

Article

Spatial Context-Driven Thermal Erosion and Urban Forest Cooling Gradients: A Multi-Scenario Simulation of Ecological Networks

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Abstract

Urban forest fragmentation can weaken ecological connectivity and reduce the spatial continuity of cooling benefits, highlighting the need for structure-function integrated planning. Using 2020 as the baseline year, this study combined the Markov Chain-Future Land Use Simulation model, Morphological Spatial Pattern Analysis, the Minimum Cumulative Resistance model, and Kernel Density Estimation to simulate the evolution of Hangzhou's forest-dominated ecological network under Business-as-Usual, Economic Development, and Ecological Conservation scenarios for 2030. A Random Forest model with Shapley Additive Explanations was further used to quantify the nonlinear relationship between landscape spatial context and land surface temperature. The results show that the Economic Development and Business-as-Usual scenarios intensify forest fragmentation and weaken the structural integrity of potential ecological corridors, whereas the Ecological Conservation scenario improves network stability through patch amalgamation, core area expansion, and reduced breakpoint density. Land surface temperature was strongly associated with built-up land adjacency. Built-up areas near forest patches showed a maximum relative cooling benefit of 8.04 degrees Celsius, and corridor cooling effects were most pronounced within 300 m, remaining detectable up to about 900 m under the Ecological Conservation scenario. These findings support structure-oriented planning for urban forest conservation and heat mitigation.

Keywords: forest-dominated ecological network; multi-scenario simulation; land surface temperature (LST); spatial context effect; canopy cooling gradient; interpretable machine learning



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1. Introduction

Forest-dominated ecological networks are essential for balancing urban expansion and ecological conservation. As a key component of urban green infrastructure, they support species movement, maintain ecosystem services, and mitigate the urban heat island (UHI) effect by regulating microclimate and facilitating the spatial diffusion of cooling benefits [1–3]. However, with continued urbanization and the expansion of impervious surfaces, urban forests have become increasingly fragmented, canopy cover has declined,

and ecological connectivity has weakened. These changes have also intensified local thermal risks, including heat accumulation and thermal degradation at forest edges.

Current studies on ecological network construction generally follow two main approaches. The first is based on species monitoring, in which connectivity is identified from the movement trajectories of selected organisms [4–6]. Although ecologically meaningful, this approach depends heavily on field observations and is difficult to scale up. The second approach is based on landscape ecological modeling, using Geographic Information Systems (GIS) and methods such as Morphological Spatial Pattern Analysis (MSPA) [7–9], the Minimum Cumulative Resistance (MCR) model [10–13], and Circuit Theory [14,15] to identify ecological sources and corridors [16]. While these methods have improved the efficiency of ecological network analysis, most existing studies remain based on static historical data and focus mainly on structural connectivity, with limited ability to capture future changes in forest patterns and associated ecological functions.

To address this limitation, multi-scenario land-use simulation models have been increasingly applied to explore future landscape dynamics. Existing studies commonly adopt a coupled “quantity-space” framework. Quantitative models, such as system dynamics [17,18], grey forecasting [19,20], and Markov chains [21,22], are used to estimate land-use demand, while spatial allocation models, including cellular automata (CA) [23,24], CLUE-S [25,26], FLUS [27,28], and PLUS [29,30], are used to simulate the spatial distribution of land-use change. Among them, integrated frameworks such as MC-PLUS can improve simulation accuracy by combining area constraints with patch-based spatial allocation. Even so, these approaches are still rarely linked with the dynamic reconstruction of ecological networks.

Another important issue is that the thermal function of forest ecological networks has not been sufficiently considered. Existing studies usually treat ecological networks as structural systems, while overlooking their role in regulating urban thermal environments, especially as potential cooling corridors [31]. At the same time, land surface temperature (LST) is influenced not only by the thermal properties of land-cover types, but also by surrounding spatial configurations and neighborhood context [32]. However, many previous studies have relied on linear models or descriptive statistics to explain LST variation, making it difficult to identify non-linear thermal responses such as forest edge effects, corridor-related cooling spillover, and distance–decay characteristics [33]. In this respect, machine learning methods provide new possibilities for uncovering complex thermal mechanisms. In particular, the combination of Random Forest (RF) and SHAP (SHapley Additive exPlanations) can effectively quantify the relative importance and non-linear effects of multiple spatial factors on LST [34].

