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Landscape Complexity as Determined by Socioeconomic Trends, Climate Change, and Broad Agricultural Policies

A Study on Multifunctional Landscapes

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ABSTRACT

Food systems face dire challenges, including climate change, biodiversity loss, and resource overuse. To ensure their long-term sustainability and resilience they need urgent transformation, while continuing to support livelihoods and address rising food insecurity. The design and management of multifunctional agricultural landscapes offer a pathway to address these challenges; and improved understanding of landscape complexity, including a diverse mix of natural and cropland covers, can help advance achievement of multiple food system goals. As land managers and decision makers plan for the future of our landscapes, they need to recognize that powerful forces outside their control will have a strong influence on the final outcome. This study explores the interplay between global drivers—such as population growth, economic trends, climate change—and landscape complexity, using a modeling system linking a global agricultural economic model to a land-use model. Global trends are described, and Kenya serves as a case study, representing broader local dynamics. Results indicate that the majority of agricultural landscapes, globally and in Kenya, are projected to experience increased complexity by 2050, primarily through cropland expansion at the expense of natural habitats. However, there are a few instances where an expansion in cropland may be liked to a decrease in landscape complexity. Patterns also vary under alternative scenarios of agricultural development. Where greater complexity is achieved through policies that further concentrate agricultural land in some areas, this is mainly associated with net gains in natural habitats and a contraction of cropland. Overall, this preliminary research underscores the need for integrated landscape management and more comprehensive scenarios to inform sustainable land-use planning aligned with global food security and environmental objectives.

Keywords: Landscape complexity, multifunctional landscapes, land use change modeling, LUCI model, IMPACT economic model

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ACRONYMS

EAP=East Asia and Pacific

EUR=Europe

FSU=Former Soviet Union

LAC= Latin America and Caribbean

MEN= Middle East and North Africa

NAM= North America

SAS= South Asia

SSA=Africa South of the Sahara

SDI: Shannon Diversity Index

1 INTRODUCTION

Food systems are facing multiple challenges, from climate change impacts to biodiversity loss, to overuse of natural resources (IPBES, 2019; IPCC, 2022). The magnitude, as well as the interconnectedness of these challenges demand urgent and simultaneous action. To address them effectively, food systems must transform and become more sustainable and resilient to shocks, while continuing to support farmers' livelihoods and strengthen their role in confronting the current and growing undernutrition and food insecurity emergencies (Myers, 2017; Béné *et al.*, 2019).

A key element of food systems transformation is to transition away from an extractive model of production that has been dominant since the Green Revolution of the 1960s, but is now deemed inadequate to deliver on several Sustainable Development Goals (SDGs) (Springmann *et al.*, 2018; Herrero *et al.*, 2021; Chaplin-Kramer, Chappell and Bennett, 2023; Fischer, Bennett and Pe'er, 2023). Historically, agricultural intensification and cropland expansion have led to the simplification of landscape structure across multiple spatial scales[1] (Landis 2017; Benton, Vickery, and Wilson 2003), leading to biodiversity loss and measurable decline in key ecosystem services, including pollination and pest control (MA, 2005; Landis, 2017; IPBES, 2019). These losses directly threaten the productivity and long-term sustainability of agriculture. Some experts have suggested that the study, design, and management of multifunctional agricultural landscapes is critical to address these challenges and make food systems more sustainable and able to respond to growing pressures (DeClerck *et al.*, 2015; Fischer, Meacham and Queiroz, 2017; Kremen and Merenlender, 2018; Manning *et al.*, 2018; Hölting *et al.*, 2019).

In agricultural landscapes, multifunctionality refers to agricultural production occurring alongside the simultaneous supply of various ecosystem services. A key feature of multifunctional landscapes is that tradeoffs between services are expected and acceptable because the goal is not to optimize any single

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[1] Landscape simplification stems from the abandonment of polycultures in favor of monocultures; as cropland expanded, non-crop habitats became more fragmented and uniform.

outcome. Instead, the objective in such landscapes is to improve overall human wellbeing by delivering a broad range of ecosystem services that benefit multiple stakeholders; these services include food production as well as biodiversity conservation, carbon storage, water quality, soil fertility, and cultural value (Bennett *et al.*, 2015; Bennett, 2017; Jones *et al.*, 2023).

A growing body of evidence shows that agricultural landscapes have the potential to meet multiple goals, and that multifunctionality can be associated with, and result from, increasing agricultural, biological and landscape complexity (Tilman, Reich and Isbell, 2012; Tilman, Isbell and Cowles, 2014; DeClerck *et al.*, 2015; Duarte *et al.*, 2018; Frei *et al.*, 2020). Landscape complexity is a result of both compositional complexity, the variety and extent of different landcover categories, and configurational complexity, which refers to their spatial arrangement across the landscape[2] (Nelson and Burchfield 2021). Complex landscapes have a matrix of multiple habitats and can host significantly more biodiversity than simpler ones, with positive effects on conservation goals and on the delivery of a variety of ecosystem services (Lefcheck *et al.*, 2015; Brauman *et al.*, 2019), including some directly beneficial to agriculture (e.g., pollination and pest control) (Dainese *et al.*, 2019; Estrada-Carmona *et al.*, 2022). Although increasing landscape complexity can produce tradeoffs vis a vis agricultural production due to loss of cropping area (Schulte *et al.*, 2017; Kleijn *et al.*, 2019; Jones *et al.*, 2023), compositional complexity has also been associated with promoting nature-based services (Ali *et al.*, 2023; Tortosa *et al.*, 2023), as well as improving yields and yield stability across large landscape scales, and to increasing resilience in the face of short-term weather shocks (Nelson and Burchfield, 2021; Nelson, Patalee and Yao, 2022). The complexity of a landscape is considered to generate redundancies[3], both functional and in response to disturbances, that are important for building system resilience in respect to delivery of multiple services (Biggs *et al.*, 2012; Schippers *et al.*, 2015).

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[2] See the Methods section for additional details

[3] For instance, through more ecosystem types per unit of area

As these findings have become clearer and more robust, the calls have grown for designing and actively managing agricultural landscapes to make them more diverse, thus increasing their complexity (Schulte *et al.*, 2017; Burchfield, Nelson and Spangler, 2019; Garibaldi *et al.*, 2019, 2021, 2023; Galpern *et al.*, 2020; Madin and Nelson, 2023). At the same time, there has been a growing understanding that simply focusing on increasing the diversity of crops grown at the farm level is inadequate for ensuring complex landscapes (Estrada-Carmona et al. 2022). Instead, a comprehensive approach across scales is needed to understand and leverage the feedback loops, dependencies, and connections between farms or fields, and the processes and dynamics that take place at the level of habitat, ecosystem and landscape (Estrada-Carmona *et al.*, 2022). Recognizing the significance of scale, some research emphasizes the necessity of designing and managing entire agricultural landscapes in order to deliver multiple services, meet the SDGs and align with the Convention on Biological Diversity (CBD) vision of living in harmony with nature by 2050 (Jeanneret *et al.*, 2021). Designing/planning and managing across-scale processes is increasingly considered as a critical tool for steering food systems toward sustainability, and a necessary condition to drive success of local-scale actions (Petit and Landis, 2023). Therefore, there is a pressing need to test the sustainability and resilience of proposed landscape designs over large areas and time scales (Landis, 2017).

As they embark in this endeavor, decision makers and land-use planners have to recognize, as well as contend with the powerful forces that shape landscapes, in particular demographic and economic trends, and climate change. Along with soil suitability, topography/elevation, and available technology[4] these are the main drivers of agricultural land use (Sloat *et al.*, 2020; Nainggolan *et al.*, 2023), and they are responsible for the changing distribution and migration of natural habitats (Chomitz and Gray, 1996; García Criado *et al.*, 2020; Ruiz-Pérez and Vico, 2020).

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[4] We are using the term “technology” to refer to the various practices and management options that farmers and other stakeholders may adopt to manage the land.

Scenario analysis and models have been widely used as decision support tools to explore and design interventions to manage agricultural landscapes (Heidenreich *et al.*, 2024). However, existing modeling work has been so far lacking in appropriately considering the effects that driving factors (e.g., abiotic, biotic, and management factors), as well as linkages to the food system (including the global food system) may have on agricultural landscapes (Heidenreich *et al.*, 2024).

To help fill this gap, and in support of better-informed decision making, we investigate how pressure from population growth, income growth, and climate change, may influence landscape compositional complexity (henceforth simply referred to as "complexity") to 2050 both globally and locally, using Kenya as an example. We do so by relying on a system of models which links IMPACT, a partial equilibrium economic model of the agricultural sector (Robinson *et al.*, 2015, 2024) , to a global land-use model which estimates shifts in both cropland and natural habitats in response to the changing climate (Robertson, De Pinto and Cenacchi, 2023). This modeling construct allows us to assess how socioeconomic, biophysical, and climate drivers may shape future landscapes. Importantly, it allows us to explicitly explore the linkages between landscapes' features and the dynamics of the global food system.

Within the constraints imposed by global drivers, broad agricultural development policies, including efforts to actively design and manage landscapes, may also significantly impact the complexity of landscapes through concentration or fragmentation of agricultural land (Landis, 2017). Therefore, we implement three alternative scenarios of agriculture development to capture possible future landscape patterns resulting from changes in agricultural policies and their interactions with climate and socioeconomic trends. We then use cluster analysis to parse and study in detail the shifts in land-cover that drive changes in landscape complexity.

We consider this study as proof of concept. It represents a continuing exploration into methods for analyzing the interactions between global socio-economic drivers, climate dynamics, and landscape transformation.

2 METHODS

2.1 Estimating agricultural landscape complexity

The complexity of an agricultural landscape increases, or decreases, depending on whether the diversity of crops grown and of natural habitats will increase or decrease (Nelson and Burchfield, 2021). The literature points to two main elements that can be quantified to estimate the complexity of an agricultural landscape: compositional complexity and configurational complexity (Nelson and Burchfield, 2021; von Jeetze *et al.*, 2023). The former is determined by the number of different land cover types and their area extent, whereas the latter hinges on the spatial arrangement of land cover types within the landscape, and the relation between the natural features and the agricultural land. Research also points to compositional complexity as the most relevant of the two in affecting the level (magnitude) and variety of ecosystem services being delivered (Nelson, Patalee and Yao, 2022; Tortosa *et al.*, 2023). For this reason, in this study we focus on changes in compositional complexity (referred to simply as "complexity"), and we use the Shannon Diversity Index to measure it. Definitions of landscape vary. In this study we apply the term to indicate a spatial mosaic of landcover types with an area of roughly 3000 square kilometers at the equator (each mosaic is a pixel – see more details in the sections below).

