Using an integrative mapping approach to identify the distribution range and conservation needs of a large threatened mammal, the Asiatic black bear, in China

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Abstract

Assessing a species' threatened status and then developing specific conservation strategies accordingly rely heavily on knowing that species' complete and accurate spatial distribution. In this study, we used the Asiatic black bear (*Ursus thibetanus*) in China to represent a large threatened species for which distribution information is limited and spatially biased. We grouped the two main sources of black bear occurrence data into two different resolutions: (1) coarse resolution data corresponded to specific management units (e.g., nature reserves) that cover large areas, and (2) fine resolution data was composed of longitude and latitude records that were bias in their geographic range. Our distribution mapping approach integrated those two data types to examine black bear spatial patterns across the country. We used both presence and absence data in the Random Forest algorithm to predict black bear distribution at coarse (30 km)

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and fine (3 km) resolutions, and then refined the coarse-scale prediction with the fine-scale prediction using a map fusion technique based on the Bayes theorem. We thus generated an integrated high-resolution range map that was both more accurate than the coarse-scale map and more representative of the black bear geographic range than was the fine-scale map. Our results showed that the total estimated range of Asiatic black bears in China was 462.3×10^3 km^2, 77.50% less than the most recent IUCN range map and 70.90% less than the area of habitat (AOH) estimation. Using those results, we identified two island and six mainland management units in China and, based on the predicted habitat conditions, proposed specific conservation strategies for each unit. Our study's results provide practical knowledge and pragmatic guidance for future conservation planning and action for this species, and our framework provides an example and template for range estimations of species with similar types of occurrence records.
Keywords: Asiatic black bear, IUCN species distribution map, species distribution modeling, management unit, conservation strategy,

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1. Introduction

Assessing threatened species' statuses and then developing effective conservation policies relies greatly on the extents and accuracies of the target species' spatial distributions (Boitani et al., 2011). However, one challenge facing conservationists and policymakers is that they usually have poor data on the most threatened species. This is especially true for large terrestrial carnivores that have long life spans, low population densities, large home ranges, and elusive behaviors (Louys, 2014). Among those species, the large carnivores in developing countries urgently need attention since they are typically under great risk of regional extinctions (Louys, 2014; Ripple et al., 2014). Lack of distribution data, especially high resolution data, is a primary obstacle to determining accurate distributions of those species, and that hinders the development of effective management strategies and conservation policies for them.

Conventionally, distribution maps for threatened species are created using expert knowledge to roughly delineate their ranges (Hortal, 2008). This method has been used in both global and regional species assessments, such as in the IUCN Red List of Threatened Species (IUCN, 2021). Because of limited knowledge of species' extant ranges, the resolutions of those maps may be restricted to 1 degree longitude/latitude or even coarser (Hurlbert and Jetz, 2007). To downscale a species' extent-of-occurrence map to a finer resolution, Brooks et al. (2019) proposed using that species' suitable habitat types and elevation range to produce its area of habitat (AOH). Although AOH has been increasingly used for conservation planning (Hanson et al., 2020), its application at fine resolutions is questionable due to various limits such as spatial mismatch and inaccurate maps drawn from expert opinion (Peterson et al., 2018). With recent advances in online, open biodiversity depositories (e.g., the Global Biodiversity Information Facility and e-Bird), using species distribution models (SDMs, Austin (2002)) integrated with environmental variables that predict the geographic range of a species provides a more rigorous method of range mapping (Peterson, 2002; Peterson et al., 2018).

The accuracy and robustness of SDMs rely not only on the quality and quantity of species occurrence data, but also on the data type (i.e., presence-only or presence with true absence) (Norberg et al., 2019). Occurrence data obtained from different sources often vary in resolution, as well as in spatial and temporal extent. Also, the canonical situation for many large, threatened mammals is that it is relatively easier to obtain occurrences of those species at coarse resolutions (e.g., in a reserve or a study site), but high-resolution occurrence data (e.g., locations with exact longitude/latitude coordinates) are limited and spatially biased. This has created a daunting challenge for conservationists, park managers, and policymakers to integrate such heterogeneous data of varied resolutions from multiple sources to create reliable species distribution maps.

Here, we have explored a way to use differently resolved types of data to create a reliable range map for the Asiatic black bear (*Ursus thibetanus*, referred hereafter as the black bear). This large mammal, classified as Vulnerable by the IUCN Red List of Threatened Species, is threatened by poaching and habitat loss that contributes to its decreasing population and shrinking range (Garshelis and Steinmetz, 2020). Black bears are widely distributed from East to Southeast Asia and inhabit various forested habitats from boreal forests to tropical rainforest (Garshelis and Steinmetz, 2020). More than half of its total range area and the largest wild population (Garshelis and Steinmetz, 2020) are found in China. But unlike some other large carnivores (e.g. tiger [*Panthera tigris*, Carroll and Miquelle (2006)] and snow leopard [*P. uncia*, Hussain (2003); Xu et al. (2008)]), that have long been flagship species with substantial socio-political resources and public enthusiasm, the black bear draws much less attention. In China, specific black bear conservation programs are scarce, more a byproduct of general conservation policies such as the hunting ban enacted in 1988 and the logging ban in 1998 (Huang and Li, 2007).

Compared to the well-researched, mainland Southeast Asia population, the black bear population within the Chinese border is one of the least studied and thus least known populations across its range (Liu et al., 2009). Because black bears are large and easily recognized, they can be by-catch of certain survey methods (e.g. camera traps and sign surveys). So, much of the information we have on the black bear in China has been collected in nature reserves during baseline surveys and routine monitoring, especially in Southwestern China where they overlap with the giant panda distribution range. This information, found mostly in the Chinese literature, has not been shared in a timely manner with the global conservation community. Additionally, black bear encounters with people and human-bear conflicts are often reported in the news. Those diverse sources of data exemplify how the black bear is a species having distribution data of varying quality.

In this study, we created a framework using gleaned data to map the black bear distribution, and we developed a hierarchical modeling approach using both presence and absence data at various resolutions. Using our approach, we produced a detailed country-wide map of the black bear distribution and identified the environmental factors affecting that distribution. Habitat patches differed in size and connectivity and were in different parts of China that each have distinct economic, social, and ecological backgrounds. Therefore, we divided the black bear range into eight management units (two island and six mainland units) and proposed specific management guidelines for each. Our framework provides an example of distribution mapping and conservation planning that may be used for other species that suffer from data deficiency.

