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Towards combining occurrence and abundance distribution models of Great Bustard for conservation: A global research template from Bohai Bay?

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Species distribution models (SDMs) have become important and essential tools in conservation and management. However, SDMs built with count data, commonly referred to as species abundance models (SAMs), are still less used so far. SDMs are increasingly used now in conservation decisions, whereas SAMs are still not widely employed. Species occurrence and abundance do not frequently display similar patterns, often they are not even well correlated. This leads to an insufficient or misleading conservation. How to combine information from SDMs and SAMs all together for unified conservation remains a challenge. In this study, we put forward for the first time a priority protection index (PI). The PI combines the prediction results of occurrence and abundance models. We used the best-available presence and count records for an endangered farmland species, Great Bustard (*Otis tarda dybowskii*) in Bohai Bay, China, as a case study. We then applied the advanced Random Forest algorithm (Salford Systems Ltd. implementation), a powerful machine learning method, with eleven predictor variables to forecast the spatial occurrence as well as the abundance distribution. The results show that the occurrence model had a decent performance (ROC: 0.77) and the abundance model had a RMSE 26.54. It is of note that environmental variables influenced bustard occurrence and abundance differently. We found that occurrence and abundance models display different spatial distribution patterns. Still, combining occurrence and abundance indices to produce a priority protection index (PI) used for conservation could guide the protection of the areas with high occurrence and high abundance (e.g. in Strategic Conservation Planning). Due to the widespread use of SDMs and the rel. easy subsequent employment of SAMs these findings have a wide relevance and applicability, worldwide. We promote and strongly encourage to further test, apply and update the priority protection index (PI) elsewhere in order to explore the generality of these findings and methods readily

available now for researchers.

Towards combining occurrence and abundance distribution models of Great Bustard for conservation: A global research template from Bohai Bay?

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ABSTRACT

Species distribution models (SDMs) have become important and essential tools in conservation and management. However, SDMs built with count data, commonly referred to as species abundance models (SAMs), are still less used so far. SDMs are increasingly used now in conservation decisions, whereas SAMs are still not widely employed. Species occurrence and abundance do not frequently display similar patterns, often they are not even well correlated. This leads to an insufficient or misleading conservation. How to combine information from SDMs and SAMs all together for unified conservation remains a challenge. In this study, we put forward for the first time a priority protection index (PI). The PI combines the prediction results of occurrence and abundance models. We used the best-available presence and count records for an endangered farmland species, Great Bustard (*Otis tarda dybowskii*) in Bohai Bay, China, as a case study. We then applied the advanced Random Forest algorithm (Salford Systems Ltd. implementation), a powerful machine learning method, with eleven predictor variables to forecast the spatial occurrence as well as the abundance distribution. The results show that the occurrence model had a decent performance (ROC: 0.77) and the abundance model had a RMSE 26.54. It is of note that environmental variables influenced bustard occurrence and abundance differently. We found that occurrence and abundance models display different spatial distribution patterns. Still, combining occurrence and abundance indices to produce a priority protection index (PI) used for conservation could guide the protection of the areas with high occurrence and high abundance (e.g. in Strategic Conservation Planning). Due to the widespread use of SDMs and the rel. easy subsequent

employment of SAMs these findings have a wide relevance and applicability, worldwide. We promote and strongly encourage to further test, apply and update the priority protection index (PI) elsewhere in order to explore the generality of these findings and methods readily available now for researchers.

Keywords: conservation decision, occurrence model, abundance model, Great Bustard (*Otis tarda dybowskii*), machine learning method, Random Forest

INTRODUCTION

The knowledge of species occurrence and abundance distribution makes for a fundamental information for conservation biology (VanDerWal et al., 2009; Drew et al., 2011; Primack, 2012; Johnston et al., 2015). Understanding how environmental factors are related to species occurrence and abundance distribution explicit in time and space represent a priority in current biodiversity conservation (Drew et al., 2011; Martín et al., 2012).

Species distribution models (SDMs) are empirical ecological models that relate species observations to environmental predictors (Guisan & Zimmermann, 2000); usually that is done with machine learning algorithms (Drew et al., 2011, see Mi et al., 2017 for an application). They have become important and essential tools in ecology, biogeography, climate change research, conservation and management based on their spatial occurrence prediction (Peterson et al., 2002; Guisan & Thuiller 2005; Elith et al., 2006; Araújo & New 2007; Mi et al., 2016). SDMs built with count data are called species abundance models (SAMs) (Elith & Leathwick 2009; Barker et al., 2014; see Yen et al 2004 for an application). SAMs are still less commonly used yet, despite their greater information for conservation and management. But increasing attention has been paid to these problems in recent years (e.g. Yen et al., 2004; Martín et al., 2012; Howard et al., 2015; Ashcroft et al., 2017; Fox et al., 2017).

In the past, spatial conservation decisions and plans are usually just based on SDMs (e.g. Suárez-Seoane et al., 2008; Gray et al., 2009; Adams et al., 2016; Mi et al., 2016). However, despite statements by Newton (2008), many scholars found species occurrence and abundance distribution

not to display similar patterns (Yen et al., 2004; Karlson et al., 2011; Yin & He 2014; Johnston et al., 2015). Therefore, conservation decisions only based on SDMs predictions are insufficient and may even be misleading, so do SAMs. In the future, one time-critical challenge and associated progress will be centered how to combine the useful information that SDMs and SAMs each offer for conservation.

In this study we chose the endangered Great bustard (*Otis tarda dybowskii*) wintering in Cangzhou at the North China Plain near Bohai bay as a case study. This area is one of the most important wintering grounds for this species (about 300 individuals, c.13.6~20.0 % of China's total wintering population (Goroshko 2010; Meng 2010). Using the Great Bustard as a case study would contribute to our conservation knowledge about habitat use of a threatened farmland species and for a better policy. By studying not only the spatial occurrence and the abundance patterns, but also combining these two model types together as a role model for predictive modeling and its inference would potentially have wider conservation implications. Our overall objective of this research was to (1) assess and develop models to predict accurately the patterns of bustard occurrence and abundance; (2) infer on environmental variables that influence occurrence and abundance of this species; (3) combine occurrence and abundance models as a new contribution to conservation decisions; and (4) investigate the overall relationship among predicted occurrence, predicted abundance and observed abundance. Well-tested and suited methods from this research could be useful for the conservation of Great Bustard, but also other rare species and biodiversity in general where SDMs and SAMs can be employed.

MATERIALS AND METHODS

Study area

This study was conducted at the wintering grounds of endangered Great Bustards in Cangzhou, southeast of the Heibei Province in the wider Bohai Bay (Fig. 1). It is located at 38°12′57″ - 38°36′51″ latitude and at 116°50′48″ - 117°24′03″ longitude in the warm temperate, semi-humid monsoon climate zone, which features the slightly marine climatic characteristic of the Bohai Sea region. The topographical and climate condition varies little in the study area. The total study area is 2,191.4 km^2, consisting of farmland (1,675.1 km^2; 76.4%), residential area (330.5 km^2, 15.1%), open water (23.5 km^2; 1.1%) and other unspecified land uses (e.g. home lots, sheds).

Put Fig. 1 Here

Most of the farms in this region produce cereal, which is grown in a 2-year rotation system. In the first year, winter cereal is cultivated from early September to the end of April the following year. Then, corn is cultivated between the end of April to early September of the same year. The study area was chosen (Fig. 1) because of its large numbers (about 300 individuals, c.13.6 ~20 % of China's total wintering population (Goroshko 2010; Meng 2010). This area is the world's largest wintering ground of the endangered *O. t. dybowskii*. This area is representative of the typical farmland situation in the North China Plain. In addition, accurate Great Bustard census data, geographic information system (GIS) data coverages and satellite imagery were readily available.