Based on the above review, the main research gaps can be summarized as follows:

- (1) Existing ecological network studies are mostly static and lack the ability to assess how forest structure and connectivity may evolve under future development scenarios [7–16].
- (2) The coupling between land-use simulation and ecological network reconstruction remains insufficient, limiting the evaluation of future corridor dynamics [17–30].
- (3) The thermal regulation function of forest ecological networks has received limited attention, and most studies still emphasize structural connectivity rather than thermal performance [31].
- (4) Current LST attribution methods are not well-suited to capturing non-linear and spatially heterogeneous thermal effects, particularly those related to forest edges, corridor adjacency, and cooling distance decay [32–34].

To address these gaps, this study develops an integrated framework of dynamic simulation-ecological network reconstruction-thermal mechanism analysis. Specifically, the MC-PLUS model, MSPA-MCR-based network identification, and kernel density esti-

mation (KDE) are combined to simulate the future evolution of forest cover and ecological corridors in Hangzhou under three scenarios in 2030: Business-as-Usual (BAU), Economic Development (ED), and Ecological Conservation (EC). In addition, the RF-SHAP method is used to quantify the non-linear relationships between spatial context and land surface temperature, with a focus on the cooling spillover range and distance–decay characteristics of forest corridors. The results are expected to provide scientific support for mitigating urban thermal risk, protecting highly connected cooling corridors, and improving spatial planning for urban ecological resilience.

2. Materials and Methods

2.1. Study Area

Hangzhou City ($118^{\circ}21'–120^{\circ}30'$ E, $29^{\circ}11'–30^{\circ}33'$ N), located in northern Zhejiang Province, eastern China, covers approximately 16,850 km² (Figures 1 and 2). The terrain is generally higher in the west and lower in the east, with mountainous and hilly areas in the west and low-lying plains in the east. This pronounced topographic gradient has resulted in substantial spatial heterogeneity in land use and ecological conditions across the study area.

Hangzhou has a typical subtropical monsoon climate, characterized by distinct seasons, abundant precipitation, and a dense river–lake network. In 2020, the mean annual temperature was 18.3 °C, and the total annual precipitation reached 1664 mm, which was noticeably higher than the long-term average. Favorable hydrothermal conditions support diverse ecological types and high forest productivity, but the hot and humid summer climate also makes the region vulnerable to thermal discomfort and urban heat stress.

As one of the major metropolitan areas in the Yangtze River Delta, Hangzhou has experienced rapid urbanization and continuous demographic growth in recent decades. By 2020, the permanent resident population had reached 11.936 million, with an average annual population growth rate of 3.21% over the previous decade. Rapid expansion of built-up land and increasing development intensity have exerted growing pressure on forest landscapes, leading to habitat fragmentation, reduced ecological connectivity, and rising thermal risks in urbanized areas. Therefore, Hangzhou provides a representative case for examining the interactions among urban expansion, forest ecological networks, and thermal environmental change.

