



Original Research Paper

Machine Learning Prediction of Human–Snake Encounters in Expanding Urban Areas

Dr. Rajvir Saini^{1*}, Dr. Sandeep Soni²

^{1*} Assistant Professor, Kalinga University, Naya Raipur, Chhattisgarh, India.

Email: ku.rajvirsaini@kalingauniversity.ac.in, ORCID: <https://orcid.org/0009-0000-6644-0795>

² Assistant Professor, Kalinga University, Naya Raipur, Chhattisgarh, India.

Email: ku.sandeepsoni@kalingauniversity.ac.in, ORCID: <https://orcid.org/0009-0000-3692-6874>

Key Words

Human-snake encounters, machine learning, urban expansion, wildlife conflict, spatial risk prediction, habitat fragmentation, public safety.

Abstract

The rapid urban growth is turning scrubland, wetlands and agricultural fringes and forest edges into impervious surfaces, fragmenting snake habitat and putting snakes and people in closer contact with one another. Most cities still respond reactively to these encounters, sending out rescuers only when they are notified that a snake was found, and traditional risk maps are static and don't account for the changes in risk seasonally or monthly caused by rain, or by building activity. This paper introduces an interpretable machine-learning model to forecast the location and time of human-snake interactions in an urban area that is growing in size. Ten-year snakebite emergency reports (2016–2025) were overlain at 500 m × 500 m resolution with monthly verified rescue and encounter data (n = 52,630) as well as land-use, vegetation, and LST indices derived from satellite imagery, infrastructure and population and waste indicators. Four classifiers were compared: Logistic Regression, Random Forest, Support Vector Machine and XGBoost, and a multilayer perceptron, with spatial-block and temporal validation. XGBoost achieved the best performance on the held-out test period (2024–2025) and the most important features were: historical encounter frequency, antecedent rainfall, built-up expansion rate, proximity to water bodies, or drains. The predicted probabilities were mapped as low, moderate and high-risk class and displayed as GIS hotspot maps with factor level explanations. The framework can help with pre-monsoon awareness campaigns, deployment of rescue teams, hospital antivenom preparedness and planning for habitat sensitivity, moving the focus of urban wildlife management from reactive response to prevention, while at the same time not encouraging the unnecessary removal of snakes.

* Corresponding Author's email: ku.rajvirsaini@kalingauniversity.ac.in

Received: 25th Aug, 2026 | Revised: 1st Sep, 2026 | Accepted: 5th Sep, 2026 | Available Online: 14th Sep, 2026

(DOI): 10.70102/AEJ.2026.18.5s.80

Introduction

Snakes form part and parcel of the urban and peri-urban ecosystems. They are macropredators, controlling the population of rodents that pests stored food and vectors zoonoses, and are in turn consumed by raptors, mongooses and other carnivores. Contrary to the belief that cities are ecological deserts, many snake species are found in remnant scrub, in parks, in the margins of lakes, in canals, drainage networks and even in artificial water bodies, with some species even found in high abundance (Mészáros et al., 2024). Ten years of rescue data from an Indian megacity have demonstrated that a diverse snake assemblage still exists in the urban matrix and that rescue data can also reveal a clear seasonality and spatial structure in snake activity (Visvanathan et al., 2026). Snakes and human beings are increasingly coming into contact with each other due to rapid urbanisation. Agricultural and natural land converted to houses, roads and construction of unoccupied plots, construction waste and uncollected waste provide new spaces for snakes to live and new habitat for rodents. Snakes are carried into compounds by storm-water drains and canals. In tropical megacities and dense urban–forest mosaics, the intensity of human–snake conflict has been correlated with the trajectory of urban expansion, and the pattern of remaining habitat (Yue et al., 2019; Ratnarathorn et al., 2026). Risk of encounter is very seasonal as well. Burrows filled by heavy rain and movement of snakes to higher ground during breeding and dispersal times, and temperature controls activity in ectotherms. Monthly and seasonal changes in encounters