Bird census data

Spatial occurrence and abundance data for Great Bustards were used to develop models. A Great Bustard census was winter survey conducted during November 2013 to March 2014. In the study area, we travelled with a small four-wheel-drive tractor along fixed routes, using speeds of 10-30 km/hour. Our team consisted of two experienced observers (one surveyor and one local resident) counting bustards and with a good knowledge of the area to be surveyed. When a flock was found, we drove slowly and stopped on the location at a 100 - 500 m distance from bustard flocks, recording its size, location, habitat type and basic behavior. This resulted in a good detection of birds and flocks in the study area because birds can be seen already from long distances (~3km) but also when flying away. The actual animal coordinates were obtained by Google Earth when combing it with our recorded location. Each census was done from dawn to dusk. During the study, we identified 94 bustard sites in the study area. To our knowledge, this census data were the best available ones in China for bustards.

GIS environmental layers

Based on environmental conditions in our study area, we selected eleven habitat and landscape (environmental) variables to construct models predicting occurrence and abundance (Table 1). In order to obtain these variables, we acquired the basemap from Google Earth (using Daogle, an open source software made by a Chinese individual http://www.daogle.com/; as used and explained in Mi et al., 2014) and derived otherwise unavailable high resolution landscape inventory information about open water pools, rivers, residential areas, national roads, provincial

roads, expressway, farmland road, ditch and farmland areas from the base map. Next we constructed a distance layer for these variables (except for the farmland area) using the Euclidean Distance tool in ArcGIS 10.1 with a 30 m×30 m spacing. This high pixel resolution was chosen in order to be consistent with remote sensing variable resolution we used.

Satellite images

A range of the best cloud-free HJ-1A/B (HuanJing (HJ)) satellite images (http://218.247.138.121/DSSPlatform/index.html#) at a 30 m×30 m resolution was obtained for each month for November 2013 to March 2014 in order to calculate the normalized difference vegetation indices (NDVI) signature for each pixel. The HJ-1A/B CCD data were run for radiometric calibration, atmospheric correction and geometric correction in order to obtain surface reflectance data and subsequent NDVI data. Radiometric calibration was finished using 2014 HJ-1A/B CCD absolute radiometric calibration coefficients provided by the China Centre for Resources Satellite Data and Application. For this study, we used maximum and mean NDVI to represent the vegetation condition (Osborne et al., 2001).

Put Table 1 Here

138 Model development

139 We employed an advanced machine learning technique, Random Forest, to model the
140 occurrence as well as abundance distribution of Great Bustards. Breiman (2001)'s Random Forest
141 implementation in SPM7 by Salford Systems Ltd is robust to over-fitting and is widely recognized
142 to produce very good predictive models. Hence, it is increasingly applied to species distribution
143 modelling (Cutler et al., 2007; Drew et al., 2011; Mi et al., 2016 for an application using bustards
144 in China). Though Random Forest performed the best to predict abundance itself (see Appendix
145 1), testing the feasibility for other data was essential for good certainty. So for an assessment on
146 the robustness of the model we pooled data from 2013 and 2014, and then used 80% abundance
147 data as training data and the remaining 20% as testing data. When we constructed initial abundance
148 models with all eleven environmental predictors, model performance is not so good (R^2 was small).
149 Likely that has to do with the regression settings in Random Forest algorithm. For a better outcome
150 we assessed a "stepwise" setting in SPM for whole abundance data (100%) to re-run models, and
151 found better results. In that way, we identified a multivariate set of four environmental predictors
152 (distance to expressway, distance to national road, distance to pool, MNNDVI), which have the
153 best performance (biggest R^2). Using these four predictors, we re-constructed the abundance model
154 based on the training data (80%) and validated it with testing data (20%). We found that the
155 regression model performance was acceptable but fair (R^2 = 0.551) between observation and
156 simulation abundance. Thus, we constructed the final abundance model based on the above four
157 selected variables and with the entire observation data. In order to obtain an abundance index more
158 close to observations we adjusted the simulation abundance according to the linear regression
159 between observation and simulation abundance (Fig. 2a).

160 Put Fig. 2 Here

Further, Random Forest was also applied to rank the relative importance of environmental variables. In SPMv7, partial dependence plots are not directly implemented in Random Forest yet, but can easily be obtained from R or are mimicked in TreeNet model as a Random Forest run. Thus, we used TreeNet with bagging settings to create partial dependence plots for each variable of the occurrence and abundance models.

About 10,000 pseudo-absence points were taken by random sampling across study areas using the freely available Geospatial Modeling Environment (GME) software (http://www.spatialecology.com/gme/) for distribution models. In SPMv7 we set balanced class weights, grew each model to 1,000 classification trees for occurrence model and 1,000 regression trees for abundance model, and used all other software default settings. We extracted the habitat information from the environmental layers for presence and pseudo-absence points for Great Bustards in GME, and then created a model file in SPM7 called a 'grove' containing the algorithm quantifying patterns of occurrence for scoring all pixels in the study area. We also extracted the habitat information from the same environmental layers for abundance points, and then generated a 'grove' file for abundance to score abundance estimates for each pixel in the study area.

For spatial occurrence and abundance distribution visualization, we applied the SPM7 grove files to a regular lattice of points (pixels; also attributed to the environmental variables) spaced at 30 m intervals across the study area. Model outputs generated relative indices of occurrence (RIO; an index of pixels from 0 to 1 representing a relative index belonging to the 'occurrence' class) and a relative abundance index (simulation abundance) for each point in the regular lattice based on its underlying environmental variables. We also adjusted the predicted abundance based on a linear regression as constructed in the previous model development steps (Fig. 2a). For a better continuous spatial visualization, the RIO and predicted abundance values were smoothed between

neighboring points across the extent of the study area using the Inverse Distance Weighting (IDW) tool in ArcGIS 10.1. This yielded spatially continuous predictive distribution and abundance raster maps of Great Bustard.

Model validation

The Random Forest performance was first assessed internally using a set of 'out-of-bag' (OOB) training points (OOB; a specific concept used with Random Forest models to describe a subset of points not used initially for model fitting; Breiman 1996, Breiman 2001). Using this out-of-bag dataset, the receiver-operating characteristic (ROC) and RMSE were used to calculate predictive performance of occurrence and abundance models, respectively (Zweig and Campbell 1993; Fielding and Bell 1997; Huettmann and Gottschalk 2010).

Priority protection analysis

In order to have a more suitable and scientific protection plan for the endangered Great Bustard, in this study we put forward for the first an index called the priority protection index (PI), which combines the predicted results of SDM and SAM. This index is calculated by the following equation for each site:

$$\boldsymbol{PI} = \frac{\boldsymbol{RIO} \times \boldsymbol{RA}}{\max\left(\boldsymbol{RIO} \times \boldsymbol{RA}\right)} \quad (1)$$

where $\boldsymbol{PI}$ = Priority protection index (an index of pixels from 0 to 1 representing the priority of conservation), $\boldsymbol{RIO}$ = relative index of occurrence, and $\boldsymbol{RA}$ = relative abundance (simulation abundance). In our study, we computed the PI for the whole study area based on RIO and the adjusted RA value of each grid cell by spatial occurrence and abundance maps. Then we used the IDW tool in ArcGIS 10.1 to generate spatially continuous priority protection index (PI) raster maps. In this equation we did not consider the weighting of biotic and socioeconomic variables.

So the justification and use of the PI should be explained a little more: When combining SDM with SAM one will not find a straight forward relationship between occurrence and abundance (see Yen et al. 2004 for an example). What the PI will do, but what has not been achieved before much, is to essentially model that relationship and provide a combined view of occurrence index and abundance index explicit in space and time. Achieving this can thereby help to prioritize pixels better with let's say high occurrence index and low abundances on pixels etc.

RESULTS

Model performance

Our distribution model obtained a decent performance (ROC: 0.77) according to Fielding and Bell (1997), and the abundance model had RMSE 26.54 (RMSE is unit-less). Such model predictions allow us to infer from such models and how they are built.

