

The impacts of climate change on the wintering distribution of an endangered migratory bird

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Abstract There is now ample evidence of the effects of anthropogenic climate change on the distribution and abundance of species. The black-faced spoonbill (*Platalea minor*) is an endangered migratory species and endemic to East Asia. Using a maximum entropy approach, we predicted the potential wintering distribution for spoonbills and modeled the effects of future climate change. Elevation, human influence index and precipitation during the coldest quarter contributed most to model development. Five regions, including western Taiwan, scattered locations from eastern coastal to central mainland China, coastal areas surrounding the South China Sea, northeastern coastal areas of Vietnam and sites along the coast of Japan, were found to have a high probability of presence and showed good agreement with historical records. Assuming no limits to the spread of this species, the wintering range is predicted to increase somewhat under a changing climate. However, three currently highly suitable regions (northeastern Vietnam, Taiwan and coastal areas surrounding the South China Sea) may face strong reductions in range by 2080. We also found that the center of the

predicted range of spoonbills will undergo a latitudinal shift northwards by as much as 240, 450, and 600 km by 2020, 2050 and 2080, respectively. Our findings suggest that species distribution modeling can inform the current and future management of the black-faced spoonbill throughout Asia. It is clear that a strong international strategy is needed to conserve spoonbill populations under a changing climate.

Keywords Climate change · Black-faced spoonbill (*Platalea minor*) · East Asia · Maxent · Species distribution modeling · Species' range shift · Wintering distribution

Introduction

In recent decades, the Earth's climate has undergone dramatic change and there is strong evidence of pending and profound changes resulting from human activities (Solomon et al. 2007). Rapid climate change leaves a clear fingerprint on global biodiversity (Gregory et al. 2009) and is a major issue for conservationists (Peterson et al. 2002; Thomas et al. 2004). For example, evidence is accumulating that climatic change has already altered the distributions of many species (Parmesan et al. 1999; Hickling et al. 2005) and that more change is inevitable (Maclean et al. 2008; Anderson et al. 2009).

Adequate conservation not only requires detailed knowledge of a species' natural history and biology but also information on the availability of suitable habitat. These data are invaluable to conservation planning and the selection of protection areas (Papeş and Gaubert 2007). There is a growing consensus that conservation strategies for managing biodiversity must take the impacts of climate

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change into consideration (Araújo et al. 2004; Hole et al. 2009). For this purpose, species distribution modeling (i.e., niche or habitat potential distribution modeling) has been suggested as an effective tool to assess the potential geographic distributions of species (Guisan and Thuiller 2005; Elith et al. 2006; Hu and Jiang 2010). Rapid progress in this area of prediction has been made and tools are now available to assess the impacts of climate change on species (Peterson et al. 2002; Hijmans and Graham 2006). A complete comparison of current and future predicted distributions of species enables conservationists to more fully develop conservation and project plans (Araújo and Rahbek 2006).

The black-faced spoonbill (*Platalea minor*) is a migratory species endemic to East Asia (del Hoyo et al. 1992). It is known to breed on islands off the Korean Peninsula (Ueta et al. 2002) and Liaoning province, China (Ding et al. 1999), and winter along the coasts of China, Japan, Vietnam and the Philippines (BirdLife International 2008). This species was described as ‘common’ in Asia prior to the 1950s (La Touche 1931–1934; Austin 1948), but by 1988, the worldwide population was only 288 individuals and it was listed as critically endangered by the International Union for Conservation of Nature (IUCN). In 2008, the population was estimated to be approximately 2,000 individuals and has since been reclassified as endangered (BirdLife International 2008; Yu 2009).

The survival of migratory species depends on the conservation and protection of not only breeding grounds but also of stop-over sites and wintering grounds (Bibby 2003; Walther et al. 2007). Given the annual movements of migratory avian species, which can sometimes span continents, their conservation is faced with a number of additional problems. For example, it is increasingly important to understand how black-faced spoonbills adapt to large-scale disturbance conditions, which are highly unpredictable in space and time and spread across multiple jurisdictions (Brown et al. 1999; Sæther et al. 2000). Due to a lack of baseline data, population dynamics and the actual distribution of this species remain unclear (BirdLife International 2008). To investigate the wintering distribution for black-faced spoonbills and how this may be impacted by climate change, we used species distribution modeling. Specifically, we asked: what environmental factors affect the wintering distribution? Where are spoonbills more likely to be found in winter? And will anthropogenic climate change alter current suitable wintering habitats? Through the models, we generated a suitability map of the current wintering distribution of spoonbills, and then predicted the future impacts to suitable habitat under climate change scenarios for 2020, 2050 and 2080. Our study will guide future field sampling and surveys and inform relevant policy makers and conservation

authorities of the potential vulnerabilities of this important species to climate change (Gregory et al. 2009).

Materials and methods

Study area and species occurrence data

The study area included the entire distribution range of black-faced spoonbills. To develop our models, we used 46 wintering records from international census conducted between 2003 and 2008 (Yu 2003, 2004, 2005, 2009; Yu and Wong 2006, 2007), and geo-referenced these localities using Global Gazetteer 2.2 (Falling Rain Genomics, Palo Alto, USA) and Google Maps (Google, Mountain View, USA).