2.2 Projections of agricultural areas & natural habitats

Global changes in future land use cover are estimated using an IFPRI global Land Use/ Cover model (LUCI). LUCI consists of a cropland and a natural vegetation component (Robertson, De Pinto and Cenacchi, 2023). The units of observation are pixels of half-degree in size (each roughly 3000 square kilometers near the equator). Each pixel is a heterogeneous mosaic of land cover patches and as such it is assumed to represent a different "landscape" (Wu, 2013). The two modeling components determine the characteristics of these mosaics; specifically, what share of each pixel's area is covered by which crops and by which natural land types in the starting year (2005) and in the end year for the projections (2050). This allows us to calculate changes in landscape complexity across time, under future climate and policy regimes.

2.2.1 Natural vegetation model

The natural vegetation component of LUCI uses the statistical relationship between vegetation and climate conditions to estimate the proportion of each pixel expected to be covered by various natural vegetation types, in 2005 and in 2050.

Climate data used in the model to generate estimates are sourced from the Princeton Global Forcing (Sheffield, Goteti and Wood, 2006). The estimates are produced for two data points, 2005, obtained by calculating the averages over the 1995-2015 time period, and 2050, an average of the 2040-2050 interval. Climate data in 2050 are extracted from five Global Climate Models (GFDL, HadGEM2, IPSL, MIROC, and NorESM) under the representative concentration pathway 8.5 (RCP 8.5) (Riahi *et al.*, 2011), and the projected changes are applied to historical data (Muller and Robertson, 2014).

In our analysis we do not include the effects of CO_2 fertilization. Although important steps have been taken to clarify the effects of CO_2 especially on global primary production (Chen *et al.*, 2022), its role in relational biome shift is uncertain and likely to be confounded and resulting from the interaction with multiple other factors including locally generated climates and the emergence of tipping points (Steffen *et al.*, 2018; Gatti *et al.*, 2021) .

In order to estimate the fraction of different natural land types in 2050, the model starts from historical natural vegetation location data. These data come from three global databases of earth land cover: MODIS (covering 2001-2012; Channan et al. 2014; Friedl et al. 2010), GLC2000 (targeting 2000; Bartholome and Belward 2005), and Globcover (targeting 2005; produced by ESA and the ESA Globcover project led by MEDIAS France/POSTEL; Bicheron 2008). The natural vegetation categories from each dataset are combined into nine types as shown in Appendix Table A. 1: barren (mainly desert), tundra (both boreal and alpine), shrubland, grassland, savanna, woody savanna, evergreen needleleaf forest (mainly boreal), deciduous/mixed forest, and evergreen broadleaf forest (mainly tropical).

The vegetation model is a fractional multinomial logit where the dependent variable is the fractions of a pixel occupied by different land categories (see Robertson et al. 2023). The model must be able to “predict” the historical land cover conditions around the year 2005 to then be reliably used to estimate 2050 shares. The information for historical natural vegetation land types covers the 2000 - 2010 timeframe; this land cover is matched with 1995-2015 climate averages to estimate the parameters underlying the natural vegetation model. The same model is used on each of the three land cover datasets (MODIS, GLC2000, Globcover). The results for both 2005 and 2050 are averaged across the three datasets to ensure that conclusions are not based on the idiosyncrasies of a particular dataset.

2.2.2 Cropland model

The cropland model is complementary to the natural vegetation model and allocates the amount of cropland needed to satisfy human and animal consumption, at pixel level, across the globe. The need for cropland is assumed to be paramount; therefore, within each pixel, area is first allocated to natural land types (by the natural vegetation model), and it is then reduced to accommodate cropland based on results from the cropland model. As cropland is allocated, each vegetation type is reduced so to maintain their relative proportions. The amount of agricultural land in 2005, and its allocation across crop commodities at the regional level for both 2005 and 2050 are extracted from the International Model for Policy Analysis of Agricultural Commodities and Trade (IMPACT) (Robinson *et al.*, 2015, 2024).

IMPACT is an integrated system of models that links information from climate models, crop simulation models, and water models with a core global, partial equilibrium, multimarket model of the agriculture sector (see Appendix 2 for more details on IMPACT). Crop models use information from the Spatial Production Allocation Model (SPAM) to determine the geographical distribution of crops as well as their water management (rainfed or irrigated) and estimate how yields may be affected by climate change shocks. Yield changes are then used as input into the core economic model and produce changes in supply and demand for crop areas. In IMPACT, total land supply over time is determined by exogenous trends on the availability of area for agriculture, and by endogenous responses to changes in area demand.

Based on outputs from IMPACT, LUCI currently tracks the areas of five major crops: maize, rice, wheat, sorghum, soybeans, representing about 52% of harvested area (FAO, 2024) and places all remaining crops into a single sixth group (we call this a 5+1 structure). For all crops, rainfed and irrigated areas are considered separately. Estimated crop area from IMPACT is allocated by the cropland model across pixel based on attractiveness indices (one for each rainfed and irrigated crop, in each pixel) that rely on both climatic and economic suitability for crop production. Each index is the weighted sum of four subindices that capture, respectively: a) travel from possible crop location to nearest city; b) change in elevation across the pixel; c) similarity between the climate in the pixel and climates historically favorable to crop production; and 4) potential yield of the crop if cultivated in that pixel, under that climate. The full allocation process is explained in more detail in (Robertson *et al.*, 2024) and some details are also included in the description of the scenarios (see section below).

2.3 Scenarios of agricultural futures

Three scenarios are designed to represent an envelope of potential futures of agricultural development. These scenarios are stylized renditions of the effects that broad agricultural policies, in combination with other decisions (at different levels of governance), may have on the spatial distribution of crops over a landscape (i.e., a pixel in the present case). Specifically, the three scenarios present different levels of agriculture concentration (i.e., how much cropland can be allowed in a single pixel, rather than being distributed across multiple pixels). A middle-of-the-road scenario (MIDD) captures and perpetuates historical trends of agricultural concentration; a lower bound scenario (SPREAD) projects a case where agriculture is more evenly spread across landscapes compared to MIDD; and an upper bound scenario (MAXX) represents a case where agriculture is more concentrated compared to MIDD.

The three scenarios are implemented in the Cropland model by imposing different rules on how crops are allocated and spread inside and between each pixel. First, to generate the MIDD scenario, a rule is established to limit the concentration of cropland as a whole within a single pixel to avoid allocating to only a few "most attractive" pixels. To force the selection of a broader set of pixels, the first step is to define an upper bound to the amount of pixel area available for cropland. Only 90% of the area equipped for irrigation is made available for allocation to irrigated crops, whereas 67% of the physical area (net of the irrigated areas) is made available to rainfed crops. A second rule restricts how much of a single pixel can be dedicated to any single crop. Higher bounds allow greater concentration (MAXX) while lower bounds force cropland onto a broader footprint (SPREAD). The thresholds for the MIDD scenario were chosen after experimentation with a series of alternative values to strike a balance between concentration, dispersion, and historical cropland distributions as interpreted by SPAM (IFPRI IIASA 2016).

2.4 Changes in landscape compositional complexity

Changes in compositional complexity between 2005 and 2050 are calculated using the Shannon diversity index for each single pixel in 2005 and again in 2050. The Shannon index appears in two forms: a) calculated for the full list of land use types across both agricultural and natural habitats, and b) calculated separately across the agricultural land use types, and then across the natural habitats. This is done following the allocation of cropland, and redistribution of natural habitats due to both socioeconomic/market pressures and climate change shocks, as described in the previous sections. Larger Shannon values indicate higher diversity, as a measure of both richness (number of landscape elements considered) and evenness (the relative area share of different landscape elements).

The focus of the results is on agricultural pixels ("ag pixels"). These are pixels where estimated total agricultural land exceeds 100ha in 2005 as well as in 2050. The rest of the pixels are called "frontier", where total cropland during the same years is less than, or equal to 100ha (For comparison, recall that a single half-degree pixel has as many as 307,000 ha near the equator.) Results show mainly differences in Shannon index between 2005 and 2050 across the three scenarios of possible agricultural futures

(SPREAD, MIDD and MAXX). Results are displayed as an average across all GCMs and across all land cover databases (Globcover, GLC2000, MODIS) for simplicity of presentation as well as to avoid the idiosyncrasies of any single dataset.

2.5 K clustering analysis

Clustering analysis is a powerful data mining tool to identify patterns and relationships within complex datasets. Different algorithms and metrics allow us to group data points in "clusters" based on a distance matrix and so gain a better understanding of the makeup of the data.

Various clustering techniques have been used to identify patterns in large datasets. Hierarchical cluster analysis is a very common technique. It produces several nested classes which can be represented through a diagram similar to a phylogenetic tree. This clustering technique reveals a relationship between the elements or classes of the tree. There are also non-hierarchical techniques (i.e., K-means clustering) which partition data in classes or groups without relying on, or finding, a relationship between such groups. In our case, because the model determines the distribution of landcover types in each pixel independently from that of neighboring pixels, we used K-means clustering analysis to explore broad trends of changes in landcover, across time. To determine an appropriate number of clusters for each dataset, we run the Calinski-Harabasz criterion in Stata (StataCorp, 2023b, 2023a), which is well suited for K-means clustering solutions with squared Euclidean distances.

