LAF
https://doi.org/10.15302/J-LAF-2026-0013
Volume 14 / Issue 4 / 260013 / 2026
Received Date | 2024-10-16 Accepted Date | 2025-05-19

Identification and Optimization of Ecological Conservation Priority Areas for Adaptation to Sea Level Rise in the Guangdong–Hong Kong–Macao Greater Bay Area

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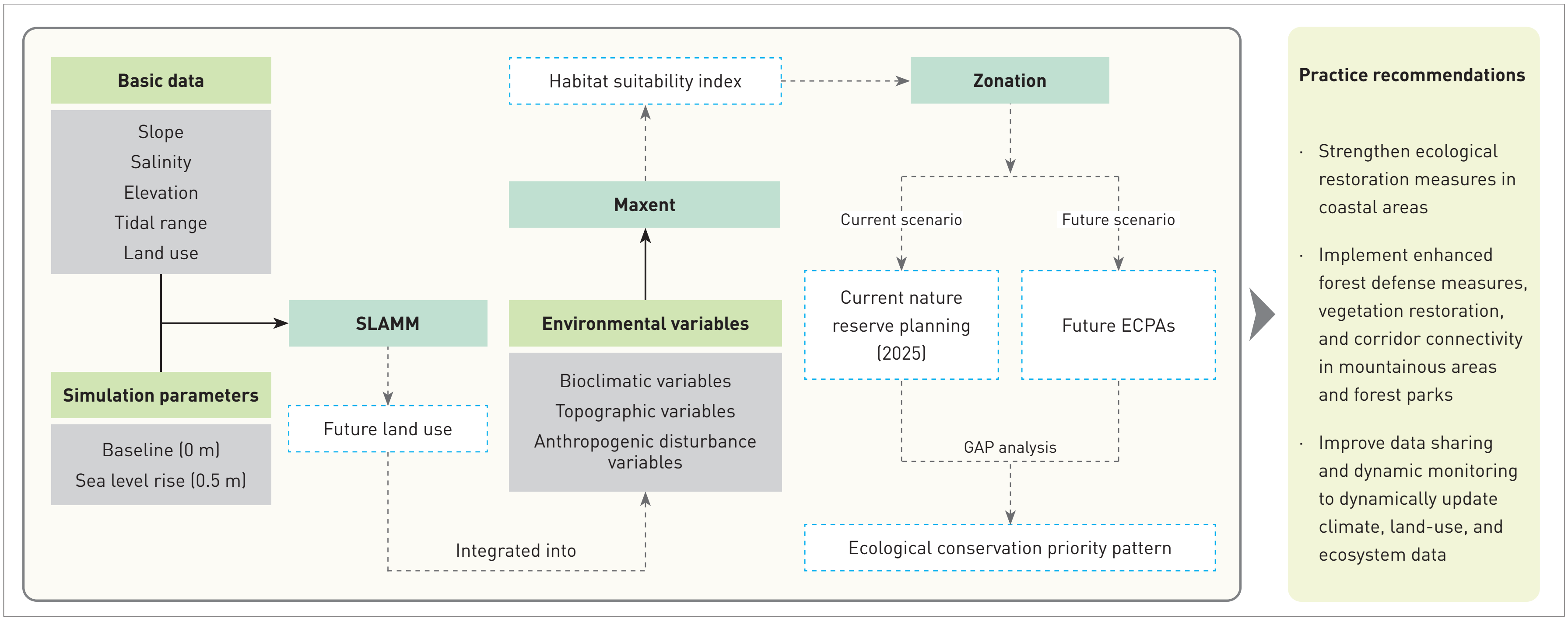
GRAPHICAL ABSTRACT



ABSTRACT

Sea-level rise poses a severe challenge to biodiversity conservation in coastal regions. Taking the Guangdong–Hong Kong–Macao Greater Bay Area (the GBA) as a case study, this research simulated a 0.5 m sea-level rise scenario by 2050. Utilizing a GIS platform, we integrated the Sea Level Affecting Marshes Model (SLAMM), the Maximum Entropy (MaxEnt) species distribution model, and the Zonation systematic conservation planning tool to analyze the changes of ecological conservation patterns from 2020 to 2050. The projected results were further compared with existing nature reserve and territorial spatial plans to identify conservation gaps. This research obtained the following results. 1) The responses of highly suitable habitats to a 0.5 m sea-level rise diverge significantly across four taxonomic groups. Specifically, the highly suitable habitats for mammals and reptiles are projected to decrease by 11.59% and 44.30%, respectively, whereas those for amphibians and birds are expected to expand by 34.61% and 21.61% driven by wetland expansion. 2) Ecological conservation priority areas (ECPAs) for terrestrial wildlife are predominantly concentrated within three distinct ecological settings: mountainous forests, coastal and shoreline ecosystems, and peri-urban nature reserves. 3) Although the predicted 2050 ECPAs largely overlap with current nature reserves (2025), critical protection gaps remain in the southern mountainous and coastal regions of Jiangmen, the central-western areas of Shenzhen, the southern coastal and eastern mountainous regions of Huizhou, national forest parks in the central-northern Guangdong, and the mountainous areas in northern Zhaoqing. This study provides a scientific basis for the adaptive planning of coastal cities in response to sea level rise.

KEYWORDS

Sea-Level Rise; Systematic Conservation Planning; Ecological Conservation Priority Area; Territorial Spatial Planning; Conservation Gap Analysis; Guangdong–Hong Kong–Macao Greater Bay Area; Biodiversity Conservation

HIGHLIGHTS

- Uses SLAMM-MaxEnt-Zonation framework to predict habitat shifts under sea-level rise
- Identifies conservation gaps by comparing projected 2050 ECPAs with current reserves
- Promotes dynamic adaptive spatial planning to support coastal climate resilience

RESEARCH FUNDS

- National Natural Science Foundation of China (No. 32271735)
- Guangdong Provincial Philosophy and Social Science Planning Project (No. GD24CYS34)
- Fundamental Research Funds for the Central Universities (No. CGPY202409)

1 Introduction

Of all the consequences of global climate change, sea-level rise is considered the most certain, direct, apparent, and widespread[1]. The Intergovernmental Panel on Climate Change (IPCC), in its latest assessment report, noted that since 2006 the rate of global sea-level rise has accelerated significantly, and this upward trend is expected to continue and remain largely irreversible. Due to differences in surface wind patterns, regional ocean thermal expansion, and varying degrees of glacial melt, the rate of sea-level rise differs across regions worldwide[2]. In April 2024, the Ministry of Natural Resources released the *China Sea Level Bulletin* (2023), reporting that from 1980 to 2023, the rate of sea-level rise along China's coast averaged 3.5 mm/year—slightly higher than the global average over the same period. It is projected that within the next 30 years, sea levels along China's coast will rise by 70–176 mm.

Sea-level rise will intensify disasters such as storm surges, flooding, coastal erosion, saltwater intrusion, and seawater encroachment, thereby exerting considerable impacts on ecological conservation, economic development, and the livelihoods of coastal populations. It poses substantial challenges to habitat integrity and biodiversity conservation in coastal regions, potentially leading to significant biodiversity loss[3]. On the one hand, rising water levels directly inundate coastal habitats (e.g., wetlands, mangroves), causing the loss of key species[4]. On the other hand, sea-level rise alters the hydrological and ecological systems of coastal regions. According to recent research, without adaptation measures, a global sea-level rise of 0.5 m by the end of this century could eliminate up to 30% of coastal wetlands worldwide, including projected drastic decline in China[5].

