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Climate change impacts on the availability of anti-malarial plants in Kenya

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ABSTRACT

In many rural East African areas, anti-malarial plants are commonly used as first-line treatment against malaria. However, spatially explicit information about the future availability of anti-malarial plant species and its relation to future suitable habitat for malaria vectors is limited. In this study we (1) model the distribution of anti-malarial plant and malaria vector species and assess the drivers of their distributions taking the example of the Samburu dryland in Kenya, (2) map the modeled overlap in this area, (3) assess the impact of future climate change on anti-malarial plant and malaria vector species and (4) report their future overlaps. Our results show that mean temperature of warmest quarter, precipitation of wettest quarter and mean temperature of coldest quarter were the most important environmental variables that affected the distribution of anti-malarial species. The effects of climate change will vary, with some areas characterized by huge losses in anti-malarial species habitat while others gained or remained stable under both SSP2-4.5 and SSP5-8.5 climate change scenarios by 2050s and 2070s. According to most of our scenarios, more than half of the anti-malarial species will become vulnerable or threatened by 2050s and 2070s. A comparison between distribution patterns of future anti-malarial species richness and malaria vector species suitable habitat suggests that the former will decrease considerably while the later will increase. Because the availability of anti-malarial species will decrease in the areas affected by malaria vectors, geographically targeted conservation strategies and further control measures against malaria vectors are all the more important.

1. Introduction

A world free of malaria is a common vision for the health community worldwide [1]. In 2015, the World Health Organization developed the Global Technical Strategy for malaria, which announced the target of lowering global malaria incidences by at least 90% by 2030 [2]. Earlier initiatives such as the Roll Back Malaria program [3] and Bill and Melinda Gates Malaria Foundation [4] also seek to eradicate the disease. Backed by these initiatives, many countries developed their own malaria control programs which resulted in only a slight decrease in malaria infections [5], due in part to the spread of drug-resistant malaria strains and declining efficacy of the cheapest and most widely used anti-malarial drugs [3]. Therefore, innovative strategies to fight the disease need to be urgently formulated [6]. With the growing unavailability of conventional anti-malarial drugs and the discovery that combining anti-malarial drugs with anti-malarial plant species lowers the treatment failure risk [7], many traditional healers; even medical practitioners prescribe the use of anti-malarial species to treat malaria [8]. Apart from the direct use of the wild anti-malarial species, they also provide a broad reservoir upon which potential conventional anti-malarial drugs can be developed [9]. Consequently, their conservation could benefit populations that rely on them and guide the discovery of new generation conventional anti-malarial drugs [8].

In Kenya, around 80% of the population (especially rural communities) still rely on anti-malarial plant species to fight malaria [10]. This has been attributed to cultural acceptability of traditional anti-malarial herbs, inaccessibility of modern healthcare centers and high cost of conventional anti-malarial drugs [8,11]. Plant species in Kenya used for malaria control are either orally consumed [11] or used as mosquito repellents [12]. Communities in the country use different plant parts from *Ajuga remota, Harrisonia abyssinica, Carissa edulis* and *Azadirachta indica* to treat malaria [10,11]. Screening of the pharmacological action of some of the plant parts of these species found that the root back extracts of *Harrisonia abyssinica* [13], *Carissa edulis* [14], and whole herb of

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Ajuga remota [15] are highly effective in malaria treatment because they have high *in vitro* antiplasmodial activity. However, leaves of *Azadirachta indica* are less effective due to their low *in vitro* antiplasmodial property based on studies carried out by Kirira et al. [13]. Consequently, different anti-malarial species are prescribed for malaria treatment depending on the severity of the illness, with the dosage varying depending on the age of the patient [11]. Some anti-malarial species such as *Azadirachta indica* and *Caesalpinia volkensii* are singly consumed to treat malaria [15]. However, others like *Ajuga remota* [15] and *Cassia didymobotrya* [16] are used in combination with other anti-malarial species; probably to mask their bitter taste [15] or due to the synergistic effect of many compounds that make them only fully active when administered in combinations [17]. Whereas most anti-malarial species are consumed, a few are used as mosquito repellents [11]. For instance, smoke from burnt leaves of *Corymbia citriodora* is highly effective in keeping away mosquitoes [12]. Apart from their use in malaria control, most anti-malarial species are also used in the management of other diseases [11]. In spite of these promising prospects for anti-malarial species in Kenya, overexploitation for medicinal use, trade, and deforestation continue to pose a threat to their population [8].

Because of the importance of anti-malarial species, knowledge on their spatial distribution is crucial. For most anti-malarial plant species, however, there is insufficient information on their distribution [9]. A crucial starting point for the future monitoring and conservation of these species would be to improve knowledge about their ecological requirements and future distribution. This may help conservationists to identify conservation priority areas [18] or suitable areas for cultivation [19]. Consensus has been reached among conservationists that protected areas enhance *in situ* conservation of plant biodiversity [20]. Therefore, one approach to *in situ* conservation of the anti-malarial plant species could be based on planning of the "best" locations of protected areas, depending on a regions distribution of the species, shifts in the species distribution under changing climate and other disturbance factors [18]. However, anti-malarial species distribution maps considering the location of protected areas or their effectiveness in conserving anti-malarial species are still unavailable [18], even in resource limited African countries where malaria is among the leading causes of death.

With limited resources to combat this disease, policy makers must target and time preventive interventions appropriately to maximize their effectiveness [1]. This requires accurate identification of regions that are most vulnerable to malaria and timely delivery of interventions to mitigate and prevent the disease in these regions [21], but most models lack accurate identification of malaria vulnerability areas. Malaria is caused by the spread of the *Plasmodium* parasite to people through bites of infected *Anopheles* mosquitoes. The potential threat of malaria distribution can be assessed by predicting the distribution of malaria vectors [6]. Earlier studies modelled malaria vectors distribution at regional scale (e.g., West Africa; [22]) or national level (e.g. Kenya; [5]). Worrisomely, recent malaria vectors distribution maps depict their spatial expansion [23]. This fact presents an evolving and fresh threat for malaria control initiatives. Despite this threat, health organizations continue to rely merely on national and regional malaria distribution maps to target anti-malarial resources [6]. Such malaria risk maps are of limited practical use for guiding intervention efforts since they do not consider the local overlap between malaria vectors and anti-malarial plant species distributions, which is critical in directing the malaria control and anti-malarial species conservation measures appropriately.

To design future malarial control and anti-malarial species conservation measures, knowledge on the impact of climate change is crucial. With unprecedented rate of climate warming due to human activities, climate change has already reshaped species distributions, including malaria vectors and their associated parasites [5]. This has raised great concern about the potential availability of anti-malarial plant species [8] and the ramifications of changing climate on future malaria risk [24]. Drylands as water-limited environments are considered to be most prone to the effects of climate change [25]. Global drylands have experienced warming at the rate of 0.06 °C/year, as compared to the global warming rate of 0.03 °C/year in the past two decades [25]. Consequently, dryland species have shifted their geographical ranges or become extinct [26]. Previous studies documented possible shifts and extinction of medicinal plants [26], and re-distribution of malaria vectors [5] due to climate warming in African drylands. However, spatially explicit information about the future availability of anti-malarial species and its relation to future suitable habitat for malaria vectors is needed for targeted conservation and management actions. Because this information is largely missing [9], this paper aims at providing it.

In this study, to improve the knowledge base for planning of anti-malarial plants recovery programs and malaria control actions, we address the following key questions: (1) What is the geographic distribution of anti-malarial plant species and malaria vector species and what are the main drivers of their distributions? (2) What is the modeled overlap? (3) What is the impact of climate change on anti-malarial plant species and on malaria vector species? (4) What is their future overlap in the Samburu dryland, Kenya? We selected Samburu dryland in Kenya as our study area as it has a high malaria burden [5]. Although the region is a stronghold for anti-malarial plants [27] and has been the focus of medicinal plants research in the past few decades [28], there is still an apparent lack of information regarding the distribution of both anti-malarial species and malaria vectors. This has hindered malaria control initiatives and efforts to conserve anti-malarial species.

2. Materials and methods

2.1. Study area

Samburu County extends over a 20,183 km^2 area of the Rift Valley from approximately 0.5 °N to 3 °N and 36.3 °E to 38.1 °W (Fig. 1). In 2019, the region was home to 310,327 people, with a density of 11 people/km^2 [29]. It has an arid and semi-arid climate and receives an annual rainfall of 694 mm which is clearly delineated bimodally from October to November (short rain) and March to April (long rain) (Fig. 2). The dry season extends from December to March and June to September. The region experiences a mean annual temperature of 22.6 °C which varies spatiotemporally depending on elevation. Elevation of the area ranges from 339 to 2795 m a.s.l. The county's vegetation is characterized by shrubs, forests, wooded grassland and savanna [27]. The distribution of these vegetation types follows variations in altitude, geological and climatic conditions. The area has two protected areas: Maralal Sanctuary and Samburu National Reserve.