Eco-geographic predictors

We used eight ecogeographic predictor variables across four types of data: (1) *Topography*: elevation and the compound topographic index (CTI, commonly referred to as the wetness index, a function of the upstream contributing area and the slope of the landscape), from the Hydro1 K dataset (USGS 2009). (2) *Climate*: annual mean temperature (ANMT), minimum temperature of the coldest month (MTCM), annual precipitation (ANPR) and precipitation of the coldest quarter (PRCQ) from WorldClim 1.4 (Hijmans et al. 2005). The choice of climate predictors reflected energy and water constraints on the distribution range of birds. These variables, on the basis of prior knowledge, impose known constraints upon species distributions as a result of widely shared physiological limitations (Crick 2004; Coetzee et al. 2009). (3) *Habitats*: land cover layer (GLC 2003). (4) *Human impact*: human influence index (HII, produced through incorporating four data types as proxies for human influence: human settlement, land transformation, accessibility and electrical power infrastructure). Data values range from 0 to 64, corresponding to no or maximum human influence on habitat (Last of the Wild Data Version 2 2005). All predictors were re-sampled to the resolution of a grid cell of $0.1^\circ \times 0.1^\circ$.

To model the wintering range of black-faced spoonbills in the future, we extracted the above climate predictors for the years 2020, 2050 and 2080 across three general circulation models (CCCMA: CGCM2, CSIRO: MK2 and HADCM3) and two Intergovernmental Panel on Climate Change Special Report Emissions Scenarios (SRES; A2a and B2a; IPCC 2001). We considered these the most advanced simulations available of global climate system responses to increased greenhouse gas concentrations. There was no future dataset available for HII or land cover and, because they are impacted upon by a large number of

socio-economic drivers, we felt any simple estimation, such as an extrapolation of past trends for these two factors, was likely to be misleading. We therefore used the current datasets for HII and land cover as conservative prognoses for the future, thus limiting any additional uncertainty (Thuiller et al. 2006).

Model building

To model our target distribution, we used a maximum entropy approach (Maxent) which is a recently developed general-purpose machine learning method (Phillips et al. 2006; Phillips and Dudík 2008). Maxent uses presence-only occurrence data and has been shown to consistently outperform some other presence-only methods such as Bioclim and Domain and presence–absence methods such as GAM, GLM and GARP, particularly for small sample sizes (Elith et al. 2006; Hernandez et al. 2006). To estimate the target distribution, Maxent fulfills a set of constraints representing the incomplete information on the distribution and that, subject to those constraints, maximizes the entropy of the probability distribution. Within the approach, given a study area composed of k pixels, a set of sample points x_1, \dots, x_m representing occurrence data and a set of features f_1, \dots, f_n representing environmental predictors or functions, each feature f_j assigns a real value $f_j(x_i)$ to each point x_i , which is, for example, elevation of point x_i . As the probability distribution π is unknown, the empirical average of the feature f_j is therefore defined as

$$\pi(f_j) = \frac{1}{m} \sum_{i=1}^m f_j(x_i).$$

Maxent then estimates the probability distribution that maximizes

$$H = \max \left[- \sum_k p_k \times \ln(p_k) \right]$$

under the constraint that for each feature

$$f_j, \pi(f_j) - \sum_{i=1}^m p_k \times f_j(x_i) \leq \beta_j,$$

for some constants β_j (also known as regularization value) and

$$\sum_k p_k = 1.$$

where $p_k(x_i)$ is the probability assigned to each pixel (Phillips et al. 2006).

We implemented Maxent 3.3.1 (Phillips et al. 2006) and generally adhered to the default settings (regularization multiplier = 1, maximum iterations = 500, convergence

threshold = 10^{-5} , maximum number of background points = 10,000) for all models. Eighty percent of occurrence records were randomly selected by Maxent as training data and 20% reserved for model testing. We ran ten cross-validation replicates for each model scenario. Selection of ‘features’ (predictors) was carried out automatically, following the default rules dependent on the number of presence records. Additionally, we selected logistic output format making the model easier to interpret (Phillips and Dudík 2008). To explore the importance of each predictor, we carried out jackknife analyses of the regularized gain with training data.

We used the receiver operating characteristic (ROC) analyses as our reliability measurement when evaluating the predictive performance of our models. The area under the curve (AUC) of the ROC plot is a threshold-independent measure of model accuracy, which relates relative proportions of correctly classified (true positive proportion) and incorrectly classified (false positive proportion) cells over a wide and continuous range of threshold levels (Pearce and Ferrier 2000). It ranges from 0.5 for models with no discrimination ability to 1.0 for models with perfect discrimination (Fielding and Bell 1997). We calculated the average AUC of the ten cross-validations (mean \pm SD), which gives a more robust estimate of the predictive performance. To further validate the models, we projected the resulting model onto highly suitable areas. This manipulation was based on a set of geo-referenced occurrence records from the Red Data Book of threatened birds of Asia (BirdLife International 2009). These historical occurrences were plotted on the predicted map using ArcGIS 9.2 (ESRI, Redland, USA).

