# Identifying the distribution range and conservation needs of a large threatened mammal through an integrative mapping approach: the case of the Asiatic black bear, China

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**Abstract**

Assessing species' threatened status and developing conservation strategies highly rely on the extent and accuracy of our knowledge on the spatial distribution of the target species. In this study, we used the Asiatic black bear (*Ursus thibetanus*) in China as a representative of large threatened species for which information on distribution is limited and spatially biased. Two main sources of occurrence data of Asiatic black bears resulted in data of different resolutions. The coarse resolution data corresponded to specific management units (e.g. nature reserves) and covered a larger area. The fine resolution data were longitude and latitude records and not representative of the species' geographic range. We developed an approach to integrate the two data types to map its distribution and examine the spatial pattern across the country. We used Random Forest algorithm with both

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presence and absence data to predict the distribution of Asiatic black bears at coarse (30 km) and fine (3 km) resolutions, respectively, and refined the coarse-scale prediction with the fine-scale prediction using a map fusion technique based on the Bayes theorem to generate an integrated high-resolution range prediction. The results showed that the integrated map was higher in accuracy than the coarse-scale map and better represented the geographic range of Asiatic black bears than the fine-scale map. Our results showed that the total estimated range of Asiatic black bears in China was $462.3 \times 10^3$ km$^2$, 77.50% less than the most recent range map of the IUCN. We identified two islands and six mainland management units in China and proposed specific conservation strategies for each unit based on the predicted habitat conditions. These results provide valuable insights and pragmatic guidance for future conservation planning and actions for this species, and our framework provides an example and template for the range estimation of species with similar types of occurrence records.
*Keywords:* Asiatic black bear, IUCN species distribution map, species distribution modeling, management unit, conservation strategy,

# 1. Introduction

Assessing species' threatened status and developing conservation policy highly relies on the extent and accuracy of our knowledge on the spatial distribution of target species (Boitani et al., 2011). However, one challenge in front of conservationists and policymakers is that those most threatened species are also normally the ones with the poorest knowledge and information. This is especially true for large terrestrial carnivores that are characterized by a long life span, low population density, large home range, and elusive behavior (Louys, 2014). Among those species, the large carnivores in the developing countries may need urgent attention since they are typically under high threats leading to a high risk of regional extinctions (Louys, 2014; Ripple et al., 2014). Lack of distribution data, especially data of high resolution, is a primary obstacle to determining the accurate distributions of such species and hinders the development of effective management strategies and conservation policies for the species accordingly.

The conventional way to create distribution maps for threatened species is using expert knowledge to roughly draw their ranges (Hortal, 2008). This method has been used in global and regional species assessment such as the IUCN Red List of Threatened Species (IUCN, 2021). Limited by the availability of knowledge on the species extant range, the resolution of these maps might be restricted to 1 degree in longitude/latitude or even coarser (Hurlbert and Jetz, 2007). In order to downscale these maps to fine resolutions, the extent-of-occurrence maps are refined by suitable habitat types and elevation range of the species to produce the species' area of habitat (AOH, Brooks et al. (2019)). Although AOH has been increasingly used for conservation planning (Hanson et al., 2020), its application at fine resolutions is questionable due to the resolution and uncertainty of expert maps (Peterson et al., 2018). With the recent advances in online open biodiversity depositories (e.g., GBIF and e-Bird), using species distribution models (SDMs, Austin (2002)) integrated with environmental variables to predict the geographic range of the species provides a more rigorous way for range mapping (Peterson, 2002; Peterson et al., 2018).

The accuracy and robustness of SDMs rely on the quality and quantity of species occurrence data, and the data type (i.e., presence-only or presence with true absence) also matters (Norberg et al., 2019). The occurrence data obtained from different sources often vary in resolution, as well as in spatial and temporal extent. Whereas, for many large threatened mammals, the canonical situation is that, it is relatively easier to obtain occurrences of the species at a coarse resolution (e.g. in a reserve or a study site), but the high-resolution occurrence data are limited and spatially biased. How to integrate such heterogeneous data of varied resolution from multiple sources to create reliable species distribution maps is a great challenge for conservationists, park managers, and policymakers

