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Abundance, activity pattern and habitat suitability of the selected wildlife species in Ob Khan National Park, Northern Thailand

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Abstract

The study on the abundance, activity patterns, and suitable habitats of the selected wild mammal species in Ob Khan National Park, Chiang Mai Province, representing the northern conservation area of the country, was conducted using camera traps between August 2021 and July 2022. The study results from 4,304 trap-nights revealed at least nine species of mammals. These included wild boar (*Sus scrofa*), followed by golden jackal (*Canis aureus*), red muntjac (*Muntiacus muntjac*), common palm civet (*Paradoxurus hermaphroditus*), rhesus macaque (*Macaca mulatta*), northern serow (*Capricornis sumatraensis*), northern tree shrew (*Tupaia belangeri*), leopard cat (*Prionailurus bengalensis*) and murid species. Most of the wildlife activity occurred during nighttime. The factors influencing the presence of the wildlife species that could be analyzed include three species: red junglefowl, common palm civet, and wild boar. The average percent contribution indicated that climate variables have the highest influence, particularly rainfall, followed by land cover variables and topographic variables. It was found that the factors influencing the presence of the three species do not differ. It also was found that more than 90% of the study area is classed as moderately suitable and less suitable for the wildlife. Therefore, management efforts should focus on highly suitable areas, including the conservation of the mixed deciduous and pine forests, while water source enhancement for wildlife conservation should be protected and improved.

Keywords: Bioclimatic variable, Common Plam Civet, Land cover variable, Northern Thailand, Topographic variable

Introduction

The northern natural areas of Thailand are characterized by intricate mountainous terrain, exhibiting continuity with the mountain ranges present in neighboring countries such as Myanmar, Laos, and China (Royal Department of Mineral Resources, 2014). The movement and settlement of populations within this northern region were influenced by the topographical features, with a significant influx of people from external sources, particularly China, specifically from the southwestern regions of China, as well as from Laos, Vietnam, Myanmar, and even Tibet (Haenssgen et al., 2023). This migration trend has been persistent over the past centuries, escalating notably before the Cold War era, largely driven by state policies. Local communities residing in the highland areas traditionally engaged in the nomadic movement, selecting settlement locations based on elevated terrain and establishing bases in areas with suitable agricultural practices aligned with their cultural norms (Haenssgen et al., 2023). The expansion of settlement areas correlated with population growth, prompting the Thai government to implement multidimensional policies covering various aspects (Morton & Baird 2019; Virapongse, 2017).

The Department of Social Development and Welfare (2016) indicated over 14 million hilltribe people inhabited the highland areas in Thailand. Numbering approximately 600,000 the hill tribes consist of 7 main groups located in the northern part of Thailand (Apidechkul, 2015; Srisoda, 2016). The consequences of habitation in these highland areas led to environmental changes, negatively impacting the natural ecosystem (Trisurat et al., 2014; 2023). In response, the Thai government initiated policies such as declaring protected natural areas as national parks and wildlife sanctuaries to mitigate the challenges arising from settlement in natural forests and watershed areas. Measures were also implemented to designate suitable areas for permanent settlement, emphasizing the conservation of quality watershed areas and the sustainable management of forest resources (Morton & Baird 2019; Virapongse, 2017). However, the conservation areas in northern Thailand, though declared protected, have still faced challenges from human activities, particularly historical deforestation for agriculture. Even in some elevated regions disturbances persist, including illegal logging, wildlife poaching, and unregulated livestock grazing. In addition, annual forest fires are a major concern that harm the natural environment and result in the loss of large wildlife populations in the region (Malhi et al., 2022).

The significant consequences resulting from the disturbance of natural areas include the emergence of crises such as haze pollution and air pollution, with implications for the overall health issues of the general population at the regional level (Pardthaisong et al., 2018). Management approaches from an educational grassroots perspective can be utilized for improvement and mitigation to address the problems associated with the degradation of biodiversity and environmental systems, as well as the decline in the wildlife population. To alleviate these issues, a comprehensive strategy for managing the natural areas has been proposed, drawing on foundational studies. This includes implementing measures to mitigate the effects of crises such as smoke pollution and deteriorating air quality. These involve reducing the impact on the wildlife population, tracking and studying wildlife populations using camera traps, and systematically surveying wildlife through organized monitoring initiatives (Wildlife Conservation Society: WCS, 2024).

This study aimed to investigate the species, abundance, and activity patterns of wildlife in areas that have been disturbed. Additionally, the study investigated a hypothesis regarding the relationship of climatic factors, including rainfall, temperature, and also topography, and land cover conditions, with the occurrence of key wildlife species in the area. The study also sought to compare the impact of these factors on the appearance of each species in the area by calculating averages and utilizing analysis of variance. The study focused on the Ob Khan National Park (OKNP), situated between Doi Suthep-Pui National Park and Doi Inthanon National Park, (Junkhiaw et al., 2013). This area had been previously disturbed and lacked comprehensive studies on wildlife through camera trapping and the associated analysis. The study aimed to provide valuable data for future conservation and management planning, emphasizing the need for continuous monitoring and analysis of the region's wildlife to preserve environmental integrity and biodiversity.

Material and methods

Study area

The OKNP was officially established in 1992. The park spans the districts of Samoeng, San Pa Tong, Hang Dong, and Mae Wang. It is adjacent to Doi Suthep–Pui National Park (DPNP) to the east, and Mae Wang National Park and Doi Inthanon National Park (DNNP) to the west and covers an area of 266 km^2 approximately. Its landscape is characterized by a diverse terrain of hills tracing the Thanon Thong Chai Mountain range, with elevations ranging from 400 to 1,909 meters above sea level. Prominent peaks within the park include Doi Pha, towering at the highest point, along with other notable summits such as Doi Pong Somrit (1,547 meters), Doi Hin Luang (1,518 meters), Doi Huai Luang (1,415 meters), Doi Mae Liap (1,311 meters), Doi Khun Mae Sa (1,251 meters), Doi Pha Lai (1,245 meters), and Doi Ngo (1,120 meters). These mountains are the sources of three main rivers: Mae Jam, Mae Wang, and Mae Tuen, flowing into the Ping River.

