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## Addressing human–elephant conflicts in Taita Taveta County, Kenya: Integrating species distribution modeling into targeted conservation strategies

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## ABSTRACT

Increasing competition for space and resources at the agriculture–conservation interface poses critical challenges to wildlife conservation, often intensifying human–wildlife conflicts throughout the globe, including Kenya. With approximately 70 % of Kenya’s wildlife residing outside protected areas, land conversion for agriculture exacerbates human–wildlife conflicts, particularly involving African elephants (*Loxodonta africana*). Taita Taveta County in Kenya represents a hotspot for human–elephant conflict, where these incidents undermine both conservation efforts and livelihoods. This study assesses multiple distribution model algorithms and ensemble models, using Kenya Wildlife Service incident data and ten geospatial variables, to predict human–elephant conflicts in the county. The study extends the spatial pattern analysis to the comprehensive comparison of outputs, such as probability and risk maps, thus filling a critical gap by offering an innovative framework for human–elephant conflict modeling. Probability maps were reclassified into risk maps, and landscape metrics were derived to evaluate the spatial patterns of conflict risk. Results highlight that the ensemble model demonstrated superior consistency, predictive accuracy, and provided a more balanced representation of human–elephant conflict risk compared to single-algorithm models. The analysis identified proximity to houses and crops as key conflict predictors, with high-risk zones concentrated near human settlements and low-risk zones confined to protected areas. This study proposes that landscape metrics can further enhance the evaluation of risk map performance. By integrating ensemble modelling and landscape metrics, this research provides policymakers with actionable tools to balance human needs with conservation priorities, fostering sustainable human–elephant coexistence in Taita Taveta County and beyond.

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## 1. Introduction

Increasing competition for space and resources at the agriculture-conservation interface poses a critical challenge to wildlife conservation, often intensifying cases of human–wildlife conflict (Mukeka et al., 2019). Land conversion for agriculture in ecosystems adjacent to national parks and other protected areas exacerbates these conflicts, heightening interactions between rural communities and wildlife (Mwangi et al., 2016; Mekonnen, 2020; Dejene et al., 2021, Meyer and Börner, 2022). Such conflicts undermine the attainment of conservation objectives (Newbold et al., 2015). In Kenya, approximately 70 % of the country’s wildlife resides outside national parks, reserves, and conservancies, inhabiting human-dominated landscapes (Mwaura, 2016; Ogutu et al., 2016). Consequently, wildlife conservation efforts and conflict mitigation strategies that focus solely on existing protected areas have proven inadequate. The African elephant (*Loxodonta africana*) accounts for most of these conflicts in Kenya (Mukeka et al., 2018; Long et al., 2020). For instance, in the Greater Tsavo Ecosystem, African elephants were implicated in 61.6 % (24,032 incidents) of the total 39,022 human–wildlife conflict cases reported over a 23-year period (1995–2017) (Mukeka et al., 2020). In Taita Taveta County, three forms of human–elephant conflict (HEC) constituted 97 % of all reported incidents over 15 years (2004–2018): threats to human safety represented the largest share (62.46 %), followed by crop raiding (32.46 %) and property damage (2.33 %) (Munyao et al., 2020). These conflict incidents—including crop raiding, property destruction, and human casualties—have significant impacts on both human livelihoods and elephant populations (Von Hagen et al., 2023). Human–elephant conflict has therefore emerged as a pressing concern for the communities of Taita Taveta County and, more broadly, for the Kenyan government due to its profound social and conservation implications. Mitigating these conflicts requires an understanding of the spatial distribution of elephants (Mlambo et al., 2024) and characteristics of conflict risk zones, which can facilitate targeted management interventions and inform policies that balance conservation priorities with human needs. Accordingly, the development of effective and efficient human–wildlife conflict mitigation strategies within the agriculture–conservation interface necessitates spatiotemporal conflict data and species distribution models (Fortin et al., 2020; Fidino et al., 2022).

Species distribution modelling has become a prominent approach in human–wildlife conflict research, offering a powerful tool to analyse the extent and patterns of human–environment interactions. It enables researchers to identify factors driving conflict risk, develop models to predict the likelihood of conflict occurrence (Mateo-Tomás et al., 2012; Kitratporn and Takeuchi, 2020), and guide management decisions and mitigation policies (Sofaer et al., 2019). In most of these studies, the prevailing approach has been the use of a single algorithm, such as Maximum Entropy (e.g., Sharma et al., 2020; Nayeri et al., 2022; Jayakody et al., 2024), Generalized Linear Models (Rani et al., 2024), Generalized Additive Models (Malviya and Krishnamurthy, 2022), or Random Forest (Xu and Tang, 2024). More recently, however, there has been a growing adoption of ensemble models in human–wildlife conflict studies. This shift reflects the ability of ensemble models to integrate predictions from multiple algorithms, leveraging their strengths while compensating for individual weaknesses (Kitratporn and Takeuchi, 2020; Xu, Jiang and Liu, 2024). Although ensemble modelling is not a novel concept, its extensive application in species distribution modelling research has highlighted its advantages (Araújo and New, 2007; Sakti et al., 2024). Comparative analyses consistently indicate that ensemble models outperform single algorithms in terms of

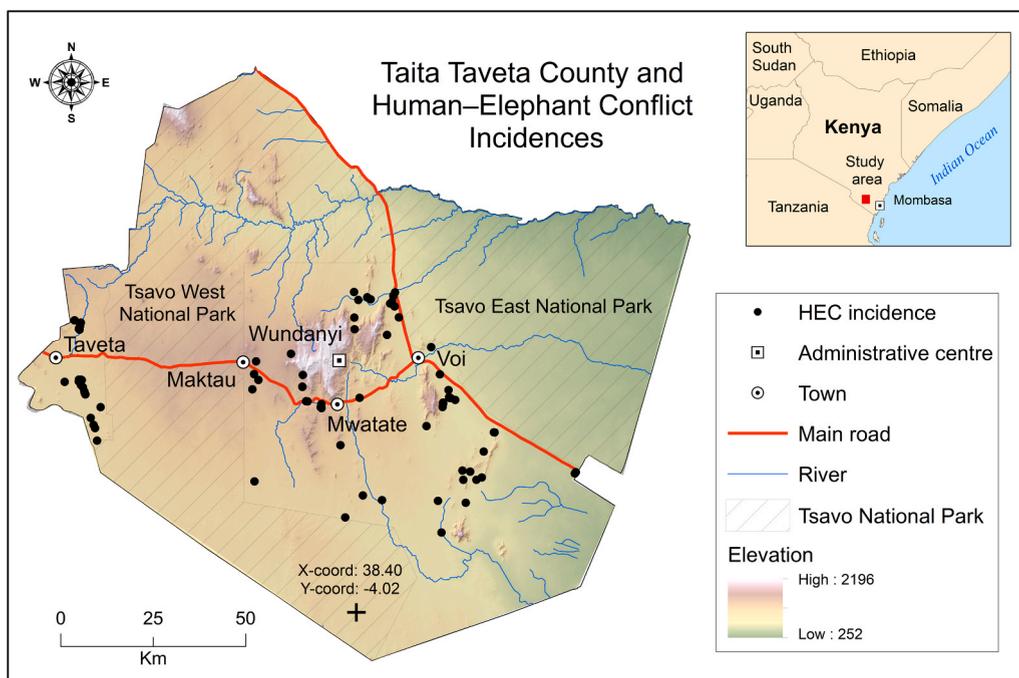
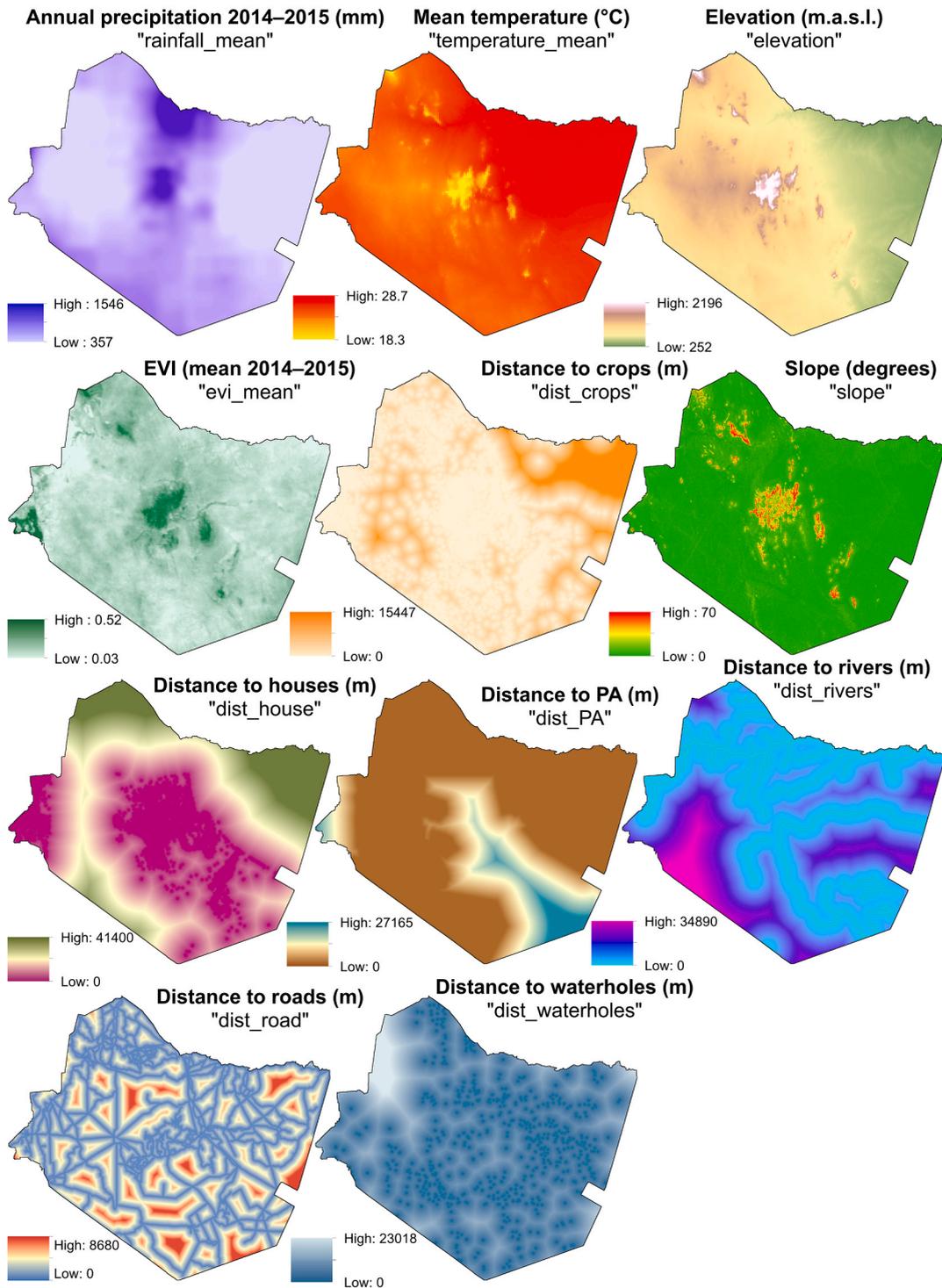


Fig. 1. The study area, Taita Taveta County with human–elephant conflict incidence points and protected areas.

predictive accuracy (e.g., Marmion et al., 2009). Research on human–wildlife conflicts using ensemble modelling has traditionally emphasised the comparative predictive accuracy of species distribution modelling algorithms and ensemble approaches. However, this study advances current research by filling a critical gap: the systematic comparison of probability maps and risk maps derived from

## Human–elephant conflict (HEC) predictor variables



**Fig. 2.** Eleven predictor variables influencing human–elephant conflict distribution. Elevation omitted from models following multicollinearity detection via the Variance Inflation Factor.

different methodological approaches. Moreover, we incorporate landscape metrics to assess the extent of variations in risk maps introduced by different species distribution model algorithms and ensemble models. This novel approach broadens the scope of spatial pattern analysis, offering deeper insights into the accuracy and reliability of human–elephant conflict modelling outputs. Although the local communities in Taita Taveta County report conflict incidents, this point based information may not wholesomely guide conflict mitigation strategies but with the generated risk maps, sites where mitigation efforts should be focused on are simply highlighted.

### 1.1. Purpose of the study

The purpose of the study is to assess multiple model algorithms and an ensemble model, using Kenya Wildlife Service’s human–wildlife conflict incident data and ten geospatial variables, to predict human–elephant conflicts in Taita Taveta County, Kenya. As a result, this study contributes to the identified research gap in the conservation ecology literature by extending the spatial pattern analysis to the comprehensive comparison of outputs, such as probability and risk maps, thus offering an innovative framework for human–elephant conflict modelling while underscoring the value of ensemble methodologies in addressing multifaceted conservation issues.

