Application of Geospatial Technology and R for the Wildlife Habitat Analysis in Mae Ping National Park, Thailand

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Abstract
Wildlife habitat characteristics are critical tool in efficient resource management. At present, Geospatial Technology (GT) and R have been academically proven for evaluating wildlife habitats. This study focuses on analyzing wildlife habitats in Mae Ping National Park (MPNP), Thailand. GT was used to gather information on the physical parameters of wildlife habitats and R to train the data by a machine learning algorithm. The Landsat 8 data set was used with supervised classification. It was found that over 95 percent of MPNP is covered with forests and water resources appropriate for wildlife habitats. Most of the trees appeared to be deciduous dipterocarp forests, followed by dry evergreen forests, with a small amount of mixed deciduous forests in the highlands. The data, acquired by the SMART Patrol Monitoring Center in Forest Conservation Area 16 (Chiang Mai), revealed that MPNP's wildlife is clustered, particularly in the area's central-eastern section, with a density of 1.80 animals per square kilometer. With regard to wildlife species, it was found that wild boars are the most prevalent, followed by muntjac and sambar deer. The chi-square test was used to analyze the existence of a causal association between environmental conditions and animal habitat distribution. The results show that distances from water resources, altitude and slope, distances from saltlicks, from roads, and from tourist attractions all have a significant relationship with the wildlife habitat at a statistical significance of $p < 0.05$. Furthermore, a cluster analysis by k-medoids algorithm suggested that wildlife habitats could be grouped into three distinct clusters.
Keywords: Wildlife Habitats, Wildlife Distribution, Geospatial Technology, Cluster Analysis

Introduction
The world's forest areas have been continuously decreasing over time and this has had a devasting impact on flora, fauna, and humans. According to the World Wildlife Fund (WWF), a well-known foundation dedicated to wildlife and forest preservation, the world's wildlife has declined by up to 60 percent over the last 40 years. (WWF, 2018)
The wildlife situation in Thailand also indicates a decrease in both the number of species and quantity. The factors for the stated incidence are human invasion, hunting and trafficking wildlife. (Office of Natural Resources and Environment Policy and Planning, 2018) To offset this, Thailand attempted to mitigate these factors by amending the Wildlife Conservation and Protection Act, designating national park areas for the preservation of wildlife and forbidding hunting zones. Nevertheless, wildlife is still being constantly threatened up to present day. (Putta et al., 2009; UN Office on Drugs and Crime, 2017; Singh et al., 2021)
Mae Ping National Park (MPNP) is a biodiversity hotspot due to its diverse geological characteristics, ranging from a mountain range to the significant water resource of the Ping river, which serves as Thailand's primary water supply. MPNP's abundant resources enable

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the local people to make a livelihood off the land, which undoubtedly has an effect on wildlife survival. (Thairath, 2016; Khaosod, 2019; Office of National Parks of Thailand, 2020)

With the advancement of Geospatial Technology (GT), wildlife habitat management has become increasingly more scientific and realistic. Wildlife managers now have access to highly accurate spatial database, which enables them to look at species-habitat relationships in much more efficiently. (Kushwaha & Roy, 2002) GT encompasses multiple sub-disciplines, including Remote Sensing (RS) which is used for aerial visual observations as well as for land use analysis, Global Navigation Satellite System (GNSS) used in ground surveys to conduct animal censuses and located feature and map boundaries of wildlife habitat. Moreover, Geographic Information System (GIS) can be used to evaluate and analyze environmental data layers and to georeference wildlife data as well. (Zhang, 2019; de Gouw et al., 2020)

Previous research of geographers and ecologists generally used GT as a conservation strategy in conducting surveys to create a map of the distribution of wildlife and to correlate this with habitat parameters to calculate the probability of wildlife presence. (Danks & Klein, 2002; Kanchanasakha & Buanun, 2002; Winitpornsawan, 2003; Chayutkul, 2006; Khiowsree et al., 2015; Planisong et al., 2019; Ariyaphitak et al., 2020) Numerous studies have adopted GT to predict potential wildlife habitats or to identify areas of wildlife habitat sensitivity. (Subedi & Subedi, 2017; Ahmad et al., 2018; Goparaju et al., 2018; Tadesse & Kotler, 2018; Uddin et al., 2019; Erena & Yesus, 2021) Nonetheless, traditional GT is still heavily reliant on computational power, especially when processing 3D images, and map rendering. (Huisman & de By, 2009; Kim et al., 2018; Park et al., 2021)

