CHARACTERIZING THE SPATIAL DISTRIBUTION OF GIANT PANDAS IN CHINA USING MULTITEMPORAL MODIS DATA AND LANDSCAPE METRICS

X.P. Ye [a, b,] *, T.J. Wang [a], A.K. Skidmore [a], A.G. Toxopeus [a]

[a] ITC, Natural Resources Department, Hengelosestraat 99, 7500AA Enschede, The Netherlands – (ye17188, tiejun, skidmore, toxopeus)@itc.nl

[b] Foping National Nature Reserve, No. 89 Huangjiawan Road, Foping, 723400 China – pandayxp@gmail.com

Commission VIII, WG VIII/11

KEY WORDS: Multitemporal, Forest, Landscape, Spatial, Configuration, Modelling, Knowledge Base

ABSTRACT:

Although forest fragmentation and degradation have been recognized as one of major threats to wild panda population, little is known about the relationship between panda distribution and forest fragmentation. This study is unique as it presents a first attempt at understanding the effects of forest fragmentation on panda spatial distribution for the entire wild panda population. Using a moving window with a radius of 3 km, landscape metrics were calculated for two classes of forest (i.e. dense forest and sparse forest) which derived from a complete year of MODIS 250 m EVI multitemporal data in 2001. Eight fragmentation metrics that had highest loadings in factor analyses were selected to quantify the spatial heterogeneity of forests. It was found that the eight selected metrics were significantly different ($P < 0.05$) between panda presence and absence. The relationship between panda distribution and forest heterogeneity was explored using forward stepwise logistic regression. Giant pandas appear sensitive to patch size and isolation effects associated with forest fragmentation. The R^2 value (0.45) of the final regression model indicates that landscape metrics partly explain the distribution of giant pandas, though a knowledge-based control for elevation and slope improved the explanation to 74.9%. Findings of this study imply that the design of effective conservation area for wild panda must include large, contiguous and adjacent forest areas.

1. INTRODUCTION

The giant panda (*Ailuropoda melanoleuca*) is one of the world's most endangered mammals. Fossil evidence suggests the giant panda were widely distributed in warm temperate or subtropical forests over much of eastern and southern China (Schaller, 1994). Today this range is restricted to temperate montane forests across five separate mountain regions, where bamboo is the dominant understory forest plant (Schaller, 1994; Hu, 2001). According to the Third National Panda Survey (State Forestry Administration of China, 2006), the number of giant panda individuals increased in the last decades, but their distribution is discontinuous, with 24 isolated populations.

Forest fragmentation and degradation have already been recognized as major threats that pose a great danger for panda population (Schaller, 1994; Hu, 1997; Hu, 2001). However, little is known about the distribution pattern of giant pandas at a national scale, as previous studies focused on the local relationships of panda occurrences and micro-environmental factors (Hu, 2001; Lindburg and Baragona, 2004). In other words, to date no quantitative and systematic studies have attempted to address the panda distribution with relation to fragmentation of forested landscapes (e.g. forest patch size, patch isolation and aggregation), especially over the entire range of wild giant pandas.

A large number of landscape metrics have been proposed to quantify landscape patterns based on land cover as derived from remotely sensed data (Hulshoff, 1995; Gustafson, 1998). Because most landscape metrics are scale-dependent and landscape elements are species-specific (Cain et al., 1997; Saura, 2004), appropriate land cover classes and spatial resolution are critical to link response variables of species (Taylor et al., 1993; Hamazaki, 1996; Corsi et al., 2000) with landscape metrics (Turner et al., 1989; Frohn, 1998; Wu et al., 2000). Time-series of 16-day composite MODIS 250 m Enhanced Vegetation Index (EVI) product, with a broad geographical coverage (swath width 2 330 km), intermediate spatial resolution and high temporal resolution, offers a new option for large area land cover classification (Bagan et al., 2005; Liu and Kafatos, 2005). EVI is designed to minimize the effects of the atmosphere and soil background (Huete et al., 2002), and was found to be responsive to canopy structure (Gao et al., 2000).

