Title: Predicting Elephant Crop-Raiding with Machine Learning to Inform Conservation Planning: A Case Study Comparing the Performance and Tradeoffs of GeoAI Algorithms in Northwestern Zimbabwe

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1. Introduction

Savanna elephants (*Loxodonta africana*) are a keystone species, acting as ecosystem engineers and important agents of seed dispersal (1,2). They are drivers for biodiversity changes, mediating flora and fauna state shifts supporting a semi-open ecosystem structure (3). Spending around 75% of the day foraging, savanna elephants consume grasses and browse, strip bark off trees, and push over and break smaller, younger trees (4–9). Their home range and large-scale movement patterns are foremost structured by human activity, followed by environmental conditions, including water availability and forage conditions (10–15). Their preference for high biomass vegetation and other crucial resources increases as scarcity increases, meanwhile less nutritious foods, such as bark and woody vegetation, are consumed in greater amounts during the dry season when crop-raiding is increasingly likely to occur (16–19).

Humans have diverse experiences living alongside elephants, ranging from coexistence to conflict. This human/elephant conflict (HEC), along with poaching and habitat loss, have led to Savannah elephants being listed as endangered on the IUCN red list (25). While HEC, which includes crop-raiding, has occurred in Africa since the dawn of agriculture (21), the effects are now magnified due to growing human populations and encroachment into elephant habitat (22–24). Human fatalities due to elephant conflict are rising in Zimbabwe (26). Local laws designed to protect wildlife can harm livelihoods and dissent about damage and losses can undermine conservation programs (27). Adopting a militarized approach of conservation can introduce violence to local people and diminish autonomy over daily activities and livelihoods (28). In protected areas within Zimbabwe, elephant management and conservation are largely the responsibility of the Zimbabwe Parks and Wildlife Management Authority, but their efforts are hindered by a small budget, low morale, and high turnover (29). Elephants that repeatedly endanger humans are killed.

HEC is a nuanced and multiscalar environmental challenge and predicting the geographic locations of crop-raiding requires consideration of natural and anthropogenic variables. Previous studies suggest elephants prefer millet, maize, sorghum (30,31) whereas others have found no effect of crop type on raiding occurrence (32). The diversity of crops within a field increases susceptibility to crop-raiding (31). Savanna elephants may balance perceived risk from humans with foraging opportunities. Previous work in Hwange National Park, Zimbabwe found crop-raiding declined with increasing distance to refuge areas along with higher household density (33). This aligns with studies elsewhere suggesting that elephant refuge is a significant predictor in crop-raiding occurrence (24,34–36). Fields in the Okavango Delta in Botswana are more likely to be raided by elephants if they are far from the village and have been raided considerably in the past, whereas fields further from waterholes, further from elephant paths, and fields raided by livestock are less likely to be raided (37). Meanwhile, reports of conflict with an increasing elephant population in Angola are more common in areas with greater human density, particularly where fields are adjacent to roads (38). The relationships between elephant density and elephant space use with crop-raiding patterns were nonlinear, and that the probability of crop-raiding is actually higher in low elephant density areas (39), affirming the complexity of predicting and understanding crop-raiding patterns in southern Africa. The spatial patterns and clusters of crop-raiding change in response to anthropogenic changes of the landscape; for example, area under cultivation was a significant positive predictor of crop-raiding in Masai Mara National Reserve in Kenya in the late 90s but the reverse relationship was found in 2014-2015 (24).

A range of mitigation and conflict deterrence methods exist, but elephants are intelligent creatures with exceptional long-term spatial memory (40–43). Experimental methods hailed as effective deterrents often become ineffective with time, as elephants learn when threats are empty (44–46). There are even reports that elephants have reacted to crop-raiding prevention methods by retaliating after previous confrontations (47–49). Further complicating human-elephant interactions are restrictions and pressure from international organizations that reduce local agency to manage elephant populations and conflict (27,45). It is in this matrix of international and national policies, novel deterrent methods, challenging agricultural conditions, and dynamic climate that humans and elephants share space and resources.

Machine learning (ML), a subset of artificial intelligence (AI) that predicts and/or understands relationships by training models using historical data, has immense potential for biodiversity conservation and monitoring wildlife and conflict (50,51). However, the use of GeoAI, the combination of artificial intelligence technologies, including ML and deep learning, with geospatial knowledge is relatively limited in regards to HEC (52,53). Regression methods have been the most popular quantitative techniques to study human-wildlife conflict(e.g.(37,54)). However, these traditional methods typically assume a specific functional form of the relationship (e.g., linearity), which may be unfounded and unrealistic for modeling elephant crop-raiding. Therefore, GeoAI techniques have been used as promising alternatives to assess human-elephant conflict patterns in Asia and to provide suggestions for mitigating conflict (55,56).

South of Victoria Falls, Zimbabwe, elephants raid subsistence-level agricultural fields and come into conflict with humans in particular areas, whereas other areas remain relatively conflict free. To effectively mitigate this type of human-wildlife conflict requires understanding the spatial pattern of crop-raiding (57). While some GeoAI approaches may be characterized as a “black box,” failing to quantify the influence of predictors on model outcomes, this limitation does not preclude their utility in predicting the spatial occurrence of conflict. If machine learning algorithms can effectively decipher the complex, nonlinear, and dynamic patterns underlying human-elephant conflict, they can facilitate more proactive and precise management interventions. In resource-limited regions, such targeted approaches are often more economically feasible and realistic than generalized strategies that may be costly and inefficient.

Our objectives are: 1) to determine the environmental factors contributing to human-elephant conflict linked to crop-raiding in the communal lands south of Victoria Falls by integrating AI with GIS and 2) to evaluate the performance and tradeoffs of advanced GeoAI techniques in modeling these complex patterns, providing a reproducible and transferable workflow suitable for environmental problem-solving. Results will expand our understanding of HEC in a region that is underrepresented in African elephant ecological research and that is growing and developing rapidly. Simultaneously, we will generate actionable knowledge for conservation planning under uncertainty and support evidence-based mitigation practices (58). By comparing different GeoAI models, we anticipate that our findings will advance existing studies on HEC, aiding scholars and practitioners in making more informed decisions on the performance and decision-making tradeoffs of the different algorithms in conflict modeling.

2. Case examination

2.1 Study site

Zimbabwe is a landlocked south African country bordered by Botswana, Zambia, Mozambique, and South Africa. The district of Hwange lies in the “horn” of Zimbabwe, south of the Zambezi River that forms the border with Zambia (Figure 1). Reported HEC occurs in the communal lands southeast of Victoria Falls (Figure 1) where elephant density is estimated to be 2.5 elephants per km^2 or over 60,000 elephants (59). Hwange is a hotspot for conflict, with more human fatalities compared to districts in the south, west, and northeast of Zimbabwe (26). The study area is just over 2000 km^2 and extends from Zimbabwe’s northern border, east of the Matetsi Safari Area and Zambezi National Park, to -18.2327 latitude, 26.4133 longitude. It includes the communal lands of Chidobe, Kachecheti, Nemananga, Zambezi and the western half of Sidinda, totalling roughly 20,000 people (60). It is within the Kavango-Zambezi Transfrontier Conservation Area, an initiative between the governments of Angola, Botswana, Namibia, Zambia, and Zimbabwe to manage over 500,000 km^2 sustainably and connect protected areas. This increased connectivity of elephant habitat coupled with the rising human population likely amplifies human-wildlife conflict (23,26).

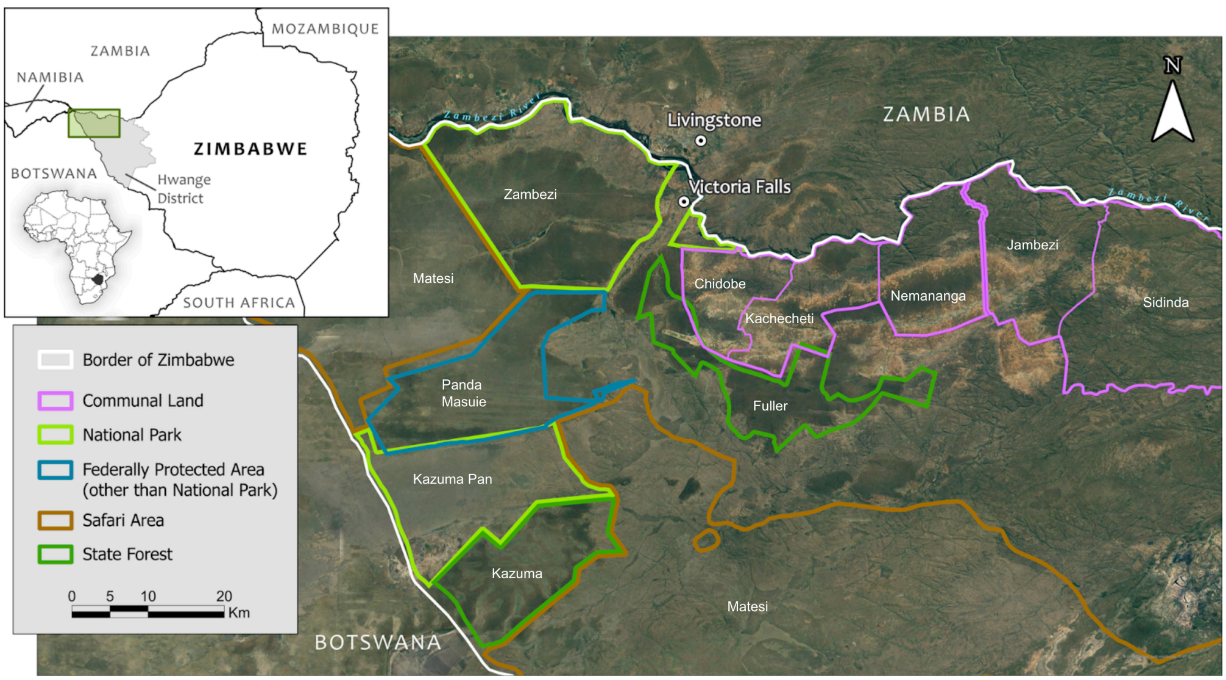

Figure 1 Location of study site in the Hwange District of Zimbabwe. Protected areas are identified by color. Satellite imagery 2023 (C) Google.

The local climate can be divided into two seasons based on precipitation: a rainy season, during which 80% of precipitation occurs, and a dry season (Figure 2) (61). This highly seasonal water availability means rivers and natural water sources are significantly reduced during the dry season. Vegetation typically responds to precipitation by one to two months (61). Dominant vegetation types are dry forests and thickets, specifically *Baikiaea* woodland interspersed with *Colophospermum* woodland (62).

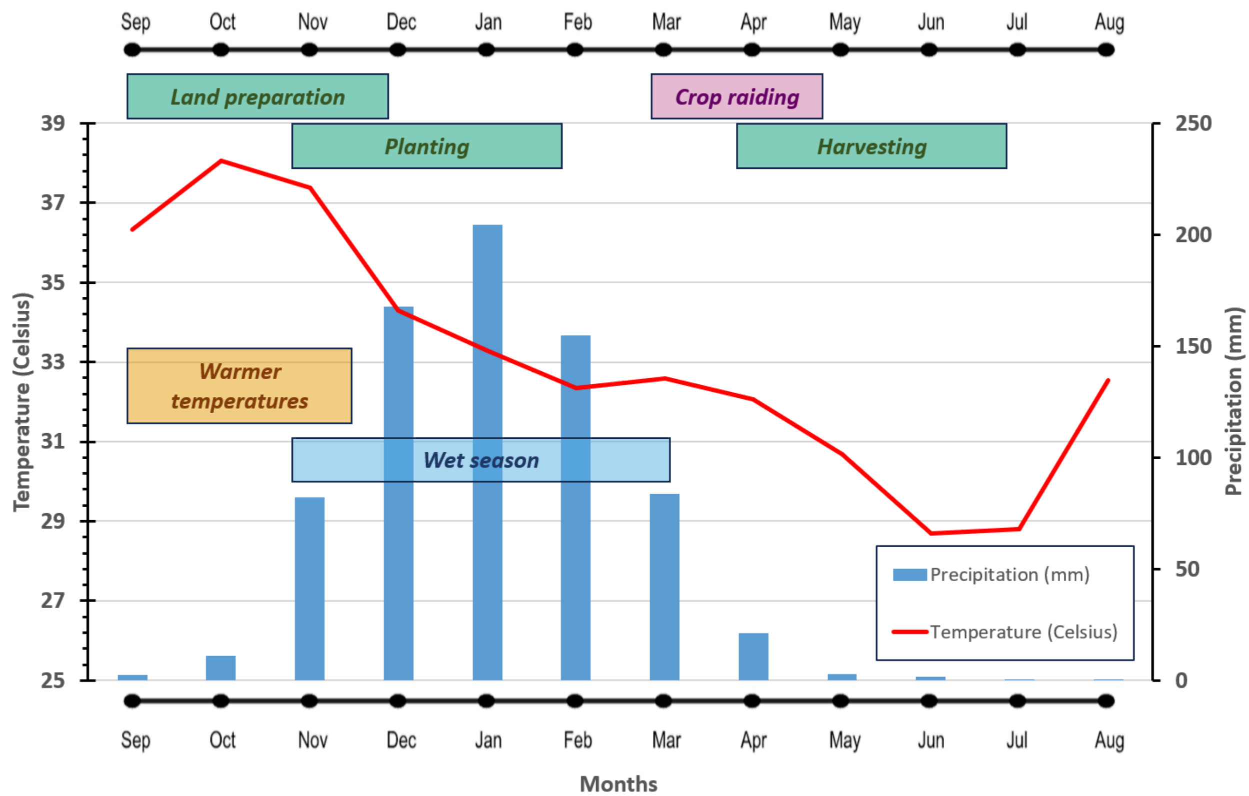

Figure 2 Typical annual timeline for agricultural activities in Hwange, Zimbabwe. Precipitation and temperature data presented were computed from 1990 to 2019 using Copernicus Climate Change Service ERA5 data (Copernicus Climate Change Service (C3S), 2017).