2. Material and methods

2.1. Data Collection

To overcome the weakness of using presence-only data for SDMs (Soberón and Nakamura, 2009), we collected both presence and absence data for model construction, training, and evaluation (Lobo et al., 2010). We collected black bear occurrence (both presence and absence) data between 2008 and 2018, considering the data collected prior to 2008 unsuitable because of the rapid land use and socioeconomic changes in China (Liu et al., 2003, 2010). All data were defined at two spatial resolutions: 1) coarse-resolution data, which had no exact coordinates but could be placed in specific nature reserves or other land units (e.g., forest park, timberland, or township) typically within an area of 30 km $\times$ 30 km, and 2) fine-resolution data that either were longitude and latitude records or could be placed within a 3 km $\times$ 3 km, area, the size closest to the smallest home range of black bears reported in East Asia (approximately 10 km^2. Hwang et al. (2010); Yamamoto et al. (2016), Table.1).

2.1.1. Coarse resolution data

Using the keywords "terrestrial mammals", "camera trapping", "trail camera", and "China" in both Chinese and English, we searched pertinent online databases, including the Web of Science, Google Scholar, the Chinese National Knowledge Infrastructure, and the Chinese Science and Technology Journal Database, for peer-reviewed articles published since 2008. That search yielded 199 articles that used camera-traps to detect the occurrences of terrestrial mammals in China. Twenty-three of those articles reported black bears in 22 study sites, primarily nature reserves, and we considered those to be coarse resolution presence sites. We identified another 23 presence sites from public news reports

Table 1: Sources, sample sizes, and primary uses of data collected for model construction, training, and evaluation. Later, all training points went through a thinning process

Spatial Resolution	Data type	Source	n	Primary use
Coarse	Presence	Literature	22	training
Coarse	Presence	News media	23	training
Coarse	Presence	Li et al. (2020b)	8	training
Coarse	Absence	Literature	4	test
Coarse	Absence	Baseline survey report	38	training
Coarse	Absence	Liu et al. (2009)	18	training
Fine	Presence	Li et al. (2020b)	132	training
Fine	Absence	Liu et al. (2009)	128	training
Fine	Presence	unpublished camera-trap data	12	test
Fine	Absence	unpublished camera-trap data	20	test

after using "black bear" and "bear" in Chinese to search Baidu and WeChat for reports from officially accredited news outlets. We only used reports that contained 1) the sight location name, and 2) photographs or videos of black bears at the location (rather than from an image server), thus proving the presence of the species at that location. Additionally, we identified eight sites from the Camera-Trapping Network for the Mountains of Southwest China database, an unpublished camera-trap dataset of a regional camera-trap network maintained by the authors in Southwest China (including Sichuan, Shaanxi, and northern Yunnan provinces; Li et al. (2020b)). Thus, the total number of coarse resolution presence sites was 53. To collect coarse resolution absence data, we first reviewed the 23 previously mentioned camera-trap papers that reported sightings of black bears and then calculated the average black bear detection rate when data was available (n = 10). It took on average 1,292 camera-days for each detection (range 17–1,896) with a minimum of eight survey stations. Assuming that detection was random and followed a Poisson process, we estimated a $1/1{,}292$ detection rate and a 4.5% (range 0%–12%) probability that one does not detect a black bear in less than 4,000 days when the species is present. Based on that information, we defined sites with 40 camera stations AND that had a survey effort of 4,000 camera-days without detecting black bears as black bear absence sites, subsequently identifying four absence sites. Those four absence sites were used only in the test set because of the possibility of false absents and for case balance during training. We next examined baseline surveys, compiled mainly in the 2000s and 2010s, of 125 Chinese nature reserves and found 38 surveys that reported no black bears, thus giving us another 38 absence sites. Given the large body size and easy-to-recognize signs of black bears, as well as an acute awareness of bear presence among local residents (Liu et al., 2011), we decided that the bear absences in those surveys were not false-negatives. We did not include the black bear presence records found in the baseline surveys because they may contain historical records and the advanced age of those surveys meant that presence data was not reliable, especially given the rapid habitat loss over the last few decades. Finally, we obtained 18 additional absence sites from Liu et al. (2009) who determined black bear presence/absence from interviews and sign transect surveys of each 15 km $\times$ 15 kmcell of a 128-cell grid covering Sichuan Province. Thus, the total number of absence sites for black bears added up to 60 (56 for training and 4 for testing).

2.1.2. Fine resolution data

We extracted 132 fine resolution presence locations (i.e., from camera survey stations with longitude/latitude coordinates) from data collected during 2008 to

2018 and compiled in the Camera-Trapping Network for the Mountains of Southwest China database (Li et al., 2020b). Another 12 presence points collected from camera-trap or sign transect surveys in Yunnan (southern China), Zhejiang (eastern China), and Jilin (northern China) Provinces (unpublished data) were used in the test set.

We used the Sichuan Province grid data gathered by Liu et al. (2009) (see section 2.1.1) to determine fine resolution absence sites. Specifically, we randomly selected one 3 km $\times$ 3 km section from each of their 15 km $\times$ 15 km absence site grid cells as fine resolution absence sites. We collected 20 additional absence points from camera-trap or sign transect surveys in Yunnan (southern China), Zhejiang (eastern China), and Jilin (northern China) Provinces (unpublished data) and used them in the test set. Thus, we had 144 presence (132 for training and 12 for the test) and 148 absence fine resolution sites (128 for training and 20 for the test).

For subsequent modeling and analysis, we used ArcGIS (ESRI, 2011) to generate geo-referenced vectorial point layers from all presence/absence data, using the centers of the grid cells as coarse resolution data points. To reduce redundancy and class imbalance prior to model construction (Breiman, 2001; Cutler et al., 2007), we conducted spatial thinning using OccurrenceThinner v. 1.04 (Verbruggen et al., 2013). This procedure estimated the (normalized) kernel density of points, discarding points with the highest 10% density, retaining points with the lowest 10% density, and randomly choosing points in between. The resulting dataset had 41 presence and 54 absence coarse resolution sites and 96 presence and 103 absence fine resolution sites. Coarse-scale data were spaced out and covered the black bear's known range, while fine-scale data points were clustered in Sichuan and part of Shaanxi Provinces (Fig. S1).