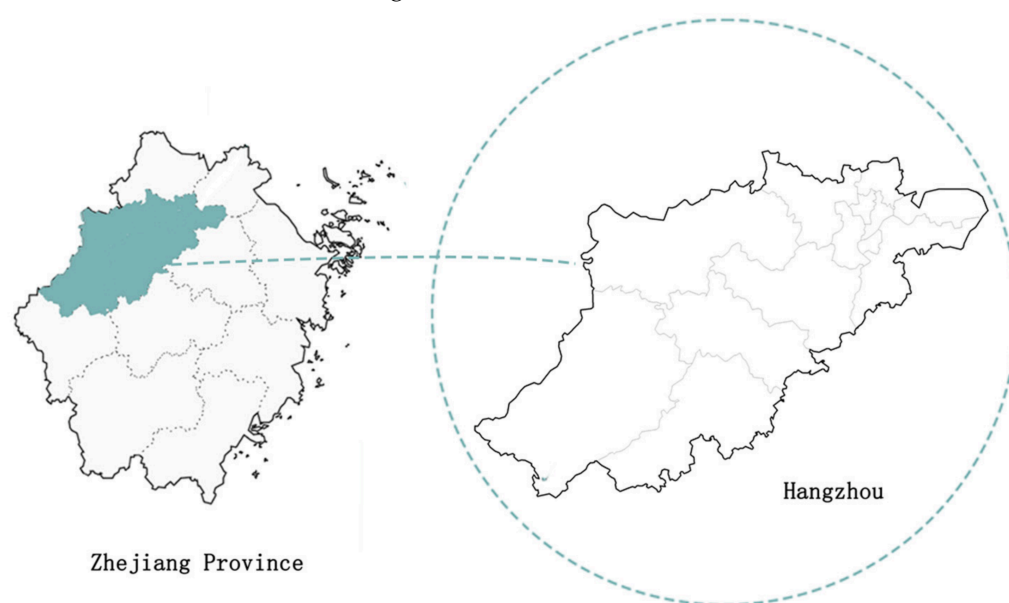


Figure 1. Geographic Location of Hangzhou.

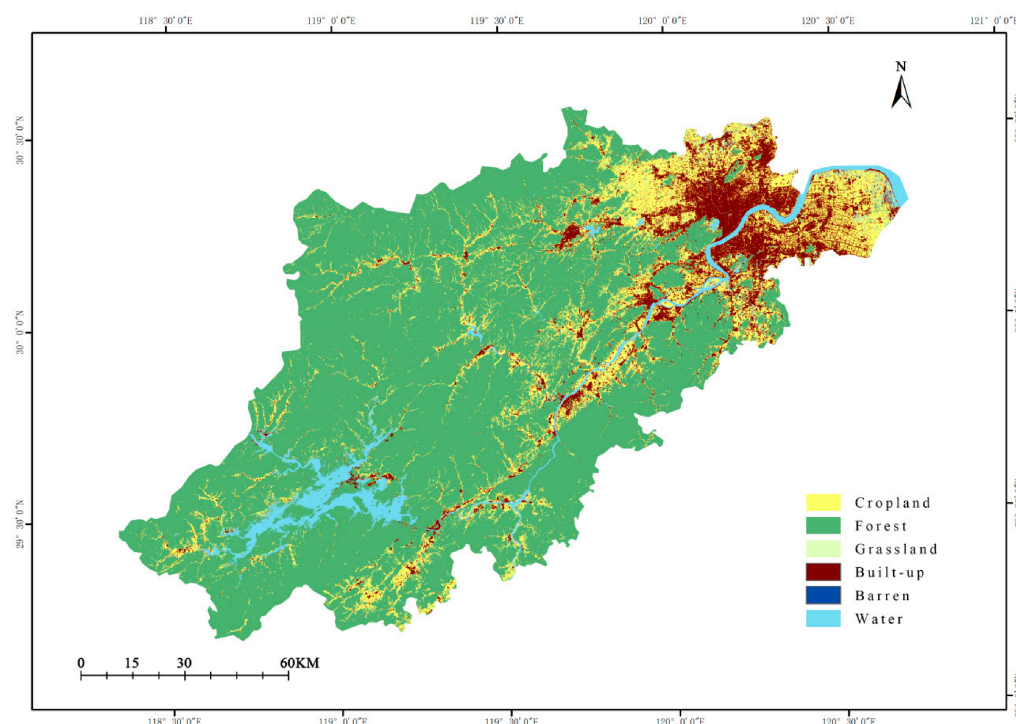


Figure 2. Land Use of Hangzhou for 2020. (source: GlobeLand30 (<https://aircas.cas.cn/>)).

2.2. Data Sources and Processing

The data sources and their attributes are detailed in Table 1. To ensure data compatibility in this study, all spatial data were projected to the WGS 1984 UTM Zone 51N coordinate system using ArcGIS 10.8 software and uniformly resampled to a spatial resolution of 30 m to enhance the spatial accuracy of the simulation.

Table 1. Main data and data sources.

