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Potential tropical climate-based spatio-temporal grass variability

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Potential tropical climate-based spatio-temporal grass variability

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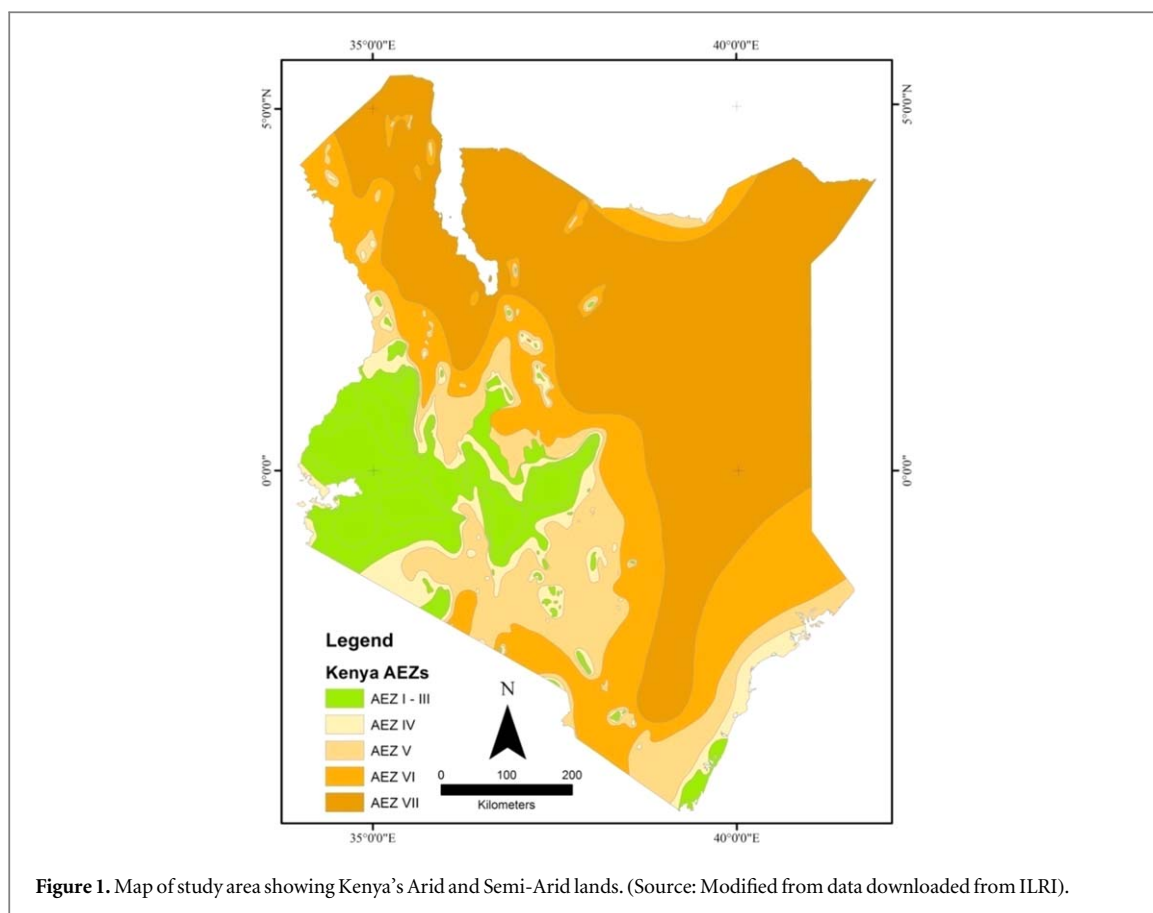
**Abstract**

Numerous international agreements aimed at reduction of greenhouse gas emissions by signatory countries have been ratified in an attempt to combat the adverse varied impacts of climate change and promote resource use sustainability. Grass is an important resource that livestock, wildlife and human beings depend on and is largely influenced by climatic conditions. The grass in Kenya supports the key economic activities of livestock and wildlife-based tourism. This significant contribution to gross domestic product underscored the need to model the impacts of climate change on the grass for the country to promote sustainable development. The study aimed at modelling the impacts of projected climate variations on the spatial and temporal distribution of grass in the base-year (1950–2000) and the future climatic periods of the years 2050 and 2070. The spatial data was sourced from United States Geological Survey, International Livestock Research Institute, and Africover Project processed and analysed in ArcGIS, DIVA-GIS, Maxent and Map Comparison Kit softwares. The models outputs were significant with the least area under receiver-operator curve (AUC) values of 0.754. The study found out that the 2050 climate will decrease grass niche suitability by 44.99%, the unsuitable will increase by 87.01%, the grass niche suitability location will shift by 76.7% and the category areas change by 46.4%; the 2070 climatic period grass niche suitability will shrink by 55.21%, the unsuitable category increase by 106.80%, the location change will be 77.8% and the category areas will vary by 66.0%. The research concluded that the rangeland vegetation (grass) will decline and shift location in the both future climatic periods.

1. Introduction

The rangelands according to WRI (1986) are defined as wild forage-producing areas under native grass and other forage plants used, among other things, for livestock, wildlife, and watershed maintenance that can be too rocky, steep, poorly drained or cold to farm. The grass which forms pasture resources support livestock kept for meat, hides, skins and wildlife which is critical for tourism and related activities. Most of grass resources are largely influenced by climatic conditions (Allen *et al* 2010, Crimmins *et al* 2011). Anomalies in climate have been documented by many researchers who also modelled the future climate scenarios (IPCC 2007, IPCC 2014).

Research has shown that the Earth has warmed up by an average of about 0.6 °C since the late 19th century and is projected that the temperature will increase to 1.4 °C–5.8 °C by 2100 at a global scale (IPCC 2007). Temperature anomalies in Kenya have been reported to be 0.4 °C–1.6 °C with climate change related deaths of 70–120 per million population (Patz and Olson 2006). The changes in temperature and rainfall patterns will have a direct impact on the land use land cover (LULC) (Stephenson 1990) and other organisms. In reference to vegetation, climate change can cause significant effects on its spatial and temporal distribution. Variations of vegetation, an important ecosystem and natural resource will disrupt both ecological and economic activities that are directly or indirectly depending on it. Ecosystems like tropical rangelands support directly and indirectly



a huge number of livestock, herbivores and carnivores that are critical to economic activities in Kenya (KIPPRA 2013). These economic activities are ranching, livestock keeping and tourism which are directly dependent on weather. The livestock development sub-sector contributes about 42 per cent of agricultural GDP, which is about 10 percent directly to the overall GDP with tourism and related activities contributing Ksh 96.02 billion (US\$ 1.2 billion) to GDP in 2012 (KIPPRA 2013).

