Assessing Spatiotemporal Dynamics of Habitat Quality under Urbanization Stress in Guangdong Province: An inVEST-MGWR Analytical Approach

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Abstract. Amid Guangdong Province's swift urban growth, our research delves into the habitat quality's spatiotemporal trends and underlying factors over the 2000-2018 period, employing the InVEST model and MGWR, grounded on comprehensive land-use data. Results indicate a relatively constant habitat quality index, averaging from 0.78 to 0.8, yet with marked regional variations: the north showing higher values than the southern, especially in the Pearl River Delta. The analysis highlights the positive role of natural elements like terrain and plant life in enhancing habitat quality. On the other hand, anthropogenic influences, including growing urban light pollution and population increase, have been detrimental. Additionally, landscape indices such as the largest patch and shape indices, and diversity in landscape, negatively impact habitat quality. These findings point to the crucial balance needed between developmental goals and ecological preservation, underlining the need to protect natural environments for sustainable progress.

Keywords: Habitat Quality; InVEST Model; Spatiotemporal Analysis;

1 Introduction

Habitat quality is a crucial ecological indicator that reflects the health and biodiversity of natural ecosystems[1]. In recent decades, the rapid pace of socio-economic development has led to an intensified human footprint on natural ecosystems[2, 3], placing biodiversity and habitat quality under unparalleled pressure globally. This has resulted in a stark increase in ecosystem degradation and decline in biodiversity[4, 5]. These detrimental changes have compromised vital ecosystem services, threatening sustainable development of human societies. Consequently, scientific assessment and continuous monitoring of habitat quality changes are vitally important for the effective conservation and restoration of ecosystems[6, 7].

Habitat quality serves as a key ecological metric that indicates a habitat's capacity to support diverse species communities[8]. It integrates various habitat conditions that are vital for the survival of species populations. Comprehensively assessing habitat quality is instrumental for biodiversity conservation and prudent management of ecosystems at multiple scales[5, 9, 10]. Analysing general trends in habitat quality, typically inferred through comparison of habitat quality indices over successive years, forms the cornerstone of such ecosystem assessments[11, 12]. This analysis elucidates whether the habitat quality in a region is on an improving upward

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trajectory or experiencing concerning degradation over time, thereby providing critical insights into ecological enhancement or decline respectively[13].

At the scale of nations, provinces, urban clusters, or watersheds, a thorough analysis of habitat quality trends offers a macroscopic overview of the changing status of regional habitats[5, 14, 15]. Grasping spatial patterns in habitat quality across geographic areas is also essential. Using spatial analytical techniques, such as hotspot analysis, can shed valuable light on the evolving spatial dynamics of habitat quality over time, effectively delineating high-value and low-value areas and their expansions or contractions[13, 16]. Regions identified with consistently high habitat quality may signify robust and resilient ecological environments[16, 17], while zones exhibiting declining habitat quality could flag potential concerns and risks, thereby informing targeted policy measures and interventions aimed at habitat quality improvement and restoration[18].

2 Material and methods

2.1 Study area

Located at China's southernmost point, Guangdong Province, known as the "Southern Gateway," embodies a dynamic blend of natural and human environments, as shown in Figure 1. Guangdong's unique geographical position, coupled with its rich biodiversity and varied topography, makes it an ideal case study for understanding the challenges and opportunities in managing and preserving ecological systems in rapidly urbanizing areas. Its diverse landscape includes mountains, grasslands, forests, fields, lakes, and coastlines, making it a microcosm of China's ecological diversity. This region, critical to the country's ecological security, is a focal point for research into ecosystem services, vital for national ecological civilization and the well-being of its people. Guangdong's unique ecological and economic significance underscores the need for sustainable management practices, balancing rapid industrial growth with environmental conservation.

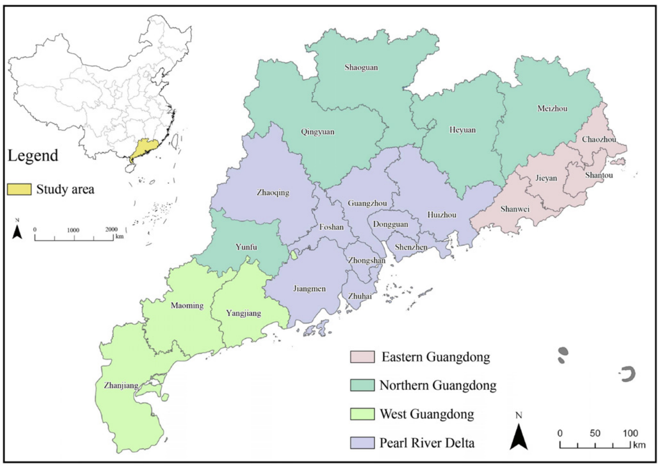

Fig. 1. The location map of Guangdong Province.

