Spatial Modeling of Forage Crops for Tiger Prey Species in the Area Surrounding Highway 304 in the Dong Phayayen-Khao Yai Forest Complex

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ABSTRACT

Spatial modeling is an analytical procedure that simulates real-world conditions using remote sensing and geographic information systems. The field data in this study were collected from 318 survey plots in the area surrounding highway 304 in the Dong Phayayen-Khao Yai Forest Complex (DPKY-FC) during the 2019 rainy season. Forage-crop biomass was collected from all plots. We focused on sambar deer (*Rusa unicolor*) and gaur (*Bos gaurus*), which are the main prey for tigers in this area. We created spatial models using generalized linear models with stepwise regression. The results indicated that the normalized difference vegetation index (NDVI) varied directly with grass biomass but inversely with shrub biomass ($p<0.05$). Elevation varied directly with forb biomass but inversely with shrub biomass ($p<0.05$). The probability of occurrence of sambar deer varied directly with distance from disturbance variables, distance from the stream, and grass biomass ($p<0.001$), but inversely with NDVI ($p<0.05$). The occurrence of gaur varied directly with NDVI ($p=0.08$), but varied inversely with slope, distance from the road, and distance from the stream ($p<0.05$). Our results demonstrate that spatial modeling can be an effective tool for wildlife habitat management in the area surrounding highway 304.

1. INTRODUCTION

The factors affecting species distributions were first described by Grinnell (1917) and comprise locally measured variables such as food, vegetation, soil, and climate. The advent of geographic information systems and remote sensing have provided spatial data covering large areas that can be used to elucidate the distribution of species. The major contribution of habitat-suitability models (HSMs) to niche theory has been the ability to test the relevance of such variables for species and environmental relationships (Grinnell, 1917; Guisan and Zimmermann, 2000). There are many available methods for generating HSMs. One of the main differences among them is dependence on the quality of data needed. Generalized linear models (GLMs) are a generalization of multiple regression analyses with a binomial distribution and logit link that can fit higher-degree polynomials (Hirzel et al., 2001). GLMs provide good predictions for virtual species distributions because they can deal with many types of predictors (Brotons et al., 2004; Engler et al., 2004). Duangchatrasiri et al. (2019) assessed whether human activity had an impact on the occurrence of wildlife by using the distance from villages and roads because wildlife is sensitive to hunting and a range of other environmental conditions such as disturbance variables inside protected areas (Lynam et al., 2012). In addition, distance to rivers and streams have also been included as covariates that reflect habitat quality near streams (Linkie et al., 2006). Land-cover data have the most diverse influences on ecological niches (Schadt et al., 2002; Sachot et al., 2003; Seoane et al., 2004). The Landsat 8 satellite provides ecologists with

infrared imagery, which allows computation of the normalized difference vegetation index (NDVI), a proxy for plant biomass (Estrada-Peña et al., 2006).

The Dong Phayayen-Khao Yai Forest Complex (DPKY-FC) in Thailand was declared a UNESCO World Heritage Site in 2005. However, recent reports have shown that tigers in the DPKY-FC were found only in Thap Lan National Park and not in Khao Yai National Park (DNP, 2016; Ash et al., 2020). The last report of tigers in Khao Yai National Park was from September 19th, 1996. Gaur, the main prey for tigers in this area, are still found on both sides of highway 304 (Simcharoen et al., 2018), but they cannot travel between sites. Also, sambar deer, which are found along the forest edge, still do not appear to use the highway 304 wildlife corridor. Therefore, the most important landscape-level issue for the DPKY-FC is the lack (in both quality and quantity) of wildlife habitat. Highway 304 passes through this forest, resulting in threat factors that prevent large wildlife from being able to move safely back and forth across the road.

This study used plot observations from a plant-community survey to investigate habitat composition and factors affecting the quality and quantity of habitat in the DPKY-FC. We used multiple scales, including plot, patch, and landscape (Cushman and McGarigal, 2002), by selecting random points to represent the study area. Information regarding habitat size, fragmentation, and resources provides the baseline for devising appropriate wildlife-management strategies at both the operational and policy levels. This is urgently needed to restore populations of tigers and other endangered wildlife.

