

Article

Impacts of Human Activities on Ecosystem Services in Watersheds: Evidence from the Taihu Lake Basin, China

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Abstract

Human activity intensity has become an increasingly significant driver of changes in ecosystem services, and understanding their spatiotemporal relationships is essential for watershed ecological governance. Taking the Taihu Lake Basin as the study area, this research utilizes multi-source geospatial data from 2003 to 2023. The InVEST model is employed to assess four key ecosystem services: water yield, soil conservation, carbon storage, and habitat quality. A human activity intensity (HAI) index is constructed using the entropy-weight method, while bivariate spatial autocorrelation and geographically weighted regression are applied to disentangle the spatiotemporal evolution, spatial associations, and local variations in the associations between HAI and ecosystem services. The results indicate that (1) HAI has continuously intensified, with high-intensity areas undergoing an approximately 9.5-fold expansion and exhibiting a distinct “high in the east, low in the west” pattern; (2) carbon storage and habitat quality show persistent declines, whereas water yield and soil conservation exhibit fluctuating upward trends, with an overall “high in the southwest, low in the northeast” distribution; (3) HAI is significantly positively correlated with water yield and negatively correlated with carbon storage, soil conservation, and habitat quality, with 2018 identified as a critical turning point; and (4) the associations exhibit notable spatial non-stationarity, with the proportion of significant grid cells following a hierarchical order of habitat quality > water yield > carbon storage > soil conservation. Zones with strong regression coefficients occur only as localized patches, while the majority of the basin is characterized by low-to-moderate driving intensity. This study further reveals three core mechanisms—land-use path dependence, policy-induced threshold responses, and spatial spillover associations—providing a scientific basis for differentiated ecological management and sustainable development in the Taihu Lake Basin.



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1. Introduction

Since the dawn of the 21st century, sustained population growth and rapid economic agglomeration have exacerbated the depletion of natural resources, imposing unprecedented pressures on natural ecosystems [1,2]. Ecosystem services (ESs), which constitute the benefits that human populations derive directly or indirectly from ecological systems,

are fundamental to regional ecological security and human well-being [3]. As natural geographical units centered on river systems, watersheds provide critical ecological functions such as water conservation, hydrological regulation, water purification, and biodiversity maintenance. They serve as vital ecological barriers for sustaining regional ecological security and supporting sustainable development, representing key areas for the provision of ecosystem services. However, in rapidly urbanizing regions, the expansion of human activities and increases in their intensity have profoundly altered land-use structures and ecological processes, leading to habitat fragmentation, biodiversity loss, and the degradation of ecological functions [4]. Studies indicate that approximately 60% of global ecosystem services are in decline [5,6]. Consequently, elucidating the complex relationships and underlying mechanisms between human activities and ecosystem services has become a critical research priority for advancing regional sustainable development.

Human activity intensity (HAI) serves as a crucial metric for quantifying the degree of human intervention in natural systems [7,8]. Considerable efforts have been devoted to developing quantitative frameworks for HAI, with existing studies primarily constructing composite indicator systems from dimensions such as population agglomeration, land-use change, and socioeconomic activity [9–11]. For example, some studies employ population density and the proportion of built-up land as core indicators to capture the direct transformation intensity of human activities on land surfaces [12]; others further incorporate nighttime light data to reflect the spatial distribution and intensity of socioeconomic activities [13,14]. With the improving availability of spatial data, multi-indicator composite assessment has become the dominant paradigm for HAI quantification [14–17]. Ecosystem services, defined as the diverse benefits that people obtain from ecosystems, act as a critical bridge connecting natural and socio-economic systems [3,18]. They are conventionally categorized into four broad types: provisioning, regulating, supporting, and cultural services [19]. Methodologically, ES assessments primarily employ biophysical quantification or monetary valuation, with valuation techniques further subdivided into direct market, revealed preference, and stated preference methods [20]. As the field has matured, a systematic research framework has emerged, encompassing the analysis of spatiotemporal dynamics, the spatial matching of supply and demand, the identification of trade-offs and synergies among services, and the elucidation of their integrated driving mechanisms [21–24].

As research in both domains has progressed, the interrelationship between human activities and ecosystem services has become a central focus. Current scholarship predominantly explores this nexus from two perspectives: (i) investigating the correlation between specific human activity factors (e.g., urbanization, agricultural expansion, transportation infrastructure) and ESs through statistical analysis and scenario simulation [25]; and (ii) identifying the human activity drivers of ES change and quantifying their directional influence and magnitude [26]. Most existing studies employ correlation or regression models to verify the direction and intensity of human impacts on ESs [27–29]. For instance, Ouyang et al. (2024) applied threshold regression models to identify nonlinear dominant factors affecting ecosystem services in response to human activity intensity in China's urban agglomerations [30]; Huang et al. (2026) employed geographically weighted regression to quantify the impacts of human activities on ecosystem services in the Yangtze River Economic Belt from spatial, economic, and energy perspectives [31]; and Deng et al. (2022) utilized segmented quantile regression and automatic linear models to reveal the effects of human activities and natural factors on the dynamic changes in relationships among ecosystem services in the Huang-Huai-Hai Plain [32]. These studies consistently confirm that human activity is a primary driver and that high-intensity development significantly undermines ES supply capacity [33]. However, such studies often adopt a global average

perspective, implicitly assuming spatially homogeneous relationships. In reality, influenced by factors such as land use patterns, topographical conditions, and urbanization gradients, the effects of human activities on ESs vary across geographical units—a phenomenon known as spatial heterogeneity. Neglecting this spatial non-stationarity can lead to “one-size-fits-all” ecological restoration policies that are ineffective. In recent years, local regression models such as geographically weighted regression (GWR) have been employed to reveal the spatial differentiation of human activity–ES relationships; nevertheless, relevant studies remain relatively limited, mostly focusing on single services or coarse administrative scales [31,34]. Systematic analyses that comprehensively examine multiple ESs and integrated HAI at a fine-grid resolution in highly urbanized watersheds—such as the Taihu Lake Basin—remain scarce [35,36]. As a representative region characterized by both high urbanization intensity and critical ecological functions, the Taihu Lake Basin provides an ideal case for addressing this research gap.

The Taihu Lake Basin, situated in the core area of China’s Yangtze River Delta, is one of the regions with the highest levels of urbanization and most intensive economic activities [37]. While supporting rapid socio-economic development, this area also sustains critical ecological functions, including water conservation, hydrological regulation, water purification, and biodiversity maintenance. However, high-intensity human activities driven by rapid industrialization and urbanization have profoundly altered regional land use structure and ecological processes [38], resulting in the significant degradation of key ESs such as water purification and habitat quality, thereby intensifying human–environment conflicts.

Consequently, this study selects the Taihu Lake Basin as the study area. Utilizing multi-temporal land use and geospatial data from 2003 to 2023, we aim to (1) construct a comprehensive human activity intensity (HAI) evaluation index system by integrating population density, nighttime light intensity, and proportion of built-up land using the entropy weight method; (2) elucidate the spatiotemporal characteristics of four key ecosystem services—water yield, soil conservation, carbon storage, and habitat quality—over the same period using the InVEST model; and (3) reveal the spatial correlation patterns and local variations in the relationship between HAI and these four ecosystem services by employing bivariate spatial autocorrelation and geographically weighted regression (GWR) at a 1 km grid resolution. The findings are expected to provide insights for the coordinated management of ecosystem services at local scales and offer a scientific basis for decision-making related to ecological protection and sustainable development in the Taihu Lake Basin.

2. Materials and Methods

2.1. Study Area

The Taihu Lake Basin is located in the eastern part of China within the Yangtze River Delta region (119°11′–121°51′ E, 30°28′–32°15′ N). Its geographical boundaries are well-defined: it is bounded by the Yangtze River to the north, the East China Sea to the east, the Qiantang River to the south, and the Tianmu and Mao mountains to the west (Figure 1). Covering a total area of approximately 36,895 km², the basin spans Jiangsu, Zhejiang, and Anhui provinces as well as Shanghai Municipality, constituting a key component of the core Yangtze River Delta region. The basin is characterized by flat topography and a predominantly plain water network landscape, with densely distributed rivers and lakes. Taihu Lake, together with Dianshan Lake, Yangcheng Lake, and others, forms a typical plain river network–lake ecosystem. Climatically, the region experiences a subtropical monsoon climate, with a mean annual precipitation ranging from 1010 to 1400 mm, providing favorable hydrothermal conditions. Owing to its distinctive physical

geographical characteristics, the Taihu Lake Basin not only serves as an ecological security barrier for the Yangtze River Delta region but also functions as an important commodity grain base. Consequently, its ecosystem services are critically linked to both regional ecological security and socio-economic development.

