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Spatio-temporal impacts of land use patterns on habitat quality: A multi-scenario development analysis

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Abstract: As a tropical island confronting the dual imperatives of tourism-driven economic growth and ecological vulnerability, Hainan's land-use sustainability critically impacts both regional development and coastal ecosystem security. This study employs a coupled PLUS-InVEST modeling framework to analyze land-use changes and habitat quality dynamics from 2000 to 2020, projecting ecological outcomes under three development scenarios for 2030. Key findings reveal: (1) A persistent bimodal habitat distribution pattern, with high-quality areas concentrated in the central forest zone and degraded areas in coastal peripheries, exhibiting a continuous decline over the 20-year period. (2) Accelerated urbanization between 2010 and 2020 resulted in the conversion of ecological land to construction use, correlating strongly with habitat fragmentation intensity. (3) Baseline projections for 2030 indicate that construction land will dominate new conversions. (4) Ecological protection scenarios demonstrate recoverable habitat potentials, particularly within coastal buffer zones. These findings provide empirical validation of scenario-driven land-use planning as a viable tool for island ecosystems, highlighting the critical need to balance tourism infrastructure development with coastal conservation imperatives in tropical island sustainability management. This methodology advances spatial decision-making for balancing island economic growth with biodiversity preservation, offering replicable strategies for global island ecosystems facing similar sustainability challenges.

Keywords: land use change; habitat quality; InVEST model; PLUS model; multi-scenario prediction

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0 Introduction

Habitat quality (*HQ*) constitutes a critical indicator of an ecosystem's capacity to sustain viable populations[1]. As a quantifiable proxy for biodiversity status, *HQ* exhibits strong land-use dependency and is particularly vulnerable to fragmentation pressures stemming from urbanization processes[2]. Contemporary analyses reveal that anthropogenic land transformations, such as agricultural intensification and urban sprawl, have precipitated measurable declines in global habitat quality since 2000, albeit with marked regional heterogeneity. In rapidly urbanizing coastal regions like Hainan, these dynamics manifest acutely.

Hainan Province is located at the southernmost tip of China. Since the establishment of Hainan Province in 1988, the region has experienced rapid economic development and drastic urban expansion. This has led to shifts in regional land-use types, declining habitat quality, increased habitat degradation, and tremendous pressure on biodiversity conservation. Consequently, utilizing the coupled PLUS-InVEST model and Level I

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land-use classifications, this study explores the characteristics of land-use evolution on Hainan Island over the past 20 years, analyzes the impact of urban expansion on habitat quality, and predicts the spatial distribution of land use for the upcoming decade. The research results provide scientific reference for the formulation of ecological protection policies and land planning in Hainan Island. Furthermore, the integration of smart agricultural technologies presents transformative opportunities for reconciling land-use conflicts in tropical island ecosystems. Precision agriculture systems, encompassing remote sensing-based crop monitoring, variable rate input application, and AI-driven decision support tools, enable agricultural intensification on existing cropland while alleviating expansion pressures on ecologically sensitive areas. Recent studies demonstrate that the deployment of intelligent agricultural equipment, including autonomous machinery and IoT-enabled irrigation systems, can increase land productivity by 20%−35% while simultaneously decreasing resource consumption and habitat disturbance. For Hainan Province, where cropland declined by 3.62% between 2000 and 2020 concurrent with rapid urbanization, the adoption of smart agriculture could stabilize food production capacity without necessitating further conversion of ecological land, thereby supporting both economic development objectives and biodiversity conservation imperatives.

The InVEST model enables multi-scale simulations of habitat quality dynamics across diverse ecosystems, ranging from metropolitan clusters and provincial territories to watershed systems and protected areas[3]. TANG et al. [4] conducted longitudinal monitoring of habitat degradation patterns in the South Four Lakes Basin, revealing significant lacustrine ecosystem deterioration and limitations in existing conservation protocols. YAN et al. [5] applied the model to coastal wetland systems, demonstrating the disproportionate sensitivity of Yellow River Delta habitats to land reclamation intensities, particularly in aquaculture and saltpan development zones. In a comprehensive regional analysis, JIA et al. [6-7] utilized InVEST-GIS integration to examine spatiotemporal variations of three critical ecosystem services, carbon sequestration, soil retention, and habitat quality, across the Taihu Lake urban cluster (1990−2020), identifying critical pressure thresholds through comparative synergy analysis. The PLUS model overcomes previous modeling limitations through its integration of the Land Expansion Analysis Strategy (LEAS) for driving factor identification and the Multi-type Random Patch Seeds (CARS) mechanism for fine-scale transitions. This demonstrates superior performance across county to provincial scales, offering enhanced multi-scenario adaptability and landscape pattern preservation capabilities[8].