Hegerl *et al* (2007) findings indicate that developing countries including Kenya will be hit most due to various reasons including the fact that Kenya's economy is largely dependent on agriculture and wildlife which are sensitive to climatic changes. For example, the impacts of the 2008–2011 drought was estimated at Ksh 968.6 billion (US\$ 12.16 billion) and was responsible for an average 2.8% per annum decline in GDP (GoK 2012). Climate change is therefore a concern for Kenya as it plans to advance sustainable utilization of its natural resources and promotion of sustainable development. To achieve these goals, it is necessary to model the effects of climate change on the spatial and temporal rangeland vegetation distribution in order provide useful information to the policy and decision makers at the local, regional and national level. Such important information includes manner and magnitude the rangeland vegetation is projected to change and thereby informing on the nature of investment by stakeholders.

2. Methodology

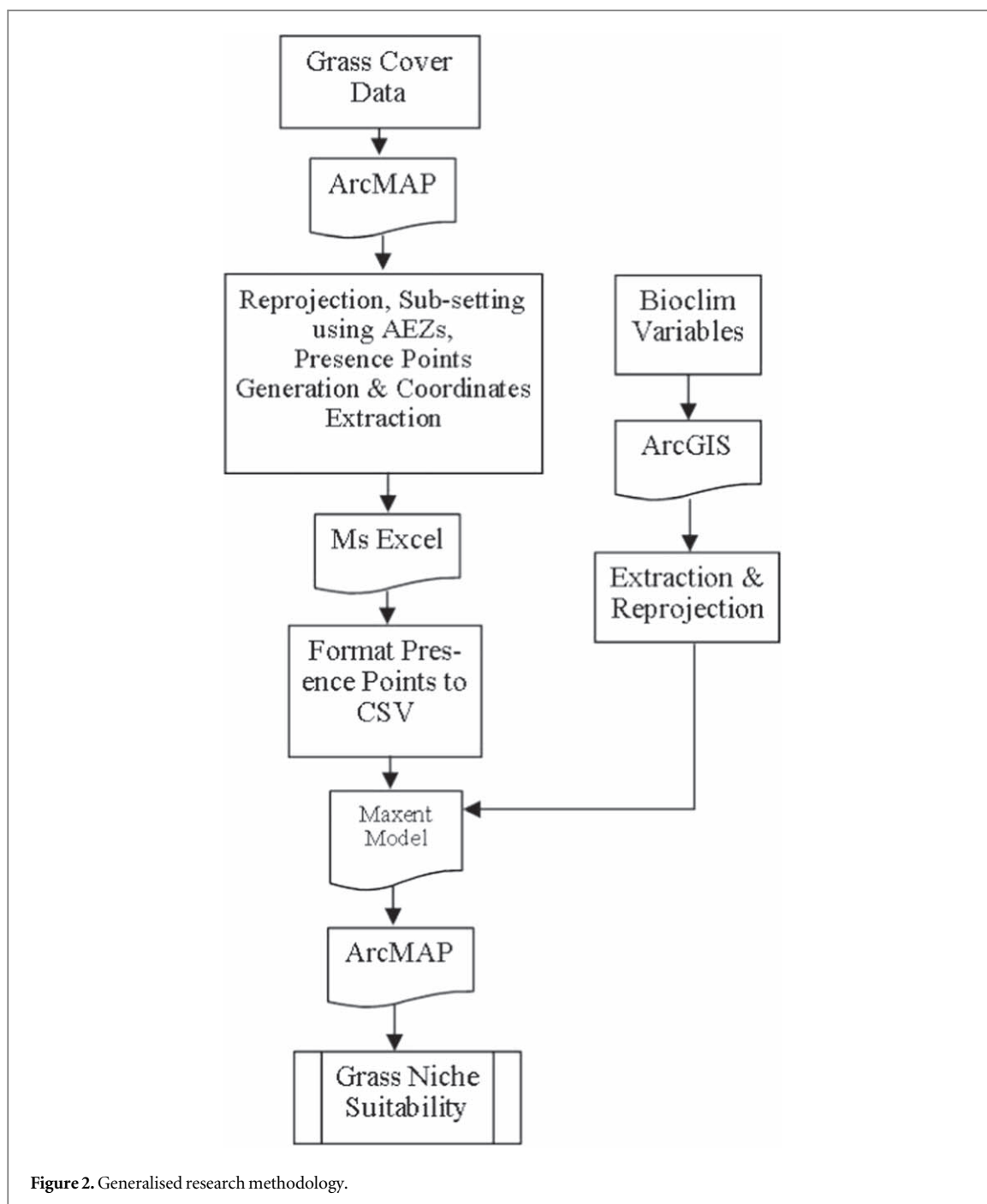
2.1. Study area

Kenya is located in the east African region covering a total of 582,646 km² with about 80% of it classified as arid and semi-arid lands (ASALs) (figure 1). It is divided into seven agroecological zones (AEZs) with AEZs I–III classified as high potential areas and the others low potential areas. The AEZs classification is based on rainfall, soil moisture pattern, soil types and vegetation types. Sombroek *et al* (1982) and PANESA (1988) summarized characteristics of the AEZs in relation to precipitation and major grass species (table 1).

AEZs IV–VII are the ASALs where rangeland vegetation is located. Here, pastoralism is a major economic activity supporting the bulk of Kenya's wildlife-based tourism. Within the ASALs, the rangelands are both managed (for the cases of ranches) and unmanaged (for the cases of communal lands) who are also nomadic. Kenya's climate is varied though dominated by a tropical wet and dry climate type. The rainfall distribution is

Table 1. A summary of AEZs IV–VII characteristics.

AEZ	Classification	Moisture index (%)	Precipitation (mm)	Major grass species
IV	Semi-humid to semi-arid	40–50	600–1100	<i>Themeda triandra</i> , <i>Pennisetum mezianum</i> , <i>P. stramineum</i> , <i>P. massaiense</i> , <i>Eragrotis</i> spp., <i>Hyperenia</i> spp., <i>Seteria</i> spp., <i>Digitaria</i> spp. and <i>Cenchrus ciliaris</i>
V	Semi-arid	25–50	450–900	<i>Eragrotis superb</i> , <i>Cenchrus ciliaris</i> , <i>Cymbopogon</i> spp., <i>Bothriochloa</i> spp., and <i>Heteropogon contortus</i>
VI	Arid	15–25	300–550	<i>Aristida adoensis</i> , <i>Stipagrostis hirtigluma</i> , <i>Aristida mutabilis</i> , <i>Cymbopogon aucheri</i> , <i>Tetrapogon</i> spp., <i>Enneapogon cenchroides</i> and <i>Chloris roxburghiana</i>
VII	Very arid	<15	150–350	<i>Aristida papposa</i> , <i>Cynodon dactylon</i> , <i>P. coloratum</i> , <i>Sporobolus</i> spp., <i>A. adoensis</i> , <i>Rhynchetrum</i> spp., <i>Enteropogon macrostachys</i> and <i>Eragrostis caespitosa</i> , <i>Eragrostis superb</i> , <i>C. roxburghiana</i> , <i>E. macrostachyus</i> , <i>P. maximum</i> , <i>E. superba</i> and <i>Chrysopogon</i> Spp.,



bimodal with peaks in April (129.1 mm) and November (93.5 mm) while the temperatures are 26.2 °C (March) and 22.9 °C (July) for maximum and minimum temperatures respectively (World Bank 2018).