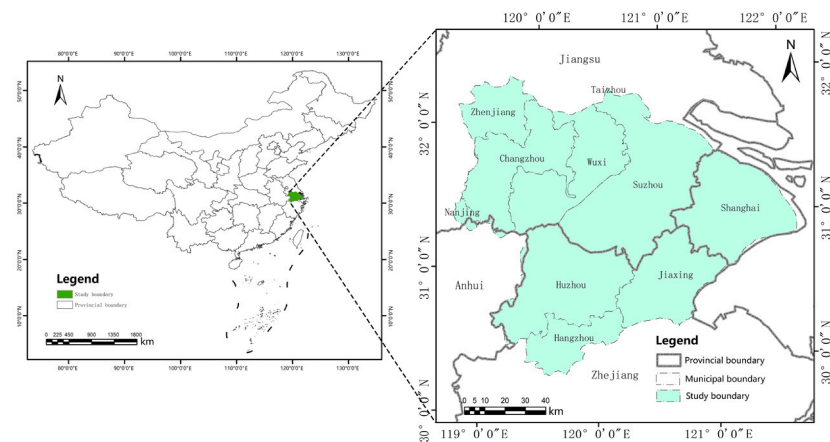


Figure 1. Location map of the study area.

2.2. Data Sources

The datasets used in this study are summarized in Table 1, including their sources, spatial resolutions, temporal coverage, and specific applications. All raster datasets were pre-processed in ArcGIS 10.8 to ensure spatial consistency. This involved resampling all layers to a uniform $30\text{ m} \times 30\text{ m}$ spatial resolution and projecting them into the WGS_1984_Albers projected coordinate system.

Resampling to the native 30 m resolution of the land use and DEM data was necessary because the InVEST model operates on a pixel-by-pixel basis; using the highest available resolution minimizes information loss before model computation. To unify the analytical scale for subsequent spatial analyses, the 30 m resolution outputs from the InVEST model were then aggregated using a $1\text{ km} \times 1\text{ km}$ fishnet grid as the fundamental analysis unit. This aggregation served two purposes: (1) to reduce the computational burden of the subsequent bivariate spatial autocorrelation and GWR analyses and (2) to suppress noise in the raw model outputs, thereby revealing broader spatial patterns. The 1 km grid has been widely adopted and validated in watershed-scale ecosystem service studies. Qiao et al. [39] systematically compared grid cells at multiple scales (30 m, 100 m, 1 km, 5 km, and 10 km) in their study of ecosystem service trade-offs in the Taihu Lake Basin, demonstrating that the 1 km grid optimally captures spatial heterogeneity while maintaining computational feasibility for multi-service analysis at the watershed scale. Similarly, Chang et al. [40] employed a 1 km grid in their multi-scale spatiotemporal analysis of ecosystem service interactions in the Taihu Lake Basin, revealing the scale-dependent nature of service interrelationships. Beyond the study area, Liu et al. [41] adopted a 1 km grid to systematically evaluate the spatiotemporal evolution of human–nature relationships across China from 2000 to 2020, validating the applicability of this scale for large-area spatial analysis. Methodologically, Wang et al. [42] demonstrated in their multi-scale study of ecosystem services in the Beijing urban–rural fringe that the 1 km grid effectively captures the spatial heterogeneity of urban–rural transition zones and exhibits good stability and explanatory power across analytical scales. Collectively, these studies confirm that the 1 km grid offers a reasonable balance between capturing regional spatial heterogeneity and ensuring computational feasibility, supporting its use as an appropriate analytical unit in the Taihu Lake Basin and similar regions.

Table 1. Summary of datasets used in this study.

Dataset Name	Spatial Resolution	Data Source	Time Span	Core Application
CLCD land use/land cover data	30 m	Wuhan University (https://essd.copernicus.org/articles/13/3907/2021/ accessed on 7 July 2026)	2003, 2008, 2013, 2018, 2023	Land use classification; fundamental data for InVEST model assessment
LandScan global population density data	1 km	Oak Ridge National Laboratory (https://landscan.ornl.gov/)	2003–2023	Construction of the human activity intensity (HAI) index
Calibrated DMSP-like long-term nighttime light dataset	1 km	Harvard Dataverse	2003, 2008, 2013, 2018, 2023	Construction of the human activity intensity (HAI) index
Annual precipitation and actual evapotranspiration data	1 km	National Tibetan Plateau Data Center (https://data.tpdc.ac.cn/)	2003–2023	Water yield module calculation of the InVEST model
SRTM digital elevation model (DEM)	30 m	Geospatial Data Cloud (http://www.gscloud.cn/)	–	Slope length and steepness factor calculation; soil conservation assessment
Harmonized World Soil Database (HWSD)	1:1,000,000	FAO and IIASA	–	Soil erodibility factor calculation; soil conservation assessment
Administrative boundary data	Vector	National Geomatics Center of China (https://www.ngcc.cn/)	–	Study area delineation and spatial projection

For the human activity intensity (HAI) index, we constructed a comprehensive evaluation system by integrating three indicators—population density, nighttime light intensity, and proportion of built-up land—using the entropy weight method to determine objective indicator weights. The resulting HAI maps were then aggregated to the same 1 km × 1 km grid by averaging all pixel values within each grid cell, ensuring consistency with the ecosystem service data for the subsequent bivariate spatial autocorrelation and GWR analyses.

2.3. Methods

2.3.1. Characterization of Human Activity Intensity

Human activity intensity (HAI) serves as a critical indicator for characterizing the degree of anthropogenic disturbance to regional ecosystems. Classic assessment frameworks such as the Human Footprint Index and land use intensity method have established widely accepted paradigms for quantifying human disturbance [27,43]. Building on these base methodologies and considering data availability, regional representativeness, and the characteristics of highly urbanized plain watersheds, this study constructs an optimized HAI evaluation index system using three indicators: population density, nighttime

light intensity, and the proportion of built-up land. Population density reflects the direct pressure of human settlements on ecological environments; nighttime light intensity captures the level and spatial distribution of socioeconomic activities; and the proportion of built-up land directly indicates the intensity of human modification of natural landscapes through land-use change. Compared with traditional single-dimensional land-use intensity measurement, this three-indicator system can more comprehensively depict the spatial pattern and impact depth of human activities across population, socio-economic, and land dimensions. To avoid subjective bias in weighting, the entropy-weight method is employed for objective indicator weighting. Its core principle is to calculate indicator weights based on the dispersion degree of indicator data: indicators with higher data dispersion carry more valid information and thus are assigned higher entropy weights. This method can effectively reduce the interference of subjective factors and realize a comprehensive quantitative evaluation of the research objects. Following established practices and adapting to the specific conditions of the study area [44], HAI is classified into five levels: low intensity ($HAI \leq 0.15$), relatively low intensity ($0.15 < HAI \leq 0.35$), medium intensity ($0.35 < HAI \leq 0.55$), relatively high intensity ($0.55 < HAI \leq 0.75$), and high intensity ($HAI > 0.75$).

Step 1: Data normalization.

To eliminate dimensional inconsistencies among the indicators, each indicator is normalized using the min-max method:

$$X_j = \frac{X_i - X_{\min}}{X_{\max} - X_{\min}} \quad (1)$$

where X_j denotes the normalized value of indicator j . X_i is the original value, and $X_{\max}$ and $X_{\min}$ represent the maximum and minimum values of the indicator, respectively.

Step 2: Construction of the raw data matrix.

For m evaluation units and n evaluation indicators, the raw data matrix is formulated as:

$$R = (r_{ij})_{m \times n} (i = 1, 2, 3 \dots m; j = 1, 2, 3 \dots n) \quad (2)$$

where R denotes the evaluation matrix, and r_{ij} represents the value of the j -th indicator for the i -th evaluation unit.

Step 3: Entropy calculation.

$$e_j = - \frac{(\sum_{i=1}^m m_{ij} \ln m_{ij})}{\ln m (i = 1, 2, 3 \dots m; j = 1, 2, 3 \dots n)} \quad (3)$$

$$m_{ij} = \frac{r_{ij}}{\sum_{i=1}^m r_{ij}} \quad (4)$$

where e_j denotes the entropy value of indicator j , and m_{ij} represents the proportion of the i -th evaluation unit's value relative to the total of indicator j . When $m_{ij} = 0$, the term $m_{ij} \ln m_{ij}$ is defined as 0. The denominator $\ln m$ is the information entropy coefficient.

Step 4: Entropy weight calculation

$$A_j = \frac{(1 - e_j)}{\sum_{j=1}^n (1 - e_j)} \quad (5)$$

where A_j denotes the entropy weight of indicator j , and e_j is the entropy value of indicator j .

