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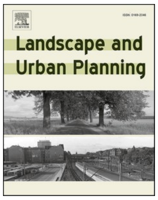

Predicting current and future species distribution of the raccoon dog (*Nyctereutes procyonoides*) in Shanghai, China

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HIGHLIGHTS

- First study to evaluate urban landscape planning and human-wildlife conflict in China.
- Raccoon dog distribution positively associated with anthropogenic factors.
- Species had great expansion potential but ignored in urban landscape planning.

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ABSTRACT

Rapid urbanization has caused drastic changes in urban ecosystems, resulting in various urgent management needs from mitigating biodiversity loss to preventing human-wildlife conflicts. Using species distribution modeling to understand urban species' distributional patterns and predict their future changes is thus important to support decision-making. Raccoon dog (*Nyctereutes procyonoides*) that previously inhabited Shanghai had been extirpated from the metropolitan area but recently returned to and expanded in almost all districts, causing hundreds of human-raccoon dog conflicts. In this study, we initiated a citizen science project, identified factors associated with raccoon dog habitat selection, and predicted its current suitable habitat as well as potential future ranges under different city development scenarios. By constructing an ensemble modeling using data from camera trap surveys, interviews and rescuing records, we found that raccoon dog distribution was positively associated with several anthropogenic factors including nighttime light, human population, and percentage area of buildings. We predicted a 156,024 ha suitable habitat for raccoon dogs throughout Shanghai, among which only 5,811 ha (3.72 %) was currently occupied. Our results indicated considerable potential of raccoon dogs' future expansion, which had been consistently ignored in previous management plans. To alleviate the increasing human-raccoon dog conflicts, we found strategies to slow down raccoon dog movement effective tools, and suggest adaptive management to provide fast response and flexible solutions. This is the first study to investigate human-wildlife conflict in China's urban environment, and our approach has substantial implications for Shanghai as well as other regions where urban species are undergoing rapid expansion.

1. Introduction

Rapid biodiversity loss is currently occurring during the sixth mass extinction wave, driven by anthropogenic activities across all ecosystems (Chapin III et al., 2000; Mendenhall et al., 2012). Urban species are uniquely affected by the Anthropocene. Increasing anthropogenic

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resources, along with species' intrinsically high diet plasticity and prolificacy, leads to rapid population growth and range expansion of urban species during later urbanization periods (Castillo-Contreras et al., 2018;Honda et al., 2018; Juhász et al., 2020; Ritzel and Gallo, 2020). Consequently, indirect and direct human-wildlife conflict has increased in recent decades (Treves and Santiago-Ávila, 2020; Abrahms, 2021). For example, rapid population growth of red fox (*Vulpes vulpes*), a vector of zoonotic diseases and predator of domestic animals (e.g., pets, poultry) inhabiting backyards, have caused increases in indirect human-wildlife conflict in Great Britain (Duduś et al., 2014). On the other hand, large and medium sized herbivores often pose great threats to traffic safety due to their larger home range and higher abundance in urban landscapes (Fehlmann et al., 2021), representing direct human-wildlife conflict that has been widely concerned. As an example, the white-tailed deer (*Odocoileus virginianus*) is responsible for 1.35 million collisions in the USA, causing approximately $4,179 damage per incident or a total $5 billion loss annually (Pfeiffer et al., 2020). In addition to traffic accidents, the risks and disturbances associated with urban species include property damages and ransacking of rubbish bins and containers (Castillo-Contreras et al., 2018), sharing diseases with pets and humans (Meng et al., 2009), and occasional attack of people (Cahill et al., 2012).

A particular challenging situation is local extinction followed by recolonization when native species leaves the city during early urbanization periods but later returns. Native wildlife in cities and surrounding rural areas have faced unprecedented threats including rapid changes from natural to artificial landscape, high human population density, and direct (i.e., hunting) or indirect (i.e., invasive species) impacts caused by human activities (Pérez et al., 2012; Gibson and Yong, 2017; Hughes et al., 2020; Gardiner et al., 2021). After urbanization slows down, native wildlife may recolonize the altered landscape in their former range (Sushinsky et al., 2013; Kalle et al., 2018). One example is bobcat (*Lynx rufus*) that previously disappeared from the urbanization and agricultural areas within Flint Hills ecoregion in North America but have returned recently (Wait et al., 2018). Consequently, this species has caused the most road kill accidents (Bencin et al., 2019), been frequently harvested as furbearers (Allen et al., 2020), and served as an intermediate and definitive host of zoonotic diseases from domestic cats (*Felis catus*) (Kellner et al., 2018).Overall, identifying when, where, and why local extinction followed by recolonization of native species occurs is critical in urban biodiversity management, and such information requires additional effort to measure the driving factors behind species current situation and future trends.

