Open Access Library Journal
2024, Volume 11, e11509
ISSN Online: 2333-9721
ISSN Print: 2333-9705

Modelling Poaching Risk Zones in Sengwa Wildlife Research Area: A Progressive Step towards Poaching Management

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How to cite this paper: Chinoitezvi, H., Kusangaya, S., Muzamba, C.P., Ndlovu, M. and Hungwe, C. (2024) Modelling Poaching Risk Zones in Sengwa Wildlife Research Area: A Progressive Step towards Poaching Management. *Open Access Library Journal*, **11**: e11509.
https://doi.org/10.4236/oalib.1111509

Received: March 29, 2024
Accepted: May 21, 2024
Published: May 24, 2024

Abstract

Protected areas offer opportunities for natural resources management including biodiversity conservation. However, their success is incessantly stalled by non-compliant activities especially illegal hunting of wildlife. The use of empirical and spatially explicit information in understanding spatial patterns of wildlife poaching risk areas within protected areas is thus of paramount importance in implementing effective law enforcement towards anti-poaching. The use of species distribution models (SDM) in the field of wildlife research offers opportunities for increasing the understanding of poacher behavior in data scarce regions. However, the application of SDM in improving the understanding of wildlife poaching is still in its infancy. Predictive modelling of wildlife poaching risk was conducted for Sengwa Wildlife Research Area (SWRA) using Maximum Entropy modeling, a presence-only SDM. Results revealed that six predictor variables explained 80% of poaching incidents. These were SAVI, slope, distance from rivers, distance from roads, distance from settlements and general wildlife distribution. Riverine areas presented the most poaching risk zones with areas of steep slopes being of least poaching risks. Findings of this research can be used as a guiding tool in SWRA by park managers, to make informed conservation management decisions and effectively establish anti-poaching strategies by prioritizing areas of high risk. These results are very informative especially in situations where conservation resources are limited. Because of limited resources, wildlife managers are constrained to explicitly identify zones with the highest poaching risks for proactive resource allocation so as to combat illegal wildlife hunting. The modelling framework used in this study provides a crucial baseline for identifying potentially high-risk poaching zones and the main predictors, knowledge that can be utilized for proactive resource allocation towards anti-poaching activities. In addition, these results can be up scaled to any other conservation areas where poaching is problematic.

Subject Areas

Environmental Sciences, Geography

Keywords

Modelling, Maximum Entropy, Poaching, Predictor Variables,
Wire Snares

1. Introduction

At a global scale, efforts are directed towards preservation and protection of biodiversity (Muzhingi, 2012) [1]. However, despite massive conservation efforts in protected areas, several wildlife species are declining in numbers due to illegal human activities such as poisoning and poaching. According to (Kassa, *et al*., 2022) [2] poaching is defined as the illicit hunting, capturing and killing of wildlife and remains one of the primary causes of biodiversity loss. Although poaching cannot be completely exterminated, in Zimbabwe, wildlife estate managers and conservationists are facing challenges in controlling poaching. This is primarily because of several factors including inadequate resources, under-motivated staff, poorly enforced laws and regulations and corruption (Muzhingi, 2012) [1]. Previous studies show that most illegal activities such as poaching are usually common in areas close to settlements. Many people living close to parks depend largely on natural resources for their livelihood and basic needs (Wittemyer, *et al*., 2008) [3]. Therefore, this entails that human footprint expansion in the form of settlements closer to protected areas is closely related to increased poaching activities. Whereas agriculture expansion closer to the park seasonally attracts wild animals, it makes these animals easier targets and hence more vulnerable to poaching. Illegal hunting is often triggered when subsistence agriculture, the main source of livelihood for local people is impacted by drought and climate change.

A study by (Iossa, *et al*., 2007) [4], reviewed some of the different kinds of traps used worldwide. The use of wire snare is one of the simplest and most effective hunting methods practiced, and posing the highest threat to species survival (Fa & Brown, 2009) [5]. Their non-selective nature imposes significant loss and extinction threat within a group of targeted animals as well as non-targeted species. Besides eroding wildlife species, (Zvidzai, *et al*., 2023) [6] state that illegal hunting in adjacent protected areas by local people elevates conflicts between local people and park rangers. However, on the other hand, local people perceive wildlife as pests responsible for the destruction of their main source of livelihood, in the form of crop raids and livestock predation. The absence of any restitution from accountable authorities results in the retaliatory killing of these problem animals (Zvidzai, *et al*., 2023) [6]. Other studies showed that poaching is a consequence of conflicts that arise from the exclusion of local people from wildlife resources, alienation of land used for agriculture and other traditional uses to be managed as protected areas.

The use of spatial modelling to understand the spatial distribution of poaching incidents is progressively becoming imperative to guide conservation planning and device mechanisms to enhance anti-poaching activities. Although normally applied in wildlife conservation studies, species distribution modeling (SDM) is becoming an indispensable tool in predicting and visualizing potential poaching risk zones (Zvidzai, *et al*., 2023) [6]. An appraisal of literature shows that the use of SDMs for analyzing poaching incidents is currently few, but on an increasing trajectory. This could be possibly due to data scarcity. According to (Mohammadi, *et al*., 2021) [7] other studies have focused on the potential spatial distribution of human-carnivore conflicts hotspots as a tool to prioritize the conservation of lions, whose populations are facing extreme threats from human-wildlife conflicts. Use of geospatial and remote sensing technologies, coupled with SDM tools such as maximum entropy (MaxEnt), is increasingly becoming a pressing requirement for providing a spatial dimension to the illegal hunting discourse. Development of effective and sustainable mitigatory strategies for poaching necessitates knowledge of the specific areas prone to poaching risks as well as clear insights into the ecological and social covariates associated with illegal activities. Although it is traditionally used for species distribution, MaxEnt is increasingly becoming a potent tool across a range of social and ecological applications, especially where data availability is constrained (Sharma, *et al*., 2020) [8] and Sengwa Wildlife Research Area (SWRA) is no exception.