At present, technological advances in computer science, i.e. machine learning, has been increasingly applied in the processing of large volumes of wildlife data because the technology is free of charge and able to simplify complex tasks. In addition, there are various algorithms that can be developed by users themselves. In research, such algorithms are commonly used for species distribution modeling and general ecological classification. (Valletta et al., 2017; Shoemaker et al., 2018; Zang et al., 2019; Mahesh, 2020; Rather et al., 2021; Saker, 2021) A powerful machine learning algorithm platform is R, an open-source programming language, because it provides a wide variety of statistical and graphical techniques and can handle the data analysis of functionalities with more efficiency. (Wang & Alexander, 2016; Kumar, 2019; Nichols et al., 2019; IBM Cloud, 2021)

This research therefore enhanced the usage of GT and R in order to add another dimension to its spatial capabilities and efficiency of data analysis, making it an invaluable tool for analyzing wildlife habitat. The organizations concerned with forestry and wildlife preservation will be able to better understand the current distributions of wildlife habitat. The findings from this study can provide some information for managing wildlife populations or creating wildlife corridors to enable wildlife friendly management.

The objective of this study was to analyze wildlife habitat in MPNP, using GT in order to portray wildlife distribution and density. Also, it aims to explore the spatial relationship between wildlife and its habitat by overlapping factors, such as land use, geographical factors, and human invasion. This information was then statistically analyzed and grouped together in order to identify the habitat clusters that have a high probability of being dense with respect to factoring in R.

Research Methodology

Area of study

Mae Ping National Park (MPNP) is situated in the northern part of Thailand. It is located between latitudes 17° 15' and 17° 57' north and longitudes 98° 37' and 98° 58' east and covers an area of 1,003.75 square kilometers, as illustrated in Figure 1. The park’s boundaries are shared by three provinces. Chiang Mai province borders the park to the north, Lamphun province to the east, and Tak province to the south and west.

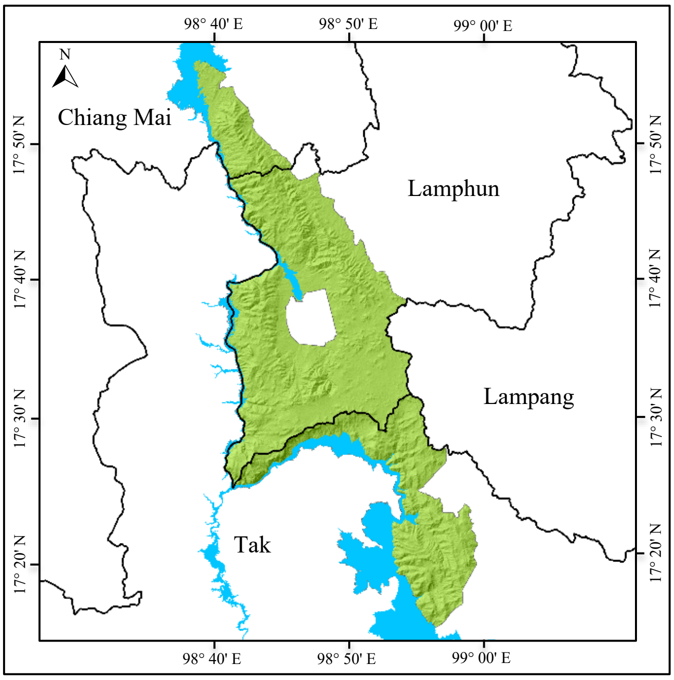

Figure 1 Map of Mae Ping National Park

Data Collection

The Spatial Monitoring and Reporting Tool (SMART) technique, which was implemented by the SMART Patrol Monitoring Center in Forest Conservation Area 16 (Chiang Mai), provided the geographic coordinates of the wildlife traces. The Landsat 8 satellite's image, with a spatial resolution of 30 meters from the United States Geological Survey (USGS), was used for supervised classification in order to determine the MPNP categories of land use through RS. The processed data from the satellite was validated by field checkpoints and also by the record from a GPS receiver which further calculated the probability of correctness at a 95 percent confidence level.

Data Analysis

The analysis of wildlife distribution was conducted using ArcGIS (ESRI, 2019). The data was assessed by analyzing the Nearest Neighbor Index (NNI) of the wildlife traced. In addition, overlay mapping was used in GIS to determine the spatial relationship between the wildlife traced and environmental features. Additionally, this study used R (R Core Team, 2017) to examine the relationship between ecological factors and wildlife distribution, employing a chi-square test to identify statistically significant factors at a $p < 0.05$ significance level. Likewise, to divide the wildlife trace positions into appropriate clusters, this study performed a cluster analysis which was based on k-medoids algorithm or partitioning around medoids (PAM), which falls under the category of unsupervised machine learning.