have been reported at Darwin and at Delhi (Parkin et al., 2021; Barhadiya et al., 2024) and climate change is likely to alter the distribution of venomous species and the geographical distribution of snakebite risk (Zacarias and Loyola, 2019). The impact is not only public health, but conservation as well. Snakebite is an under-prioritized disease in South Asia and risk is a combination of snake ecology and human behaviour (Goldstein et al., 2021; Ochoa et al., 2021). Often, the presence of fear causes residents to kill harmless or protected species. In particular, much of the current management is reactive, with rescuers reacting to an encounter having already occurred, and current encounter maps are snapshots of the past and do not predict where next month's encounters will occur. This study aims to tackle the issue of predicting the dangerous places and times in a growing urban area. It sets out to create a machine-learning framework, interpretable and location-aware, for preventive action. The aims are (i) to combine heterogeneous ecological, climatic, temporal and urban-development data at cell–month level; (ii) to contrast five machine-learning models under leakage-aware spatial and temporal validation; (iii) to explain model predictions at global and local level through SHAP; and (iv) to translate predicted probabilities into operational risk classes, hotspot maps and alerts. Only verified human–snake encounters are considered, not a model of the distribution of all species. The main achievements are an integrated data model that combines rescue, health, remote-sensing and urban-infrastructure data; a set of features that explicitly models the rate of urban expansion in addition to ecological and climatic drivers; a

well-defined comparison of classifiers in the spatial-block and temporal testing setting; and an explainable early-warning output geared towards prevention rather than removal.

Background And Design Motivation

Human–Snake Interactions in Urban Landscapes

From garden and stairwell sightings to kitchen, vehicle and drain snake encounters. Although the majority of encounters are non-venomous species, public perceptions do not distinguish between them and a small proportion of encounters with medically significant species will lead to bites that require antivenom. Thousands of snakes are relocated annually by rescue organisations, but snake relocation is time consuming and the ecological effects are not guaranteed. Records from Hong Kong, Darwin and Delhi show that sightings tend to cluster in specific neighbourhoods and months, implying that risk can be predicted if sighting drivers are caught (Yue et al., 2019; Parkin et al., 2021; Barhadiya et al., 2024).

Environmental and Anthropogenic Drivers

Activity, prey availability and flooding of refuges are regulated by temperature, rainfall and humidity. Ecological factors include vegetation cover, and close proximity to water bodies and rodent activity, which are often around markets, stores for grain, and garbage dumps. Anthropogenic factors include human population density, the likelihood of encountering and reporting a snake; road networks, which fragment habitat and kill snakes; encroachment of housing

on previously natural land; and waste disposal practices. Snakes may be clustered around high housing density at urban lakes and their artificial shorelines (Mészáros et al., 2024), and high-impact construction may drive snakes away from their original lakeshore habitat, causing them to be found on neighboring properties (Ratnarathorn et al., 2026).

Existing Encounter-Prediction Approaches

Field surveys are accurate, but expensive and limited in terms of spatial extent. GIS mapping of rescue and bite data can be used to identify temporal and spatial clusters and has been used to describe the spatiotemporal occurrence in Australian cities (von Takach et al., 2024). Under a One Health approach, statistical and geospatial models have been used to generate high-resolution snakebite risk maps (Ochoa et al., 2021) and agent-based models have simulated the interactions between farmer behaviour and snake ecology (Goldstein et al., 2021). Ecological niche and species-distribution models predict ranges and abundance of threatened species (Kirk et al., 2021) and range shifts under climate change (Zacarias and Loyola, 2019). Recent work on other related topics, like wildlife–vehicle collision mitigation (Nandutu et al., 2022), or hybrid deep learning–IoT and GIS pipelines for real-time failure prediction in urban infrastructure and vehicle systems (Mishra et al., 2024; Babu et al., 2026) have illustrated that such pipelines can operate at city scale.

Research Gaps

There are four gaps that this study should address. Firstly, few studies have combined ecological variables to urban development variables, such as built-up expansion rate, vacant plots and drainage density. Second, the majority of analyses are static or descriptive in nature, do not involve spatial and seasonal predictions jointly, and lack the operational resolution. Third, encounter datasets are very imbalanced, with most cell-periods showing no encounter, leading to high accuracy and yet revealing little of the performance of detection of true hotspots. Fourth, current models rarely provide interpretable results, or even ready to use early-warning systems, that can be used by agencies outside the specialist field.