3 RESULTS

3.1 Global and regional results

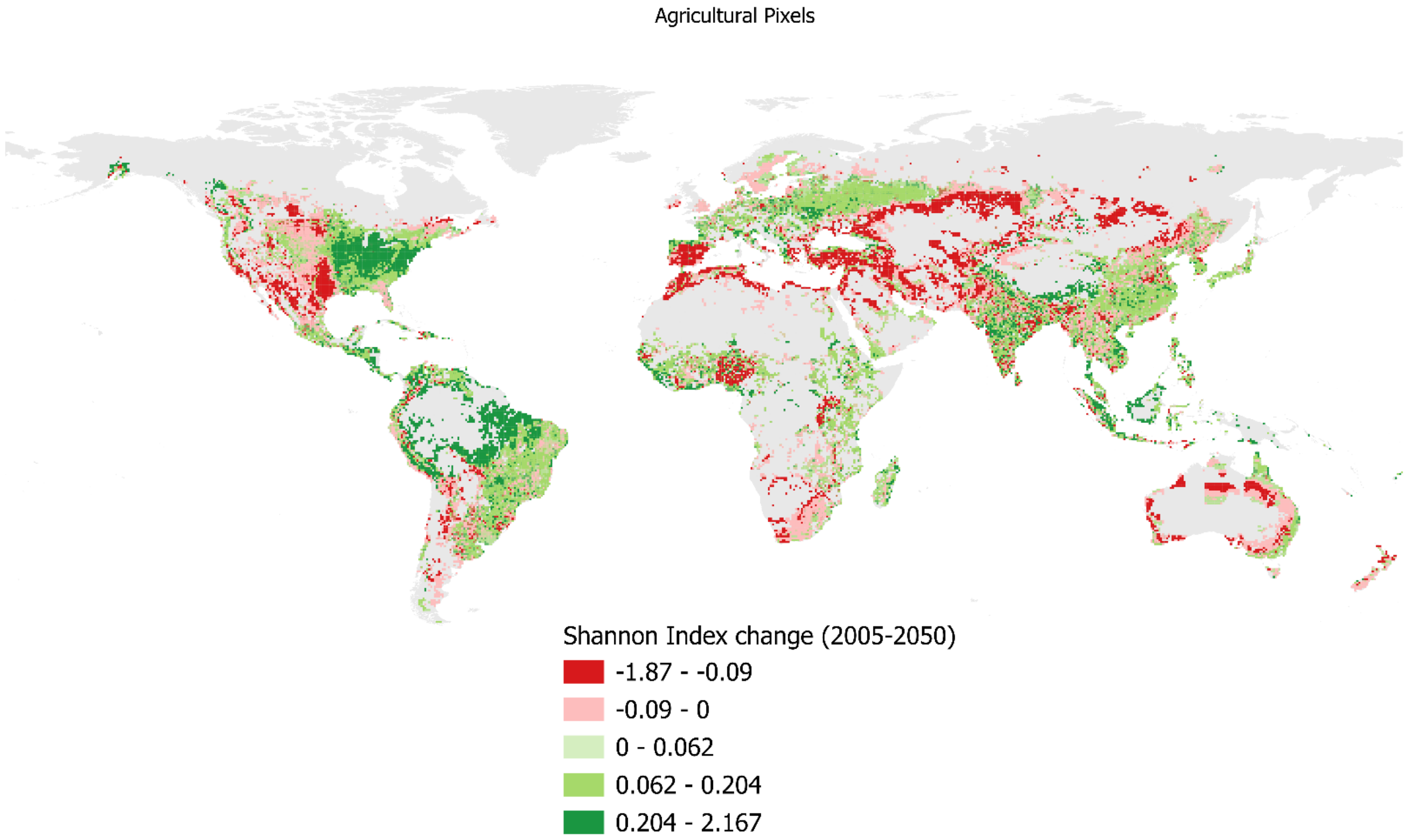
The picture of future landscape complexity across the globe appears similar under the MAXX and MIDD scenarios, with close to 60% of the agricultural pixels (agpixels) and 35% of the frontier pixels experiencing an increase in complexity between 2005 and 2050 (Figure 3.1, Figure 3.2 and Table 3.1). In a scenario where agriculture land is more evenly distributed (SPREAD), only 50% of the agpixels and 16% of the frontier pixels experience an increase in complexity. Note that for ease of interpretation, results are averaged across the five Global Climate Models as well as across the three global datasets of land use cover (see methodology section).

Table 3.1 Share of agricultural pixels (agpixels) and frontier pixels globally where landscape complexity based on the Shannon diversity index increases, decreases, or remains unchanged between 2005 and 2050. Three scenarios of agricultural future (MAXX, MIDD, SPREAD)

	Landscape complexity (Shannon index)	**MAXX**	**MIDD**	**SPREAD**
agpixels	No change	0.5%	0.0%	
	Decrease	42.9%	41.7%	49.9%
	Increase	56.6%	58.3%	50.1%
frontier	No change	0.2%	0.2%	2.3%
	Decrease	64.5%	64.5%	82.1%
	Increase	35.3%	35.3%	15.6%

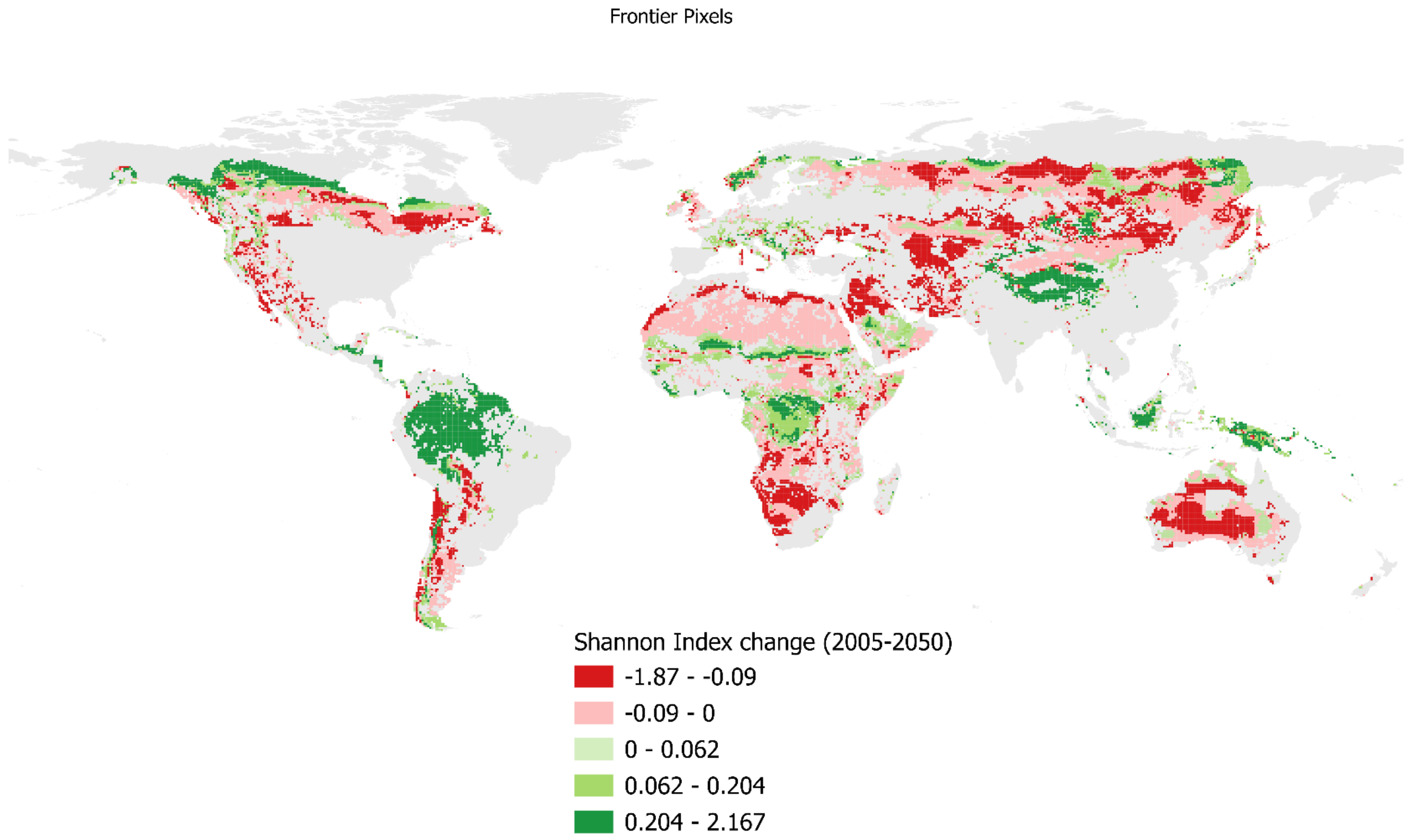
Source: Authors based on simulation results from the LUCI model

Figure 3.1 Change in landscape complexity across the globe between 2005 and 2050 -MIDD scenario (raw difference in Shannon index). Agricultural pixels


Agricultural Pixels

Source: Authors based on simulation results from the LUCI model

Figure 3.2 Change in landscape complexity across the globe between 2005 and 2050 -MIDD scenario (raw difference in Shannon index). Frontier pixels



Source: Authors based on simulation results from the LUCI model

Although this study primarily examines changes across agricultural pixels, it is worth noting that frontier pixels in several major biodiversity hotspots – such as the Amazon, Congo Basin, and the Indonesian archipelago - are projected to experience an increase in complexity (see Figure 3.2). Taking the Amazon as an example, our results indicate little to no change in agriculture encroachment into natural habitats between 2005 and 2050. Instead, there is a substantial reshuffling of natural land covers; the dominance of broadleaf forest is reduced while other natural habitats expand, especially grassland and savanna. This transition leads to higher levels of both diversity and evenness (the latter mainly driven by the decrease in broadleaf forest cover), consistent with an increase in complexity as measured by the Shannon Index.

The net increase in landscape complexity across agricultural pixels observed at global scale also holds true at the regional level for the MIDD scenario; the only exceptions are the former Soviet Union (FSU), where areas are evenly split, and the Middle East and North Africa region (MEN) where the majority of the agricultural pixels may experience a reduction in complexity (Table 3.2). Under the MAXX and SPREAD scenario the direction of change is maintained for most regions, but the majority of agricultural pixels in FSU experiences a reduction in complexity, as in MEN.

Table 3.2 Share of agricultural pixels, by region, where landscape complexity increases, decreases, or remains stable between 2005 and 2050. Three scenarios of agricultural future (Highlight for MIDD)

	Landscape complexity (Shannon index)	**EAP**	**EUR**	**FSU**	**LAC**	**MEN**	**NAM**	**SAS**	**SSA**
MAXX	No change	0.4%	0.8%	1.0%		0.5%	0.4%	0.1%	1.6%
	Decrease	42.7%	36.7%	49.9%	35.5%	65.5%	43.6%	33.9%	41.1%
	Increase	57.0%	62.5%	49.1%	64.5%	34.0%	55.9%	66.1%	57.3%
MIDD	No change	0.1%		0.0%					
	Decrease	41.0%	36.6%	50.0%	31.9%	68.0%	41.5%	44.8%	35.1%
	Increase	58.9%	63.4%	50.0%	68.1%	32.0%	58.5%	55.2%	64.9%
SPREAD	Decrease	49.8%	44.5%	68.8%	27.8%	79.3%	48.3%	45.0%	40.8%
	Increase	50.2%	55.5%	31.2%	72.2%	20.7%	51.7%	55.0%	59.2%

Source: Authors based on simulation results from the LUCI model
Note: EAP=East Asia and Pacific; EUR=Europe; FSU=Former Soviet Union; LAC= Latin America and Caribbean; MEN= Middle East and North Africa; NAM= North America; SAS= South Asia; SSA=Africa South of the Sahara

Focusing on the MIDD scenario, Figure 3.3 shows the main shifts in area underlying the positive changes in landscape complexity between 2005 and 2050, on a regional basis. Agricultural pixels in most regions experience a net increase in cropland and a mirror net decrease in natural land. The exceptions are Europe (EUR), and South Asia (SAS), where the agricultural pixels that grow more diverse show a net decrease in cropland and a net increase in natural habitats (Table A. 2).It is important to note how the MEN region also diverges from these general trends, as most agricultural landscapes decline in complexity, while cropland still increases at the cost of natural land cover. This appears to be largely caused by a reduction in area across seven different types of natural habitats, replaced by a single cover type, with substantial loss of both diversity and evenness. Although cropland cover increases, and it becomes more diverse, the change is not enough to counteract the loss of complexity in the natural land covers.

