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7 authors, including:

Xinhai Li
Institute of Zoology CAS

Huidong Tian
Swedish University of Agricultural Sciences

Renqiang Li
Chinese Academy of Sciences

Ming Xu
Rutgers, The State University of New Jersey

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ORIGINAL ARTICLE

Vulnerability of 208 endemic or endangered species in China to the effects of climate change

Xinhai Li · Huidong Tian · Yuan Wang · Renqiang Li · Zengming Song · Fengchun Zhang · Ming Xu · Dianmo Li

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Abstract We assessed the vulnerability of 208 endemic or endangered species in China to the effects of climate change, as a part of the project "Research on China's National Biodiversity and Climate Change Strategy and Action Plans". Based on the China Species Information System, we selected comprehensive species as analysis targets, covering taxa including mammals, birds, reptiles, amphibians and plants. We applied nine species distribution models in BIOMOD (a package of R software) to estimate the current (1991–2010) ranges and predicted future (2081–2100) ranges of these species, using six climate variables based on Regional Climate Model version 3 (RegCM3) and A1B emission scenario. The model results showed that different taxa might show diverse potential range shifts over time. The range sizes of half of the species (104 species) would decrease, and those of another half would increase. We predicted that the future remaining ranges (intersection of current and future ranges/current ranges) of 135 species would be less than 50 % of their current range sizes. Species that are both endemic and critically endangered would lose more of their range than others. In summary, the most vulnerable species are currently found on the Qinghai-Tibetan Plateau, in the Hengduan Mountain Range, and southern China. Future action plans dealing with climate change in China should be prepared with consideration for vulnerable species and their habitats.

Keywords BIOMOD · Climate change · Conservation action plans · Range shift · Vulnerability

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X. Li (✉) · H. Tian · Y. Wang · D. Li
Key Laboratory of the Zoological Systematics and Evolution, Institute of Zoology, Chinese Academy of Sciences, 1-5 Beichen West Road, Beijing 100101, China
e-mail: lixh@ioz.ac.cn

R. Li · Z. Song · M. Xu
Key Laboratory of Ecosystem Network Observation and Modeling, Institute of Geographic Sciences and Natural Resources Research, Chinese Academy of Sciences, Beijing 100101, China

F. Zhang
Foreign Economic Cooperation Office, Ministry of Environmental Protection, Beijing 100035, China

Introduction

Climate change has been recognized as one of the most important driving forces affecting biodiversity and species distribution (Araújo and Rahbek 2006; Beaumont et al. 2007). A number of studies have showed that species have range shifts toward the poles or higher elevations or have even become extinct due to the effects of global warming (Parmesan and Yohe 2003; Root et al. 2003). Climate change may also continue cause species extinction in the future (Schwartz et al. 2006; Shoo et al. 2006; Sekercioglu et al. 2008; Li et al. 2010; Alkemade et al. 2011). It is of fundamental importance to evaluate how species will respond to future climate change for the successful management and conservation of biodiversity (Erasmus et al. 2002; McMahon et al. 2011; Hughes 2011).

China is a large country with rich biodiversity, encompassing more than 10 % of the world's vascular plants and terrestrial vertebrate species (Liu et al. 2003). Based on the latest report concerning the national environmental status, China has a total of 6,481 vertebrate species, including 581 mammals, 1,331 birds, 412 reptiles, 295 amphibians and 3,862 fishes (Ministry of Environmental Protection 2010). Among them, 420 animal species are on the national protection list (Ministry of Forestry and Ministry of Agriculture 1989). China has 34,984 vascular plants, including 2,541 bryophyte, 2,270 pteridophyte, 245 gymnosperm species and 29,816 angiosperm species (Ministry of Environmental Protection 2010).

China will be substantially impacted by future climate change (IPCC 2007). The temperature in the Tibetan region is expected to rise by 3–6 °C by 2100 under the projected climate change scenarios (IPCC 2007). Over the past 50 years, mountain glaciers in northwestern China have melted by 21 % of their original area (China's National Assessment Report on Climate Change Committee 2007).

The Chinese Government currently supports more conservation activities than ever before (e.g., Wang et al. 2007; Niu et al. 2011). Facing the challenges of climate change, the key questions are: where are the most vulnerable places in China which are most threatened by climate change, and which are the most vulnerable species and ecosystems. These questions are relevant to deciding how to allocate limited resources to the most urgent conservation targets. The Ministry of Environmental Protection of China is considering initiating a national strategy on biodiversity and climate change, which intends to identify the most vulnerable ecosystems and species under possible future climate change scenarios and suggest corresponding conservation actions, as well as relevant climate adaptation and mitigation issues.

