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Estimating the occurrence and detection of human-elephant conflict in India through a Bayesian occupancy modeling framework

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ABSTRACT

Human-elephant conflict (HEC) poses a significant challenge to wildlife conservation and rural community well-being in agricultural landscapes. Understanding the environmental and anthropogenic drivers of conflict and their spatiotemporal dynamics is essential for effective mitigation. Using a Bayesian spatiotemporal occupancy modeling framework, we analyzed over 20,000 verified, farmer-reported HEC incidents (2015–2023) surrounding Bandipur and Nagarahole National Parks in Karnataka, India. Situated within the Western Ghats biodiversity hotspot, these parks support some of India's largest elephant populations. Our results identified cropland area and seasonal nighttime light radiance, an indicator of human economic and agricultural activity, as the strongest predictors of HEC occurrence. Additional landscape attributes, such as proximity to refuge sites, slope, and seasonal vegetation, further explained variation in conflict occurrence. Detection probability increased with cropland extent and survey effort but declined with higher seasonal temperatures and greater distances from protected areas and refuge sites. Across the modeled landscape, mean HEC occupancy, or the probability that HEC occurs at least once per season, was estimated at 16%. Mean detection probability, that an HEC incident was reported after having occurred, was 31.7%. Occupancy was highest during the post-monsoon season, coinciding with peak harvest periods, while detection was consistently lower during the pre-monsoon dry season. Our findings highlight pronounced spatial and seasonal heterogeneity in both HEC occurrence and detection. They underscore the need for adaptive, spatiotemporally targeted mitigation and monitoring strategies to effectively reduce the impact of HEC incidents on local communities and promote coexistence in this biodiversity-rich and conflict-prone landscape.

1. Introduction

Human-wildlife conflict (HWC) represents a pressing conservation challenge, occurring where vulnerable wildlife populations interact with expanding human settlements and agricultural landscapes (Ravenelle and Nyhus, 2017). Such interactions often intensify where natural habitats are degraded or fragmented (Puyravaud et al., 2019), and communities depend heavily on natural resources (Madhusudan et al., 2015), leading to escalating tensions that can erode public tolerance towards wildlife (Hoare, 2015; Kansky et al., 2016; Manral et al., 2016). The global scale and increasing severity of HWC are well-documented, with over 73% of governments from 70 countries reporting rising levels of conflict incidents (Bank, W., 2024). From elephants foraging in agricultural mosaics (Anoop et al., 2023b; Bastille-Rousseau et al., 2020), large carnivores navigating human-dominated landscapes (Bauer and Iongh, 2005; Bhattarai and Fischer, 2014; Davoli et al., 2022), and ungulates competing for resources with livestock systems (Brook, 2009; Eshtiaghi et al., 2024; Ficetola et al., 2014), HWC incidents pose significant threats to biodiversity conservation efforts and human livelihoods.

Effectively addressing HWC requires understanding where and when it occurs in the landscape to enable accurate prediction and targeted mitigation (Miller, 2015; Treves et al., 2004). Occupancy models provide a robust framework for such analyses by explicitly separating the ecological processes (occupancy, the true occurrence of conflict) from the observational processes of detection (whether an occurring event is

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reported) (Goswami et al., 2015; MacKenzie et al., 2003). Unlike traditional approaches that overlook imperfect detection and risk a biased inference (Kellner and Swihart, 2014), occupancy models explicitly account for variation in reporting efficiency (Athreya et al., 2015; Schmidt et al., 2023). Extensions of such models, incorporating spatiotemporal frameworks, further allow probabilities of occurrence and detection to vary across locations and seasons (Diana et al., 2022). By jointly estimating the probability of occurrence and detection, these models have become increasingly popular for HWC research, especially in contexts where direct observations are scarce or records come from opportunistic sources, such as compensation claims, community surveys, or agency responses (Altwegg and Nichols, 2019; Guillera-Arroita, 2017; Schmidt et al., 2023). Applications of such models range from mapping elephant distributions (Jathanna et al., 2015; Lakshminarayanan et al., 2016; Ram et al., 2024) and identifying spatiotemporal drivers of crop depredation (Goswami et al., 2015)), to examining human-carnivore interactions (Athreya et al., 2015; Gould et al., 2019; Srivathsa et al., 2019), and identifying conflict hotspots by linking species distributions with human activity (Fidino et al., 2022; Petracca et al., 2019; Warrier et al., 2021).

Building on this growing body of work, we focus on human-elephant conflict (HEC), a pressing form of HWC that poses serious conservation and livelihood challenges (Gross et al., 2020; Shaffer et al., 2019), particularly in Asia's highly fragmented and densely populated landscapes (Leimgruber et al., 2003). HEC incidents are common across Asian elephants' (*Elephas maximus*, Linn) range, including Sri Lanka (Gunawansa et al., 2023; Köpke et al., 2021), Thailand (Supanta et al., 2025; Water and Matteson, 2018), Nepal (Acharya et al., 2016; Ram et al., 2024), and India (Dash et al., 2025; Roy et al., 2025), due to their frequent utilization of agricultural–forest mosaics bordering protected areas and other refuge sites (Krishnan et al., 2019; Naha et al., 2019). This proximity often leads to HEC incidents causing crop damage, property loss, human injury, and death (Karanth et al., 2018; Monney et al., 2010), threatening food security and causing psychological distress in rural communities (Barua et al., 2013; Sampson et al., 2021). Unaddressed conflict incidents may trigger retaliatory killings that hinder elephant conservation (Milda et al., 2020). The objective of our study was to leverage a long-term dataset of HEC observations in agricultural landscapes adjacent to protected areas to a) estimate the spatio-temporal trends of occurrence and detection of HEC within an agricultural landscape, explicitly separating ecological from observational processes, and b) generate predictive maps of HEC occurrence across data-sparse regions to support landscape-level monitoring and mitigation strategies. Our findings contribute to global understanding of HWC dynamics by demonstrating the application of advanced spatial occupancy models to conflict data derived from compensation reporting systems while providing actionable insights for management across fragmented landscapes.