2.2. Occurrence data

Distribution records for all anti-malarial plant species used by the locals in Samburu County were collected from Global Biodiversity Information Facility [32], and supplemented with records from the East Africa Herbarium (EA) and our field survey data. During our field survey, we visited 90 sites selected by random stratified sampling based on soil type [33], protected area status [34] and land cover type [35], and recorded all anti-malarial plant species in 80 × 80 m plots (Appendix I). Stratification was based on land cover and soil type because they are thought to affect plant distribution in Samburu [36], which would help to cover the full environmental space that can be occupied by the anti-malarial species [37]. In addition, protected area status was used for stratification so as to capture sites inside and outside the protected areas [38].

The malaria vector species data were obtained from the MARA/AMRA database [39], Global Biodiversity Information Facility [32], contacts with local malariologists and recent scientific publications [5]. These data consisted of geographically referenced locations of the three main malaria vector species in Africa: *Anopheles arabiensis, Anopheles gambiae* and *Anopheles funestus* [24] surveyed from 1996 to 2017.

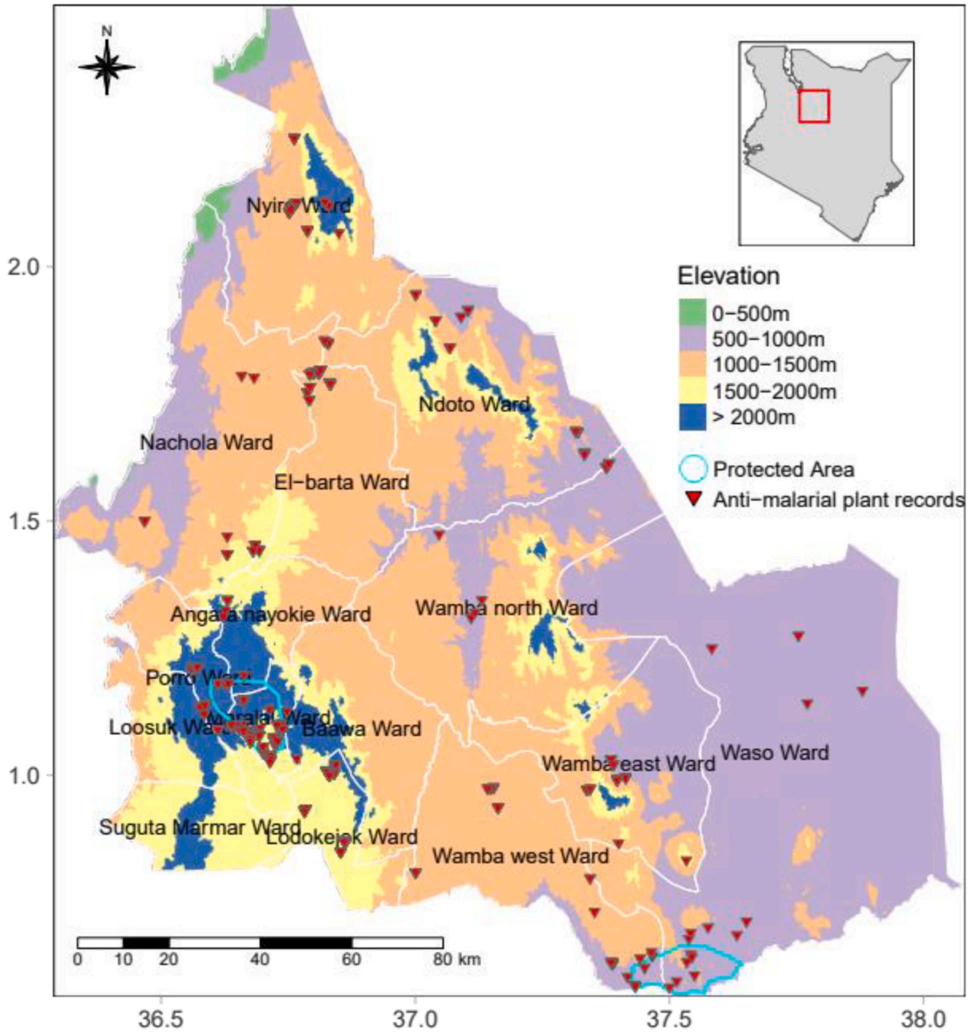

Fig. 1. Map of Kenya showing the location of our study area. Map of Samburu County showing the 15 administrative wards, elevation, protected areas and distribution records of all anti-malarial plants recorded during the field survey.

We removed duplicated or poorly georeferenced observations (i.e. those found in areas where plant species are not normally found such water bodies) before the analysis. To reduce spatial-autocorrelation in our occurrence records, we used the spThin package in the R language environment [40] to spatially thin each species' records to a distance of 3 km, which is a value bigger than the grid cell size of our variables [19]. Thereafter, only species with more than 30 occurrence records were considered to ensure accurate predictions [41]. We therefore ended up with 21 anti-malarial plant species and three malaria vector species.

2.3. Environmental variables

We used 19 bioclim variables from the WorldClim database version 2.1 (in 30 arc-second resolution) as candidate predictors (Table 1) ([42]; http://www.worldclim.org, accessed on 10th August 2022). This data layers are derived from monthly rainfall and temperature recordings from weather stations worldwide (1950–2000) and have proven to support informative models of plant and invertebrate distributions due to close association with growth and development [5,43]. In addition to the bioclim variables, we used Digital Elevation Model (DEM) downloaded from Shuttle Radar Topography Mission (SRTM) [44], sand, clay and soil pH data downloaded from the Google Earth Engine (GEE; [45]) platform for modeling the anti-malarial species. We also supplemented the bioclim variables with gridded human density population data [46], Digital Elevation Model (DEM) [44] and NDVI calculated from sentinel 2 image acquired from Google Earth Engine (GEE; [45]) for modeling malaria vector species. All predictors with coarse resolution were resampled to bioclim variables to harmonize them with the bioclimatic variables.

We downloaded the climate change data from worldclim version 2.1 (http://www.worldclim.org) at 30 arc-second resolution [42]. The future climate data were based on the Coupled Model Intercomparison Project Phase 6 (CMIP6; [47]), which has models that tend to be highly sensitive to climate [47]. We selected two Shared Socioeconomic Pathways (SSPs): SSP5–8.5 and SSP2–4.5 for 2050s (2050 averaged over a 20 year period) and 2070s (2070 averaged over a 20 year period). SSP2–4.5 represents an optimistic climate scenario of mitigation and adaptation, characterized by moderate population growth and insignificant changes of socioeconomic and technological trends from the historical patterns. On the other hand, SSP5–8.5 represents a pessimistic scenario of many challenges for mitigation and few challenges for adaptation, characterized by high exploitation of fossil fuels and emission of GHGs (see [48] for detailed explanation). These two scenarios were adopted to assess the impacts of climate change on species under both extreme and optimistic climate change scenarios. To reduce the uncertainty of reliance on a single Global Climate Model (GCM), we used an ensemble of various GCMs. For the two SSP scenarios, we used a mean ensemble of five CMIP6 models: ACCESS-CM2, BCC-CSM2-MR, HadGEM3-GC31-LL, CNRM-CM6–1 and MIROC6. The models have been widely used to examine the impact of climate change on African species

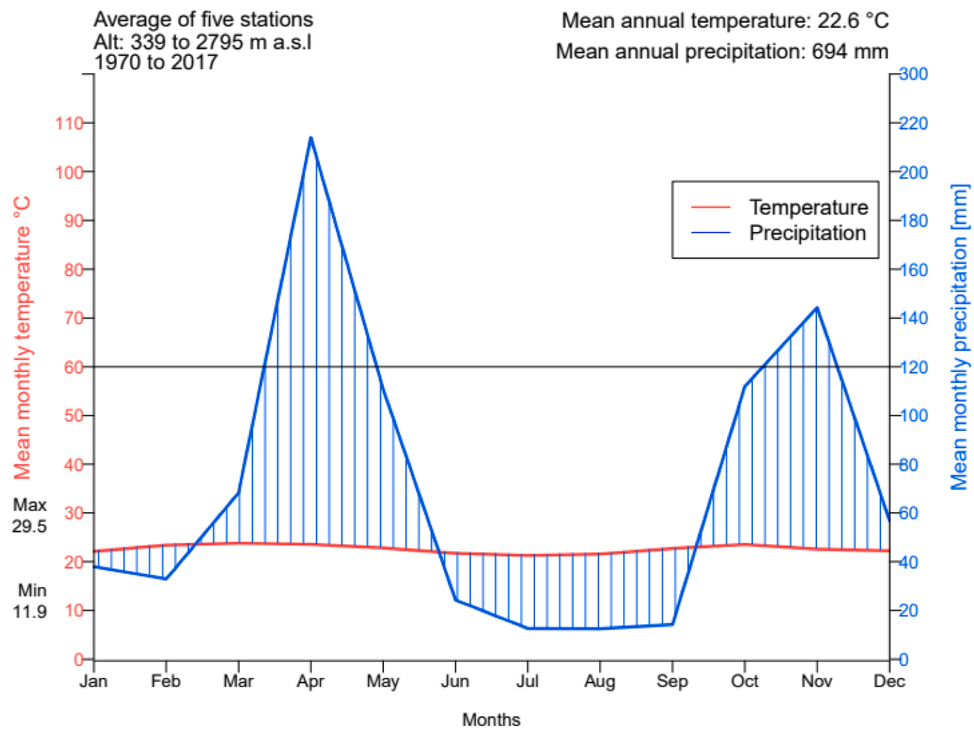

Fig. 2. Climate diagram of Samburu County according to Walter and Lieth [30], based on Climatic Research Unit Gridded Time Series data [31]. The blue shaded-area that overcuts the red line indicates the rainy season while the blue-shaded area that undercuts the red line indicates the dry season.