The primary aim of this paper was to understand how the entire giant panda population relates to forest fragmentation. Specific research questions included: (1) Which landscape metrics characterize fragmentation of forests occupied by giant pandas? (2) What are the relationships between the distribution of giant pandas and forests fragmentation? (3) Do landscape metrics explain what proportion of the distribution of the giant panda?

2. MATERIALS AND METHODS

2.1 Study Area

The study area (Figure 1) incorporates the 45 administrative counties in Shaanxi, Gansu, and Sichuan provinces of China which cover the entire giant panda distribution area, and

---

* Corresponding author.

sampled during the Third National Panda Survey (State Forestry Administration of China, 2006). The total area is about 160 000 km^2, with the elevation ranging from 560 m to 6 500 m. The study area cross five mountain regions along the eastern edge of the Tibetan Plateau: Qinling, Minshan, Qionglai, Xiangling, and Liangshan. Qinling region is the northernmost area of the present-day distribution of the giant panda (Hu, 2001), in which covered with deciduous broadleaf and subalpine coniferous forests (Ren, 1998). Minshan and Qionglai regions, with steep terrain, cool and humid climate, are the biggest distribution area of the giant panda (Hu, 2001), in which dense coniferous forests with an understory of bamboo thrive in the middle and upper elevations (China Vegetation Compiling Committee, 1980). Xiangling and Liangshan regions are southernmost panda distribution area, covered by evergreen broadleaf forests and coniferous forests (China Vegetation Compiling Committee, 1980).

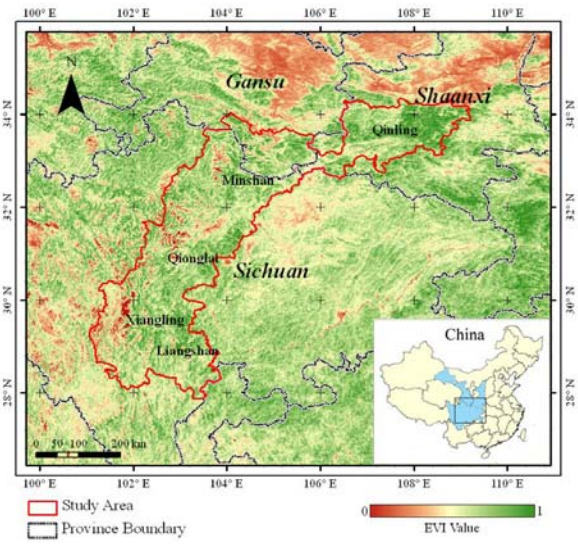

Figure 1. Map of the study area delineated in red polygon. The image presented is MODIS 250m EVI 16-day composite during Julian day 193-209 of 2001.

2.2 Environmental and Species Data

2.2.1 Remote Sensing Data Preparation: MODIS 250 m EVI time-series were downloaded and extracted by tile, mosaicked, reprojected from the Sinusoidal to the Albers Equal Area Conic projection using a nearest neighbour operator, and subset to the study area. To diminish the noise mainly caused by remnants of clouds, a clean, smooth time-series of EVI were reconstructed from raw EVI time-series by employing an adaptive Savitzky–Golay smoothing filter in TIMESAT package (Jönsson and Eklundh, 2004). The resulting smoothed time-series for 2001 (23 dimensions) were transformed into principal components (PCs) using a Principal Component Analysis (Byrne et al., 1980; Richards, 1984) to reduce data volume, and the first five PCs (accounting for 99.1% of variance in smoothed EVI time-series) were retained for further analysis.

Ancillary data that were used in this study included the National Land Cover Map of China (NLCD-2000), a digital elevation model (DEM), and the Bio-Climatic Division Map of China. The NLCD-2000 Map, which developed from hundreds of TM and ETM images in 2000 (Liu et al., 2002), was geometrically reprojected to form a mosaic with a pixel size of 250 m for reference data extraction. The DEM was clipped from the Shuttle Radar Topography Mission (SRTM) 90 m seamless digital topographic data and resampled to 250 m using a nearest neighbour operator. The Bio-Climatic Division Map of China (Liu et al., 2003) was rasterized with a pixel size of 250 m to improve land-cover classification. All data were geometrically rectified and geo-referenced to ensure proper mutual registration and geographic positioning.