2. Methodology

2.1. Study area

We selected the agricultural matrix surrounding the Bandipur (872.24 km^2 core; 584.06 km^2 buffer) and Nagarahole (643.35 km^2 core; 562.41 km^2 buffer) National Parks in Karnataka, India, as our study area. Located within the Western Ghats biodiversity hotspot (Mittermeier et al., 1998), these parks are critical strongholds for several charismatic and conflict-prone megafauna, particularly the Asian elephant, with densities estimated at around two individuals per km^2 (Jathanna et al., 2015; Madhusudan et al., 2015). They are contiguous with other high–elephant–density protected areas in neighboring states and are linked by well-defined corridors essential for dispersal and maintaining genetic connectivity (De et al., 2021; Puyravaud et al., 2017). To the north, the landscape transitions sharply into agricultural lands dotted with human settlements. This zone has a well-documented history of HWC, driven by its proximity to the parks and the year-round cultivation of crops and livestock rearing by local communities (Anoop et al., 2023b; Jathanna et al., 2015; Karanth et al., 2013a).

2.2. HEC data collection and processing

We obtained HEC incident data from the 'Wild Seve' program, launched in 2015 to improve reporting, response, and ex-gratia compensation processing for incidents in forest ranges surrounding Bandipur and Nagarahole (Karanth and Vanamamalai, 2020). The program established a toll-free helpline for farmers to report HWC incidents, with staff visiting each reported location within 24–48 h to document cases through photographs, GPS coordinates, and species identification. All incidents underwent field verification by local governmental authorities before ex-gratia compensation claims were processed. Only incidents that were reported, assessed, and approved were included in our analysis. Our dataset comprised 20,888 incidents documented between July 2015 and June 2023 (96 months), with 20,867 involving crop or property damage and 21 resulting in human injury or death. Given the dual verification process by both project staff and local authorities, we assumed all records to be accurate with no false positives. Such verified records can be regarded as reliable proxies for elephant presence (Sengupta et al., 2020; Sitati et al., 2003) and have underpinned various conflict modeling studies (Chen et al., 2016; Gubbi, 2012; Warrier et al., 2021).

We generated a fishnet of 558 grids (4 km^2 each) in ArcGIS Pro v.3.3.0 (ESRI, 2024), covering the program implementation area surrounding the protected areas (Fig. 1). This grid size was selected to prevent the misattribution of single HEC events to multiple cells, while remaining sufficiently detailed for the analysis of HEC drivers and management insights (Goswami et al., 2015). Daily HEC were spatially aggregated to grid cells and assigned a binary value for each month of the study period. Each grid was assigned a value of '1' if at least a single HEC incident was recorded within a given month, or '0' to indicate the absence or non-detection of conflict. Additionally, we collected detailed operational data from the program to construct a spatial dataset on survey effort, recorded monthly as binary values (1 or 0) indicating active status for each grid cell. The survey effort was constructed using monthly project coverage, publicity campaign frequency, forest department collaboration, and COVID-19 operational restrictions within the grid cell.

2.3. Covariate selection

Covariates were selected based on elephant habitat suitability and conflict modeling literature to capture factors influencing both HEC occurrence and detection (Table 1). We defined seasons as four-month periods corresponding to monsoon (July–October), pre-monsoon (March–June), and post-monsoon (November–February) cycles (Sanjeevaiah et al., 2021), aligning with cropping patterns that affect resource availability and HEC occurrence (Choudhury, 2004; Karanth and Vanamamalai, 2020). All covariates were extracted at their native resolution from Google Earth Engine accessed through the 'rgee' package in R (Aybar et al., 2020; Gorelick et al., 2017; R Core Team, 2024), calibrated using recommended coefficients, and extracted to grids using packages 'terra' and 'raster' in R (Hijmans, 2022; Hijmans, 2014). For seasonal covariates, mean values were calculated across the four months comprising each season for every grid cell.

Occupancy covariates captured site-specific and seasonal factors influencing HEC occurrence. Static covariates included average slope and cropland area within each grid cell. Forested patches outside protected areas were digitized from aerial imagery and, together with protected areas, designated as potential elephant refuge sites. Distance from each grid centroid to the nearest refuge site was included as a covariate. Seasonal covariates included Enhanced Vegetation Index (EVI), rainfall, and nighttime light radiance (NTL) (Table 1). A priori, we