## 2. Materials and methods

### 2.1. Study area

The study area, Taita Taveta County is in southeastern Kenya between latitude 246 and 410 south and longitude 3736 and 3014 east (Fig. 1) and located in the semi-arid Tsavo-Mkomazi Ecosystem, where the mean annual rainfall varies between 250 mm and 500 mm. The agroecological zones with more intensive agriculture at higher elevations in the Taita Hills receive over 1200 mm (Taita Taveta County Government, 2013). In 2019, the county had 340,670 inhabitants (Kenya National Bureau of Statistics, 2019). Agriculture is an important land use in the county, although only 2.5 % of the land has high potential. The county’s land area is approximately 17,000 km<sup>2</sup>, with 62 % covered by the Tsavo East and Tsavo West National Parks, the two largest protected areas in Kenya. In addition, there are private ranches and community conservancies. The county is known for its rich wildlife and home to Kenya’s largest elephant population. An aerial wildlife census in the Tsavo-Mkomazi Ecosystem, with a land area of over 49,611 km<sup>2</sup>, counted 11,158 elephants in 2014 and 12,866 in 2017, indicating a 14.7 % population increase over the three-year period (Ngene et al., 2017).

### 2.2. Human–elephant conflict incidence data and predictor variables

This study utilized human–wildlife conflict incident data collected in Taita Taveta County between January 2014 and September 2015. The data were derived from 3027 compensation request forms submitted to the Kenya Wildlife Service. From these records, 94 human–elephant conflict incidents with verified geographic coordinates were identified, including 70 crop raiding events and 24

**Table 1**

Predictor variables with description and data sources. Elevation variable omitted from the HEC models following multicollinearity detection via the Variance Inflation Factor.

Variable	Description	Original spatial resolution	Min	Max	Mean	StdDev	Source
dist_crops	Distance to crops	20 m	0	15447	2977.4	3978.4	Taita Taveta County land cover map (Abera et al. 2022)
dist_house	Distance to houses	100 m	0	41400	14148	14554.7	digitized from Google satellite imagery
dist_PA	Distance to protected areas	100 m	0	27165	3554.3	6559.9	Kenya Wildlife Service
dist_rivers	Distance to rivers	100 m	0	34890	8068.8	7545.7	topographic maps at a 1:50 000 scale by the Survey of Kenya
dist_road	Distance to roads	100 m	0	8680	2001.2	1809.6	topographic maps at a 1:50 000 scale by the Survey of Kenya
dist_waterholes	Distance to waterholes	100 m	0	23018	4648.6	4197	digitized from Google satellite imagery
elevation	Elevation m.a.s.l. from the DEM	30 m	163	2196	687.4	244.4	NASADEM_HGT 30 m (NASA AppEEARS)
evi_mean	Enhanced Vegetation Index (EVI) 2014–2015	500 m	0.03	0.52	0.21	0.05	MODIS, MOD13A1 (NASA AppEEARS)
rainfall_mean	Mean annual precipitation 2014–2015 (mm)	0.05 deg.	356.8	1546.3	652.4	194.7	CHIRPS 3.0 (Funk et al., 2015)
slope	Slope (degrees) derived from the DEM	30 m	0	70	2.2	3.9	NASADEM_HGT 30 m (NASA AppEEARS)
temperature_mean	Annual mean temperature (°C)	30 sec.	18.3	28.7	26	1.4	AFRICLIM 3.0 (Platts et al., 2015)

human-related incidents. The human-related incidents were categorized into human death ( $n = 6$ ), human injury ( $n = 6$ ), human threat ( $n = 11$ ), and property damage ( $n = 1$ ). These data points were compiled into a unified human–elephant conflict incidence point dataset (Fig. 1). Before integrating the dataset into the modelling framework, a two-step validation process was undertaken. First, a detailed review of the compensation request forms was conducted to ensure data consistency. Second, a field survey was carried out to verify the spatial accuracy of incident locations containing coordinate information. This validation ensured the reliability of the dataset for subsequent analyses.

This study examined predictor variables that influence human–elephant conflicts, selecting factors with strong support in the literature (e.g., Hoare, 1999; de Knecht et al., 2011; Rohini, et al., 2016; Williams et al., 2018; Sharma et al., 2020; Baskaran et al., 2024) (Fig. 2). For climate data, annual mean temperature was obtained from AFRICLIM 3.0 (Platts et al., 2015), while annual mean precipitation data for 2014–2015 was sourced from CHIRPS v3.0 (Funk et al., 2015) and spline-interpolated to a spatial resolution of  $100 \times 100$  m. Vegetation data, specifically the MODIS Enhanced Vegetation Index (EVI) MOD13A1 product, were downloaded from NASA's AppEEARS platform and averaged over the study period 2014–2015 (Huete et al., 2002). Elevation data were acquired from NASADEM\_HGT (30 m resolution) through AppEEARS, and slope (in degrees) was calculated from these elevation values. Using the Euclidean Distance tool in ArcGIS, we calculated distances to rivers, waterholes, roads, and protected areas based on geospatial data from 1:50,000 scale topographic maps by the Survey of Kenya and Google satellite imagery. Since spatial data on human dwellings were unavailable for Taita Taveta County, we manually digitised all household locations from Google satellite imagery and calculated Euclidean distances to houses in ArcGIS. Cropland data were obtained from the Taita Taveta County land cover map layer (Abera et al., 2022), with distances to crops similarly calculated. Each predictor layer was clipped to the county boundary and reprojected to the WGS 1984 UTM Zone 37S coordinate system. The layers were standardized to a  $100 \times 100$  m resolution, a scale deemed suitable for regional human–elephant conflict studies based on prior research (Li et al., 2023). We assessed multicollinearity among the eleven predictor variables using the Variance Inflation Factor method (Besley et al., 1980), with a threshold of 5 applied via the *vif.step* function in *usdm* (Naimi et al., 2014). Elevation was excluded due to collinearity, leaving ten predictor variables for model analysis, as detailed in Table 1.

### 2.3. Data analysis and predictive human–elephant conflict modelling

Human–elephant conflict modelling was conducted using the species distribution modelling framework *sdm* (Naimi and Araújo, 2016) within the R software environment (version 4.3.3) (R R Core Team, 2024). Species distribution models are statistical models that uses species occurrence data, together with environmental data, to produce a correlative model of the environmental conditions that meet a species' ecological needs, and which can determine the potential habitat of a given species (Guisan and Zimmermann, 2000; Elith, et al., 2008; Guisan et al., 2017). Species distribution modelling has been also used recently successively in human–wildlife conflict and human–elephant conflict studies see e.g. (Sharma et al., 2020; Jayakody et al., 2024; Xu, Jiang and Liu, 2024). In this study, we implemented six well-established species distribution modelling algorithms using 5-fold cross-validation. The selected algorithms were Generalized Linear Models (GLM), Generalized Additive Models (GAM), Boosted Regression Trees (BRT), Maximum Entropy (Maxent), Random Forest (RF), and Support Vector Machines (SVM). These algorithms, except for Maxent, require both presence and absence data. Therefore, background data (pseudo-absences) were randomly generated across the study area using the *gRandom* function in the *sdm* R package. In accordance with the recommendations of Barbet-Massin et al. (2012), we employed 1000 background points when the number of valid occurrence records was 100 or less. However, earlier studies have demonstrated significant variability in predictions across different modelling algorithms, complicating model selection (Pearson et al., 2006; Thuiller et al., 2009). To address this uncertainty, we adopted an ensemble modelling approach (see e.g., Araújo and New, 2007; Hao et al., 2019; Marmion et al., 2009). Ensemble models were built by averaging weighted outputs using the TSS method (*opt=2*) within the *sdm* package (Naimi and Araújo, 2016), optimising the threshold to maximise true skill statistics (TSS). Our species distribution modelling methodology employed five-fold cross-validation, with 70 % of the data used for training in each fold and 30 % for validation (Guisan and Zimmermann, 2000). For our primary model performance evaluation method, we used the True Skill Statistic (TSS). The true skill statistics has proven to be a good metric for describing model performance given imbalanced binary class datasets because it places equal weight on the model's ability to predict both classes (Allouche et al., 2006). The true skill statistics values range from  $-1$  to  $+1$ , with values approaching  $+1$  indicating better predictive ability. In contemporary species distribution modelling studies, true skill statistics is often preferred alongside other metrics to provide a more comprehensive assessment of model performance. We therefore also include the area under the receiver operating characteristic curve (AUC ROC) (Fielding and Bell, 1997) as a performance metric, even though AUC has been criticised for potentially misleading predictive accuracy (Lobo et al., 2008). This decision was justified because AUC has been commonly applied in the species distribution modelling literature for model evaluation. Area under the receiver operating characteristic curve values range from 0 to 1, with higher values indicating better performance (Fielding and Bell, 1997). In general, AUC values of 0.5–0.7 are considered low and represent poor model performance, values of 0.7–0.9 are considered moderate, and values above 0.9 represent excellent model performance (Swets, 1988). In the results, we report the mean true skill statistics and AUC across the model replicates and show the AUC curves for each modelling algorithm. Additionally, we visualize the predictors' partial response curves calculated as a mean response from the six modelling algorithms. We further utilised the *getVarImp* function from the *sdm* package to assess the relative importance of variables in our models. This function calculates scores that highlight the predictors contributing most significantly to the model's predictive accuracy. Further, we developed a ranking method to determine predictors importance for all the human–elephant conflict models. In addition, we investigated the relationship between the conflict prediction raster maps (GLM, GAM, BRT, Maxent, RF, SVM, and Ensemble) by calculating Pearson's Correlation Coefficient ( $r$ ) using the *layerStats* function in the R raster package.

#### 2.4. Human–elephant conflict risk maps and risk class level landscape index analysis

We developed human–elephant conflict risk maps using both individual algorithmic predictions and ensemble prediction generated by species distribution models. Probability values were categorized into five levels of conflict risk: ‘low risk’ (0–0.2), ‘below average risk’ (0.21–0.4), ‘average risk’ (0.41–0.6), ‘high risk’ (0.61–0.8), and ‘very high risk’ (0.81–1). This classification methodology has been utilized in prior studies (Ansari and Ghoddousi, 2018; Zhang et al., 2019, Obunga et al., 2022). To assess spatial structure across classified risk maps, we conducted a quantitative analysis of landscape indices using FRAGSTATS v4.3 (McGarigal et al., 2023), a dedicated software for computing landscape metrics. We calculated nine class-level metrics for risk maps produced by six species distribution modelling algorithms and the ensemble approach. The selected indices included Class Area (CA), Percentage of Landscape (PLAND), Number of Patches (NP), Landscape Shape Index (LSI), Mean Patch Area (AREA\_MN), Euclidean Nearest Neighbour (ENN\_MN), Percentage of Like Adjacencies (PLADJ), Interspersion and Juxtaposition Index (LJI), and Aggregation Index (AI). These metrics were chosen for their capacity to quantify spatial heterogeneity, patch configuration, and connectivity, all of which are critical factors in understanding human–elephant conflict risk. Additional details on metric definitions and their computational procedures are provided in [Supplementary Materials 1](#). This methodological framework facilitated a systematic evaluation of the spatial patterns predicted by different modelling approaches, enabling a robust assessment of conflict risk classification.

#### 2.5. Human–elephant conflict risk combination analyses to evaluate risk map performances

To rigorously evaluate and compare the performance of each human–elephant conflict risk map, which was derived through various modelling algorithms including GLM, GAM, BRT, Maxent, RF, SVM, and an Ensemble approach, we developed a novel analytical approach to analyse all possible risk raster combinations. For each of the seven risk maps, classified into four possible categories, the initial analysis considered 16,384 potential combinations. We then generated a combination matrix and computed Pearson’s correlation coefficients ( $r$ ) for each algorithmic pairing. This methodology provided a robust metric for assessing the differences and similarities of the risk models calculated in this study.

### 3. Results

#### 3.1. Model performances

Predictive accuracies of all species distribution modelling algorithms were generally good in terms of both true skill statistics (TSS) and area under the receiver operating characteristic curve (AUC). The model performance, with five-fold cross-validation of six model algorithms, with mean TSS and AUC values, is presented in [Table 2](#) and [Fig. 3](#). The AUC ROC curves for each modelling algorithm during training and testing are illustrated in [Fig. 4](#). Altogether, the models provided reliable estimates for human–elephant conflict distributions. The mean true skill statistics varied between 0.74 SVM and 0.86 RF, while the mean AUC ranged from 0.91 to 0.96 respectively. GAM, Maxent, and RF achieved the highest performance out of all six algorithms based on mean TSS values, whereas, based on AUC values, RF performed the best. The standard deviation of the models was fairly constant, indicating that the models are robust and reliable in their predictions ([Fig. 3](#)). [Supplementary Materials 2 \(Fig. S1 to S6\)](#), shows the AUC ROC curves for each model run for each modelling algorithm and Mean ROC curves for model training and testing.