In this paper, we focus on species vulnerability analysis. We selected 208 species that are endemic or endangered in China and applied species distribution models to predict their range shifts, caused by climate change, over time. We aimed to: (1) assess the extent to which currently suitable habitat of these species of conservation concern may become climatically unsuitable by 2050 and 2100, (2) identify for different taxa geographic regions containing species that are likely to be particularly vulnerable to climate change and (3) assess whether species with higher International Union for Conservation of Nature (IUCN) classifications and/or smaller range sizes are projected to lose a greater portion of their current distribution than other species with a lower classifications and larger range sizes.

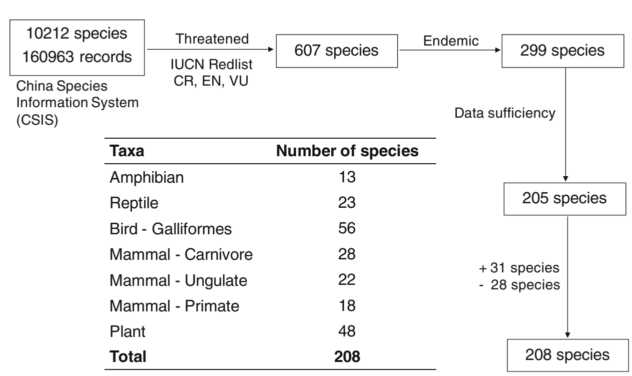
Methods

Species data

The ultimate goal of our study is to support national conservation planning in order to cope with climate change. One challenge for a national-level conservation plan is how to select species to represent biodiversity that is vulnerable to climate change in China. We set five standards for species selection: threatened, endemic, less mobile, climate sensitive and sufficient data.

In total, we selected 208 species as analysis targets (Fig. 1. See Supplementary Table 1 for the list of species). The source data are the China Species Information System (CSIS) developed by the Institute of Zoology, Chinese Academy of Sciences (http://monkey.ioz.ac.cn/bwg-cciced/english/cesis/csispage.htm) (Xie et al. 2004). CSIS contains species occurrence records in China, covering most published literature regarding species distributions. From over ten thousand species, we selected 299 endemic or threatened species as initial target species. We removed 94 species because their occurrences are not enough to represent their current ranges. We further removed 28 species because the relationship between these species and climate change is especially complex (such as migratory birds), or the species distributions are limited by non-climatic factors (such as human activity). We added 31 species, which are endemic species in China, and fairly abundant (not categorized as critically endangered, endangered, or vulnerable in the IUCN Red List (IUCN 2004) and well surveyed (meaning that the occurrences of species can well represent their current distributions).

In summary, the 208 species consists of 16 critical endangered (CR), 55 endangered (EN), 93 vulnerable (VU), 19 lower risk (LR), 14 that are data deficient (DD) and 11 that not evaluated (NE), based on the IUCN Red List. Among the 208 species, 87 occur only in China (strictly endemic); 66 are listed as first class protected species under the State Key Protected Species List and 19 are listed as second class in China (Ministry of Forestry and Ministry of Agriculture 1989; State Forestry Administration and Ministry of Agriculture 1999).



Taxa	Number of species
Amphibian	13
Reptile	23
Bird - Galliformes	56
Mammal - Carnivore	28
Mammal - Ungulate	22
Mammal - Primate	18
Plant	48
Total	**208**

