EVALUATING THE SPREAD OF 10 INVASIVE WEEDS IN CHINESE NATURE RESERVES UNDER CLIMATE CHANGE SCENARIOS IN CONSIDERATION OF DIFFERENT SCALES

WANG, C.-J.[1,2] – YIN, G.-J.[3] – SONG, Z.-M.[3] – WAN, J.-Z.[1*]

[1]*State Key Laboratory of Plateau Ecology and Agriculture, Qinghai University 810016 Xining, China*

[2]*College of Agriculture and Animal Husbandry, Qinghai University, 810016 Xining, China*

[3]*Qinghai Forest Seedling Station, 810016 Xining, China*

**Corresponding author*
e-mail: wan1276@163.com

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Abstract. Species distribution models are powerful tools for predicting species distributions and for assessing whether particular areas are at risk from invasive weeds, but they may produce different results when different climate data scales are used in the estimate. The results of species distribution models were compared across different spatial scales, and then evaluated the spread of invasive weeds in Chinese nature reserves under several models of climate change. We used Maxent software to estimate the potential spread of 10 phylogenetically diverse alien weeds in the largest 333 Chinese nature reserves. The estimates of invasive weed spread in nature reserves were not stable against changes in spatial scale. The 2.5 arc-minute data was selected to evaluate the ability of invasive weeds to spread in Chinese nature reserves under climate change. Nature reserves with a high risk of invasive weed spread were mainly distributed in southern China. We found a significant relationship between increased invasive weed spread and low and high concentration scenarios, suggesting we should prioritize the prevention and control of invasive weeds now to lessen their impact on nature reserves in the future. It is suggested that other studies may benefit from integrating different scales into the distribution models of invasive weeds.
Keywords: *ALIEN weeds, China, climate change, plant spread risk, Maxent, nature reserves, scale effect*

Introduction

Species distribution models (SDMs) are powerful tools for predicting species distributions and thus they support biological conservation and risk assessment of biological invasion in nature reserves (Alagador et al., 2011; Araújo et al., 2011; Elith et al., 2011; Velásquez-Tibatá et al., 2013; Wan and Wang, 2018). These models have used climate data to assess the distributions of invasive weeds (Chejara et al., 2010; Costa et al., 2013; Sheppard, 2013; Qin et al., 2014). Because invasive weeds represent introduced plant species with generally broad physiological niches and/or some special traits and may respond quickly to changing environmental conditions (Stratonovitch et al., 2012), climate change may increase the possibilities for invasive weeds to invade nature reserves and subsequently damage the efficacy of nature reserves for conservation (Ingwell and Bosque-Pérez, 2015; Thalmann et al., 2015; Merow et al., 2017). Hence, the management of invasive weeds in nature reserves is urgent (Foxcroft et al., 2017). The use of SDMs in biological invasion gives us the new insights into the prevention and control of invasive weeds in nature reserves.

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However, there are still many technical challenges associated with the use of SDMs in the prediction of invasive weeds. Understanding the effects of input data on SDM outputs may increase the precision of the models, thereby improving their usefulness to the risk management of invasive weeds in nature reserves (Elith et al., 2011; Merow et al., 2013).

One notable challenge with SDMs is that their predictive accuracy may vary at the different scales of input data (Rahbek and Graves, 2001; Wang et al., 2012). Some studies have demonstrated that SDMs at finer scales may reduce the uncertainty of the model output (Franklin et al., 2013; Bean et al., 2014). However, a particular scale of input localities may not meet the requirements of the model due to spatial bias in the species distribution data. This would have the potential to strongly distort our view of large-scale biodiversity patterns (Beck et al., 2014). For instance, some studies have shown that databases such as Global Biodiversity Information Facility (GBIF) have a spatially biased dataset due to uneven effort of sampling, data storage and mobilization (Beck et al., 2013, 2014). These studies have found that the most robust estimates of potential species distributions use the data at coarse resolutions (Beck et al., 2013, 2014). SDMs at coarser scales may over-estimate the size of a species distribution in the present and under different climate scenarios (Bean et al., 2014; Suárez-Seoane et al., 2014). These findings suggest that selecting the appropriate spatial scale is important for researchers to accurately estimate robust distribution models (Franklin et al., 2013).

Climate change studies have found that distribution patterns and the variables that determine distribution ranges vary when different spatial scales are used (Rahbek and Graves, 2001; Wang et al., 2012; Porfirio, 2014; Wan et al., 2016). One reason for this variation may be that the scale effect may be particularly pronounced in ecologically complex situations such as climate change (Rahbek and Graves, 2001). On the other hand, as a species expands its area of distribution, the explanatory power of climate variables may also increase, while the explanatory power of habitat heterogeneity and human activities may decrease (Wang et al., 2012). Hence, spatial scale affects estimates of the potential distribution of species under climatic change and the most appropriate scale to model the species distribution must be identified. Franklin et al. (2013) proposed selecting the appropriate scale by finding the smallest bias between results from different scales. There is usually a linear relationship between SDM model estimates at fine and coarse scales (Franklin et al., 2013). This relationship suggests that SDMs need to balance data scale with distribution estimate accuracy (Metzger et al., 2005; Wan et al., 2016).

Previous studies have used different scales (from 0.5 to 10.0 arc-minutes) to model the potential species distributions in nature reserves and did not consider the effect of spatial scales (Araújo et al., 2011; Elith et al., 2011; Jiménez-Alfaro et al., 2012; Thalmann et al., 2015). Not only that, few studies used SDMs to evaluate the risk of weed spread in nature reserves by predicting the potential distributions of invasive weeds at a large spatial scale. Thus, a challenging question is to predict whether and how invasive weeds spread in nature reserves that have been established to protect threatened native species, habitats and ecosystems under future climate change (Vanderhoeven et al., 2011). Therefore, we propose a method to integrate different spatial scales into SDMs in order to assess the vulnerability of Chinese nature reserves to invasive weeds under three climate change scenarios. To address the issue of spatial scale, a simple method was developed to improve SDM estimates for nature reserves

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using data at several different spatial scales, and to identify the appropriate scale with which to model potential distributions of invasive weeds.

The main aim of our study is to evaluate the spread of 10 invasive weeds in Chinese nature reserves under climate change scenarios in consideration of different scales. For achieving this aim, we used 10 important invasive weeds in 333 Chinese nature reserves as the study cases. The Maxent software was used to model the current and future potential distributions of 10 invasive weeds across four spatial scales (grid resolution ranged from 1 to 256 km^2; Crall et al., 2015) and quantified the ability of invasive weeds to spread in nature reserves. Our approach is useful to identify the appropriate data scale for SDMs and our method can be especially useful to assess the spread of invasive weeds.

Materials and methods

Nature reserves in China

In 2012 China had 2,588 nature reserves covering a total area of ca. 149 million km^2 and representing ca. 14.17% of the land area (www.nre.cn). The world database of protected areas (WDPA; www.protectedplanet.net) was used to identify nature reserves (IUCN I–VI) in China with areas greater than 256 km^2 and thus, covering at least one grid cell of 256 km^2.

Invasive plant data

We modelled the potential spread of 10 invasive weeds including Bidens pilosa, Amaranthus spinosus, Cassia mimosoides, Conyza Canadensis, Daucus carota, Euphorbia hirta, Medicago sativa, Physalis angulate, Sonchus oleraceus and Vicia sativa in 333 nature reserves in China (Li, 1998; Xu and Qiang, 2011; *Table A1* in the Appendix). The species were chosen for this study according to four criteria: (1) the species had the most distribution records in China based on the study of Xu and Qiang (2011) and on the Chinese Virtual Herbarium (CVH; www.cvh.org.cn), (2) species occurrence records were dense enough to support a robust SDM (Phillips and Dudík, 2008), (3) species were widely distributed in China (Xu and Qiang, 2011) and (4) species have the negative impact on a variety of endangered plant species and ecosystem (Xu and Qiang, 2011). Occurrence records for the 10 invasive weeds, especially herbarium specimens or recorded sightings, were compiled from GBIF (www.gbif.org) and CVH (www.cvh.org.cn; Bird et al., 2014; Crall et al., 2015). We used descriptions of species locations in CVH to determine the localities within Google Earth and ArcGIS 10.2 (Bird et al., 2014; Zhang and Zhang, 2014; ESRI, 2014; *Table A1*). The occurrence records of 10 invasive weeds can cover the distribution range of species in China.

Bioclimatic data

The current potential distributions of invasive weeds in nature reserves were modelled using 19 bioclimatic variables available on the WorldClim database (averages from 1950-2000; www.worldclim.org). We removed those with absolute Pearson correlation coefficients > 0.8 in order to eliminate multi-collinearity effects in the parameter estimates of species distribution models (Sheppard, 2013; Porfirio, 2014). The resulting eight bioclimatic variables (the same as future bioclimatic

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variables) can influence the distribution and physiological performance of invasive weeds (Sheppard, 2013; *Table A2*). We used the average values of four global climate models for the 2080s (2071-2099; GCMs; i.e., bcc_csm1_1, csiro_mk3_6_0, gfdl_cm3 and mohc_hadgem2_es) and two greenhouse gas concentration scenarios, i.e., Representative Concentration Pathways (RCPs): 4.5 (mean: 780 ppm; range: 595 to 1005 by 2100) and 8.5 (mean: 1685 ppm; range: 1415 to 1910 by 2100; IPCC 5th Assessment Report) to model the future potential distributions of invasive weeds in the 2080s (2071-2099; www.ccafs-climate.org; Liang and Fei, 2014). RCP 4.5 is different from RCP 8.5 in that RCP 8.5 has a greater cumulative concentration of carbon dioxide than RCP 4.5. Thus, RCP 8.5 predicts a different climate due to anthropogenic accumulation of greenhouse gases and other pollutants. RCP 8.5 and RCP 4.5 were used as the high and low concentration scenarios, respectively (http://www.ipcc.ch/). We used bioclimatic variables at four levels of resolution (0.5, 2.5, 5.0 and 10.0 arc-minutes, namely, 1-256 km^2) because these are the most commonly used data types in SDMs.