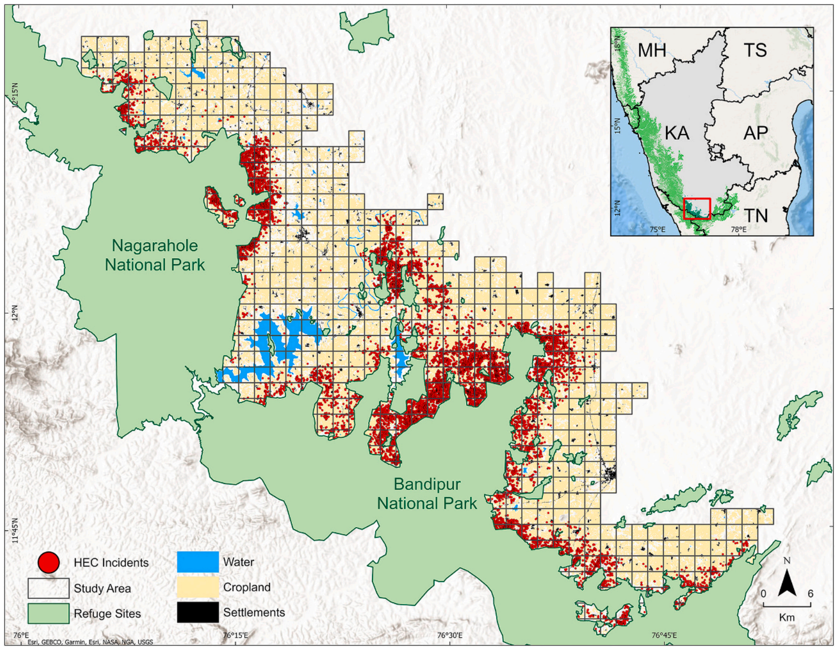

Fig. 1. Map of the primary Study Area and reported HEC incidents. The map depicts the national parks of Nagarahole and Bandipur in Karnataka, India, along with the surrounding landscape where incidents of human-elephant conflict (HEC) were recorded. The study area consists of 2 × 2 km grid cells surrounding the national parks and refuge sites. The inset map highlights the Western Ghats biodiversity hotspot, with the network of protected areas shown in green and the study area indicated by a red box for spatial reference. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Table 1
Summary of key covariates used in the spatiotemporal occupancy modeling of human-elephant conflict, including site and seasonal anthropogenic and environmental variables. Covariates are presented with values ranges (mean, standard deviation), native spatial resolution, source datasets, and references.

Description	Range (mean, SD)	Native resolution	Source dataset	References
Distance to Protected Area or Refuge Site (m)	0–11,978.601 (mean = 1373.41, SD = 1907.477)	Derived (calculated)	Calculated in R ('terra')	(Chen et al., 2016; Naha et al., 2019)
Area of Cropland within a Grid cell (%)	0.01–96.013 (mean = 54.607, SD = 27.838)	10 m	ESA WorldCover v200 (Zanaga et al., 2022)	(Chen et al., 2016; Goswami et al., 2015; Thapa et al., 2019)
Area of Settlement within a Grid cell (%)	0–10.633 (mean = 1.526, SD = 1.735)			
Slope (°)	0.753–13.467 (mean = 3.566, SD = 1.965)	30 m	NASA SRTM Digital Elevation (Farr et al., 2007)	(Mills et al., 2018; Thapa et al., 2019)
Enhanced Vegetation Index	0.037–0.523 (mean = 0.309, SD = 0.066)	250 m	MOD13Q1.061 Terra Vegetation Indices (Didan, 2021)	(Mills et al., 2018)
Land Surface Temperature Day (°C)	21.934–43.07 (mean = 32.054, SD = 3.67)	1000 m	MOD11A1.061 Terra Land Surface Temperature (Wan et al., 2021)	
Mean Rainfall (mm)	0.918–60.87 (mean = 17.502, SD = 11.973)	5566 m	CHIRPS Pentad (Funk et al., 2015)	(Goswami et al., 2015)
Nighttime Light Radiance (nanoWatts/sr/cmˆ2)	0.002–2.569 (mean = 0.483, SD = 0.231)	463.83 m	NOAA VIIRS V1 (Elvidge et al., 2017)	(Naha et al., 2019)
Survey Effort	0–1 (mean = 0.87, SD = 0.336)	4 km^2	(Karanth and Vanamamalai, 2020)	

expected positive associations between HEC occurrence and slope, cropland area, and seasonal EVI, as these factors may provide foraging opportunities or reduce human disturbance. We expected a negative association with seasonal NTL and distance to refuge sites, as they reflect increased human presence and reduced accessibility for elephants. We expected the seasonal variation in rainfall to have an indirect influence on occurrence due to its impact on vegetation dynamics, but we did not have a strong directional expectation for this relationship.

Detection covariates accounted for factors affecting HEC observation and reporting, including static covariates (cropland area, settlement area, distance to refuge sites) and seasonal covariates of daytime land surface temperature (LST) and program survey effort. We hypothesized that detection probability would be positively associated with the survey effort, proximity to refuge sites, and settlement area, due to increased human activity and incident visibility.

2.4. Occupancy model

Spatiotemporal occupancy models estimate the probability of a species or event occurrence and its variation in response to environmental drivers across space and time, while accounting for imperfect detections (Diana et al., 2022; Royle and Kéry, 2007). These models require two types of replication, namely, spatial replication across multiple sampling units (grid cells) and temporal replication through repeated sampling occasions within primary sampling periods (MacKenzie et al., 2003; Miller et al., 2019). In our framework, months serve as secondary sampling occasions (replicates) nested within seasons (primary periods), allowing estimation of detection probability while assuming closure within seasons but permitting occupancy to vary between seasons.

