Giant Panda Habitat Distribution Across its Entire Geographic Range: A Preliminary Assessment

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Summary

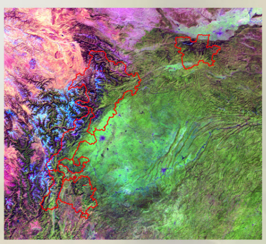
The world-famous endangered giant pandas (*Ailuropoda melanoleuca*) depend on forest overstory as shelter and understory bamboo as staple food. Although giant pandas had a wide geographic distribution in the past, they are currently restricted to five major mountainous regions in China. To understand the distribution of giant panda habitat across its entire geographic range, we have acquired relevant field and remotely sensed data. The spatial locations of panda evidence (feces, tracks, and eaten bamboo shoots) were recorded in the field using global positioning system receivers. These were used to develop presence/availability models by means of Ecological Niche Factor Analysis, using time series of different vegetation indices (obtained from MODIS) as predictor variables. We assessed the performance of the models created with each of the predictor data sets using two different validation procedures (Minimal Predicted Area and Prediction Success). In addition, a series of landscape metrics were calculated for each mountain region in order to evaluate the degree of fragmentation of the habitat for the pandas. Preliminary analyses reveal that the habitat for the giant panda in its entire geographic range exhibits a high degree of fragmentation, particularly in the southern part of the geographic range. In addition, the temporal variability of vegetation indices provides a phenological characterization of the land surface that represents a suitable environmental predictor for giant panda habitat mapping. These results suggest that MODIS data has considerable potential for endangered wildlife species habitat mapping and management.

Study Area

Field Data

Remote Sensing Data

Time series (32-day composites) of MODIS Surface Reflectance imagery (500m) acquired in 2004



Canopy Biophysical Characteristics

Derived from Spectral Vegetation Indices used as proxies

*f*APAR

$$\mathrm{NDVI} = \frac{R_{NIR} - R_{Red}}{R_{NIR} + R_{Red}}$$

Percent Canopy Cover

$$\mathrm{VARI} = \frac{R_{Green} - R_{Red}}{R_{Green} + R_{Red} - R_{Blue}}$$

Canopy Chlorophyll Content (Green LAI)

$$\text{Green Ratio} = \frac{R_{NIR}}{R_{Green}} - 1$$

Canopy Moisture Content

$$\text{MIR Ratio} = \frac{R_{NIR}}{R_{MIR}} - 1$$

Habitat Modeling

Model based only on Topography (Topographic Potential)

From a Digital Elevation Model (obtained by the Shuttle Radar Topography Mission):

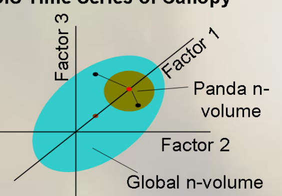
- Elevation: 1200 – 3800 m
- Slope: < 30°

Model based on Topography and the 2004 MODIS Time Series of Canopy Biophysical Characteristics

Ecological Niche Factor Analysis (ENFA)

Presence/Availability Model (Hirzel et al., 2002):

- Global n-volume (Defined by the total areal extent)
- Panda n-volume (Defined by the pixels with panda occurrence)
- Habitat Suitability (HS) for each pixel in the global n-volume is inversely proportional to the distance to the centroid of the Panda n-volume



Validation

Traditional validation techniques based on contingency tables cannot be applied due to the use of presence-only data. Therefore we used:

Prediction Success (Boyce et al., 2002):

- Frequency of cross-validation plots is calculated in four HS bins
- Spearman-rank correlation is calculated for the frequency of cross-validation plots in each bin vs. bin rank
- A good model should have high Spearman-rank correlation coefficient

Minimal Predicted Area (Engler et al. 2004):

A good HS map should predict the smallest potential habitat area that comprises 90% of the panda occurrences (rule of parsimony)

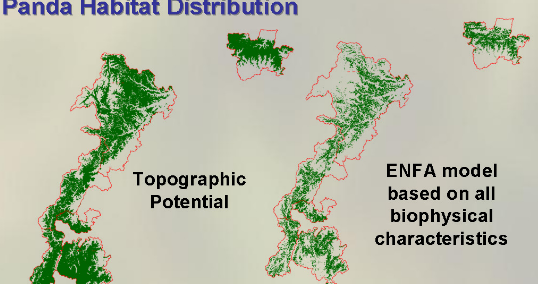
Landscape Metrics

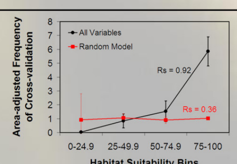
FRAGSTATS was used to calculate a series of landscape metrics on the panda habitat obtained using both the topographic potential and the ENFA model, per mountain region:

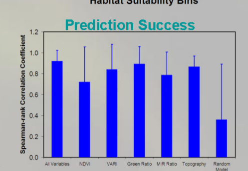
- **Fragmentation** (e.g., number patches, patch density, perimeter/area, shape index)
- **Connectivity** (e.g., patch cohesion, patch aggregation)
- **Complexity** (e.g., fractal dimension)

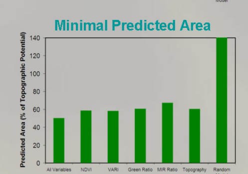
As a measure of the degree of habitat fragmentation and isolation, we calculated (per mountain region) the Euclidean Distance, in the multi-dimensional space of landscape metrics, between the topographic potential and the results from the ENFA model.

Panda Habitat Distribution







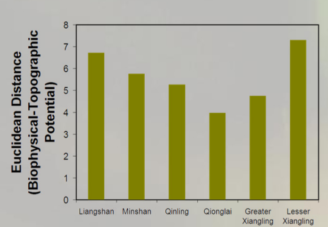


While the topographic potential predicts a habitat area of *ca.* 56,000 km², the ENFA model (based on all biophysical characteristics) predicts about half that value. Therefore not all pixels with the topographic potential are panda habitat.

All ENFA models developed with topographic data only, or with a single biophysical characteristic, performed better than random. The model that used all biophysical characteristics (including topography) exhibited higher accuracy (based on the two validation techniques).

Habitat Fragmentation

The larger the Euclidean distance between the topographic potential and the ENFA model (based on all biophysical characteristics), the larger the degree of habitat fragmentation and isolation.



Preliminary Conclusions

- Time series of canopy biophysical characteristics (derived from MODIS) constitute suitable environmental predictors for giant panda habitat modeling
- The current area of panda habitat constitutes around half of the topographic potential
- All mountain regions exhibit a high degree of habitat fragmentation and complexity, as well as high degree of isolation (i.e., low connectivity)
- Current habitat in Qionglai is closer to the topographic potential (in terms of landscape metrics) than in any other mountain region

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