Fig. 1 The processes of selecting target species

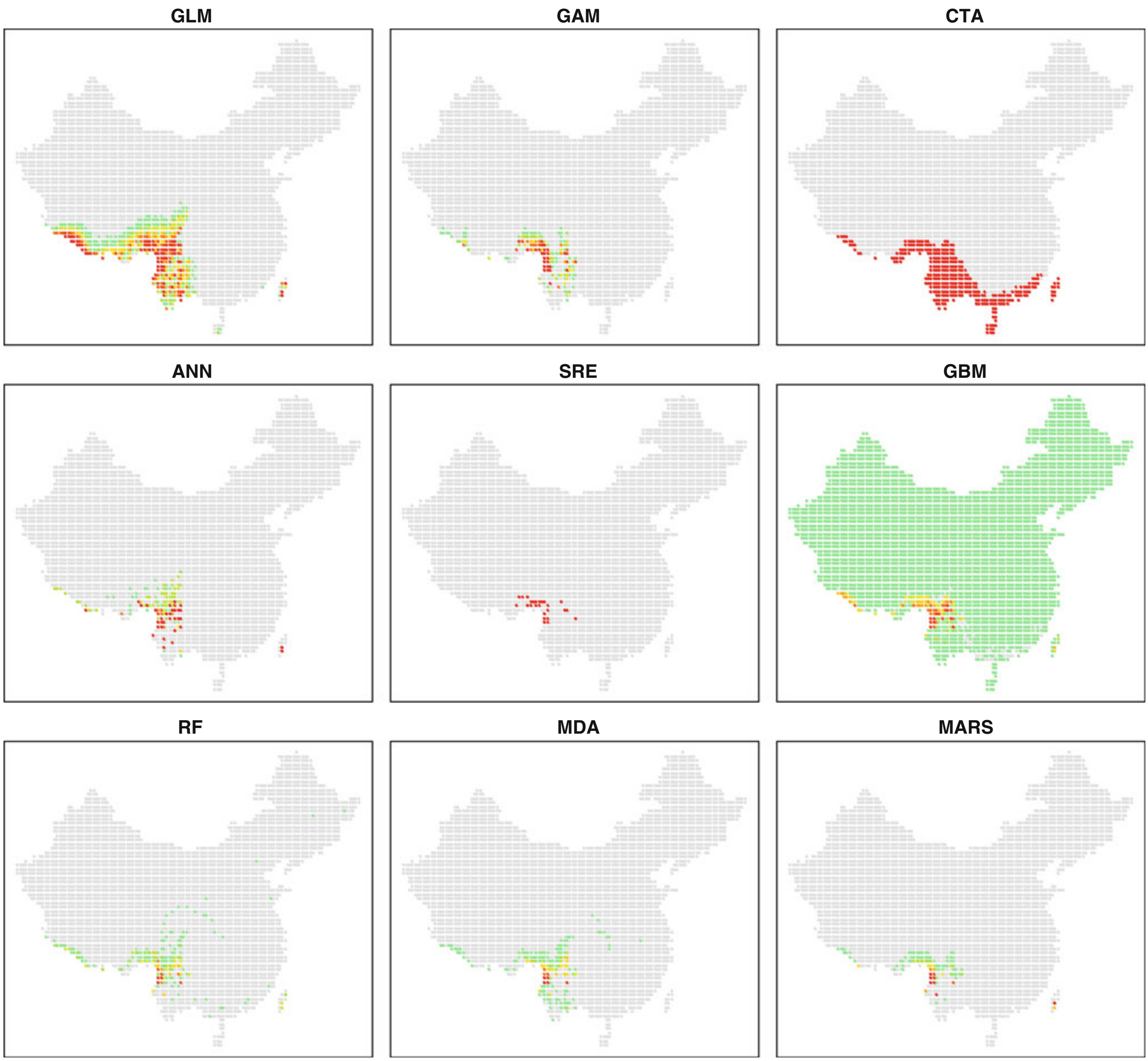


Fig. 2 The predicted current distributions of black snub-nose monkey using the nine models in BIOMOD

Climate data

We used Regional Climate Model version 3 (RegCM3) (Pal et al. 2007) to simulate current (1991–2010) and future (two periods, 2041–2060 and 2081–2100) climate data. The spatial resolution is 30 arc-second (about 1 km). The emission scenario of A1B was used, which represents a moderate warming situation (IPCC 2007). We selected six climate variables, including average temperature in January, average temperature in July, annual average temperature, annual total precipitation, variation of seasonal precipitation and drought index. The variables are stored in a GIS database as raster layers with a resolution of one square km. In total, we have 18 layers of climate variables (six variables multiplied by three time periods).

Modeling

The relationship between species and climate change is complex (Morin and Thuiller 2009; Pearson et al. 2006; Wiens et al. 2009), and species distribution models can provide insightful information for studying effects of climate change (Beaumont et al. 2007; Thuiller et al. 2009b; Hirzel et al. 2006; Marmion et al. 2009). However, there is a great challenge to overcome the uncertainty of model applications (Conroy et al. 2011; Fuller et al. 2008; Patt

Table 1 The model evaluation results based on Kappa index and ROC index generated by BIOMOD, using the black snub-nosed monkey (*Rhinopithecus bieti*) as an example