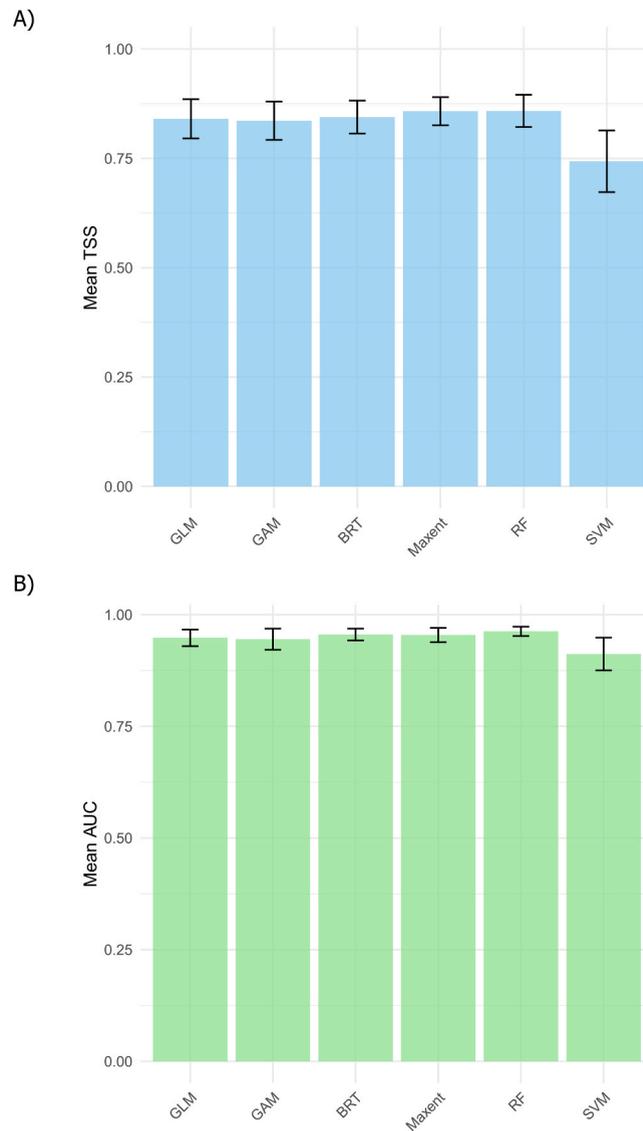
#### 3.2. Predictors contribution to human–elephant conflicts

[Table 3](#) shows the mean relative contribution of predictors (%) based on the AUC metric of each predictor within the models. The distance to house (*dist\_house*) variable was the major contributor for all the models, followed by the distance to crops (*dist\_crops*), distance to protected areas (*dist\_PA*), distance to waterholes (*dist\_waterholes*) and distance to river (*dist\_rivers*). All the other variables contributed less. Predictor contribution in each model differed slightly across modelling algorithms, and the SVM model exhibited the greatest differences compared to the other models.

**Table 2**

Modelling algorithm performance with mean true skill statistics (TSS) and area under the receiver operating characteristic curve (AUC) values and deviance. Total number of replicates per model is 25.

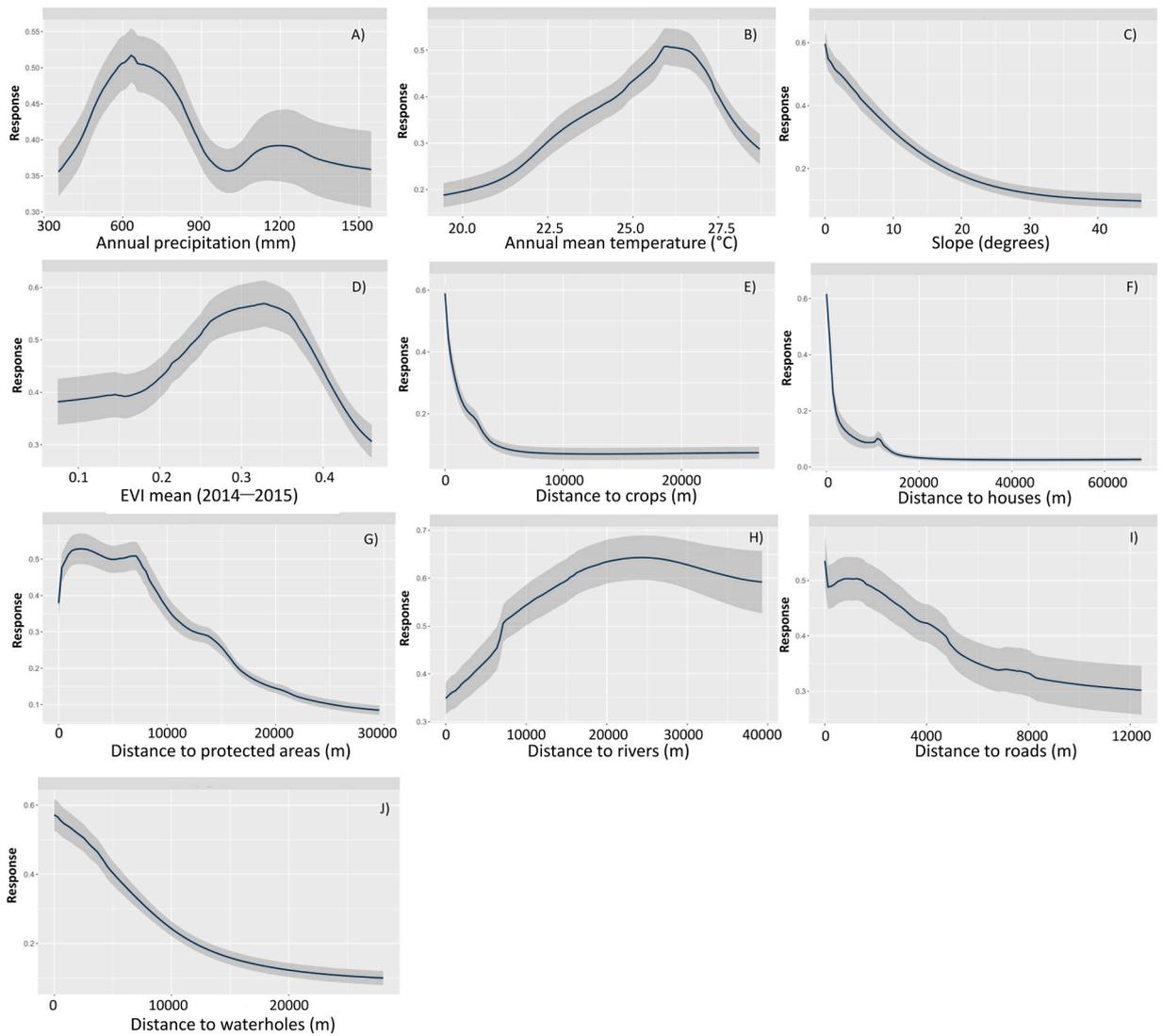
Algorithm	TSS	AUC	Deviance
GLM	0.84	0.95	0.30
GAM	0.84	0.95	0.36
BRT	0.84	0.96	0.32
MAXENT	0.86	0.95	0.30
RF	0.86	0.96	0.25
SVM	0.74	0.91	0.35



**Fig. 3.** Mean True Skill Statistics (TSS) (A) and area under the receiver operating characteristic curve (AUC) (B) values and standard deviation for each modelling algorithm of human–elephant conflict models. GLM = Generalized Linear Model, GAM = Generalized Additive Model, BRT = Boosted Regression Tree, Maxent = Maximum Entropy, RF = Random Forest, SVM = Support Vector Machine. Total number of replicates per model is 25.

### 3.3. Predictors importance ranking for human–elephant conflict models

The distance to house (*dist\_house*) was the most important predictor variable, followed by distance to crops (*dist\_crops*), highlighting their consistent role in predicting human–elephant conflicts (Table 4). Distance to protected areas (*dist\_PA*) ranked third among the predictors with conflict probability peaking at a distance of 3–7 km from protected area boundaries. Distance to waterholes (*dist\_waterholes*) ranked fourth and distance to river (*dist\_river*) ranked fifth. The response to the Enhanced Vegetation Index (*evi\_mean*) was positive, with conflict risk increasing alongside higher vegetation index values (Fig. 5). Slope variable (*Slope*) was a relatively poor predictor, because in the study area elephants are mostly located in relatively flat terrain (no slope). Both climate predictors—annual mean temperature (*temperature\_mean*) and precipitation (*rainfall\_mean*)—performed poorly in our study and the distance to road variable (*dist\_road*) was the least significant variable in this study. Table 4. shows predictor importance ranking performances for all seven human–elephant conflict modelling methods. In this ranking, the most influential variable receives a score of 10 for an independent model, while the least influential is assigned a score of 1. Consequently, the maximum possible score sum for the most important predictor is 70, whereas the lowest possible score sum is 7.



**Fig. 4.** Modelled mean response curves obtained from the six modelling algorithms. (A) annual precipitation in 2014–2015 (mm), (B) annual mean temperature (°C), (C) Slope (degrees), (D) Mean Enhanced Vegetation Index (2014–2015), (E) distance to crops, (F) distance to houses, (G) distance to protected areas, (H) distance to rivers, (I) distance to roads, (J) distance to waterholes. The X-axis presents the predictor variable, while the Y-axis depicts the probability of occurrence of human–elephant conflict.

**Table 3**

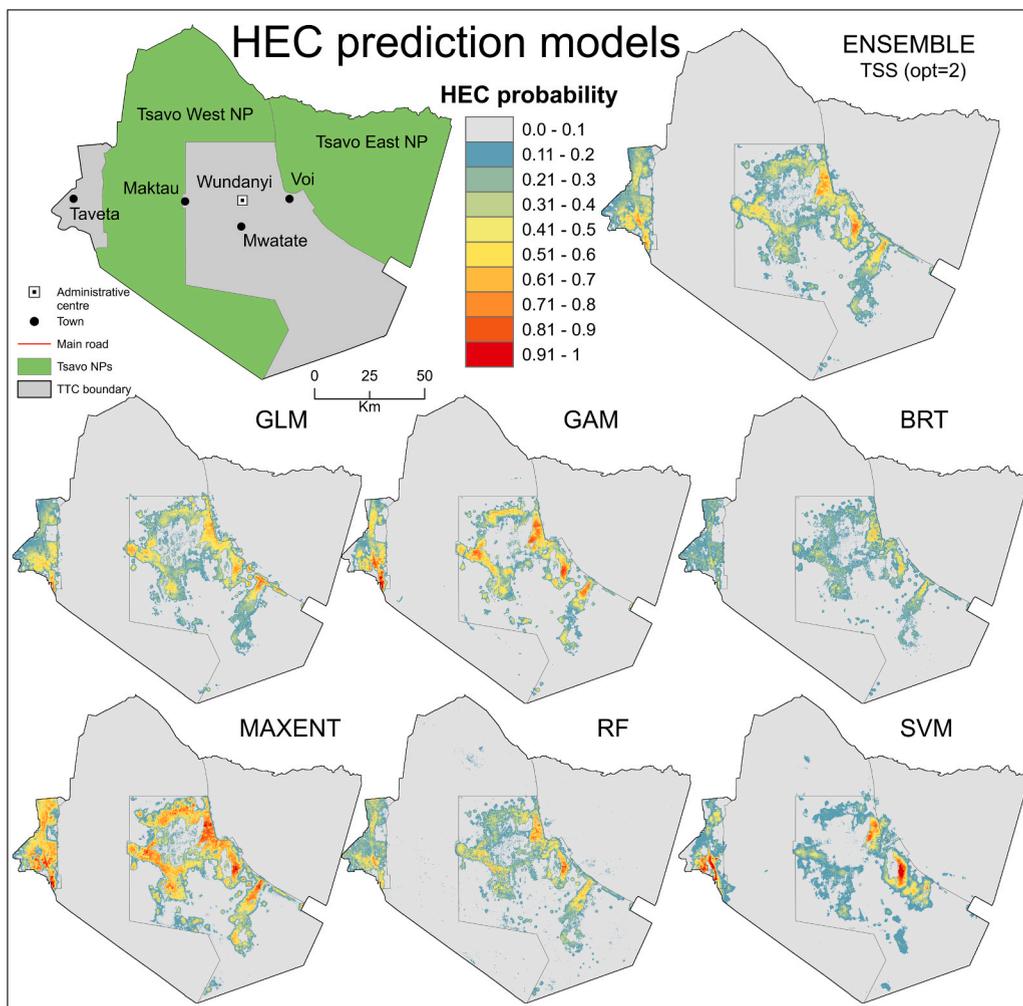
Mean relative contribution of predictors (%) for all human–elephant conflict models (total number of replicates per model is 25).

Variable	Mean relative contribution of predictors (%) based on AUC metric						
	GLM (AUC)	GAM (AUC)	BRT (AUC)	Maxent (AUC)	RF(AUC)	SVM (AUC)	ENSEMBLE (AUC)
dist_crops	32.1	23	2.3	19.5	1.1	21.9	3.8
dist_house	60.6	60.3	40.2	56.9	13	30.7	24.2
dist_PA	1.8	5	1.9	4.5	1	6.6	3
dist_rivers	1.4	1.1	1.5	1	0.7	2.5	1.6
dist_road	0.1	1.1	0.2	0.6	0.2	3.1	0.7
dist_waterholes	1.7	2.6	0.7	2.3	0.5	5.3	1.4
evi_mean	0.1	0.4	0.4	0.5	0.4	9.2	0.5
rainfall_mean	0.2	2.6	0.3	0.6	0.2	2.9	0.7
slope	1.7	1	0.4	2.2	0.2	2.6	1.1
temperature_mean	0.2	2.7	0.9	0.8	0.3	3.6	1

**Table 4**

Predictor importance ranking for all human–elephant conflict models based on Table 3 (per model highest score given is 10 and lowest is 1).