Poor soils and erratic precipitation engender onerous and limited growing conditions in Hwange (63–65). Poverty is increasing, and the region experiences chronic food insecurity, with climate change, drought, and crop and livestock predation by wildlife all considered major threats (66).

2. 2. Methods

To identify potential drivers of HEC, we employed positive and negative cases to train GeoAI models. We used points of reported HEC for positive cases and created pseudo-absence points of HEC as negative cases. An equal number of pseudo-absences to crop-raiding points was generated for each year. Pseudo-absence points were randomly generated within 100 m to 1 km from conflict locations. We calculated and tested nine environmental and six anthropogenic metrics to evaluate their explanatory power. Following exploratory analysis, we tested four GeoAI models: support vector machine (SVM), random forest (RF), deep neural network (DNN), and multi-layer perceptron (MLP) neural network.

Figure 3 shows a general overview of our methods.

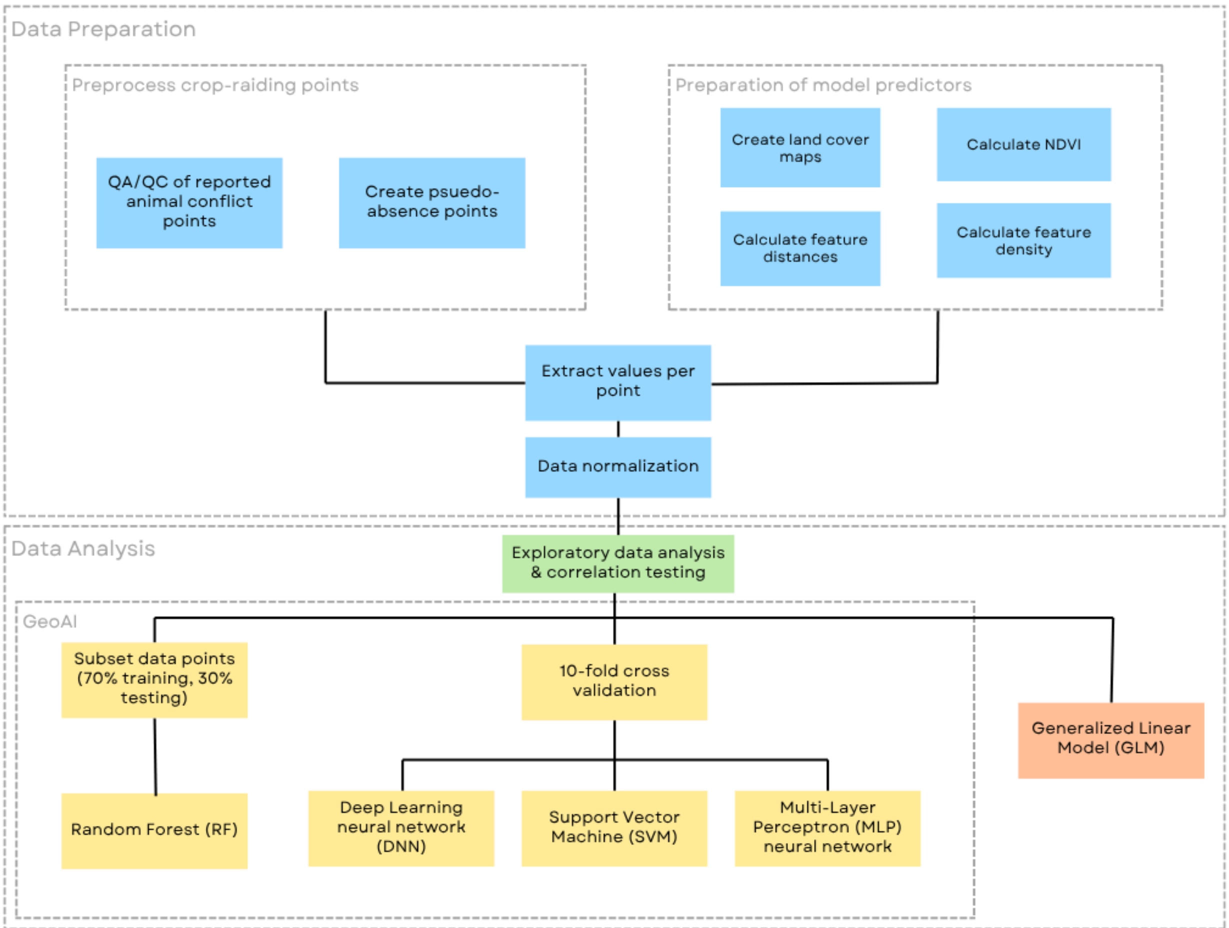

Figure 3. Methodology. Preprocessing steps to generate necessary inputs for further analysis are represented in blue. QA/QC indicates quality assurance/quality control. Exploratory data analysis (in green) consisted of plotting the distribution of variables and checking for correlation. Processes in yellow are GeoAI methods along with separation of training and testing data. A binomial generalized linear model (orange) was also used to elicit further information about the relationship between conflict and predictors.

To test the sensitivity of our analysis to the exact location of pseudo-absence points, we created three additional sets of pseudo-absence points. Results of this sensitivity analysis are reported in Supplementary Information.

2.3.1 Crop-raiding data

We used 713 documented and georeferenced HEC locations from 2015-2021 (Figure 4). Distribution of the number of points collected per year and the months points were collected can be found in Supplementary Information. Points are routinely collected *in-situ* by Victoria Falls Wildlife Trust, Hwange Rural District Council, and Connected Conservation rangers. Conflict is voluntarily reported year-round by calling the Hwange Rural District Council. A trained enumerator collects and verifies conflict data *in-situ*. There is no compensation for crop damage or incentive for reporting problematic wildlife. HEC in this region primarily arises when elephants seek out crops and anthropogenic food sources.

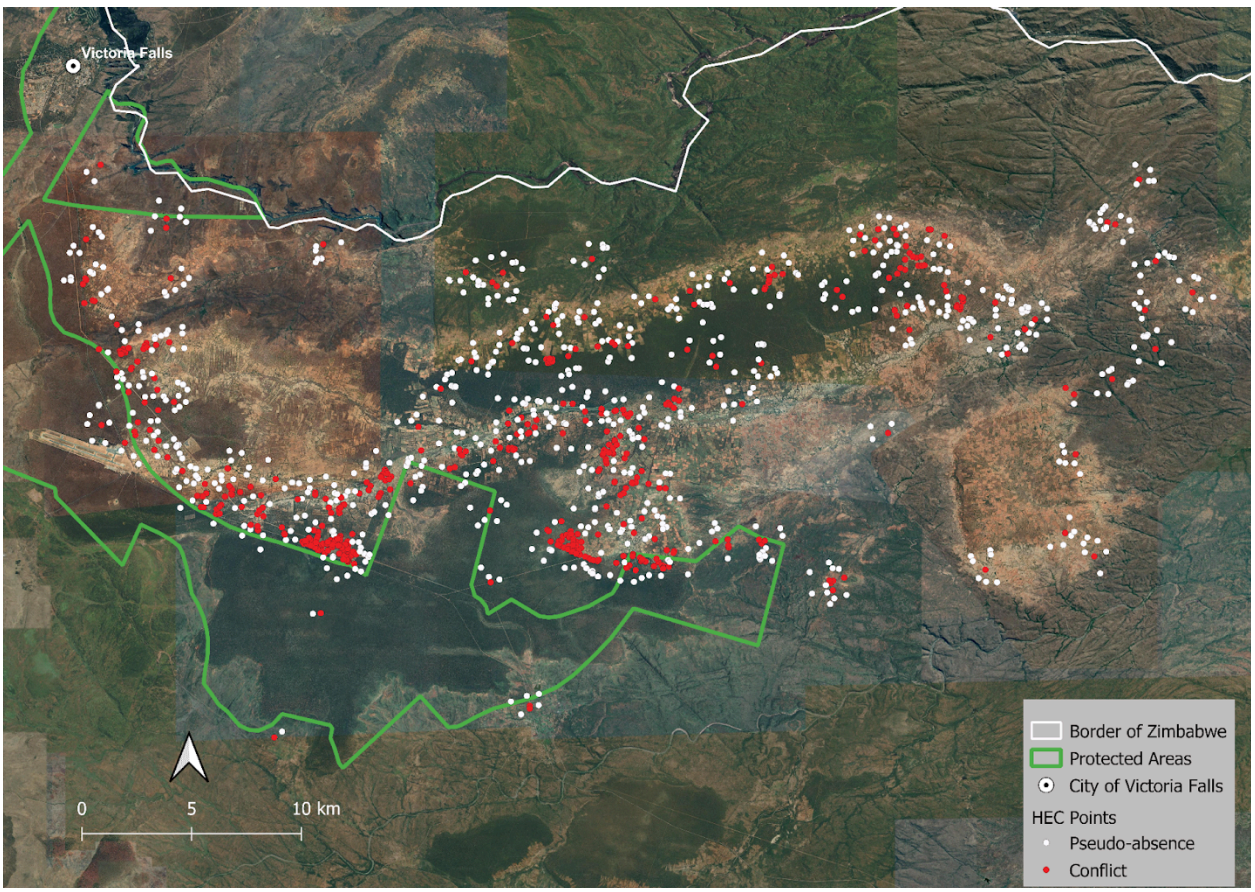

Figure 4 Study area. Red points are crop-raiding locations. White points are pseudo-absence points created randomly within 100 m to 1 km from conflict points. Protected areas that are not mixed use are outlined in green. Satellite imagery 2023 (C) Google.

2.3.2 Data preparation and exploratory analysis

Fifteen geospatial predictors across environmental and anthropogenic domains of HEC were calculated and considered (refer to Table 1 for resolutions and descriptions). The distributions of potential predictors were plotted and visualized (correlation matrix in Supplemental Information). Correlation was calculated using Pearson's r correlation matrix and those with correlation values exceeding ∓0.7 were excluded, as the assumption of independence is violated, standard errors are inflated, and predictor effects can be challenging to determine (67,68). When ∓0.7 was exceeded, the variable that displayed the greatest overlap with other potential predictors was generally removed, but refer to Supplemental Information for further details.

Table 1. Description of data along with resolution and source.