Species distribution modelling

The Maxent software (ver. 3.3.3k; http://biodiversityinformatics.amnh.org/open_source/maxent/) was used to model the current and future potential distributions of the 10 invasive weeds across four spatial scales (0.5, 2.5, 5.0 and 10.0 arc-minute resolutions; Franklin et al., 2013). Maxent estimated the function of the potential distributions of the 10 invasive weeds based on maximum entropy and then modeled the geographic locations of the distributions based on environmental variables (Phillips and Dudík, 2008; Elith et al., 2011). Pixels in the Maxent results map with a value of 1 have the highest possibility of the species being located there, while pixels with a value of 0 have the lowest possibility of the species being located there (Phillips and Dudík, 2008; Elith et al., 2011). The pixel value reflects the potential distribution that was used to evaluate the risk of invasive weeds for nature reserves (Hoffman et al., 2010; Bean et al., 2014).

Climatic variables at four arc-minute resolutions were used as environmental input layers in Maxent. We used a 4-fold cross-validation approach to divide the presence dataset into 4 approximately equal partitions, and used 75% of the occurrence points for each species to train the model and the remaining 25% were used to test the model (each run used a different random sample of points; Merow et al., 2013). We set the regularization multiplier (beta) to 2.0 to produce a smooth and general response (Radosavljevic and Anderson, 2014). Auto features were used and other values were kept at default settings of Elith et al. (2011). The importance of bioclimatic variables was tested using the jackknife method (Phillips and Dudík, 2008; Elith et al., 2011).

The receiver operating characteristic (ROC) curves evaluated each value of the prediction result as a possible judging threshold. We assessed the performance of the Maxent model using the area under the ROC curve (AUC; Phillips and Dudík, 2008). This statistic regards each value of the estimate as a possible threshold based on the corresponding sensitivity and specificity when randomly selected background points are removed from the dataset. To ensure the high precision of SDM on four spatial scales, we only used SDMs with AUC values greater than 0.7 (Phillips and Dudík, 2008; Elith et al., 2011; Suárez-Seoane et al., 2014).

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Evaluating the spread of invasive weeds in nature reserves

Alagador et al. (2011) used a fixed threshold to match plant species with a nature reserve when the data were at different resolutions of environmental data. However, some studies have indicated that thresholds are problematic and can produce bias in predictions (Calabrese et al., 2014; Merow et al., 2013). The method of Alagador et al. (2011) and Calabrese et al. (2014) was used to evaluate the possibility of the potential distribution of all 10 invasive weeds in each pixel at the scales of 0.5, 2.5, 5.0 and 10.0 arc-minutes in ArcGIS 10.2, respectively (ESRI, 2014) (*Eq. 1*):

$$E_j = \sum_{k=1}^{k} p_{i,k} \tag{Eq.1}$$

where E_j represents the potential for invasive weeds to be present in each pixel j; k is the number of species in pixel j; i is species i; and $P_{i,k}$ is the probability of the appropriate potential distribution for species i in pixel j.

We also assessed the ability of the 10 invasive weeds to spread in each nature reserve in ArcGIS 10.2 as follows (Araújo et al., 2011; Calabrese et al., 2014; ESRI, 2014) (*Eq. 2*):

$$S_t = \sum_{j=1} X_j Y_j \tag{Eq.2}$$

where S_t is the ability of all 10 invasive weeds to spread in nature reserve t; X_j represents the potential for the presence of invasive weeds in each pixel j in nature reserve t; Y_j is the distribution area percentage of all invasive weeds in nature reserve t.

Several studies have shown that the scale of the data can potentially affect the SDM estimate (Pineda and Lobo, 2012; Franklin et al., 2013; Bean et al., 2014). There is a significant linear relationship between the potential distributions of species and fine and coarse spatial scales of the input data, and the medium prediction results computed by the scales would be stable (Kunin, 1998; Wilson et al., 2004; Franklin et al., 2013). Here, the medium results (S_t) was selected to assess the change in the ability of invasive weeds to spread within a nature reserve under climate change (Franklin et al., 2013).

We calculated the change in the ability of invasive weeds to spread within a nature reserve between the current scenario and the 2080s (in the low and high concentration scenarios) (*Eq. 3*):

$$A_t = \frac{S_{Future} - S_{Current}}{S_{Current}} \tag{Eq.3}$$

where A_t is the change in the ability of invasive weeds to spread in nature reserve t and S_{Future} and $S_{Current}$ are the future and current ability of invasive weeds to spread in nature reserve t.

Finally, we assessed the aggressiveness of each invasive weed by calculating the average values of the potential distribution possibilities of pixels within 333 studied nature reserves in China at medium scales.

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Results

The WDPA identified 333 Chinese nature reserves with an area greater than 256 km^2 that we sampled for our study (*Fig. 1*). There was no significant correlation between the number of invasive weed locations and AUC ($P > 0.05$). However, AUC measurements of SDM accuracy were greater than 0.9 (from 0.9030 to 0.9816; *Table A1*), indicating highly accurate predictions (*Fig. 2*). The most important variables for the 10 invasive weeds across all of the spatial scales were temperature seasonality and mean diurnal range (*Table A3*). We found no significant differences in the importance of bioclimatic variables for any of the species associated with changes in the spatial scales (correlation coefficient (R) > 0.935 across all the scales; $P < 0.001$; *Table A3*). However, the response of all the species to particular bioclimatic variables differed between scales (*Table A3*). For example, the average temperature seasonality range changed quite a bit from 0.5 to 10.0 arc-minutes for all the invasive weeds (from 26.660 ± 12.994 to 30.527 ± 13.388; *Table A3*).

The average ability of invasive weeds to spread in nature reserves would logically increase by using a coarser spatial scale (e.g., from 0.5 to 10.0 arc-minutes) (*Fig. 3*). Invasive weeds were able to increase their distribution the most using a data scale of 10.0 arc-minutes, and they increased their distribution the least using a scale of 0.5 arc-minutes (*Fig. 3*). We found that Maxent predictions of the spread of invasive weeds were unstable. In other words, they fluctuated when using different data scales (*Figs. 3* and *A1* in the *Appendix*). Jiaxi is a good example to show the various results of different data scales (*Fig. A1*). We found that using 2.5 arc-minute data could have the medium results to estimate invasive weed distributions in nature reserves at all data scales in the present and future (*Fig. 3*). Therefore, we selected the 2.5 arc-minute data as the appropriate data scale to evaluate the risk of invasive weed spread in Chinese nature reserves under climate change.