Finally, the HAI for the Taihu Lake Basin from 2003 to 2023 is derived through weighted summation, as follows:

$$HAI = \sum_{j=1}^n X_j \times A_j \quad (6)$$

where HAI represents the human activity intensity index; X_j is the normalized value of indicator j ; A_j denotes the entropy weight of indicator j ; and j refers to the human activity indicator.

2.3.2. Ecosystem Service Assessment

Ecosystem services derive from complex ecological processes. To accurately quantify these services, this study employed the InVEST model to assess four key indicators: water yield, soil conservation, carbon storage, and habitat quality. The assessment methods are detailed in Table 2.

2.3.3. Bivariate Spatial Autocorrelation

To gain deeper insights into the spatial dependence and interactions between human activities and ecosystem services, this study employed a bivariate spatial autocorrelation approach [7]. This method effectively detects the degree of spatial association between two distinct geographical variables and identifies whether significant spatial clustering or dispersion patterns exist. Specifically, we calculated the Global Bivariate Moran's I and generated Local Indicators of Spatial Association (LISA) cluster maps to systematically analyze the spatial relationship between human activity intensity and ecosystem services in the Taihu Lake Basin from 2003 to 2023. The formula is as follows:

$$I = \frac{n}{\sum_{i=1}^n \sum_{j=1}^n W_{ij}} \times \frac{\sum_{i=1}^n \sum_{j=1}^n W_{ij} (x_i - \bar{x})(x_j - \bar{x})}{\sum_{i=1}^n (x_i - \bar{x})^2} \quad (7)$$

where W_{ij} is the spatial weight matrix between spatial units i and j ($i, j = 1, 2, 3, \dots, n$); x_i and x_j are the observed values; I is the global bivariate Moran's I ; and $\bar{x}$ is the mean value.

2.3.4. Geographically Weighted Regression (GWR)

To investigate the spatial variation in the impacts of human activities on ecosystem services, this study introduced the Geographically Weighted Regression (GWR) model [49]. By establishing local regression relationships between human activity intensity and ecosystem services, this model generates spatial distribution maps of regression coefficients, enabling the quantification of both the magnitude and direction of these impacts across different geographical units within the Taihu Lake Basin. This approach thereby reveals the spatial heterogeneity inherent in the driving mechanisms. We employed a univariate GWR model with human activity intensity (HAI) as the sole independent variable. The formula is as follows:

$$y_i = \beta_0(u_i, v_i) + \beta_1(u_i, v_i)x_i + \varepsilon_i \quad (8)$$

where y_i is the dependent variable; (u_i, v_i) represents the geographic coordinates of the i -th spatial unit; x_i is the independent variable (human activity intensity) for spatial unit i ; ε_i is the random error term; $\beta_0(u_i, v_i)$ is the local intercept at spatial unit i ; and $\beta_1(u_i, v_i)$ is the local regression coefficient for the independent variable at spatial unit i , reflecting the magnitude and direction of the impact of human activity intensity on the ecosystem service.

Table 2. Ecosystem assessment method.

Ecosystem Service	Assessment Method	Formula	Notes
Water yield	The InVEST model's water yield module estimates water yield for each grid cell as precipitation minus actual evapotranspiration, based on mean annual precipitation and the Budyko curve [45], using raster inputs including climate and elevation data.	$Y_x = \left(1 - \frac{AET_x}{P_x}\right) \times P_x$	where Y_x is the annual water yield for grid cell x (mm), AET_x is the annual actual evapotranspiration for grid cell x (mm), and P_x is the annual precipitation for grid cell x (mm).
Soil conservation	The soil conservation module of the InVEST model is calculated based on the Universal Soil Loss Equation (USLE), where the amount of soil conservation is determined as the difference between potential and actual soil erosion [46].	$RKLS_x = R_x \times K_x \times LS_x$ $USLE_x = R_x \times K_x \times LS_x \times C_x \times P_x$ $SEDRET_x = RKLS_x - USLE_x$	where $SEDRET_x$, $RKLS_x$, and $USLE_x$ represent the soil conservation (t), potential soil erosion (t), and actual soil erosion (t) for grid cell x , respectively; R_x , K_x , LS_x , C_x , and P_x denote the rainfall erosivity factor, soil erodibility factor, slope length and steepness factor, vegetation cover factor, and supporting practice factor, respectively.
Carbon storage	The carbon storage module of the InVEST model quantifies regional carbon storage by comprehensively assessing four major carbon pools associated with different land use/land cover types. Based on the average carbon density data for each land use type, combined with their spatial distribution areas, this module estimates ecosystem carbon storage on a per-grid-cell basis [47].	$C = C_{above} + C_{below} + C_{dead} + C_{soil}$	where C is the total carbon storage (t), C_{above} is the aboveground carbon storage (t), C_{below} is the belowground carbon storage (t), C_{dead} is the dead organic matter carbon storage (t), and C_{soil} is the soil carbon storage (t).
Habitat quality	The habitat quality module of the InVEST model simulates the spatial distribution pattern of habitat quality by assessing the sensitivity of different land use types to external threat factors, while integrating the intensity, spatial reach, and weights of these threats [48]. This module defines habitat quality as a function of local landscape types, surrounding threat factors, and their sensitivities, thereby enabling a quantitative assessment of regional biodiversity conservation capacity.	$Q_{xj} = H_j \times \left(1 - \frac{D_{xj}^z}{D_{xj}^z + K^z}\right)$	where Q_{xj} is the habitat quality index for grid cell x in land use type j ; D_{xj} is the threat level for grid cell x in land use type j ; H_j is the habitat suitability of land use type j , ranging from 0 to 1; and K is the half-saturation parameter.

3. Results

3.1. Dynamics of Human Activity Intensity

Based on the entropy-weight method, the weights of the three indicators were determined as follows: population density (0.44), proportion of built-up land (0.29), and nighttime light intensity (0.26). Statistically, population density has the highest entropy weight, indicating that this indicator has the most significant spatial differentiation across the Taihu Lake Basin and the strongest ability to distinguish the spatial pattern of human activity intensity. In terms of practical connotation, population agglomeration is also one of the core drivers of the expansion of human activities in the basin, which exerts joint impacts with land development and socioeconomic activities. The proportion of built-up land and nighttime light intensity jointly captured the intensity of land development and socioeconomic activity, respectively, thereby complementing the multidimensional characterization of human interference across the basin. From 2003 to 2023, HAI in the Taihu Lake Basin exhibited a sustained increasing trend, with notable expansion of medium- and high-intensity areas. In terms of proportional changes across intensity grades, the low-intensity area decreased from 77.27% to 58.75%, whereas the relatively low-intensity area increased from 12.76% to 16.57%. Meanwhile, the medium-intensity area steadily rose from 4.66% to 9.55%, while the relatively high-intensity area expanded from 5.23% to 14.37%. Notably, the proportion of high-intensity area increased substantially from 0.08% to 0.76%, corresponding to an approximately 9.5-fold expansion over the 20-year study period. Collectively, these trends indicate a persistent elevation of HAI across the basin, with pronounced expansion in medium- and high-intensity zones, exerting continuous potential pressure on ecosystem services.

Spatially, HAI in the Taihu Lake Basin exhibited a distinct pattern of “core agglomeration in the east with a gradient of decreasing intensity outward,” which was highly consistent with the spatial distributions of the three constituent indicators. High-intensity areas were predominantly concentrated in the built-up urban cores of Shanghai, Suzhou, Wuxi, and Changzhou in the eastern part of the basin—a region characterized by the convergence of high population density, peak nighttime light values, and contiguous built-up land, which collectively drove HAI to the highest levels across the basin. In 2003, high-intensity areas appeared as sporadic patches, but gradually evolved into a contiguous spatial configuration from 2008 to 2023, eventually forming a high-intensity agglomeration belt centered on Shanghai and interconnected with the Suzhou–Wuxi–Changzhou metropolitan area. Relatively high-intensity areas expanded extensively from the core cities toward the central and southern parts of the basin, encompassing suburban zones and industrial parks. This region, characterized by rapid industrialization and urbanization, experienced the most significant increase in HAI and served as the primary spatial domain of expansion. Medium-intensity areas were sporadically distributed along urban fringes and township peripheries, with their extent progressively enlarging alongside urban expansion. Low-intensity areas, with the exception of the main water body of Taihu Lake, were mainly located in the mountainous and hilly zones peripheral to high- and relatively high-intensity areas, where the radiative influence from core urban areas was limited, resulting in relatively slow HAI growth. Relatively low-intensity areas, which accounted for a considerable proportion in the southwestern part of the basin (e.g., Huzhou and Jiaxing), exhibited a declining trend over time. These areas, mostly characterized by hilly terrain and dense river networks, have experienced relatively limited urban and industrial impacts, thereby maintaining more stable ecological baseline conditions.