2.2. *Species Distribution Modeling*

We collected a set of 24 candidate variables (19 climate from Fick and Hijmans (2017), 2 topology, 1 land cover, and 2 anthropogenic impact variables) that could affect the suitability of black bear habitat. We first examined paired correlations between the 19 climate variables and excluded the ones that had a Pearson correlation coefficient ≥ 0.7 with one or more of the other variables. We chose the smallest subset of predictors where all selected predictors were not highly correlated ($\rho < 0.7$). After that culling, six climate variables remained: Annual Mean Temperature (BIO1), Mean Diurnal Temperature Range (BIO2), Isothermality (BIO3), Temperature Seasonality (BIO4), Annual Precipitation (BIO12), and Precipitation Seasonality (BIO15). We also retained all the other variables: elevation (ELEV), topographic ruggedness (RUGG), forest cover (COVER), human population density (POPU), and protection status (PROT) (Table.S1), where protection status was defined as whether a pixel was covered or partly covered by a nature reserve. We constructed coarse- and fine-scale models by resampling those 11 predictors to raster layers of either 30 km or 3 km resolutions (bilinear for the continuous and nearest neighborhood for categorical) for coarse- and fine-scale models, respectively. The fine-resolution points were spatially biased (Fig.S1), and thus did not represent the gradient of all environmental variables at the national scale. Therefore, to properly construct the fine-scale model, we compared the range of variables of those points with the range of our 11 variables across China and retained five environmental variables that represented the conditions across China. We used the Random Forest algorithm (Cutler et al., 2007; Breiman, 2001) to construct species distribution models that predict the probability of black bear existence at the coarse- and fine-scales using data points at the corresponding scale. We used 10-fold cross-validation and Receiver Operating Characteristic curves (ROC) (Thuiller et al., 2016) to evaluate model performances. We used the average Gini importance computed by the Random Forest algorithm during the 10-fold cross-validations to evaluate the relative importance of the environmental variables at different resolutions (Cutler et al., 2007; Breiman, 2001).

2.3. Map Integration and Habitat Patch Analysis

We combined species distribution modeling with map fusion techniques widely used in remote sensing (Chen and Stow, 2003; Lu and Weng, 2007; Weng, 2012) to synthesize predictions of black bear distributions at the two resolutions. We adopted the strategy of "comparing *a posteriori* probabilities from multiple resolutions" (Chen and Stow, 2003) to generate an integrated map that used the Bayes rule to calculate posterior probabilities of existence. To begin, we resampled the coarse-scale map to a 3 km resolution so that both the fine- and coarse-scale maps had the same grid system. We combined the two maps' predicted probabilities of the existence by viewing the coarse-scale map as the prior probability of existence and the fine-scale map as the likelihood probability of existence at each pixel. We denoted the coarse-scale prediction at pixel k as $p_k(exist) = 1 - p_k(absent)$, while the fine-scale prediction at pixel k was $P(k|exist) = 1 - P(k|absent)$ (Chen and Stow, 2003). Then, according to the Bayes theorem, we calculated the posterior probability of existence at pixel k as

$$\frac{p_k(exist)P(k|exist)}{p_k(exist)P(k|exist) + p_k(absent)P(k|absent)}$$

We randomly paired the 10 sets of coarse- and fine-scale maps obtained from the 10-fold cross-validation process to generate 10 integrated maps, each with a spatial resolution of , 3 km $\times$ 3 km and then we validated those maps using presence and absence points that were not used for model training. We used both coarse- and fine-resolution points to test the model because the fine-scale data points were spatially biased. Considering that black bear presence in a 30 km $\times$ 30 km grid did not ensure the presence of black bears in every 3 km $\times$ 3 km grid within the larger grid, we drew a 15-km buffer around a coarse-scale point and used the average prediction within the buffer as the response corresponding to that point during the ROC-area under the curve (AUC) analysis. To examine whether integrating fine-scale data improved predictive accuracy, we calculated the ROC-AUC values of the coarse-scale map with fine-scale test set (see Table 1) and compared the values of the coarse and corresponding integrated maps. We produced final predictions for the coarse, fine, and integrated maps by taking the average probability of the set of 10 maps. Finally, by setting a threshold of 0.39 when the maximum sum of sensitivity and specificity on the test set was achieved, the prediction of the integrated map was converted to a binary distribution map and then processed using a low-pass filter with default parameters in ArcGIS 10.3.1 to eliminate noise. The resulting map was compared with the IUCN and AOH range maps. We divided the predicted black bear habitats into multiple management units. Each unit was a group of habitat patches that were separated from other groups by large geographic or anthropogenic barriers (e.g., large mountains, rivers and channels, and human-dominant landscapes). We calculated two metrics for each unit: the total core area, using a buffer depth of 5 km, and the area-weighted average of the Core Area Index (the average percentage of core area weighted by the total area of a patch McGarigal and Marks (1995)). We also calculated one connectivity index for each unit as the averaged proximity index of all patches within the unit. The proximity index of a focal patch is defined as the sum of the ratio between the size of a patch within or overlapping the 5-km buffer area of the focal patch and the minimum edge-to-edge distance between the two patches squared. An index with a high value indicates that the patches around the focal patch are both nearby and large (Gustafson and Parker, 1992). All indexes were calculated using FRAGSTATS v.4 (McGarigal and Marks, 1995). To finish, we ranked all management units by their potential risks and conservation priorities based on the characteristics of the black bear habitats within each unit.

3. Results

3.1. Predicted Range and Important Environmental Factors

The 10-fold cross-validation revealed an average AUC of 0.925 (SD $=$ 0.058) for the coarse-scale map (Fig.1) and 0.996 (SD $=$ 0.007) for the integrated map. When using fine-scale data as the test set, the coarse-scale map had an AUC of 0.610, while the integrated map's was 0.867, indicating that using the fine-scale map to refine the prediction of the coarse-scale map greatly improved range prediction accuracy. Black bear range size in our final integrated map was 462.3×10^3 km^2. In the ten coarse-scale models, the three most important distribution range predictors were Mean Diurnal Range (BIO2), topographic ruggedness (RUG), and Precipitation Seasonality (BIO15) in the ten coarse-scale models, and changed to human population density, topographic ruggedness , and forest coverage in the ten fine-scale models (Fig.2). Those three variables were also the most important predictors evaluated by the average Gini importance calculated during the 10-fold cross-validation in the fine-scale model (Fig.2).