Data	Description	Resolution	Source
Normalized Difference Vegetation Index (NDVI)	Maximum and minimum NDVI values from Landsat 8 Operational Land Imager (OLI) Tier-1 surface reflectance	Temporal: 16-day repeat, restricted to crop-raiding months, as defined in Table 1 in SI Spatial: 30m	US Geological Survey, Landsat 8 OLI Tier-1 surface reflectance
Precipitation	Maximum precipitation values modeled based on satellite and ground station data	Temporal: daily, restricted to crop-raiding months, as defined in Table 1 in SI Spatial: 0.05°	Climate Hazards Group InfraRed Precipitation with Station data (CHIRPS) Daily
Buildings	Nearest distance from buildings	Temporal: data accessed Aug, 2022 Spatial: N/A	Open Street Map

Protected areas	Boundaries of conservation areas such as national parks, forestry lands, etc.	Temporal: updated Oct, 2020 Spatial: N/A	Protected Planet
Roads	Major and secondary roads, both paved and unpaved	Temporal: data accessed Aug, 2022 Spatial: N/A	Open Street Map
Water	Potential water sources: major rivers, and streams, ponds, lakes, wastewater sites, and reservoirs	Temporal: data accessed Aug, 2022 Spatial: N/A	Open Street Map
Land cover	Nearest distance from agriculture and nearest distance from closed canopy forest	Temporal: Jan-March of 2015-2021 Spatial: 30m	Created by lead author from Landsat 8 OLI imagery from the first quarter of each year
Digital elevation model	Slope	Temporal: data collected 2009 20 with methodological improvements in subsequent versions Spatial: ~30m	Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER) Global Digital Elevation Model V003
PALSAR-2/PALSAR Yearly Mosaic, version 2	HV polarization backscattering dB	Temporal: annual from 2015-2021 Spatial: 25m	Japan Aerospace Exploration Agency Earth Observation Research Center

2. 3.3 GeoAI models

GeoAI models were chosen based on their suitability for binary classification, their overall ease of use, and to evaluate the tradeoffs between interpretability and predictive power. A binomial generalized linear model (GLM) was also used to provide additional information about the relationship between predictors and crop-raiding occurrence.

Predictive models were created with the locations of elephant crop-raiding as the dependent variable and potential geospatial drivers of conflict as the independent variables. Pseudo-absence points were created between 100 m to 1 km from conflict points. For constructing the RF model, 70% of all points were used for training and 30% for testing. The RF modeling technique uses ensemble methods to improve accuracy of results by combining multiple models, but the other three GeoAI techniques lack such a mechanism. Therefore to verify the performance of the SVM, DNN, and MLP models, we applied 10-fold cross validation. For ML hyperparameters, see Supplemental Information.

2. 4. Results

2. 4.1 Predictors most important to modeling crop-raiding

RF indicates the importance of predictors within the model. HV backscattering was the most important predictor variable, with a mean decrease in accuracy of 439 compared to the next most important variable, distance from protected areas, which had a mean decrease in accuracy of 350 (Figure 5).

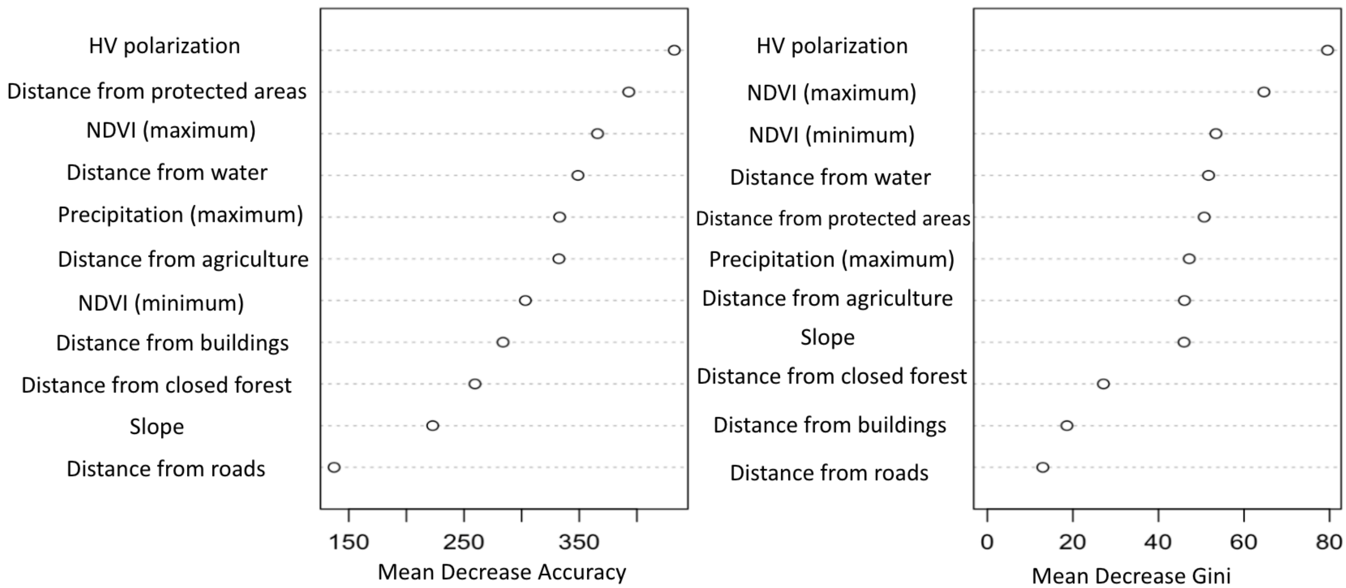

Figure 5. Variable Importance Plot of variables included in random forest model.

GLM also indicates the relationship between the predictors and the outcome, thus we used a binomial GLM to gain further insight into the relationships between predictors and crop-raiding occurrence. Predictors that negatively impacted crop-raiding include distance from protected areas (estimate ∓ SE = -0.42 ∓ 0.09,P<0.001), distance from agriculture (estimate ∓ SE = -0.26 ∓0.08 ,P<0.001), distance from roads (estimate ∓ SE = -0.16 ∓0.07,P<0.05), distance from closed forest (estimate ∓ SE = -0.22 ∓ 0.07,P<0.01), maximum NDVI (estimate ∓ SE = -0.46 ∓0.08,P<0.001), and HV (estimate ∓ SE = -0.13 ∓ 0.02,P<0.001). The only predictors to contribute positively included distance from buildings (estimate ∓ SE = 0.24 ∓ 0.07, P<0.001) and distance from water (estimate ∓ SE = 0.25 ∓ 0.08,P<0.01).

SVM, DL, and MLP are all “black box” models; no information is available concerning how predictors impact model performance nor the direction of any relationships.

2. 4.2 Comparison of GeoAI outcomes

The SVM model with the best performance used a radial kernel with the tuning parameter sigma held constant, and a tuning length of 10. This SVM model resulted in a sigma of 0.07 and a cost of 128. Calculated as the proportion of classifications that were correct out of all classifications made, accuracy was 77.0%. Precision, the number of predicted positives that are true positives, was 73.8%. Recall, also referred to as sensitivity and calculated as the number of actual instances of crop-raiding that the model successfully identified as crop-raiding, for the SVM model was 81.4%. The F1 score (the harmonic mean of precision and recall) was 0.77. Table 2 shows the confusion matrix for all GeoAI models.

Table 2. Confusion matrix for testing data using SVM, RF, DNN, and MLP.

	SVM		**RF**		**DNN**		**MLP**	
	Predicted absence	Predicted raid	Predicted absence	Predicted raid	Predicted absence	Predicted raid	Predicted absence	Predicted raid
Actual pseudo-absence	**507.7**	205.3	**179**	48	**505.7**	207.3	**684.4**	28.6
Actual raid	132.6	**580.4**	35	**170**	224.1	**488.9**	36.2	**676.8**

Total accuracy using testing data was 81.5% for the RF model. Of the predicted crop-raiding occurrences, 79.4% were correct. The RF model was able to correctly recall 83.0% of crop-raiding occurrences. This model's F1 score was 0.81.

The most successful parameterization of tested DNN used a sequential DL neural network model with two layers using the rectified linear unit activation (ReLU) function, a third layer using a sigmoid activation function so that the network output is binary, and the Adam optimizer. Five thousand epochs were used and a batch size of 200. A total of 276 parameters were used to train the DNN model. Average model accuracy was 69.0%. Model precision was 70.2%, recall 68.6.%, and the F1 score was 0.69.

MLP neural network classifier defaults were used with the exception of a maximum number of iterations of 100,000 and three hidden layers with 100 neurons in each. Model accuracy on average was 79.5%. Of the crop-raiding locations predicted by MLP, 95.9% were true crop-raiding occurrences. The model correctly recalled 94.9% of all of the crop-raiding locations it was tested on. The F1 score was 0.95%.

2. 5. Discussion

With arduous growing conditions, high food insecurity, and an increasing number of HEC-related deaths, precisely predicting where conflict will occur south of Victoria Falls remains exigent. Our study contributes to the broader HEC literature by determining the environmental factors precipitating conflict in a region underrepresented in African elephant ecological research and contending with rapid development. Able to discern complex, nonlinear relationships within geospatial datasets, advanced GeoAI frameworks show promise for deciphering the intricacies of HEC despite their limited use (52). Our results applying and evaluating the performance and tradeoffs of advanced GeoAI techniques in modeling HEC could engender targeted approaches that are more economically feasible in an area encumbered by low morale and limited budget (29). Such precise mitigation methods may be paramount, given rising human fatalities in this HEC hotspot (26).

2. 5.1 Characteristics of crop-raiding in communal lands

From the RF and binomial regression models, we are able to characterise HEC south of Victoria Falls. Variables that contributed most to the RF model were distance from agriculture, HV backscattering (indicator of biomass), and distance from protected areas. The most statistically significant relationships

(P<0.001) discovered through binomial regression were distance from protected areas, distance from buildings, distance from agricultural areas, and HV backscattering values.

Elsewhere across Africa, the risk of crop-raiding increases closer to protected areas or refuge (30,34,35,69). Our findings are in alignment, as evidenced by the negative relationship between distance from protected areas and crop-raiding occurrence, reinforcing prior conclusions and extending their generalizability to a new nation Farms in greater proximity to Fuller State Forest, a protected area in the Hwange district of Zimbabwe, are at higher risk of crop raiding. Elephants may retreat to the safety of Fuller to avoid mitigation attempts such as chasing elephants while beating drums, shooting elephants with chili powder, fire, or a combination of methods designed to deter elephants. In addition to protected areas and dense vegetation acting as a refuge for elephants, human activity generally acts as a deterrent. We found HEC is less common in areas with higher building density, a finding consistent with previous research reporting reduced risk in lower density areas and further from buildings, suggesting the relationship between greater human activity and lower conflict holds across diverse geographical regions (30,37,70). Overall, our findings denote that elephants to the south of Victoria Falls are more likely to raid in areas with comparatively lower risk, as indicated by a lower presence of human activity and a greater presence of natural refuge.

While we found that areas with lower maximum NDVI values (generally indicating less dense vegetation) are associated with crop-raiding, work in Tanzania from roughly the same time period found crop-raiding increased as average NDVI increased (69). However, in Mozambique, HEC increases as NDVI declines in protected areas and crops mature, with elephants selecting plants with high biomass, which may occur after NDVI peaks (71,72). The relationship between NDVI and vegetation is complex; connecting remotely sensed imagery to crop yield typically requires modeling using statistics or machine learning or data assimilation. The relationship between NDVI and yield can vary by region and crop type

(73–75). As we did not apply any site-specific calibration to NDVI values, the relationship between yield and NDVI may have eluded us. Future work could explore other indicators in relation to vegetation biomass.

2. 5.2 Insights from GeoAI outcomes

As the application of AI continues to expand within conservation efforts, it is essential to identify the most effective algorithms for addressing specific challenges (50,51). For HEC, we evaluated binomial algorithms designed to model conflict occurrence. While particular ML models may be hard to interpret due to their "black box" nature and the dearth of information they provide on relationships between inputs, such limitations do not diminish their ability to predict areas of potential HEC in this region and other areas affected by wildlife conflict. The greater performance of said "black box" models thus present conservation managers with a decision-making tradeoff: greater predictive accuracy for mitigation efforts versus understanding the underlying drivers of conflict.

In general, all ML algorithms performed well, with accuracy scores reaching, and in most cases exceeding, 70% for testing data. Comparatively, our results indicate that more advanced or complex ML algorithms are not necessarily the most effective option for predicting conflict. Of algorithms tested, the DNN performed the worst; it had an accuracy of roughly 70% and a number of false negatives and false positives. The SVM performed moderately (testing accuracy ~76%) with good recall but lower precision. The RF model, which allows us to determine the importance of variables, had an accuracy of roughly 80% using testing data with balanced recall and precision scores.

While the RF results are certainly respectable, they are considerably lower than the MLP neural network. The MLP neural network was the prevailing model, predicting conflict occurrence of test datasets with an accuracy of 95.5%, a precision of 95.9%, 94.9% recall, and an F1 score of 0.95 and with accuracy scores for the sensitivity analysis ranging from 90-96%. The strong performance of the MLP neural network on testing data suggests that this model has the potential to be effectively applied to other regions and is not simply the result of overfitting the dataset. While this ML algorithm is a “black box” model and does not provide insight into individual predictor contributions, it far surpasses the accuracy of RF, which does provide such insights. The MLP neural network may be particularly beneficial for managerial applications, while potentially offering limited utility for scholarly research.