Kenya's current population is estimated to be 46,748,000 which is projected to be 95,504,636 and 125,137,459 in 2050 and 2070 respectively (PopulationPyramid.net 2015). Kenya is divided into 47 counties that drive their own economic development agenda in the agriculture and tourism sectors. Most of the counties are located in the ASALs and are facing serious climate related challenges. Kenya's gross domestic product was Ksh 1.7 trillion (US\$ 17 billion) for the 2014/2015 financial year (PBO 2014) with the bulk of it from agriculture-based activities. Other notable economic activities dependent on weather patterns are wildlife-based tourism which is under threat from climatic variability. A generalised methodology used in the research is presented in figure 2.

2.2. Grass and agroecological zones data

The spatial rangeland vegetation data was sourced from the United Nations website www.un-spider.org (United Nations 2015). The Africover Project prepared and presented these data in shapefiles with varying grassland coverage of polygons ranging from 30%–100%. For spatial modelling analysis, grassland data coverage of 60%–

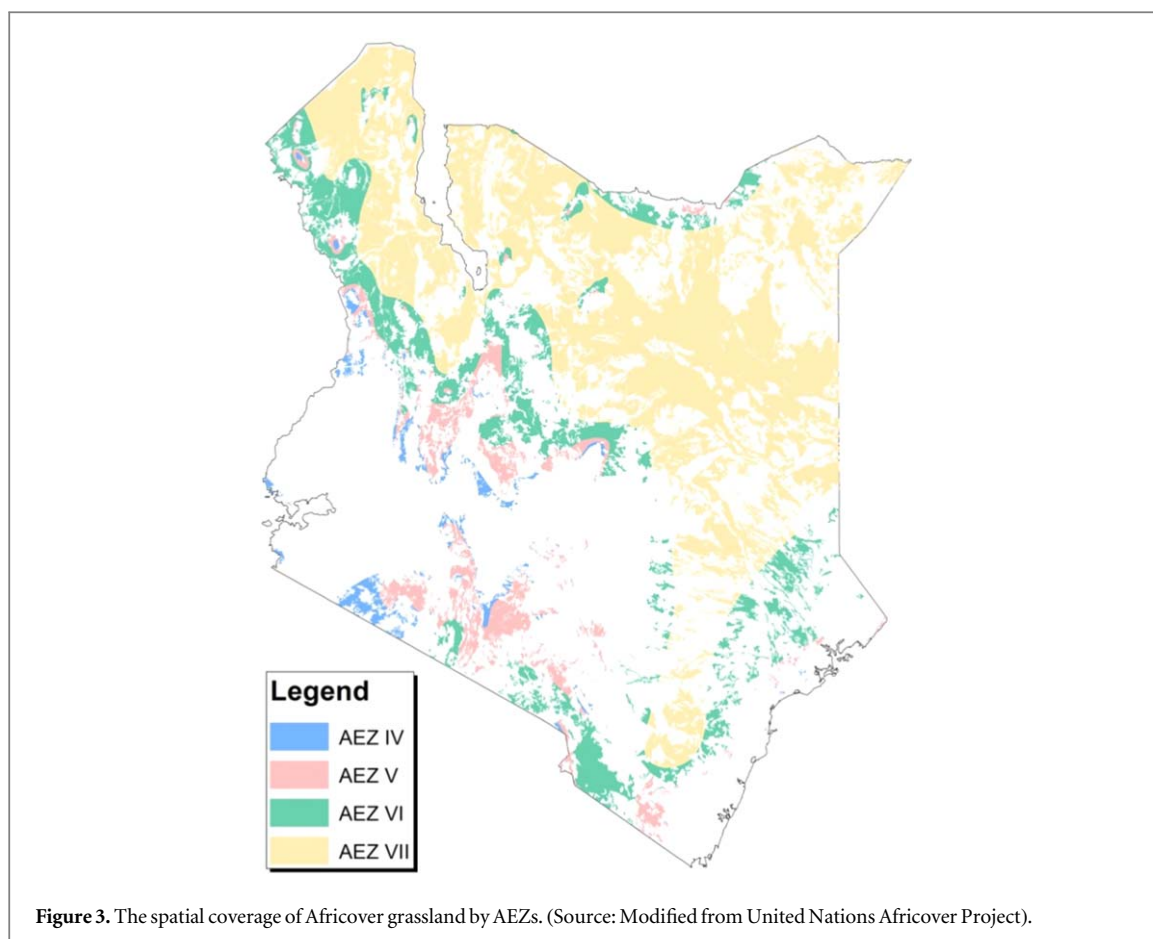


Table 2. Grass presence points by AEZs.

AEZ	Presence points
Zone IV	89
Zone V	495
Zone VI	1,341
Zone VII	5,938

100% was used in each AEZ (figure 3). The use of 60%–100% polygon coverage data was informed by the fact that the grass coverage should be more than 50% for the polygon to represent grass thereby increasing the accuracy of the data. The grass data signified the grass niche which in this case is represented by all the grass species found in that particular ecosystem and its sub-setting was based on the AEZs. The AEZs spatial data was downloaded from International Livestock Research Institute (ILRI) website (<http://192.156.137.110/gis/>) and processing done in ArcMAP.

The AEZs IV–VII were each treated as having homogeneous climatic parameters and formed the basis of extraction and subdivision of grass cover spatial data. The grass polygon data were converted to grass point data (to represent points at which the grass is growing) for use in Maxent model (discussed in the next section). Within the grassland polygons, a total of 7,863 grass presence points, at least 1000 m apart (table 2) were generated and mapped (figure 4).

The AEZs IV–VII with potential evaporation rate of $>50\%$ (Sombroek *et al* 1982) are the regions where livestock keeping and tourism-based wildlife are the major economic activities in Kenya. The AEZs IV–VII were extracted and a buffer of -5000 m was established for extraction of random presence points in each AEZ. The presence points coordinates were then generated for running Maxent ecological niche model (Phillips *et al* 2006). A detailed explanation of Maxent model was done by Elith *et al* (2011).