2. METHODOLOGY
2.1 Study site

The study was conducted in a 450.35 km^2 area of the DPKY-FC comprising parts of Khao Yai National Park and Thap Lan National Park in Nakhon Ratchasima and Prachin Buri Provinces (14°05′-14°30′N, 101°45′-102°00′E) (Figure 1). The elevation was 38-877 m.a.s.l. Field data were collected from the immediate area surrounding highway 304.
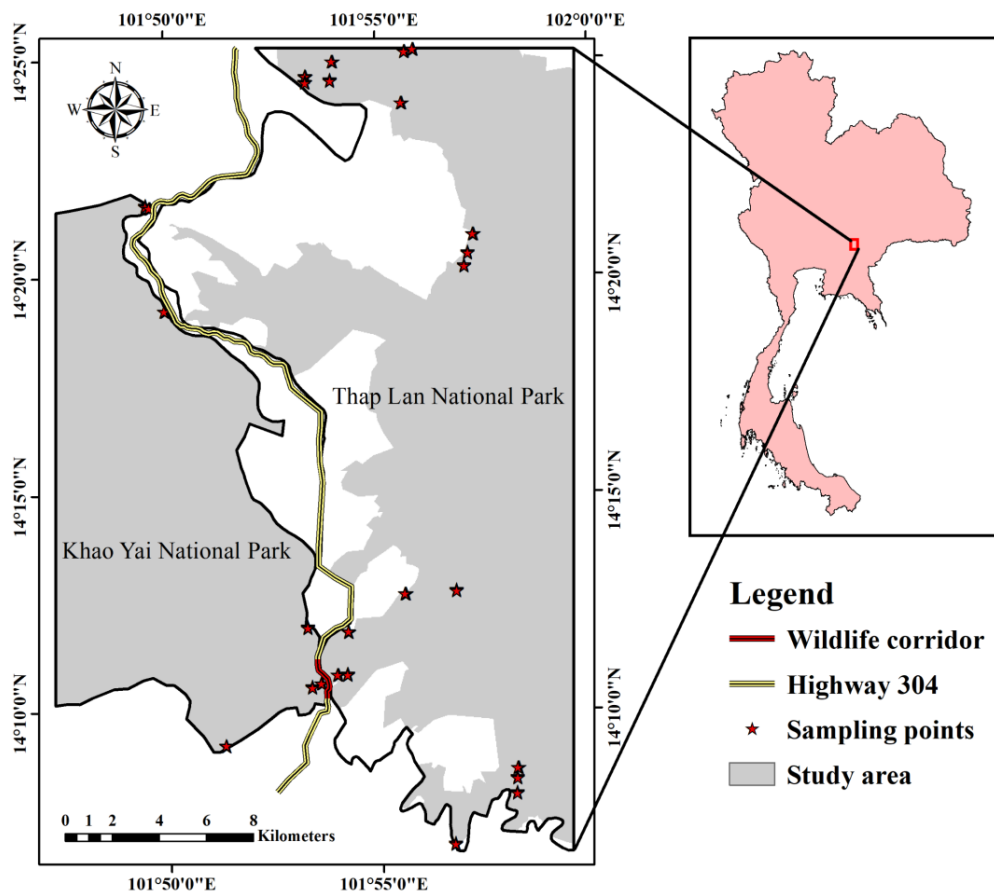

Figure 1. Study area showing the wildlife corridor and sampling points surrounding highway 304 in Khao Yai National Park and Thap Lan National Park.

2.2 Survey design

We surveyed sampling points in 318 plots to study the grasslands according to the abundance of sambar deer and gaur, which are the main prey for tigers. The coordinates of the centers of the plots were recorded as the sampling points. We used tiger and prey occurrence data from the Wildlife Research Division, Department of National Parks, Wildlife and Plant Conservation, to create species distribution models (SDMs) of tigers (*Panthera tigris*) and their main prey species, particularly sambar deer (*Rusa unicolor*), gaur (*Bos gaurus*), and wild boar (*Sus scrofa*). A model was created using the SDMs with maximum entropy (MaxEnt) (Phillips et al., 2006). The coordinates of the sampling points were randomly selected to represent the study area. The following factors were considered for each sampling point: the distribution or occurrence of tigers and prey in the study area, including the density of prey and tiger population; three forest types, including evergreen forest (Ever), deciduous forest (Deci), and mixed deciduous forest (Misc); elevation; and slope. The value of each factor was normalized from 0 to 100. The study area was then divided into 10 clusters according to the scores of each factor using K-means clustering (Table 1). Cluster characteristics can be described according to the scores of various factors as follows: for wildlife habitat suitability, a value of 0 indicated that the area was not suitable, whereas a value of 100 indicated that the area was most suitable; for the forest type, a value of 0 indicated that the area did not have a specific forest type, whereas a value of 100 indicated that the area had a specific forest type; and for elevation and slope, a value of 0 indicated that the area was flat, whereas a value of 100 indicated that the area had a very high elevation and a steep slope.

