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Environmental influence on the spatial abundance of tiger prey monitored using camera traps in Thap Lan and Pang Sida National Parks, Thailand

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Abstract. *Meeamnart B, Pakpian S, Khongmueang J, Kamsudsang P, Paansri P, Duengkae P, Suksavate W. 2025. Environmental influence on the spatial abundance of tiger prey monitored using camera traps in Thap Lan and Pang Sida National Parks, Thailand. Biodiversitas 26: 1500-1511.* The decline in prey populations within the Dong Phayayen-Khao Yai Forest Complex (DPKY), Thailand, has likely contributed to the local extinction of tigers, raising urgent concerns about the future of this iconic species in the region. Environmental factors play a crucial role in the fluctuations in prey densities. This study estimated the spatial density of five key tiger prey species (gaur, banteng, sambar deer, muntjac, and wild boar) using the Random Encounter and Staying Time (REST) and Royle-Nichols (RN) occupancy models. The REST model produced density estimates of 1.05±0.35, 0.01±0.11, 0.62±0.79, 1.10±0.49, and 1.46±0.38 individuals/km² for gaur, banteng, sambar deer, muntjac, and wild boar, respectively. The RN model yielded slightly higher estimates: 1.51±1.26, 0.05±0.14, 0.82±0.58, 2.62±1.25, and 3.06±1.74 individuals/km². These findings highlight the significant influence of variables like vegetation cover, proximity to human settlements, elevation, and salt licks on prey abundance and distribution, with muntjac and wild boar consistently showing higher densities than other species. This spatial modeling approach provides a novel framework for predicting animal density, which can inform conservation and management strategies for tiger prey populations in DPKY, thereby aiding in tigers' persistence within these protected areas.

Abbreviation: REST: Random Encounter and Staying Time; RN: Royle-Nichols

Keywords: Camera trap, prey, Random Encounter and Staying Time model, Royle-Nichols model, tiger

INTRODUCTION

The tiger (*Panthera tigris*) is the largest of the wild cats and plays a crucial role in maintaining ecosystem balance (Proverbio et al. 2021). Based on genetic and morphological studies, it is classified into six extant subspecies (Liu et al. 2018). Tigers are currently found across 13 range countries: Russia, China, India, Nepal, Bhutan, Bangladesh, Myanmar, Thailand, Laos, Vietnam, Cambodia, Malaysia, and Indonesia (Harihar et al. 2018). The species was most recently assessed for the IUCN Red List of Threatened Species in 2021 and is classified as globally endangered (Goodrich et al. 2022). Large carnivores, including tigers, are among the most threatened species worldwide (Ripple et al. 2014). Since 2010, conservation efforts for tigers have increased significantly. However, the success of tiger population recovery in the wild varies across countries (Jhala et al. 2021). In Thailand, Dong Phayayen-Khao Yai Forest Complex (DPKY) has been recognized as a UNESCO World Heritage Site since 2005, is pivotal for the recovery of Indochinese tiger subspecies (*Panthera tigris corbetti*), harboring a critically important breeding population (Ash et al. 2020). The Indochinese tigers are slightly smaller and darker than the Bengal tiger, with shorter, narrower stripes. This subspecies is medium-sized, weighing approximately 130-200 kg (WCS Thailand 2021a). Recent assessments, however, indicate that the tiger population within DPKY, particularly in Thap Lan and Pang Sida National Parks, has dwindled to approximately 20 individuals (DNP 2016; WCS Thailand 2021b). Information from the Spatial Monitoring and Reporting Tool (SMART) suggests that tigers might be locally extinct in significant portions of DPKY. This decline aligns with a reduction in their principal prey populations (Jornburom 2016), attributed to the loss and degradation of suitable habitats in terms of both quality and quantity (Paansri et al. 2022). The lack of precise population data has obscured these declines (Ash et al. 2021b), making urgent the need for detailed data to guide recovery efforts for both tigers and their prey. Tigers, being apex predators, predominantly feed on large ungulates such as gaur (*Bos gaurus*), banteng (*Bos javanicus*), sambar deer (*Rusa unicolor*), muntjac (*Muntiacus muntjak*), and wild boar (*Sus scrofa*) (Petdee 2000; Shah et al. 2024). These prey species have faced population declines due to habitat loss, degradation, and over-hunting (Wolf and Ripple 2017). Evaluating the status of these prey populations is essential for achieving recovery goals through strategic interventions (Marescot et al. 2020).

Camera traps have demonstrated their effectiveness in monitoring wildlife, providing valuable data for estimating population density and abundance (Burton et al. 2015; Nakashima et al. 2021). These tools are crucial for exploring how ecological or human-induced factors influence density variations. While capture-recapture methods using camera traps are effective for species with recognizable markings like tigers (Royle 2009), estimating density for unmarked species is challenging due to the inability to recognize individuals. To address this, models like the Royle-Nichols occupancy model (RN) have been developed, which account for variations in detection probability linked to species abundance (Royle and Nichols 2003). Rowcliffe et al. (2008) proposed the Random Encounter Model (REM) to estimate absolute animal density based on ideal gas model principles. This was further refined by Nakashima et al. (2018) into the Random Encounter and Staying Time (REST) model, enhancing density estimation accuracy by integrating several assumptions and habitat covariates (Nakashima et al. 2018). Although alternative methods exist (Ramsey et al. 2015; Howe et al. 2017), camera trap data remains a key resource for evaluating the density and distribution of tiger prey, thus facilitating informed conservation management.

This study aims to spatially estimate the density of five tiger prey species (gaur, banteng, sambar deer, muntjac, and wild boar) within DPKY by employing both the REST (Nakashima et al. 2018) and the Royle-Nichols occupancy (RN) models (Royle 2009). These approaches allow for abundance estimation without individual identification by leveraging the variability in capture characteristics. By incorporating ecologically significant covariates, we can model how various environmental factors influence the distribution and density of these prey species across the DPKY landscape. Comparative analysis between these models will assess their utility and performance. The spatial modeling insights derived here will crucially inform conservation strategies for managing tiger prey populations, thereby enhancing the prospects for tiger persistence in this protected area.