Such impressive predictive results from the MLP can enable conflict mitigation methods that are precisely applied, thus allowing natural resource managers to allocate their time, effort, and resources more efficiently than with more generalized predictions requiring uniform coverage across space. For example, results from the MLP can be used to guide community patrols. In the broader context of HEC mitigation in northwestern Zimbabwe, where there is a high degree of conflict and reducing HEC has been identified as a priority, implementing targeted mitigation strategies can have a meaningful and long-term positive impact on local livelihoods (26,76). Furthermore, wildlife managers can mobilize preventive interventions, such as the use of chili deterrents, in areas identified as high-risk (77,78). Coupled with data, such as seasonal rainfall and elephant movement, the MLP model could support early warning systems, making costly technology more accessible through targeted placement of necessary sensors (79,80). Thus, conservation managers face a trade-off between greater transparency regarding the underlying drivers of conflict and the increased accuracy provided by the “black box” model, which, while opaque, offers its own merits through enhanced predictive performance.

The relative successes and shortcomings of the tested algorithms provide lessons on the intrinsic structural relationships within our dataset. The smaller size of our dataset may have contributed to the relatively poor performance of the DNN. It is also plausible that it overfit the data or that the dataset contains fewer hierarchical features within its structure (81,82). The radial SVM was able to discern many conflict locations but misclassified the psuedo-absences. The weak performance of the SVM indicates that the relationship between conflict occurrence and our predictor variables cannot be smoothly delineated in a single, fixed feature space and that the decision surface the model creates based on Euclidean distances is not well-suited (83,84). The strong performance of the RF suggests that the relationships between conflict occurrence and our predictor variables are nonlinear and locally complex (85). Thus, implementing a fixed buffer zone or other linear mitigation methods are unlikely to succeed. The excellent performance of the MLP further supports that patterns within our dataset are nonlinear and moderately complex; thus a few layers are capable of modeling them (86,87). The MLP generalized well, indicating that the predictor variables are highly relevant to the occurrence of conflict.

2. 5.3 HEC and the future

Agricultural land across Zimbabwe is expanding (88). High elephant density coupled with growing demand from humans for natural resources is likely to exacerbate conflict as elephants and humans encounter each other more regularly. As damage from crop-raiding increases, tolerance for elephants declines, threatening development and conservation goals (89). Meanwhile, Zimbabwe's leadership would like to stymie any such conflict and has made coexistence a noted priority of their wildlife management goals (76).

Multiple methods exist to prevent elephant crop raiding. Across southern Africa traditional methods include burning, planting unpalatable vegetation, using drums to scare off elephants along with high-tech methods such as electrical fencing and more creative methods such as using bees, but the effectiveness of many of these methods declines as elephants learn when the threat is empty (46,90,91). The majority of elephant deterrents are ineffective or impossibly expensive, and farmers might place themselves in harm's way to defend their livelihood (46). Our results underscore that employing the most complex neural network architecture is not inherently essential for accurately and precisely predicting conflict occurrence. Achieving such high levels of accuracy as our MLP has the potential to transform HEC mitigation strategies by enabling the deployment of expensive technologies at specific, high-risk locations rather than across entire regions.

Furthermore, beyond the logistical benefits of using GeoAI models to identify precise, priority areas for amelioration using technologies that would typically be impossibly expensive or intractable at large scales, high accuracy GeoAI models present a potential shift in governance. Providing geospatial intelligence directly to local stakeholders can increase local agency and transfer the science of conservation and HEC from centralized, often militarized agencies to a more progressive management model. For example, a warning system requiring sensors to notify residents of impending risk from crop-raiding elephants could be implemented only at high-risk farms. Alternatively, community patrols that require significant manpower could be arranged only in high-risk areas. This autonomy is crucial, as farmers will not apply a mitigation method if it is unaffordable or they lack the manpower required to implement it (92,93). Methods shown to be the most effective at discouraging elephants, but which are typically impossibly expensive or intractable, may be feasible at smaller scales and with local adherence. HEC strategies should address the needs of local people, empower them to adequately handle conflict, and prioritize their needs in addition to the needs of wildlife (94).

As our understanding of HEC advances, it is imperative that we do not overlook the tangible impact this issue has on affected populations. Disregarding the merit of the MLP model solely on the basis that it does not enhance our comprehension of the underlying drivers of conflict is shortsighted. Such a perspective neglects the genuine harm and suffering inflicted by HEC.

2. 5.4 Limitations

Human-elephant conflict occurs in a variety of situations influenced by a myriad of factors operating at varying scales. Our work is limited by its use of pseudo-absences of conflict. Using reported absences with information concerning whether or not crops were actively being cultivated, plant growth stage, any elephant deterrents in use, as well as the planting and conflict history of that field would be ideal.

Data collection efforts were impacted by the COVID-19 pandemic and shutdown of services in Zimbabwe. Southeast of Victoria Falls, the crop-raiding period typically lasts a few months. The first year in which data collection returned to normal following the end of the COVID-19 shutdown was 2021, and conflict was reported in all months for which we have data. Reports from residents indicate that elephants and wildlife were much more active in anthropogenic areas and bolder in their behavior in comparison to pre-COVID-19 pandemic levels. Thus, data from 2021 might not represent typical patterns for this region.

3. Conclusion

Predictors distance from protected areas, buildings, and agricultural areas, and HV backscattering values suggest elephants are more likely to raid crops close to areas of refuge and further from anthropogenic activity. The relative performance of ML algorithms tested suggests our predictors were relevant to conflict occurrence and that patterns within our dataset are nonlinear and moderately complex. MLP outperformed other algorithms in predicting conflict, although it does not provide information about which predictors contribute most to model accuracy. Thus, the ML algorithm most capable of predicting conflict to aid in management decisions may be one disregarded by scholars for its dearth of information concerning the relationship of predictors.

Predicting HEC is notably complicated and dependent on the temporal and geographic scale of data collected (32,95). As elephant populations rise in Zimbabwe, predicting HEC in this region grows exigent. Our results should provide local context and highly specific information on where conflict is likely to occur south of Victoria Falls. This information guides wildlife management, evidence-based mitigation methods, and informs agricultural planning.

4. Case Study Questions

1. If you were a conservation manager with limited budget and resources, which model would you prioritize for mitigating conflict and why?
2. How could the adoption of advanced GeoAI tools affect the autonomy of local farmers in managing HEC? Could these tools empower local communities to handle conflict or do they risk further centralizing management power with international, national, or regional agencies?
3. Under what circumstances might understanding why conflict is occurring be more important than higher predictive accuracy?
4. How might wildlife managers account for temporal anomalies, such as the COVID-19 pandemic that affected 2021 data, when using GeoAI models to predict future conflict?
5. Discuss the transferability of this GeoAI framework, which incorporates Google Earth Engine, OpenStreetMap data, and satellite-derived indices and measures. How might this framework need to be adapted to other human-wildlife conflict scenarios in various geographic areas?
6. How should managers in regions characterized by limited budgets and low morale identify high-risk areas in need of mitigation? What are the potential consequences of false negatives, or failing to predict conflict, versus false positives, or implementing mitigation strategies where no conflict occurs?
7. How can GeoAI frameworks be designed to ensure that the agency and knowledge of local communities is preserved and furthered rather than replaced by automated frameworks derived from satellite data?

Author Contributions

Katherine E. Markham and Sergio Bernardes wrote the original draft of the manuscript. Katherine E. Markham and Sergio Bernardes created the visualizations in this published work. Katherine E. Markham, Marguerite Madden, Ferrel V. Osborn, Malvern Karidozo, William R. Langbauer Jr., and X. Angela Yao contributed to the development of the methodology. The human-elephant conflict data was provided by Ferrel V. Osborn and Malvern Karidozo. Katherine E. Markham conducted Marguerite Madden, Sergio Bernardes, Ferrel V. Osborn, and X. Angela Yao, and Andrew Grundstein provided supervisory guidance throughout the initial research process. All authors provided critical comments on the manuscript and contributed to the final editing.

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Competing Interests

The authors have no competing interests to declare.

References

1. Bunney K, Bond WJ, Henley M. Seed dispersal kernel of the largest surviving megaherbivore—the African savanna elephant. Biotropica. 2017;49(3):395–401. doi:10.1111/btp.12423

2. Dudley JP. Seed Dispersal by Elephants in Semiarid Woodland Habitats of Hwange National Park, Zimbabwe. Biotropica. 2000;32(3):556–61.

3. Gordon C, Greve M, Henley M, Bedetti A, Allin P, Svenning JC. Elephant rewilding affects landscape openness and fauna habitat across a 92-year period. Ecological Applications. 2023 Jan 24;33(3). doi:https://doi.org/10.1002/eap.2810

4. Barnes RFW. Elephant feeding behaviour in Ruaha National Park, Tanzania*. African Journal of Ecology. 1982;20(2):123–36. doi:10.1111/j.1365-2028.1982.tb00282.x

5. Dublin HT, Sinclair ARE, McGlade J. Elephants and Fire as Causes of Multiple Stable States in the Serengeti-Mara Woodlands. Journal of Animal Ecology. 1990;59(3):1147–64. doi:10.2307/5037

6. Mapaure IN, Campbell BM. Changes in miombo woodland cover in and around Sengwa Wildlife Research Area, Zimbabwe, in relation to elephants and fire. African Journal of Ecology. 2002;40(3):212–9. doi:10.1046/j.1365-2028.2002.00355.x

7. Plumptre A j. The effects of trampling damage by herbivores on the vegetation of the Pare National des Volcans, Rwanda. African Journal of Ecology. 1994;32(2):115–29. doi:10.1111/j.1365-2028.1994.tb00563.x

8. Ruggiero RG. Seasonal forage utilization by elephants in central Africa. African Journal of Ecology. 1992;30(2):137–48. doi:10.1111/j.1365-2028.1992.tb00487.x

9. Wyatt JR, Eltringham SK. The daily activity of the elephant in the Rwenzori National Park, Uganda. African Journal of Ecology. 1974;12(4):273–89. doi:10.1111/j.1365-2028.1974.tb01037.x

10. Wall J, Wittemyer G, Klinkenberg B, LeMay V, Blake S, Strindberg S, et al. Human footprint and protected areas shape elephant range across Africa. Current Biology. 2021 Jun 7;31(11):2437-2445.e4. doi:10.1016/j.cub.2021.03.042 PubMed PMID: 33798431.

11. Bohrer G, Beck PS, Ngene SM, Skidmore AK, Douglas-Hamilton I. Elephant movement closely tracks precipitation-driven vegetation dynamics in a Kenyan forest-savanna landscape. Movement Ecology. 2014 Jan 29;2(1):2. doi:10.1186/2051-3933-2-2

12. Chamaillé-Jammes S, Mtare G, Makuwe E, Fritz H. African Elephants Adjust Speed in Response to Surface-Water Constraint on Foraging during the Dry-Season. PLOS ONE. 2013 Mar 15;8(3):e59164. doi:10.1371/journal.pone.0059164

13. Loarie SR, Aarde RJV, Pimm SL. Fences and artificial water affect African savannah elephant movement patterns. Biological Conservation. 2009 Dec 1;142(12):3086–98. doi:10.1016/j.biocon.2009.08.008

14. Tshipa A, Valls-Fox H, Fritz H, Collins K, Sebele L, Mundy P, et al. Partial migration links local surface-water management to large-scale elephant conservation in the world's largest transfrontier conservation area. Biological Conservation. 2017 Nov 1;215:46–50. doi:10.1016/j.biocon.2017.09.003

15. Thaker M, Gupte PR, Prins HHT, Slotow R, Vanak AT. Fine-Scale Tracking of Ambient Temperature and Movement Reveals Shuttling Behavior of Elephants to Water. Front Ecol Evol. 2019 Jan 25;7. doi:10.3389/fevo.2019.00004

16. Tsalyuk M, Kilian W, Reineking B, Getz WM. Temporal variation in resource selection of African elephants follows long-term variability in resource availability. Ecological Monographs. 2019;89(2):e01348. doi:10.1002/ecm.1348

17. Guy PR. The feeding behaviour of elephant (Loxodonta africana) in the Sengwa area Rhodesia. South African Journal of Wildlife Research. 1976;6(1):55–63.

18. Osborn FV. Seasonal variation of feeding patterns and food selection by crop-raiding elephants in Zimbabwe. African Journal of Ecology. 2004;42(4):322–7.

19. Williamson BR. The condition and nutrition of elephant in Wankie National Park. National Museums and Monuments of Rhodesia; 1983.