Results and Discussion

Land use classification using Landsat 8 satellite imagery

MPNP is primarily covered by deciduous dipterocarp forest (DD) with 582.57 square kilometers (58.04 percent), followed by dry evergreen forest (DF) with 230.53 square kilometers (22.97 percent), water resources (W) with 84.26 square kilometers (8.39 percent), mixed deciduous forest (MD) with 61.46 square kilometers (6.12 percent), grassland (G) with 20.15 square kilometers (2.01 percent), abandoned fields (AF) with 13.85 square kilometers

(1.38 percent), and agricultural areas (A) with 10.93 square kilometers (1.03 percent), respectively, as shown in Figure 2.

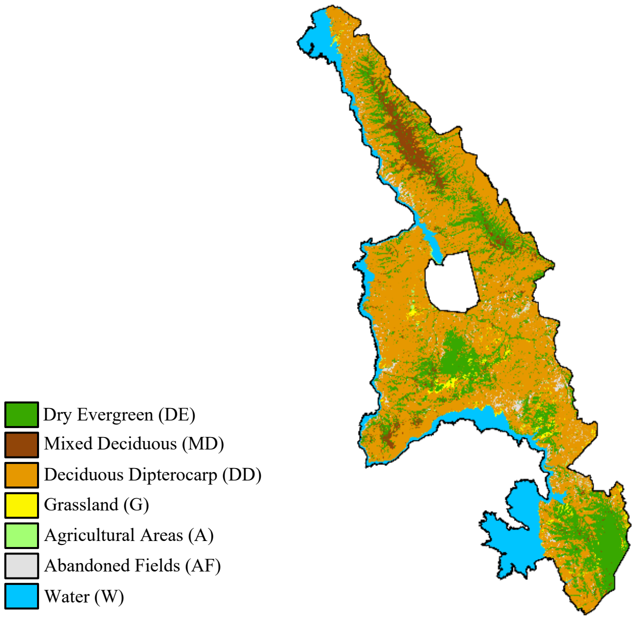

Figure 2 Land use in Mae Ping National Park

Wildlife habitat distribution

Within the region of MPNP, 948 wildlife traces, were found through a combination of footprints, tracts, and feces left behind by animals. The bulk of traces (39.16 percent) are from wild boars, followed by muntjac (30.42 percent) and sambar deer (10.96 percent). Additionally, various animal species such as brown-antlered deer, palm civet, brush-tailed porcupine, junglefowl, and Indian hog deer were reported.

The distribution of wildlife habitats was analyzed using the Nearest Neighbor Index (NNI). The results suggest three categories of distribution patterns: clustered, random, and dispersed. The study results showed that NNI was 0.47, with p-value equal to 0.000, indicating the wildlife in MPNP had clustered distribution patterns with a statistical significance of $p < 0.01$.

Additionally, the specific density of wildlife, a measure of population density per area where traces of wildlife were found, was conducted without utilizing the total area of MPNP. The study area was divided into 340 square grids of 2x2 km. The square grids were numbered and the population for each square grid was counted using ArcGIS. The study results found that traces of wildlife were found in 132 square grids, representing 38.82 percent of the total area. Therefore, the number of wildlife traces per square grid was 7.18 animals per square grid. As each grid has an area of 4 square kilometers, the density of wildlife per area was 1.80 animals per square kilometer. The distribution of each animal species and its wildlife density are illustrated in Table 1 and Figure 3.

At a statistically significant level ($p < 0.05$), the wildlife distribution pattern is mostly clustered in the eastern area of MPNP. Due to the fact that the eastern portion of the geographical area is a highland area with a lesser degree of slope, the area is appropriate for the settlement of the majority of species. In accordance with the nature of junglefowl, which frequently inhabits dry evergreen forests or the transition zone between dry evergreen and deciduous dipterocarp forests, the junglefowl's preferred boundaries were found to be dispersed across MPNP, implying a random dispersal pattern.

Furthermore, the study discovered that Indian hog deer lives primarily in deciduous dipterocarp forest and is absent from grassland. This finding contradicts prior research by Prempree et al (2013), which indicated that Indian hog deer prefer grassland habitats due to grass being a primary source of nourishment. A plausible explanation would be the percentage of grassland in the area. The grassland region covers only two percent of MPNP, forcing the Indian hog deer to adapt to the deciduous dipterocarp forest which previously covered most of the park.
Additionally, the study suggests that the brown-antlered deer is primarily found in deciduous dipterocarp forest and prefers to reside near water resources.
This finding is consistent with an earlier work of Prempree et al (2013), who found that brown-antlered deer often avoid high-density forest in favor of lower-density forest types such as deciduous dipterocarp forest or clear/open woodland near a water resource. The study, however, contradicts the findings of Puwinsaksakul et al (2014) who found that brown-antlered deer favor grassland. Nevertheless, as indicated previously in relation to the Indian hog deer problem, grassland is considered a minor feature of the park.