Variable	GLM (AUC)	GAM (AUC)	BRT (AUC)	Maxent (AUC)	RF (AUC)	SVM (AUC)	ENSEMBLE (AUC)	Predictor importance sum	Predictor importance
dist_house	10	10	10	10	10	10	10	70	1
dist_crops	9	9	9	9	9	9	9	63	2
dist_PA	8	8	8	8	8	7	8	55	3
dist_waterholes	7	6	5	7	6	6	6	43	4
dist_rivers	5	4	7	5	7	1	7	36	5
temperature_mean	3	7	6	4	4	5	4	33	6
slope	6	2	3	6	1	2	5	25	7
evi_mean	2	1	4	1	5	8	1	22	8
rainfall_mean	4	5	2	2	2	3	2	20	9
dist_road	1	3	1	3	3	4	3	18	10



**Fig. 5.** Prediction of human–elephant conflict (HEC) probability. The maps show the probability values for each modelling algorithm of conflict models. GLM = Generalized Linear Model, GAM = Generalized Additive Model, BRT = Boosted Regression Tree, Maxent = Maximum Entropy, RF = Random Forest, SVM = Support Vector Machine, and Ensemble is a mean model of all algorithms (150 model runs). Upper left map depicts the main towns and roads of Taita Taveta County.

### 3.4. Predictor variables response curves

Predictors partial response curves were used as additional components in interpreting the performance of the human–elephant conflict models (Fig. 4). The mean response curves from the six modelling algorithms suggests that conflict incidents are more likely to

occur in areas characterised by lower annual precipitation, higher annual temperatures, and flat terrain (no slope) in Taita Taveta County (Fig. 4A, B, and C). The relationship between human–elephant conflict occurrence and the average Enhanced Vegetation Index is curvilinear (Fig. 4D), with peak conflict occurrences at an average index value of approximately 0.35. This could be explained by the fact that conflict incidents are more likely to occur in areas with more dense vegetation, such as croplands or savanna woodlands. The curvilinear decay in the curve suggests that areas with above average Enhanced Vegetation Index values may have a higher probability of conflict, rather than the highest index values which in study area may refer to indigenous forests in the Taita Hills. For distance-based predictors (Fig. 4E to J), clear patterns emerge, showing a higher likelihood of human–elephant conflicts in areas near human settlements, croplands, roads, and waterholes.

### 3.5. Human–elephant conflict prediction maps

The human–elephant conflict prediction maps for six algorithms and the ensemble model are presented in Fig. 5. These maps highlight notable patterns: high conflict probabilities are concentrated near villages, while low probabilities occur primarily within protected areas, which is expected. Visual analysis reveals significant differences among the models. For example, the Maxent model exhibits unique patterns with high conflict probabilities, potentially suggesting overfitting. In contrast, the BRT model underpredicts high-probability areas, while the SVM model displays large areas of very high probability that are less pronounced in other maps. The Ensemble model, however, provides a visually balanced representation of high and low human–elephant conflict values. To further investigate the relationships between the models, Pearson's correlation coefficients ( $r$ ) were computed (Table 5). The correlation analysis aligns with the visual observations, showing the lowest correlation ( $r = 0.62$ ) between the SVM and BRT models. This discrepancy arises from the BRT model predicting fewer high-probability areas, whereas the SVM model identifies extensive regions of elevated conflict risk. To investigate all the other correlative relationships between the predicted models, refer to Table 5.

In our study, the Ensemble model demonstrates consistency and balance, offering a harmonised prediction of human–elephant conflict probabilities.

### 3.6. Human–elephant conflict risk maps and risk class level landscape index analysis

The risk maps presented in Fig. 6 show four risk classes, whereas in Fig. 7 these only depict areas with high and very high human–elephant conflict. These figures indicate that the highest risk of conflict was predicted in areas close to villages. The risk maps for different modelling algorithms also show clear variations in the risk areas.

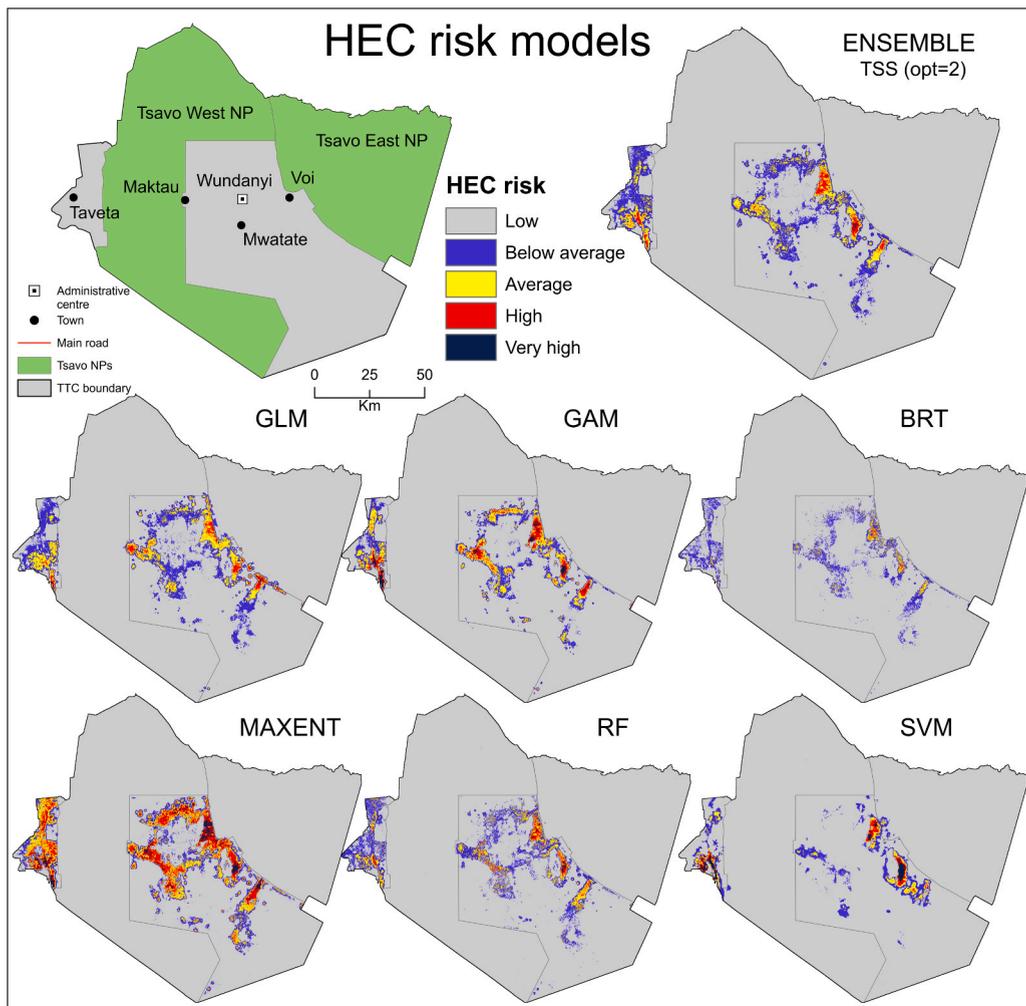
Human–elephant conflict risk maps were constructed using seven modelling approaches. The first percentage of land area for conflict based on risk classes for six modelling algorithms and the Ensemble model was computed (Table 6). The majority of the area is classified into the low-risk class across all models, with percentages ranging from 87.88 % Maxent to 95.53 % BRT model. Notably, BRT model exhibits the highest coverage, indicating its tendency to favour a conservative classification of low risk. SVM also assign substantial portions of the area to this class, with 95.35 %. The Ensemble model aligns closely with the general trend, at 91.29 %. The below-average risk class represents a smaller percentage, with the models showing 2.90 % SVM model to 6.19 % GLM coverage. GLM model and the Ensemble model produce similar coverage levels, suggesting a moderate inclination towards assigning below average risk zones compared to the other algorithms. SVM model has the lowest coverage here, likely reflecting its stronger focus on low risk assignments. The average risk class exhibits variability, with 0.67 % BRT model as the lowest and 3.91 % Maxent as the highest. Maxent's higher value indicates a broader identification of moderate risk zones, diverging significantly from other algorithms like BRT, which classifies minimal areas into this category. The Ensemble model predicts 2.19 %, striking a balance among the algorithms. The high risk class zones account for 0.08 % BRT model to 3.05 % Maxent, with most algorithms predicting less than 1 % of the area in this category. Maxent notably classifies the highest percentage, demonstrating a stronger emphasis on detecting potentially critical areas of conflict. Conversely, models such as BRT, RF and SVM are highly conservative in their high-risk designations and the Ensemble, classify 0.5 % of the area in this class. The very high risk class category is consistently small across all algorithms, with predictions ranging from 0.00 % BRT model to 0.70 % Maxent. The Maxent model again stands out, predicting the highest proportion of critical risk, while most other models, including. Notably, the Ensemble model predicts only 0.02 %, indicating its conservative aggregation of very high-risk zones.

This study used FRAGSTATS v4.3 to analyse spatial patterns in landscapes classified into five risk classes: low risk, below average risk, average risk, high risk, and very high risk. For each risk class, landscape maps generated by seven modelling algorithms were assessed using nine key metrics, providing a detailed quantitative understanding of the spatial configurations of human–elephant

**Table 5**

Pearson's correlation coefficients ( $r$ ) computed between the human–elephant conflict models.

HEC model	ENSEMBLE	BRT	GAM	GLM	MAXENT	RF	SVM
ENSEMBLE	1	0.92	0.96	0.95	0.97	0.95	0.78
BRT	0.92	1	0.86	0.85	0.88	0.96	0.62
GAM	0.96	0.86	1	0.90	0.93	0.88	0.73
GLM	0.95	0.85	0.90	1	0.91	0.86	0.71
MAXENT	0.97	0.88	0.93	0.91	1	0.91	0.69
RF	0.95	0.96	0.88	0.86	0.91	1	0.69
SVM	0.78	0.62	0.73	0.71	0.69	0.69	1

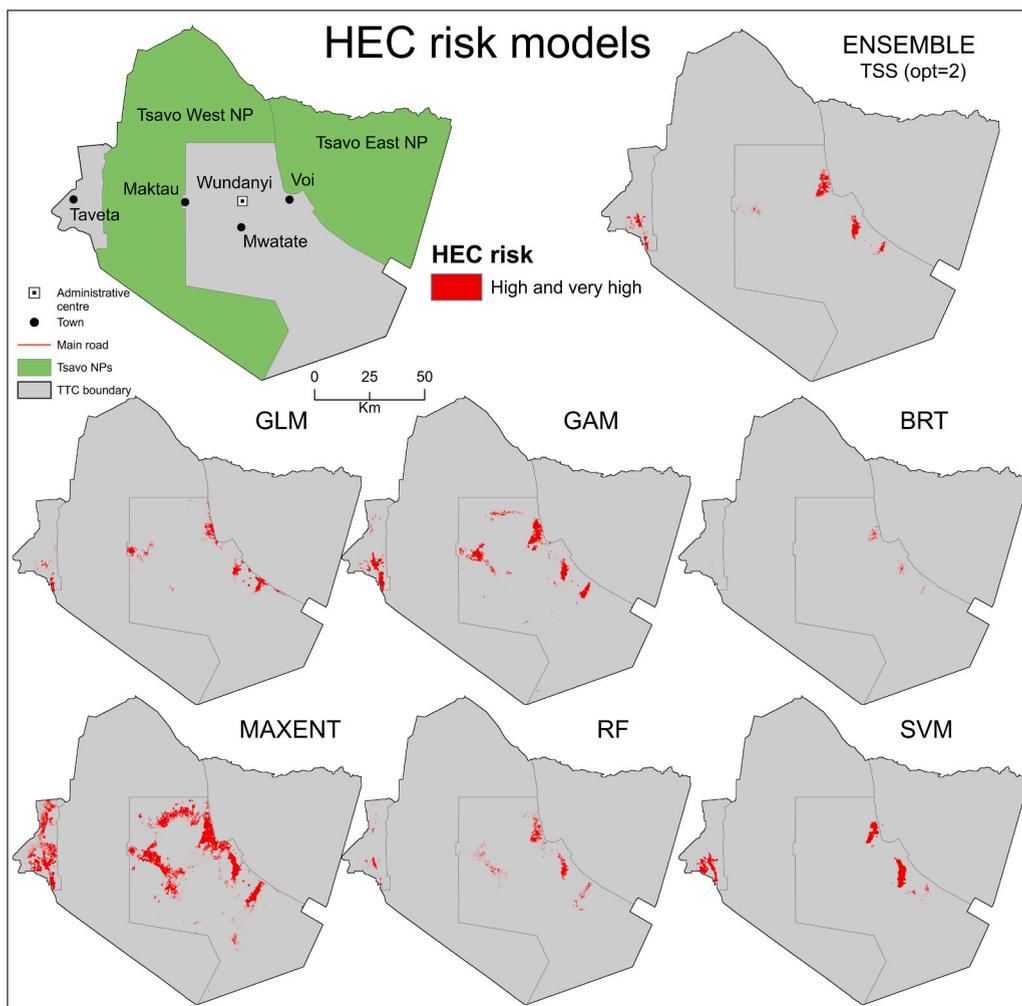


**Fig. 6.** Human–elephant conflict (HEC) risk maps. The maps show the conflict risk classes for each modelling algorithm of HEC models. GLM = Generalized Linear Model, GAM = Generalized Additive Model, BRT = Boosted Regression Tree, Maxent = Maximum Entropy, RF = Random Forest, SVM = Support Vector Machine and Ensemble is a mean model of all algorithms (150 model runs). Upper left map depicts the main towns and roads of the Taita Taveta County. The risk maps were derived from probability values by reclassify into four HEC risk classes: ‘low risk’ (0–0.2), ‘below average risk’ (0.21–0.4), ‘average risk’ (0.41–0.6), ‘high risk’ (0.61–1) and ‘very high risk’ (0.81–1).