Here, we take the Asiatic black bear (*Ursus thibetanus*, referred to as black bear hereafter) as an example to explore the possible solutions of creating a range map with different-resolution data. Black bears widely distribute through East to Southeast Asia and inhabit various forested habitats from boreal forests to tropical rainforest (**?**). Throughout its range, black bears have been suffering from heavy poaching and illegal wildlife trade for their meat and body parts (e.g., gallbladder and fat for Chinese traditional medicine Lin et al. (1997); Liu et al. (2011)). They are also killed or poisoned by locals as vengeance for crop damage and livestock loss during human-bear conflicts (Charoo et al., 2011; Liu et al., 2011; Malcolm et al., 2014). The IUCN Red List evaluates black bear as

Vulnerable given its undergoing threat of poaching, habitat loss, its decreasing population, and shrinking range (Garshelis and Steinmetz, 2020). Unlike some other large carnivores, such as tiger (*Panthera tigris*, Carroll and Miquelle (2006)) and snow leopard (*P. uncia*, Hussain (2003); Xu et al. (2008)), which have long been considered as flagship species and obtained substantial socio-political resources and public enthusiasm, black bear draws much less attention and is poorly studied. Although China comprises more than half of black bear's total range area and the largest wild population (Garshelis and Steinmetz, 2020), the population within the Chinese border is one of the least studied and thus least known populations across its range (Liu et al., 2009) due to lack of robust state-wide assessment and monitoring.

In this study, we aimed to create a framework using gleaned data from diverse sources to map the black bear distribution and examine its spatial pattern in China. We developed a hierarchical modeling approach using both presence and absence data at varied resolutions. We further identified eight management units for black bears in China based on the predicted distribution map, and proposed management recommendations for each unit based on the results of habitat patch analysis and risk assessment. Our framework may provide an example for distribution mapping and conservation planning of other species that suffer from data deficiency elsewhere.

## 2. 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 the occurrence (both presence and absence) data of black bears between 2008 and 2018 and considered the data prior to 2008 unsuitable for this mapping given 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 located into specific nature reserve 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 which were longitude and latitude records or could be located within an area of $3$ km $\times$ $3$ km, a size close to the smallest home range of black bears reported in East Asia (approximately $10$ km$^2$. Meihsiu et al. (2010); Yamamoto et al. (2016)).

We searched camera-trap literature and public news reports to collect coarse-resolution presence data of black bears. We conducted a comprehensive literature review through online databases, including Web of Science, Google Scholar, CNKI (Chinese National Knowledge Infrastructure), and CSTJ (Chinese Science and Technology Journal Database), for peer-reviewed articles published since 2008 using the searching terms "terrestrial mammals", "camera trapping", "trail camera", and "China" in both Chinese and English. We collected 199 articles that use camera-trap to detect the occurrence of terrestrial mammals in China. Twenty-two study sites (from 23 articles), primarily nature reserves, where black bear detection was reported were considered presence sites. We identified additional 23 presence sites from public news reports containing photographs or videos of black bears. Additionally, eight sites were identified from an unpublished camera-trap dataset of a regional camera-trap network (i.e., Camera-Trapping Network for the Mountains of Southwest China) maintained by the authors in Southwest China (including Sichuan, Shaanxi, and northern Yunnan provinces, Li et al. (2020b)). Thus, the total number of presence sites at coarse resolution added up to 53.

We also obtained coarse-resolution absence data from the same camera-trap literature as mentioned above. We reviewed the 23 camera-trap literature which detected black bears and calculated the average detection rate of the species when data available (n=10). It took 1,292 camera-days per detection (range 17-1,896) and the minimum number of survey stations was eight. If assuming detection coming at random following a Poisson process, the detection rate can be estimated as 1/1,292 and the probability one does not see a detection longer than 4,000 days when the species is present is 4.5% (range 0-12%). Based on this information, we defined sites with a survey effort of 4,000 camera-days AND 40 camera stations without detecting black bears as black bear absence sites (n=4). Those four absence sites were only used in the test set because of the possibility of being false absence2, and also for case balance during training. Additionally, we collected 38 absence sites based on the baseline survey reports of 125 nature reserves across China, and no black bears are listed in the reports for these sites. Given the large body size and easy-to-recognize signs of black bears, and high awareness among local residents when present(Liu et al., 2011), , we considered that the baseline surveys shall not have false-negative records for this animal. However, we did not use the presence records in the reports because the species list of the baseline survey often contains historical records and does not imply the recent presence of black bears in the reserves, especially given the rapid habitat changes over the last few decades. We obtained additional 18 absence sites from Liu et al. (2009), which established a field procedure to determine the presence/absence of black bears using interviews and sign transect surveys for each $15$ km $\times$ $15$ km survey grid in Sichuan Province and generated 128 absence grids. Thus, the total number of absence sites for black bears added up to 60 (56 for training and 4 for test).