2.2 Data sources

This study zeroes in on Guangdong Province, exploring the spatiotemporal dynamics of habitat quality from 2000 to 2018 through the lens of habitat quality assessment models and multiscale geographically weighted regression approaches. The breadth of data harnessed for this research is extensive, spanning meteorological, topographical, socio-economic, and land-use datasets. Meteorological data, procured from the China Meteorological Administration's station records, were spatially interpolated to produce rasterized climatic data across various years. The topographic data set includes Digital Elevation Models, Normalized Difference Vegetation Index, among others. Socio-economic variables are represented by data on population, GDP, and nocturnal light indices. To ensure analytical coherence, all data was uniformly transformed into a grid format with a resolution of 1 km*1km using ArcGIS Pro, providing a robust, multi-sourced dataset that forms the empirical backbone for dissecting the patterns and drivers of habitat quality evolution in Guangdong(Table 1).

Table 1. Data types and sources used in the study.

Data type	Data	Data sources
Meteorological data	Precipitation(PRE)	https://data.cma.cn/
	Temperature(TEMP)	https://data.cma.cn/
Topographic data	Soil properties(SP)	https://iiasa.ac.at/
	Digital elevation mode(DEM)	https://www.earthdata.nasa.gov/
	Normalized difference vegetation index(NDVI)	https://modis.gsfc.nasa.gov
Land use data	Land cover types(LULC)	https://www.resdc.cn/
Socioeconomic	Gross domestic product (GDP)	https://www.resdc.cn/
data	Population(POP)	https://www.resdc.cn/
	Night-time lighting(NL)	https://eogdata.mines.edu/products/vnl/

2.3 Research Methods

Habitat Quality. The InVEST framework is applied for examining ecosystem alterations due to human activities, typically using a production function method to evaluate and quantify ecosystem services. Within this framework, the habitat quality model serves as a vital instrument for assessing ecological conditions, determining habitat quality in the context of land use/cover transformations through the dynamics of various land use/cover types and associated ecological threats.

In the InVEST habitat quality assessment, the primary output is a series of habitat quality maps, produced using land use/cover raster data along with data on factors threatening biodiversity. The model employs the following calculation formula (1) [6, 19, 20]:

$$Q_{xj} = H_j\left(1-\left(\frac{D_{xj}^z}{D_{xj}^z+k^z}\right)\right) \quad (1)$$

In this formula, Q_{xj} denotes the habitat quality of a specific grid within a land use type; k represents the half-saturation constant, which is typically set to half of D_{xj} maximum value, as outlined in equation (2); H_j signifies the suitability of the habitat for a particular land use type; z serves as a normalization constant, generally established at 2.5; D_{xj} i reflects the level of stress encountered by grid x of land use type j The equation to calculate D_{xj} is as follows:

$$D_{xj} = \sum_{r=1}^{R}\sum_{y=1}^{Y_r}\left(\frac{w_r}{\sum_{r=1}^{R} w_r}\right) r_y i_{rxy} \beta_x S_{jr} \quad (2)$$

In this context, R ymbolizes the stress factor.; y is counts the grid cells within the stress factor's raster layer; Wry stands for the weight assigned to the stress factor; R_y represents the stress factor's value in grid y; βx indicates the accessibility of grid x; $Sjrx$ reflects how sensitive the habitat type is to the stress factor r; and i_{rxy} (3-4) is the stress level imposed by the stress factor value R_y on habitat grid x. The model distinguishesbetween linear and exponentialtypes:

$$\text{Linear: } i_{rxy} = 1 - \frac{d_{xy}}{d_{rmax}} \quad (3)$$

$$\text{Exponential: } i_{rxy} = e^{\wedge}\left(\frac{-0.299 d_{xy}}{d_{rmax}}\right) \quad (4)$$

Where d_{xy} represents the direct distance between grid cells x and y, and d_{rmax} denotes the maximum influence distance of the threat factor r. ln this study, based on the land use/cover type, followingexisting literature and model manuals, farmland, urban and rural areas, industrial and miningareas. and residential land were selected as stress factors, Habitats highly impacted by thesethreat factors, such as forest lands (including forested, shrub, sparse forest, and other forestands), were assigned a suitability value of 1, while urban and rural areas, industrial and miningresidential lands, and unused lands not affected by threat factors were assigned a value of 0. Detailed parameter settings are provided in the following Table 2 and Table 3.

