

Article

Impacts of Climate Change on Vegetation in Kenya: Future Projections and Implications for Protected Areas

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Abstract: Climate change will cause substantial vegetation shifts across the world. Africa may face varying dynamics such as tree decline, savannization, and woody encroachment due to rising temperatures and rainfall changes. This study examines the potential effects of climate change on Kenyan vegetation and vegetation shifts for 2050 and 2100, employing a statistical model to predict vegetation state as driven by environmental variables, including temperature, soil moisture, livestock density, and topography. We evaluate the model by hindcasting it from 2020 to 2000 and then project future vegetation states for 2050 and 2100 under SSP 2–4.5 and SSP 5–8.5. In response to moderate emissions, a notable increase in arid-associated shrubland vegetation (53–58%) is forecasted, leading to the expansion of drylands at the expense of savannas, grasslands, and forests. Under high-emission scenarios, savannas are forecasted to expand (52–65%) at the expense of forested areas. Overall, dense forest cover declines across scenarios, affecting protected areas by promoting increased savanna cover and reducing forest area (40% to 50%). These projected shifts in major vegetation types would likely alter ecosystem functioning and associated services, impacting pastoralists and wildlife and raising biodiversity concerns. Protected areas in Kenya could lose 50% of their forests, highlighting the urgency of climate change mitigation. These findings offer a crucial foundation for future research and action on Kenya’s vegetation.

Keywords: Africa; climate change; vegetation shift; ecosystem degradation; protected area; SSP; ERA5



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1. Introduction

Climate change is already promoting important changes in the spatial extent and distribution of vegetation types worldwide [1,2]. Africa is one of the most vulnerable continents to climate change. According to various climate models, it is predicted that the temperature in Africa will increase within a range of 3 °C to 4 °C by the end of the 21st Century, which is approximately 1.5 times greater than the global mean response [3–5]. The Intergovernmental Panel on Climate Change (IPCC) has reported that the continent is already experiencing more frequent and intense heat waves, droughts, and floods, with substantial impacts on natural ecosystems, including vegetation [5–7].

These large changes in climate may result in vegetation shifts across Africa [4,8]. Indeed, climate is a main driving force that shapes the distribution of biomes across the globe, with temperature and precipitation patterns playing a crucial role in determining their distribution [9]. However, vegetation shifts in Africa do not show a consistent pattern. For instance, tree density declines and species composition changes have led to a southward shift of the savanna vegetation zone in the African Sahel and West Africa into previously more humid areas [10]. At the same time, increased woody cover in savannas has been

reported in many sites across Africa [11,12], including West Africa [13], East Africa [14], and southern Africa [15]. Savannas are characterized by a continuous grassy cover and varying degrees of woody plant cover. However, savannas may often climatically support forests or dense woodlands without a grassy understory [16]. Fire regimes and megafauna browsing and grazing naturally generate and maintain an open or semi-open savanna state, which additionally may be promoted by human activities such as livestock grazing and tree cutting [17–21]. However, many savanna systems across Africa experience woody encroachment [12], suggesting that vegetation shifts from an open savanna state toward a tree-dominated woodland are ongoing due climatic and atmospheric changes, mainly the increase in atmospheric CO₂ concentrations [15,18,22,23], and the reduction in fires in human-used landscapes [24]. Climate-driven vegetation changes in Africa have already been observed also within protected areas [25]. In addition, increasing human population, urbanization, socio-economic development, deforestation, and agricultural expansion near protected area boundaries often cause changes within reserves [26,27]. Anthropogenic pressures are expected to increase and exacerbate these dynamics for most protected areas and regions in Africa in the future [25].

In East Africa, where the expansion of croplands and the rising demand for wood fuel are placing greater strain on woody vegetation in the lowlands, it is suggested that climate change is implicated in the expansion of woody cover in the highlands [28]. Yet, it remains uncertain whether these contrasting patterns have resulted in a net loss or gain in fractional woody cover [29]. In this context, nationally focused studies may not only provide a more detailed understanding of vegetation trends, but are also key to gaining deeper insights into greenhouse gas emissions and carbon stock [30]. Investigating vegetation state and biome dynamics is instrumental in understanding both carbon and biodiversity dynamics. The predominant features of East Africa encompass arid and semi-arid lands, yet the region also embraces the presence of Afromontane forests. One of the main economic activity is subsistence rain-fed agriculture and pastoralism [31]. Consequently, climate change is likely to have profound impacts on both wildlife and people that depend on these ecosystems for their livelihoods [31,32]. As highlighted by the IPCC [4], vegetation shift emerge from complex processes and are likely to have major ecological and socio-economic impacts. Therefore, it is essential for scientists and policymakers to monitor this phenomenon and develop strategies to mitigate its negative effects, such as the loss of biodiversity and the displacement of human communities. To ensure the sustainable livelihoods of those whose primary source of income relies on land, it is crucial to address the interconnected challenges posed by climate change and environmental degradation [33]. In Kenya specifically, it is estimated that by 2100 the impact of climate change will result in a rise of 3–4 °C in mean annual temperature, accompanied by an increase in rainfall variability [3,4,34,35]. Sizeable alterations in the timing and length of rainfall in Kenya are already evident, particularly in the form of more frequent and severe droughts [7]. This can drastically impact vegetation cover and distribution considering its sensitivity to precipitation, especially for the 83% of the country which comprises arid and semi-arid lands [32]. Notably, a recent and comprehensive analysis of a 34-year time series has revealed a robust correlation between interannual rainfall patterns and African vegetation dynamics [36]. Remarkably, this study reveals that this positive correlation persists in about 80% of the entire study area, which includes diverse semi-arid regions, such as East Africa [36]. The research highlights that in semi-arid regions across Africa, characterized by limited annual precipitation, the primary limiting factor for plant growth and development is water availability [36]. This observation emphasizes the critical role of precipitation in shaping vegetation productivity within these areas, aligning with prior research [37]. Sensitivity to precipitation pertains to both crop-based agriculture, natural vegetation, and livestock production, itself dependent on vegetation productivity [38]. Climatic variability are of great concern, particularly for inland vegetation [39]. The impact of these oscillations was already evident in 2011 when a severe drought caused unpredictable and insufficient rainfall for two consecutive growing seasons, resulting in adverse effects on natural vegetation as well as agricultural

production [39]. The severe consequences included poor pastoral performance, resulting in a major loss of livestock and widespread food shortages, leading to a critical state of food insecurity [39]. Kenya stands out as a prominent economy in East Africa, where agriculture remains a cornerstone of the country's economic foundation, contributing 26% to the GDP (Gross Domestic Product) and serving as a source of livelihood for nearly 80% of the population [40]. Concurrently, pastoralism also plays a major role, contributing 13% to the GDP, with a valuation of approximately US \$1.13 billion [41]. In this context, the profound impact of climate change on these socio-economic aspects, in addition to its known effects on biodiversity and habitat conservation [25], provides a compelling foundation for an in-depth case study.

