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Range-wide evaluation of wildlife habitat change: A demonstration using Giant Pandas

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ABSTRACT

Information on wildlife habitat distribution and change is crucial for the design and evaluation of conservation efforts. While habitat distribution has been evaluated for many species, information on habitat change is often unclear, particularly across entire geographic ranges. Here we use the iconic giant panda (*Ailuropoda melanoleuca*) as a model species and present an advanced approach to evaluate its habitat change across an entire geographic range through the integration of time-series satellite imagery and field data. Our results show that despite a few areas showing habitat degradation, both the overall habitat suitability and habitat area increased between the early 2000s and the early 2010s. Our results also indicate that conservation efforts in China have achieved success beyond the boundaries of nature reserves, since panda habitat outside nature reserves shows a higher proportional growth than inside the reserves. Despite these promising trends, we found habitat fragmentation remains a threat to the species' long-term survival. These results provide valuable information to assess the appropriateness of recent decision by the International Union for the Conservation of Nature (IUCN) that down-listed the giant panda from endangered to vulnerable species, while laying a good foundation for the design of future conservation efforts. The approach described here may also be easily implemented for evaluating range-wide habitat change for many other species around the world and thus help achieve biodiversity conservation objectives such as those set by the Aichi Biodiversity Targets and the Sustainable Development Goals.

1. Introduction

Habitat loss and fragmentation have been threatening the survival of many wildlife species around the world (Haddad et al., 2015; Pogson, 2015). To address these challenges, range-wide information on wildlife habitat status across space and time is crucial to support effective conservation actions for entire species (Lengyel et al., 2008). Armed with this knowledge, conservation practitioners can easily detect human and natural disturbances of wildlife habitat and identify the regions that require additional conservation efforts (Viña et al., 2010). Also, such information is fundamental to evaluate the effectiveness of existing conservation efforts, and thus assist in the design of future efforts (Stem et al., 2005). Unfortunately, for many threatened or endangered species, spatially specific information on habitat change is inadequate, especially across entire geographic ranges (Tuanmu et al., 2011; Viña et al., 2010). This is the case of the giant panda (*Ailuropoda melanoleuca*), a global icon of biodiversity conservation (Liu et al., 2001).

Giant panda once roamed most of China and part of northern Myanmar, and northern Vietnam (Pan, 2014), but this range drastically shrunk over the past centuries mainly due to human activities (e.g., agricultural expansion, infrastructure development, logging) (Fig. 1). The current giant panda population inhabits a small fraction of its historical range in southwestern China (Wei et al., 2015). The imperiled status of giant pandas prompted the Chinese government to design and implement a set of conservation policies to protect and restore panda habitat (Liu et al., 2016; Wei et al., 2015). In addition to the designation of 67 nature reserves specifically for panda conservation (State Forestry Administration, 2015a), the Chinese government has been implementing two of the world's largest payment for ecosystem services programs, which cover the entire panda geographic range: the Grain-to-Green Program (GTGP) and the Natural Forest Conservation Program