Table 2. The stress factor parameter

Maximum Impact Distance (km)	Weight	Stress Factor	Decay Function
8	0.7	Farmland	linear
10	1	Urban Land	exponential
5	0.6	Rural Residential Area	exponential
0.3	0.5	Construction Land	linear

Table 3. The threat factor sensitivity schedule

Land Type Code	Name	Habitat Suitability	Farmland	Urban Land	Rural Residential Areas	Industrial and Mining Land
11	Paddy Field	0.4	0.3	0.7	0.6	0.5
12	Dry Land	0.6	0.3	0.6	0.6	0.5
21	Forested Land	1	0.8	0.85	0.9	0.6
22	Shrub Land	1	0.5	0.6	0.65	0.5
23	Sparse Forest	1	0.9	0.8	0.9	0.7
24	Other Forest Land	1	0.9	0.85	0.85	0.7
31	High Coverage Grassland	0.8	0.6	0.6	0.55	0.2
32	Medium Coverage Grassland	0.7	0.55	0.7	0.5	0.3
33	Low Coverage Grassland	0.6	0.5	0.6	0.5	0.4
41	Rivers and Channels	0.8	0.6	0.6	0.5	0.3
42	Lakes	0.9	0.65	0.75	0.6	0.4
43	Reservoirs and Ponds	0.7	0.6	0.6	0.5	0.5
45	Tidal Flats	0.6	0.6	0.7	0.65	0.5
46	Beaches	0.6	0.6	0.7	0.65	0.5
51	Urban Land	0	0	0	0	0
52	Rural Residential Land	0	0	0	0	0
53	Other Construction Land	0	0	0	0	0
61	Sandy Land	0	0	0	0	0
63	Saline Land	0	0	0	0	0
64	Marshland	0	0	0	0	0
65	Bare Land	0	0	0	0	0

Landscape pattern index analysis. Analysis of Landscape Pattern Indices. Landscape indices serve as condensed metrics offering insights into landscape patterns, encapsulating details about the composition and spatial arrangement of landscape elements. In our analysis focusing on the Guangdong Province's specific landscape characteristics and research goals, we opted for four key indices: the Largest Patch Index (LPI), Landscape Shape Index (LSI), Isolation Index, and Shannon's Diversity Index (5-8). These indices, detailed in Table 4, are instrumental in evaluating aspects like landscape fragmentation, shape intricacy, the degree of landscape dispersion, and overall diversity of the landscape[21-23].

Table 4. Calculation of landscape pattern index

Index	Description	Mathematical algorithms
LPI	Assesses the dominant landscape type or model, reflecting the prevalence of the dominant type.	$\mathrm{LPI} = \frac{\max_{j=1}^{n}(a_{ij})}{A}(100)$ (5) a_{ij} the area of a specific type patch; A the total landscape area.
LSI	Captures the degree of variation in landscape shape.	$\mathrm{LSI} = \frac{0.25E*}{\sqrt{A}}$ (6) E^* signifies the total edge length of landscape patches.
SPLIT	Describes the extent of landscape fragmentation.	$\mathrm{SPLIT} = \frac{A^2}{\sum_{i=1}^{m}\sum_{j=1}^{n} a_{ij}^2}$ (7) a_{im} represents the weighted area of type i in landscape patches.
SHDI	Indicates landscape heterogeneity and diversity.	$\mathrm{SHDI} = -\sum_{i=1}^{m}(P_i^{\circ}\ln P_i)$ (8) P_i denotes the proportion of each patch type within the total landscape area.

Driving force analysis model. Given the scale-dependency of ecosystem services, using a singular scale for analysis often falls short in effectively capturing the impacts of various driving factors. In response, our research adopts the Multi-Scale Geographically Weighted Regression (MGWR) model, which allows for assessing the spatially variable relationships between independent and dependent variables across diverse spatial scales.The formula (9) is as follows:

$$y_i = \beta_0(U_i, V_i) + \sum_j \beta_{bwj}(U_i, V_i)x_{ij} + \varepsilon_i \qquad (9)$$

In this equation y_i denotes the dependent variable, $\beta_0(U_i, V_i)$ i represents the intercept term, x_{ij} is the predictor variable for ij, β_{bwj} indicates the bandwidth for the calibration condition association, and ε_i is the residual error term.