Within this framework, the use of remote sensing is important for both local and global vegetation monitoring [29,42]. Satellites offer numerous advantages over traditional survey approaches, including high spatial resolution, frequent temporal coverage, and the ability to capture multiple spectral information [29,43,44]. Although it is acknowledged that satellite remote sensing has limitations compared to on-field surveys, it is essential to highlight its strengths. Satellite remote sensing offers an efficient, cost-effective, and timely approach for conducting accurate vegetation analysis [28,29]. These capabilities make it a valuable tool for gaining insights into changing landscapes, especially when large-scale, repetitive, or remote monitoring is required [28,29]. Vegetation indices derived from specific spectral reflectance bands constitute a powerful tool for vegetation monitoring [45]. In this context, the primary purpose of the Moderate Resolution Imaging Spectroradiometer (MODIS) is to offer uniform, spatiotemporal evaluations of worldwide vegetation conditions, and it provides the Normalized Difference Vegetation Index (NDVI) and the Enhanced Vegetation Index (EVI) at global scale (250-m, 500-m, and 1-km resolutions) with 16-day compositing periods [46]. Moreover, EVI demonstrated a robust and consistent correlation with vegetation productivity across a diverse array of vegetation types [47,48].

In this context, in this study we aimed to provide an overview of the potential effects of climate change on vegetation in Kenya in the near (2050) and far future (2100) under two Shared Socioeconomic Pathway (SSP) and Representative Concentration Pathway (RCP) scenarios (SSP2-RCP4.5 and SSP5-RCP8.5). Our study was based on the analysis and projection of a standard remote sensing vegetation index at the national scale to assess the impact of climate change on an environment already under strong anthropogenic pressure, with widespread land degradation [49]. The main goals were (a) to project future vegetation states and vegetation shifts under different climate-change scenarios (SSP2-RCP4.5 and SSP5-RCP8.5), and (b) to quantify the magnitude of projected vegetation shifts in protected and semi-protected areas to evaluate potential impacts on biodiversity conservation.

2. Materials and Methods

2.1. Study Area

The study region is Kenya, East Africa (Figure 1). Kenya covers approximately 582,650 km². The geography of Kenya is highly diverse, and the complex geomorphological features shaping the local climate dominate different parts of the country [7,50]. Rainfall occurs in two seasons: 'long rains' from March to May, and 'short rains' from October to December [7,29,50]. Climate ranges from arid and semi-arid in the lowlands to humid in the highlands [29,50]. Therefore, in Kenya, the landscapes vary greatly, encompassing a diverse range of ecosystems. These include the dry and sparsely vegetated regions in the north, the lowlands and humid rainforests along the eastern coast, the fertile lands in the central part and around Lake Victoria [39]. Inlands are broad plains and numerous hills, and in the central is home of the biodiverse mountain forests of Mount Kenya (5199 m above sea level) [39,50]. Shrublands are located in the arid and semi-arid region in the northern and eastern part of Kenya [50]. Specifically, this region is dominated by the *Acacia-Commiphora* bushlands and thickets ecosystem (ACBT) and is characterized by 3–5 m tall deciduous and drought-resistant bushlands and thickets [29,51–53]. Only the coastal lowlands experience the constant high temperatures and humidity associated with equatorial latitudes [50]. The

moist coastal forest ecosystem occurs in this region and is dominated by semi-deciduous, broad-leaved trees [53]. The western and south-central region is characterized by highlands and woody vegetation, woody savanna ecosystem in the Victoria Basin forest–savanna ecoregions [29], and moist montane forest characterized by evergreen broad-leaved trees and multi-layered canopies [29,50].

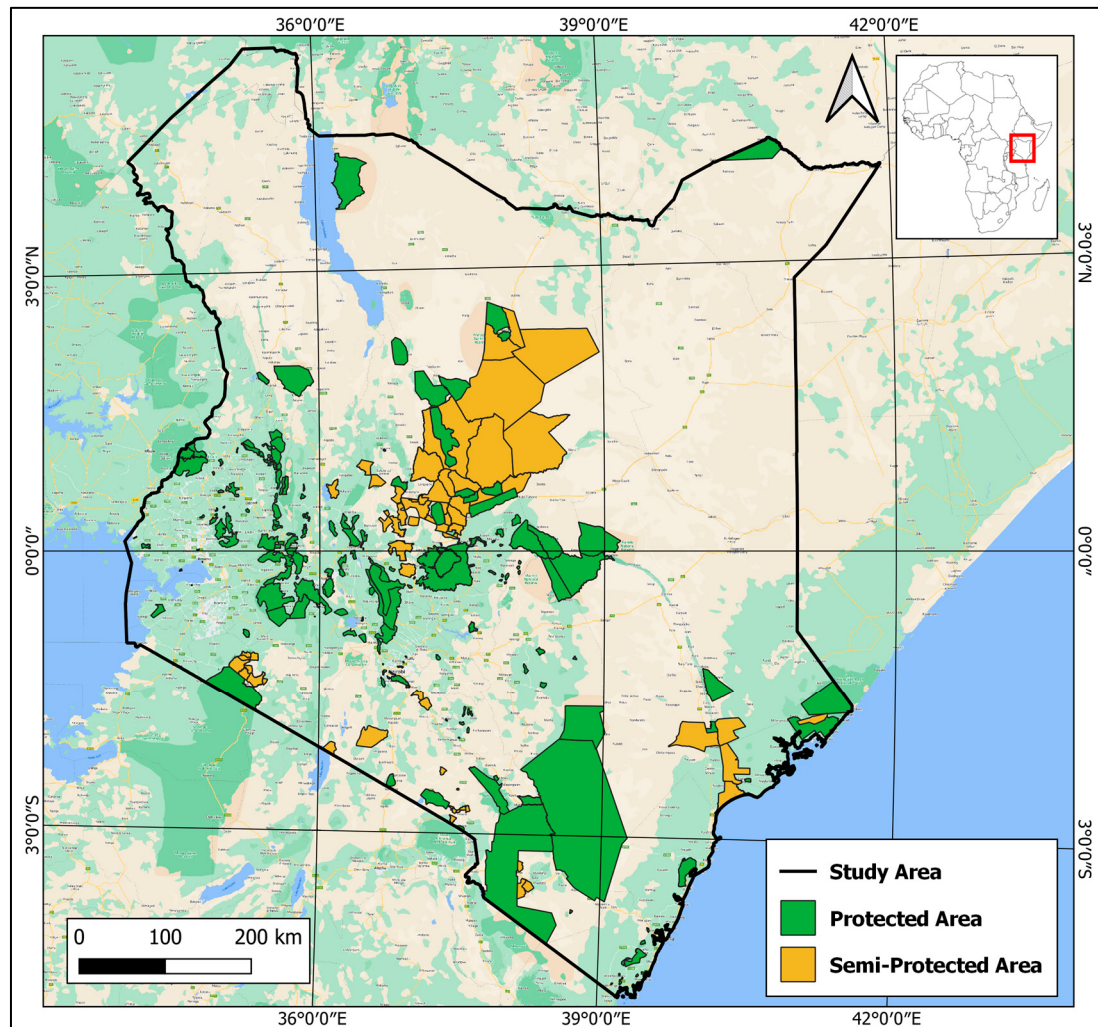


Figure 1. Study area and administrative boundaries of Kenya with protected and semi-protected areas.