Table 1. The characteristics of 10 clusters based on the scoring of factors considered at the sample plots.

Clusters	Tiger	Gaur	Sambar deer	Elevation	Slope	Ever	Deci	Misc
1	12.12	0.00	0.00	70.70	100.00	100.00	0.00	0.00
2	100.00	22.45	11.59	100.00	46.83	99.84	0.00	0.19
3	24.96	4.65	11.54	87.23	76.65	0.00	100.00	0.00
4	0.30	23.22	24.81	6.20	29.59	100.00	0.00	0.00
5	8.23	46.40	48.08	79.74	26.59	100.00	0.00	0.00
6	1.66	56.20	54.35	20.06	5.63	0.00	0.00	100.00
7	1.70	100.00	100.00	38.83	0.00	100.00	0.00	0.00
8	0.00	14.78	7.76	0.00	34.21	0.00	100.00	0.00
9	32.74	86.18	97.43	48.76	13.69	0.00	100.00	0.00
10	84.71	78.10	94.91	63.97	7.66	100.00	0.00	0.00

2.3 Field data collection methods

The coordinates of the center point of the sample plots were recorded using the UTM WGS84 coordinate system. Grassland data were collected in four steps: (1) at each sample plot, four sub-plots (1 × 1 m) were created (Figure 2); (2) the density of grass and other plants was measured using a 10 × 10 cm quadrat frame; (3) the height of the grass (from the ground) was measured using a measuring stick to measure the height of the grass that was the closest to the height of the measuring stick by measuring the height of the quadrat frame, not less than 3 frames; and (4) all aboveground biomass was cut and separated into grasses, forbs, and shrubs following Cordova and Wallace (1975) and Holechek (1984). To account for variation in biomass, plant specimens were dried in an oven at a temperature of 70°C for 48 h or until the weight of the specimens was stable. A sample was taken to determine dry weight and calculate the moisture content (percentage) of the biomass following Pattanakiat (1988). In addition, direct sightings, tracks, and fresh dung of sambar deer and gaur were recorded at every sub-plot at each sample plot.

2.4 Statistical analysis

We used Gaussian and Poisson GLMs to relate limiting factors to environmental variables (all variables used a resolution of 30 × 30 m). The logistic regression analysis (GLM with binomial distribution and logit-link function; McCullagh and Nelder, 1989) included limiting factors such as shrub biomass, forb biomass, grass biomass, and occurrence of wildlife (sambar deer and gaur); and environmental variables such as slope (degree), elevation, distance from the road, distance from the stream, distance from villages, and NDVI from the Landsat 8 satellite (Table 2; Figure

4). The analyses were performed using the MASS package (Venables and Ripley, 2002) in R (R Core Team, 2017). We used automatic stepwise selection to select the model with the lowest Akaike Information Criteria (Akaike, 1998). The processing workflow for the spatial modeling is presented in Figure 3.
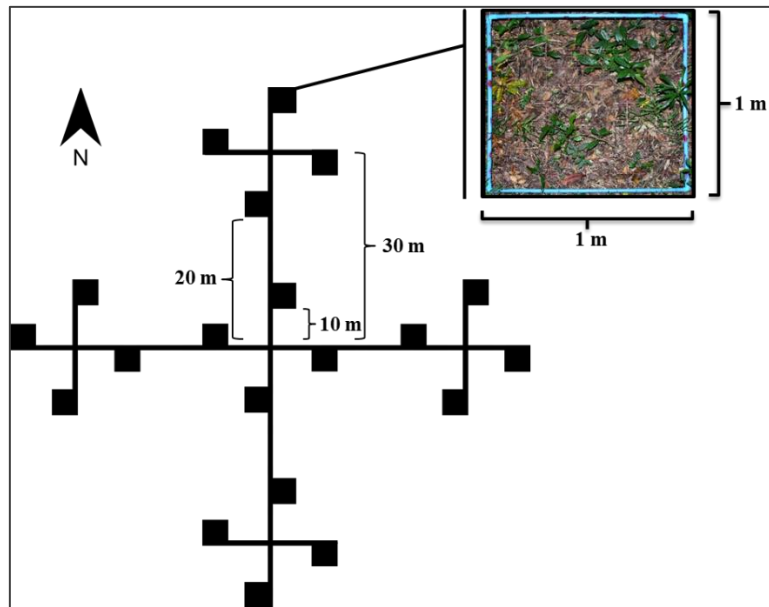