The closure assumption requires the true occupancy state of each grid cell to remain constant within a season, enabling occupancy estimates to be interpreted as the probability of at least one event occurring in a cell within that season (Bailey et al., 2004). This assumption is reasonable in our system as the four-month seasonal periods align with relatively stable agricultural cycles and elephant movement patterns. Additionally, the underlying factors driving HEC potential (crop availability, elephant habitat use, human activity) remain relatively consistent within seasons, while seasonal boundaries correspond to distinct phenological phases that represent discrete ecological and agricultural periods in the study region. As the data were collected via a continuous-response program rather than fixed visits, we conceptualized 'effort' as the presence or absence of program coverage over a 4-month seasonal period, rather than as discrete replicate-level events. Program operations depended on factors like publicity and outreach, with detection driven by whether the program was active in a grid cell during the season. Aligning effort with seasonal occupancy closure ensured consistency between ecological and observation processes. In our study, the occupancy parameter (psi, ψ) represents the probability that at least one HEC event occurs within a 4km^2 grid cell during a given season. As true HEC activity may fluctuate monthly within a season, detection probabilities should be interpreted as the product of the probability that an HEC event occurs in a given month (given that it occurred at least once during the season) and the probability that the event was successfully detected and reported.

The HEC history, along with the scaled covariates and coordinates of each grid centroid, were modeled in a Bayesian spatiotemporal occupancy framework using the 'stPGOcc' function in the 'spOccupancy' package in R (Doser et al., 2022). This model accounts for any residual spatial autocorrelation in HEC occupancy probability using a Nearest Neighbour Gaussian Process with an exponential covariance function, which acts to improve model predictions across non-sampled locations (Datta et al., 2016; Johnson et al., 2012). We fit the spatiotemporal occupancy model using grid cells with a history of survey effort (n = 389), while unsurveyed grids without any survey presence during the study period (n = 169) were designated as prediction sites.

We compared candidate models encompassing all combinations of covariates for occupancy and detection using a model selection procedure based on the Watanabe-Akaike Information Criterion (WAIC; Watanabe, 2010) to identify the most parsimonious model. Each candidate model included up to four covariates per component to limit complexity. The occupancy history, scaled covariates, and grid coordinates were modeled in a Bayesian spatiotemporal occupancy framework using a Nearest Neighbour Gaussian Process to account for residual spatial autocorrelation. Models were fit via Markov chain Monte Carlo (MCMC), with three chains for 150,000 iterations, a burn-in period of 15,000 iterations, and a thinning rate of twenty, resulting in 20,250 posterior samples per chain. All prior distributions were set to their default values (Doser et al., 2022).

3. Results

We selected the top-performing, most parsimonious model among candidate models within two WAIC of each other (Supplementary Table 1). This model included two occurrence covariates, the area of cropland within a grid cell (mean = 0.47; 95% Bayesian credible interval [BCI] = [0.26, 0.68]) and the average seasonal nighttime light radiance (mean = 0.47; 95% BCI = [0.34, 0.61]). Both covariates showed a positive association with occupancy probability, indicating that areas with greater croplands and higher seasonal nighttime light radiance were more likely to experience HEC (Fig. 2; Table 2). When all covariates were held at their mean values, the negative model intercept (mean = −1.65; 95% BCI = [−3.91, 0.79]) corresponded to an estimated average occupancy probability of 16.0% (95% BCI = [2.0%, 69.0%]) after applying the inverse logit transformation.

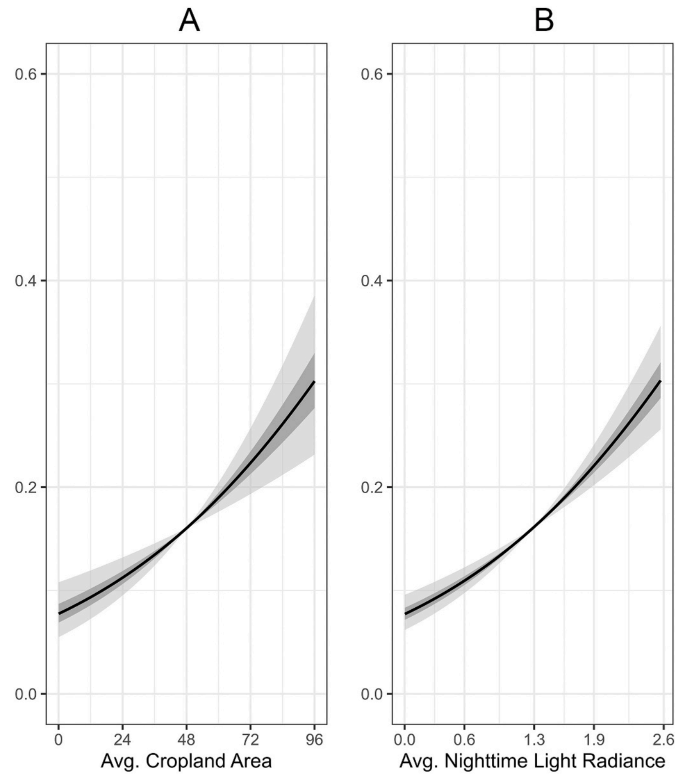

Fig. 2. Covariate Effects on Occupancy Probability. Predicted occupancy probability of human-elephant conflict as a function of covariates (a) cropland area (expressed as a percentage of grid cell area), and (b) the seasonal nighttime light radiance (in nanoWatts/sr/cmˆ2). Solid black lines represent the mean response, and shaded ribbons represent 95% (light gray) and 50% (dark gray) credible intervals, derived from posterior distributions of the model.