	Cross validation	Independent data	Total score	Sensitivity	Specificity
Model evaluation results based on Kappa index					
ANN	0.735	0.31	0.617	100	98.2
CTA	0.459	0.481	0.855	100	99.5
GAM	1	0.553	1	100	100
GBM	0.703	0.508	0.821	93.3	99.5
GLM	0.648	0.586	0.937	100	99.8
MARS	0.765	0.514	0.846	93.3	99.6
FDA	0.597	0.426	0.766	66.7	99.9
RF	0.79	0.857	1	100	100
SRE	0.296	0.468	0.636	53.3	99.8
Model evaluation results based on ROC index					
ANN	0.984	0.991	0.993	100	98.2
CTA	0.772	0.996	0.998	100	99.5
GAM	1	0.996	1	100	100
GBM	0.987	0.997	0.997	100	99.3
GLM	0.978	0.997	0.999	100	99.8
MARS	0.994	0.994	0.998	100	99.4
FDA	0.987	0.987	0.993	100	97.4
RF	0.994	0.999	1	100	100
SRE	NA	NA	NA	NA	NA

The first column is the average of the cross validation of all the repetitions. The second one is the score when the model is evaluated on independent data if any is available, and the following columns are results obtained from the final model itself (Thuiller et al. 2009a)

Table 2 The weight of six climate variables in the nine models, using the black snub-nosed monkey (*Rhinopithecus bieti*) as an example

	Annual total precipitation	Drought index	Variation of seasonal precipitation	Annual average temperature	Average temperature in January	Average temperature in July
ANN	0.331	0.153	0.346	0.675	0.826	0.165
CTA	0.000	0.000	0.000	0.000	0.846	0.923
GAM	0.000	0.722	0.559	0.000	0.896	0.967
GBM	0.002	0.002	0.001	0.063	0.646	0.948
GLM	0.000	0.000	0.000	0.000	0.791	0.965
MARS	0.312	0.304	0.285	0.715	0.806	0.262
FDA	0.491	0.649	0.119	0.110	0.384	0.000
RF	0.084	0.078	0.040	0.241	0.371	0.738
SRE	0.737	0.339	0.230	0.052	0.052	0.000

et al. 2005; Cressie et al. 2009; Morin and Thuiller 2009; Dormann et al. 2008; Pearson et al. 2006). Therefore, hybrid or ensemble model frameworks were suggested recently to make reliable and robust predictions of the potential distribution of species (e.g., Coetzee et al. 2009; Conroy et al. 2011; del Barrio et al. 2006; McRae et al. 2008; Morin and Thuiller 2009; Thuiller et al. 2009b; Araújo and New 2007).

In this study, we applied nine models that were combined in BIOMOD (Thuiller et al. 2009b), a package of statistical software R (R Development Core Team 2011). The nine models are: generalized linear models (GLM), generalized additive models (GAM), classification tree analysis (CTA), artificial neural networks (ANN), mixture discriminant analysis (MDA), multivariate adaptive regression splines (MARS), generalized boosting models (BRT), random forest (RF) and surface range envelope (SRE). We used the default settings to run BIOMOD. The default setting is suitable for most cases. For example, the default settings for GLM are: TypeGLM = "poly", Test = "BIC", meaning that the polynomial terms (rather than linear or quadratic terms) of explanatory variables are

