Zoology and Ecology, 2024, Volume 34, Number 2
Online ISSN: 2165-8013
https://doi.org/10.35513/21658005.2024.2.4

HARNESSING ENSEMBLE MODELLING TO PREDICT HUMAN-WILD BOAR CONFLICT RISK ZONES IN TAMIL NADU, INDIA

Thekke Thumbath Shameer, Priyambada Routray, A. Udhayan, Nihar Ranjan, Manikka Govindan Ganesan, Arulmani Manimozhi, Dhayanithi Vasantha Kumari

Advanced Institute for Wildlife Conservation, Tamil Nadu Forest Department, Vandalur, Chennai 600048, Tamil Nadu, India

*Corresponding author. Email: shameerh4u@yahoo.com
Thekke Thumbath Shameer: https://orcid.org/0000-0002-2306-1821

Shameer, T.T., Routray, P., Udhayan, A., Ranjan, N., Ganesan, M.G., Manimozhi, A., Kumari, D.V. 2024. Harnessing ensemble modelling to predict human-wild boar conflict risk zones in Tamil Nadu, India. *Zoology and Ecology* 34 (2) 111–121.
https://doi.org/10.35513/21658005.2024.2.4

Article history
Received: 28 May 2024;
Accepted: 24 September 2024

Keywords:
Agriculture; conflicts; conservation; ensemble modelling; southern India

Abstract. Growing human populations and destruction of natural habitats intensify human-wildlife conflicts, particularly with wild boar (*Sus scrofa*). To minimize the conflicts and undertake mitigation measures predicting conflict risk zones and identifying the predictors is necessary. Accordingly, we conducted a study by collecting secondary data on conflicts across forest divisions of Tamil Nadu from 2016 to 2021. Of the 3301 incidents we collected, 94.4% were related to crop damage. Using ensemble modelling we predicted a conflict risk zone of approximately 79,753 km^2, which represents 61.34% of the total area of Tamil Nadu. Variables such as the human modification index and mean annual temperature contributed the most to model performance. Our model indicates that areas with cultivated lands close to the fringes of forests, especially in regions with a higher degree of human modification, have greater levels of conflict risk. The study's outcome will help managers undertake proactive measures to mitigate HWBC in Tamil Nadu.

INTRODUCTION

Human population growth and subsequent development near natural habitats have substantially increased human-wildlife conflict (HWC) (Karami and Tavakoli 2022; Nhyus 2016). HWC is a much-discussed term that occurs when the needs of humans and wildlife overlap in space or time, resulting in a negative interaction between both (Mekonen 2020; Dickman 2010; Naughton-Treves et al. 2003). The rapid increase of HWC has emerged as a critical threat to global biodiversity conservation (Mekonen 2020; Karanth et al. 2018; Amaja et al. 2016). HWC can take various forms, including crop damage, property destruction, and human and animal casualties (Shameer et al. 2024). With the increased dependency of humans on natural resources and the overexploitation of natural habitats, the incidents of HWC are likely to increase, making it a complex issue to address (Rawat et al. 2021; Sharma et al. 2021; Woodroffe et al. 2005). HWC is driven by multiple factors, including habitat loss and fragmentation, changes in land use, forest cover, agricultural practices, human encroachment into wildlife habitat, and poaching (Sharma et al. 2020). It can lead to interactions between humans and wildlife (Treves et al. 2009) and be influenced by social and economic factors, such as overwhelming population growth, poverty, and lack of alternative livelihood options (Nyhus 2016). Understanding the complex drivers of human-wildlife conflict is crucial for developing effective management strategies that foster coexistence between humans and wildlife while ensuring the welfare of biodiversity and the well-being of local communities (Treves and Bruskotter 2014).

Species distribution modelling (SDM) is one of the most potent tools in conservation planning, and researchers have been implementing it in various studies (Abedin et al. 2024; Rocha et al. 2024). The ensemble modelling framework suggested by Araujo and New (2007) has gained popularity for predicting reliable SDMs. Ensemble modelling is a powerful approach for improving the accuracy and robustness of species distribution models (SDMs), which involves fitting multiple models using different algorithms, predictors, or modelling techniques and combining the predictions using a weighted average or other aggregation methods. This approach can help reduce the effects of overfitting, account for model uncertainty, and capture the complexity of the relationship between species and the environment. Ensemble modelling has been proven to improve the accuracy and reliability of SDMs in many applications, such as predicting the distribution of species, modelling the effects of climate change on biodiversity, identifying priority areas for conservation, and predicting HWC (Karami and Tavakoli 2022; Ahmed et al. 2021; Mpakairi et al. 2018).

The wild boar is a generalist species known for its flexibility and prolific reproduction (Lowe et al. 2000). It is distributed over many parts of the world and tends to exploit locally abundant food sources (Schley and Roper 2003). This behaviour results in conflicts with humans when they come into contact with crops or other human-dominated areas (Schley et al. 2003). This has made wild boar a significant economic threat in many parts of the world. Human-wild boar conflict (HWBC) is an evolving issue that has attracted increasing attention recently. HWBC is a critical issue in India, particularly in the southern parts of the country, which makes it of utmost importance to address it to minimize its adverse effects. The increasing wild boar population without proportional growth in forest areas has resulted in HWBC. Several studies have recognized habitat loss and fragmentation, urbanization, and agricultural practices as the fundamental drivers of HWBC (Milda et al. 2022; Chauhan et al. 2009).

Predicting the conflict risk zones and identifying the predictors of HWBC can help managers develop effective mitigation strategies. Accordingly, we conducted a study on HWBC in Tamil Nadu to i) understand the distribution of HWBCs and their temporal pattern, ii) identify the drivers of HWBC, and iii) predict the conflict risk zones using ensemble modelling.

MATERIALS AND METHODS

Study area

The state of Tamil Nadu (approximately 11.1271° N and 78.6569° E) (Figure 1) is located in southernmost India. As mentioned in the Indian State of Forest Report 2021, Tamil Nadu constitutes 26,451 km^2 of forest cover, about 17.41% of the state's total area. This state witnesses an average rainfall of about 950 mm to 1170 mm, and the annual average temperature ranges from approximately 19 °C and 37 °C (Shameer et al. 2024). Since Tamil Nadu experiences various types of climatic conditions that support a diverse range of forest types, starting with tropical wet evergreen forest, tropical semi-evergreen forest, and ending with sub-tropical hill forest and montane wet temperate forest, these many varied forests hold a diverse range of flora and fauna.

Data collection

We collected data between 2016 and 2021 on HWBC incidents across the forest divisions of Tamil Nadu from both secondary sources and field visits. As part of the Tamil Nadu Forest Department conflict mitigation plan, G.O (Ms). No.141 and G.O (D). No.14 conflict records are collected and maintained in forest divisions. These data had information about HWBC, such as date of occurrence, latitude and longitude, type of conflict (i.e., crop damage, human injury, and human death), crop name, and compensation details. While visiting the conflict location, we collected information about the frequency, terrain information, and any other ground factors that could influence HWBC in the region. As most of the data were related to crop damage, we segregated the specific data performed analysis and ensemble modelling.