[49], and have indicated better performance.

2.4. Statistical analysis

SDMs are well-established tools in predicting species' spatial occurrence, habitat suitability and geographical distribution [49]. To date, SDM have been widely applied in ecology including: predicting areas for re-introduction of threatened species [43] and identification of suitable habitats [9]. They correlate occurrence data (presence or presence/absence data) to the prevailing environmental conditions to estimate the relative suitability of a given habitat, thereby providing a prediction of the species' potential distribution. However, occurrence records of many species are often few and spatially clustered, which makes it difficult to model their suitable habitat since such data give limited information for determining the association between the species and their environment. In such cases, MaxEnt models are an interesting option because they have been demonstrated to work well with few presence records [9], tend to have high predictive power and relies on background points to contrast observed occurrences [50]. MaxEnt estimates a species probability distribution (interpreted as a relative index of habitat suitability) by finding probability distribution of maximum entropy, subject to a set of environmental constraints [50]. MaxEnt modeling has been extensively used in the field of conservation i.e. to predict the distribution of medicinal plants [18].

2.4.1. Variable reduction

For each species, bioclim variables 8,9,18 and 19 were excluded because they have spatial artifacts which generate abrupt differences between neighboring pixels [51]. Next, from the remaining candidate variables, we calculated the Pearson correlation coefficient and removed variables with correlation $r \geq \pm 0.7$ to avoid redundancy within the variables which may affect prediction accuracy [43]. The variable with the greatest ecological relevance (based on our knowledge and literature analysis) was retained among the correlated variables.

2.4.2. MaxEnt model optimization, calibration and validation

The potential distribution of each species was predicted using the MaxEnt algorithm [50] available within the dismo R package version 1.3–8 [52]. MaxEnt model has two fundamental modifiable parameters: (1) Regularization Multiplier (RM) and (2) FC (Feature Class). Besides, the model has five FC, namely, hinge (H), linear (L), quadratic (Q), product (P) and threshold (T) [50]. MaxEnt's default parameters are FC = LQHPT and RM=1 [50]. In our case, the two parameters of RM and FC were adjusted by the *ENMeval* R package of Muscarella et al. [53]. To optimize the model, we increased the RM from the default value of 1, with selected range from 0.5 to 4, by 0.5 each time, resulting in 8 RM parameters [19] and used six feature combinations, namely, L, H, LQ, LQH, LQHP and LQHPT [53]. The occurrence record of each species (in Africa) was sub-divided into 4 equal groups by the *ENMeval* package using the block technique, of which three groups were used for training and the remaining one was used for testing [53]. We then used the *ENMeval* package to assess the 48 (6 FC × 8 RM) aforementioned parameter combinations. Here, we assessed two performance statistics to select the optimal model parameters. First, we selected the parameter combinations of models which had the lowest average omission rate based on the 10% training presence omission rate (OR10) [54]. In cases where multiple models had the same OR10, we chose the model with the highest average validation AUC [54].

We imported the distribution records of our species into MaxEnt. Each species model was trained using occurrence records all over Africa to take account of conditions that are currently not encountered in our study area. 80% of the occurrence data was used to calibrate models while 20% was used for validation. The selected parameter combination of FC and RM was used in model fitting. To ensure that both the background points and occurrence records had the same geographical bias, we created a bias file for use in MaxEnt modeling [55]. For each species, we stacked the selected variables and used the raster stack to rasterize the occurrence records to estimate a two-dimensional kernel density [56]. In the MaxEnt model, 10,000 background points (across Africa) which also captures the full extent of accessible environmental conditions were used. During modeling, we used the cross-validation method

Table 1
Table of variables with those used in modeling highlighted in gray.

Variable	Description	Resolution	Unit
Bio1	Annual Mean Temperature	30 arc s	Degrees Celsius
Bio2	Mean Diurnal Range (Mean of monthly (max temp- min temp))	30 arc s	Degrees Celsius
Bio3	Isothermality (BIO2/BIO7) (* 100)	30 arc s	Percentage
Bio4	Temperature Seasonality (standard deviation *100)	30 arc s	Degrees Celsius
Bio5	Max Temperature of Warmest Month	30 arc s	Degrees Celsius
Bio6	Min Temperature of Coldest Month	30 arc s	Degrees Celsius
Bio7	Temperature Annual Range (BIO5-BIO6)	30 arc s	Degrees Celsius
Bio8	Mean Temperature of Wettest Quarter	30 arc s	Degrees Celsius
Bio9	Mean Temperature of Driest Quarter	30 arc s	Degrees Celsius
Bio10	Mean Temperature of Warmest Quarter	30 arc s	Degrees Celsius
Bio11	Mean Temperature of Coldest Quarter	30 arc s	Degrees Celsius
Bio12	Annual Precipitation	30 arc s	Millimeters
Bio13	Precipitation of Wettest Month	30 arc s	Millimeters
Bio14	Precipitation of Driest Month	30 arc s	Millimeters
Bio15	Precipitation Seasonality (Coefficient of Variation)	30 arc s	Percentage
Bio16	Precipitation of Wettest Quarter	30 arc s	Millimeters
Bio17	Precipitation of Driest Quarter	30 arc s	Millimeters
Bio18	Precipitation of Warmest Quarter	30 arc s	Millimeters
Bio19	Precipitation of Coldest Quarter	30 arc s	Millimeters
Sand	Proportion of sand in the soil	250m	Kilogram/ Kilogram
Clay	Proportion of clay in the soil	250m	Kilogram/ Kilogram
Soil pH	Proportion of pH in the soil water	250m	Kilogram/ Kilogram
NDVI	Normalized Difference Vegetation Index	10 m	Nil
Human Population	Human population as pixel density	30 arc s	~ 1km
DEM	Digital Elevation Model	30 arc s	Meters

with 5 repeats and averaged the results. The MaxEnt output format was set as logistic and the number of iterations was increased to 3000 to enable the model to have enough time to converge, thereby preventing over-prediction or under-prediction [57]. We also used the “fade-by--clamping option” to avoid extrapolations that are outside the environmental range of the species [50]. Additionally, the Jackknife importance and the response curves of the model variables were developed. Moran’s I was used to test for spatial auto-correlation in models residuals with the ’spatstat’ package [58] in program R. The models were later transferred to Samburu County under present and future scenarios.

We evaluated the model performance using three different approaches, based on the testing dataset. First, we used the adapted Area Under the Receiving Operator Curve (ROC) according to Phillips et al. [50]. Second, we calculated the True Skill Statistics (TSS), as a threshold dependent measure. TSS compares the difference between the number of correct predictions and those that are attributed to random guesswork, to that of the hypothetical perfect predictions [59]. We used TSS because it considers both commission and omission, is independent of occurrence prevalence and is not affected by the validation dataset size [59]. Third, we used the Kappa statistic with binary maps since it considers both commission and omission errors, resulting in a less biased predictability measure [60]. TSS and Kappa values range from -1 to $+1$, where values of zero or less are considered as performance no better than random while values close to 1 (TSS$>$0.3) indicate a good predictive power [59].

2.4.4. *Variables contribution, current and future distribution areas for anti-malarial plant and malaria vector species*

We determined the factors affecting the distribution of the under-study species using the scores of the jackknife of test gain [50]. This test excludes one environmental variable each time when running the model and subsequently shows the variables which reduced model test AUC most when omitted and how much unique information each variable provides [60]. Those environmental variables are presumed to be the most important in explaining the distribution of the species [60]. We then ranked the environmental variables for each species in terms of their order of importance and identified the most dominant environmental variables across all the species considering their ranking [61]. The response curve of each species was further examined to explain the effect of each environmental variable on species suitable habitat. For generating binary range maps for each species under current and future climate scenarios, we used the maximum sensitivity plus specificity threshold. This threshold maximizes sensitivity (true positive rate) and specificity (true negative rate) [62] and proved to outperform other thresholds because it is sensitive to the selection of pseudo-absences and optimizes discrimination within the presence-absence records [63]. The final anti-malarial species richness maps for current and future scenarios were generated by combining the binary maps of the 21 species and counting the total number of species in each pixel [18]. To generate the final malaria vector species distribution map under current and future scenarios, we selected the pixels which had species presences in any of the three malaria vector species binary maps [21].

For present and future climate scenarios, we created a 9-km buffer zone around each protected area and assessed the pixels that lay within each buffer zone and inside the protected areas [18]. The 9 km distance was a trade-off between a large value (to ensure that as many pixels lay within each protected area) and a small value (to ensure that the area outside the protected area is as similar as possible to that inside it) [20]. Thereafter, we calculated the mean species richness based on anti-malarial species count in each pixel within the buffer area (outside protected area) and within the protected areas (inside). Using the *t*-test, we compared the mean species richness values outside and inside the protected areas. Here, we sought to test whether Samburu’s protected areas are effective in conserving the region’s anti-malarial species [18].