MATERIALS AND METHODS

Study area

The study area covered 3,080 km^2, and an altitude range of 100-1,351 m asl, including two protected areas in the Dong Phayayen-Khao Yai Forest (DPKY): Thap Lan National Park (TLNP) and Pang Sida National Park (PSNP), in northeastern and eastern Thailand, respectively (Figure 1). Protected areas in DPKY are included in the United Nations Educational, Scientific and Cultural Organization (UNESCO) World Heritage List (UNESCO 2017). Annual rainfall in the study area ranges from 3,000 mm in the west to under 1,000 mm in the east. The wet season occurs mainly during the southwest monsoon period, from May to October (IUCN 2005). The DPKY encompasses dry evergreen, mixed deciduous, and deciduous dipterocarp forests (IUCN 2005), as well as deforested scrubland, grasslands, and secondary forests of various types (Ash et al. 2021a).

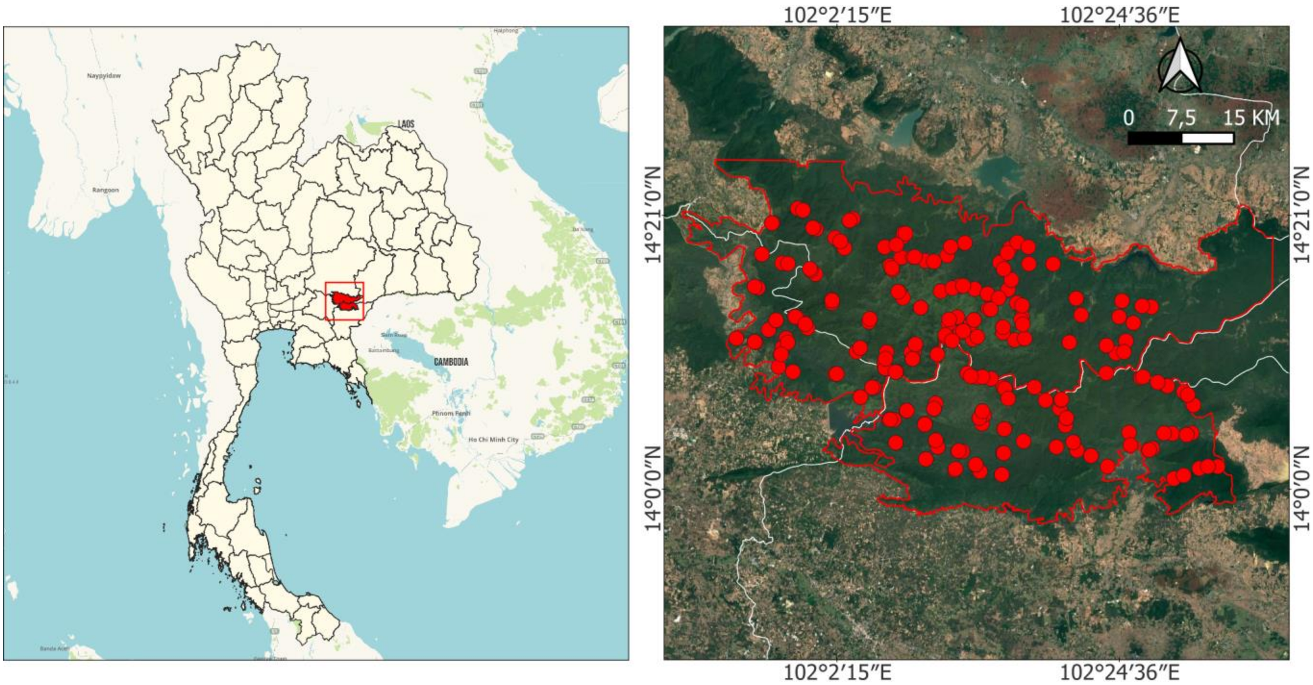

Figure 1. The study areas encompass two protected areas, Thap Lan National Park and Pang Sida National Park, Thailand (14º05′-14º33′N, 101º50′-102º40′E). The camera trap locations are indicated with red dots

Field data collection

The camera trap survey was conducted from February 2019 to March 2021. Trapping was conducted yearly, from November to June of the following year. Camera traps were installed semi-systematically, at intervals of approximately 3-4 km (Figure 1) in locations with specific geographical or topological characteristics and access roads or trails that were likely to be used frequently by tigers and their prey (Karanth and Nichols 1998). A total of 260 camera trap stations were established across the study area, with each station consisting of a pair of cameras set approximately 7 m apart and 40-50 cm above the ground, which allowed the cameras to capture full-body images of medium-sized to large mammals (Zhang et al. 2018) All camera trap stations were visited every 2-3 weeks to change batteries and download images. The images were uploaded from a memory card to a computer and classified using the Camera Trap Manager program (Zaragozi et al. 2015). We identified five species of prey captured by tigers. For each individual captured within the effective focal area of the camera, we measured time spent in the detection area ("staying time") as the difference between the first and last photograph that captured the individual. Prey density was estimated using the Random Encounter and Staying Time (REST) model and included data only relating to animals that passed within a triangular effective focal area of 5.08 m^2. Each instance of an individual entering and exiting this area was considered an independent event. No bait was used to attract wildlife, and camera traps remained in fixed locations throughout the survey period.

Data analysis

Environmental data

The distribution and abundance of animal populations can be influenced by factors such as topography, food resources, and water availability (Marini et al. 2007). We used indices of vegetation productivity, nitrogen content, and other features of high-quality food availability, such as the Normalized Difference Vegetation Index (NDVI), derived from remotely sensed Landsat 8 satellite imagery. These indices are often used to predict the distribution and abundance of herbivores (Pettorelli et al. 2011). To determine the probability of tiger prey occupancy, we analyzed ecological and anthropogenic covariates obtained from publicly available geographic information system data and the Spatial Monitoring and Reporting Tool (SMART), which includes monitoring data for protected areas. We used a total of eight statistical covariates, at a resolution of 30 m: NDVI, distance to the closest village, distance to the closest road, distance to the closest stream, distance to the closest salt lick, elevation, slope, and distance to the closest threat occurrence (Figure 2). All distances were calculated between the centroids of the source and target grids.