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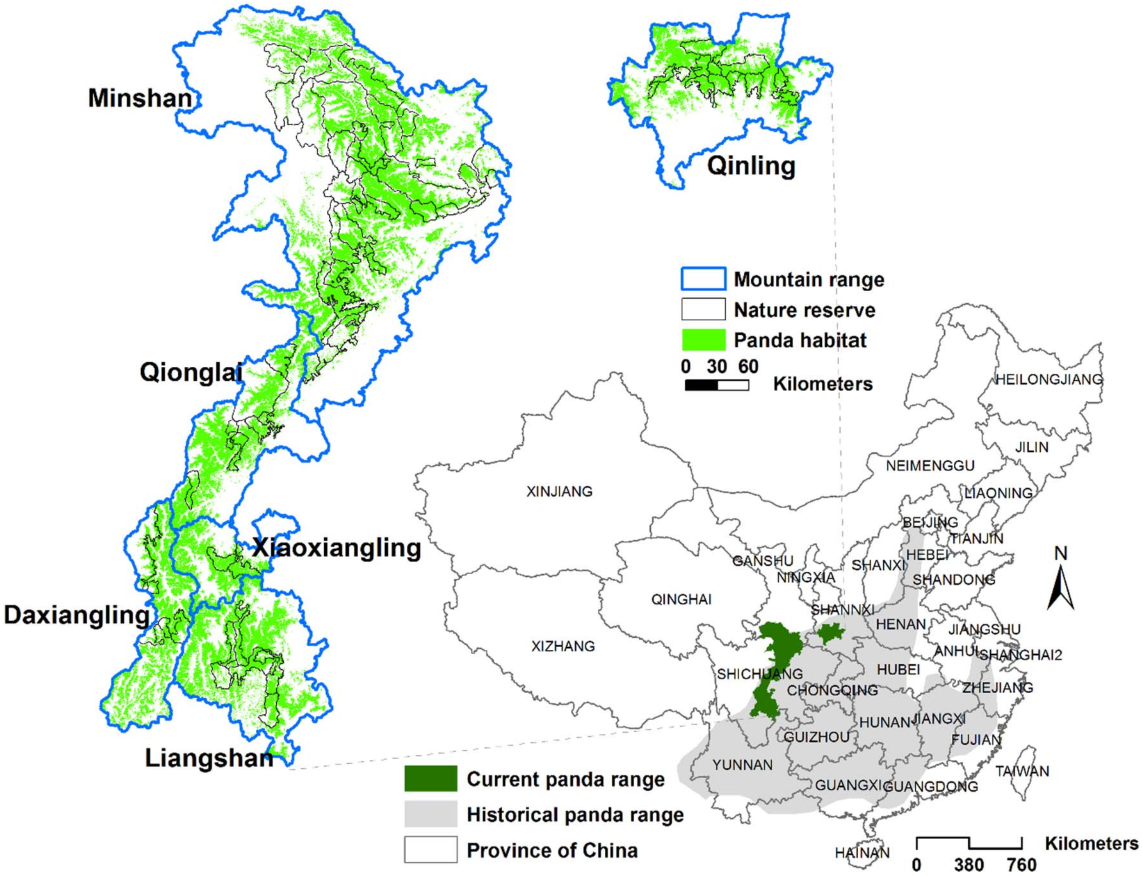

Fig. 1. Giant panda habitat distribution in China. The current geographic range of the species encompasses six mountain regions in China, including Qinling, Minshan, Qionglai, Daxiangling, Xiaoxiangling, and Liangshan.

(NFCP) (Liu et al., 2008a). These programs started in the late 1990s and were financed with multi-billion-dollar support from the Chinese government (Liu et al., 2008b; Ouyang et al., 2016). The GTGP pays rural farmers to convert sloping cropland to forestland or pastureland (Chen et al., 2012), while the NFCP provides financial resources to local governments or forest enterprises for monitoring and afforestation activities (Liu et al., 2008b). Evidence from previous local (e.g., Tuanmu et al., 2016) and regional (e.g., Li et al., 2013) studies show that the strict forest protection and active reforestation measures promoted by these programs have greatly benefited panda habitat recovery.

Recently, the International Union for the Conservation of Nature (IUCN) down-listed the giant panda's extinction risk from “endangered” to “vulnerable” (IUCN, 2016). This decision was mainly supported by results from the Fourth National Giant Panda Survey (fourth panda survey) performed between 2011 and 2014, which found that giant panda habitat increased as compared to the Third National Giant Panda Survey (third panda survey) conducted between 1999 and 2003 (IUCN, 2016; State Forestry Administration, 2006, 2015a).

However, some limitations exist in this evaluation of habitat change. The habitat area estimations of the two panda surveys were based on delineation around panda presence locations from field observations (State Forestry Administration, 2006, 2015a). However, this approach is sensitive to survey extent (i.e., area surveyed) and survey intensity (i.e., number of transects per unit area), which differed between the third and fourth panda surveys, thereby may compromise the reliability of the reported habitat change. The third panda survey covered 25,398 km^2, and collected data along 11,174 transects (State Forestry Administration, 2006), while the fourth panda survey covered an area 1.72 times larger (43,583 km^2), and collected data along 20,513 transects (State Forestry Administration, 2015b). In addition, range-wide information on changes in panda habitat quality (including changes in habitat suitability and degree of habitat fragmentation) is missing in this habitat change evaluation. Thus, a range-wide assessment of habitat change in both quantity and quality using a consistent approach is warranted. Such evaluation will help assess if the IUCN's decision was appropriate and will aid the design of future panda conservation efforts.

Although many studies have investigated the extent, quality, and fragmentation of panda habitat (e.g., Liu et al., 2001; Tuanmu et al., 2011; Viña et al., 2010), they mostly focused on habitat status at a single period or in a single place (e.g., in a single nature reserve). Therefore, panda habitat change across its entire geographic range remain little known, and conservation practitioners are still in need of an overall picture of habitat change for the entire species (Viña et al., 2010).