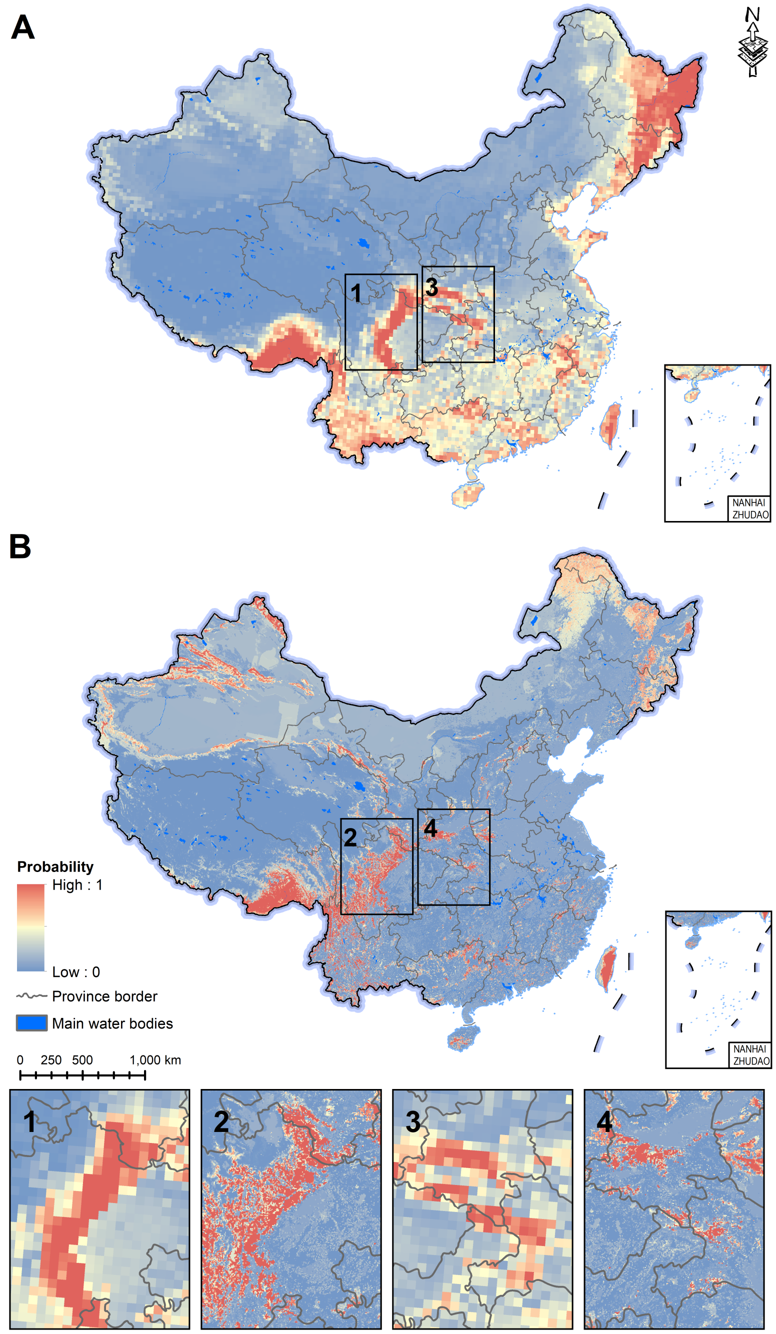

Figure 1: Coarse- (A) and fine- (B) resolution models predicting the Asiatic black bear distribution in China. The four inset maps are enlarged to show the details of the Hengduan (1,2) and Qinling Mountains (3,4) as examples.

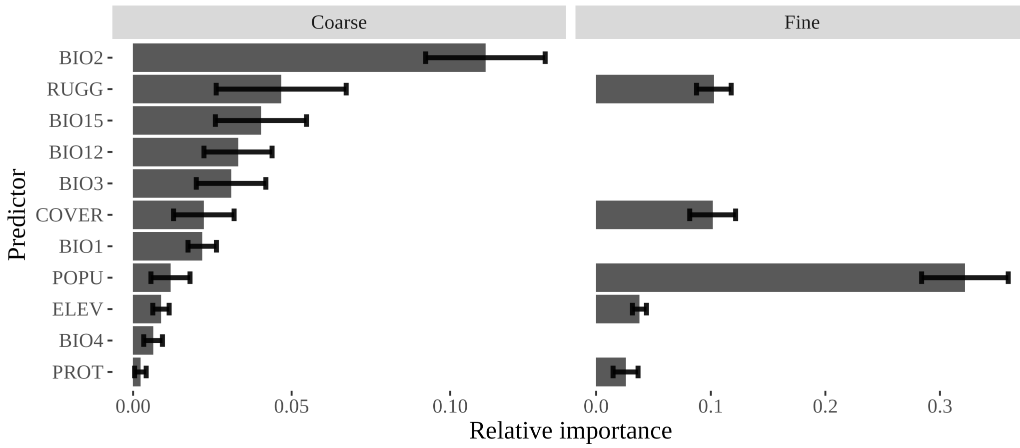

Figure 2: Relative importance of each variable in the coarse- (left) and fine-scale (right) models from Fig. 1. BIO2: mean diurnal range, RUGG: topographic ruggedness, BIO15: precipitation seasonality, BIO12: annual precipitation, BIO3: isothermality, COVER: forest cover, BIO1: annual mean temperature, POPU: human population density, ELEV: elevation, BIO4: temperature seasonality, PROT: protection status. Error bars show the standard deviation of 10 Gini importance calculations made during the 10-fold cross-validation.

3.2. Management Units and Their Habitat Characteristics

We identified eight management units, two on islands (i.e., Hainan and Taiwan) and six on the mainland (Fig.3, Table 2). The Northeast China unit was far from the other five mainland units which included two in Southeast China (i.e., the Wuyi Mountains in Zhejiang, Fujian, and Jiangxi provinces, and the Nanling Mountains in Guangdong Province), one in central China (the Qinba Mountains), and two in Southwest China (the Hengduan Mountains and East Himalayas). The Hengduan Mountains unit, followed by the Northeast China and the East Himalayas units, contained the largest areas of black bear habitat in China. Because they were much larger than the other units, we placed those three units at the lowest risk of loss of both habitat and core habitat areas (Table 2). The Qinba Mountains unit and the Taiwan unit were ranked having medium risk because of their moderate core areas and fragmentation statuses. Because they contained small, highly fragmented areas of habitat, the units of Wuyi and Nanling Mountains were both ranked high risk and urgently in need of attention (Table 2). The Hainan unit habitat was small and fragmented and no black bears were detected on that island despite extensive, island-wide camera-trapping survey efforts (e.g., Li et al. (2020a)). Thus, the black bear population on Hainan Island is likely either extirpated or existing at very low density.