It is worth noting that the 2018–2023 study window covers the COVID-19 pandemic period (2020–2022). In terms of growth rate comparison, the intensity of human activities in the basin increased by approximately 9.9% during 2013–2018 and 9.8% during 2018–2023.

The growth rates of the two periods were basically flat with no abnormal decline. Meanwhile, high-value areas maintained an expanding trend in 2023. This indicates that the short-term activity restrictions caused by the pandemic did not alter the overall trajectory of a continuous rise in human activity intensity under the long-term trend of the 5-year scale. Annual-scale data effectively smooth intra-annual fluctuations, and the post-pandemic socio-economic recovery dominated the overall pattern in 2023 (Figure 2).

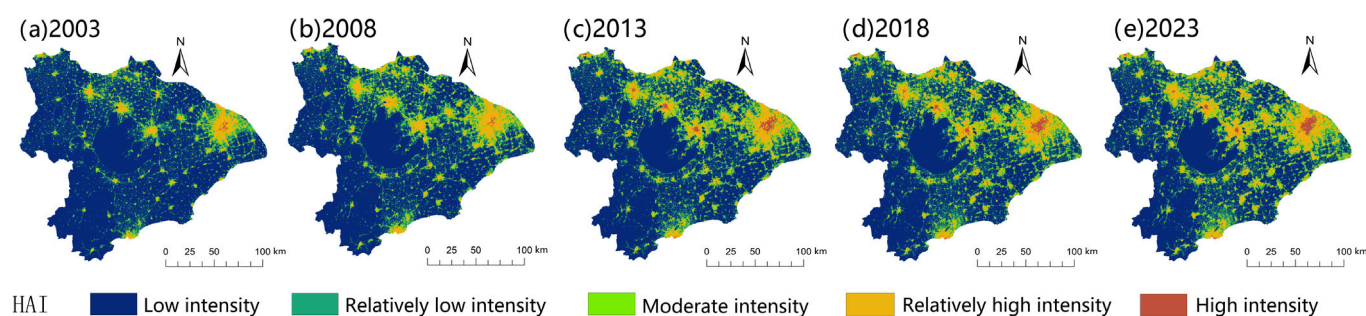


Figure 2. Spatiotemporal distribution of human activity intensity in the Taihu Lake Basin from 2003 to 2023.

3.2. Spatiotemporal Dynamics of Ecosystem Services

From 2003 to 2023, the four ecosystem services (ESs) in the Taihu Lake Basin exhibited pronounced spatiotemporal differentiation (Figure 3). Carbon storage exhibited an overall fluctuating downward trend: it decreased sharply from 108.1 t/ha in 2003 to 98.9 t/ha in 2013, then the rate of decline slowed markedly, dropping slightly to 98.6 t/ha by 2023, with a multi-year mean of 101.2 t/ha. Water yield exhibited a marked “stepwise growth” pattern, increasing sharply from 268.05 mm in 2003 to 548.78 mm in 2023, with particularly notable gains during 2018–2023, reflecting the combined effects of precipitation variability and land surface feedback. Soil conservation improved amid fluctuations, rising from 309.3 t/ha in 2003 to 520.7 t/ha in 2023, with the most rapid increase occurring during 2018–2023, suggesting the gradual effectiveness of later-stage ecological engineering. Habitat quality, by contrast, showed a continuous decline, from 0.282 in 2003 to 0.241 in 2023, indicating persistent disturbance to ecosystem structure. Overall, the declines in carbon storage and habitat quality reveal the encroachment of urbanization on ecological land, whereas the increases in water yield and soil conservation are jointly driven by climatic fluctuations and ecological restoration initiatives.

Spatially, the four ESs exhibited highly heterogeneous patterns. Carbon storage followed a “high periphery, low lake-area” distribution, with high-value areas consistently located in the densely vegetated Tianmu Mountain remnants in the southwest and the mountainous areas in the southeast. In contrast, the urban agglomerations surrounding the lake remained carbon storage lowlands due to built-up land expansion. This pattern clearly reflects the encroachment of urbanization on ecological land, with the later stabilization potentially attributable to enhanced ecological awareness and moderated urban expansion. Water yield displayed a “south high, north low” pattern, with high-value areas concentrated in the southern and southeastern parts of the basin, where precipitation is more abundant and topography steeper. Low-value areas in the northern and lake-surrounding regions were closely associated with the expansion of impervious surfaces. The dramatic increase in water yield resulted from the interplay between precipitation variability and ecological restoration in the later period, with precipitation serving as the primary driver and ecological restoration playing a synergistic role by improving underlying surface conditions. Soil conservation exhibited a polarized “south high, elsewhere low” pattern, with high-value areas concentrated in the hilly and mountainous regions of the southern

basin, where dense vegetation cover and topographic relief jointly enhance soil retention capacity. In contrast, soil conservation remained generally weak in the plains surrounding Taihu Lake and in the northern agricultural areas. This positive shift highlights the notable effectiveness of multiple soil and water conservation and ecological restoration projects implemented across the basin. Habitat quality followed a “lake-area high, periphery low” pattern, with high-value areas further contracting toward the lake-surrounding zone, while urban expansion areas in the east and north enlarged, accompanied by intensified habitat fragmentation. This suggests that although certain regulating services have improved, the core habitat structures supporting biodiversity remain under considerable pressure, revealing the persistent encroachment of rapid urbanization on natural habitats.

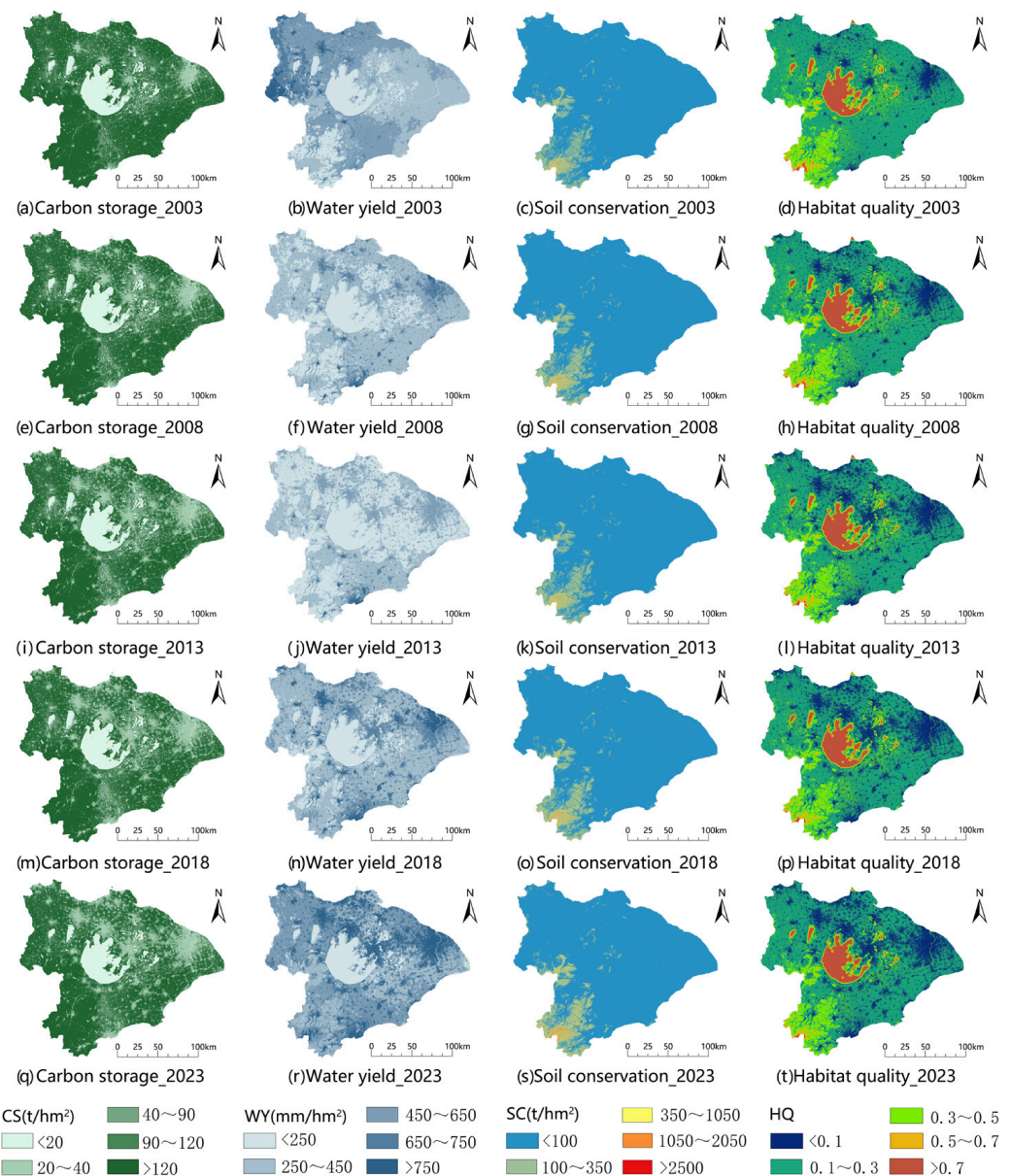


Figure 3. Spatiotemporal distribution of ecosystem services in the Taihu Lake Basin from 2003 to 2023.