At the fine resolution, we extracted 132 presence locations (i.e., camera survey stations) with longitude/latitude coordinates collected during 2008 – 2018 from the database of the camera-trap network maintained by the authors (Li et al., 2020b). The absence sites for our study were generated based on the 128 absence grids of Liu et al. (2009) , by randomly selecting one $3$ km $\times$ $3$ km grid from each of their $15$ km $\times$ $15$ km grid as an absence site for our study. We collected additional presence (n=12) and absence (n=20) 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 as the test set. In total, we had 144 presence (132 for training and 12 for the test) and 148 absence grids (128 for training and 20 for the test) at the fine resolution. A summary of all collected data at both resolutions is provided in Table.1.

All presence/absence data at both resolutions were processed using ArcGIS (ESRI, 2011) to generate geo-referenced vectorial point layers by taking the center of each grid for data with no accurate latitude and longitude coordinates, respectively, for subsequent modeling and analysis. We conducted a spatial thinning approach following Verbruggen's Occurrence Thinner (Verbruggen et al., 2013) to reduce the redundancy and the class imbalance prior to model construction (Breiman, 2001; Cutler et al., 2007), This procedure estimated the (normalized) kernel density of points and discard points with the highest 10% density and retain points with the lowest 10% density, and chose points in between at random, resulting in a dataset of 41 presence and 54 absence sites at the coarse-scale and 96 presence and 103 absence points at the fine-scale. Coarse scale data were spaced out and covered the known range of black bear, while fine-scale data points were clustered in Sichuan and part of Shaanxi Province (Fig.S1).

Table 1: Data sources, sample size, and primary usage. All training points later on went through thinning process

| Resolution | Data type | Source | n | Primary use |
|---|---|---|---|---|
| Coarse | Presence | Literature | 22 | training |
| Coarse | Presence | News | 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 |

### *2.2. Species Distribution Modeling*

We collected a set of 24 candidate variables (19 of climate, two of topology, one of land cover, and two of anthropogenic impact) that may affect the habitat suitability of black bears. We first examined the paired correlation between the 19 climate variables and excluded the ones which had a correlation coefficient $\geq$0.7 with one or more other variables. We chose the most ecological meaningful ones to form the smallest subset of predictors when multiple variables were correlated. Six climate variables were retained after the examination, namely Annual Mean Temperature (BIO1), Mean Diurnal Temperature Range (BIO2), Isothermality

(BIO3), Temperature Seasonality (BIO4), Annual Precipitation (BIO12), and Precipitation Seasonality (BIO15). The other predictors used were altitude, topographic ruggedness, forest coverage, human population density, and protection status (Table.S1), where the protection status was defined as whether a pixel was covered or partly covered by nature reserves. All the 11 remaining predictors were resampled to raster layers of 30 km and 3 km resolution (bilinear for the continuous and nearest neighborhood for categorical), respectively, for the construction of coarse- and fine-scale models. The fine-resolution points were spatially biased (Fig.S1), and thus did not represent the gradient of all environmental variables at the national scale. To account for this, we compared the range of variables of the fine resolution points with the range of these variables across China and retained only the five environmental variables that could represent the conditions across China for the fine-scale model construction.

We used Random Forest (RF) algorithm (Cutler et al., 2007; Breiman, 2001) to construct the species distribution models and predict the probability of the existence of black bear at the coarse and fine-scale with data points at the corresponding scale, respectively. We used 10-fold cross-validation and Receiver Operating Characteristic curve (ROC) (Thuiller et al., 2016) to evaluate the model performance. We used the average Gini importance reported by the RF algorithm during the 10 fold cross-validation to evaluate the relative importance of the environmental variables at different resolutions (Cutler et al., 2007; Breiman, 2001).