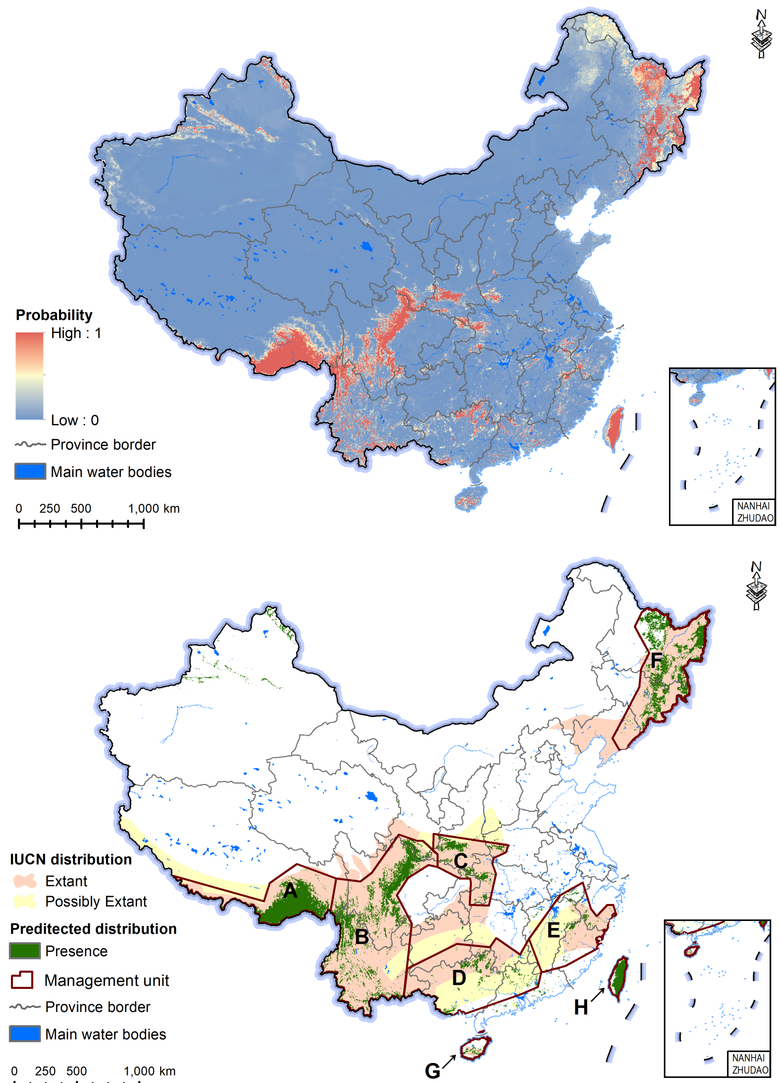

Figure 3: Final predicted distributions of Asiatic black bears in China include a heat map of presence probability as predicted by the final, integrated model (upper) and the eight management units (A-H) outlined on the binary distribution map (lower), which was drawn from the predictions of the integrated map. The units overlay the IUCN and area of habitat (AOH) distributions (See Table 2). A: East Himalayas unit, B: Hengduan Mts. unit, C: Qinba Mts. unit, D: Wuyi Mts. unit, E: Nanling Mts. unit, F: Northeast China unit, G: Hainan unit, H: Taiwan unit.

Table 2: Habitat characteristics and conservation priorities of the eight Asiatic black bear management units in China.

Management Units	Total Area $\times 10^3$ km^2	Total CORE Area $\times 10^3$ km^2	Mean Core Area Index %	Mean proximity index[b]	Priority[c]
Mainland					
A. East Himalayas	101.78	84.26	82.78	728.46	+
B. Hengduan Mts.	154.38	61.79	40.02	127.17	+
C. Qinba Mts.	30.36	11.78	38.79	41.64	++
D. Wuyi Mts.	13.85	2.51	18.11	3.34	+++
E. Nanling Mts.	27.32	6.04	22.10	6.04	+++
F. Northeast China	109.32	50.00	45.74	129.82	+
Island					
1. Taiwan	22.35	19.27	86.18	224.15	++
2. Hainan[a]	2.86	0.65	22.72	6.32	

[a] Since the black bear population on Hainan Island is likely extirpated, we assigned no conservation priority to the Hainan unit. [b]The average of the proximity indexes of all patches within a unit, where the proximity index of a patch is the sum of the ratio between the size of a patch within or overlapping the 5-km buffer area of the patch and the minimum edge-to-edge distance between the two patches squared.[c]+, low priority; ++, medium priority; +++, high priority.

4. Discussion

IUCN species distribution data is mainly compiled from expert knowledge, so its accuracy and reliability rely heavily on the availability of existing data (Barve et al., 2011; Hurlbert and Jetz, 2007; Fourcade, 2016). For lesser-studied species, the distribution range sketched by experts may deviate greatly from that species' actual situation (Fourcade, 2016). Although most of our predicted black bear habitat fell within the IUCN extant range, our more refined predictions showed 77.50% less habitat area than that supposed within the IUCN range. That is a higher percent difference than those reported by previous studies that showed that certain bird species occupy only 40%–65% of their proposed range (Hurlbert and White, 2005, 2007), . This finding demonstrates that caution must be exercised when using global-scale data for regional and local species assessments (Fourcade, 2016; Herkt et al., 2017).