Since its emergence, the concept of systematic conservation planning (SCP)[6] has been widely applied in biodiversity and ecosystem conservation both domestically and internationally[7–11]. To improve the conservation planning efficiency, multiple SCP tools have been developed based on different algorithms, with Marxan, Zonation, and C-Plan being the most commonly used[12]. Existing studies typically combine these tools with sea-level rise impact models to simulate changes in species or community distributions and identify the ecological priority conservation areas (ECPAs) under sea-level rise[13–14]. Another approach integrates species distribution models or habitat models with sea-level rise impact models to first identify vulnerable habitats, subsequently applying SCP tools to designate the ECPAs[15].

The *Outline Development Plan for the Guangdong–Hong Kong–Macao Greater Bay Area* explicitly highlights the construction of a biodiversity conservation system and the enhancement of overall ecosystem quality as priority tasks. However, biodiversity conservation studies in the Greater Bay Area in the context of sea-level rise remain limited. Against this backdrop, it is essential to adopt systematic planning methods and frameworks that explore spatial patterns of ecological conservation in alignment with conservation goals at multiple levels. Such approaches are critical for addressing the challenges posed by sea-level rise and developing scientific strategies and management measures to protect biodiversity in the region.

2 Study Area

The Guangdong–Hong Kong–Macao Greater Bay Area (GBA), located in south China, comprises nine mainland cities—Guangzhou, Shenzhen, Zhuhai, Foshan, Dongguan, Huizhou, Zhongshan, Jiangmen, and Zhaoqing—along with the two special administrative regions of Hong Kong and Macao, covering a total area of 56,000 km^2[16]. The GBA holds a pivotal role in China's national development strategy. Statistics from the Guangdong Provincial Bureau of Statistics, the Census and Statistics Department of the Government of the Hong Kong Special Administrative Region, and the Statistics and Census Service of the Government of Macao Special Administrative Region indicate that the population density within the GBA has reached 1,551.5 persons/km^2. Boasting an aggregate GDP of CNY 14.05 trillion, the area constitutes one of the primary drivers propelling China's macroeconomic expansion[17].

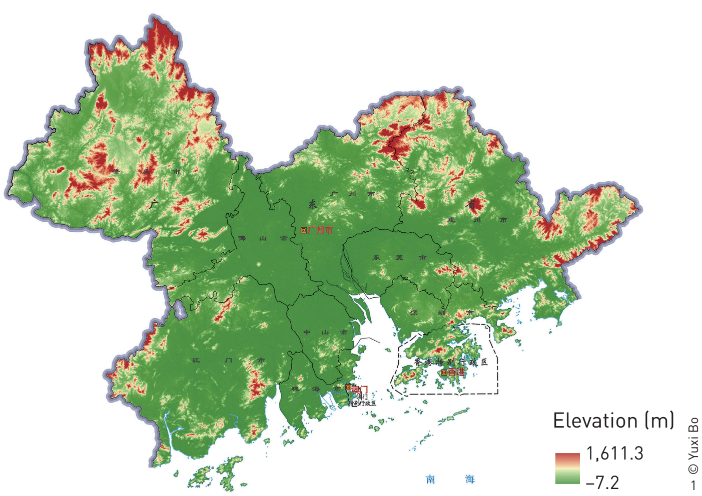
The GBA has a humid subtropical climate, with a mean annual temperature of 22.9°C and abundant precipitation. It harbors high biodiversity, including mammals, birds, amphibians, reptiles, fish, and invertebrates[18]. As shown in Fig. 1, the GBA is primarily situated on the alluvial plain of the Pearl River Delta. It is surrounded on three sides by low mountains and hills and faces the South China Sea to the south. Its location in a sea–land interaction zone, with a highly indented coastline, numerous estuaries, and pronounced tidal influence, gives rise to complex geomorphological features[19]. Areas at or below sea level account for 583 km^2, representing about 9% of the GBA's total area[20].

As a result, the GBA faces severe challenges in mitigating habitat inundation risks and conserving biodiversity under sea-level rise scenarios. These risks call for urgent attention and the implementation of targeted adaptive measures to address potential ecological threats.

3 Methods and Materials

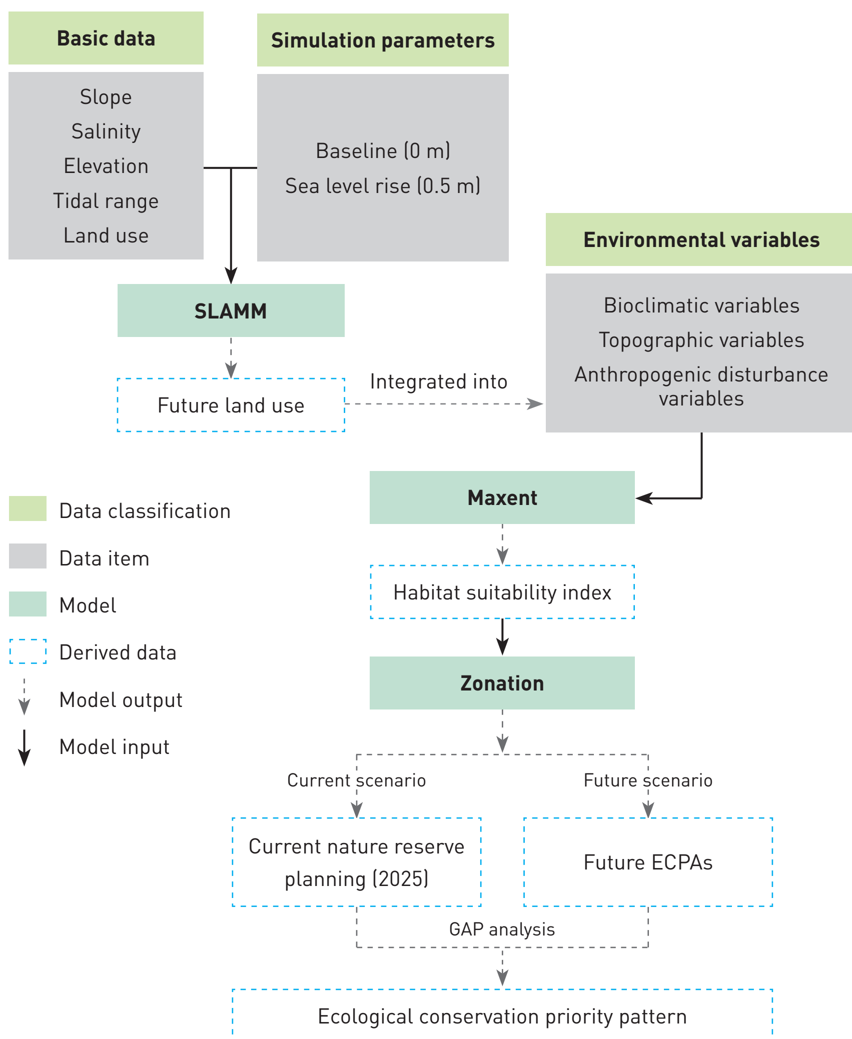
The technical framework of this study is illustrated in Fig. 2. Based on basic data of the study area (i.e., land use, elevation, slope, tidal range, salinity) and sea-level rise scenario data, we employed the Sea Level Affecting Marshes Model (SLAMM) to simulate future land-use changes under a 0.5 m sea-level rise scenario. The Maximum Entropy (MaxEnt) model was then applied to simulate

Fig. 1 Elevation map of the GBA.



1 © Yuxi Bo

Fig. 2 Technical framework of this study.