2.2.2 Land-cover Characterization: Land-cover map for the study area was derived from retained five PCs in ENVI 4.3 (ITT Industries, Inc). Because the giant panda has a strong preference for high forest canopy cover (Hu et al., 1985; Hu, 2001), we used five categories based on the NLCD-2000 land-cover classification system (Liu et al., 2002) to represent the land-cover. Using a combination of unsupervised and supervised methods and integrated with the DEM and bio-climatic division data, land covers were classified as dense forest (canopy cover > 30%), sparse forest (canopy cover < 30%), grassland, cropland, and nonvegetated. The resulting land cover map with a grain size of 250 m and an overall accuracy of 84% (kappa 0.8) was used for landscape metrics computation.

2.2.3 Panda Presence-Absence Data: Because panda occurrence data were collected by an exhaustive survey throughout the study area (State Forestry Administration of China, 2006), any panda occurrence-free location can be potentially considered as a true absence. By buffering the occurrence points, it becomes possible to generate randomly distributed pseudo-absences and ameliorate the set towards true absences (Olivier and Wotherspoon, 2006). Initially 3 000 random points were sampled within the forested areas with the minimum distance of 3 km between each other and minimum distance of 3 km to forest edges. Similar to the method of Olivier and Wotherspoon (2006), points were overlapped with a 3-km buffer of panda occurrence points, 1 124 points that completely lay within the buffer zone were selected as panda presence samples, and 1 278 points that (1) located outside the buffer zone and (2) at a minimum distance of 3 km to the boundary of the buffer zone were selected as panda absence samples. In light of the giant panda biology (Hu, 2001), samples located in the areas above 3 500 m or with a slope greater than 50º were discarded. The Moran's I statistic (Moran's I = 0.03, Z = 1.91, P > 0.05) indicated that the spatial autocorrelation was insignificant in the samples (Upton and Fingleton, 1985).

2.3 Selection of Landscape Metrics for Quantifying Forest Fragmentation

Initially 26 landscape metrics (Table 1) were computed from the land cover map with a constant spatial extent for the two forest classes in FRAGSTATS 3.3 (McGarigal and Marks, 1995). A moving window radius for computation was set to 3 km, so as to have a landscape extent equivalent to the territory of an adult giant panda (Hu, 2001; Pan, 2001). After computation, values of metrics were extracted to panda presence-absence points by an extraction tool in Spatial Analyst Tools of AcrGIS 9.2 (ESRI Inc. 2007).

To obtain a set of redundancy-free metrics for quantifying the spatial configurations of forest, firstly a partial correlation analysis with controlling for the effect of elevation was employed to eliminate highly correlated metrics. Of the pairs of metrics with correlation coefficients ≥ |0.9|, only one metric was retained based on the criteria: (1) metrics that commonly used in literatures; (2) density metrics and distribution statistics metrics were preferred to absolute metrics (Riitters et al., 1995; Griffith et al., 2000). With the remaining metrics, a factor analysis (Riitters et al., 1995; Cain et al., 1997) was performed, and non-correlated factors were extracted using a principal components method with orthogonal rotations and retained by the Kaiser rule that factor's eigenvalue > 1 (Bulmer, 1967). The metrics with highest absolute loading on each of retained factors were selected as landscape variables. By this process, the multicollinearity in metrics was no longer problematic (Variance-Inflation Factors < 5 and tolerance > 0.2 (Sokal and Rohlf, 1994)).

Acronym	Metric name
LPI	Largest Patch Index
LSI	Landscape Shape Index
PD	Patch Density
PLAND	Percentage of Landscape
ED	Edge Density
AREA	Mean Patch Area
GYRATE	Radius of Gyration Distribution
CONTIG	Contiguity Index
FRAC	Fractal Dimension Index
PARA	Perimeter Area Ratio
SHAPE	Shape Index
CPLAND	Core Percentage of Landscape
DCAD	Disjunct Core Area Density
DCORE	Disjunct Core Area Distribution
CAI	Core Area Index
CORE	Core Area
COHESION	Patch Cohesion Index
CONNECT	Connectance Index
ENN	Euclidian Nearest Neighbour Index
PROX	Proximity Index
AI	Aggregation Index
CLUMPY	Clumpy Index
DIVISION	Landscape Division Index
IJI	Interspersion Juxtaposition Index
PLADJ	Percentage of Like Adjacencies
SPLIT	Splitting Index

Table 1. Landscape metrics used in this study. All metrics were computed for dense forest and sparse forest. Detailed descriptions refer to McGarigal and Marks (1995).