Design Motivation

A useful system can be subject to class imbalance, it needs to be explainable to rescue teams and municipal officers, and it has to be place sensitive and seasonal. It ought to be used to prevent the snakes (e.g. remove debris, secure drains, coincide with timing of awareness campaigns) and not to pre-emptively catch and kill snakes.

System Model and Requirements

Study Area and Spatial Units

The study area is a fast-growing tropical metropolitan region comprising of about 1078 km² area of core city and peri-urban belt in the southern part of India. The built-up area has grown from 38% to 57% of the region between 2015 and 2025, mainly along the main roads and the former agricultural land on the outskirts of the

city. Climate is tropical and monsoon dominated with a distinct wet season and hot pre-monsoon months. Habitat includes remnant scrub, lakes and wetlands, agricultural fringes, parks, and riparian strips and a dense network of open storm water drains. The area was subdivided into 4,312 regular cells in a 500 m × 500 m grid, which allows for a spatial detail while maintaining the spatial uncertainty of the rescue records and can be aggregated to administrative area reporting.

Data Sources

Six data sources were used: (i) verified records of snake encounters and rescues by the city rescue helpline and forest department (date, location, species); (ii) snakebite and emergency-response data (date, location, species) from city government hospitals and the ambulance service; (iii) daily rainfall, temperature and humidity data from meteorological stations and gridded reanalysis data; (iv) land-use/land-cover, NDVI data and land-surface temperature data from satellite images (Landsat-8/9 and Sentinel-2); (v) building density data, roads, drainage channels and vacant plots data from GIS layers provided by the municipality and the OpenStreetMap project; and (vi) population data and waste-generation data from census and solid-waste-management data sets.

Input Variables and Prediction Target

The climatic (rainfall, temperature, humidity, land-surface temperature), ecological (vegetation indices, distance to water and green space, wetland proportion), urbanisation (built-up proportion and rate of change, road, drainage, vacant-plot, waste and population density) and

temporal-historical (month, season, lagged encounter counts) features were used. A binary primary target, $y = 1$, is defined as an encounter by at least one verification in cell i during month t ; $y = 0$, otherwise. There are also two alternative targets for the framework: encounter frequency modelled as a count and a three-level low/moderate/high risk category.

Functional Requirements

The system needs to be able to (FR1) clean and integrate all the different types of tabular, raster and vector data, (FR2) generate spatial and temporal features for each cell-month, (FR3) make a prediction for the probability of an

encounter, (FR4) determine what factors influence each prediction, and (FR5) produce interpretable hotspot maps and alerts for end-users.

Non-Functional Requirements

Predictions need to be accurate, especially for recall areas that are deemed high-risk; the pipeline needs to scale to $> 500,000$ cell-months and provide monthly maps in minutes; predictions should be readily understandable to non-specialists; household and patient localizations should not be disclosed; and the model should be able to be retrained to accommodate newly urbanizing areas.