1　Materials and Methods

1.1　Materials

1.1.1　Overview of the study area

Hainan Island features a topography characterized by a central highland surrounded by lower elevations. Wuzhi Mountain (elevation 1 867 m) and Yinggeling (elevation 1 811 m) form the core of this central uplift. Descending from the central region to the periphery, the landscape transitions through mountains, hills, terraces, and plains. Geographically, Hainan Island is situated in the northern part of the South China Sea. It is China's largest special economic zone, benefiting from specific economic policies and opening-up measures. The island consists of 21 districts and counties, with a current registered population of 10.48 million. Haikou City, as the provincial capital, is the most populous city on the island; Sanya City, a renowned tourist hotspot, ranks second in the province. Hainan has attracted substantial foreign capital and talent, promoting the rapid development of tourism, modern service industries, and high-tech sectors, thereby becoming a new engine for China's economic growth. However, rapid economic development has adversely affected the ecological environment. Population growth, intensified human interference, and the frequent expansion of construction land have posed significant threats to the habitat quality of Hainan Island.

1.1.2　Land use data

The three-phase land-use data required for this study were obtained from the Resource and Environmental Science and Data Center of the Chinese Academy of Sciences (http://www.resdc.cn),

featuring a resolution of 30 m and a comprehensive accuracy of ＞90%. The land-use data for each period were reclassified into six categories: cropland, forest, grassland, water area, building land, and unused land (Figure 1).

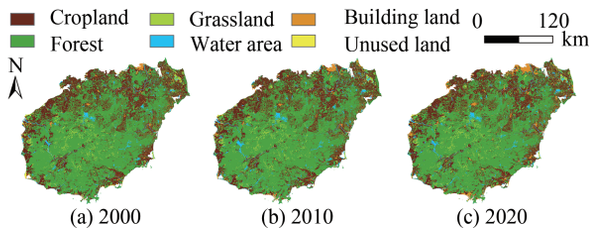


Figure 1 The land use status of Hainan Island in the third phase

1.1.3 Land use change driver data

Simulation and prediction using the PLUS model require two types of data: land use and its driving factors. Based on actual conditions and relevant literature, a total of 14 driving factors for land-use change were selected from three dimensions: natural conditions, socio-economic conditions, and transportation location conditions[9]. Land-use change is closely correlated with the natural environment, transportation accessibility, and socio-economic development.

Considering data availability and literature research, this paper selected the primary spatial variables affecting land-use change, including natural factors (DEM, slope, soil type, temperature, and precipitation), traffic location factors (points of interest, water, railways, highways, first-class roads, secondary roads, and tertiary roads), and socio-economic factors (population and GDP) (Table 1)[10].

Table 1 Main influencing factors of land use change

Type	Name	Data time	Spatial resolution	Data source	Data processing and use
Basic data	Hainan Island land use data	2000,2010,2020	30 m	Resource and Environmental Science Data Center of the Chinese Academy of Sciences	ArcGIS was used to reclassify the land use data of the third period into six categories to simulate and predict future land use changes
	Administrative boundaries of Hainan Island	2020	—		
Natural drivers	DEM	2020	30 m	Geospatial Data Cloud	
	Slope	2020	30 m		
	Soil type	2020	30 m	Resource and Environmental Science Data center of the Chinese Academy of Sciences	
	Temperature	2000,2010,2020	30 m		
	Precipitation	2000,2010,2020	30 m		
Socio-economic drivers	Hainan GDP spatial distribution grid data	2000,2010,2020	1 km		Use ArcGIS raster data conversion tools to convert GDP and population data to 30 m resolution
	Hainan population spatial grid distribution data	2000,2010,2020	1 km		
Traffic location drivers	Distance to pois	2020	—	National Geographic Information Resources Directory Service System	ArcGIS was used to perform Euclidean distance analysis on the data, which was used by the PLUS model to predict future land use changes
	Distance to river				
	Distance to railway				
	Distance to highway				
	Distance to first-class road				
	Distance to secondary road				
	Distance to tertiary road				

1.2 Methods

1.2.1 Research framework

The framework employs Random Forest algorithms within the Land Expansion Analysis Strategy (LEAS) to process land-use data and driving factors, yielding "Growth Probabilities". A Markov chain is then established for multi-scenario prediction. The land-use simulation for 2020 was generated using the CARS module and verified against actual 2020 land-use data. Upon validating accuracy standards, land-use data for three future scenarios were generated. Finally, threat factors and sensitivity tables were configured in InVEST to obtain habitat quality distribution maps under these three scenarios.