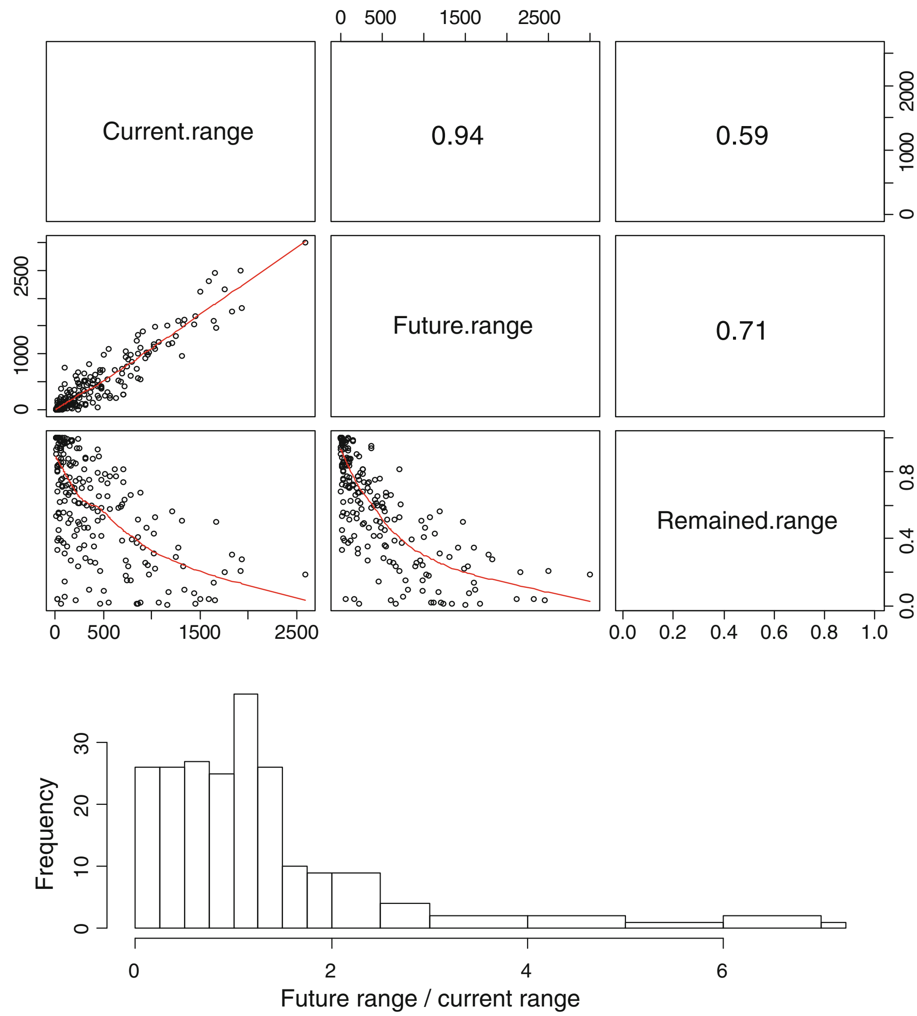


Fig. 3 The correlation of current (1991–2010) and future (2081–2100) ranges and proportion of remained ranges (future range/current range) of the 208 species in China. The unit of ranges is half degree in latitude times half degree in longitude (about 1,700 km^2)

used, and stepwise model selection is based on BIC criteria.

We used occurrences of the species as the present data, and we generated 3,846 uniformly distributed points in China (half degree apart) as pseudo-absence data. All the nine models were run independently. The area under the curve (AUC) of receiver operating characteristic (ROC) and Cohen's Kappa coefficient was used to rank the performance of the nine models. We selected the best model to estimate the current ranges and predict the future ranges of species.

The nine species distribution models provided the *p* values (the probability of presence) of the 3,846 uniformly distributed points. We defined the points with *p* value >0.5 as presence, and the rest as absence. The value 0.5 is a subjective threshold, which is not ideal for determining the presence or absence of a species (Liu et al. 2005). However, when the model performance was good, the predicted *p* values clustered around 0 (true negative) and 1 (true positive), so that the determination of presence and absence was not sensitive to the threshold. When the model performance was poor, the *p* values would be more random, and the selection of threshold was important because the determination of presence and absence is largely dependent on the threshold value. For the analysis, we only used the results from the best model. We determined the best model on the basis of ROC curves and Cohen's Kappa coefficients.

Results

The model performance was varied among the nine models (Fig. 2; Table 1) and also among the 208 species. The weights of climate variables were also different in the nine models (Table 2). Random forest had the overall best performance, and neural network ranked second. For random forest, the values of the AUC of the ROC curves were over 0.9 for most species, and Cohen's kappa indices were around 0.7 for most species.