3 Results

3.1 Temporal Variations in Habitat Quality

Temporal Changes. Over the 2000-2018 timeframe, Guangdong Province's habitat quality demonstrated notable stability (Table 5). The habitat quality index consistently hovered around 0.78 to 0.8, reflecting steady ecological conditions. Between 2000 and 2015, a minor dip was observed, with the index falling from 0.8 to 0.78. However, a rebound occurred in the 2015-2018 phase, where the index rose to an average of 0.79. This pattern indicates relative stability in the region's habitat quality, interspersed with yearly variations. The recent uptick in habitat quality could be attributed to effective environmental management and ecological conservation efforts, emphasizing the critical role of ecosystem protection and sustainable practices in maintaining high habitat quality standards for future sustainability.

Table 5. The interannual variation of habitat quality in Guangdong Province

Index	2000	2005	2010	2015	2018
Average	0.80	0.79	0.78	0.78	0.79
Standard Deviation	0.30	0.30	0.31	0.31	0.31

Spatial Variation. Guangdong Province, as illustrated in Figure 2, reveals a striking gradient in habitat quality, with the northern regions exhibiting higher quality compared to the lower quality along its southern coastline. This variation highlights the diverse ecological tapestry within the province, influenced by a combination of geographical elements and the intrinsic qualities of the natural environment. The areas displaying lower habitat quality are primarily located in densely urbanized zones such as the Pearl River Delta and Chaoshan plains. These regions, marked by intense human activity, exhibit ecological strains resulting from urban sprawl and industrialization. This is particularly evident in major urban hubs, where habitat quality is diminishing due to expanding urban footprints and escalating human interference.

Throughout the study period, the most significant shifts in habitat quality were observed in the urban agglomerations of the Pearl River Delta, notably in key cities like Foshan, Dongguan, and Shenzhen. These areas have undergone substantial transformation, reflecting a move towards more integrated and continuous urban development. In stark contrast, changes in habitat quality in other parts of the province were more fragmented, evolving from isolated changes to forming a network of interconnected ecological shifts. This pattern underlines the complex interplay between urban development, natural habitat preservation, and the need for sustainable planning to ensure ecological integrity across Guangdong's diverse landscapes.

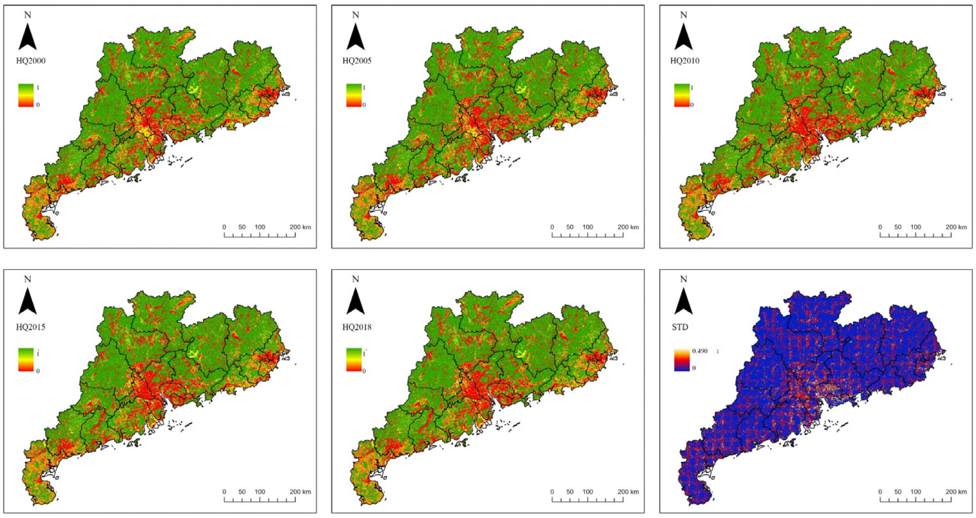

Fig. 2. Spatial changes of habitat quality in Guangdong Province from 2000 to 2018

3.2 Habitat Quality Driving Force Analysis

Impact Index Analysis. The application of the MGWR model in our habitat quality analysis yielded remarkable results, achieving an R^2 value of 0.942. This high coefficient indicates the model's strong capability to explain the variance in habitat quality due to various independent variables, as elaborated in Table 6. In the model, factors were ranked according to their regression coefficients, with slope (0.481) and NDVI (0.221) emerging as the most influential. Conversely, factors like precipitation (-0.050) and the shape of the largest patch index (-0.031) showed lesser impact.

