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Use of Bayesian, Lasso Binary Quantile Regression to Identify Suitable Habitat for Tiger Prey Species in Thap Lan National Park, Eastern Thailand

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ABSTRACT

A Bayesian approach was used to develop binary quantile regression models featuring the lasso penalty. The models afford the advantages of all quantile regression models, such as robustness and detailed insights into covariate effects; they also handle issues associated with overfitting well. Thus, this model was used to investigate habitat suitability for the management of tiger prey species. Field data were collected from 150 sampling sites (2,416 sub-plots) in Thap Lan National Park of the Dong Phayayen-Khao Yai Forest Complex (DPKY) from August 2019 to March 2021. We focused on sambar deer (*Rusa unicolor*) and gaur (*Bos gaurus*) because they are the principal prey species of tigers. Vegetation was sampled for biomass and nutrient content to identify suitable habitat. The "bayesQR" package of R was used to identify habitats appropriate for these species. The correlation between forage crop biomass and the normalized difference vegetation index (NDVI) was significantly associated with tiger prey species presence. The habitat can be improved by increasing grass and forb biomasses as the prey species prefer open habitats, such as grassland and open areas of dry evergreen forest. Habitat management has ensured that the grass biomass of open forest is significantly higher than that of dense forest. In addition, the hemicellulose content of open forest was significantly greater than that of dense forest. We found that spatial modeling combined with Bayesian, lasso binary quantile regression could aid wildlife habitat management in a Thai National Park.

1. INTRODUCTION

The statistical theory of regression quantiles has been developed by econometricians over the past 40 years (Bassett and Koenker, 1986; Koenker and Bassett Jr, 1982), but ecological applications have been published only recently (Brennan et al., 2015; Cade and Noon, 2003; Chamaillé-Jammes and Blumstein, 2012; Muggeo et al., 2013). The statistical properties of the regression quantile estimates are used to test hypotheses and construct confidence intervals that reveal the effects of ecological limiting factors; the models find many ecological applications (Krause et al., 2002). The statistical distributions of ecological data often exhibit unequal variation given the complex interactions among factors affecting various organisms; not all can be measured and incorporated into statistical models (Brennan et al., 2015). Thus, to obtain a more complete picture of the relationships among variables missed by other quantile regression methods, we initially used the binary quantile regression model of Manski (1985). However, Kordas (2006) found that quantile regression afforded a much more comprehensive view than binary regression for how predictor variables influence the responses of even binary cases. However, most studies of binary quantile regression have employed median binary regression. Bayesian binary quantile regression estimates, and the associated variable selection procedures, are insensitive

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to outliers, and the methods thus identify variables that are important predictors of the various response distribution quantiles of the dependent variable (Benoit et al., 2013). We used this model to investigate habitat suitability for tiger prey species.

This study is the first wildlife habitat management work to employ Bayesian, lasso binary quantile regression to investigate habitat suitability and factors affecting habitat quality and quantity in Southeast Asia. We used foraging resource productivity and composition data to seek associations between ecological factors and the quality of wildlife habitat. Protein and digestibility value have been especially emphasized as major factors for pasture quality evaluation for animal performance (Seven and Cerci, 2006). Information on nutritive value of these pastures is scarce and in fragmented form and often assumptions are made for estimating feed contribution from this important source. We employed a spatial distribution model to examine the associations among underlying characteristics and to predict the quality of wildlife habitat at several levels (Cushman and McGarigal, 2002). We created a decision-support model that yields deep insights into wildlife habitat composition and configuration at the landscape and regional levels. This will inform decision-making and policy.

2. METHODOLOGY

2.1 Study site

Thap Lan National Park, part of the Dong Phayayen-Khao Yai Forest Complex (DPKY), was declared a UNESCO World Heritage Site in 2005. Ash et al. (2021), Duangchatrasiri et al. (2017), and Ngoprasert and Gale (2017) studied the status of the tiger (*Panthera tigris*) and tiger prey species in the DPKY. Tiger density was high in Thap Lan and Pang Sida National Parks but no tigers were found in Khao Yai National Park. The principal tiger prey species [sambar deer (*Rusa unicolor*) and gaur (*Bos gaurus*)] were widespread in the DPKY. Areas with high densities of tigers and their prey must be protected from human interference. The study was conducted in a 1,638 km^2 area of Thap Lan National Park that lies in the provinces of Nakhon Ratchasima, Buri Ram, and Prachin Buri (14°05′-14°33′N, 101°50′-102°40′E) (Figure 1). The elevation range is 37-925 m.a.s.l.