Data Category	Variables/Data Name	Data Source
Basic data	Land use data of Hangzhou (2000–2020)	GlobeLand30 (https://aircas.cas.cn/)
Thermal environment data	Land surface temperature (LST) remote sensing data (2020)	Landsat 8 TIRS
Natural driving factors	DEM, slope, aspect, temperature, precipitation, etc.	Resource and Environment Science and Data Center (https://www.resdc.cn/)
Economic driving factors	GDP, nighttime light data	Resource and Environment Science and Data Center (https://www.resdc.cn/)
Social driving factors	Distance to administrative centers Distance to highways Distance to green spaces Distance to medical facilities Distance to main roads Distance to secondary roads Distance to water bodies	OpenStreetMap (https://www.openstreetmap.org/)
Constraint factors	Water bodies	Relevant planning documents

2.3. Methodology

This study constructs a workflow comprising “MC-PLUS multi-scenario land use simulation—MSPA source identification—MCR corridor construction and evaluation—spatial overlay” (Figure 3). The MC-PLUS model is employed to capture the impacts of land use driving factors and land expansion mechanisms on land use patterns, predicting land use change trends under different development scenarios. The MSPA-MCR model is utilized to identify the core ecological sources of Hangzhou under various scenarios and delineate ecological corridors and their connectivity pathways under the constraint of resistance surfaces, thereby revealing the spatial structure and connectivity relationships of the ecological network. Furthermore, by overlaying the ecological network elements across multiple scenarios, this study evaluates the impacts of different development strategies on the ecological network, identifies priority conservation areas, and provides support for the scientific formulation of regional ecological protection and restoration strategies.

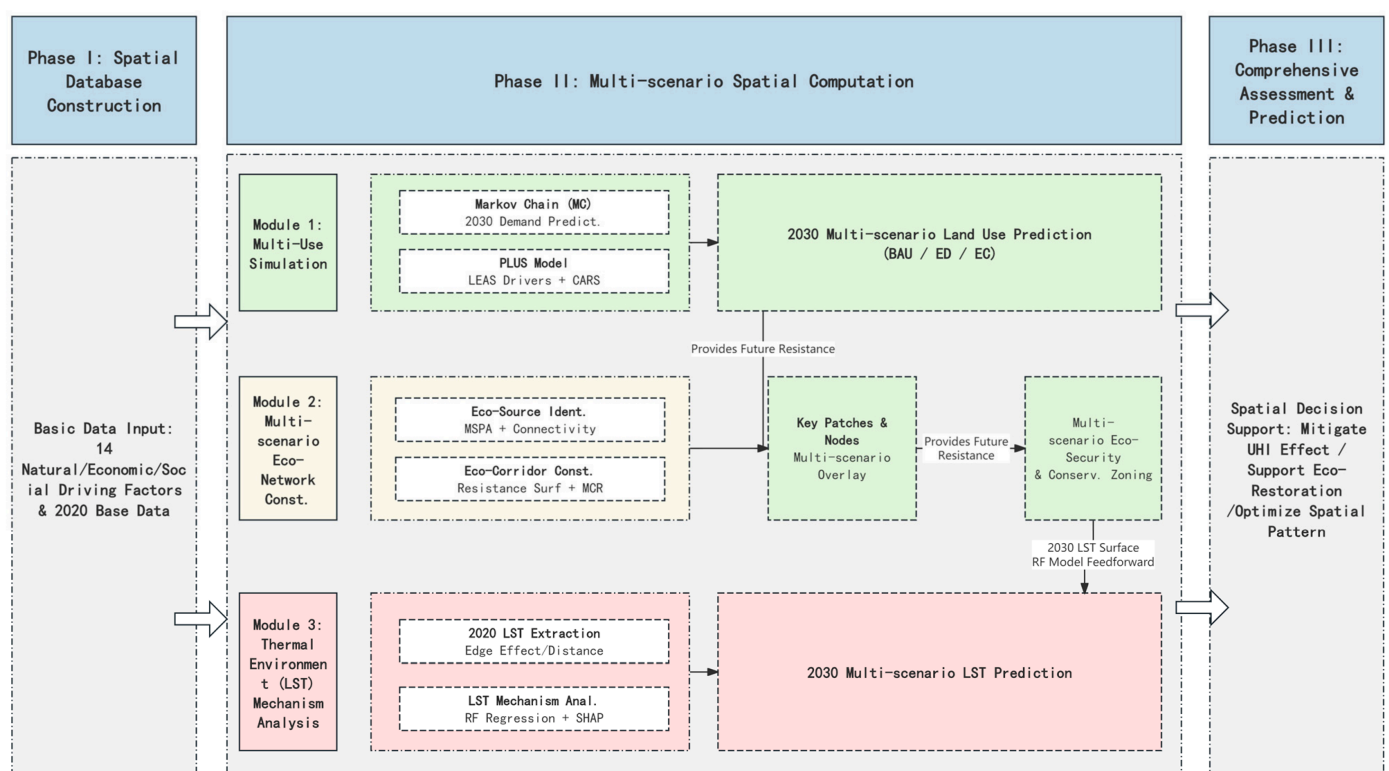


Figure 3. Methodological framework.

