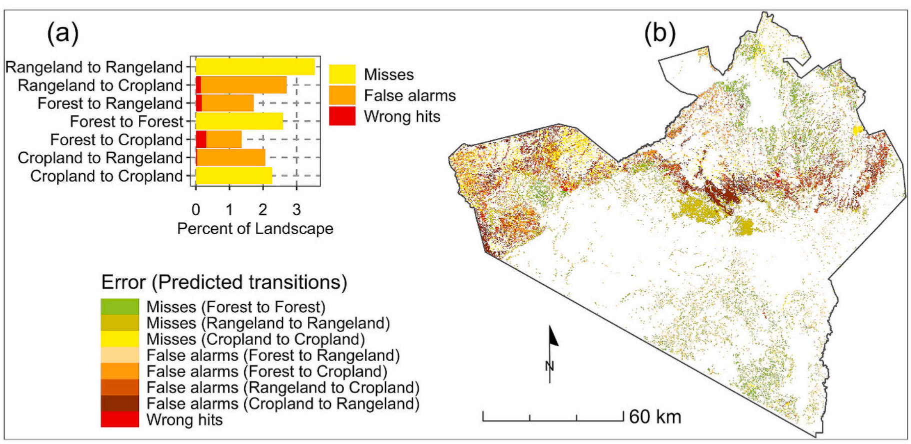

Fig. 6. Proportion (a) and spatial pattern (b) of model prediction errors and the associated predicted transitions.

sensed vegetation indices also emerged as important predictors of the transitions such that forest persistence was associated with relatively high values of average NDVI and relatively high start of season (SOS) EVI values. Cropland to rangeland transitions were primarily associated with average temperature conditions and proximity to existing rangeland. Peak of season EVI values also emerged as good indications of the transitions in that highest peak EVI values occurred on cropland than on rangeland. Collectively, these results show that LULC was determined as a combination of factors related to landscape context (e.g., distance to similar land covers), social and biophysical characteristics. The variables aligning spatially with LULC differed among specific land use transitions.

Interestingly, results show that while the relative importance of these factors may not be evident at the landscape scale when all variables are considered together, they become important at finer spatial scales. For example, transitions varied across tenure categories, indicating different associations between static tenure contexts and transition potentials (Fig. 8a). Specifically, most rangeland to cropland, forest to cropland, and cropland to rangeland transitions occurred on areas that were historically group ranch but that have transitioned to private ownership. Current group ranch and conservancy areas were dominated by forest to rangeland transitions. Landscape context was additionally important, evidenced by the result that degradation of forest to rangeland primarily occurred on small, isolated forest patches (Fig. 8b) and mainly within relatively flat terrain (Fig. 8d), while direct conversions to cropland occurred uniformly across all forest patch types (Fig. 8b). Cropland to rangeland transitions were more dominant in areas with higher average temperature (Fig. 8c) and on relatively flat terrain (Fig. 8d), both characteristic of the arid and semi-arid plains of Narok.

4. Discussion

Simulating the dynamics of land use change in multifunctional landscapes requires an approach that accounts for both biophysical and socioeconomic drivers. In ASALs, where land is under increasing pressure from competing uses, modeling tools such the LCM offer valuable insights into the spatial and temporal patterns of land transitions. Our results indicated that land use transitions are not uniform through time and space, nor driven by a single factor. Instead, they reflect a complex interplay of drivers that vary among land use types and evolve over time. Interestingly, our results highlighted the role of spatial adjacency (proximity to similar existing land use) in determining the spatial pattern of class transitions. Moreover, we found that transition potentials varied across tenure categories, reflecting long-standing land

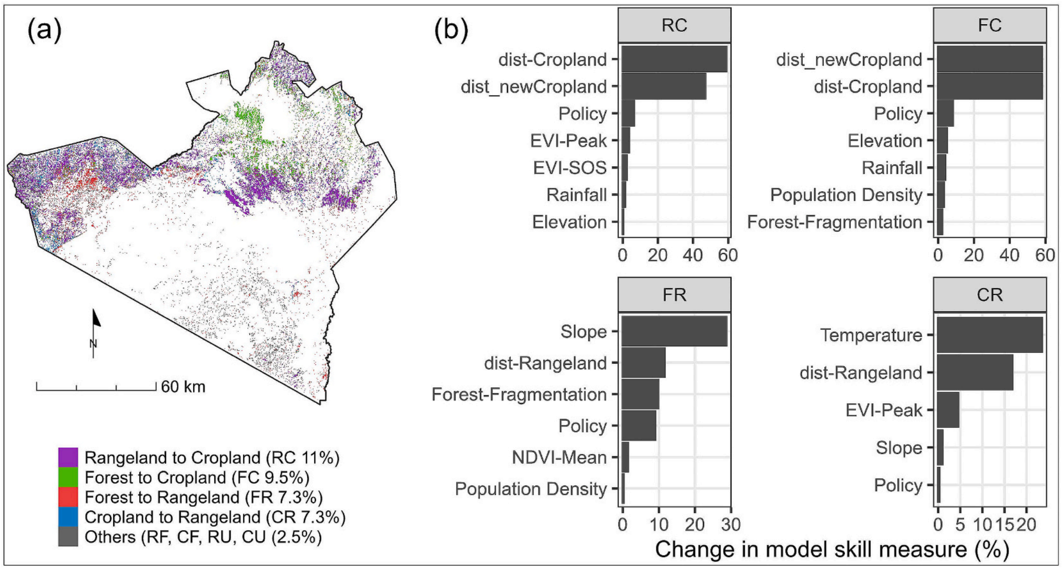

Fig. 7. Observed LULC transitions between the initial year (2000) and final year (2010) of model calibration (a) Proportions of the initial class that transitioned to another is shown in brackets on the legend. (b) shows the relative importance of variables for four sub-models that represent the most observed transitions. The percent change in model skill measure is the proportion by which the skill measure reduces if a variable in the sub-model is held constant. Larger percentage values indicate greater variable importance.