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the current and future potential distributions of target species. On this basis, the SCP model Zonation was used to identify and comparatively analyze current and future multi-species ECPAs. Finally, the predicted future ECPAs were compared with the existing ecological conservation zones delineated in the *Guangdong Nature Reserve Plan*, the *Guangdong Territorial Spatial Ecological Restoration Plan* (2021–2035), and the *Guangdong Territorial Spatial Plan* (2035). This integrated approach aims to optimize the priority pattern of ecological conservation in the GBA and to provide scientific support for regional conservation strategies.

3.1 Research Methods

3.1.1 SLAMM Simulation of Future Land Use: Impacts on Coastal Wetlands

The SLAMM is primarily applied to assess the impact of sea-level rise on land use, especially the coastal wetlands. Built upon a Geographic Information System (GIS) framework, the model integrates spatial data (e.g., elevation, initial land cover) with simulation parameters (e.g., projected sea-level rise and accretion rate). It quantifies land-use changes during sea-level rise through geometric relationships[21].

In this study, the SLAMM 6.7 model was used under the SSP5-8.5 scenario. By incorporating regional site parameters (including slope and tidal range), the model simulated the spatial distribution and extent of coastal wetlands in the GBA under a 0.5 m sea-level rise scenario by 2050.

3.1.2 Operation and Optimization of MaxEnt Model

MaxEnt predicts species distributions using known occurrence data, estimating the potential distribution that satisfies maximum entropy under different environmental conditions[22]. In this study, the MaxEnt model was used to predict the potential distributions of 28 key terrestrial species in the GBA:

$$H(\pi) = -\sum_{\chi} \pi(\chi) \ln \pi(\chi), \tag{1}$$

where χ is the environmental variable, $\pi(\chi)$ is the probability of the environmental variable occurring, and $H(\pi)$ is the entropy value. The probability distribution that satisfies the maximum entropy principle is[23]:

$$\pi^* = \arg\max_{\pi \in \Pi} H(\pi). \tag{2}$$

To assess the final impact of each environmental variable on species distribution, the Jackknife method was used for 10 repeated trials, and the average data was calculated as the prediction result.

3.1.3 Zonation Model

Zonation has been widely used to simulate large-scale spatial prioritization for conservation[24]. Compared with other software, it can identify priority areas of single or multiple species habitats and emphasizes landscape connectivity to enhance the value of biodiversity conservation[25]. In this study, Zonation v5 was applied to prioritize conservation areas based on species distribution models for 2020 and 2050. Among the two most commonly used marginal loss rules—Additive Benefit Function (ABF) and Core-Area Zonation (CAZ)—the ABF prioritizes areas with higher mean coverage of all species but may underrepresent rare species, while the CAZ prioritizes rare or high-weight species but may overlook areas of high overall biodiversity value[26–27]. As the objective of this study was to protect habitats with the highest species richness, the ABF rule was selected, summing the conservation values of all species within each grid cell[28].

In Zonation, the selection of the warp factor value determines the number of grid cells to be removed during each iteration[29]. Lower warp factor values yield superior solutions, which means more precise conservation priority rankings in this research[30]. Therefore, this study sets the warp factor to “1” to ensure the optimal results and adopted the default values of all other parameters to guarantee the stability and reliability of the outcomes. Given the significant impact and constraints of artificial land use imposed on conservation zoning, this study employed the Hierarchical Removal Mask function to exclude unsuitable areas, thereby enhancing the accuracy of simulation results.

As species vary in conservation value, assigning appropriate weights is crucial for improving resource allocation and strategy formulation in multi-species spatial prioritization[18,31]. Following the weighting scheme developed by Mingjian Zhu et al.[18], this study classified species into five levels according to rarity, endangered status, and socio-economic value: 8 for critically endangered (CR) or national grade I protected species; 4 for endangered (EN); 2 for vulnerable (VU) or national grade II species; and 1 for near threatened (NT) or least concern (LC) species.

In accordance with the global 2030 ecosystem conservation targets set by the *Convention on Biological Diversity* (2022) and the *China’s National Biodiversity Conservation Strategy and Action Plan* (2023–2030), the top 30% of the landscape with the highest conservation values in the Zonation outputs was designated as ECPAs. To facilitate further analysis, the Zonation results were reclassified using the Reclassify tool in ArcGIS 10.8 into three hierarchical levels based on 10% intervals: Class I (priority value ≥ 0.9), Class II (0.8 ≤ priority value < 0.9), and Class III (0.7 ≤ priority value < 0.8)[32].

3.2 Data Sources and Processing

3.2.1 Sea-Level Rise Scenarios and Data Sources

According to the Sixth Assessment Report of the IPCC released in 2023, the rate of global sea-level rise accelerated to 3.7 mm/year during 2006–2018. Under a high emission scenario (SSP5-8.5), the global mean sea level is projected to reach 0.20–0.30 m by 2050[33]. Other studies have further indicated that due to uncertainties such as marine ice cliff instability, the projected rise could reach about 0.4 m under medium–low emission scenarios, and up to about 0.6 m under high emission scenarios[34]. Therefore, this study adopted an average value of 0.5 m as the representative sea-level rise scenario for the research area.

3.2.2 Data Preparation and Preprocessing

The SLAMM model requires input datasets including land use, elevation, slope, tidal range, and salinity, with the conservation scenario set as "protect developed dry land"[19–35]. All datasets (Table 1) were preprocessed to meet SLAMM input requirements, including harmonization of geographic coordinate systems, raster formats, and conversion into ASCII files[19,36].

3.2.3 Selection of Key Terrestrial Wildlife Species and Data Sources

Given the pivotal role of biodiversity research in ecological conservation and resource management[37], and addressing the scarcity of high-resolution spatial distribution data, this study followed the framework of Zhu et al.[18] to select 28 priority terrestrial wildlife species as representative conservation targets in the GBA. These species include 11 birds, 5 mammals, 6 amphibians, and 6 reptiles (Table 2). Selection criteria were strictly based on the IUCN Red List of Threatened Species, the List of National Key Protected Wild Animals (China), and the List of Key Protected Terrestrial Wild Animals of Guangdong Province.

Occurrence data were synthesized from the Global Biodiversity Information Facility (GBIF), the China Bird Report, and field sampling records, yielding a total of 23,049 raw records. To ensure the reliability and predictive accuracy of the species distribution models, a rigorous quality control workflow was implemented as follows.

1) Filtering and deduplication. Species with fewer than five valid occurrence records within the study area were excluded. Duplicated points within a 1 km × 1 km grid were removed using ENMTools to mitigate model bias caused by spatial autocorrelation.

2) Thresholding and evaluation. The dataset was split into training (75%) and validation (25%) sets. Predictive performance was assessed using the Area Under the Receiver Operating Characteristic Curve (AUC), with only species achieving an AUC > 0.7(indicating acceptable performance) retained for the final analysis. AUC values were categorized as: poor (0.6–0.7), fair (0.7–0.8), good (0.8–0.9), and excellent (0.9–1.0)[38].