We had ten current distribution models and 180 future distributions [=10 models \times 18 projections (=3 global circulation \times 2 special report emission scenarios \times 3 time slices)]. We used an ensemble-forecasting approach (i.e., the use of multiple models) to reach a consensus scenario (Araújo and New 2007; Marmion et al. 2009).

In order to transform the results of our species distribution models from habitat suitability to presence–absence distribution, we used the average predicted probability of the model-building data as the threshold as it is considered a more robust approach (Liu et al. 2005). We considered areas with an occurrence probability above the threshold as ‘presence’ and those below as ‘absence’.

Spatial analysis of potential effects of climate change

We assessed the potential effects of climate change on predicted wintering ranges using three approaches. First, to evaluate potential range variation at the pixel level, we summed the potential range loss (RL) by pixel and related this to the predicted current range (CR) by pixel. The percentage of range gained (RG) by pixel (under the

assumption that the spoonbill could reach the new potential location, referred to as the full dispersal hypothesis hereafter) was assessed by the same procedure. We estimated the percentage of predicted range change using

$$C = 100 \times (RG - RL) / CR$$

and turnover by pixel under the assumption of migration using

$$T = 100 \times (RL + RG) / (CR + RG).$$

Second, we compared the current and future suitable range predicted with a formula that uncovers the maximal divergence among time slices:

$$\text{DIVERG}_{\max} = \max(|a - b|, |a - c|, |a - d|, |b - c|, |b - d|, |c - d|),$$

where $||$ was the absolute value of the difference between two time slices; max operator was the maximum of difference between time slices; a , b , c , and d represented current, 2020, 2050, and 2080 models in the sequence given.

Third, to explore distributional responses to climate change, we characterized trends in the predicted ranges of different time slices by their position (latitude and longitude of the predicted range center). The range center was calculated as the mean longitude and latitude of pixel cores where the species was predicted to be present. We estimated the distance and direction between current and future range centers. Under the full dispersal hypothesis, we assumed that the spoonbill would be able to move through the landscape without physiological or environmental impediments, a reasonable hypothesis for this species given its migratory and dispersal abilities (Ueta et al. 2002).

Results

Explanatory predictors

Jackknife analysis revealed that elevation, human influence index (HII) and precipitation of the coldest quarter (PRCQ) contributed most to model development when used in isolation (Fig. 1). In contrast, compound topographic index (CTI) and land cover made only small contributions to model development. The predictors that most strongly decreased the training gain when omitted were elevation, land cover and HII. Omitting annual precipitation (ANPR) had a negligible effect on gain (Fig. 1).

Predicted wintering distribution

The ROC analyses revealed that the model performed well with high predictive accuracy compared to the value

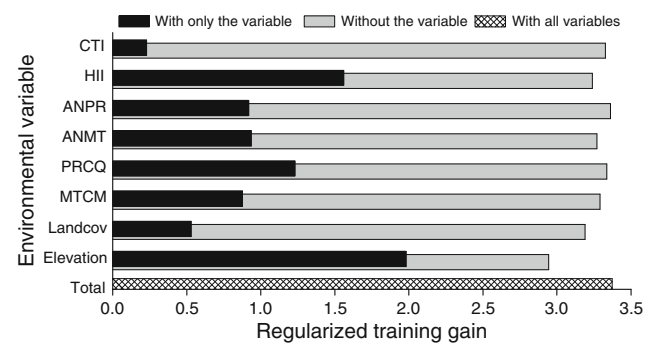


Fig. 1 Jackknife analyses of individual predictor importance for black-faced spoonbill (*Platalea minor*) applied to the Maxent model in relation to overall model quality or “total gain” (*grid bar*). *Black bars* indicate the gain achieved when including that predictor only and excluding remaining predictors; *gray bars* show how the total gain is diminished without the given predictor. *CTI* Compound topographic index, *HII* human influence index, *ANPR* annual precipitation, *ANMT* annual mean temperature, *PRCQ* precipitation of the coldest quarter, *MTCM* minimum temperature of the coldest month, *Landcov* land cover