1.2.2 InVEST model

The Habitat Quality module in the InVEST 3.14.2 model was used to quantitatively assess the habitat quality level of Hainan Island. Elevated habitat indices correlate positively with enhanced habitat quality, increased regional biodiversity, and improved ecosystem stability. High habitat quality reflects the integrity of ecosystem structure and function within its historical dynamic range. The calculation equations are shown in Equations (1) to (4)[11-12].

$$Q_{xj}=H_j\left[1-\frac{D_{xj}^2}{D_{xj}^2+K^2}\right] \tag{1}$$

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

$$i_{rxyl}=1-\frac{d_{xy}}{d_{r\max}} \tag{3}$$

$$i_{rxye}=\exp\left(-\frac{2.99}{d_{r\max}}\times d_{xy}\right) \tag{4}$$

where Q_{xj} is the habitat quality of grid x in land use type j. H_j is the habitat suitability of land use type j. D_{xj} is the habitat degradation degree of grid unit x in land use type j. k is the half-saturation coefficient (default value is 0.5). Y_r is the number of stress factor grid cells. y represents all stress factor grid cells. R is the number of stress factors. W_r is the weight of stress factor r. r_y represents the value of the stress variable for raster y. i_{rxy} is the stress level of stress factor r_y from raster y to raster x. β_x is the accessibility of the stress factor to raster x. S_{jr} is the sensitivity of habitat type j to stress factor r, with a value range of (0, 1). d_{xy} is the linear distance between grids x and y. $d_{r\max}$ is the maximum stress distance for stress factor r. In accordance with the specific conditions of the study area, cropland, building land, and unused land were identified as threat factors[13-15]. Based on recommended InVEST model values and relevant research, the impact distance, weight, and sensitivity of different habitat types to threat factors were determined (Table 2, Table 3). These parameters were input into the model to generate the habitat quality map. The resulting habitat quality indices range between [0, 1]. Higher values indicate superior habitat quality. Conversely, lower values indicate poorer habitat quality [16-17]. The natural discontinuity method was employed to classify habitat quality into five levels: Worst (0—0.3), Poor (0.3—0.5), Medium (0.5—0.7), Good (0.7—0.9), and Excellent (0.9—1.0)[18].

Table 2　Threat sources, impact distances and their weights

Threat source	Maximum impact distance/km	Weight	Spatial decay type
Cropland	1.1	0.12	Linear
Building land	1.4	0.18	Exponential
Unused land	8	0.8	Linear

Table 3　Habitat suitability of each specie and Sensitivity to different threat factors

Land types	Habitat suitability	Sensitivity		
		Cropland	Building land	Unused land
Cropland	0.45	0.3	0.7	0.2
Forest	0.9	0.75	0.6	0.2
Grassland	0.95	0.65	0.6	0.55
Water area	0.75	0.3	0.6	0.5
Building land	0	0	0	0.25
Unused land	0.15	0.25	1	1

1.2.3 PLUS model

This study utilized the PLUS model to simulate three scenarios for 2030. The PLUS model is a cellular automata (CA) model based on raster data, designed for land-use simulation and prediction. It employs linear regression and Markov models to predict land-use demand in 2030. The LEAS (Land Expansion Analysis Strategy) module uses a random forest classification algorithm to explore the probability of land-use type changes, analyze the relationship between

driving forces and land use, and calculate land-use expansion from the initial to the final stage. The parameters for this module were set as follows: numbers of regression trees are 20, sampling rate is 0.01, mTry is 14, and Thread is 20. The CARS module is a CA model based on multi-class random patch seeds, used to simulate spatial changes in complex scenarios. The CARS module parameters were: neighborhood size is 3, Thread is 20, patch generation threshold is 0.2, expansion coefficient is 0.1, and seed percentage is 0.000 1. The neighborhood weight for each land-use type was calculated according to standard formulas and references. The calculation equation is shown in Equation (5)[19-20].

$$X^* = \frac{X - X_{min}}{X_{max} - X_{min}} \quad (5)$$

where X^* represents the standardized value of deviation, and X is the area of change between each land class in the two-period land-use data; X_{max} represents the maximum value of area change among all land types, and X_{min} represents the minimum value.