2.4.6. *Current overlap between malaria vector species and anti-malarial species richness*

The current anti-malarial species richness and binary malaria vector maps were overlaid. We then identified the regions that had an overlap between malaria vectors and high (15–21), moderate (8–14) and low (1–7) anti-malarial species richness respectively.

2.4.7. *Impact of climate change on anti-malarial species*

The potential impact of climate change on anti-malarial species in Samburu was analysed applying species richness, gain and loss of species, turnover rate and threat level based on the IUCN Red List [64]. We calculated the loss of climatically suitable habitat, gain in suitable habitat and turnover rate using methods by Thuiller et al. [65]. Gain was measured when the species was present in future binary prediction but absent in the current binary prediction. Loss was calculated based on the species being absent in future binary prediction but present in the current binary prediction. Loss has a negative value, gain has a positive value, while stable has a value of 0.

Species turnover rate (change in species composition between the current and future) was calculated for each climate change scenario. Here, we used the formular $T = 100 \text{ x } (\mathrm{SL}+\mathrm{SG})/(\mathrm{SR}+\mathrm{SG})$, where SL is the number of species lost in each grid cell, SG is the number of species gained in each grid cell and SR is the current species richness [65]. The formular usually shows turnover as a percentage of species richness in each grid cell, but it was unsuitable in the study of anti-malarial plant species in some areas of Samburu since extremely high richness in some regions resulted in unreasonably large proportional turnover values

[20]. The turnover rate normally ranges from 0 to 100, where a value of 100 indicates complete change in species composition at a site, whereas a turnover value of 0 indicates that the composition would remain the same. Turnover rate was classified as follows: low (0–34), moderate (35–64) and high (>65).

For each anti-malarial species, we assessed the threat level under future scenarios by determining the proportional change in distribution under climate change scenarios. During this assessment, we used the IUCN Red List criterion A3 which considers a time frame of 50 years(c) [64]. The criterion uses projected species' geographic range loss as a proxy for population reduction to allocate a given threat category based on the following classes: Extinct (E) when species projected loss is 100%, Critically Endangered (CR) when projected loss is 80–100%, Endangered (EN) when projected loss is 50–80%, Vulnerable (VU) when projected loss is 30–50%, Near threatened (NT) when projected loss is <30 and Least Concern (LC) species has no predicted loss. The anti-malarial species considered as critically endangered or endangered (ie CR or EN) under the four climate change scenarios were classified as of highest conservation priority in future [61].

2.4.8. Future overlap between malaria vector species and anti-malarial species richness

We overlaid the future binary malaria vectors maps and future species richness maps and identified regions featuring overlaps between malaria vectors and high, moderate and low anti-malarial species richness, respectively.

3. Results

3.1. Model performance

The mean of AUC, TSS and Kappa for all models are given in appendix I and II. The worst model had an average AUC of 0.74, while the best model had an average AUC of 0.96. Maps resulting from the models are provided in appendix III, while the ROC curves are given in appendix IV and V. No significant spatial auto-correlation was found in the model residuals.

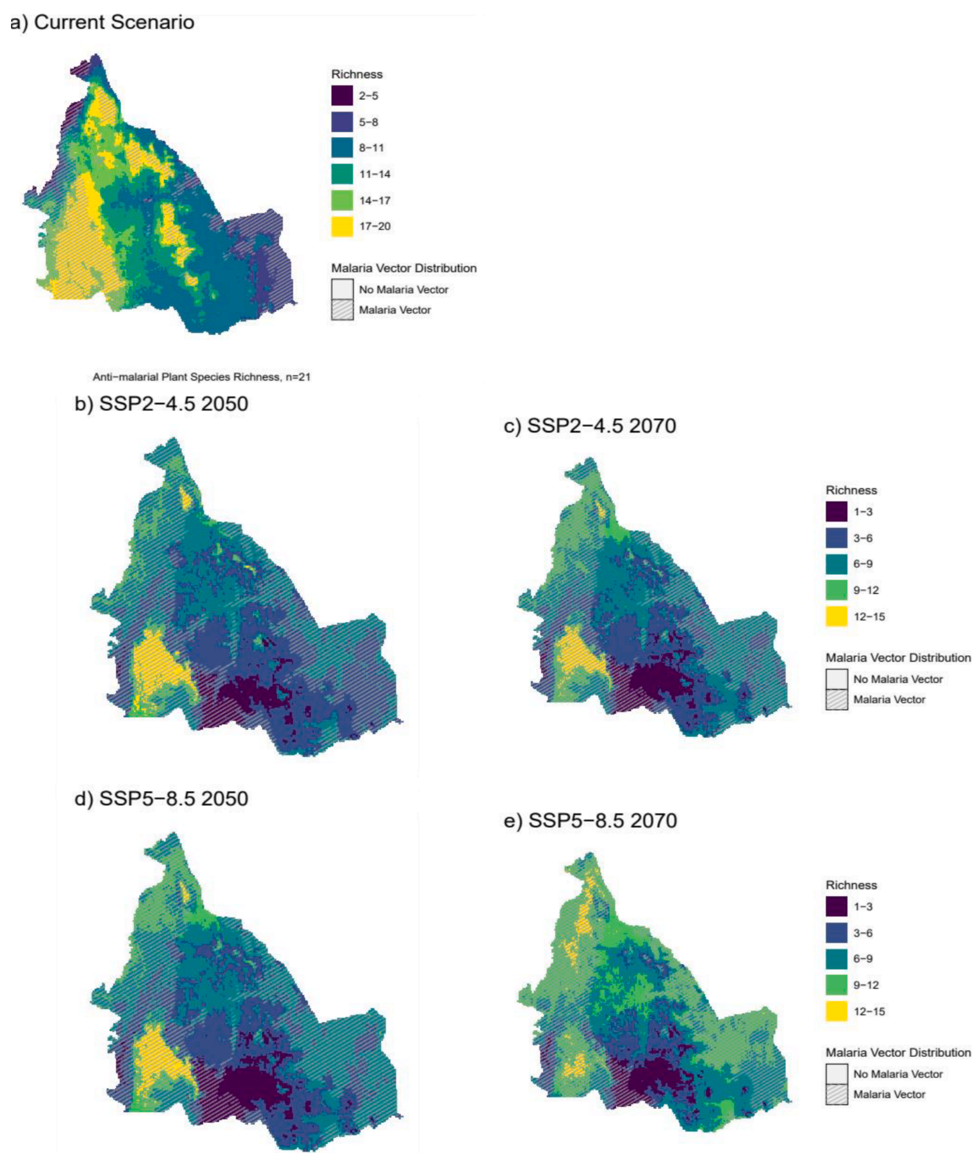

Fig. 3. Predicted malaria vectors suitable habitat and anti-malarial plant species richness under the current scenario and future climate scenarios. Results show that north western and south eastern regions currently have suitable malaria vectors habitat but the anti-malarial species richness in these regions is low. The overlap between malaria vectors suitable habitat and areas of low anti-malarial species richness will increase under future climate scenarios.

3.2. Environmental drivers of anti-malarial plant species distributions

Each anti-malarial species was influenced by a different combination of environmental variables (Appendix VI and VIII). Accordingly, the main variables shaping the distribution of anti-malarial species included bio10 (mean temperature of warmest quarter), bio16 (precipitation of wettest quarter), bio11 (mean temperature of coldest quarter) and elevation (Appendix VI and VIII). In contrast, sand and clay content were least influential variables. Highest anti-malarial species richness was predicted in areas with low mean temperature of warmest quarter, precipitation of wettest quarter, mean temperature during the coldest quarter and high elevation (see response curves; Appendix X). Anti-malarial species richness is predicted to range from a low of 2 species per 1 km^2 cell to a high of 20 species per cell (Fig. 3). The highest richness was predicted in the south-western region, pockets of north-eastern and central regions i.e. Loosuk and Nyiro wards, while the lowest was found in north west and south east. Besides, paired *t*-test showed that the mean species richness was significantly higher inside the protected areas than outside (Appendix XIV and XV).

3.3. Variables contribution and distribution areas of malaria vector species

Each malaria vector species was influenced by a different combination of variables (Appendix VII and IX). The key environmental variables affecting the distribution of malaria vectors were bio4 (temperature seasonality), elevation, population density and Bio13 (precipitation of wettest month, Appendix VII and IX). NDVI did not add any information for increasing the performance of the models. Highest malaria vectors distribution is predicted in areas with moderate temperature seasonality, low elevation, high population and moderate precipitation of wettest month (Appendix XIII). Currently, 37% of Samburu is prone to malaria due to high habitat suitability for malaria vectors (Fig. 3). However, most of the southern region and a few scattered pockets of the south eastern are predicted to have no suitable habitat for malaria vectors.