Although AOH is a refinement of the IUCN's range map (Brooks et al., 2019), our prediction showed 70.60% less habitat area than that in the AOH. Additionally, the AOH generated an AUC of 0.71 on the same test set we used to test our map, while our final map had an AUC of 0.86. These results suggest that AOH maps may not greatly improve range estimations for the generalist species, such as black bears, that occur in a relatively wide range of ecological conditions. (According to the IUCN, black bears occupy diverse habitat types at an elevations between 0–4300 m. Garshelis and Steinmetz (2020)). An AOH is more an *a priori* environment envelope model (Walker and Cocks, 1991) having a rectangular envelope in which a two-dimensional niche space and no interactions between environmental predictors are usually considered. By integrating SDMs, our map fusion approach accounts for both more complex ecological niches in the niche space and important factors that are missing in an AOH approach (e.g., human pressure). Importantly, the integrated approach best uses available distribution data to generate a distribution map. Although our fine-scale data was spatially biased, it was still a well-covered sample in some subspaces within the whole multi-dimensional niche space. Therefore, we chose environmental predictors that were fully represented in our fine-scale data to construct the fine-scale model. Compared to the fine-scale prediction, the coarse-scale prediction has a better range coverage, so after integrating the two models, we obtained a better map than those generated by either model alone. Black bear presence or absence at the coarse scale was mainly determined by climate and topography, while the fine-scale range was mainly determined by habitat conditions and human disturbances (e.g., forest cover and human population density as proxies). The fine-scale predictors are consistent with the IUCN statement that habitat loss and human activities are the major threats to black bears (Garshelis and Steinmetz, 2020). Essentially, the coarse-scale predictions selected areas of the country with suitable climate and topography for black bears, while the fine-scale predictions refined the areas of bear distribution by focusing on the effects of habitat and anthropogenic pressures. Given the differences in data resolutions and the variables used in the model, the coarse-scale model tended to overestimate the species' distribution range but the fine-scale model tended to underestimate it. The integrated map, a trade-off between those two models, will better reflected actual black bear distribution across the country. Those improved results provided richer information and more reliable support than previously available for the development of black bear conservation policies in China. By integrating species distribution modeling with map fusion techniques widely used in remote sensing, we demonstrated how datasets may be combined to improve species distribution estimates for species with data from various sources and that differ in spatial extent and resolution. However, our study differed slightly from the remote sensing setting because our fine resolution data were spatially biased, a common result for poorly studied species that have rather large ranges. We successfully overcame that bias by selecting predictors that had ranges representative of the whole study area (i.e., the whole of China). However, in other cases such selection may yield too few environmental factors to run the models or may filter out potentially important predictors. In such cases, rather than starting with the whole study area, we suggest generating fine-scale predictions in a feasible region and then conducting regional refinement using map fusion techniques. Even a refined regional map can provide more detailed information for conservation than a coarse resolution map can. It would be most interesting to integrate data from multiple sources to improve the coverage and accuracy of a predicted, species distribution range; for example, by combining a correlative species distribution model with expert knowledge of the target species' biology (Johnson et al., 2012; Reside et al., 2019). Or, a model-based approach could be used to integrate presence/absence data and presence-only data (Gormley et al., 2011). Compared with model-based data integration methods, our *post-hoc* and model-free map fusion technique can be used to fuse output from different mapping methods in a way that provides great flexibility. Our refined black bear distribution map lays the foundation for developing future surveys for this large mammal species in China. Now, we require additional field-collected data to further examine the differences between our map and the IUCN and AOH range maps. For example, our predicted range in Northeast China extended much farther northwest than what the IUCN range map had, and 2.50% of our entire predicted range (11.33×10^3 km^2) was located within the possibly extant IUCN range. These new findings emphasize the need for surveys that may verify the possible existence of black bears in our newly identified areas. Because the fine resolution data were confined mainly to Sichuan Province, locating more black bears in other parts of China will improve the performance of the fine-scale distribution model. Moreover, to investigate whether our results underestimate black bear habitats, field surveys are needed in the IUCN distribution range areas that our study did not predict to be suitable habitat. The eight management units we identified accounted for differences in habitat patch size, fragmentation, and connectivity—all important features upon which good black bear conservation plans can be developed. To begin, we categorized three management units to be at lowest risk (i.e., Northeast China, the Hengduan Mountains, and the East Himalayas) because they have large, relatively intact areas connected to black bear distribution areas outside China (Garshelis and Steinmetz, 2020; Sayakumar and Cououry, 2007). Therefore, the primary management strategy for those units should be to strengthen the management of existing habitats, both within and outside the protected areas, to avoid large-scale habitat loss and degradation. Next, the other two mainland units (i.e., the Wuyishan and Nanling Mountains) were each small and highly fragmented. Thus, the primary management strategy for those units should be to eliminate direct threats to local bear populations by strengthening laws and enforcement against poaching and by mitigating possible human-bear conflicts to reduce the retaliatory killing (Liu et al., 2010). Meanwhile, those units require forest restoration programs that gradually restore suitable black bear habitat and increase the connectivity between current habitat patches. Intensive investigations to determine whether there are still black bears on Hainan Island are needed immediately. The Taiwan unit, where a small population of black bears is known to be distributed along the Central Mountains of the island (Hwang et al., 2010), needs both specific management plans for small populations (Garshelis and Steinmetz, 2020; Doko et al., 2011; Ahmadzadeh et al., 2008) and elimination of direct threats such as poaching. Similar conservation strategies, as well as habitat restoration that establishes linkages with adjacent habitat patches, are needed for bear conservation in the Qinba Mountains. We suggest that the appropriate state administrative departments and agencies develop a national Asiatic black bear conservation action plan in which the distribution range and management units identified in this study will serve as a reference.

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References

Ahmadzadeh, F., Liaghati, H., Hassanzadeh Kiabi, B., Mehrabian, A.R., Abdoli, A., Mostafavi, H., 2008. The status and conservation of the Asiatic black bear in Nikshahr County, Baluchistan District of Iran. Journal of Natural History 42, 2379–2387.

Austin, M., 2002. Spatial prediction of species distribution: an interface between ecological theory and statistical modelling. Ecological Modelling 157, 101–118. doi:https://doi.org/10.1016/S0304-3800(02)00205-3.

Barve, N., Barve, V., Jiménez-Valverde, A., Lira-Noriega, A., Maher, S.P., Peterson, A.T., Soberón, J., Villalobos, F., 2011. The crucial role of the accessible area in ecological niche modeling and species distribution modeling. Ecological Modelling 222, 1810–1819. doi:10.1016/j.ecolmodel.2011.02.011.

Boitani, L., Maiorano, L., Baisero, D., Falcucci, A., Visconti, P., Rondinini, C., 2011. What spatial data do we need to develop global mammal conservation strategies? Philosophical Transactions of the Royal Society B: Biological Sciences 366, 2623–2632. doi:10.1098/rstb.2011.0117.

Breiman, L., 2001. Random forests. Machine Learning 45, 5–32. URL: http://dx.doi.org/10.1023/A:1010933404324, doi:10.1023/a:1010933404324.

Brooks, T.M., Pimm, S.L., Akçakaya, H.R., Buchanan, G.M., Butchart, S.H., Foden, W., Hilton-Taylor, C., Hoffmann, M., Jenkins, C.N., Joppa, L., et al., 2019. Measuring terrestrial area of habitat (AOH) and its utility for the IUCN Red List. Trends in ecology & evolution 34, 977–986.

Carroll, C., Miquelle, D.G., 2006. Spatial viability analysis of Amur tiger *panthera tigris altaica* in the Russian Far East: the role of protected areas and landscape matrix in population persistence. Journal of Applied Ecology 43, 1056–1068. doi:10.1111/j.1365-2664.2006.01237.x.

Chen, D.M., Stow, D., 2003. Strategies for integrating information from multiple spatial resolutions into Land-Use/Land-Cover classification routines. Photogrammetric Engineering & Remote Sensing 69, 1279–1287. doi:10.14358/PERS.69.11.1279.