The detection covariates were consistent across the top models, highlighting key factors that influenced the likelihood of observing HEC incidents (Fig. 3). Detection probability was positively associated with the proportion of cropland (mean = 0.55; 95% BCI = [0.49, 0.62]) and the seasonal survey effort (mean = 0.56; 95% BCI = [0.48, 0.64]), indicating that well-surveyed agricultural areas were more likely to detect HEC incidents. Detection probabilities decreased with the distance of the grid centroid to the nearest protected area or refuge site (mean = −0.84; 95% BCI = [−0.99, −0.70]) and the seasonal daytime surface temperature (mean = −0.10; 95% BCI = [−0.15, −0.05]). The negative model intercept for detection (mean = −0.76; 95% BCI = [−0.84, −0.69]) corresponded to an average probability of 31.7% (back-transformed 95% BCI = [30.0%, 33.3%]) when all covariates were at their mean values.

Spatio-temporal random effects accounted for residual variation in occupancy beyond that explained by the fixed covariates in our model. The spatial variance parameter was estimated at 11.52 (95% BCI = [5.85, 19.87]), indicating pronounced heterogeneity in occupancy probability across the landscape. The spatial decay parameter (phi) was nearly zero, revealing strong spatial autocorrelation and minimal decay over increasing distance, indicating that occupancy probabilities remained highly correlated even across broad spatial extents. In contrast, the temporal variance parameter (sigma.sq.t; mean = 0.65; 95% BCI = [0.35, 1.16]) suggests more moderate variation in HEC occurrence across the different sampling periods (Table 2). The Gelman-Rubin 'R-hat' values for all parameters were close to 1, indicating adequate model convergence across the MCMC simulations (Gelman and Rubin, 1992).

We further examined seasonal variations in HEC by averaging values

Table 2
Summary output of the top-performing spatiotemporal occupancy model parameters. The parameter estimates for occurrence, detection, and spatiotemporal covariance from the top performing Bayesian spatiotemporal occupancy model are highlighted along with the mean, standard deviation (SD), 2.5th percentile, median (50%), and 97.5th percentile of the posterior distributions for each parameter. The Rubel-Gelman convergence parameter (Rhat) and effective sample sizes (ESS) indicate adequate model convergence.

Component	Parameter	Mean	SD	2.5%	50%	97.5%	Rhat	ESS
Occurrence	Intercept	−1.6556	1.1935	−3.9153	−1.7297	0.7982	1.0007	240
(logit scale)	Cropland Area	0.4741	0.1082	0.2635	0.4737	0.6873	1.0001	29,080
	Seasonal Nighttime Light Radiance	0.476	0.0698	0.34	0.4753	0.614	1.0004	55,361
Detection	Intercept	−0.7693	0.0395	−0.847	−0.7691	−0.6925	1.0001	50,357
(logit scale)	Cropland Area	0.5584	0.0347	0.4902	0.5583	0.6265	1	55,061
	Distance to Refuge Site	−0.8466	0.0732	−0.99	−0.8464	−0.703	1	47,534
	Seasonal Land Surface Temperature	−0.1045	0.026	−0.1553	−0.1045	−0.0537	1.0001	60,750
	Seasonal Survey Effort	0.5647	0.0404	0.4847	0.565	0.6436	1.0002	59,301
Spatio- temporal Covariance	Spatial Variance (sigma.sq)	11.5192	3.7554	5.8538	10.9318	19.8716	1.0005	3225
	Spatial Correlation (phi)	0.0001	0	0	0.0001	0.0001	1.0002	3622
	Temporal Variance (sigma.sq.t)	0.6513	0.2117	0.3529	0.6133	1.1668	1.0003	53,487
	Temporal Correlation (rho)	0.2527	0.1425	−0.0385	0.258	0.5167	1	51,902