Almost all mammalian species in the SWRA and Sebungwe region of Zimbabwe have declined as recorded by aerial surveys which have been carried out since the 1980s. Poaching is the often cited driver of herbivore declines (Mahakata, 2022) [9]. This, therefore, necessitates the need for increased understanding of poaching risk zones in order to enhance conservation planning programs such as ranger patrols. Studies have also shown that water sources such as springs and rivers are associated with high wildlife densities making them more convenient for wildlife poaching activities (Pisa & Katsande, 2021) [10]. In his study, Mahakata (2022) [9] highlighted that recurring wire snaring in SWRA poses a major threat to the survival of animal species and effective monitoring and understanding of wire-snare occurrence and distribution is critical to reducing massive killing of wild animals both targeted and non-targeted species.

This work is one of the few that combines the use of SDM technologies with ecological factors to improve the understanding and geographical dimension of poaching risk occurrences in a data-scarce region like SWRA. Specifically, the study sought to identify the ecological characteristics that predict the prevalence of poaching hotspot zones. The study also employs SDM approaches to create a spatially explicit poaching risk map, which serves as a tool for informing effective and proactive conservation and mitigation efforts. This is critical for guiding the strategic prioritization and deployment of sometimes limited conservation resources in monitoring and controlling poaching in order to optimize benefits for both wildlife and humans.

2. Materials and Methods

2.1. Study Area

The study was conducted in Sengwa Wildlife Research Area (18˚10"S, 28˚14"E) which is situated at the southern end of Chirisa Safari Area in Gokwe South District, north-western Zimbabwe (**Figure 1**). SWRA covers an area of 373 km^2, the area was set aside in the late 1960s for long term wildlife and ecological research (Tafangenyasha, *et al.*, 2018) [11]. The area experiences three climatic seasons, a hot-wet period extending from November to April, a cool-dry period stretching from May to July and a hot-dry period from August to October. SWRA is a semi-arid ecosystem with low and irregular rainfall patterns, having a mean annual rainfall of 670 mm with a range from 347 mm to 960 mm recorded over a period of 50 years (1968-2018), (Department of Meteorological Services unpublished data). The mean annual recorded temperature is 22.2˚C. The regularly

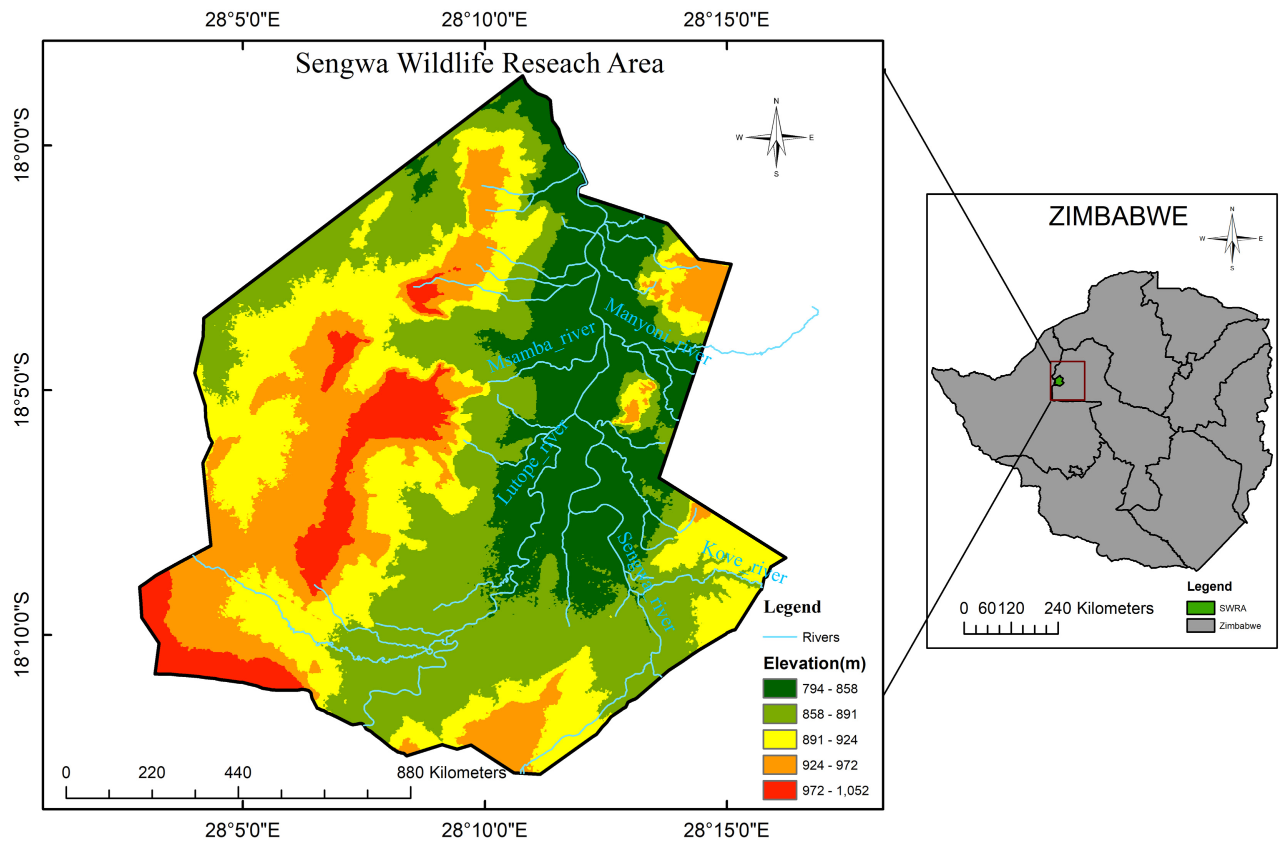

Figure 1. Location of Sengwa Wildlife Research Area (SWRA).

sighted large mammal species are impala (*Aepyceros melampus*) with a density of 3.3 km^{-2}, African Buffalo (*Syncerus caffer*) with a density of 1.3 km^{-2}, African Elephant (*Loxodonta africana*) with a density of 1.1 km^{-2}, Eland (*Taurotragus oryx*) with a density of 0.8 km^{-2} and Kudu (*Tragelaphus strepsiceros*) with a density of 0.3 km^{-2} (Mhiripiri & Mlambo, 2021) [12]. Approximately 75% of the park shares the boundary with densely inhabited communal lands of Gokwe South and Binga Districts. SWRA still holds one of the largest remaining assemblages of wild ungulates in the Kavango-Zambezi component of Zimbabwe, but continues to face pressures from illegal hunting activities.