3) Targeted model optimization. For models with initial AUC values between 0.7 and 0.9, spatial thinning was performed using

Table 1: SLAMM input data

Data	Unit	Resolution	Source	Preprocessing
Land use	—	30 m	2020 China Land-Use and Cover Change dataset (CNLUCC), by the Resource and Environmental Science Data Platform, Chinese Academy of Sciences	—
Elevation	m	30 m	Copernicus Digital Elevation Model (DEM), 2021, European Space Agency	—
Slope	(°)	30 m	Derived from DEM	Generated using the Slope tool in ArcGIS
Tidal range	m	30 m	National Marine Science Data Center	Calculated mean annual maximum–minimum differences using daily data (4 times/day) from 27 GBA coastal stations over the past three years; surface generated via Kriging interpolation (range: 1.39–2.05 m) (source: Ref. [19])
Salinity	‰	30 m	Ref. [36]	Current salinity values were adjusted using projected salinity change rates under the sea-level rise of 0.5 m; the interpolated future salinity map was generated using the Kriging tool in ArcGIS

Table 2: Selection of key terrestrial wildlife species and the simulation results

No.	Species	Endangered class			Number of occurrence records	AUC
		IUCN Red List of Threatened Species	List of National Key Protected Wild Animals (China)	China's Red List of Biodiversity		
Amphibian						
1	*Hoplobatrachus rugulosus*	EN	II	EN	72	0.813
2	*Kalophrynus interlineatus*	LC	—	NT	18	0.878
3	*Paramesotriton hongkongensis*	NT	II	NT	686	0.890
4	*Polypedates megacephalus*	LC	I	LC	758	0.883
5	*Quasipaa exilispinosa*	VU	—	VU	150	0.870
6	*Sylvirana guentheri*	LC	—	LC	604	0.897
Bird						
7	*Aerodramus brevirostris*	LC	—	NT	24	0.760
8	*Corvus pectoralis*	VU	—	NT	324	0.725
9	*Emberiza rustica*	LC	—	VU	115	0.824
10	*Emberiza tristrami*	LC	—	NT	116	0.914
11	*Halcyon pileata*	LC	—	VU	779	0.930
12	*Himantopus himantopus*	LC	—	LC	5,815	0.898
13	*Nycticorax nycticorax*	LC	—	LC	6,923	0.893
14	*Platalea minor*	EN	II	EN	266	0.718
15	*Rallina eurizonoides*	VU	—	LC	252	0.795
16	*Recurvirostra avosetta*	LC	—	LC	3,632	0.913
17	*Zapornia fusca*	LC	—	NT	18	0.717
Mammal						
18	*Lutra lutra*	NT	II	EN	11	0.893
19	*Manis pentadactyla*	CR	II	CR	13	0.919
20	*Muntiacus vaginalis*	LC	—	NT	32	0.899
21	*Prionailurus bengalensis*	LC	II	VU	72	0.913
22	*Viverricula indica*	LC	II	VU	17	0.886

(Continued)

Table 2: Selection of key terrestrial wildlife species and the simulation results (Continued)

No.	Species	Endangered class			Number of occurrence records	AUC
		IUCN Red List of Threatened Species	List of National Key Protected Wild Animals (China)	China's Red List of Biodiversity		
		Reptile				
23	*Bungarus fasciatus*	EN	—	LC	84	0.845
24	*Calotes versicolor*	LC	—	LC	1,614	0.867
25	*Naja atra*	VU	—	VU	182	0.846
26	*Ophiophagus hannah*	EN	—	VU	34	0.860
27	*Pelodiscus sinensis*	EN	—	VU	44	0.872
28	*Physignathus cocincinus*	EN	—	VU	356	0.863

the "thin" package in R to address point density bias and reduce the risk of overfitting[39]. Furthermore, pseudo-absence points were generated via the convex hull method to enhance the models' ability to discriminate complex environmental gradients[40].

3.2.4 Processing and Sources of Environmental Variables

Environmental variables exert a significant influence on species distribution and are typically categorized into bioclimatic variables, topographic variables, and anthropogenic disturbance variables (Table 3)[41].

1) Bioclimatic variables. In this study, bioclimatic variables were selected as the primary predictors, as they directly influence the physiological constraints and survival of the target species. A total of 19 bioclimatic variables were sourced from WorldClim. Both current conditions as in 2020[42] and the future projections were applied in the research. The future projections were obtained by averaging the values for the period of 2040–2060 under the SSP5-8.5 scenario, based on the BCC-CSM2-MR global climate model at a 2.5 arc-minute.

2) Topographic variables. Elevation and slope were assumed constant, while the land-use component was updated using the SLAMM-simulated 2050 projections.

3) Anthropogenic disturbance variables. To account for human interference, spatial data for transportation networks—including railways, highways, and national roads—were acquired via the Baidu API (2020). Administrative boundaries for the GBA were derived from the Public Map Service System of Guangdong Province,

Table 3: Summary of environmental variables

Code	Environmental variable	Unit
	Bioclimatic variable	
Bio1	Annual mean temperature	℃
Bio2	Monthly mean diurnal temperature range	℃
Bio3	Isothermality	%
Bio4	Standard deviation of temperature seasonal change	—
Bio5	Max temperature of the warmest month	℃
Bio6	Min temperature of the coldest month	℃
Bio7	Range of annual temperature	℃
Bio8	Mean temperature of the wettest quarter	℃
Bio9	Mean temperature of the driest quarter	℃
Bio10	Mean temperature of the warmest quarter	℃
Bio11	Mean temperature of the coldest quarter	℃
Bio12	Annual average precipitation	mm
Bio13	Precipitation of the wettest month	mm
Bio14	Precipitation of the driest month	mm

(Continued)

Table 3: Summary of environmental variables (Continued)

Code	Environmental variable	Unit
	Bioclimatic variable	
Bio15	The coefficient of variation of precipitation	—
Bio16	Precipitation of the wettest quarter	mm
Bio17	Precipitation of the driest quarter	mm
Bio18	Precipitation of the warmest quarter	mm
Bio19	Precipitation of the coldest quarter	mm
	Topographical variable	
Dem	Altitude	m
Slope	Slope	(°)
Aspect	Aspect	(°)
	Anthropogenic disturbance variable	
Landuse	Land use/land cover type	—
Dis_river	Distance to water body	m
Dis_build	Distance to built-up area	m
Dis_road	Distance to road	m
People	Population density	people/km^2
Buildland	Distribution of built-up area	m^2

map No. GS Yue (2023) 1032, while gridded population density data for 2019 (5 km resolution) were obtained from Resource and Environmental Science Data Platform, with values standardized to 10,000 persons per 25 km^2.

Data preprocessing included the following steps conducted in ArcGIS 10.8. First, DEM, bioclimatic, and anthropogenic disturbance data were extracted within the boundary of the GBA at a 30 m resolution. Second, hydrological analysis was performed on the DEM data, and the Euclidean distance from each grid cell to the nearest water body was calculated. Third, artificial land use was extracted from the land use dataset and their Euclidean distance from each grid cell were calculated. All raster data were finally converted into ASCII format for model input.

3.2.5 Habitat Richness Assessment and Aggregation

To assess the impacts of a 0.5 m sea-level rise, habitat richness for the 28 key species was calculated. Species were categorized into four taxa: amphibians, birds, mammals, and reptiles. Taxon-specific richness datasets were generated by overlaying binary habitat grids using the ArcGIS 10.8 Raster Calculator. These datasets were normalized to facilitate cross-scenario comparisons, with higher values representing multi-species habitat hotspots. This spatial aggregation enables the identification of critical biodiversity zones and their shifts under projected sea-level rise.

3.2.6 Identification of ECPAs

Potential distribution data for 28 species and environmental variables for 2020 and 2050 were analyzed using the Zonation model. Input rasters were weighted by conservation status, and the top 30% of highest-value areas were designated as ECPAs. These ECPAs were categorized into three hierarchical tiers: 1) primary ECPAs (top 10%), which represent the core habitats with the highest conservation priority; 2) secondary ECPAs (10%–20%), which represent the significant habitats serving as vital buffer zones; 3) general ECPAs (20%–30%), which represent the priority regions contributing to regional biodiversity resilience.