2.3.1. Multi-Scenario Simulation Based on MC-PLUS

To verify the accuracy of the simulation results and the applicability of the modeling framework, a retrospective validation was conducted using historical data. Specifically, the transition probability matrix was derived from the land use changes between 2000 and 2010 to simulate the spatial distribution of land use in 2020. The Kappa coefficient and overall accuracy were employed to quantitatively evaluate the spatial consistency between the simulated 2020 land use map and the actual 2020 observation. Typically, a Kappa value greater than 0.75 indicates high simulation accuracy and model robustness. The comparison between the PLUS-simulated results and the actual 2020 land use (Figure 4) yielded a Kappa coefficient of 0.9254 and an overall accuracy of 0.9652. These metrics demonstrate a highly consistent spatial distribution, confirming that the coupled MC-PLUS model effectively captures the underlying trends of regional land use changes and is highly reliable for projecting future multi-scenario spatial patterns.

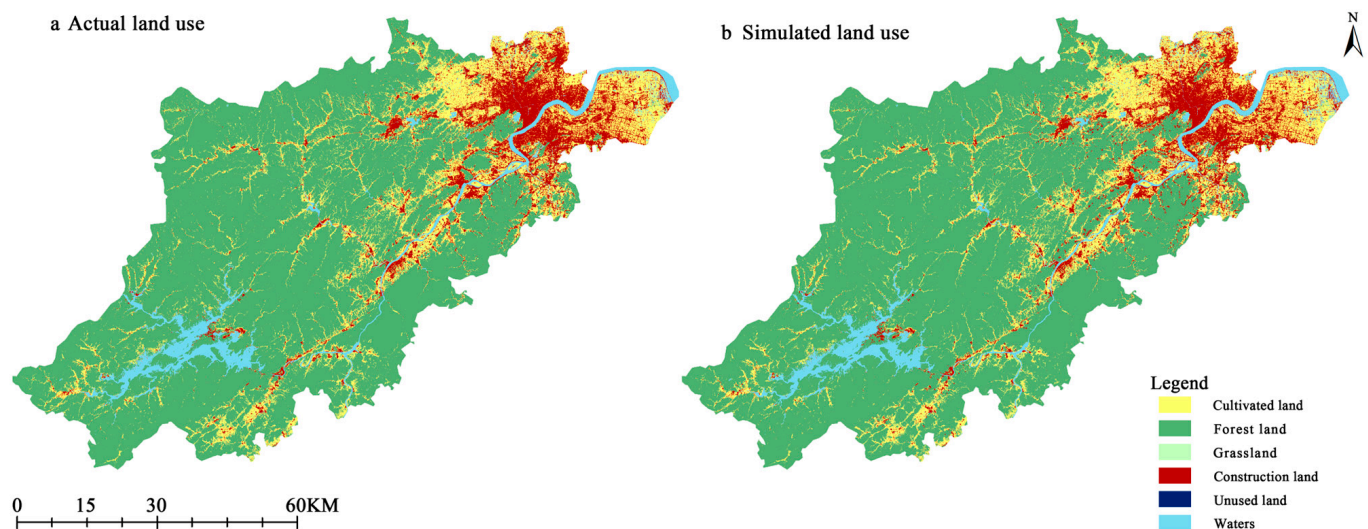


Figure 4. Comparison of actual and simulated land use in Hangzhou in 2020.

The mechanism of the predictive framework consists of two main stages. First, the Markov Chain (MC) model calculates the transition probability matrix based on the historical land use dynamics from 2000 to 2020, thereby predicting the macroscopic quantitative demand for each land use type in 2030 [35,36] (Equation (1)).

$$S_{(n)} = S_{(n-1)} \times P_{ij}, \quad (1)$$

where $S(n)$ represents the land use state vector at period n , $S(n-1)$ is the state vector at the preceding period, and P_{ij} denotes the transition probability matrix of land use types. Within this matrix, every transition probability is non-negative and does not exceed 1, with the sum of probabilities in each row equaling 1 (indicating that a specific land use type must either transition to another type or remain unchanged). P is an $n \times n$ square matrix, where n indicates the number of land use types.