REST model

We estimated the tiger prey population size using the REST model, based on camera trap data, including the time (T) spent by an animal within the Field of View (FOV) of the camera. As input for the REST model, prey density D is estimated as follows (Nakashima et al. 2020):

$$D = \frac{E(y)E(T)}{sH} \quad \text{(Eq. 1)}$$

Where, s is the survey area (km^2), calculated based on the effective focal area, H is the duration of the survey period (s), E(y) is the expected number of encounters, and E(T) is the expected staying time (s). The model (Eq. 1) is based on maximum likelihood estimation, in which the goal was to determine the negative binomial regression coefficients and expected staying time that will minimize the negative log-likelihood. This method allows the direct estimation of standard error (Nakashima et al. 2020; Yokoyama et al. 2020). Thus, the REST model uses ecological covariates to explain variation in animal density across different locations, as follows:

$$\log\left(E(D_i)\right) = \beta_0 + \sum_k X_{ik}\beta_k \quad \text{(Eq. 2)}$$

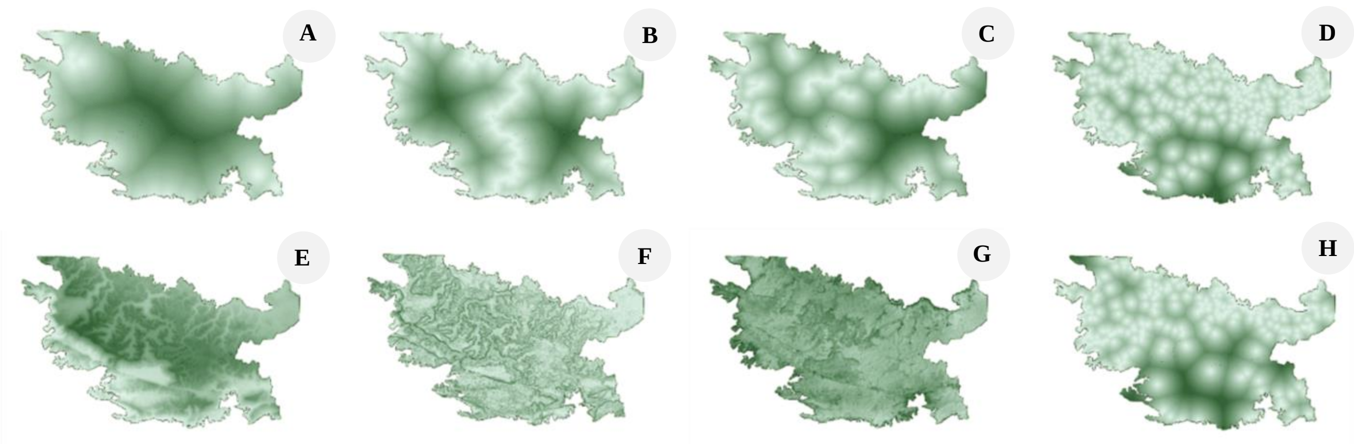

Figure 2. Mapped covariates. A. Distance to the closest village (VLG); B. The average distance to the closest road (ROD); C. Distance from the stream (STM); D. Distance to salt lick (SLK); E. Elevation (ELV); F. Slope (SLP); G. Normalized Difference Vegetation Index (NDVI); H. Distance to threat (TET)

The expected density at site (i), denoted E(D_i) s modeled as a function of regression covariates, X_{ik} for covariate (k) at site (i), β_0 as the intercept, and β_k are the regression coefficients (Eq. 2). To estimate the staying time and density of each species, we developed a hierarchical model that incorporates both encounter rate and staying time data. This model was run using a template model builder formulated in C++, implemented using the TMB package (Kristensen et al. 2016) in R (R Core Team 2017). Within the negative log-likelihood function, the staying time and encounter rate were modeled using an exponential distribution and a negative binomial distribution, respectively, incorporating survey parameters including the survey period, proportional activity duration, and detection zone. The function was minimized to estimate model parameters based on joint covariate effects (Eq. 1) and the encounter rate (Eq. 2). The model output was the estimated staying time and density for each species, which allowed us to quantify the abundance and behavioral patterns of the tiger prey species. Environmental variables such as elevation; slope; distance to the closest stream, road, salt lick, and village; threat intensity; and normalized NDVI were included into the regression model to estimate density. All analyses were performed using R. Stepwise model selection was applied to identify the model with the lowest Akaike Information Criterion (AIC) (Akaike 1998), and the optimal model was used to determine the spatial distribution of prey encounters and their expected staying time. The population and density of tiger prey species were then estimated through spatial modeling.

Royles-Nichol (RN) occupancy model

To account for potential heterogeneity in the probability of detection, which is common for camera trap data (Tobler et al. 2015), we employed a Royle–Nichols (RN) occupancy model (Royle and Nichols 2003). Compared with a standard binary model, the RN model shows better performance at estimating abundance of a given species i at site j (a_{ij}), based on a Poisson distribution with the density parameter (λ_{ij}), such that

$$a_{ij} \sim \text{Poisson}(\lambda_{ij}) \qquad \text{(Eq. 3)}$$

Occupancy (Ψij) is then calculated as the probability of at least one individual occurring at a site, as follows:

$$\Psi ij = \Pr(aij \geq 0) = 1 - e^{-\lambda ij} \qquad \text{(Eq. 4)}$$

We applied the RN occupancy model to our camera trap data for tiger prey species, which consisted of presence (1) or absence (0) data for each species at each site over a 1-month sampling period. Abundance was estimated using the Poisson distribution with a rate parameter. Occupancy was calculated as the probability of at least one individual occurring at a site. To investigate the influence of environmental factors on occupancy, we incorporated the nine environmental covariates into a log-link generalized linear model with the same set of covariates used in the REST model. Then, we identified the optimal model through stepwise model selection based on the lowest AIC. The density parameters of each spatial unit from the optimal model were used to generate spatial predictions of tiger prey abundance and estimate overall population abundance within the study area.

RESULTS AND DISCUSSION

A total of 260 camera stations were deployed, accumulating 13,908 camera trap nights during the survey. Between 2019 and 2021, we recorded and identified five key tiger prey species along with Indochinese tigers in protected areas within the Dong Phayayen-Khao Yai Forest Complex (Figure 3).