We then combined species distribution modeling with map fusion techniques widely used in remote sensing (Chen and Stow, 2003) to synthesize the prediction of black bear distribution at the two resolutions. We adopted the strategy of "comparing *a posteriori* probabilities from multiple resolutions" (Chen and Stow, 2003) to generate the integrated map, which uses the Bayes rule to calculate posterior probabilities of existence. We first resample the coarse-scale map to a resolution of $3$ km so that two maps had the same grid system. We combined the predicted probability of the existence of the two maps 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. Denote the coarse-scale prediction at a pixel $k$ as $p_k(exist) = 1 - p_k(absent)$ (Chen and Stow, 2003) while the fine-scale prediction at pixel $k$ as $P(k|exist) = 1 - P(k|absent)$ (Chen and Stow, 2003). Then by 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 with a spatial resolution of $3$ km $\times$ $3$ km, and then validated these 10 integrated 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 as the fine-scale data points were spatially biased. Considering that presence of black bears in a $30$ km$\times 30$ km grid did not ensure the presence of black bears in every $3$ km $\times$ $3$ km grids within the larger grid, we draw 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-AUC analysis. To examine whether integrating fine-scale data improved the accuracy of the prediction, 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 the final prediction for the coarse, fine, and integrated maps, respectively, by taking the average probability of the set of ten 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 the noise.

### *2.3. Management Units and Risk Analysis*

We divided the predicted habitats of black bears 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, or human-dominant landscapes). We calculated two metrics for each unit, namely the total core area using a buffer depth of 5 km, and the area-weighted average of 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, which was 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 overlapped with the 5-km buffer area of the focal patch and the minimum edge-to-edge distance between the two patches squared. The index with a high value indicates the patches around the focal patch are close to it and large in size (Gustafson and Parker, 1992). These indexes were calculated using FRAGSTATS (McGarigal and Marks, 1995). We then ranked all management units for potential risk and conservation priority based on the characteristics of black bear habitats within each unit.

## 3. Results

The 10-fold cross-validation showed an average AUC of 0.925 (sd=0.058) for the coarse-scale map (Fig.1) and an average AUC of 0.996 (sd=0.007) for the integrated map. When using fine-scale data as the test set, the coarse-scale map showed an AUC of 0.610, while the integrated map showed an AUC of 0.867, indicating that using the fine-scale map to refine the prediction of the coarse-scale map greatly improved the accuracy of the range prediction. The first three most important predictors were Mean Diurnal Range (BIOCLIM2), topographic ruggedness (RUG), and Precipitation Seasonality (BIOCLIM15) in the ten coarse-scale models, and changed to human population density, topology roughness, and forest coverage in the ten fine-scale models (Fig.2). The first three most important predictors evaluated by the average Gini importance calculated during the 10 fold cross-validation in the fine-scale model changed to human population density, topology roughness, and forest coverage (Fig.2).