Second, based on the projected quantities, three core development scenarios for 2030 were established to reflect different urban governance strategies:

- (1) Business-as-Usual (BAU) scenario: Imposes no specific policy restrictions, simulating the spontaneous urban expansion trajectory based strictly on the historical 2000–2020 transition probabilities.
- (2) Economic Development (ED) scenario: Grants construction land greater expansion potential to reflect intensified land competition during rapid urbanization.
- (3) Ecological Conservation (EC) scenario: Emphasizes the protection of natural ecological land, strictly prohibiting its conversion into construction land while preserving forest ecosystems and potential ecological corridors.

To operationalize the ED and EC scenarios mathematically, a $\pm 20\%$ perturbation was applied to selected elements of the BAU transition probability matrix. This adjustment was defined with reference to historical transition tendencies in the study area [37] and to scenario-elasticity settings commonly adopted in comparable land-use simulation studies, where transition probabilities are frequently increased or reduced by approximately 20%–35% to represent contrasting development priorities [38,39]. For instance, in the EC scenario, the probability of forest converting to built-up land is reduced by 20%, while in the ED scenario, the probability of non-built-up land converting to built-up land is increased by 20%. After applying the perturbation, the probability rows are re-normalized so that their sum strictly equals 1, ensuring mathematical validity.

The quantitative projection of future land-use demand and its spatial allocation are two distinct phases in this study. It is important to clarify that the Markov Chain (MC) model is applied strictly as a statistical approach to calculate the future numerical demand (pixel quantities) for each land-use type based on historical transition matrices. It does not determine spatial configurations.

To address the spatial allocation of these predicted quantities, the PLUS model (Equations (2) and (3)) is employed. Drawing on existing research findings [40–43], 14 spatial driving factors covering natural, economic, and social categories were selected to represent the complex socio-economic and environmental drivers of land-use change. Detailed definitions, spatial resolutions, reference years, and the expected roles of each factor are systematically outlined in Table 2.

Table 2. Descriptions and details of the selected driving factors in the PLUS model.

Category	Driving Factor	Description/Proxy	Resolution	Year	Expected Role in LEAS
Natural	Temperature	Annual mean temperature representing climatic suitability.	1 km (RESDC/GPRChinaTemp1km, HRLT, and other standard 1 km climate grids in China)	2020	Influences vegetation growth and ecological land distribution.
	Precipitation	Annual cumulative precipitation.	1 km (RESDC standard 1 km annual precipitation dataset)	2020	Affects water resources, agriculture, and ecological suitability.
	DEM (Elevation)	Digital Elevation Model indicating terrain height.	30 m (China 30 m DEM)	2020	Constraints on urban expansion and agricultural suitability.
	Slope	Terrain gradient derived from DEM.	30 m (Derived from 30 m DEM)	2020	Determines construction difficulty and ecological sensitivity.
	Aspect	Slope orientation derived from DEM.	30 m (30 m DEM)	2020	Affects microclimate, solar radiation, and vegetation types.
Social	Distance to administrative office land	Euclidean distance to government/administrative centers.	30 m (OSM vector data calculated and rasterized)	2020	Reflects policy-driven urban attraction and infrastructure focus.
	Distance to expressway	Euclidean distance to the nearest expressway.	30 m (OSM/road vector data calculated and rasterized)	2020	Represents regional accessibility and industrial/urban expansion corridors.
	Distance to primary roads	Euclidean distance to the nearest primary road.	30 m (OSM vector data calculated and rasterized)	2020	Indicates main traffic accessibility for human activities.
	Distance to secondary road	Euclidean distance to the nearest secondary road.	30 m (OSM vector data calculated and rasterized)	2020	Indicates localized traffic accessibility and settlement connectivity.
	Distance to medical and health care land	Euclidean distance to hospitals and clinics.	30 m (POI/vector data calculated and rasterized)	2020	Reflects public service availability and residential attractiveness.
	Distance to green spaces	Euclidean distance to parks or major green infrastructure.	30 m (Vector data calculated and rasterized)	2020	Influences residential preference and ecological constraints.
	Distance to waters	Euclidean distance to rivers, lakes, or major water bodies.	30 m (Water vector data calculated and rasterized)	2020	Attracts agricultural/urban use but also acts as an ecological boundary.
Economic	2020 GDP	Gross Domestic Product spatial distribution grid.	1 km (RESDC China GDP spatial distribution 1 km grid dataset standard product)	2020	Represents economic development intensity and urbanization pressure.
	Nightlight	Nighttime light intensity imagery.	500 m (NPP-VIIRS product)	2020	Proxy for human activity density and built-up area vitality.