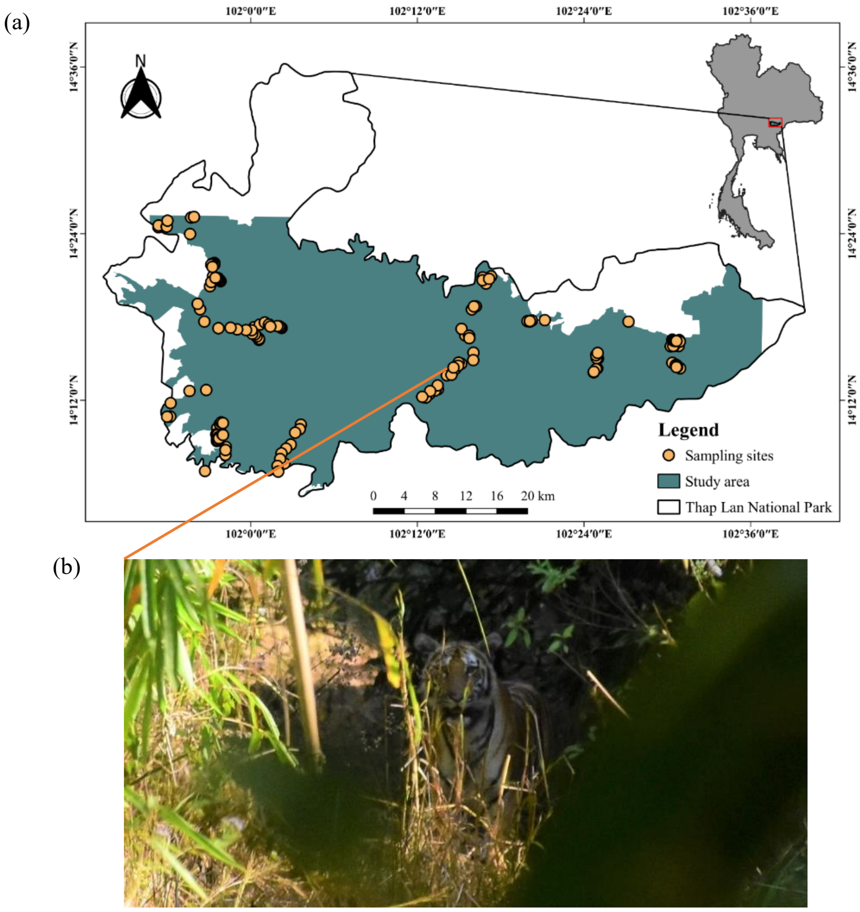

Figure 1. (a) The study area (Thap Lan National Park, part of the Dong Phayayen-Khao Yai Forest Complex (DPKY)). We focused on the areas that are habitats for tiger prey species. Therefore, the village part and agricultural areas were excluded. (b) Tiger at Thap Lan National Park from direct observation, was taken on December 19, 2019.

2.2 Survey design

Sampling sites were surveyed in terms of forage resources and the abundance of sambar deer and gaur (the principal tiger prey). The sampling sites were randomly selected over the study area. The following factors were considered when selecting sites: the occurrences/distributions (and densities) of tigers and their prey, the forest type (evergreen, deciduous, and mixed deciduous) (RFD, 2018), and the topography (elevation and slope) created from Google Earth Engine (Gorelick et al., 2017). The study area was divided into 10 strata by reference to the scores for each factor. 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, following Paansri et al. (2021) (Figure 2).

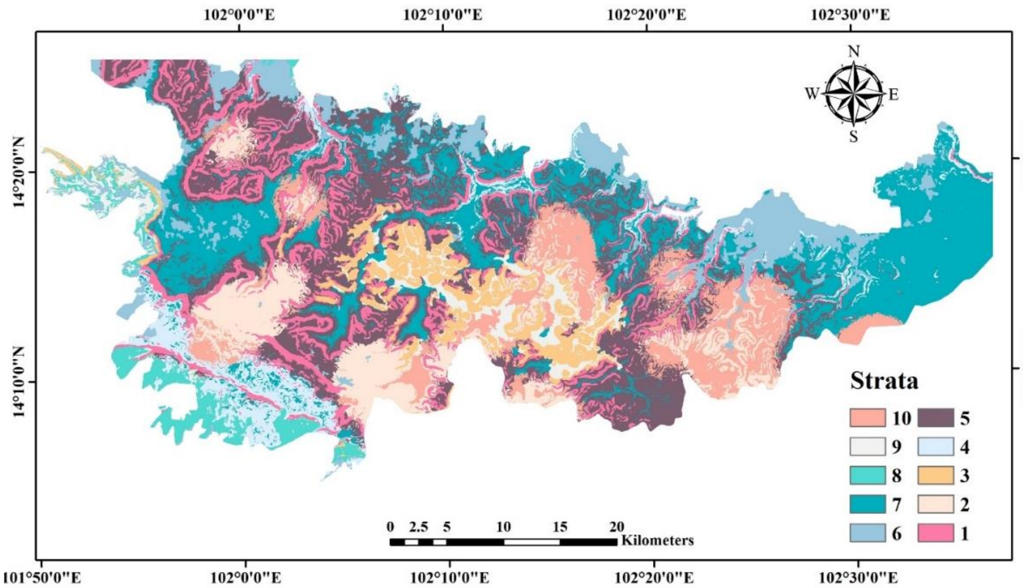

Figure 2. A map of the 10 strata of the study area derived using the K-means method

2.3 Field data collection

Forage crop data were collected from 20 sub-plots per each sample site (Figure 3), and all aboveground biomass was cut and separated into forbs, grasses, and shrubs following Holechek (1984). All specimens were dried in an oven at 70°C for 48 h or until the weights became stable. Dry weights and moisture contents (percentages) were calculated following Pattanakiat (1988). Then, analysis of forage crops used by sambar deer and gaur was conducted; the crude protein (CP), neutral detergent fiber (NDF), acid detergent fiber (ADF), acid detergent lignin (ADL), cellulose, and hemicellulose levels were measured in the Animal Nutrition Laboratory, Department of Animal Science, Kasetsart University. Presence data from habitat use of sambar deer and gaur with sightings, tracks, and fresh dung (the way an animal uses the physical and biological resources in a habitat) was recorded for every sub-plot at each sample site.

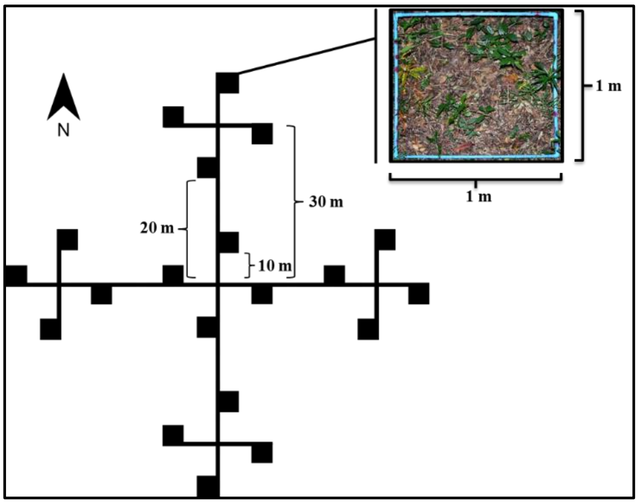

Figure 3. 20 Sub-plots (each 1×1 m) at each sample site (An inaccessible sub-plots are excluded from data collection and analysis)