2.2. Poaching Incidents Data

The poaching data were obtained from SWRA's spatial monitoring and reporting tool database. The data were collected by rangers during their mobile and extended patrols. Data were recorded in two formats, firstly the location of the incident in the form of x and y coordinates in decimal degrees format and secondly in a descriptive format naming the general area where an incident was observed. The data were cleaned to remove all information which was not relevant for the study. The data were cleaned using Microsoft excel 2016 and Quantum GIS 3.3. A total of 182 poaching incident records were used following data cleaning. (See **Figure 2**)

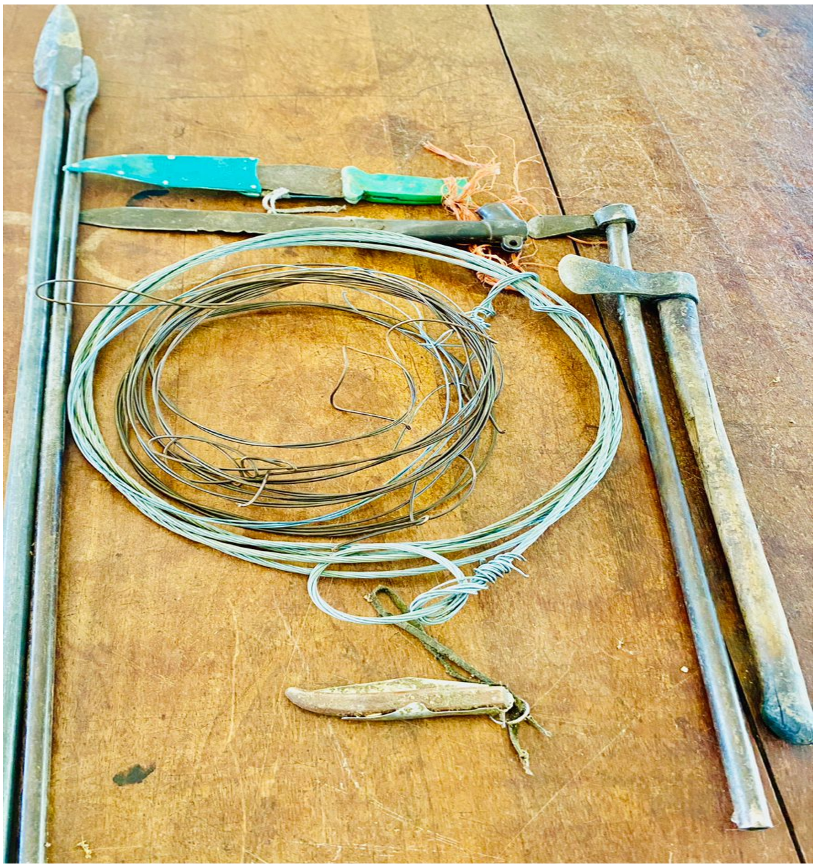

Figure 2. Types of equipment used by poachers in SWRA (Photo credits H Chinoitezvi).

2.3. Predictor Variables That Were Used for Modelling

To predict the probability of poaching incidents occurrence, six predictor variables relating to environmental and human dimensions and expected to influence poaching activities were taken into consideration. The predictor variables included distance from settlements, distance from roads, distance from rivers, slope angle, wildlife distribution and SAVI. All datasets were rasterized and resampled to a spatial resolution of 30 m. The raster data layers were then clipped using the boundary of SWRA.

2.4. Distance from Settlements

The location of human settlements influences accessibility and may exacerbate the vulnerability of an area (Manyenye, 2008) [13]. Settlement data was downloaded from (bbbike.org) in excel comma separated value format and later on visualized in ArcMap in the form of points. Distance of settlements into the park was calculated using the Euclidean distance function under the spatial analyst tool in ArcMap 10.8. Resultant distance layer was resampled to the spatial resolution of 30 meters as other layers. The distance to settlements layer was then clipped using the boundary of the study area. Distance from settlements was considered as a predictor variable contributing to poaching activities within SWRA, since it is hypothesized that people living near the park are often tempted to poach due to short distances into the park premises and they often face losses from wildlife without any compensation hence retaliatory killing and poaching of wildlife.

2.5. Distance from Roads

Roads were digitized from SWRA topographical maps using Quantum GIS 3.30. The distance from roads was calculated using the Euclidean distance function under the Spatial Analyst tools in ArcMap 10.8. The resultant raster layer was clipped to match the spatial extent of the study area. Distance from park roads was considered a predictive factor because roads within the park frequently serve as access routes for poachers. Roads within the park can provide poachers with easy entry and exit options into the protected area. Poachers often rely on a quick escape after conducting their crime within the park. According to ranger reports in SWRA, the presence of access roads often allows poachers to rapidly depart the site before park guards can respond.

2.6. Distance from Rivers

Distance from rivers was used as a proxy of access to water as in (Zvidzai, *et al.*, 2023) [6]. Distance from surface water sources (rivers) was used because of the associated microhabitat that exist and characteristics of vegetation that favor or discourage occupancy by herbivores (Muposhi, *et al.*, 2016) [14]. Water is essential for wildlife therefore many wild animals are usually located near water sources hence poachers may set snares in these areas to exploit the increased likelihood of encountering animals. Rivers were digitized in Quantum GIS 3.30. Distance from rivers were calculated using the Euclidean distance function in ArcMap 10.8.