1.2.4 Three development scenario designs

Natural Development Scenario (NS): This scenario is based on the extrapolation of existing development trends without parameter adjustment. It continues the land-use change trends observed from 2000 to 2020, considering only changes caused by natural conditions while ignoring the impact of potential policy factors. Conversions between different land types are permitted.

Cropland Protection Scenario (CS): Considering cropland as the guarantor of food security, the transfer of farmland to other land types is prohibited in this scenario. The probability of forest and grassland transferring to cropland is increased by 35%, and the probability of unused land transferring to cropland is increased by 15%[21].

Ecological Protection Scenario (ES): Aligned with the Territorial Spatial Planning (2021—2035), this scenario aims to stabilize forest coverage rates. It focuses on protecting forests and grasslands, strictly restricting the conversion of forest, grassland, and water areas to other types, and increasing the probability of converting cropland, grassland, and water areas to forest by 20%[22]. Based on these requirements, a land-use conversion matrix under the three scenarios for 2030 was constructed (Table 4), where 0 represents non-convertible and 1 represents convertible[23-25].

Table 4 Land use conversion matrix under three scenarios simulation

Scenario	LUCC	Cropland	Forest	Grassland	Water area	Building land	Unused land
NS	Cropland	1	1	1	1	1	1
	Forest	1	1	1	1	1	1
	Grassland	1	1	1	1	1	1
	Water area	1	1	1	1	1	1
	Building land	1	1	1	1	1	1
	Unused land	1	1	1	1	1	1
CS	Cropland	1	0	0	0	0	0
	Forest	1	1	1	0	1	1
	Grassland	1	1	1	1	1	1
	Water area	1	0	1	1	1	1
	Building land	1	0	1	1	1	1
	Unused land	1	1	1	1	1	1
ES	Cropland	1	1	1	1	1	1
	Forest	0	1	0	0	0	0
	Grassland	0	1	1	0	0	0
	Water area	0	1	1	1	0	0
	Building land	1	1	1	1	1	1
	Unused land	1	1	1	1	1	1

2　Results

2.1　Analysis of land use change

2.1.1　Changes in land use types during the study period

Our analysis reveals transformative land-use dynamics on Hainan Island from 2000 to 2020, characterized by accelerated urbanization and ecological conversion. Built-up areas expanded progressively from 735.96 km² to 884.97 km² during 2000 to 2010, then surged to 1 385.60 km² during 2010 to 2020. This spatial transformation coincided with systematic declines in agricultural and ecological land cover: cropland decreased by 1.37% (2000−2010) followed by a 2.25% reduction (2010−2020), while forest cover diminished by 0.36% and 1.36% in respective decades, accompanied by the persistent depletion of unused land throughout both periods. Notably, the second decade exhibited a 3.36-fold acceleration in urban expansion rates and intensified ecological land conversion compared to 2000−2010 (Table 5), reflecting mounting anthropogenic pressures during China's rapid economic transition phase.

Table 5　Land use changes from 2000 to 2020 and in 2030 under three development scenarios　Unit: km²

Land type		Cropland	Forest	Grassland	Water area	Building land	Unused land
2000		8 962.272 9	21 737.998 8	1 225.338 3	930.039 3	735.964 2	130.467 6
2010		8 839.803 6	21 659.188 5	1 127.994 3	1 125.160 2	884.968 2	84.966 3
2020		8 640.570 6	21 365.030 7	1 146.458 7	1 106.343 9	1 385.604 9	78.073 2
2030	NS	8 463.177 9	21 082.428 9	1 170.623 7	1 090.188 9	1 843.142 4	72.519 3
	CS	8 866.079 1	21 020.956 2	1 167.803 1	1 090.035 9	1 504.854 9	72.351 9
	ES	8 479.062 9	21 476.088 0	1 113.704 1	1 085.994 0	1 494.714 6	72.517 5

2.1.2　Land use changes under three progressive scenarios

Natural Development (NS): Projected continuation of 2010−2020 trends reveals sustained land conversion pressures, with built-up areas expanding by 33.02% (from 1 385.60 km² to 1 843.14 km²) through 2020—2035. This urbanization occurs alongside countervailing losses in ecological and agricultural lands, specifically cropland (−2.05%) and forest cover (−1.32%). The progression maintains annualized conversion rates consistent with previous patterns (Table 6), suggesting entrenched land-use pathways in the absence of policy intervention.

Cropland Protection (CS): Regulatory intervention prohibiting cropland conversion alters transitional probabilities, increasing forest/grassland-to-cropland transfers by 35%. This produces an 8.61% expansion of built-up areas relative to 2020 levels, a significant deceleration versus NS Scenario's 33.02% growth. The resulting landscape exhibits stabilized agricultural reserves coupled with moderated urban sprawl, demonstrating the effectiveness of targeted land-use zoning.