conflict risk classes (Table 7). The landscape metrics revealed that across all models, low-risk zones overwhelmingly dominated the landscape in both areal extent and aggregation. For instance, BRT and SVM models predicted the highest PLAND values for low-risk classes (95.6 % and 95.3 %, respectively), with very high Aggregation Index values ( $AI > 99$ ), indicating a high degree of spatial continuity. SVM additionally exhibited the largest mean patch size ( $AREA\_MN = 6942.9$  ha) for low-risk zones, suggesting compact and consolidated low-conflict areas. In contrast, models such as RF and BRT produced highly fragmented below-average risk zones, with RF yielding 2405 patches and a Landscape Shape Index (LSI) of 85.3, reflecting a complex and disaggregated structure. High-risk and very high-risk zones were sparse and markedly fragmented across all models. These classes showed low PLAND values (generally  $< 3$  %), with elevated LSI and ENN\_MN scores, indicating isolated and irregularly shaped patches. Notably, Maxent generated the most extensive high-risk zone ( $PLAND = 3.0$  %) with the highest NP (2223), suggesting widespread but disconnected high-risk locations. The ensemble model produced moderate levels of fragmentation across most classes, offering a balance between spatial cohesion and complexity. Very high-risk zones remained negligible across all models, both in terms of area and spatial integration, with AI values generally below 70 and PLADJ values often near 50 %.

### 3.7. Human–elephant conflict risk combination analyses to evaluate risk map performances

To evaluate and compare the performance of human–elephant conflict risk maps generated by six modelling algorithms and ensemble approach, we computed seven risk maps. Each map was initially classified into four risk classes, yielding a total of 47 (16,384) possible risk combinations. However, due to the absence of a high-risk class in the BRT model, which was limited to three



**Fig. 7.** High- and very high human–elephant conflict (HEC) risk areas. The maps show the conflict risk areas for each modelling algorithm of human–elephant conflict models. GLM = Generalized Linear Model, GAM = Generalized Additive Model, BRT = Boosted Regression Tree, Maxent = Maximum Entropy, RF = Random Forest, SVM = Support Vector Machine and Ensemble is a mean model of all algorithms (150 model runs). Upper left map depicts the main towns and roads of Taita Taveta County The risk maps were derived from probability values by reclassifying into binary risk classes: ‘high and very high’ (0.61–1).

**Table 6**  
Percentage of land area for human–elephant conflict based on risk classes for six modelling algorithms and the Ensemble model.

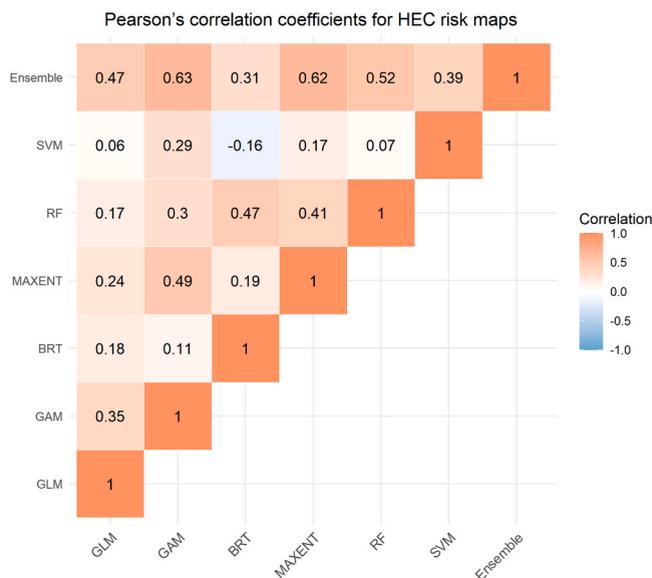
Risk class	GLM	GAM	BRT	Maxent	RF	SVM	ENSEMBLE
low	90.33	92.10	95.63	87.88	92.10	95.35	91.29
below average	6.19	4.05	3.62	4.46	5.39	2.90	6.01
average	2.80	2.52	0.67	3.91	1.94	0.93	2.19
high	0.66	1.07	0.08	3.05	0.51	0.47	0.50
very high	0.02	0.26	0.00	0.70	0.06	0.36	0.02

classes, the number of potential combinations was reduced to  $46 \times 3$  (12,288). In this study, 1539 unique risk map combinations were identified. Pearson’s correlation coefficients were calculated across this combination matrix to assess associations between different conflict models. The analysis revealed a range of correlation values, indicating varying degrees of similarity in the spatial risk patterns produced by each model (Fig. 8). The strongest correlation is between the Ensemble and GAM models (0.63), followed closely by the correlations of Ensemble with Maxent (0.62) and RF (0.52). These high values indicate that these models generate comparable risk maps, potentially due to shared or complementary data patterns. In contrast, the SVM model shows very low correlations with several models, particularly with GLM (0.06), and RF (0.07) and, exhibited negative correlation with BRT (-0.16). These low correlations suggest that SVM identifies different aspects of the human–elephant conflict risk landscape compared to other methods, resulting in

**Table 7**  
FRAGSTATS-based risk class level landscape index analysis for nine metrics classified into four risk classes.

Model type and risk class	CA	PLAND	NP	LSI	AREA_MN	ENN_MN	PLADJ	IJI	AI
low-risk GLM	1532480	90.3	573	10.3	2674.5	309.8	99.2	1.9	99.3
low-risk GAM	1562585	92.1	322	7.4	4852.7	316.0	99.4	4.1	99.5
low-risk BRT	1622496	95.6	601	13.0	2699.7	253.9	99.0	2.8	99.1
low-risk MAXENT	1490914	87.9	356	10.1	4188.0	341.2	99.2	8.8	99.3
low-risk RF	1562792	92.1	1023	14.1	1527.7	272.6	98.9	3.3	98.9
low-risk SVM	1617685	95.3	233	5.7	6942.9	300.1	99.5	13.8	99.6
low-risk ENSEMBLE	1548775	91.3	531	9.5	2916.7	334.8	99.2	0.7	99.3
below average-risk GLM	105030	6.2	1527	54.0	68.8	322.1	83.3	48.1	83.6
below average-risk GAM	68784	4.1	1030	50.9	66.8	313.0	80.6	51.0	80.9
below average-risk BRT	61406	3.6	1886	76.5	32.6	332.7	69.1	49.3	69.4
below average-risk MAXENT	75736	4.5	2712	73.7	27.9	288.6	73.2	56.5	73.5
below average-risk RF	91495	5.4	2405	85.3	38.0	319.7	71.8	51.4	72.0
below average-risk SVM	49183	2.9	851	33.2	57.8	397.2	85.0	48.1	85.4
below average-risk ENSEMBLE	101908	6.0	1409	55.5	72.3	305.7	82.6	49.8	82.8
average-risk GLM	47527	2.8	961	41.3	49.5	366.2	81.0	43.3	81.4
average-risk GAM	42783	2.5	847	44.2	50.5	388.4	78.6	49.2	79.0
average-risk BRT	11385	0.7	1057	46.7	10.8	334.3	56.1	41.8	56.7
average-risk MAXENT	66338	3.9	2431	78.5	27.3	273.7	69.5	60.2	69.8
average-risk RF	32946	1.9	2201	70.6	15.0	314.7	61.0	42.9	61.3
average-risk SVM	15718	0.9	367	23.1	42.8	337.5	81.6	61.8	82.2
average-risk ENSEMBLE	37071	2.2	1307	48.8	28.4	352.2	74.6	34.8	75.0
high-risk GLM	11209	0.7	499	23.5	22.5	516.6	77.8	16.4	78.5
high-risk GAM	18094	1.1	577	29.4	31.4	449.9	78.1	41.7	78.7
high-risk BRT	1300	0.1	170	18.2	7.6	299.1	48.8	10.8	50.3
high-risk MAXENT	51673	3.0	2223	64.7	23.2	293.1	71.5	52.2	71.8
high-risk RF	8580	0.5	815	38.6	10.5	312.3	58.2	43.7	58.8
high-risk SVM	7974	0.5	162	14.8	49.2	444.7	83.3	71.1	84.3
high-risk ENSEMBLE	8528	0.5	300	20.2	28.4	480.0	78.1	23.4	79.0
very high-risk GLM	341	0.0	36	7.1	9.5	722.8	61.7	0.0	65.3
very high-risk GAM	4341	0.3	177	12.7	24.5	302.6	80.6	2.0	81.9
very high-risk MAXENT	11926	0.7	1893	42.5	6.3	341.0	61.0	22.3	61.6
very high-risk RF	981	0.1	119	14.2	8.2	283.4	54.4	9.2	56.2
very high-risk SVM	6027	0.4	49	7.5	123.0	324.3	90.3	47.3	91.5
very high-risk ENSEMBLE	305	0.0	42	8.7	7.3	311.7	49.8	0.0	52.9

(Note: CA=Class Area, PLAND=Percentage of Landscape, NP=Number of Patches, LSI=Landscape Shape Index, AREA\_MN=Mean Patch Area, ENN\_MN=Mean Euclidean Nearest Neighbor Distance, PLADJ=Percentage of Like Adjacencies, IJI=Interspersion and Juxtaposition Index, AI=Aggregation Index).



**Fig. 8.** Pearson's correlation analysis for human–elephant conflict (HEC) risk combinations to evaluate risk map performances.

largely independent outputs. The BRT and RF models show moderate correlation (0.47), which aligns with their methodological similarities as tree-based algorithms. The GLM shows only modest correlations, with values of 0.47 for Ensemble and 0.35 for GAM, indicating unique conflict risk features not fully captured by other models. These findings show that while some models, such as Ensemble and GAM, share high similarities, others like SVM offer distinct risk profiles, adding depth to human–elephant conflict risk analysis. Fig. 8 correlation matrix highlights that the Ensemble model displays consistently high correlations with the risk maps generated by single modelling algorithms.

## 4. Discussion

### 4.1. Implications for conservation—risk maps and risk class level landscape index analysis comparison

While many species distribution modelling studies focus on habitat suitability mapping and the comparison of different algorithms (e.g., Buebos-Esteve et al., 2024), there remains a notable gap in research investigating variations in human–wildlife conflict and human–elephant conflict risk maps. Our results demonstrate significant differences in risk maps generated by various algorithms, highlighting the critical importance of thorough understanding of their performance for conservation efforts. Simply comparing model performance metrics, such as the area under the curve of receiver operating characteristics and true skill statistics, is insufficient for gaining deeper insights into the nuances of risk map performance. The risk maps (Figs. 6 and 7) illustrate these differences, which were further validated using landscape indices. In conservation practice, such substantial variations between human–wildlife conflict risk maps—where, for instance, the commonly used Maxent algorithm appears to overpredict human–elephant conflict risks, while BRT model fails to account for high-risk areas—can have profound implications. These findings raise questions about the reliability of earlier human–elephant conflict studies that relied solely on single algorithms without conducting meaningful comparative analyses. Our study demonstrates that ensemble-based risk mapping provides consistency and balance as well as harmonised risk maps that avoid over- or under-predicting risk classes. This finding is in line with earlier studies that have made comparative analyses of species distribution modelling using single algorithms and Ensemble technique see e.g. (Kitratporn and Takeuchi, 2020; Xu, Jiang, and Liu, 2024). Furthermore, the analysis of human–elephant conflict risk classes, as conducted in this research, represents an innovative contribution to the field, filling a critical gap in conservation studies and providing a robust framework for more accurate and actionable conservation planning. Interpretation of landscape structure analysis metrics in the context of conflict risk maps offers valuable insights into the spatial organisation of the landscape and its implications for managing conflict risk. Table 8 summarises the human–elephant conflict-specific implications derived from the FRAGSTATS landscape structure analysis metrics.