Table 1 Distribution pattern and wildlife density for each wildlife species

Animal species	**Number of Traces found**	**Density (per sq.km)**	**NNI**	**Distribution Pattern**
Wild boar	381 (39.16%)	0.92	0.64	clustered
Muntjac	296 (30.42%)	1.14	0.48	clustered
Sambar deer	104 (10.69%)	0.76	0.44	clustered
Brown-antlered deer	52 (5.34%)	0.72	0.28	clustered
Palm Civet	35 (3.60%)	0.42	0.77	clustered
Brush-tailed porcupine	32 (3.29%)	0.35	0.53	clustered
Junglefowl	26 (2.67%)	0.27	0.88	random
Indian hog deer	22 (2.26%)	0.39	0.70	clustered
Total	948	1.80	0.47	clustered

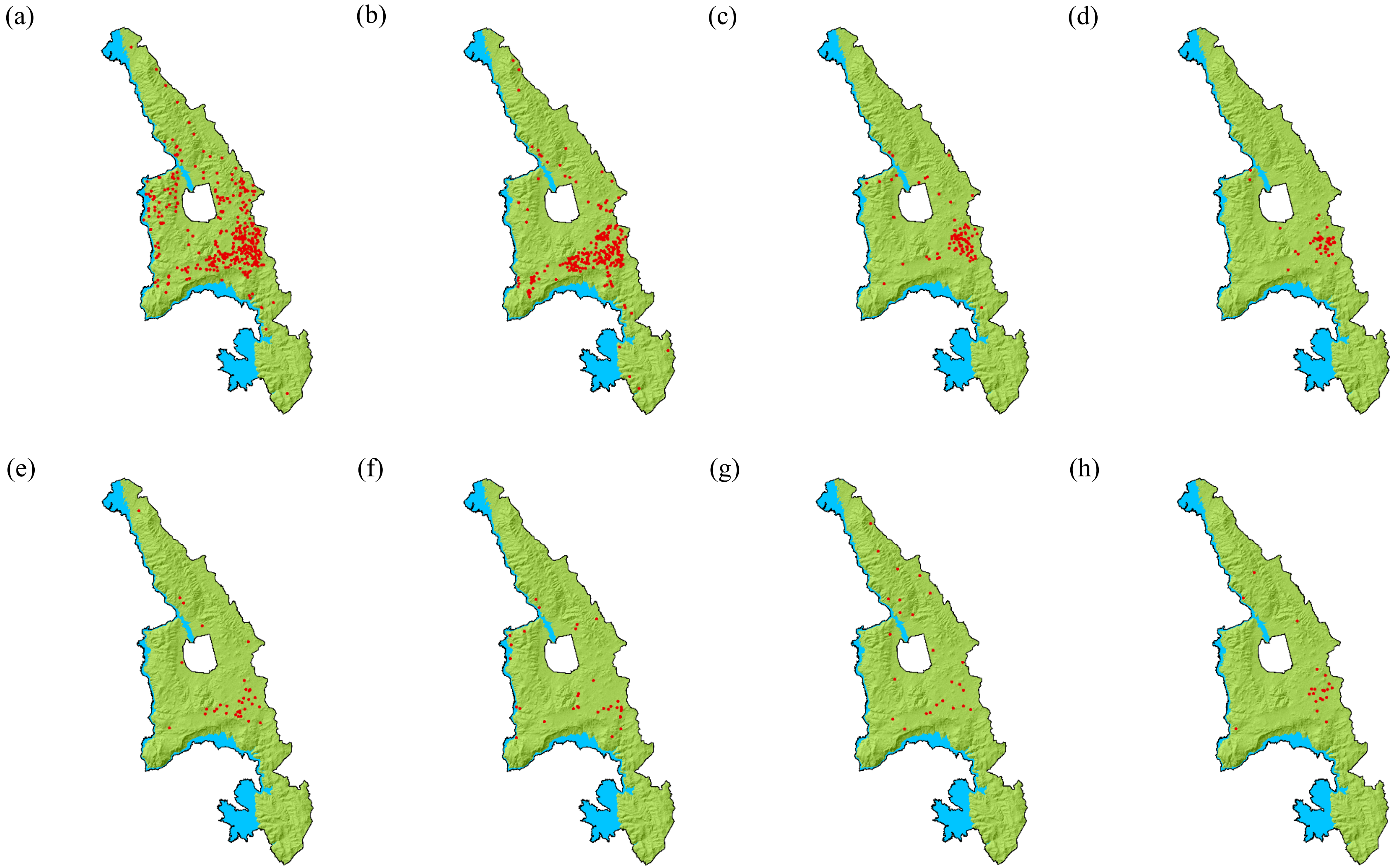

Figure 3 Distribution maps for each species of wildlife: (a) wild boar, (b) muntjac, (c) sambar deer, (d) brown-antlered deer, (e) palm civet, (f) brush-tailed porcupine, (g) junglefowl, and (h) Indian hog deer

Relationship between wildlife distribution and factors

The relationship between environmental conditions and the dispersal of animals is analyzed using two approaches: data overlaying and statistical analysis. Numerous factors are believed to influence wildlife distribution, including land use, distance from water sources, from saltlicks, altitude, slope, aspect, distance from roads, and from tourist attractions, as can be seen from the data overlaying the maps in Figure 4.