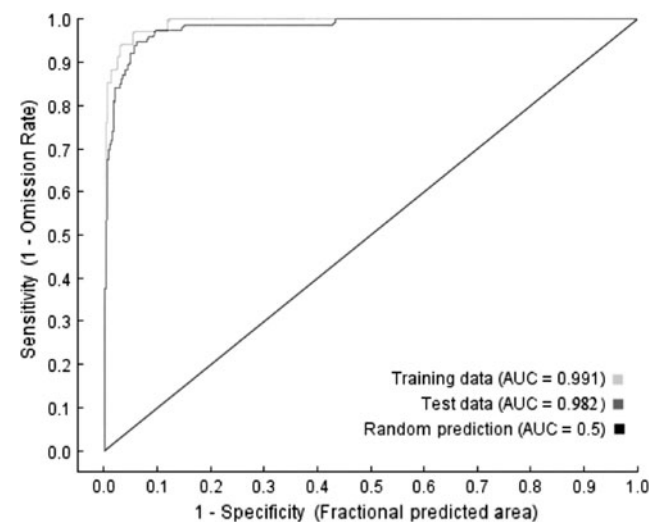


Fig. 2 Accuracy assessment of the Maxent model through the receiver operating characteristic (*ROC*) curve. Sensitivity equals the proportion of test localities correctly predicted as presence (1-extrinsic omission rate). The quantity (1-specificity) equals the proportion of all map pixels predicted to have suitable conditions for black-faced spoonbills

expected (0.5) from a random prediction (Fig. 2). It was supported by both training (mean = 0.9914 ± 0.0019) and test AUC values (mean = 0.9815 ± 0.0203).

Model outputs clearly identified five regions as containing highly suitable habitat for black-faced spoonbills: China (western Taiwan, scattered locations from eastern coastal to central mainland and coastal areas of the South China Sea), northeastern coastal areas of Vietnam and scattered locations along the coast of Japan (Fig. 3). In contrast, spoonbills were generally predicted as absent

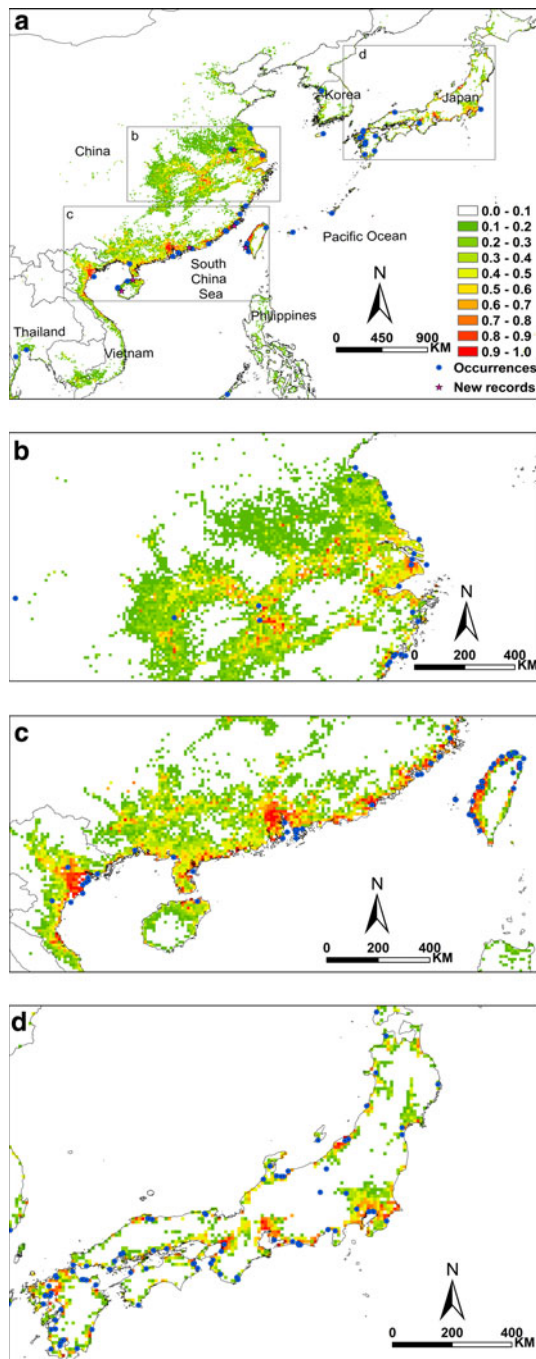


Fig. 3 Predicted probability wintering distribution maps for black-faced spoonbills across **a** their entire distribution, **b** eastern coastal to central mainland China, **c** western Taiwan, coastal areas of the South China Sea and Vietnam, and **d** Japan. Blue circles indicate current occurrence records in (a) and historical occurrence records in (b–d). Values range from 1.0 (highest probability) to 0 (lowest probability)

from most regions in the study area such as western and northern China.

Projection of the predicted wintering distribution indicated good agreement with historical occurrence records for the main regions identified as suitable (Fig. 3b–d). The