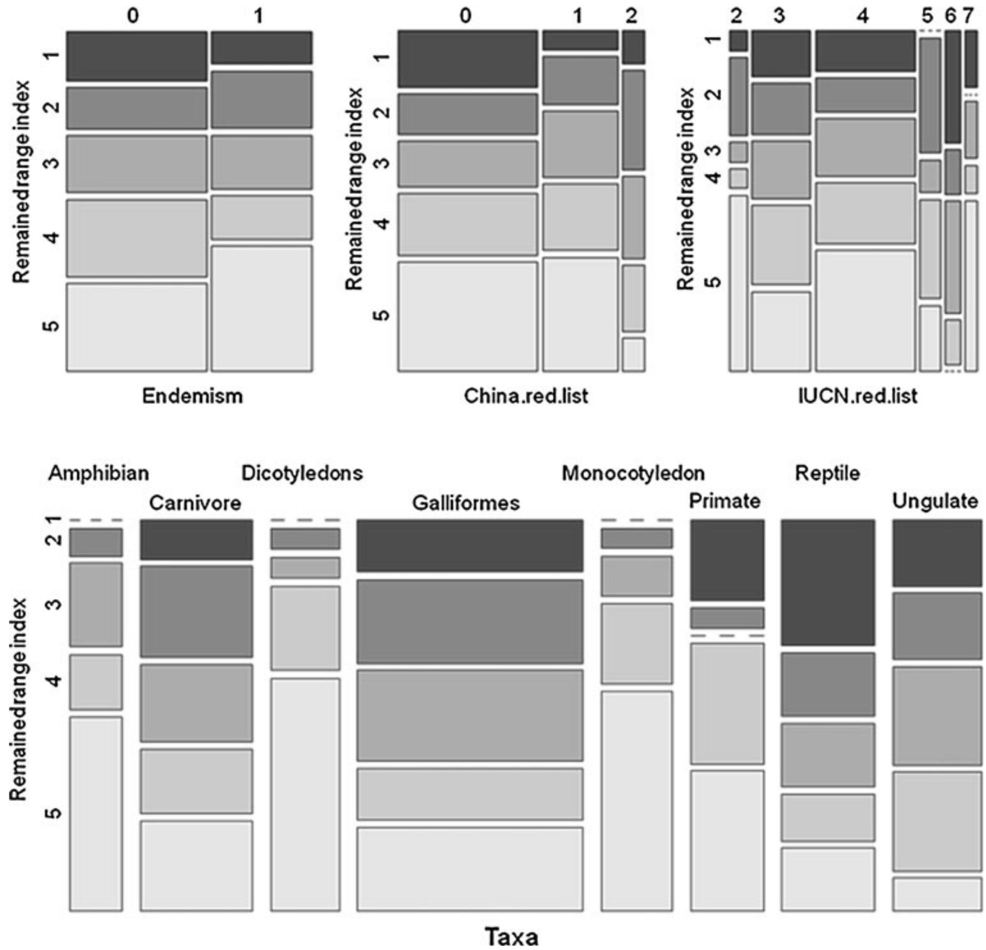


Fig. 4 The proportion of remained ranges (represented by the areas of the *rectangles*) of the 208 species for endemic or non-endemic species, different categories of China national protection species, different categories of IUCN red list and different taxa. The meanings of the categories are: *Endemism*: 0, non-endemic species; 1, endemic species. *China red list*: 0, not listed; 1, class one (the highest level) protection species; 2, class two protection species. *IUCN red list*: 2, critical endangered (CR); 3, endangered (EN); 4 vulnerable (VU); 5, lower risk (LR); 6, data deficient (DD); 7, not evaluated (NE). *Remaining range index*: 1, 0–20 %; 2, 21–40 %; 3, 41–60 %; 4, 61–80 %; 5, 81–100 %

Based on the RegCM3 climate model and the A1B emission scenario, we projected that the range sizes of half of the species (104 species) would decrease, and those of another half would increase (Fig. 3). The habitat area currently classified as suitable would decline by more than 50 % for 135 species, and some species (e.g., Przewalski's gazelles (*Procapra przewalskii*), hoolock gibbon (*Hylobates hoolock*), white-cheeked gibbon (*Hylobates leucogenys*), Marbled cat (*Pardofelis marmorata*), Tibetan spring snake (*Thermophis baileyi*), Chinese crocodile lizard (*Shinisaurus crocodilurus*), among others) would lose all of their original habitat in the period of 2081–2100 (Supplementary Table 1). In general, species with small ranges were found to be more vulnerable (i.e., the proportion of the remaining range is low) (Fig. 3). Endemic and endangered species would lose more habitat than others (Fig. 4).

We mapped the current ranges of species whose remaining range would be less than 20 % in 2100 and found that the most vulnerable species occur mainly on the Qinghai-Tibetan Plateau, the Hengduan Mountain Range, and in southern China (Fig. 5). The spatial distribution patterns of the different taxa of vulnerable species in are quite different. The most vulnerable carnivores are in Western China, the Hengduan Mountain Range and Yunnan province; primates are in the south-western Hengduan Mountains; ungulates are on the Qinghai-Tibetan Plateau; pheasants are in the Hengduan Mountain Range, the Qinling Mountains, the Daba Mountains, the Wuyi Mountain Range and on the Yungui Plateau; reptiles are on the Yungui Plateau and in the lower Yangtze River Basin; the vulnerable amphibians are in the Hengduan Mountain Range; and, finally, the most vulnerable plants are in the southern China (Fig. 5).