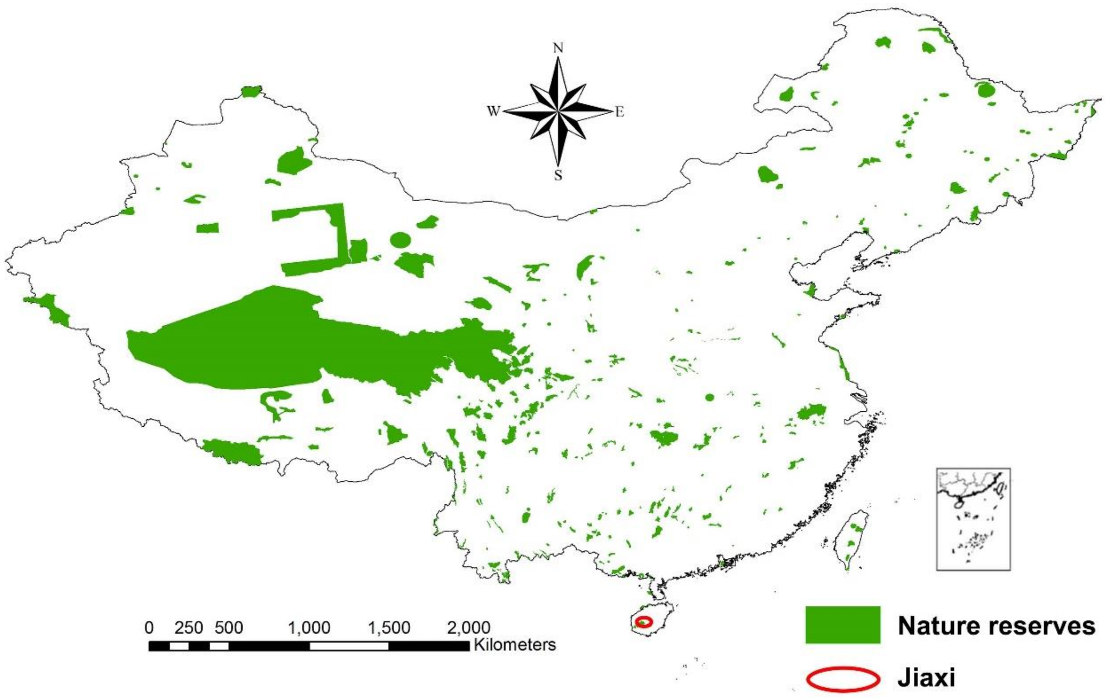

Figure 1. *Locations of the sampled nature reserves in China*

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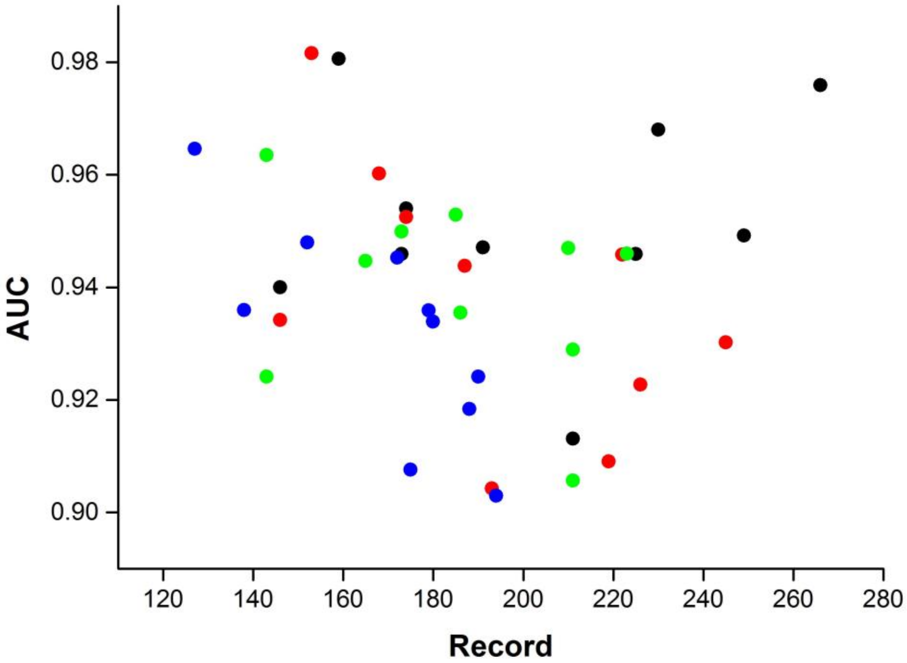

Figure 2. *The number of occurrence records and AUC values for 10 invasive weeds when using these different data scales. The black points represent 0.5 arc-minutes; the red points represent 2.5 arc-minutes; the green points represent 5.0 arc-minutes; the blue points represent 10.0 arc-minutes*

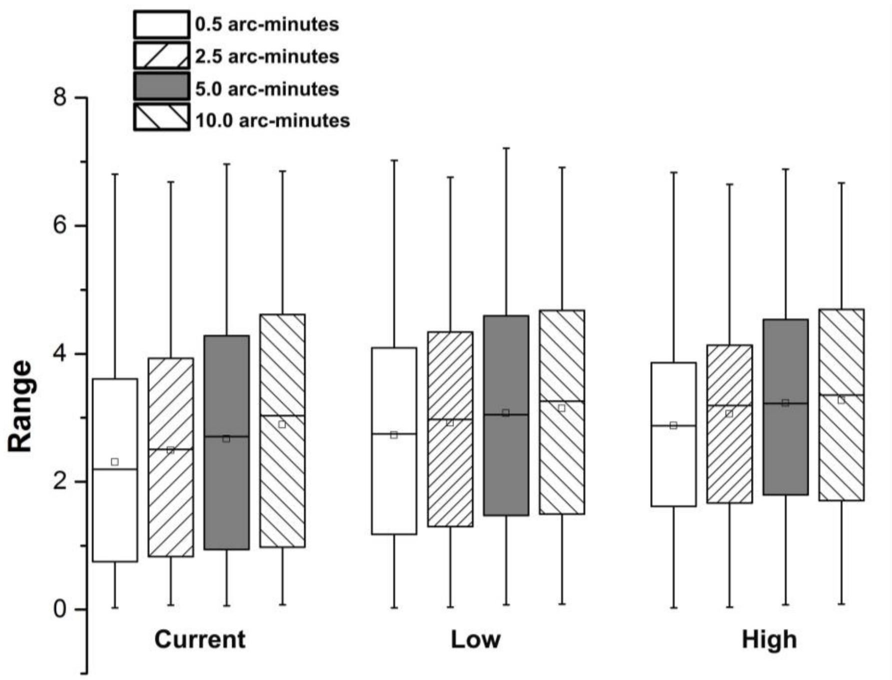

Figure 3. *The ability of invasive weeds to spread in nature reserves modeled using different spatial scales in current, low and high gas-concentration scenarios. Range: the ability of invasive weeds to spread in nature reserves bounded by horizontal bars; Current: present day; Low: low-gas-concentration scenario predicted into the future; High: high-gas-concentration scenario predicted into the future. The block point of the box is the mid-value value of the range and the line of box is the mean value of the range*

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There was a significantly positive relationship between the spread of invasive weeds in nature reserves with low and high concentration scenarios, suggesting pressure from invasive plants will continue at a similar rate even when different data scales are considered at either low and high concentration scenarios ($R^2 > 0.943$; $P < 0.001$; R^2 of 2.5 arc-minutes: 0.9618; $P < 0.001$). Furthermore, the average increase in the ability of invasive weeds to spread within nature reserves was larger in the high concentration scenario than the low concentration scenario (+70.25% (high) *vs.* +37.08% (low); *Table A4*). Hence, we used a high concentration scenario to map the spread risk of invasive weeds in nature reserves.

We found that *M. sativa* had the largest ability to spread within nature reserves, and *A. spinosusin* had the smallest spread ability in current and high concentration scenarios (*Table 1*). Meanwhile, *D. carota* and *M. sativa* would have the most significant increasing trends of spread risk under climate change (*Table 1*). Nature reserves with a high risk of invasive weed spread (e.g., Wuzhishan, Jiaxi, Jianfengling (Hainan province) and Tawushan (Sichuan province)) were mainly distributed in southern China (*Fig. 4a; Table A4*). These nature reserves are currently dominated by invasive weeds and our estimates predict many of them will continue to be so in the future (*Fig. 4a* and *b; Table A4*). We found that 291 of 333 nature reserves would be at higher risk for all 10 invasive weeds in the high concentration scenarios than in the present day (*Fig. 4; Table A4*). In addition, 303 of 333 nature reserves would be at higher risk of all 10 invasive weeds in the low concentration scenarios (*Table A4*). We found that nature reserves that had the highest increases in their risk for invasive weeds in the high concentration scenario were distributed in southwestern, northwestern and northeastern China (*Fig. 4c; Table A4*). In southern China, nature reserves had increased risk of invasive weeds, but the change in risk was not as large as in the rest of the country (*Fig. 4*). Jiaxi and Wuzhishan had the highest risk of all 10 invasive weeds in the current and future concentration scenarios (*Table A4*), and Kekexili and Aerjinshan had the highest increases in their risk for invasive weeds under climate change (*Table A4*).

Table 1. *Potential risk of the spread of 10 invasive weeds in Chinese nature reserves in the present day and high gas-concentration scenario at a spatial scale of 2.5 arc-minutes. Current indicates the spread of 10 invasive weeds in the nature reserves in the present days. High indicates the spread of 10 invasive weeds in the nature reserves in the high concentration scenario. High-change indicates the changes in the ability of invasive weeds to spread in the nature reserves in the high concentration scenario*

Species	Family	Current	High	High-change
Bidens pilosa	Compositae	0.042	0.064	0.535
Amaranthus spinosus	Amaranthaceae	0.024	0.044	0.807
Cassia mimosoides	Leguminosae	0.035	0.048	0.372
Conyza canadensis	Compositae	0.089	0.176	0.988
Daucus carota	Umbelliferae	0.078	0.174	1.244
Euphorbia hirta	Euphorbiaceae	0.027	0.047	0.721
Medicago sativa	Leguminosae	0.184	0.428	1.325
Physalis angulata	Solanaceae	0.042	0.066	0.584
Sonchus oleraceus	Compositae	0.099	0.188	0.905
Vicia sativa	Leguminosae	0.117	0.235	1.009