The conservation and management needs of raccoon dogs (*Nyctereutes procyonoides*) in Shanghai is an example of how modeling driving factors and predicting future trends of an urban native species helps management planning (Kauhala and Kowalczyk, 2011). Due to its adaptability in diverse habitats, high reproductive success rate, and great ability to disperse in its native environment, raccoon dogs have been involved in various human-wildlife conflicts in different regions of Shanghai (Deplazes et al., 2004; Lee et al., 2004; Saeki and Macdonald, 2004). As an urban native species, raccoon dogs were recovered in most of its original range in Shanghai, and complaints from city residents have increased from zero in 2015–2016 to 32 in 2017–2018, and reached 95 in 2020–2021 (Shanghai Municipal Forestry Administration, unpublished data). However, very limited information is available on its habitat association or potential future ranges, resulting in difficulties in alleviate human-wildlife conflict and maintaining urban biodiversity in Shanghai.

To fill in the knowledge gap, we present the first study of raccoon dogs in urban, China, to demonstrate how species distribution modeling (SDM) and scenario analysis can benefit management planning. Our goal was to understand the distribution of raccoon dogs and thereby aid in the management of the species. To address this goal, our objectives were to: 1) identify environmental factors associated with raccoon dog habitat selection; and, 2) model current suitable habitats and predict future ranges under different urban development scenarios by using SDM.

2. Material and methods

2.1. Study area

The study area is the municipality of Shanghai (hereafter Shanghai, 120°51′- 122°12′ E, 30°40′-31°53′ N). Shanghai has an area of 6,340 km^2 and a population of 24,281,400 (Fig. 1; Wei et al., 2020). The city is located in the alluvial plain of the Yangtze River, at the center of the Yangtze River Delta Urban Agglomeration, with gross domestic product up to 3,815.53 billion RMB (approximate 597.51 billion USD) in 2019 (http://tjj.sh.gov.cn/). Shanghai has a northern subtropical monsoon climate, with annual average precipitation of 1122 mm and annual mean temperature of 15.8 °C (Wu et al., 2012). The area surrounding Shanghai is originally rich in biodiversity, e.g., a survey in 2004 reported 760 vertebrate species, consisted of 40 mammals, 424 birds, 32 reptiles, 14 amphibians, and 250 fish species (Shanghai Agriculture and Forestry Bureau, 2004). However, numerous species experienced local extinction, including leopard cat (*Prionailurus bengalensis*), small Chinese water deer (*Hydropotes inermis*), and Asian badger (*Meles leucurus*) (Nie et al., 2020).

2.2. Data collection

Shanghai Municipal Forestry Bureau (SMFB) recorded raccoon dog sighting locations from 2019 to 2021, in which the sighting of at least one raccoon dog (alive, wounded or dead) was considered a presence. In addition to the SMFB database, we also conducted an online survey on China's mainstream social media platforms (Weibo, WeChat etc.) during December 2019 to September 2021. We developed an online portal called "Shanghai Citizen Scientist", through which participants could report the location of raccoon dog sighting or signs, upload evidence (e. g., pictures of individual raccoon dog, den, or fecal matter), and describe the surrounding environment (Mueller et al., 2019). When a raccoon dog sighting was reported, we conducted field survey with 24 h to confirm the species' occurrence.

For the above-mentioned field survey, we followed a protocol to search for raccoon dog individuals and fecal signs within 10 m distance of both sides of transects. Two rules were used to avoid false positives or false negatives: 1) every location reported in SMFB or online survey database was visited; and 2) a buffer zone of approximately 3 km around each raccoon dog present location was surveyed until no raccoon dog signs could be found (Saeki et al., 2007). The surveys were conducted during 10p.m. to 12p.m. to match the activity peak of the nocturnal raccoon dogs (Kauhala et al., 2007). Upon arrival at each survey locations, we first located residents and security guards with sufficient knowledge, and collected background information such as raccoon dog sighting history, population size and trends. After interviewing knowledgeable residents, we ground-verified the records by searching for species presence evidence (e.g., individual sighting, calls, fecal matter, or dens) (Fig. 2). This was achieved either by requesting the interviewee to lead us to animal signs, or by conducting transects in the most possible areas (Liu et al., 2009). The length of transects were 100 m to 300 m, and we used a 1 m/ second speed to search along the transect. For locations that we did not locate any raccoon dog sighting or sign, the survey was repeated three times to avoid false negative result (Levitan et al., 2004). A reported location was labeled 'verified' if any signs (e.g., fecal and individuals) were found, and only verified reports were later used to construct species distribution modeling.