Discussion

We predicted the range shifts of 208 species in China and provided information about the regions in which the most vulnerable species occur. Although the uncertainty of modeling was minimized by such an ensemble modeling framework, our predictions are mostly based on the future trends of species range shifts and cannot be adopted as completely reliable predictions, due to possible impact of

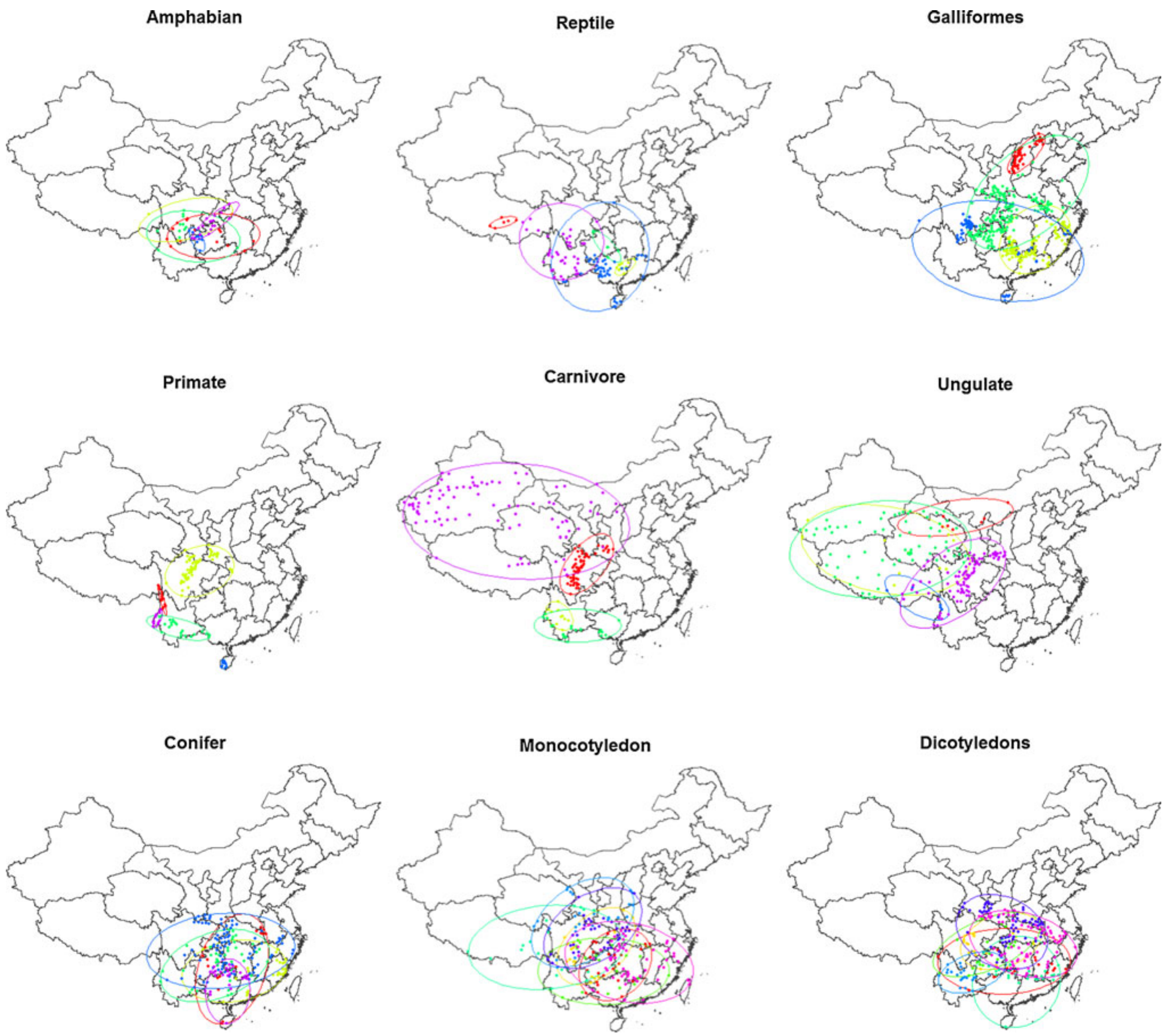


Fig. 5 The occurrences and ranges in China of the most vulnerable species (remaining range <20 %). Name list of the species: *Primate*: Black snub-nosed monkey, Chinese snub-nosed monkey, Black-crested gibbon, Hainan black gibbon, Hoolock gibbon, White-cheeked gibbon, White-handed gibbon, Tibetan macaque, Capped langur. *Carnivore*: Giant panda, Marbled cat, Bearcat, Chinese desert cat, Wild cat. *Ungulate*: Przewalski's gazelles, Tibetan antelope, Tibetan wild ass, Tawny musk deer, Takin, Wild yak, Black muntjac, White-lipped deer, Tibetan gazelle. *Galliformes*: Brown eared pheasant, Cabot's tragopan, Reeves's pheasant, Sichuan partridge, Sclaters' monal pheasant, Rusty-necklaced partridge, Chinese monal pheasant, Mikado pheasant, Elliot's pheasant, Hainan peacock-pheasant, Yellow-throated pheasant. *Reptile*: Tibetan spring snake, Chinese crocodile lizard, *Oligodon lungshenensis*, Wattle-necked softshell turtle, Black-bordered rat snake, Chinese sharp-nosed viper. *Amphibian*: Emei moustache toad, Round-tubercled cat-eyed toad, Rufous-spotted torrent frog, Red-tailed knobby newt, *Oreolalax rhodostigmatus*, *Oreolalax multipunctatus*. *Monocotyledon*: Luohe dendrobium, Hancock dendrobium, Guangdong dendrobium, Xizang ladyslipper, Hair ladyslipper, Green ladyslipper, *Calanthe graciliflora*. *Dicotyledons*: *Eurycorymbus cavaleriei*, Phoebe zhennan, Dove tree, *Semiliquidambar cathayensis*, Chinese evergreen magnolia, Sprenger's magnolia, Yulan magnolia, Chinese filbert, Houpu magnolia, Min nanmu. *Conifer*: Hainan white pine, Chinese swamp cypress, Oliver's plum yew, Chinese weeping cypress, Kwangtung pine

other factors; human impact on vulnerable ecosystems, for example, might ultimately be more significant than climate change alone (e.g., Ceballos and Ehrlich 2002).

We used nine models to predict species range shift. The results, performance and weight of variables were varied among different models, especially for species with small sample sizes or species that occur in various habitat types (it is difficult to make predictions for habitat generalists). However, overall model performance was good, especially for random forest and neural network. One reason for good model performance was that we carefully selected data-sufficient target species. Our results indicate that species with small ranges, in a single homogenous habitat and at high elevation area, are most vulnerable. Compared with Huntley et al.'s prediction that the range shift for 431 European breeding birds in 2070–2099 was 47–69 % (Huntley et al. 2008), and Sekercioglu et al.'s prediction that 400–550 land birds may go extinct by 2100 (Sekercioglu et al. 2008), our predicted range shifts are much more moderate.