4 Results and Analysis

4.1 Land Use Change Under Sea-Level Rise

According to the statistical results (Table 4, Fig. 3), from 2020 to 2050, the areas of tidal flats and estuarine open water are projected to increase by 234.83 km^2 and 259.09 km^2, respectively. The expansion of these coastal wetlands is mainly attributed to the saline intrusion into inland open water and the inundation of low-lying coastal areas. Inland freshwater marshes, salt marshes, and mangrove forests show expansion of 12.13 km^2, 49.62 km^2, and 13.23 km^2, respectively, largely resulting from the transition of low-density land covers such as shrublands and grasslands. The growth of perennial flood marsh and ocean beaches mainly originates from the conversion of artificial ponds, dry fields, and other marginal lands.

Meanwhile, the area of inland open water is projected to decrease from 2,111.29 km^2 in 2020 to 1,564.45 km^2 in 2050, as it primarily transitions into estuarine open water and tidal flats. Rice paddy decreases from 8,657.93 km^2 to 8,640.29 km^2, with the lost area (17.64 km^2) primarily transitioning into tidal flats and salt marshes. Similarly, artificial ponds decrease from 1,802.59 km^2 to 1,784.95 km^2, mostly converting into perennial flood marsh.

Table 4: Land use changes under 0.5 m sea level rise scenario

Land use type	2020		2050		2020–2050	
	Area (km^2)	Percentage (%)	Area (km^2)	Percentage (%)	Area change (km^2)	Area change rate (%)
Rice paddy	8,657.93	14.78	8,640.29	14.75	–17.64	–0.20
Dry field	3,618.41	6.18	3,612.89	6.17	–5.52	–0.15
Tree canopy	25,670.61	43.81	25,668.41	43.81	–2.2	–0.01
Shrubland	880.90	1.50	880.90	1.50	0	0
Grassland	1,184.09	2.02	1,182.98	2.02	–1.11	–0.09
Artificial pond	1,802.59	3.08	1,784.95	3.05	–17.64	–0.98
Town and village	4,414.41	7.53	4,414.41	7.53	0	0
Swamp	13.23	0.02	13.23	0.02	0	0
Salt marsh	137.81	0.24	187.43	0.32	49.62	36.01
Mangrove forest	72.77	0.12	86.00	0.15	13.23	18.18
Tidal flat	854.44	1.46	1,089.27	1.86	234.83	27.48
Sparse tree cover	2,622.85	4.48	2,620.64	4.47	–2.21	–0.08
Inland open water	2,111.29	3.60	1,564.45	2.67	–546.84	–25.90
Rural residential area	1,737.54	2.97	1,736.44	2.96	–1.1	–0.06
Industrial and transportation area	2,248.00	3.84	2,245.79	3.83	–2.21	–0.10
Inland freshwater marsh	762.93	1.30	775.06	1.32	12.13	1.59
Perennial flood marsh	0	0	22.05	0.04	22.05	—
Inundated developed dryland	28.67	0.05	28.67	0.05	0	0
Ocean beach	0	0	5.51	0.01	5.51	—
Estuarine open water	0	0	259.09	0.44	259.09	—
Other	1,778.33	3.03	1,778.33	3.03	0	0

4.2 Results of Maxent Model: Comparison of Species Habitats

Under the projected 0.5 m sea-level rise scenario, habitat richness exhibited distinct spatial heterogeneity across the four taxonomic groups (Fig. 4). The normalized richness values for amphibians, birds, mammals, and reptiles ranged from 0–7, 0–11, 0–5, and 0–6, respectively. Higher richness values indicate areas capable of supporting a greater number of species.

Under the 0.5 m sea-level rise scenario, selected mammals

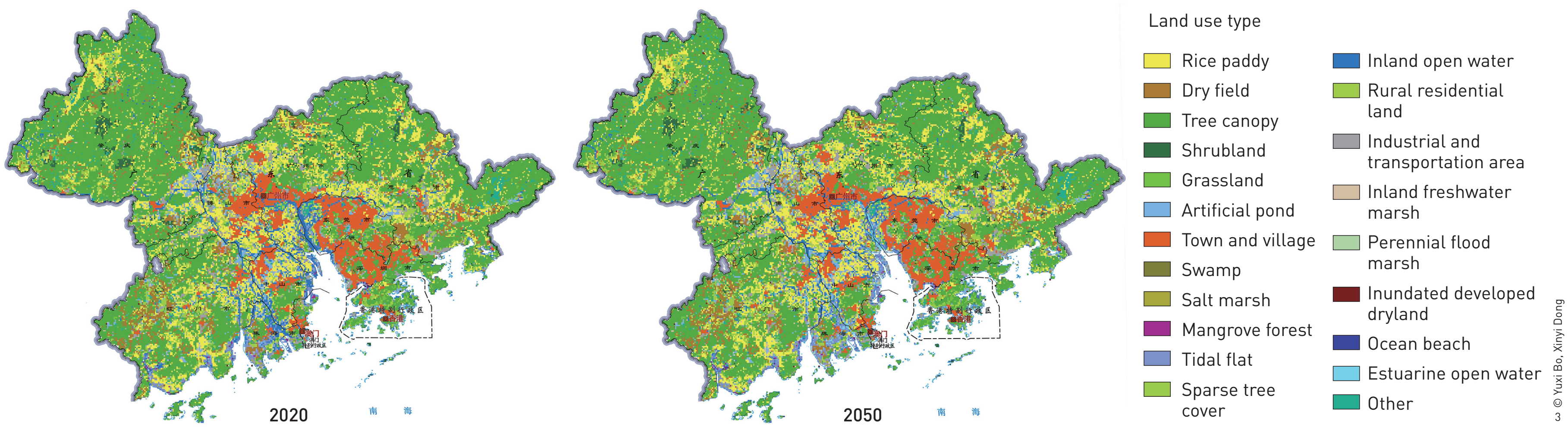


Fig. 3 Simulation of land-use change under 0.5 m sea-level rise in the GBA.