2.7. Slope

Slope was calculated in degrees from DEM using the spatial analyst tool in ArcMap 10.8 at a 30 m resolution. The DEM was extracted from the Open topography website (https://opentopography.org/) as in (Zvidzai, *et al*., 2023) [6]. Slope angle was used a predictor variable since it determines the habitat preferences, resource availability and movement pattern of different wildlife species. Slope angle also determine poacher behavior and strategies, poachers may avoid steep slopes due to safety concerns or choose areas with flatter terrain that provide easier movement and navigation.

2.8. Soil Adjusted Vegetation Index

Soil Adjusted Vegetation Index (SAVI) was used to indicate the vigor and density of vegetation in a specified geographical areas (Asmaa, *et al*., 2020) [15]. SAVI was utilized because of its ability to adjust the effect of soil reflectance on vegetation reflectance (Asmaa, *et al*., 2020) [15]. Firstly, a Landsat 8 imagery with a cloud cover less than 20 percent was downloaded from USGS portal. The imagery was preprocessed in ArcMap using a band combination of band 4 and 5, band 5 representing NIR and band 4 representing Red. SAVI was calculated in ArcMap using the raster calculator in spatial analyst tool using the formula:

$$\mathrm{SAVI} = \frac{(\mathrm{NIR} - \mathrm{RED})}{(\mathrm{NIR} + \mathrm{RED} + \mathrm{L})} \times (1 + \mathrm{L})$$

where NIR is the Near Infrared reflectance, Red is the red reflectance, L is the soil adjustment factor usually set to 0.5. The resultant SAVI map was clipped in order to match the extent of the study area in **Figure 3**.

2.9. Wildlife Distribution

Wildlife sightings data were derived from the spatial monitoring and reporting tool (SMART) database for SWRA. The obtained data were of all herbivores prone to poaching within the research area. The data were obtained by rangers during their mobile and extended patrols using cyber mobile applications. All herbivore sightings data (presence data) were processed against bioclimatic variables derived from WorldClim (https://www.worldclim.org/bioclim) in order to estimate potential animal distribution in SWRA using Maxent version 3.4.4. The output map was later on re-projected in ArcMap in order to have the same spatial extent as other predictor variables.

2.10. Poaching Risk Zones Modelling

MaxEnt model was used to identify and predict poaching risk areas. Wire snare and poaching incidents data were used as presence-only data against six predictor

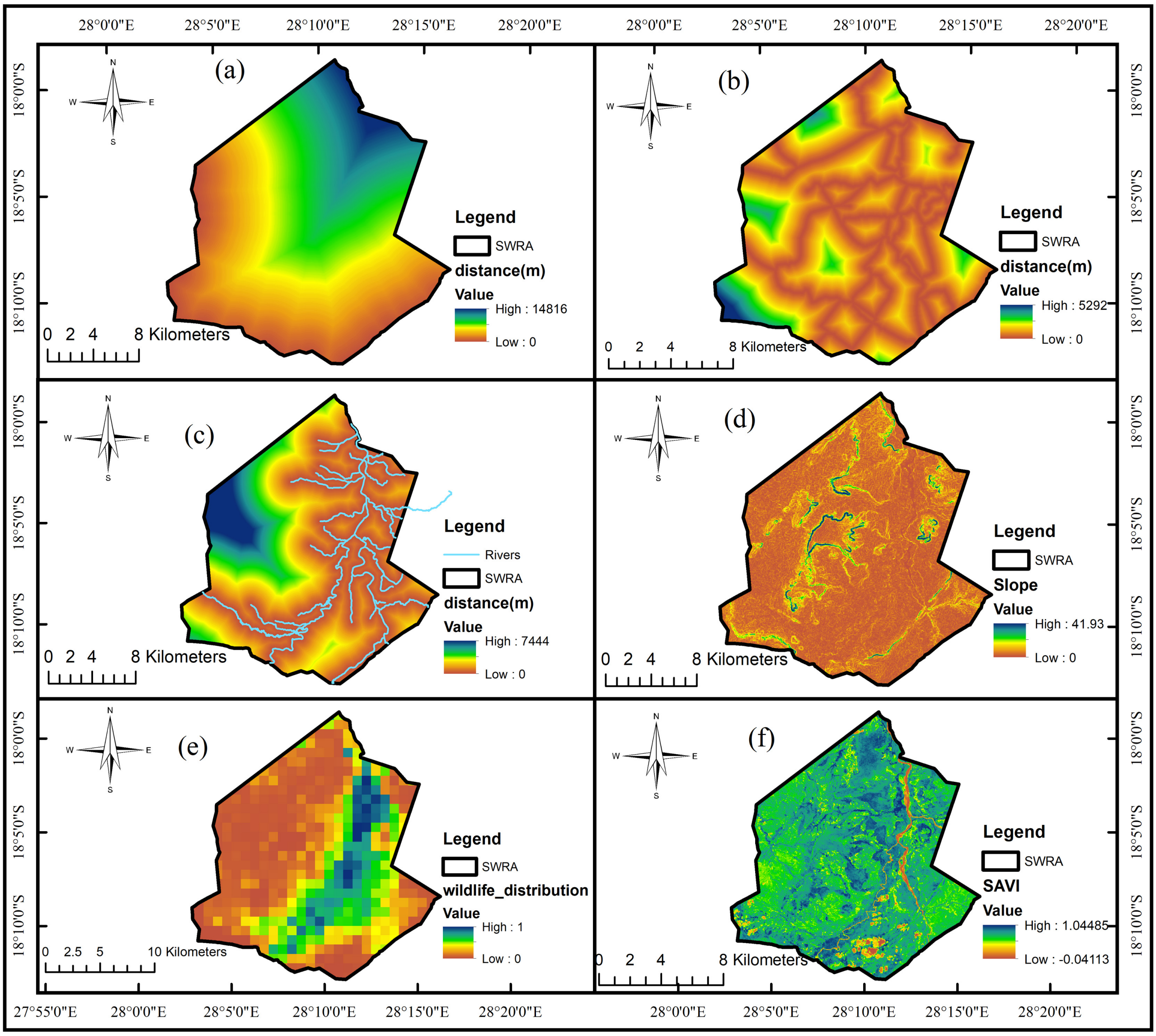

Figure 3. Predictor variables used to model the spatial distribution of poaching risk areas: (a) distance from settlements; (b) distance from roads; (c) distance from rivers; (d) slope; (e) wildlife distribution probability and (f) SAVI.