2.2. Data Sets and Pre-Processing

We used the Enhanced Vegetation Index (EVI) [54] to analyze the vegetation response to climate change in Kenya in 2050 and 2100. We used EVI, instead of other vegetation indices, because of the dryness of our study region. EVI has been proposed as a more robust proxy for biomass than the NDVI in areas with high soil exposure and in dense vegetation, because of its improved resilience to saturation and resistance to soil and atmospheric contamination [46,55]. EVI was obtained from MODIS Vegetation Indices products (MOD13A2v061, 1×1 km resolution [56]) by NASA's Land Processes Distributed Active Archive Center (LP DAAC). We decided to use MODIS data since it offers a 1-km resolution, which is more manageable compared to higher-resolution products for many purposes. Working with Landsat or Sentinel data, with spatial resolutions of 30 and 10 m, respectively, comes with greater computational challenges. Furthermore, historical and future climate data are not usually accessible at such a finely detailed spatial resolution. Reflecting such considerations, MODIS data are extensively used in vegetation studies across Africa and other regions [57,58]. The MODIS EVI has a temporal resolution of

16 days, so we first calculated the yearly mean and then the multi-year mean of the reference period (2000–2005 and 2015–2020). There is a slight difference between the two datasets because the first available data for 2000 is from February 18th. Nevertheless, the collection of 5 years' worth of data for each timeframe minimizes the significance of this disparity. Using GEE, EVI data were pre-processed and downloaded for further analysis in R.

We selected four primary drivers (Table 1), which are known to have impacts on vegetation condition and distribution as predictor variables. They are listed as follows: topographic variation [59], livestock distribution [60], air temperature [61–64], and soil moisture [65,66].

Table 1. Variables used in the multiple linear regression of the mean EVI with their data source, original spatial resolution, and reference period. The Livestock Density and TRI variables were derived through processing of the original variables.

Variable	Type	Code	Dataset/Source	Original Resolution	Time
Enhanced Vegetation Index	Historical	EVI	MOD13A2v061	1 × 1 km	2000–2005 and 2015–2020
Terrain Ruggedness Index	Historical	TRI	DEM - GMTED10	1 × 1 km	2010
2 m air temperature	Historical	T	ERA5-Land dataset from Copernicus Climate Data Store (CDS -ECMWF)	9 × 9 km	2000–2005 and 2015–2020
Volumetric soil water layer 1	Historical	SM	ERA5-Land dataset from Copernicus Climate Data Store (CDS -ECMWF)	9 × 9 km	2000–2005 and 2015–2020
Livestock Density	Historical	Livestock Density	Gridded Livestock of the World (GLW)–FAO	10 × 10 km	2010
2 m air temperature	Projection	T	CMIP6 dataset from Copernicus Climate Data Store (CDS -ECMWF)	9 × 9 km	2045–2050 and 2095–2100
Volumetric soil water layer 1	Projection	SM	CMIP6 dataset from Copernicus Climate Data Store (CDS -ECMWF)	9 × 9 km	2045–2050 and 2095–2100

Terrain Ruggedness Index (TRI) was used as a morphometric index. It gives a measure of topographic heterogeneity and variation [67], and was calculated with QGIS function by using the 1 × 1 km Digital Elevation Model from GMTED10 [68]. TRI is the mean of the absolute differences in elevation between a focal cell and its 8 surrounding cells and quantifies the total elevation change across the 3 × 3 cells [69].

The livestock density across Kenya was obtained from the Gridded Livestock of the World (GLW) of the Food and Agriculture Organization of the United Nations [70]. We used the third version of the 2010 GLW, and it includes global density distributions of cattle, buffaloes, sheep, goats, horses, pigs, chickens and ducks at a spatial resolution of 5 min of arc, approximately 10 km at the equator [70]. We used the spatial distribution of the major grazing and browsing livestock species in the region, such as cattle (*Bos indicus* and *B. taurus*), horse (*Equus ferus caballus*), domestic goat (*Capra aegagrus hircus*), and domestic sheep (*Ovis aries*). Other species were excluded because they either are not primarily grazers and browsers (e.g., chicken (*Gallus gallus domesticus*)) or are not present in the study area (e.g., water buffalo (*Bubalus bubalis*)). The layer for the density per pixel of each of the included species were summed to obtain a single 'livestock' variable, and then resampled to a 1 × 1 km cell size using the nearest neighbors resampling function.

We then used historic climate variables provided by ERA5-Land. The ERA5 product family (ERA5 and ERA5-Land) are the latest and most advanced global reanalysis products created by the European Center for Medium-range Weather Forecasting (ECMWF) [71–73]. ERA5 has been demonstrated to improve data accuracy compared to previously published climate data products [74]. In this study, we used air Temperature ('2 m air temperature',

henceforth called “T”) because of its well-known effect on vegetation [61–65], and moisture in upper portion of soil column (‘Volumetric soil water layer 1’, henceforth called “SM”) representing water availability for vegetation, as a more direct proxy of local water regimes compared to other drought indices especially in drylands [65,66]. The T and SM yearly mean and then the multi-year mean over the two reference period (2000–2005 and 2015–2020) were obtained and preprocessed using the KrigR R-package [71]. The ERA5-Land climate reanalysis data are available at a 9×9 km spatial resolution of global coverage and was statistically downscaled to 1×1 km cell size using the kriging functions available in KrigR package [71]. Kriging is a statistical downscaling process that requires covariates both at the resolution of training data and at the spatial resolution of target [71]. We used elevation as a covariate for temperature, and saturated water content, saturated capillary potential, pore size distribution, saturated hydraulic conductivity, heat capacity of solid soils, thermal conductivity of saturated soil, and thermal conductivity for dry soil for SM [75]. All covariates used in the statistical downscaling process were obtained through the specific function of the KrigR package. The KrigR package acquires the elevation data from the USGS GMTED 2010 open-access database [68], and all the soil property data from the Land-Atmosphere Interaction Research Group [76].

We used temperature and soil moisture future projections from CMIP6 models to analyze the vegetation changes and their possible relations with meteorological variables under multiple climate change scenarios. Projections from two SSP-based climate change scenarios of CMIP6 were used, SSP 2–4.5, and SSP 5–8.5, as these represent the medium part and the high end of the range of future forcing pathways, respectively [77]. The SSP 2–4.5 and 5–8.5 scenarios represent the intermediate and high level of greenhouse gas (GHG) emissions, respectively. Future monthly projections of T and SM for 2045–2050 and 2095–2100 were obtained from Copernicus Climate Data Store, and the yearly mean and then the multi-year (6-year) mean were calculated (henceforth referred to as ‘2050’ and ‘2100’ respectively). Moreover, using KrigR it is possible to create high-resolution climate projection products [71]. So, as with historical climate variables, the future projections of T and SM were statistically downscaled to 1×1 km cell size using KrigR package [71]. The same covariates that were used in the statistical downscaling of historical climate variables were utilized for the statistical downscaling of future climate variables. Finally, to remove model biases in regional T and SM and to retain the realistic spatial variability obtained from the ERA5-Land reanalysis, we subtracted the future projections from the historical products to obtain T and SM anomalies, and then added these to the downscaled ERA5-Land historical layers [71]. This approach enabled us to make use of CMIP6 projections for temperature and soil moisture changes across various scenarios, all while preserving the realistic spatial and seasonal fluctuations in temperature and soil moisture as obtained from the ERA5-Land historical reanalysis [71].