The area is subject to the southwest monsoon's influence, which manifests in three distinct seasons: a hot period extending from March to May, a rainy season lasting from June to November, and a cooler interval from December to February. The average annual temperature hovers around 20 degrees Celsius. Throughout the cool season, temperatures usually fluctuate between 15 to 17 degrees Celsius, occasionally dipping to lows of 10 to 14 degrees Celsius. Annual rainfall typically ranges between 2,000 to 2,100 millimetres.

The OKNP showcases a rich variety of forest ecosystems distinguished by elevation. Elevations between 400 to 1,000 meters harbor mixed deciduous forests. In the 400–900-meter range, especially along hills or slopes, dry dipterocarp forests are prominent. Pine forests flourish at elevations of 900 to 1,500 meters above sea level, while montane forests dominate at altitudes exceeding 1,000 meters. The park is home to a diverse array of wildlife, such as barking deer, wild boar, macaque, white-handed gibbon, binturong, dhole, and pangolin, as well as numerous species of forest birds, reptiles, and amphibians (Department of Wildlife, National Parks, and Plant Conservation Department: DNP, 2024) (Fig. 1 and Fig. 2).

A B C D

Figure 1. General characteristics of the study area and data collecting activities.

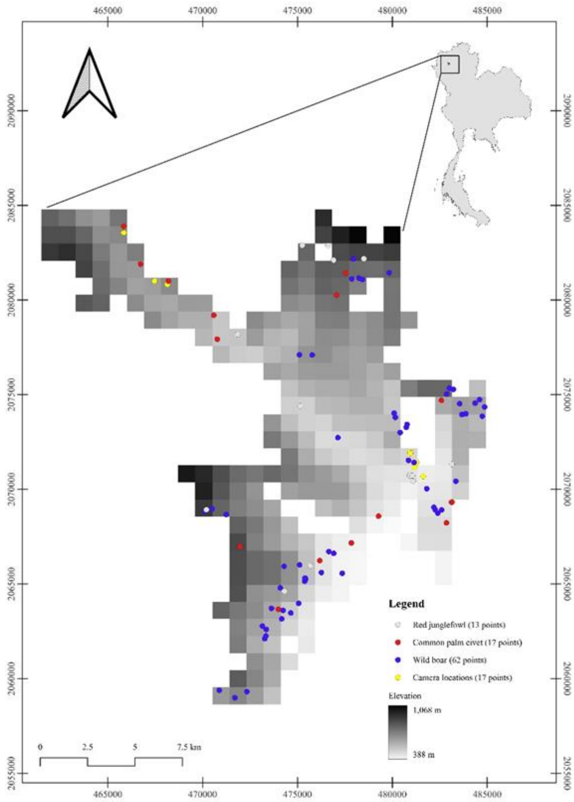


Figure 2. Location of the study area and occurrence points of red junglefowl, Asian palm civet, and wild boar.

Field data procedure

This involved the installation of 15 automatic camera traps (Trail Camera Model Essential E3). The camera traps were placed alternately, with varying numbers in each location, totaling 20 camera locations and a cumulative total of 4,304 trap nights. The study's methodology is as follows: a 1 square kilometer area was marked out on a topographic map at a scale of 1:50,000. One camera trap was installed per grid square, resulting in one camera for each square kilometer. Camera traps were set up in 10 to 15 grid squares at a time, and they remained in each location for 60 days before being moved to a new location. Typically, each camera trap installation location was more than 500 m from the next, ensuring independence in obtaining images within each grid and reducing the probability of capturing the same animal with multiple cameras (Rafatpey et al., 2023). The locations of the camera traps and the study area can be seen in Figure 1. Selecting a camera trap location involved considering the suitability of each area, such as animal paths, traces, and checkpoint routes (Wearn and Glover-Kapfer, 2017; Palencia et al., 2022). Records were made of detailed information about plant communities, roads, surveillance routes, permanent water sources, and salt licks in the area. Installation of the camera traps was carried out approximately 30-40 cm above the ground, positioned 3-4 m away from the target area, or as deemed appropriate based on the local conditions.

The camera was set to capture photos when motion sensors were triggered, taking 3 images spaced 10 seconds apart, continuously throughout the day and night. Camera traps were initially deployed for 30 days. After this duration, they were relocated to a new site, using a Global Positioning System (GPS) device to record the precise location where the camera trap was installed. Transfer of the photos from the memory card to a computer and classification of the images used the Camera Trap Manager Program (Zaragozi et al., 2015).

The data collection involved recording the presence of the key wildlife species of each patrol unit responsible for monitoring in the national park or the SMART program (WCS, 2024). There were in total 5 patrol units, each comprising 5 – 8 park rangers (WCS, 2024). These ranger units conducted patrols two times a month, with each patrol lasting between 3 to 5 days. Whenever they encountered signs, tracks, or direct sightings of key wildlife species, the information was documented using a data recording form. The data were collected from patrol unit reports starting from January 2021 until December 2022. This data collection aimed to compile high-quality qualitative records of the key species' sightings within the boundaries of the park.

Data analysis

The species that could be photographed were identified and recorded. Using common names and zoological names after Lekagul & McNeely (1988); Lekagul & Round (1991); and the International Union for Conservation of Nature: IUCN (2024), only identifiable images have the date and time shown on the photograph. Pictures with more than one animal in the same image were counted as one and would be an independent figure or event. The criteria for independence of animal photographs are (1) consecutive images of different animals; that may be of the same species or different species; (2) consecutive images of the same animal of the same species; more than 30 minutes apart, and (3) discrete images of the same animal of the same species.