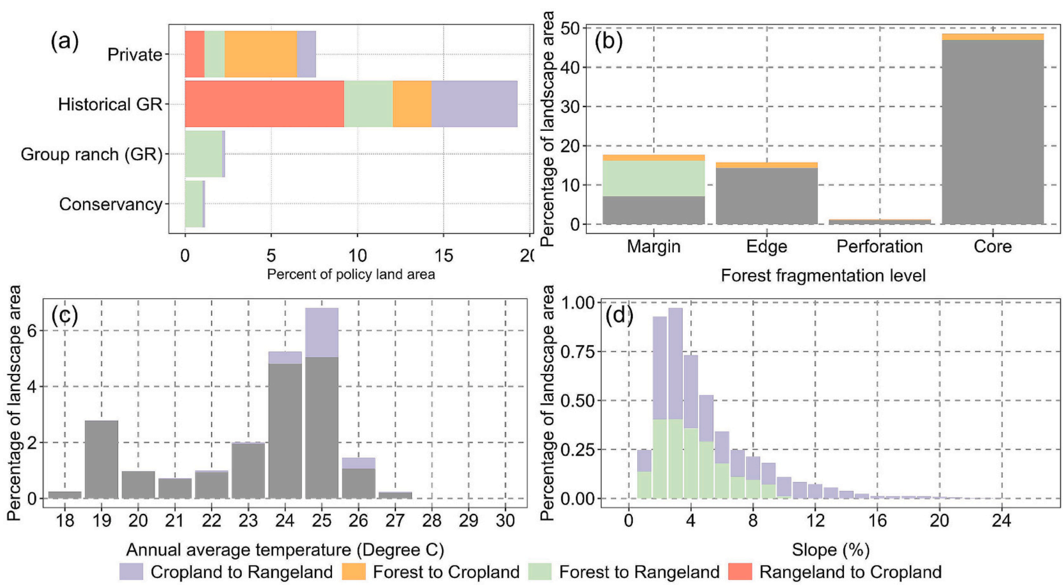

Fig. 8. Predicted LULC transitions as a function of the percent of land (a) under a specific land policy category, (b) transitioning from forest according to levels of forest fragmentation, (c) transitioning from cropland to rangeland along the temperature gradient, and (d) transitioning from cropland and forest to rangeland along the slope gradient (d). Grey bars on (b) and (c) respectively represent forest persistence and cropland persistence.

governance contexts and pre-existing land use trajectories, rather than dynamic tenure processes. Further, spatial misallocation of land use transitions had clear localized patterns, suggesting fine-scaled socio-economic factors not directly represented in the model. Because the modeling framework is correlational and represents land tenure as a static contextual layer, results are interpreted as spatial associations rather than causal effects, clarifying the scope and limits of inference. By examining these patterns, we deepen our understanding of the mechanisms behind land use change and underscore key considerations for land use modeling of multifunctional ASALs.

4.1. Spatial aggregation in the predicted LULC map

At the landscape level, the predicted 2018 LULC map demonstrated a high degree of spatial agreement with the observed 2018 reference map, indicating that the calibrated model effectively captured the dominant patterns of land use transitions across the landscape. However, at the patch level, the predicted map exhibits a higher degree of spatial homogeneity compared to the reference map, particularly in the distribution of cropland, which appears to be more spatially aggregated in the predicted map. Quantitative measures of aggregation (Contagion, Edge density) indicated greater homogeneity in the predicted, compared to the reference map. In our case, the smoothing effect is likely a result of predictor variables that were derived from coarse-resolution datasets, which can obscure localized environmental and socioeconomic variability critical for capturing nuanced land use dynamics (Cai and Wang, 2020). Specifically, precipitation, temperature, and population density were derived from coarse resolution (~5 km for precipitation and temperature, administrative ward level for population) data that is appropriate for analysis at broader scales but may insufficiently characterize variability at finer resolutions that may be important for understanding, for example, transitional zones or fine-scaled heterogeneity in cropland patches. In addition, our thematic aggregation of historical LULC data likely contributed to the smoother spatial pattern in predicted maps, as transitions among finer vegetation subclasses (e.g., shrub encroachment, woodland degradation) could not be represented explicitly. However, modeling with the original ten classes produced substantially higher misclassification and unstable transition estimates, confirming that aggregated classes provided the most reliable basis for analyzing dominant livelihood-linked land transitions in this landscape.

However, reduced heterogeneity in the predicted map may also reflect inherent neighborhood dynamics in land use change processes. Numerous studies have shown that land use transitions are not spatially random but exhibit strong adjacency effects, where proximity to similar land uses significantly increases the likelihood of conversion. For example, Tepe (2024) found that neighborhood and proximity effects played a key role in shaping land development patterns through spatial autocorrelation and spillover effects. Similarly, Verburg et al. (2004) and Irwin and Geoghegan (2001) emphasized that adjacency strongly influences the spatial pattern of land use change by reinforcing clustering, although it operates as a neighborhood effect rather than a primary causal driver. These findings underscore that incorporating spatial context, particularly adjacency to similar land uses, is essential for accurately modeling and understanding land use change.

4.2. Key drivers of land use

Interestingly, we showed that each land use transition was driven by a different set of predictor variables, underscoring the complexity and context-specific nature of factors influencing land use change in multifunctional landscapes. This finding aligns with broader literature emphasizing that land use transitions are rarely governed by a single driver, but rather by a constellation of interacting biophysical, socioeconomic, and institutional variables that vary across space and time (Lambin et al., 2003). Although spatial adjacency emerged as a consistently influential factor across all modeled transitions, adjacency operates alongside socioeconomic and biophysical drivers, consistent with broader literature (e.g., Verburg et al., 2004).

For example, land tenure emerged as a meaningful contributor to the predictive performance of LULC transition models across all transition classes. Though not as influential at the landscape level as other biophysical or adjacency-related factors, its influence was evident for individual class-level transitions and for areas that experienced key land tenure transitions in colonial and post-colonial periods in Kenya's history. For example, rangeland to cropland and cropland to rangeland were more common in areas classified as former group ranches (HGR), reflecting the spatial imprint of past privatization rather than modeling of privatization itself. In addition, forest to rangeland transitions were predominantly in areas that are still group ranch and on conservancies.