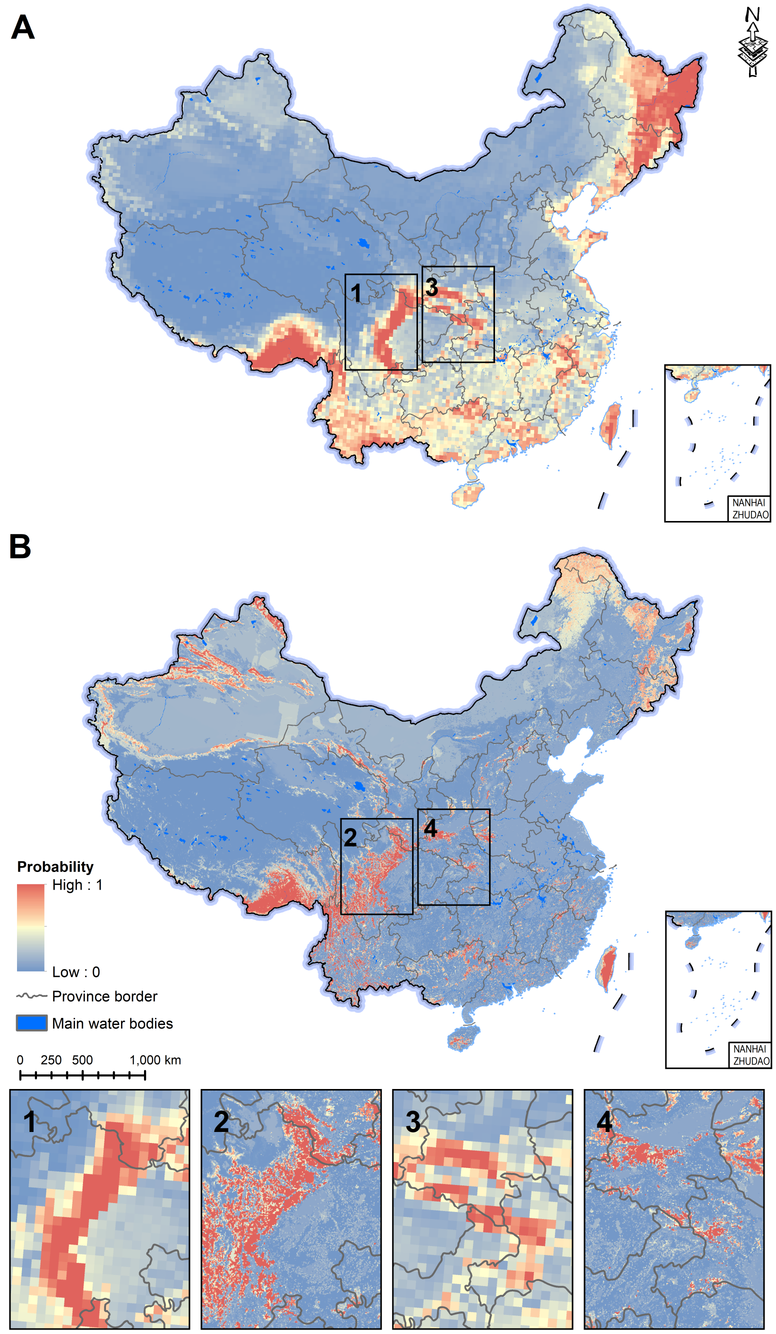


Figure 1: Model predicted distribution of Asiatic black bear in China at coarse (A) and fine (B) resolution, respectively. The four zoom-in maps at the bottom showed the details of the Hengduan Mountains (1,3) and Qinling Mountains (2,4) as indicated by the two frames in the main maps.

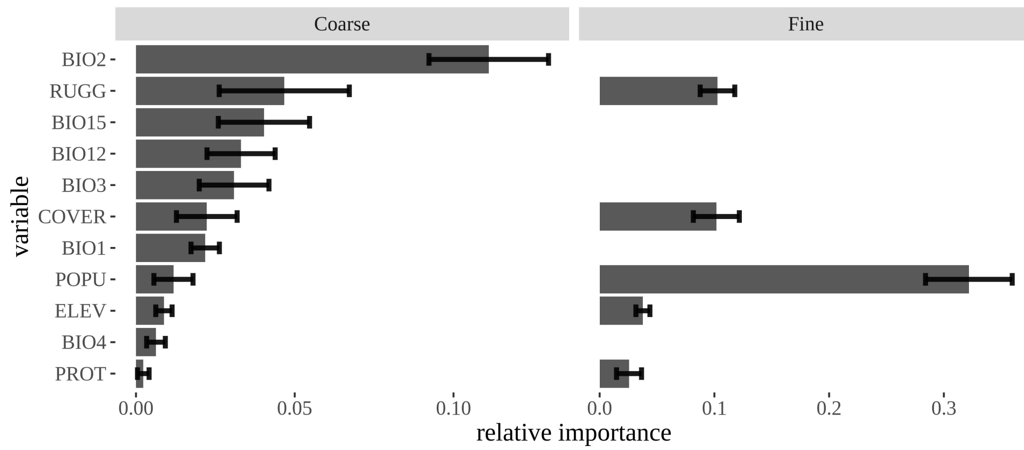


Figure 2: Relative importance of variables in coarse- (left) and fine-scale (right) models. BIO2: mean diurnal range, RUGG: topographic ruggedness, BIO15: precipitation seasonality, BIO12: annual precipitations, BIO3: isothermality, COVER: forest cover, BIO1: annual mean temperature, POPU: population density, ELEV: elevation, BIO4: temperature seasonality, PORT: protection status. Error bar indicated standard deviation of 10 Gini importance calculated during the 10-fold cross validation.