Overall, the dominant “southwest high–northeast low” spatial pattern is fundamentally shaped by land use structure: areas with concentrated ecological land support high carbon storage, habitat quality, and soil conservation, whereas regions dominated by built-up and agricultural land generally exhibit low ecological functions.

3.3. Spatiotemporal Patterns of Human Activity Intensity and Ecosystem Services

Based on 1 km × 1 km grid cells, bivariate spatial autocorrelation analysis was conducted for the Taihu Lake Basin from 2003 to 2023, with all results subjected to 999 permutations (pseudo- $p < 0.001$). The bivariate global Moran's I revealed differentiated spatial association patterns between HAI and the four ecosystem services (Table 3). HAI exhibited a consistently significant positive spatial correlation with water yield, with the Moran's I increasing from 0.346 in 2003 to a peak of 0.594 in 2018, before declining slightly to 0.563 in 2023. This trajectory indicates an overall trend of initial strengthening followed by stabilization in their spatial synergy. In contrast, carbon storage, soil conservation, and habitat quality all demonstrated persistently significant negative spatial associations with HAI, highlighting pronounced spatial tradeoffs. The negative correlation for carbon storage intensified over the study period, with the Moran's I declining from -0.247 to -0.378 ; soil conservation followed a similar pattern, with the Moran's I decreasing steadily from -0.134 to -0.192 , reflecting progressively stronger trade-off effects. Habitat quality exhibited the strongest suppression by human activities, with Moran's I values ranging from -0.374 to -0.494 , and the negative association deepened consistently over time. Overall, while urbanization in the Taihu Lake Basin effectively enhanced regional water yield capacity, it exerted basin-wide suppression on carbon storage, soil conservation, and habitat quality, resulting in a differentiated pattern in which synergies and trade-offs coexisted in the human-environment relationships across various ecosystem services.

Table 3. Bivariate Moran's I and dominant cluster types for HAI vs. ecosystem services (2003–2023).

Year	Ecosystem Service	Bivariate Moran's I	p -Value (Pseudo)	Dominant Cluster Type	Proportion of Dominant Cluster (%)
2003	Carbon storage	-0.247	0.001	Low-High	13.93
	Water yield	0.346	0.001	High-High	8.14
	Soil conservation	-0.134	0.001	Low-Low	18.84
	Habitat quality	-0.374	0.001	High-Low	10.07
2008	Carbon storage	-0.300	0.001	Low-High	14.08
	Water yield	0.563	0.001	Low-Low	14.39
	Soil conservation	-0.157	0.001	Low-Low	18.16
	Habitat quality	-0.444	0.001	High-Low	13.46
2013	Carbon storage	-0.333	0.001	Low-High	14.61
	Water yield	0.570	0.001	High-High	12.93
	Soil conservation	-0.174	0.001	Low-Low	18.08
	Habitat quality	-0.470	0.001	High-Low	15.35
2018	Carbon storage	-0.348	0.001	Low-High	25.63
	Water yield	0.594	0.001	Low-Low	20.17
	Soil conservation	-0.182	0.001	Low-Low	29.08
	Habitat quality	-0.482	0.001	High-Low	19.81
2023	Carbon storage	-0.378	0.001	Low-High	14.35
	Water yield	0.563	0.001	High-High	14.68
	Soil conservation	-0.192	0.001	Low-Low	17.99
	Habitat quality	-0.494	0.001	High-Low	16.88

From 2003 to 2023, the proportions of LISA cluster types for different ecosystem services exhibited distinct temporal trajectories. Both carbon storage and soil conservation displayed an inverted U-shaped trend in their dominant cluster types: the Low-High cluster for carbon storage increased from 13.93% in 2003 to 25.63% in 2018, then decreased to 14.35% in 2023; the Low-Low cluster for soil conservation rose from 18.84% in 2003 to 29.08% in 2018, followed by a decline to 17.99% in 2023. Both cluster types peaked in 2018, indicating

that urban expansion continuously encroached upon ecologically high-value areas prior to 2018, while the implementation of ecological governance policies after 2018 alleviated the spatial mismatch between human activities and ecosystem services. For water yield, the High-High and Low-Low clusters alternated as the dominant type, with their combined proportion exhibiting a fluctuating upward trend, reflecting progressively intensifying spatial agglomeration effects, although a stable long-term dominant pattern failed to emerge. Habitat quality was dominated by the High-Low cluster, with its proportion increasing from 10.07% in 2003 to 19.81% in 2018, before declining slightly to 16.88% in 2023. The persistently high proportion of this stress-type cluster underscores the long-term and entrenched nature of habitat degradation induced by urbanization. Collectively, 2018 emerged as a critical turning point in the evolution of human-environment relationships in the basin. The period 2003–2018 was characterized by accelerating spatial differentiation, whereas the period 2018–2023 witnessed a general contraction of extreme cluster sizes, a rebound in spatial heterogeneity, and a gradual shift toward dynamic equilibrium in regional human-environment interactions.

The LISA clusters in the Taihu Lake Basin formed a three-tier spatial structure comprising a western ecological high-value belt, a central-eastern urban stress continuum, and a lake-plain low-value homogeneous zone (Figure 4). The mountainous and hilly areas of the western Tianmu Mountain range constitute the core ecological service supply zone of the basin, where Low-High clusters for carbon storage, soil conservation, and habitat quality overlapped extensively and remained stable. Characterized by low human interference and high vegetation cover, this region exhibits superior ecological functions and forms a stable spatial coupling pattern of “low HAI–high ESs.” In stark contrast, the central-eastern urban agglomeration presents an opposing stress pattern: High-Low clusters of habitat quality were distributed contiguously along urban built-up areas and their peripheries, with intensive land development and landscape fragmentation serving as the primary drivers of habitat degradation. Meanwhile, the expansion of urban impervious surfaces increased surface runoff coefficients, leading to the concentration of High-High clusters for water yield in this region. High-Low clusters for carbon storage and soil conservation were scattered at urban fringes, reflecting the disruption of local ecological functions by anthropogenic disturbance. The main water body of Taihu Lake and the eastern agricultural plains were predominantly characterized by Low-Low clusters, where sparse vegetation in water areas and weak ecological baselines in croplands collectively resulted in generally low carbon storage and soil conservation capacity, forming extensive low-value zones. In addition, transitional clusters—including Low-High and High-Low types—exhibited strip-like distributions along the boundaries of different functional zones, reflecting the gradual encroachment of urbanization spillover effects on ecosystem services. Overall, the spatial patterns of human activities and ecosystem services in the basin are jointly shaped by urban expansion and ecological protection policies: ecologically favorable areas coincide closely with low-HAI zones, while urbanized regions generally exhibit pervasive ecological degradation.