Camera traps provide a non-invasive way to observe and quantify animal activity at the population level in a relatively cost-effective manner (Tanwar et al., 2021). Data were summarized by the active period obtained from the camera trap, both by combining the data and classifying by type by dividing the time between 06:01 - 17:59 as the daytime and between 18:00 - 06:00 as the nighttime, which was classed differently into 5 groups. If the number of night shots exceeds 85%, the data are categorized as exhibiting a strong nocturnal pattern. Nighttime images representing 61% to 84% fall under the category of the most active pattern. When the number of images taken during both day and night falls between 40% and 60%, it is grouped as displaying a cathemeral overlapped activity pattern (mostly nocturnal and diurnal). Images captured during the daytime within the range of 61% to 84% are associated with predominantly diurnal activity patterns, while more than 85% of daytime images are classified as strongly diurnal activity patterns. Spatial and temporal data are collected using camera trap positions to capture images when wildlife is present (coded as 1) and when it is not present (coded as 0). These data are recorded for each hour of the day. We used the time stamp metadata obtained to compute a kernel density function using R programs (Naderi et al., 2021; The R Core Team, 2022).

Habitat modeling

The MaxEnt program was used to construct the habitat suitability map by quantifying the factors affecting the occurrences of the species. This methodology, as described by Phillips and Dudík (2017), serves to analyze and quantify the relationship between the species occurrences and key environmental variables, thereby enhancing our understanding of the factors that influence the presence of wildlife in a given environment. To perform the analysis, the data need to be transformed into ASCII format for use in the MaxEnt program (Naqibzadeh et al., 2022).

The data consists of two types: continuous data and categorical data. The continuous data is composed of Slope (degree), and Forest Canopy Cover (percent). The categorical data is composed of plant community types. Each category should be assigned a unique numerical value to represent it in the analysis. The data will be split into two sets: a training set and a testing set, with a 75:25 ratio. The training set (75%) will be used to train the MaxEnt model, while the testing set (25%) will be used to evaluate its performance. The equal training sensitivity and specificity criterion is applied, and a logistic threshold is chosen to distinguish the presence and absence of the pheasants. To assess the importance of each environmental factor, metrics such as percentage contribution and percentage permutation can be used, which are derived from model testing. We selected the predictor variables from the layer of the present time, which were >10% for percent contribution (Khanum et al. 2013). The areas under the curve (AUC) of a receiver operating characteristics (ROC) plot were considered to evaluate the performance of the models. The higher AUC values are associated with higher accuracy (Morasca & Lavazza 2020). The contribution of each selected variable was assessed from the percentage contribution and permutation importance. These metrics help indicate the relationship between the presence of the species and the primary environmental variables. Finally, these transformed datasets and analyses can be employed to show the relationships between the presence of the species and the main environmental variables. This analytical process follows the methodology described by Phillips & Dudík (2017).

The logistic threshold is utilized to categorize data based on whether its value is greater than or equal to the logistic threshold, indicating presence, or if it is less than or equal to the threshold, indicating absence. Subsequently, the testing of the accuracy of the models derived from the data categorized at different logistic thresholds is performed. This evaluation employs the area under the curve (AUC) under the graph, which represents the analysis results ranging between 0.00 and 1.00. There are six values, namely minimum training presence, 10th percentile training presence, equal training sensitivity plus specificity, maximum training sensitivity plus specificity, equal test sensitivity plus specificity, and maximum test sensitivity plus specificity. These values are used for assessing accuracy and making predictions to identify the suitable model pattern. This approach aims to find a model that best fits the data and its patterns. The values mentioned above are employed to ascertain accuracy and predictive capabilities, following the methodology as outlined by Trisurat et al., (2019).

The area under the curve (AUC) under a receiver operating characteristics (ROC) curve indicates the accuracy of a model. When the AUC value approaches 1, it suggests that the model has high sensitivity and specificity (Fawcett, 2006). The logistic threshold is employed to categorize data as either "present" if it is greater than or equal to the threshold, or "absent" if it is less than or equal to the threshold. The accuracy of models derived from data categorized at different logistic thresholds is then tested using the AUC under the ROC curve, both at significance levels of $P<0.05$ and $P<0.01$. Additionally, the duration of appearance is calculated as a percentage. A map of the probability of the species' presence is generated. The habitat suitability is classified into four levels: (1) unsuited, (2) low or poor suited, (3) moderately suited, and (4) highly suited. The study of the suitability of habitats for wild animals was carried out as follows, by using geographic coordinate data obtained from finding wildlife tracks in the SMART program and from camera traps. The data are then exported to a file with the extension "CSV" for use as an import file for the program MaxEnt Version 3.4.1 to create a model. Together with environmental data, data for bioclimatic parameters from Worldclim (2024) (http://www.worldclim.org) are freely available and have a resolution of 30 arcseconds. Such data can be used in modeling (Hijmans et al., 2005; Berhanu et al., 2022). Spatial environmental factors including slope direction, slope, and water source (Kamyo & Asanok 2020) were selected as input variables for the model. It is Digital Elevation Model (DEM) data from Shuttle Radar Topography Mission (SRTM) data (http://www.srtm.usgs.gov/index.php) (U.S. Geological Survey 2024).