Data thinning

We performed a spatial thinning to reduce the spatial autocorrelation among independent conflicts. Spatial thinning stands as the best method to reduce spatial sampling biases. This strategy involves the selective removal of data while maintaining crucial information to mitigate the influence of sampling biases. The package "spThin" (Aiello-Lammens et al. 2015) in R (R Core Team 2023) employs a randomization approach and returns a maximum number of records within a thinning distance while analysed with sufficient iterations. We removed the conflict records that exhibited spatial autocorrelation and consolidated multiple occurrences.

Environmental variables

We chose three bioclimatic variables, Annual Mean Temperature (Bio1), Isothermality (Bio3), and Annual Precipitation (Bio12), downloaded from Worldclim (http://www.worldclim.org) (Hijmans et al. 2005). We used the SRTM 30 m digital elevation model (DEM) (Farr et al. 2007) and calculated the terrain ruggedness index (TRI) using the R packages raster (Hijmans 2023) and rgdal (Bivand et al. 2023). We further extracted the layers such as forest cover, croplands, and build-up areas from the ESA World Cover 2022 (Zanaga et al. 2022) database in 30 m resolution using httr (Wickham 2023) and raster packages. Further, we converted these rasters to polygons and calculated their Euclidean distances using the package rgeos (Bivand and Rundel 2021). The Normalized Difference Vegetation Index (NDVI) was downloaded from the MODIS (modis.gsfc.nasa.gov) database, and its average was calculated from 2016–2021 of our study period using the raster package. The water layers were downloaded from Humanitarian OpenStreetMap (https://data.humdata.org/), and their Euclidean distance was calculated. We further downloaded Global Human Modification of Terrestrial Systems (HMI), v1 (2016), which provides a cumulative measure of the human modification of terrestrial lands across the globe at a 1-km resolution (Kennedy et al. 2020). All the environmental covariates were rescaled to 1 km2 resolution using the raster package in R. These environmental variables were tested for multicollinearity using Pearson correlation coefficient analysis with a threshold of 0.75 in R. We did not find any collinearity between the variables; hence, all the variables were retained and used for the modelling.

Modelling procedure

The "sdm" package (Naimi and Araujo 2016) provides multiple combinations of algorithms for ensemble modelling. This enables users to create a set of candidate models, evaluate their performance, and combine them into an ensemble using various methods such as boosting bagging or random forests. Using the same package, we generated pseudo-absence records equal to our presence records (data obtained after thinning). In studies seeking to identify unsurveyed sites with a high probability of occurrence for species, pseudo-absences that are more likely to be true absences help improve model accuracy (Barbet-Massin et al. 2012). We employed nine candidate models available in the sdm package, including RF (Random Forest), MDA (Mixture Discriminant Analysis), RPART (Recursive Partitioning and Regression Trees), MAXLIKE (Maximum Likelihood), MARS (Multivariate Adaptive Regression Splines), BRT (Boosted Regression Trees), GLM (Generalized Linear Model), FDA (Flexible Discriminant Analysis), and GAM (Generalized Additive Model), to build an ensemble model. Out of the 865 conflict occurrence records, we randomly selected 30% (n = 259) to test the accuracy of the models, while the remaining 70% (n = 606) was used for training. This procedure trains the model with enough data (70%) to ensure stability, reducing the risk of overfitting. The testing data (30%) is used to evaluate the model's accuracy on unseen data. We repeated this process five times to calculate the mean values of sensitivity, specificity, True Skill Statistics (TSS), kappa and Area under the Curve (AUC), thereby evaluating the accuracy of the models.

To ensure unbiased predictive accuracy with low variance, we employed the bootstrapping replication method, following previous studies (Ahmed et al. 2021; Harrell et al. 1996; Lima et al. 2019), to run the individual algorithms. The independent algorithms were then assembled using the weighted averaging method, with TSS as the evaluation statistic and a threshold value of maximum sensitivity and sensitivity. We used QGIS 3.36.1 (QGIS Development Team 2024) to visualise and generate the final map from the ensemble model output. The model's output was divided into four distinct categories to highlight the conflict risk zones: "Very Low Risk" (between 0 and 0.25), "Low Risk" (0.25–0.5), "High Risk" (0.5–0.75), and "Very High Risk" (0.75–1). We calculated the area of the conflict risk zones by adding up the areas designated as "High Risk" and "Very High Risk".

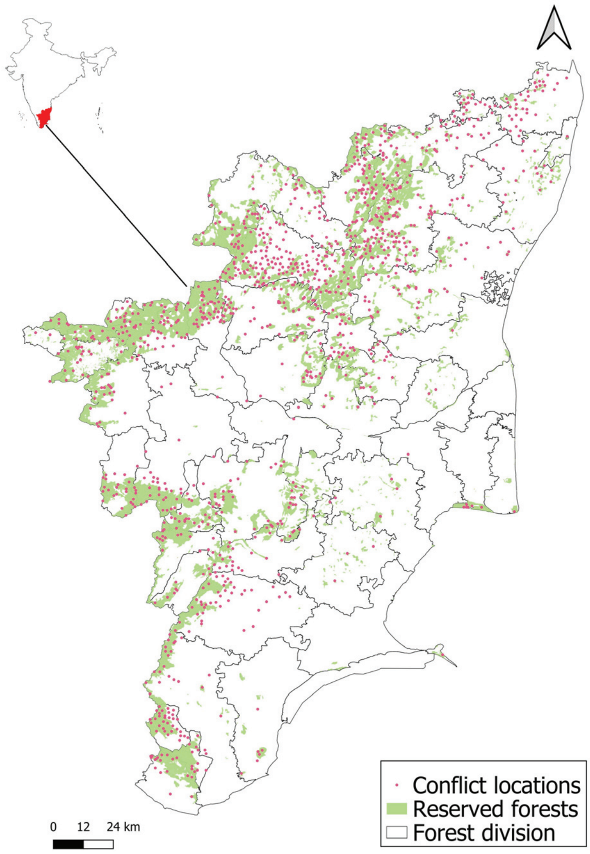


Figure 1. The study area map indicates the conflict locations (red dots) and forest reserves (green areas).

RESULTS

Data profile of HWPC

We obtained 3293 independent (based on different dates of occurrence) crop damage events from the data. After data thinning, the occurrence records decreased from 3293 to 623 (Figure 1). The Dharmapuri (n = 678) and Thrivullavur (n = 550) forest divisions had the highest crop damage (Figure 2).