Proposed Machine Learning Framework

Framework Overview

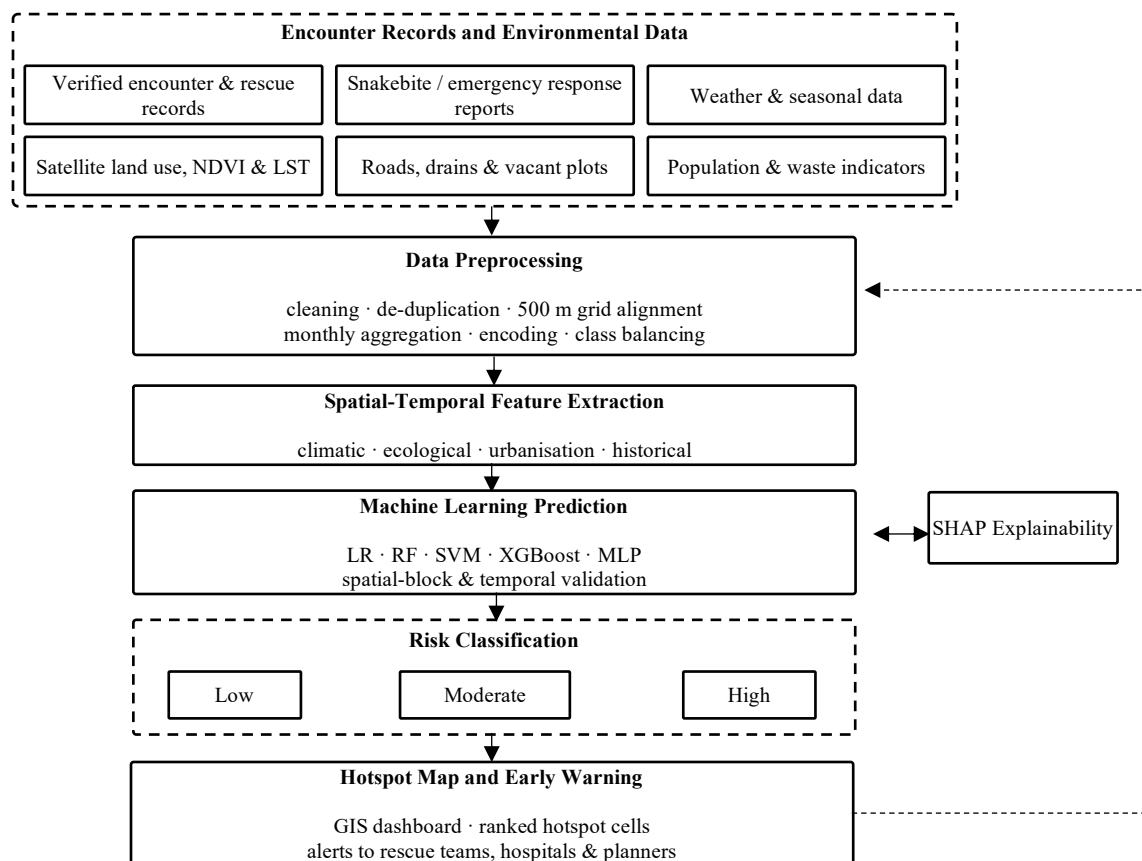


Figure 1: Proposed Machine-Learning Framework for Predicting Human–Snake Encounters

The framework has six stages: Pre-processing of encounter records and environmental data to create spatial–temporal features; feeding spatial–temporal features to a machine-learning predictor; classification of predictor results into risk categories; creation of hotspot maps; and delivery of early warnings Figure 1. A SHAP module runs in parallel with the predictor and the newly verified reports are then fed back for periodic retraining.

Data Preprocessing

Calls without valid coordinates or dates were excluded and duplicate calls (within 100 m and 24 h) were combined. Coordinates were projected to a common UTM reference and snapped to grid cells; rasters were resampled to 500 m. Weather data was summarized from daily to monthly and antecedent window. Gaps in weather data were filled by inverse-distance weighting from nearby weather stations, and gaps in satellite indices were filled by temporal linear interpolation. One-hot encoding was performed on categorical variables while training-period statistics were used for standardisation of continuous variables. Class imbalance was treated with class weights for all models and SMOTE was added only within training folds.

Feature Engineering

A total of thirty-one candidate features were obtained. These comprise the Euclidean distance to the nearest water body, drain and green space, the 5 year rate of built up expansion, the mean NDVI and land-surface temperature, the cumulative rainfall of the last 7, 14 and 30 day periods, the month, monsoon and dry-season

indicators, the densities of roads, drains, vacant plots, waste collection points and population as well as the previous historical encounter counts in the same cell and the 8 neighbouring cells after 1 and 12 months. One of each pair of features with a Spearman $|\rho| > 0.85$ was removed and recursive feature elimination was applied, resulting in 24 features.

Prediction Models

The five classifiers tested were: Logistic Regression (LR) as an interpretable statistical baseline, Random Forest (RF), Support Vector Machine (SVM) with a radial basis function kernel, XGBoost and a multilayer perceptron (MLP). An operationally simple "naïve historical-frequency" model based on the number of sightings recorded in the previous year was used as a baseline. The model with the highest recall and PR–AUC along with the native capability for exact SHAP explanations was chosen as the proposed predictor.

Risk Mapping and Alert Generation

The isotonic regression was applied to the validation year and the results were classified into three classes: low ($p < 0.30$), moderate ($0.30 \leq p < 0.60$) and high ($p \geq 0.60$). The classes were converted to monthly GIS hotspot maps. An alert is triggered when a cell moves to the high classification or moves two classification levels from one month to the next, or moves to the moderate classification due to extreme antecedent rainfall.