2.4 Characterizing the Panda Distribution with Metrics

2.4.1 Significance Testing: Representative metrics were compared between forest areas with panda presences and absences. Because some metrics did not meet the assumption of homogeneity of variances and some were non-normally distributed, a Brown-Forsythe's *F* test (Rutherford, 2001) and nonparametric Mann-Whitney *U* test were employed to test whether metrics are significantly different between panda presences and absences. Metrics with significant difference were used for further model building. All tests were conducted in SPSS 15.0 (SPSS Inc. 2006).

2.4.2 Logistic Regression Analysis: The binomial logistic regression, a common statistical method used to estimate occurrence probabilities in relation to environmental predictors (Cowley et al., 2000), was employed for delineating the relation between panda presence-absence and representative metrics. Stepwise model-fitting with forward selection was used to help construct a model with good fit to the data, in which the variable with the most significant change in deviance at each stage was incorporated into the model until no other variables were significant at the $P < 0.05$. The best model was selected based on Nagelkerke R^2 and Hosmer-Lemeshow goodness of fit test (Hosmer and Lemeshow, 2000; Davis, 2002). The panda presence-absence samples were randomly split into two parts, one for model building (n = 2 000), another for model evaluation (n = 402). All statistical analyses were conducted in SPSS 15.0 (SPSS Inc. 2006).

2.4.3 Spatial Implementation of Model: Because the logistic regression model was built only on landscape metrics, whereas the distribution of the giant panda was limited by a range of environmental conditions such as terrain features, the model may overestimate panda distribution regardless of environmental tolerances and preferences of the giant panda. Hence, a knowledge-based control was applied by integrating the logistic regression model with elevation and slope to mitigate the risk of over-prediction, described as below:

$$P_i' = P_i \times C_{ele} \times C_{slope} \quad (1)$$

where P_i' = refined probability
P_i = probability estimated by logistic regression model
C_{ele} = conditional probability related to elevation
C_{slope} = conditional probability related to slope

The knowledge-based rules for control were formulated based on the integration of knowledge from several sources: (1) literatures (Hu, 2001; Pan, 2001); (2) detailed discussion with several specialists; (3) knowledge acquired from field observations. Spatial implementations of the logistic regression model and knowledge-based control were achieved in ERDAS IMAGINE 9.1 (LLC, 2006).

2.4.4 Model Evaluation: The performance of final logistic regression model was assessed by overall accuracy, sensitivity and specificity, kappa coefficient and *Z*-test using an independent panda presence-absence data (n = 402). Sensitivity is defined as the proportion of correctly predicted presence to the total number of presence in testing samples; and specificity is the proportion of correctly predicted absence to the total number of absence in testing samples (Fielding and Bell, 1997). The kappa coefficient and its variance (Cohen, 1960; Congalton, 1991; Skidmore et al., 1996) were computed and the effect of the knowledge-based control was examined through a *Z*-statistic using kappa coefficients (Cohen, 1960; Congalton, 1991). A threshold of 0.5 was arbitrarily selected to convert the continuous probability surface to a discrete panda presence-absence map. A probability greater than or equal to 0.5 was coded as presence, and less than 0.5 was absence. However, this value may not be optimal in all cases (Manel et al., 1999). Hence, a sensitivity analysis was conducted to consider thresholds from 0.3 to 0.7.

3. RESULTS

3.1 Representative Metrics for Forest Fragmentation Quantification

From the factor analyses, eight metrics were selected as representative metrics for quantifying forest fragmentation, four metrics measure dense forest and four metrics measure sparse forest (Table 2). In general, these eight metrics measure three aspects of the forests: patch area/edge, patch connectivity, and patch aggregation.

Statistical tests show that all eight representative metrics were significantly different (P < 0.05) between panda presences and absences (Table 2), indicating these metrics are important factors for the distribution of giant pandas. Patches of forest occupied by giant pandas tended to be larger, closer together and more contiguous. All metrics were used for logistic regression model building.