Ecological Conservation (ES): Enhanced environmental safeguards yield divergent outcomes: forest coverage increases by 111.06 km² compared to 2020, while built-up areas contract by 348.43 km². These differentials highlight the potential for (1) curbing urban expansion through development restrictions, and (2) achieving net reforestation via ecological red line policies. The 1.13:1 ratio of gained forest to lost construction land suggests possibilities for sustainable land-use optimization (Figure 2).

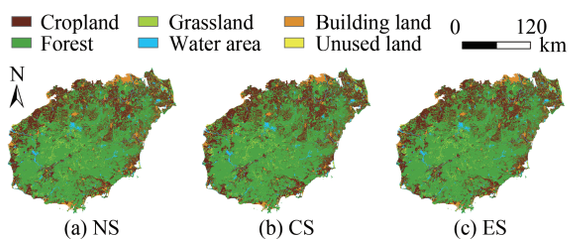


Figure 2　LUCC diagram of three development scenarios in 2030

The projected land-use changes under different scenarios have significant implications for precision agriculture and the deployment of intelligent agricultural equipment in Hainan. Under the Natural Development Scenario, the anticipated 33.02% expansion of built-up areas and 2.05% reduction in cropland necessitate agricultural intensification through smart farming

technologies. The spatial heterogeneity revealed by our PLUS model projections indicates that high-quality cropland zones in central-eastern regions (Qionghai, Wenchang) require integrated soil-crop-atmosphere monitoring networks and variable rate application technologies to maximize yield per unit area. Conversely, the Cropland Protection Scenario's spatial consolidation patterns favor the deployment of large-scale intelligent machinery, including GPS-guided tractors, automated harvesting systems, and AI-powered pest monitoring drones, in preserved agricultural zones where field fragmentation decreases by 15%—20%. Additionally, coastal agricultural zones facing habitat degradation require precision irrigation systems integrated with real-time soil moisture sensors and climate forecasting algorithms to achieve water-use efficiency improvements of 25%—30% while reducing ecological impacts on adjacent sensitive habitats. These smart agriculture interventions align synergistically with the Ecological Protection Scenario, where optimized resource utilization through intelligent systems can help achieve the observed habitat quality improvements (mean *HQ*: 0.728) while maintaining agricultural productivity[26-29].

2.1.3 Land use conversion analysis

Our land-use transition matrix analysis (2000—2020) reveals fundamental landscape restructuring on Hainan Island, characterized by asymmetric conversion patterns favoring anthropogenic development. Built-up areas demonstrated a net gain of 649.64 km², with inflow primarily sourced from cropland (332.17 km², 44.97%) and forests (336.32 km², 45.53%). Concurrently, water bodies expanded through a net conversion of 176.30 km², primarily deriving from cropland (104.00 km², 36.77%) and forests (103.57 km², 36.61%). This systematic conversion depleted 1 929.29 km² of natural systems, with cropland and forest losses accounting for 36.99% (713.83 km²) and 40.43% (779.95 km²) of total transfers, respectively. The dominant "one-to-many" transition pattern (Table 6) reveals that 47.05% of transferred parcels were ultimately converted to the built environment or water features. These metrics quantify how rapid tourism-driven urbanization and water infrastructure development have systematically transformed Hainan's landscapes through economic prioritization over ecological preservation. The growth of building land and water areas was mainly at the expense of cropland and grassland, indicating that Hainan Island has developed rapidly in the past 20 years, and the expansion of building land has encroached on other land types.

Table 6 Land use over Matrix from 2000 to 2020

Unit: km²

	Cropland	Forest	Grassland	Water area	Building land	Unused land	Transfer out
Cropland	8 248.440 6	257.679	15.981 3	104.003 1	332.173 8	3.995 1	713.832 3
Forest	273.265 2	20 958.048 9	60.665 4	103.574 7	336.323 7	6.120 9	779.949 9
Grassland	14.573 7	84.430 8	1 049.590 8	49.519 8	26.761 5	0.461 7	175.747 5
Water area	46.589 4	27.721 8	8.579 7	823.471 2	22.567 5	1.109 7	106.568 1
Building land	37.165 5	32.379 3	1.644 3	17.737 2	646.946 1	0.091 8	89.018 1
Unused land	20.536 2	4.770 9	9.997 2	8.037 9	20.832 3	66.293 1	64.174 5
Transfer In	392.13	406.981 8	96.867 9	282.872 7	738.658 8	11.779 2	

2.2 Analysis of habitat quality changes

2.2.1 Spatiotemporal evolution of habitat quality

Hainan Island experienced progressive habitat quality (*HQ*) degradation from 2000 (mean *HQ*=0.744) to 2020 (mean *HQ*=0.731), with an accelerated decline during 2010—2020. This 20-year reduction of 1.75% coincided with China's rapid economic growth phase, aligning particularly with Hainan's 2010 tourism development initiatives. The nonlinear deterioration pattern suggests compounding anthropogenic pressures beyond direct land conversion.