Based on the magnitude of area shifts for each land cover type, LAC, NAM and EAP show a substantial reorganization of land cover between 2005 and 2050. LAC is projected to lose over 100 million hectares (ha) of broadleaf forest and 10 million ha of mixed forest, while grasslands expand by 70 million ha, and savannah and brushland by over 10 million ha each. At the same time, rainfed cereals increase by 17.5 million ha and rainfed other-crops by almost 15 million. In EAP the same shifts take place for natural land, whereas cropland is dominated by an increase in other-crops both irrigated and rainfed. In comparison, SAS shows changes of smaller magnitude. The net decrease in cropland is driven by a 20 million ha drop in other-crops rainfed, which more than offsets the increase in irrigated cereals and irrigated other-crops, and a net expansion in natural land, especially grassland, woody habitats and savanna. In this reshuffling of land covers, MEN and SSA stand apart because of a more “unidirectional” trend, characterized by an increase in all crops, and a loss across all natural land types (with the only exception of grassland).

The single largest change for natural habitats happens in LAC, due to the large losses in broadleaf forest and gains in grassland described above, and the largest changes for cropland appear in SSA with gains of over 25 million ha for rainfed cereals.

Based instead on the magnitude of net change for both cropland and natural land, SSA appears to have the largest shifts. Projections show a net increase of almost 55 million ha of cropland, and a corresponding loss of the same amount of natural land. LAC is the second largest, with over 45 million ha gained by cropland and lost by natural habitats.

Globally, trends for net area change are similar under the MIDD and SPREAD scenarios. In both, an increase in landscape complexity is accompanied by a substantial expansion of agricultural land and a corresponding loss of natural habitats, particularly broadleaf forests and tundra-like forests. In contrast, under the MAXX scenario, which emphasizes agricultural concentration, the effect is reversed: increases in complexity are linked to a net decrease in cropland and a corresponding increase in natural habitats. Despite these contrasting outcomes, natural habitat losses under MAXX take place across the same four land types that drive losses across the MIDD and SPREAD scenarios - broadleaf forests, tundra-type forests, needle-leaf forests, and mixed forests - suggesting a strong underlying influence of climate change on these trends.

Still focusing on landscapes at increasing complexity, the global patterns noted across scenarios are mostly but not always reflected at the regional level. The EAP, FSU, MEN, and NAM regions closely mirror the global trends. In contrast, LAC and SSA exhibit agricultural expansion and natural habitat loss across all three scenarios. In SAS, MAXX and MIDD show a net decrease in agricultural land and gains in natural habitats, while SPREAD shows the opposite. In EUR, all three scenarios consistently indicate a loss of agricultural land (Table A. 3).

Figure 3.3 Changes in area for each land type, by region, between 2005 and 2050. MIDD scenario, only agricultural pixels with positive change in Shannon Index.

Source: Authors based on simulation results from the LUCI model

3.2 Country example – changes in landscape complexity across agricultural pixels in Kenya

Regional analysis shows that SSA is the region where shifts in future landscape complexity are associated with the largest net changes in either cropland or natural land. As an exercise to further explore regional dynamics, we selected Kenya as a test case. We observe that landscape complexity across the country is projected to increase for the majority of agricultural pixels, in all three future scenarios (Table 3.3). Future changes show a greater similarity between the MIDD and SPREAD scenarios. The agriculture concentration scenario (MAXX) appears to offer the lowest improvements in complexity.

Table 3.3 Share of Kenya agricultural pixels experiencing an increase (Positive) or a decrease (Negative) in complexity.

		MAXX	**MIDD**	**SPREAD**
agpixels	Decrease	39.4%	23.6%	26.0%
	Increase	60.6%	76.4%	74.0%

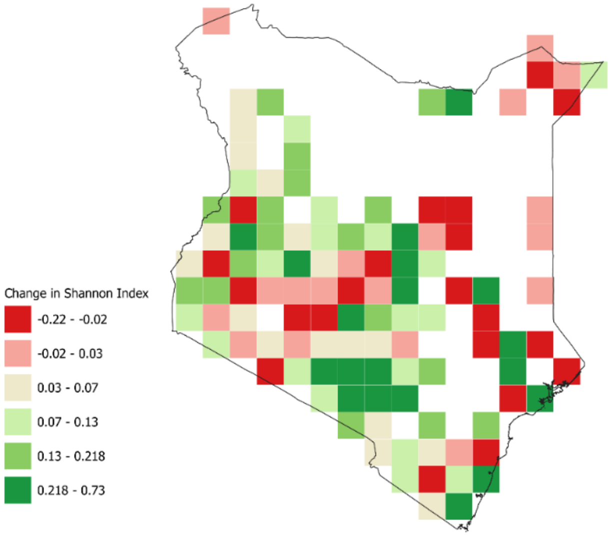
Source: Authors based on simulation results from the LUCI model

The sections below offer an in-depth look at the shifts in cropland or natural land types across agricultural pixels, between 2005 and 2050. To facilitate the analysis, we look at what happens within the group of pixels that experience a decrease in complexity, separately from what happens to the group of pixels where complexity increases.

3.2.1 Totals – changes in total agricultural and natural land across Kenya

Agricultural pixels where the change in the Shannon index is negative or positive between 2005 and 2050 are distributed fairly equally across the center south of the country (Figure 3.4).

Figure 3.4 Agpixles across Kenya. MIDD scenario. Negative change in Shannon index (red) and positive change in Shannon index (green) between 2005 and 2050.



Source: Authors based on simulation results from the LUCI model

Focusing on the agricultural pixels whose complexity decreases (negative change in Shannon index) between 2005 and 2050, cropland gains a net total of about 245,000 hectares (ha) in the MIDD scenario. Interestingly, 378,000ha of cropland are gained across 88% of the pixels (23 pixels), while losses are concentrated in only three pixels (133,400ha) (Table 3.4). The results for natural land are the mirror image of cropland, with a net loss of about 245,000ha. A net increase in cropland is also taking place under the two alternative scenarios, but especially under MAXX, with an area gain of over 3 million ha, and an equal loss of natural land.

Table 3.4 Cropland and Natural land across Kenya. Area (ha) gained or lost and relative number of pixels, for each scenario. Agpixels with negative change in the Shannon index.

		MAXX		**MIDD**		**SPREAD**	
		Area difference	Number of pixels	Area difference	Number of pixels	Area difference	Number of pixels
Total cropland	Gain	3,292,857	38	378,187	23	683,919	51
	Loss	-1	1	-133,400	3		
	Total	**3,292,856**	**39**	**244,787**	**26**	**683,919**	**51**
Total natural land	Equal0	0	1				
	Gain			133,401	3		
	Loss	-3,292,860	38	-378,187	23	-683,925	51
	Total	**-3,292,860**	**39**	**-244,786**	**26**	**-683,925**	**51**

Source: Authors based on simulation results from the LUCI model
Note: Equal0 indicates cases where area (either of cropland or natural) doesn't change between 2005 and 2050

Results are more mixed when examining those agpixels where complexity increases (positive change in Shannon) between 2005 and 2050 (Table 3.5). Both under the MIDD and SPREAD scenario total net cropland increases by over 2 million ha, at the expense of natural land. The trend is reversed in the MAXX scenario[5], with a net gain of nearly 680,000ha of natural habitats. In the MIDD scenario a net gain of 2.4 million ha of cropland is the result of a gain of more than 3.6 million ha over 86% of the pixels (72 pixels) and a 1.2 million ha loss across the rest (12 pixels).

Table 3.5 Cropland and Natural land across Kenya. Area (ha) gained or lost and relative number of pixels, for each scenario. Agpixels with positive change in Shannon index

		MAXX		MIDD		SPREAD	
		Area difference	Number of pixels	Area difference	Number of pixels	Area difference	Number of pixels
Total cropland	Gain	1,124,094	48	3,605,696	72	2,002,328	145
	Loss	-1,811,093	12	-1,232,077	12		
	Total	**-686,999**	**60**	**2,373,620**	**84**	**2,002,328**	**145**
Total natural land	Equal0	0	3				
	Gain	1,803,676	11	1,232,082	12		
	Loss	-1,124,096	46	-3,605,706	72	-2,002,321	145
	Total	**679,580**	**60**	**-2,373,623**	**84**	**-2,002,321**	**145**

Source: Authors based on simulation results from the LUCI model
Note: Equal0 indicates cases where area (either of cropland or natural) doesn’t change between 2005 and 2050

3.2.2 Shifts in crops and natural land types – focus on the MIDD scenario

What type of shifts in land types are behind the changes in landscape complexity? We use K cluster analysis to explore broad patterns of change across all the land types used for the calculation of the Shannon index. The focus is on the main shifts we observe for cropland and for natural habitats, their geographical distribution, and what underpins them.

Across the agpixels characterized by decreasing complexity between 2005 and 2050 (i.e., negative change in Shannon index), the K clustering analysis identifies 5 clusters. The largest number of agpixels are contained in cluster#2, followed by #1 (Figure 3.5).

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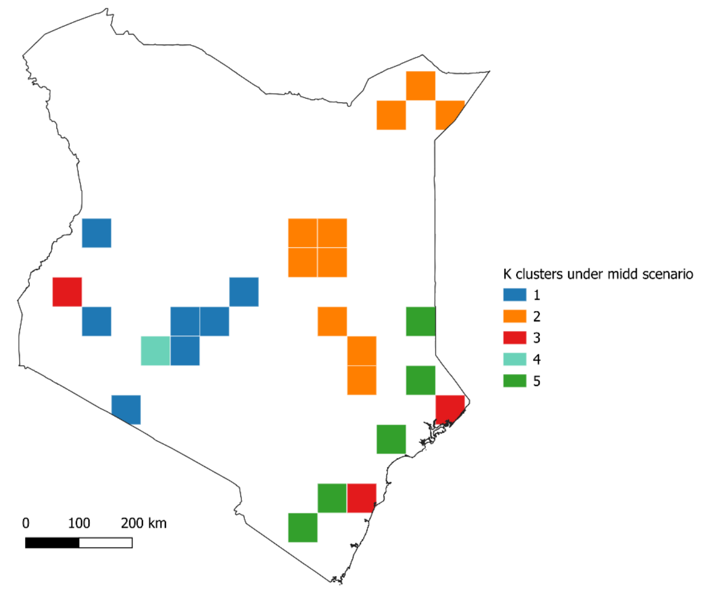
[5] This reversal under MAXX, for the positive pixels, is consistent with the regional results described in the previous section.