Explainability Mechanism

TreeExplainer algorithm was used to calculate SHAP values. Global importance is

reported as the mean absolute SHAP value per feature, while local explanations list the three top features that contribute to the risk of each high-risk cell, for example a heavy rainfall recently and an open drain nearby.

Implementation Details

Dataset Preparation

This research will take place over a 10-year period (January 2016 – December 2025). The 58,914 raw records and 52,630 verified encounter records after cleaning the records – including all the 4,312 cells. Indian rat snake (*Ptyas mucosa*, 31%), spectacled cobra (*Naja naja*, 22%), checkered keelback (*Fowlea piscator*, 14%), Russell's viper (*Daboia russelii*, 7%) and common krait (*Bungarus caeruleus*, 5%) were the most frequently recorded species. Of 517,440 cell–months, 40,878 (7.9%) recorded at least one encounter. Data from 2016–2022 (70%) were used for training, 2023 (10%) for validation and 2024–2025 (20%) for testing.

Experimental Setup

The pipeline was developed using Python 3.11, scikit-learn, XGBoost, imbalanced-learn, SHAP, GeoPandas and Rasterio, and with cartographic support in QGIS, and satellite composites in Google Earth Engine. Experiments ran on a workstation with a 16-core CPU, 64 GB RAM and an NVIDIA RTX-series GPU. All stochastic steps were repeated with a fixed random seed of 42 and hyperparameters were optimized by a five-fold cross-validation using $2 \text{ km} \times 2 \text{ km}$ spatial blocks.

Model Configuration

XGBoost used 600 trees, a maximum depth of 6, a learning rate of 0.05, row and column subsampling of 0.8, a positive-class weight of 11.7 (the negative-to-positive ratio) and early stopping after 50 rounds without improvement in validation PR–AUC. RF used 500 trees, a minimum leaf size of 5 and balanced subsample weights. For tractability, SVM was trained on a 20% subsample (stratified) using $C = 10$ and Platt scaling. LR was applied by using L2 regularisation with equal weights. A MLP with 2 hidden layers (128 units, 64 units, ReLU and dropout 0.3) was trained with Adam (learning rate 10⁻³, batch size 512) and weighted binary cross-entropy. The decision threshold $\tau = 0.30$ was chosen on the validation year to maximise the recall-weighted F2-score, and is equivalent to the lower end of the moderate-risk class.

Training and Validation

Random k-fold splitting results in neighboring spatially autocorrelated cells being put in both the training set and test set, which inflates the scores. model selection was thus done by spatial-block cross-validation, with the last two years kept as an untouched temporal test set that represents a realistic deployment scenario.

System Output

A GIS dashboard is available online and provides monthly maps of risk along with ranked-highest-risk cells and the top factors contributing to each cell and suggested response priorities, such as pre-positioning rescuers, alerting nearby hospitals to check antivenom stock, or sending municipal personnel to clear debris or cover drains.

Security And Performance Evaluation

Evaluation Metrics

1. Accuracy (Acc.)

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \quad (1)$$

Equation (1) is the overall proportion of all correct classifications of encounter and non-encounter.

2. Precision (Prec.)

$$Precision = \frac{TP}{TP + FP} \quad (2)$$

Equation (2) is the probability of a predicted positive encounter being a true encounter.

3. Recall

$$Recall = \frac{TP}{TP + FN} \quad (3)$$

The number of the actual encounters that are correctly detected by the model is measured by equation (3).

4. F1-Score (F1)

$$F1 = 2 \times \frac{Precision \times Recall}{Precision + Recall} \quad (4)$$

The harmonic mean of precision and recall, provided by equation (4), balances precision and recall.

5. ROC-AUC

$$ROC-AUC = \int_0^1 TPR(FPR) d(FPR) \quad (5)$$

Equation (5) reflects the model's capacity to differentiate amongst positive and negative classes at varying thresholds.

6. PR-AUC

$$PR-AUC = \int_0^1 Precision(Recall) d(Recall) \quad (6)$$

Equation (6) is a measure of the model performance for the identification of positive encounter, which is applicable in the case of imbalanced data.