Variable importance

Table 2 presents the variable importance ranking of occurrence and abundance models obtained from the Random Forest method. We found that the area of farmland, distance to residential area (buildings), to ditch and to expressway were the top four most important variables influencing bustard occurrence. Those come as a multivariate package. The NDVI which represents vegetation condition was less important than the other nine predictors. As for the abundance model, the most important factors were distance to national road and to expressway, followed by water factors (distance to pool) and food-related factors (MNNDVI)

Put Table 2 Here

Partial dependence plots

Partial dependence plots could interpret the functional relationships and effects of each variable

by representing a variable's marginal effects on the response (Elith et al., 2008; Johnstone et al., 2010). It helps to find the signal in the data; Fig. 3a indicated that the occurrence preference of bustards for farmland area was between 0.6 and 7.5 km^2. Distance to residential area ranging from 250 to 2,500 m (Fig. 3b), distance to ditch ranging from 100 to 4,500 m (Fig. 3c), and distance to expressway from 6,000 to 19,000 m (Fig. 3d) were bustard preferences. While for abundances, more individuals would occur beyond 2,300 m, but less than 9,500 m away from national roads (Fig. 3e), and be found in the range between 7,000 and 11,000 m away from expressway (Fig. 3f). Moreover, this species kept themselves away from pools (larger than 1,500 m, Fig. 3g) and with more vegetation (mean NDVI during the investigation larger than 0.13, Fig. 3h). The information for other variables, more marginal, can be found in Appendix 2.

Put Fig. 3 Here

Occurrence, abundance distribution patterns and priority protection

Fig. 4 shows the maps of RIO (relative index of occurrence), adjusted RA (relative abundance) and PI (priority protection index). From the RIO map (Fig. 4a), we found that the distribution area of high RIO of bustards is high. The regions of high occurrence possibility of bustards were concentrated in the south-central study area; and the whole habitats represented a fragmented distribution. The abundance distribution had a different pattern, showing high populations occurring in the central and northwestern study area (Fig. 4b). Based on the occurrence and abundance distribution results, we used equation (1) and obtained the result of Fig. 4c. It displays that a high PI is located in the center, north and northeast of the study area and it shows a sporadic fragmented distribution which would be the priority protection site if a conservation decision is to be made.

Put Fig. 4 Here

DISCUSSION

The occurrence and abundance models of Great Bustard developed here were designed to identify relevant locations for where to prioritize conservation, and to assess the effects of each variable that influenced this species occurrence and abundance (Fig. 3). Area of farmland, distance to residential area, distance to ditch and to expressway were among the top four most important predictors for bustard occurrence in a multivariate perspective; while for the abundance model they consisted of another multivariate package of distance to national road, distance to expressway, distance to pool and mean NDVI (Table 2). We found that high RIO habitats had a fragmented distribution throughout the entire study area (Fig. 4a). The abundance model showed that high population usually occurred in the central and northwestern part of our study area (Fig. 4b). The center, north and northeast of the study area with a high priority protection index (PI) and with a severely fragmented distribution should be the priority site for protection (Fig. 4c). This not only confirms our own records but with the help of the PI can now be quantified and modeled further for an effective conservation!

In our study area, human disturbance was very strong, such as density of roads and residential areas (Fig. 1). During our study we also found other threats to this endangered species: farmers grazed their sheep; famers sprinkled poison baits in the wheat field to avoid sheep entering; some bird photographers pursued bustards by walking or following on motor vehicles to take photos, which they wanted to show off to others; hunters with dogs chasing hare and ring-necked pheasant during day and night; some local people hunted bustards; increasing power lines setting in agriculture land, bustards sometimes collided with wires and were injured or even died when starting to fly in foggy days or when in a hurry (Janss & Ferrer 2000); and the interference of firecracker sounds during Chinese Spring Festival as well as oil rigs and wind farms. Though

carrying a high disturbance and for a stress synthesis (e.g. “death by thousand cuts”), still, a large number of wintering bustards (about 300, c. 13.6 ~20.0 % of China’s total wintering population; Goroshko 2010; Meng 2010) wintered in this area. In times of climate change, it can be assumed the population widens (Mi et al., 2016). Thus, this is an area of essential importance for bustards in China either way. A feasible conservation plan should therefore be made, based on our model prediction result, combined with local public customs and financial support and a wider buy-in. In our opinion, improved education on animal protection to local people as we usually did over the years would be useful. The same applies to increasing budgets, enforcement and frequency of patrol by the local management and conservation NGOs in the region with high PI value and the local community, with corresponding government financial support. Patrol route designation in the field should avoid getting too close to bustards though, so as not to disturb and stress the regular wintering activities of bustards. For the benefit of this species and its habitats we suggest to not change crop farmland into nursery farmland; and we encourage farmers to harvest their crops with a machine, which is a more beneficial harvesting method for bustards based on our previous research results (Mi et al., 2014). We also highly recommend, if possible, to bury power lines into the ground and to collect hunting guns from local public.

In this study, occurrence and abundance did not display identical spatial distribution patterns which was reported in some previous studies (Conlisk et al., 2007; Karlson et al., 2011; Yin & He 2014; Johnston et al., 2015). There is actually no reason to assume a presence site just shows one animal individual, or a linear relationship between RIO and abundance. Technically-speaking, ‘presence’ can mean 1-infite animals and details depend on the actual pixel set-up and how it fits into the obtained model. So while the relationship is not automatically clear this could be due to several reasons and depending on specific habitat details: Firstly, environmental variables that

296 contributed to occurrence and abundance were different, as Table 2 indicated. Secondly, predictor
297 preference in bustard occurrence and abundance models were different. For instance, bustards
298 occur at a distance to expressway from 6,000 to 19, 000m (Fig. 3d), while most populations occur
299 between 7,000 and 11,000m from expressway for abundance (Fig. 3f) (see more details in Fig. 3
300 and Appendix 2). Thirdly, they differed in their spatial distribution for occurrence and abundance
301 (Fig. 4a, b). Based on the analysis of overlaying observation sites with RIO and observation
302 abundance (Fig. 5a, b), estimated relative index of occurrence (RIO) do not consistently relate with
303 the relative index of abundance (Fig. 5a). All locations of observed abundance had high RIO (Fig
304 5a), and the relationships between occurrence and abundance estimates were nonlinear (Fig. 5b).
305 These differences may represent a mixture of effects reflecting differences between the underlying
306 biological processes that give rise to specific abundance and occurrence at a pixel, as well as
307 limitations imposed by the data and methodology to estimate these patterns (Johnston et al., 2015;
308 see Buckland et al., 2016 for Distance Sampling and detectability problems). In addition, how to
309 understand the inconsistency between these two indices of plant prediction is a problem waiting
310 to be resolved further. For instance, between crop occurrence index (equal to habitat suitability
311 index) and crop abundance (e.g. production).

312 Put Fig. 5 Here

313 When treating all presences as equal in species distribution models (SDMs; occurrence model,
314 habitat niche model) -regardless of the abundance of individuals that the habitat supports - this
315 could provide us with information on the suitability of habitat loss (Howard et al., 2014). Applying
316 models based on abundance data even at a relatively coarse scale can help to predict spatial patterns
317 of occurrence modelled with even greater refinement (Howard et al., 2014). Conservation decision-
318 making should use as much knowledge and information as possible to optimize the benefits of

conservation action (Sutherland et al., 2004; Segan et al., 2011). The use of species distribution models (SDMs) of occurrence has been an important tool in optimizing the selection of protected areas (Franklin 2013; Guisan et al., 2013, Mi et al., 2016; Han et al., 2017) based on the ecological niche space (Drew et al., 2011), but relative abundance is often perceived a more relevant metric because it can quantify animals on a pixel, and thus, populations (Johnston et al., 2015). Modeling abundance requires methods that can handle large numbers of zero counts as well as the rare, but important, high counts (Welsh et al., 1996) without a solid research design, according to frequentist statistics. However, Yen et al., (2004), Magness et al., (2008) and Fox et al., (2017) showed already how machine learning can change this perspective and provide very powerful solutions.