2.4 Statistical analysis

Gaussian and Poisson generalized mixed models (GLMs) were used to link limiting factors to environmental variables (all at resolutions of 30×30 m). The logistic regression analysis (featuring a GLM with a binomial distribution and a logit-link function; McCullagh and Nelder, 2019) included the limiting factors of shrub, forb, and grass biomasses; sambar deer and gaur occurrences; and environmental variables such as the slope (in degrees); elevation; distances from a road, a stream, and villages; canopy cover; and normalized difference vegetation index (NDVI) data from the Landsat 8 satellite. All analyses were performed using the MASS package (Venables and Ripley, 2013) of R (R Core Team, 2017). Automatic stepwise selection was used to derive the model with the lowest Akaike Information Criterion (Akaike 1998). The processing workflow for the spatial modeling is presented in Figure 4. The "bayesQR" package (Benoit and Van den Poel, 2017) was used to investigate habitat suitability by wildlife occurrence; estimations and inferences were made employing Bayesian, lasso binary quantile regression following Li et al. (2010). Both the frequentist approach and a more recent Bayesian approach based was used on an asymmetric Laplace distribution (ALD) (Benoit and Van den Poel, 2012). Bayesian-binary quantile regression yields estimates and variables, and is insensitive to outliers, heteroskedasticity, and other anomalies that challenge existing assumptions. The regression identifies variables that are important predictors of the various quantiles of the dependent variable response distributions (Benoit and Van den Poel, 2017). The processing workflow for the Bayesian, lasso binary quantile regression modeling is presented in Figure 5.

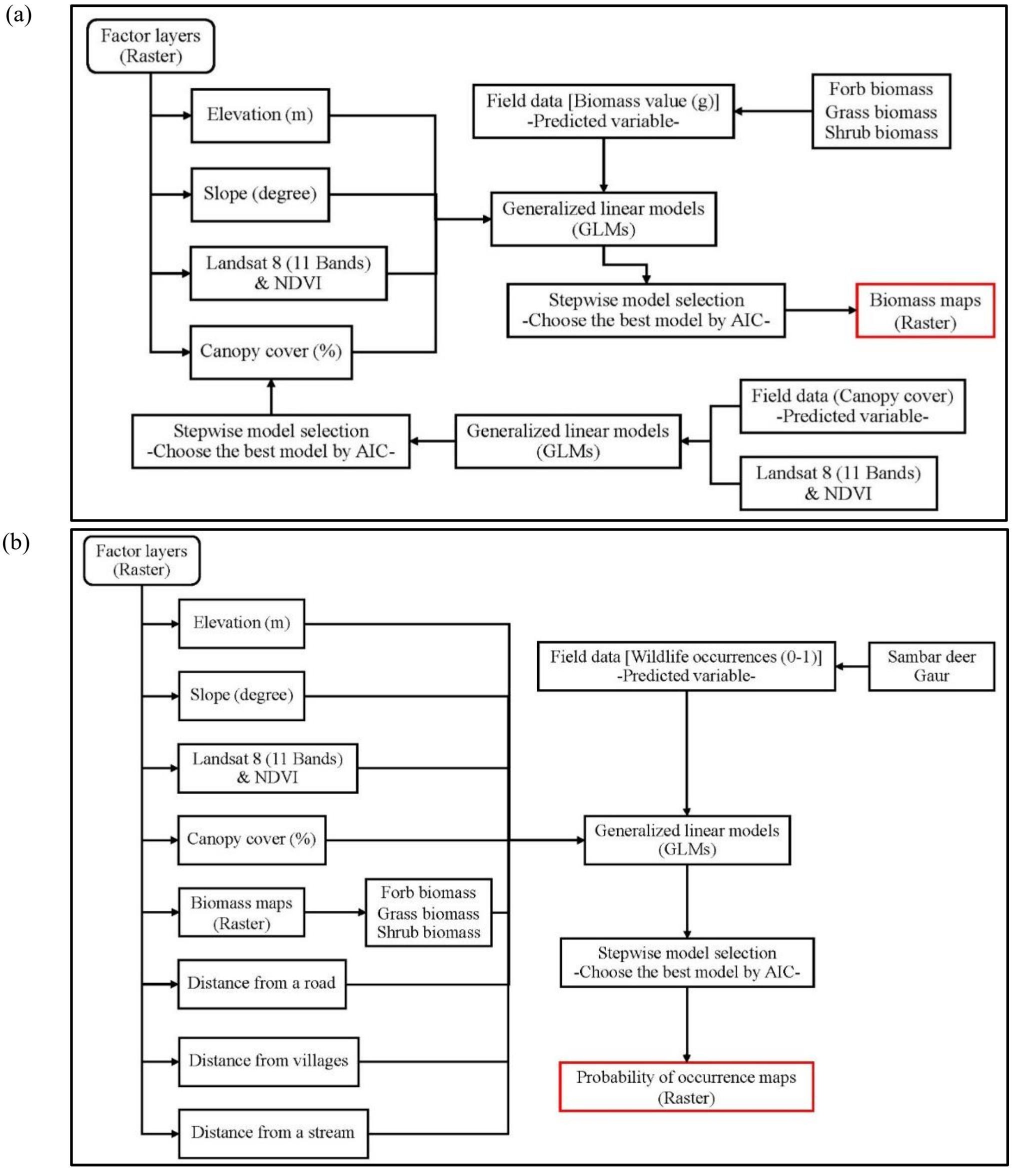

Figure 4. Flowchart of the processing performed for the (a) forage-crop models and (b) habitat-suitability models

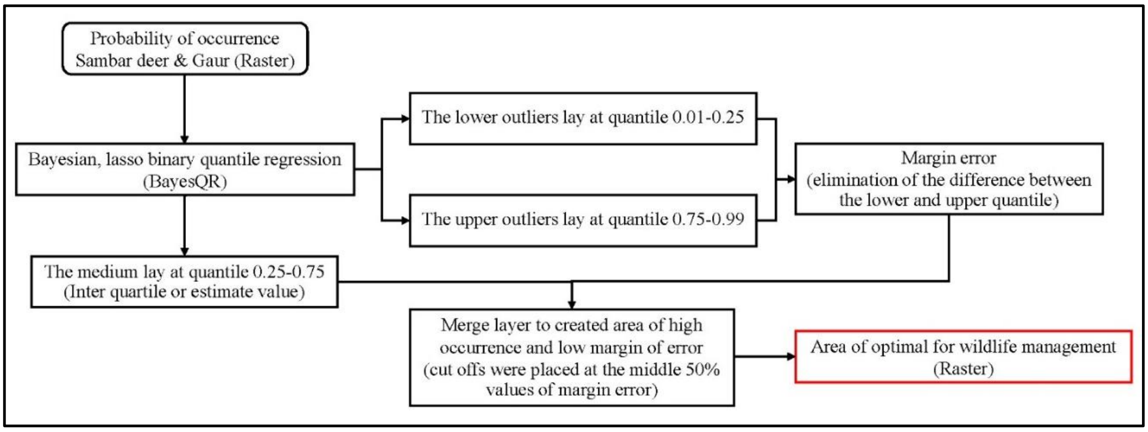

Figure 5. Flowchart of the processing performed for the Bayesian, lasso binary quantile regression modeling to create the area of optimal for wildlife management

3. RESULTS AND DISCUSSION

3.1 The abundance of tiger prey species

A total of 150 sampling sites (2,416 Sub-plots) were surveyed. The presence of tiger prey species was recorded at 1,466 points (60.68%), composed of 740 points of sambar deer (30.63%), and 726 points of gaur (30.05%) (Figure 6). The presence of tiger prey species in each the strata is summarized in Table 1.