Figure 2. Sub-plots (1 × 1 m) at each sample plot.

Table 2. Variables (predictors) used to generate biomass and the virtual habitat-suitability map.

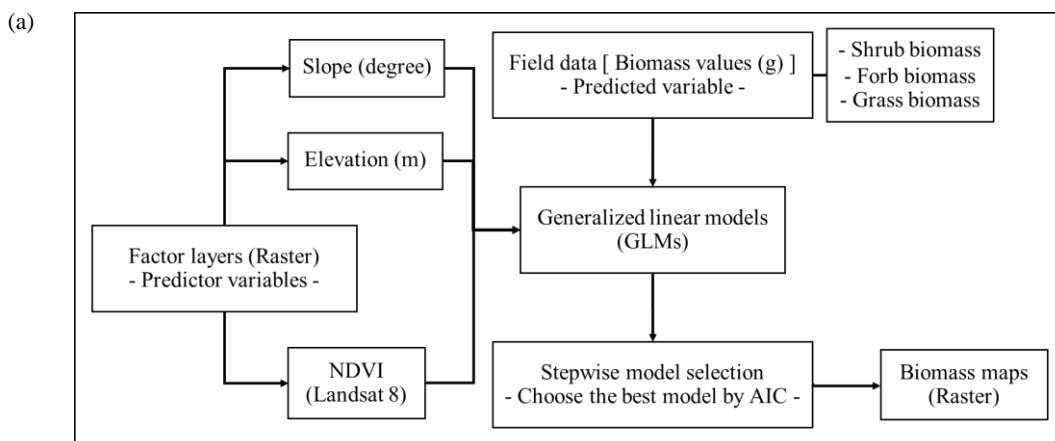| Type	Predictor	Code
Limiting factors	Shrub biomass	S_wgt
	Forb biomass	F_wgt
	Grass biomass	G_wgt
	Occurrence of wildlife	Sambar deer
		Gaur
Environment variables	Meters above sea level	Elevation
	Slope	Slope
	Normalized difference vegetation index	NDVI
	Distance from the road	Dist_road
	Distance from the stream	Dist_stream
	Distance from villages	Dist_villages

Figure 3. Flowchart of the processing performed for the (a) forage-crop models; and (b) habitat-suitability models.
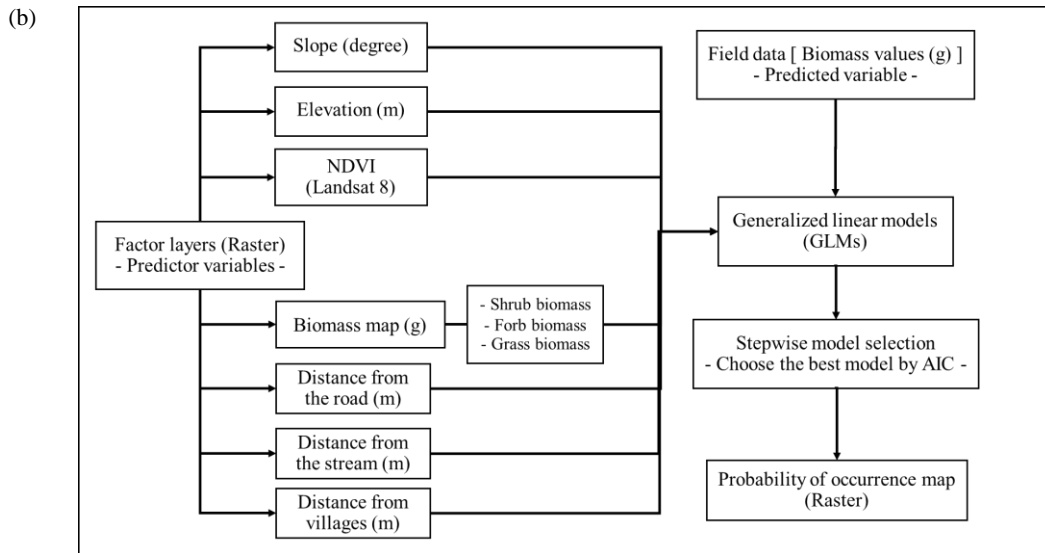
(b)