Spatial analysis revealed persistent *HQ* gradients, with core mountainous regions functioning as ecological refugia. During the period of 2000—2020, the habitat

quality of Hainan Island showed relatively consistent spatial distribution characteristics (Figure 3). Habitat quality was highest in the central region of Hainan Island. Moving from the center to the periphery, the increasing impact of human activities and economic construction led to a gradual decline in habitat quality. Especially in the edge areas of the island, flat terrain, dense population, urban expansion, and tourism development caused habitat fragmentation, reduced ecosystem functions, and relatively poor habitat quality.

In all three periods, the "Good" grade accounted for the highest proportion of Hainan Island's *HQ* (>68%). The "Good" grade proportions were 69.76%, 69.13%, and 68.98% respectively, reflecting the generally high habitat quality of Hainan Island. However, the "Worst" grade increased rapidly on the northeastern edge of Hainan Island, concurrent with the rapid expansion of building land. During the study period, the proportion of the "Worst" grade index increased, while the proportion of the "Excellent" grade index decreased (Table 7). From 2010 to 2020, the habitat quality of the "Excellent" grade decreased the most (0.56%), while the "Poor" grade increased the most (0.59%). This may be attributed to the International Tourism Island policy implemented since 2010. Consequently, intensified human activities and urbanization have caused substantial damage to the ecosystem.

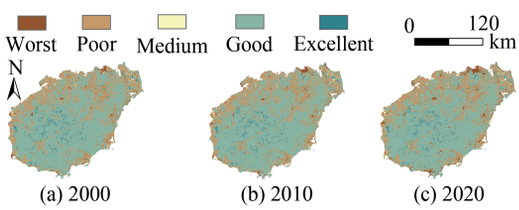


Figure 3　Distribution of habitat quality grades in Hainan Island from 2000 to 2020

Table 7　Proportion of habitat quality grades in Hainan Island from 2000 to 2020

Year	Average	Classification				
		Worst	Poor	Medium	Good	Excellent
2000	0.744	0.16%	26.51%	0.81%	69.76%	2.76%
2010	0.742	0.23%	26.87%	0.90%	69.13%	2.87%
2020	0.731	0.29%	27.46%	0.96%	68.98%	2.31%

2.2.2　Comparison of habitat quality under three scenarios

Scenario 1 (NS): Projections under the natural development scenario reveal a 2.05% decline in mean habitat quality (*HQ*) from 2020 levels (ΔHQ= 0.015). Critical class transitions show a doubled prevalence of "Worst" *HQ* areas (0.29% → 0.58%) and reductions in "Good" (−1.59%) and "Excellent" (−0.13%) zones. This indicates that under the natural development scenario, the habitat quality of Hainan Island faces the risk of large-scale degradation.

Scenario 2 (CS): The cropland protection scenario demonstrates moderated ecological impacts, reducing "Worst" *HQ* areas by 0.06% versus Scenario 1 (0.58% → 0.23%). While partially restoring "Excellent" areas (+0.13%) compared to 2020, residual degradation persists in coastal zones. This bifurcated pattern highlights the limited efficacy of agricultural zoning alone against secondary urbanization pressures from tourism infrastructure expansion. This suggests that while the cropland protection scenario improves habitat quality in some areas of Hainan Island, its overall effects are limited.

Scenario 3 (ES): Under the ecological protection scenario, mean *HQ* surpasses other scenarios by 0.07−0.12 compared to the natural development scenario. This is driven by a 2.14% reduction in "Poor" class areas and synergistic gains in "Excellent" (+0.46%) and "Good" (+2.29%) zones. This demonstrates that the ecological protection scenario effectively improves overall habitat quality (Table 8, Figure 4).