variables regarded as the key poaching drivers in SWRA. MaxEnt was chosen because of its ability to efficiently predict species distribution from presence-only data, its ability to handle complex interactions between response and predictor variables yet sensitive to small samples, its potential to predict certain poaching hotspots (Ndaimani, *et al.*, 2016) [16]. Wire snare presence data were exported from poaching database for the year 2022 to 2023, which is primarily recorded by park rangers during their mobile, local and extended patrols. As stated above, the following predictor variables were used for modelling the distribution of poaching activities: distance from settlements, distance from roads, slope, wildlife distribution, distance from rivers and SAVI. The predictor variables were converted to MaxEnt readable ASCII file format from GeoTiff.

To show the relevance of each predictor variable, a Jackknife significance tests was performed (Padalia, *et al.*, 2014) [17]. To assess the correlations between probability of poaching occurrence and the six predictor variables, response curves were used. The output was used to generate the poaching risk map since it gives an estimate of the relative suitability of one pixel compared to the other (Zvidzai, *et al.*, 2023) [6]. A range between 0 (lowest) and 1 (highest) was used to represent the probability of poaching risk (Philip, 2005) [18]. The area under the ROC curve (AUC) was used to assess the performance of the poaching risk model, which uses a value range between 0 and 1 where all values <0.5 represent no discrimination, 0.5 - 0.69 represent poor performance, 0.7 - 0.79 reasonable performance, 0.8 - 0.89 excellent and all values >0.9 suggesting exceptional performance of the model (Sharma, *et al.*, 2020) [8].

3. Results

3.1. Wildlife Distribution

The MaxEnt results of wildlife sightings against 18 bio-climatic variables revealed that high distribution of wildlife is along major rivers which are Sengwa and Lutope. The result also identified that wildlife is lower or less in areas near boundaries. (See **Figure 4**)

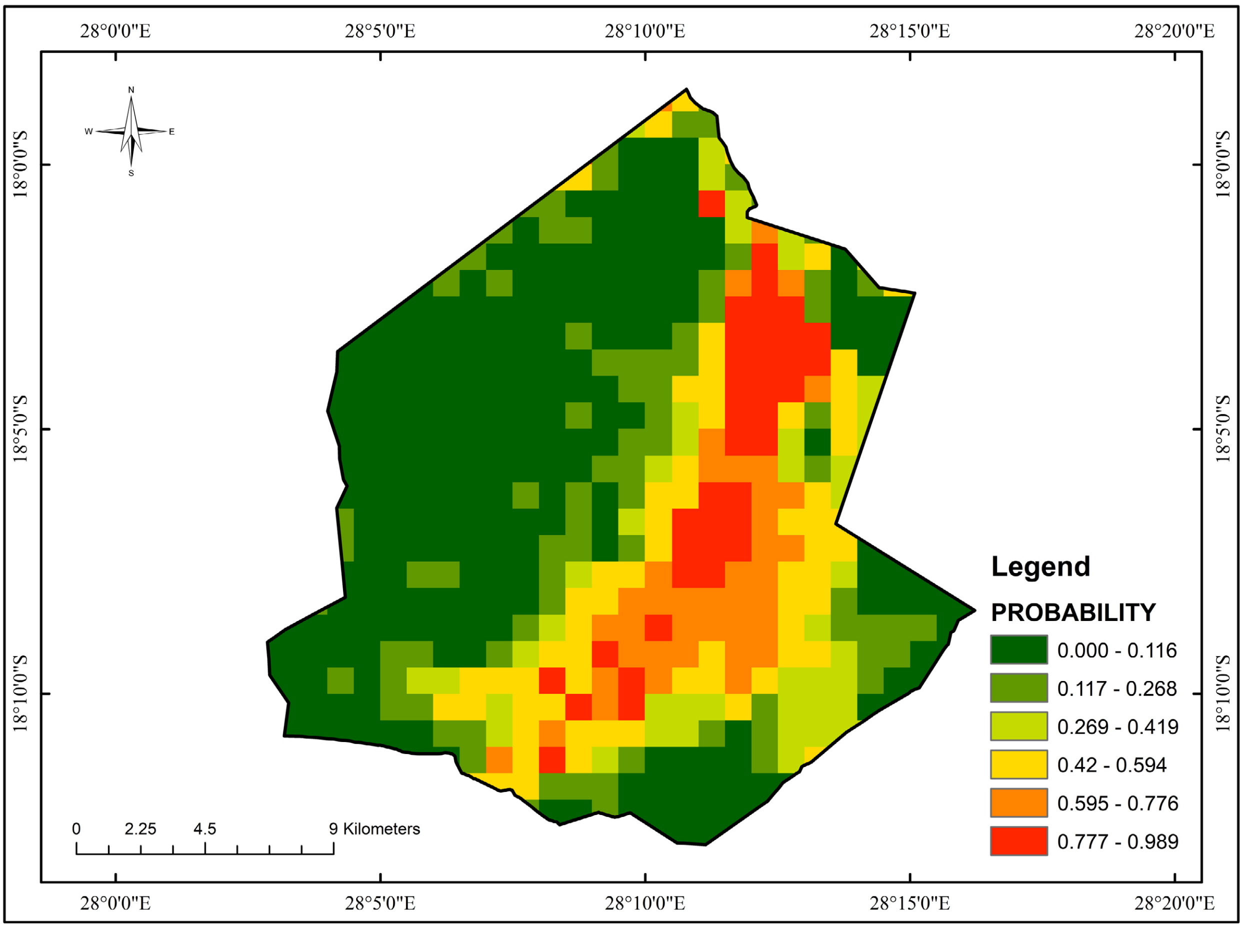

Figure 4. Wildlife distribution probability in SWRA.