2.3. Data processing and environmental covariates selection

To reduce the impact of potential pseudo-replication when samples are nested or hierarchically organized, we pre-processed the raccoon dog presence records by retaining only one if two or more locations were

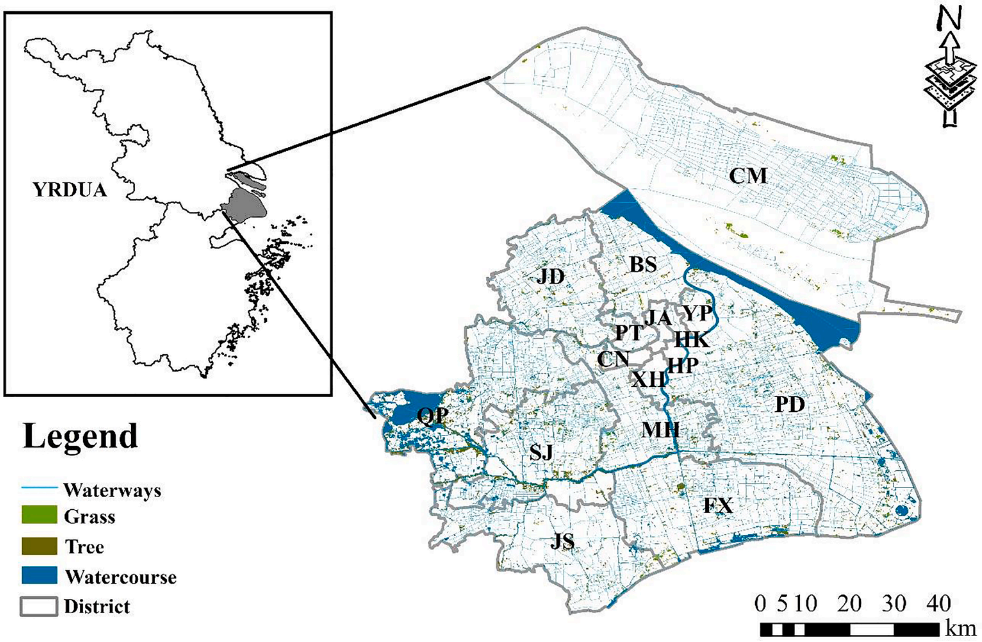

Fig. 1. Our study area, Shanghai, located in the Yangtze River Delta Urban Agglomeration. The administrative districts are Chongming (CM), Baoshan (BS), Jiading (JD), Yangpu (YP), Jiang'an (JA), Jiading (JD), Putuo (PT), Huangpu (HP), Xuhui (XH), Changning (CN), Minhang (MH), Songjiang (SJ), Qingpu (QP), Jinshan (JS), Fengxian (FX), and Pudong (PD) District.

Fig. 2. Raccoon dogs live in ventilation ducts, photo uploaded by online survey participants.

Fig. 3. Raccoon dogs in residential area, Songjiang District, Shanghai. More than five raccoon dogs were attracted to this stray cat feeding site.

positioned within 0.5 km from each other (Saito and Koike, 2013). Because field surveys yielded presence-only data, to use statistical algorithms that require both presence and absence locations, we followed Iturbide et al. (2015) and generated random pseudo-absent locations. Pseudo-absent locations were generated at least 0.5 km from any of the presence points considering species' home range size (approximately 3 km^2; Barbet-Massin et al., 2012). We acknowledge that presence–absence data generated from the above protocol represent indices of raccoon dog occurrences rather than the true occupancy status.

We reviewed previous raccoon dog studies, and identified factors that potentially affect raccoon dog occurrence, including food resources (Meyrier et al., 2017), habitat structure (Milanovich et al., 2012), habitat corridors (Angold et al., 2006) and human population (Li et al., 2013). The main urban food resources for raccoon dogs in Shanghai are aquatic organisms in ponds and watercourses, kitchen waste, and cat food (Fig. 3) around buildings (McKinney et al., 2002). We chose the total area of watercourses and buildings in a 300 m buffer to represent urban food resources, and used urban green area, urban tree area in a 300 m buffer, and Normalized Difference Vegetation Index (NDVI, indictor of ground vegetation growth) to represent habitat structure (Haklay and Weber, 2008; Chen et al., 2016). Distance to waterway and road density were calculated based on the observation that raccoon dogs frequently utilize roads and waterways to disperse (Saeki and Macdonald, 2004). We used the intensity of nighttime light and human population to represent the level of human stressors, which may influence raccoon dog reproduction and survival (Elvidge et al., 2017; Jeschke and Strayer, 2006) (Table 1). All environment data was download from 2020 database, and were resampled to 300 m × 300 m resolution using the projection of WGS 1984 51 N.

Prior to model construction, we used Variance Inflation Factor (VIF) as a descending dimension algorithm to examine multicollinearity among covariates (Salmerón Gómez et al., 2016). We found that there was no evidence of multicollinearity and all the covariates had VIF < 5 (Table 1), that can be retained in the following analysis (O'Brien, 2007). We used the ArcGIS 10.2 (ESRI, 2013) to process variables and R

Table 1
Predictive covariates to construct species distribution models, and Variance Inflation Factor (VIF) results indicated low multicollinearity. All variables had VIF < 5 and were included in further analysis. Data sources include Environmental Systems Research Institute (ESRI), Open Street Map (OSM), WorldPop Country Dataset (WorldPop), and Google Earth Engine (GEE).