Moreover, the study was conducted on a national scale, but results were also derived specifically for protected and semi-protected areas. The boundaries of all protected areas were obtained through the World Database on Protected Areas [78]. Out of the 269 polygons provided by the database, 19 were excluded as marine/freshwater protected areas. The remaining 250 polygons were divided into protected and semi-protected areas, with a distinction based on the type of management (‘GOV_TYPE’) assigned to each area. All areas with ‘federal or national ministry or agency’ government, as well as 2 Ramsar sites and 1 world heritage site, were considered protected areas (186 in total). Of these 186 protected areas, 129 are ‘Forest Reserves’, 22 are ‘National Parks’, 28 are ‘National Reserves’, 4 are ‘National Sanctuaries’, and finally, 2 are ‘Ramsar Sites, Wetlands of International Importance’, and 2 is a ‘World Heritage Site’. Furthermore, of these protected areas, 27 are in the IUCN Protected Area Management Category II, and 12 are in Category IV; the IUCN management category was not reported for all the other areas. The remaining areas were considered semi-protected areas (59 in total).

All data preparation was conducted using Google Earth Engine (GEE) and QGIS (3.22.11).

2.3. Statistical Analysis

To predict vegetation response to climate change, the average EVI of 2015–2020 was set as the baseline to build a model with climatic and morphometric predictors. Before generating future predictions, we assessed the predictive capabilities of our model by testing it with historical EVI values (2000–2005). Finally, we used the model to predict future EVI in 2050 and 2100 under SSP 2–4.5 and SSP 5–8.5 climate change scenarios.

To assess the relative importance of the selected drivers, we used a linear modelling approach [65,66]. First, the correlation between the variables was assessed using Pearson correlation coefficient and Variance Inflation Factor (VIF). Correlation analysis between the variables reported acceptable Pearson's coefficient values ($r \leq 0.5$) for all except for T and SM ($r = -0.78$). However, VIF reported acceptable values for all variables ($VIF < 4$). Since excluding T or SM led to the loss of explanatory power of the model and considering the low VIF, we decided to keep all variables in our model after checking that the inclusion of both variables did not alter their estimated effects in the model.

We developed a multiple linear regression of the mean EVI over the period 2015–2020 with TRI, livestock density, T and SM as predictor variables, with the following equation:

$$EVI_i = \beta_0 + \beta_{i,T} \times T_m + \beta_{i,SMm1} \times SM_{m1} + \beta_{i,TRI} \times TRI + \beta_{i,Ld} \times L_d + \epsilon_i$$

where β_0 serves as the intercept, T_m represents the average air temperature, SM_{m1} denotes the average soil moisture data at depth level 1, TRI stands for the values of the Terrain Ruggedness Index, and L_d represents the livestock density data. All the final coefficients are listed in Table 2.

Table 2. Coefficients (β) of the multiple linear regression of the mean EVI in Kenya over 2015–2020 with mean temperature (T), soil moisture (SM), Terrain Ruggedness Index (TRI), and livestock density. The Standard Error (SE), 95% confidence intervals (95% CI), and p value (p) are also shown.

Variable	β	SE	95% CI		p
			Lower	Upper	
(Intercept)	1.64401	0.0105804	1.62328	1.664751	<0.001
T	−0.0052	3.468×10^{-5}	−0.0052	−0.005093	<0.001
SM	0.59195	0.0013796	0.58924	0.594652	<0.001
TRI	0.00016	9.176×10^{-7}	0.00016	0.00016	<0.001
Livestock	3.2×10^{-8}	9.058×10^{-9}	1.4×10^{-8}	4.93×10^{-8}	<0.001

To validate this model, the same model was used to predict historical average EVI values (2000–2005). We checked the correlation between the historical EVI values predicted by the model and the observed values in the same time frame by means of Pearson correlation coefficient to assess the predictive power of the model. In addition, we calculated the Root Mean Squared Error (RMSE) of the model residuals. Furthermore, we mapped the RMSE to identify potential areas with low prediction accuracy [66].

Subsequently, the model was used to predict average EVI values with future projections of T and SM, in the two different scenarios for 2050 and 2100. To comprehensively analyze the historical, present, and future distribution of Kenya's key ecosystem types, we related the average EVI and the current land cover. Using the ESA World Cover 2020 [79], we extrapolated the nationwide distribution of predominant vegetation types in Kenya for 2020. We then overlaid the distribution of vegetation types and the vegetation index, aiming to identify specific EVI ranges that effectively differentiate between these vegetation types. This was achieved despite the inherent spatial resolution differences between the EVI layer and ESA World Cover. Our underlying assumption was that the EVI ranges currently associated with Kenya's primary vegetation types would remain valid for accurately representing these types in future projections.

All analyses were conducted using R (4.2.1).

3. Results

Based on the ERA5-Land reanalysis data, it is evident that the future holds substantial changes in store for Kenya's climate. Specifically, when comparing the current situation (2015–2020) to future scenarios (SSP 2–4.5 and SSP 5–8.5), it is evident that temperatures in Kenya are projected to rise in both the near (2045–2050) and far future (2095–2100). The impact of this temperature rise will be less pronounced in central Kenya and smaller regions in the northwest. In terms of soil moisture, the data suggests that under the moderate SSP 2–4.5 scenario, there will be a slight decrease in soil moisture across the country in the near future. However, specific small areas within central Kenya and the northeast region will experience an increase. Looking further ahead, in the SSP 2–4.5 far future, an increase in soil moisture is projected for most regions of the country due to increased rainfall, except for larger areas in the southern part of Kenya. In contrast, under the SSP 5–8.5 scenario, in the near future, we can expect to see a rise in soil moisture levels across the eastern region of Kenya, while the western part, including a section of the coastal zone, will experience a decrease. In the SSP 5–8.5 far future, an overall rise in soil moisture is predicted for nearly the entire country due to increased precipitation, with the exception of minor coastal areas and small portions in the southwest.

Our EVI model had a moderately high explanatory power (adjusted- $R^2 = 0.63$) and showed a significant negative effect of the temperature (T) on the average EVI and, in contrast, significant positive effects of soil moisture (SM), TRI, and livestock (Table 2).

Importantly, the model's ability to predict historical EVI values in 2000–2005 was similarly strong, as shown by the relationship between predicted and observed mean EVI in 2000–2005 ($r = 0.78$, $R^2 = 0.61$, Figure 2) and the overall RMSE is 0.06. In addition, only 0.1% of pixels showed RMSE values between 0.3 and 0.5.