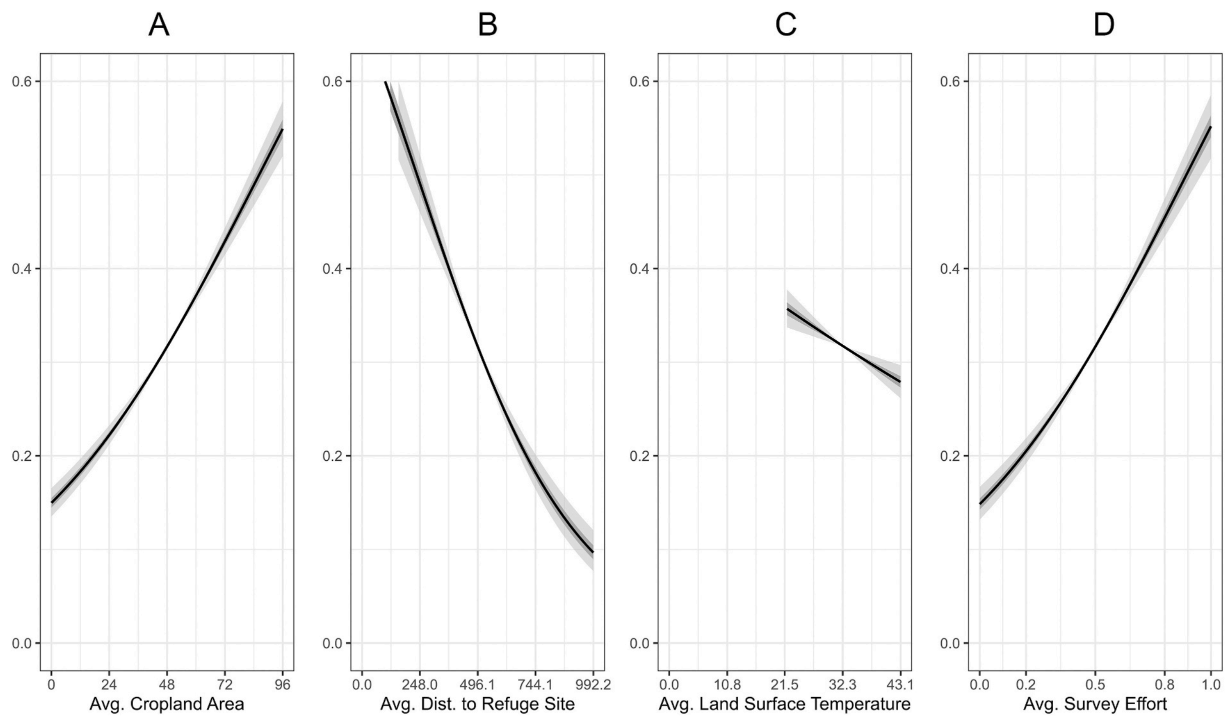

Fig. 3. Covariate Effects on Detection Probability. Predicted detection probability of human-elephant conflict as a function of covariates (a) cropland area (expressed as a percentage of grid cell area), (b) distance to nearest refuge site or protected area (in m), (c) seasonal land surface temperature (at daytime, Celsius), and (d) seasonal survey effort. Solid black lines represent the mean response, and shaded ribbons represent 95% (light gray) and 50% (dark gray) credible intervals, derived from posterior distributions of the model.

across all grid cells for each MCMC iteration to calculate mean seasonal probabilities. Occupancy probabilities were highest during the post-monsoon season (mean = 0.35, 95% BCI = [0.33, 0.37]), followed by the monsoon season (mean = 0.31, 95% BCI = [0.29, 0.32]), and lowest during the pre-monsoon season (mean = 0.26, 95% BCI = [0.25, 0.28]). The non-overlapping credible intervals for all pairwise comparisons indicated significant seasonal differences (Fig. 4a). Detection probabilities were highest during the monsoon season (mean = 0.38, 95% BCI = [0.36, 0.39]; Fig. 4b), followed by the post-monsoon season (mean = 0.36, 95% BCI = [0.34, 0.37]), and lowest during the pre-monsoon season (mean = 0.33, 95% BCI = [0.31, 0.34]).

Using the selected model, we generated predictions for HEC occurrence and detection in the unsurveyed grid cells ($n = 169$) to provide landscape-level insights into HEC patterns. Mapping HEC occurrence and detection probabilities for both surveyed and unsurveyed regions across the landscape highlighted regions where conflicts are likely but underreported, providing actionable insights for targeted monitoring and mitigation strategies (Fig. 5).

4. Discussion

4.1. *Drivers of human-elephant conflict*

This study advances our understanding of human–elephant conflict (HEC) in the Western Ghats by leveraging farmer-reported HEC incidents collected as part of a long-term human-wildlife conflict (HWC) monitoring program in the agricultural and human-dominated landscapes surrounding Bandipur and Nagarahole National Parks in Karnataka, India (Karanth and Vanamamalai, 2020). By employing a Bayesian spatiotemporal occupancy modeling framework, we estimated patterns of HEC occurrence and detection, extending these insights to unsurveyed regions to inform targeted mitigation and monitoring strategies.

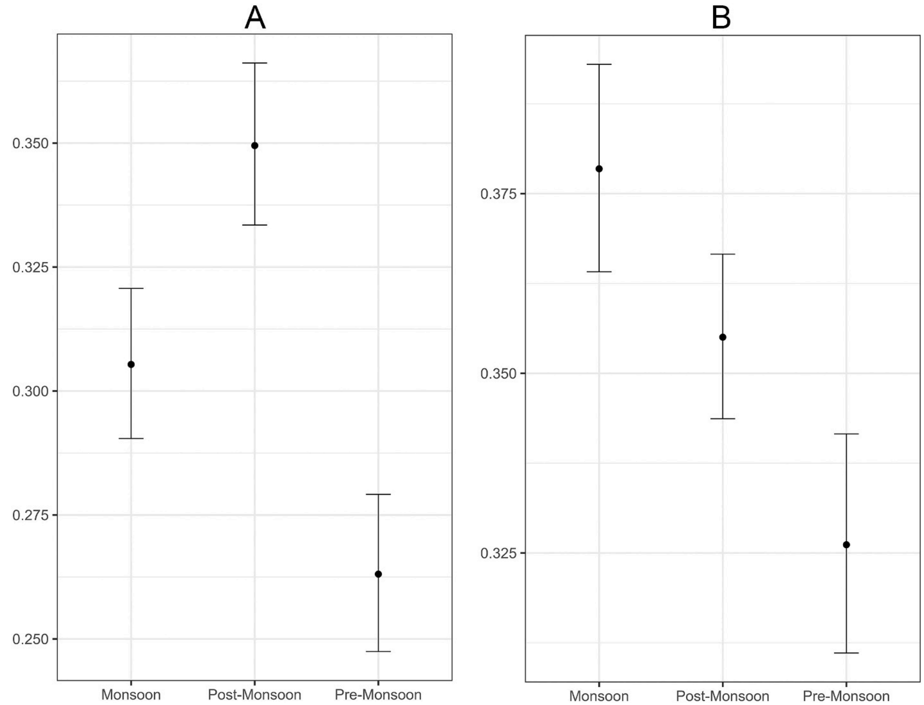

Fig. 4. Seasonal Variation in Occupancy and Detection Probabilities. Seasonal differences in estimated probabilities. Panel (a) shows the mean occupancy probability, and panel (b) shows the mean detection probability across the monsoon, post-monsoon, and pre-monsoon seasons from the modeled grid cells. Error bars indicate 95% Bayesian Credible Intervals.