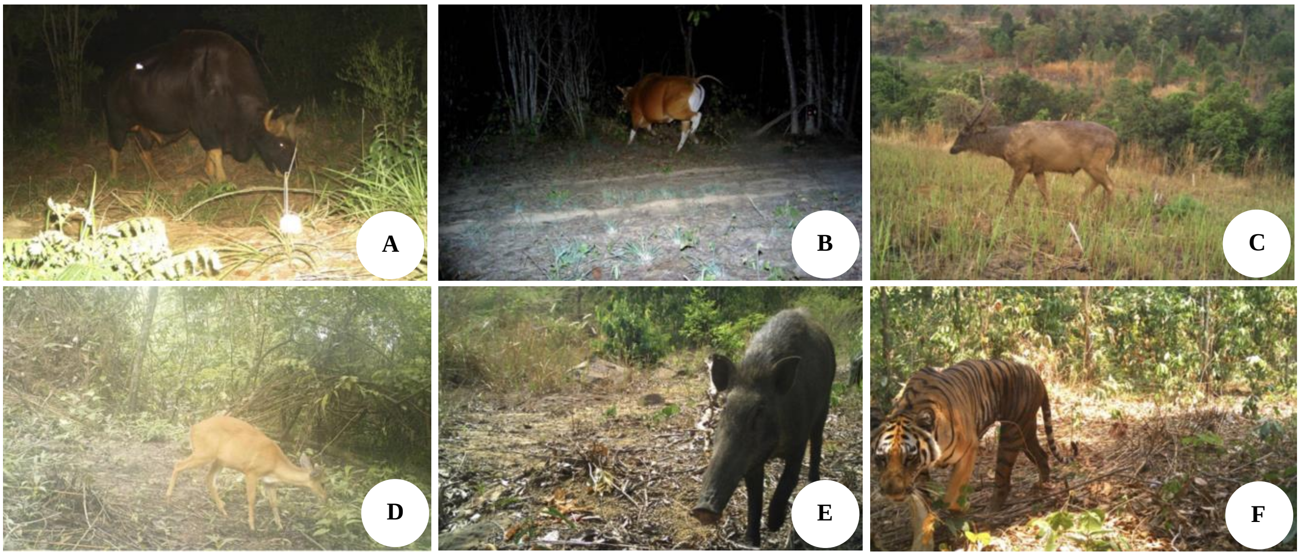

Figure 3. Five key tiger prey species and tiger captured by camera traps at different locations in Dong Prayayen-Khao Yai (DPKY), Thailand including: A. Gaur (*Bos gaurus*); B. Banteng (*Bos javanicus*); C. Sambar deer (*Rusa unicolor*); D. Muntjac (*Muntiacus muntjak*); E. Wild boar (*Sus scrofa*); F. Indochinese tiger (*Panthera tigris corbetti*). Photo by DPKY Wildlife Research Station

Tiger prey staying time

As input for the REST model, we measured the staying time of animals (time spent in the detection area, in seconds) within the focal area, and determined the expected staying time for five key tiger prey species: gaur (9.38±0.51 s), banteng (8.49±3.46 s), sambar deer (9.28±0.31 s), muntjac (7.51±0.23 s), and wild boar (10.91±0.28 s) (Table 1). The proportions of daily activity recorded by the cameras for these species were 0.487, 0.230, 0.539, 0.410, and 0.571, respectively (Figure 4).

Tiger prey density

We surveyed 260 camera stations over 13,908 nights of filming, and estimated prey density for the five key tiger prey species. Prey density estimates were calculated using two modeling approaches, REST and RN (Table 2). For gaur, banteng, sambar deer, muntjac, and wild boar, the REST model yielded prey density estimates of 1.05±0.35, 0.01±0.11, 0.62±0.79, 1.10±0.49, and 1.46±0.38 individuals/km^2, respectively (Figures 5-9), whereas the RN model generally produced slightly higher estimates, at 1.51±1.33, 0.05±0.14, 0.82±0.58, 2.62±1.25 and 3.06±1.74 individuals/km^2, respectively. Across both models, density levels were highest for muntjac and wild boar and lowest for banteng.

Covariate effects on prey abundance estimates

Both the REST and RN models were parameterized to identify environmental factors influencing abundance, encounter frequency, and site occupancy of five tiger prey species. The REST model revealed significant relationships between tiger prey density and environmental predictors (Table 3), such as vegetation cover (i.e. NDVI), elevation, slope, proximity to human features (i.e. roads and threat occurrence), and the presence of salt licks. An RN occupancy model with a negative binomial link clarified the variables influencing the probability of a species occupying particular sites (Table 4).

Table 1. The staying time of tiger prey species

Species	***Mean ±SE***
Gaur (*Bos gaurus*)	9.38±0.51
Banteng (*Bos javanicus*)	8.49±3.46
Sambar deer (*Rusa unicolor*)	9.28±0.31
Muntjac (*Muntiacus muntjak*)	7.51±0.23
Wild boar (*Sus scrofa*)	10.91±0.28

Table 2. Estimated density of tiger prey species

Method	Species	D±SE	*N*
REST model	Gaur (*Bos gaurus*)	1.05±0.35	3273
	Banteng (*Bos javanicus*)	0.01±0.11	31.18
	Sambar deer (*Rusa unicolor*)	0.62±0.79	1544
	Muntjac (*Muntiacus muntjak*)	1.10±0.49	3430
	Wild boar (*Sus scrofa*)	1.46±0.38	4553
RN model	Gaur *(Bos gaurus*)	1.51±1.26	4708
	Banteng (*Bos javanicus*)	0.05±0.14	139.62
	Sambar deer (*Rusa unicolor*)	0.82±0.58	2556
	Muntjac (*Muntiacus muntjak*)	2.62±1.25	6640
	Wild boar (*Sus scrofa*)	3.06±1.74	7749