Baseline Comparison

All models have been compared in Table 1 on the temporal test set. All machine-learning models improved upon the historical-frequency baseline, validating the value of the dynamic climatic and urbanization features in providing information beyond past encounter counts.

Table 1. Performance on the Held-Out 2024–2025 Test Period (Positive Class = Encounter, $\tau = 0.30$).

Model	Acc.	Prec.	Recall	F1	ROC-AUC	PR-AUC
Historical freq.	0.865	0.312	0.588	0.408	0.781	0.334
Logistic Reg.	0.878	0.358	0.694	0.472	0.832	0.401
SVM (RBF)	0.889	0.389	0.712	0.503	0.851	0.437
MLP	0.907	0.447	0.768	0.565	0.889	0.531
Random Forest	0.913	0.468	0.781	0.585	0.901	0.552
XGBoost (proposed)	0.926	0.521	0.834	0.641	0.927	0.618

It is evident that tree ensembles outperformed LR and SVM. XGBoost demonstrated the best result for Recall (0.834), F1-score (0.641) and PR–AUC (0.618) which is 0.284 greater than the historical baseline. At $\tau = 0.30$, its confusion matrix had 6,819 true positive, 6,270 false positive, 1,357 false negative and 89,042 true negative test cell–months in total 103,488 test cell–months

Spatial and Temporal Evaluation

Under spatial-block cross-validation, XGBoost achieved a PR–AUC of 0.594 ± 0.029 , compared with 0.681 under random k-fold, confirming that random splitting overstates performance. Recall was highest in monsoon months (0.871) and lowest in the dry season (0.768), when encounters are sparse. Performance was stronger in rapidly expanding peri-urban cells (PR–AUC 0.652) than in the stable urban core (0.571), and remained consistent between 2024 (0.629) and 2025 (0.607).

Robustness and Generalizability

The 20% of the weather values randomly masked and imputed, PR–AUC only dropped to 0.601. When class weighting was not used and the data was not resampled, recall decreased to 0.612, which demonstrates the importance of imbalance handling. Recall increased to 0.889 for months in the extreme rainfall decile (top 10% of rainfall months). Eight administrative zones were tested using leave-one-zone-out testing, and the mean PR–AUC was 0.562 (range 0.51–0.60), which could be considered reasonable transfer to unseen urban zones.

Security, Privacy and Ethical Considerations

Household and patient locations were blurred by 'snapping' the point to cell centroids and by limiting the number of records in a cell to three in public outputs. Rescue and health records were securely stored in encrypted format with role-based access control and audit trails. The exact location of snakes – especially rare or protected species – can only be seen by rescue and forest personnel, who have been authorised to do so, and not by others, so that the snakes cannot be misused for poaching purposes or for illegal collection. The outputs are stated at a zone level with public maps, with a focus on providing guidance for sanitation and drain management and awareness, rather than to trigger snake persecution.

Discussion

The strongest indicators as shown in Fig. 2 were historical encounter frequency, the 14 days antecedent rainfall, distance to water bodies and drains, and the rate of built-up expansion. The high importance of antecedent rainfall is in line with the increased movement after precipitation and the flooding of burrows, the proximity to water and drains is related to the use of canals and lake margins as habitat and corridors (Mészáros et al., 2024). The impact of built-up expansion and abandoned plots and waste deposition reinforce the idea that the construction displaces snakes and that abandoned areas have the potential to attract rodents (Ratnarathorn et al., 2026).