High counts and their locations are particularly important because the pixels with the highest densities of animals are potentially of greatest interest for conservation planning (Johnston et al., 2015). In our study, we found that the regressions in Random Forest performed imperfectly for low and high counts (Fig. 2b) although it showed a highly linear relationship between observed and simulation abundance (R^2=0.844; Fig 2a). Therefore, we argue that the regression method in Random Forest algorithm should optimize low and high count predictions. We recommend to classify abundances in bins (e.g. high, medium, low with associated abundance estimates) because Random Forest is exceptionally strong for classification problems. This remains an open field of research, for now. However, we find our progress remains substantial.

Abundance data could also provide valuable baselines against which to assess future changes (Cumming 2007) (e.g. climate change, land use change). Such changes in abundance will be much more rapidly apparent, and hence more rapidly detected than changes in presence-absence patterns across ranges (Gregory et al., 2005). However, only a few spatial distribution modelers derived models with the collection of abundance data (e.g. Yen et al. 2004, Fox et al. 2017). This may be

because collection of abundance data is more cost or resource demanding than collecting presence - absence data especially for highly mobile animals. Such data are sophisticated in structure and research design, and still they are rarely shared (see in GBIF.org). We therefore recommend that abundance data could be collected (easily to be turned into presence-absence data, too), even at only relatively coarse numerical scales because the benefits are considerable (as stated by Howard et al., 2014). One thing that should be mentioned is that plenty of abundance data and (non-linear regression) models did not perform well and abundance were extremely difficult to predict (Oppel et al., 2012). Finding the underlying causes that influence abundance model accuracy and constructing more accurate models would be extreme important and useful in future applications towards individual-based policy applications.

For a spatial priority protection of mobile species, one should note that high numbers of individuals are not always present in the same habitats and pixels, instead low numbers may occur in one place many times. And this may have implications for spatial priority protection for mobile species. Previous studies have used analytical approaches to deal with some of these challenges (e.g. Nichols et al., 2009; Kery & Andrew Royle 2010; Oppel et al., 2012; Jiguet et al., 2013). However, no general modeling framework has been proposed for dealing with all of these analytical challenges simultaneously. This is exactly where our PI offers progress. We also thought the situation of mobile species selecting habitats could be divided into five scenarios: higher numbers and multi frequency, higher numbers and lower frequency, low numbers and multi frequency, low numbers and low frequency, none. When a conservation plan is made for a species, one should consider not only occurrence index and frequency, but also abundance. Here we proposed the priority protection index (PI; equation (1) and Fig. 4) based on the distribution of occurrence and abundance pattern as more helpful for a fast priority protection plan than indices

and it's only based on distribution of occurrence or abundance.

To date, quantitative estimates of population size during global and local changes have actually proven to be difficult to forecast. This is a major hindrance for effective management, as population size and trend are considered among the best correlates of extinction risk (O'Grady et al., 2004). Such measures are commonly used in determining the conservation status of a species (e.g. IUCN (2001)). We argue that habitat loss remains the one and only powerful metric that can be obtained quickly on a landscape-scale in the absence of proper trends and abundances (e.g. Drew et al. 2011). The relationship between predicted environmental suitability and abundance - as presented here - may provide us with a possible method for predicting population size and its changes associated with distributional changes, particularly appropriate for non-mobile species (e.g. plants, fungi). However, this method is not particularly suitable for mobile species, especially for highly mobile species such as many birds, bats, and flying insects. They may move over a large landscape within just a single day, and abundance and the environment can vary seasonally and spatially. When computing population size or population density using abundance, the primary task will be how to determine the unit area of investigation and for conservation management.

This study is the first that has combined model-predicted occurrence (representing species distribution model) and abundance indices (representing species abundance model) to produce a priority protection index (PI), which may contribute to spatial conservation and management decisions worldwide. We strongly encourage other researchers to test, apply and update the priority protection index (PI) to explore the generality of these findings further.

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388 software.

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531

Table 1(on next page)

Table

1 **Tables**

2 Table 1 Comparison of features around 94 sites occupied by great bustards and 10 000 random points. Values are means ± standard deviations.

Layer	Variable	Description	Bustard sites	Random points
1	Distance to pool	Distance to pool in meter	1179.0 ± 734.5	1378.0 ± 910.3
2	Distance to river	Distance to river in meter	2302.0 ± 1751.2	2630.0 ± 2483.0
3	Distance to residential	Distance to residential in meter	935.0 ± 586.8	980.2 ± 723.8
4	Distance to national road	Distance to national road in meter	5280.0 ± 4234.2	5855.0 ± 4036.9
5	Distance to provincial road	Distance to provincial road in meter	8730.0 ± 5928.7	9217.0 ± 6112.4
6	Distance to expressway	Distance to expressway in meter	10010 ± 5750.0	9585.0 ± 6666.7
7	Distance to farmland road	Distance to farmland road in meter	477.4 ± 385.3	524.9 ± 455.8
8	Distance to ditch	Distance to ditch in meter	1522.0 ± 1722.7	2120.0 ± 2078.1
9	Area of farmland	Area of farmland in kilometers	3.3 ± 3.2	5.3 ± 6.2
10	MNNDVI	The average value of the normalized difference vegetation index from November, 2013 to March, 2014	0.14 ± 0.04	0.13 ± 0.05
11	MAXNDVI	The maximum value of the normalized difference vegetation index from November, 2013 to March, 2014	0.23 ± 0.06	0.21 ± 0.07

3

Table 2 Variables importance ranking of occurrence and abundance models

Ranking	Occurrence model	Abundance model
1	Area of farmland	Distance to national road
2	Distance to residential	Distance to expressway
3	Distance to ditch	Distance to pool
4	Distance to expressway	MNNDVI
5	Distance to pool	--
6	Distance to river	--
7	Distance to provincial road	--
8	Distance to national road	--
9	Distance to farmland road	--
10	MAXNDVI	--
11	MNNDVI	--

Figure 1

Figure 1

Study area and bird abundance and occurrence data for Great Bustard in Cangzhou, China. Photograph of Great Bustard by Jianguo Fu.