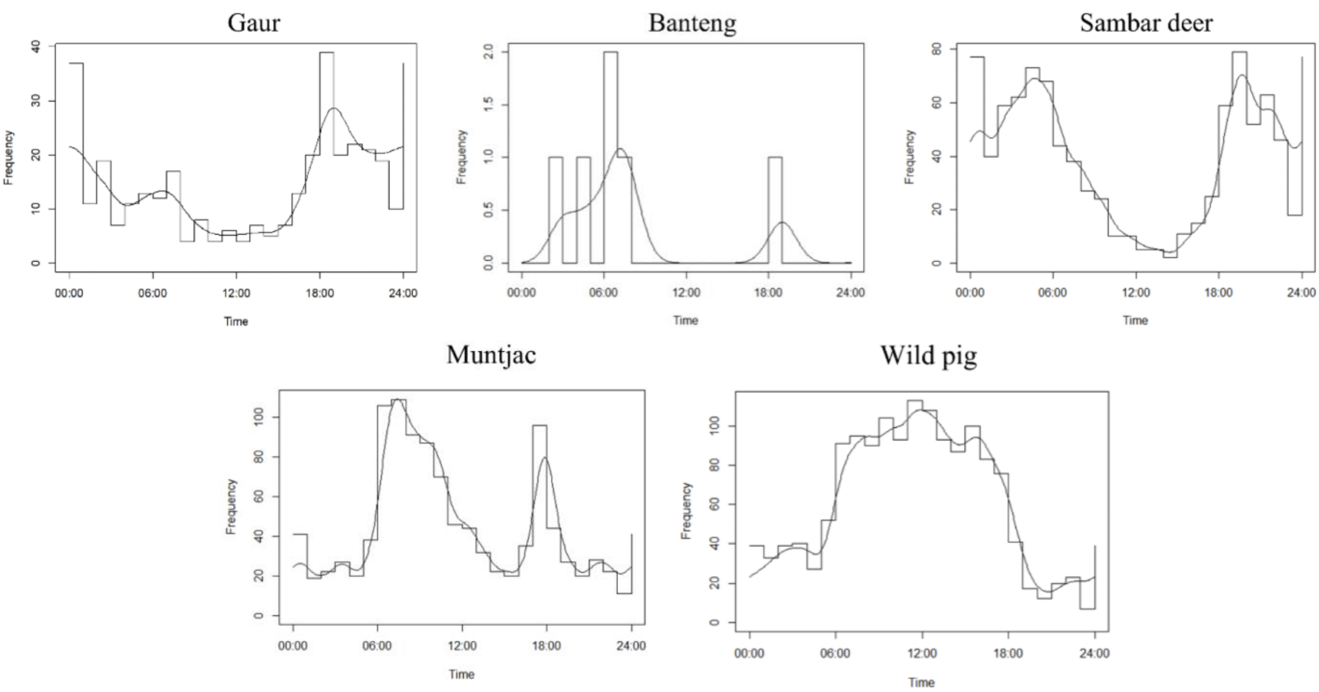

Figure 4. Proportion of active time during the day for five tiger prey species, based on camera trap records. The grey steps represent observed frequencies, and the curves represent fitted circular kernel distributions

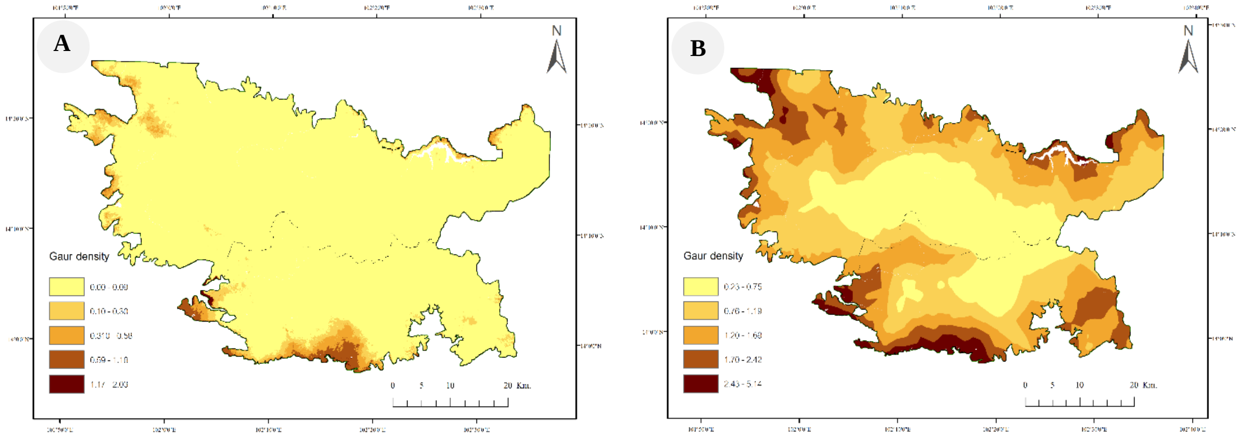

Figure 5. Estimated density of gaur, predicting densities using the REST Model (A) and RN model (B). There is more variability across the landscape because it uses different environmental factors, as it identifies specific areas with varying density levels. Darker shades indicate higher density (individuals/km²)

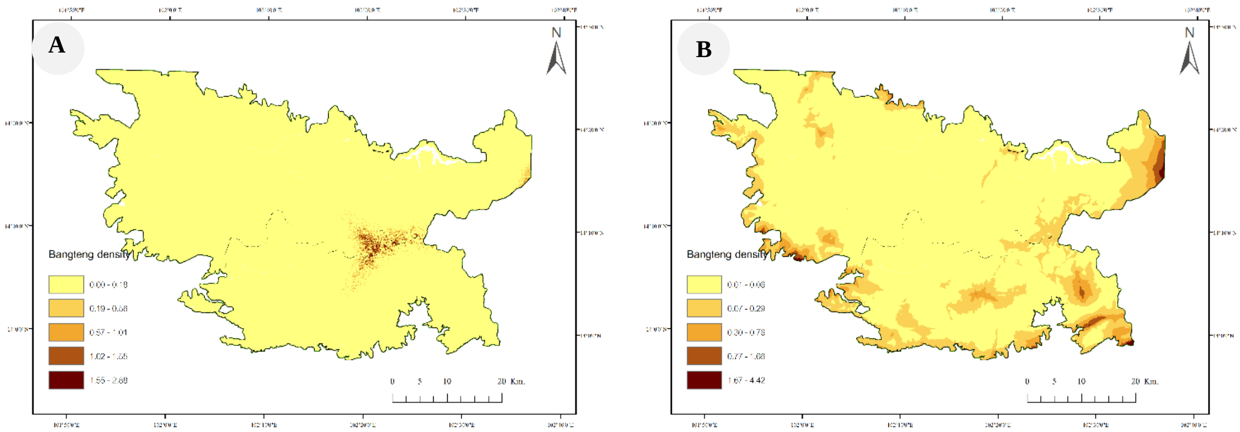

Figure 6. Estimated density of banteng, predicting densities using the REST Model (A) and RN model (B). There is more variability across the landscape because it uses different environmental factors, as it identifies specific areas with varying density levels. Darker shades indicate higher density (individuals/km²)