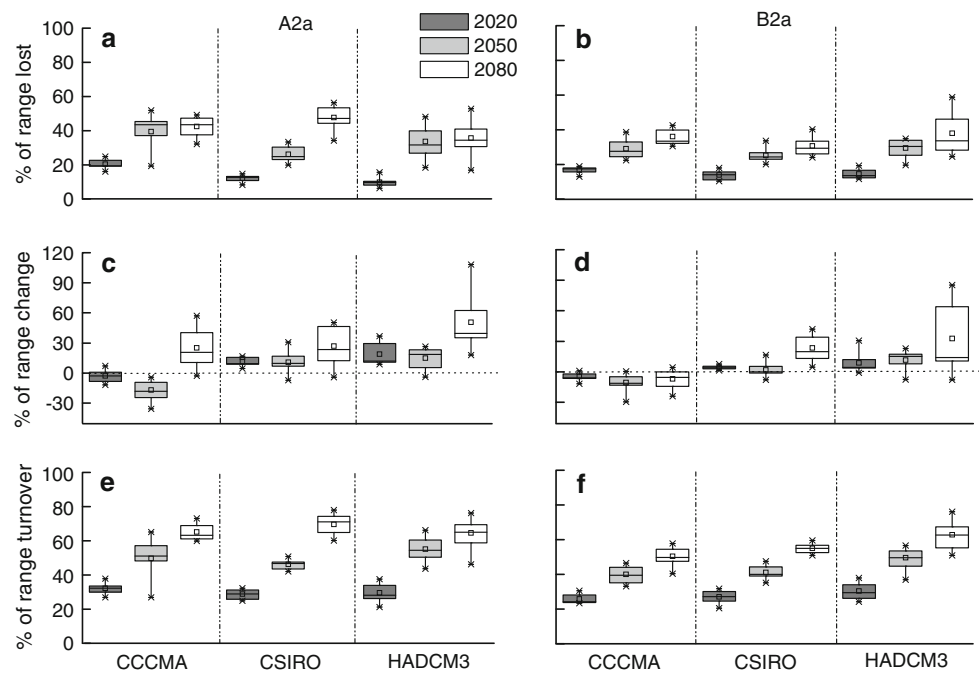
majority of these areas, including western Taiwan, coastal areas of the South China Sea, eastern coastal areas of Vietnam and Japan, showed desirable matching and contained sufficient records (Fig. 3c, d). The region of eastern coastal to central mainland China was predicted to contain numerous locations with a high probability of presence; however, central mainland China had few occurrence records (Fig. 3b).

Potential effects of climate change

The effects of climate change on the predicted wintering range were discernible (Fig. 4). For the general circulation models and special report emissions scenarios, it was clear that as the time horizon increased the strength of the effects from climate change increased. For the years 2020, 2050 and 2080, the average percentage of range loss was 15, 31 and 38%, respectively (Fig. 4a, b). However, the average percentage of range gain for the same years was 21, 32 and 64%. This gave an average percentage of turnover in range of 29% by 2020, 47% by 2050 and 61% by 2080 (Fig. 4e, f). Under the full dispersal hypothesis, small to moderate range increases were projected of 6% by 2020, 2% by 2050 and 25% by 2080. For the change in predicted range, an interesting pattern was found between the average percentage and model scenarios: under CCCMA-A2a for 2020 and 2050 and CCCMA-B2a across all three time slices a reduction in range was projected but under other model scenarios range was projected to increase (Fig. 4c, d).

Three key regions were identified as vulnerable to major losses of suitable habitat under future climate scenarios (Fig. 5). Northeastern Vietnam was predicted to experience a reduction in suitable habitat and therefore spoonbill range of 57%, Taiwan of 20% and coastal areas of the South China Sea (centred on Hainan and Guangdong) of 10% by 2020. This reduction in habitat was predicted to continue and by 2050 northeastern Vietnam will have lost 89%, Taiwan 37% and coastal areas of the South China Sea 59% of present spoonbill habitat. Modeled habitat loss by 2080 was extreme in these three areas as we found that climate change may result in a 98% reduction in the range of black-faced spoonbills in northeastern Vietnam, 61% in Taiwan and 85% across coastal areas of the South China Sea. Spatially explicit comparison across time slices revealed high divergence in certain areas and also consistently highlighted these three key regions as undergoing reductions in suitable habitat under future climate change scenarios (see $DIVERG_{max}$ in Fig. 5g, h). $DIVERG_{max}$ identified another small range disagreement among time slices for eastern coastal areas to central mainland China and this was due to predicted range gain under climate change in the future.

Fig. 4 Percentage of range loss, range change and range turnover as predicted using presence by pixel for 2020, 2050 and 2080 and the two storylines (A2a and B2a) under the three general circulation models (CCCMA, CSIRO and HADCM3). Solid line is median, square is mean, edges of box are quartiles and whiskers are 5th and 95th percentiles



The center of the predicted wintering range was found to shift in a northeasterly direction over time (Fig. 6). Compared to the model based on current data, the latitude of the center of the range was predicted to have moved northward approximately 240 km by 2020, 450 km by 2050 and 600 km by 2080.