20. Thouless CR, Dublin HT, Blanc JJ, Skinner DP, Daniel TE, Taylor RD, et al. African Elephant Status Report 2016: an update from the African Elephant Database. [Internet]. Gland, Switzerland: IUCN?SSC African Elephant Specialist Group; 2016. p. 44. (Occasional Paper Series of the IUCN Species Survival Commission). Report no.: 60. Available from: https://portals.iucn.org/library/sites/library/files/documents/SSC-OP-060_A.pdf

21. Naughton-Treves L. Whose animals? A history of property rights to wildlife in Toro, western Uganda. Land Degradation & Development. 1999;10(4):311–28. doi:10.1002/(SICI)1099-145X(199907/08)10:4<311::AID-LDR362>3.0.CO;2-3

22. Di Minin E, Slotow R, Fink C, Bauer H, Packer C. A pan-African spatial assessment of human conflicts with lions and elephants. Nat Commun. 2021 May 20;12(1):2978. doi:10.1038/s41467-021-23283-w

23. Stoldt M, Göttert T, Mann C, Zeller U. Transfrontier Conservation Areas and Human-Wildlife Conflict: The Case of the Namibian Component of the Kavango-Zambezi (KAZA) TFCA. Sci Rep. 2020 May 14;10(1):7964. doi:10.1038/s41598-020-64537-9

24. Tiller LN, Humle T, Amin R, Deere NJ, Lago BO, Leader-Williams N, et al. Changing seasonal, temporal and spatial crop-raiding trends over 15 years in a human-elephant conflict hotspot. Biological Conservation. 2021 Feb 1;254:108941. doi:10.1016/j.biocon.2020.108941

25. The IUCN Red List of Threatened Species [Internet]. 2025 [cited 2026 Jun 29]. Available from: https://www.iucnredlist.org.

26. Kavhu B, Mutema C, Mpakairi KS, Gandiwa E, Muvengwi J. Mapping human fatalities from

megafauna to inform coexistence strategies. Sci Rep. 2025 Sep 30;15(1):33856. doi:10.1038/s41598-025-04934-0

27. Naughton-Treves L, Treves A. Socio-ecological factors shaping local support for wildlife: crop-raiding by elephants and other wildlife in Africa. In: Woodroffe R, Thirgood S, Rabinowitz A, editors. People and Wildlife, Conflict or Co-existence? [Internet]. Cambridge: Cambridge University Press; 2005 [cited 2024 Jul 23]. p. 252–77. Available from: https://www.cambridge.org/core/product/identifier/CBO9780511614774A025/type/book_part doi:10.1017/CBO9780511614774.017

28. Mushonga T, Matose F. Dimensions and corollaries of violence in Zimbabwe's protected forests. Geoforum. 2020 Dec 1;117:216–24. doi:10.1016/j.geoforum.2020.10.005

29. Ncube H. A call to embrace adaptive management for effective elephant conservation in Zimbabwe. South African Journal of Science. 2019 Apr;115(3–4):1–3. doi:10.17159/sajs.2019/5413

30. Hariohay KM, Munuo WA, Røskaft E. Human–elephant interactions in areas surrounding the Rungwa, Kizigo, and Muhesi Game Reserves, central Tanzania. Oryx. 2020 Sep;54(5):612–20. doi:10.1017/S003060531800128X

31. Matsika TA, Masunga GS, Makati A, McCulloch G, Stronza A, Songhurst AC, et al. Crop diversity and susceptibility of crop fields to elephant raids in eastern Okavango Panhandle, northern Botswana. Ecology and Evolution. 2023;13(3):e9910. doi:10.1002/ece3.9910

32. Buchholtz EK, McDaniels M, McCulloch G, Songhurst A, Stronza A. A mixed-methods assessment of human-elephant conflict in the Western Okavango Panhandle, Botswana. People and Nature. 2023;5(2):557–71. doi:10.1002/pan3.10443

33. Guerbois C, Chapanda E, Fritz H. Combining multi-scale socio-ecological approaches to understand the susceptibility of subsistence farmers to elephant crop raiding on the edge of a protected area. Journal of Applied Ecology. 2012;49(5):1149–58. doi:10.1111/j.1365-2664.2012.02192.x

34. Graham MD, Notter B, Adams WM, Lee PC, Ochieng TN. Patterns of crop-raiding by elephants, Loxodonta africana, in Laikipia, Kenya, and the management of human–elephant conflict. Systematics and Biodiversity. 2010;8(4):435–45.

35. Oppong S, Danquah E, Sam M. An update on crop-raiding by elephants at Bia Conservation Area, Ghana from 2004 to 2006. Pachyderm. 2008 Jun 30;44:59–64.

36. Thant ZM, May R, Røskaft E. Pattern and distribution of human-elephant conflicts in three conflict-prone landscapes in Myanmar. Global Ecology and Conservation. 2021;25:e01411.

37. Songhurst A, Coulson T. Exploring the effects of spatial autocorrelation when identifying key drivers of wildlife crop-raiding. Ecology and Evolution. 2014;4(5):582–93. doi:https://doi.org/10.1002/ece3.837

38. Köhler E, Bollig M. Elephant corridors in the Kavango-Zambezi transfrontier conservation area (KAZA TFCA): environmental infrastructures for a greener anthropocene in Namibia's Mudumu

landscape. Rev Reg Res. 2025 Mar 5. doi:10.1007/s10037-025-00230-6

39. Pozo RA, Cusack JJ, McCulloch G, Stronza A, Songhurst A, Coulson T. Elephant space-use is not a good predictor of crop-damage. Biological Conservation. 2018 Dec 1;228:241–51. doi:10.1016/j.biocon.2018.10.031

40. Bates LA, Sayialel KN, Njiraini NW, Poole JH, Moss CJ, Byrne RW. African elephants have expectations about the locations of out-of-sight family members. Biology Letters. 2007 Dec 4;4(1):34–6. doi:10.1098/rsbl.2007.0529

41. Fritz H. Long-term field studies of elephants: understanding the ecology and conservation of a long-lived ecosystem engineer. Journal of Mammalogy. 2017 May 29;98(3):603–11. doi:10.1093/jmammal/gyx023

42. Hart BL, Hart LA, Pinter-Wollman N. Large brains and cognition: Where do elephants fit in? Neuroscience & Biobehavioral Reviews. 2008 Jan 1;32(1):86–98. doi:10.1016/j.neubiorev.2007.05.012

43. Polansky L, Kilian W, Wittemyer G. Elucidating the significance of spatial memory on movement decisions by African savannah elephants using state–space models. Proceedings of the Royal Society B: Biological Sciences. 2015 Apr 22;282(1805):20143042. doi:10.1098/rspb.2014.3042

44. Davies TE, Wilson S, Hazarika N, Chakrabarty J, Das D, Hodgson DJ, et al. Effectiveness of intervention methods against crop-raiding elephants. Conservation Letters. 2011;4(5):346–54. doi:10.1111/j.1755-263X.2011.00182.x

45. O’Connell-Rodwell CE, Rodwell T, Rice M, Hart LA. Living with the modern conservation paradigm: can agricultural communities co-exist with elephants? A five-year case study in East Caprivi, Namibia. Biological Conservation. 2000 May 1;93(3):381–91. doi:10.1016/S0006-3207(99)00108-1

46. Osborn FV. Mitigating measures to reduce human-elephant conflict: What do we know? In: Braack L, Smuts R, editors. Towards Rationalizing Transboundary Elephant Management and Human Needs in the Kavango/mid-Zambezi Region. Cape Town, South Africa: Centre for Biodiversity Conservation, Kirstenbosch Botanical Gardens,; 2010.

47. Barua M. Bio-Geo-Graphy: Landscape, Dwelling, and the Political Ecology of Human-Elephant Relations. Environ Plan D. 2014 Oct 1;32(5):915–34. doi:10.1068/d4213

48. Mwamidi D, Mwasi SM, Nunow A. THE USE OF INDIGENOUS KNOWLEDGE IN MINIMIZING HUMAN-WILDLIFE CONFLICT: THE CASE OF TAITA COMMUNITY, KENYA. International Journal of Current Research. 2012 Jan 1;4:26.

49. Zimmermann A, Simon P, Linnell J, Glickman J, Marchini S, Hill C, et al. Introduction. In: IUCN SSC guidelines on human-wildlife conflict and coexistence. First. Gland, Switzerland: IUCN; 2023.

50. Ojija F, Ogwu MC, Ally J, John JP, Stephano A, Felix N, et al. Artificial intelligence-driven solutions for mitigating human–wildlife conflict in biodiversity hotspots. Sci Prog. 2025 Nov 19;108(4):00368504251394584. doi:10.1177/00368504251394584 PubMed PMID: 41259221;

PubMed Central PMCID: PMC12638633.

51. Tuia D, Kellenberger B, Beery S, Costelloe BR, Zuffi S, Risse B, et al. Perspectives in machine learning for wildlife conservation. Nat Commun. 2022 Feb 9;13(1):792. doi:10.1038/s41467-022-27980-y

52. Saha S, Soren R. Human-elephant conflict: Understanding multidimensional perspectives through a systematic review. Journal for Nature Conservation. 2024 Jun 1;79:126586. doi:10.1016/j.jnc.2024.126586

53. Janowicz K, Gao S, McKenzie G, Hu Y, Bhaduri B. GeoAI: spatially explicit artificial intelligence techniques for geographic knowledge discovery and beyond. International Journal of Geographical Information Science. 2020 Apr 2;34(4):625–36. doi:10.1080/13658816.2019.1684500

54. Naughton-Treves L. Predicting Patterns of Crop Damage by Wildlife around Kibale National Park, Uganda. Conservation Biology. 1998;12(1):156–68. doi:https://doi.org/10.1111/j.1523-1739.1998.96346.x

55. Jayakody S, Estacio I, Sianipar CPM, Onitsuka K, Basu M, Hoshino S. Maxent modeling for predicting the potential distribution of human-elephant conflict risk in Sri Lanka. Applied Geography. 2024 Dec 1;173:103447. doi:10.1016/j.apgeog.2024.103447

56. Naha D, Sathyakumar S, Dash S, Chettri A, Rawat GS. 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. 2019 Feb 1;14(2):e0210580. doi:10.1371/journal.pone.0210580

57. Linkie M, Dinata Y, Nofrianto A, Leader-Williams N. Patterns and perceptions of wildlife crop raiding in and around Kerinci Seblat National Park, Sumatra. Animal Conservation. 2007;10(1):127–35. doi:https://doi.org/10.1111/j.1469-1795.2006.00083.x

58. Gross RB, Heinsohn R. Elephants Not in the Room: Systematic Review Shows Major Geographic Publication Bias in African Elephant Ecological Research. Diversity. 2023 Mar;15(3):3. doi:10.3390/d15030451

59. Bussière EMS, Potgieter D. KAZA Elephant Survey 2022, Volume I: Results and Technical Report [Internet]. Kasane, Botswana: Kavango Zambezi Transfrontier Conservation Area (KAZA TFCA) Secretariat; 2023. Available from: https://www.kavangozambezi.org/kaza-elephant-survey/

60. Zimbabwe National Statistics Agency. 2022 Population and Housing Census [Internet]. https://dataportal.opendataforafrica.org/: African Development Bank Data Repository; 2024. Available from: https://zimbabwe.opendataforafrica.org/anjlptc/2022-population-housing-census

61. Mberego S, Gwenzi J. Temporal patterns of precipitation and vegetation variability over Zimbabwe during extreme dry and wet rainfall seasons. Journal of Applied Meteorology and Climatology. 2014;53(12):2790–804.

62. Timberlake JR, Nobanda N, Mapaure I. Vegetation survey of the communal lands, North and West Zimbabwe. Kirkia. 1993;14(2):171–270.

63. Manatsa D, Mushore T, Gwitira I, Wuta M, Chemura A, Shekede M, et al. Revision of Zimbabwe's Agro-Ecological Zones [Internet]. 2020. p. 1–94. Available from: https://www.researchgate.net/publication/347966377_Report_on_Revised_Agroecological_Zones_of_Zimbabwe_in_press

64. Moyo S. The Political Economy of Land Acquisition and Redistribution in Zimbabwe, 1990-1999. Journal of Southern African Studies. 2000 Mar;26(1):5–28. doi:10.1080/030570700108351

65. Vincent V, Thomas RG. An agroecological Survey of Southern Rhodesia Part 1: Agro-ecological Survey. Salisbury, Rhodesia: Government Publisher; 1960. 125 p.