Figure 3. Flowchart of the processing performed for the (a) forage-crop models; and (b) habitat-suitability models (cont.).
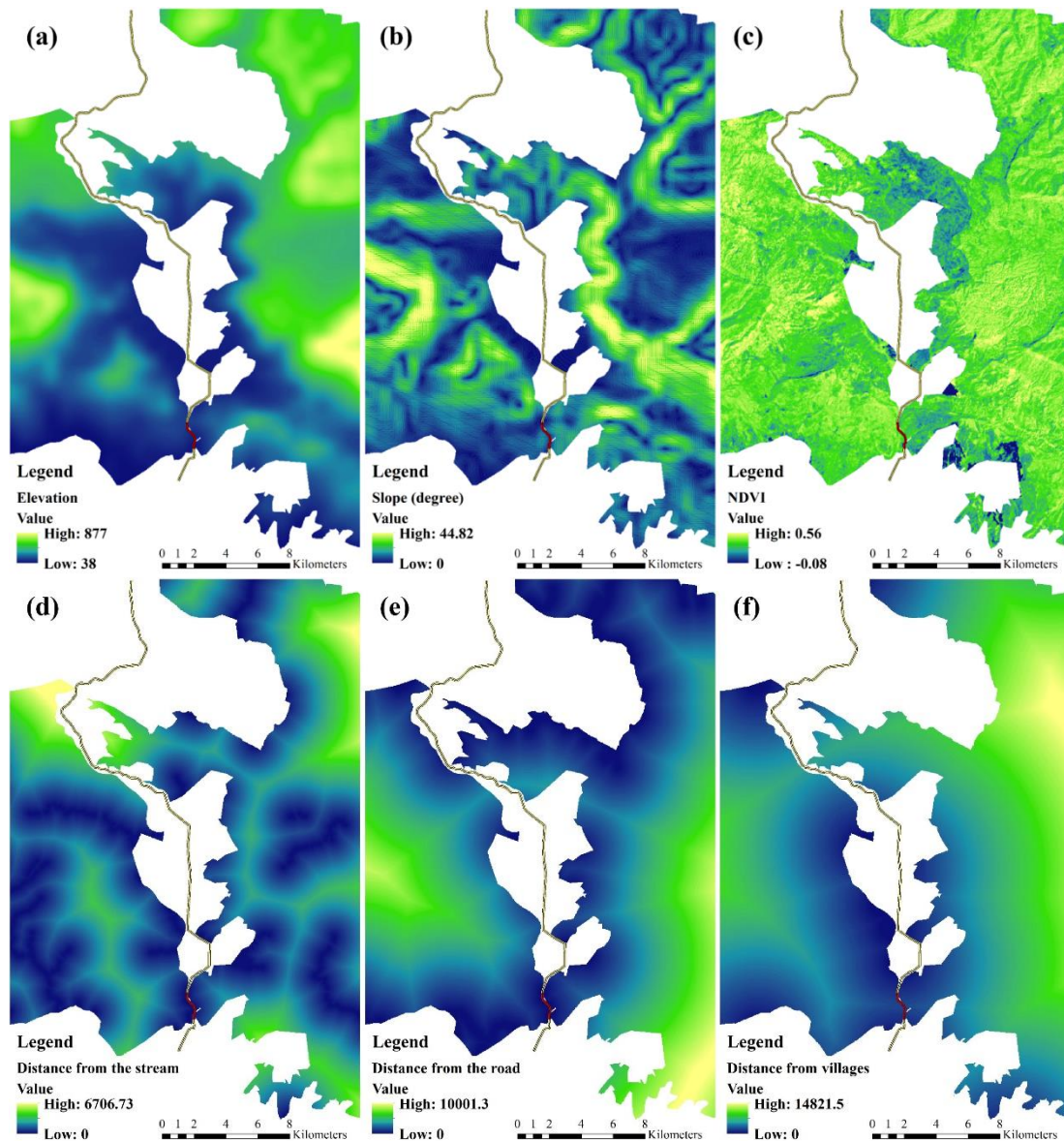

Figure 4. Environment factor layers (raster, resolution 30 × 30 m) including: (a) elevation; (b) slope; (c) NDVI; (d) distance from the stream; (e) distance from the road; and (f) distance from villages.