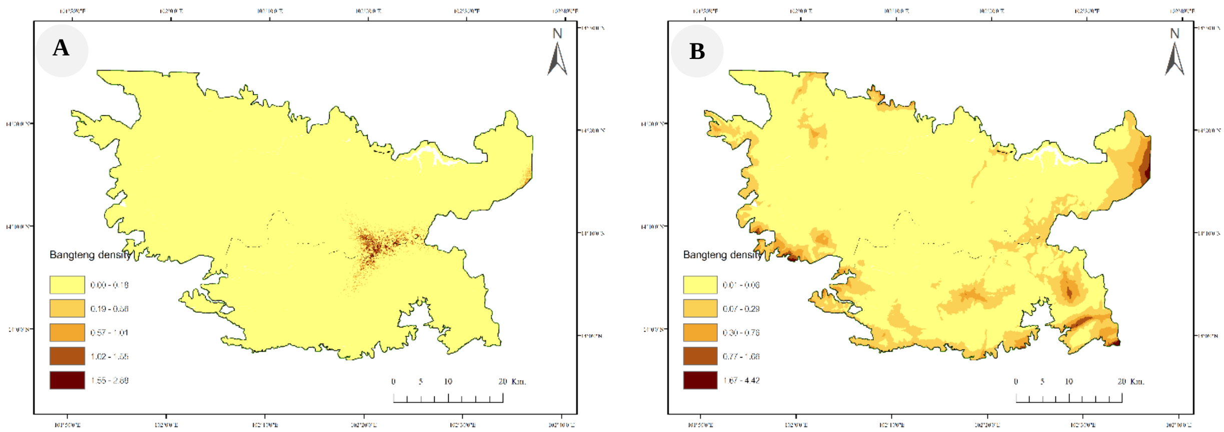

Figure 7. Estimated density of sambar deer, predicting densities using the REST Model (A) and RN model (B). There is more variability across the landscape because it uses different environmental factors, as it identifies specific areas with varying density levels. Darker shades indicate higher density (individuals/km²)

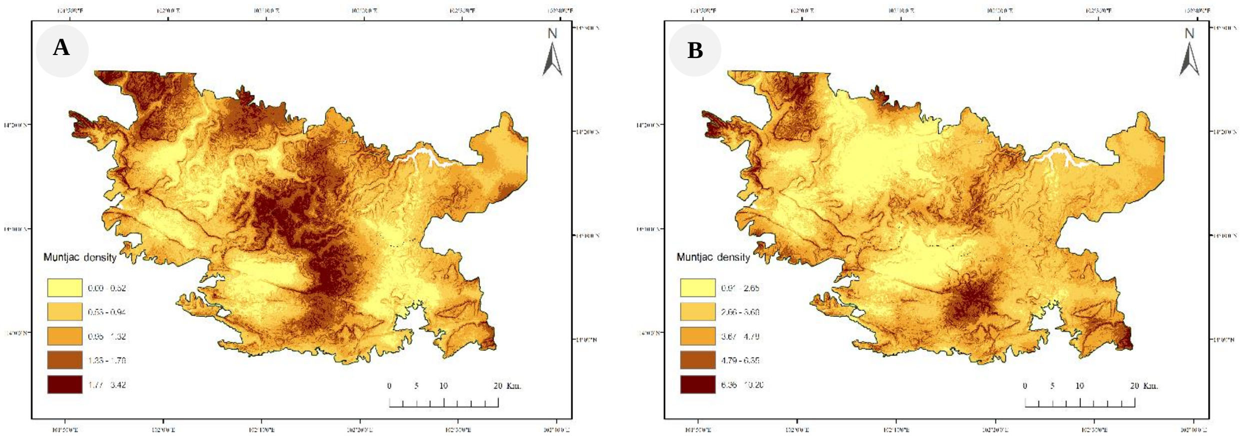

Figure 8. Estimated density of muntjac, predicting densities using the REST Model (A) and RN model (B). There is more variability across the landscape because it uses different environmental factors, as it identifies specific areas with varying density levels. Darker shades indicate higher density (individuals/km²)

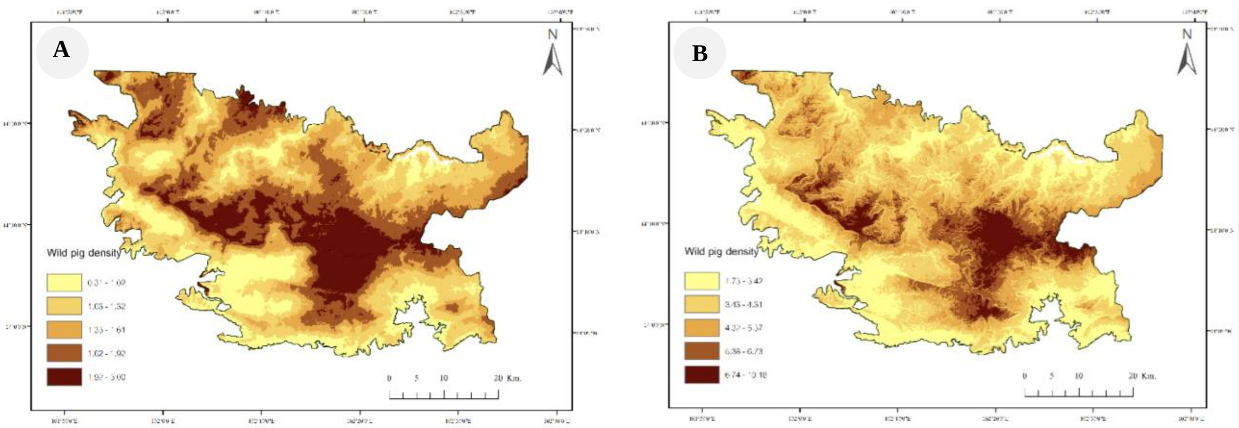

Figure 9. Estimated density of wild boar, predicting densities using the REST Model (A) and RN model (B). There is more variability across the landscape because it uses different environmental factors, as it identifies specific areas with varying density levels. Darker shades indicate higher density (individuals/km²)