Metrics	Presence (n=1124)	Absence (n=1278)	Brown-Forsythe's	Mann-Whitney
	Mean ± S.D.	Mean ± S.D.	*F* test	*U* test
ED of dense forest	22.6 ± 5.6	16.8 ± 7.2	507.0 (P < 0.01)	-20.2 (P < 0.01)
LPI of dense forest	53.4 ± 21.8	33.7 ± 25.4	416.3 (P < 0.01)	-19.1 (P < 0.01)
PROX of dense forest	16.1 ± 10.9	9.9 ± 9.4	218.0 (P < 0.01)	-12.8 (P < 0.01)
CLUMPY of dense forest	0.4 ± 0.1	0.4 ± 0.3	62.1 (P < 0.01)	-14.5 (P < 0.01)
AREA of sparse forest	75.9 ± 124.1	184.3 ± 280.3	156.3 (P < 0.01)	-14.4 (P < 0.01)
LSI of sparse forest	4.0 ± 0.8	3.7 ± 0.8	97.9 (P < 0.01)	-10.3 (P < 0.01)
PROX of sparse forest	6.1 ± 6.3	9.46 ± 8.6	121.5 (P < 0.01)	-8.8 (P < 0.05)
CLUMPY of sparse forest	0.4 ± 0.2	0.4 ± 0.2	89.3 (P < 0.01)	-13.1 (P < 0.01)

Table 2. Summary statistics and results of Brown-Forsythe's *F* test and Mann-Whitney *U* test for eight representative metrics between panda presence and absence.

3.2 The Logistic Regression Model

Of eight representative metrics, four metrics were significant at P < 0.01 (Table 3) and the rest were not included into the final model (at P < 0.05), indicating that patch size, edge density, and clumpiness of dense forest play significant roles in defining panda distribution.

Parameter	Coefficient	S.E.	P
ED of dense forest	0.160	0.010	< 0.001
LPI of dense forest	0.042	0.003	< 0.001
CLUMPY of dense forest	-1.475	0.335	< 0.001
AREA of sparse forest	0.001	0.000	< 0.01
Constant	-4.736	0.363	< 0.001

Table 3. Parameter estimates of the final logistic regression model.

3.3 Model Performance

The logistic regression model explains around 45% of the overall variance of the metrics in training dataset (R^2 = 0.45). However, the Hosmer-Lemeshow statistic was 15.864 (df = 8, P = 0.04), pointing out that the model might not fit the data adequately. By applying the knowledge-based control to the model, the overall accuracy and specificity increased around 5% and 13% respectively (Table 4), and predicted panda presence shrank mainly in Qionglai, Xiangling, and Liangshan (Figure 2). The Z-test for kappa coefficients shows that the accuracy of the mapping was significantly improved by applying the knowledge-based control (P < 0.05). The sensitivity analysis indicated that the threshold of 0.5 is appropriate for transforming continuous probabilities of panda occurrence to discrete panda presence-absence, where the sensitivity-specificity difference (Liu et al., 2005) reaches the minimum.