Discussion

Potential wintering distribution

Our models indicated five regions that contain habitat of high suitability for black-faced spoonbill wintering, and these locations were consistent with historical occurrence records. While our models suggest that environmental conditions in areas of high suitability may be similar to known black-faced spoonbills locations, some areas did not overlap with historical occurrence records. For example, inland fresh waters systems of China hold scant records. This could be due to under sampling of the areas in question rather than a modeling weakness (Kaliontzopoulou et al. 2008). This species has been sighted at East Dongting Lake, Hunan, and in Nanchong City, Sichuan, and one specimen was collected at Caohai, Guizhou, from an elevation of approximately 2,300 m, but this isolated record was definitely marginal (Zheng 1998). A number of explanations may explain why some areas predicted as being highly suitable in the current model are currently unoccupied. For example, (1) large areas where this species is present, but has not been detected, could exist, (2) this

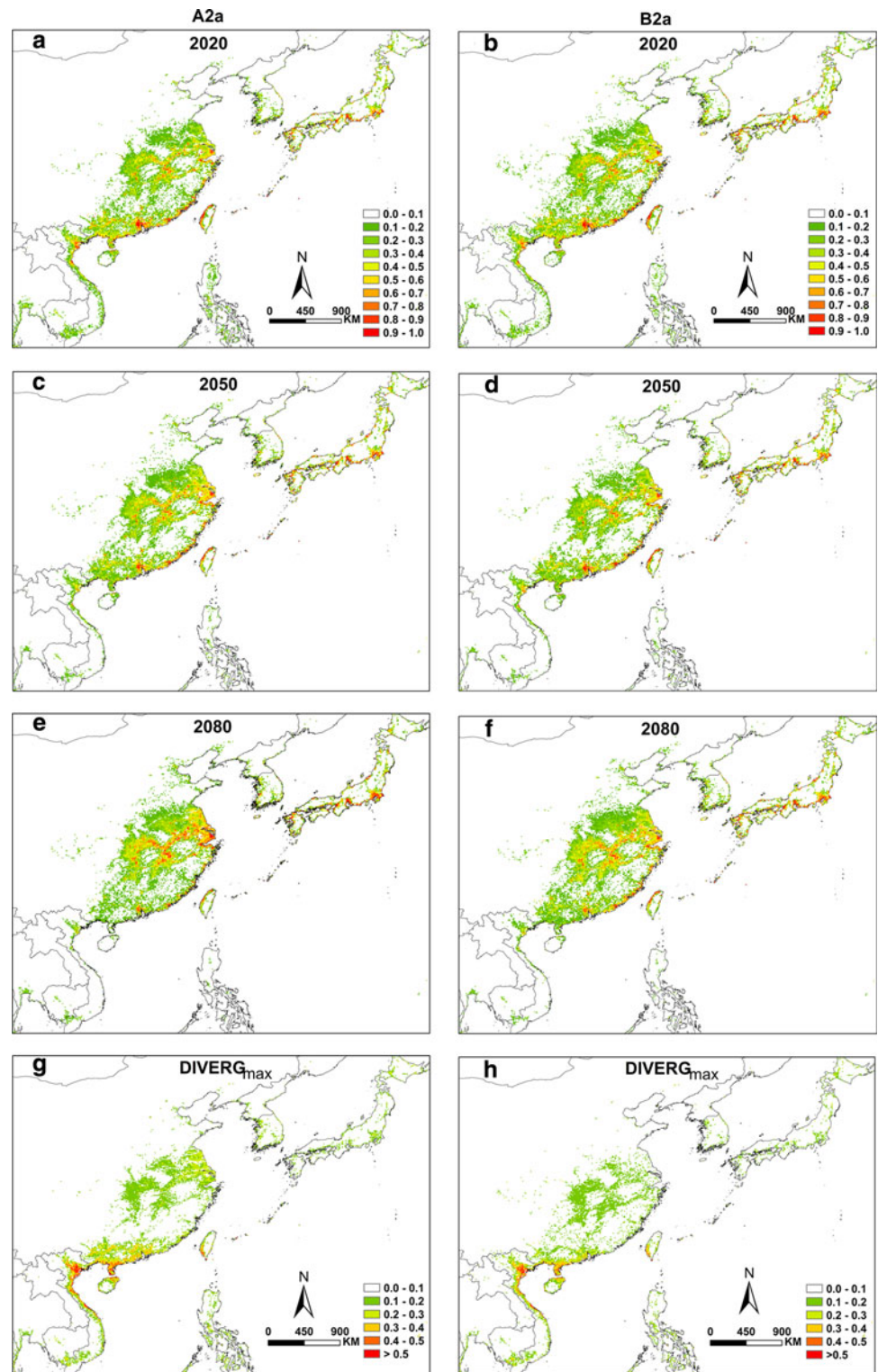
species has not currently occupied all potential suitable habitat due to insufficient recruitment, or (3) alternative reasons (e.g. predation pressure, interspecific competition) not captured in the model have limited its occurrence.

International censuses have investigated the spoonbill wintering population annually since 1993 (Yu 2009). New records were detected recently, such as at Bajhang Estuary, Houshui Bay, Beili Bay, Haifeng wetland, Xinghua Bay and Nanjing, China, and were part of increasing wintering populations along eastern and southern coastal areas of mainland China (Yu and Wong 2007; Hu et al. 2009; Yu 2009). In 2001, this species was also rediscovered in the Philippines (Mendoza et al. 2002). Zheng (1998) suggests that environmental conditions across a number of southern coastal areas in mainland China are similar to those of Tsengwen River estuary area, Taiwan, which hosts the largest wintering population of black-faced spoonbills. These areas reflect the potential expansion of the target wintering range and suggest that further new and important wintering sites/populations may be detected.