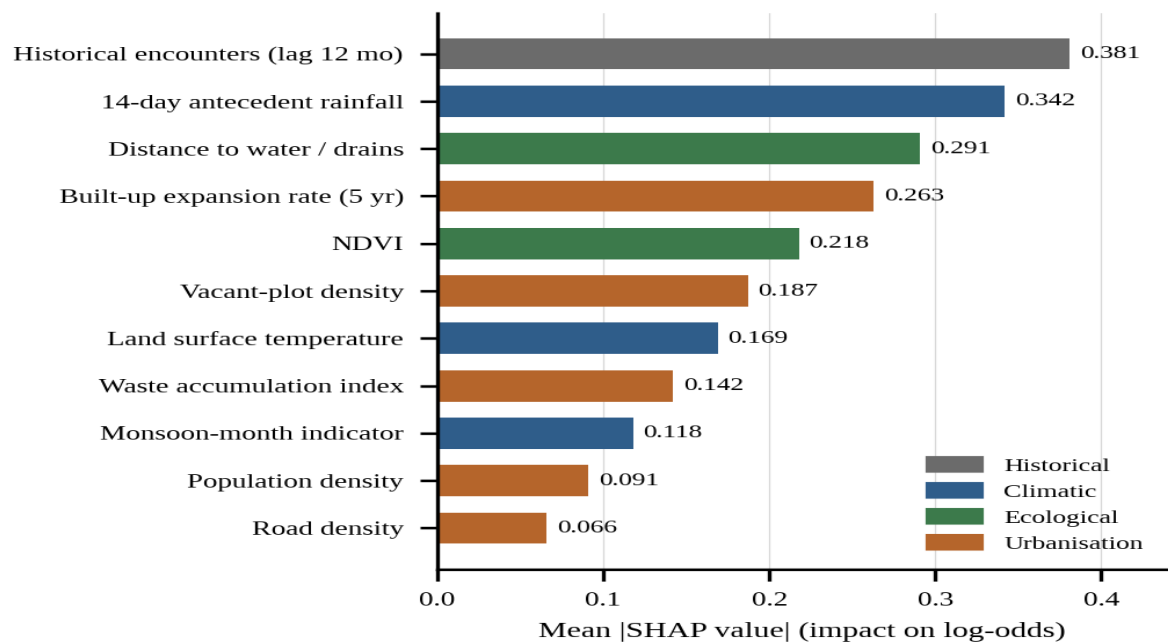


Figure 2: Global Feature Importance of the XGBoost Model (mean |SHAP|), Coloured By Feature Group

Risk was focused along the growing urban fringe and near lakes and major drains and increased significantly at the onset of the monsoons. The patterns are consistent with reported seasonal peaks at Darwin and Delhi (Parkin et al., 2021; Barhadiya et al., 2024), and spatial clustering as has been described at Hong Kong and Australian cities (Yue et al., 2019; von Takach et al., 2024). The present framework is different from those descriptive studies, in that it predicts and accounts for future risk.

The outputs are targeted to a number of user groups. Rescue teams could position volunteers in advance of peak months, hospitals could get confirmation of antivenom stock levels, planners could prioritise covering of drains and removal of debris and residents could be given specific, non-alarmist advice. The results also have conservation implications; the maintenance of vegetation around lakes and planning green corridors away from housing could reduce

conflict while maintaining connectivity, consistent with the landscape scale risk approaches (Ochoa et al., 2021). Several limitations remain. Rescue data are subject to reporting bias – more encounters are reported by densely populated and affluent areas, which over-emphasises historical population/population features. Outages of the system result in incomplete species records, callers may misidentify species and the model was trained in one region only and may not be transferable for that reason. Agent-based studies (Goldstein et al., 2021) pointed to behavioural factors, which were not captured directly.

Conclusion

In this paper, the authors proposed an integrated and interpretable machine-learning framework for predicting human–snake encounters in expanding urban areas. The spatial and temporal strictness of the validation led to the

best balance of recall and PR–AUC for the predictor built on the XGBoost, that is, using verified rescue records, health reports, weather and remote-sensing and urban infrastructure data. Antecedent rainfall, nearness to water and drains, urban sprawl and past experiences proved to be the most important predictors. The transformation of predictions into risk classes, hotspot maps and explained alerts helps to move from reactive rescue towards proactive prevention and conserve snake populations. Future efforts will involve live feeds of current weather conditions, citizen scientist participation via mobile apps, push notifications to citizens, multi-city validation and species-specific prediction for medically relevant snake species.