Temporal pattern of HWPC

Our data showed that 2020 saw the highest number of crop damage incidents (Figure 3). Temporal analysis showed crop damages were the highest in August to December (Figure 4). April, May, and June had comparatively fewer crop damages. The crop-wise temporal analysis showed that the banana crop had the highest number of conflict incidents, specifically from November to March. Wild boars mostly damage sugarcane in January, but the trend can continue from September until March. Tapioca, on the other hand, can be damaged from June to September. They prefer groundnuts mainly in the month(s) of August to October, but the conflict can occur from August until March. Crop damage incidents of corn can start in October and last until January. Paddy

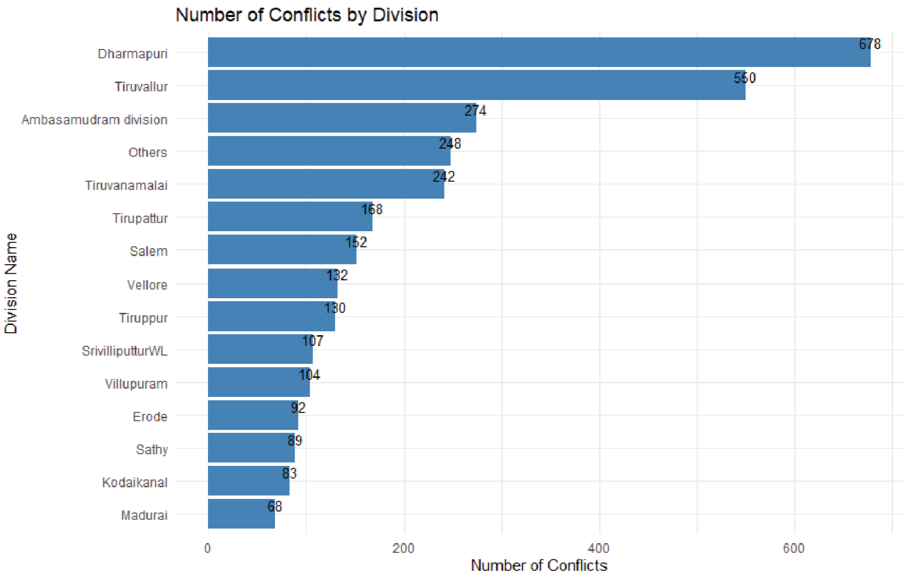


Figure 2. Frequency distribution of conflicts across forest divisions.

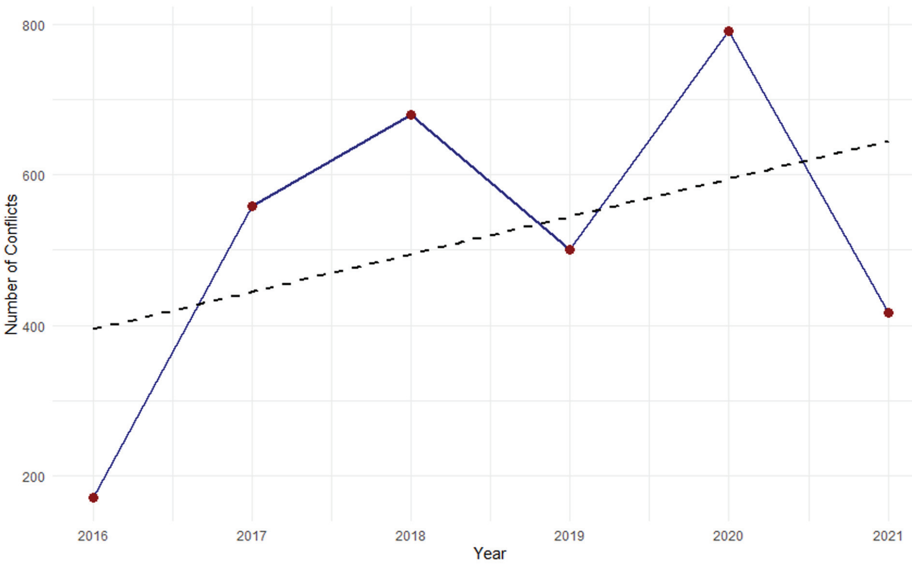


Figure 3. Year-wise distribution of conflicts across forest divisions.

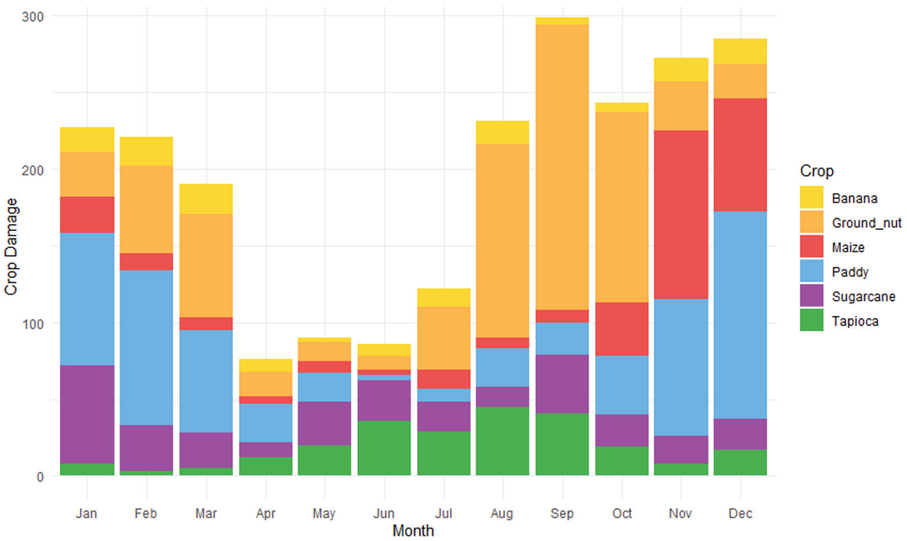


Figure 4. Temporal distribution of conflicts across forest divisions for specific crops.

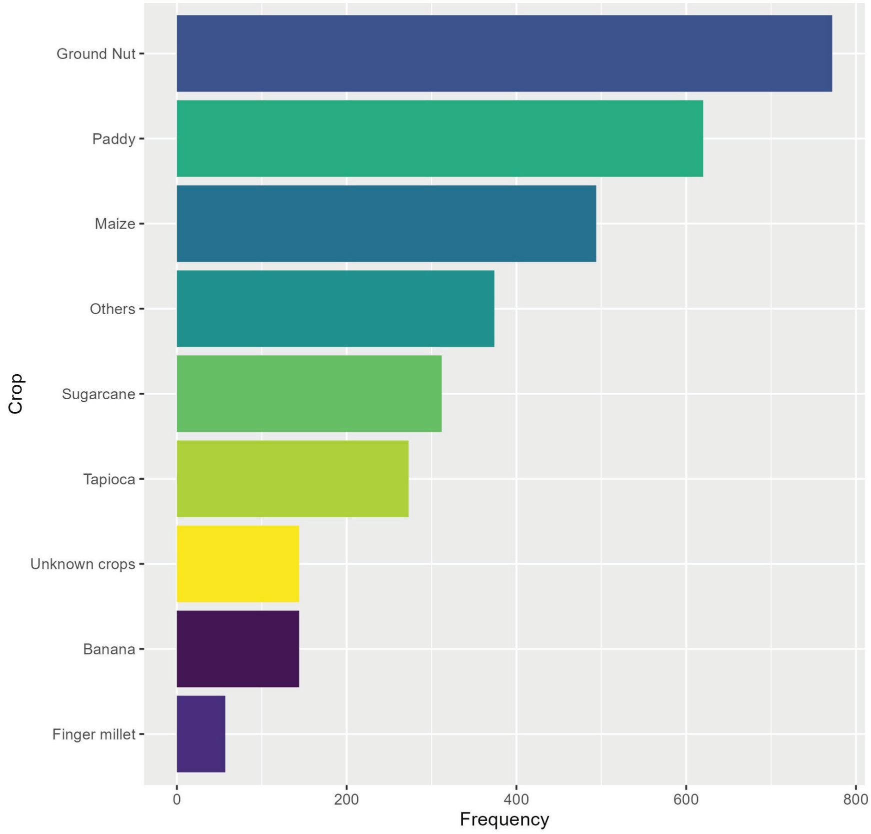


Figure 5. Frequency of HWBC categorised by different crops.

crops were damaged from November to March, while maize was damaged from October to January. Ground nuts, paddy, and maize were major crops susceptible to damage (Figure 5).