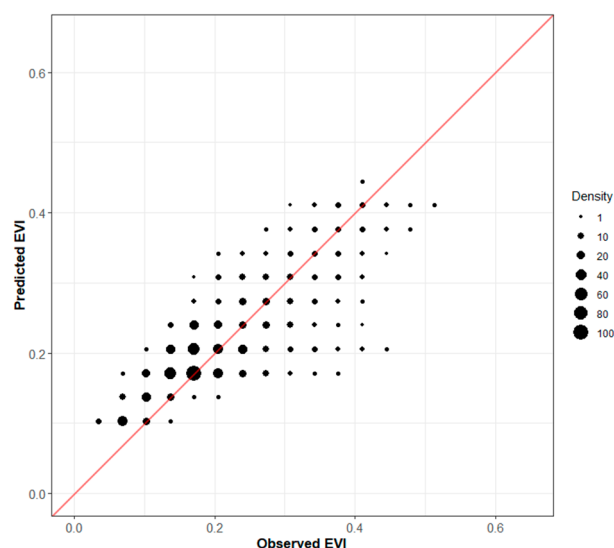


Figure 2. Relationship between mean EVI values observed and predicted for 2000–2005 by linear regression using TRI, livestock density, temperature (T), and soil moisture (SM) as predictor ($R^2 = 0.61$; $r = 0.78$; $p < 0.0001$).

We identified three categories of EVI that accurately depict the distribution of vegetation types in 2020. These were low EVI, ranging from 0.0 to 0.20; medium EVI, ranging from 0.20 to 0.40; and high EVI, greater than 0.40. Specifically, within the low EVI category, shrubland encompasses 51% of the landscape, followed by grassland at 40%, and bare soil at 8% (Figure 3). The medium EVI category exhibits 65% shrubland, 20% grassland, and forest at 9% (Figure 3). In contrast, the high EVI category showcases a dominance of 61% forest, 28% shrubland, and a mere 9% grassland (Figure 3). Consequently, low EVI values (0.0–0.20) primarily correspond to regions characterized by sparse bushland, often accompanied by grassland and shrubland displaying mixed arid-tolerant vegetation, as

well as areas of bare soil. Moving into the medium EVI range (0.20–0.40), the landscape is largely indicative of savannah and grassland areas, where dense shrublands become more prevalent and woody plants start to emerge. On the other hand, high EVI values (>0.40) are primarily associated with forested areas, where the dominant land cover is trees and other dense vegetation.

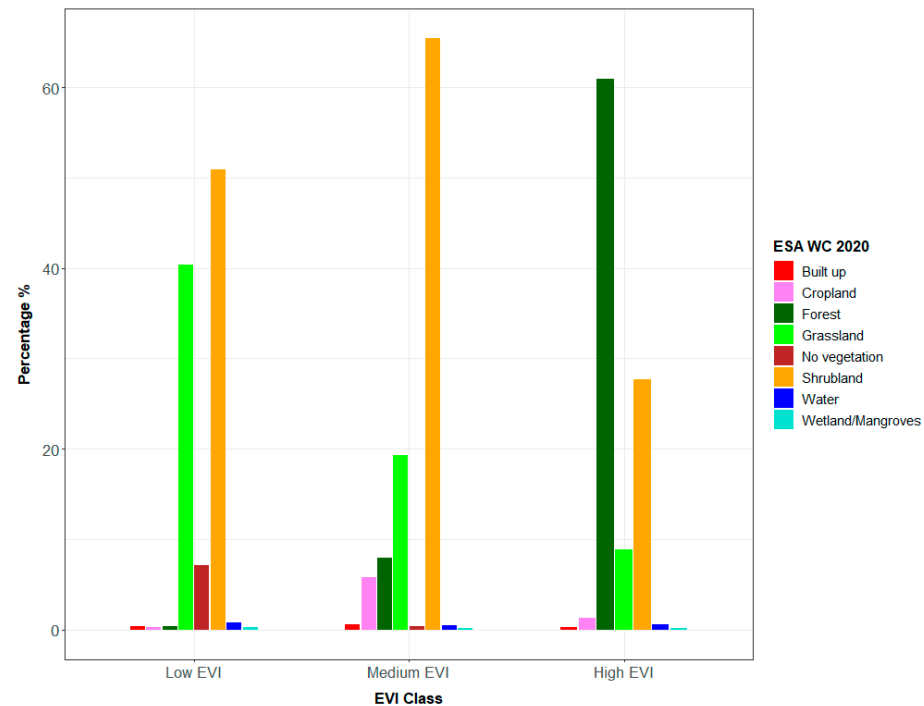


Figure 3. Chart representing the land cover percentages (%) x -axis) within the three EVI categories (y -axis), generated through the overlay of ESA World Cover 2020 land cover data and average observed EVI values from 2020.

When we used the model to generate future EVI projections, it showed that with intermediate levels of GHG emissions (SSP 2–4.5, in 2050) a major proportion of Kenya (58%) will experience a decrease in average EVI. For the same scenario, a balance between an increase and decrease in EVI was detected in 2100. However, when only considering areas with strong EVI changes (>0.1), decreases were more than 4 times as common as increases (Table 3). Under the high-emission SSP 5–8.5 scenario, we again found a relative balance between EVI increases and decrease by 2050, similar to SSP 2–4.5. However, by 2100 more than two-thirds (67%) of Kenya will be subject to EVI increase (Table 3).

Table 3. Percentages of Kenya’s land area that will experience increase (‘Inc’) and decrease (‘Dec’) in mean EVI in the future. Results are shown for the near future (2050) and far future (2100) for both scenarios. Percentages are expressed in relation to the whole territory.

SSP	Year	% EVI Increases		% EVI Decreases	
		Inc	Inc > 0.1	Dec	Dec > 0.1
SSP 2–4.5	2050	42%	1.2%	58%	10.2%
	2100	50%	2.0%	50%	8.8%
SSP 5–8.5	2050	53%	1.4%	47%	8.7%
	2100	67%	5.5%	33%	6.6%

Under both scenarios and time frames greening and browning is unequally distributed across the country. Southeast and southwest Kenya, especially the coastal region, will be

subject to the strongest browning regardless of the scenario used for prediction (Figure 4). In contrast, most of the northern and central parts of the country are forecasted to experience future greening.

In the moderate emissions SSP 2–4.5, more than half of Kenya’s surface area will be characterized by low EVI values characteristic of the driest areas (Table 4). Therefore, compared to 2020, sparse bushland will expand in this scenario, with varying strength depending on the future time (Table 4).

In the high-emission SSP 5–8.5 scenario, more than half of Kenya’s territory will be characterized by medium EVI values, reaching 65% by 2100 (Table 4). Therefore, compared to 2020, with the SSP 5–8.5 there will be a reduction in areas with sparse bushlands, and an expansion of savanna areas with woody plants and dense shrubland.