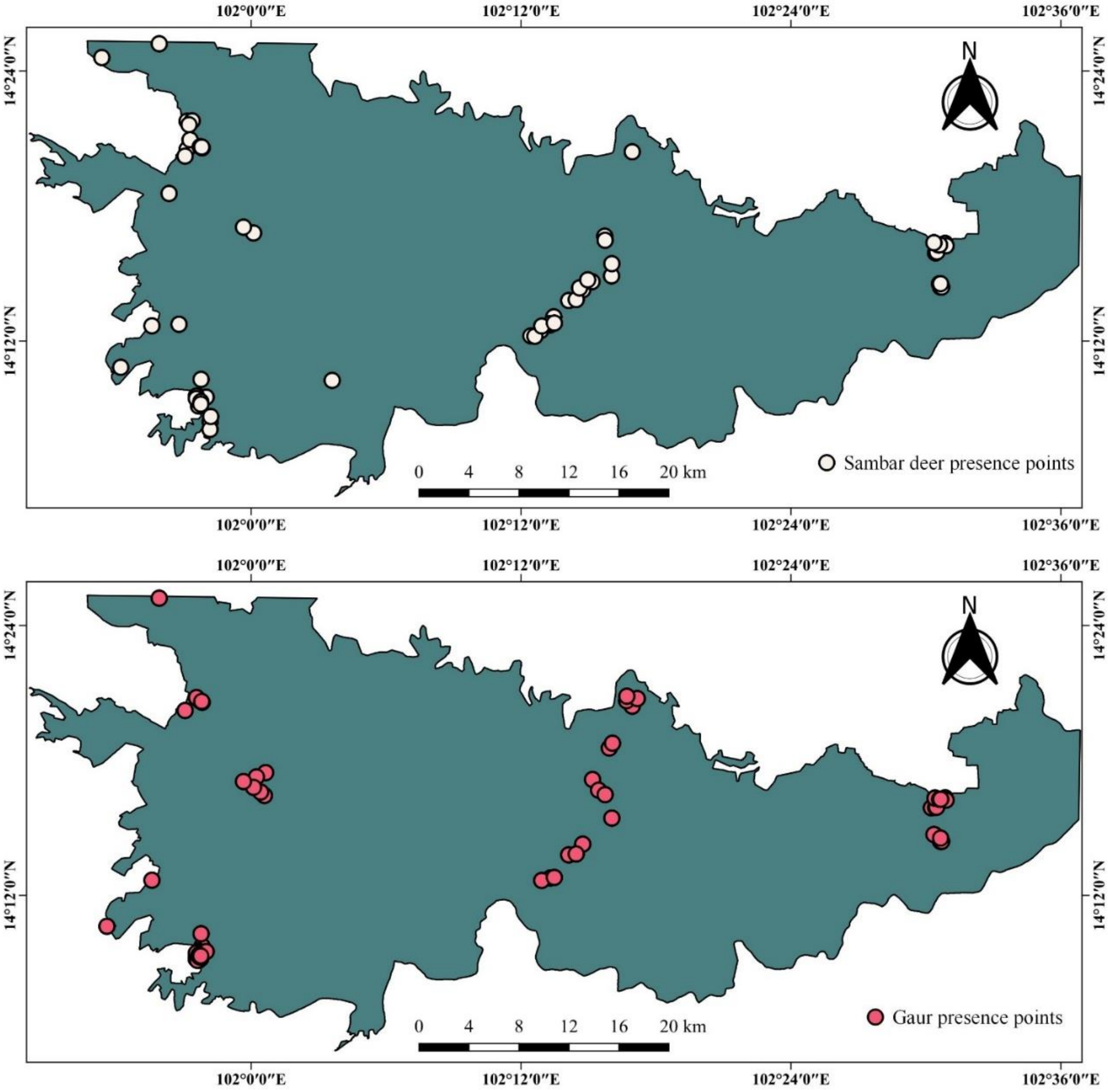

Figure 6. A map of the tiger prey species distribution from habitat use of sambar deer and gaur for every sub-plots

Table 1. The number of sub-plots (each 1×1 m) and presence points of tiger prey species in the strata

Strata	Sub-plots	Sambar deer		Gaur	
	Count	Presence	%	Presence	%
1	163	53	32.52	24	14.72
2	78	24	30.77	48	61.54
3	44	40	90.91	12	27.27
4	213	36	16.90	36	16.90
5	191	48	25.13	24	12.57
6	676	235	34.76	366	54.14
7	467	98	20.99	132	28.27
8	373	36	9.65	12	3.22
9	130	98	75.38	36	27.69
10	82	72	87.80	36	43.90
Sum	2,416	740	30.63	726	30.05

3.2 Spatial prediction models

The spatial prediction models (Table 2) were those with the lowest AICs. A canopy cover model with six variables exhibited the highest efficiency. The spatial predictions lay between 0-100%; the model exhibited a stronger predictive ability than did the NDVI data ($p<0.01$), as in Li and Mao (2020) and Wu et al. (2013), who nonetheless found that the NDVI was a good predictor of, and the most important variable affecting, canopy cover. The NDVI values vary between dense and open forests in terms of vegetation greenness (Moreno-de las Heras et al., 2015). Moreover, the differences in the Landsat 8 reflectances of band 2 (Blue), band 3 (Green), band 9 (Cirrus), band 10 (Thermal Infrared 1), and band 11 (Thermal Infrared 2) imagery, were all significant at $p<0.01$.