3.4. Current anti-malarial plant species richness and malaria vector species habitat

The predicted coincidence of malaria vectors suitable habitat and high anti-malarial species richness is located in the south-western, pockets of north-eastern and central regions i.e. Porro and Ndoto wards (Fig. 3). These regions were classified as 'low vulnerability' malaria areas. However, parts of the north western and south eastern regions are currently predicted to have suitable habitat for malaria vectors while anti-malarial species richness is low. These areas were classified as 'high vulnerability' malaria areas (e.g. Nyiro and Waso wards). Most of the southern region (i.e. Wamba west) is predicted to have moderate species richness and unsuitable habitat for malaria vectors, and were classified as 'monitored'. The current scenario shows decreased malaria vulnerability in low anti-malarial species richness areas and an increase in high richness areas (Fig. 4).

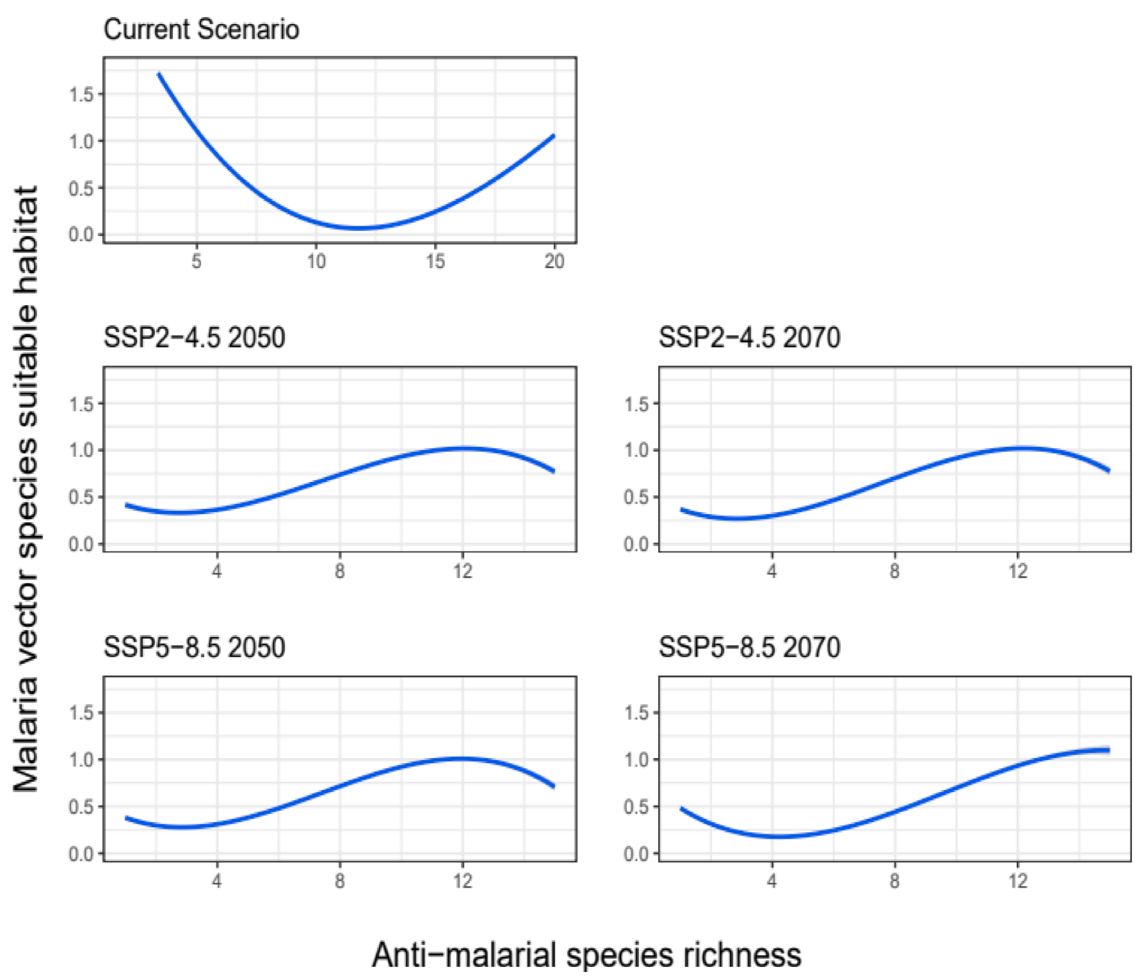

Fig. 4. Malaria vulnerability plot under the current and future climate change scenarios.

3.5. Impact of climate change on anti-malarial plants

The overall patterns of loss, gain and stable areas are similar in Samburu. For all climate change scenarios, two regions of high anti-malarial species loss were noticeable (Figs. 5, 6). The first is situated in the anti-malarial species-poor area in the north west (Nyiro ward), which showed very high anti-malarial species losses (4–7 species for SSP2–4.5 for 2050s and 2070s and 7–10 species for SSP5–8.5 for 2070s). The second was the south eastern region. The absolute numbers of anti-malarial species loss in this region were lower than for the north western region. Species loss is predicted to be greater in areas with high current mean temperature of warmest quarter and low precipitation of wettest quarter (Figs. 5, 6, appendix XII).

On the contrary, gains in anti-malarial species is predicted, with the south western region exhibiting the highest gain. The highest gain is predicted to occur in areas which may have more suitable habitat for the species in future. For all future scenarios, climate change would lead to stable numbers in parts of the south western, central and south eastern regions (Figs. 5, 6).

Under climate change scenarios, the turnover rate is expected to range from 14% to 76%, with all areas undergoing some changes in anti-malarial species composition (see Figs. 7 and 8). The highest change is expected in the south western and southern regions (i.e.Porro and Wamba east wards), which have low current temperature. Besides, high turnover rate in anti-malarial species-poor area will occur in the north west, including Nyiro ward.

Compared to the current scenario, mean anti-malarial species richness will decrease for future scenarios (appendix XVI). The richness is expected to range from a low of 1 species per 1 km^2 cell to a high of 15 species per cell (Fig. 3). Specifically, the southern western and north eastern regions will still have the highest anti-malarial species richness, although it would be fewer compared to the current. Parts of the south western region which currently have high anti-malarial species richness areas will have low richness in future (Fig. 3). These parts have high current temperature and low precipitation. The mean species richness was predicted to be significantly higher outside the protected area than inside, regardless of the climate change scenarios (Appendix XIV and XV).

Our application of the IUCN Red List criterion revealed that under all future scenarios, 14–24% of the species will be CR (Fig. 9). Species that will be CR under all scenarios include *Salvadora persica* and *Acacia xanthophloea* (Appendix XVIII). Besides, up to 29% of the species appeared EN by future climate change under SSP2–4.5 by 2050s. Between 33% and 43% of the species will suffer a loss of <30% and were classified as NT for SSP5–8.5 by 2050s and 2070s. Very few species were classified as VU under all climate change scenarios, while 14–19% of the species will be of LC under all scenarios i.e. *Harrisonia abyssinica* and *Euclea divinorum*.

3.6. Impact of climate change on malaria vector species distribution

Suitable habitat for malaria vectors is predicted to expand to most areas that are currently unsuitable and cover between 58 and 65% of Samburu (Fig. 3), as compared to the current 37%. These areas are mostly situated in the south eastern and southern regions, featuring low current temperature seasonality and high precipitation. Most areas in Samburu which currently have suitable habitat for malaria vectors are expected to remain habitable, while a few pockets of the southern eastern region are predicted to be converted from suitable habitat to unsuitable habitat.

3.7. Relating future anti-malarial species richness to malaria vector species distribution

Worrisomely, the overlap between suitable habitat for malaria vectors and areas with low anti-malarial species richness (high vulnerability malaria areas) will increase especially in areas with low current precipitation and temperature seasonality e.g. south east (Fig. 3). For the southern region, which currently has no suitable habitat for malaria vectors and moderate anti-malarial species richness, our predictions show that the area will have suitable habitat for malaria vectors and low anti-malarial species richness. Besides, the overlap between suitable habitat for malaria vectors and high anti-malarial species richness (low vulnerability malaria areas) is expected to shrink especially in areas with low current temperature i.e. south west. Generally, the future scenarios will witness increased malaria vulnerability in both areas of low and high richness (Fig. 4).