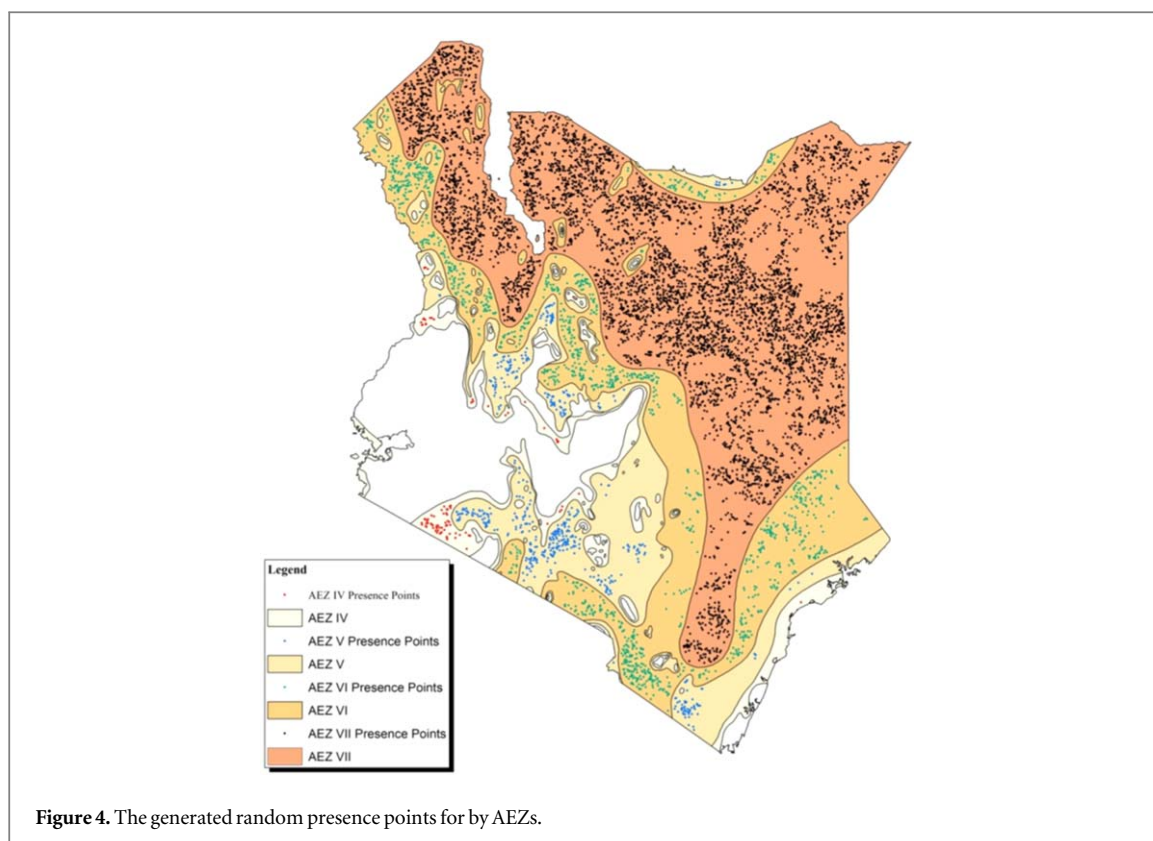


Figure 4. The generated random presence points for by AEZs.

2.3. Bioclim datasets

The Bioclim climate dataset comprising precipitation, minimum and maximum temperature at intervals of 30 year period was used. These data comprised the base-year period (1960–2000) and future (2050 and 2070) climatic periods. The climate data with a resolution of 1 km was sourced from global climate data website (www.worldclim.org) (WorldClim 2015). The Coupled Model Intercomparison Project provides four different scenarios among them is Representative Concentration Pathways (RCP) 4.5 which this study used. The RCP 4.5 data were used as it is one of the two medium stabilisation levels indicating that CO₂ levels in the atmosphere will be 650 ppm causing a radiative forcing of 4.5 W m⁻² (Watts per square meter) in the year 2100 (Moss *et al* 2010).

2.4. Maxent modelling and geospatial analysis

The data used for spatial and temporal modelling were climate elements and presence-only grass points. Using Maxent and ArcMAP, the base-year and years 2050 and 2070 potential spatial distribution of grass vegetation were modelled and spatial output processed. A total of 12 different Maxent models were run following procedures developed by Phillips *et al* (2006). Maxent 3.3.3 downloaded from www.cs.princeton.edu/~schapire/maxent/ was used in the modelling. The Maxent model generated probability curves for each bioclim variable resulting in probability maps of the vegetation likely occurrence based on a scale from 0 to 1. Further processing and analysis generated ‘unsuitable’ and the ‘suitable’ data. The ‘10 percentile training presence logistic threshold’ generated the ‘unsuitable’ niche, a range of 0—threshold value while the ‘suitable’ grass niche areas were scaled from threshold value –0.5, 0.5–0.6, 0.6–0.7 and 0.7–1.0. These processes were performed for each AEZ and mosaicking procedure derived new datasets for the whole country. Using the base-year potential grass niche spatial distribution as the basis of comparison, the future rangeland vegetation distribution were quantified and mapped.

2.5. Temporal and spatial change in grass niche

The modelled potential grass niche suitability comparison in both category and location was performed according Hagen (2003) and Visser and de Nijs (2004) using map comparison kit (MCK). The generated maps were in five categories at intervals of 0–0.2327, 0.2327–0.5, 0.5–0.6, 0.6–0.7 and 0.7–1.0 representing different levels of grass niche suitability. Both spatial shift and quantitative changes of the grass niche analysis used Kappa Location (K_{Loc}) and Kappa Histogram (K_{Histo}).

The Kappa statistics evaluation was based on scales developed by Altman (1991). The scale has five categories of ‘Poor’ (0–0.2), ‘Fair’ (0.21–0.40) ‘Moderate’ (0.41–0.60), ‘Good’ (0.61–0.80) and ‘Very Good’ (0.81–1.00). However, for this study a threshold of 0.5 was used and generated binary data of ‘Not similar’ (0.00–0.49) and

Table 3. Base-year climatic period grass niche binary range by area.

	AEZ IV	AEZ V	AEZ VI	AEZ VII
Area (km ²)				
Unsuitable	29,522	57,414	45,846	60,539
Suitable	9,239	37,713	100,184	243,977
10 percentile Threshold	0.2856	0.3499	0.3407	0.4325
% area				
Unsuitable	76.16	60.36	31.39	19.88
Suitable	23.84	39.64	68.61	80.12

Note: the 10 percentile threshold were generated by the model.