The forage crop model indicated that forb biomass varied directly with only the NDVI ($p<0.01$). Grass biomass varied directly with slope and the NDVI (both $p<0.01$) but inversely with elevation and canopy cover (both $p<0.01$). Shrub biomass varied directly with elevation and canopy cover (both $p<0.05$) but inversely with elevation ($p<0.01$). The forb biomass was 0-262.4 kg/ha, the grass biomass was 0-2,998 kg/ha, and the shrub biomass was 0-440.4 kg/ha. The model of shrub biomass exhibited a negative relationship with elevation, consistent with the data of Ensslin et al. (2015) on tropical forests and Paansri et al. (2021) on areas surrounding highway 304 in the region of our study. Shrub biomass decreased significantly with elevation. The models for forage crops included the additive and interactive effects of canopy cover. In forested habitats, the relationship between canopy cover and ground vegetation biomass was positive for shrubs but negative for grass, consistent with Aranha et al. (2020), who reported that canopy closure is positively correlated with shrub biomass because photosynthetic capacity is more strongly related to canopy cover (Kaur 2007; Moreno-de las Heraset al., 2015). Canopy cover was a strong (negative) predictor of grass biomass; increasing canopy cover significantly reduced grass (Randle, 2018). Most grasses were C4 grasses that were exposed to frequent fires (Hoffmann, 1999), and were therefore restricted to high-light-intensity open ecosystems; such grasses are shade-intolerant and thus very susceptible to competitive exclusion as woody cover increases (Sage and Kubien, 2003).

The habitat-suitability models (HSMs) showed that the probability of sambar deer presence (a value between 0 and 0.87) varied directly by slope, the forb and grass biomasses, and distances from villages (all $p<0.01$) but inversely with elevation, shrub biomass, the distance from a road, and the NDVI (all $p<0.05$). The probability of gaur presence (a value between 0 and 0.9) varied directly by slope, forb and grass biomasses, the distance from a stream, and distances from villages (all $p<0.05$) but inversely by elevation, shrub biomass, and the NDVI (all $p<0.05$). The relationships are analyzed in the next section.

3.3 Investigation of habitat suitability via Bayesian, lasso binary quantile regression

The factors yielded by the models (with the lowest AICs) of tiger prey presence (Table 2) were subjected to Bayesian-binary quantile regression analysis. The lower outliers lay at quantile 0.01-0.25 and the upper outliers are at quantile 0.75-0.99; the medium (interquartile or estimate value) lay at quantile 0.25-0.75 (this is the probability of a value between 0 and 1) (Dicker et al., 2006; Wan et al., 2014) (Figure 7). The medium quantiles indicate the relationships between environmental factors and tiger prey presence, as shown by Ji et al. (2012), and afford a very comprehensive insight into how predictor variables influence the response of a binary case. Thus, for every performance measure and every type of data-generation process, the lasso afforded the best performance (Benoit et al., 2013).

Table 2. The spatial predictions of the generalized linear model using the predictor variables with the lowest AICs

Model	Predictor	Coefficient	Standard error	P-value	AIC
Canopy cover	Intercept	9.42E+01	4.28E+01	<0.05	1161.6
	Band 2	4.56E-03	6.94E-04	<0.01	
	Band 3	-4.82E-03	5.42E-04	<0.01	
	Band 9	-2.35E-02	8.40E-03	<0.01	
	Band 10	-1.96E-03	5.83E-04	<0.01	
	Band 11	2.85E-03	8.29E-04	<0.01	
	NDVI	1.71E+01	1.12E+00	<0.01	
Forb biomass	Intercept	3.88E+00	1.99E+00	0.05	26312
	NDVI	4.11E+01	6.22E+00	<0.01	
Grass biomass	Intercept	1.17E+02	8.66E+00	<0.001	32690
	Slope	2.07E+00	4.72E-01	<0.001	
	Elevation	-8.92E-02	2.19E-02	<0.001	
	NDVI	4.14E+02	4.64E+01	<0.001	
	Canopy cover	-3.11E+02	1.86E+01	<0.001	
Shrub biomass	Intercept	1.04E+01	1.82E+00	<0.01	25477
	Slope	3.10E-01	1.15E-01	<0.01	
	Elevation	-4.32E-02	5.35E-03	<0.01	
	Canopy cover	3.51E+01	2.39E+00	<0.01	
Probability of occurrence (Sambar deer)	Intercept	-1.06E+01	2.52E+00	<0.001	2875.1
	Slope	1.22E-01	3.55E-02	<0.001	
	Elevation	-1.42E-02	4.18E-03	<0.001	
	Forb biomass	1.49E+00	3.22E-01	<0.001	
	Grass biomass	3.46E-02	1.06E-02	<0.01	
	Shrub biomass	-4.88E-01	1.03E-01	<0.001	
	Distance from a road	-6.01E-05	1.58E-05	<0.001	
	Distance from villages	3.72E-05	1.27E-05	<0.001	
	NDVI	-1.31E+01	6.13E+00	<0.05	
Probability of occurrence (Gaur)	Intercept	-7.93E+00	2.58E+00	<0.01	2791.9
	Slope	1.24E-01	3.38E-02	<0.001	
	Elevation	-2.36E-02	3.91E-03	<0.001	
	Forb biomass	1.80E+00	3.09E-01	<0.001	
	Grass biomass	2.58E-02	1.09E-02	<0.05	
	Shrub biomass	-6.96E-01	9.47E-02	<0.001	
	Distance from a stream	8.35E-05	3.07E-05	<0.01	
	Distance from villages	3.57E-05	1.33E-05	<0.01	
	NDVI	-1.58E+01	6.26E+00	<0.05	