Model performance and prediction

Supplementary Table 1 depicts the performance of models using different evaluation techniques. The top-performing model was RF, with an AUC of 0.92, TSS of 0.70 and Kappa of 0.70. We also evaluated model accuracy using the receiver operator characteristics (ROC) curve, which shows the proportion of the true presence and absence rates. Supplementary Figure 1 shows all models' ROC curves, indicating RF as the best model. Of the ten predictor variables, the human modification index and mean annual temperature contributed the most to model performance (Supplementary Figure 2). The partial response curves of bio1 indicate that the conflict risk peaks at moderate temperatures. Bio12 suggests that regions with moderate rainfall experience higher conflicts. Similarly, Bio3 indicates an increased risk in regions with more stable temperatures. The distance to built-up areas shows that conflicts increase at mid-range distances. Distance to cropland indicates that conflict risk decreases with increasing distance. Elevation shows an apparent decline in risk, as shown by rising values. Distance to forest cover indicates higher risk at mid-

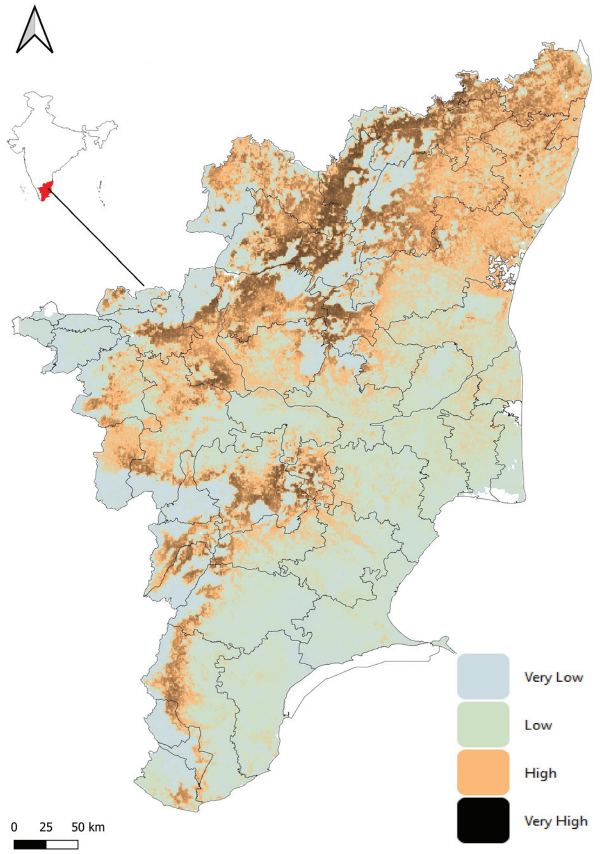


Figure 6. Predicted risk zone of HWBC using ensemble modelling.

range distances. HMI suggests that areas with more remarkable human alteration are prone to conflict risk. However, NDVI didn't reflect any pattern. TRI and distance to water reveal that flatter terrains near water sources are more prone to conflicts (Supplementary Figure 3). The ensemble model predicts a conflict risk zone covering approximately 79,753 km^2, which represents 39.67% of the total area of Tamil Nadu. These risk zones were mainly located between the northeast, northwest, and south-western parts of Tamil Nadu (Figure 6).

DISCUSSION

Crop damage has emerged as a significant global concern in HWBC (Boyce et al. 2020; McKee et al. 2020; Fischer et al. 2019; Lombardini et al. 2016; Chauhan et al. 2009). Wild boar has experienced a population increase due to the absence of natural predators, coupled with favourable conditions created by human activities near their habitats (Ickes 2001; Lewis et al. 2019; Waithman et al. 1999). These factors give them easy access to food and water sources in human settlements near forest edges (Milda et al. 2022). A consistent pattern emerged in the recorded instances of crop damage, with certain crops that they preferred significantly more. The primary targets were Groundnut, paddy, sugarcane, tapioca, maize, and banana. These crops, commonly cultivated in open fields, are particularly vulnerable to wild boar damage due to their accessibility and the proficiency of wild boars as diggers. A study by Vasudeva et al. (2015) also confirmed these crops' susceptibility to damage by wild boars as diggers. The temporal analysis to understand the seasonal patterns of crop damage revealed interesting trends. For instance, the banana crop exhibited the highest damage from November to March, aligning with its typical harvesting time. Certain crops grow in seasons corresponding to wild boars' active foraging pattern. It is important to note that these temporal patterns provide insights into the crop preferences and raiding behaviour of wild boars. They help in understanding the peak periods of crop vulnerability and can aid in developing targeted mitigation strategies.

Previous studies conducted by Karami and Tavakoli (2022) and Ficetola et al. (2014) have demonstrated the effectiveness of species distribution models (SDMs) in accurately predicting wild boar conflicts. The findings in this study highlight the reliability of SDMs as a robust approach for predicting the risk of HWBC. Therefore, we can consider our modelling approach as an exemplary method for predicting and assessing the potential risks associated with HWBC. From ensemble modelling, it is clear that certain variables significantly contributed to the model's performance. The predictor variables, such as human modification index, mean annual temperature, elevation, and distance to cropland, stood out as having the highest contribution and influence in the HWBC model (Supplementary Material 2). These variables likely played a crucial role in influencing the occurrence and intensity of HWBC.

The partial response curve indicates that the human settlements near wild boar habitats or potential foraging areas will likely have increasing trends in HWBC. Several studies indicate that crop damage by wild boar is usually happening at the forest fringes (Liu et al. 2019; Thurfjell et al. 2015; Jin et al. 2021). The cultivated lands near forest fringes provide a favourable habitat for wild boar. They adapt well to such heterogeneous landscapes, utilising natural and human-altered environments (Johann et al. 2020). The contribution of DEM provides information about topographical features that influence wild boar movement patterns and their accessibility to human-dominated areas.

There is a strong correlation between temperature and the distribution of wild boars. McClure et al. (2015) noted that the distribution of wild boar was most strongly limited by cold temperatures, and a high probability of occurrence was associated with frequent high temperatures. They also reported that they are likely to occur where potential home ranges have higher habitat heterogeneity, providing access to multiple vital resources, including water, forage, and cover. A strong correlation is found between high NDVI values and an increased likelihood of conflict events. In conflict zones, croplands with abundant vegetation, such as dense crops or areas with tall grasses, can serve as favourable refuge habitats for wild boars, offering protection from predators and human disturbances (Barasona et al. 2021). Similarly, a higher likelihood of conflict risk was observed to correlate with an increasing human modification index. Rutten et al. (2019) revealed that wild boars demonstrate remarkable behavioural and physiological adaptability in response to human-dominated landscapes. This suggests that the proximity to these features or land uses may increase the likelihood of conflicts between humans and wildlife, potentially due to factors such as resource availability, human disturbance, or the attraction of wildlife to these areas, which is also evident from several HWC studies (Sharma et al. 2020; Huang et al. 2018; Markovchick-Nicholls et al. 2007). These findings highlight the importance of considering landscape features and land use patterns when understanding and managing HWBC. They suggest that conserving and managing forested areas while considering the spatial relationships between human settlements, croplands, built-up areas, and wildlife habitats can mitigate conflicts and promote coexistence between humans and wildlife.