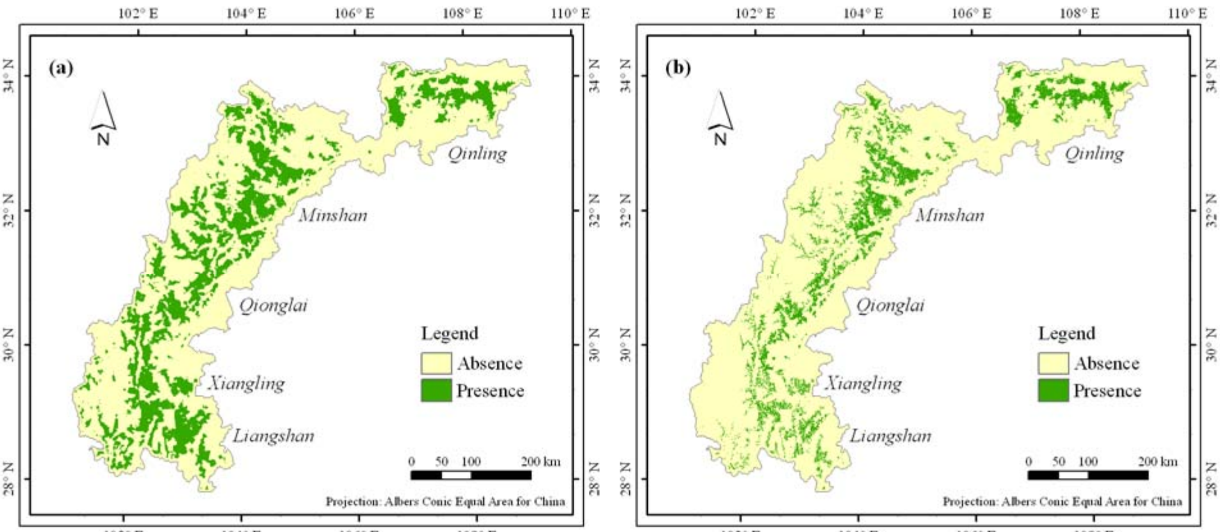

Figure 2. Presence-absence of the giant panda predicted by the logistic regression model (threshold = 0.5): (a) without knowledge-based control; (b) with knowledge-based control for elevation and slope.

	Modelling	
	Without control	With control
Overall accuracy	69.9%	74.9%
Sensitivity	79.5%	77.6%
Specificity	58.5%	71.6%
Kappa	0.39	0.49
Kappa variance	0.00048	0.00044
Z	3.42 ($P < 0.05$)	

Table 4. Statistics for evaluation of model performance.

4. DISCUSSION

4.1 Distribution of giant pandas in relation to forest fragmentation

From an ecological point of view, every species has its particular position in the ecosystem, which is termed ‘niche’ (Elton, 2001). The giant panda is a forest inhabitant with exclusive territory, thus the spatial pattern and forest patch plays an important role in the distribution of the giant panda. In this study, both the Brown-Forsythe's F test and nonparametric Mann-Whitney U test showed that eight representative metrics were significantly different between panda presence and absence, indicating the heterogeneity of forest has a significant contribution to the distribution of giant pandas. Of the four metrics included in the logistic regression model, three metrics measure patch area/edge, pointing out that the giant panda appear sensitive to patch size and isolation effects associated with forest fragmentation. The giant panda tends to occur in larger, more contiguous (or less fragmented), but less aggregated dense forest patches. A larger dense forest patch or contiguous patches can potentially provide good conditions of food and shelter because of the high patch connectivity. The preference of less aggregated forest patches may relate to panda migration or dispersal, because high aggregated patches will increase the cost of migration or dispersal, e.g. high risk of being preyed, lack of shelter.

4.2 Model performance and its factors

As demonstrated in this study, logistic regression model with knowledge-based control for the effect of elevation and slope is capable of predicting the spatial distribution of the giant panda using landscape metrics. Logistic regression itself is a transformed linear regression which merely depends on explanatory variables included in the model, whereas the distribution of the giant panda is also limited by other physical conditions of environment. The absence of those factors may result in the bias in modelling. This problem can be diminished by applying an appropriate knowledge-based control, However, to design an ecologically meaningful control needs adequate relevant knowledge and well-understanding of the relationship between the species and the environmental factors.

A fundamental assumption of this study is that bamboo is sufficient and thus not a constraint of panda distribution. In fact, bamboo resources are unevenly distributed across five mountain regions (State Forestry Administration of China, 2006). To accurately map the distribution of giant pandas or design corridors, spatial pattern and quality information of bamboo forests is required. In addition to bamboo information, other environmental factors, such as forest compositions and road network, are also necessary since they have direct or indirect influences on giant pandas.

The random panda presence-absence data may also affect the accuracy of prediction, mainly because the data were inferred based on panda occurrences records instead of ground truth. Exhaustive searches should be conducted in limited areas in order to provide accurate data on absences as they refine the model, as suggested by Brotons et al. (2004). In addition, the heterogeneity in forests across the panda distribution area can also increase within-group variance in the training samples, and consequently decrease the power of the model. This may be mitigated by dividing the study area into several homogeneous forested landscapes.