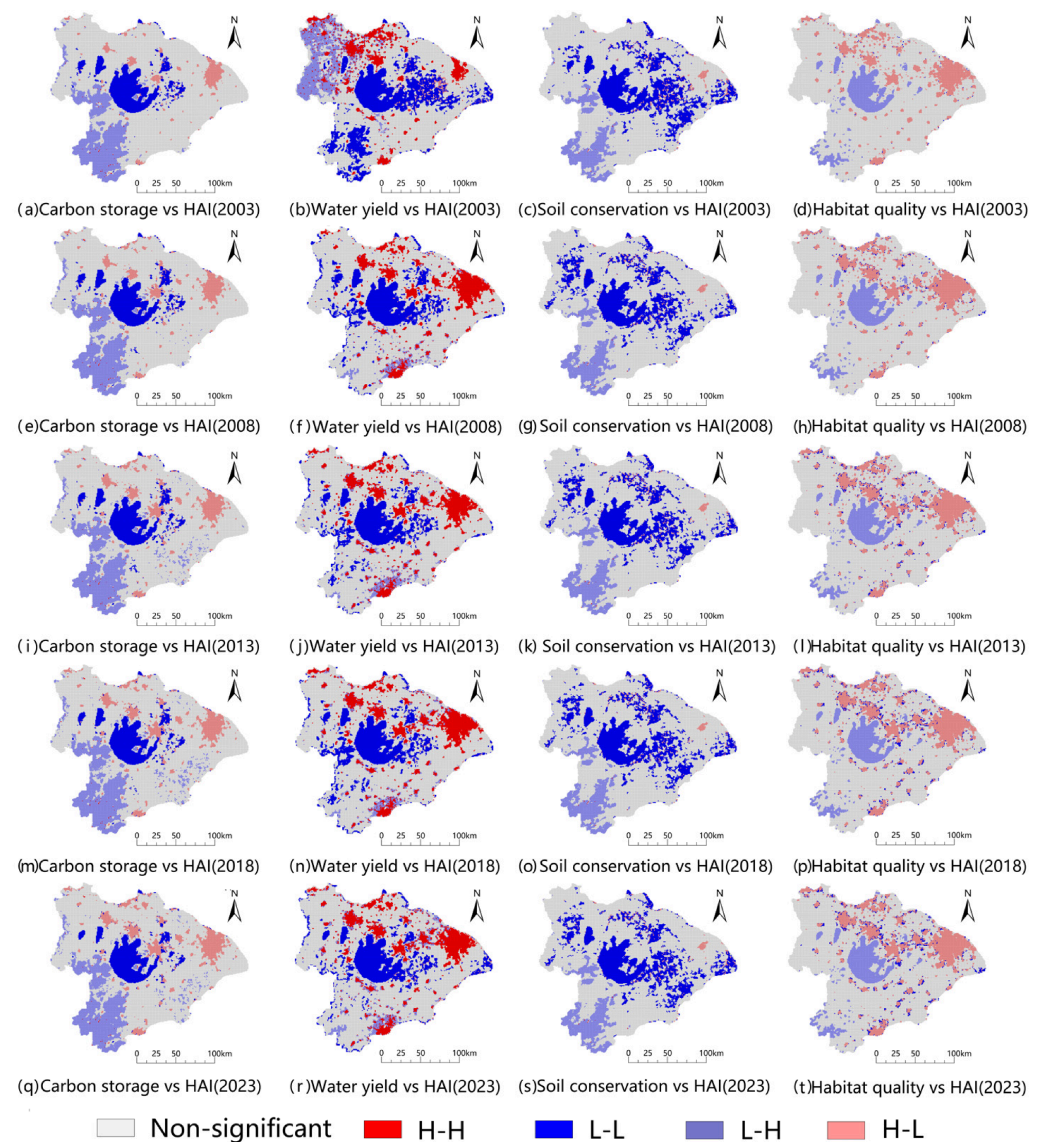


Figure 4. Bivariate spatial clustering patterns in the Taihu Lake Basin during 2003–2023.

3.4. Spatial Heterogeneity in the Associations Between Human Activity Intensity and Ecosystem Services

Using $1 \text{ km} \times 1 \text{ km}$ grid cells as the basic analytical unit, this study constructed a geographically weighted regression (GWR) model to reveal the spatial non-stationarity of the associations between human activity intensity (HAI) and multiple ecosystem services. The overall goodness-of-fit (R^2) of the models exceeded 0.82, and all explanatory variables passed the global significance tests ($p < 0.05$), indicating strong explanatory power of the models. To further assess the reliability of the local coefficient estimates, we calculated the proportion of grid cells with statistically significant coefficients ($p < 0.05$) for each ecosystem service. The results showed a clear hierarchical differentiation in the proportion of significant cells across service types (Table 4): habitat quality ranked highest (67.67–83.83%), followed by water yield (62.98–76.01%), carbon storage (48.91–70.78%), and soil conservation (13.97–14.83%). This gradient essentially reflects the differential intensity of spatial non-stationarity in the responses of various ecosystem services to HAI. Specifically, soil conservation is predominantly constrained by natural background conditions such as topography and rainfall erosivity, with the influence of HAI being highly localized—its marginal effects passed the significance test only in a few specific terrain units but remained insignificant across the majority of spatial units. Consequently, the spatial heterogeneity

of HAI's effects on soil conservation is far weaker than that on carbon storage and habitat quality, which are more directly driven by land use change.

Table 4. Proportion of grid cells with significant GWR coefficients of human activity intensity on ecosystem services ($p < 0.05$).

Year	Carbon Storage: Significant Proportion (%)	Water Yield: Significant Proportion (%)	Soil Conservation: Significant Proportion (%)	Habitat Quality: Significant Proportion (%)
2003	48.91	62.98	13.97	67.67
2008	54.46	70.81	13.96	75.69
2013	61.98	76.01	14.01	79.63
2018	65.92	75.61	14.45	81.77
2023	70.78	75.91	14.83	83.83

From 2003 to 2023, the response intensity and fluctuation characteristics of the four ecosystem services to HAI in the Taihu Lake Basin exhibited significant differentiation, with evolutionary trajectories mutually corroborating the hierarchical differences in local significance. The association between HAI and carbon storage showed strong temporal stability, with the upper bound of GWR coefficients remaining stable at approximately 21.00 over the long term, only slightly rising to 29.00 during 2013–2018 due to the concentrated implementation of ecological restoration projects; the lower bound followed a trajectory of “rapid narrowing—fluctuating adjustment—stabilization,” contracting from -22.70 in 2003 to -5.78 in 2013, and further stabilizing at -4.95 by 2023. Overall, the positive and negative driving effects of HAI on carbon sequestration function remained in a relatively balanced state of dynamic adjustment, without abrupt directional shifts. Soil conservation exhibited a pattern of periodic fluctuation, with negative suppression maintaining long-term dominance. The negative extremes remained within a high-intensity range of -24.01 to -39.96 throughout the study period, with the sphere of suppression expanding further in 2023; the positive extremes narrowed continuously from 3.98 in 2008 to 1.55 in 2018, and although they recovered somewhat in 2023, the overall intensity remained limited. This indicates that the negative association between HAI and soil conservation remains prominent in localized cultivated areas, and the positive effects of soil and water conservation projects have not yet fully covered high-risk zones. The negative association between HAI and habitat quality showed a trend of weakening disturbance intensity, characterized by continuously weakening disturbance intensity and progressively optimized spatial patterns. The negative extreme increased significantly from -72.75 in 2003 to -37.82 in 2023, with the absolute value nearly halved, indicating a marked contraction of high-intensity disturbance areas; although the positive extreme declined from 74.16 to 38.30 , it remained at a relatively high level. These changes suggest that sustained measures such as ecological redline delineation and the Grain-for-Green and wetland restoration programs have achieved notable success, effectively alleviating anthropogenic pressure on habitat quality. Water yield exhibited the most complex evolutionary pattern, characterized by a phased trajectory of “symmetric stability—interval narrowing—fluctuating expansion.” During 2003–2008, the coefficient range remained stable at $[-11.31, 12.39]$, with essentially symmetric positive and negative effects; in 2013, influenced by large-scale water conservancy construction and unified water resource regulation, the range narrowed to $[-7.83, 7.27]$; from 2018 to 2023, with urbanization and irrigation district renovation, the range expanded again to $[-13.33, 17.34]$, slightly exceeding the levels at the beginning of the study period. This fluctuating process aligns closely with the cycles of water conservancy construction and adjustments in water resource management policies in the basin.

The HAI driving effects on the four types of services exhibited a common characteristic of “concentrated intensity across the majority of the basin, with localized distribution of extreme-value zones,” which mutually corroborates the differences in significant proportions. For carbon storage, the regression coefficients of significant grid cells were predominantly concentrated in the low-to-moderate range of -1.0 to 3.0 , constituting the spatial majority; strong negative effects (<-3.5) appeared only as isolated patches concentrated in urban built-up cores, while strong positive effects (>3.0) were scattered in the western and southern hilly forested areas. No continuous urban-rural gradient zones were formed, with spatial differences manifesting primarily as intensity variations at local extreme points. For soil conservation, due to its significant proportion being less than 15%, the spatial pattern was only evident in limited significant areas: strong negative effects (<-6.0) were locally distributed along the margins of hills with concentrated steep-slope cultivation, while strong positive effects (>3.0) were scattered in areas with terrace renovation and soil and water conservation projects. The spatial pattern exhibited weak coupling with topography, with limited high-intensity zones and a relatively homogeneous overall configuration. Habitat quality exhibited the most pronounced local heterogeneity among the four services, consistent with its highest significant proportion. The majority of the basin remained dominated by the low-to-moderate range of -2.0 to 5.0 ; grid cells with strong negative regression coefficients (<-40.0) were highly concentrated in small patches within urban core built-up areas, while strong positive effects (>5.0) were scattered in natural conservation and ecologically isolated areas distant from urban centers. The heterogeneity was primarily manifested as strong negative extremes at urban core points, without forming complete circular gradient zones of continuous attenuation outward from the city. Water yield exhibited the most pronounced spatial homogenization, with regression coefficients of significant grid cells concentrated within a narrow range of -1.0 to 0.35 . The combination of “high significant proportion (62.98–76.01%) but extremely narrow coefficient range” indicates that although the influence of HAI on water yield is widely significant due to the large sample size, the magnitude of marginal effects is extremely small with limited spatial variation. Only sporadic, weak, negative, and extreme patches appeared in large irrigation districts and new urban areas, with no extensive high-intensity zones, further confirming the weak influence of HAI on the spatial pattern of water yield (Figure 5).