Land use: Data overlaying showed that the wildlife in MPNP primarily settled in the deciduous dipterocarp forest area, accounting for 66.67 percent of all traces, followed by dry evergreen forest, accounting for 26.90 percent. The remaining land categories are underutilized, as evidenced by the traces detected in grassland, mixed deciduous forest, abandoned fields, and agricultural areas, which contained only 2.74 percent, 2.22 percent, 1.05 percent, and 0.42 percent of the traces, respectively. Additionally, while the majority of animals prefer deciduous dipterocarp forest to other types of forests, grassland and mixed deciduous forest had an equal number of junglefowl, which indicated a random pattern of distribution.

Distances from water resources: MPNP's primary water resource is the Ping river, which flows for approximately 140 kilometers along the park's western border. Additionally, there are minor water resources in the park's central area that originate from the Ping river. Overlapping data revealed that the majority of wildlife is present in surroundings with water resources, with the number of species diminishing as one goes farther away from the water resource in consideration. Five-eighths of the animals lived within a radius of 0-500 meters of water resources, 23.95 percent within 501-1,000 meters and 17.19 percent within a radius greater than 1,000 meters.

Distances from saltlicks: Saltlicks are classified as salt earth or spring mouths and are found throughout MPNP in 70 locations. According to overlapping data, 46.65 percent of species lived more than 1,000 meters from saltlicks, while 31.22 percent and 24.58 percent of the fauna lived between 501 and 1,000 meters and less than 500 meters, respectively. Sambar deer are typically found near saltlicks among other living organisms, whereas Indian hog deer have been discovered both near and far from saltlicks.