In addition, predicted transitions between land cover classes generally aligned with biophysical variables that influence site suitability, such as precipitation, elevation, and slope (Briassoulis, 2009). For example, transitions to cropland (whether from rangeland or forest) were concentrated in areas with higher precipitation and elevation. Forest to rangeland transitions occurred on flat to relatively gentle slopes than steep slopes consistent with expectations of easy access for pastoralists.

Transitions from cropland to rangeland were strongly associated with higher temperature areas, which may reflect the influence of environmental change on cropland productivity. Elevated temperatures exacerbate agricultural water scarcity in ASALs and can lead to significant reductions in crop productivity, potentially increasing the likelihood of cropland abandonment (Liu et al., 2025). While our study does not necessarily indicate permanent abandonment, the co-occurrence of these transitions with high temperature zones suggests declining crop suitability. Although such transitions are common in mixed agriculture-livestock systems or crop rotation, some studies link them to cropland abandonment following intensification in more suitable areas (Rudel et al., 2009). In another study, transitions between cropland and rangeland are contextualized in terms of interactions between ecosystem state changes and land use change (Bestelmeyer et al., 2015). In this study, the concentration of these changes along the transition zone between humid and arid areas (also cropland-rangeland interface) likely suggests a dynamic pattern of land use changes driven by changing environmental conditions. However, the possibility that these transitions signal state changes due to persistently scarce and variable rainfall is worth further investigation.

On the other hand, some of the predictor variables we expected would influence land use were not found to be important. For example, it has been established that proximity to roads and markets affects accessibility, transportation costs, and economic opportunities, which in turn influences how land is used and developed (Kasraian et al., 2016; Liu et al., 2020). However, these factors did not emerge as important in influencing any of the modeled transitions. The low importance of distance-to-roads likely reflects proxy absorption by cropland adjacency and the variable's limited measurement scope (proximity, not quality/travel-time), rather than a lack of accessibility effects per se. First, proximity to existing cropland is a strong spatial proxy bundling unobserved correlates such as soil quality, micro-climate, informal tracks/paths, and incumbent investments, that together reduce the unique variance attributable to formal distance to roads. Second, in a land-scarce, mixed agropastoral system, neighborhood contagion (adjacency to similar uses) can dominate the location of new conversions, again diminishing the marginal role of formal road distance in the MLP sub-models. It is also likely that due to an acute shortage of land resources including arable land, forest, and grazing land (Lambin and Meyfroidt, 2011), accessibility and markets are not key limitations to resource exploitation. (Kaczan, 2020; Laurance et al., 2009). Distance to rivers is another variable that we expected would influence transitions to cropland due to availability of irrigation water. While riparian irrigation is a common practice in Narok, it happens at a relatively small scale (partly due to the small size of rivers and their non prermanent nature) compared to rainfall-depended farming and thus was not sufficient to influence landscape level land use modeling.

The selected predictors represent a theory-driven subset aligned with the study's spatial scale and objectives. Remaining variance is interpreted as evidence of unmodeled socioeconomic processes (e.g. land leasing, informal markets, seasonal decision-making, development interventions), rather than as model bias. Therefore, spatially clustered misallocation is treated as diagnostic information, highlighting dynamic frontiers (e.g., tenure transition zones, humid-arid ecotones) where missing socioeconomic processes are most influential and where future data collection or model extensions would be most valuable.

4.3. Modeling challenges in dynamic socio-ecological landscapes

The lack of spatially explicit representation of potential drivers remains a key limitation to land use change modeling of ASALs especially in sub-Saharan Africa. This is because localized socioeconomic factors frequently outweigh biophysical constraints in driving land-use change. At the local (household or community) level, factors such as irrigation infrastructure, land leasing arrangements, production costs, crop prices, and cultural norms can influence land use decisions and generate highly heterogeneous and sometimes counterintuitive land-use changes (Briassoulis, 2009). In Narok County, access to irrigation water has enabled farmers to grow crops in dry environments, thus overcoming the constraints of rainfed agriculture (ILEPA, 2018; MoALFC, 2021). At the same time, land-leasing arrangements where absentee landowners lease parcels to commercial or non-local tenants can instigate a high degree of unpredictability into land-use trajectories. This is because, in this kind of arrangement, tenants often prioritize short-term yields over sustainable land management, leading to accelerated degradation that diverges from traditional community practices (Salmerón-Manzano and Manzano-Agugliaro, 2023). In addition, the variability of lease durations can range from a single season to several years leading to rapid and heterogeneous shifts between cropping and grazing land uses. It is challenging to capture such land use dynamics using conventional models which typically assume stable local decision-making.

Humid-arid ecotones exhibit steep gradients in temperature and moisture and are highly sensitive to both climatic variability and human activity (Food and Agriculture Organization, 1986; C. Fu, 1992), making them highly dynamic and challenging to model. These transitional zones often form complex mosaics of vegetation and land uses that shift in response to environmental conditions (J. Chen et al., 2024; Gao et al., 2024). Within our study area in Narok, this ecotone generally aligns with the cropland-rangeland interface, where we observed persistent underestimation of rangeland to cropland transitions in low rainfall regions (typically receiving less than 700 mm annually). Typically, during unusually wet years, farmers frequently expand cultivation into adjacent grasslands to capitalize on temporary moisture availability (Demissie et al., 2025). However, in dry years, these marginal lands are often abandoned or left fallow, gradually reverting to rangeland or pasture. This cyclical pattern underscores the fluidity of land use in humid-arid ecotones, posing a significant challenge for land use modeling in ASALs, where conventional models often fail to capture the temporally adaptive and opportunistic nature of land use decisions. In our case, this limitation is compounded by the fact that the LCM does not incorporate antecedent memory: it cannot simulate lagged climatic effects, cyclical cultivation patterns, or year-to-year decision dynamics. Transition potentials are estimated from a single calibration interval (2000–2010) and are applied uniformly during prediction, restricting the model's ability to represent opportunistic land-use pulses (e.g., wet-year cultivation) that characterize humid-arid ecotones in Narok.