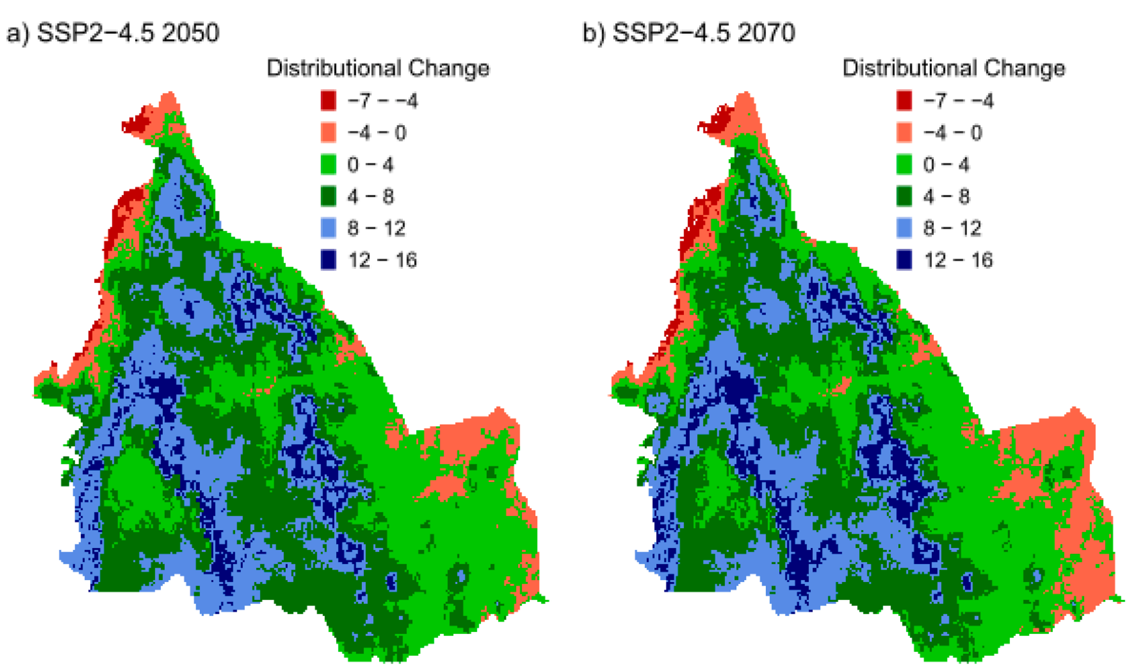

Fig. 5. Predicted distributional change of 21 anti-malarial species in Samburu under SSP2-4.5 2050s and SSP2-4.5 2070s.

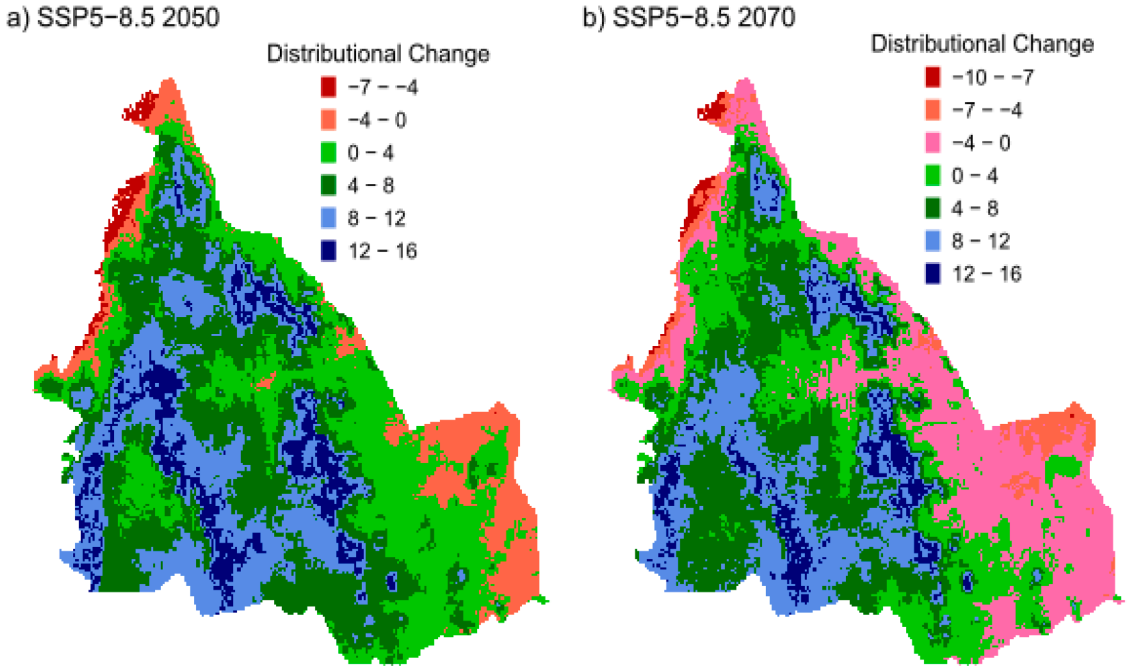

Fig. 6. Predicted distributional change of 21 anti-malarial species in Samburu under SSP5-8.5 2050s and SSP5-8.5 2070s.

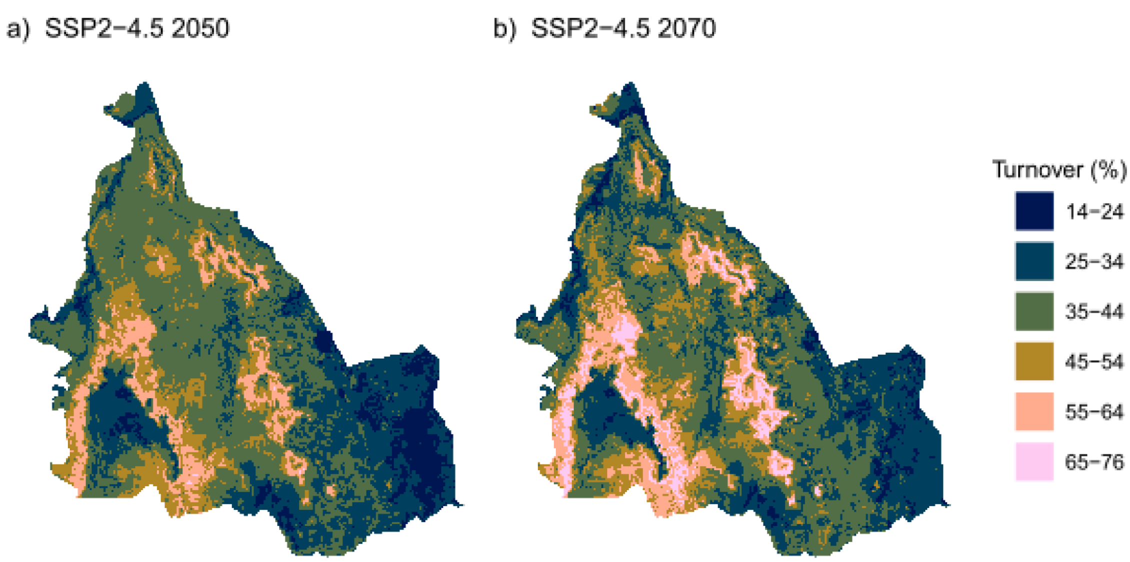

Fig. 7. Predicted anti-malarial species turnover rate in percentage under SSP2-4.5 2050s and SSP2-4.5 2070s.

4. Discussion

In the current study, the impact of climate change on anti-malarial plant and malaria vector species is explored. To our knowledge, this is the first study to have predicted the future distribution of both anti-malarial plant species and suitable habitat for malaria vector species, and their future overlap.

4.1. Numbers of anti-malarial plant species and their environmental drivers

The most important variables shaping the distribution of anti-malarial species were mean temperature of warmest quarter, precipitation of wettest quarter, mean temperature of coldest quarter and elevation. This makes ecological sense because precipitation and temperature influence many ecological processes like seedling growth, flowering and fruiting, and consequently change the composition of species in a community [66], thereby shaping anti-malarial species distribution. Importantly, [18] in Egypt and [67] in Brazil showed that mean temperature of the coldest month and elevation are the major drivers of medicinal plant species distribution in drylands. Therefore, it is not surprising that the two were also the driving forces behind the distribution of the anti-malarial species in Samburu dryland. However, some variables like sand and clay content were the least important for anti-malarial species distribution, even though [27] found otherwise.

Regions with high anti-malarial species richness are currently the high elevation and low temperature regions of Samburu i.e. southwest. Low temperatures ensure availability of soil water which leads to high anti-malarial species richness [67]. The elevation gradient influences temperature, radiation, precipitation and soil characteristics [7], which, in concert, drive anti-malarial species numbers. A positive effect of elevation on medicinal plant species in water-limited areas has been

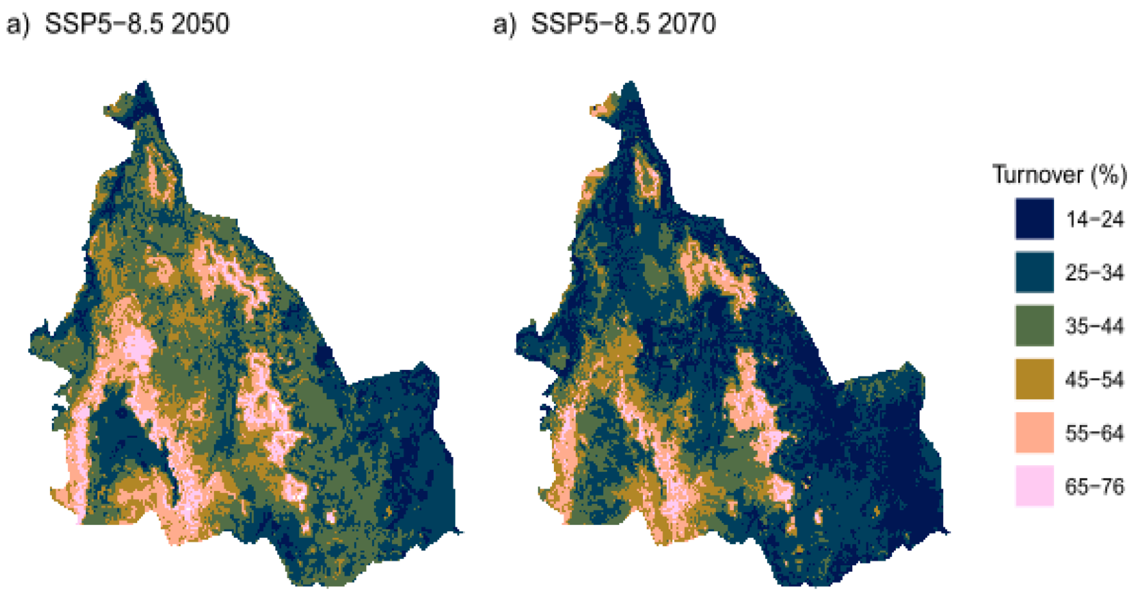

Fig. 8. Predicted anti-malarial species turnover rate in percentage under SSP5-8.5 2050s and SSP5-8.5 2070s.