### 4.2. The key predictor variables of human–elephant conflicts in the Taita Taveta County

Distance to house and distance to crops were the most influential predictor variables for all human–elephant conflict models (Tables 3 and 4). This highlights their consistent role in predicting the conflicts and agrees with prior research that conflict risk increases closer to settlements and agricultural areas (Sitati et al., 2003; Li et al., 2023; Köpke et al., 2024; Rani et al., 2024). Even though our analysis did not include human population density, it is logical to assume that the number of humans per area unit is higher where

**Table 8**  
Summary of human–elephant conflict -specific implications for landscape structure analysis metrics.

Metric	Full Name	HEC-Specific Implication	Notable Observations from Data
CA	Class Area (ha)	Indicates the total spatial extent of each risk class; larger areas suggest broader zones of potential conflict.	Low-risk areas dominate across all models; high- and very high-risk zones are spatially limited, often < 1 % of landscape.
PLAND	Percentage of Landscape	Proportion of the landscape under each risk class; helps prioritize spatial extent of management.	Ensemble and SVM showed balanced PLAND distributions; BRT produced very small high-risk coverage.
NP	Number of Patches	Reflects landscape fragmentation; high NP suggests scattered conflict hotspots and higher monitoring challenges.	MAXENT and RF produced high NP for average to high-risk classes—more fragmented conflict areas.
LSI	Landscape Shape Index	Indicates patch shape complexity; higher values suggest irregular patch shapes, possibly aligning with habitat edge effects or human land-use boundaries.	BRT and MAXENT showed complex LSI in risk areas; GAM and SVM had more regular, compact shapes.
AREA_MN	Mean Patch Area (ha)	Larger mean patch areas imply more cohesive zones; small values suggest highly fragmented risk areas.	SVM generated large, cohesive low-risk patches; BRT produced small, fragmented high-risk zones.
ENN_MN	Euclidean Nearest Neighbour (m)	Measures isolation of patches; higher values imply sparse and potentially more isolated risk hotspots.	High-risk zones often had elevated ENN_MN, especially in SVM and GLM outputs.
PLADJ	Percentage of Like Adjacency	Higher values suggest contiguous, homogeneous risk zones—important for corridor identification or buffer zoning.	Low-risk zones had high PLADJ across models; high-risk zones varied considerably, often lower.
IJI	Interspersion and Juxtaposition Index	Measures how evenly risk patches are interspersed; important for predicting movement patterns or spill-over risk.	SVM and MAXENT showed higher IJI in average to high-risk zones, suggesting wide dispersal of conflict areas.
AI	Aggregation Index	Indicates how clumped or dispersed patches are; higher values suggest stronger clustering and possibly localized conflict risk.	Low-risk zones showed consistently high AI (>98 %); high-risk zones less aggregated, especially in MAXENT and RF.

the total number of houses is the highest. Thus, our result contrasts with Hoare (1999) who found no associations between the human–elephant conflict incidents and human population density, and with Pozo et al. (2017) who showed that conflict is not significantly driven by the absolute number of humans and elephants but is more likely determined by the use of space and competition for resources between them. In the same predictor importance rankings, distance to protected areas ranked third among the human–elephant conflict predictors, with conflict probability peaking at a distance of 3–7 km from their boundaries. This finding diverges slightly from previous studies, which often report the highest conflict risks occurring closer to protected areas (e.g., Gubbi, 2012; Guerbois et al., 2012; Naha et al., 2019; Shaffer et al., 2019; König et al., 2020; Tiller et al., 2021; Sanare et al., 2022). The models' prediction of elevated conflict probability near protected areas is a realistic assessment, as most elephants in the study area predominantly reside within the national parks (Ngene et al., 2013). Land-use change and connectivity of protected areas are emerging to become major threats affecting elephant movement and contributing to the rise in conflicts. Anthropogenic changes around protected areas can display different patterns as diverse as landscapes are, which may explain the contradicting results. Hence, when the findings are interpreted for management applications, caution should be taken to ensure these reflect the unique dynamics in the landscape of interest. Distance to waterholes ranked fourth, reflecting elephants' reliance on water sources, particularly during dry seasons (Wato et al., 2018; Mlambo et al., 2024). The distance to rivers was only the fifth most important variable and this diverges slightly with findings from previous human–elephant conflict studies (Fritz, 2017; Naha et al., 2019; Montero-Botey et al., 2024), where distance to rivers was a significant predictor. The result also contrasts with Sanare et al. (2022) who found no significant association between these conflicts and water body distribution in northern Tanzania. This anomaly could be attributed to the predominantly ephemeral nature of rivers in Taita Taveta County, which flow only briefly after rainfall events and remain dry for most of the year. As a result, rivers do not provide a consistent water source for elephants, which are highly water-dependent (Wato et al., 2018) and congregate wherever there is water, especially during scarcity in the dry season. To address this water scarcity, water supplementation through the creation of water pans and drilling of boreholes is common. These waterholes ensure sustained availability for wildlife, often lasting three to four months after rainfall events. Borehole-fed waterholes, equipped with solar pumps, ensure a continuous water supply. Such interventions help distribute wildlife more evenly across the landscape and mitigate habitat degradation caused by overconcentration near natural water sources. The response to the Enhanced Vegetation Index in our study was positive, with conflict risk increasing alongside higher vegetation index values. This result aligns with previous studies (Sanare et al., 2022; Shameer et al., 2024; Xu, Jiang and Liu, 2024), which associate elevated vegetation indices like Enhanced Vegetation Index and Normalized Difference Vegetation Index with crops at their peak growth stages, attracting elephants. Elephants choose food sources with the highest rates of nutrient intake (Osborn, 2004) and, therefore, favour greener vegetation with higher water content. This illustrates the importance of vegetation indices in the models. However, the overall performance of the Enhanced Vegetation Index as a predictor in our models was relatively poor. This may be attributable to its calculation as a 2014–2015 average, which could mask seasonal variations. Earlier research indicates that the predictive utility of vegetation indices in species distribution modelling improves when indices are split into dry and wet seasons (Mlambo et al., 2024). Additionally, in the Taita Taveta County landscape, the prevalence of irrigated croplands could influence the relationship between vegetation indices and human–elephant conflicts. Elephants are known to move to areas with abundant vegetation during different seasons (Bohrer et al., 2014), making seasonally sensitive vegetation indices potentially more effective for modeling conflict risk in such contexts. Similarly, crop raiding by elephants may have been influenced by the variety of crops grown, since most farmers grow more than one crop on their farms. Elephants forage selectively on palatable crops (Rohini et al., 2016), and show high preference for maize (Matsika et al., 2023), the dominant crop in the study area. Despite the dry conditions, the impact of crop raiding by elephants on households is of overriding importance in Taita Taveta County (Von Hagen et al., 2023).

The different agro-ecological zones of Taita Taveta County likely impact the distribution of human–elephant conflicts there. Taveta sub-county, located west of the Tsavo West National Park (Fig. 1), is more humid and has more intensive year-round agriculture, such as irrigated crop farming. Hence, when other areas of the county experience dry seasons with no crops, farms in Taveta produce crops at different stages of growth. More intensive agriculture attracts crop raiding by elephants (Tiller et al., 2021), which places Taveta at a disadvantage in comparison to the other areas in the county.

The climate predictors, namely annual mean temperature and mean precipitation 2014–2015, performed poorly in the predictor importance rankings, contrasting with earlier research where these variables ranked among the top predictors (Shameer et al., 2024). A likely explanation for this underperformance is the absence of seasonality in the climate data used for this analysis. Previous studies, such as Naha et al. (2019), emphasize the critical role of seasonal variations, particularly dry and wet seasons, in influencing human–elephant conflict dynamics. Naha et al. specifically identified annual mean precipitation as a key spatial predictor of conflict. These findings suggest that incorporating seasonal fluctuations into climate data could enhance the predictive accuracy of human–elephant conflict models, particularly for climate-related variables. The mean response curves of the predictor variables suggest that conflict incidents are more likely to occur in areas with lower annual precipitation, higher annual temperatures, and flat terrain (no slope) in Taita Taveta County. This finding is consistent with the idea that conflict events tend to occur in lowland savanna regions, which is a logical expectation as elephant habitats are currently restricted only to these semi-arid lowland plain areas. The distance to road was the least influential predictor in this study. This low ranking contrasts with earlier studies where proximity to roads was identified as a significant predictor of conflict (Chen et al., 2016; Lala et al., 2021). The relatively lower importance of this variable in our study may reflect the specific spatial dynamics of the study area, where roads are less associated with human–elephant interactions compared to other landscape features.

### 4.3. Limitations and future research directions

While we are confident that this study addresses an important research gap and provides a comprehensive comparative analysis of species distribution modelling algorithm performance and risk map comparisons using novel approaches, we acknowledge several limitations in the human–elephant conflict modeling presented. The modeling of potential conflict distribution through species distribution models relies heavily on the availability and quality of presence and environmental data. In this study, the human–elephant conflict incidence data were derived exclusively from Kenya Wildlife Service claim forms, which may not comprehensively capture the full spectrum of incidents. Moreover, a significant limitation was the absence of precise geographical coordinates in many of the claim forms, rendering them unusable for spatial analysis. Imperfect detection and reporting of human–elephant conflict incidents in the study area, may result in biased and incorrect conclusions of the spatiotemporal drivers of the phenomenon (Goswami et al., 2015). Future studies would benefit from a more comprehensive dataset that includes a broader scope of conflict incidences, potentially improving the model's accuracy and generalizability for regional assessments. Some key variables were excluded from this study due to data unavailability, but they may have important implications for conflict modeling in future research. These include: (i) crop types, which could influence the likelihood of elephant crop raiding as elephants show high preference for maize (Matsika et al., 2023; Montero-Botey et al., 2024); (ii) canopy cover, which provides shaded areas known to attract elephants (McKnight, 2015); (iii) fences, which restrict elephant movements between areas (Amara et al., 2020); (iv) cattle distribution, as elephants tend to avoid areas with high cattle populations (Ngene et al., 2017); (v) traditional migratory routes and paths of elephants that are important components in the distribution of human–elephant conflicts (Naughton et al., 1999); and (vi) seasonal variations such as wet and dry seasons that affect elephant movements and the frequency of conflict (Mlambo et al., 2024). These factors should be carefully considered in future studies to improve the robustness and predictive power of human–elephant conflict models.

## 5. Conclusions

The six modelling approaches offer a comprehensive perspective on human–elephant conflict risk, with each algorithm capturing different spatial patterns and contributing unique insights. While single models may emphasize specific risk areas, the ensemble model synthesizes their strengths, reducing potential biases and providing a more reliable and balanced prediction. This comparative approach supports decision-making by first identifying high-risk zones, allowing conservation managers to implement targeted strategies such as deterrents, habitat modifications, and land-use planning. Secondly, it facilitates efficient resource allocation by ensuring that conservation funds are prioritized in areas where conflict risk is highest and where multiple models show agreement. Thirdly, these maps promote community-driven solutions by providing local stakeholders with accessible, data-driven insights for developing mitigation measures. Fourthly, given the importance of Open Access publishing, researchers should prioritize making their findings widely available so that local authorities, conservationists, and community groups can readily access and apply them. Lastly, assessing model consensus strengthens confidence in intervention strategies, as consistently predicted high-risk areas indicate urgent priorities for mitigation. From a scientific standpoint, this study underscores the limitations of relying on a single model, such as Maximum Entropy, which may over- or underpredict conflict risk. By demonstrating the advantages of an ensemble approach, our findings contribute to improving predictive accuracy and guiding evidence-based management strategies for mitigating human–elephant conflict.

Human–wildlife conflict represents a significant challenge for conservation efforts and local livelihoods across many regions, including Taita Taveta County, Kenya. The negative impact of human–elephant conflict incidents on both wildlife conservation and human communities underscores the urgency of developing effective mitigation strategies. This study used species distribution models and ensemble modelling to examine the relationship between human–elephant conflict incidents and ten environmental predictors, subsequently generating and evaluating both probability and risk maps. In addition, landscape indices were calculated to assess the spatial structure of conflict risk, and a novel method for combining risk metrics was introduced to enhance the evaluation of risk map performance. Our findings provide a critical contribution to the conservation ecology literature by offering a novel framework for human–elephant conflict modelling. To summarise our findings: (i), the results show significant variation among individual species distribution model algorithms, underscoring the limitations of single-model approaches in predicting conflict risk; (ii) the ensemble model provided consistent and balanced results, offering a harmonised human–elephant conflict prediction, which highlights the importance of ensemble methodologies in addressing complex conservation challenges; (iii) distance to houses and distance to crops were identified as the most influential predictors of conflict; (iv) landscape indices contributed to improved interpretation of risk maps. This study not only advances our understanding of the spatial dynamics of human–elephant conflict but also provides a valuable tool for conservation practitioners seeking to mitigate conflict and protect both human livelihoods and wildlife populations. Policy makers can adopt our findings to identify priority areas for human–elephant conflict mitigation. This is sorely needed, because human–elephant conflict is highlighted among the top threats facing elephant conservation within its range (Kenya Wildlife Service, 2008; Shaffer et al., 2019). In addition, complementing the scientific methods proposed here with local ecological knowledge at a relevant scale can contribute to better understanding and prediction of landscape use by elephants (Buchholtz et al., 2020). Integrating the prediction models on human–elephant conflicts with the indigenous knowledge of Taita communities on the nondestructive practices of conflict management (Mwamidi et al., 2012) could aid in developing prevention and mitigation strategies that are more inclusive, locally appropriate, and spatially targeted to the predicted high-risk human–elephant conflict areas.