Despite these challenges, the LCM proved useful in unraveling some of these complex dynamics. By highlighting spatial patterns of change and associated errors and identifying areas where transitions are more likely to occur, the simulations provided insights into potential model biases and, moving forward, offers opportunities to further refine model specifications. In the future, scenario-based modeling approaches, when grounded in a nuanced understanding of the adaptive and context-specific nature of land use in these ecotones, can also be used to explore the implications of alternative land use decisions under varying climate and policy futures, ideally capturing local realities and supporting the design of more relevant and resilient land management strategies. Overall, the model's ability to incorporate multiple explanatory variables and simulate future scenarios makes it a valuable tool for exploring how different combinations of environmental and socioeconomic factors may shape land use trajectories.

At the same time, these limitations underscore a broader challenge in land-use change modeling: the need to simplify inherently complex and interrelated social and ecological processes into a tractable set of explanatory variables. Consequently, conclusions regarding driver importance are conditioned by the modeling framework and predictor selection strategy employed. Finally, the predictor selection strategy represents one of several valid approaches to modeling land-use change. While we adopted a theory-guided parsimonious framework to enhance interpretability, reduce redundancy among predictors, and maintain model tractability, we acknowledge that correlated variables often reflect meaningful ecological and social relationships rather than statistical artifacts. Consequently, correlation filtering was not intended to eliminate ecological relationships, but to reduce redundancy within the selected modeling framework. Alternative approaches may retain a larger set of predictors and potentially explain additional variance or reveal complementary patterns of association. Accordingly, the identified drivers should be interpreted as dominant associations within the selected model structure rather than a complete representation of all processes governing landscape change. Future research could evaluate the sensitivity of results to alternative predictor-selection strategies and modeling frameworks.

4.4. Implications for conservation and livelihoods under resource constraint

Several of the dominant land-use transitions we identify occur in spatial zones where conservation objectives, agropastoral livelihoods, and climatic sensitivity intersect, creating areas of heightened policy relevance due to competing land-use demands. Similar projections for Kenyan ASALs suggest that increasing competition among land uses, combined with climate variability, will intensify these spatial trade-offs, particularly in regions undergoing rapid land-use transition (Adoyo et al., 2024). In multifunctional arid landscapes such as Narok County, conservation areas, croplands, and pastoral systems frequently occupy the same spatial units, requiring land-use decisions that involve unavoidable trade-offs rather than win-win outcomes. As a result, persistence of land cover does not necessarily imply social or ecological well-being. Apparent land-cover stability may coexist with declining livelihood security, restricted pastoral mobility, or gradual ecological degradation, while rapid land-use change can reflect short-term coping strategies under stress, rather than adaptive success.

These patterns underscore that resilience is contested, uneven, and conditional, shaped by historical land tenure arrangements, environmental stress gradients, and differential institutional and governance contexts. From a policy perspective, interventions framed solely around enhancing resilience risk obscuring these underlying trade-offs. Areas that appear stable may mask accumulating vulnerability, while zones of active transition, particularly along tenure transition boundaries and humid-arid ecotones, often represent landscapes where conservation restrictions, livelihood pressures, and climate variability are most tightly coupled. In such contexts, development aid, conservation investment, or land-use regulation is likely to redistribute costs and benefits unevenly across land users.

For resource-constrained planning environments typical of much of sub-Saharan Africa, this implies that interventions, whether conservation enforcement, agricultural intensification programs, or climate adaptation funding, cannot be evaluated independently of their spatial and governance context. Land-change models such as the one applied here do not prescribe optimal land-use solutions; rather, they function as diagnostic tools that help identify where land-use trade-offs are most acute, where thresholds of potentially irreversible change may be approached, and where additional governance attention or participatory planning is most urgently needed. By making these spatial tensions explicit, such models can support more transparent and contextualized decision-making in landscapes where people and conservation must coexist on the same land under increasing climatic and institutional constraint.

5. Conclusion

This study demonstrates that land-use change in the multifunctional arid and semi-arid landscapes of Narok County is shaped by interacting environmental, governance, and spatial-context factors. Land tenure, climatic conditions, and proximity to existing land uses emerged as important correlates of observed land-cover transitions, while model errors were concentrated in humid-arid ecotones and tenure-transition areas characterized by high social-ecological complexity. These findings highlight the influence of both biophysical gradients and historical governance legacies on contemporary landscape dynamics.

Although the model successfully reproduced broad spatial patterns of change, localized misallocations indicate that additional socio-economic processes operating at finer scales remain important determinants of land-use outcomes. As such, the model should be interpreted as a diagnostic tool for identifying areas where competing land uses, environmental pressures, and governance conditions converge, rather than as a precise predictor of future landscapes.

More broadly, our results underscore the value of spatially explicit land-change modeling for informing land-use planning in data-scarce dryland regions. By identifying where conservation, cultivation, and pastoral livelihoods are most likely to compete for limited resources, this approach can support more transparent and context-sensitive planning under increasing climatic and socio-economic pressures.

CRediT authorship contribution statement

Susan M. Kotikot: Writing – review & editing, Writing – original draft, Methodology, Formal analysis, Data curation, Conceptualization. **Erica A.H. Smithwick:** Writing – review & editing, Writing – original draft, Supervision, Funding acquisition, Conceptualization. **Sarah E. Gergel:** Writing – review & editing, Supervision, Funding acquisition, Conceptualization. **Jedidah Nankaya:** Writing – review & editing, Validation. **Romulus Abila:** Writing – review & editing, Validation.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Funding

This work was supported by the National Science Foundation BCS Award No. 2149244.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.ecoinf.2026.103959.

Data availability

All data and codes used in this study are publicly available. All input datasets, processed driver layers, and model outputs (transition potential maps, predicted land-use maps, and error diagnostics) are archived in an open repository on Zenodo (DOI: 10.5281/zenodo.20142764) and provided in standard GIS formats compatible with QGIS and R. The analysis scripts are available on GitHub (https://github.com/skotikot/Modeling-Multifunctional-Landscape-Change). While model calibration and allocation were conducted using LCM in Terrset, the exported layers allow independent inspection, comparison, and reuse of results in open-source GIS environments.