66. Hwange District Food and Nutrition Security Profile [Internet]. Government of Zimbabwe, World Food Programme; 2022. p. 52. Available from: https://fnc.org.zw/wp-content/uploads/2023/04/Hwange-District-Profile.pdf

67. Booth GD, Niccolucci MJ, Schuster EG. Identifying proxy sets in multiple linear regression: an aid to better coefficient interpretation [Research paper INT]. USA: US Dept of Agriculture Forest Service; 1994.

68. Dormann CF, Elith J, Bacher S, Buchmann C, Carl G, Carré G, et al. Collinearity: a review of methods to deal with it and a simulation study evaluating their performance. Ecography. 2013;36(1):27–46. doi:10.1111/j.1600-0587.2012.07348.x

69. Sanare JE, Valli D, Leweri C, Glatzer G, Fishlock V, Treydte AC. A Socio-Ecological Approach to Understanding How Land Use Challenges Human-Elephant Coexistence in Northern Tanzania. Diversity. 2022 Jul;14(7):7. doi:10.3390/d14070513

70. Sitati NW, Walpole MJ, Leader-Williams N. Factors affecting susceptibility of farms to crop raiding by African elephants: using a predictive model to mitigate conflict. Journal of Applied Ecology. 2005;42(6):1175–82. doi:10.1111/j.1365-2664.2005.01091.x

71. Branco PS, Merkle JA, Pringle RM, Pansu J, Potter AB, Reynolds A, et al. Determinants of elephant foraging behaviour in a coupled human-natural system: Is brown the new green? Journal of Animal Ecology. 2019;88(5):780–92. doi:10.1111/1365-2656.12971

72. Garroutte EL, Hansen AJ, Lawrence RL, Garroutte EL, Hansen AJ, Lawrence RL. Using NDVI and EVI to Map Spatiotemporal Variation in the Biomass and Quality of Forage for Migratory Elk in the Greater Yellowstone Ecosystem. Remote Sensing. 2016 May 10;8(5). doi:10.3390/rs8050404

73. Johnson DM, Rosales A, Mueller R, Reynolds C, Frantz R, Anyamba A, et al. USA Crop Yield Estimation with MODIS NDVI: Are Remotely Sensed Models Better than Simple Trend Analyses? Remote Sensing. 2021 Oct 20;13(21). doi:10.3390/rs13214227

74. Panek E, Gozdowski D. Relationship between MODIS Derived NDVI and Yield of Cereals for Selected European Countries. Agronomy. 2021 Feb 13;11(2). doi:10.3390/agronomy11020340

75. Turvey CG, Mclaurin MK. Applicability of the Normalized Difference Vegetation Index (NDVI) in Index-Based Crop Insurance Design. Weather, Climate, and Society. 2012 Oct 1;4(4):271–84.

doi:10.1175/WCAS-D-11-00059.1

76. Zimbabwe National Elephant Management Plan (2021 – 2025) [National Legislation] [Internet]. Zimbabwe Parks and Wildlife Management Authority; 2021 Jan. p. 1–88. Available from: https://www.zimparks.org.zw/wp-content/uploads/2024/05/Zimbabwe-Elephant-Management-Plan-FINAL.pdf

77. Osborn F, Parker G. Community-based methods to reduce crop loss to elephants: experiments in the communal lands of Zimbabwe. Pachyderm. 2002 Dec 30;33:32–8. doi:10.69649/pachyderm.v33i1.1107

78. Osborn FV. Capsicum Oleoresin as an Elephant Repellent: Field Trials in the Communal Lands of Zimbabwe. The Journal of Wildlife Management. 2002;66(3):674–7. doi:10.2307/3803133

79. Loo YY, Avicena NR, Thong N, Haque AM, Nhlabatsi YT, Abakar SYA, et al. WildTechAlert: Deep Learning Models for Real-Time Detection of Elephant Presence Using Bioacoustics in an Early Warning System to Support Human-Elephant Coexistence. In: Ren J, Hussain A, Liao IY, Chen R, Huang K, Zhao H, et al., editors. Advances in Brain Inspired Cognitive Systems. Singapore: Springer Nature; 2024. p. 385–99. doi:10.1007/978-981-97-1417-9_36

80. Rastogi S, Bhattacharyya S, Vimal K, Dinerstein E, Shah WA, Nagano Y, et al. Promoting human–elephant coexistence through integration of AI, real-time alerts, and rapid response. Conservation Science and Practice. 2025;7(12):e70186. doi:10.1111/csp2.70186

81. Bianchini M, Scarselli F. On the complexity of neural network classifiers: a comparison between shallow and deep architectures. IEEE Trans Neural Netw Learn Syst. 2014 Aug;25(8):1553–65. doi:10.1109/TNNLS.2013.2293637 PubMed PMID: 25050951.

82. Steinert S, Ruf V, Dzsotjan D, Großmann N, Schmidt A, Kuhn J, et al. A refined approach for evaluating small datasets via binary classification using machine learning. PLoS One. 2024;19(5):e0301276. doi:10.1371/journal.pone.0301276 PubMed PMID: 38771767; PubMed Central PMCID: PMC11108166.

83. Badiane M, Cunningham P. An empirical evaluation of kernels for time series. Artif Intell Rev. 2022 Mar 1;55(3):1803–20. doi:10.1007/s10462-021-10050-y

84. Xu Z, Weinberger KQ, Chapelle O. Distance Metric Learning for Kernel Machines [Internet]. arXiv; 2013 [cited 2025 Nov 5]. Available from: http://arxiv.org/abs/1208.3422 doi:10.48550/arXiv.1208.3422

85. Yaghoubi E, Yaghoubi E, Khamees A, Vakili AH. A systematic review and meta-analysis of artificial neural network, machine learning, deep learning, and ensemble learning approaches in field of geotechnical engineering. Neural Comput & Applic. 2024 Jul 1;36(21):12655–99. doi:10.1007/s00521-024-09893-7

86. Beyazit E, Kozaczuk J, Li B, Wallace V, Fadlallah B. An Inductive Bias for Tabular Deep Learning. Advances in Neural Information Processing Systems. 2023 Dec 15;36:43108–35.

87. Winkler DA, Le TC. Performance of Deep and Shallow Neural Networks, the Universal Approximation Theorem, Activity Cliffs, and QSAR. Mol Inform. 2017 Jan;36(1–2). doi:10.1002/minf.201600118 PubMed PMID: 27783464.

88. Useya J, Chen S, Murefu M. Cropland Mapping and Change Detection: Toward Zimbabwean Cropland Inventory. IEEE Access. 2019;7:53603–20. doi:10.1109/ACCESS.2019.2912807

89. Malley GS, Gorenflo LJ. Shifts in the conflict-coexistence continuum: Exploring social-ecological determinants of human-elephant interactions. PLOS ONE. 2023 Mar 28;18(3):e0274155. doi:10.1371/journal.pone.0274155

90. King LE, Douglas-Hamilton I, Vollrath F. African elephants run from the sound of disturbed bees. Current Biology. 2007 Oct 9;17(19):R832–3. doi:10.1016/j.cub.2007.07.038

91. Parker GE, Osborn FV. Dual-season crop damage by elephants in eastern Zambezi Valley, Zimbabwe. Pachyderm. 2001;30:49–56.

92. Denninger Snyder K, Rentsch D. Rethinking assessment of success of mitigation strategies for elephant-induced crop damage. Conserv Biol. 2020 Aug;34(4):829–42. doi:10.1111/cobi.13433 PubMed PMID: 32406988.

93. Vogel SM, Songhurst AC, McCulloch G, Stronza A. Understanding farmers’ reasons behind mitigation decisions is key in supporting their coexistence with wildlife. People and Nature. 2022 Oct;4(5):1305–18. doi:10.1002/pan3.10397

94. Madden F. Creating Coexistence between Humans and Wildlife: Global Perspectives on Local Efforts to Address Human–Wildlife Conflict. Human Dimensions of Wildlife. 2004 Dec 1;9(4):247–57. doi:10.1080/10871200490505675

95. Pozo RA, Coulson T, McCulloch G, Stronza AL, Songhurst AC. Determining baselines for human-elephant conflict: A matter of time. PLOS ONE. 2017 Jun 5;12(6):e0178840. doi:10.1371/journal.pone.0178840

SI 1

GeoAI reproducibility

Fifteen predictors of HEC were calculated and considered: building density (1), distance from fences (2), distance from agriculture, distance from buildings (1), distance from roads (3), distance from protected areas (areas with formal protection for wildlife) (4), slope and elevation (5), distance from closed canopy forest, maximum and minimum NDVI as derived from Landsat, HV polarization backscattering (6), distance from water (7), and standard deviation and maximum precipitation (8).

To tabulate distance from agricultural areas and distance from closed canopy forest, annual land cover maps were generated via a random forest classification using Landsat 8 OLI surface reflectance data in Google Earth Engine (GEE). Overall accuracy ranged from 88-97%. Building density was calculated by using a kernel density estimation with a radius of 10km and a quartic kernel shape. Distance measures from water sources, protected areas, roads, buildings, and closed canopy forest and agriculture land cover types were all "as the crow flies" distances as opposed to cost distance.

Sensitive to ecosystem conditions and the most popular index for assessing vegetation coverage, the normalized difference vegetation index (NDVI) was used (9–12). Using GEE, NDVI for each pixel was calculated from Landsat 8 OLI imagery. In RStudio Version 1.1.423, for each year, measures of central tendency for NDVI were calculated per point and values extracted for months during which crop-raiding occurred. Synthetic Aperture Radar (SAR), a form of active remote sensing, has also proved useful for vegetation studies as an estimate of biomass (13–15). HV backscattering values were gathered per point from the PALSAR-2 Yearly Mosaic (6). Precipitation values were sourced from CHIRPS, a global precipitation dataset designed for drought monitoring (8).

The distributions of potential predictors were plotted and visualized (correlation matrix in Supplemental Information). All predictors were centered and scaled and correlation was calculated using Pearson's r correlation matrices (16). Potential predictors with correlation values exceeding ∓0.7 were excluded, as the assumption of independence is violated, standard errors are inflated, and predictor effects can be challenging to determine (16,17). When ∓0.7 was exceeded, the variable that displayed the greatest overlap with other potential predictors was removed, with the exception of building distance and building density, in which case building density was removed to simplify calculations for replication. Table 1 in the manuscript lists all predictors ultimately included.

GeoAI models were chosen based on their suitability for binary classification, their overall ease of use, and to evaluate the tradeoffs between interpretability and predictive power. A binomial generalized linear model (GLM) was also used to provide additional information about the relationship between predictors and crop-raiding occurrence.

Predictive models were created with the locations of elephant crop-raiding as the dependent variable and potential geospatial drivers of conflict as the independent variables. Pseudo-absence points were created between 100 m to 1 km from conflict points and were assigned the same date as crop-raiding points. An equal number of pseudo absences to crop-raiding points was generated for each year.. As some reported conflict occurs just outside of agricultural areas, we chose not to limit possible pseudo-absence points to agricultural areas but to use a buffer area, ensuring a pseudo-absence point could not overlay a conflict point but environmental conditions were likely to be relatively comparable. For constructing the RF model, 70% of all points were used for training and 30% for testing. The RF modeling technique uses ensemble methods to improve accuracy of results by combining multiple models, but the other three GeoAI techniques lack such a mechanism. Therefore, we applied 10-fold cross validation when constructing the SVM, DNN, and MLP models to verify their performance. In 10-fold cross validation, the dataset is randomly split into ten parts; each time, one part is used for testing and the remaining nine for training, rotating through all parts.

As SVM is sensitive to parameter settings (Burges, 1998; Vapnik, 1999), different cost values and linear, polynomial, radial, and sigmoid kernel types were all evaluated to optimize model performance and accuracy. This model was run in RStudio (Posit team, 2023) using the ‘caret’ package (Kuhn, 2008).

The RF algorithm was also run in RStudio using the ‘randomForest’ package version 4.7 (Liaw & Wiener, 2002). The number of trees was adjusted iteratively to improve model accuracy using multiple model runs and evaluations. Ultimately, five thousand trees were employed to train 70% of the reference data. All other default model settings were used.

Both neural network algorithms were run using Jupyter Notebook 6.1.4. A DNN was created using the Keras Python and TensorFlow libraries (Bernico, 2018). A sequential model was used and various activation functions, loss functions, and optimizers, such as stochastic gradient descent, RMSprop, and Adam were tested (Duchi et al., 2011; Kingma & Ba, 2014). A batch size of 200, 5000 epochs, the binary cross entropy loss function, and the AdaGrad optimizer were selected. For MLP, the ‘sklearn’ package version 0.0 was used (Pedregosa et al., 2011). Three hidden layers with sizes of 100 were used and the maximum number of iterations was set to 100,000.