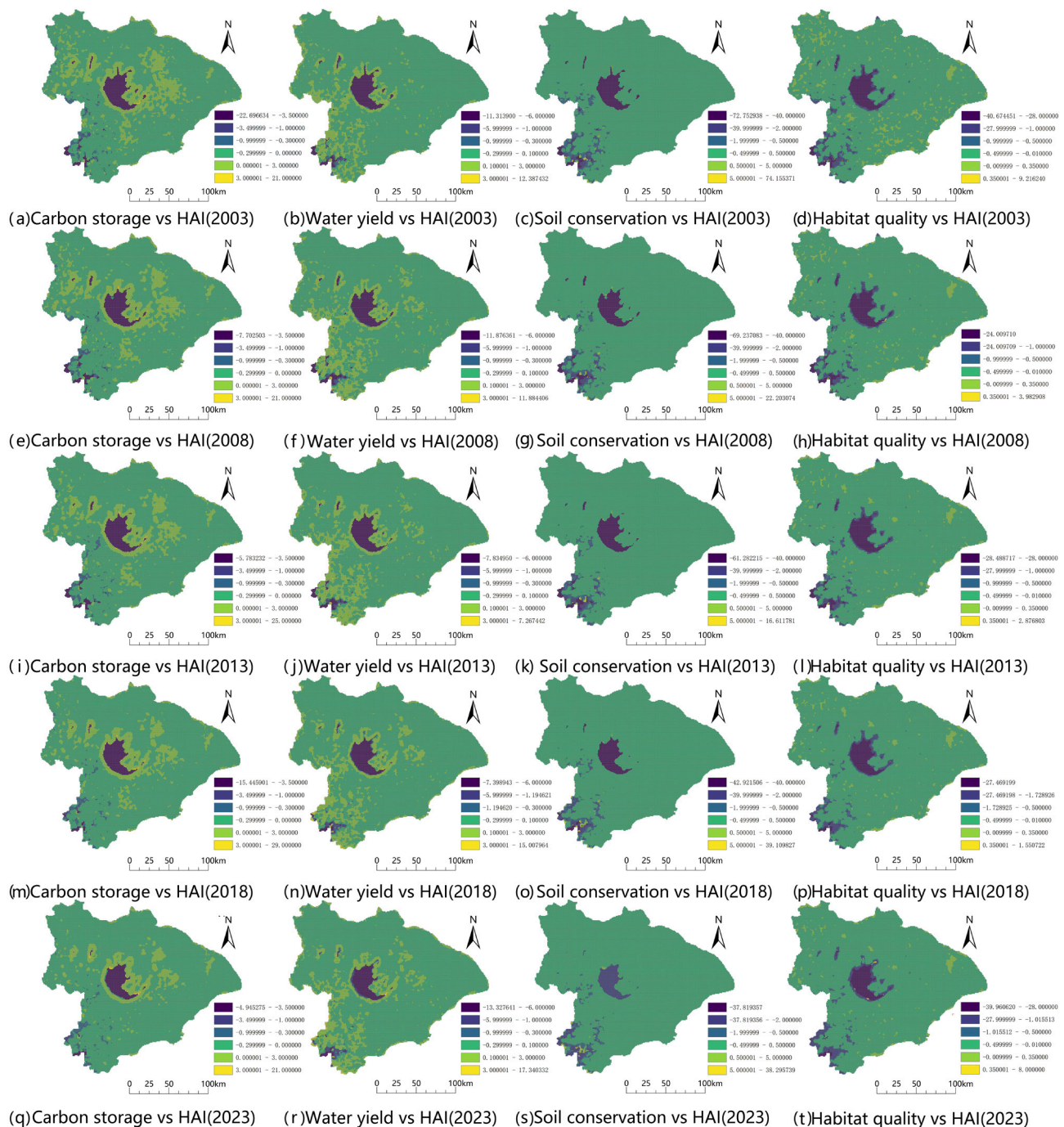


Figure 5. Maps of Regression coefficients between ecosystem services and human activity intensity in the Taihu Lake Basin from 2003 to 2023.

4. Discussion

4.1. Core Mechanisms Linking Human Activities and Ecosystem Services

Building on the spatiotemporal differentiation of human activity intensity (HAI) and ecosystem services, as well as the spatially heterogeneous driving effects verified by the GWR model in the preceding sections, this study distills three core mechanisms underlying the human–ecosystem interaction in the Taihu Lake Basin. Specifically, the path dependence of land-use conversion forms the fundamental driver of long-term ecological function degradation, policy intervention induces threshold responses in the dynamic evolution of services, and the hydrological and landscape connectivity of the watershed shapes the spatial spillover effect of anthropogenic impacts.

(1) Land-use path dependence. Built-up land encroachment on ecological land constitutes the core transmission pathway through which HAI affects ESs, fundamentally driven by a self-reinforcing feedback loop among population agglomeration, land development, and economic activity. Population density carried the highest weight (0.44), serving as the primary driver: population concentration in core cities propelled built-up land expansion while intensifying socioeconomic activity, collectively compressing ecological space and driving the degradation of carbon storage and habitat quality. GWR results indicate that strong negative effects are concentrated in patches within urban built-up cores without forming extensive continuous gradients, corroborating the irreversibility of ecological land conversion. Compared with highly urbanized watersheds in northern China [36,50], the ecological function decline in this area is more moderate, benefiting from both a higher initial ecological baseline and the buffering effects of urban greening and conservation policies.

(2) Threshold response to policy interventions. The response of ESs to HAI is nonlinear; when anthropogenic disturbance exceeds ecosystem self-repair thresholds, well-designed policies can effectively reverse functional degradation. After 2018, soil conservation accelerated significantly, while the negative driving intensity of HAI on soil conservation did not intensify with the overall rise in HAI; instead, the positive driving range exhibited a fluctuating recovery. This turning point stems from the concentrated implementation of soil and water conservation projects (e.g., Grain-for-Green and terrace renovation), with positive interventions breaking through the threshold bottleneck to natural restoration. It is also associated with structural optimization of human activities: industrial upgrading has driven a shift toward intensive economic development, reducing ecological stress per unit of economic activity, while population and built-up land development have transitioned toward connotative improvement. Unlike the topographical restoration mechanism across the entire Loess Plateau [51], the benefits of soil and water conservation in this basin are concentrated in localized western hilly slopes, consistent with the finding that soil conservation has the lowest proportion of significant GWR grid cells.

(3) Spatial spillover associations. The associations between HAI and ESs manifest as multi-dimensional spatial spillover effects through water system connectivity and landscape pattern transmission. Bivariate spatial autocorrelation reveals that the southwestern Tianmu Mountain area maintains stable “low HAI–high ESs” clusters, while eastern urbanized areas exhibit “high HAI–low ESs” clusters, corresponding precisely to the positive and negative extreme patches of GWR coefficients without forming continuous gradients. The outward diffusion of population and industries from core cities drives built-up land expansion and economic intensification in peri-urban areas, with ecological stress spilling outward accordingly. Meanwhile, the western ecological conservation area delivers high-quality soil conservation and carbon storage services downstream to lake-surrounding areas through water system connectivity, collectively forming a pattern of “ecological supply in the southwest, development-induced stress in the northeast.” Unlike the gradient-based coupling dynamics in large river basins [52,53], the Taihu Lake Basin—characterized by its small area and urban-rural interspersions—exhibits “patch-based” spillover effects, providing empirical evidence for horizontal ecological compensation mechanisms. Noteworthily, the critical turning point around 2018 falls just before the COVID-19 pandemic period (2020–2022). Our 5-year interval data cannot disentangle the causal impact of the pandemic, and the interplay between policy interventions and post-pandemic socio-economic recovery on the HAI–ES relationship deserves further exploration.