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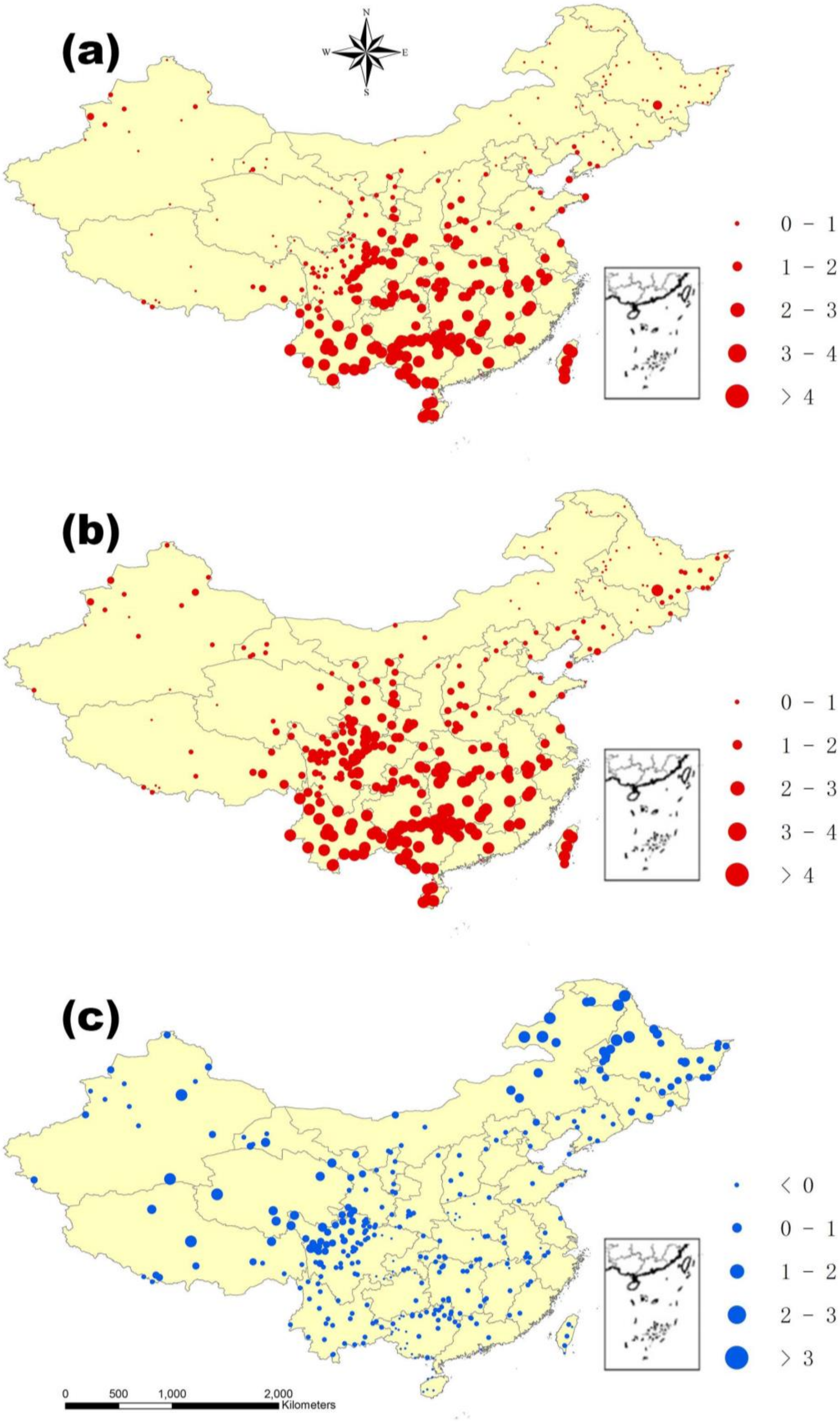

Figure 4. *The spread of invasive weeds in nature reserves (a) in the present day and (b) in high gas-concentration scenario at a spatial scale of 2.5 arc-minutes and (c) the changes in the spread of invasive weeds in the high gas-concentration scenario at a spatial scale of 2.5 arc-minutes*

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Discussion

Our study is an example of how SDMs can be applied to estimate the risk of weed spread in nature reserves with the different scales. Our results showed that using different spatial scales results in different estimates of invasive weeds distributions in current, low and high concentration future scenarios. This indicates that the spatial scale may under- or over- estimate the ability of invasive weeds to increase their distribution in nature reserves. We also found that the risk of invasive weeds in nature reserves was largest at scales of 10.0 arc-minutes. Thus, SDM prediction uncertainty caused by spatial scales could result in inaccurate estimates of invasive weed distributions and their effect on nature reserves. Previous studies have determined the appropriate scale of data to use in SDMs by comparing relationships of potential distributions between fine and coarse scales and subjectively choosing the “best” data scale based on the results (Franklin et al., 2013; Suárez-Seoane et al., 2014). Franklin et al. (2013) selected the appropriate scale by computing the extent and location of the predicted distribution area under current climate conditions depending on the differences in the estimates between fine and coarse scales. The selection of an appropriate data scale should incorporate the variance found when using different scales in SDMs (based on *Fig. 2*) and stabilize the predicted distribution of invasive weeds (Franklin et al., 2013). Hence, by comparing the SDM results of different scales, we used 2.5 arc-minutes, the second-finest scale (also, the medium scale), to evaluate invasive weed risk in nature reserves under climate change scenarios.

Millions of dollars have been invested in the global control of invasive weeds and many scientists have proposed methods to prevent and control the invasion of invasive weeds (Dewey et al., 1995; Rinella and Luschei, 2007). Some scientists have proposed designing long-term management plans at the regional or national scale to mitigate weed spread due to climate change (Chejara et al., 2010; Bohan et al., 2011; Sheppard, 2013; Qin et al., 2014). However, few studies paid attention to the spread of invasive weeds in nature reserves at the national scale. The spread of invasive weeds into nature reserves may cause serious problems (Van Wilgen et al., 2012; Lindenmayer et al., 2015). The invasive weeds can displace native species, alter community structure and ecosystem functions, and cause landscape change and habitat fragmentation (Lindenmayer et al., 2015; Thalmann et al., 2015). Consequently, nature reserves may lose their function of protecting concerned species, habitats or ecosystems (Ingwell and Bosque-Pérez, 2015; Thalmann et al., 2015). We found that nature reserves in southern China are currently dominated by invasive weeds and our estimates predict most of them will continue to be so in the future. Our data supports the need for long-term monitoring of these nature reserves to prevent the spread of invasive weeds due to climate change (Wang et al., 2017). Our finding that the ability of invasive weeds to spread within nature reserves would increase more severely in the high concentration scenario than the low concentration scenario indicated that climate change due to the increasing gas concentration may facilitate the spread of invasive weeds in nature reserves. More importantly, we found a significant relationship between increased invasive weed distributions and low and high concentration scenarios, suggesting we should prioritize the prevention and control of invasive weeds now to lessen their impact on nature reserves in the future (Rannow et al., 2014). Therefore, the prevention and control of invasive weeds in nature reserves is extremely urgent now. The challenge for biological conservationists will be in minimizing the opportunities for invasive plant species to be introduced into nature reserves under climate change. Based on the assessment of expansion risk for invasive weeds and nature reserves, we propose the following measures: (1) detailed monitoring of climate change, (2) improvement of

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effective management for human activities near or inside nature reserves, and (3) control of the introduction of invasive weeds with a high ability to naturally disperse (Foxcroft et al., 2017; Merow et al., 2017).

Our suggestion is that researchers integrate model evaluation of several different spatial scales (0.5, 2.5, 5.0 and 10.0 scales widely used in SDM studies) into their SDM analyses on invasive weeds. Although our study did not validate the Maxent estimates with ground truthing or ecological monitoring this work should be prioritized as a way to test our approach for quantifying invasive species risk (Alagador et al., 2011). Using the correct scale for SDM may lead to more accurate predictions that allow researchers and land managers to make reasonable decisions regarding the management of invasive weeds (Costa et al., 2013; Sheppard, 2013; Qin et al., 2014). Therefore, studies on the effect of data scales on SDMs must continue. We hope that future studies can expand the application of SDMs to provide practical suggestions for mitigating the impact of scale effects on SDM predictions of weeds.

Conclusion

We put forward a simple method to balance various results modeled by different spatial scales for avoiding the over- or under-estimation of SDM results due to the selection of spatial scales, and take the impact of different scales on SDM results into consideration for invasion risk of weeds. Nature reserves with a high risk of invasive weed spread were mainly distributed in southern China. We should prioritize the prevention and control of invasive weeds now to lessen their impact on nature reserves in the future. Here, we proposed the useful suggestions for the evaluation of risk of invasive species: (1) we need to compute two indicators: the ability of invasive weeds to spread in nature reserves and spread potential of invasive weeds for nature reserves; (2) we should balance the various impacts of different spatial scales on the results of SDMs; (3) we should determine the regional scales of spread risk of invasive weeds under climate change. Finally, we hope that future studies can expand the application of SDMs to provide feasible suggestions for risk evaluation of invasive species under climate change.