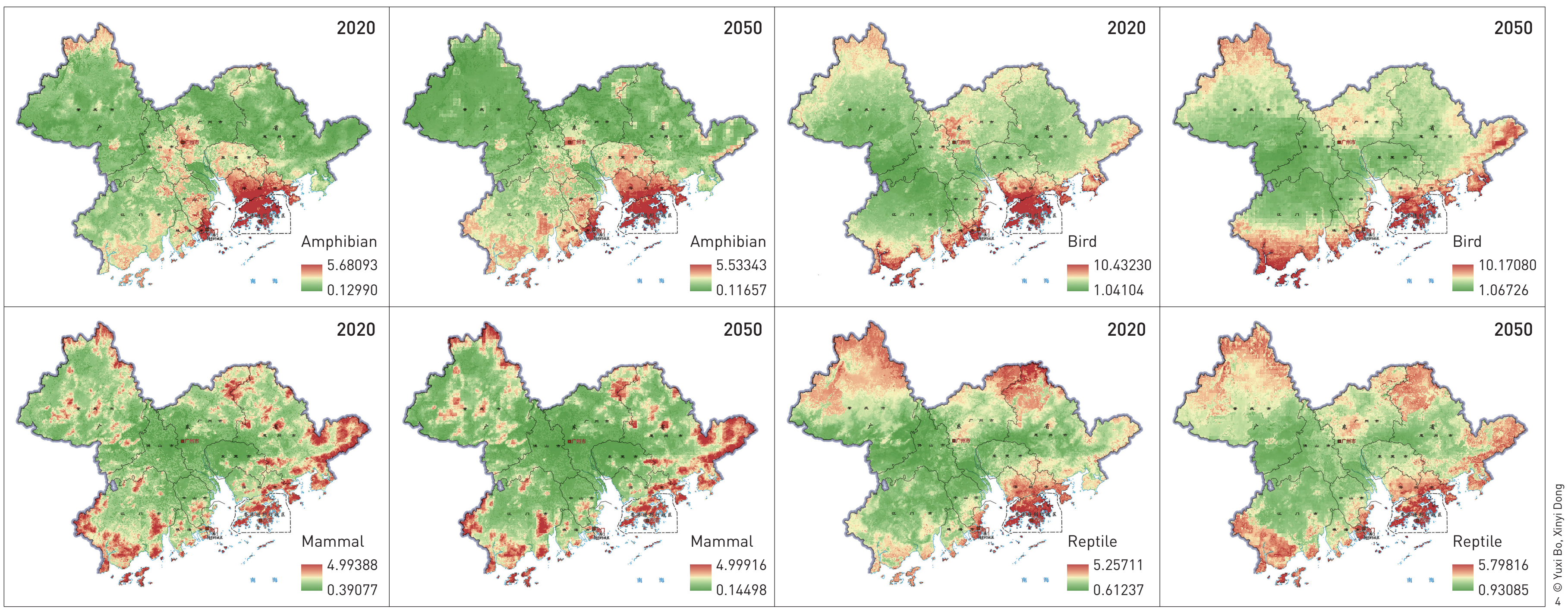


Fig. 4 Potential species habitat suitability under 0.5 m sea-level rise for 2020 and 2050 in the GBA.

and reptiles are primarily dependent on forests, river wetlands, farmland, and habitats at the edge of human activities, while amphibians and birds rely more on diverse aquatic and moist habitats, including wetlands, rivers, lakes, forest streams, farmland, and urban edges. As a result, mammals and reptiles are more likely to face heightened survival pressures due to habitat loss, whereas amphibians and birds may benefit from the expansion of wetland habitats.

Highly suitable habitats for the key species were identified by reclassifying the habitat suitability index (HSI) dataset into two categories: non-highly suitable (0–0.8) and highly suitable (0.8–1.0). Under the future scenario, the highly suitable habitats for mammals and reptiles are projected to decrease by 11.59% and 44.3%, respectively. Conversely, amphibians and birds are expected to experience habitat expansions of 34.61% and 21.61% (Table 5). These results reveal critical thresholds of habitat change, suggesting

Table 5: Area changes of highly suitable habitats for key species under 0.5 m sea-level rise

Category	2020		2050		2020–2050	
	Number of grids	Area (km^2)	Number of grids	Area (km^2)	Area change (km^2)	Change rate (%)
Amphibian	471	51.93	634	69.90	17.97	34.61%
Bird	347	38.26	422	46.53	8.27	21.61%
Mammal	3,089	340.56	2,731	301.09	–39.47	–11.59%
Reptile	1,009	111.24	562	61.96	–49.28	–44.30%

that the expansion of wetlands may partially offset the habitat losses caused by sea-level rise.

4.3 Spatial Patterns of ECPAs Identified by Zonation

4.3.1 Distribution of ECPAs

Systematic prioritization identified ECPAs for key terrestrial wildlife in the GBA for 2020 and 2050 (Fig. 5). Comprising the top 30% of the landscape's conservation value, these zones delineate critical areas for regional biodiversity maintenance across three hierarchical tiers.

The distribution of ECPAs exhibits significant spatial heterogeneity, typically bypassing densely urbanized zones to cluster in topographically complex terrains. These ECPAs are predominantly situated within three distinct ecological settings: mountainous forest regions, coastal and shoreline ecosystems, and peri-urban nature reserves.

In mountainous forest regions, areas such as Dinghu Mountain and Seven Star Crags in northern and central Zhaoqing, national forest parks in northern Guangdong, the Gutian Nature Reserve in Huidong, and Lianhua Mountain Forest Park along the Huizhou–Shanwei boundary form extensive continuous forest habitats that serve as critical refugia for multiple terrestrial species. In coastal and shoreline ecosystems, including the western and southern parts of Jiangmen, central to southern Zhuhai, central to northeastern Zhongshan, the coastal wetlands and mangroves of the Pearl River Estuary, and coastal zones from western to eastern Shenzhen (e.g., Shenzhen Bay Mangrove Reserve and Dapeng Peninsula), the model identified key habitats essential for both aquatic and terrestrial species. These areas play a pivotal role in sustaining regional ecological functions and biodiversity. Peri-urban nature reserves, such as Yinping Mountain Nature Park in southeastern Dongguan, forest and wetland parks in Macao, Meilinshan Country Park in Shenzhen, and coastal country parks in Hong Kong (e.g., Lantau Island and Ma On Shan), continue to provide valuable ecological habitats for diverse wildlife despite their close proximity to dense urban development.

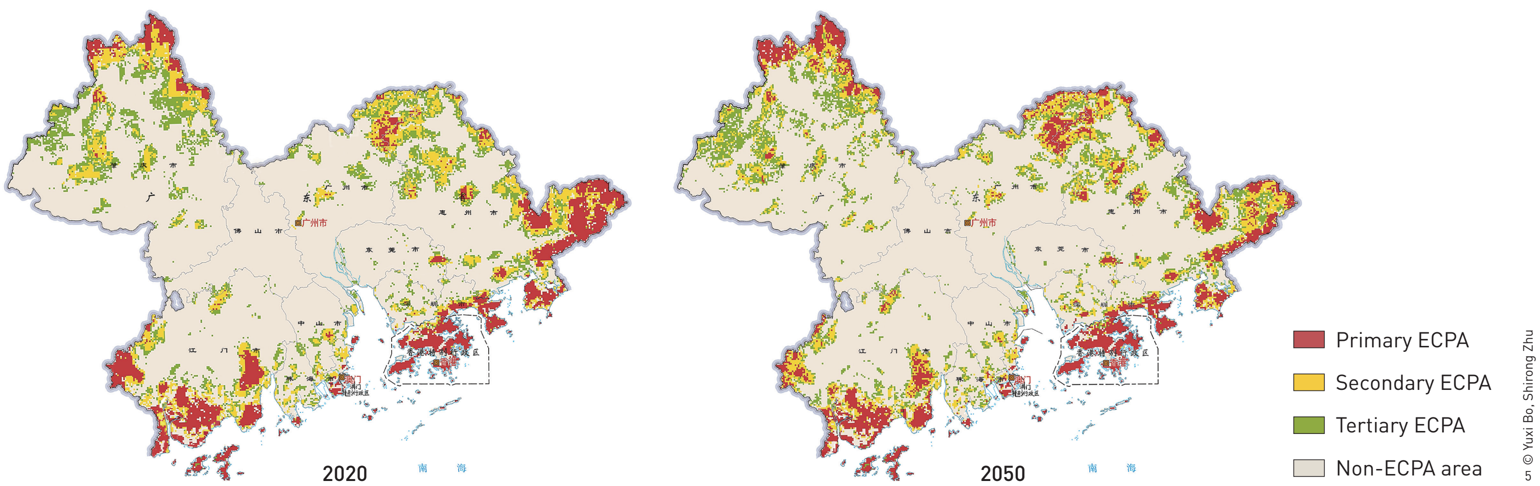


Fig. 5 Spatial distribution of ECPAs for 2020 and 2050 in the GBA.

Under the 0.5 m sea-level rise scenario, the total extent of future ECPAs in the GBA is projected to decline (Fig. 6). Huizhou experiences the most substantial reductions across all three tiers of priority areas, with contraction rates of 98.00%, 97.75%, and 94.82%, respectively. These results highlight the extreme vulnerability of coastal lowland ecosystems and the severe loss of critical habitats, emphasizing the urgency of adjusting the spatial configuration and management strategies of existing reserves to mitigate climate-induced threats to species survival and preserve ecological functionality.