The range size of black bears in our final integrated map was $462.3 \times 10^3$ km$^2$. We identified eight management units, including 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 units on the mainland. The other five mainland units 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 Eastern Himalayas). The Hengduan Mountains unit held the largest area of black bear habitat in China, followed by two units, Northeast China and the Eastern Himalayas. These three units were considered with the least risk for their areas of both habitat and core habitat were much larger than the other units (Table.2). The Qinba Mountains unit and the Taiwan unit were ranked as middle class with moderate core areas and fragmentation status. The units of Wuyi Mountains and Nanling Mountains contained small areas of habitat that were highly fragmented, for which both were ranked as top priorities requiring urgent attention (Table.2). The habitat in the Hainan unit was small and fragmented. The black bear has not been detected on this island despite extensive camera-trapping survey efforts throughout the Island (e.g. Li et al. (2020a)). The black bear population on Hainan Island probably has gone extinct or, if not already, at very low density.

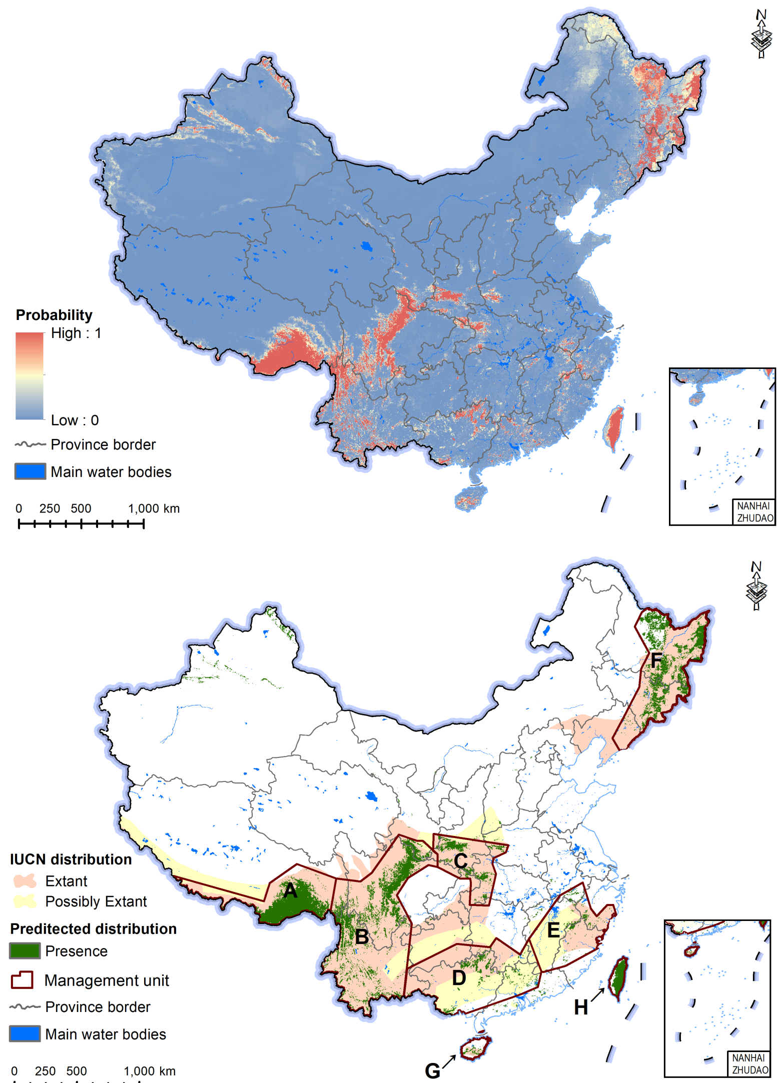


Figure 3: The presence probability (upper) of Asiatic black bears as predicted by the final integrated model, and the eight management units (lower) identified based on the binary distribution map in China (See Table.2)

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

| Unit | Total Area $\times 10^3$ km$^2$ | Total CORE Area $\times 10^3$ km$^2$ | Mean Core Area Index % | Mean proximity index | Priority |
|---|---|---|---|---|---|
| **Island** | | | | | |
| 1. Taiwan | 22.35 | 19.27 | 86.18 | 224.15 | ++ |
| 2. Hainan* | 2.86 | 0.65 | 22.72 | 6.32 | |
| **Mainland** | | | | | |
| 3. Northeast China | 109.32 | 50.00 | 45.74 | 129.82 | + |
| 4. Wuyi Mts. | 13.85 | 2.51 | 18.11 | 3.34 | +++ |
| 5. Nanling Mts. | 27.32 | 6.04 | 22.10 | 6.04 | +++ |
| 6. Qinba Mts. | 30.36 | 11.78 | 38.79 | 41.64 | ++ |
| 7. Hengduan Mts. | 154.38 | 61.79 | 40.02 | 127.17 | + |
| 8. East Himalayas | 101.78 | 84.26 | 82.78 | 728.46 | + |

*: We assigned no conservation priority for the Hainan unit and considered possible extirpation of the black bear population on the Hainan Island.