3.2. Analysis of Predictor Variables

In terms of predicting, the AUC value showed an excellent predictive performance with a mean AUC of 0.800 (**Figure 5**) This suggest that the six predictor variables used in the study explains about 80% of spatial variability of poaching incidents, hence it proves that the model is effective and appropriate for explaining the probability of poaching risks and occurrence in Sengwa Wildlife Research Area (Zvidzai, *et al*., 2023) [6].

3.3. Predictor Variables Influence on Poaching Activities

The analysis of various predictor variables, revealed their influence on poaching activities. According to the analysis wildlife distribution and distance from rivers were found to be the most significant influencing factors of poaching activities within the research area, this implies that areas with a high frequency of wildlife sightings and those closer to rivers are more prone to poaching incidents. Following these factors, distance from roads and SAVI were identified as having a moderate influence on poaching activities, this suggest that areas in proximity to roads and those with dense vegetation are also associated with increased likelihood of poaching incidents. On the other hand, distance from settlements proved to have a relatively lower influence on poaching activities, this therefore implies that distance from human settlements has a lower influence on the occurrence of poaching incidents. Lastly the analysis indicated that slope, which refers to the steepness of the terrain has the lowest influence on poaching activities. Slope showed a significant negative relationship with poaching this implies that poaching events relatively occurs in flat areas (Manyenye, 2008) [13]. (See **Figure 6** and **Figure 7**)

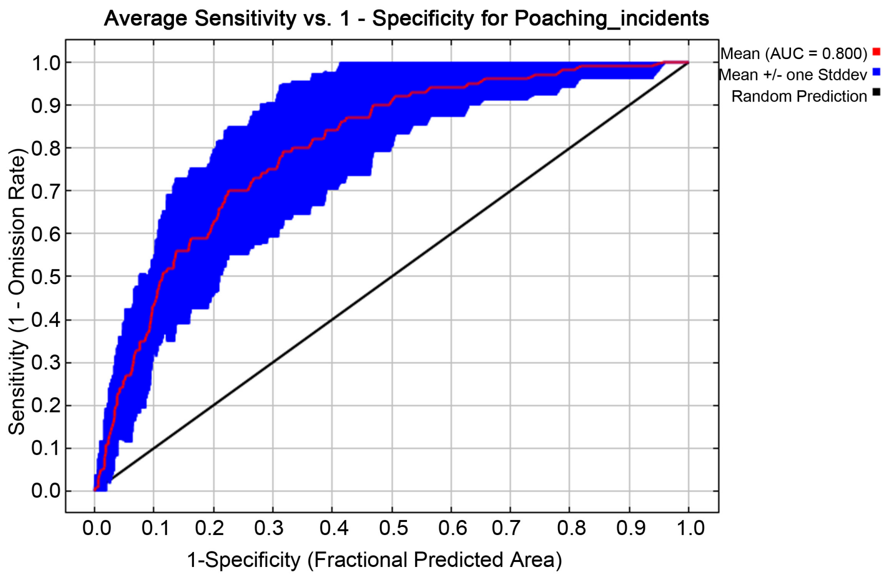

Figure 5. Receiver operator characteristics curve of the Area under Curve (AUC) test for the model performance where (x-axis) represents how correctly absences are predicted and sensitivity (y-axis) tests how well the data correctly predicts presence.

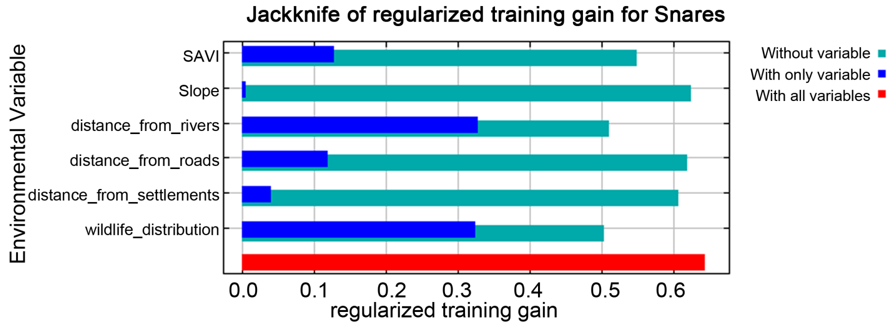

Figure 6. Jackknife test for relative variable importance.