3. RESULTS AND DISCUSSION

3.1 The forage-crop models

The models were based on 318 1×1 m plots from the area surrounding highway 304. The results of the forage-crop model (Table 3) indicated that shrub biomass varied directly with NDVI but inversely with elevation ($p<0.05$) and slope ($p=0.051$). Forb biomass varied directly with elevation ($p<0.001$). Grass biomass varied inversely with NDVI ($p<0.01$). Shrub biomass was 0.001-141.346 g, forb biomass 9.392-51.063 g, and grass biomass 0-124.889 g (Figure 5).

Table 3. Forage-crop models for the generalized linear model with all predictor variables.

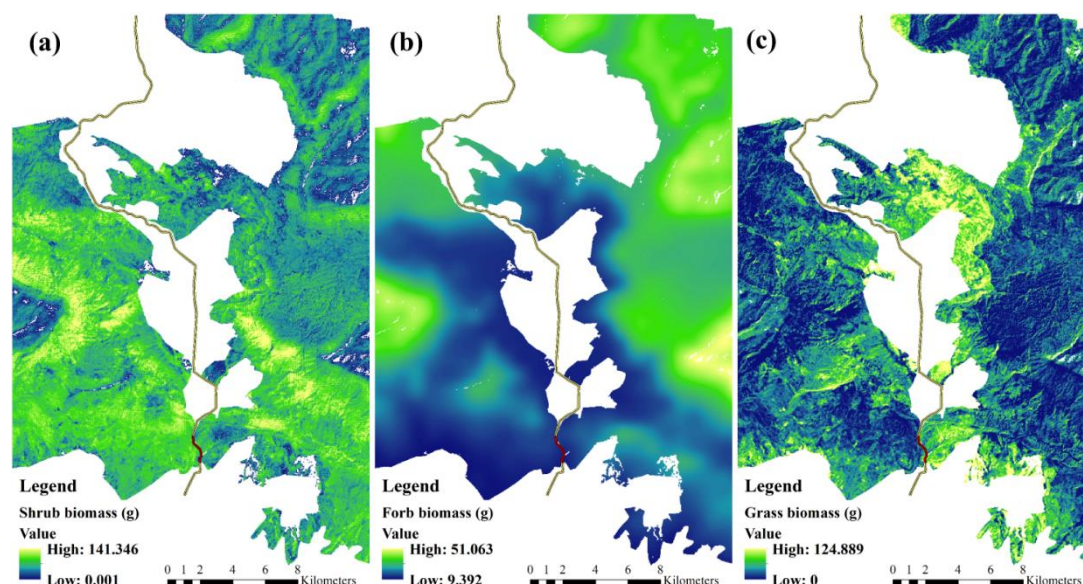| Model	Predictor	Coefficient	Standard error	p	AIC
S_wgt ~ Elevation + Slope + NDVI	Intercept	-52.929	33.487	0.115	3562.5
	Slope	1.627	0.831	0.051	
	Elevation	-0.068	0.018	<0.001	
	NDVI	288.485	93.713	<0.05	
F_wgt ~ Elevation	Intercept	7.505	4.816	0.12	3351.8
	Elevation	0.05	0.012	<0.001	
G_wgt ~ NDVI	Intercept	110.98	23.46	<0.001	3373.8
	NDVI	-259.45	62.82	<0.001	

Figure 5. Biomass from the forage-crop models for (a) shrub biomass; (b) forb biomass; and (c) grass biomass in the area surrounding highway 304.