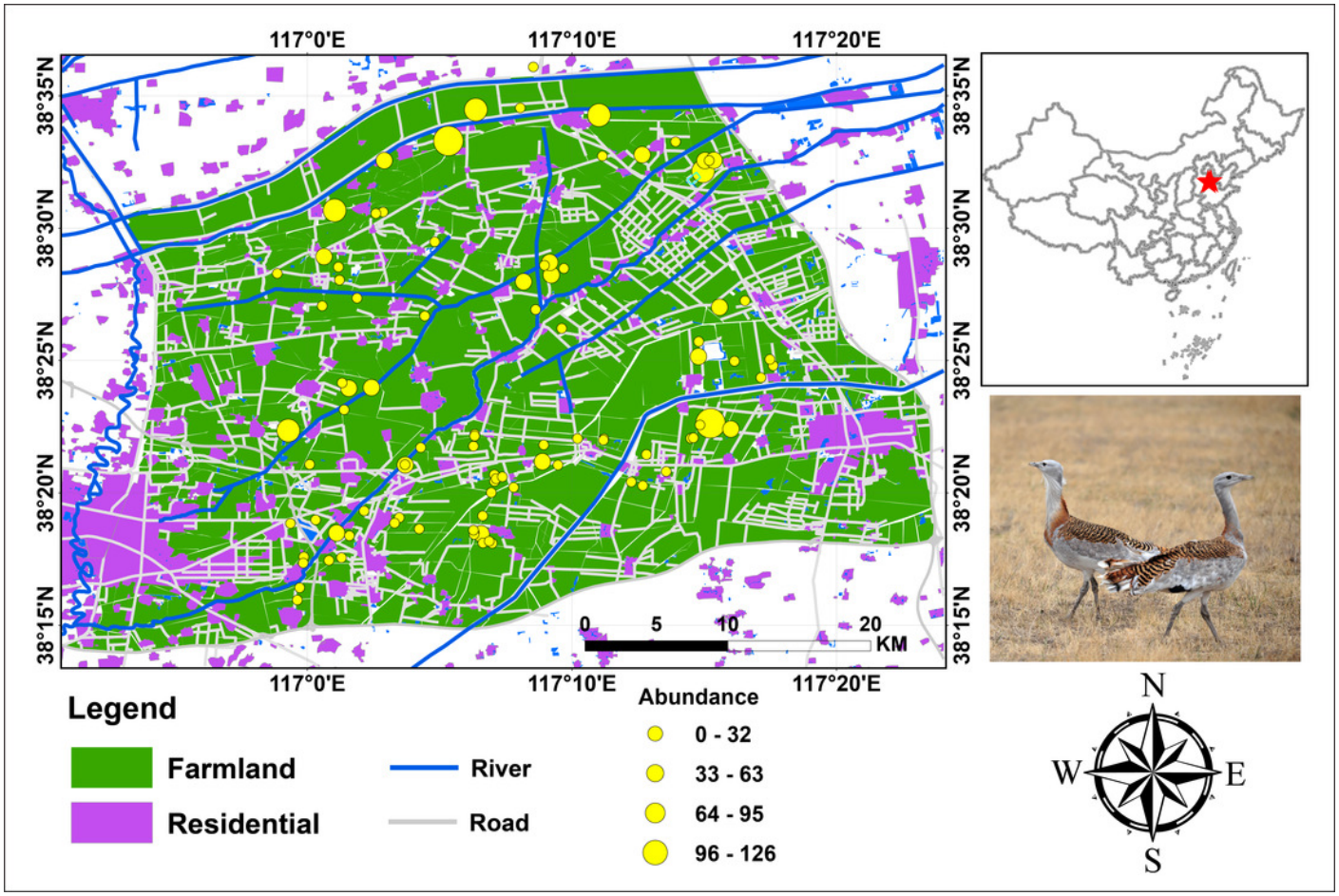
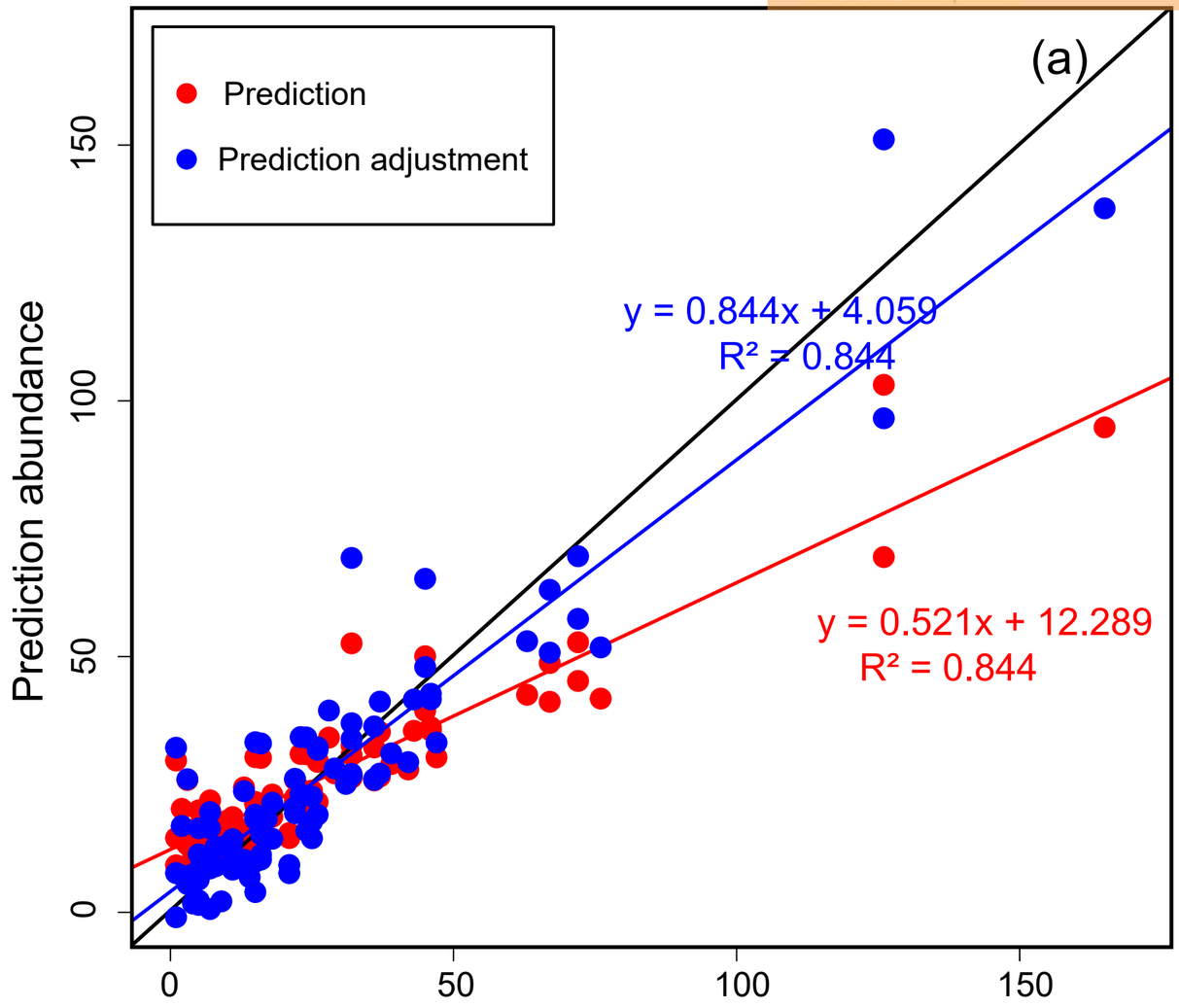


Figure 2(on next page)

Figure 2

Figure 2 The relationship between observation and prediction abundance using Random Forest for Great Bustards. (a) Scatter plot of observation abundance with prediction and adjustment prediction abundance, and (b) lines and points plot of observation, prediction and adjustment prediction abundance.