The bioclimatic factors and spatial characteristics data were created in "GRID" format. The raster data had a grid size of 30 arc seconds and were then converted to "ASCII" format (Scheldeman & Zonneveld, 2010) to create data that can be analyzed together with the MaxEnt program by rating the suitability of living habitats on a level of 0 (areas that are of minimum suitability) to 1 (highest suitability area) to create the spatial distribution of wildlife in ARCGIS. MaxEnt was then used to generate response curves for each predictor variable using the Jackknife method to highlight the relative influence of the individual variables (Khanum et al., 2013; Swanti et al., 2018). The percentage used for random testing is set at 20 percent, while other values are set according to the default values of the program. In addition, the omission-commission rate is used depending on criteria that are determined from the prediction area (Phillips & Dudik, 2017). Variable selection improves model power by eliminating multicollinearity between variables and reducing the number of variables required (Dormann et al., 2007; 2013; Yi et al., 2016). The variance inflation factors (VIFs) of 25 environmental variables were tested using the "usdm" package in R studio (Naimi et al., 2014). VIFs are based on correlation coefficients. Variables with VIFs >5 were eliminated (Chatterjee & Hadi 2006). Ultimately, 10 variables were selected for inclusion in the model: forest type, slope, distance to a stream, NDVI, BIO3, BIO7, BIO14, BIO15, BIO17, and BIO19.

All environmental variables used in the developed models were resampled using the bilinear re-sampling technique (Ren et al. 2016) and clipped to the same dimensions at a 30-arc second resolution (~1-km spatial resolution) in ASCII format using R studio (R Core Team, 2022). By incorporating a range of topographic and bioclimatic variables, the habitat suitability models provide a comprehensive understanding of the environmental factors influencing the presence of red junglefowl, Asian palm civet, and wild boar in OKNP, which can inform assessments of current and future habitat suitability to assist conservation and management efforts (Table 1).

Table 1. Environmental variables for each scenario.

Environmental variables	**Year**	**Sources**
Land cover variables		
Percentage tree cover	year 2000-2022 (Download from Google Earth)	The Terra Moderate Resolution Imaging Spectrora Diameter, Vegetation Continuous Fields (MODIS VCF) (Dimiceli et al. 2015)
Forest type	year 2018	Royal Forest Department: RFD, Ministry of Natural Resources and Environment (RFD, 2018)
Normalized difference vegetation index (NDVI)	year 2013-2023 (Download from Google Earth)	Landsat 8 (U.S. Geological Survey, 2024)
Topographic variables		
Elevation	Download from Google Earth	The National Aeronautics and Space Administration, Shuttle Radar Topography Mission (NASA SRTM) (Farr et al. 2007; Gorelick et al. 2017)
Slope	Download from Google Earth	The National Aeronautics and Space Administration, Shuttle Radar Topography Mission (NASA SRTM)

		(Farr et al. 2007; Gorelick et al. 2017)
Distance to a stream	year 2023	Regional Center of Geo-Informatics and Space Technology (GISTNU) (Gistnu, 2023)
Bioclimatic variables	year 1970-2000	https://www.worldclim.org (WorldClim version 2.1) (Fick & Hijmans 2017)

Habitat suitability model

The habitat suitability models were constructed using the MaxEnt algorithm implemented in MaxEnt ver. 3.4.4 (Phillips et al., 2017). The models were built and tested on 10 replicate units using a subsample training method and a maximum of 500 iterations with the default of 10,000 backgrounds; 75% of the data were assigned for training and the remaining 25% for testing. The outputs were in log-log (clog-log) format (Trisurat et al., 2014; Ab Lah et al., 2021; Mcgarvey et al., 2021; Khan et al., 2022). The models were calibrated to assign suitability values ranging from 0 to 1, with 0 being the minimum suitable and 1 being the maximum suitable, classified into four levels: unsuitable, 0.00–0.25; poorly suitable, 0.25–0.50; moderately suitable, 0.50–0.75; and highly suitable, 0.75–1.00.

Results

The encounter rate based on camera trap data

Results of the installation of camera traps in 15 locations in the area between August 2021 and July 2022 encompassed a total of 4,304 trap nights. A total of 9 species of wild mammals from 7 families were found. The encounter rate per 100 trap nights of the mammals included wild boar (1.51%), golden jackal (1.32%), red muntjac (0.95%), common palm civet (0.37%), rhesus macaque (0.34%), serow (0.25%), northern tree shrew (0.25%), and leopard cat (0.06%), for which the total encounter rate of wild animals was 5.13%. Four aves species can be recorded from camera traps from 4 families: crested serpent eagle (*Spilornis cheela*), emerald dove (*Chalcophaps indica*), red junglefowl (*Gallus gallus*), and verditer flycatcher (*Eumyias thalassinus*), with the red junglefowl being the most common. In the case of the aves species group, the total encounter rate was 0.28%. The details are shown in Table 2.

Table 2. Wild mammal species according to taxonomy, conservation status, number of independent wildlife images, and % ER gained by camera trapping in the OKNP, Chiang Mai Province from August 2021 to July 2022.

No	Common name	Scientific name	Event	No. of location found	%ER	Status	
						IUCN	NS
Mammal							
Family Suidae							
1	Wild Boar	*Sus scrofa*	65	8	1.51	LC	LC
Family Canidae			0				
2	Golden Jackal	*Canis aureus*	57	12	1.32	LC	VU
Family Muntiacidae			0				
3	Red Muntjac	*Muntiacus muntjak*	41	7	0.95	LC	NT
Family Viverridae			0				
4	Common Palm Civet	*Paradoxurus hermaphroditus*	16	7	0.37	LC	LC
Family Cercopithecidae							
5	Rhesus macaque	*Macaca mulatta*	15	2	0.34	VU	EN
Family Tupaiidae							
6	Northern Treeshrew	*Tupaia belangeri*	11	3	0.25	LC	LC
Family Bovidae							
7	Serow	*Capricornis sumatraensis*	11	1	0.25	VU	VU
Family Felidae							
8	Leopard Cat	*Felis bangalensis*	3	1	0.06	LC	LC
Family Muridae							
9	Rattus spp.		2	2	0.05	-	-
		Total	221		5.13		
Aves							
Family Accipitridae							
1	Crested Serpent Eagle	*Spilornis cheela*	3	2	0.06	LC	LC
Family Columbidae							
2	Emerald Dove	*Chalcophaps indica*	3	2	0.06	LC	LC
Family Phasianidae							
3	Red Junglefowl	*Gallus gallus*	4	6	0.09	LC	LC
Family Muscicapidae							
4	Verditer Flycatcher	*Eumyias thalassinus*	2	2	0.05	LC	LC
		Total	12		0.28		
	Total		233	15	5.41		