Urban attributes of species habitat	Predictive covariates	Source	VIF
Urban food resources	Area of watercourses (ha)	ESRI	1.030
	Area of buildings (ha)	ESRI	1.857
Habitat structure	Urban grass area fragmentation (ha)	ESRI	1.031
	Urban tree area fragmentation (ha)	ESRI	1.054
	Normalized difference vegetation index (NDVI)	ESRI	1.592
Corridors	Distance to waterways (km)	OSM	1.670
	Road density	ESRI	2.282
Human distribution	Human population	WorldPop	1.562
	Nighttime light (lux)	GEE	1.869

software (version 3.1.3; R Development Core Team, 2015) to perform species distribution modeling.

2.4. Species distribution modeling

To capture the spatial similarity pattern caused by environmental similarity and rapid population expansion, we first followed Wang et al. (2018) and compared the discriminative performance of an environmental-only model (hereafter ENV) that did not account for spatial autocorrelation (hereafter SAC) (Merckx et al., 2011) with a residual autocovariated model (hereafter RAC), which included an autocovariate term that accounted for spatial autocorrelation (Crase et al., 2014). Considering that the urban landscape shaped by city development planning, and corresponding spatial autocorrelation is much higher than the natural landscape, we used ENV model to predict the ideal raccoon dogs' distribution patterns, and used RAC model to predict the local diffusion areas of raccoon in a short time (Kowe et al., 2019). The ensemble SDM approach incorporates multiple SDM algorithms to provide a more robust result on species occurrence–environment associations than using each algorithm alone (Thuiller et al., 2016; Tanaka et al., 2020). Six SDM algorithms including Flexible Discriminant Analysis (FDA), Generalized Additive Model (GAM), Gradient Boosted Machine Learning (GBM), Generalized Linear Model (GLM), Multivariate Adaptive Regression Splines (MARS), and Random Forest Classifier (RF) were first constructed separately to predict occurrence probability of raccoon dogs across the study area (Ray et al., 2021). We then followed Thuiller et al. (2016) to weighted-average different algorithms based on their discriminative performances. Each model was calibrated using 70 % of observations that randomly selected from the initial dataset, and was then evaluated against the 30 % reserved data (Acevedo et al., 2012; Thuiller et al., 2019). Two cross-validation performance metrics were used, including the area under curve of the receiver operating characteristic (AUC; Fawcett, 2006) and the true skill statistic (TSS; Barbet-Massin and Jetz, 2015). We plotted Moran's I correlogram to further quantify the remaining spatial autocorrelation in model residuals (Legendre and Legendre, 2012). We estimated the weight of each predictor with the formulae developed by Friedman (2001) that implemented in the R "gbm" library (Friedman, 2001).

Based on species-environment associations derived from ensemble modeling, we predicted raccoon dog habitat suitability, and gridded to a 0.5° resolution (Wang et al., 2018). Each grid cell was assigned a predicted value of habitat suitability index (0–1). To better demonstrate the species' habitat pattern, we used a threshold that maximized the sum of modeling sensitivity and specificity (ENV: 0.479; RAC: 0.600, calculated using "biomod2" package in R environment) to transform the continuous habitat suitability index to binary predictions of suitable/unsuitable habitat (Freeman and Moisen, 2008; Liu et al., 2005).

2.5. Scenario analysis

To evaluate how alternative urban development strategies affect raccoon dog expansion, we first simulated hypothetical future urban landscapes. We then predicted future raccoon dog ranges under each scenario based on occurrence-environment relationships obtained from ENV and RAC models. Eventually, we compared the predicted raccoon dog distributions to their current range to understand potential range expansions.

The urban landscape development scenario settings were derived from discussions with the local forestry department and management options announced in recent government plans (Zhou and Gao, 2017). The three most widely discussed management options for green spaces in Shanghai were: (1) city tree restoration, which is announced in Shanghai 2035 urban planning (Kauhala and Auttila, 2010); (2) extensive human activities, representing rapid economic developments (Chen et al., 2016); and (3) urban comprehensive transport system construction, for which the primary purpose is to increase the township connectivity and accessibility showed in Shanghai City Master Plan 2017–2035 (Ma et al., 2018). For the city tree area restoration scenario, we assumed that with proper green space management, the area of the existing green space would be doubled in percentage area coverage. For the extensive human activity scenario, we assumed that rapid economic growth would result in brighter nighttime lights. For the urban comprehensive transport system construction scenario, we assumed an increase in the road density throughout Shanghai. We predicted raccoon dog occurrence probability under each scenario, and compared distribution patterns among different scenarios.

3. Results

3.1. Model selection

After data pre-processing, 215 raccoon dog present locations were retained (Supporting Information Fig. S4). We found strong residual spatial autocorrelation for the ENV model (Moran's $I = 0.14$, $p < 0.01$; Fig. S1, S2). Incorporating the RAC term reduced the residual spatial autocorrelation (Fig. S2; Table S3) and improved the discriminative ability of the RAC model (Fig. 4).