Cutler, D.R., Edwards, T.C., Beard, K.H., Cutler, A., Hess, K.T., Gibson, J., Lawler, J.J., 2007. Random forests for classification in ecology. Ecology 88, 2783–2792. doi:10.1890/07-0539.1.

Doko, T., Fukui, H., Kooiman, A., Toxopeus, A., Ichinose, T., Chen, W., Skidmore, A., 2011. Identifying habitat patches and potential ecological corridors for remnant Asiatic black bear (*Ursus thibetanus japonicus*) populations in Japan. Ecological Modelling 222, 748–761.

ESRI, 2011. ArcGIS Desktop: Release 10.3. Redlands, CA: Environmental Systems Research Institute.

Fick, S.E., Hijmans, R.J., 2017. Worldclim 2: new 1-km spatial resolution climate surfaces for global land areas. International journal of climatology 37, 4302–4315.

Fourcade, Y., 2016. Comparing species distributions modelled from occurrence data and from expert-based range maps. implication for predicting range shifts with climate change. Ecological Informatics 36, 8–14.

Garshelis, D., Steinmetz, R., 2020. *Ursus thibetanus* (amended version of 2016 assessment). The IUCN Red List of Threatened Species 2020: e.T22824A166528664. https://www.google.com/url?q=https://dx.doi.org/10.2305/IUCN.UK.2020-3.RLTS.T22824A166528664.en.

Gormley, A.M., Forsyth, D.M., Griffioen, P., Lindeman, M., Ramsey, D.S., Scroggie, M.P., Woodford, L., 2011. Using presence-only and presence–absence data to estimate the current and potential distributions of established invasive species. Journal of Applied Ecology 48, 25–34.

Gustafson, E.J., Parker, G.R., 1992. Relationships between landcover proportion and indices of landscape spatial pattern. Landscape ecology 7, 101–110.

Hanson, J.O., Rhodes, J.R., Butchart, S.H., Buchanan, G.M., Rondinini, C., Ficetola, G.F., Fuller, R.A., 2020. Global conservation of species' niches. Nature 580, 232–234.

Herkt, K.M.B., Skidmore, A.K., Fahr, J., 2017. Macroecological conclusions based on IUCN expert maps: a call for caution. Global Ecology and Biogeography 26, 930–941.

Hortal, J., 2008. Uncertainty and the measurement of terrestrial biodiversity gradients. Journal of Biogeography 35, 1335–1336. doi:10.1111/j.1365-2699.2008.01955.x.

Huang, H., Li, Z., 2007. Bear farming and bear conservation in china, in: Proceedings of the 4th International Symposium on the Trade in Bear Parts. TRAFFIC East Asia–Japan, Citeseer. pp. 37–49.

Hurlbert, A.H., Jetz, W., 2007. Species richness, hotspots, and the scale dependence of range maps in ecology and conservation. Proceedings of the National Academy of Sciences 104, 13384–13389. URL: http://www.pnas.org/content/104/33/13384.abstract, doi:10.1073/pnas.0704469104.

Hurlbert, A.H., White, E.P., 2005. Disparity between range map-and survey-based analyses of species richness: patterns, processes and implications. Ecology Letters 8, 319–327.

Hurlbert, A.H., White, E.P., 2007. Ecological correlates of geographical range occupancy in North American birds. Global Ecology and Biogeography 16, 764–773.

Hussain, S., 2003. The status of the snow leopard in Pakistan and its conflict with local farmers. Oryx 37, 26–33. doi:10.1017/S0030605303000085.

Hwang, M.H., Garshelis, D.L., Wu, Y.H., Wang, Y., 2010. Home ranges of asiatic black bears in the Central Mountains of Taiwan: Gauging whether a reserve is big enough. Ursus 21, 81–96.

IUCN, 2021. The IUCN Red List of Threatened Species. version 2021-1. https://www.iucnredlist.org.

Johnson, C.J., Hurley, M., Rapaport, E., Pullinger, M., 2012. Using expert knowledge effectively: lessons from species distribution models for wildlife conservation and management, in: Expert Knowledge and Its Application in Landscape Ecology. Springer, pp. 153–171.

Li, J., Wang, X., Yang, M., Chen, D., Wang, X., Luo, P., Liu, F., Xue, Y., Li, G., Zhang, Y., et al., 2020a. Construction progress of camera-trapping database from the nature reserves biological specimen resources sharing sub-platform. Biodiversity Science 28, 1081–1089.

Li, S., McShea, W.J., Wang, D., Shen, X., Bu, H., Guan, T., Wang, F., Gu, X., Zhang, X., Liao, H., 2020b. Construction progress of the camera-trapping network for the mountains of southwest China. Biodiversity Science 28, 1049–1058.

Liu, F., McShea, W., Garshelis, D., Zhu, X., Wang, D., Gong, J., Chen, Y., 2009. Spatial distribution as a measure of conservation needs: An example with Asiatic black bears in south-western China. Diversity and Distributions 15, 649–659.

Liu, F., McShea, W.J., Garshelis, D.L., Zhu, X., Wang, D., Shao, L., 2011. Human-wildlife conflicts influence attitudes but not necessarily behaviors: Factors driving the poaching of bears in China. Biological Conservation 144, 538–547.

Liu, J., Liu, M., Zhuang, D., Zhang, Z., Deng, X., 2003. Study on spatial pattern of land-use change in China during 1995–2000. Science in China Series D: Earth Sciences 46, 373–384.

Liu, J., Zhang, Z., Xu, X., Kuang, W., Zhou, W., Zhang, S., Li, R., Yan, C., Yu, D., Wu, S., et al., 2010. Spatial patterns and driving forces of land use change in China during the early 21st century. Journal of Geographical Sciences 20, 483–494.

Lobo, J.M., Jiménez-Valverde, A., Hortal, J., 2010. The uncertain nature of absences and their importance in species distribution modelling. Ecography 33, 103–114. doi:10.1111/j.1600-0587.2009.06039.x.

Louys, J., 2014. The large terrestrial carnivore guild in Quaternary Southeast Asia. Quaternary Science Reviews 96, 86–97. URL: http://www.sciencedirect.com/science/article/pii/S0277379113002266, doi:10.1016/j.quascirev.2013.06.014.

Lu, D., Weng, Q., 2007. A survey of image classification methods and techniques for improving classification performance. International journal of Remote sensing 28, 823–870.