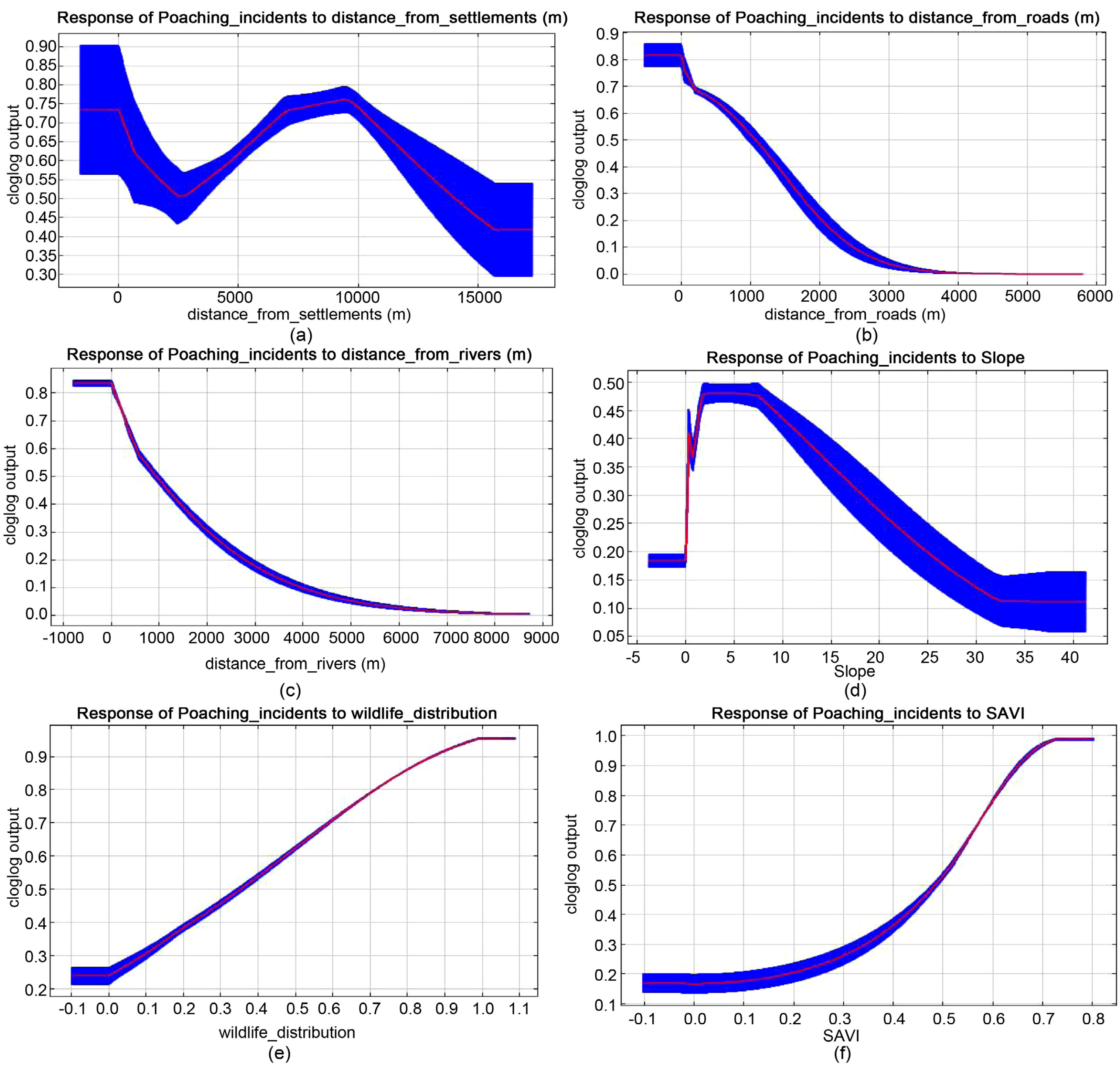

Figure 7. Response curves showing different patterns of probabilities of areas where poaching activities are likely to occur as a function of some predictor variables. (a) Distance from settlements; (b) distance from roads; (c) distance from rivers; (d) slope; (e) wildlife distribution probability and (f) SAVI.

3.4. Poaching Risk Zones Model

The model predicted that areas near rivers and areas of high wildlife distribution are more prone to poaching. The model also highlighted that poaching pattern is extremely high along Sengwa, Lutope and Manyoni rivers which are the major rivers in the research area. The model further detected that poaching risk is moderately high in areas along and near roads. Considering distance from settlements, the risk zone map presents that poaching risk is independent of distance from human settlements. However, the results map also indicates that poaching risk occurrence is low to none in areas of steep gradient. Areas of steep slopes e.g. in edges of cliffs were predicted to have low probability of poaching occurrence. (See Figure 8)

4. Discussion and Conclusion

By modeling poaching risk zones the study revealed a better understanding of factors that contribute to poaching incidents and identified areas where poaching is more likely to occur. Identifying the underlying key drivers of