By contrast, Guangzhou and Zhaoqing exhibit increases in the extent of ECPAs, suggesting that wetland expansion in some low-lying regions may create new habitat opportunities and demonstrate greater ecological resilience and adaptive capacity. Overall, non-ECPA areas in the GBA decreased from 38,575 km^2 to 34,369 km^2 (reduction of 10.9%), indicating that sea-level rise exerts substantial ecological pressure on the region and reinforcing the need for adaptive conservation responses under climate change.

According to the statistical results (Table 6), the extent of Primary ECPAs is projected to decrease substantially, from 5,412 km^2 in 2020 to 4,010 km^2 in 2050. Huizhou exhibits the most pronounced decline, with Primary ECPAs shrinking from 1,703 km^2 to only 34 km^2. In contrast, Guangzhou and Zhaoqing experience modest increases of approximately 193 km^2 and 253 km^2, respectively.

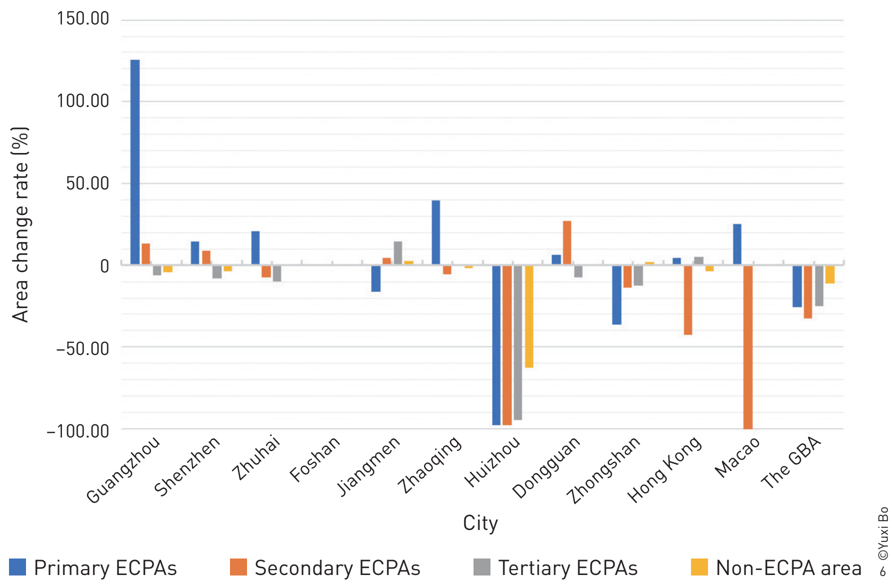


Fig. 6 Area statistics of ECPAs in 2050 under a 0.5 m sea-level rise compared with 2020.

Table 6: Area statistics of ECPAs in 2050 under a 0.5 m sea-level rise compared with 2020

City/region	Primary ECPAs (km^2)			Secondary ECPAs (km^2)			Tertiary ECPAs (km^2)			Primary ECPAs (km^2)		
	2020	2050	Change	2020	2050	Change	2020	2050	Change	2020	2050	Change
Guangzhou	154	347	193	604	686	82	628	588	−40	5,804	5,569	−235
Shenzhen	301	345	44	172	187	15	170	156	−14	1,282	1,237	−45
Zhuhai	140	169	29	210	195	−15	188	169	−19	971	976	5
Foshan	5	5	0	20	20	0	82	82	0	3,692	3,692	0
Jiangmen	1,749	1,468	−281	1,060	1,109	49	569	650	81	5,939	6,090	151
Zhaoqing	641	894	253	1,440	1,360	−80	2,269	2,288	19	10,541	10,349	−192
Huizhou	1,703	34	−1,669	1,866	42	−1,824	1,468	76	−1,392	6,202	2,298	−3,904
Dongguan	32	34	2	33	42	9	82	76	−6	2,303	2,298	−5
Zhongshan	11	7	−4	89	77	−12	107	94	−13	1,538	1,567	29
Hong Kong	672	702	30	49	28	−21	20	21	1	282	272	−10
Macao	4	5	1	1	0	−1	0	0	0	21	21	0
Total	5,412	4,010	−1,402	5,544	3,746	−1,798	5,583	4,200	−1,383	38,575	34,369	−4,206

The area of Secondary ECPAs is expected to decline from 5,544 km^2 to 3,746 km^2. Once again, Huizhou shows the largest reduction, whereas Jiangmen, Dongguan, and Shenzhen display slight increases. Tertiary ECPAs contract from 5,583 km^2 to 4,200 km^2. Huizhou accounts for the most substantial decline, followed by reductions in Zhongshan and Guangzhou.

4.3.2 Comparison Between 2050 ECPAs and Current Nature Reserve Planning

Overlaying the 2050 predicted ECPAs with the 2025 Natural Reserve Planning map (Fig. 7) shows substantial overlap, though gaps remain in some regions.

5 Discussion

5.1 Planning Discrepancies and Optimization Strategies

By comparing the predicted ECPAs for 2050 with the spatial configurations proposed in the Territorial Spatial Master Plan (2035) and the Guangdong Provincial Ecological Restoration Plan (2020–2035), it is evident that the predictions generally encompass the "one chain, two shields, and multiple corridors" conservation framework articulated in these plans, thereby supporting the reliability of the simulation results. However, when compared with the 2025 Nature Reserve Planning, the predicted ECPAs for 2050 exhibit spatial mismatches with the southern mountainous and coastal regions of Jiangmen, the central and western areas of Shenzhen, the southern coastal and eastern mountainous areas of Huizhou, the national forest parks in central and northern Guangzhou, and the northern mountainous regions of Zhaoqing.

These discrepancies may stem from differences in data sources and analytical approaches. Planning documents typically rely on historical datasets and static, macro-level assessments, whereas this study integrates high-resolution spatial datasets and advanced ecological modeling, incorporating a broader range of environmental variables and dynamic ecological processes. Consequently, this methodological divergence leads to differing interpretations of future ecosystem conditions and species conservation needs. Based on the predicted ECPAs for 2050, and drawing upon domestic and international best practices, this study proposes the following strategies to enhance the region's capacity to mitigate the potential adverse effects of sea-level rise, accounting for diverse land-use transformation trends and species extinction risks.

5.1.1 Strategies for Coastal Protection

Given the low-lying terrain in the southern regions of Jiangmen and Huizhou, which are highly vulnerable to sea-level rise, it is essential to strengthen ecological restoration measures such as wetland rehabilitation and mangrove afforestation. Mangroves play a crucial role in buffering storm impacts, stabilizing coastlines, and absorbing tidal surges; therefore, expanding mangrove planting will enhance regional flood resilience. In addition, the construction of ecological corridors in adjacent areas should be integrated with flood-control levees and vegetated buffer zones to establish an effective natural barrier that protects biodiversity while mitigating the effects of extreme coastal weather events.