## 4. Discussion

Our mapping result generally agreed with the IUCN range map of black bears, with most of our predicted habitat occurring within the IUCN extant range. The major difference between our predictions and the IUCN range map is that our more refined prediction had 77.50% less habitat area than the IUCN extant range. Focusing on monitoring and protecting black bears in our predicted areas could largely improve the efficiency of black bear conservation in China. In addition, our predicted range in Northeast China extended much farther northwest than the IUCN range map, and 2.50% of our predicted range ($11.33 \times 10^3$ km$^2$) were located within the possibly extant range of the IUCN, suggesting that further surveys are needed to verify the possible existence of the species in these newly identified areas.

The important predictors of black bear distribution at the coarse and fine scales were different. At the coarse scale, the presence or absence of the species was mainly determined by climate and topography, while the fine-scale range was mainly determined by habitat conditions and human disturbance (e.g., forest cover and human population density). The finding at the fine-scale is 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 prediction selected areas of the country with suitable climate and topography for black bears, while the fine-scale prediction refined the areas of bear distribution by focusing on the effects of habitat and anthropogenic pressure on their distribution. Given the differences in the spatial representativeness and resolution of the data and variables used in the model, the coarse-scale prediction tended to overestimate the species' distribution range, whereas the fine-scale prediction tended to underestimate it. The integrated map, therefore, made a trade-off between the two and better reflected the actual distribution of black bears across the country. The improved results provided much richer information and more reliable support for species distribution assessment, regional biodiversity assessment, and the development of conservation policies for black bears in China.

Our results demonstrated that one could combine species distribution modeling with map fusion techniques widely used in remote sensing (Chen and Stow, 2003; Lu and Weng, 2007; Weng, 2012) to synthesize data from various sources with varied spatial resolutions. Slightly different from the remote sensing setting is that, in our case, fine resolution data were spatially biased, which is quite common for poorly studied species with a rather large range. We tried to overcome biased spatial sampling by selecting predictors with a range representative of the predicted area (the whole of China in our case) and the results were successful. Our assumption here may not be met when the environmental factors turn out to be too few to run the models or potentially important predictors may be filtered out. In such cases, we suggest generating fine-scale predictions in a feasible region and conducting regional refinement using map fusion techniques rather than refinement for the whole study area. Even a regional refinement can provide more detailed information for conservation comparing to a coarse resolution map. It is of great interest to integrate data of multiple sources to improve the coverage and accuracy of the predicted species distribution range, for example, by combining species distribution maps built on expert knowledge with modern SDMs (Johnson et al., 2012; Reside et al., 2019). Comparing with models proposed to deal with this (Miller et al., 2019) developed a model-based approach that used statistical models to account for generating process of both presence/absence data and presence-only data (Gormley et al., 2011), map fusion technique is *post-hoc* and model-free which could be used to fuse output of different mapping method that brings large flexibility.

Our results showed that the habitat area, fragmentation degree, and connectivity varied broadly across the eight proposed management units of black bears in China, suggesting that different units require differentiated conservation policies and management approaches. The three management units categorized as least risks (i.e., the Northeast China, Hengduan Mountains, and East Himalayas) are large in area and relatively intact. They contained the most important black bear habitats and may harbor the largest black bear populations in China. Meanwhile, all three units are cross-boundary units that connect to the distribution area of black bears outside China (Garshelis and Steinmetz, 2020; Sayakumar and CououRY, 2007), forming even larger regional distribution areas and regional populations. We suggest that the primary management strategy for them should be to strengthen the management of existing habitats both within and outside the protected areas to avoid large-scale habitat loss and degradation. The other two mainland units (i.e., the Wuyishan and Nanling Mountains) were small in size and highly fragmented. Thus, the primary management strategy should be eliminating the direct threat to local bear populations by strengthening law enforcement against poaching and mitigating possible human-bear conflicts to reduce the retaliatory killing (Liu et al., 2010). Meanwhile, forest restoration programs should be conducted to gradually restore the suitable habitat of black bears and increase the connectivity between current habitat patches. Investigative efforts are urgently needed to determine whether there are still black bears on Hainan Island. For the Taiwan unit, black bears are known to be distributed along the Central Mountains of Taiwan Island, but the overall population size is small (Hwang et al., 2010). Specific management plans for small populations (Ahmadzadeh et al., 2008; Doko et al., 2011; Garshelis and Steinmetz, 2020) and eliminating direct threats such as poaching are urgently needed. Similar conservation strategies are necessary for bear conservation in the Qinba Mountains, and habitat restoration aiming to establish linkages with adjacent habitat patches would also be helpful. We suggest the state administrative departments and agencies develop a national conservation action plan for this species, in which the distribution range and management units identified in this study could serve as a reference.