Notes: IUCN: International Union for Conservation of Nature (2024),
NS: National Conservation Status (2021) VU – Vulnerable, LC - Least Concerned;
NT: Near threaten, EN: Endangered

Activity patterns

The study findings revealed that the common palm civet was classified as strongly nocturnal, while serow, red muntjac, and golden jackal were categorized as mostly nocturnal. Leopard cat, rhesus macaques, and wild boar were grouped as cathemeral. The northern treeshrew was categorized as strongly diurnal (Figure 3). This classification was based on the analysis results depicted in Figure 4.

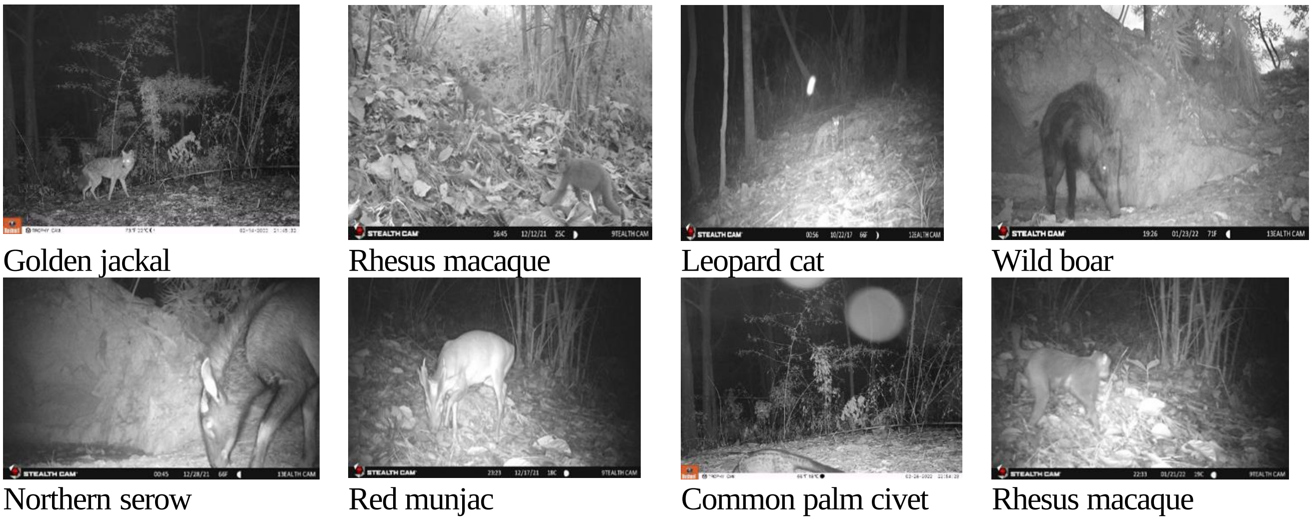


Figure 3. An example of the key wildlife species pictures gained from camera trap techniques in the OKNP during 2021 – 2022.

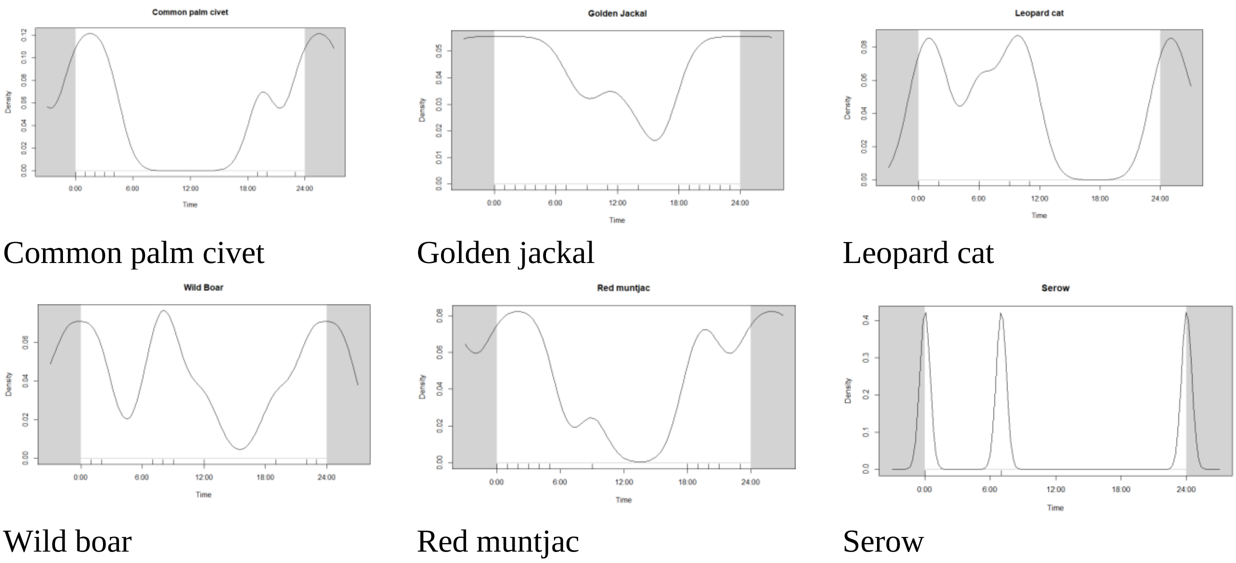


Figure 4. An example of the activity pattern of the wildlife activity captured on a camera trap in the OKNP.