Table 8　Average habitat quality and grade proportion under three scenarios

Scenario	Average	Classification				
		Worst	Poor	Medium	Good	Excellent
NS	0.716	0.58%	28.65%	1.20%	67.39%	2.18%
CS	0.721	0.23%	27.74%	0.94%	68.51%	2.58%
ES	0.728	0.23%	26.51%	0.94%	69.68%	2.64%

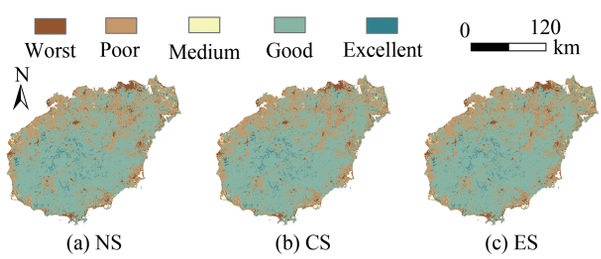


Figure 4　Distribution of habitat quality levels in 2030 under three scenarios

2.2.3 Comparison of habitat quality in various counties

Based on the bar chart of habitat quality changes in various districts and counties of Hainan Island from 2000 to 2020 (Table 9), the ordinate was unified for convenient observation and analysis. The degradation of habitat quality on Hainan Island displays distinct spatial characteristics, with the habitat index gradually decreasing from the middle to the surrounding areas. Slightly degraded areas include Qiongzhong County, Baisha County, Wuzhishan City, and Baoting County; moderately degraded areas include Qionghai City and Dongfang City; and severely degraded areas include Meilan District, Longhua District, Lingao County, and Wenchang City.

Table 9 Histogram of habitat quality changes in counties and districts of Hainan Island

	2000	2010	2020	NS	CS	ES
Meilan	0.599	0.593	0.543	0.508	0.524	0.535
Lingao	0.617	0.619	0.612	0.594	0.601	0.608
Wenchang	0.650	0.645	0.628	0.609	0.617	0.626
Longhua	0.657	0.633	0.617	0.593	0.599	0.614
Danzhou	0.660	0.659	0.645	0.625	0.632	0.640
Xiuying	0.671	0.640	0.560	0.545	0.559	0.574
Dingan	0.673	0.671	0.666	0.655	0.659	0.666
Lingshui	0.689	0.692	0.678	0.652	0.666	0.670
Chengmai	0.708	0.708	0.691	0.641	0.679	0.689
Qiongshan	0.718	0.715	0.700	0.679	0.683	0.697
Changjiang	0.727	0.726	0.720	0.708	0.713	0.718
Qionghai	0.739	0.738	0.729	0.708	0.712	0.727
dongfang	0.745	0.744	0.736	0.728	0.731	0.735
Haitang	0.747	0.731	0.699	0.670	0.678	0.693
Tunchang	0.750	0.750	0.744	0.733	0.735	0.744
Wanning	0.755	0.754	0.740	0.721	0.729	0.738
Jiyang	0.769	0.738	0.697	0.661	0.671	0.693
Yazhou	0.787	0.782	0.756	0.737	0.745	0.752
Ledong	0.788	0.787	0.786	0.779	0.780	0.785
Tianya	0.838	0.827	0.817	0.804	0.807	0.815
Baoting	0.841	0.840	0.834	0.828	0.828	0.834
Baisha	0.853	0.853	0.850	0.844	0.845	0.850
Qiongzhong	0.865	0.864	0.861	0.855	0.855	0.861
Wuzhishan	0.867	0.866	0.863	0.859	0.860	0.863

As the most severely degraded area on Hainan Island over the past 20 years, Meilan District's habitat index remained below 0.600 during the study period. Xiuying District exhibited the fastest degradation rate, dropping from 0.671 in 2000 to 0.640 in 2010, and further to 0.560 in 2020. Both Meilan and Xiuying Districts are located in the northeast of Hainan Island, a region with high GDP. Their built-up areas are constantly expanding, which has promoted economic development; however, this large-scale expansion has disrupted the regional ecosystem balance, resulting in a persistently low regional habitat index.

During the study period, habitat quality in Qiongzhong County, Baisha County, Wuzhishan City, and Baoting County in the central region declined slightly but remained generally good. Due to the higher forest coverage in the central region, along with effective natural conditions and protective policies, the ecological environment was less affected by anthropogenic factors, maintaining stable habitat quality. Under the ES scenario, the habitat index of marginal cities in Hainan Island showed significant improvement compared to the central area. This demonstrates that ecological protection scenarios offer recoverable habitat potential, particularly in coastal buffer zones.