Management implications

The conflict risk map predicted using ensemble modelling will have several management implications. This model will help managers in identifying probable regions for conflict risks to undertake proactive measures. The identified high-risk areas can also be selected for targeted mitigation measures. For instance, strategic placement of fencing or deterrents can be focused on locations predicted to be in higher conflict risk zones. As areas are prioritised, interventions such as enhanced fencing or community-based deterrent strategies and resource allocation can be effective. Utilising predictive modelling approaches will help develop proactive mitigating strategies that will lead to better management of HWC.

ACKNOWLEDGEMENTS

The authors acknowledge the Tamil Nadu Forest Department, the PCCF and the Chief Wildlife Warden for granting the necessary permissions and all the forest department officials for providing full cooperation and support during our field visits.

Author Contribution

TTS conceptualised and designed the study. TTS and PR did the fieldwork and analysed the data. TTS and PR constructed figures. TTS and PR wrote the manuscript. U, NR, MGG, AM and DVK mobilized the funds, procured permission, and provided field and logistical support. All authors contributed to the manuscript's writing.

Conflict of Interest

The authors declare no conflict of interest.

Data availability

All the data used in the manuscript are available as graphs or tables. The corresponding author can be contacted for further inquiries.

Funding details

The Tamil Nadu Forest Department funded the study.

REFERENCES

Abedin, I., Tanoy, T., Kim, A.R., Kim, H.W., Kang, H.E., & Kundu, S. 2024. Distribution Model Reveals Rapid Decline in Habitat Extent for Endangered Hispid Hare: Implications for Wildlife Management and Conservation Planning in Future Climate Change Scenarios. *Biology* 13(3), 198. Multidisciplinary Digital Publishing Institute (MDPI). doi:10.3390/biology13030198

Ahmed, N., Atzberger, C., & Zewdie, W. 2021. Species Distribution Modelling performance and its implication for Sentinel-2-based prediction of invasive Prosopis juliflora in lower Awash River basin, Ethiopia. *Ecological Processes* 10(18). https://doi.org/10.1186/s13717-021-00285-6

Aiello-Lammens, M.E., Boria, R.A., Radosavljevic, A., Vilela, B., & Anderson, R.P. 2015. spThin: an R package for spatial thinning of species occurrence records for use in ecological niche models. *Ecography* 38(5), 541–545. https://doi.org/10.1111/ecog.01132

Amaja, L.G, Debela, H.F., & Tariku, M.G. 2016. Assessment of types of damage and causes of human-wildlife conflict in Gera district, south western Ethiopia. *Journal of Ecology and The Natural Environment* 8(5), 49–54. https://doi.org/10.5897/jene2015.0543

Araujo, M., & New, M. 2007. Ensemble forecasting of species distributions. *Trends in Ecology & Evolution* 22(1), 42–47. https://doi.org/10.1016/j.tree.2006.09.010

Baral, K., Sharma, H.P., Kunwar, R., Morley, C., Aryal, A., Rimal, B., & Ji, W. 2021. Human Wildlife Conflict and Impacts on Livelihood: A Study in Community Forestry System in Mid-Hills of Nepal. *Sustainability* 13(23), 13170.

Barasona, J.A., Carpio, A., Boadella, M., Gortazar, C, Piñeiro, X., Zumalacárregui, C., & Viñuela, J. 2021. Expansion of native wild boar populations is a new threat for semi-arid wetland areas. *Ecological Indicators* 125, 107563. https://doi.org/10.1016/j.ecolind.2021.107563

Barbet-Massin, M., Jiguet, F., Albert, C.H., & Thuiller, W. 2012. Selecting pseudo-absences for species distribution models: How, where and how many? *Methods in Ecology and Evolution* 3(2), 327–338. https://doi.org/10.1111/j.2041-210X.2011.00172.x

Bivand, R., & Rundel, C. 2021. rgeos: Interface to Geometry Engine – Open Source ('GEOS'). Retrieved from https://r-forge.r-project.org/projects/rgeos/, https://libgeos.org, http://rgeos.r-forge.r-project.org/index.html

Bivand, R., Keitt, T., & Rowlingson, B. 2023. rgdal: Bindings for the 'Geospatial' Data Abstraction Library. Retrieved from http://rgdal.r-forge.r-project.org, https://gdal.org, https://proj.org, https://r-forge.r-project.org/projects/rgdal/

Boyce, C., VerCauteren, K., & Beasley, J. 2020. Timing and extent of crop damage by wild boar (*Sus scrofa* Linnaeus) to corn and peanut fields. *Crop Protection* 133, 105131. https://doi.org/10.1016/j.cropro.2020.105131

Chauhan, N.S., Barwal, K.S., Kumar, D., & Náhlik, A. 2009. Human-wild boar conflict in selected states in India and mitigation strategies. *Acta Silvatica & Lignaria Hungarica* 5, 189–197.

Dickman, A.J. 2010. Complexities of conflict: the importance of considering social factors for effectively resolving human-wildlife conflict. *Animal Conservation* 13(5), 458–466. https://doi.org/10.1111/j.1469-1795.2010.00368.x

Farr, T.G., Rosen, P.A., Caro, E., Crippen, R., Duren, R., Hensley, S., Kobrick, M., Paller, M., Rodriguez, E., Roth, L., Seal, D., Shaffer, S., Shimada, J., Umland, J., Werner, M., Oskin, M., Burbank, D., & Alsdorf, D. 2007. The Shuttle Radar Topography Mission. *Reviews of Geophysics* 45(2). https://doi.org/10.1029/2005RG000183

Ficetola, G.F., Bonardi, A., Mairota, P., Leronni, V., & Padoa-Schioppa, E. 2014. Predicting wild boar damages to croplands in a mosaic of agricultural and natural areas. *Current Zoology* 60(2), 170–179. https://doi.org/10.1093/czoolo/60.2.170

Fischer, J.W., Greiner, K., Lutman, M.W., Webber, B.L., & Vercauteren, K.C. 2019. Use of unmanned aircraft systems (UAS) and multispectral imagery for quantifying agricultural areas damaged by wild boars. *Crop Protection* 125, 104865. https://doi.org/10.1016/j.cropro.2019.104865

Harrell, F.E., Lee, K.L., & Mark, D.B. 1996. Multivariable prognostic models: issues in developing models, evaluating assumptions and adequacy, and measuring and reducing errors. *Statistics in Medicine* 15(4), 361–387. https://doi.org/10.1002/(SICI)1097-0258(19960229)15:4%3C361::AID-SIM168%3E3.0.CO;2-4

Hernández, F.A., Carr, A.N., Milleson, M.P., Merrill, H.R., Avery, M.L., Parker, B.M., & Wisely, S.M. 2020. Dispersal and Land Cover Contribute to Pseudorabies Virus Exposure in Invasive Wild boars. *EcoHealth* 17(4), 498–511. https://doi.org/10.1007/s10393-020-01508-6

Hijmans, R. 2023. raster: Geographic Data Analysis and Modelling. *R package version 3.6-28*. https://rspatial.org/raster.