## CRediT authorship contribution statement

**Tino Johansson:** Writing – original draft, Project administration, Supervision, Funding acquisition. **Martha Munyao:** Writing – Review & Editing, Resources, Data curation. **Petri Pellikka:** Visualization, Writing – Review & Editing, Supervision, Funding acquisition. **Sakari Äärilä:** Conceptualization, Methodology, Investigation, Data curation, Writing – original draft. **Patrick Omondi:** Resources, Reviewing. **Mika Siljander:** Conceptualization, Methodology, Investigation, Data curation, Validation, Visualization, Formal analysis, Writing – original draft, Supervision.

## Ethics

Not applicable: This manuscript does not include human or animal research.

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## Declaration of Competing Interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests

Tino Johansson reports financial support was provided by European Commission. Petri Pellikka reports financial support was provided by European Commission. Petri Pellikka reports financial support was provided by Research Council of Finland. Mika Siljander reports financial support was provided by Kone Foundation. If there are other authors, they declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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## Appendix A. Supporting information

Supplementary data associated with this article can be found in the online version at [doi:10.1016/j.gecco.2025.e03604](https://doi.org/10.1016/j.gecco.2025.e03604).

## Data availability

The authors do not have permission to share data.

## References

- Abera, T.A., Vuorinne, I., Munyao, M., Pellikka, P.K.E., Heiskanen, J., 2022. Land cover map for multifunctional landscapes of taita taveta county, kenya, based on sentinel-1 radar, sentinel-2 optical, and topoclimatic data. *Data* 7 (3), 36.
- Allouche, O., Tsoar, A., Kadmon, R., 2006. Assessing the accuracy of species distribution models: prevalence, kappa and the true skill statistic (TSS). *J. Appl. Ecol.* 43, 1223–1232.
- Amara, E., Adhikari, H., Heiskanen, J., Siljander, M., Munyao, M., Omondi, P., Pellikka, P., 2020. Aboveground biomass distribution in a multi-use savannah landscape in southeastern kenya: impact of land use and fences. *Land* 9 (10), 381. <https://doi.org/10.3390/land9100381>.
- Ansari, M., Ghoddousi, A., 2018. Water availability limits brown bear distribution at the southern edge of its global range. *Ursus* 29 (1), 13–24.
- Araújo, M.B., New, M., 2007. Ensemble forecasting of species distributions. *Trends Ecol. Evol.* 22, 42–47. <https://doi.org/10.1016/j.tree.2006.09.010>.
- Barbet-Massin, M., Jiguet, F., Albert, C.H., Thuiller, W., 2012. Selecting pseudo-absences for species distribution models: how, where and how many? *Methods Ecol. Evol.* 3 (2), 327–338. <https://doi.org/10.1111/j.2041-210x.2011.00172.x>.
- Baskaran, N., Sathishkumar, S., Vanitha, V., Arjun, M., Keerthi, P., Bandhala, N.G., 2024. Unveiling the hidden causes: identifying the drivers of human–elephant conflict in Nilgiri Biosphere Reserve, Western Ghats, Southern India. *Animals* 14, 3193. <https://doi.org/10.3390/ani14223193>.
- Besley, D., Kuh, E., Welsch, R., 1980. *Regression Diagnostics: Identifying Influential Data and Sources of Collinearity*. Wiley, New York. <https://doi.org/10.1002/0471725153>.
- Bohrer, G., Beck, P.S.A., Ngene, S.M., Skidmore, A.K., Douglas-Hamilton, I., 2014. Elephant movement closely tracks precipitation-driven vegetation dynamics in a Kenyan forest-savanna landscape. *Mov. Ecol.* 2 (1), 1–12. <https://doi.org/10.1186/2051-3933-2-2>.
- Buchholtz, E.K., Fitzgerald, L., Songhurst, A., McCulloch, G.P., Stronza, A.L., 2020. Experts and elephants: local ecological knowledge predicts landscape use for a species involved in human-wildlife conflict. *Ecol. Soc.* 25 (4), 26. <https://doi.org/10.5751/ES-11979-250426>.

- Buebos-Esteve, D.E., Redena-Santos, J.C., Dagamac, N.H.A., 2024. Ensemble modeling to identify high conservation value areas for endemic and elusive large-sized mammals of the Philippines. *J. Nat. Conserv* 80, 126657. <https://doi.org/10.1016/j.jnc.2024.126657>.
- Chen, Y., Marino, J., Chen, Y., Tao, Q., Sullivan, C.D., Shi, K., Macdonald, D.W., 2016. Predicting hotspots of human–elephant conflict to inform mitigation strategies in Xishuangbanna, Southwest China. *PLoS ONE* 11 (9), e0162035. <https://doi.org/10.1371/journal.pone.0162035>.
- Dejene, S.W., Mpakairi, K.S., Kanagaraj, R., Wato, Y.A., Mengistu, S., 2021. Modelling continental range shift of the African elephant (*Loxodonta africana*) under a changing climate and land cover: implications for future conservation of the species. *Afr. Zool.* 56 (1), 25–34. <https://doi.org/10.1080/15627020.2020.1846617>.
- Elith, J., Leathwick, J.R., Hastie, T., 2008. A working guide to boosted regression trees. *J. Anim. Ecol.* 77 (4), 802–813. <https://doi.org/10.1111/j.1365-2656.2008.01390.x>.
- Fidino, M., Lehrer, E.W., Kay, C.A.M., Yarmey, N.T., Murray, M.H., Fake, K., Adams, H.C., Magle, S.B., 2022. Integrated species distribution models reveal spatiotemporal patterns of human–wildlife conflict. *Ecol. Appl.*, e2647 <https://doi.org/10.1002/eap.2647>.
- Fielding, A.H., Bell, J.F., 1997. A review of methods for the assessment of prediction errors in conservation presence/absence models. *Environ. Conserv* 24 (1), 38–49. <https://doi.org/10.1017/S0376892997000088>.
- Fortin, D., Brooke, C.F., Lamirande, P., Fritz, H., McLoughlin, P.D., Pays, O., 2020. Quantitative spatial ecology to promote human–wildlife coexistence: a tool for integrated landscape management. *Front. Sustain. Food Syst.* 4, 600363. <https://doi.org/10.3389/fsufs.2020.600363>.
- Fritz, H., 2017. Long-term field studies of elephants: understanding the ecology and conservation of a long-lived ecosystem engineer. *J. Mammal.* 98 (3), 603–611. <https://doi.org/10.1093/jmammal/gyx023>.
- Funk, C., Peterson, P., Landsfeld, M., et al., 2015. The climate hazards infrared precipitation with stations—a new environmental record for monitoring extremes (Article). *Sci. Data* 2, 150066. <https://doi.org/10.1038/sdata.2015.66>.
- Goswami, V.R., Medhi, K., Nichols, J.D., Oli, M.K., 2015. Mechanistic understanding of human–wildlife conflict through a novel application of dynamic occupancy models. *Conserv. Biol.* 29 (4), 1100–1110.
- Gubbi, S., 2012. Patterns and correlates of human–elephant conflict around a south Indian reserve. *Biol. Conserv* 148 (1), 88–95 <https://doi.org/10.1016/j.biocon.2012.01.046>.
- Guerbois, C., Chapanda, E., Fritz, H., 2012. Combining multi-scale socio-ecological approaches to understand the susceptibility of subsistence farmers to elephant crop raiding on the edge of a protected area. *J. Appl. Ecol.* 49, 1149–1158.
- Guisan, A., Zimmermann, N., 2000. Predictive habitat distribution models in ecology. *Ecol. Model.* 135 (2–3), 147–186.
- Guisan, A., Thuiller, W., Zimmermann, N.E., 2017. *Habitat suitability and distribution models: With applications in R*. Cambridge University Press.
- Hao, T., Elith, J., Guillera-Arroita, G., Lahoz-Monfort, J.J., 2019. A review of evidence about use and performance of species distribution modelling Ensembles like BIOMOD. *Divers. Distrib.* 25 (5), 839–852. <https://doi.org/10.1111/ddi.12892>.
- Hoare, R.E., 1999. Determinants of human–elephant conflict in a land-use mosaic. *J. Appl. Ecol.* 36 (5), 689–700.
- Huete, A., Didan, K., Miura, T., Rodriguez, E.P., Gao, X., Ferreira, L.G., 2002. Overview of the radiometric and biophysical performance of the MODIS vegetation indices. *Remote Sens. Environ.* 83 (1–2), 195–213. [https://doi.org/10.1016/S0034-4257\(02\)00096-2](https://doi.org/10.1016/S0034-4257(02)00096-2).
- Jayakody, S., Estacio, I., Sianipar, C.P.M., Onitsuka, K., Basu, M., Hoshino, S., 2024. Maxent modeling for predicting the potential distribution of human–elephant conflict risk in Sri Lanka. *Appl. Geogr.* 173. <https://doi.org/10.1016/j.apgeog.2024.103447>.
- Kenya National Bureau of Statistics, 2019. Kenya Population and Housing Census Volume 1: Population by County and Sub-County. In, 2019 Kenya Population and Housing Census. Retrieved from (<https://www.knbs.or.ke/>).
- Kenya Wildlife Service, 2008. Conservation and Management Strategy for Elephant in Kenya 2012–2021. Retrieved from (<https://www.kws.go.ke/>).
- Kitratporn, N., Takeuchi, W., 2020. Spatiotemporal distribution of human–elephant conflict in eastern Thailand: a model-based assessment using news reports and remotely sensed data. *Remote Sens* 12 (1), 90. <https://doi.org/10.3390/rs12010090>.
- de Knegt, H.J., van Langevelde, F., Skidmore, A.K., Delsink, A., Slotow, R., Henley, S., Prins, H.H.T., 2011. The spatial scaling of habitat selection by African elephants. *J. Anim. Ecol.* 80 (1), 270–281. <https://doi.org/10.1111/j.1365-2656.2010.01764.x>.
- König, H.J., Kiffner, C., Kramer-Schadt, S., Fürst, C., Keuling, O., Ford, A.T., 2020. Human–wildlife coexistence in a changing world. *Conserv. Biol.* 34, 786–794. <https://doi.org/10.1111/cobi.13513>.
- Köpke, S., Withanachchi, S.S., Chinthaka Perera, E.N., et al., 2024. 2024. Factors driving human–elephant conflict: statistical assessment of vulnerability and implications for wildlife conflict management in Sri Lanka. *Biodivers. Conserv* 33, 3075–3101. <https://doi.org/10.1007/s10531-024-02903-z>.
- Lala, F., Chiyo, P.I., Kanga, E., Omondi, P., Ngene, S., Severud, W.J., Morris, A.W., Bump, J., 2021. Wildlife roadkill in the tsavo ecosystem, Kenya: identifying hotspots, potential drivers, and affected species. *Heliyon* 7 (3), e06364. <https://doi.org/10.1016/j.heliyon.2021.e06364>.
- Li, W., Liu, P., Yang, N., Pan, H., Chen, S., Zhang, L., 2023. Spatio-temporal trend and mitigation of human–elephant conflict in Xishuangbanna, China. *J. Wildl. Manag.* 87, e22485. <https://doi.org/10.1002/jwmg.22485>.
- Lobo, J.M., Jiménez-Valverde, A., Real, R., 2008. AUC: A misleading measure of the performance of predictive distribution models. *Glob. Ecol. Biogeogr.* 17, 145–151.
- Long, H., Mojo, D., Fu, C., Wang, G., Kanga, E., Oduor, A.M.O., Zhang, L., 2020. Patterns of human–wildlife conflict and management implications in Kenya: a national perspective. *Hum. Dimens. Wildl.* 25, 121–135. <https://doi.org/10.1080/10871209.2019.1695984>.
- Malviya, M., Krishnamurthy, R., 2022. Multiscale spatially explicit modelling of livestock depredation by reintroduced tiger (*Panthera tigris*) to predict conflict risk probability. *ISSN 2351-9894 Glob. Ecol. Conserv* 40, e02313. <https://doi.org/10.1016/j.gecco.2022.e02313>.
- Marmion, M., Parviainen, M., Luoto, M., Heikkinen, R.K., Thuiller, W., 2009. Evaluation of consensus methods in predictive species distribution modelling. *Divers. Distrib.* 15 (1), 59–69. <https://doi.org/10.1111/j.1472-4642.2008.00491.x>.
- Mateo-Tomás, P., Olea, P.P., Sánchez-Barbudo, I.S., Mateo, R., 2012. Alleviating human–wildlife conflicts: identifying the causes and mapping the risk of illegal poisoning of wild fauna. *J. Appl. Ecol.* 49, 376–385. <https://doi.org/10.1111/j.1365-2664.2012.02119.x>.
- Matsika, T.A., et al., 2023. Crop diversity and susceptibility of crop fields to elephant raids in eastern Okavango Panhandle, northern Botswana. *Ecol. Evol.* 13 (3), 1–11. <https://doi.org/10.1002/ece3.9910>.
- McGarigal K., Cushman, S.A., Ene, E., 2023. FRAGSTATS v4: Spatial Pattern Analysis Program for Categorical Maps. Computer software program produced by the authors; available at the following web site: (<https://www.fragstats.org/>).
- McKnight, B.L., 2015. Relationship between group dynamics and spatial distribution of African elephants in a semi-arid environment. *Afr. J. Ecol.* 53 (4), 439–446. <https://doi.org/10.1111/aje.12223>.
- Mekonnen, S., 2020. Coexistence between human and wildlife: the nature, causes and mitigations of human wildlife conflict around Bale Mountains National Park, Southeast Ethiopia. *BMC Ecol.* 20, 51. <https://doi.org/10.1186/s12898-020-00319-1>.
- Meyer, M., Börner, J., 2022. Rural livelihoods, community-based conservation, and human–wildlife conflict: Scope for synergies? *Biol. Conserv* 272, 109666. <https://doi.org/10.1016/j.biocon.2022.109666>.
- Mlambo, L., Adam, E., Shekede, M.D., Odindi, J., 2024. The influence of biophysical characteristics on elephant space use in an African savanna. *Ecol. Inf.* 82, 102724. <https://doi.org/10.1016/j.ecoinf.2024.102724>.
- Montero-Botey, M., Kivuyo, E., Sitati, N., Perea, R., 2024. Deforestation and water availability as main drivers of human–elephant conflict. *ISSN 2351-9894 Glob. Ecol. Conserv* 54, e03068. <https://doi.org/10.1016/j.gecco.2024.e03068>.
- Mukeka, J.M., Ogutu, J.O., Kanga, E., Roskaft, E., 2018. Characteristics of human–wildlife conflicts in Kenya: examples of tsavo and maasai mara regions. *Environ. Nat. Resour. Res.* 8 (3), 148. <https://doi.org/10.5539/enr.v8n3p148>.
- Mukeka, J.M., Ogutu, J.O., Kanga, E., Roskaft, E., 2019. Human–wildlife conflicts and their correlates in Narok County, Kenya. *April 2019 Glob. Ecol. Conserv* 18, e00620. <https://doi.org/10.1016/j.gecco.2019.e00620>.
- Mukeka, J.M., Ogutu, J.O., Kanga, E., Roskaft, E., 2020. Spatial and temporal dynamics of human–wildlife conflicts in the Kenya Greater Tsavo Ecosystem. *Hum. Wildl. Inter.* 14 (2), 255–272.
- Munyao, M.N., Siljander, M., Johansson, T., Makokha, G., Pellikka, P., 2020. Assessment of human–elephant conflicts in multifunctional landscapes of Taita Taveta County, Kenya. *Glob. Ecol. Conserv* 24, e01382. <https://doi.org/10.1016/j.gecco.2020.e01382>.