The forage-crop models showed a negative relationship between shrub biomass and elevation. This is consistent with Ensslin et al. (2015), who found that shrub biomass decreased significantly with elevation. Conversely, when tropical elevation (i.e., 100–60 0 m, which is in the range we studied) increases, forest density also increases (Clark et al., 2015). Therefore, higher elevations promote canopy closure. Tropical saplings and species highly associated with gaps (i.e., low-density forests) show a rapid rise in relative growth rate with increasing light level. The inability of light to shine through to the ground is an important factor that influences shrub growth. The model of shrub biomass differed from that of forb biomass. Forb biomass had a positive relationship with elevation because forbs have no persistent woody stem above ground (Mongkhonsin et al., 2019). The height changes when an area has no light or high forest density. The higher shade avoidance, shade tolerance, and specific leaf area of forbs, as well as with their more frequent occurrence under denser canopies, all suggest that the herbaceous climbing-plant strategy is suitable for low-light conditions. Forbs appear to invest in greater shade avoidance and shade tolerance, and they tend to have

a slightly higher specific leaf area than co-occurring plants (Bitomský et al., 2019).

Model selection was conducted for models of shrub biomass and grass biomass, which included additive and interactive effects of NDVI. In the forested habitat, the relationship between NDVI and ground vegetation biomass was positive for shrubs and negative for grass because vegetation greenness and photosynthetic capacity have stronger relationships with NDVI for shrubs than for grass (De las Heras et al., 2015). Grassland also has lower NDVI reflectivity. Therefore, models using NDVI show different effects for forest and grassland areas (Borowik et al., 2013). Meanwhile, grass cover decreased as canopy cover increased because of lower transmission of light to understory vegetation, an important factor for the appearance of grass cover (Widenfalk and Weslien, 2009). Both of the conservation areas studied here are intersected by highway 304 and are adjacent to villages (Figure 1). In some areas, forest cover was cleared due to encroachment and livestock has been introduced, resulting in higher grass biomass than in other areas. Therefore, management of these areas affects the type and amount of forage crops. The most important properties were open canopy vs. dense forest cover because light is critical for determining the amount of shrub and grass biomass; however, this did not significantly affect forb biomass.

3.2 The habitat-suitability models

The HSMs showed that the probability of sambar deer occurrence varied directly with distance from the road, distance from the stream, distance from villages, and grass biomass but inversely with NDVI ($p < 0.05$). The probability of gaur occurrence varied directly with NDVI ($p = 0.084$) but inversely with slope, distance from the road, and distance from the stream ($p < 0.05$) (Table 4).

Table 4. The habitat-suitability models for the generalized linear model with all predictor variables.

Model	Predictor	Coefficient	Standard error	p	AIC
Sambar deer ~ G_wgt + Dist_road + Dist_stream + Dist_villages + NDVI	Intercept	-0.762	1.354	0.573	271.7
	G_wgt	1.20E-02	4.43E-03	<0.05	
	Dist_road	3.05E-04	7.62E-05	<0.001	
	Dist_stream	9.29E-04	1.22E-04	<0.001	
	Dist_villages	7.03E-04	1.00E-04	<0.001	
	NDVI	-11.330	3.676	<0.05	
Gaur ~ Slope + Dist_road + Dist_stream + NDVI	Intercept	-1.797	1.839	0.328	253.92
	Slope	-0.258	0.046	<0.001	
	Dist_road	-4.20E-04	1.48E-04	<0.05	
	Dist_stream	-4.39E-04	1.08E-04	<0.001	
	NDVI	9.013	5.220	0.084	

The HSMs showed that the probability of sambar deer occurrence varied positively with grass biomass but negatively with NDVI, and generally corresponded to the model of grass biomass. Although the sambar deer is remarkably flexible in its habitat affinities, it mainly prefers closed canopy and the tallgrass ecotone between dense forest and open canopy, as well as areas relatively free from human disturbance (Kushwaha et al., 2004; O'Brien et al., 2003). The probability of gaur occurrence varied positively with NDVI because gaur can tolerate rugged terrain and dense forest better than other ungulates, as long as there are adequate water sources available (Smith et al., 2010).