Hijmans, R.J., Cameron, S.E., Parra, J.L., Jones, P.G., & Jarvis, A. 2005. Very high resolution interpolated climate surfaces for global land areas. *International Journal of Climatology* 25(15), 1965–1978. https://doi.org/10.1002/joc.1276

Huang, C., Li, X., Shi, L., & Jiang, X. 2018. Patterns of human-wildlife conflict and compensation practices around Daxueshan Nature Reserve, China. *Zoological Research* 39(6), 406–412. https://doi.org/10.24272/j.issn.2095-8137.2018.056

Ickes, K. 2001. Hyper-abundance of Native Wild boar (*Sus scrofa*) in a Lowland Diptero carp Rain Forest of Peninsular Malaysia1. *Biotropica* 33(4), 682–690. https://doi.org/10.1111/j.1744-7429.2001.tb00225.x

India State of Forest Report. 2021. Forest Survey of India, Ministry of Environment, Forest and Climate Change, Government of India. ISBN 978-81-950073-1-8

Jin, Y., Kong, W., Yan, H., Bao, G., Liu, T., Ma, Q., & Zhang, M. 2021. Multi-Scale Spatial Prediction of Wild Boar Damage Risk in Hunchun: A Key Tiger Range in China. *Animals* 11(4), 1012. https://doi.org/10.3390/ani11041012

Johann, F., Handschuh, M., Linderoth, P., Dormann, C.F., & Arnold, J. 2020. Adaptation of wild boar (*Sus scrofa*) activity in a human-dominated landscape. *BMC Ecology* 20(4). https://doi.org/10.1186/s12898-019-0271-7

Karami, P., & Tavakoli, S. 2022. Identification and analysis of areas prone to conflict with wild boar (*Sus scrofa*) in the vineyards of Malayer County, western Iran. *Ecological Modelling* 471, 110039. https://doi.org/10.1016/j.ecolmodel.2022.110039

Karanth, K.K., Gupta, S., & Vanamamalai, A. 2018. Compensation payments, procedures and policies towards human-wildlife conflict management: Insights from India. *Biological Conservation* 227, 383–389. https://doi.org/10.1016/j.biocon.2018.07.006

Kennedy, C.M., Oakleaf, J.R., Theobald, D.M., Baruch-Mordo, S., & Kiesecker, J. 2020. Global Human Modification of Terrestrial Systems. Palisades, New York. *NASA Socioeconomic Data and Applications Center (SEDAC)*. https://doi.org/10.7927/edbc-3z60. Accessed 26/ 04/2023

Lewis, J.S., Corn, J.L., Mayer, J.J., Jordan, T.R., Farnsworth, M.L., Burdett, C.L., & Miller, R.S. 2019. Historical, current, and potential population size estimates of invasive wild boar (*Sus scrofa*) in the United States. *Biological Invasions* 21(7), 2373–2384. https://doi.org/10.1007/s10530-019-01983-1

Lima, T.A., Beuchle, R., Langner, A., Grecchi, R.C., Griess, V.C., & Achard, F. 2019. Comparing Sentinel-2 MSI and Landsat 8 OLI Imagery for Monitoring Selective Logging in the Brazilian Amazon. *Remote Sensing* 11(8), 961. https://doi.org/10.3390/rs11080961

Liu, Q., Yan, K., Lu, Y.F., Li, M., & Yan, Y.Y. 2019. Conflict between wild boars (*Sus scrofa*) and farmers: distribution, impacts, and suggestions for management of wild boars in the Three Gorges Reservoir Area. *Journal of Mountain Science* 16(10), 2404–2416. https://doi.org/10.1007/s11629-019-5453-4

Lombardini, M., Meriggi, A., & Fozzi, A. 2016. Factors influencing wild boar damage to agricultural crops in Sardinia (Italy). *Current Zoology* 63(5), 507–514. zow099. https://doi.org/10.1093/cz/zow099

Lowe, S., Browne, M., Boudjelas, S., & De Poorter, M. 2000. 100 of the world's worst invasive alien species: a selection from the global invasive species database. *The Invasive Species Specialist Group (ISSG), Auckland* 12, 12–14.

Markovchick-Nicholls, L., Regan, H.M., Deutschman, D.H., Widyanata, A., Martin, B., Noreke, L., & Ann hunt, T. 2007. Relationships between Human Disturbance and Wildlife Land Use in Urban Habitat Fragments. *Conservation Biology* 22(1), 99–109. https://doi.org/10.1111/j.1523-1739.2007.00846.x

McClure, M.L., Burdett, C.L., Farnsworth, M.L., Lutman, M.W., Theobald, D.M., Riggs, P.D., & Miller, R.S. 2015. Modelling and Mapping the Probability of

Occurrence of Invasive Wild boaracross the Contiguous United States. *PLOS ONE* 10(8), e0133771. https://doi.org/10.1371/journal.pone.0133771

McClure, M.L., Burdett, C.L., Farnsworth, M.L., Lutman, M.W., Theobald, D.M., Riggs, P.D., Grear, D.A., & Miller, R.S. 2015. Modelling and mapping the probability of occurrence of invasive wild boars across the contiguous United States. *PLoS ONE* 10(8). https://doi.org/10.1371/journal.pone.0133771

McKee, S., Anderson, A., Carlisle, K., & Shwiff, S.A. 2020. Economic estimates of invasive wild boar damage to crops in 12 US states. *Crop Protection* 132, 105105. https://doi.org/10.1016/j.cropro.2020.105105

Mekonen, S. 2020. Coexistence between human and wildlife: the nature, causes and mitigations of human wildlife conflict around Bale Mountains National Park, Southeast Ethiopia. *BMC Ecology* 20(51). https://doi.org/10.1186/s12898-020-00319-1

Milda, D., Ramesh, T., Kalle, R., Gayathri, V., Thanikodi, M., & Ashish, K. 2022. Factors driving human-wild boar interactions: implications for wildlife conflict management in southern parts of India. *Biological Invasions* 25(1), 221–235. https://doi.org/10.1007/s10530-022-02911-6

Mpakairi, K., Ndaimani, H., Vingi, K., Madiri, T.H., & Nekatambe, T. 2018. Ensemble modelling predicts Human Carnivore Conflict for a community adjacent to a protected area in Zimbabwe. *African Journal of Ecology* 56(4), 957–963. https://doi.org/10.1111/aje.12526

Naimi, B., & Araújo, M.B. 2016. sdm: a reproducible and extensible R platform for species distribution modelling. *Ecography* 39(4), 368–375. https://doi.org/10.1111/ecog.01881

Naughton-Treves, L., Treves, A., Chapman, C., & Wrangham, R. 2003. Temporal patterns of crop-raiding by primates: linking food availability in croplands and adjacent forest. *Journal of Applied Ecology* 35(4), 596–606. https://doi.org/10.1046/j.1365-2664.1998.3540596.x

Nyhus, P.J. 2016. Human-Wildlife Conflict and Coexistence. *Annual Review of Environment and Resources* 41(1), 143–171. https://doi.org/10.1146/annurev-environ-110615-085634

R Core Team. 2023. R: A language and environment for statistical computing. *R Foundation for Statistical Computing, Vienna, Austria*. URL https://www.R-project.org/

Rawat, P.K., Pant, D.B., Pant, D.K.K., & Pant, D.P. 2021. Geospatial Analysis of Alarmingly Increasing Human-Wildlife Conflict in Jim Corbett National Park's Ramnagar Urban Buffer Zone: Ecological and Socioeconomic Perspectives. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.3938066