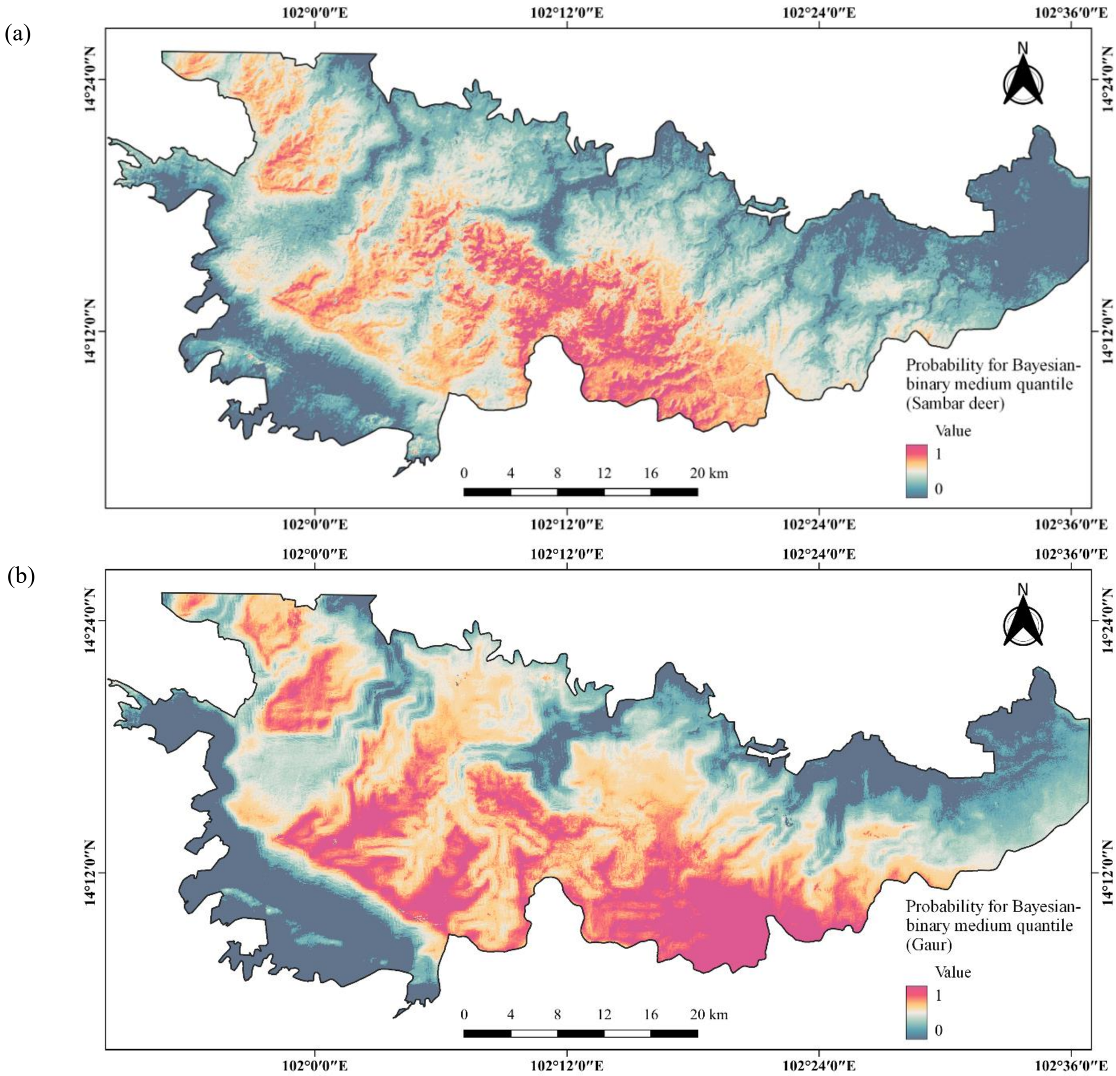

Figure 7. Probabilities yielded by the Bayesian-binary medium quantile (0-1) for (a) sambar deer and (b) gaur presence

Therefore, the region occupied by tiger prey species requires a low margin of error (thus elimination of the difference between the upper and lower quartile; represents the low-risk area of variability) and a high model estimate for the medium quantile (John, 2015) (Figure 7). Cutoffs were placed at the middle 50% values of the margin errors, and the model estimates formed the medium quantile when ordered from lowest to highest (Dodge, 2008). The stable areas available to manage and increase the populations of sambar deer and gaur were 296.7 km^2 and 385.7 km^2, respectively (Figure 8); gaur require more (and better connected) habitat than sambar deer (Chetri, 2006), consistent with McShea and Bhumpakphan (2011), who found that gaur in Thailand prefer grassland and open areas of moist evergreen, dry evergreen, semi-evergreen, and mixed deciduous forests. Gaur used both closed and open forest. The habitat preferences of sambar deer were higher in areas close to the main river at lower elevations, where the predominant habitat was mixed deciduous forest (Chatterjee, 2014; Rai, 2019; Simcharoen et al., 2014); sambar deer preferred the more open habitat (Lynam et al., 2012). The regression coefficients for the NDVI data in the HSMs of sambar deer and gaur were -13.1 and -15.8, respectively (Table 2), indicating that both prey species lived in open areas. Thus, both species preferred grassland (of low NDVI reflectivity). NDVI-based models yielded different results for forest and grassland (Borowik et al., 2013). Grass cover decreased as canopy cover increased because of lower transmission of light to the understory; grass requires light (Widenfalk and Weslien, 2009). The grass biomass increased significantly with a reduction in the canopy cover (Table 2) in the conservation area, which has more open than dense forest (Paansri et al., 2021), particularly in Thap Lan National Park.

The habitat suitabilities derived via Bayesian, lasso binary quantile regression are presented in Figure 7. Next, we focused on manageable environmental factors (Table 2). In both models, the relationships between manageable environmental factors and sambar deer and gaur presence were all statistically correlated (grass and forb biomasses positively but shrub biomass negatively), consistent with Lamont et al. (2019), who found that ungulates select grassy areas well away from disturbances (Duangchatrasiri et al., 2019). Therefore, an increased grass biomass, associated with a more open canopy, promotes habitat use by ungulates. However, in certain areas, sambar deer and gaur consume large amounts of forbs and shrubs, primarily when green grass is unavailable. Such ungulates strongly avoid shrubs high in volatile oils because they lack mechanisms to reduce the toxic effects of such substances (Cappai and Aboling, 2020).