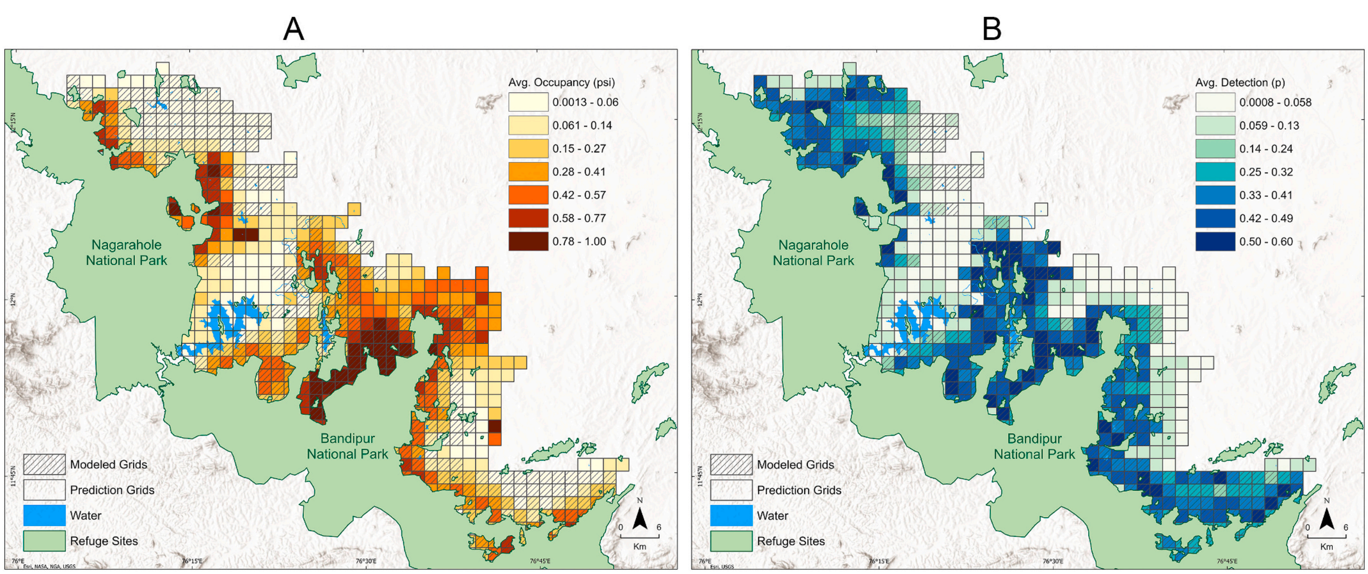

Fig. 5. Spatial distribution of average occupancy and detection probabilities. Panel (a) shows average occupancy estimates, and panel (b) shows average detection estimates across the study area. Modeled (hashed) grids represent cells used in the Bayesian spatiotemporal model, and prediction grids represent areas with inferred values from the model.

Cropland extent emerged as the most consistent and robust predictor of HEC occurrence across all top candidate models (Supplementary Table 1), with a positive coefficient estimate. This finding aligns with our predictions and corroborates previous studies (Ruda et al., 2018; Talukdar et al., 2023; Tripathy et al., 2021), underscoring the role of forage availability as a primary driver of conflict in this region. Agricultural mosaics offer energy and nutrient-rich forage for elephants (Chama et al., 2025; Sukumar, 1990), particularly when positioned adjacent to protected areas, enabling elephants to combine foraging with access to secure habitat (Matsika et al., 2024). Seasonal nighttime light radiance (NTL) also exhibited a positive association with HEC occurrence, contrary to our initial expectation that artificial illumination would deter elephant activity. NTL serves as a proxy for human economic activity and productivity (Asher et al., 2021), with seasonal variation in NTL likely reflecting intensified agricultural activities during post-monsoon harvests. This interpretation is supported by the spatial-temporal alignment between NTL peaks and observed HEC occurrences during the post-monsoon season, when crop vulnerability and human agricultural activity are both elevated. The positive association between NTL and HEC occurrence likely reflects spatial and temporal overlap between human agricultural activities and elephant foraging patterns, rather than illumination serving as a deterrent. Future research quantifying the relationship between NTL around protected areas and biodiversity hotspots (Guetté et al., 2018; Zhao et al., 2023), measurable agricultural activity patterns (e.g., harvest timing, labor intensity, crop phenology), and HEC occurrence would clarify the specific mechanisms underlying this association.

Alternative covariates in models with comparable predictive power (ΔWAIC <2; Supplementary Table 1) provided additional insights into HEC drivers. Terrain slope was positively associated with HEC occurrence in some models, suggesting that elephants may preferentially utilize undulating or steeper terrain when crop raiding. Seasonal vegetation (EVI) was positively associated with HEC occurrence, aligning with expectations that conflict increases during periods of higher vegetation growth corresponding to agricultural productivity (Anoop et al., 2023a). Distance to refuge sites showed an inverse relationship with HEC occurrence, confirming that conflict incidents concentrate near protected area edges where elephants can readily access forested refugia (Kumar and Singh, 2010; Matsika et al., 2024).