3.2. Raccoon dog habitat selection

According to the ENV model, four predictors (i.e., percentage area of buildings, NDVI, human population, and nighttime light) had a model weight > 0.1 (Table 2). The habitat suitability of raccoon dogs was high in areas that had brighter nighttime light (0.37 model weight), but decreased when the intensity of nighttime light was higher than 60 (Fig. 5). The habitat suitability of raccoon dog increased when NDVI was moderately high, but decreased when NDVI was above 0.8 (0.19 model weight). Raccoon dog habitat suitability index was positively associated with moderate human population density (0.12 model weight) and higher percentage area of buildings (0.11 model weight). Area of watercourses, urban grass area fragmentation, urban tree area fragmentation, distance to waterways, and road density had no significant effects on raccoon dog habitat selection (<0.1 model weight; Table 2). In RAC model, the species-environment associations were similar (Fig. 5), but no predictor had a model weight above 0.10; NDVI had the highest model weight of 0.09.

3.3. Current and future suitable habitats of raccoon dogs

Both ENV and RAC models estimated large suitable habitat patches in middle SJ, northern MH, and small regions in BS, CN, QP, XH, and YP district (Fig. 6). However, the ENV model predicted a more

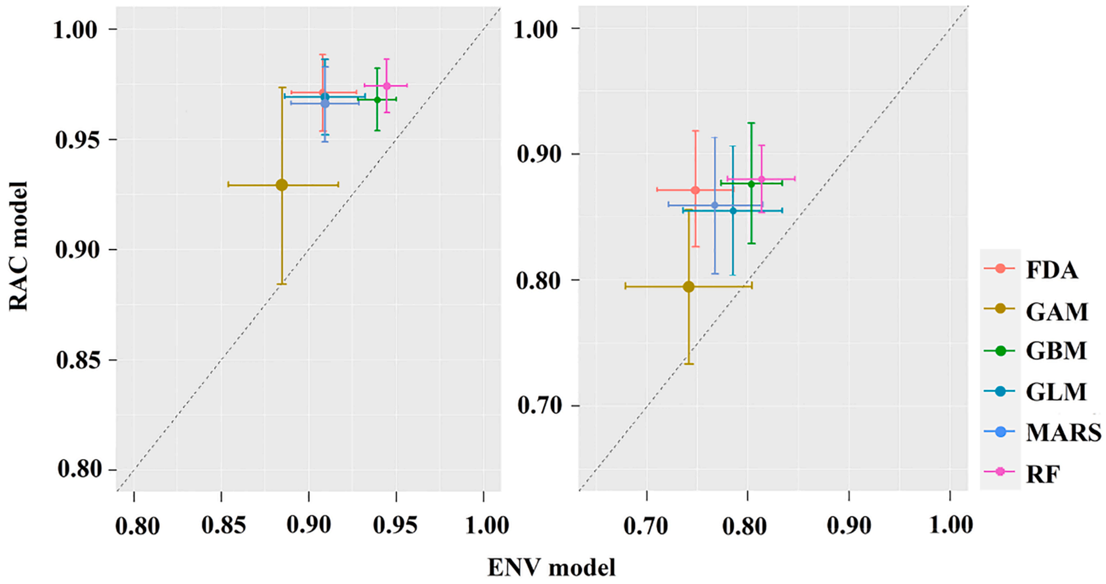

Fig. 4. Cross-validation results using (A) AUC and (B) TSS to compare the performance of RAC model and ENV models. Each crossing symbol indicates the mean and variance of AUC and TSS tests for model replicates. All AUC and TSS result are above dashed line (slope = 1). Higher values for RAC models indicate improved model discriminative performance when spatial term was incorporated. Abbreviations are as follows. Flexible Discriminant Analysis: FDA, Generalized Additive Model: GAM, Gradient Boosted Machine Learning: GBM, Generalized Linear Model: GLM, Multivariate Adaptive Regression Splines: MARS, Random Forest Classifier: RF.

Table2
The relative importance of the predictive covariates in modeling raccoon dog habitat suitability. Bold numbers indicate variables had a relative importance > 0.1.

Urban attributes of species habitat	Predictive covariates	ENV	RAC
Urban food resources	Percentage area of watercourses (ha)	0.01	0.01
	Percentage area of buildings (ha)	**0.11**	0.06
Habitat structure	Urban grass area fragmentation (ha)	0.01	0.01
	Urban tree area fragmentation (ha)	0.07	0.03
	Normalized difference vegetation index (NDVI)	**0.19**	0.09
Corridors	Distance to waterways (km)	0.02	0.01
	Road density	0.09	0.08
Human distribution	Human population	**0.12**	0.06
	Nighttime light (lux)	**0.37**	0.03

decentralized habitat pattern, whereas the RAC model predicted a centralized and clustered habitat pattern. The ENV model predicted a 156,016 ha suitable habitat, accountings for 24.6 % of the total area of Shanghai (634,000 ha), whereas the RAC model predicted a much smaller area of 63,828 ha suitable habitat, accounting for 10.1 % of the total area of Shanghai (Fig. 7).