Building on our previous panda habitat mapping approach (Tuanmu et al., 2011; Viña et al., 2010), we integrate remotely sensed vegetation phenology information with elevation, field data, and habitat modeling to evaluate the habitat change of giant pandas across its entire geographic range between the early 2000s (2001 to 2003) and the early 2010s (2011 to 2013). A previous study (Tuanmu et al., 2010) shows that remotely sensed vegetation phenology can provide timely and rich vegetation information, including the distribution of understory species such as bamboo, a crucial determinant of panda habitat. Therefore, as compared with other panda habitat modeling methods that ignored bamboo distribution (e.g., Liu et al., 2001) or utilized temporally mismatched bamboo data (e.g., Xu et al., 2009), including vegetation phenology information in habitat modeling can provide a more reliable estimation of panda habitat. Specific objectives of this study are to assess the performance of our habitat change mapping approach at the range-wide scale, map the distribution of panda habitat in the periods from 2001 to 2003 and from 2011 to 2013, and evaluate changes in

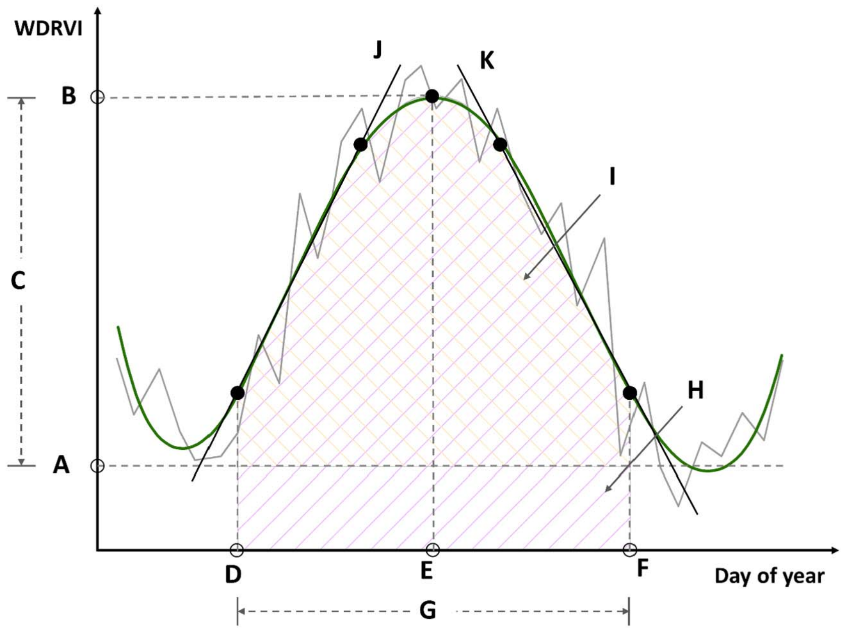

Fig. 2. Illustration of the phenology metrics derived from the annual dynamic curve of the wide dynamic range vegetation index (WDRVI). The solid gray and green lines represent the dynamics of WDRVI before and after smoothing, respectively. The phenology metrics (A–K) are calculated based on the smoothed WDRVI dynamic curve. A, base level; B, maximum level; C, amplitude; D, date of the start of the season; E, date of the middle of the season; F, date of the end of the season; G, length of the season; H, large integral; I, small integral; J, increase rate; and K, decrease rate. This figure is modified from Fig. 2 in Tuanmu et al. (2010).

habitat suitability, extent, and degree of fragmentation.

2. Materials and methods

2.1. Study area

Our study area encompasses six mountain regions (Minshan, Qinling, Qionglai, Liangshan, Daxiangling, and Xiaoxiangling) in Gansu, Shaanxi and Sichuan provinces, which cover the entire geographic range of the giant panda, a total area of about 125,170 km^2 (Fig. 1). This region is characterized by high mountains and deep valleys (elevation ranging from 70 m to 6250 m), with high variation in climatic (e.g., temperature) and physical (e.g., soil type) conditions (Viña et al., 2010). The rich flora and fauna in this region make it one of the most biologically diverse in the world (Myers et al., 2000). Besides this rich biodiversity, there are over 10 million people living in the region, most of whom are farmers (State Forestry Administration, 2015a). The encroachments of human activities (e.g., agricultural expansion, logging, fuelwood collection, livestock rearing, road construction for tourism and transportation) into panda habitat have been major threats to panda survival (Hull et al., 2011; Liu et al., 2012; Wei et al., 2015). To address this issue, the Chinese government implemented a set of conservation policies to protect and restore panda habitat, such as the aforementioned establishment of nature reserves, together with payment for ecosystem services programs (i.e., NFCP and GTGP) (Liu et al., 2016; Wei et al., 2015).