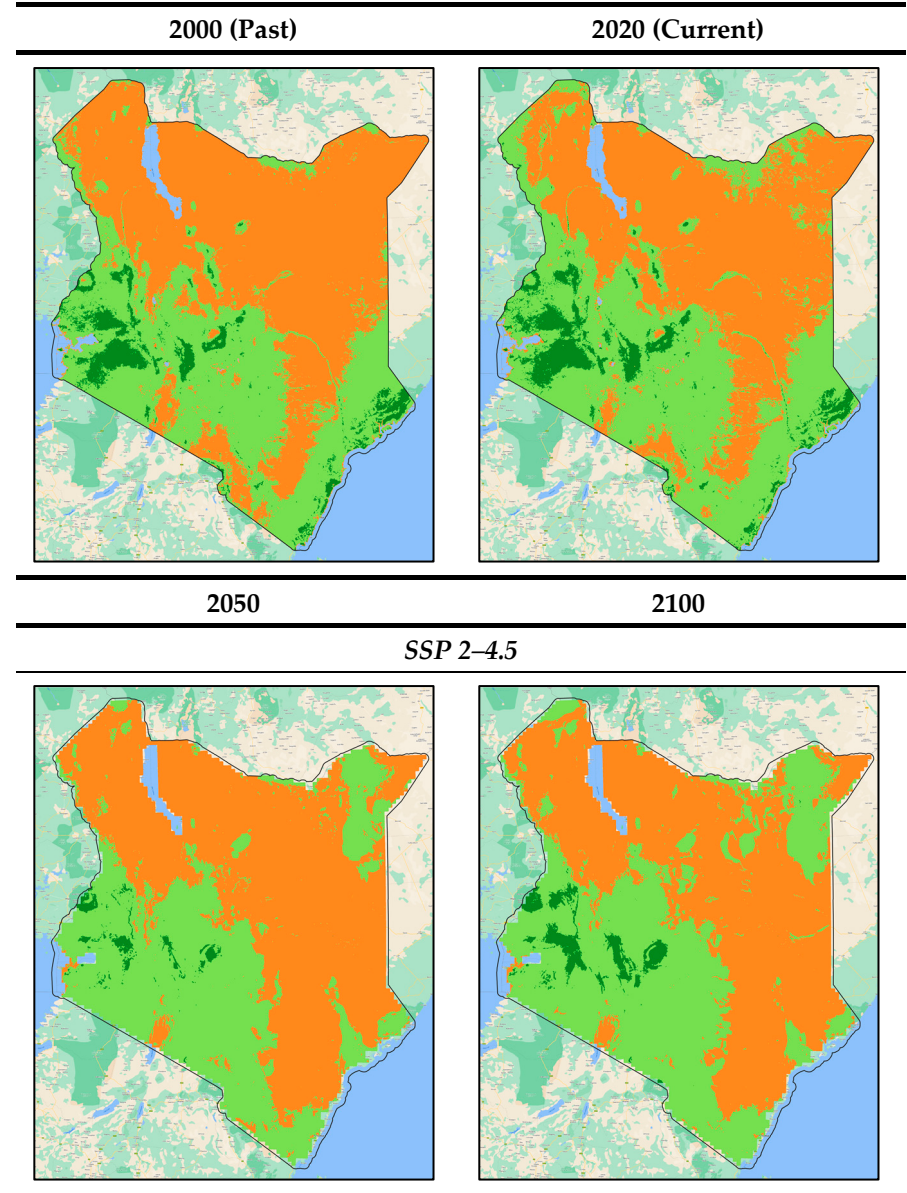


Figure 4. Cont.

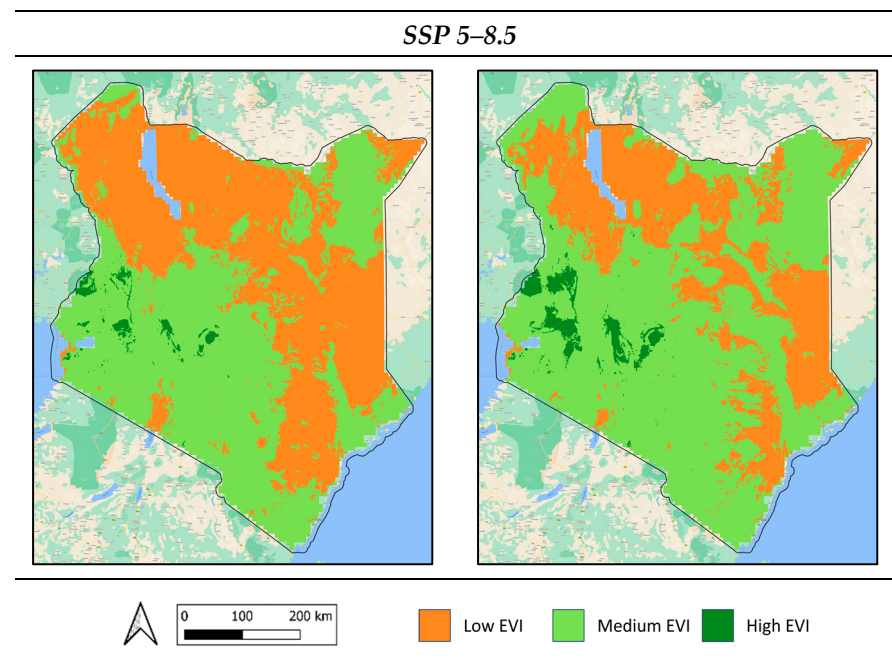


Figure 4. Maps of past (2000), current (2020) and future (2050–2100) EVI levels divided into three categories: ‘low’ (0.0–0.20, orange), ‘medium’ (0.20–0.40, light green), ‘high’ (>0.40, dark green). The legend for the EVI categories is provided, along with a north indicator and spatial scale, consistent across all images.

Our modelling forecasted substantial decreases in the proportion of dense forest areas under all future scenarios, with reductions to 16–50% of current values (Table 4). While a noticeable decline in forested regions is projected by 2050, our results suggest a greater potential for forest by 2100, especially in the western half of Kenya.

Table 4. The proportion of Kenya’s territory characterized by ‘low’ (0.0–0.20), ‘medium’ (0.20–0.40), and ‘high’ (>0.40) average EVI values in the past and future.

SSP	Year	% Low EVI	% Medium EVI	% High EVI
Past	2000	56%	39%	5%
Current	2020	49%	45%	6%
SSP 2–4.5	2050	58%	41%	1%
	2100	53%	44%	3%
SSP 5–8.5	2050	47%	52%	1%
	2100	32%	65%	3%

Over the past 20 years, Kenya has experienced an increase in the percentage of areas characterized by high and medium EVI values (Table 4). This trend would be reversed in the moderate-emission SSP 2–4.5, with a sharp increase in low-EVI areas. In the high-emission SSP 5–8.5 scenario, a loss of extreme values, both high and low EVIs, would increase areas with medium EVIs. Specifically, under the SSP 2–4.5 scenario, over 53% of the country’s landscape is projected to exhibit sparse vegetation and bushland. However, under the SSP 5–8.5, the regions classified as having low vegetation cover will be limited to a range of 32% to 47%. Instead, savannah and grassland with presence of woody plants and dense shrublands is expected to encompass approximately 52% to 65% of the country.

In the SSP 2–4.5 scenario, the expansion of areas with low EVI will be uniform in its spatial distribution, although less pronounced in the far future, especially in the north-eastern parts of the country (Figure 4). Compared to 2020, areas with low EVI values will expand southward and westward in this scenario. Under the SSP 5–8.5 scenario, areas with

medium EVIs will expand uniformly but to a greater extent in the far future (Figure 4). In particular, under SSP 5–8.5, in both the near and far future, the areas in the northeast and northwest will be most prone to this phenomenon. These areas will show higher EVI values than in 2020. The loss of high-EVI forest was detected in both the coastal and southwestern areas under all scenarios (Figure 4).