References

Adoyo, B., Kehbila, A., Lutta, A., Opiyo, R.O., Onyango, S.A., Mungo, C., Osano, P., 2024. Land cover scenarios in four Kenyan arid and semi-arid regions by 2050. SEI Working Paper. Stockholm Environment Institute. https://doi.org/10.51414/sei2024.029.

An, L., 2012. Modeling human decisions in coupled human and natural systems: review of agent-based models. Ecol. Model. 229, 25–36. https://doi.org/10.1016/j.ecolmodel.2011.07.010.

Assede, E.S.P., Orou, H., Biaou, S.S.H., Geldenhuys, C.J., Ahononga, F.C., Chirwa, P.W., 2023. Understanding Drivers of Land Use and Land Cover Change in Africa: A Review. Curr. Land. Ecol. Rep. 8 (2), 62–72. https://doi.org/10.1007/s40823-023-00087-w.

Barbier, E.B., Hochard, J.P., 2016. Does land degradation increase poverty in developing countries? PLoS One 11 (5). https://doi.org/10.1371/journal.pone.0152973.

Bestelmeyer, B.T., Okin, G.S., Duniway, M.C., Archer, S.R., Sayre, N.F., Williamson, J.C., Herrick, J.E., 2015. Desertification, land use, and the transformation of global drylands. Front. Ecol. Environ. 13 (1), 28–36. Ecological Society of America. https://doi.org/10.1890/140162.

Bradfer-Lawrence, T., Dobson, A.D.M., Finch, T., Fuentes-Montemayor, E., Hanley, N., Matthiopoulos, J., Nthambi, M., Simpson, K., Watts, K., Whytock, R.C., Park, K.J., 2025. Spillovers and legacies of land management on temperate woodland biodiversity. Nat. Ecol. Evol. 9 (6), 1009–1020. https://doi.org/10.1038/s41559-025-02688-6.

Briassoulis, H., 2009. Factors influencing land-use and land-cover change. In: Land Cover, Land Use and the Global Change, Encyclopaedia of Life Support Systems (EOLSS), 1, pp. 126–146.

Brown, D.G., Robinson, D.T., 2006. Effects of heterogeneity in residential preferences on an agent-based model of urban sprawl. Ecol. Soc. 11 (1). http://www.jstor.org/stable/26267798.

Brown, D.G., Goovaerts, P., Bumlckl, A., Li, M.-Y., 2002. Stochastic simulation of land-cover change using geostatistics and generalized additive models. Photogramm. Eng. Remote Sens. 68 (10), 1051–1061.

Cai, L., Wang, M., 2020. Effect of the thematic resolution of land use data on urban expansion simulations using the CA-Markov model. Arab. J. Geosci. 13, 1250. https://doi.org/10.1007/s12517-020-06248-z.

Cao, Q., Liu, Y., Georgescu, M., Wu, J., 2020. Impacts of landscape changes on local and regional climate: a systematic review. Landsc. Ecol. 35 (6), 1269–1290. Springer. https://doi.org/10.1007/s10980-020-01015-7.

Chen, H., Pontius, R.G., 2010. Diagnostic tools to evaluate a spatial land change projection along a gradient of an explanatory variable. Landsc. Ecol. 25 (9), 1319–1331. https://doi.org/10.1007/s10980-010-9519-5.

Chen, J., Yang, H., Jin, T., Wu, K., 2024. Assessment of terrestrial ecosystem sensitivity to climate change in arid, semi-arid, sub-humid, and humid regions using EVI, LAI, and SIF products. Ecol. Indic. 158. https://doi.org/10.1016/j.ecolind.2023.111511.

Chrispus, N., 2022. Uganda's land tenure systems and their impact on development. Makerere Law J. 51. https://www.researchgate.net/publication/307631527.

de Jong, L., De Bruin, S., Knoop, J., van Vliet, J., 2021. Understanding land-use change conflict: a systematic review of case studies. J. Land Use Sci. 16 (3), 223–239. https://doi.org/10.1080/1747423X.2021.1933226.

Demissie, T., Diro, G.T., Duku, C., Solomon, D., Jimma, T.B., 2025. Current and projected changes in climate extremes and agro-climatic zones over East Africa. Theor. Appl. Climatol. 156 (3). https://doi.org/10.1007/s00704-025-05405-2.

Didan, K., 2015. MOD13Q1 MODIS/Terra Vegetation Indices 16-Day L3 Global 250m SIN grid V006 [Data set]. https://doi.org/10.5067/MODIS/MOD13Q1.006.

Eastman, J.R., Toledano, J., 2018. A short presentation of the land change modeler (LCM). In: Camacho Olmedo, M.T., Paegelow, M., Mas, J.-F., Escobar, F. (Eds.), Geomatic Approaches for Modeling Land Change Scenarios. Springer International Publishing, pp. 499–505. https://doi.org/10.1007/978-3-319-60801-3_36.

Eastman, J.R., Jin, W., Kyem, P.A.K., Toledano, J., 1995. Raster procedures for multi-criteria /multi-objective decisions. Photogramm. Eng. Remote. Sens. 61 (5), 539–547.

Estacio, I., Sianipar, C.P.M., Onitsuka, K., Basu, M., Hoshino, S., 2023. A statistical model of land use/cover change integrating logistic and linear models: an application to agricultural abandonment. Int. J. Appl. Earth Obs. Geoinf. 120. https://doi.org/10.1016/j.jag.2023.103339.

FAO, 2002. Land Tenure and Rural Development. https://www.fao.org/3/y4307e/y4307e00.htm.

Fick, S.E., Hijmans, R.J., 2017. WorldClim 2: new 1-km spatial resolution climate surfaces for global land areas. Int. J. Climatol. 37 (12), 4302–4315. https://doi.org/10.1002/joc.5086.

Fischer, G.F., Nachtergaele, S., Prieler, H.T., van Velthuizen, L., Verelst, D.W., 2008. Global Agro-Ecological Zones Assessment for Agriculture (GAEZ 2008). IIASA, FAO, Laxenburg, Austria, Rome, Italy.

Food and Agriculture Organization, 1986. Irrigation water management: Irrigation water needs. In: Brouwer, C., Heibloem, M. (Eds.), Training Manual. FAO.