The predicted raccoon dog future ranges under three urban development scenarios varied. The current raccoon dog distribution remained stable (i.e., BS, JD, PD, MH, SJ, XH and QP). However, the suitable habitat outside current ranges under different urban development scenarios diverged. For the city tree area restoration scenario, 126,094 ha (ENV), and 63,882 ha (RAC) suitable habitat was predicted. Compared to current ENV model, FX decreased the maximum proportion of area by 25 % and PD increased the most area by 8853 ha. Compared to current RAC model, YP increased the maximum proportion of area by 2 % and QP increased the most area by 36 ha under city tree area restoration scenario.

For the extensive human activity scenario, ENV model predicted a 168,479 ha suitable habitat and RAC model predicted a 63,432 ha suitable habitat. Compared to current ENV model, HP decreased the maximum proportion of area by 92 % and FX decreased the most area by 5,166 ha. Compared to current RAC model, JA decreased the maximum proportion of area by 17 %, and SJ decreased the most area by 144 ha under extensive human activity scenario.

For urban comprehensive transport system construction scenario, 157,080 ha and 63,954 ha suitable habitat was precited by the ENV and RAC models, respectively. Compared to current ENV model, CM increased the maximum proportion of area by 43 %, and QP increased the most area by 1,296 ha. Compared to current RAC model, JS increased the maximum proportion of area by 5 %, and PD increased the most area by 67 ha under urban comprehensive transport system construction scenario (Table S5).

4. Discussion

We constructed species distribution modeling and incorporated a spatial covariate (RAC term) to capture the potential residual autocorrelation. We found significant residual spatial autocorrelation in the ENV model, which could be substantially reduced by applying the RAC term (Fig. 4). We found that accounting for residual autocorrelation improved model performance and changed the estimation of species-environment relationships. The results from RAC models proved that raccoon dogs in urban areas may have wider environmental envelop to vegetation and anthropogenic activities, so the species can persist and even rapid expand under various urban circumstances.

Besides improving discriminative abilities of species distribution modeling, we believe there could be subtle differences in how to interpret results from ENV and RAC modeling results. The RAC term is calculated from the residuals of ENV models, and thus represents factors other than the predictive covariates already included in the ENV models. In this study, we believe the limits in raccoon dog dispersal may have caused residual spatial autocorrelation patterns in the ENV model, but such effects are difficult to quantify in a non-spatial model but need to be accounted for using the RAC term. We speculate that ENV models predicted potential suitable habitats raccoon dogs that were not fully realized due to limitations in dispersal, while RAC models predicted a much smaller realized suitable habitats that mainly gathered around current core ranges (Fig. 5). To better utilize different analytical approaches, we suggest using RAC model to predict the current suitable habitats of species, and using ENV model to predict the future suitable habitats that does not meet dispersal constraints.