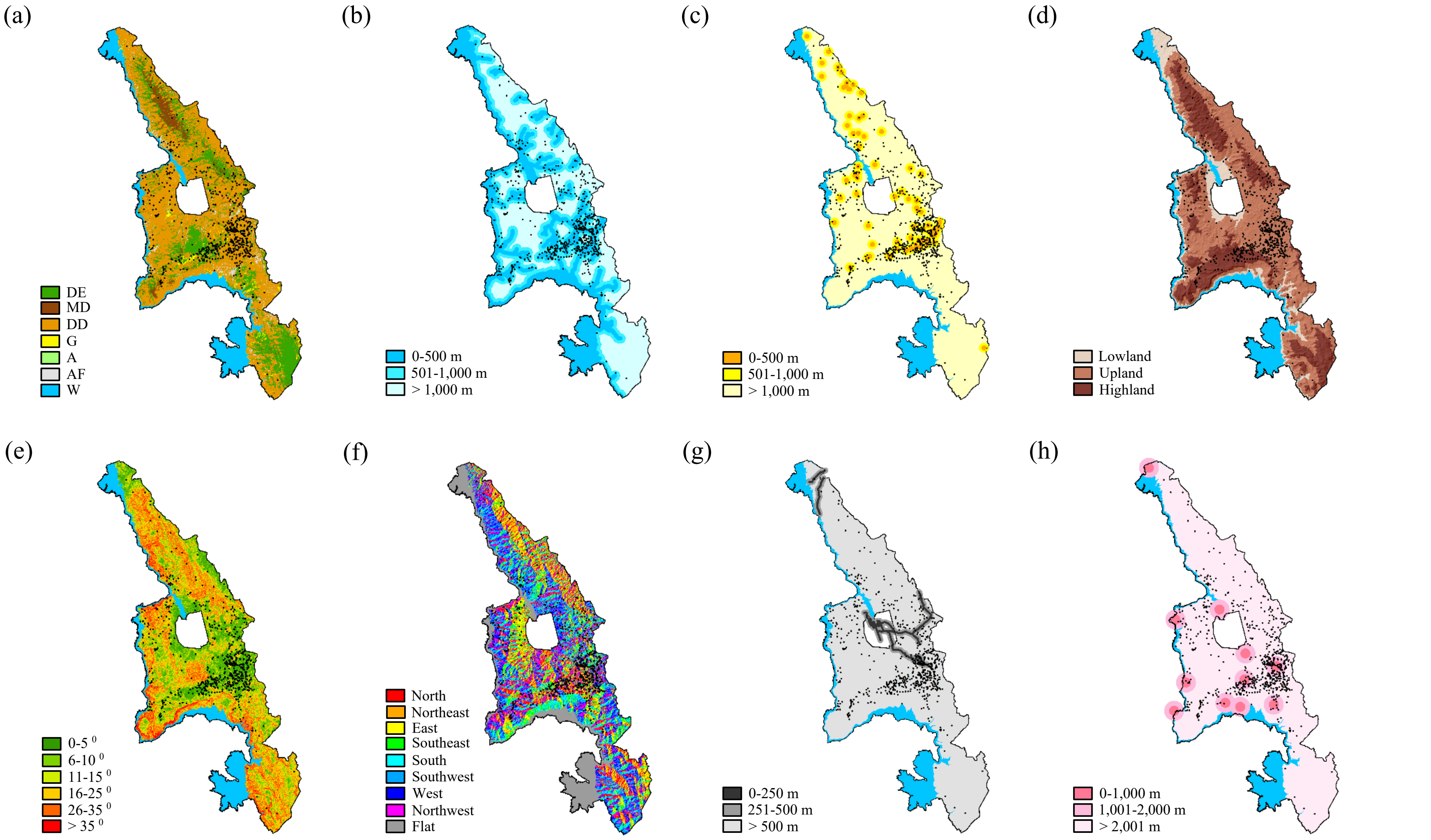

Figure 4 Maps of wildlife distribution according to: (a) land use, (b) distances from water resources, (c) distances from saltlicks, (d) altitude, (e) slope, (f) aspect, (g) distances from roads, and (h) distances from tourist attractions

Altitude: MPNP is primarily a mountainous region. The average elevation is 400-800 meters above mean sea level, with the highest peak being Doi Huay Lao at 1,334 meters. Overlapping data revealed that the majority of wildlife (77.53 percent) lives in upland areas (351-700 meters), while only 4.75 percent lives in lowland areas. In the highlands above 700 meters above sea level, traces of animals were discovered in approximately 17.72 percent of the area. Wild boars were found in all altitude groups indicating that wild boars are capable of adjusting to their surroundings.

Slope: Six different grades of slopes exist in MPNP: (1) low (0-5 degrees), (2) moderately low (6-10 degrees), (3) moderate (11-15 degrees), (4) moderately steep (16-25 degrees), (5) steep (26-35 degrees), and (6) extremely steep (over 35 degrees). MPNP's wildlife is concentrated in areas with low and moderately low slopes, accounting for 42.72 percent and 33.86 percent of the park's total area, respectively. At higher degrees of slope, animals were scarcely detectable; 11.71 percent, 8.97 percent, 1.69 percent, and 1.05 percent of animals were detected residing at moderate, moderately steep, steep, and extremely steep degrees of slope, respectively. Only wild boars, muntjac, and palm civet were found at the maximum degree of slope.

Aspect: The angle of the slope is a factor that indicates the angle of the sun. Thailand's geography, being in the northern hemisphere, typically receives sunlight from the south, resulting in a 90-degree angle between the sun and the south slope aspect. The stated direction of the sun causes the land to be drier and hotter than the area on the slope's northern face. By superimposing data, it was determined that the number of animals distributed across the slope is not significantly different. The area with the western aspect of the slope had the highest density of animals (15.19 percent), while the area with the southern aspect of the slope had the lowest density of animals (8.23 percent).

Distances from roads: The national park's roads are entirely asphalt, with an average width of three meters. The road is predominately used for forest agent inspections and connects the adjacent province to the community in the parks' middle section, which was settled prior to the official announcement of the park's establishment. The overlaying method revealed that 88.08 percent of all animals live at least 500 meters away from roads. Only 6.33 and 5.59 percent of animals, respectively, were found between 0 and 250 meters and 251 and 500 meters from roads. Brush-tailed porcupine were not observed anywhere between 0 and 250 meters from roads.

Distances from tourist attractions: MPNP's tourist attractions include waterfalls, caves, and temples, which are located in the middle eastern area of the park. Water-based activities such as a sightseeing cruise along the Ping river and fishing are popular tourist activities. Overlapping data revealed that the majority of wildlife stayed within a distance of more than two kilometers of tourist attractions, at 67.83 percent. Only 8.65 percent of animals were found within a radius of 1,000 meters of the tourist attractions, while 23.52 percent were found within a radius of 1,001-2,000 meters.

Statistical relationship

This study analyzed the wildlife distribution data with respect to the factors mentioned above to see if there were any statistical relationships using chi-square at a 95 percent confidence level. The overall results showed that the relationship between wildlife distribution and distances from water resources, distances from saltlicks, altitude, slope, distance from roads, and distance from tourist attractions are all significant factors affecting wildlife distribution ($p < 0.05$). Table 2 shows, on the other hand, that despite the fact that two-thirds of the national park's land is covered by deciduous dipterocarp forest, land use has no significant impact on the distribution of wildlife. Similarly, with regard to aspects, the southern aspect of the slope was found to have fewer numbers of wildlife compared to other aspects, as it receives sunlight at a direct 90 degree-angle, but the number of animals is not significantly different from that of the other aspects.