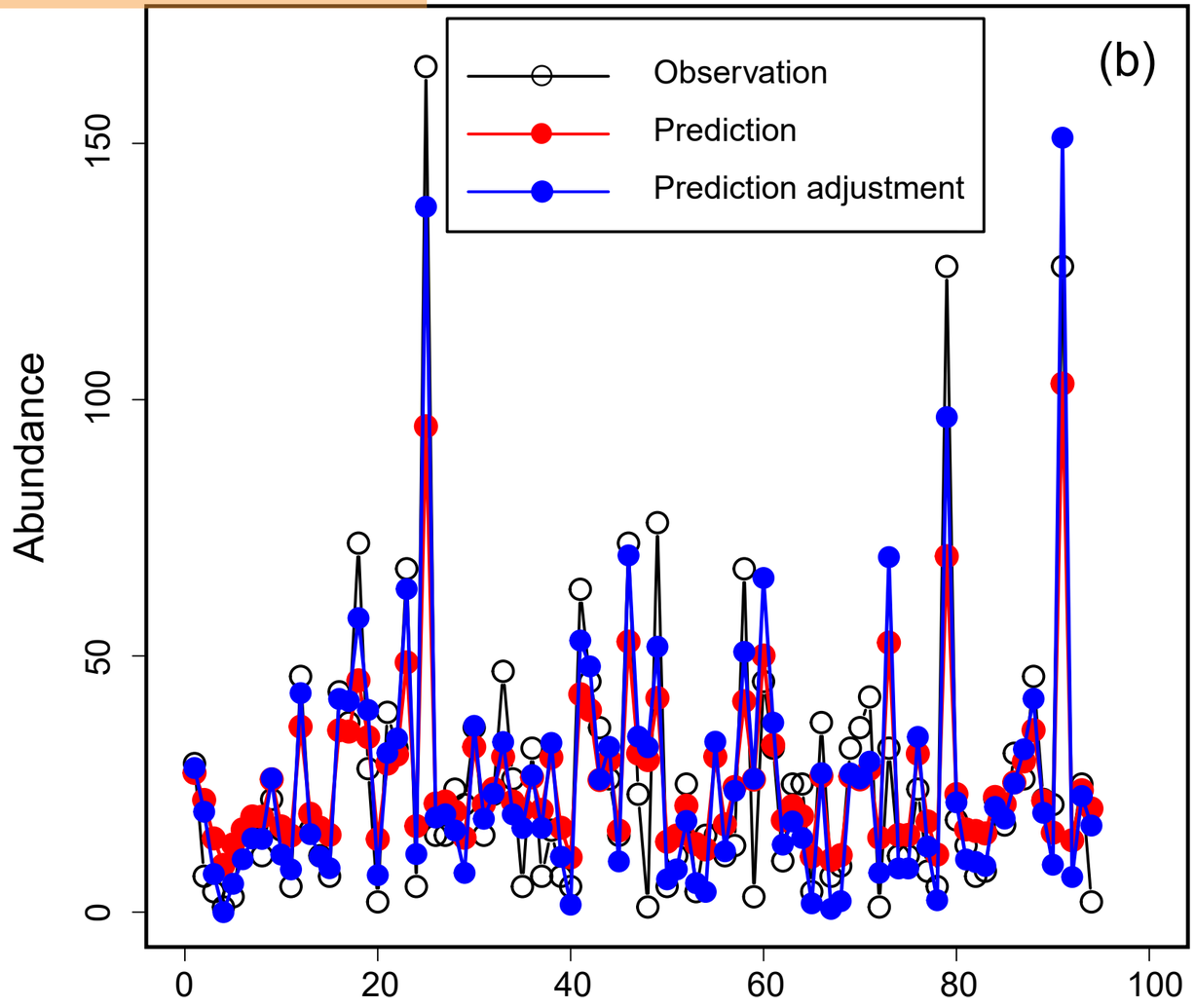


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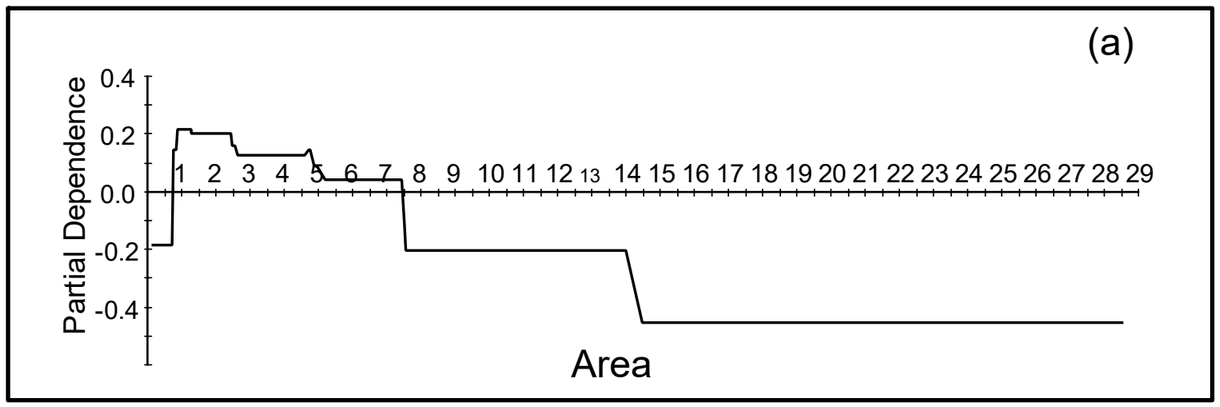
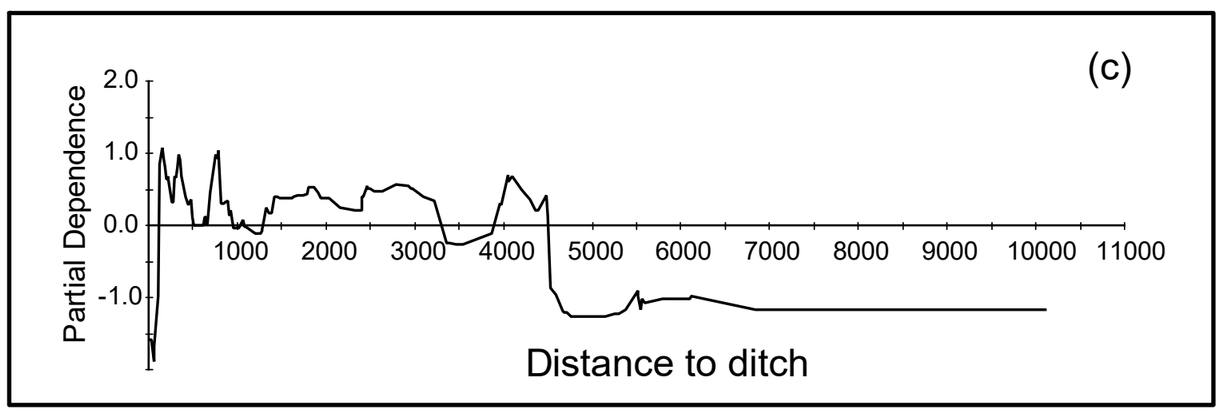
Figure 3(on next page)

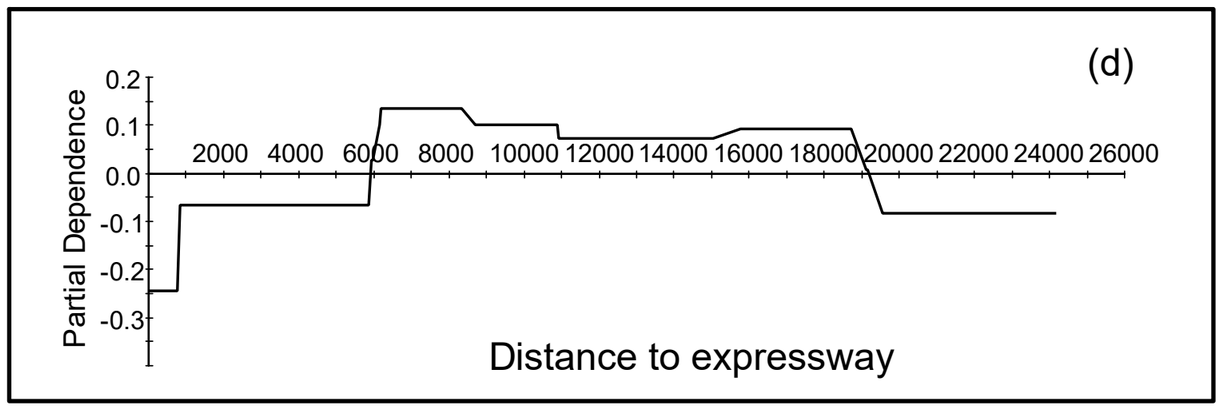
Figure 3

Partial dependence plots for the top four most influential variables in the occurrence and abundance distribution models for Great Bustards, respectively**:** (a) area of farmland in occurrence distribution model; (b) distance to residential in occurrence distribution model; (c) distance to ditch in occurrence distribution model; (d) distance to expressway in occurrence distribution model; (e) distance to national road in abundance distribution model; (f) distance to expressway in abundance distribution model; (g) distance to pool in abundance distribution model; and (h) mean NDVI in abundance distribution model.