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APPENDIX

Table A1. *Occurrence records and AUC values of study species. Records: the number of recorded occurrences of each study species; AUC: AUC values of study species. 0.5: 0.5 arc-minute, 2.5: 2.5 arc-minutes, 5.0: 5.0 arc-minutes, 10.0: 10.0 arc-minutes*

Species	Family	0.5 arc-minutes		2.5 arc-minutes		5.0 arc-minutes		10.0 arc-minutes	
		Records	AUC	Records	AUC	Records	AUC	Records	AUC
Bidens pilosa	Compositae	266	0.9759	245	0.9302	223	0.946	190	0.9241
Amaranthus spinosus	Amaranthaceae	159	0.9806	153	0.9816	143	0.9635	127	0.9646
Cassia mimosoides	Leguminosae	173	0.9459	168	0.9602	165	0.9447	152	0.948
Conyza canadensis	Compositae	211	0.9131	193	0.9043	186	0.9355	175	0.9076
Daucus carota	Umbelliferae	174	0.954	174	0.9525	173	0.9499	172	0.9453
Euphorbia hirta	Euphorbiaceae	249	0.9492	226	0.9227	211	0.9289	179	0.9359
Medicago sativa	Leguminosae	191	0.9471	187	0.9438	185	0.9529	180	0.9339
Physalis angulata	Solanaceae	230	0.968	219	0.9091	210	0.947	188	0.9184
Sonchus oleraceus	Compositae	225	0.9459	222	0.9458	211	0.9057	194	0.903
Vicia sativa	Leguminosae	146	0.94	146	0.9342	143	0.9241	138	0.936

Table A2. *WorldClim bioclimatic variables used in the analysis. Bioclimatic variables were used as environmental layers for the species potential habitat distribution models in Maxent; C of V represents the coefficient of variation*

Code	Bioclimatic variables	Unit
Bio1	Annual mean temperature	°C
Bio2	Mean diurnal range	°C
Bio4	Temperature seasonality	SD*100
Bio8	Mean temperature of the wettest quarter	°C
Bio10	Mean temperature of the warmest quarter	°C
Bio12	Annual precipitation	mm
Bio14	Precipitation of the driest month	mm
Bio15	Precipitation seasonality	C of V

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Table A3. *The average and standard deviation values of the importance of bioclimatic variables based on Maxent jackknife test. The codes that were used in this table are defined in Table A2*

Code	0.5 arc-minutes	2.5 arc-minutes	5.0 arc-minutes	10.0 arc-minutes
Bio1	19.986±13.494	18.055±14.905	17.966±10.469	12.517±11.458
Bio2	20.470±12.681	20.359±15.160	24.238±17.660	23.131±14.188
Bio4	29.833±14.493	30.527±13.388	26.660±12.994	30.508±10.700
Bio8	4.129±3.577	4.529±3.807	3.573±3.530	5.662±4.441
Bio10	4.987±3.373	4.283±1.651	5.419±3.246	5.854±4.117
Bio12	7.912±5.462	10.075±6.505	8.288±3.559	11.475±5.658
Bio14	3.343±2.016	2.954±2.913	3.928±2.781	3.866±3.030
Bio15	9.339±10.249	9.217±7.524	9.930±9.652	6.986±9.917

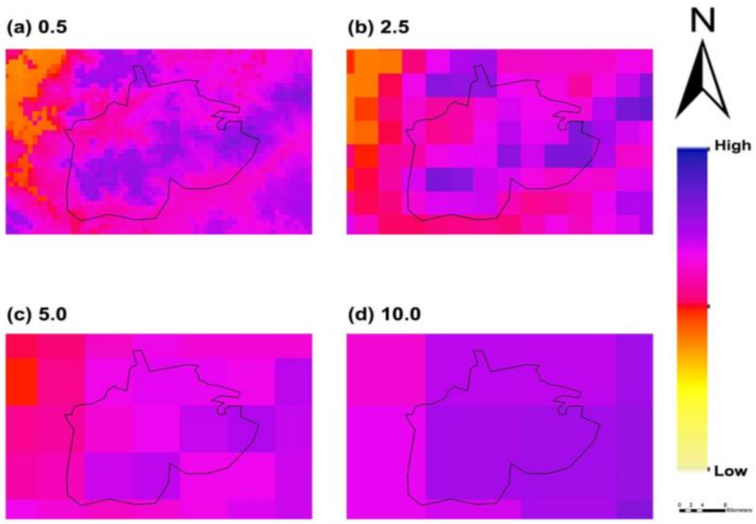

Figure A1. *The spread of invasive weeds in Jiaxi nature reserve in the present day at different spatial scales (i.e., 0.5, 2.5, 5.0 and 10.0 arc-minute resolutions)*

Table A4. *Potential risk of the spread of 10 invasive weeds in Chinese nature reserves at a spatial scale of 2.5 arc-minutes. Name refers to the names of nature reserves based on WDPA database. Current refers to the spread of 10 invasive weeds in the nature reserves in current concentration scenario. Low signifies the spread of 10 invasive weeds in the nature reserves in the low concentration scenario. High indicates the spread of 10 invasive weeds in the nature reserves in the high concentration scenario. Low-change: the changes in the ability of invasive weeds to spread in the nature reserves in the low concentration scenario; High-change: the changes in the ability of invasive weeds to spread in the nature reserves in the high concentration scenario*

Name	Current	Low	High	Low-change	High-change
Aerjinshan	0.068180366	0.1775214	0.3933055	1.603702655	4.76860353
Ailaoshan	4.218334732	4.9194589	5.5215848	0.166208756	0.308948946
An'jilongwangshan	3.610529992	4.000187	3.7872113	0.107922385	0.048935006
Anxijihanhuangmo	0.811199047	1.1095888	1.6160121	0.367837899	0.99212771
Anzihe	3.473078712	3.9443094	4.0854224	0.13568097	0.176311492
A'rengou	1.389479549	2.8543233	3.5136993	1.054239159	1.528788065
Badagongshan	3.578065628	4.0938891	3.972425	0.144162664	0.110215802
Baidongheshuiyuanlin	4.884217508	4.6070336	4.3879747	-0.056750935	-0.101601292
Baihe (Sichuan)	2.355475977	3.2660591	3.2499793	0.386581367	0.379754806

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Name	Current	Low	High	Low-change	High-change
Baijitan	1.805230733	2.4081005	2.4963897	0.333957181	0.382864614
Baimaxueshan	2.38405453	3.1118643	3.1947595	0.30528235	0.340053031
Baishuijiang	3.507968046	4.0925835	3.7023217	0.166653586	0.055403485
Baiyang	2.526666136	3.227808	3.2619489	0.277496838	0.291009071
Bajie	1.184312121	2.0891855	2.7071695	0.764049749	1.285858138
Bamianshan	4.008368154	4.6635722	4.6239197	0.163459049	0.153566619
Banli	4.943201904	4.8011102	4.8733824	-0.028744872	-0.014124348
Baohuashan	3.25073457	3.4565137	3.4192301	0.063302348	0.051833063
Bayinbuluketiane	0.166414421	0.2370796	0.3055153	0.424633746	0.835870342
Bitahai	2.231175582	2.4913757	2.9686196	0.116620189	0.330518147
Buergenheli	0.72121909	1.3040109	1.5471167	0.80806487	1.145141083
Buliuheshuiyuanlin	4.69673285	4.7488565	4.5295667	0.011097853	-0.035592007
Cangshanerhai	3.959751105	4.8609742	5.2486132	0.227595895	0.325490684
Cenwanglaoshanshuiyuanlin	4.673200934	5.0158726	4.9457915	0.07332697	0.05833059
Changbaishan	0.340824228	0.5910087	0.8382921	0.734057181	1.459602432
Changjiangxinluoduanbaijitun (Hubei)	3.638086006	3.9493103	3.758875	0.085546162	0.033201248
Changjigangshidi	0.281764871	0.5188044	0.9337151	0.841267146	2.313809478
Changningzuhai	4.322759185	4.3419296	3.900583	0.004434764	-0.097663591
Changqing	3.019663695	3.4678836	3.3351798	0.148433717	0.104487167
Changshagongma	0.470046796	0.9273012	1.5938657	0.972784854	2.390866002
Chaqinsongduo	0.81403072	1.5976287	2.5128852	0.962614752	2.086966055
Chayucibagou	2.041112011	2.9757539	3.2698697	0.457908181	0.602004046
Chayuhu	0.430203311	0.7933017	0.9610103	0.844015794	1.233851473
Chengbiheshuiyuanlin	4.896073856	4.7630283	4.5597921	-0.027173928	-0.068683963
Chichengdahaituo	0.829301289	0.9031788	1.1233997	0.089084042	0.354633973
Chuandonghe	4.606035769	4.6140348	4.3998648	0.001736641	-0.044761044
Cuiyunlanggubai	3.859620279	4.0159084	3.5892596	0.040493134	-0.070048518
Dabashan	3.328029459	3.7531105	3.5995671	0.127727548	0.081591117
Dafengmilu (Jiangsu)	2.90771915	3.2236214	3.2242437	0.108642628	0.108856645
Daguisi	3.264832547	3.476791	3.4729822	0.064921692	0.063755078
Daheishan (Heilongjiang)	0.291439772	0.5273876	0.8503797	0.809593785	1.917857416
Dahongjiangshuiyuanlin	4.71794787	4.684868	4.6164774	-0.007011495	-0.021507332
Dahongshanyinxing	3.448675483	3.4305483	3.2224149	-0.005256274	-0.065607966
Dahuofangshuiyuanshuiku	0.956092565	1.2316865	1.0782893	0.288250265	0.127808477
Dalaihu	0.108859393	0.2305818	0.5355734	1.118161728	3.91986392
Dalinuoerniaolei	0.285656861	0.5563217	0.8753719	0.947517375	2.064417557
Damingshanshuiyuanlin (Guangxi)	4.889718323	4.9585741	5.01487	0.014081747	0.025594864
Danxianbaidiebei	4.985318304	4.6786053	4.8319898	-0.061523254	-0.030756011
Daozhendashahe	3.680527407	4.0983071	3.9235606	0.113510822	0.066032165
Dasuganhu	0.562605599	1.0260591	1.405613	0.823762689	1.498398527
Dawanglingshuiyuanlin	5.014520129	4.9281845	4.7289345	-0.017217127	-0.056951736
Daxiaolangou	3.590334076	3.7437164	3.5987411	0.042720906	0.002341572
Dayaoshanshuiyuanlin (Guangxi)	4.439299765	4.9065495	4.6764125	0.105253026	0.053412193
Dazhongshan	4.649500182	5.4927152	5.8394917	0.181356057	0.255939665
Dianchi	4.499969969	5.1899584	5.330356	0.153331786	0.184531461
Donganshunhuangshan	3.867737555	4.5718572	4.8515843	0.182049489	0.254372674
Dongdongtinghu (Hunan)	3.886313855	4.3183458	4.1328029	0.111167538	0.063424894
Dongzhai niaolei	3.316473124	3.4241928	3.4126855	0.03248019	0.029010449
Dugoula	0.907013901	1.5785688	2.674138	0.740401992	1.948287779
Dunhuang	0.404149414	0.7933638	1.2392571	0.963045776	2.066334027
Em Ei Shan	3.992729896	4.2901553	4.1393044	0.074491742	0.036710348
Fanjingshan (Guizhou)	3.570361712	3.9039159	3.9035081	0.09342308	0.093308862
Fenghuangshan (Heilongjiang)	0.682192057	1.1025248	1.5767282	0.616150157	1.311267309
Fenglin	0.224479499	0.3988635	0.6667784	0.776837091	1.970330934