Potential effects of climate change

Given the overwhelming evidence that anthropogenic climate change will lead to massive species extinctions (Thuiller et al. 2006; Bässler et al. 2010), biologists need to predict the effects of these changes on the distributions of species (Araújo and Rahbek 2006). When environmental change occurs over short temporal and large spatial scales, vagile species are expected to move by tracking their climatic niches through time (Tingley et al. 2009). The

Fig. 5 Predicted probability wintering distribution range (a–f), obtained with an ensemble-forecast approach across the three general circulation models CCCMA, CSIRO and HADCM3 for three time slices (2020, 2050 and 2080) and the two storylines (A2a and B2a). Disagreement of the models among time slices (current, 2020, 2050 and 2080) estimated through maximal divergences ($DIVERG_{max}$) for A2a (g) and B2a (h)



present study supports the use of climatic niche modeling to predict future ranges of birds as a result of climate change (Walther et al. 2007; Hole et al. 2009; Tingley et al. 2009). As expected, our results revealed potential changes in the wintering range of black-faced spoonbills under

future climate change scenarios. Under a full dispersal assumption, the wintering range was projected to increase, but current suitable habitat will be lost and some areas will experience a reduction in spoonbill habitat by up to 98% by 2080.

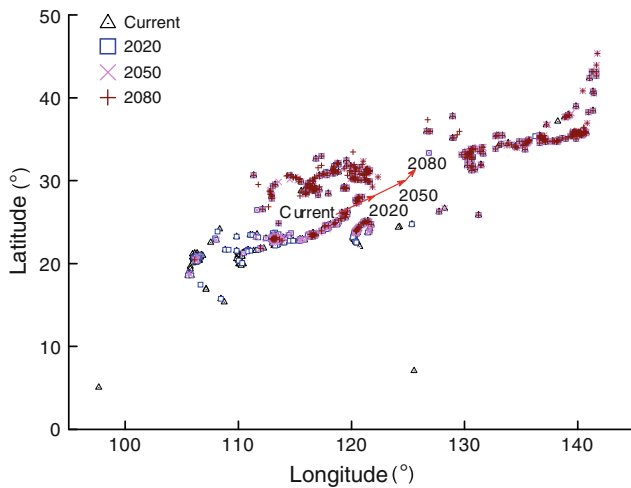


Fig. 6 Shift in wintering ranges as predicted for 2020, 2050, and 2080 under the full dispersal hypothesis. The vector chains are derived by linking a straight line through the location of the center of the wintering range (red) predicted for each time slice. The arrows are plotted such that the start and end points correspond to the locations of the centers predicted between two time slices

Bird species exhibit generally predictable responses to shifts in temperature and precipitation. Climate change may push some sites or populations closer to the centroid of their climatic niche and other sites or populations farther away (Tingley et al. 2009). In a similar manner to the range shifts that have occurred in European and North American winter avifauna (La Sorte and Thompson 2007; Maclean et al. 2008), our results provide broad-scale geographic evidence that the spoonbill may encounter a poleward shift in wintering range. Black-faced spoonbills are known to breed on the coastal islands of the Korean Peninsula (Ueta et al. 2002) and in Liaoning province, China (Ding et al. 1999). As proposed for other waders (Austin and Rehfisch 2005; Maclean et al. 2008), the spoonbill studied here may shift closer to its breeding grounds (Visser et al. 2009). If birds are wintering at higher northern latitudes, they will experience a different photoperiodic regime and this may in turn affect the timing of their spring migration to breeding grounds (Coppack et al. 2003; Murphy-Klassen et al. 2009). This is of concern because the timing of the arrival to breeding grounds is a key determinant of reproductive success, survivorship and fitness in migrating birds (Both and Visser 2001).

Climate change models and scenarios

Uncertainty surrounding the degree to which climate change will impact upon species presents a challenge for environmental management and policy making (Webster et al. 2003). Identifying and quantifying sources of variation is crucial to improve the reliability of projections of

shifts in species range (Thuiller 2004). Beaumont et al. (2008) suggest that uncertainty in species distribution model output may arise due to differences among alternate models, species characteristics and future climate scenarios. It is known that climate scenarios induce different results from species distribution models (McKenney et al. 2007; Barbet-Massin et al. 2009); however, little attention has been paid to the choice of climate scenarios incorporated into species distribution models. Selecting appropriate climate scenarios to reduce climate-related uncertainty in the output of these models is a necessity if we are to build reliable projections of a species' response to climate change (Beaumont et al. 2008).