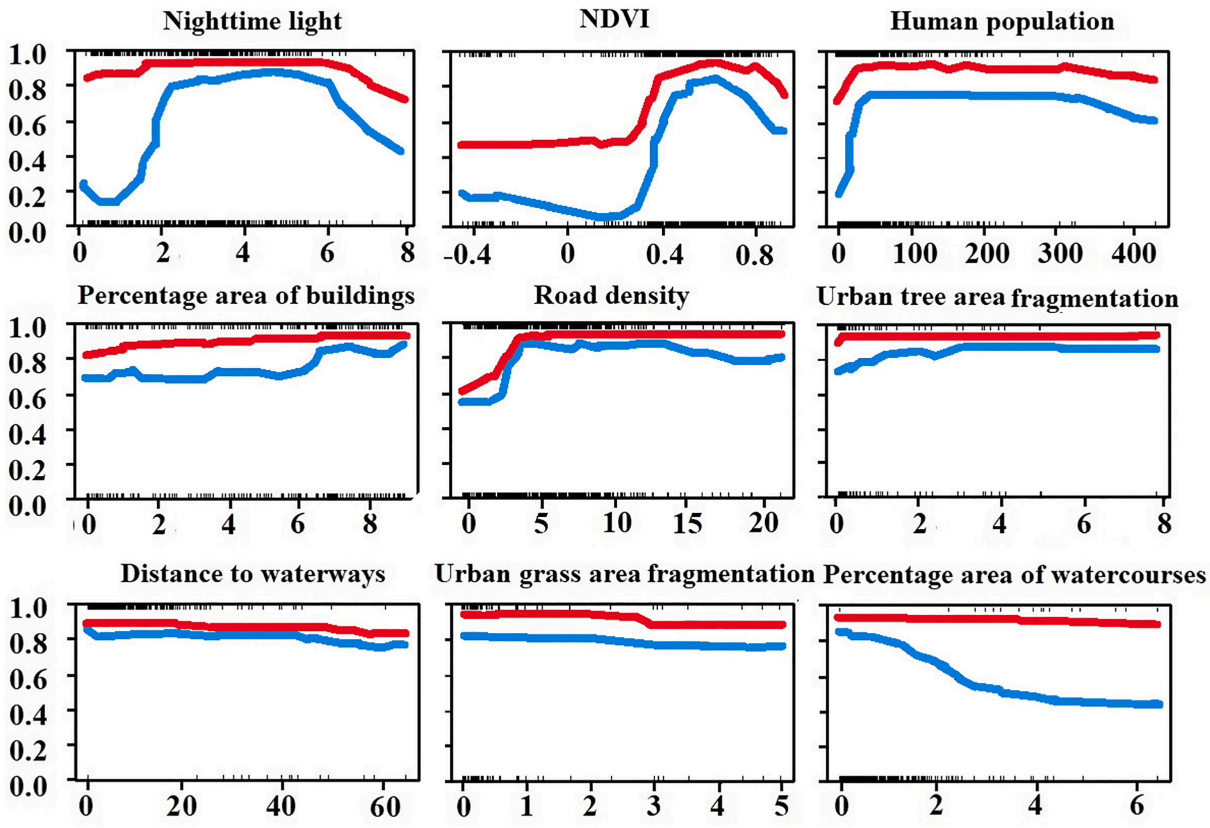

Fig. 5. Partial dependence plots for ENV models (blue lines) and RAC models (red lines) for nine predictive covariates, indicating the associations of raccoon dog occurrence on each predictor. Raccoon dog habitat suitability is high with medium to high nighttime light brightness (>40 lx), medium NDVI (approach 0.5), moderate human population (>56/ha and < 320/ha), and higher percentage area of buildings (>7 ha). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

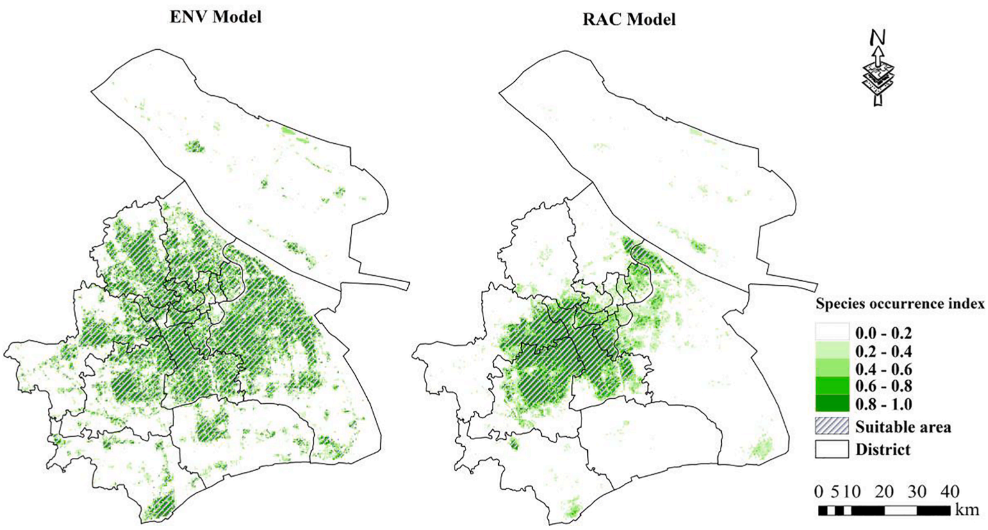

Fig. 6. Species occurrence probability map and suitable habitat of raccoon dogs, predicted by ENV (left) and RAC (right) models. The suitable habitat of raccoon dog predicted by ENV model covered 156,016 ha, accountings for 24.6 % of the total area of Shanghai, whereas the RAC model predicted a more concentrated habitat pattern, covering 63,828 ha.

Since the first half of the 20th century, the raccoon dog has become an alien species in Europe and has been increasing rapidly (Kauhala and Kowalczyk, 2011). Similarly, in China, its country of origin, raccoon dogs are urban native species that experienced local extinction followed by recolonization in Shanghai and throughout the much larger Yangtze River Delta Urban Agglomeration. Contrary to previously research which reported that urban species tend to hide in darker environment (Gaynor et al., 2018; Wevers et al., 2020; Lopucki et al., 2021), our results demonstrated that raccoon dogs had higher occurrence probability in densely human-populated areas (>56/ha and <320/ha) with brighter lights (>40 lx). One important reason to this increase may be the high accessibility of man-made food in urban environment (e.g.,