Factors affecting the appearance of the species

After conducting a thorough examination and establishing correlations through the calculation of Pearson correlation coefficients to select variables significantly related to the presence of any one of the three types of wildlife with values exceeding 90%, it was found that six climatic factors out of 19 had an impact on the occurrence. These factors included Isothermality (BIO3), Temperature Annual Range (BIO7), Precipitation of Driest Month (BIO14), Precipitation Seasonality (BIO15), Precipitation of Driest Quarter (BIO17), and Precipitation of Coldest Quarter (BIO19). The analysis revealed that for each wildlife species, climatic factors influenced the appearance differently. For red junglefowl, it was observed that climatic factors accounted for 72.7% of the occurrence, with precipitation contributing 70.5%, temperature 2.20%, and land cover variables, specifically forest type, influencing 26.5%, followed by distance to a stream at 0.8%. Considering the appearance of the Asian palm civet, climatic factors explained 50.1% of the occurrence, with temperature contributing 42.3%, precipitation 7.8%, and land cover variables, particularly forest type, accounting for 26.5%, and NDVI at 3.8%, with distance from water sources at 7.7%. In the case of wild boar, climatic factors were found to have an 83.10% influence on the occurrence, with precipitation contributing 78.30%, temperature 4.8%, and topographic variables, including slope at 5.3%, and distance to a stream at 5.9%. Land cover variables, such as forest type, played a role at 3.9%, and NDVI at 1.7%, with distance from water sources at 7.7%. When considering the average influence of factors on the occurrence of all wildlife species, climatic factors were found to be the most influential at 68.63%, with precipitation contributing 52.20%, temperature 16.43%, and land cover variables, particularly forest type, at 24.73%. Forest type had an impact of 22.9%, NDVI at 1.83%, and topographic variables at 6.6%, including slope at 1.8%, and distance from water sources at 4.8%. Figure 4 considers the extent of environmental factors affecting the appearance of wild animals found. It was found that the slope area was in the range of 1.37 - 10.90% and the distance from the water stream was in the range of 122.06 - 602.74. The forest types that were important to wildlife were mixed forests, followed by pine forests and open areas, respectively, while the cover value of groups of trees (NDVI) has a value between 0.64 - 0.819. Isothermality (BIO3) has a value between 49.30-51.23. Temperature Annual Range (BIO7) has a value between 21.66 - 22.95. Precipitation of the Driest Month (BIO14) has a value between 2.0-2.56. Precipitation Seasonality (BIO15) has a value of 80.71-83.06 while Precipitation of Driest Quarter (BIO17) has a value of 17.0-23.12. Precipitation of Coldest Quarter (BIO19) at 17.0-64.78 is important to the appearance of each type of wild animal, as detailed in Table 3. The factors influencing the presence of the three species do not differ significantly according to the results of the Kruskal-Wallis Test ($H=1.27$; $P=0.52$).

Habitat suitability

The suitable habitats of the species were categorized into 4 levels: unsuitable, 0.00–0.25; poorly suitable, 0.25–0.50; moderately suitable, 0.50–0.75; and highly suitable, 0.75–1.00. The results of the analysis are shown in Figure 3. The area under the curve (AUC) value is more than 0.70, which represents a standard level of reliability in each species. These were red junglefowl, common palm civet, and wild boar, with area under the curve (AUC) values of 0.70, 0.79, and 0.76, respectively.

Table 3. The models' relative percentage contributions (RCs) and the average values of environmental variables within the samples of red junglefowl, Asian palm civet, and wild boar habitat suitability in the OKNP.

Environmental variable	Red junglefowl (AUC = 0.700)		Common palm civet (AUC = 0.798)		Wild boar (AUC = 0.767)		Average RC (%)
	RC (%)	Sample Average (± SD)	RC (%)	Sample average (± SD)	RC (%)	Sample average (± SD)	
Land cover variable	**26.5**		**42.1**		**5.6**		**24.73**
Forest type	26.5	Mixed Deciduous Forest	38.3	Mixed Deciduous Forest	3.9	Mixed Deciduous Forest	22.90
NDVI	0	0.74 ± 0	3.8	0.72 ± 0	1.7	0.73 ± 0	1.83
Topographic variable	**0.8**		**7.8**		**11.2**		**6.60**
Slope	0	5.34 ± 0.22 degrees	0.1	4.61 ± 0.21 degrees	5.3	5.47 ± 0.15 degrees	1.80
Distance to a stream	0.8	243.93 ± 12.34 m	7.7	275.6 ± 12.83 m	5.9	232.84 ± 6.3 m	4.80
Bioclimatic variable	**72.7**		**50.1**		**83.1**		**68.63**
Isothermality (BIO3)	2	50.05 ± 0.05 %	5.1	50.08 ± 0.05 %	3	49.99 ± 0.02 %	3.37
Temperature Annual Range (BIO7)	0.2	22.31 ± 0.02 ˚C	37.2	22.42 ± 0.04 ˚C	1.8	22.24 ± 0.02 ˚C	13.07
Temperature	**2.20**		**42.3**		**4.8**		**16.43**
Precipitation of Driest Month (BIO14)	57.1	2 ± 0 mm	1.5	2 ± 0 mm	1.7	2 ± 0 mm	20.10
Precipitation Seasonality (BIO15)	13.4	82.12 ± 0.05 %	0	82.19 ± 0.08 %	59.6	81.94 ± 0.05 %	24.33
Precipitation of Driest Quarter (BIO17)	0	19.8 ± 0.12 mm	6.3	19.66 ± 0.1 mm	6.8	19.62 ± 0.05 mm	4.37
Precipitation of Coldest Quarter (BIO19)	0	23.01 ± 1 mm	0	23.45 ± 1.14 mm	10.2	26.71 ± 0.96 mm	3.40
Precipitation	**70.5**		**7.8**		**78.3**		**52.20**