Climate models are currently the strongest tools for simulating future climate scenarios. However, all climate models are not equally useful and contain a variety of uncertainties at all spatial and temporal scales (Beaumont et al. 2008). The models tested here disclosed potential effects of climate change on the spoonbill's wintering range. Based on our results, the severity of the three climate models with respect to predicted variation in wintering range was: HADCM3 > CCCMA > CSIRO. The CCCMA consistently predicted greater range loss than either CSIRO or HADCM3 over time; while HADCM3 predicted more range gain, range change and range turnover than either CCCMA or CSIRO. This indicates that the variance of the global circulation models can lead to important variation across the projected distributions of the focal species. As proposed by McKenney et al. (2007), we used the ensemble-forecast approach to obtain the central tendency when predicting the wintering range.

One method adopted by modelers looking at the impacts of climate change is to select future climate scenarios based on a conservative and an extreme emissions scenario (McKenney et al. 2007). Here, scenario A2a generally made predictions of wintering range with larger variations than the B2a scenario across the three time slices. This was not surprising, given that IPCC scenarios A2a and B2a reflect the potential impact of different assumptions about demographic, socio-economic and technological development on the release of greenhouse gases. The A2a scenario describes a heterogeneous world with both larger global population and greenhouse gas emissions than B2a (Nakicenovic and Swart 2000).

Modeling approach

Many studies have addressed the methodological details inherent in species distribution modeling, leading to refinements and a stronger framework (Peterson and Nakazawa 2008). When dealing with rare species, only a small number of occurrence records are available (Gibson

et al. 2007) and this affects model accuracy (Pearce and Ferrier 2000; Stockwell and Peterson 2002). Therefore, reducing the minimum number of sample localities required to build models would greatly increase the proportion of species to which this technique can be applied (Pearson et al. 2007). For example, in Mexico, ≥ 50 localities are available for 20% of bird species, ≥ 20 localities for 39% of species, ≥ 10 localities for 65% of species, and 88% of species would be included when reducing the requirement to ≥ 5 localities (Stockwell and Peterson 2002; Pearson et al. 2007). In this regard, Maxent outperforms other methods as it is accurate and stable across all sample-size categories tested (Elith et al. 2006; Hernandez et al. 2006). This was supported by our results which are highly accurate despite a relatively small sample size.

Sample biases resulting from survey accessibility (e.g., roads, towns and rivers) when estimating species distribution are of concern (Funk and Richardson 2002; Kadmon et al. 2004). Investigators might be more likely to visit and revisit areas that are considered to be rich in species (Dennis 2001). Additionally, since the original aim of the survey was to locate the species, site selection was largely based on historical occurrence records and consequent assumptions about habitat suitability, rather than being stratified to incorporate the full geographical variability of the region (Gibson et al. 2007). Black-faced spoonbills are rare and found at a small number of wintering sites. As some of these sites are difficult to approach, we need to acknowledge that some bias in our occurrence records may exist.

Two types of errors, omission (exclusion of areas inhabited) and commission (inclusion of areas not actually inhabited), often exist in species distribution models (Fielding and Bell 1997). Commission error seems to be more frequent than omission error in many circumstances (Thuiller et al. 2004; Elith et al. 2006). Insufficient sampling and ignoring the potential non-equilibrium distribution tend to increase the first type of error; failing to take into account interactions among species (mutualism, competition, and predation), anthropogenic disturbance, and other restricting factors could lead to a gap between real and predicted distributions resulting from both types of errors. Approaches that consider these processes will result in predictions of greater accuracy and provide better insight into specific factors restricting the distribution of rare species (Zhu et al. 2007). Here, the ROC plots in Maxent were generated using presence and randomly selected background samples, not pseudo-absences, and is one recognized solution to both types of errors (Phillips et al. 2006). Our high AUC value (>0.9) also suggests that our models performed well and that their ability to discriminate suitable habitat from random was high.

Conservation implications

A major objective in conservation planning is the identification of a network of representative areas which would allow the persistence of target species (Araújo and Williams 2000). A large proportion of the wintering population of black-faced spoonbills is confined to traditional sites in Taiwan and in the Pearl River Estuary (Yu 2009). Moreover, large tracts of the suitable areas identified here are under intense pressure from human activities and development. Expanding agriculture, aquaculture and industry has resulted in a rapid loss of estuaries, wetlands and tidal areas. For example, approximately 50% of the initial area of the Futian Nature Reserve in Shenzhen, Guangdong province, has been lost, and residential buildings have been built along the eastern border of Mai Po Nature Reserve in Hong Kong, China. Changes such as these may force black-faced spoonbills to smaller regions (Yeung et al. 2006). Some efforts such as securing existing protected areas and establishing new reserves should be undertaken in the five regions identified as containing suitable habitat for spoonbills in the current model. Austin and Rehfish (2005) and Maclean et al. (2008) suggest that overwintering migratory waders have already exhibited marked responses to a changing climate. It has also been clearly shown that climate change can drive species out of reserves if areas are not purposely selected to account for climate-change impacts on biodiversity (Araújo et al. 2004). Changes predicted in the black-faced spoonbill's wintering range here are, after all, only modeled predictions (Araújo and Rahbek 2006), but will be substantial for this endangered species. We suggest an integration of existing knowledge and future understanding of the likely effects of climate change when deciding on management plans and reserve design for black-faced spoonbills throughout Asia.

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