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Name	Current	Low	High	Low-change	High-change
Fengtongzhai (Sichuan)	3.081397331	3.6091109	3.8951259	0.171257878	0.264077781
Fengwugou	0.826358234	1.2335944	1.7518904	0.492808263	1.120013244
Foping	2.894701462	3.4591989	3.3299122	0.195010589	0.150347365
Funiushan	2.804172271	2.9782938	2.7362375	0.062093735	-0.024226319
Fuyushuiqing (Shuiqing)	0.256543428	0.4779255	0.8550919	0.862941895	2.333127286
Gajinxueshan	1.066909829	2.1621586	2.8080534	1.026561703	1.631950071
Ganjiahu (Xinjiang)	1.300586638	1.5906694	1.5038426	0.223039937	0.156280217
Ganligahai-zecha	0.997468313	2.1067952	2.8403099	1.112142484	1.847518927
Gaoligongshan	3.134970181	3.7814828	4.0319559	0.206226082	0.286122568
Gemu	0.909843507	1.2958836	1.6658613	0.424292848	0.830931679
Genieshenshan	1.088408407	1.7106679	2.050123	0.571715074	0.883597174
Gonggashan (Sichuan)	1.402533989	2.0132685	2.252333	0.435450774	0.605902615
Gouxiheshidi	4.079206322	4.1594578	3.728884	0.019673307	-0.08588002
Guangwushan	3.669389547	4.0787234	3.7616593	0.111553665	0.025145805
Guhaian (Tianjing)	1.329830276	1.5704211	1.5878316	0.180918444	0.194010716
Guniujiang	3.57206942	4.3096911	3.9605627	0.206497017	0.108758603
Guposhanshuiyuanlin	4.035366563	4.9541409	4.7622043	0.227680515	0.180116905
Haiyangshanshuiyuanlin	4.123817147	4.810177	4.6425934	0.166437994	0.125800014
Haizishan	0.736253343	1.118952	1.6183143	0.519792081	1.198040003
Hanasi	0.492735606	0.7246338	1.4470392	0.470634132	1.936745757
Hanma	0.096370639	0.1567511	0.3420536	0.626544159	2.549354903
Heilihe	0.666124926	0.9969191	1.3844194	0.496594799	1.078317964
Heilonggong	0.320917678	0.5791164	0.7352973	0.804563724	1.291233392
Heishantou	0.113505814	0.2222014	0.5145099	0.957621307	3.532894676
Heishuihe	3.047325448	3.6869272	3.8800535	0.209889545	0.273265218
Helanshan (Ningxia)	1.422396867	2.0784923	2.2252012	0.46126046	0.56440249
Helanshanshuiyuanhanyanglin (Neimeng)	1.299201368	1.8780089	2.0024912	0.445510254	0.541324732
Hepu rugen	5.011440922	5.0482994	5.1063827	0.007354866	0.018945006
Hesigechuor	0.184012734	0.4104674	0.6653623	1.230646712	2.615849216
Hongba	1.514917419	2.2236418	2.3874644	0.467830373	0.575969997
Honghe	0.375266436	0.6961311	1.0984756	0.855031607	1.927188511
Honghua'er'jichangzhangzisonglin	0.150298859	0.2506426	0.5995992	0.667628096	2.989379587
Honghushidi	3.714843677	3.9892489	3.8569874	0.073867233	0.038263716
Houhe	3.423165934	3.955298	4.0340362	0.155450269	0.178451842
Huagaoxi	4.045582902	4.2214755	3.884153	0.04347769	-0.039902755
Huang Long	1.468625458	2.3589348	2.7255073	0.606219467	0.855821908
Huang Shan	3.581699243	4.4166519	4.0191771	0.233116351	0.122142544
Huanghegudaoshidi	1.719022713	1.9421119	1.8753494	0.129776754	0.09093928
Huanghesanjiaozhou	1.692432243	2.1877714	1.9383856	0.29267887	0.145325379
Huangheshidi	2.604529637	2.5749698	2.3813474	-0.011349396	-0.085690035
Huangheshouqu	1.198754052	2.4242601	2.8997985	1.022316501	1.419010384
Huanglianshan	5.200654594	5.466738	5.847181	0.051163445	0.124316352
Huanglianshanshuiyuanlin	4.87267502	5.0452256	4.8449926	0.035411879	-0.005681155
Huaping	3.957146575	4.660721	4.7623428	0.177798424	0.203478999
Huashuichongshuiyuanlin	4.240136494	5.0120098	4.8664545	0.182039731	0.147711756
Huihe	0.119540898	0.236545	0.5829069	0.978778844	3.87621316
Humahe	0.159231741	0.3347174	0.7894514	1.102077123	3.957877086
Huochengsizhualugui	2.65524078	2.8764318	2.7659642	0.083303564	0.041699955
Huzhong	0.103698918	0.1655946	0.3709349	0.596878764	2.577037323
Jianfengling	6.427512043	6.4288437	6.0850099	0.000207181	-0.053286892
Jiangcun	1.321870747	1.5581834	1.9513201	0.178771377	0.476180712
Jiangxiwuyishan	4.16857114	4.5717325	4.9945192	0.096714521	0.198136971
Jiaqiaolingshuiyuanlin	4.251732296	4.7277762	4.5093215	0.111964694	0.06058453
Jiaxi	6.456783457	6.5712797	6.3103195	0.017732706	-0.022683734