2.2. Mapping spatiotemporal changes of giant panda habitat

2.2.1. Mapping approach

It is difficult to determine whether the absence of giant pandas – or lack of evidence of pandas – means a particular place is not suitable panda habitat. To more accurately evaluate panda habitat suitability we chose the presence-only Maximum Entropy (Maxent) modeling framework (Phillips et al., 2006). As compared to other habitat modeling methods, Maxent exhibits higher predictive accuracy (Elith et al., 2006; Phillips et al., 2006). It estimates the probability of a species presence by finding a probability of maximum entropy (i.e., maximum uniformity) where the expected value of each predictor variable matches the empirical average of known occurrence locations (Phillips et al., 2006). The output of Maxent is an occurrence probability map that can be interpreted as a habitat suitability index (HSI), ranging from 0 (unsuitable) to 1 (perfectly suitable).

In this study, we trained a panda habitat model with 3239 panda presence locations randomly selected from the presence dataset collected in the third panda survey, together with remotely sensed environmental predictors (see the following section) for the 2001 to 2003 period at these panda presence locations. The model was then applied to remotely-sensed environmental predictors across the entire range of giant panda for the 2001 to 2003 and 2011 to 2013 periods to map habitat suitability and to evaluate habitat change.

2.2.2. Remotely sensed environmental predictors

We generated a set of environmental variables for panda habitat prediction, including vegetation phenology metrics derived from time-series Moderate Resolution Imaging Spectroradiometer (MODIS) imagery (eight-day L3 Global 250 m product, MOD09Q1) and elevation information from the Shuttle Radar Topography Mission (SRTM). The spatial resolution of the elevation data (30 m/pixel) was resampled to 250 m using the bilinear interpolation algorithm. Previous studies show that the vegetation phenology captured by the MODIS imagery, together with elevation, can provide crucial information on the determinants of panda habitat (e.g., forest cover, bamboo presence, topography) (Hull et al., 2016; Tuanmu et al., 2010; Tuanmu et al., 2011).

We acquired the time-series MODIS imagery between 2001 and 2003, and between 2011 and 2013. We then calculated the wide dynamic range vegetation index (WDRVI) (Gitelson, 2004) for each eight-day composite image. Unlike other vegetation indices (e.g., normalized difference vegetation index), the WDRVI exhibits less saturation under conditions of high vegetation biomass and is therefore more suitable for detecting phenologic change in areas with high vegetation biomass, such as our study region (Gitelson, 2004; Tuanmu et al., 2010). We then used TIMESAT 3.2 (Jönsson and Eklundh, 2007) to generate annual dynamic curves of the WDRVI. To minimize the impacts of pixels with poor data quality, we weighted the WDRVI curves using the data quality information of the MOD09Q1 product as suggested by Jönsson and Eklundh (2007). Based on the shape of the WDRVI dynamic curves, we obtained 11 phenology metrics for each year, including the base level, maximum level, amplitude, date of the start of the season, date of the middle of the season, date of the end of the season, length of the season, large integral, small integral, increase rate, and decrease rate (Fig. 2) (Jönsson and Eklundh, 2007; Tuanmu et al., 2010). The three-year averages of these phenology metrics from 2001 to 2003 and from

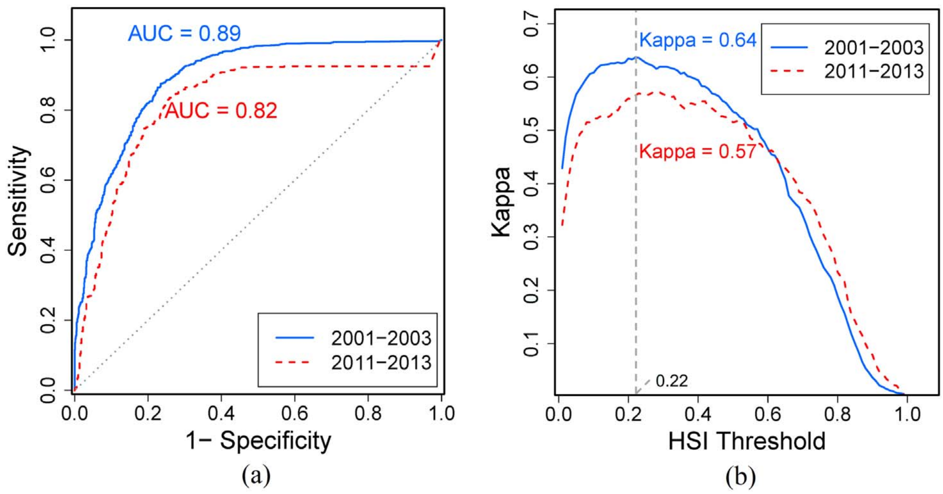

Fig. 3. Results of the validation procedures: (a) The area under the receiver operating characteristic curve (AUC) and (b) Kappa. The optimal HSI threshold to differentiate habitat pixels from non-habitat pixels was selected to be 0.22 as it maximizes the Kappa value of the 2001–2003 binary habitat map. The Kappa values corresponding to this threshold (0.64 for the 2001–2003 binary habitat map and 0.57 for 2011–2013 binary habitat map) represent these binary habitat maps' accuracies.