Fu, C., 1992. Transitional climate zones and biome boundaries: A case study from China. In: Hansen, A.J., di Castri, F. (Eds.), Landscape Boundaries: Consequences for Biotic Diversity and Ecological Flows. Springer New York, pp. 394–402. https://doi.org/10.1007/978-1-4612-2804-2_20.

Fu, B., Liu, Y., Zhao, W., Wu, J., 2025. The emerging "pattern-process-service-sustainability" paradigm in landscape ecology. Landsc. Ecol. 40 (3), 54. https://doi.org/10.1007/s10980-025-02063-7.

Gao, M., Wang, Y., Ren, Y., Zhan, J., Xie, T., 2024. Manipulated microtopography alters plant community development in fragile farm–pastoral transition zone. J. Plant Ecol. 17 (5). https://doi.org/10.1093/jpe/rtae070.

Garbarino, M., Weisberg, P.J., 2020. Land-use legacies and forest change. Landsc. Ecol. 35 (12), 2641–2644. Springer Science and Business Media B.V. https://doi.org/10.1007/s10980-020-01143-0.

Gergel, S.E., Powell, B., Baudron, F., Wood, S.L.R., Rhemtulla, J.M., Kennedy, G., Rasmussen, L.V., Ickowitz, A., Fagan, M.E., Smithwick, E.A.H., Ranieri, J., Wood, S. A., Groot, J.C.J., Sunderland, T.C.H., 2020. Conceptual links between landscape diversity and diet diversity: a roadmap for transdisciplinary research. BioScience 70 (7), 563–575. Oxford University Press. https://doi.org/10.1093/biosci/biaa048.

Govender, T., Dube, T., Shoko, C., 2022. Remote sensing of land use-land cover change and climate variability on hydrological processes in Sub-Saharan Africa: key scientific strides and challenges. Geocarto Int. 37 (25), 10925–10949. https://doi.org/10.1080/10106049.2022.2043451.

Hogland, J., Affleck, D.L.R., 2019. Mitigating the impact of field and image registration errors through spatial aggregation. Remote Sens. 11 (3). https://doi.org/10.3390/rs11030222.

Huang, X., Liu, J., Zhu, W., Atzberger, C., Liu, Q., 2019. The optimal threshold and vegetation index time series for retrieving crop phenology based on a modified dynamic threshold method. Remote Sens. 11 (23). https://doi.org/10.3390/rs11232725.

Huang, S., Tang, L., Hupy, J. P., Wang, Y., & Shao, G. (2021). A commentary review on the use of normalized difference vegetation index (NDVI) in the era of popular remote sensing. In J. For. Res. (vol. 32, number 1). Northeast Forestry University. Doi: https://doi.org/10.1007/s11676-020-01155-1.

Huete, A.R., Justice, C.O., Van Leeuwen, W.J.D., 1999. MODIS vegetation index (MOD 13). Version 3. Algorithm theoretical basis document. NASA Goddard Space Flight Cent, Greenbelt, MD, USA. , 7.

ILEPA, 2018. Community Irrigation and Water Conservation in Narok County. Riparian Irrigation Practices, Kenya. https://ilepa-kenya.org/prog/fostering-livelihoods-resilience-and-diversification/.

Irwin, E.G., Geoghegan, J., 2001. Theory, data, methods: developing spatially explicit economic models of land use change. Agric. Ecosyst. Environ. 85 (1–3), 7–24. https://doi.org/10.1016/S0167-8809(01)00200-6.

Kasraian, D., Maat, K., Stead, D., & van Wee, B. (2016). Long-term impacts of transport infrastructure networks on land-use change: an international review of empirical studies. In Transp. Rev. (vol. 36, 6, pp. 772–792). Routledge. Doi: https://doi.org/10.1080/01441647.2016.1168887.

Kaczan, David, J., 2020. Can roads contribute to forest transitions? World Development, 129. https://doi.org/10.1016/j.worlddev.2020.104898.

Kotikot, S.M., Smithwick, E.A.H., Greatrex, H., 2024. Observations of enhanced rainfall variability in Kenya, East Africa. Sci. Rep. 14 (1), 12915. https://doi.org/10.1038/s41598-024-63786-2.

Kotikot, S.M., Smithwick, E.A.H., Gergel, S., Nankaya, J., Abila, R., Mabwoga, S., 2025a. Historical land policies influence contemporary landscape patterns in agropastoral landscapes. Landsc. Ecol. 40 (8). https://doi.org/10.1007/s10980-025-02178-x.

Kotikot, S.M., Smithwick, E.A.H., Nankaya, J., Gergel, S., Zimmerer, K.S., Abila, R., 2025b. Heterogeneous perceptions of rainfall patterns among agropastoral land users in Sub-Saharan Africa. Ann. Am. Assoc. Geogr. https://doi.org/10.1080/24694452.2025.2482899.

Lambin, E.F., Geist, H.J., 2006. In: Lambin, E.F., Geist, H. (Eds.), Land-Use and Land-Cover Change Local Processes and Global Impacts, 1st ed. Springer, Berlin, Heidelberg.

Lambin, E.F., Meyfroidt, P., 2011. Global land use change, economic globalization, and the looming land scarcity. Proc. Natl. Acad. Sci. U. S. A. 108 (9), 3465–3472. https://doi.org/10.1073/pnas.1100480108.

Lambin, E.F., Geist, H.J., Lepers, E., 2003. Dynamics of land-use and land-cover change in tropical regions. Annu. Rev. Environ. Resour. 28, 205–241. https://doi.org/10.1146/annurev.energy.28.050302.105459.

Laurance, W.F., Camargo, J.L.C., Luizão, R.C.C., Laurance, S.G., Pimm, S.L., Bruna, E.M., Stouffer, P.C., Bruce Williamson, G., Benítez-Malvido, J., Vasconcelos, H.L., Van Houtan, K.S., Zartman, C.E., Boyle, S.A., Didham, R.K., Andrade, A., Lovejoy, T.E., 2011. The fate of Amazonian forest fragments: A 32-year investigation. Biol. Conserv. 144 (1), 56–67. https://doi.org/10.1016/j.biocon.2010.09.021.