The environmental factors that affected gaur density were complex and interconnected. The REST model indicated that gaur density increased with higher NDVI values and increasing distance to the nearest salt lick and village, whereas the RN model indicated that gaur density decreased with increasing distance to the closest stream and village. Banteng density increased with elevation and possibly with distance from the nearest stream according to the REST model, whereas the RN occupancy model indicated that banteng density decreased with increasing proximity to villages. The REST model showed that sambar deer density was negatively influenced by distance to the closest road, salt lick, and stream, and positively influenced by NDVI and distance to the nearest village. The REST model indicated that sambar deer density decreased significantly with increasing slope and proximity to threat occurrence, while the RN occupancy model suggested that sambar deer density was negatively influenced by increasing distance to threat occurrence, the nearest salt lick, and slope, and positively influenced by NDVI. Sambar deer density decreased significantly with increasing distance from the nearest stream and decreasing distance to the nearest village. Muntjac density increased with distance to the closest road and stream and with higher elevation, and decreased significantly with increasing proximity to threat occurrence according to the REST model, whereas the RN occupancy model showed that muntjac density increased with slope and distance to the closest road, and decreased with distance to the nearest villages, but increased significantly with distance from the nearest stream. The density of wild boars was positively influenced by distance to the closest stream and threat occurrence, as well as by elevation, and negatively influenced by distance to the closest road, slope, and NDVI according to the REST model. The RN occupancy model showed that wild boar density was higher in locations with higher elevation and increased distance to threats and the nearest stream, but lower in those with higher NDVI and slope.

Table 3. Coefficients of the REST model, exponential link with the lowest AICs

Species	Predictor	Coefficient	Standard error	P-value	AIC
Gaur	Intercept	-0.145	0.122	0.2390	2922.42
	NDVI	-0.296	0.119	0.0129	
	SLK	0.326	0.107	0.0023	
	VLG	-0.430	0.122	< 0.001	
Banteng	Intercept	-4.813	1.061	< 0.0001	90.11
	STM	1.721	0.628	0.0062	
	ELV	-2.103	0.756	0.0054	
Sambar deer	Intercept	0.200	0.152	0.190	6770.72
	ROD	-0.634	0.193	0.0011	
	SLK	-0.352	0.176	0.0453	
	SLP	-0.533	0.145	< 0.0001	
	TET	-0.811	0.203	< 0.0001	
	VLGI	0.479	0.147	0.0012	
	STM	-0.482	0.194	0.0132	
	NDVI	0.327	0.174	0.060	
Muntjac	Intercept	1.084	0.077	< 0.0001	7780.78
	ROD	-0.486	0.083	< 0.0001	
	STM	0.207	0.087	0.0183	
	TET	0.241	0.071	< 0.001	
	ELV	0.249	0.082	0.0024	
Wild boar	Intercept	1.505	0.075	< 0.0001	11512.51
	STM	0.294	0.098	0.0028	
	NDVI	-0.227	0.083	0.0064	
	ELV	0.270	0.092	0.0036	
	TET	0.117	0.078	0.1340	
	ROD	-0.166	0.081	0.0427	
	SLP	-0.124	0.084	0.1407	

Table 4. Coefficients of RN occupancy of the negative binomial link predicting encounters with the lowest AICs

Species	Predictor	Coefficient	Standard error	P-value	AIC
Gaur	Intercept	0.342	0.3002	0.2543	684.84
	STM	-0.176	0.0996	0.076	
	SLK	0.241	0.0891	0.0067	
	VLG	-0.368	0.0976	< 0.001	
Banteng	Intercept	-3.20	2.217	0.1486	44.72
	ELV	-1.97	0.981	0.0448	
	STM	2.23	0.959	0.0202	
	VLG	-1.37	0.836	0.1009	
Sambar deer	Intercept	-0.527	0.159	< 0.001	570.51
	TET	-0.213	0.124	0.0870	
	NDVI	0.342	0.117	0.0035	
	STM	-0.615	0.110	0.0001	
	SLK	-0.257	0.130	0.0481	
	SLP	-0.222	0.116	0.0553	
	VLG	0.721	0.109	< 0.0001	
Muntjac	Intercept	1.292	0.2479	< 0.0001	817.01
	STM	0.340	0.0701	< 0.0001	
	ROD	-0.190	0.0662	0.0042	
	SLP	0.142	0.0612	0.0206	
	VLG	-0.188	0.0626	0.0026	
Wild boar	Intercept	1.4711	0.2561	< 0.0001	772.85
	ELV	0.1863	0.0791	0.0186	
	TET	0.1110	0.0624	0.0749	
	NDVI	-0.1249	0.0644	0.0523	
	STM	0.1242	0.0714	0.0818	
	SLP	-0.0982	0.0643	0.127	

Discussion

Our findings reveal the intricate relationships between tiger prey species and environmental covariates within the DPKY. The results identified that vegetation cover, proximity to human settlements and roads, elevation, and the availability of resources like streams and salt licks strongly influence prey species' abundance. Employing both the Random Encounter and Staying Time (REST) model and the Royle-Nichols (RN) occupancy model, we found consistent agreement in density estimations. Muntjac and wild boar notably showed the highest abundances across both models, which align with previous research suggesting that these mammal species are highly adaptable to diverse habitats and potential resilience to human disturbance (Brodie et al. 2015; Pratumthong and Khlaipet 2022). This observation prompts questions about potential interspecific interactions, where muntjac and wild boar's success might impede other species crucial for tiger recovery, like gaur, banteng, and sambar deer. Future research should delve into how these species interact, examining aspects like resource partitioning, dietary overlap, and displacement effects. Studies by Carswell et al. (2023) on the impacts of wild boar on native ungulates suggest that competition can significantly alter community dynamics, which is crucial for tiger recovery. Our analysis also sheds light on how habitat covariates drive prey distribution, with high NDVI values correlating positively with sambar deer densities, suggesting that areas with denser vegetation offer superior foraging opportunities. The significant role of salt licks on prey distribution further emphasizes the importance of protecting these vital resources and managing their availability.