Rocha, E.C., Silva, J., Silva, D.P., Lemos, F.G., & de Castro, M.C. 2024. Distribution of the greater naked-tailed armadillo Cabassous tatouay (Desmarest, 1804) in South America, with new records and species distribution modelling. *Studies on Neotropical Fauna and Environment* 59(1), 166–174. https://doi.org/10.1080/01650521.2022.2085018

Rutten, A., Casaer, J., Swinnen, K.R., Herremans, M., & Leirs, H. 2019. Future distribution of wild boar in a highly anthropogenic landscape: Models combining hunting bag and citizen science data. *Ecological Modelling* 411, 108804. https://doi.org/10.1016/j.ecolmodel.2019.108804

Schley, L., & Roper, T.J. 2003. Diet of wild boar *Sus scrofa* in Western Europe, with particular reference to consumption of agricultural crops. *Mammal Review* 33(1), 43–56. https://doi.org/10.1046/j.1365-2907.2003.00010.x

Shameer, T. T., Routray, P., Udhayan, A., Ranjan, N., Ganesan, M. G., Manimozhi, A., & Vasanthakumari, D. 2024. Understanding the patterns and predictors of human-elephant conflict in Tamil Nadu, India. European Journal of Wildlife Research, 70(95). https://doi.org/10.1007/s10344-024-01848-6

Sharma, P., Chettri, N., Uddin, K., Wangchuk, K., Joshi, R., Tandin, T., & Sharma, E. 2020. Mapping human-wildlife conflict hotspots in a transboundary landscape, Eastern Himalaya. *Global Ecology and Conservation* 24, e01284. https://doi.org/10.1016/j.gecco.2020.e01284

Sharma, P., Chettri, N., & Wangchuk, K. 2021. Human-wildlife conflict in the roof of the world: Understanding multidimensional perspectives through a systematic review. *Ecology and Evolution* 11(17), 11569–11586. https://doi.org/10.1002/ece3.7980

Sharma, P., Chettri, N., & Wangchuk, K. 2021. Human-wildlife conflict in the roof of the world: Understanding multidimensional perspectives through a systematic review. https://doi.org/10.22541/au.162495471.10485884/v1

Sherchan, R., & Bhandari, A. 2017. Status and trends of human-wildlife conflict: A case study of Lelep and Yamphudin region, Kanchenjunga Conservation Area, Taplejung, Nepal. *Conservation Science* 5(1), 19–25. https://doi.org/10.3126/cs.v5i1.24296

Thurfjell, H., Spong, G., Olsson, M., & Ericsson, G. 2015. Avoidance of high traffic levels results in lower risk of wild boar-vehicle accidents. *Landscape and Urban Planning* 133, 98–104. https://doi.org/10.1016/j.landurbplan.2014.09.015

Treves, A., & Bruskotter, J. 2014. Tolerance for Predatory Wildlife. *Science* 344(6183), 476–477. https://doi.org/10.1126/science.1252690

Treves, A., Wallace, R.B., & White, S. 2009. Participatory Planning of Interventions to Mitigate Humanâ Wildlife Conflicts. *Conservation Biology* 23(6), 1577–1587. https://doi.org/10.1111/j.1523-1739.2009.01242.x

Vasudeva Rao, V., Sudhakar, C., Ravinder Reddy, V., Naresh, B., & Venkateswarlu, P. 2015. Efficacy of different physical barriers around maize crop to control wild boar (Sus scrofa) at Southern Telangana zone, Telangana State. *Research Journal of Agriculture and Forestry Sciences* 3(1), 12–15.

Waithman, J.D., Sweitzer, R.A., Vuren, D.V., Drew, J.D., Brinkhaus, A.J., Gardner, I.A., & Boyce, W.M. 1999. Range Expansion, Population Sizes, and Management of Wild boar in California. *The Journal of Wildlife Management* 63(1), 298. https://doi.org/10.2307/3802513

Wickham, H. 2023. *httr: Tools for Working with URLs and HTTP*. https://httr.r-lib.org/, https://github.com/r-lib/httr

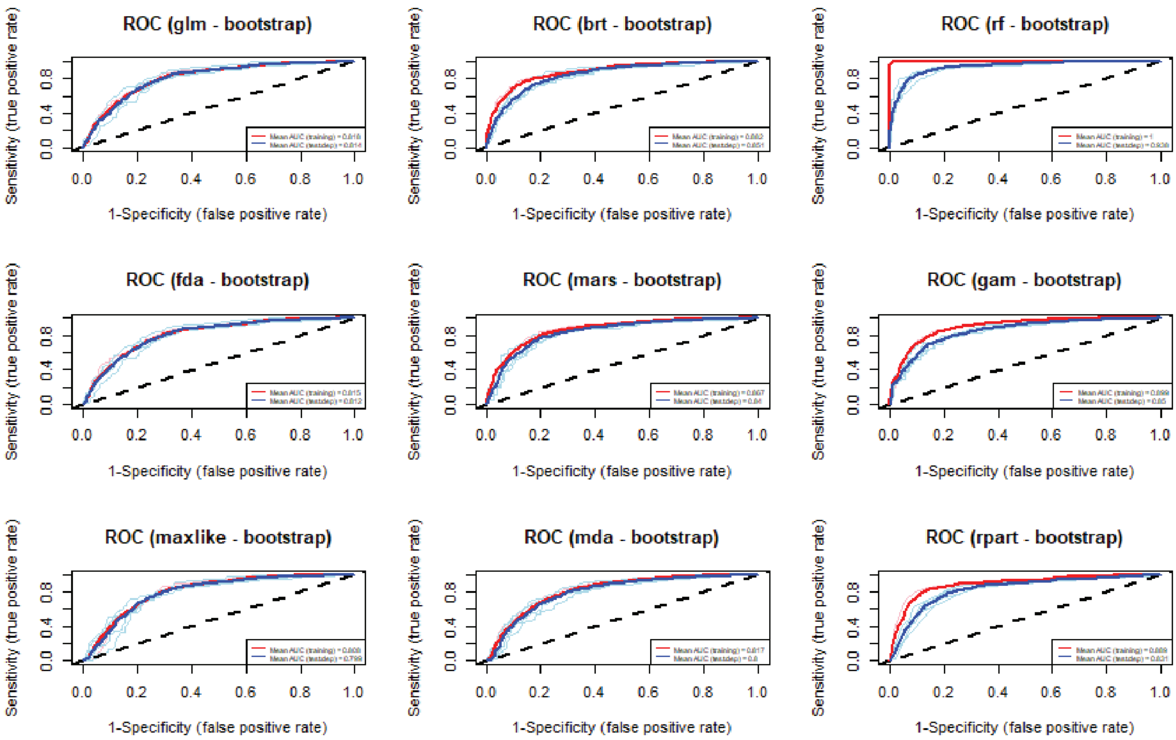
Woodroffe, R., Lindsey, P., Romañach, S., Stein, A., & Ole Ranah, S.M. 2005. Livestock predation by endangered African wild dogs (*Lycaon pictus*) in northern Kenya. *Biological Conservation* 124(2), 225–234. https://doi.org/10.1016/j.biocon.2005.01.028