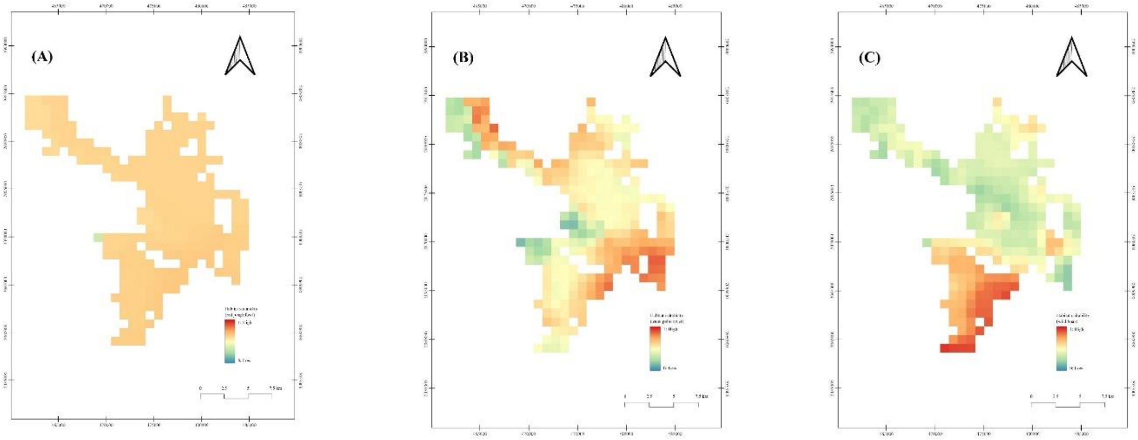
Results from the analysis of suitable habitat for red junglefowl indicated that the moderately suitable area had been 265 km^2, constituting 99.62% of the total area. Following that, the poorly suitable area covered 1 km^2, accounting for 0.38% of the total area. For the Asian palm civet, it was determined that the highly suitable area was 31 km^2, representing 11.65% of the total area. The area with unsuitable conditions for habitation was 5 km^2, or 1.88% of the total area. Moderately suitable areas encompassed 155 km^2, making up 58.27%, followed by a poorly suitable area of 73 km^2, equivalent to 27.44% of the total area. Concerning wild boar, the highly suitable area covered 31 km^2 or 11.65% of the total area. Areas with unsuitable conditions for habitation occupied 7 km^2, representing 2.63% of the area. Poorly suitable areas had the highest value at 166 km^2, constituting 62.41% each, followed by moderately suitable areas at 64 km^2 or 24.06% of the total area. Upon considering the overall average for all types, it was observed that the majority were moderately suitable areas, making up 60.65% of the area, with highly suitable residential areas accounting for 7.77% of the area, as detailed in Table 4 and Figure 5.

Discussion

Considering the diversity of wildlife found in the area, ungulates such as red muntjac, serow, and wild boar still coexist. Additionally, rhesus macaque, northern tree shrew, leopard cat, golden jackal, and common palm civet are present in the area but are found in mixed deciduous forests with high humidity, which are green areas during the dry season. These areas are essential for conservation efforts, and activities such as releasing domestic animals, poaching, and the use of fire for land improvement affect wildlife presence. There is a risk of climate change due to the impact on their environmental systems, while other species have lower risks. The significant events related to climate conditions, coupled with human-induced stress factors, affect the ecological balance and wildlife resource distribution. Understanding the influence of climate factors on wildlife resources is crucial for adaptive management and biodiversity conservation (Kupika et al., 2018). The high areas in the northern mountain range are considered important habitats for wildlife if severe climate change occurs (Pomoim et al., 2022; Masud et al., 2016; Trisurat et al., 2023).

Table 4. Suitable habitat for red junglefowl, Asian palm civet, and wild boar in the OKNP.

Habitat Suitability		**Red junglefowl**	**Asian palm civet**	**Wild boar**	**average**
Unsuitable	area (km^2)	0	7	5	4.00
	% of OKNP	0.00	2.63	1.88	1.50
Poorly suitable	area (km^2)	1	73	166	80.00
	% of OKNP	0.38	27.44	62.41	30.08
Moderately suitable	area (km^2)	265	155	64	161.33
	% of OKNP	99.62	58.27	24.06	60.65
Highly suitable	area (km^2)	0	31	31	20.67
	% of OKNP	0.00	11.65	11.65	7.77
Summary area of OKNP (km^2)		266	266	266	266



Red junglefowl Common plam civet Wild boar

Figure 5. Habitat suitability for (A) Red junglefowl, (B) Asian palm civet, and (C) Wild boar in the OKNP.

Thinphovong (2023) reported a total of at least 20 wild mammal species, including Indochinese serow (*Capricornis milneedwardsi*), red muntjac (*Muntiacus muntjak*), northern pig-tailed macaque (*Macaca leonina*), leopard cat (*Prionailurus bengalensis*), Asian golden cat (*Catopuma temminckii*), back-striped weasel (*Mustela strigidorsa*), dhole (*Cuon alpinus*), golden jackal (*Canis aureus*), greater hog badger (*Arctonyx collaris*), small Asian mongoose (*Herpestes javanicus*), common palm civet (*Paradoxurus hermaphroditus*), large Indian civet (*Viverra zibetha*), Asian black bear (*Ursus thibetanus*), wild boar (*Sus scrofa*), northern tree shrew (*Tupaia belangeri*), variable squirrel (*Callosciurus finalaysonii*), Indochinese ground squirrel (*Menetes berdmorei*), Chinese pangolin (*Manis pentadactaly*), lesser bamboo rat (*Cannomys badius*), various species of murid rodents, and bats along a gradient of a human-dominated habitat in the Nanthaburi National Park, Nan Province, Northern Thailand during November 2021 and December 2022 based on 25 camera trap locations. This study found a total of 13 mammal species, including 9 species of wild mammals, indicating disturbance in the area and the adaptation of wildlife in the disturbed habitat (Kupika et al., 2018). Simultaneously, it highlighted the potential of the northern region of Thailand as a habitat for wildlife if restoration efforts and natural area conservation in the national park are implemented.