Furthermore, landscape metrics may be sensitive to the level of detail in categorical map data that is determined by the schemes used for map classification (Turner et al., 2001). In this study, forests were categorized into dense forest (canopy cover > 30%) and sparse forest (canopy cover < 30%). The division is practical as it was used in UNEP-WCMC's forest classification (http://www.unep-wcmc.org/forest/fp_background.htm). It is also ecologically meaningful because giant pandas have been proven that have a strong preference for forest patches with a high canopy cover (Hu, 2001). The test for the sensitivity of landscape metrics towards different division of forests may help the understanding of the relationship between forest spatial patterns and the response of the giant panda; but this is beyond the objective of this study.

5. CONCLUSION

This study demonstrated a successful approach for modelling the spatial distribution of giant pandas from multitemporal MODIS 250 m EVI data and landscape metrics. Eight metrics were selected to quantify forest fragmentation. All metrics were significantly different between the forest patches with panda presences and absences. Forest patch size, edge density, and patch aggregation were found play more significant roles in panda distribution. Selected landscape metrics partly explained the distribution of giant pandas, though a knowledge-based control for elevation and slope improved the explanation significantly. Findings of this study have profound implications for wild giant panda conservation.

REFERENCES

Bagan, H., et al., 2005. Land cover classification from modis evi times-series data using som neural network. International Journal of Remote Sensing 26(22): 4999 - 5012.

Brotons, L., et al., 2004. Presence-absence versus presence-only modelling methods for predicting bird habitat suitability. Ecography(27): 437-448.

Bulmer, M. G., 1967. Principles of statistics. Dover, New York, 252.

Byrne, G. F., et al., 1980. Monitoring land-cover change by principal component analysis of multitemporal landsat data. Remote Sensing of Environment 10: 175-184.

Cain, D. H., et al., 1997. A multi-scale analysis of landscape statistics. Landscape Ecology 12(4): 199-212.

China Vegetation Compiling Committee, C., 1980. China vegetation. Science Press, Beijing.

Cohen, J., 1960. A coefficient of agreement for nominal scales. Edu. Psychol. Measure 20: 37-46.

Congalton, R. G., 1991. A review of assessing the accuracy of classifications of remotely sensed data. Remote Sensing of Environment 37(1): 35-46.

Corsi, F., et al., 2000. Modeling species distribution with gis. In: Research techniques in animal ecology : controversies and consequences / Boitani, L. and Fuller T.K. ed. - 2000. pp. 389-434.

Cowley, M. J. R., et al., 2000. Habitat-based statistical models for predicting the spatial distribution of butterflies and the day-flying moths in a fragmented landscape. Journal of Applied Ecology 37(Suppl. 1): 60-72.

Davis, J. C., 2002. Statistics and data analysis in geology. Wiley & Sons, New York etc., 638.

Elton, C. S., 2001. Animal ecology. University of Chicago Press, Chicago.

Fielding, A. H. and J. F. Bell, 1997. A review of methods for the assessment of prediction errors in conservation presence/absence models. Environmental Conservation 24(1): 38-49.

Frohn, R. C., 1998. Remote sensing for landscape ecology : New metric indicators for monitoring, modeling, and assessment of ecosystems. Lewis, Boca Raton etc., 99.

Gao, X., et al., 2000. Optical-biophysical relationships of vegetation spectra without background contamination. Remote Sensing of Environment 74(3): 609-620.

Griffith, J. A., et al., 2000. Landscape structure analysis of kansas at three scales. Landscape and Urban Planning 52(1): 45-61.

Gustafson, E. J., 1998. Quantifying landscape spatial pattern: What is the state of the art? Ecosystems 1(2): 143-156.

Hamazaki, T., 1996. Effects of patch shape on the number of organisms. Lands Ecol(11): 299-306.

Hosmer, D. W. and S. Lemeshow, 2000. Applied logistic regression, 2nd edition. Wiley, New York.

Hu, J., 1997. Existing circumstances and prospect of the giant panda. Journal of Sichuan Teachers College (Natural Science) 18(2): 129-133.

Hu, J., 2001. Research on the giant panda. Shanghai Scientific & Technological Education Publishers, Shanghai, 402.

Hu, J., et al., 1985. The giant panda in wolong. Sichuan Science and Technology Press, Chengdu, 225.