Beyond these three core mechanisms, the transformation of development types within the basin may serve as an important micro-mechanism regulating the ecological effects of human activities. In view of the overall urban development characteristics of the Taihu Lake

Basin, the eastern urban belt has gradually entered the stock development stage since 2010. It is widely recognized that the proportion of industrial land continues to decline while the proportion of supporting green spaces in urban residential land increases in this region. This transformation trend is highly consistent with the time node of weakened negative driving intensity of HAI on habitat quality after 2018 observed in this study, and aligns with the conclusion of Zamaletdinov et al. [54] that the conversion from industrial land to residential land with supporting green spaces can effectively alleviate ecological pressure. Although the total area of construction land is still expanding, the green transformation of development types may have buffered the ecological costs of urbanization to a certain extent, which needs to be further verified by subsequent studies with more refined land use classification.

These three mechanisms interact and collectively shape human-environment relationships in the basin: path dependence constitutes the underlying logic of ecological degradation, threshold response defines the conditions for effective policy interventions, and spatial spillover reveals basin-scale operational principles. Their synergy forms a fundamental analytical framework for understanding human-environment evolution in rapidly urbanizing plain watersheds.

4.2. Basin Management Zoning Based on HAI–ES Spatial Associations

Based on the spatial differentiation of GWR coefficients and the bivariate clustering patterns, and following the principle of “targeted zoning and precision management,” the Taihu Lake Basin is delineated into three management zones.

(1) Urban Core Stress Control Zone. This zone is primarily distributed across western Shanghai and the Suzhou–Wuxi–Changzhou built-up areas, representing the core region with the strongest negative associations between HAI and habitat quality and carbon storage. The objective of management is to reduce disturbance intensity and enhance the supply capacity of urban ecosystem services. Priority measures include strictly controlling the disorderly expansion of built-up land and implementing an “ecological land occupation–replenishment balance” system; advancing urban ecological restoration by constructing continuous ecological corridors along water systems and transportation arteries to mitigate habitat fragmentation; concurrently promoting sponge city development to optimize the layout of impervious surfaces; and establishing a monitoring and early-warning mechanism based on the dynamics of habitat quality and carbon storage.

(2) Urban–Rural Transition Buffer Restoration Zone. This zone is concentrated in peri-urban transition belts, and the western steep-slope cultivation areas, representing an ecotone where the negative associations with soil conservation are pronounced, and habitat quality is moderately degraded—and where the potential for ecological restoration is greatest. Priority measures include continuously promoting the Grain-for-Green program and sloping farmland remediation, with all cropland on slopes above 25° returned to forest or grassland, and slopes between 15° and 25° managed through contour farming and terrace reconstruction; constructing check dams, sediment-retention dams, and riparian buffer strips, while promoting conservation tillage; and conducting regular assessments of soil conservation and habitat quality improvements to dynamically adjust restoration strategies.

(3) Ecological Conservation Enhancement Zone. This zone consists primarily of the southwestern Tianmu Mountain remnant ranges and the lake-surrounding wetlands, characterized by low HAI and concentrated positive driving effects on carbon storage and habitat quality, serving as a critical ecological security barrier for the basin. Priority measures include strictly protecting existing forestland and wetlands by incorporating them into the ecological protection redline and prohibiting new built-up land; continuously

promoting ecological public-welfare forest protection and wetland restoration projects; and improving horizontal ecological compensation mechanisms, whereby downstream beneficiary zones provide compensation funds to this zone, thereby realizing a virtuous cycle of “protectors benefit, beneficiaries compensate.”

4.3. Limitations and Future Research Directions

This study systematically reveals the mechanisms by which human activities affect ecosystem services from a spatiotemporal heterogeneity perspective. Nevertheless, several limitations remain due to data availability and methodological constraints.

First, the HAI indicator system warrants further refinement. Although the composite index constructed from the three core dimensions of population agglomeration, land development, and economic activity provides a more comprehensive measure of anthropogenic disturbance than single indicators, certain deficiencies persist. Population density, as the highest-weighted indicator, is derived from static annual-average statistical data that fail to capture diurnal and holiday-versus-workday-related population mobility, potentially compromising the accuracy of HAI in characterizing actual anthropogenic disturbance. Moreover, the 5-year temporal intervals employed in this study are well-suited for capturing long-term trends but are insufficient for detecting short-term perturbations such as the COVID-19 pandemic (2020–2022), during which stringent mobility restrictions may have temporarily altered human activity patterns and their ecological impacts. While the 2018–2023 interval brackets this period, our annual-scale data products cannot resolve intra-annual fluctuations caused by the pandemic. Nighttime light data suffer from saturation effects in city centers, limiting their capacity to differentiate intra-urban variations in economic activity intensity and introducing bias in characterizing core urban areas. Additionally, the proportion of built-up land reflects only the areal extent of construction without distinguishing the differential ecological impacts of industrial, residential (low-rise vs. high-rise), and transportation land uses. As demonstrated by Zamaletdinov et al. [54], different urban functional zones exhibit markedly different impacts on biodiversity and ecosystem services over multi-year assessments, suggesting that the transition from industrial to residential development with green spaces may yield ecological benefits even when built-up area remains unchanged. Future research should incorporate additional indicators such as road network density and pollutant emission intensity, alongside dynamic population data (e.g., mobile phone signaling data) and higher-temporal-resolution nighttime light data, to construct a more comprehensive multidimensional HAI measurement system capable of detecting both long-term trends and short-term exogenous shocks.

Second, methodological refinements are warranted. This study employs a conventional GWR model to isolate the spatial effects of the composite HAI index, which effectively identifies localized differentiation in anthropogenic disturbance. However, the conventional GWR assumes a uniform spatial scale for all variables, limiting its capacity to capture the multi-scale effects of different driving factors. Moreover, the study does not incorporate natural control variables such as precipitation and topography, nor does it account for the mediating and moderating roles of trade-offs and synergies among the four ESs, leaving room for deeper mechanistic interpretation. Future studies could employ multi-scale geographically weighted regression (MGWR) in combination with structural equation modeling to more precisely characterize the multi-factor, multi-scale driving mechanisms and elucidate the complete causal pathway of “human activities → ecological processes → ecosystem services.”

Third, the uncertainty brought by the analytical scale needs to be clarified. Based on computational feasibility and regional research conventions, this study adopts a fixed 1 km grid as the analytical unit without systematic multi-scale sensitivity tests. Therefore, the

findings are subject to the Modifiable Areal Unit Problem (MAUP). Specifically, the fixed 1 km grid, on the one hand, will smooth the micro-ecological effects of small urban green spaces and riparian ecological belts and fail to capture micro-ecological differences at the street scale, so the conclusions are not applicable to refined landscape design scenarios. On the other hand, it will produce an aggregation effect on the heterogeneous landscapes in the peri-urban transition zone, which may weaken local strong driving signals. Although the bivariate spatial autocorrelation and GWR analyses reveal robust spatial patterns at the 1 km scale, the generalizability of the conclusions to other spatial levels remains to be verified. Future research can carry out multi-scale sensitivity analysis to evaluate the scale dependence of the association between HAI and ecosystem services and improve the robustness of the conclusions.

5. Conclusions

Based on multi-source geospatial data for the Taihu Lake Basin from 2003 to 2023, this study integrated the InVEST model, bivariate spatial autocorrelation, and geographically weighted regression to systematically analyze the spatiotemporal evolution, spatial associations, and driving heterogeneity in the relationship between human activity intensity (HAI) and four key ecosystem services (ESs). The main conclusions are as follows:

(1) HAI in the Taihu Lake Basin continuously increased, with high-intensity areas expanding approximately 9.5-fold (from 0.08% to 0.76%), forming a “high in the east, low in the west” spatial pattern. The eastern urban agglomeration centered on Shanghai and the Suzhou–Wuxi–Changzhou metropolitan area constituted a contiguous high-intensity belt, while the western Tianmu Mountain hilly area and Taihu Lake maintained relatively low intensity, closely mirroring urbanization trajectories.

(2) The four ESs exhibited pronounced spatiotemporal differentiation: carbon storage and habitat quality declined persistently, whereas water yield and soil conservation showed fluctuating increases. Spatially, ESs displayed a “high in the southwest, low in the northeast” pattern, with western hilly areas serving as core supply zones and eastern urbanized areas as low-value depressions, closely coupled with land use and topography.

(3) HAI showed consistently significant positive correlation with water yield and negative correlations with carbon storage, soil conservation, and habitat quality. The year 2018 marked a critical turning point, after which extreme spatial clusters contracted and the intensity of the negative association between HAI and habitat quality weakened, forming a three-tier spatial structure: a western ecological high-value belt, a central-eastern urban stress belt, and a lake-plain low-value homogeneous zone.

(4) The associations between HAI and ESs exhibited significant spatial non-stationarity, with significant grid cells following a hierarchical order: habitat quality > water yield > carbon storage > soil conservation. Driving forces were predominantly low-to-moderate intensity basin-wide, with strong regression coefficients occurring only as localized patches in urban cores and hilly ecological zones.

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