‘Similar’ (0.50–1.00). The grass niche suitability changes by climatic periods were obtained and display binary data of where the grass niche suitability level categories are either equal or unequal as explained by Visser and de Nijs (2004). Accompanying the spatial data is Kappa statistics including K_{Loc} and K_{Histo} for both future climatic periods.

2.6. Model performance and accuracy assessment

The Maxent model performance analysis was based on the area under receiver-operator curve (AUC) scores returned from the constructed models which discriminates between presences and background points (Phillips *et al* 2009). The AUC scores range from 0–1 and the significant value scaled as ≥ 0.5 indicating better than random and denotes higher predictive power and ≤ 0.49 is worse than random.

3. Results and discussion

3.1. Modelled spatial and temporal rangeland vegetation distribution

The results of Maxent model are presented for each AEZ in both binary and scaled formats. The base-year grass distribution processing was based on AEZ while analysis was done at the country level through aggregation. The various figures generated display the potential spatial distribution and change with time while the tables provide quantitative information of the same. The future projections showed both increase and decrease characterized by shifting, expansion and shrinking in grass niche suitability levels for different locations.

3.2. Base-year climatic period grass niche range

The Maxent unsuitable and suitable grass niche areas were different in all the AEZs (table 3). The modelled suitable grass niche covered different fractions in each AEZ with 66.92% and the 33.08% being unsuitable and suitable respectively in the country. The percent of suitable grass niche increased from a minimum of 23.84% in AEZ IV to a maximum of 80.12% in AEZ VII. The others were 39.64% for AEZ V and 68.61% for AEZ VI.

The generated binary raster for all the AEZs shows the distribution of both suitable and unsuitable grass niche in Kenya in the base-year (figure 5). The analysis was based on the spatial extent of each AEZ with the corresponding 10 percentile training presence logistic threshold obtained from the Maxent models.

The suitability levels analysis of the aggregated raster used 0 (least suitable)—1.0 (most suitable) range. The specific scale values were 0–0.2327 (unsuitable), 0.2327–0.5 (low suitability), 0.5–0.6 (medium suitability), 0.6–0.7 (high suitability) and 0.7–1.0 (excellent suitability) (table 4). The individual modelled grass niche AEZ maps were aggregated to generate a new raster (figure 6).

The aggregated base-year climatic period modelled grass niche suitable area covered 385,964 km² representing 66.04% while the area classified as unsuitable was 198,471 km² covering 33.96% of Kenya. The first category of 0–0.2327 represents the unsuitable areas from zero to 10 percentile threshold suitability in the aggregated raster data and comprised 198,471 km² (33.96%) of the total area. Most regions in this category are the high potential areas restricted to the AEZs I–III with different climatic regimes compared to the AEZs IV–VII. The excellent grass niche suitability category represents 2.63% of the area covering 15,393 km² spreading out across all the AEZs. A region of 7.46% representing 43,611 km² of the area was under high grass niche suitability category followed by medium category at 192,397 km² (32.92%). This medium category together with low category covering 134,563 km² (23.02%) is restricted to the north and north eastern parts of the country. Apparently, these are the areas where pastoralism and wildlife-based tourism are largely practised as the main economic activities.