Huete, A., et al., 2002. Overview of the radiometric and biophysical performance of the modis vegetation indices. Remote Sensing of Environment 83(1-2): 195-213.

Hulshoff, R. M., 1995. Landscape indices describing a dutch landscape. Landscape Ecology(10): 101-111.

Jönsson, P. and L. Eklundh, 2004. Timesat - a program for analyzing time-series of satellite sensor dat. Computers and Geosciences 30: 833–845.

Lindburg, D. e. and K. e. Baragona, 2004. Giant panda's : Biology and conservation. University of California Press, Berkeley etc., 308.

Liu, C., et al., 2005. Selecting thresholds of occurrence in the prediction of species distributions. Ecography 28: 385-393.

Liu, J., et al., 2002. The land-use and land-cover change database and its relative studies in china. Journal of Geographical Sciences 12(3): 275-282.

Liu, J. Y., et al., 2003. Land-cover classification of china: Integrated analysis of avhrr imagery and geophysical data. International Journal of Remote Sensing 24(12): 2485 - 2500.

Liu, X. and M. Kafatos, 2005. Land-cover mixing and spectral vegetation indices. International Journal of Remote Sensing 26(15): 3321-3327.

Manel, S., et al., 1999. Comparing discriminant analysis, neural networks and logistic regression for predicting species distributions: A case study with a himalayan river bird. Ecological Modelling 120(2/3): 337-347.

McGarigal, K. and B. J. Marks (1995). Fragstats: Spatial pattern analysis program for quantifying landscape structure.U. S. Forest service general technical report. Portland, OR, USA.

Olivier, F. and S. Wotherspoon, 2006. Modelling habitat selection using presence-only data: Case study of a colonial hollow nesting bird, the snow petrel. Ecological Modelling(195): 187-204

Pan, W., 2001. The opportunity of survival. Beijing University Press, Beijing, 522.

Ren, Y., 1998. Vegetation within the giant panda's habitat in qinling mountains. Shaanxi Science and Technology Press, Xi'an, 488.

Richards, J. A., 1984. Thematic mapping from multitemporal image data using

the principal components transformation. Remote Sensing of Environment 16: 25-46.

Riitters, K. H., et al., 1995. A factor analysis of landscape pattern and structure metrics. Landscape Ecology 10(1): 23-39.

Rutherford, A., 2001. Introducing anova and ancova: A glm approach. CA: Sage Publications, Thousand Oaks.

Saura, S., 2004. Effects of remote sensor spatial resolution and data aggregation on selected fragmentation indices. Landscape Ecology 19(2): 197-209.

Schaller, G. B., 1994. The last panda. University of Chicago Press, Chicago ; London, xx, 299 [16] of plates.

Skidmore, A. K., et al., 1996. An operational gis expert system for mapping forest soils. . Photogrammetric Engineering and Remote Sensing 62(5): 501– 511.

Sokal, R. R. and F. J. Rohlf, 1994. Biometry : The principles and practice of statistics in biological research. W.H. Freeman, New York, 887.

State Forestry Administration of China, S., 2006. The third national survey report on giant panda in china. Science Press, Beijing, 280.

Taylor, P. D., et al., 1993. Connectivity is a vital element of landscape structure. Oikos 68(3): 571-573.

Turner, M. G., et al., 2001. Landscape ecology in theory and practice : Patterns and process. Springer, Berlin etc., 401.

Turner, M. G., et al., 1989. Effects of changing spatial scale on the analysis of landscape pattern. Landscape Ecology 3(3): 153-162.

Upton, G. J. G. and B. Fingleton, 1985. Spatial data analysis be example:Volume 1 point pattern and quantitative data. John Wiley and Sons, New York, 410.

Wu, J., et al., 2000. Multiscale analysis of landscape heterogeneity: Scale variance and pattern metrics. . Geographical Information Science(6): 6-19.

ACKNOWLEDGEMENT

This study was sponsored by Erasmus Mundus Fellowship Program as part of a MSc research project undertaken at the International Institute for Geo-information Science and Earth Observation, the Netherlands. Many thanks to Dr. Changqing Yu (Tsinghua University, China), Xuelin Jin (Beijing Forestry University, China), and Dr. Lars Eklundh (Lund University, Sweden) for technical supports.