A number of studies have compared the predictive accuracy of different species distribution models (e.g., Thuiller et al. 2009b; Morin and Thuiller 2009; Marmion et al. 2009; Coetzee et al. 2009; Phillips and Dudik 2008; Olden et al. 2008; Meynard and Quinn 2007; Kampichler et al. 2010; Aertsen et al. 2010; Elith and Graham 2009; Elith et al. 2006; Breiman 2001). Model performance usually changes for species with various geographical and environmental distributions (Segurado and Araujo 2004), and no single model can beat all others. In some cases, simpler models work best. For example, Aertsen et al. (2010) modeled the distribution of three tree species using five models and found GAM was the best and ANN was the worst, compared with GLM, CART and GBM. However, in general, complex models have better overall performance than simpler models (e.g., Phillips and Dudik 2008; Olden et al. 2008; Meynard and Quinn 2007; Prasad et al. 2006), because model complexity may contribute to predictive accuracy (Tsoar et al. 2007).

Theoretically, vulnerability of a species to climate change is the sum of sensitivity and exposure (IPCC 2001). In this paper, we used the proportion of remaining range to represent vulnerability, that is, the less habitat remained indicates higher vulnerability. The remaining range of species was projected using species distribution models, which incorporated sensitivity (represented by the six climate variables) and exposure (differences between the current status and the future scenario of the six climate variables). Extensive range shift does not mean the species will decline equally as much, since the species could move and survive in new habitats. However, if the species is less mobile, the prediction of a large range shift suggests the species will likely be at risk in the future.

We demonstrated the ranges of vulnerable species and suggested the regions of those species (Fig. 5). Such information is instructive to China's national biodiversity and climate change strategy and action plans. When developing conservation action plans, more attention must be paid to vulnerable species and their habitats. Future studies should address various climate change models, multiple climate change scenarios and species not listed in the IUCN red list.

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