Figure 3.5 Geographical location of K clusters (left) and number of agpixels per cluster (right)– negative change in Shannon index. MIDD scenario



Kclusters	Number of agpixels
1	7
2	10
3	3
4	1
5	5

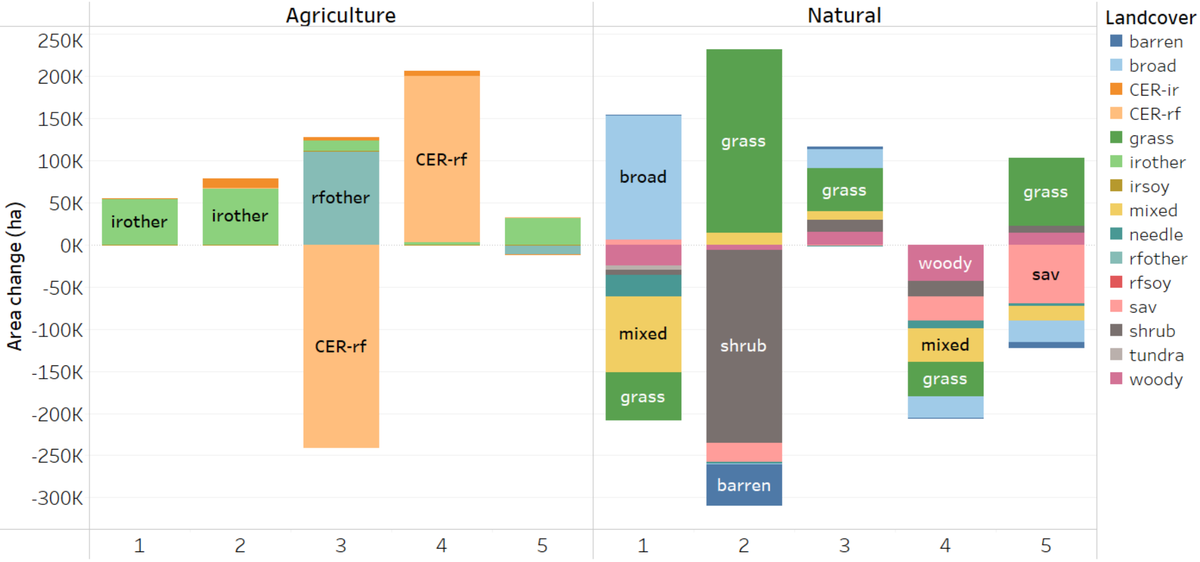
Source: Authors based on simulation results from the LUCI model

Looking at changes in cropland, cluster #1 and #2 are mainly characterized by a net increase in area for other-crops irrigated (Figure 3.6). Cluster #3 contains pixels that together amount to substantial losses in rainfed cereals (maize and sorghum, see Table A. 4), and a gain in other-crops rainfed, in addition to smaller gains in other-crops irrigated and irrigated cereals (maize). Cluster #4 contains a single pixel which is dominated by a gain in rainfed cereals (maize and sorghum -see Table A. 4), almost equivalent to the total loss across the pixels in cluster #3. Cluster #5 is characterized by a gain of other-crops irrigated, and a loss of other-crops rainfed.

Changes in natural land are dominated by losses across most land types, but especially shrubland in cluster #2 (loss of over 200,000ha), mixed forest in #1 and #4, and savanna in #5 and #4. Some gains in grassland are estimated, especially for cluster #2, followed by #3, and #5.

Overall, clusters #1, #2, #4, and #5 show a net gain of cropland with corresponding loss of land under natural habitats, whereas #3 show a net reduction in agricultural area and gain in natural area. The net total increase in cropland across all the clusters and pixels is driven by a large increase in other-crops both rainfed and irrigated (Table 3.6). Cropland expansion takes place at the expense of most natural habitats, but especially shrubland, mixed forest and savanna. The only natural habitats that grow between 2005 and 2050 are grassland and broad leaf forests, which expand respectively by over 250,000 ha and 100,000ha (Table 3.6)

Figure 3.6 Top: changes in area for each land type in each cluster, and Bottom: net area gains or loss in each cluster. Only agpixels with negative change in Shannon index. MIDD scenario



Net area gain or loss (ha)

Agriculture					Natural				
1	2	3	4	5	1	2	3	4	5
54,976	78,246	-114,316	205,586	20,295	-54,978	-78,248	114,319	-205,586	-20,293

Source: Authors based on simulation results from the LUCI model
Note: X axis shows k-clusters from 1 to 5. Y axis shows area change by landcover type. CER-ir: all irrigated cereals; CER-rf: all rainfed cereals; irsoy: irrigated oy; rfsoy: rainfed soy; irother: irrigated other crops; rfother: rainfed other crops; barren: mainly desert; broad: evergreen broadleaf forest; grass: grassland; mixed: deciduous/mixed forest; needle: evergreen needleleaf forest; sav: savanna; shrub: shrubland; tundra (boreal and alpine); woody: woody savanna.

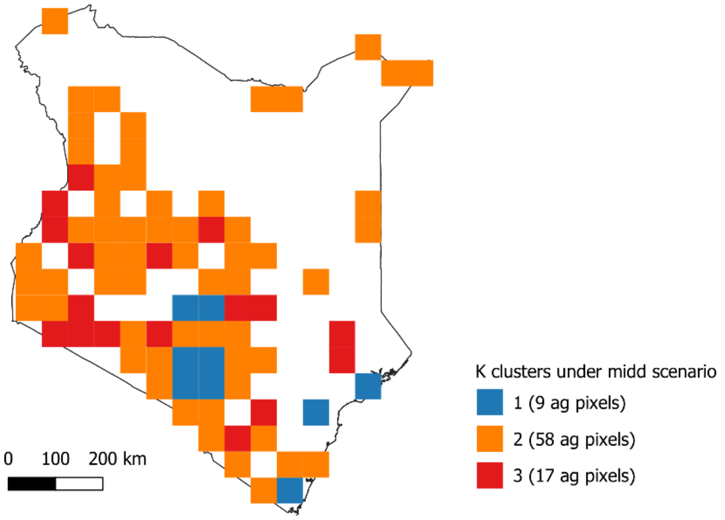
Table 3.6 Net change in both crops area and natural habitats across agpixels with negative complexity change between 2005 and 2050. MIDD scenario

Landcover (cereals)	Landcover	Agriculture (ha)	Natural (ha)
Cereals-irrigated	irmaize	9,746	
	irrice	9,479	
	irsorg	664	
	irwheat	0	
Cereals-rainfed	rfmaize	-84,722	
	rfrice	0	
	rfsorg	41,319	
	rfwheat	0	
Other-cropland	irother	168,247	
	irsoy	0	
	rfother	100,055	
	rfsoy	0	
Natural land types	barren		-53,831
	broad		116,181
	grass		252,637
	mixed		-122,114
	needle		-41,362
	sav		-115,047
	shrub		-229,871
	tundra		-5,551
	woody		-45,828

Source: Authors based on simulation results from the LUCI model
Notes: irmaize: irrigated maize; irrice: irrigated rice; irsorg: irrigated sorghum; irwheat: irrigated wheat; irsoy: irrigated soy; irother: irrigated other crops; rfmaize: rainfed maize; rfrice: rainfed rice; rfsorg: rainfed sorghum; rfwheat: rainfed wheat; rfsoy: rainfed soy; rfother: rainfed other crops; barren: mainly desert; broad: evergreen broadleaf forest; grass: grassland; mixed: deciduous/mixed forest; needle: evergreen needleleaf forest; sav: savanna; shrub: shrubland; tundra (boreal and alpine); woody: woody savanna

Across the agpixels characterized by increasing complexity between 2005 and 2050, the K clustering analysis identified three clusters (Figure 3.7). Cluster #2 stretches from the northwest to the south and contains almost 70% of all agpixels, characterized by relatively small changes in either cropland or natural area. Cluster #1 and #3 contain few pixels but show larger shifts in area.

Figure 3.7 Geographical location of K clusters (left) and number of agpixels per cluster (right)– positive change in Shannon index under the MIDD scenario



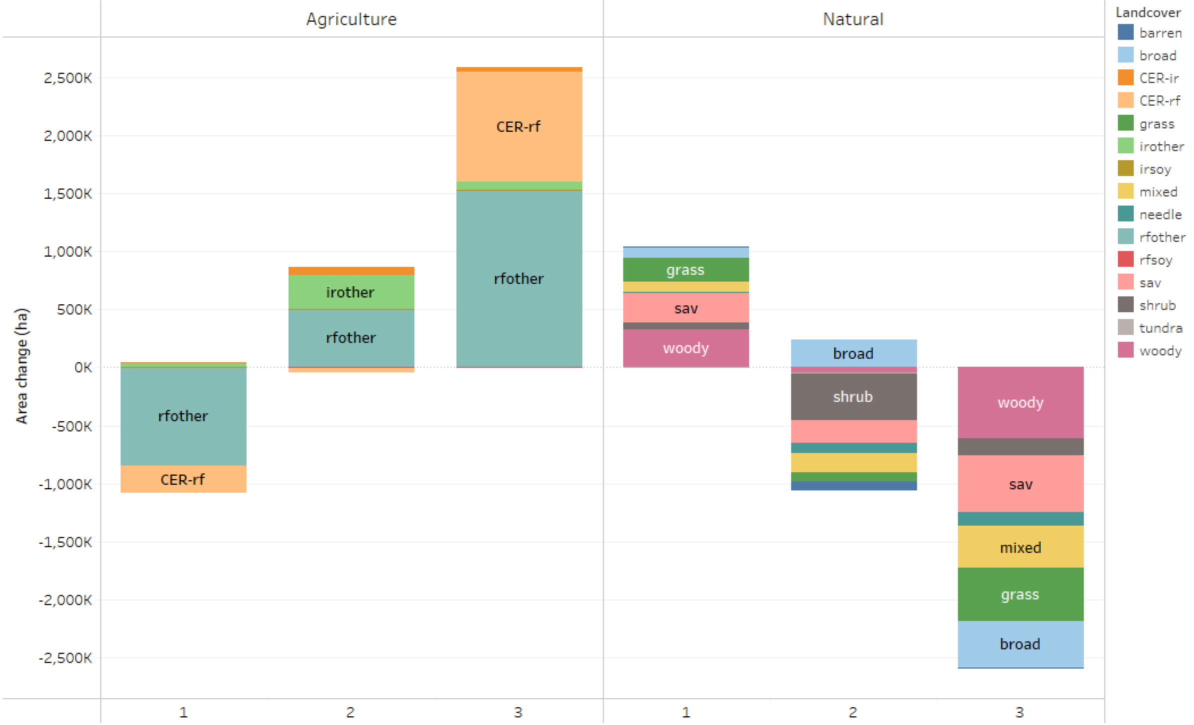
Kclusters	**Number of agpixels**
1	9
2	58
3	17