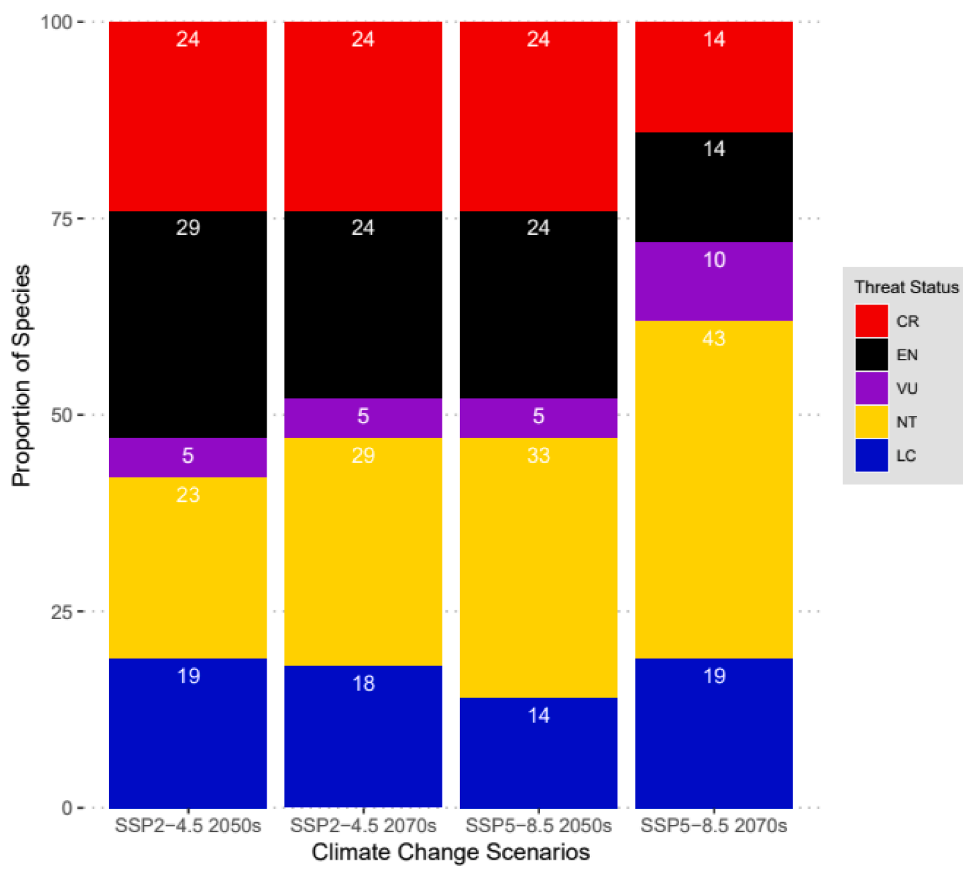

Fig. 9. Proportion of anti-malarial species threat level under different future climate scenarios.

previously found for Samburu by Gafna et al. [27] and this follows a general pattern in plant species richness in Kenya [66].

Protected areas are considered as beneficial for *in situ* conservation of medicinal plants by limiting ecosystem degradation [18]. It is apparent that the predicted anti-malarial species richness is currently significantly higher inside the protected areas than outside, as Kaky and Gilbert [18] found for medicinal plants in Egypt. Consequently, Samburu's protected areas are currently effective in conserving anti-malarial species and may be considered as possible areas for high priority anti-malarial species conservation. Many protected areas in the world are located in land of little value; which are not necessarily suited for biodiversity conservation [20]. Samburu's protected areas are rather new and seem to have been well chosen to support the area's biodiversity. Much could still be done because considerable human pressure presence was observed during fieldwork despite the laws regulating resource extraction, and the north eastern region which has many anti-malarial species is not covered by the protected areas. The region should be prioritized when extending existing protected areas.

4.2. Environmental drivers of malaria vectors and their distribution

The distribution of malaria vectors was influenced by temperature seasonality [68], elevation [21], population density [6] and precipitation of wettest month [69]. Mordecai et al. [70] demonstrated that temperature seasonality affects the life cycle of malaria vectors from egg to adult; and the rate of malaria vectors development increases at moderate temperature seasonality because it is ideal for them. It is likely that elevation shapes malaria vector species distribution due to its influence on temperature. Low temperature at high elevations reduces the development or occurrence of the species at high altitudes [21]. Our results showed that malaria vectors habitat suitability peaked in densely populated areas. This is justifiable because high human population ensures availability of blood feed for the vectors [1]. Consequently, suitable habitat for malaria vectors was found in south west and north west [5], characterized by current high population, moderate temperature seasonality and low elevation. NDVI did not add any information for the performance of malaria vectors models (in agreement with [6]), though it is thought to be a critical predictor of malaria vectors distribution [71]. NDVI is related to vegetation greenness, moisture availability and vegetation productivity, which are strongly associated with malaria vectors reproduction [6]. However, it is likely that NDVI was a poor predictor because most parts of Africa are arid with low values of NDVI [18]. Furthermore, healthy vegetation (i.e. with high NDVI) are found in high elevation areas that are very cold to permit malaria vectors occurrences, eroding NDVI's capacity to differentiate between unsuitable and suitable malaria vectors habitat [6].

Suitable habitat for malaria vectors is currently predicted in 37% of Samburu. However, care should be taken when interpreting these results, since the sheer suitability of a habitat for malaria vectors does not automatically translate into malaria incidences [24]. This is because human population and mosquitoes, which act as reservoirs for the *Plasmodium* parasites must be found in areas with suitable malaria vectors habitat for malaria incidences to be reported [24]. Additionally, other factors such as greater access to medical services, better water management and improved housing may limit malaria cases in an area [6], despite its habitat suitability.

Our malaria vectors models had some limitations. First, we did not incorporate other parameters which determine malaria vectors distribution i.e. land use, humidity, cattle hoof prints and floods. In our case, we used climatic variables, population density and elevation. Our use of these variables does not mean that we were unaware that they are just among the several variables that influence malaria vectors distribution [24]. Rather, we argue that, whereas the other unused variables are likely to influence malaria vectors distribution at a fine scale [6], climatic variables, population density and elevation are likely to determine their distribution at a large spatial scale [6]. Second, our models did not incorporate biotic interactions between malaria vector species and other species i.e. Fish [72]. Competition and predation between species may influence malaria vectors distribution [24]. Previous studies showed that malaria vectors avoid habitats which have competitors [73].

4.3. Assessing current malaria vulnerability

The overlap between suitable habitat for malaria vectors and areas of high anti-malarial species richness is found in south western, north eastern and central regions. The current malaria control actions are low in the southwest, and high in the northeast and central regions [23], while medicinal plant species conservation efforts are currently low in south west and central regions [27]. However, we recommend high prioritization of anti-malarial species conservation and malaria control measures in southwest and central regions, as this would ensure utilization of the limited malaria control and anti-malarial species conservation resources (i.e. *ex situ* and *in situ* conservation actions, insecticides spraying, distribution of mosquito nets/anti-malarial drugs). Worrisomely, the north west and south east have suitable habitat for malaria vectors and low anti-malarial species richness (high vulnerability malaria areas). Currently, these regions are under both low malaria control [23] and medicinal species conservation efforts [28]. We propose prioritization of malaria control in these regions, whereas anti-malarial species conservation efforts should remain low since the anti-malarial species richness is low either way. The southern region was predicted to have no suitable habitat for malaria vectors and moderate anti-malarial species richness. The region currently has high malaria control activities [23], while anti-malarial species conservation efforts are moderate [28]. We suggest that malaria control measures need to be revisited to low, whereas anti-malarial species conservation should remain moderate.