2011 to 2013 were used as our phenology predictors for mapping panda habitat.

2.2.3. Validation and classification

We evaluated the accuracy of the two habitat suitability maps from 2001 to 2003 and from 2011 to 2013 using the receiver operating characteristic (ROC) curve (Hanley and McNeil, 1982). The ROC analysis is a common method for evaluating the accuracy of classification results (Fielding and Bell, 1997). The area under the ROC curve (AUC) provides a good measure of habitat prediction accuracy, with its value ranging from 0 to 1. Normally, a habitat map's accuracy is considered good when AUC > 0.8 (Boyce et al., 2002). Although accurate AUC estimation requires both presence and absence data, we calculated AUC values by using locations randomly selected from the study area (i.e., background locations) as approximations of absence data as suggested by Phillips et al. (2006). Therefore, the AUC values calculated represent conservative estimates of the accuracy of our habitat suitability maps. We performed the ROC analysis to evaluate the habitat suitability map corresponding to the period from 2001 to 2003 with the remaining 1079 giant panda presence records from the third panda survey and the same amount of random background locations. Similarly, we evaluated the habitat suitability map corresponding to the period from 2011 to 2013 with another ROC analysis using 534 giant panda presence records from the fourth panda survey and 534 randomly selected background locations.

To evaluate the areal change of panda habitat, it was necessary to find a threshold to convert the continuous HSI value into a binary value representing either habitat or non-habitat areas. We chose this optimal threshold as the one that maximized the index of Kappa when applied to all possible HSI thresholds. The Kappa index is a common measure used to assess the accuracy of a categorical map (Cohen, 1960). The value of Kappa ranges from 0 to 1 and a categorical map is considered accurate if its Kappa > 0.4 (Araújo et al., 2005). We first determined the optimal threshold (i.e., the HSI value that can maximize the Kappa value of the corresponding binary habitat map) to partition the 2001–2003 habitat suitability map using the same validation dataset for the ROC analysis. We then applied the threshold to partition the 2011–2013 habitat suitability map and calculated the corresponding Kappa value using the aforementioned 534 presence records and 534 random background locations to evaluate the binary habitat map's accuracy.

2.3. Habitat change analyses

To evaluate the change in panda habitat quality, we calculated the difference in HSI for every pixel across the study area between the two periods from 2001 to 2003 and from 2011 to 2013. In addition, besides the total areal change of panda habitat (after thresholding the HSI), we also assessed the change in the area of all habitat patches that are large enough to support a local panda population. Previous studies have shown that for many wildlife species, including the giant panda, habitat patches of small size often cannot support the long-term survival of a local population (Qing et al., 2016; Wang et al., 2010). For giant panda, Qing et al. (2016) estimated that the minimum habitat patch size required to support a local population is 114.7 km^2 (Qing et al., 2016). Therefore, we calculated the total area of habitat patches larger than 114.7 km^2 and evaluated its change with the two binary habitat maps corresponding to 2001 to 2003 and 2011 to 2013.

To evaluate the outcome of China's forest conservation efforts outside nature reserves, we compared the proportional change in habitat area inside and outside panda nature reserves. It is normally expected that habitat areas outside nature reserves experience larger negative effects than those inside them due to more pronounced human disturbances (Watson et al., 2014). Therefore, if a comparable or higher proportional habitat growth is observed outside panda nature reserves, we hypothesize that China's conservation efforts achieved success at protecting the habitat of giant panda beyond nature reserves.

To evaluate the change in panda habitat fragmentation, we calculated the clumpiness index using the software FRAGSTATS (McGarigal et al., 2002). The value of this index ranges from − 1 to 1, with a lower value indicating a higher level of fragmentation. This index is independent of habitat area, making it suitable for comparing the degree of habitat fragmentation across different periods (Neel et al., 2004). Since different mountain regions may have different biophysical and socioeconomic conditions, we also performed the evaluation analyses mentioned above in each of the six mountain regions within the panda's geographic range to understand the spatial variation in panda habitat change.