Source: Authors based on simulation results from the LUCI model

Other-crops rainfed show the largest net changes in area across clusters, with a net loss of over 800K ha in cluster #1, a net gain of 500K in cluster #2 and a large gain of over 1.5 million ha in cluster #3 (Figure 3.8). Cluster #1 also shows a net loss of rainfed cereals due to an almost 300K ha loss of maize along some smaller gains in sorghum and wheat area (see Table A. 5). To offset these losses, the net rainfed cereal area grows by almost a million ha in cluster #3, driven by over 600k ha increase in maize, and also increases in sorghum and wheat area (Table A. 5). Other-crops irrigated also increase across the clusters, but especially in cluster #2 (net of +293K ha), and smaller net increases are also estimated for irrigated cereals (maize and rice especially).

The land lost by cropland in Cluster #1 is occupied by a variety of natural habitats, especially woody forest, savanna and grassland (Figure 3.8 and Table A. 5). A similar, but mirror picture, can be observed for cluster #2 and #3, where increases in cropland are carved out of all natural land types, especially shrubland and savanna in cluster #2 and woody forest, savanna, and grassland in cluster #3.

Figure 3.8 Top: changes in area for each land type in each cluster, and Bottom: net area gains or loss in each cluster - Positive Shannon agpixels only. MIDD scenario



Net area gain or loss (ha)

Agriculture			Natural		
1	2	3	1	2	3
-1,037,700	818,177	2,593,143	1,037,703	-818,181	-2,593,145

Source: Authors based on simulation results from the LUCI model

Overall, clusters #2, and #3 show a net gain of cropland with corresponding loss of land under natural habitats, whereas #1 show a net reduction in agricultural area and gain in natural area. The net total increase in cropland across all agpixels is driven by a net increase in other-crops rainfed of over a million ha, and close to 800k ha increase in cereals area, mostly rainfed maize and sorghum . Cropland expansion takes place at the expense of most natural habitats, but especially shrubland, mixed forest and savanna (Table 3.7)

Table 3.7 Net change in area across agpixels with positive complexity change between 2005 and 2050. MIDD scenario

Landcover (cereals)	Landcover	Agriculture (ha)	Natural (ha)
Cereals-irrigated	irmaize	64,399	
	irrice	68,446	
	irsorg	617	
	irwheat		
Cereals-rainfed	rfmaize	398,368	
	rfrice		
	rfsorg	173,453	
	rfwheat	89,519	
Other-cropland	irother	391,262	
	irsoy	0	
	rfother	1,190,047	
	rfsoy	-2,492	
Natural land types	barren		-77,191
	broad		-58,953
	grass		-338,085
	mixed		-448,038
	needle		-191,115
	sav		-434,785
	shrub		-486,644
	tundra		-9,640
	woody		-329,173

Source: Authors based on simulation results from the LUCI model

3.2.3 Additional Shannon analysis – complexity across agriculture, and across natural lands

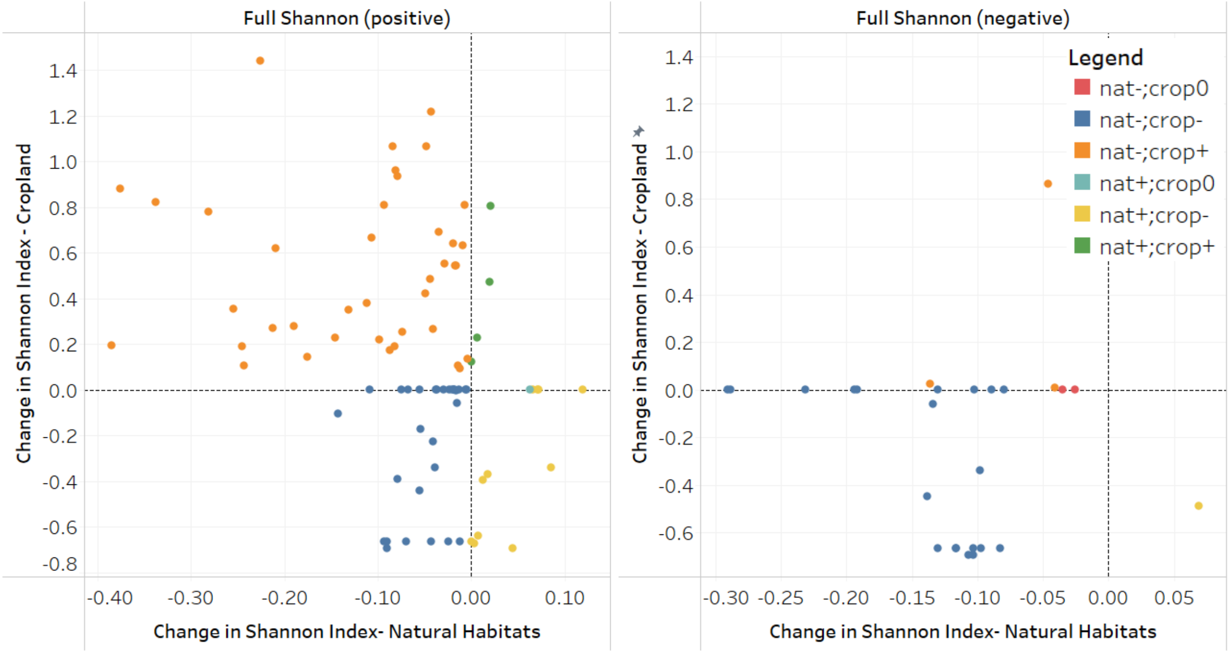
Complexity across the whole agricultural landscape affects the delivery of a range of ecosystem services. This is why the sections above focused on the calculation of the Shannon index across both agricultural and natural land covers.

An effort to increase complexity on agricultural land (or cropland) may help support the delivery of ecosystem services even if the habitat around farms has limited complexity; however, such an effort may be of little consequence if the habitats, ecosystems, and landscapes around the farming land are truly impoverished. Conversely, flourishing and complex natural habitats can help support productivity and ecosystem services even on homogeneous farmland. Therefore, when the intent is to evaluate the potential effects of landscape complexity on the agriculture sector, it is useful to look at how complexity changes, across cropland, and across natural habitats separately. We divide the analysis into two parts. We first take the group of agricultural pixels across Kenya where the complete Shannon index (i.e., Shannon measured using both cropland and natural land types) decreases between 2005 and 2050 (full Shannon negative). Within this group we also calculate the Shannon index only using the agricultural land types, and only using the natural land types, and observe how complexity for cropland and natural land changes across time. The analysis is then repeated within the group of pixels where the complete Shannon index increases between 2005 and 2050 (full Shannon positive).

Across the full Shannon negative group, most pixels (77%) have a combination of decreasing complexity both across the natural land and across cropland (right panel of Figure 3.9). When the same analysis is performed across the full Shannon positive group, only 5% of the pixels show both an increase in complexity across cropland, and across natural land types. Most pixels (46%) show an increase in complexity across cropland and decreasing complexity across natural land types. Interestingly, 35% of the agpixels show decreasing complexity in both cropland and natural land types. Overall, an increase in complexity over natural habitats is projected only across 19% of the pixels.

These results reflect the “nature” of the Shannon Index as a measure of both richness and evenness. Large differences in the area extent of our land cover-types create low-evenness conditions that can lower the Index. The effect of evenness on the Index can be larger with relatively small numbers of categories (e.g., land types in our case). As the number of land types increases (i.e., when we calculate Shannon considering all cropland types and all natural land types together), the effect of evenness may be more “diluted”.

Figure 3.9 Changes in three different Shannon indices between 2005 and 2050 (agpixels in Kenya). MIDD scenario



Source: Authors based on simulation results from the LUCI model

Note: the left panel focuses on the group of pixels where the complete Shannon index is growing between 2005 and 2050. The right panel focuses on the group of pixels where the complete Shannon index is decreasing. Y axis is the difference in Shannon across cropland, the X axis shows the difference in Shannon across only natural land types. In the legend nat: natural land; crop:cropland. + sign indicates increase in complexity, - signs indicates decrease in complexity. 0 indicates that Shannon does not change between 2005 and 2050.

4 DISCUSSION

Decision-makers engaged in development planning and land use planning, regardless of the geographical scale at which they operate, have a vested interest in understanding how the complexity of landscapes might evolve in the future. The global food system and its global market dynamics, along with demographic and climatic trends may affect the complexity of landscapes in ways that should be factored in when planning for biodiversity conservation, climate change adaptation and mitigation, resources management and sustainable land use. These changes should also be of concern for broader development efforts, urban and regional planning, the safeguard of cultural and social values, and economic considerations such as tourism and recreation, as well as cost savings related to disaster management and restoration efforts.

Our target audience includes a range of institutions responsible for land use planning and management. These organizations vary depending on a country's administrative structure, operating at local, regional, state, or federal level. They would benefit from greater insight into the complex factors that influence land use, and from integrating this knowledge into their decision-making processes. Key actors typically include local and state planning commissions, zoning boards, regional or state planning and environmental agencies, as well as relevant ministries, such as those responsible for transportation and infrastructure, agriculture, land, public works, housing, and urban development, among others.

In an effort to inform long-term decision making on landscape management, this study aims to contribute to existing research by simulating how future changes in the global food market, coupled with climate change, could drive shifts in the complexity of agricultural landscapes. The land use model used in this study (LUCI) allocates area shares across cropland types based on attractiveness indices (which include the suitability of climate, and better yields, along with other factors), thus incorporating some degree of active adaptation in our scenarios. Therefore, the three scenarios of agricultural development can represent a variety of landscape management practices informed by policies, with some active adaptation taking place within the constraints of those management choices. As agriculture adapts to climate change, cropland moves out of some areas and into new ones. Here we notice that in at least two scenarios of agricultural development the migration of cropland into some areas, and corresponding decrease in the extent of natural habitats, causes landscape complexity to increase. In other words, the increase in complexity is associated with an expansion of cropland. As noted by Roberston et al. (2024) the majority of cropland appears to undergo some level of reshuffling by 2050, and the magnitude of the change is such that some level of planned adaptation will be required to facilitate the transition.