With respect to protected areas, our modelling forecasts that most of the protected areas will experience browning in the future (Table 5). Indeed, in all scenarios, more than half of the land within protected areas (42–69%) will suffer a decrease in EVI. On the other hand, semi-protected areas are located mainly in the central region, which will mainly be subjected to greening in all scenarios (Table 5). In particular, semi-protected areas will experience an increase in EVI in 73–82% of their area. These dynamics contrast with the dynamics in the past 20 years, where protected areas have experienced an increase in average EVI, and semi-protected areas have remained fairly stable and characterized by low average EVIs.

Table 5. Proportion of Kenya’s Protected (PA) and semi-protected areas (SEMI) characterized by observed (past and current) and predicted (future) ‘low’ (0.0–0.20), ‘medium’ (0.20–0.40), and ‘high’ (>0.40) EVI values.

SSP	Year	PA			SEMI		
		% Low	% Medium	% High	% Low	% Medium	% High
Past	2000	37.66	46.72	15.62	70.86	28.17	0.97
Current	2020	29.28	53.13	17.59	67.94	31.14	0.92
SSP 2–4.5	2050	39.89	54.71	5.40	60.48	39.52	0.00
	2100	32.96	56.06	10.98	49.30	50.62	0.08
SSP 5–8.5	2050	24.13	70.90	4.97	38.32	61.68	0.01
	2100	12.10	78.51	9.38	24.95	75.00	0.06

4. Discussion

Our results provide an overview of potential landscape transformations in Kenya due to vegetation shifts under future climate change in the near and far future. In the face of ongoing global climate changes, Africa is poised to undergo profound climatic transformations [4], with Kenya serving as a noteworthy example [3,7,34]. In particular, our findings highlight the substantial and positive influence of soil moisture on vegetation biomass with soil moisture encompassing not only the effects of precipitation but also various soil-related factors, making it a more accurate indicator of plant water availability [65] and, subsequently, vegetation activity (EVI). Furthermore, despite the complex bimodal rainfall pattern prevalent in East Africa, which could suggest the importance of further teasing apart impacts of seasonal rather than annual rainfall [80], the relationship between annual rainfall and vegetation in East Africa remains consistently positive [36]. Furthermore, a focus on seasonal rainfall complicates large-scale studies since seasonal patterns will vary across the study area and are likely not captured adequately by standard bioclimatic variables on rainfall and temperature seasonality. These considerations support that our model possesses the necessary sensitivity to forecast large-scale vegetation dynamics. From a methodological perspective, our study introduces some advances, including (a) the integration of Sentinel 2-derived land cover maps (ESA Worldcover) to enhance our interpretation of MODIS EVI data; (b) the adoption of ERA5 soil moisture data (also statistically downscaled), a superior alternative to the commonly employed rainfall data in terms of precision and ecological effect [65]; (c) the incorporation of livestock density, a variable frequently overlooked in vegetation modeling studies despite being consistently acknowledged as a potentially relevant factor, e.g., [13,29]; and (d) a comprehensive eval-

uation of our model using historical data before making future projections, a step often omitted in conventional forecasting approaches, e.g., [13,25].

Our predictions indicate a potential expansion of low EVI ecosystems under the moderate SSP 2–4.5 scenario, characterized by sparse bushland, grasslands, and exposed soil. This expansion will come at the cost of savanna and grassland areas, as well as forests. This outcome is likely due to the competitive advantage exhibited by C_4 - over C_3 -plants in drier conditions, a factor also underscored by Martens et al. (2021) [13]. On the other hand, in the most extreme scenario (SSP 5–8.5), climate change will result in a major shift toward widespread savannization, with an increase in savannas at the expense of currently arid zones and forested areas. The phenomenon of habitat conversion to savanna, characterized by medium EVI values, has already been predicted under the most extreme scenarios in other regions around the world [10,81]. Thus, our findings align with some previous estimates for both Africa and other continents, albeit based on a different methodology and offering a comprehensive national overview for Kenya. Overall, a consistent pattern is observed in both scenarios: a reduction in areas characterized by high EVI values, and consequently, a decrease in forested areas. This suggests a shift in the landscape composition towards land cover types with lower EVI values. The slight re-expansion of forests observed in the southwest between 2050 and 2100 could potentially be attributed to the expected increase in soil moisture during that period, coupled with a less pronounced temperature increase in the same region [23,38]. It is important to note that our projections focus solely on potential vegetation changes driven by climate factors. However, for a successful forest recovery, the presence of ecological factors such as viable seed sources and dispersal corridors is crucial. In addition, based on our results, it is clear that the expansion of arid zones will extend over a substantial portion of coastal regions in all considered scenarios at the expenses of forested areas. The coastal areas of Kenya will be highly prone to desertification, carrying profound implications for local ecosystems. Notably, this region is forecasted to witness the substantial loss of extensive savanna and grassland landscapes, as well as the near-complete loss of forests. The coasts, especially in Kenya, have already been identified as highly susceptible regions, serving as prominent hotspots for drought and desertification [82,83].

When considering the distant future under the SSP 5–8.5 scenario, we forecast an overall increase in EVI rather than a decrease, aligning with the findings of Martens et al. (2021) [13]. However, a disparity arises concerning the expansion of forested regions. Although their projections suggest an increase in forested areas, our approach utilizes EVI categories and foresees a rise in ecosystems classified as having a medium EVI, indicating savanna landscapes inclusive of varying amounts of dense shrubland and other woody vegetation rather than closed forest. In fact, our predictions indicate a reduction in areas characterized by high EVI, suggesting a decrease in overall forested regions. Similar trends are observed within protected areas. While their predictions pointed toward an encroachment of woody plants by the end of the century [25], our projections under SSP 5–8.5 suggest a potential reduction in areas characterized by both low and high EVI values, coupled with an expansion of regions exhibiting medium EVI values. Nevertheless, it is important to note that a decline in tree cover has already manifested as a prominent trend in Kenya since 2001 [29]. Analyzing data spanning from 2001 to 2019, Abera et al. (2022) [29] reveal that the decrease in woody cover across both Ethiopia and Kenya was four times more pronounced than the corresponding increase, resulting in a marked overall decline. Furthermore, it is worth highlighting that savanna ecosystems exhibited a relatively higher propensity for recovering woody cover compared to other types of ecosystems over the same period [29]. Importantly, similar to the observations made by Martens et al. (2021) [13], differences in projections regarding biome changes among various studies can be traced back to differences in modeling methodologies and climate datasets. For instance, the study by Martens et al. (2021) [13] focused on changes at a continental scale, primarily examining the influence of CO_2 level, and did not include projections for 2050.