References

- [1] Babu, K., S. Rama Sree, K. N. Dhakshayini, V. Sutha, and Pradeepa. 2026. "Adaptive Self-Healing Urban IoT Network Management Using Hybrid Deep Learning–Machine Learning Models for Real-Time Infrastructure Failure Prediction and Mitigation." *International Academic Journal of Science and Engineering* 13 (1): 345–358.
- [2] Barhadiya, Gaurav, Jayaditya Purkayastha, Ashis Kumar Saha, and Chirashree Ghosh. "Spatial and temporal assessment of snake encounters in urban Delhi, India." *Scientific Reports* 14, no. 1 (2024): 5506.
- [3] Goldstein, Eyal, Joseph J. Erinjery, Gerardo Martin, Anuradhani Kasturiratne, Dileepa Senajith Ediriweera, Hithanadura Janaka de Silva, Peter Diggle, David Griffith Lalloo, Kris A. Murray, and Takuya Iwamura. "Integrating human behavior and snake ecology with agent-based models to predict snakebite in high risk landscapes." *PLoS neglected tropical diseases* 15, no. 1 (2021): e0009047.
- [4] Kirk, David Anthony, Sahebeh Karimi, Jared R. Maida, Jessica A. Harvey, Karl W. Larsen, and Christine A. Bishop. "Using ecological niche models for population and range estimates of a threatened snake species (*Crotalus oreganus*) in Canada." *Diversity* 13, no. 10 (2021): 467.
- [5] Mészáros, Boglárka, József Bürgés, Mónika Tamás, Blanka Gál, Dénes Schmera, and Andrew J. Hamer. "Urban oasis? Abundant dice snake (*Natrix tessellata*) populations along artificial lakeside habitats in urban landscapes." *Landscape Ecology* 39, no. 7 (2024): 124.
- [6] Mishra, Nidhi, Abhijeet Madhukar Haval, Akanksha Mishra, and Sushree Sasmita Dash. "Automobile maintenance prediction using integrated deep learning and geographical information system." *Indian Journal of Information Sources and Services* 14, no. 2 (2024): 109-114.
- [7] Nandutu, Irene, Marcellin Atemkeng, and Patrice Okouma. "Intelligent systems using sensors and/or machine learning to mitigate wildlife–vehicle collisions: A review, challenges, and new perspectives." *Sensors* 22, no. 7 (2022): 2478.

- [8] Ochoa, Carlos, Marta Pittavino, Sara Babo Martins, Gabriel Alcoba, Isabelle Bolon, Rafael Ruiz de Castañeda, Stephane Joost, Sanjib Kumar Sharma, Francois Chappuis, and Nicolas Ray. "Estimating and predicting snakebite risk in the Terai region of Nepal through a high-resolution geospatial and One Health approach." *Scientific reports* 11, no. 1 (2021): 23868.
- [9] Parkin, Tom, Chris J. Jolly, Alana De Laive, and Brenton Von Takach. "Snakes on an urban plain: temporal patterns of snake activity and human–snake conflict in Darwin, Australia." *Austral Ecology* 46, no. 3 (2021): 449-462.
- [10] Ratnarathorn, Napat, Budda Chotimanvijit, Nipit Sanunsilp, Panithi Laoungbua, Vachirapong Charoennitiwat, Chalita Kongrit, and Phakhawat Thaweepradej. "Effects of rapid urbanisation on human–snake conflicts in a tropical mega-city: Challenges to biodiversity conservation and healthcare systems." *Landscape and Urban Planning* 269 (2026): 105582.
- [11] Visvanathan, Avinash C., Swapnil Kiran, Sathwik Mohan Vangari, Aditya Kesav Kolli, Pawan Nandakishore, and Karthikeyan Vasudevan. "Urban snake ecology revealed through the lens of decadal data on snake rescues in a megacity." *Global Ecology and Conservation* (2026): e04233.
- [12] von Takach, Brenton, Damian Christopher Lettoof, Tom Parkin, Alana de Laive, Luke Allen, and Chris J. Jolly. "Analysing spatiotemporal patterns of snake occurrence in an Australian city to help manage human-wildlife conflict." *Biodiversity and Conservation* 33, no. 1 (2024): 347-360.
- [13] Yue, Sam, TimoThY C. BoneBrake, and Luke GiBSon. "Human-snake conflict patterns in a dense urban-forest mosaic landscape." *Herpetol Conserv Biol* 14, no. 1 (2019): 143-54.
- [14] Zacarias, Daniel, and Rafael Loyola. "Climate change impacts on the distribution of venomous snakes and snakebite risk in Mozambique." *Climatic Change* 152, no. 1 (2019): 195-207.