4.4. Distributional change in anti-malarial species

Increased temperatures and decreased precipitation due to climate change in Samburu will lead to loss, gain or no change in suitable anti-malarial species habitat. The loss will be greater in anti-malarial species-poor areas, currently featuring low precipitation and high temperature, as future condition in the areas will be unsuitable for anti-malarial species due to shifts in bioclimatic zones. Another plausible reason for the loss of anti-malarial species is that climate change will probably replace the cold adapted anti-malarial species with the warm adapted species [74]. Many studies reported the loss of medicinal plant species due to changing climate [20,67], which concurs with our projections. The anti-malarial species loss will have ramifications on the pharmaceutical industries and livelihoods of several vulnerable populations that rely on them [67]. Therefore, regions that will lose should be given priority for *ex situ* conservation measures such as collection and storage of anti-malarial species germplasm in seed banks [49].

Anti-malarial species that will be able to track their suitable habitats are expected to gain suitable habitat [20]. The gains were predicted to occur in areas with more future anti-malarial species suitable habitat or where warmer climate will favor them [61] i.e. south-western region. Notably, the region is well endowed with anti-malarial species which are pre-adapted to water stress [28] and can thrive in climate warming. Continuous monitoring of the anti-malarial species is advisable in areas that will gain since an influx of new anti-malarial species could alter the competitive interactions in such areas [20], and because factors other than climate change may threaten the existence of anti-malarial species [65]. Further, we propose *in situ* conservation of anti-malarial species alongside sustainable utilization, assisted migration, assisted seedling growth, removal of invasive species in areas that gain and overlap with protected areas [61,16].

Mean anti-malarial species richness for future scenarios was low, compared to the current scenario; similar findings have been reported in other parts of the world (i.e. studies on medicinal plants; [61,67]). Most areas of high richness (i.e. south west) are predicted to decrease due to increased warming [67], while only a small region in the north west will witness a slight increase in richness. Consequently, climate change will pose a challenge to availability of anti-malarial species. However, regions of future high anti-malarial species richness should be considered as conservation areas for restoration and rewilding under climate change. Contrary to our results, a study in Egypt [20] reported increased medicinal plant species richness due to climate change. These differences may be due to use of other bioclimatic variables, and climate scenarios. Besides, plants in Egypt may not share the same ecological niche location as those in Samburu. Under future scenarios, the mean anti-malarial species richness outside the protected areas is predicted to be higher than inside, contrary to the findings of Kaky and Gilbert [20] in a study on medicinal plants. This suggests that due to their placement in unsuitable future climates, the current protected areas may not adequately conserve anti-malarial species in future. They should be complemented through effective management and extension to cover future suitable habitats. Conservationists should also adopt anti-malarial species conservation measures beyond the current protected area network to conserve anti-malarial plants in future.

Assessing the impact of climate change on plant species may be overestimated since it is usually difficult to consider the interactions between the population character or species and their habitat [65]. A species may gain suitable habitat, but may be unable to move to the habitat due to limiting factors like altitude and human activities in the surrounding area [20]. Besides, plant population size may not adequately predict long-term population viability because of the time lag associated with its response to habitat deterioration [61]. However, the patterns of loss and gain in species suitable habitat may remain [65]. Regarding the choice of future variables, our study considered soil factors and elevation as static variables and climatic factors as dynamic. However, future climate scenarios will also witness changes in soil factors and elevation [75]. Therefore, future research should consider this for more accurate results.

4.5. Turnover

The overall average turnover rates for anti-malarial species was positive, meaning gain in distribution area will be higher than loss. Consequently, high turnover in anti-malarial species-poor areas may improve the health of locals therein as they will gain some anti-malarial species [61]. High turnover was predicted in areas with high current precipitation and low temperature, associated with high soil water which enhances anti-malarial species development [20]. For areas with high turnover, systematic monitoring of the species may help to formulate scientific conservation measures to adapt to climate change [61]. Low anti-malarial species turnover will occur in the south eastern region (has low current precipitation and high temperature) probably because of little change in future environmental conditions [65]. The region should nonetheless be continuously monitored, since we suspect that the safety or even quality of anti-malarial species therein may be affected by climate change, as increase in CO_2 concentration and temperature affects plant chemical metabolites [16].

4.6. Identifying priority species for conservation

Under all future scenarios, 14–24% of the species will be CR while 14–29% will be EN, which may strongly affect the locals' healthcare. However, only 15–29% of the species will be of least concern. These results are in line with those by Gafna et al. [27] suggesting that most anti-malarial species in Samburu dryland are threatened by climate change. Drylands such as Samburu are sensitive to climatic changes because they have already reached the threshold of water availability and temperature [27]. In agreement with Thuiller et al. [65], two species with narrow climatic tolerances and limited population size (i.e. *Salvadora persica* and *Acacia xanthophloea*) were listed as CR under all scenarios, since they would have to fully shift their distribution range to keep pace with the changing climate. Both species grow in environments with low temperatures [16], which might make them less likely to adapt to the future climatic conditions. These species should be given the highest conservation priority. Compared to CR non-medicinal plants, CR anti-malarial species are more vulnerable to extinction because they face over-harvesting [76]. Therefore, we suggest the establishment of plant micro-reserves in concentration areas of the CR anti-malarial species, especially in areas with low future temperatures. Likewise, the population size of CR anti-malarial species with a weak ability to regenerate in the wild could be improved using appropriate artificial intervention [76]. Such actions aimed at conserving CR anti-malarial species could also benefit other VU species that are inadequately conserved [77]. As expected *Harrisonia abyssinica* and *Euclea divinorum* were classified as of LC, since they were projected not to lose any suitable habitat. They grow in different environmental conditions, which makes them highly adaptable to environmental stress [7], and are likely to survive the future changing climate.

4.7. Impact of climate change on malaria vector species distribution

Suitable habitat for malaria vectors will expand to most areas that are currently unsuitable, thereby exposing new populations to malaria. This shows the potential challenge to Samburu's ambitious goal of eliminating malaria. Increased temperatures will increase the rate of malaria vectors development and the frequency of blood feeding by mosquitoes, while droughts due to climate change may convert rivers into water pools which provide optimal mosquito breeding sites [24]. In Kenya, [5] mapped malaria vectors distribution under climate change. Our findings agree with their study; however, our work displayed a much broader expansion, which may reflect the fact that our occurrence records were drawn from a large area. Pockets in the south east will be converted from suitable malaria vectors habitat to unsuitable, thereby reducing the malaria burden on some populations. Very high temperature and low precipitation in these areas may make it unbearable for malaria vectors to survive in future [5]. Worrisomely, most areas predicted to have suitable malaria vectors habitat in future are also currently predicted as suitable habitats. This repeated and prolonged exposure to malaria may lead to immunity and development of resistance to anti-malarial species or drugs among populations in these areas [23].

When transferring the malaria vector species models to future conditions, we assumed that the current association between malaria vectors presences and predictor variables based on present day data will still hold true under future climate scenarios [24], which may not be the case. This is likely because the potential evolution of malaria vectors in response to climate change (i.e. temperature tolerance) may affect their shifts in geographical range [78]. Whereas the impact of climate change on malaria vector species distribution may be altered by the evolutionary changes [79], many species evolve much slower than the changing climate [80], or may not even evolve at all. Besides, the lack of future human population data may limit the scope of our models [24].

4.8. Assessing the impacts of climate change on future malaria vulnerability

The overlap between suitable habitat for malaria vectors and low anti-malarial species richness will increase, especially in the eastern and southern regions, potentially exposing locals to increased malaria vulnerability burden [1]. In future, malaria control interventions in the south should be revisited from the currently low malaria control measures [23] to high, while the anti-malarial species conservation efforts should be low, as this will take into account how climate change will alter malaria vulnerability. We suggest that future malaria vector control measures should be devoid of insecticides since their effectiveness will likely decrease with increased temperatures due to climate change [21]. Instead, biological control should be adopted i.e. predatory fish [72]. There is need to create awareness in the current low vulnerability malaria areas that are likely to become high vulnerability malaria areas, to enhance preparedness. Besides, concerted efforts to increase resilience among locals in these areas should be scaled up in order to strengthen adaptive capacity and reduce vulnerability. We propose review of resource allocation in the high vulnerability malaria areas that will be converted to low vulnerability areas i.e. north west.

5. Implications for management

Since our results suggest a possible loss of anti-malarial plant species, decrease in future anti-malarial species richness, expansion of malaria vectors suitable habitat and thus spread of high vulnerability malaria areas, there is need to urgently initiate more effective anti-malarial species conservation and malaria control interventions. Sustainable harvesting practices, effective enlargement of protected areas and supporting *in-situ* and *ex-situ* conservation (with focus on anti-malarial species of highest conservation priority) can ameliorate the processes. For effective anti-malarial plant species conservation and malaria control actions, interventions should take into account the climatic patterns, for a greater impact. Land managers should monitor the changing trends in precipitation and temperature as they determine the region's ability to hold anti-malarial species and malaria vector species. There is also need to revisit current and future anti-malarial species conservation actions and malaria control interventions as outlined by the current study.

Author contributions

Conceived and designed the experiments: DG, KD, SS. Analyzed the data: DG. Collected the data: DG Contributed materials used in the field: JO. Wrote the paper: DG. Read and revised the paper: KD, SS, JMK, JO.

Declaration of Competing Interest

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

Data availability

The data in regards to this study can be availed by the corresponding author, DG, upon reasonable request.

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Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.ecochg.2023.100070.

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