Laurance, W.F., Goosem, M., Laurance, S.G.W., 2009. Impacts of roads and linear clearings on tropical forests. Trends Ecol. Evol. 24 (12), 659–669. https://doi.org/10.1016/j.tree.2009.06.009.

Liu, Y., Cao, X., Li, T., 2020. Influence of accessibility on land use and landscape pattern based on mapping knowledge domains: review and implications. J. Adv. Transp. 2020. https://doi.org/10.1155/2020/7985719. Hindawi Limited.

Liu, Z., Jiao, L., Lian, X., 2025. Changes in compound extreme events and their impacts on cropland productivity in China, 1985–2019. Earth's Future 13 (3). https://doi.org/10.1029/2024EF005038.

Mander, Ü., Helming, K., Wiggering, H., 2007. Multifunctional land use: Meeting future demands for landscape goods and services. In: Mander, Ü., Wiggering, H., Helming, K. (Eds.), Multifunctional Land Use: Meeting Future Demands for Landscape Goods and Services. Springer Berlin Heidelberg, pp. 1–13. https://doi.org/10.1007/978-3-540-36763-5_1.

Manson, S., 2006. Land use in the southern Yucatán peninsular region of Mexico: scenarios of population and institutional change. Comput. Environ. Urban. Syst. 30 (3), 230–253. https://doi.org/10.1016/j.compenvurbsys.2005.01.009.

Memarian, H., Kumar Balasundram, S., Bin Talib, J., Teh Boon Sung, C., Mohd Sood, A., Abbaspour, K., 2012. Validation of CA-Markov for simulation of land use and cover change in the Langat Basin, Malaysia. J. Geogr. Inf. Syst. 04 (06), 542–554. https://doi.org/10.4236/jgis.2012.46059.

Misra, A.K., Lata, K., Shukla, J.B., 2014. Effects of population and population pressure on forest resources and their conservation: a modeling study. Environ. Dev. Sustain. 16 (2), 361–374. https://doi.org/10.1007/s10668-013-9481-x.

MoALFC, 2021. Climate Risk Profile for Narok County. Kenya County Climate Risk Profile Series.

Mogonong, B.P., Twine, W., Feig, G.T., Van der Merwe, H., Fisher, J.T., 2024. Influences of Climate Variability on Land Use and Land Cover Change in Rural South Africa. Remote Sens. 16 (7). https://doi.org/10.3390/rs16071200.

Mutale, B., Qiang, F., 2024. Modeling future land use and land cover under different scenarios using patch-generating land use simulation model. A case study of Ndola district. Front. Environ. Sci. 12. https://doi.org/10.3389/fenvs.2024.1362666.

NASA JPL, 2013. NASA Shuttle Radar Topography Mission Global 1 arc Second [Data set]. https://doi.org/10.5067/MEaSUREs/SRTM/SRTMGL1.003.

National Research Council, 2014. Advancing Land Change Modeling: Opportunities and Research Requirements. The National Academies Press. https://doi.org/10.17226/18385.

Nicholson, S.E., 2017. Climate and climatic variability of rainfall over eastern Africa. Rev. Geophys. 55 (3), 590–635. https://doi.org/10.1002/2016RG000544.

Numata, I., Cochrane, M.A., 2012. Forest fragmentation and its potential implications in the Brazilian Amazon between 2001 and 2010. Open J. Forest. 02 (04), 265–271. https://doi.org/10.4236/ojf.2012.24033.

OpenStreetMap contributors. (2025). Planet Dump. Retrieved from https://download.geofabrik.de/africa.html.

Nxumalo, N., Nzimande, N.P., Xulu, S., 2026. Remote Sensing Applications for Land-Use and Land-Cover Change Research in South African Landscapes: A Review. Earth 7 (2). https://doi.org/10.3390/earth7020054.

Parker, D.C., Manson, S.M., Janssen, M.A., Hoffmann, M.J., Deadman, P., 2003. Multi-agent Systems for the Simulation of land-use and land-cover change: a review. Ann. Assoc. Am. Geogr. 93 (2), 314–337. https://doi.org/10.1111/1467-8306.9302004.

Pielke, R.A., Avissar, R., 1990. Influence of landscape structure on local and regional climate. In: Landscape Ecology, vol. 4. SPB Academic Publishing bv.

Pijanowski, B.C., Brown, D.G., Shellito, B.A., Manik, G.A., 2002. Using neural networks and GIS to forecast land use changes: a land transformation model. Comput. Environ. Urban. Syst. 26 (6), 553–575. https://doi.org/10.1016/S0198-9715(01)00015-1.

Place, F., Otsuka, K., 2002. Land tenure systems and their impacts on agricultural investments and productivity in Uganda. J. Dev. Stud. 38 (6), 105–128. https://doi.org/10.1080/00220380412331322601.

Pongratz, J., Schwingshackl, C., Bultan, S., Obermeier, W., Havermann, F., Guo, S., 2021. Land use effects on climate: current state, recent progress, and emerging topics. Curr. Clim. Chang. Rep. 7 (4), 99–120. Springer Science and Business Media Deutschland GmbH. https://doi.org/10.1007/s40641-021-00178-y.

Pontius, R.G., Boersma, W., Castella, J.C., Clarke, K., Nijs, T., Dietzel, C., Duan, Z., Fotsing, E., Goldstein, N., Kok, K., Koomen, E., Lippitt, C.D., McConnell, W., Mohd Sood, A., Pijanowski, B., Pithadia, S., Sweeney, S., Trung, T.N., Veldkamp, A.T., Verburg, P.H., 2008. Comparing the input, output, and validation maps for several models of land change. Ann. Reg. Sci. 42 (1), 11–37. https://doi.org/10.1007/s00168-007-0138-2.

Potapov, P., Hansen, M.C., Pickens, A., Hernandez-Serna, A., Tyukavina, A., Turubanova, S., Zalles, V., Li, X., Khan, A., Stolle, F., Harris, N., Song, X.P., Baggett, A., Kommareddy, I., Kommareddy, A., 2022. The global 2000-2020 land cover and land use change dataset derived from the Landsat archive: first results. Front. Remote Sens. 3. https://doi.org/10.3389/frsen.2022.856903.