Our results show that the combination of projected socio-economic trends and average changes in climate will drive most global agricultural landscapes toward a net increase in complexity. The trend is broadly consistent across all regions of the world, except for the MEN region, where most agricultural landscapes appear to be declining in complexity. Under a future that traces historical patterns of cropland allocation and crop distribution (MIDD scenario), the increase in complexity, as measured by the Shannon index, is associated with a net increase in cropland and a corresponding loss of natural habitats across most of the globe. Notable exceptions are Europe and SAS where the increase in complexity is linked to a decrease in cropland and an increase in natural land.

Similarly to the global picture, most agricultural landscapes in Kenya are projected to become more complex and show an increase in cropland to the detriment of natural land. Similar outcomes are projected under a scenario of agricultural development where cropland is more evenly distributed across suitable areas (SPREAD scenario), although with distinct regional patterns of gain and loss of complexity. The picture is different in a future where policies manage to concentrate cropland on a smaller footprint of suitable area (MAXX scenario); both at global scale, and for Kenya, net cropland contracts across landscapes where complexity is increasing, and net area under natural habitats is expanding.

In general, combinations of changes in diversity and evenness across all cover types may lead to opposite results vis a vis the complexity of an agricultural landscape. In some cases, an expansion in cropland may be associated with an increase in complexity, while in some other cases (e.g., the MEN region) complexity may decrease even though cropland is expanding, because of associated changes in the number and extent of natural habitats. While greater complexity is an important goal in support of multifunctionality, the changes that happen within the agricultural component and the natural habitat component of a landscape may be desirable, or lead to unwanted trade-offs, depending on one's goal.

As an example, the finding that increased complexity across agricultural pixels may be associated with loss of natural habitats is concerning given that one of the reasons for pursuing more complex landscapes is the preservation of biodiversity. This is compounded by the observation that for a large share of agricultural landscapes in Kenya the increase in complexity is associated with a decrease in diversity across natural lands. Taken together, these patterns raise important questions, as increased natural cover is associated with higher provisioning of ecosystem services, some of which are essential to agricultural production (Grab *et al.*, 2018; Dainese *et al.*, 2019), and some field-scale studies suggest that a larger footprint of natural cover may also contribute to higher yields (Grab *et al.*, 2018; Martin *et al.*, 2019). We have evidence that at global scale, climate change is the main driver of loss for tundra and evergreen broadleaf forest[6]; cropland encroachment has a smaller effect on natural habitat loss, and therefore mitigation of climate change is the most critical instrument to protect many natural vegetation types (Robertson et al. 2023). However, in absence of rapid and broad mitigation actions, specific policies in support of conservation targets may be necessary to preserve natural habitats and their contribution to landscape complexity. Therefore, the design and inclusion of more comprehensive scenarios representing conservation policies would enrich the current analysis and allow to explore potential synergies and trade-offs between agricultural development and environmental protection objectives. Such scenarios are

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[6] This is mainly tropical forest, and the effects are quite different on a regional basis.

critical because, as highlighted by Robertson et al (2023), the interactions between climate and agriculture lead to complex changes in land use, that can either facilitate or hinder conservation efforts.

Moreover, while the strength of this study lies in its modeling construct, which explores the combined effects of socioeconomic and biophysical shocks, we recognize the need to isolate the individual effects of climate change and socioeconomic factors. Decision makers seeking to act on the insight presented here would benefit greatly from understanding whether climate or socioeconomic trends are the primary drivers of the results, and how their influence may vary by region and location. Such knowledge is crucial for shaping targeted policies and land management strategies. Isolating these effects will require additional scenarios, which will be a key component of any follow-up study.

Finally, a limitation of the study is that we do not assume any productivity feedback loops between models. As cropland shifts (and with it landscape complexity), yields are likely to shift due to changes in climatic and other biophysical conditions (i.e., soil type and solar exposure, among others). However, at the moment these changes are not fed back into the core economic model to estimate changes in supply and demand. Higher yields would also represent improved adaptation to climate change and likely trigger a lower need for cultivated land in 2050, which, when reflected back to the land use model, might reduce some losses of natural habitats. This option will be included in the next step of this study. Part of the future analysis will also need to overcome the current limit of LUCI for crops allocation, namely the fact that only the five major crops are treated, and the rest is aggregated in a single other- crops ensemble.

This paper takes note of the accumulating evidence on the importance of managing agricultural landscapes for food system transformation. It does so by trying to empower decision makers to identify trends that will be relevant for a number of choices necessary to make landscapes truly multifunctional.

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6 APPENDIX

6.1 Appendix 1. Tables and Figures

Table A. 1 Harmonized natural vegetation types and their elements

Harmonized category	GLC2000	Globcover	MODIS
tundra	latitude north of 58N or elevation above 4000m: herbaceous cover, closed to open (13) sparse herbaceous or sparse shrub cover (14) OR latitude north of 48N or elevation above 4000m: shrubcover, closed to open evergreen (broadleaved or needleleaved) (11) shrubcover, closed to open, deciduous (broadleaved or needleleaved) (12) OR latitude north of 35N: treecover burnt (mainly boreal forests) (10) mosaic of tree cover & other natural vegetation (crops possible) (9)	latitude north of 58N or elevation above 4000m: mosaic forest or shrubland/grassland (110) closed to open (broadleaved or needleleaved, evergreen or deciduous) shrubland (130) sparse vegetation (150) mosaic grassland/forest or shrubland (120) closed to open herbaceous vegetation (grassland, savannas or liches/mosses) (140) bare areas (200) OR latitude north of 48N or elevation above 4000m: closed to open grassland or woody vegetation on regularly flooded or waterlogged soil - fresh, brackish or saline water (180)	latitude north of 48N: closed shrublands (6) open shrublands (7) woody savannas (8) savannas (9) permanent wetlands (11) OR latitude north of 58N or south of 58S: grasslands (10) OR elevation above 4000m: open shrublands (7) grasslands (10) barren/sparse (16)
evergreen needleleaf forest	tree cover, needleleaved evergreen, closed to open (4)	closed needleleaved evergreen forest (70 open needleleaved deciduous or evergreen forest (90) closed to open mixed broadleaved and needleleaved forest (100)	evergreen needleleaf (1)
evergreen broadleaf forest	tree cover, broadleaved evergreen, closed to open (1) tree cover, closed to open, regularly flooded; swamp (7)	Closed to open broadleaved evergreen or semi-deciduous forest (40) closed to open broadleaved forest regularly flooded (semi-permanently or temporarily) - fresh or brackish water (160)	evergreen broadleaf (2)
deciduous/mixed forest	tree cover, broadleaved deciduous, closed (2) tree cover, needleleaved deciduous, closed to open (5) tree cover, mixed leaftype, closed to open (6) shrubcover, closed to open, evergreen (broadleaved or needleleaved) (11)	closed broadleaved deciduous forest (50)	deciduous needleleaf (3) deciduous broadleaf (4) mixed forest (5)
shrubland	no clear analogue	NOT already tundra: mosaic forest or shrubland/grassland (110)	NOT already tundra: closed shrublands (6) open shrublands (7)
woody savanna	NOT already tundra: tree cover, broadleaved deciduous open (3)	NOT already tundra: open broadleaved deciduous forest/woodland (60)	NOT already tundra: woody savanna (8)

Harmonized category	GLC2000	Globcover	MODIS
	mosaic of tree cover & other natural vegetation (crops possible) (9)	closed to open (broadleaved or needleleaved, evergreen or deciduous) shrubland" (130) closed broadleaved forest or shrubland permanently flooded - saline or brackish water (170) closed to open grassland or woody vegetation on regularly flooded or waterlogged soil - fresh, brackish or saline water (180)	
savanna	NOT already tundra: shrubcover, closed to open, evergreen (broadleaved or needleleaved) (12)	no clear analogues	NOT already tundra: savanna (9)
grassland	NOT already tundra: herbaceous cover, closed to open (13) sparse herbaceous or sparse shrub cover (14)	NOT already tundra: mosaic grassland/forest or shrubland (120) closed to open herbaceous vegetation (grassland, savannas or lichens/mosses) (140) sparse vegetation (150)	NOT already tundra: grasslands (10)
barren	bare areas (19)	NOT already tundra: bare areas (200)	NOT already tundra: barren/sparse (16)
excluded (*cropland*)	*cropland (16)* *mosaic of cropland/treecover/other natural vegetation (17)* *mosaic of cropland/shrub or herbaceous cover (18)* tree cover, closed to open, flooded; mangrove forest (8) regularly flooded (15) water bodies (20) unnamed but clearly water (23) urban areas (22) snow or ice (21)	*post-flooding or irrigated croplands (or aquatic) (11)* *rainfed croplands (14)* *mosaic cropland/vegetation (grassland/shrubland/forest) (20)* *mosaic vegetation (grassland/shrubland/forest)/cropland (30)* water bodies (210) no data but usually water (230) artificial surfaces and associated areas (urban areas) (190) permanent snow and ice (220)	water (0) permanent wetlands (11) [south of 48N] *croplands (12)* *cropland/natural mosaic (14)* urban/built-up (13) snow and ice (15)

Note: Numbers in parentheses indicate the code in the original datasets. Italicized entries indicate categories associated with cropland

Table A. 2 Changes in area (hectares) across agricultural pixels experiencing an increase in landscape complexity. Regional results between 2005 and 2050. MIDD scenario