Our occupancy modeling framework explicitly separated factors influencing HEC occurrence from those affecting detection probability, revealing important observational biases in farmer-reported incidents. Detection probability was positively associated with cropland extent, reflecting both increased visibility of crop damage and higher farmer field presence in agricultural areas. Small landholdings typical of the region encourage frequent farmer presence, increasing the likelihood of immediate incident detection and reporting (Karanth et al., 2013b). Proximity to refuge sites also enhanced detection, where elevated conflict frequencies incentivize reporting for ex-gratia compensation (Bal et al., 2011; Borah et al., 2021; Talukdar et al., 2023). Detection probability was observed to decrease with seasonal land surface temperatures, suggesting reduced reporting of conflict during hotter or drier pre-monsoon periods. This pattern likely reflects decreased agricultural activity and reduced farmer field visits during extreme heat, though it may also be confounded with genuinely lower HEC occurrence when elephants remain near water sources within protected areas during the dry season (Jathanna et al., 2015; Lakshminarayanan et al., 2016). Notably, survey effort significantly enhanced detection, demonstrating that active monitoring programs substantially improve reporting rates. The average detection probability (31.7%) reveals substantial underreporting even with systematic monitoring, consistent with earlier research (Goswami et al., 2015; Sengupta et al., 2020; Schmidt et al., 2023)underscoring the critical importance of accounting for imperfect detection in HWC analyses.

4.2. HEC monitoring and mitigation strategies

Our spatiotemporal predictions indicate substantial variation and spatial heterogeneity in HEC occurrence and detection across the landscape. Regions with consistently elevated levels of both are well-suited for targeted, evidence-based interventions (Supplementary Fig. 2). Coordinated crop protection strategies, such as encouraging farmers to adopt non-palatable crop varieties or adjusting harvest schedules to avoid peak HEC periods, can minimize the overlap between elephant activity and the availability of high-value vegetation (Anoop et al., 2023a; Gross et al., 2016; Matsika et al., 2024; Webber et al., 2011). Systematic and context-specific evaluations of current deterrence strategies employed by community and government initiatives, such as trenches, fencing, night watches, and patrols (Karanth and Kudalkar, 2017; Prasad et al., 2025; Shaffer et al., 2019), as well as bee fences, capsaicin-based barriers, and visual-auditory deterrents (Pozo et al., 2019; Thuppil and Coss, 2016), are essential given their variable effectiveness across ecological and socioeconomic settings (Graham and Ochieng, 2008). Physical barriers like electrified or railway-line fences, favored by local communities, are expensive (Saklani et al., 2018) and often misplaced in low-conflict areas, potentially disrupting natural dispersal and genetic connectivity between fragmented elephant habitats (De et al., 2021; Natarajan et al., 2021; Puyravaud et al., 2022). Complementary landscape-scale interventions, such as strategic reduction of agricultural activity in key movement corridors, habitat restoration, and the promotion of biodiversity-friendly agroforestry practices can help mitigate conflict while providing alternative livelihoods for farmers (Bal et al., 2011; Nyhus and Tilson, 2004; Plieninger et al., 2020; Silori and Mishra, 2001). Seasonal, rotational, or adaptive deterrent deployment may prevent elephant habituation and maintain effectiveness over extended periods (Grange et al., 2022). Regions with low detection require enhanced monitoring capacity. While governmental ex-gratia compensation systems maintain HEC records, spatial and temporal resolution are limited by inconsistent local engagement and underreporting (Sengupta et al., 2020). Increasing monitoring frequency, community outreach, and participation in incident documentation can improve data quality and ex-gratia compensation access to those impacted by conflict incidents (Gunaryadi et al., 2017; Nayak and Swain, 2022; Ogra and Badola, 2008). Additionally, policy reforms promoting integrated public-private monitoring and expanded elephant tracking via research permits could enhance data quality, community awareness, and support more efficient conflict monitoring and mitigation (Lindsey et al., 2021; Pilliod et al., 2022).

5. Conclusion

This study demonstrates the utility of occupancy modeling for understanding human-wildlife conflict in data-sparse systems while accounting for imperfect detection. The identification of cropland extent, and seasonal nighttime light radiance as key drivers of HEC occurrence, coupled with the heterogeneity in detection probabilities across the landscape, provides actionable insights for targeted mitigation. Strategic interventions near protected area boundaries and during peak post-monsoon agricultural periods, combined with adaptive monitoring and streamlined compensation mechanisms, can reduce the impact of conflict incidents, foster tolerance towards wildlife, and ensure the long-term sustainability of conservation efforts in biodiverse and conflict-prone agricultural landscapes. Ultimately, success in human-elephant coexistence requires integrated land-use planning, informed by evidence-based identification of conflict drivers and mitigation priorities, that explicitly accommodates elephant movement and foraging needs while supporting agricultural productivity and local livelihoods.

CRediT authorship contribution statement

Anubhav Vanamamalai: Writing – review & editing, Writing – original draft, Visualization, Methodology, Formal analysis, Conceptualization. **Krithi K. Karanth:** Writing – review & editing, Supervision, Resources, Conceptualization. **Jeffrey W. Doser:** Writing – review & editing, Software, Methodology. **Ruth DeFries:** Writing – review & editing, Supervision, Conceptualization.

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Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.biocon.2026.112054.

Data availability

The datasets include sensitive spatial details on endangered taxa and affected villages. Requests for access can be directed to the corresponding author.

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