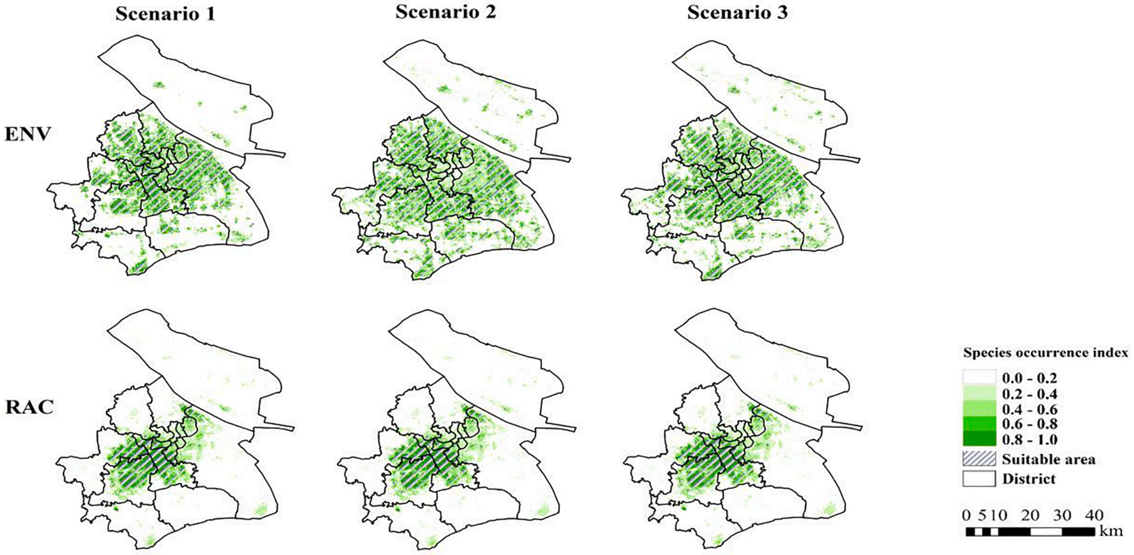

Fig. 7. Future species occurrence probability and suitable habitat of raccoon dogs, predicted by ENV (top) and RAC (down) models under three management scenarios: (1) tree area restoration scenario (left); (2) extensive human activity scenario (middle); and (3) urban comprehensive transport system construction scenario (right). Predicted raccoon dog suitable habitat of ENV and RAC models varies greatly in different district under diverse urban development strategies scenarios.

domestic waste, vegetable ingredients in parks and gardens, pet food and direct feeding). Limiting the availability of cat food to wild urban carnivores has been advocated in various urban environment studies (Contesse et al., 2004; Theimer et al., 2015). During our on-site surveys, we found exceptionally high number of stray cats feeding sites, providing unlimited water and food sources for raccoon dogs, as well as hedgehog, civets, and squirrels. Based on these findings, we strongly suggested Shanghai authorities to initiate educational programs for citizens, propagate the necessity of reducing stray animal's feedings and access to garbage/waste to slower the expansion speed of raccoon dog as well as reduce its dependence to human activities.

Comparing the current raccoon dog distribution (5,811 ha, 0.9 % of the total area of Shanghai) with its potentially suitable habitat (ENV: 156,016 ha, 24.6 % of the total area of Shanghai, RAC: 63,828 ha, 10.1 % of the total area of Shanghai), we conclude that raccoon dogs have great potential to further colonization Shanghai urban areas in near future. While there have never been raccoon dog records on Chongming Island, it is predicted to have large suitable habitat patches. Considering the short distance from Shanghai mainland to Chongming Island, we suggest stricter control be set up at ports and cross sea tunnels to prevent raccoon dogs from threatening the island ecosystems (Fig. S5).

An interesting project development is that, other than sampling interviewing online survey participates, we initiated a citizen science project in which social groups, residents, scientists, and decision makers all played different roles. Different groups of participates are responsible for various tasks including collecting information, giving advice, and making decisions for management. For reducing human-related food sources (e.g., stray cat feeding), many residents have set up guardrail and launched educational initiatives. For habitat corridors management (e.g., waterways and road), government decision makers have incorporated safer wildlife movement corridors designs into future urban landscape planning. For anthropogenic factors management (e.g., nighttime light intensity), environmental NGOs negotiated with communities to reduce light sources (Table 3). To ensure the long-term sustainable in city development, societies must generally demonstrate the ability to: (1) buffer disturbance, (2) self-organize, and (3) learn and adapt (Trosper, 2002). We believe, in addition to providing the information for the first urban native species that experienced local extinction followed by recolonization in China, our study also demonstrated how citizen science project support management of urban biodiversity and thus can be applied to other rapid urbanization areas.

Table 3
Management applications of the drivers for raccoon dog presence in the urban area of Shanghai identified in this study.

Factor	Variable	Measure	Feasibility
Urban food resources	Proximity to watercourses	Set up guardrail	High
	Feeding of cat food	Awareness campaign	High
Habitat structure	Urban green area	Vegetation change to native species and keep it trimmed	High
Corridors	Waterways and road	Wildlife movement corridor	Medium
	Ecological corridor	Avoid connecting suitable habitats	Medium
Human distribution	Nighttime light	Reduce light sources	Low

5. Conclusion

We predicted a 156,024 ha suitable habitat for raccoon dogs throughout Shanghai, among which only 5,811 ha (3.72 %) was currently occupied. Raccoon dog had considerable potential to future expansion, which had been consistently ignored in previous management plans. To alleviate the increasing human-raccoon dog conflicts, we found strategies to slow down raccoon dog movement effective tools, and suggest adaptive management to provide fast response and flexible solutions.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.landurbplan.2022.104581.

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