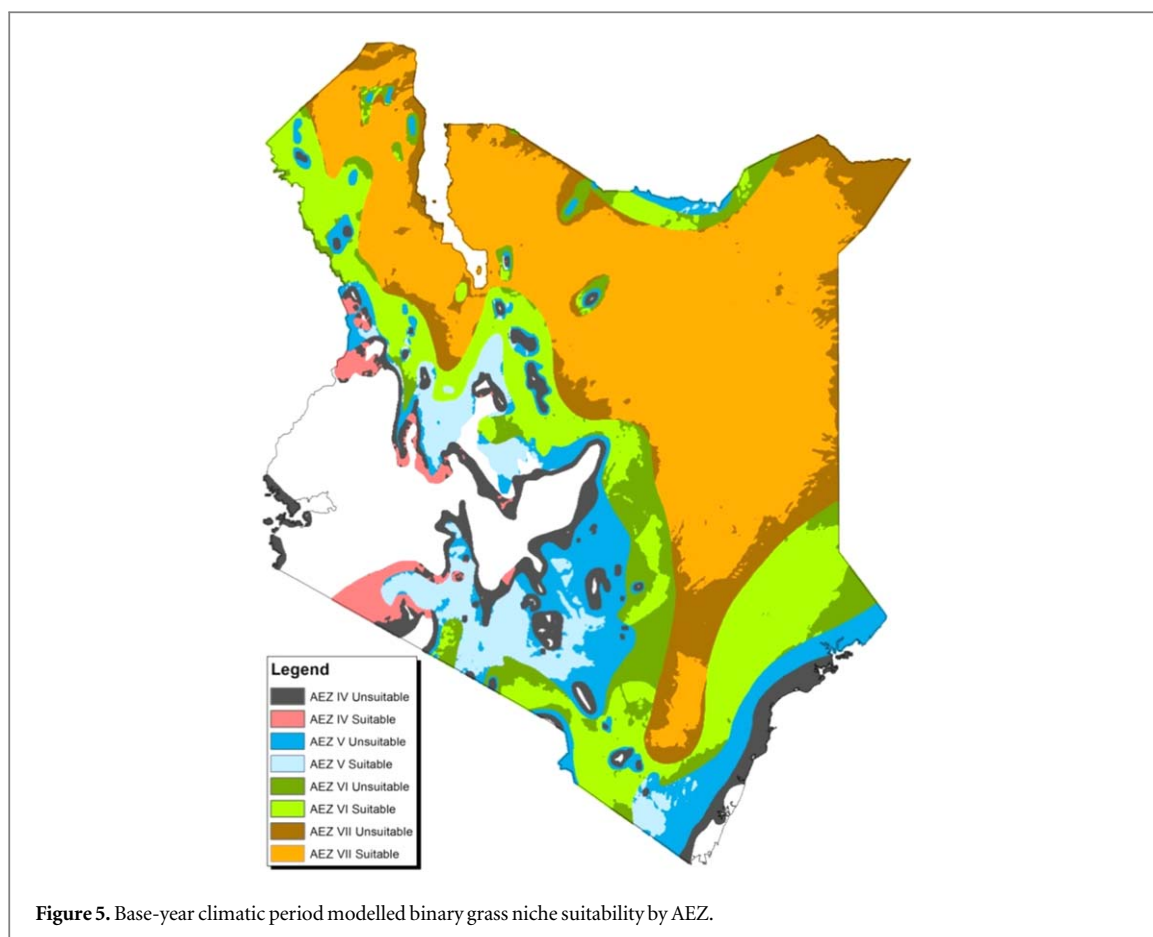


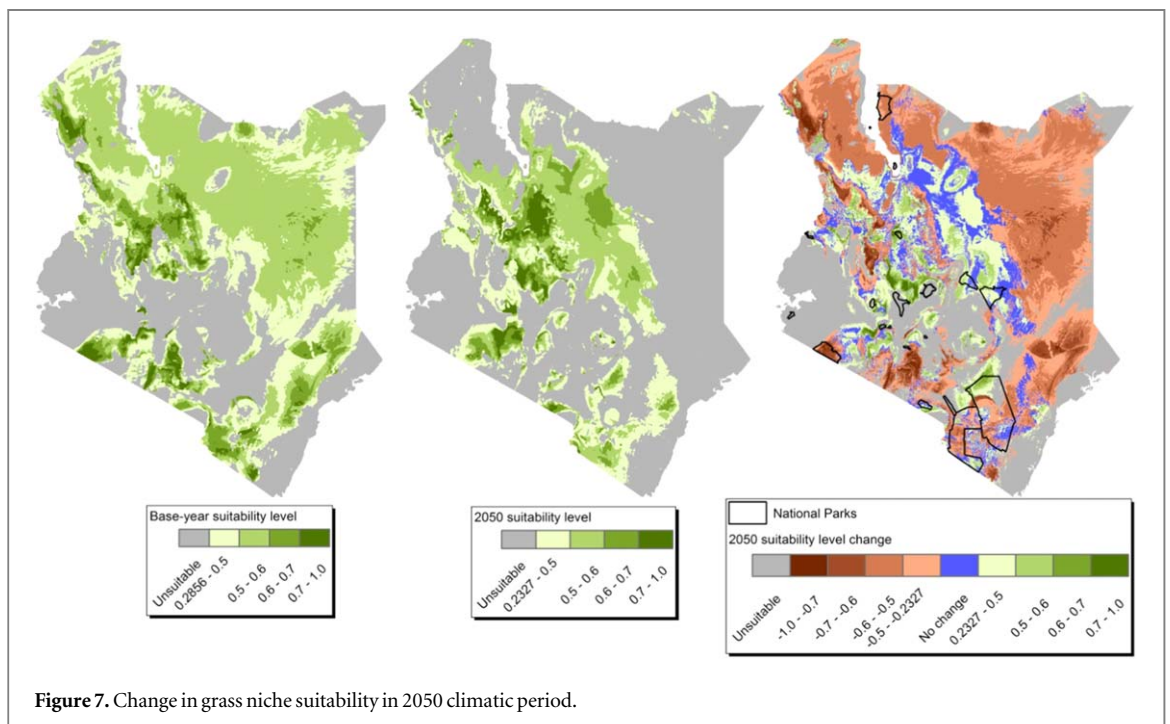
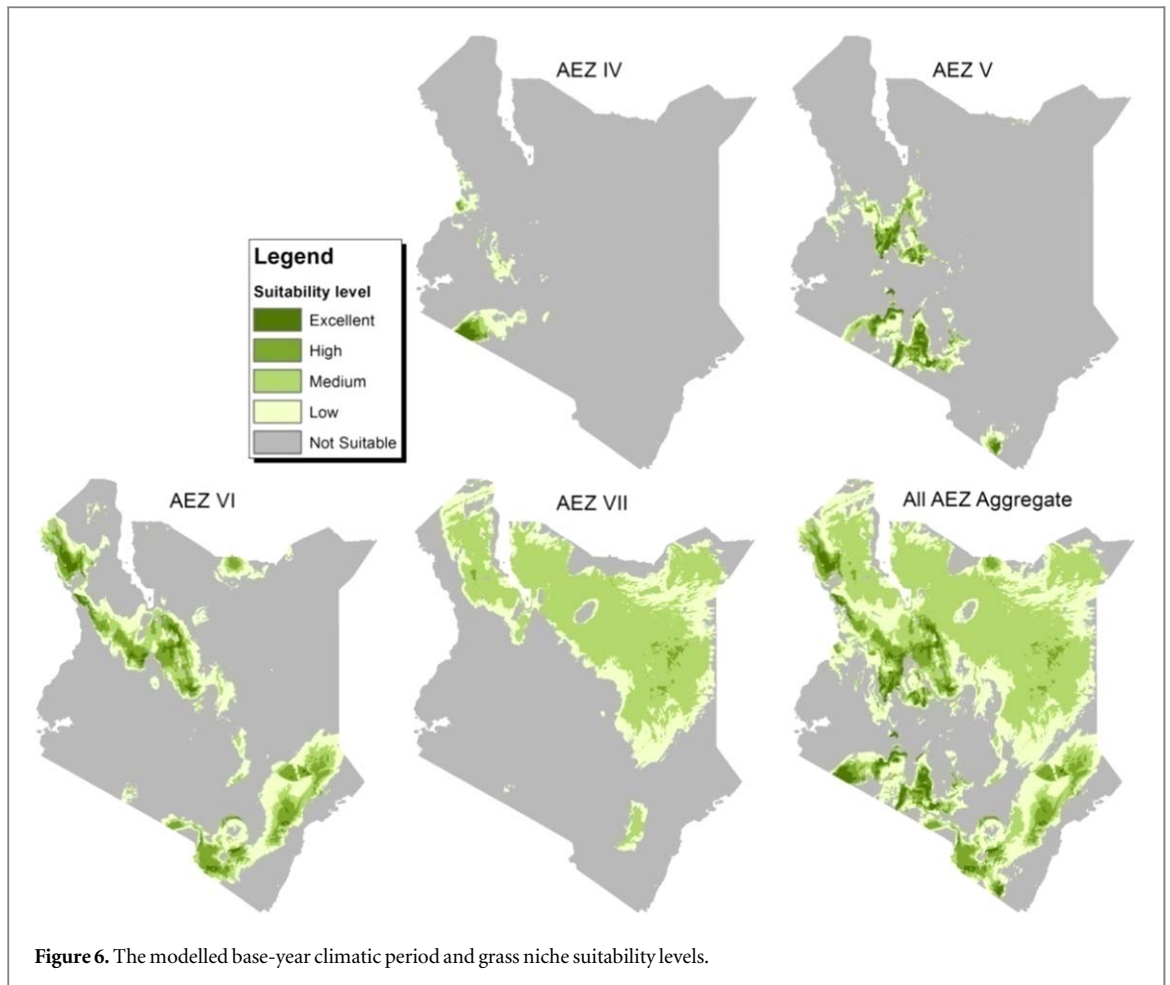
Table 4. The three climatic periods summary of grass niche suitability categories by area.