The IUCN species distribution data is mainly produced on the basis of expert knowledge, and therefore its accuracy and reliability highly rely on the availability of existing data (Barve et al., 2011; Hurlbert and Jetz, 2007; Fourcade, 2016). For species with few studies, the distribution range sketched by experts may have a large deviation from its actual situation (Fourcade, 2016), and caution should be exercised when using such global-scale data for local or regional species assessments (Fourcade, 2016; Herkt et al., 2017). In the case of the black bear, the IUCN distribution map is relatively in finer details outside China, such as mainland Southeast Asia with more research and available data. Whereas the distribution map in China is relatively coarse, and the area and proportion of uncertain areas (possible extent and possibly extinct) are large. Most of the existing black bear records are in research papers and monographs published in Chinese (e.g., Li et al. (2020b); Wan et al. (2020)), and this information has not been reflected in a timely manner in the global conservation community. We suggest that field surveys should be conducted to generate a more accurate and dynamic map of bear distribution in China and collaborations should be promoted among countries to support the assessments for species with cross-boundary distributions to support cross-boundary conservation.

## 5. Acknowledgment

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# Supplementary Materials

## *Spatial distribution of data points*

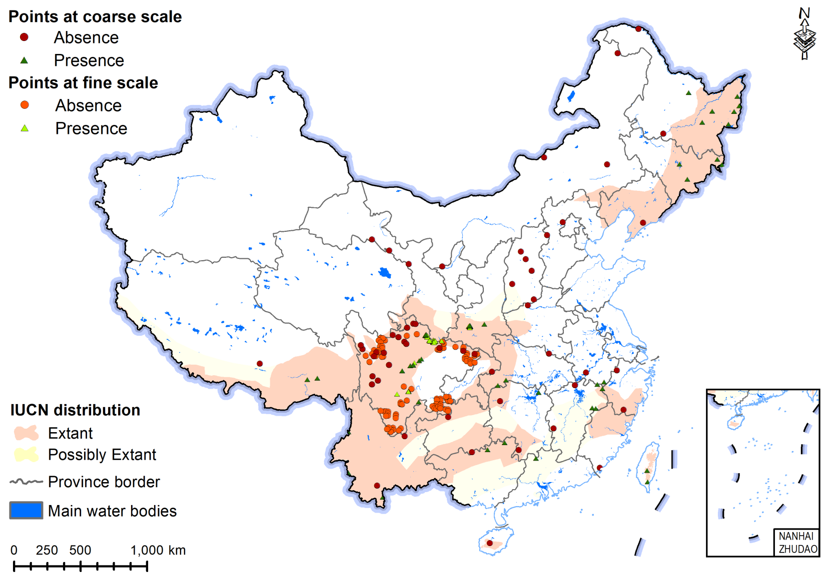


Figure S1: Presence and absence data points of Asiatic black bears used in this study at the coarse and fine resolutions, with the range map of the IUCN showing the extant and possibly extant areas of black bears in China.

## *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.

| Name | abbr. | Source | Type | Used resolution |
|---|---|---|---|---|
| Elevation (m) | ELEV | NASA SRTM | continuous | both |
| Roughness (m) | RUGG | from ELEV | continuous | both |
| Annual mean temperature ($^{\circ}$C $\times 100$) | BIO1 | BIOCLIM | continuous | coarse |
| Mean temperature diurnal range ($^{\circ}$C $\times 100$) | BIO2 | BIOCLIM | continuous | coarse |
| isothermality (unitless) | BIO3 | BIOCLIM | continuous | coarse |
| temperature seasonality($^{\circ}$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 | continuous | both |
| Population density (/km$^2$) | POPU | Harvard IQSS | continuous | both |
| Protection status (Protected/Non-protected) | PORT | The authors | categorical | both |