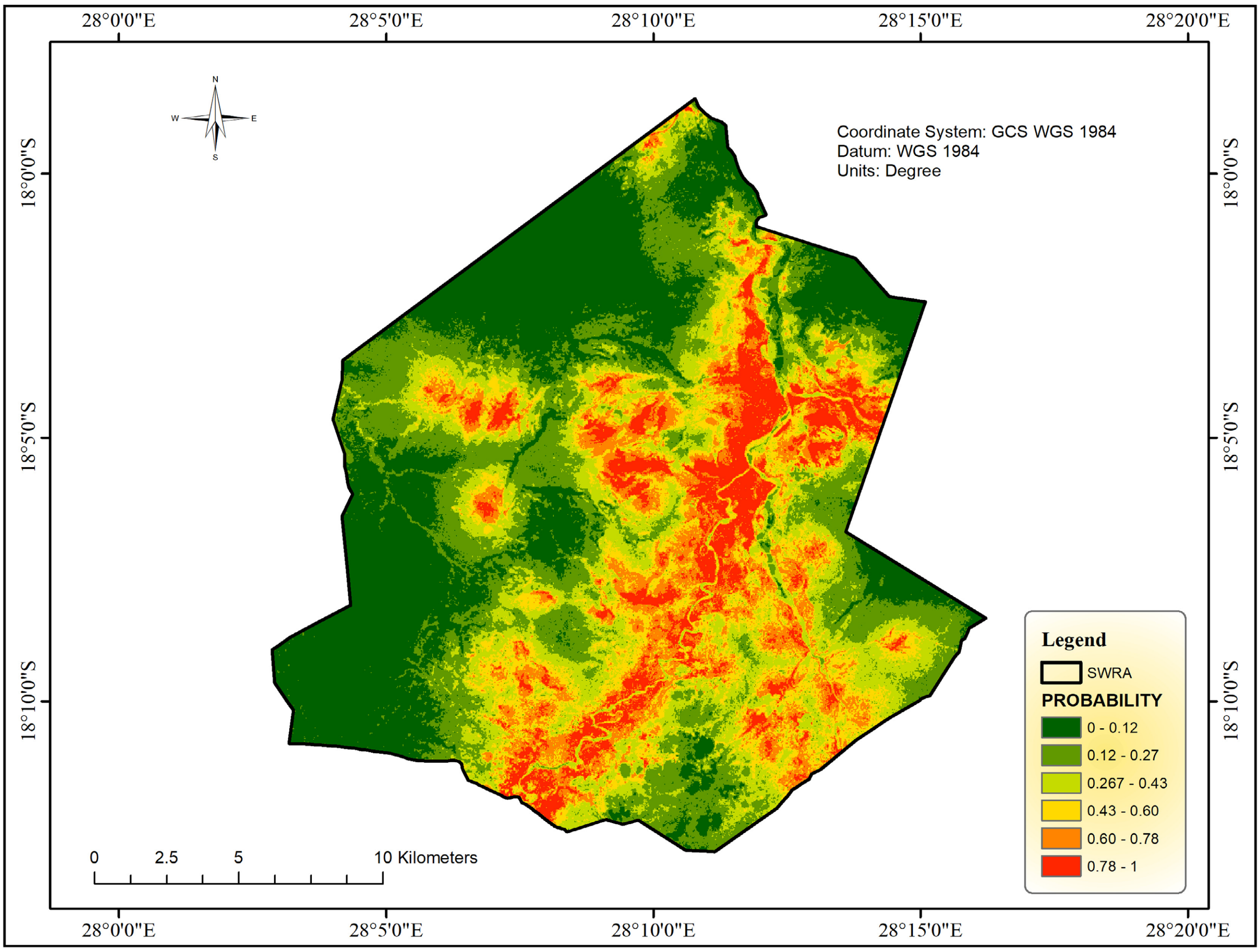

Figure 8. Model showing poaching probability risk areas. Green shade indicates areas of low risk and the red indicates areas of high risk.

poaching and understanding how they interact and structure poaching risk offer great value to park managers seeking to strategically prioritize the distribution and allocation of limited resources (Thiault, *et al*., 2019) [19]. Results from this study will provide a powerful tool when it comes to anti-poaching strategies since law enforcement agencies will use the identified risk areas to guide patrol routes and the deployment of park rangers.

This study is the first of its kind to use SDM in predicting poaching risk zones in SWRA along with analyzing the significant impacts of correlated predictor variables. A key finding from the current study is that the risk of poaching within the research area is not distributed randomly across the landscape, but rather strongly follows a linear pattern. Specifically, the study's findings suggest a significant positive association between the chance of unlawful hunting occurrences and distance from rivers, as well as animal distribution. These findings reflect the influences of resource availability on animals' behavior and distribution (Sibanda, *et al*., 2016) [20]. Despite that rivers are the main perpetual sources of water for game life, riverine habitats are also associated with greener vegetation and cover ideal for diverse herbivore species leading to high animal concentrations that attract poaching activities.

Our findings resonated with results from (Mahakata, 2022) [9] which also reported that the distribution of wire snaring incidents in the same study area is mostly along or close to rivers. In support of this vulnerability of wildlife to poaching in the riverine landscape, a previous study in the Tarangire ecosystem (National Park) in Tanzania revealed that most poaching incidents occurred in the areas of high wildlife distribution such as water sources (Manyenye, 2008) [13]. SAVI and distance from roads proved to have a positive impact on poaching activities. Several reasons could explain such a finding, and areas with high vegetation cover as captured by SAVI index provide favorable habitats for wild animals. However, vegetation density impairs the vision of rangers (Muzhingi, 2012) [1] while providing camouflage for poachers, making it a preferred area for illegal hunting. In terms of distance from roads highest risk of poaching was predicted in areas near roads ranging from 0 to1000 m (**Figure 7**). Similar patterns have been reported in several studies such as (Muzhingi, 2012 [1]; Haines, *et al*., 2012 [21]; Manyenye, 2008 [13]). These revealed that poaching incidents likelihood is high in areas proximity to roads. Distance from settlement had a relatively lower influence on poaching activities, poaching activities occurred heedlessly of distance from settlement. Slope angle proved to have the lowest significance on poaching activities. Our study revealed that areas of steep slopes have a low probability of poaching risk while flat surfaces are highly prone to poaching. According to Mannathoko, *et al*. (1990) [22], slope steepness of an area has an influence on the walking speed of people and areas with gentle slopes are easier to walk rather than areas with steep slopes. Our findings on wildlife distribution indicate that the areas with steep slopes have low game count is low compared to areas of gentle slopes therefore are unlikely to attract poachers.

The methodology used in this study was regarded as appropriate and effective since it successfully managed to predict potential poaching risk areas (**Figure 8**). Maxent modeling has proved to be very effective at predicting risk zones since it relies only on presence data, lacks many of the complications associated with presence-absence analytical methods, and is relatively insensitive to spatial errors associated with location data. Our results hold several implications, and guide wise use of limited finance and inadequate human resources to effectively patrol against poaching incidents. As a limitation, the relatively low historical snare data availability (2022-2023), means that we were not able to integrate the temporal dimension and identify when such patrols should be deployed. Future applications based on a higher number of incidence data collected over a longer period of time would provide more generalizable and dynamic predictions.

Acknowledgements

Special thanks go to the Director General (Dr. F. U. Mangwanya) of the Zimbabwe Parks and Wildlife Management Authority for permission to carry out the research in SWRA. Many thanks go to SWRA, Zimbabwe Parks and wildlife rangers for their unlimited support in data collection.

Authors' Contribution

All authors contributed to the editing and discussion of the manuscript. Software and data were prepared by Chinoitezvi Honour. All authors have read and agreed to the published version of the manuscript.

Conflicts of Interest

The authors declare no conflict of interest.

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