3. Results

Our validation results (Fig. 3) show that both the continuous habitat suitability maps and the binary habitat maps have high accuracy, suggesting that our habitat model developed with data collected from 2001 to 2003 can be reliably used to map habitat distribution not only from 2001 to 2003 but also from 2011 to 2013. The AUC values (Fig. 3(a)) corresponding to the two habitat suitability maps are 0.89 and 0.82 respectively, both are larger than the threshold of 0.80, indicating good mapping accuracies. The optimal HSI threshold that maximizes the capacity to differentiate habitat pixels from non-habitat pixels based on the Kappa analysis is 0.22 (Fig. 3(b)). The corresponding Kappa values for the 2001–2003 and the 2011–2013 binary habitat maps are 0.64 and 0.57 respectively, both larger than the threshold of 0.40, indicating our binary habitat maps are also accurate.

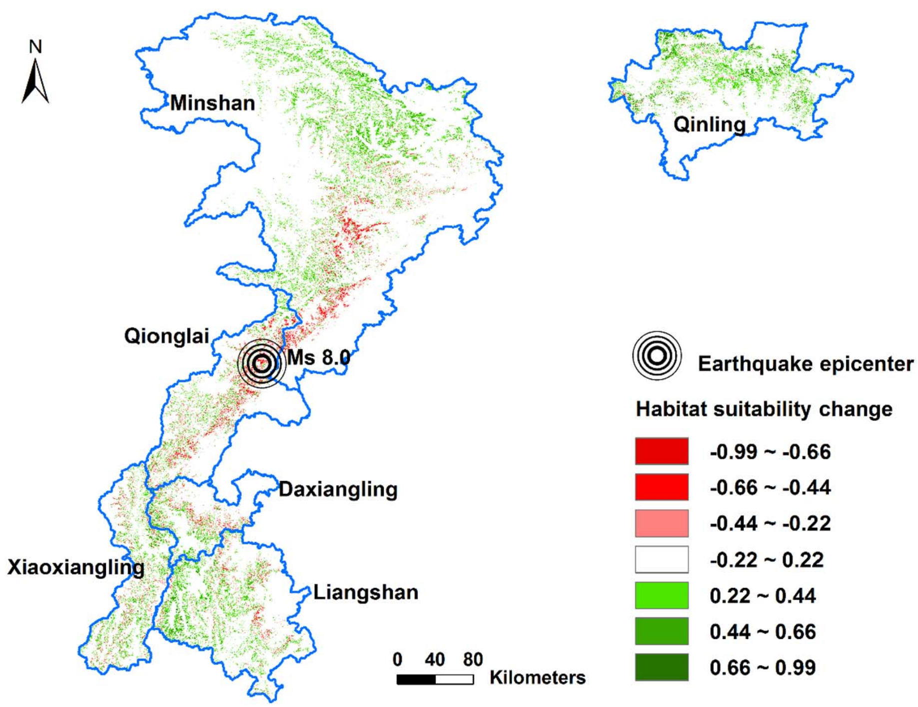

Fig. 4. Change in habitat suitability index values between 2001-2003 and 2011–2013. Also shown is the epicenter of the 2008 Wenchuan Earthquake which caused landslides and losses in forest cover and panda habitat.

The habitat suitability change results (Fig. 4) show that the overall habitat quality was enhanced across the entire geographic range, although some degradation occurred in the Qionglai and the southern Minshan regions. A conspicuous habitat suitability increase (HSI change > 0.22) was observed in an area of 11,231 km^2, which is almost three times larger than the area (4212 km^2) that experienced a significant suitability decrease (HSI change < − 0.22). The suitability improvement mostly occurred in the northern (Qinling and northern Minshan) and southern (Xiaoxiangling and Liangshan) regions of pandas' geographic range while habitat degradation mostly concentrated in the central part of the geographic range (Qionglai and southern Minshan). The latter can be explained by the devastating Wenchuan Earthquake of 2008 and its associated landslides (Ouyang et al., 2008).

The results of the areal changes in panda habitat (Fig. 5(a)) show that except in the Qionglai mountain region, all other mountain regions experienced an increase in panda habitat area. Across the entire range, the habitat area increased by about 5765 km^2 (19.8%). Minshan, Qinling, and Liangshan experienced the largest amount of habitat areal increase (92.1% of the total areal increase), while Qionglai experienced an opposite trend with a loss of about 6.4% (about 316 km^2).

The total area of habitat patches with a size large enough to support a local panda population (path area > 114.7 km^2) shows similar change patterns (Fig. 5(b)). Across the entire geographic range, this area increased by about 5271 km^2 (22.6%). Except Qionglai [which decreased by 491 km^2 (10.6%)], all mountain regions experienced an increase in this total habitat patch area (ranging from 280 km^2 in Daxiangling to 2238 km^2 in Minshan).