	Landcover	**EAP**	**EUR**	**FSU**	**LAC**	**MEN**	**NAM**	**SAS**	**SSA**
Cropland	rfother	13,158,019	-7,587,382	1,658,914	14,672,938	3,636,854	1,192,988	-21,311,277	21,380,245
	irother	8,255,272	692,094	441,518	2,931,149	1,312,344	2,497,494	8,720,847	4,085,482
	rfsoy	3,353,601	280,385	338,973	7,439,308	14,220	4,183,922	1,135,385	-96,260
	CER-ir	1,912,311	351,154	680,367	1,685,694	894,459	1,187,734	9,448,956	3,522,341
	irsoy	778,417	86,378	28,978	902,290	29,439	1,837,148	1,415,154	22,755
	CER-rf	200,480	692,338	8,347,823	17,504,386	2,234,735	5,233,468	-1,784,981	25,866,276
	NET TOTAL	***27,658,101***	***-5,485,033***	***11,496,573***	***45,135,765***	***8,122,050***	***16,132,755***	***-2,375,916***	***54,780,840***
Natural habitats	grass	18,998,703	7,234,854	16,959,533	69,104,754	34,272	38,088,419	4,112,944	2,979,197
	woody	7,429,413	7,527,248	5,227,241	-4,018,117	-1,129,908	7,641,053	2,616,763	-19,370,053
	sav	6,938,163	3,643,882	3,064,601	14,533,505	-549,432	2,429,084	2,908,381	-3,096,294
	shrub	5,009,168	4,089,241	3,312,364	10,031,081	-1,483,163	8,173,278	876,020	-3,502,805
	barren	2,593,718	-44,858	-101,083	1,784,105	368,382	-321,856	1,229,395	-3,584,289
	needle	-7,578,902	-7,923,284	-27,516,839	-3,081,616	-2,080,166	-23,567,117	-1,958,802	-3,337,896
	mixed	-15,620,869	-5,211,988	-2,022,572	-10,218,905	-2,884,426	-35,395,622	-1,746,109	-9,207,059
	tundra	-17,506,676	-4,323,828	-10,768,466	-10,305,283	-279,067	-12,889,567	-4,965,884	-152,800
	broad	-27,813,127	453,161	352,806	-112,967,861	-145,040	-264,350	-596,122	-15,510,686
	NET TOTAL	***-27,550,409***	***5,444,428***	***-11,492,414***	***-45,138,338***	***-8,148,548***	***-16,106,679***	***2,476,585***	***-54,782,685***

Table A. 3 Net changes in cropland or area under natural habitats (Natural) between 2005 and 2050 across agricultural pixels. Results for all regions under the three scenarios of agricultural development (hectares)

		EAP	EUR	FSU	LAC	MEN	NAM	SAS	SSA
MAXX	Agriculture	-9,033,860	-13,074,794	-14,667,057	6,285,653	-3,392,527	-6,089,137	-1,649,947	10,142,566
	Natural	8,918,021	12,833,083	14,531,777	-6,473,476	3,232,110	6,164,280	1,600,570	-10,243,631
MIDD	Agriculture	27,658,101	-5,485,033	11,496,573	45,135,765	8,122,050	16,132,755	-2,375,916	54,780,840
	Natural	-27,550,409	5,444,428	-11,492,414	-45,138,338	-8,148,548	-16,106,679	2,476,585	-54,782,685
SPREAD	Agriculture	27,759,274	-1,288,692	3,907,543	42,825,640	2,687,483	10,329,891	4,171,693	53,230,008
	Natural	-27,747,091	1,287,152	-3,903,414	-42,825,532	-2,687,513	-10,329,857	-4,171,630	-53,229,792

Table A. 4 Changes in area for land types across clusters. Kenya, MIDD scenario, negative Shannon change between 2005 and 2050 (hectares)

Landcover (group)	**Landcover (cereals)**	**Landcover**	**1**	**2**	**3**	**4**	**5**
Agriculture	Cereals-irrigated	irmaize		653	3,798	5,295	
		irrice		10,297	-389		-429
		irsorg		664			
		irwheat					
	Cereals-rainfed	rfmaize			-178,578	93,856	
		rfrice					
		rfsorg			-62,797	104,116	
		rfwheat			0	0	
	Other-cropland	irother	54,976	66,633	12,200	2,320	32,118
		irsoy					0
		rfother			111,449		-11,394
		rfsoy					
Natural		barren	21	-49,758	3,074	-19	-7,149
		broad	147,608	-1,210	21,601	-25,973	-25,845
		grass	-57,147	217,744	51,733	-39,916	80,223
		mixed	-89,252	14,275	9,952	-40,040	-17,050
		needle	-25,955	-1,806	-201	-9,833	-3,567
		sav	5,830	-22,526	-1,096	-27,845	-69,409
		shrub	-5,708	-228,162	14,398	-18,872	8,473
		tundra	-5,194	-34	-121	-135	-67
		woody	-25,181	-6,771	14,979	-42,956	14,100

Note: rf indicates rainfed and ir indicates irrigated.

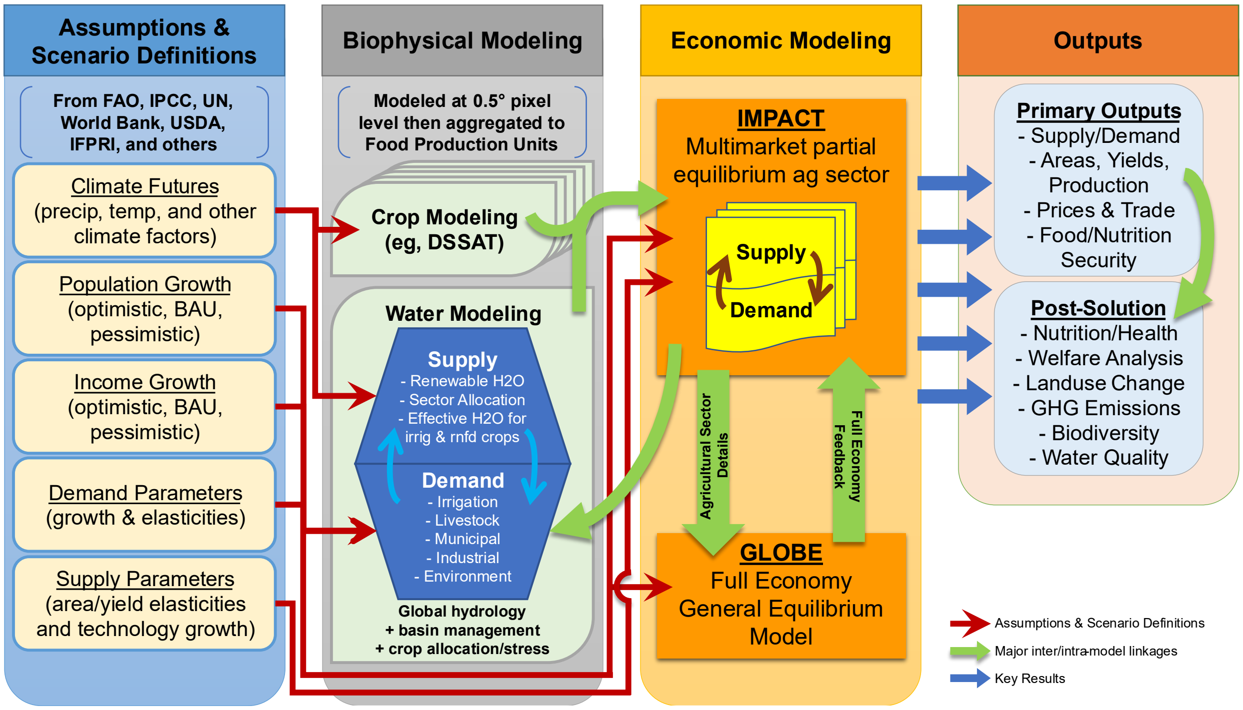
Table A. 5 changes in area for land types across clusters. Kenya, MIDD scenario, positive Shannon change between 2005 and 2050 (hectares)

Landcover (group)	**Landcover (cereals)**	**Landcover**	**1**	**2**	**3**
Agriculture	Cereals-irrigated	irmaize	375	37,839	26,185
		irrice	16,558	35,768	16,120
		irsorg		456	161
		irwheat			
	Cereals-rainfed	rfmaize	-270,719	22,543	646,544
		rfrice	0	0	0
		rfsorg	6,862	50,307	116,285
		rfwheat	22,022	-119,267	186,763
	Other-cropland	irother	29,944	292,977	68,341
		irsoy			
		rfother	-842,742	500,045	1,532,744
		rfsoy	0	-2,492	
Natural		barren	1,678	-71,646	-7,223
		broad	96,832	239,216	-395,001
		grass	205,235	-80,356	-462,964
		mixed	85,004	-165,619	-367,423
		needle	6,968	-89,238	-108,845
		sav	255,466	-195,594	-494,657
		shrub	63,670	-404,175	-146,139
		tundra	-248	-6,805	-2,588
		woody	323,097	-43,965	-608,305

6.2 Appendix 2. Brief description of the IMPACT model

The amount of cropland is determined by the IMPACT model (Robinson *et al.*, 2015, 2024). IMPACT is a partial-equilibrium economic model that simulates national and global markets of agricultural production, demand, and trade associated with 62 agricultural commodities across 159 countries. The core IMPACT economic model integrates data on population and income growth with data from crop and climate models (i.e., yield changes driven by shifts in temperature and precipitation) and estimates of water availability from water models (see schematic figure below). Its outputs thus reflect the interaction of both biophysical and socio-economic factors.

IMPACT modeling framework



Climate-mediated changes in yields come from direct effects through temperature and precipitation, simulated through the integration of crop and climate models, and indirectly through water availability captured through linked water models (Muller and Robertson, 2014). Agricultural production is specified by models of land supply, and by allocation of land (irrigated and rainfed) to crops. Production is modelled at sub-national level, across 320 regions called “food production units” or FPUs.

The main drivers of the baseline suite of IMPACT scenarios are gross domestic product (GDP), population, and intrinsic agricultural productivity growth. GDP growth is obtained from the OECD (Dellink *et al.*, 2017) and population growth from IIASA (2013). The choices of GDP and population growth are made to allow the IMPACT model to reproduce the Shared Socioeconomic Pathways (SSP scenarios) adopted by the Intergovernmental Panel on Climate Change Sixth Assessment Report (IPCC AR6). The intrinsic yield growth rates are based on past trends and expert opinion. Details of all the input data to the IMPACT model, the equations at the core of the model, and relevant citations can be found in the IMPACT documentation (Robinson et al 2015).

IMPACT has a long record of applications and it has been employed in a wide range of analyses, from assessing the potential effects of climate change on global food production and nutrition (Nelson *et al.*, 2010; Springmann *et al.*, 2016), to explore linkages between agriculture production and food security at the national and regional levels (Sulser *et al.*, 2011; Hachigonta *et al.*, 2013; Waithaka *et al.*, 2013), to interdisciplinary assessment of economic models (Nelson *et al.*, 2014; Wiebe *et al.*, 2015) to evaluating the global effects of biofuels production, to the assessment of economic effects of alternative climate smart policies and technologies (De Pinto *et al.*, 2016, 2020) and the global simulation of technology adoption (Rosegrant *et al.*, 2014) to the future of dietary diversity (Mason-D'Croz *et al.*, 2019) or the global consequences of animal disease outbreaks (Mason-D'Croz *et al.*, 2020).

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