Preiser, R., Biggs, R., De Vos, A., Folke, C., 2018. Social-ecological systems as complex adaptive systems: organizing principles for advancing research methods and approaches. Ecol. Soc. 23 (4). https://doi.org/10.5751/ES-10558-230446.

Qacami, M., Khattabi, A., Lahssini, S., Rifai, N., Meliho, M., 2023. Land-cover/land-use change dynamics modeling based on land change modeler. Ann. Reg. Sci. 70 (1), 237–258. https://doi.org/10.1007/s00168-022-01169-z.

Ramirez-Villegas, J., Thornton, P.K., 2015. Climate change impacts on African crop production. In: CCAFS Working Paper no. 119. CGIAR Research Program on Climate Change, Agriculture and Food Security (CCAFS). Copenhagen, Denmark. Available online at: www.ccafs.cgia.

Rippke, U., Ramirez-Villegas, J., Jarvis, A., Vermeulen, S.J., Parker, L., Mer, F., Diekkrüger, B., Challinor, A.J., Howden, M., 2016. Timescales of transformational climate change adaptation in sub-Saharan African agriculture. Nat. Clim. Chang. 6 (6), 605–609.

Rudel, T.K., Schneider, L., Uriarte, M., Turner, B.L., DeFries, R., Lawrence, D., Geoghegan, J., Hecht, S., Ickowitz, A., Lambin, E.F., Birkenholtz, T., Baptista, S., Grau, R., 2009. Agricultural intensification and changes in cultivated areas, 1970–2005. Proc. Natl. Acad. Sci. 106 (49), 20675–20680. https://doi.org/10.1073/pnas.0812540106.

Salmerón-Manzano, E., Manzano-Agugliaro, F., 2023. Worldwide research trends on land tenure. Land Use Policy 131, 106727. https://doi.org/10.1016/j.landusepol.2023.106727.

Shah, M.I., Abbas, S., Olohunlana, A.O., Sinha, A., 2023. The impacts of land use change on biodiversity and ecosystem services: An empirical investigation from highly fragile countries. Sustain. Dev. 31 (3), 1384–1400. https://doi.org/10.1002/sd.2454.

Sleeter, B.M., Marvin, D.C., Cameron, D.R., Selmants, P.C., Westerling, A.L., Kreitler, J., Daniel, C.J., Liu, J., Wilson, T.S., 2019. Effects of 21st-century climate, land use, and disturbances on ecosystem carbon balance in California. Glob. Chang. Biol. 25 (10), 3334–3353. https://doi.org/10.1111/gcb.14677.

Soille, P., Vogt, P., 2022. Morphological spatial pattern analysis: open-source release. Int. Arch. Photogr. Remote Sens. Spat. Inf. Sci. ISPRS Arch. *48* (4/W1-2022), 427–433. https://doi.org/10.5194/isprs-archives-XLVIII-4-W1-2022-427-2022.

Sun, M., Li, W., Zhu, L., Guo, Z., Zhao, Z., Meng, N., Han, M., Wang, N., Zhang, X., 2025. Degradation in edge forests caused by forest fragmentation. Carbon Res. 4 (1). https://doi.org/10.1007/s44246-025-00206-8.

Tajbakhsh, S.M., Memarian, H., Moradi, K., Afshar, A.H.A., 2018. Performance comparison of land change modeling techniques for land use projection of arid watersheds. Glob. J. Environ. Sci. Manag. 4 (3), 263–280.

Tepe, E., 2024. History, neighborhood, and proximity as factors of land-use change: a dynamic spatial regression model. Environment and Planning B: Urban Analytics and City Science 51 (1), 7–22. https://doi.org/10.1177/23998083231164397.

Turner, M.G., Gardner, R.H., 2015. Landscape Ecology in Theory and Practice: Pattern and Process, 117, p. 3035.

Turner, M.G., O'neill, R.V., Gardner, R.H., Milne, B.T., 1989. Effects of changing spatial scale on the analysis of landscape pattern. In: Landscape Ecology, vol. 3. SPB Academic Publishing bv.

Varga, O.G., Pontius, R.G., Singh, S.K., Szabó, S., 2019. Intensity analysis and the figure of merit's components for assessment of a cellular automata – Markov simulation model. Ecol. Indic. 101, 933–942. https://doi.org/10.1016/j.ecolind.2019.01.057.

Verburg, P.H., Overmars, K.P., 2009. Combining top-down and bottom-up dynamics in land use modeling: exploring the future of abandoned farmlands in Europe with the dyna-CLUE model. Landsc. Ecol. 24 (9), 1167–1181. https://doi.org/10.1007/s10980-009-9355-7.

Verburg, P.H., Schot, P.P., Dijst, M.J., Veldkamp, A., 2004. Land use change modelling: current practice and research priorities. GeoJournal 61, 309–324. https://doi.org/10.1007/s10708-004-4946-y.
Vogt, P., Riitters, K., 2017. GuidosToolbox: universal digital image object analysis. Euro. J. Remote Sens. 50 (1), 352–361. https://doi.org/10.1080/22797254.2017.1330650.
Wales, M., Chabari, F.N., 1979. District Ranch Development Briefs. Working Document (13). https://hdl.handle.net/10568/4462.
WorldPop (www.worldpop.org - School of Geography and Environmental Science, U. of S. D. of G. and G. U. of L. D. de G. U. de N, Center for International Earth Science Information Network (CIESIN), 2018. Global High Resolution Population Denominators Project - Funded by The Bill and Melinda Gates Foundation (OPP1134076).
Zhang, L., Schwärzel, K., 2017. Applying multifunctionality to address the challenges and benefits of land-use management. In: Zhang, L., Schwärzel, K. (Eds.), Multifunctional Land-Use Systems for Managing the Nexus of Environmental Resources. Springer International Publishing, pp. 1–9. https://doi.org/10.1007/978-3-319-54957-6_1.
Zhuang, D., Abbas, J., Al-Sulaiti, K., Fahlevi, M., Aljuaid, M., Saniuk, S., 2022. Land-use and food security in energy transition: role of food supply. Front. Sustain. Food Syst. 6, 1053031.