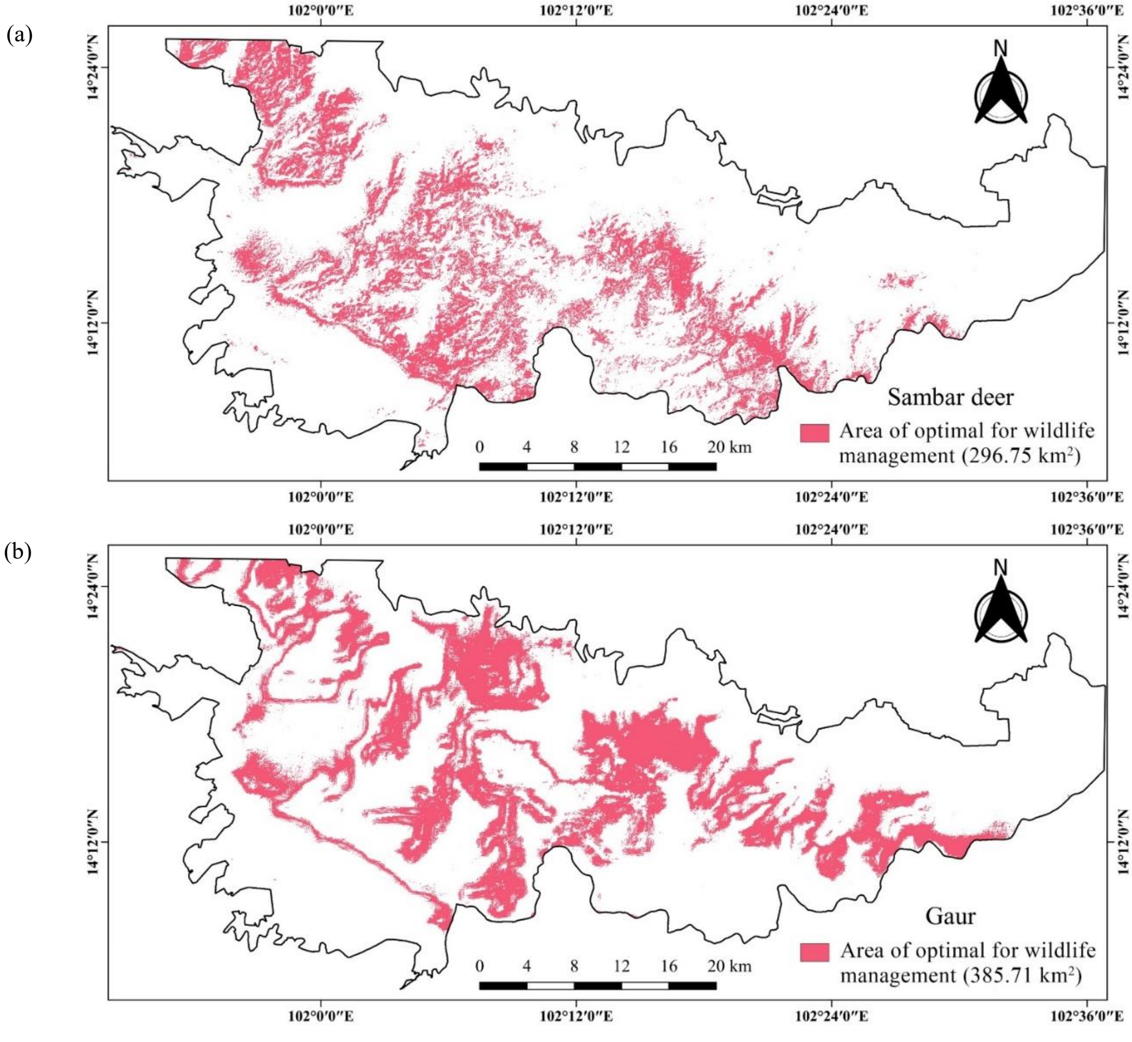

Figure 8. Area of optimal for wildlife management of (a) sambar deer (296.75 km)^2 and (b) gaur (385.71 km)^2; High abundance of tiger prey species, high-quality habitat, and the region occupied by tiger prey species requires a low margin of error; represents the low-risk area of variability and worth for habitat management

3.4 Biomass production and nutritional characteristics of forage crops

The results of forage crop biomass by canopy cover revealed 1,645 dense forest plots (0-40% of the sky was obstructed by tree canopies) and 415 open forest plots (≥40% of the sky obstructed). In dense forest, the forb biomass was 18.73±0.78 g/m^2, the grass biomass was 9.24±1.19 g/m^2, and the shrub biomass was 22.08±1.01 g/m^2; the figures for open forest were 12.46±2.25, 164.15±9.60, and 35.27±0.71 g/m^2, respectively (Table 3). The forb and shrub biomasses of dense forest were significantly higher than those of open forest (both $p<0.05$) but the grass biomass of dense forest was lower than that of open forest ($p<0.05$).

Table 3. Forage crop biomasses by the extents of canopy cover as revealed by the SFR (2001)

Life form	Dense forest (n=1,489)			Open forest (n=415)		
	Mean±SE	95% CI		Mean±SE	95% CI	
	(g/m^2)	lower	upper	(g/m^2)	lower	upper
Forb biomass	18.73±0.78*	17.19	20.27	12.46±2.25*	8.04	16.88
Grass biomass	9.24±1.19*	6.91	11.57	164.15±9.6*	145.31	182.99
Shrub biomass	22.08±1.01*	20.1	24.05	5.27±0.71*	3.89	6.66

*=Significantly different at the statistical level <0.05 of two sample t-test

Eighty-seven forage crop species of habitat use by sambar deer and gaur in the study area. Of these, 38 were grasses, 27 were shrubs, and 22 were forbs. The nutritional parameters of forbs and shrubs growing in either dense or open forest did not significantly differ. For grasses, however, the NDF and hemicellulose percentages of dense forest species (59.96±3.14 and 16.76±2.15%, respectively) were significantly lower than those of species of open forest (68.53±1.44 and 23.70±0.90%, respectively) (both p<0.05) and the CP percentage of dense forest grasses (8.76±0.60%) was significantly higher than that of open forest grasses (5.68±0.53%; p<0.05; Table 4, Figure 9).