To test the sensitivity of our analysis to the exact location of pseudo-absence points, we created three additional sets of pseudo-absence points: a set 1km from conflict points, 500m from conflict points, and 100m from conflict points. Distances were no more than 1km from an observed conflict point to ensure a similar landscape matrix as found at locations of known conflict. We then repeated the entire analysis with each set of pseudo-absence points. Results of these analyses are reported in later in Supplementary Information.

References

1. Open Street Map Contributors. Buildings [Internet]. OpenStreetMap; 2022. Available from: openstreetmap.org

2. Open Street Map Contributors. Barriers/Fence [Internet]. OpenStreetMap; 2022. Available from: openstreetmap.org

3. Open Street Map Contributors. Highways/Streets [Internet]. OpenStreetMap; 2022. Available from: openstreetmap.org

4. Protected Planet: The World Database on Protected Areas (WDPA) [Internet]. Cambridge, UK: UNEP-WCMC and IUCN.: UNEP-WCMC and IUCN; 2020. Available from: www.protectedplanet.net

5. NASA/METI/AIST/Japan Space Systems and U.S./Japan ASTER Science Team. ASTER Global Digital Elevation Model V003 [Internet]. NASA EOSDIS Land Processes DAAC; 2019. Available from: https://doi.org/10.5067/ASTER/ASTGTM.003 doi:10.5067/ASTER/ASTGTM.003

6. Shimada M, Itoh T, Motooka T, Watanabe M, Shiraishi T, Thapa R, et al. New global forest/non-forest maps from ALOS PALSAR data (2007–2010). Remote Sens Environ. 2014 Dec 1;155:13–31. doi:10.1016/j.rse.2014.04.014

7. Open Street Map Contributors. Waterways [Internet]. OpenStreetMap; 2022. Available from: openstreetmap.org

8. Funk C, Peterson P, Landsfeld M, Pedreros D, Verdin J, Shukla S, et al. The climate hazards infrared precipitation with stations—a new environmental record for monitoring extremes. Sci Data. 2015 Dec 8;2(1):1. doi:10.1038/sdata.2015.66

9. Goward SN, Tucker CJ, Dye DG. North American vegetation patterns observed with the NOAA-7 advanced very high resolution radiometer. Vegetatio. 1985 Dec 1;64(1):3–14. doi:10.1007/BF00033449

10. Huang S, Tang L, Hupy JP, Wang Y, Shao G. A commentary review on the use of normalized difference vegetation index (NDVI) in the era of popular remote sensing. J For Res. 2021 Feb 1;32(1):1–6. doi:10.1007/s11676-020-01155-1

11. Myneni RB, Hall FG, Sellers PJ, Marshak AL. The interpretation of spectral vegetation indexes. IEEE Trans Geosci Remote Sens. 1995 Mar;33(2):481–6. doi:10.1109/TGRS.1995.8746029

12. Ollinger SV. Sources of variability in canopy reflectance and the convergent properties of plants. New Phytol. 2011;189(2):375–94. doi:10.1111/j.1469-8137.2010.03536.x

13. Bouvet A, Mermoz S, Le Toan T, Villard L, Mathieu R, Naidoo L, et al. An above-ground biomass map of African savannahs and woodlands at 25m resolution derived from ALOS PALSAR. Remote Sens Environ. 2018 Mar 1;206:156–73. doi:10.1016/j.rse.2017.12.030

14. Kasischke ES, Melack JM, Craig Dobson M. The use of imaging radars for ecological applications—A review. Remote Sens Environ. 1997 Feb 1;Spaceborne Imaging Radar Mission59(2):141–56. doi:10.1016/S0034-4257(96)00148-4

15. Urbazaev M, Thiel C, Mathieu R, Naidoo L, Levick SR, Smit IPJ, et al. Assessment of the mapping of fractional woody cover in southern African savannas using multi-temporal and polarimetric ALOS PALSAR L-band images. Remote Sens Environ. 2015 Sep 1;166:138–53. doi:10.1016/j.rse.2015.06.013

16. Booth GD, Niccolucci MJ, Schuster EG. Identifying proxy sets in multiple linear regression: an aid to better coefficient interpretation [Research paper INT]. USA: US Dept of Agriculture Forest Service; 1994.

17. Dormann CF, Elith J, Bacher S, Buchmann C, Carl G, Carré G, et al. Collinearity: a review of methods to deal with it and a simulation study evaluating their performance. Ecography. 2013;36(1):27–46. doi:10.1111/j.1600-0587.2012.07348.x

SI 2

Table 1. Distribution of number of crop-raiding points for each year, months raiding were observed, and comments on collections.

Year	Number of HEC points collected	Months of HEC point collection	Comments
2015	33	January through March	First year data was systematically recorded
2016	124	January through April	
2017	95	March through May	
2018	241	February through May	
2019	0	-	Collection limited by crop failure due to drought
2020	2	March	Collection limited by lockdown due to COVID-19
2021	218	January through November	

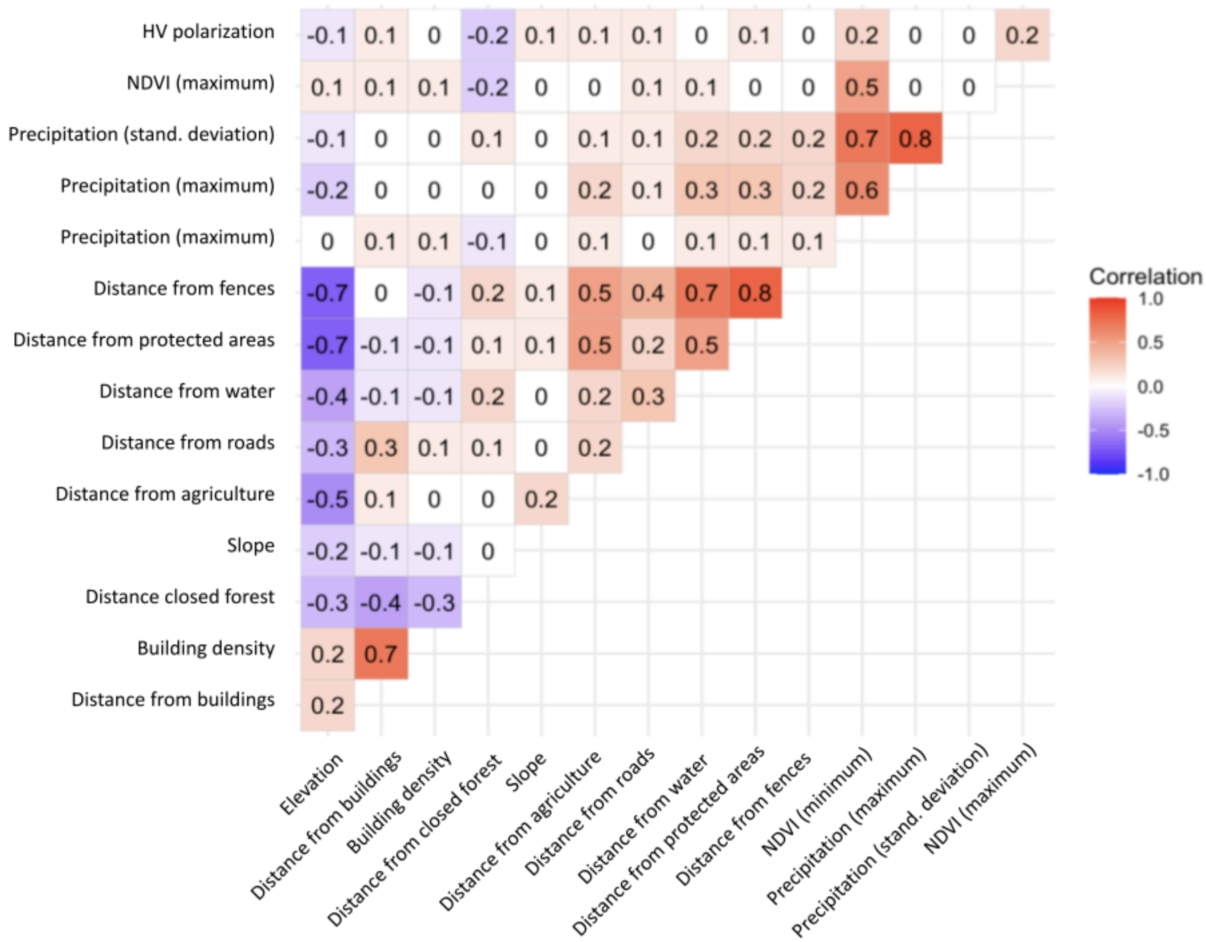

Figure 1. Correlation matrix of potential predictor variables for reported elephant crop-raiding locations. Positively correlated variables are in red and negatively correlated variables are in purple. Darker shades indicate stronger correlation. Correlation coefficients are imposed on squares.

SI 3

Results using pseudo-absences generated within a 1 km buffer:

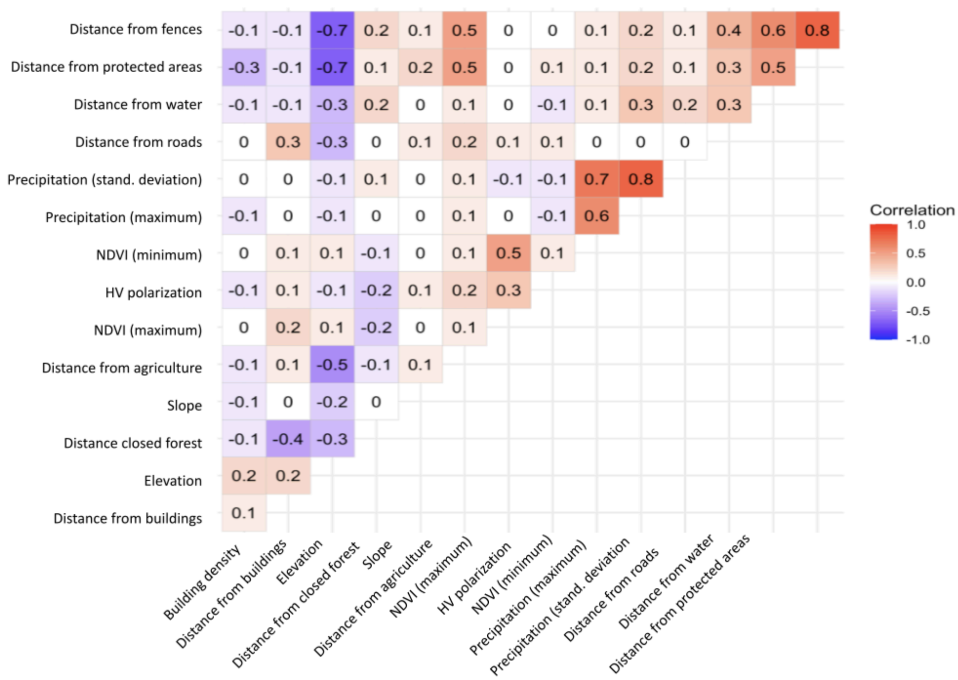

Figure 2. Correlation matrix of potential predictor variables for reported elephant crop-raiding locations using pseudo-absences generated within a 1 km buffer. Positively correlated variables are in red and negatively correlated variables are in purple. Darker shades indicate stronger correlation. Correlation coefficients are imposed on squares.

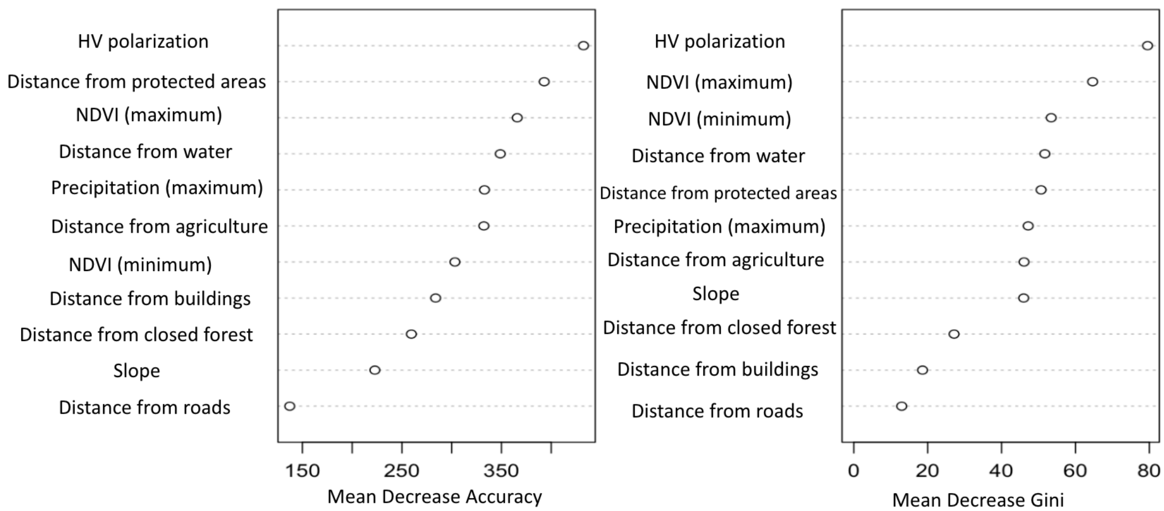

Figure 3. Variable Importance Plot of variables included in random forest model.