Moreover, climate change is set to trigger major transformations in ecosystem functioning and the delivery of ecosystem services across Kenya. Key ecosystem services encompassing food supply, timber resources, climate regulation, provision of clean water, recreational opportunities, and conservation efforts will all face the impacts of shifting vegetation patterns [81]. These changes in the spectrum of ecosystem services, brought about by alterations in vegetation patterns, will undoubtedly have varying effects on different groups of stakeholders. For example, the projected expansion of arid landscapes primarily marked by scattered shrub vegetation stands to substantially decrease the available grazing capacity, likely imposing sizable impacts on both wildlife and pastoralists who depend on grassland habitat [84]. Besides climate factors, the depletion of protective vegetation cover through deforestation, along with intense livestock grazing, can exacerbate this phenomenon, accelerating soil erosion and advancing desertification [85–87]. In addition, numerous species exhibit a strong correlation with specific biome types [88]. An abrupt alteration in vegetation is also undoubtedly poised to lead to substantial reductions in biodiversity [9,89]. The depletion of forests in Kenya will have a large impact on the biodiversity of these habitats. Particularly within Kenya's protected areas, we forecast an alarming forest loss exceeding 50%, intensifying the urgency of addressing these ecological challenges. Taking into account the large scale and rapid pace of this transformation, a central point of discussion emerges: the extent to which species can adapt to survive the climatic changes [9,81]. Furthermore, based on our model, we forecast two widespread types of vegetation shifts across Kenya: one suggests a transformation from savanna and forest to scattered shrubland, while the other envisions a shift from forest to savanna. Overall, these predictions imply a process of landscape simplification, which could lead to an increased risk of species extinctions [90,91].

For a forward-looking perspective aimed at gaining deeper insights into the impacts of climate change and vegetation shifts, there is potential to develop more sophisticated models that consider alternative methodological approaches and other potential drivers of vegetation changes. These may include factors such as changes in soil nutrients and CO₂ levels, as well as projections related to population growth and increased livestock density. In Kenya, soil fertility and crop production have steadily decreased due to continuous soil plowing and insufficient soil nutrient levels, compounded by a growing population [92]. Consequently, prioritizing soil nutrient conservation and optimizing rainwater utilization could prove to be significant [92], but are unlikely to be major drivers of future national-scale dynamics. A more substantial limitation of our study is the absence of consideration for the direct physiological impact of future CO₂ increases on vegetation. This topic is underscored by previous research [13,93]. For instance, it has been suggested that elevated carbon dioxide (CO₂) levels can influence the growth rate of juvenile plants, potentially impacting tree recruitment and the transition from open savannahs to woodlands [93]. Furthermore, there is evidence from other studies that increased CO₂ concentrations are correlated with greater woody plant density when other global drivers like rainfall remain consistent [15]. However, it is worth noting that attributing these changes to global drivers, including CO₂, has been a topic of debate, as other factors such as grazing and fire patterns are likely also involved [93]. Changes in arid savannahs appear to have a less clear-cut connection to the effects of CO₂ and may be more strongly influenced by overgrazing [93]. In summary, these limitations highlight the need for developing a more comprehensive understanding of the complex interplay of factors influencing vegetation changes in the region. Regarding the projected population increase, from around 230 million in 1950, Africa's human population increased to over 1 billion in 2010, with projections foreseeing a potential further rise to as much as 5.7 billion by the end of the twenty-first century [94]. This remarkable growth has triggered the expansion of agricultural areas and the decline of native forests and other woody vegetation [95–97]. Indeed, the influence of population on woody vegetation has been observed in Africa; regions with rapid population expansion tend to exhibit a decline in woody vegetation on average [98]. The southwestern region of Kenya, where our model predicts alarming forest loss in the future, is also the most densely

populated region in the country [99]. As a result, the effects of population growth could potentially amplify our projections. Moreover, the southwestern region of Kenya is also currently the one with the highest density of livestock [70]. In our findings, we observed a modest yet positive influence of livestock density on EVI. This positive relationship between the EVI and livestock density can be explained by several relations. It may arise from the presence of more livestock in regions with greater productivity, which does not necessarily imply a direct impact of livestock on vegetation. Instead, it could also suggest that livestock contributes to woody encroachment. As demonstrated for example by Archer et al. (2017), the encroachment of woody plants coincided with the global intensification of livestock grazing [100]. This intensification, through the reduction of fine fuels, resulted in a decrease in both the frequency and intensity of fires, subsequently facilitating woody plant encroachment. From a conservation perspective, woody plant encroachment poses a threat to the preservation of grassland and savanna ecosystems, as well as their unique biodiversity [100]. This is particularly relevant considering that over the next three decades, the consumption of livestock products is projected to slow down in developing countries, with the notable exception of Africa [101]. Significantly, this continent is expected to experience an increase in demand for animal products, which could result in the relocation of livestock production closer to urban areas [101]. In Sub-Saharan Africa, meat and milk consumption are projected to grow by 3.4% and 2.9% per year, respectively, surpassing growth in other developing regions [101]. This phenomenon is likely to have significant and unprecedented effects on the livestock sector, impacting the environment and public health [101]. It has already been emphasized that socioeconomic pressure factors will need to be carefully considered in the future, e.g., when devising management plans for protected areas in the region [25].

5. Conclusions

Our research indicates potential future major landscape changes across Kenya due to climate-driven vegetation shifts. In the moderate SSP 2–4.5 scenario, low EVI ecosystems are forecasted to expand at the expense of savannas, grasslands, and forests. In the extreme SSP 5–8.5 scenario, there could be widespread savannization, reducing both arid-zone vegetation and forests. In both scenarios, high EVI areas decrease in area, likely leading to reductions in forested lands. However, our findings were obtained through model projections, which inherently involve assumptions and uncertainties. One of these limitations could be the simplicity of the model used; however, considering that the primary objective of this study was to provide a national-scale overview, we chose not to employ overly complex models, such as machine learning models like artificial neural networks or random forests. While these models may have a better ability to capture non-linear and monotonic relationships, they could potentially complicate the interpretation of the direction and strength of the individual drivers' effects on vegetation. In a region characterized by a seasonally dry and hot climate, we could reasonably anticipate monotonic relationships between EVI and each of the predictors. Therefore, our approach may represent the best compromise for capturing such relationships while maintaining model simplicity. Another factor to consider is the lack of accounting for certain other factors that might impact vegetation, e.g., rising atmospheric CO₂ levels. Despite these limitations, our study serves as a starting point in advancing our understanding of the complex ongoing and potential future dynamics in vegetation on the influence of anthropogenic global change. Hence, our study can be regarded as an initial step in the more comprehensive analysis of potential future vegetation changes in Kenya under anthropogenic climate change, with the primary goal of offering a comprehensive national-scale perspective. In conclusion, the analysis of ecosystem projections for the near- and longer-term future climate scenarios is of utmost importance in shaping effective policymaking, guiding infrastructure decisions, and facilitating assessments of climate change's repercussions on ecosystems [82]. Such climate scenarios and associated forecasts of impacts on ecosystems and society play a pivotal role in formulating robust strategies encompassing drought adaptation, resilient ecosystem

conservation, as well as climate change mitigation actions. Through the findings of this study, a quantitative, spatially explicit overview of potential future vegetation conditions in Kenya is provided, providing an important part of the basis for informed and targeted efforts in climate change adaptation and mitigation.

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