Our results (Fig. 5(c)) also indicate that China's conservation efforts achieved success beyond the boundaries of nature reserves. Across the entire geographic range, the proportional increase of habitat outside panda nature reserves (25.7%) was higher than inside them (10.6%). All five mountain regions that experienced habitat areal growth show a consistent pattern: the habitat proportional growth outside nature reserves was higher than inside them. Even in the Qionglai mountain region which experienced habitat loss, the percentage of habitat decrease outside panda nature reserves (4.6%) was lower than inside them (9.7%).

Despite these promising trends, our results (Fig. 5(d)) show that habitat fragmentation remains a threat to the pandas' long-term survival. Across the entire geographic range, the clumpiness index has slightly decreased from 0.76 (2001 to 2003) to 0.75 (2011 to 2013), indicating a slight increase in habitat fragmentation. Qionglai experienced the most severe habitat fragmentation, where the clumpiness index decreased from 0.78 (2001 to 2003) to 0.74 (2011 to 2013). Only Xiaoxiangling showed a reduction in habitat fragmentation since the clumpiness index increased from 0.67 (2001 to 2003) to 0.69 (2011 to 2013).

4. Discussion

To achieve biodiversity protection objectives such as those targeted by the Aichi Biodiversity Targets (Secretariat of the C.B.D., 2010) and Sustainable Development Goals (United Nations, 2015), the conservation community needs a better understanding of wildlife habitat change across the entire geographic ranges in order to design effective conservation efforts (O'Connor et al., 2015). Our study illustrates that the integration of remotely derived vegetation phenology information and habitat modeling constitutes a suitable tool to efficiently obtain this crucial information across entire geographic ranges of wildlife species. Although our illustration here focuses on evaluating habitat change of giant panda, the approaches may be easily applied to many other species as vegetation phenology captures rich information for characterizing wildlife habitat. Previous studies show that vegetation phenology can not only differentiate land-cover types, but also can reflect some vegetation attributes (e.g., floristic composition) and extreme events (e.g., drought) that are common determinants of wildlife habitat (Anderson et al., 2010; Tuanmu et al., 2010; Viña et al., 2016a; Viña et al., 2012). Even when species presence data are available only for a single period, our results show that the trained habitat model using remotely sensed data can reliably be used to predict wildlife habitat distribution across different time periods. This is important because repeated field surveys across broad geographic regions are often unavailable for many endangered species due to time constraints and financial costs (Tuanmu et al., 2011).

Findings from our range-wide analysis also provide valuable information to assess the appropriateness of the IUCN's recent decision that down-listed the giant panda from an endangered to a vulnerable