Factors contributing to the disturbance included sloped areas ranging from 1.37% to 10.90%, and distances from rivers ranging from 122.06 to 602.74, with significant forest types being mixed deciduous forests followed by hill evergreen forests and open areas, respectively. The normalized difference vegetation index (NDVI) ranged from 0.64 to 0.819, while temperature seasonality (BIO3) ranged from 49.309 to 51.237, annual temperature (BIO7) ranged from 21.66 to 22.95, mean temperature of the driest quarter (BIO14) ranged from 2.0 to 2.56, temperature annual range

(BIO15) ranged from 80.71 to 83.06, precipitation of the driest month (BIO17) ranged from 17.0 to 23.12 mm, and precipitation of the warmest quarter (BIO19) ranged from 17.0 to 64.78 mm.

In the case of red junglefowl, Sukmasuang et al. (2023) reported the encounter rate was 2.28 photos per 100 trap nights in Khao Ang Rue Nai Wildlife Sanctuary. The factors influencing the presence of the red jungle fowl included climate factors (55.30%) followed by biophysical and topography factors, respectively. Their study's results highlight the importance of climate factors on the appearance of the pheasants, even in lowland areas. The results showed that the pheasants responded more positively to the secondary forests, and the grassland followed by dry dipterocarp forest than to other forest types, while this study showed the red junglefowl responded positively to bioclimatic variables determined from %RC (72.7%) especially rainfall (70.50%), while in the lowland forest there was 17.9 percent contribution for precipitation and 37.4 percent contribution for temperature reflecting the dryness of the high mountain condition to the red junglefowl of the OKNP. In the case of land cover which is the forest type, NDVI was found to have the second strongest effect on the appearance of red junglefowl after the bioclimate environmental factor, which confirms the difference in climate conditions of the two areas that affects the appearance of red junglefowl. In the case of wild boar, global climate change effects contribute to the exceptional growth of wild boar populations (Vetter et al., 2015; Vetter et al., 2020; Gethöffer et al., 2023).

Common palm civets have the characteristic of being able to live in a variety of habitat types to an altitude of 2,400 above mean sea level. This mammal species lives in forests, plantations, dense vegetation areas, grasslands, agricultural land, open land, vacant land, and residential areas. Therefore, they are categorized as multiple landscape users (Nakashima et al., 2013; Parikesit et al., 2018; Dehaudt et al., 2022). The results of this study present a report on the relationship of the appearance of the common palm civet with the environment, including bioclimate, land cover variables, and topographic variables. It was found that temperature was most important to the appearance of the common palm civet (42.3 percent contribution), followed by land cover (42.1 percent contribution), which corresponded to the activity of common palm civet, which is active at night. This study identified environmental factors in the analyzed period and found that the environmental factors of wildlife analyzed did not differ. The results of this study revealed that it was a period of environmental conditions influencing the presence of wildlife in the area. In the case of suitable habitat areas for the 3 key wild species of the area that can be said to be representative of important wildlife in the area, we found that, on average, there is mostly moderately suitable area, accounting for 60.65% of the total area. Poorly suitable areas accounted for 30.08% and unsuitable areas covered 1.50% of the total area, while highly suitable areas accounted for 7.77% of the total area. Therefore, it should be a target area for the management of each species of wildlife for further conservation management.

The OKNP is located between the DPNP and the DNNP, the highest peak of the national park of Thailand. Thai National Parks (2024); and Avibase - The World Bird Database (2024) reported 642 wildlife species composed of 533 bird species, 50 wild mammal species, 50 reptiles, and 53 amphibian species in the DNNP. Thus, the park can be a potential conservation area to address and restore biodiversity loss and mitigate climate change impacts (Kopsieker & Disselhoff 2024). Based on this study, the area is still home to key wildlife species. However, some suggestions should be taken in terms of management, including the prevention and control of forest fires that occur in mixed deciduous forests, pine forests, and mountain forests during the dry season. The release of livestock entering the area should be prevented by cooperation with leading people. This is because the tracking results from the camera traps and the animal's signs can be recorded in the area, which may pose a threat of disease outbreak. Vehicle usage management is also important, particularly for motorcycles that are smuggled into the area. In areas with slight slopes that are remote and can be controlled, food sources for wildlife, and water sources should be improved, including continuous monitoring and study with camera traps.

Conclusion

In conclusion, the results of studying wildlife species using camera traps during the year within the OKNP show that this is an area that was previously disturbed by human activities. At least nine species of wild mammals from eight families were photographed. The most prominent species based on the encounter rate per 100 trap-nights were wild boar, golden jackal, red muntjac, common palm civet, rhesus macaque, northern tree shrew, serow, and leopard cat, respectively, and the species were found to be mostly active at night. Wild birds that live on the ground and were photographed include 4 species from 4 families, as the results of analysis of suitable habitat areas for important wildlife. When considering year-round data from the SMART patrolling system, three species were analyzed: red junglefowl, common civet, and wild boar. It was found that factors contributing to the disturbance included sloped areas, distances from rivers, forest types, normalized difference vegetation index (NDVI), temperature seasonality (BIO3), annual temperature range (BIO7), mean temperature of the driest quarter (BIO14), temperature annual range (BIO15), precipitation of the driest month (BIO17), and precipitation of the warmest quarter (BIO19). The factors affecting the highest occurrence of wildlife were climate conditions, followed by condition of land cover. Important forest types include the mixed deciduous forest and the pine forest, and highly suitable habitat for management goals can be determined from the study results, which cover only 7.77% or approximately 20.67 km^2 of the total area.

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