3 Discussion

3.1 Conclusion

This study systematically analyzed the spatiotemporal impacts of land-use changes on habitat quality in Hainan Island from 2000 to 2020 and predicted ecological evolution trends under three development scenarios for 2030 using a coupled PLUS-InVEST modeling framework. The main contributions include: (1) The deep integration of the PLUS model's Multi-type Random Patch Seeds (CARS) mechanism with the InVEST model's habitat quality assessment function, achieving precise simulation of tropical island ecosystem spatiotemporal dynamics; (2) The construction of a multi-scenario analysis framework covering natural development, cropland protection, and ecological protection scenarios, providing scientific decision support for sustainable island development; (3) The revelation of bidirectional spatial differentiation

patterns of tourism-driven urbanization impacts on Hainan's habitat quality, specifically, the maintenance of high-quality habitats in central mountainous areas versus intensified degradation in coastal peripheries. These findings provide new theoretical perspectives for understanding spatial coupling mechanisms between tropical island ecological vulnerability and economic development pressures, offering replicable research paradigms for global island ecosystem management facing similar challenges.

The study revealed significant spatial differentiation in habitat quality changes on Hainan Island, presenting a "center-periphery" gradient distribution pattern. From 2000 to 2020, mean habitat quality declined from 0.744 to 0.731. The rate of decline during 2010—2020 (1.48%) significantly exceeded that of 2000—2010 (0.26%), coinciding closely with the implementation of the Hainan International Tourism Island construction policies. Coastal developed areas like Meilan and Longhua Districts consistently maintained habitat indices below 0.600, while central mountainous counties such as Qiongzhong and Baisha maintained high-quality levels above 0.850. This spatial differentiation pattern reflects the inherent tension between tourism economic development and ecological protection.

3.2 Implications and applications for agricultural mechanization development

Our study quantitatively analyzes land-use change and habitat quality evolution on Hainan Island, offering critical practical guidance for the development of agricultural mechanization.

3.2.1 Supporting the structural adjustmen

Spatial heterogeneity and diversity in land-use changes create new requirements for agricultural machinery, emphasizing multifunctionality and intelligence. For instance, small, intelligent machinery or plant protection drones should be promoted in marginal and sloped ecological areas. In areas designated for ecological restoration or reforestation, specialized machinery for forestland and orchard management is required. The spatial data in our study enables precise selection, upgrading, and regional optimization of machinery equipment by related industries.

3.2.2 Providing decision-making support

Our study indicates that rapid urban expansion could further degrade ecosystems, whereas ecological protection measures can significantly improve habitat quality. This provides important references for adjusting the trajectory of agricultural mechanization. It is recommended that ecological constraints be strengthened in the promotion of mechanization, encouraging the adoption of green technologies such as conservation tillage, straw incorporation, and energy-saving/low-emission machines, thereby achieving the coordinated development of mechanized agricultural production and ecological protection.

3.2.3 Supporting agricultural mechanization social services

Along with population shifts and changes in cultivated land structures, the demand for socialized agricultural mechanization services is rapidly increasing. The spatial analysis in this study can inform the scientific placement of machinery service stations, maintenance centers, intelligent dispatching systems, and emergency disaster response mechanisms, thereby improving the accessibility and service capacity of machinery in ecologically fragile and remote areas.

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土地利用格局对生境质量的时空影响:多情景发展分析

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摘要:作为一个面临旅游驱动的经济增长与生态脆弱性双重压力的热带岛屿,海南的土地利用可持续性对区域发展与海岸带生态系统安全具有关键影响。本研究采用耦合的 PLUS-InVEST 建模框架,分析了2000—2020年土地利用变化与栖息地质量动态,并在3种2030年发展情景下预测生态结果。主要结论包括:(1) 栖息地质量的双峰分布格局持续存在,高质量区域集中于中部森林地区,而沿海边缘地带普遍退化,整体呈现20年来持续下降的趋势。(2) 2010—2020年加速的城镇化将生态用地转为建设用地,并与栖息地破碎化强度上升相对应。(3) 2030年基线情景预测显示,新增用地转换将以建设用地为主导。(4) 生态保护情景表明存在可恢复的栖息地潜力,尤其是在沿海缓冲带。这些发现为情景驱动的土地利用规划作为岛屿生态系统管理的有效工具提供了实证验证,强调在热带岛屿可持续性治理中必须在旅游基础设施发展与沿海保护刚性需求之间实现平衡。该方法为在经济增长与生物多样性保护之间进行空间决策提供了支撑,并为面临类似可持续挑战的全球岛屿生态系统提供了可复制的策略。

关键词:土地利用变化;栖息地质量;InVEST模型;PLUS模型;多情景预测