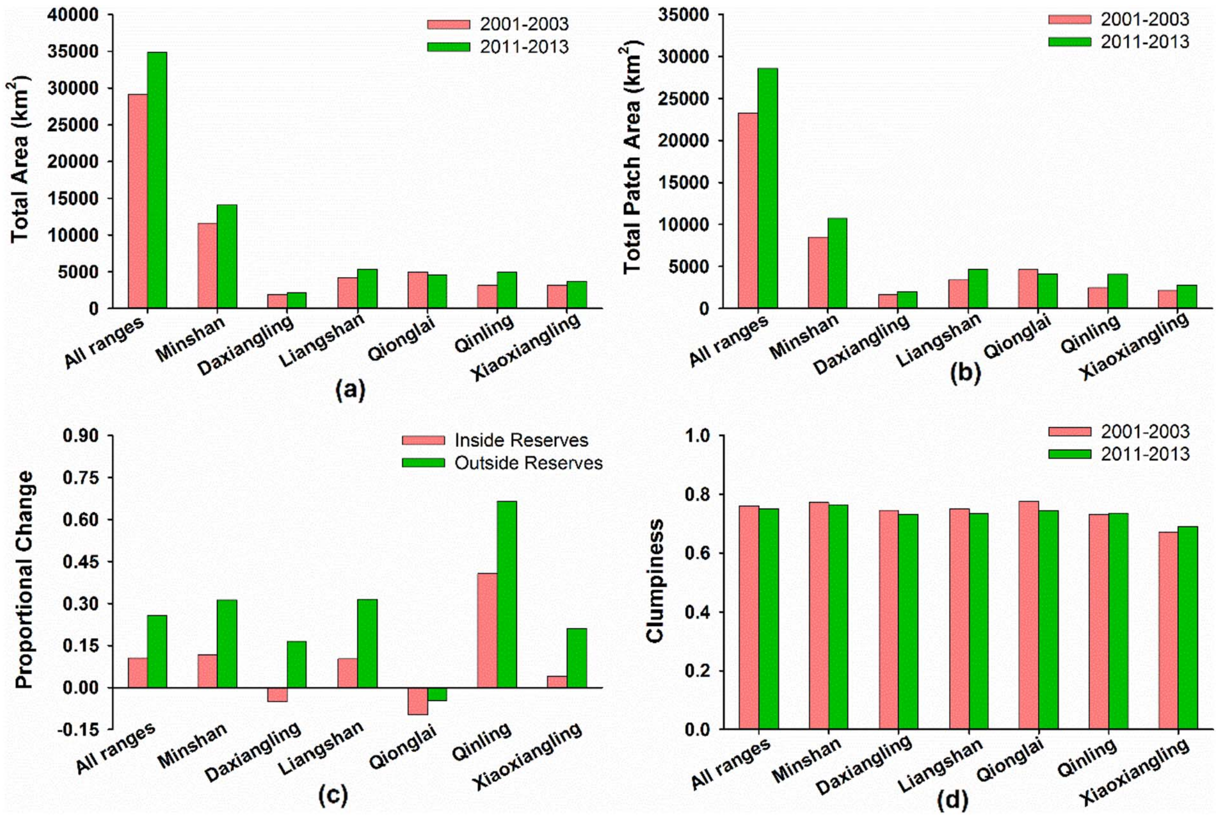

Fig. 5. Results of giant panda habitat change analyses across the entire geographic range and in each of the mountain regions between 2001-2003 and 2011–2013: (a) areal change of panda habitat; (b) areal change of the patches with sizes larger than 114.7 km^2; (c) Proportional change of panda habitat inside and outside panda nature reserves; and (d) changes in the degree of habitat fragmentation as measured by the clumpiness index.

species. Our results show that while there are reasons to celebrate the panda conservation successes over the past few years, there are still threats to the giant pandas' long-term survival. We empirically confirmed the expanding trend of panda habitat found in the fourth panda survey. Across the entire geographic range, both the total habitat area and the area of habitat patches that meet the criteria to support a local panda population increased. In addition to this increase, we also found improved suitability of giant panda habitat. Our results show that 11,231 km^2 of the land across the pandas' geographic range experienced a significant improvement in habitat suitability. Besides being larger than the habitat area that was degraded, this suitability-improved area is almost twice as large as the total habitat areal increase (5765 km^2), which indicates that habitat suitability increases occurred not only in areas that were unsuitable for pandas during 2001 to 2003 but also in areas that were already suitable then.

However, our results also show that the degree of habitat fragmentation during 2011 to 2013 was higher than during 2001 to 2003 when the giant panda was still listed as an endangered species. There are both human and natural factors driving this issue. Although many types of human disturbances (e.g., logging and fuelwood collection) have been reduced due to China's conservation efforts (Viña et al., 2016b; Yang et al., 2013), other human disturbances (e.g., livestock husbandry, construction of roads and dams) are still common (State Forestry Administration, 2015a; Zhang et al., 2017). Tectonic activity further exacerbated the habitat fragmentation (Viña et al., 2011; Zhang et al., 2011). Due to the steep topographic characteristic of the region, the 2008 Wenchuan Earthquake and associated landslides caused conspicuous losses of panda habitat, leading to more habitat fragmentation (Xu et al., 2009).

A better understanding of panda habitat change across the entire geographic range lays a good foundation for the design of future conservation efforts. For example, to address the continuing threat of habitat fragmentation, future conservation efforts should focus more on establishing corridors, especially in the regions where fragmentation has increased over the past decade (e.g., southern Minshan and Qionglai). Our evaluation also suggests that conservation in areas outside panda nature reserves deserves more support in the future. Although panda nature reserves received more conservation investments, our results show that the proportional habitat growth outside them was higher. This pattern occurred perhaps because nature reserves were often established in areas with more panda habitat (Viña and Liu, 2017) and thus have less room for habitat improvement than outside areas. As human disturbances were reduced by the NFCP and GTGP, the proportional growth of panda habitat outside nature reserves would be higher than inside them. The gains of suitable habitat outside nature reserves are important as they may help connecting isolated habitat patches and increase the area that giant pandas can utilize.

Despite the expanding global conservation efforts, biodiversity loss is continuing in many parts of the world (Butchart et al., 2010). We hope that range-wide evaluations of wildlife habitat like the one described in this study will help to establish a better understanding of habitat change for many other species around the world. Armed with such knowledge, scientists and conservation practitioners may be able to better identify conservation priorities and develop effective conservational strategies to ensure the long-term survival of wildlife species and reduce if not halt the biodiversity decline around the world.

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