Both occurrence models were consistent with Lynam et al. (2012). The results indicated that sambar deer were sensitive to villages and roads (disturbance variables), and places where sambar deer were detected had more open habitat. Sambar deer have suffered poaching pressure and have been targets for market-driven poaching across Thailand. They were found farther away from roads and villages, consistent with the study of Jornburom et al. (2020) in Thailand's Western Forest Complex, suggesting a sensitivity to hunting as well as to a range of other environmental conditions inside protected areas. Distance to the stream had a negative relationship with occurrence of sambar deer. The river itself was likely not the main attractor of sambar deer; rather, the geographic features associated with the valley likely produced a desirable habitat for sambar deer, especially in the area surrounding highway 304 (Simcharoen et al., 2014).

Gaur were not sensitive to roads or slope because they were found mostly in lowland forests. The probability of gaur occurrence was greatest at the forest edge, especially at the wildlife corridor of highway 304 (Figure 6). This information may be useful for managing gaur crossing between the two conservation areas. The gaur HSMs were consistent with Lynam et al. (2012), who also found that gaur showed stronger avoidance of villages than sambar deer. Distance from the stream had a positive relationship with the wildlife corridor, which has a river (Khlong Yang) on the Khao Yai National Park side.

Sambar deer and gaur are considered to be grazers and browsers (Duckworth et al., 2016; Masters and Flach, 2015). The regression coefficient for grass biomass in the sambar deer HSMs was 0.012 (Table 3), indicating that grass biomass had a stronger effect on the occurrence of sambar deer than on that of gaur.

The regression coefficients for NDVI in the HSMs of sambar deer and gaur were -11.330 and 9.013, respectively, indicating that sambar deer were more likely to live in open areas than gaur. This corresponded to grass biomass on the edge of the conservation area, which has more open space than in the conservation area (Figure 1). This was consistent with Lamont et al. (2019), whose results showed that ungulates selected grass-covered areas farther from roads. Therefore, increased grass biomass, associated with more open canopy, promotes increased use by ungulates. However, in some areas, ungulates aside from sambar deer and gaur consume large amounts of forbs and shrubs, primarily when green grass is unavailable. These ungulates show a strong avoidance of shrubs high in volatile oils because they lack mechanisms to reduce the toxic effects of these substances (Cappai and Aboling, 2020).
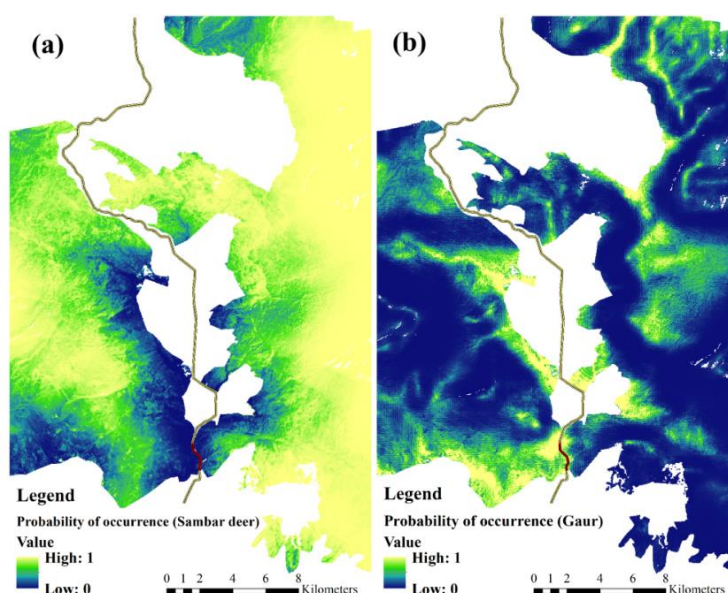

Figure 6. Habitat-suitability models showing the probability of occurrence (0-1) of (a) sambar deer; and (b) gaur.

4. CONCLUSION

We modeled the relationships of shrub biomass and grass biomass with NDVI to facilitate the use of Landsat 8 data for managing the area surrounding highway 304 in Thailand. The forage-crop models can be used to predict HSMs and elucidate the exploitation of sambar deer and gaur. This is critical for wildlife management. Sukmasuang et al. (2020) reported observations of sambar deer and gaur around the wildlife corridor of highway 304 taken with camera traps. Thus, future studies of forage crops could include temporal variations in NDVI at locations where these ungulates have been observed and elucidate disturbance variables affecting the willingness of sambar deer and gaur to cross the forest boundary. Improved management of forage crops and tiger prey species may help tigers from Thap Lan National Park translocate to Khao Yai National Park via the highway 304 wildlife corridor 304.

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