The varying responses of prey species to these environmental factors have significant implications for targeted conservation and management strategies within the DPKY. The potential positive effect of proximity to agricultural areas on gaur density, as noted by Prayoon et al. (2024), suggests adaptability but also raises concerns about increased human-wildlife conflict and the risk of disease transmission, such as Foot-and-Mouth Disease (FMD) (Rout et al. 2017). Conversely, the low density of banteng in areas accessible to humans underlines their vulnerability to habitat loss and hunting pressure (Phoonjampa et al. 2021). Thus, protecting banteng habitats and mitigating human encroachment are pivotal for their conservation. Moreover, ongoing monitoring of these populations is crucial for assessing trends and identifying both threats and opportunities for appropriate management (Harihar et al. 2014).

Our results from DPKY align with regional trends where adaptable species like muntjac and wild boar thrive. This is consistent with findings from Cambodia's Eastern Plains where banteng and muntjac densities are high yet lower than in South Asia due to historical hunting pressures (Gray et al. 2016). Similarly, in Thailand's WEFCOM, human proximity impacts gaur and sambar distribution (Jornburom et al. 2020). Despite reduced poaching, recovery for these species remains limited, pointing to the need for habitat and population management (Phumanee et al. 2020). In Myanmar's Hukaung Valley, the success of prey species in less disturbed areas (Naing et al. 2023) supports our observations on the negative impact of human presence. The link between tiger distribution and prey occupancy in WEFCOM (Duangchatrasiri et al. 2019) mirrors our findings on the importance of prey density for the recovery of the tiger population. Additionally, the management of human activities at habitat edges during banteng reintroduction in Thailand (Chaiyarat et al. 2023) underscores our observations on the vulnerability of certain species to human influence. In Malaysia, logged forests differentially affect ungulate species, with wild boar showing resilience (Linkie 2020), paralleling our insights on species-specific responses to environmental changes. Seasonal occupancy study in Nepal's Churia habitat (Thapa and Kelly 2017) further emphasize the dynamic nature of prey distribution affecting predator’s, a pattern reflected in our study. Thus, our conservation strategies in DPKY should focus on habitat restoration, minimizing human impact, and enhancing prey availability, leveraging these regional insights to bolster tiger recovery efforts.

It is crucial to acknowledge that the average time an animal spends in front of the camera can vary significantly due to factors including animal movement patterns, species size, population density, and camera placement. For instance, larger animals like gaur or banteng might cover more ground, triggering the camera less often than smaller, more active species like wild boar (Urbanek et al. 2019). This inherent variability in staying time highlights the necessity to recognize the limitations of the REST model, which depends on precise measurements of this metric. Additionally, the effectiveness of our density estimates hinges on the assumptions of both the REST and RN models. The REST model presumes that the time an animal is in front of a camera represents its general activity pattern, which may not hold true if behavior changes with environmental conditions or seasons. Similarly, the RN model's assumption of uniform detection probability across sites can be problematic in heterogeneous landscapes where detectability might vary due to vegetation changes or human disturbances, potentially skewing density estimates, especially for species like banteng with low detection rates, leading to an underestimation of their true population size. When compared to other camera trapping methods for abundance estimation, REST is particularly advantageous in high abundance scenarios, while methods like distance sampling and the random encounter model are preferable when abundance is low or camera performance is not optimal (Palencia et al. 2021). Despite these limitations, both RN and REST models offer valuable tools for estimating animal density on a landscape scale and identifying key habitat relationships (Nakashima et al. 2020).

Our findings underscore key implications for tiger conservation in the DPKY, where prey densities, especially larger species like banteng, are much lower than in Huai Kha Khaeng Wildlife Sanctuary, Thailand’s home of largest tiger population (Saisamorn et al. 2024). In Huai Kha Khaeng, sambar deer drive prey occupancy (Duangchatrasiri et al. 2019), aligning with DPKY’s dominant species occupancy (Pla-ard et al. 2022) and this study's density estimates, suggesting Huai Kha Khaeng's long-term protection contrasts with DPKY's ongoing recovery. In Batang Gadis National Park, Indonesia, camera traps show high muntjac abundance in permanent plots and wild boar prevalence in non-permanent plots (Rambe et al. 2021). Conversely, in Cambodia's Eastern Plains Landscape, wild pig densities exceed banteng and muntjac, but all are critically decreasing due to snaring (Groenenberg et al. 2020). This suggests that the larger prey availability might be a limiting factor for tiger recovery in many protected areas, necessitating focused management efforts on habitat restoration, population enhancement, conflict mitigation with humans, and tiger repopulation. Specific strategies should aim to improve habitat quality for prey species. One key approach is enhancing the availability of salt licks, which we identified as significant for several species. This could involve strategic placement or artificial provisioning where natural licks are scarce. Managing vegetation to increase NDVI in key habitats could benefit species like sambar deer, potentially leading to greater prey availability for tigers. Moreover, habitat enrichment, translocations, and community engagement programs might be necessary. On the policy level, our results advocate for stringent land-use regulations to restrict human encroachment into crucial prey habitats, particularly around villages and agricultural lands, to reduce human-wildlife conflicts. The policy should also encourage the expansion of conservation areas or the creation of wildlife corridors to reconnect fragmented habitats, aiding in the natural recovery of prey populations. Continuous monitoring is vital to track prey population trends and evaluate the effectiveness of these interventions against ongoing threats. Future research should investigate the long-term impacts of environmental change and conservation efforts on prey species, focusing on changes in vegetation, water availability, and disease prevalence and exploration of human-wildlife interactions within the DPKY landscape. By understanding these relationships between tiger prey species and their environment, we can better inform management decisions, contributing to the long-term sustainability of this critical ecosystem.

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