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Name	Current	Low	High	Low-change	High-change
Jiejingkou	0.3406554	0.6530771	0.9676376	0.91711947	1.840517426
Jin Zhai Gou	1.58088584	2.5481558	2.8900921	0.611853137	0.828147249
Jinfoshan	3.783649179	4.0667182	3.8758498	0.07481376	0.024368174
Jingangtai	3.317290761	3.469444	3.4888029	0.045866718	0.051702474
Jingbohu	0.551775952	0.9941344	1.2141727	0.801699397	1.200481365
Jinggangshan	3.972931325	4.6766994	4.4803111	0.17714076	0.127709173
Jinpingfenshuiling	4.499785327	4.7277904	5.0365844	0.050670211	0.119294374
Jintangkongyu	1.921151073	2.5756459	3.0938951	0.34067848	0.610438213
Jinyunshan	4.457848275	4.4195618	3.9280611	-0.008588555	-0.118843698
Jinzhongshan	4.687741682	5.1219961	4.9311732	0.092636166	0.05192938
Jiudingshan	2.62135821	3.2398644	3.3155459	0.235948749	0.264819851
Jiugongshan	3.396543347	4.2514869	3.9315731	0.25170989	0.157521839
Jiuwanshanshuiyuanlin	4.195228936	4.5764742	4.7234784	0.090875914	0.125916719
Jiuyishan	4.087967301	4.9634151	4.6755687	0.214152349	0.143739261
Kalamailishan	1.216526787	1.5187629	2.0973507	0.248441807	0.724048104
Kashahu	1.311950373	2.4513161	3.0544196	0.868451849	1.328151783
Keerxin	0.43003141	0.7316846	0.8073818	0.701467807	0.877494949
Kekexili	0.116443458	0.4856354	0.664697	3.170568346	4.708324121
Kenting	4.650508798	3.7180358	3.6024545	-0.200509888	-0.225363362
Ku'erbin	0.21556771	0.3929574	0.6830063	0.822895461	2.168407272
Labahe	2.928455529	3.5021062	3.7542428	0.195888469	0.281987301
Langcun	0.829746806	1.6189519	2.6268773	0.951139659	2.16587817
Laoshan	3.502353489	4.0273222	3.6781209	0.14989027	0.050185514
Laoshan	2.47116014	2.9672197	2.5445171	0.200739544	0.029685231
Laotudingzi	0.520627921	0.8766302	0.9796121	0.683794058	0.881597318
Laoxiancheng	2.801765329	3.3794668	3.2922669	0.206191955	0.175068756
Leigongshan	3.617425677	4.1193028	4.4312704	0.138738752	0.224978976
Leiwuqi	0.717355376	1.4067066	2.5502438	0.960961954	2.555063341
Leizhou Rare Marine Life	0.279471662	0.2804547	0.2664467	0.003517487	-0.046605663
Lian Huan Hu	0.366932889	0.5407905	0.811421	0.473813104	1.211360781
Liancheng	1.26867781	2.3219657	2.8948438	0.830224886	1.281780116
Liangucheng	0.996566208	1.5130357	2.0309251	0.518249051	1.037922903
Liangyeshan	4.473078984	5.086663	5.5386353	0.137172632	0.238215404
Lingnan	3.765201678	4.5642651	4.0691275	0.212223273	0.080719666
Lingqiuqingtun	1.463160215	1.807377	1.4957921	0.235255703	0.022302332
Lishan	2.383144667	2.6577278	2.4785096	0.115218827	0.040016426
Liupanshan	2.247728102	2.9802779	3.1895395	0.325906767	0.419005927
Longbao	0.539827103	1.0910366	2.1039936	1.021085258	2.897532355
Longganhu	3.629671022	4.263526	3.5162698	0.174631523	-0.031242838
Longwan	0.38756117	0.6466648	0.8194125	0.668548993	1.114279147
Longxihongkou	3.214561441	3.6995559	3.7267688	0.150874223	0.159339732
Luanheyuancaodi	4.867275133	4.3397563	4.2873983	-0.10838073	-0.119137878
Luoshan	1.825088565	2.4842113	2.6502165	0.361145617	0.452102956
Luoxu	0.627191882	1.2530207	2.0602264	0.997826719	2.284842261
Lushan	3.933653669	4.6004531	4.2564231	0.169511474	0.082053342
Lushidani	3.064114253	3.158907	2.8135776	0.030936427	-0.081764788
Luyashan	0.950415949	1.5357447	1.7078583	0.615865876	0.796958797
Mabiandafengding	3.150848417	3.7765117	3.7137125	0.198569782	0.178638896
Mangkang	1.508791551	2.2683431	2.3152967	0.503417154	0.534537159
Mangshan	3.956484796	4.7755036	5.0121092	0.207006686	0.266808659
Manzetangshidi	1.108426009	1.9325509	2.9870393	0.74350916	1.694847717
Maoershan	3.717741689	4.5665343	4.7695168	0.228308657	0.28290699
Maoershan	0.420672612	0.7190534	0.9726003	0.709294543	1.312012411
Maojieniaolei	4.799302307	5.2228477	5.0493304	0.088251451	0.052096758

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Maolan	4.27280106	4.5967033	4.6510033	0.075805598	0.088513889
Maoshan	0.192927715	0.4251202	0.7912416	1.203520629	3.101233459
Mayangheheiyehou	3.865217812	4.1581757	3.8065134	0.075793371	-0.015187866
Meigudafengding	2.985776711	3.6786022	3.6260661	0.232041963	0.214446508
Meihuashan	4.669146936	5.2814537	5.9372162	0.131138894	0.271584784
Mengda	1.552720746	2.5167115	3.0781737	0.620839746	0.982438702
Mianshan	2.087279858	2.2833927	2.1241097	0.09395618	0.017644899
Micangshan	3.62645716	3.8435796	3.589351	0.059871779	-0.010232069
Minjiangbai	1.804775928	2.4589164	3.4289343	0.362449688	0.899922448
Momoge	0.391668358	0.580151	0.8334726	0.481230199	1.12800596
Mudanfeng	0.51741769	0.9507688	1.3357585	0.837526661	1.581586455
Mulinzi	3.422753301	3.9917032	3.9998137	0.166225798	0.168595382
Mulun	4.354657004	4.6045431	4.647664	0.057383646	0.067285895
Mupinghu	3.800973992	4.3609185	4.0455318	0.147316059	0.064340826
Namusilai	0.870281819	1.2314424	1.1692505	0.414992676	0.343530882
Nandongtihu Shidi and Shuiqin	3.802469437	4.388544	3.971799	0.154129987	0.044531472
Nangunhe	4.957876728	5.4808349	6.0436073	0.105480269	0.218991038
Nanling	3.970448966	4.7750611	5.0630911	0.202650164	0.275193597
Nansihu	2.302205243	2.6691182	2.3885047	0.159374564	0.037485562
Nanwenghe	0.146800332	0.2856544	0.7191587	0.945870259	3.898890147
Nanyangkonglongdanhuashiqaun	3.083725701	2.9745135	2.6665973	-0.035415666	-0.135267673
Nanyuehengshan	4.19229214	4.9305377	4.8986686	0.176095924	0.168494093
Nazoushuiyuanlin	4.95240428	5.2613022	5.0417035	0.062373325	0.018031488
Neixiangbaotianman	2.87574233	2.9890161	2.6838037	0.039389402	-0.066744029
Nianlong	0.673981487	1.113588	2.3452111	0.652253098	2.479637268
Nonggang	4.942850266	4.7402721	4.5984173	-0.040984079	-0.069683067
Panzhihuasutiesutie	4.376400448	4.6101161	4.6956361	0.053403626	0.072944799
Pishangou	0.743091317	1.0304883	1.0897775	0.386758634	0.466545867
Poyanghulijiyuchanluanchang	3.683235151	4.2913702	3.6359704	0.165108939	-0.012832401
Qianfoshan	3.456355012	3.8333341	3.6747835	0.109068393	0.063196196
Qiangtang	0.142320064	0.3363909	0.5623604	1.363622462	2.951378212
Qianjiadongshuiyuanlin	3.99580901	4.9413833	4.8074861	0.236641513	0.203132104
Qilianshan	0.585662053	1.2939186	1.9769024	1.20932634	2.375500239
Qinghaihuniaodao	0.620402936	1.775535	2.3756885	1.861906185	2.829267017
Qingliangfeng	3.638672235	4.2046866	3.8935602	0.155555194	0.070049718
Qingshitanshuiyuanlin	4.086825363	4.7388727	4.7408752	0.159548618	0.160038607
Qixinghe	0.496490676	0.8872769	1.208391	0.787096803	1.433864438
Qixinglazi	0.377813653	0.7623187	1.231765	1.017710832	2.260244806
Queershan	1.034280414	2.3431316	2.9973743	1.265470339	1.898028677
Quomolangma	0.402532064	0.6339384	0.9115877	0.574876778	1.264633756
Ribaxueshan	0.91896993	1.7143432	2.4622932	0.865505218	1.679405625
Riganqiaoshidi	1.395896878	2.8567253	3.0943032	1.046516003	1.216713318
Rongchengtianee	2.400741937	0.9815751	0.8954855	-0.591136771	-0.626996352
Ruoergaishidi	1.191480653	2.7467948	3.0479123	1.305362486	1.558087949
Sandagu	1.101322859	1.9048686	2.5908522	0.729618689	1.352491078
Sanjiang	0.392006461	0.7188821	1.097434	0.833852682	1.799530388
Sanjiangyuan	0.409948785	0.8813389	1.4625438	1.149875624	2.567625649
Sanpihushuiyuanlin	4.413829766	4.6808017	4.380299	0.060485326	-0.007596751
Selincuoheijinghe	0.242026402	0.6159431	1.2225865	1.54494177	4.051459221
Shankou hongshulin	4.648508413	4.694658	4.5818393	0.009927827	-0.014342044
Shapotou	1.767804306	2.3346807	2.5180899	0.320666938	0.424416657
Shedao-laotieshan	2.35352009	3.0046636	2.5923355	0.276667921	0.101471583
Shei-Pa	5.529632737	5.8106414	5.9472897	0.050818685	0.075530688
Shenmuchoubai	1.572859382	2.0394837	1.9446701	0.296672623	0.236391582