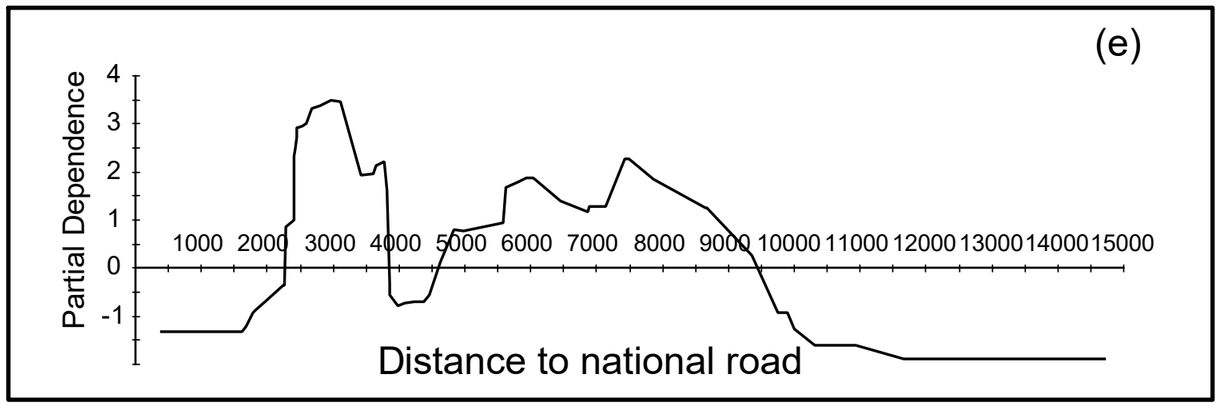
Occurrence model

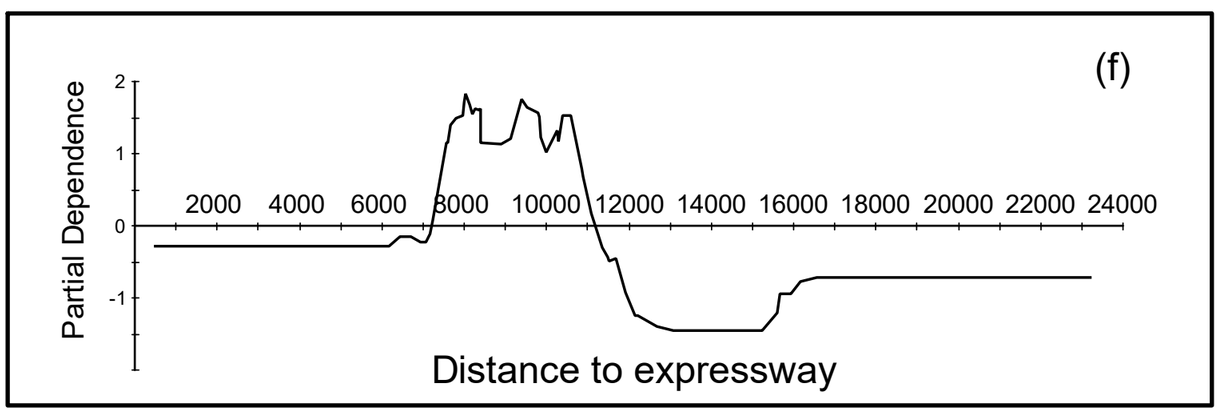


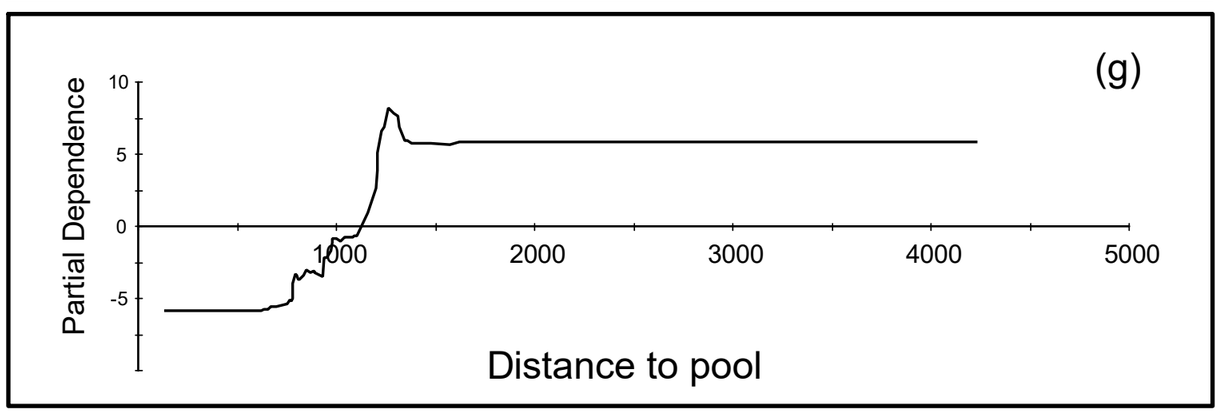




Abundance model







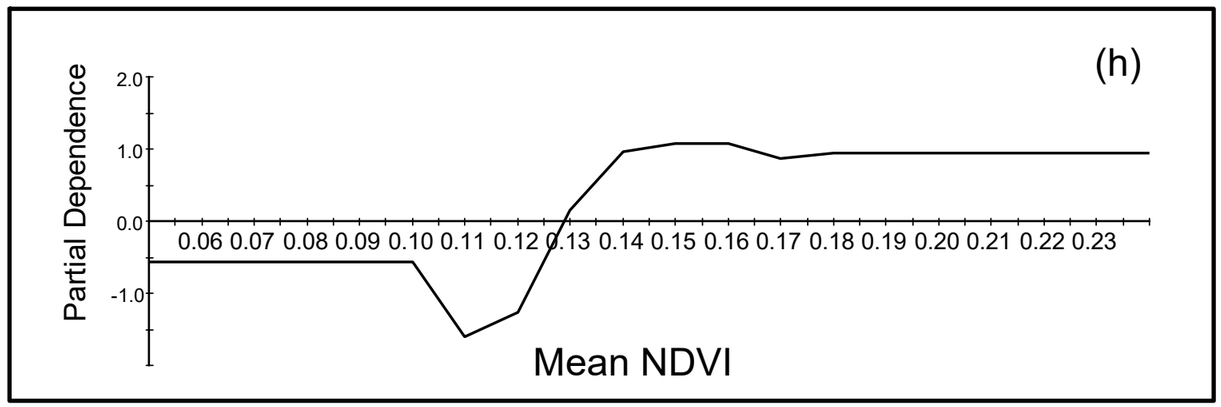


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Figure 4

Figure 4

Spatial distribution map of relative index of occurrence (RIO), relative abundance (RA) and priority protection index (PI). (a) Map of relative index of occurrence (RIO); (b) map of adjusted relative abundance (RA); and (c) map of priority protection index (PI).

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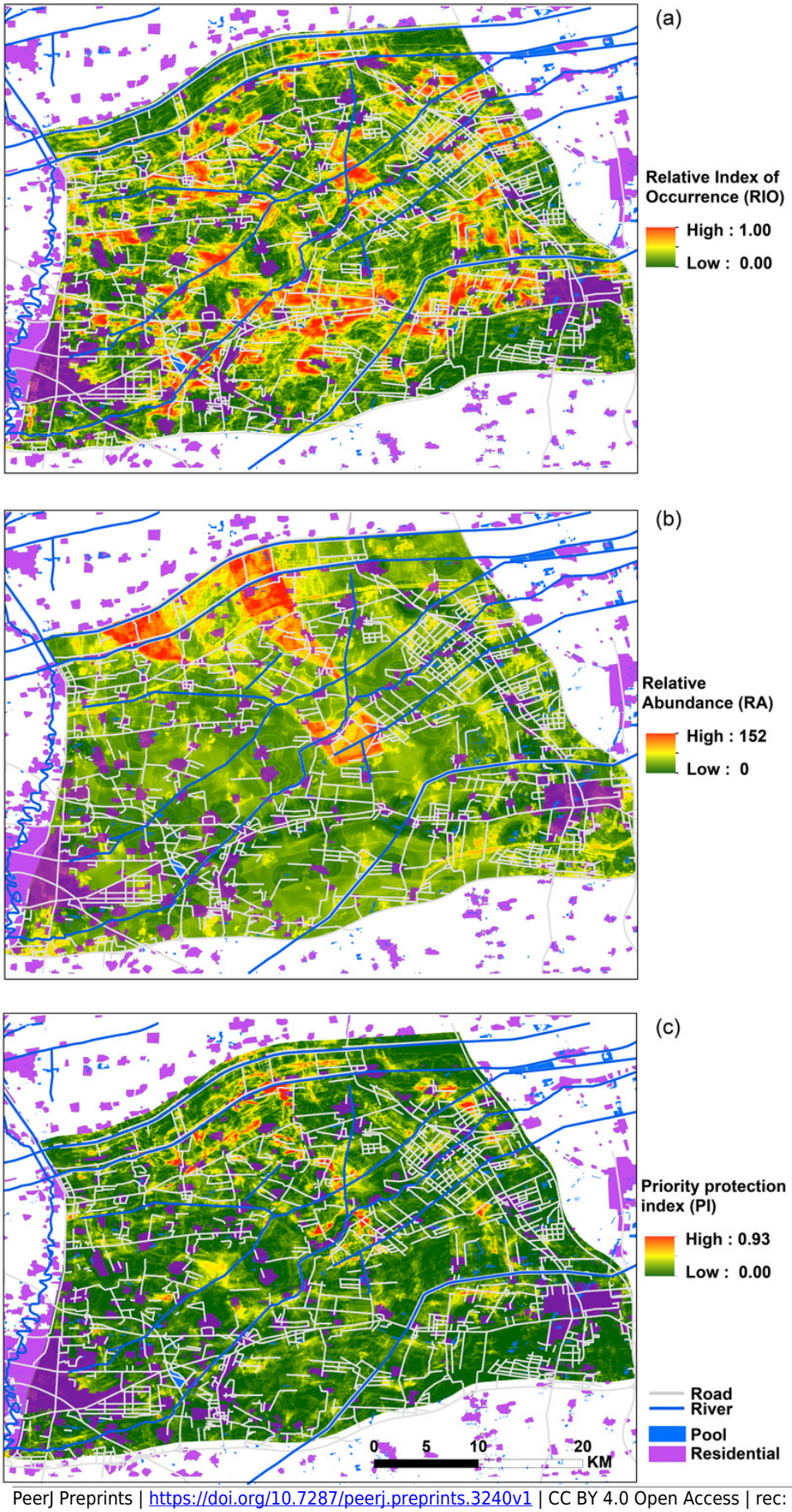