Zanaga, D., Van De Kerchove, R., Daems, D., De Keersmaecker, W., Brockmann, C., Kirches, G., Wevers, J., Cartus, O., Santoro, M., Fritz, S., Lesiv, M., Herold, M., Tsendbazar, N.E., Xu, P., Ramoino, F., & Arino, O. 2022. *ESA WorldCover 10 m 2021 v200.* https://doi.org/10.5281/zenodo.7254221

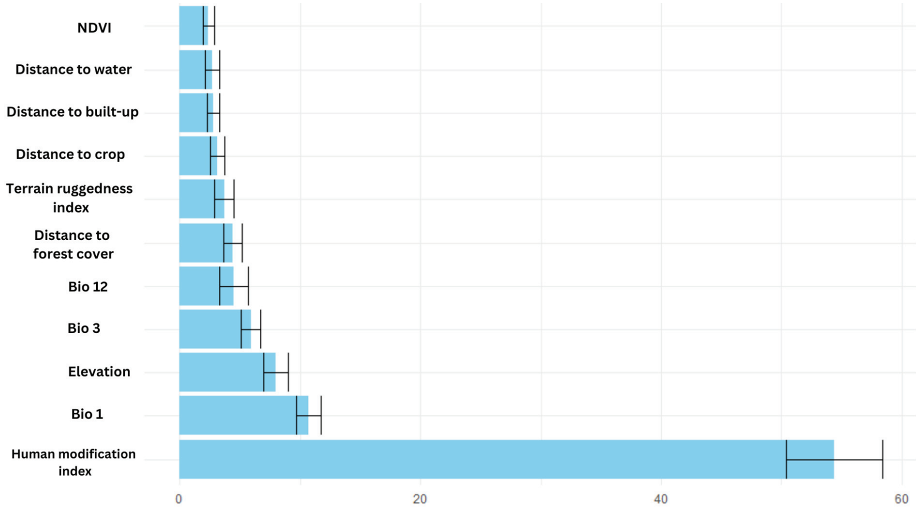
Supplementary Table 1. Performance of models using different evaluation techniques. The table presents key evaluation metrics for model performance, including AUC (Area under the Curve), COR (Correlation), TSS (True Skill Statistics), Deviance, Threshold, Sensitivity, and Specificity.

Model	AUC	COR	Deviance	Prevalence	TSS	Kappa	Threshold	Sensitivity	Specificity
RF	**0.92**	0.74	0.74	0.42	0.70	0.70	0.45	0.85	0.85
MDA	0.82	0.55	1.03	0.42	0.49	0.48	0.42	0.74	0.74
RPART	0.81	0.54	1.05	0.42	0.49	0.48	0.45	0.74	0.74
MAXLIKE	0.80	0.52	1.07	0.42	0.47	0.47	0.43	0.74	0.74
MARS	0.80	0.51	1.13	0.42	0.48	0.47	0.56	0.74	0.74
BRT	0.80	0.51	1.17	0.42	0.46	0.46	0.42	0.73	0.73
GLM	0.75	0.43	1.18	0.42	0.37	0.37	0.44	0.69	0.69
FDA	0.75	0.42	1.18	0.42	0.37	0.37	0.45	0.69	0.69
GAM	0.74	0.44	1.19	0.42	0.40	0.39	0.50	0.71	0.69

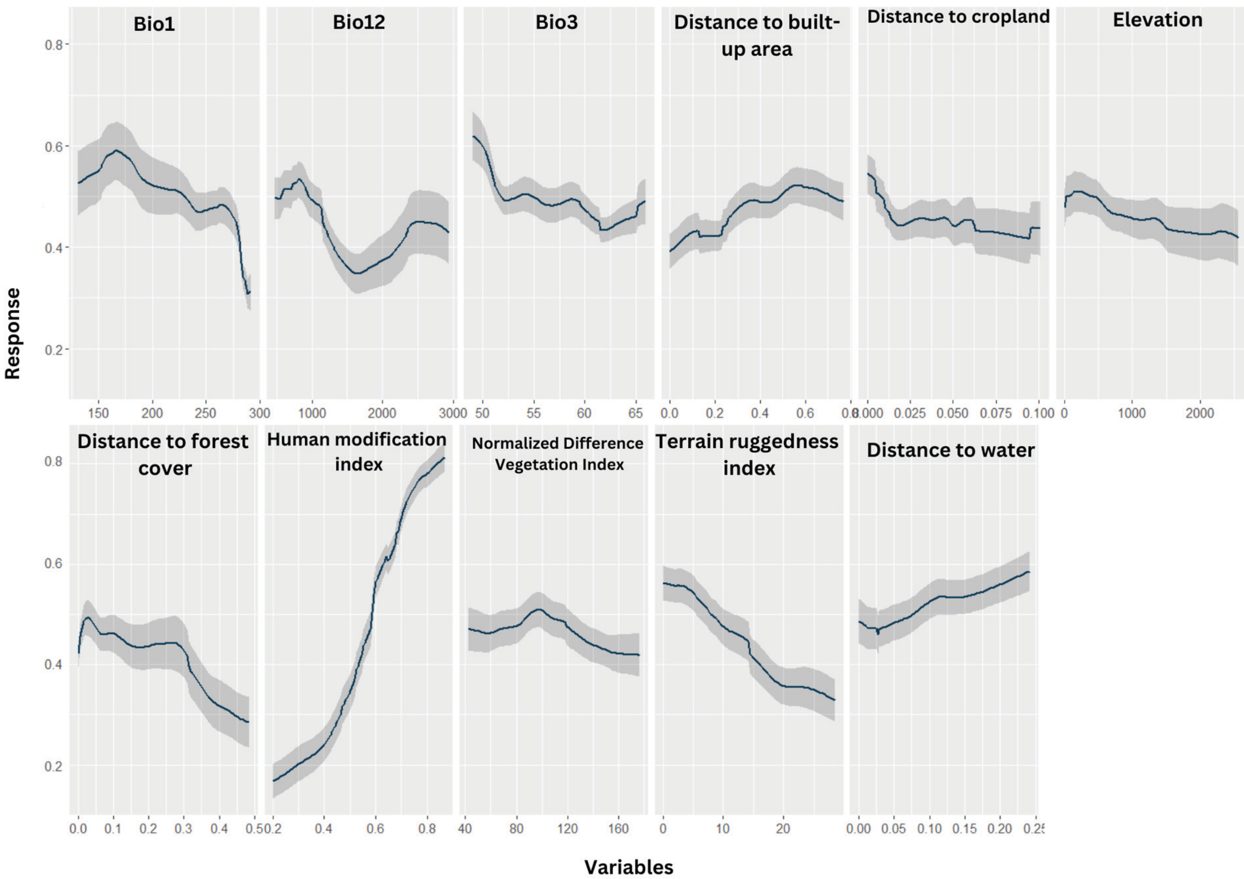
Supplementary Table 1 depicts the performance of models using different evaluation techniques. The table presents key evaluation metrics for model performance, including AUC (Area under the Curve), COR (Correlation), TSS (True Skill Statistics), Deviance, Threshold, Sensitivity, and Specificity.



Supplementary Figure 1. Receiver Operating Characteristic (ROC) curve, depicting the model's performance.



Supplementary Figure 2. Relative variable importance for correlation and AUC metrics.



Supplementary Figure 3. Partial Response Curve, showing the relationship between the independent variables and their impact on the prediction outcome.