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Shennongjia	3.03960801	3.3772771	3.455241	0.111089683	0.13673901
Shimenhupingshan	3.522257613	4.0369354	4.0200765	0.146121563	0.141335172
Shimentai	4.34055815	4.9686015	5.2527353	0.144691841	0.21015204
Shiwandashanshuiyuanlian	5.361982368	5.2986107	5.2353774	-0.011818701	-0.023611597
Shouchengshuiyuanlin	4.136012421	4.6743513	4.5535564	0.130158913	0.10095327
Shoulushan	1.329549648	2.2403738	2.7076785	0.685062159	1.036538089
Shuangtaihekou	1.280107139	1.3249515	1.5153521	0.035031725	0.183769744
Shuguang	0.495156359	0.8889053	1.3803384	0.79520122	1.78768186
Simianshan	4.342941694	4.2967751	3.8913278	-0.010630259	-0.103988017
Songfengshan	0.311807626	0.5730393	0.739885	0.837797578	1.372889366
Songhuaba	4.136122479	4.6244788	5.0062412	0.118071049	0.210370637
Songhuajiangsanhu	0.487841987	0.7779641	0.8678869	0.59470509	0.779032808
Suoxiyu	3.744563228	4.0814605	3.9500149	0.089969711	0.054866659
Susu	0.427362245	0.7864597	1.1640926	0.840264809	1.723901359
Tachengyebadanxing	1.113086442	1.5539888	2.244644	0.396107922	1.016594503
Taibaishan	2.190025012	2.8556487	2.9680267	0.303934286	0.355247855
Taitong - kongdongshan	2.479497096	3.1889538	3.2369633	0.286129274	0.30549187
Talimuhuyanglin (Tarim)	0.731850107	0.7827091	1.4347354	0.069493729	0.960422478
Tangjiahe	3.26731949	3.9000298	3.6454454	0.19364813	0.115729702
Taoyuandong	4.010578083	4.65248	4.5882173	0.160052218	0.144028917
Taroko	6.40065087	6.4569357	6.3754622	0.00879361	-0.003935329
Tashikuerganyeshengdongwu	0.374775574	0.4841934	1.0601476	0.291955596	1.828753189
Tawushan	6.449766139	6.5764015	6.6226019	0.019634101	0.026797214
Tianchi (Xinjiang)	0.413640792	0.8270696	1.8216088	0.999487517	3.403842259
Tianma	3.260532899	3.7689337	3.9094255	0.155925677	0.199014278
Tiebu	1.49233669	2.6581784	3.1729697	0.781218955	1.126175495
Tiexi	0.757873908	1.1927998	1.6746278	0.573876324	1.209639074
Tongbiguan	4.695141012	5.708225	5.9362822	0.215772857	0.264345881
Touersantan	3.485723924	3.9518337	3.5432415	0.133719648	0.016500898
Tunhuangxihu	0.78660997	0.8856022	1.2197254	0.125846651	0.550610145
Tuomuerfeng	0.247492323	0.4853855	0.6563681	0.961214369	1.652074586
Wahuishan	1.008375306	1.3062069	1.6669644	0.295357881	0.653119022
Wanglang	1.966656941	2.913366	3.0888863	0.481379868	0.060246567
Wawushan	3.393578096	3.9592295	3.9729427	0.16668289	0.170723816
Weiyuanjiang	5.296218996	5.3039563	5.541466	0.001460911	0.046306054
WenchuanCaopo	2.482182373	3.0895488	3.3849365	0.244690492	0.363693714
Wenlanjiang	5.512020513	5.3077275	5.3905429	-0.037063181	-0.022038672
Wenshanlaojunshan	4.625134114	5.0914454	5.5123206	0.100821138	0.191818543
Wolong	2.226933152	2.9311619	3.341406	0.316232549	0.500451864
Wu Ling Yuan	3.706937481	4.1440955	4.016746	0.117929698	0.083575329
Wudalianchihuoshan	0.192568797	0.4054511	0.8224395	1.105487007	3.270886628
Wujiao	2.506918055	3.3708793	3.3205089	0.344630828	0.324538269
Wulatelenglenglin--mengguyelv	0.552223979	0.8240096	1.1897453	0.492165555	1.154461496
Wuliangshan	4.276610942	4.9705823	5.6408029	0.162271333	0.318989026
Wuliangsuhainiaolei	0.642323075	1.0380845	1.0480873	0.616140756	0.631713605
Wulingshan	0.785673619	1.0396885	1.2165839	0.3233084	0.548459654
Wulushan	2.115315374	2.6604441	2.54036	0.257705651	0.200936764
Wuyishan	4.249849161	4.6599941	5.1109583	0.096508117	0.202621106
Wuzhishan	6.686374936	6.7594269	6.6454659	0.010925496	-0.006118268
Xianghai	0.405432707	0.7253346	0.817071	0.789038199	1.015306081
Xiangshan	3.268353297	3.8189908	3.7705003	0.168475514	0.153639144
Xiangtoushan	5.40113347	5.9018235	5.6097032	0.092700918	0.038615919
Xianrendong	1.406685222	2.025562	1.9842726	0.439953991	0.410601725
Xiaohe	3.564841683	3.9950627	4.0655956	0.120684467	0.14047017

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Xiaohegou	2.628934089	3.4445591	3.3231073	0.310249319	0.264051204
Xiaosuganhu	1.02197917	1.3578324	1.6552772	0.328630211	0.619678021
Xiaowutaishan	0.859756071	1.2860287	1.2326404	0.495806477	0.433709446
Xiaoxi	3.597079523	3.9896132	4.0923405	0.10912566	0.137684189
Xiaozhaizigou	2.561513663	3.1436491	3.2286073	0.227262281	0.260429467
Xidamingshanshuiyuanlin	4.953416169	4.7663636	4.8259502	-0.037762337	-0.025732942
Xi'e'erduosi	1.280985413	1.8391057	1.8368926	0.435696052	0.433968398
Xilinguolecaoyuan	0.24001529	0.5176482	0.7557911	1.156730098	2.14892897
Xingdoushan	3.624776709	4.1074179	3.969299	0.133150599	0.095046487
Xingkaihu	0.801902821	1.2059164	1.7160298	0.503818628	1.139947329
Xinglongshan	1.592556376	2.5735305	3.1120161	0.615974504	0.954101058
Xinjiangluobupoyeshuangfengtuo	0.377652057	0.6351586	1.0385473	0.681861884	1.750010971
Xinningshunhuangshan	3.985194504	4.6291497	4.7515863	0.161586893	0.192309759
Xionglongxi	1.126909278	1.9786615	2.5893394	0.755830339	1.297735453
Xishuangbanna	5.576098026	5.8063043	5.7907511	0.041284474	0.038495212
Xishuangbanna	5.624244814	5.88671	5.8572166	0.046666743	0.041422768
Xishuizhongyaredaisenlin	3.929326843	4.1611994	3.882315	0.059010758	-0.01196435
Xitianshan	1.282375399	1.5494784	1.6335789	0.208287683	0.273869493
Xuebaoding	2.815380854	3.4853574	3.4141119	0.237970129	0.212664317
Xunbielahe	0.229326621	0.4875641	0.8174838	1.126068478	2.564713928
Yading	1.381329549	1.6796899	1.9996408	0.215995054	0.447620375
Yalujiangbinhaishidi	1.779385149	2.3025369	2.1080035	0.294007035	0.184680844
Yaluzangbudaxiagu	2.811536007	3.53505	3.8080543	0.257337623	0.3544391
Yaluzangbujiangzhongyouheguoheijinghe	0.536832254	1.0595916	1.5541322	0.973785279	1.895005262
Yanboyezeshan	1.158267795	2.2741909	2.973453	0.963441365	1.567155033
Yancheng	2.570085802	2.3541128	2.3982959	-0.084033382	-0.066842088
Yangchengmanghemihou	2.564979596	2.6777729	2.3767916	0.043974347	-0.073368223
Yangxianzhuhuan	3.636850474	3.7548798	3.3665618	0.03245372	-0.074319435
Yangzie	3.604495881	4.0008207	3.5960218	0.109952912	-0.002350975
Yihuanghuananhu	3.873180847	4.3230026	4.2315213	0.116137555	0.092518389
Yindingshanshuiyuanlin	4.077412271	4.8908244	4.6513785	0.199492245	0.140767279
Yiwulushan	1.141283391	1.3711778	1.5506742	0.20143499	0.358710915
Yongzhoudupangling	4.042135196	4.9242673	4.744988	0.218234191	0.173881568
Youyi	0.94899932	1.8821107	2.7550495	0.983258218	1.903110089
Yuanbaoshanshuiyuanlin	3.949066789	4.60341	4.7112504	0.165695656	0.193003474
Yuanshan	1.966113109	2.4518978	2.0421601	0.24707871	0.038678848
Yueyahu	0.592437574	0.9492332	1.4326278	0.602250164	1.418191997
Yuke	0.952112713	1.8103647	2.7074516	0.901418472	1.843625091
Yulongxueshan	2.427936926	2.8823653	3.1887478	0.187166466	0.313356935
Yunchengtianee	2.721900784	2.9060026	2.5767111	0.067637225	-0.053341284
Yunling	3.607845269	4.1090513	4.4952158	0.138921155	0.245955817
Yunnandaweishan	5.732517823	5.7859962	5.9304935	0.009328951	0.034535554
Yunwushancaoyuan	2.126109799	2.7576579	3.0100536	0.297043973	0.415756421
Yushan	5.693405357	5.9928932	6.0700757	0.052602586	0.066159059
Zhagashenshan	1.11401156	1.8823403	2.5351139	0.689695482	1.275662113
Zhalong	0.288557936	0.519417	0.8907593	0.800044065	2.086933987
Zhangjiajiedani	3.746332725	4.1066225	3.9822749	0.096171323	0.062979504
Zhangmukouan	1.299713281	1.4389909	1.970977	0.107160265	0.516470616
Zhouzhijinsihou	3.039861443	3.4981733	3.3203029	0.150767351	0.092254684
Zhuchanggou	1.490779594	2.1443633	3.1438463	0.438417395	1.108860567
Zhujiangkouzhonghuabaijitun	0.274393703	0.0371043	0.0371043	-0.864777145	-0.864777145
Zhujiangyuantou	4.046219123	4.5566399	4.8763739	0.126147587	0.205168023
Zhumulangmafeng	0.346179922	0.55216	0.9369674	0.595008737	1.706590823
Ziyunwanfengshan	3.674821498	4.3552625	4.7189632	0.185163008	0.284133992

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