The analysis revealed that both slope and NDVI positively affect habitat quality, enhancing ecological conditions. On the other hand, negative influences were observed from factors such as increased nighttime light, population density, landscape diversity, and patch indices. Notably, the NDVI and the largest patch index exerted their influence primarily at a local level, while other variables impacted habitat quality more globally. The effects of the landscape dispersion index and GDP were found to be statistically insignificant in this model.

These results underscore that areas with robust vegetation cover and gentler slopes are conducive to better habitat quality. In contrast, urbanization-related factors—high nighttime light intensity, dense populations, and landscape fragmentation—negatively affect the ecological environment. The insights from this study provide a scientific basis for enhancing habitat quality and underscore the critical role of ecological conservation in regional development planning.

Table 6. Results of regression coefficients of MGWR model for habitat quality

Variable	Mean	Standard Deviation	Minimum	Median	Maximum	Bandwidth (%)	Significance (%)
DEM	0.061	0.001	0.058	0.061	0.064	1594 (100.00)	1594 (100.00)
SLOPE	0.481	0.001	0.477	0.481	0.482	1594 (100.00)	1594 (100.00)
PRE	-0.050	0.001	-0.052	-0.050	-0.050	1594 (100.00)	1594 (100.00)
TEMP	0.135	0.001	0.133	0.135	0.138	1594 (100.00)	1594 (100.00)
NDVI	0.221	0.096	0.013	0.218	0.389	225 (14.12)	1381 (86.64)
GDP	0.020	0.000	0.019	0.020	0.020	1594 (100.00)	0 (0.00)
POP	-0.070	0.001	-0.072	-0.070	-0.068	1594 (100.00)	1594 (100.00)
NL	-0.220	0.000	-0.221	-0.220	-0.219	1594 (100.00)	1594 (100.00)
LPI	0.012	0.062	-0.157	0.016	0.150	192 (12.05)	180 (11.29)
LSI	-0.031	0.003	-0.038	-0.029	-0.028	1594 (100.00)	423 (26.54)
SPLIT	0.023	0.001	0.022	0.023	0.024	1594 (100.00)	0 (0.00)
SHDI	-0.111	0.002	-0.116	-0.111	-0.108	1594 (100.00)	15940.00)

Dominant factors of ecosystem service. Within the realm of natural environmental factors, temperature emerges as a notable influencer on habitat quality in Guangdong Province(Figure 3), exhibiting a negative correlation (regression coefficients ranging from -0.049 to -0.052), with its impact gradually lessening from the northeast to the southwest. This consistent climatic pattern underscores a uniform influence on habitat quality across the region. The slope of the land, with coefficients between 0.477 to 0.482, significantly impacts habitat quality, showing a decrease in quality moving away from the core of the Pearl River Delta. Conversely, elevation contributes positively to habitat quality, increasing from west to east, as higher and steeper regions typically experience less economic development, thereby supporting superior habitat conditions.

The vegetation index, displaying a broad range of coefficients from 0.012 to 0.389, enhances habitat quality, particularly noticeable in the Pearl River Delta and western Guangdong, benefitting from extensive reforestation initiatives. On the other hand, socio-economic factors such as increased nighttime light pollution universally detract from habitat quality. Additionally, population growth, with coefficients between -0.068 to -0.072, notably diminishes habitat quality from west to east. Complex interactions are observed with economic elements like GDP and population density, indicating nuanced relationships with ecological conservation.

Landscape pattern analysis further reveals that the Largest Patch Index in Zhanjiang (coefficients ranging from -0.105 to -0.157) and the LPI in the western region (coefficients from -0.032 to -0.036) both exhibit a negative association with habitat quality. Similarly, the LSI (coefficients between -0.108 to -0.115) adversely affects habitat quality, particularly in the southeastern coastal to inland areas, suggesting that a decrease in landscape diversity, characterized by the dominance of specific land patches, leads to diminished ecosystem functionality. The study also finds a strong correlation between land use patterns and habitat quality: regions with high ecological value, such as forests, typically maintain higher habitat quality, while urbanized areas tend to have lower habitat quality, underscoring the impact of human activities on the natural environment.