	Base-Year		2050		2070	
Suitability level	Area (km ²)	% Area	Area (km ²)	% Area	Area (km ²)	% Area
Unsuitable	198,471	33.96	373,104	63.84	412,505	70.58
Low	134,563	23.02	86,718	14.84	64,020	10.95
Medium	192,397	32.92	79,334	13.57	66,674	11.41
High	43,611	7.46	30,647	5.24	28,457	4.87
Excellent	15,393	2.63	14,632	2.50	12,779	2.19

3.3. The 2050 climatic period modelled projected potential grass niche range

The 2050 climatic period projected potential grass niche suitabilities were generated for each AEZ and analysed as aggregated data for the whole country. The spatial data show that the grass niche suitable areas are mostly in parts of northern, north eastern, southern and the coastal regions of the country. The Maxent output grass niche suitability levels (table 4) summarises the modelled grass niche suitabilities and their respective areas. The unsuitable areas cover a total of 373,104 km² (63.84%) of the country and consist mainly the current AEZs I–III, which comprise of many parts of the eastern, north eastern and northern parts of the country. The modelled grass niche suitable areas ranged from a minimum of 14,632 km² (2.50%) to a maximum of 86,718 km² (14.84%) in excellent and low suitability categories respectively. The other categories of high grass niche suitability covered 30,647 km² (5.24%) with the medium suitability occupying an area of 79,334 km² (13.57%).

Change analysis between the base-year and 2050 climatic periods revealed that some regions will change in the positive, others will experience a decrease while in some cases there will be no changes in the grass niche suitability levels. The nature, magnitude and spatial extent of the grass niche suitability changes (figure 7) indicate a net decline of grass niche suitability in Kenya. These changes ranged from -1 – 1 and were scaled from 0 – 0.2327 , 0.2327 – 0.5 , 0.5 – 0.6 , 0.6 – 0.7 , and 0.7 – 1.0 in both positive and negative directions. The negative changes were in northern, north eastern, coastal and southern parts of the country. Of particular concerns are the national parks namely Sibiloi, Maasai Mara, Amboseli, Chulu, Tsavo East and Tsavo West where grass niche suitability levels are projected to decline. The central region of the country largely under AEZs IV–VI registered

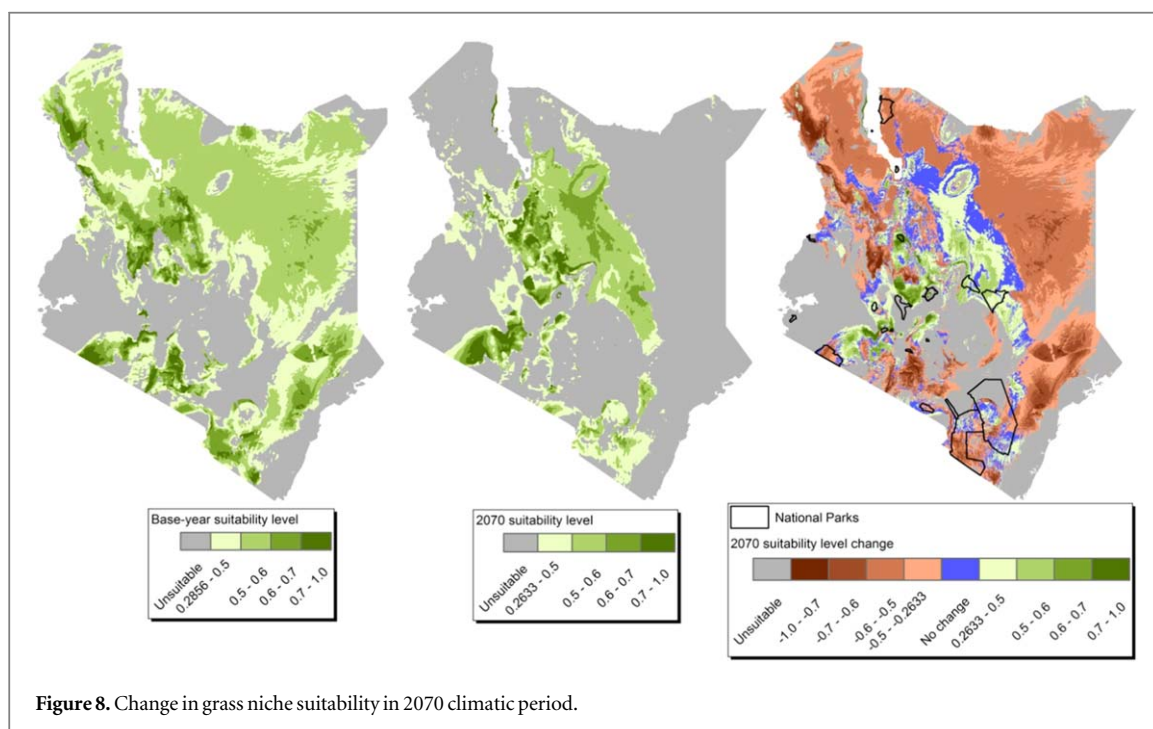


an increase in grass niche suitability though in a scattered pattern. Further, some regions will not experience any changes and are spread all over the country.

The specific 2050 grass niche suitability changes (table 5) are presented per suitability category comprising unsuitable, no change, increased and decreased ranging from values of -1 – 1 . The spatial coverage and areas

Table 5. The grass niche suitability and area changes in the 2050 and 2070 climatic periods.

Suitability category	2050		2070	
	Area (km ²)	% Area	Area (km ²)	% Area
Unsuitable	150,560	25.76	163,587	27.99
Declining	269,110	46.04	285,044	48.77
No change	61,762	10.57	51,893	8.88
Increasing	103,003	17.62	83,910	14.36



change analysis was based on the area classified as suitable in the base-year climatic period. A total of 150,560 km² (25.76%) of Kenya was classified unsuitable for grass niche with an area of 269,110 km² (46.06%) indicating a decline of grass niche suitability level. The no change category covered 61,762 km² (10.75%) while a combined total area of 103,003 km² (17.62%) pointed towards an increase in grass niche suitability.

3.4. The 2070 climatic period modelled projected potential grass niche range

The 2070 climatic period projected potential grass niche distribution modelling was done at AEZ levels and aggregated for the whole country. The suitable grass niche area in this climatic period is projected to shrink and restricted to the north, central, eastern, southern and some pockets of coastal region of the country. The Maxent output of grass niche suitability levels (table 4) summarises the areas and percent changes compared to the base-year climatic period. The combined suitable areas cover 171,930 km² (29.42%) with the rest of the country being unsuitable for the grass and covering an area of 412,505 km² (70.58%).