Table 2. Confusion matrix for testing data using SVM, RF, DL, and MLP.

	SVM		**RF**		**DL**		**MLP**	
	Predicted absence	Predicted raid	Predicted absence	Predicted raid	Predicted absence	Predicted raid	Predicted absence	Predicted raid
Actual pseudo-absence	**504.8**	208.2	**180**	46	**522.6**	190.4	**683.8**	29.2
Actual raid	136.9	**576.1**	34	**168**	212.7	**500.3**	38.1	**674.9**

Predictors that negatively impacted crop-raiding, as evident in the binomial GLM, include distance from protected areas ($P<0.001$), distance from agriculture ($P<0.001$), distance from closed forest ($P<0.01$), NDVI minimum ($P<0.05$), maximum NDVI ($P<0.001$) and HV polarization ($P<0.001$). The predictors that contributed positively included building density ($P<0.01$) and distance from buildings ($P<0.001$).

Results using pseudo-absences generated within a 500 m buffer:

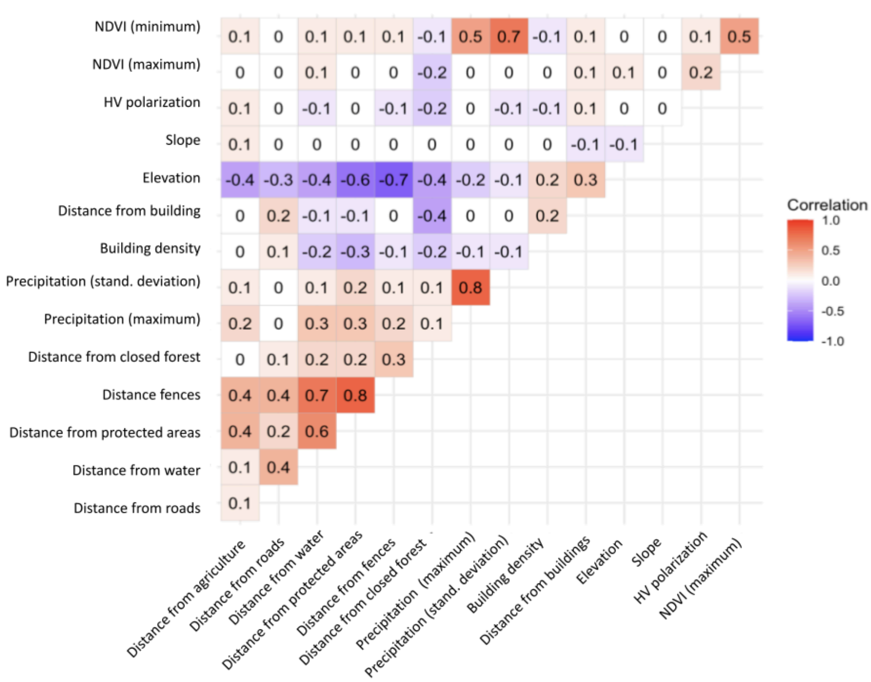

Figure 4. Correlation matrix of potential predictor variables for reported elephant crop-raiding locations using pseudo-absences generated within a 500 m buffer. Positively correlated variables are in red and negatively correlated variables are in purple. Darker shades indicate stronger correlation. Correlation coefficients are imposed on squares.

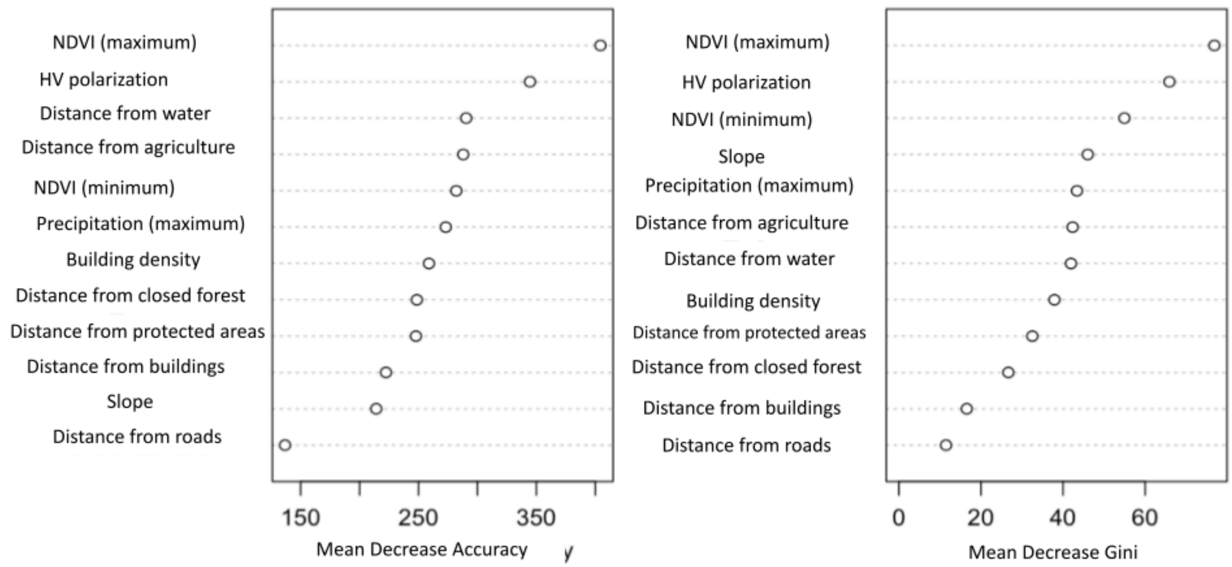

Figure 5. Variable Importance Plot of variables included in random forest model.

Table 3. Confusion matrix using SVM, RF, DL, and MLP.

	SVM		RF		DL		MLP	
	Predicted absence	Predicted raid	Predicted absence	Predicted raid	Predicted absence	Predicted raid	Predicted absence	Predicted raid
Actual pseudo-absence	**486.3**	226.7	**167**	61	**507.3**	205.7	**680.2**	32.8
Actual raid	148.3	**564.7**	47	**153**	254.5	**458.5**	46.6	**666.4**

The binomial GLM showed predictors that negatively impacted crop-raiding include distance from roads (P<0.05), distance from agriculture (P<0.01), distance from closed forest (P<0.001), NDVI minimum (P<0.05), maximum NDVI (P<0.001) and HV polarization (P<0.001). The predictors that contributed positively included building density (P<0.01) and distance from buildings (P<0.001).

SI 4

Results using pseudo-absences generated within a 100 m buffer:

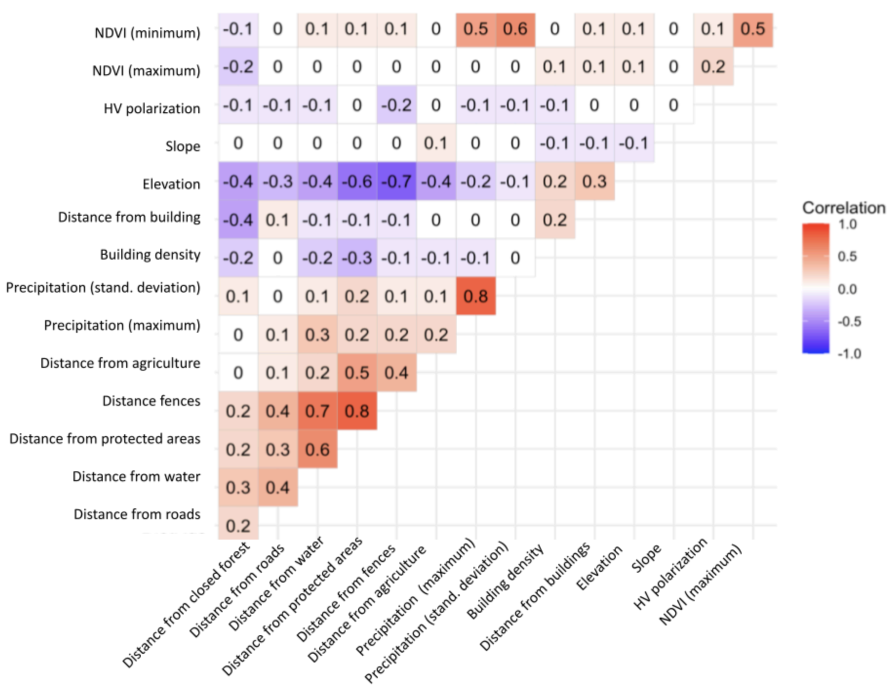

Figure 5. Correlation matrix of potential predictor variables for reported elephant crop-raiding locations using pseudo-absences generated within a 100 m buffer. Positively correlated variables are in red and negatively correlated variables are in purple. Darker shades indicate stronger correlation. Correlation coefficients are imposed on squares.

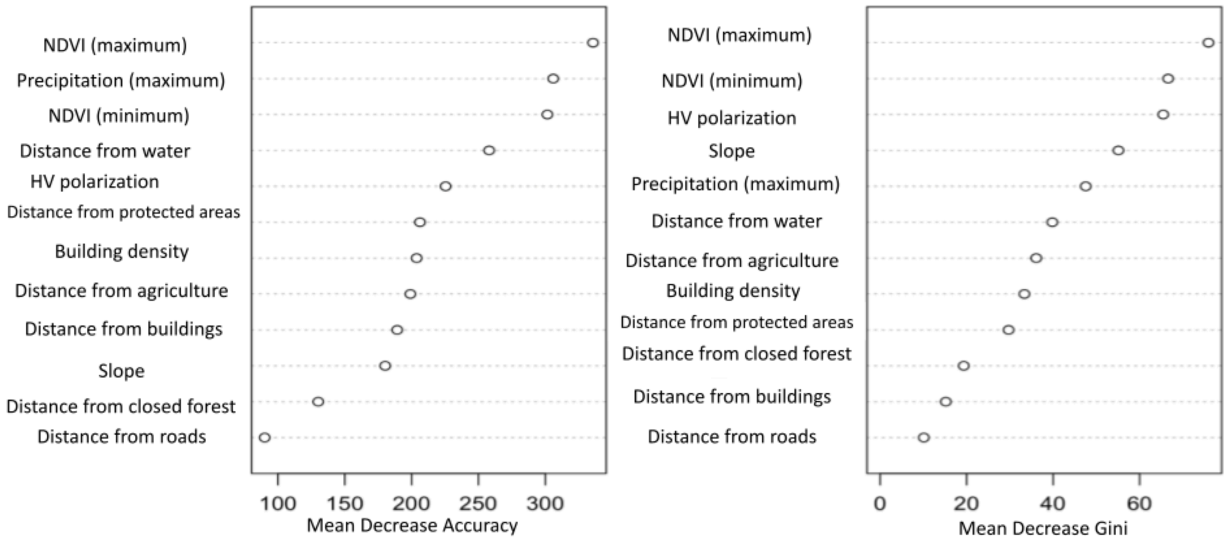

Figure 6. Variable Importance Plot of variables included in random forest model.

Table 4. Confusion matrix using SVM, RF, DL, and MLP.

	SVM		RF		DL		MLP	
	Predicted absence	Predicted raid	Predicted absence	Predicted raid	Predicted absence	Predicted raid	Predicted absence	Predicted raid
Actual pseudo-absence	**420.7**	292.3	**154**	67	**481.4**	231.6	**684.4**	28.6
Actual raid	219.6	**493.4**	60	**147**	279.6	**433.4**	36.2	**676.8**

Using pseudo-absence points created within 100m of reported raids, predictors negatively impacting HEC occurrences in the binomial GLM include maximum NDVI (P<0.001) and distance from agriculture ($P<0.05$). Those with a positive impact include distance from building ($P<0.001$) and building density ($P<0.01$).