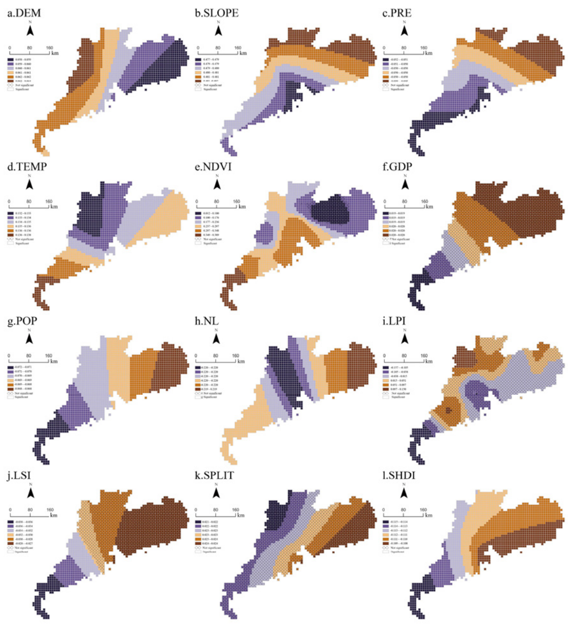

Fig. 3. Spatial of regression coefficients of MGWR model for habitat quality

4 Discussion

4.1 Necessity of Habitat Quality Research in Guangdong

In Guangdong Province, habitat quality has shown minimal interannual variation but significant spatial heterogeneity[24, 25]. The northern regions generally exhibit higher habitat quality compared to the lower quality in the southern coastal areas, particularly in the Pearl River Delta and Chaoshan plains[10, 26], largely affected by urbanization and industrialization[27]. Notably, habitat quality changes in the Pearl River Delta[27], including in cities like Foshan, Dongguan, and Shenzhen, were more pronounced, evolving from isolated to more interconnected patterns[4]. This highlights the need for focused ecological interventions in southern coastal regions, emphasizing reforestation to enhance vegetation cover and habitat quality[28].

4.2 Natural Factors Dictating Habitat Quality

The quality of habitats in Guangdong is fundamentally influenced by natural environmental factors. Temperature negatively impacts habitat quality[6], with a diminishing effect from the northeast to the southwest, while slope significantly affects habitat quality, particularly in steeper areas like the Pearl River Delta[27, 29]. Elevation's influence, although less pronounced, grows from west to east[30]. The vegetation index, indicating the positive impact of forest cover and reforestation, shows the highest values in the Pearl River Delta and western regions[31]. These insights underscore the need for slope management and soil erosion prevention, especially in ecologically sensitive areas.

4.3 Human Activities Leading to Habitat Quality Decline

Human activities significantly degrade habitat quality[9]. Nighttime light, indicative of urbanization, uniformly impacts habitats, whereas population growth predominantly affects the western regions[32]. The largest patch index in Zhanjiang and the largest shape index in western Guangdong highlight the negative effects of urban sprawl on habitat quality[33]. Additionally, the landscape diversity index shows a global negative trend, particularly in southeastern coastal areas. Strategic land-use planning in urban areas is crucial to mitigate these impacts and promote landscape diversity for ecosystem integrity[31].

4.4 Limitations

This study has several limitations. The model used is based on certain assumptions that may not fully capture the complexities of environmental changes, especially given the predictive nature of variables like population growth and economic development. Additionally, data limitations might have led to an incomplete representation of certain areas within Guangdong Province. The simulation results, while informative, require further validation with field data, as they are limited by the methodologies and data accuracy used. Moreover, the strategies suggested are contingent on the current policy and technological landscape, which may evolve over time. Despite these constraints, the study provides valuable insights for future research and policy development in habitat quality management.

5 Conclusions

In Guangdong Province from 2000 to 2018, habitat quality has shown a strong stability, with the habitat quality index averaging between 0.78 and 0.8 despite some interannual variation. However, a marked difference in habitat quality is evident between urban and rural areas, notably with the southern coastal cities exhibiting lower habitat quality compared to the northern hilly and mountainous regions. Natural elements like slope and elevation significantly influence habitat quality, as higher altitudes and steeper terrains are associated with better conditions, suggesting the critical supportive role of these natural factors. Positive changes in vegetation cover, which may be attributed to ecological initiatives such as reforestation, also play a vital role in enhancing habitat quality. On the other hand, anthropogenic factors pose significant threats and challenges. The ongoing economic growth and population increase, especially the rise in GDP and population density, have exerted pressure on habitat quality. The rapid urbanization and industrialization in the southern coastal areas further exacerbate these impacts, highlighting the need for sustainable development practices. Changes in landscape patterns, including the largest patch and shape indices as well as landscape diversity, have been identified as altering factors, adding complexity to the challenge of maintaining habitat quality. Policymakers must balance development with ecological conservation to ensure the sustainability of habitats in Guangdong Province.

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