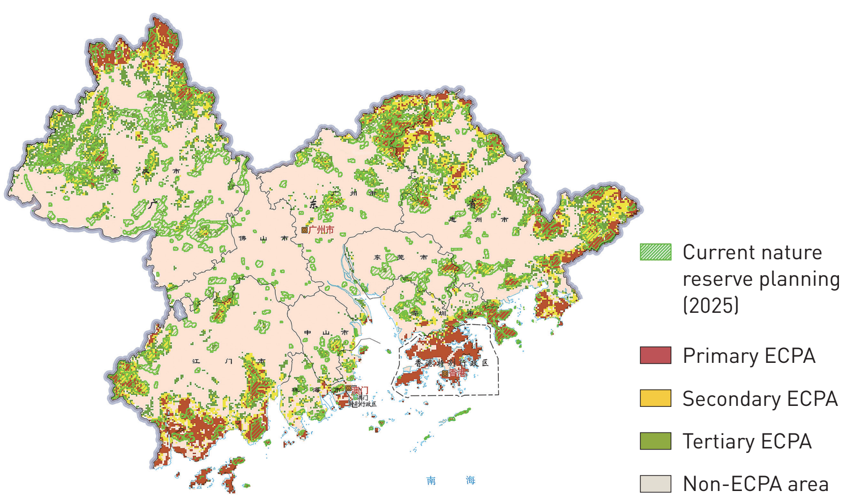
5.1.2 Strategies for Mountainous Areas and Forest Parks

Although located inland, the mountainous areas in western and central Shenzhen, eastern Huizhou, and northern Zhaoqing face climate-induced risks such as altered hydrological patterns, soil degradation, and increased forest fire frequency. Enhanced forest defense measures, vegetation restoration, and corridor connectivity are essential to strengthen ecosystem resilience. National forest parks in central and northern Guangdong should be prioritized for reserve designation, as indirect impacts of sea-level rise may disrupt hydrological cycles. Future planning should incorporate updated species distribution data and dynamic habitat information to maintain forest ecosystem functions and biodiversity.

5.1.3 Improving Data Sharing and Dynamic Monitoring

To address discrepancies arising from data variation, closer collaboration between government agencies and research

Fig. 7 Spatial distribution of the current nature reserve planning (2025) and simulated ECPAs for 2050 in the GBA.



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institutions is needed to establish an integrated monitoring platform that dynamically updates climate, land-use, and ecosystem data. This will improve planning accuracy and enable adaptive responses to uncertainty. Notably, some dispersed forest and country parks in Dongguan, Foshan, and Zhongshan were not fully captured as ECPAs by the model, likely due to species selection biases and inherent ecosystem complexity. Future planning should account for ecosystem heterogeneity and adopt more refined, site-specific conservation and management strategies.

5.2 Outlook

This study employed multiple analytical tools to systematically simulate the potential impacts of sea-level rise on ecosystems, demonstrating the capacity of advanced ecological models to handle complex environmental variables and predict habitat and species responses under alternative scenarios. By integrating interactions among ecosystem types and species groups, the research offers a broader ecological perspective that supports more comprehensive guidance for conservation planning. The findings provide a scientific basis for territorial spatial planning in coastal cities, particularly regarding ecological redline delineation, protected area adjustment, and the construction of coastal–inland ecological corridors to address the challenges posed by sea-level rise.

Nonetheless, several limitations warrant further investigation. First, while this study simulated land-use transitions driven by sea-level rise, it did not incorporate future anthropogenic land-use dynamics. Considering rapid regional urbanization, future work should integrate socio-economic development scenarios to enable more robust assessments of ecosystem vulnerability and adaptive capacity. Second, the key species selected may not fully capture the ecological requirements of the region's entire biodiversity. Differences in ecological roles and interspecies relationships may lead to partial interpretations of ecosystem health. Future studies should expand species coverage and employ community-level ecological approaches to improve reliability. Third, although Zonation using the ABF rule accounts for multiple species' habitat importance, its priority allocation may be biased toward species with more accessible data, potentially overlooking other key ecological components. Integrating the CAZ rule or alternative ecological modeling approaches may enhance the comprehensiveness and accuracy of priority area identification. Finally, limitations in territorial spatial planning vector data reduced the depth and reliability of spatial analysis. Strengthening collaboration and data sharing between government agencies and research institutions is essential for supporting evidence-based conservation and resource management.

6 Conclusions

This study examined the impacts of sea-level rise in the GBA, integrating the SLAMM model, the species distribution model MaxEnt, and the multi-species conservation planning tool Zonation to project ecosystem and biodiversity patterns by 2050. The key findings are as follows.

1) Under a 0.5 m sea-level rise scenario, central coastal wetlands in the GBA experience substantial change. Inland open-water areas show a marked decrease, while estuarine waters and tidal flats expand significantly.

2) Sea-level rise leads to pronounced highly suitable habitat loss for mammals and reptiles, with declines of 11.59% and 44.30%, respectively. In contrast, amphibians and birds benefit from wetland expansion, gaining 34.61% and 21.61% of highly suitable habitat area. These contrasting responses highlight strong interspecific differences and indicate that wetland expansion may partially alleviate pressures on certain taxa.

3) ECPAs for terrestrial wildlife are primarily concentrated in the northern and central mountainous regions of Zhaoqing, central Jiangmen, the central-to-southern coastal zones of Zhuhai, central and northeastern Zhongshan, the border areas between central Guangdong and Huizhou, central-to-coastal Huizhou; southeastern Dongguan, the central–western and coastal regions of Shenzhen, northern and southern Macao, and the coastal areas of Hong Kong.

4) Priority areas identified by Zonation show high spatial congruence with existing nature reserves; however, critical protection gaps remain in the southern mountainous and coastal regions of Jiangmen, the central–western areas of Shenzhen, the southern coastal and eastern mountainous regions of Huizhou, national forest parks in central–northern Guangdong, and northern Zhaoqing.

ELECTRONIC SUPPLEMENTARY MATERIAL

Supplementary material is available in the online version of this article at https://doi.org/10.15302/J-LAF-2026-0013.

Competing interests | The authors declare that they have no competing interests.

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LAF | https://doi.org/10.15302/J-LAF-2026-0013
第14卷 / 第4期 / 260013 / 2026
收稿日期 | 2024-10-16　录用日期 | 2025-05-19
中图分类号 | TU984　文献标识码 | A

粤港澳大湾区适应海平面上升的生态保护优先区识别与优化

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摘要

海平面上升对沿海地区的生物多样性保护构成了严峻挑战。本研究以粤港澳大湾区为案例，模拟了2050年海平面上升0.5 m的情景。基于GIS平台，研究耦合了SLAMM、MaxEnt与Zonation模型，旨在分析2020至2050年间生态保护格局的演变，并将模拟结果与现行自然保护地体系及国土空间规划进行了对比评估。研究结果表明：1）在海平面上升0.5 m情景下，不同类群的栖息地响应呈现显著分化。其中，哺乳动物和爬行动物的高度适宜栖息地分别缩减了11.59%和44.30%，而受湿地扩张驱动，两栖动物和鸟类的高度适宜栖息地则分别增加了34.61%和21.61%；2）研究区内的生态保护优先区主要集中分布于山地森林、沿海及海岸带生态系统、近郊自然保护区这3类典型生态环境中；3）预测所得2050年生态保护优先区虽与多数现有自然保护区高度重叠，但在江门南部山地与沿海、深圳中西部、惠州南部沿海与东部山地、粤中北部的国家森林公园和肇庆北部山区，仍存在明显的保护空缺。本研究可为沿海城市制定应对海平面上升的适应性规划提供科学决策支持。

关键词

海平面上升；系统保护规划；保护优先区；国土空间规划；保护空缺分析；粤港澳大湾区；生物多样性保护

文章亮点

- 运用SLAMM-MaxEnt-Zonation框架预测海平面上升下的栖息地演变
- 对比预测保护优先区与现行自然保护体系，精准识别空间保护空缺
- 呼吁转向动态适应性空间规划，为沿海城市气候韧性建设提供决策支持

基金项目

- 国家自然科学基金项目（编号：32271735）
- 广东省哲学社会科学规划项目（编号：GD24CYS34）
- 中央高校业务费项目（编号：CGPY202409）