This study focused on Crude protein and hemicellulose; these are good estimators of ungulate food quality (Bukombe et al., 2019) and hemicellulose are the main fuel for ruminants, typically providing up to 80% of their energy (Barboza et al., 2009; Rautiainen et al., 2021). The CP and hemicellulose data in this study were consistent with Mobashar et al. (2017); shrubs and forbs have higher CP contents than grasses. Our CP values are similar to those of Jasra and Johnson (2000), who studied shrubs, forbs, and grasses of Baluchistan grasslands. In general, plant CP content is high in the vegetative stage and declines later (Mountousis et al., 2008; Tufarelli et al., 2010). The CP of forbs is of particular importance to ruminants, both ensuring appropriate rumen function and providing biosynthetic substrates. Wallmo et al. (1977) showed that a minimum CP level of 7% is required to maintain ruminant herbivores. Cook et al. (2001) and Verme and Ullrey (1972) reported that dry matter CP levels in fawn forage or a diet should be 13% and 20%, respectively to ensure optimal growth, and recommended supplementary feeding, because percentages of 16-17% are needed to meet the maximum requirements of most ungulates including lactating dose. Thus, the CP concentrations in the forbs and shrubs that we studied met the protein requirements of all ungulates. In terms of hemicellulose, Mobashar et al. (2017) reported that the hemicellulose contents of grasses ranged from 18.4% to 29.4%, being lowest at one month of age and highest at three months. For other plants, the season and extent of plant maturity affect the levels of complex carbohydrates. Ruminants efficiently use cellulose and hemicellulose; rumen microbes readily digest these materials (Holechek et al., 1998).

Table 4. Nutritional parameters of the forage crops of dense forest (DF) and open forest (OP)

% Nutrient	Forb		Grass		Shrub	
	DF (n=18)	OF (n=4)	DF (n=12)	OF (n=26)	DF (n=24)	OF (n=3)
NDF	51.91±1.50	51.67±7.34	59.96±3.14*	68.53±1.44*	51.10±1.40	49.36±4.27
ADF	44.97±1.17	45.58±5.49	43.20±2.43	45.99±1.07	45.61±1.23	42.88±3.32
ADL	12.38±0.89	9.67±1.54	6.95±0.69	8.28±0.90	15.18±1.23	15.29±1.72
Crude protein	10.83±0.61	9.65±1.58	8.76±0.60*	5.68±0.53*	10.89±0.57	13.00±1.09
Cellulose	32.59±1.48	34.99±4.21	36.26±1.98	37.71±0.91	30.44±1.08	27.58±1.86
Hemicellulose	7.39±0.68	6.09±1.93	16.76±2.15*	23.70±0.90*	6.10±0.95	6.49±1.19

*=Significantly different at the statistical level <0.05 of two sample t-test

3.5 Integrated habitat management; habitat suitability and forage crops

This study of tiger prey habitat, biomass production, and the nutritional characteristics of forage crops indicates that increases in the populations of tiger prey species require increases in the grass and forb biomasses of open forest. For gaur, this may also be the case for some closed forest. In terms of forage crop management efficiency, an increase in grass biomass is more achievable in open than in dense forest (Table 3). The hemicellulose content of open forest grass was significantly higher than that of dense forest grass (Table 4). Hemicellulose is important in terms of the ungulate diet; wild herbivores similarly process plant tissues with high concentrations of cellulose and hemicellulose (Capoani, 2019). Specifically, as sambar deer exhibit a well-developed gastrointestinal structure, they can use plant materials that are high in cellulose and hemicellulose, such as leaves, bark, and woody twigs; these are efficiently digested (Tajchman et al., 2018). Such materials are the principal ruminant fuels, typically providing up to 80% of energy (Barboza et al., 2009). González-Hernández and Silva-Pando (1999) reported that the CP level was a good estimator of food quality. Fiber quality greatly affects the rumen microbiome and the amount of energy that is produced (Van Soest et al., 1991); CP is an essential component of an ungulate diet (Bayoumi and Smith, 1976). The CP content of open forest is significantly less than that of closed forest, because the biomass is less. Open habitat management is more efficient than closed habitat management (Chaiyarat et al., 2021; Frank et al., 2016; Ofstad et al., 2016; Tschöpe et al., 2011). Suggested pilot area optimal for tiger prey species are shown in Figure 8.

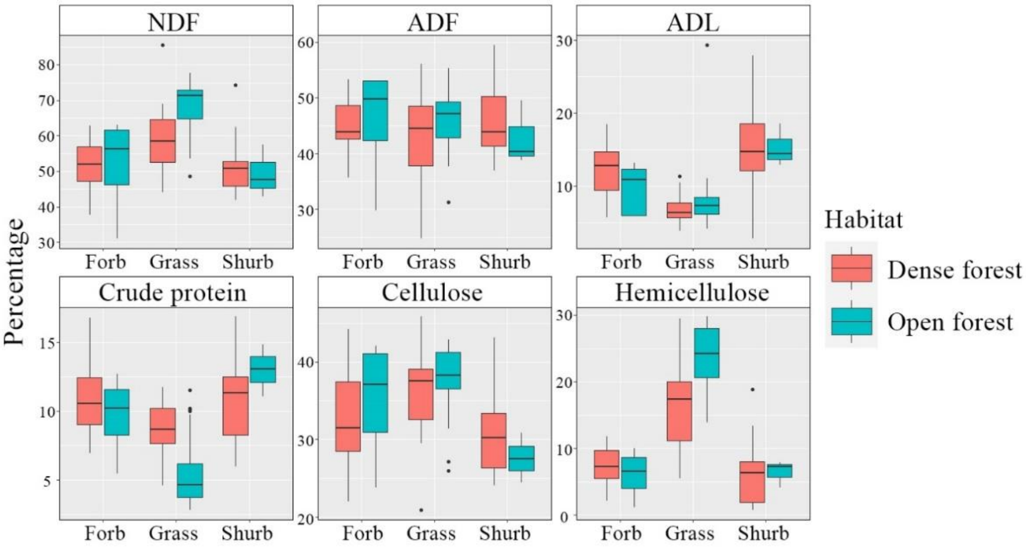

Figure 9. Nutritional parameters of forage crops by the extent of canopy cover

4. CONCLUSION

Identification of suitable habitats via Bayesian, lasso binary quantile regression can be used to facilitate optimal management of large areas. The models in this study show correlations between NDVI and grass, forb, and shrub biomasses significantly influenced the probabilities that sambar deer and gaur would be present. These factors can be managed/controlled. If an area is conducive to open habitat, it should be regularly managed as a grassland (to ensure good prey species nutrition). Pilot management of optimal areas in Thap Lan National Park should be selected according the stable areas available to manage; such areas are shown in Figure 8. However, further study of the forage crop quality of local plants is required to enhance the management of tiger prey species.

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