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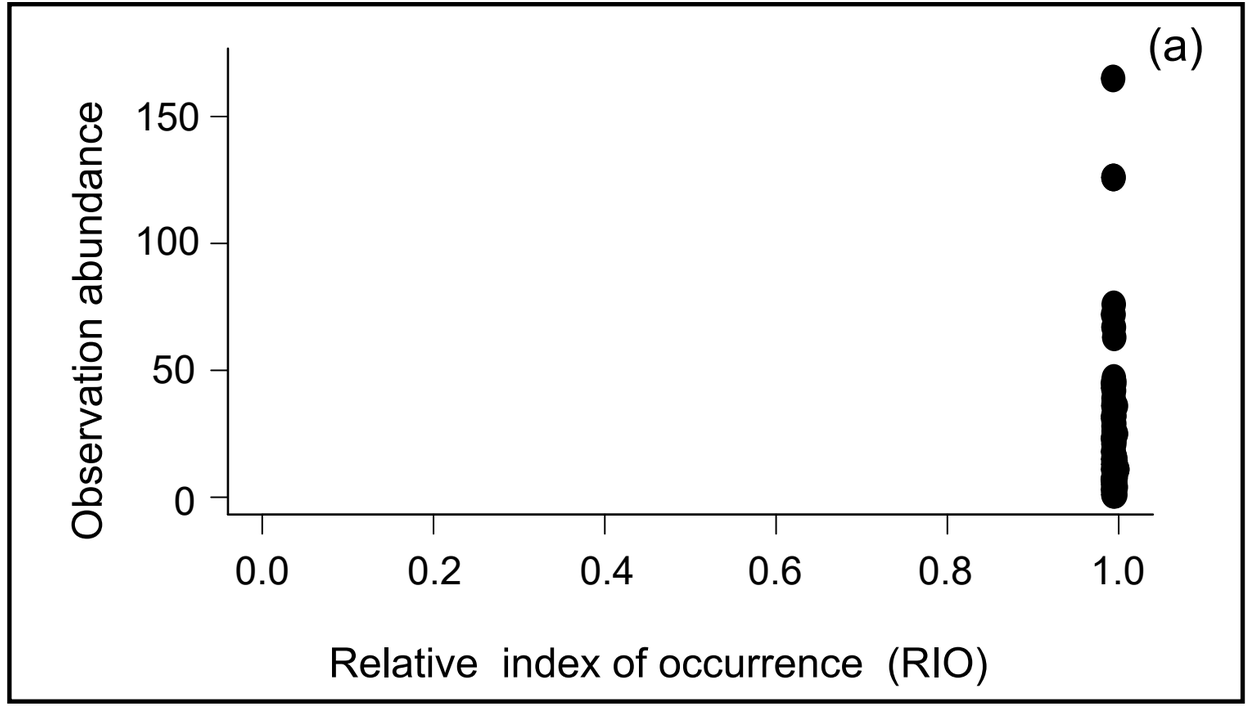
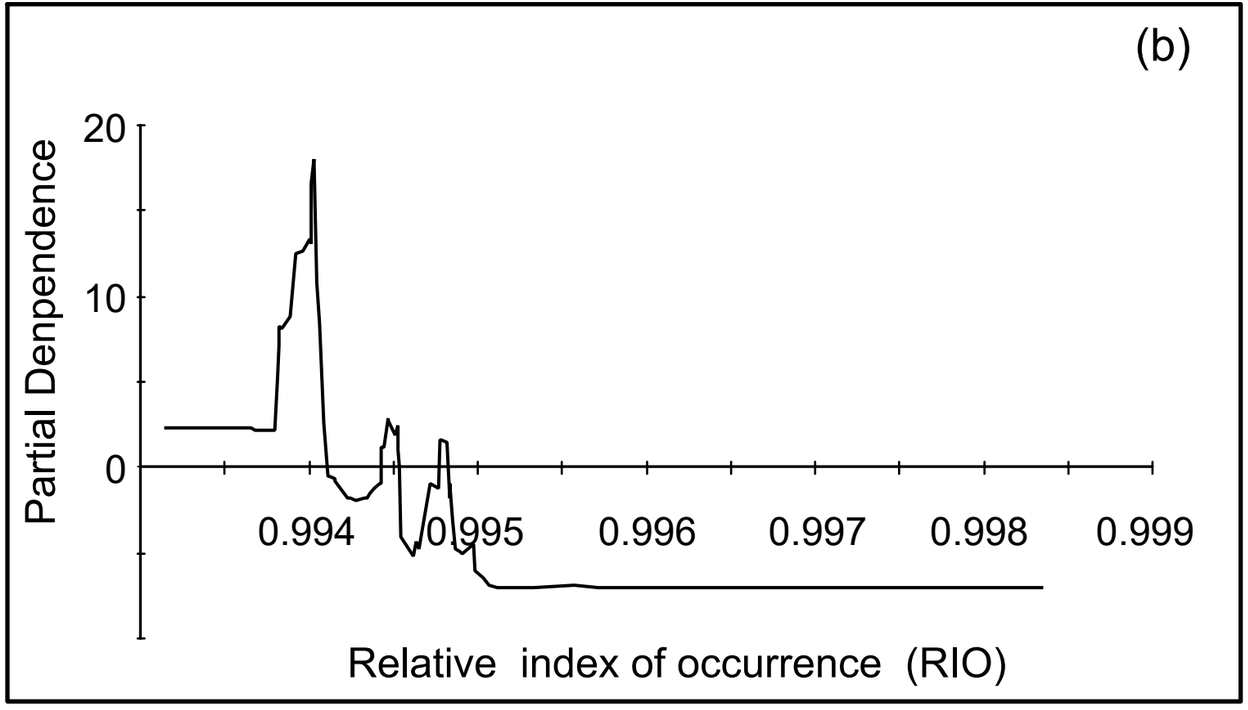
Figure 5(on next page)

Figure 5

Plots of the relationship between relative index of occurrence (RIO) and observation abundance. (a) Scatter plot between relative index of occurrence (RIO) and observation abundance; and (b) partial dependence plot between relative index of occurrence (RIO) and observation abundance (obtained from TreeNet, non-parametric method).





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