The suitable grass niche categories were further grouped into four with excellent and high suitability categories covering 12,779 km² (2.19%) and 28,457 km² (4.87%) respectively. The other categories were medium category occupying 66,674 km² (11.41%) and low category covering 64,020 km² (10.95%). The grass niche suitability change analysis in the 2070 climatic period compared to the base-year climatic period was also done. It revealed that some regions will favour while others will limit the growth of grass. Some areas will not change with others becoming unsuitable. The grass niche suitability spatial change in the 2070 climatic period shows the location, nature and magnitude of change (figure 8). These changes ranged from -1 to 1 and were scaled from $0-0.2633$, $0.2633-0.5$, $0.5-0.6$, $0.6-0.7$, and $0.7-1.0$ in the positive and negative direction (table 4). The national parks under threat from declining grass niche suitability are Sibiloi, Maasai Mara, Tsavo East and West, Amboseli and Chulu. The negative changes were in northern, north eastern, coastal and southern parts of the country. The central region of the country registered an increase in grass niche suitability though in patches while some areas did not show any changes.

Table 6. AUC results from the Maxent models.

AEZ	Base-year		2050		2070	
	AUC	SD	AUC	SD	AUC	SD
IV	0.962	0.037	0.963	0.018	0.973	0.018
V	0.942	0.001	0.942	0.001	0.942	0.001
VI	0.886	0.003	0.886	0.003	0.886	0.003
VII	0.754	0.001	0.754	0.001	0.754	0.001

Particular changes in the 2070 climatic period modelled results (table 5) revealed variations in both location and coverage of suitability categories in comparison to the base-year climatic period. The variabilities in the spatial coverage and areas were based on the total area classified as suitable in the base-year climatic period. The area that had an increased suitable grass niche covered 14.36% (83,910 km²) with the area indicating declining grass niche suitability covering 285,045 km² (48.77%). The no change category occupied an area of 51,893 km² (8.88%). The changes in grass niche suitability levels and spatial coverage was also concluded by Sala *et al* (2005) in their study on biodiversity across projected scenarios. Projections to 2020 and 2050 based on 1970 statuses found that the biomes with the higher rates of habitat and local species diversity losses are warm mixed forests, savannas, scrub, tropical forests, and tropical woodlands. Briske (2017) pointed out that consequences of climate change relevant to rangelands are modification of forage quantity and quality, livestock metabolism, and plant community composition. Further, trend analysis evaluation from 1961–1990 indicated substantial spatial differences in the direction and magnitude for both rainfall and simulated forage production across Australian rangelands McKeon *et al* (2009).

3.5. Modelled potential grass niche suitability similarity analysis

The applied Categorical Kappa method revealed different Kappa Location (K_{Loc}) and Kappa Histogram (K_{Histo}) similarities between the base-year and the future levels of grass niche suitability. The comparison between the base-year and 2050 suitability levels returned K_{Loc} of 0.233 and 0.536 for K_{Histo} . This implies that location similarity of the grass niche categories were 23.3% and 53.6% in quantitative (area) similarity aspects.

The modelled grass niche suitability apart from shifting location by 76.7% also experienced change in area of 46.4% in the 2050 climatic period. The base-year and 2070 comparison statistic indicated that the K_{Loc} similarity was 0.222 with a K_{Histo} of 0.440. This denotes that the grass niche location similarities were 22.2% while quantitative (area) similarity was 44.0%. These kappa statistics can also be interpreted as that the grass niche suitability levels shifted by 77.8% and 66.0% quantitatively (area). For the purpose of judging the kappa values obtained, Altman (1991) proposed a benchmark scale of five categories ranging from poor to very good. The classes are 0–0.2—‘Poor’, 0.21–0.40 denotes ‘Fair’ and 0.41–0.60 stands for ‘Moderate’. The other scales are ‘Good’ and ‘Very Good’ represented by 0.61–0.80 and 0.81–1.00 respectively. Using this scale, it was therefore concluded that in both future climatic periods, the K_{Loc} and K_{Histo} the grass niche suitability levels falls under categories of ‘Fair’ and ‘Moderate’ similarities respectively. This projected variability in grass niche suitability concluded a spatial and quantitative change and will affect both livestock and wildlife.

3.6. Model performance

Several climate change impacts research on organism’s niche have been conducted in different regions using Maxent under different climate change scenarios (Rebelo and Jones 2010, Yates *et al* 2010, Elith *et al* 2011, Kigen *et al* 2014). While it is possible to assess the base-year modelled grass niche accuracy, Phillips *et al* (2006) pointed that a major weakness of Maxent is lack of actual data for validation to assess model accuracy. Thus, the Maxent future projections have some level of uncertainty.

The Maxent model performance was derived from AUC (area under receiver-operator curve) and gives the probability that the model correctly ranks random presence site versus random absence site (Pontius and Schneider 2001, Phillips *et al* 2009). The AUC has a range of 0–1 with a minimum threshold of 0.5 (randomness) and a maximum of 1.0 (perfect simulation) Rebelo and Jones (2010). The model performances were all significant (table 6) for all the models. In the base-year, the highest average test AUC for the replicate runs was 0.962 with standard deviation of 0.037 in AEZ IV and the least was 0.754 with standard deviation of 0.001 in AEZ VII. The future climatic periods Maxent models performance and were all significant (table 6).

The AEZ IV in 2070 had the highest AUC of 0.973 and standard deviation of 0.018. The AEZ VII in both climatic periods had identical AUC and standard deviation of 0.754 and 0.001 respectively. Limited guidelines are available for judgement of the Maxent model receiver operating characteristic (ROC) values. However, Pontius and Schneider (2001) stated that any value of AUC more than 0.50 is statistically better than random while a value of 0.7 is considered acceptable for land use land cover modelling. Further, Hosmer and Lemeshow

(2000) classified AUC values beyond 0.8 as excellent and more than 0.9 as outstanding. Using these guidelines, the generated Maxent models for AEZs IV and V were outstanding, AEZ VI excellent and AEZ VII acceptable for all climatic periods.

4. Conclusion

Kenya will experience both increase and decrease in climate-based grass niche suitability in different locations with a general net decrease. Further, the 2050 climatic period will decrease grass niche suitability by 44.99% while the unsuitable will increase by 87.01%. Further, the grass niche suitability levels locations will change by 76.7% and 46.4% in areas under the different categories used. In the 2070 climatic period grass niche suitability will shrink by 55.21% with an increase of the unsuitable category by 106.80%. Moreover, the location suitability levels will shift by 77.8% while the areas under the different categories will change by 66.0%.

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