Table 2 Chi-square test of relationship between environmental factors and wildlife distribution

Factors	Chi-square	
	Value	**p-value**
Land use	40.260	0.249
Distance from water resources	29.828	0.008*
Distance from saltlicks	69.276	< 0.001*
Altitude	59.969	< 0.001*
Slope	75.290	< 0.001*
Aspect	57.997	0.177
Distance from roads	34.943	0.001*
Distance from tourist attractions	62.914	< 0.001*

Remark: *statistically significant level at $p < 0.05$.

The distance from saltlicks is a significant factor in the distribution of sambar deer, brown-antlered deer, and brush-tailed porcupine, as these animals are all herbivores. Saltlicks are a vital source of the minerals required by animals which consume plants. Additionally, it was found that the slope has a significant inverse relationship with the habitat distribution of sambar deer ($p < 0.05$), which means the higher the degree of the slope, the smaller the number of sambar deer which inhabit it. These results correspond to those of Kanchanasakha & Buanun (2002), Molina et al (2014), Planisong et al (2019), and Ali et al (2021)

At a statistically significant level ($p < 0.05$), the distance to water resources also has an inverse relationship with the distribution of muntjac, wild boar, and brush-tailed porcupine, implying that the greater the distance from water resources, the fewer the wildlife found. These results are consistent with those of previous studies conducted by Prommakul (2003); Thunhikorn (2003); Winitponsawan (2003); and Khiowsree et al (2015) which showed that wildlife congregates near water resources, particularly wild boar, wild buffalo, and brown-antlered deer which need damp conditions to regulate their body temperature and eliminate pest infestation.

As with factors affecting human invasion, such as distances from roads and distances from tourist attractions, certain factors were found to have a direct relationship with the distribution of Indian hog deer, brown-antlered deer, and junglefowl. This means that the further away from roads or tourist attractions, the more wildlife is found. These findings corroborate those of existing studies conducted by Chumsangsri et al (2003); Chayutkul (2006); Ladle et al (2018); Olson et al (2018); Ariyaphithak et al (2020); and Dean et al (2019) which explain that wildlife usually avoids humans.

Cluster analysis of wildlife habitat

The factors and distribution data of wildlife habitats in the preceding sections were statistically classified to assess wildlife habitat categorization using cluster analysis. Cluster analysis is a subset of unsupervised machine learning in which cases or variables with similar properties are grouped together. Due to the presence of numerical and nominal scale data, a cluster analysis was performed using the k-medoids algorithm or partitioning around medoids (PAM).

The results indicate that MPNP provides a wildlife habitat that can be classified into three distinct clusters, as illustrated in Figure 4. Cluster 1 is dominated by upland covered with deciduous dipterocarp forest. It is located in isolation from water resources and tourist attractions but is close to saltlicks. In comparison to cluster 1, cluster 2 is principally covered with deciduous dipterocarp forest but is located close to water resources and tourist attractions. Cluster 3 has a high proportion of land covered by dry evergreen forest, a steeper slope, a greater distance from water resources, and a greater distance from roads than in the other clusters. The characteristics and major animal species found in each cluster are listed in Table 3, with the exception of muntjac and wild boars, which are found in all three clusters.