- Mwamidi, D.M., Mwasi, S.M., Nunow, A.A., 2012. The use of indigenous knowledge in minimizing human-wildlife conflict: the case of Taita community, Kenya. *Int. J. Curr. Res.* 4 (2), 26–30. ([http://journalcra.com/sites/default/files/issue-pdf/1565\\_0.pdf](http://journalcra.com/sites/default/files/issue-pdf/1565_0.pdf)).
- Mwangi, D.K., Akinyi, M., Maloba, F., Ngotho, M., Kagira, J., Ndeereh, D., Kivai, S., 2016. Socioeconomic and health implications of human–wildlife interactions in Nthongoni, Eastern Kenya. *Afr. J. Wildl. Res.* 46 (2), 87–102. <https://doi.org/10.3957/056.046.0087>.
- Mwaura, F., 2016. Wildlife heritage ownership and utilization in Kenya – the past, present and future. In: Deisser, A.-M., Njuguna, M. (Eds.), *Conservation of Natural and Cultural Heritage in Kenya: A Cross-Disciplinary Approach*, 1st ed. UCL Press, pp. 125–142 (<http://www.jstor.org/stable/j.ctt1gxxpc6.15>).
- Naha, D., Sathyakumar, S., Dash, S., Chettri, A., Rawat, G.S., 2019. Assessment and prediction of spatial patterns of human-elephant conflicts in changing land cover scenarios of a human-dominated landscape in North Bengal. *PLoS ONE* 14 (2), e0210580. <https://doi.org/10.1371/journal.pone.0210580>.
- Naimi, B., Araújo, M.B., 2016. sdm: a reproducible and extensible R platform for species distribution modelling. *Ecography* 39, 368–375. <https://doi.org/10.1111/ecog.01881>.
- Naimi, B., Hamm, N.A., Groen, T.A., Skidmore, A.K., Toxopeus, A.G., 2014. Where is positional uncertainty a problem for species distribution modelling. *Ecography* 37, 191–203.
- Naughton, L., Rose, R., Treves, A., 1999. The social dimensions of human-elephant conflict in Africa: A literature review and case studies from Uganda and Cameroon. Report to the African Elephant Specialist, Human-Elephant Task Force of IUCN. 82 pp. Glands, Switzerland.
- Nayeri, D., Mohammadi, A., Hysen, L., Hipolito, D., Huber, D., Wan, H.Y., 2022. Identifying human-caused mortality hotspots to inform human-wildlife conflict mitigation. *Glob. Ecol. Conserv.* 38, e02241. <https://doi.org/10.1016/j.gecco.2022.e02241>.
- Newbold, T., et al., 2015. Global effects of land use on local terrestrial biodiversity. *Nature* 520, 45–50. <https://doi.org/10.1038/nature14324>.
- Ngene, S., et al., 2017. Aerial total count of elephants, buffalo and giraffe in the Tsavo-Mkomazi ecosystem (February 2017). Technical Report. Kenya Wildlife Service, Arusha.
- Ngene, S., Ihwagi, F., Nzisa, M., Mukenka, J., Njumbi, S., Omondi, P., 2013. Total aerial census of elephants and other larger mammals in the Tsavo-Mkomazi ecosystem. *Pachyderm* 53, 38–50.
- Obunga, G., Siljander, M., Maghenda, M., Pellikka, P.K.E., 2022. Habitat suitability modelling to improve conservation status of two critically endangered endemic Afrotropical forest bird species in Taita Hills, Kenya. *J. Nat. Conserv.* 65, 126111. <https://doi.org/10.1016/j.jnc.2021.126111>.
- Ogutu, J.O., Piepho, H.P., Said, M.Y., Ojwang, G.O., Njino, L.W., Kifugo, S.C., Wargute, P.W., 2016. Extreme wildlife declines and concurrent increase in livestock numbers in Kenya: what are the causes? *PLoS ONE* 11 (9), 1–46. <https://doi.org/10.1371/journal.pone.0163249>.
- Osborn, F.V., 2004. Seasonal variation of feeding patterns and food selection by crop-raiding elephants in Zimbabwe. *Afr. J. Ecol.* 42 (4), 322–327. <https://doi.org/10.1111/j.1365-2028.2004.00531.x>.
- Pearson, R.G., Thuiller, W., Araújo, M.B., Martinez-Meyer, E., Brotons, L., McClean, C., Miles, L., Segurado, P., Dawson, T.P., Lees, D.C., 2006. Model-based uncertainty in species range prediction. *J. Biogeogr.* 33, 1704–1711.
- Platts, P., Omeny, P., Marchant, R., 2015. AFRICLIM: high-resolution climate projections for ecological applications in Africa. *Afr. J. Ecol.* 53, 103–108. <https://doi.org/10.1111/aje.12180>.
- Pozo, R.A., Coulson, T., McCulloch, G., Stronza, A.L., Songhurst, A.C., 2017. Determining baselines for human-elephant conflict: a matter of time. *PLoS ONE* 12 (6), e0178840. <https://doi.org/10.1371/journal.pone.0178840>.
- R Core Team, 2024. R: A language and environment for statistical computing. R Foundation for Statistical Computing, Vienna, Austria. URL <https://www.R-project.org/>.
- Rani, M., Panda, D., Allen, M.L., Pandey, P., Singh, R., Kumar Singh, S., 2024. Assessment and prediction of human-elephant conflict hotspots in the human-dominated area of Rajaji-Corbett landscape, Uttarakhand, India. *J. Nat. Conserv.* 79, 126601. <https://doi.org/10.1016/J.JNC.2024.126601>.
- Rohini, C.K., Aravindan, T., Vinayan, P.A., Ashokkumar, M., Anoop Das, K.S., 2016. An assessment of human-elephant conflict and associated ecological and demographic factors in Nilambur, Western Ghats of Kerala, southern India. *J. Threat. Taxa* 8, 8970–8976. <https://doi.org/10.11609/jott.2536.8.7.8970-8976>.
- Sakti, A.D., Adillah, K.P., Santoso, K., Faruqi, I. al., Hendrawan, V.S.A., Sofan, P., Rustam, Fauzi, A.I., Setiawan, Y., Utami, I., Zain, A.F.M., Kamal, M., 2024. Modeling proboscis monkey conservation sites on borneo using ensemble machine learning. *Glob. Ecol. Conserv.* 54. <https://doi.org/10.1016/j.gecco.2024.e03101>.
- Sanare, J.E., Valli, D., Leweri, C., Glatzer, G., Fishlock, V., Treydte, A.C., 2022. A socio-ecological approach to understanding how land use challenges human-elephant coexistence in Northern Tanzania. *Diversity* 14, 513. <https://doi.org/10.3390/d14070513>.
- Shaffer, L.J., Khadka, K.K., Van Den Hoek, J., Naithani, K.J., 2019. Human-elephant conflict: a review of current management strategies and future directions. *Front. Ecol. Evol.* 6, 235. <https://doi.org/10.3389/fevo.2018.00235>.
- Shameer, T.T., Routray, P., Udhayan, A., et al., 2024. Understanding the patterns and predictors of human-elephant conflict in Tamil Nadu, India. *Eur. J. Wildl. Res.* 70, 95. <https://doi.org/10.1007/s10344-024-01848-6>.
- Sharma, P., Panthi, S., Yadav, S.K., Bhatta, M., Karki, A., Duncan, T., Poudel, M., Acharya, K.P., 2020. Suitable habitat of wild Asian elephant in Western Terai of Nepal. *Ecol. Evol.* 10, 6112–6119. <https://doi.org/10.1002/ece3.6356>.
- Sitati, N.W., Walpole, M.J., Smith, R.J., Leader-Williams, N., 2003. Predicting spatial aspects of human–elephant conflict. *J. Appl. Ecol.* 40, 667–677. <https://doi.org/10.1046/j.1365-2664.2003.00828.x>.
- Sofaer, H.R., Jarnevich, C.S., Pearse, I.S., Smyth, R.L., Auer, S., Cook, G.L., Edwards, T.C., Guala Jr., G.F., Howard, T.G., Morissette, J.T., Hamilton, H., 2019. Development and delivery of species distribution models to inform decision-making. *BioScience* 69 (7), 544–557. <https://doi.org/10.1093/biosci/biz045>.
- Swets, J.A., 1988. Measuring the accuracy of diagnostic systems. *Science* 240, 1285–1293. <https://doi.org/10.1126/science.3287615>.
- Taita Taveta County Government, 2013. County integrated development plan. 278 pp.
- Thuiller, W., Georges, D., Engler, R., 2009. BIOMOD2: Ensemble platform for species distribution modeling. 5 pp.
- Tiller, L.N., Humle, T., Amin, R., Deere, N.J., Lago, B.O., Leader-Williams, N., Sinoni, F.K., Sitati, N., Walpole, M., Smith, R.J., 2021. Changing seasonal, temporal and spatial crop-raiding trends over 15 years in a human-elephant conflict hotspot. *Biol. Conserv.* 254, 108941. <https://doi.org/10.1016/j.biocon.2020.108941>.
- Von Hagen, L., Schulte, B.A., Dunning, K., Steury, T.D., Githiru, M., Zohdy, S., Lepczyk, C.A., 2023. Farmer attitudes on climate change, farming practices, and livelihood threats, and the impact to conservation in the Kasigau Wildlife Corridor, Kenya. *Hum. Ecol.* <https://doi.org/10.1007/s10075-023-00426-9>.
- Wato, Y.A., Prins, H.H.T., Heitkönig, I.M.A., Wahungu, G.M., Ngene, S.M., Njumbi, S., van Langevelde, F., 2018. Movement patterns of African Elephants (*Loxodonta africana*) in a Semi-arid Savanna suggest that they have information on the location of dispersed water sources. *Front. Ecol. Evol.* 6 (OCT), 1–8. <https://doi.org/10.3389/fevo.2018.00167>.
- Williams, H.F., Bartholomew, D.C., Amakobe, B., Githiru, M., 2018. Environmental factors affecting the distribution of African elephants in the Kasigau wildlife corridor, SE Kenya. *Afr. J. Ecol.* 56 (2), 244–253. <https://doi.org/10.1111/aje.12442>.
- Xu, H., Jiang, L., Liu, Y., 2024. Mapping the potential distribution of Asian elephants: Implications for conservation and human–elephant conflict mitigation in South and Southeast Asia. *Ecol. Inf.* 80. <https://doi.org/10.1016/j.ecoinf.2024.102518>.
- Xu, Y., Tang, J., 2024. Examining the rationality of Giant Panda National Park's zoning designations and management measures for habitat conservation: Insights from interpretable machine learning methods. *Sci. Total Environ.* 920. <https://doi.org/10.1016/j.scitotenv.2024.170955>.
- Zhang, J., Jiang, F., Li, G., Qin, W., Li, S., Gao, H., Cai, Z., Lin, G., Zhang, T., 2019. Maxent modeling for predicting the spatial distribution of three raptors in the Sanjiangyuan National Park, China. *Ecol. Evol.* 9 (11), 6643–6654.