McGarigal, K., Marks, B.J., 1995. FRAGSTATS: spatial pattern analysis program for quantifying landscape structure. Gen. Tech. Rep. PNW-GTR-351. Portland, OR: US Department of Agriculture, Forest Service, Pacific Northwest Research Station. 122 p 351, 1–122.

Norberg, A., Abrego, N., Blanchet, F.G., Adler, F.R., Anderson, B.J., Anttila, J., Araújo, M.B., Dallas, T., Dunson, D., Elith, J., et al., 2019. A comprehensive evaluation of predictive performance of 33 species distribution models at species and community levels. Ecological Monographs 89, e01370.

Peterson, A.T., Navarro-Sigüenza, A.G., Gordillo, A., 2018. Assumption-versus data-based approaches to summarizing species' ranges. Conservation Biology 32, 568–575.

Peterson, D.R.S..A.T., 2002. Effects of sample size on accuracy of species distribution models. Ecological Modelling 148 (2002), 1–13.

Reside, A.E., Critchell, K., Crayn, D.M., Goosem, M., Goosem, S., Hoskin, C.J., Sydes, T., Vanderduys, E.P., Pressey, R.L., 2019. Beyond the model: expert knowledge improves predictions of species' fates under climate change. Ecological Applications 29, e01824.

Ripple, W.J., Estes, J.A., Beschta, R.L., Wilmers, C.C., Ritchie, E.G., Hebblewhite, M., Berger, J., Elmhagen, B., Letnic, M., Nelson, M.P., et al., 2014. Status and ecological effects of the world's largest carnivores. Science 343.

Sayakumar, S., Cououry, A., 2007. Distribution and status of the Asiatic black bear *Ursus thibetanus* in India. Journal of the Bombay Natural History Society 104, 316–323.

Soberón, J., Nakamura, M., 2009. Niches and distributional areas: concepts, methods, and assumptions. Proceedings of the National Academy of Sciences 106, 19644–19650.

Thuiller, W., Georges, D., Engler, R., Breiner, F., 2016. biomod2: Ensemble platform for species distribution modeling. R package version 3.3-7.

Verbruggen, H., Tyberghein, L., Belton, G.S., Mineur, F., Jueterbock, A., Hoarau, G., Gurgel, C.F.D., De Clerck, O., 2013. Improving transferability of introduced species' distribution models: new tools to forecast the spread of a highly invasive seaweed. PLoS One 8, e68337.

Walker, P., Cocks, K., 1991. Habitat: a procedure for modelling a disjoint environmental envelope for a plant or animal species. Global Ecology and Biogeography Letters , 108–118.

Weng, Q., 2012. Remote sensing of impervious surfaces in the urban areas: requirements, methods, and trends. Remote Sensing of Environment 117, 34–49.

Xu, A., Jiang, Z., Li, C., Guo, J., Da, S., Cui, Q., Yu, S., Wu, G., 2008. Status and conservation of the snow leopard *Panthera uncia* in the Gouli Region, Kunlun Mountains, China. Oryx 42, 460–463.

Yamamoto, T., Tamatani, H., Tanaka, J., Yokoyama, S., Kamiike, K., Koyama, M., Seki, K., Kakefuda, S., Kato, Y., Izawa, N., 2016. Annual and seasonal home range characteristics of female Asiatic black bears in Karuizawa, Nagano Prefecture, Japan. Ursus 23, 218–225.

Supplementary Materials

Spatial distribution of data points

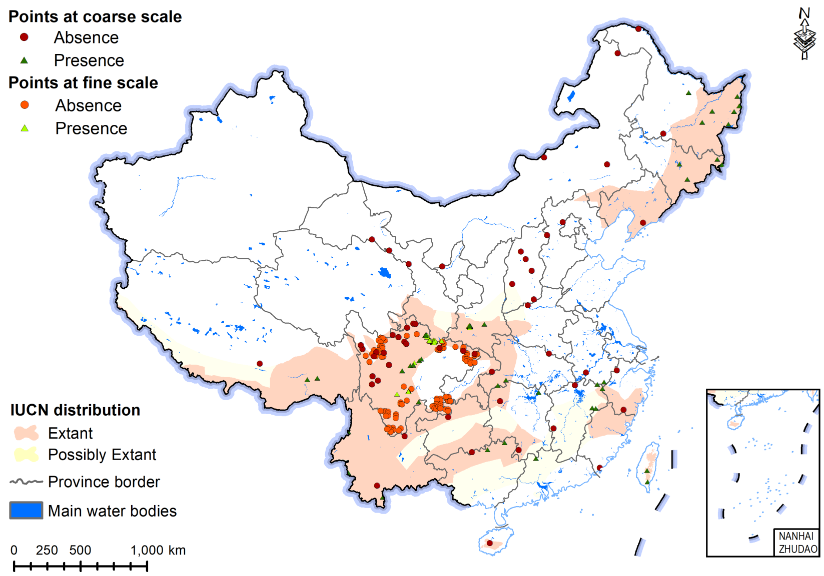

Figure S1: Presence and absence data points of Asiatic black bears used in this study at the coarse and fine resolutions, with the range map of the IUCN showing the extant and possibly extant areas of black bears in China.

Environmental predictors

Table S1: Sources and abbreviations of environmental predictors used to predict the potential habitat of Asiatic black bears at the coarse and fine resolutions, respectively.

Environmental predictors		Source	Data type	Resolution type (fine/coarse)
Name (units)	Abbreviations			
Elevation (m)	ELEV	NASA SRTM[a]	continuous	both
Roughness (m)	RUGG	from ELEV	continuous	both
Annual mean temperature (°C $\times 100$)	BIO1	BIOCLIM[b]	continuous	coarse
Mean temperature diurnal range (°C $\times 100$)	BIO2	BIOCLIM	continuous	coarse
Isothermality (unitless)	BIO3	BIOCLIM	continuous	coarse
Temperature seasonality(°C)	BIO4	BIOCLIM	continuous	coarse
Annual precipitations (mm)	BIO12	BIOCLIM	continuous	coarse
Precipitation seasonality(mm)	BIO15	BIOCLIM	continuous	coarse
Forest cover rate (0-1 unitless)	COVER	Global Forest Watch[c]	continuous	both
Population density (/km^2)	POPU	Harvard IQSS[d]	continuous	both
Protection status (Protected/Non-protected)	PORT	The authors	categorical	both

Notes: [a]NASA Shuttle Radar Topography Mission, [b]bioclimatic variables supplied by Worldclim (https://www.worldclim.org/data/bioclim.html), [c]https://www.globalforestwatch.org/, [d]Harvard Institute for Quantitative Social Science