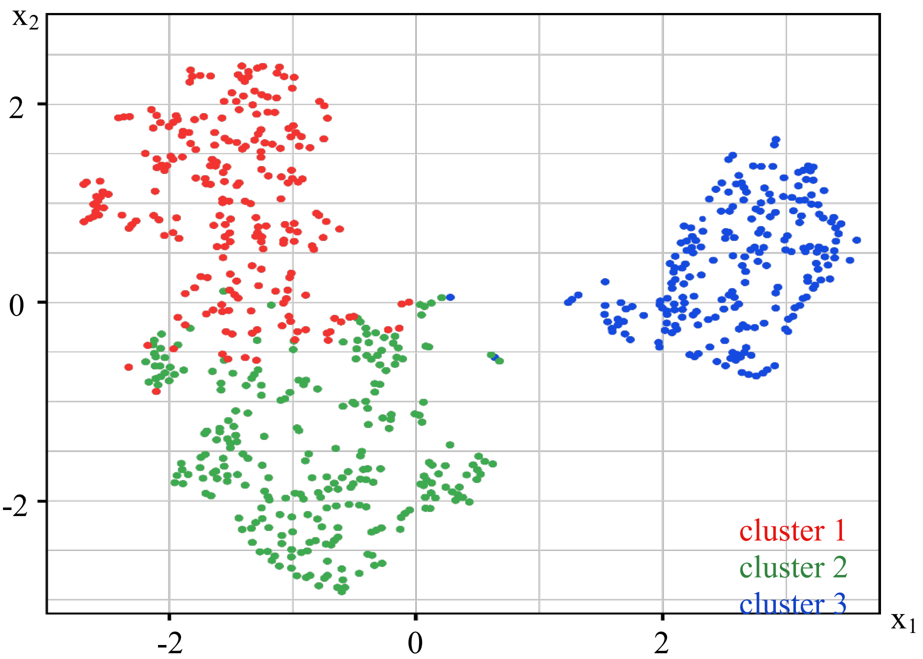

Figure 4 The scatter plot of clustered data

Table 3 Characteristics of ecological factors for each cluster

Animal species	Cluster 1	Cluster 2	Cluster 3
Land use	deciduous dipterocarp forest[a]	deciduous dipterocarp forest[a]	dry evergreen forest[a]
Distance from water resources (m)	692.43 (653.18)[b]	526.16 (505.66)[b]	559.33 (568.44)[b]
Distance from saltlicks (m)	1,274.06 (1,145.19)[b]	1,286.00 (1,546.78)[b]	1,361.04 (1,637.73)[b]
Altitude (m)	601.31 (117.53)[b]	569.14 (114.19)[b]	588.07 (129.75)[b]
Slope (degree)	7.45 (6.50)[b]	7.36 (6.50)[b]	8.16 (6.91)[b]
Aspect (degree)	78.30 (54.49)[b]	265.46 (53.27)[b]	169.86 (105.27)[b]
Distance from roads (m)	3,923.67 (3,331.91)[b]	4,035.05 (4,399.22)[b]	4,474.85 (3,960.23)[b]
Distance from tourist attractions (m)	3,673.64 (2,462.55)[b]	3,056.08 (2,528.67)[b]	3,210.14 (2,620.31)[b]
Primary animal species	muntjac, wild boar, brush-tailed porcupine, palm civet	muntjac, wild boar, sambar deer, brush-tailed porcupine, brown-antlered deer	muntjac, wild boar, Indian hog deer

Remark: [a] The land use mostly found in the cluster
[b] Numbers in brackets are the standard deviation within the cluster

Conclusion

Most of the areas in Mae Ping National Park are upland and highland with average elevations ranging from 400 to 800 meters above mean sea level. These areas are covered with forests, especially deciduous dipterocarp forest, as well as water resources, which make them suitable for wildlife habitats. The distribution pattern of wildlife in MPNP indicated that it was densely clustered in the central eastern area of the park, with a statistical significance of 0.05 and a population density of 1.80 animals per square kilometer. Regarding animal species, it was found that wild boar was the most prevalent wild animal, followed by muntjac and sambar deer, which were the second and third most common, respectively. Junglefowl, Indian hog deer, brush-tailed porcupine, brown-antlered deer, and palm civet were also found, among other animals. The distribution pattern of most wildlife was clustered, except for junglefowl, which had a random distribution pattern.

With the assistance of the chi-square test, it was possible to establish a relationship between environmental factors and wildlife habitat distribution. It was found that distances from water resources, from saltlicks, altitude, slope, distances from roads and from tourist attractions were factors that affected relationships with wildlife habitats with a statistical significance of 0.05. However, no relationship was discovered between land use and any of the aspects of wildlife habitat.

When the k-medoids algorithm was applied to the location data of wildlife traced in the cluster analysis, it was found that wildlife habitat in MPNP could be divided into three clusters. The first type of cluster consists of deciduous dipterocarp forest and areas close to saltlicks, where brush-tailed porcupine and palm civet were frequently encountered. The second type of cluster was also deciduous dipterocarp forest but was located in close proximity to water resources and tourist attractions, where sambar deer and brown-antlered deer could frequently be found. The third type of cluster contained steep-sloped dry evergreen forest, where Indian hog deer were often found in large numbers. Wild boar and muntjac, on the other hand, could be found in all of the clusters, regardless of the environmental conditions.

Research limitations

There are some limitations within which the findings need to be interpreted carefully. This study was limited by the positions of wildlife since the data were only been recently surveyed by government agencies. As a result, the length of the database presented was quite short: only one year, which made it impossible to conduct a time-scale study. In addition, the data integrity of this study also depended on the wildlife survey routes of related agencies. Therefore, an area without trace of wildlife in this study does not mean that the area does not have a wildlife presence. Nonetheless, the data obtained was sufficient for the analysis of main features of wildlife habitats.

Recommendations for future research

In the future, comparative studies of the effectiveness of data analysis between GT and R should be conducted, such as comparison of land cover classification accuracy or comparison of species distribution models from the development of both tools. Studies may also be conducted to integrate with other disciplines such as biology, environmental science, forestry, and sociology in order to widen the research perspective, data collection techniques or different bodies of knowledge to further develop the available information on wildlife habitats.

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