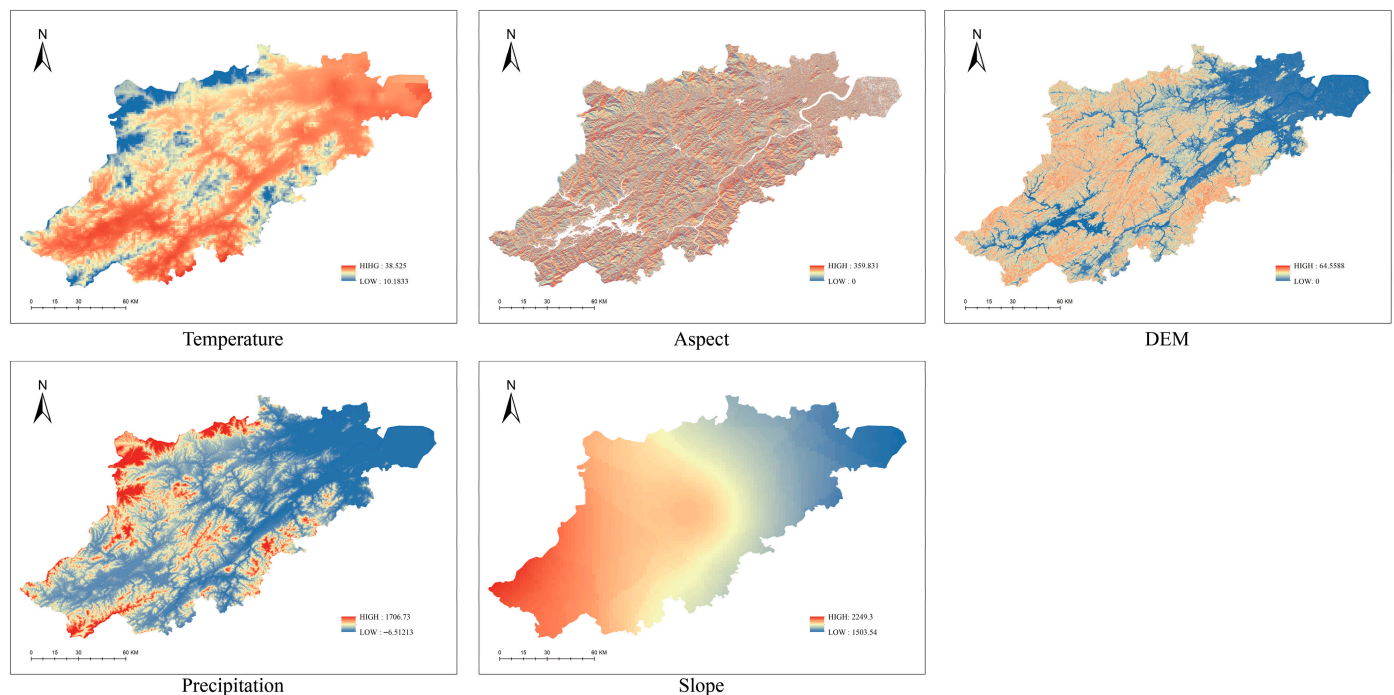
These 14 driving factors are explicitly integrated into the simulation through the Land Expansion Analysis Strategy (LEAS) module of the PLUS model. Specifically, LEAS extracts spatial samples from the historical land expansion areas and utilizes a Random Forest algorithm to mine the non-linear relationships between these factors and historical land-use dynamics (Figure 5). This machine-learning process outputs a spatial probability surface for each land-use type, quantifying the likelihood of expansion at the pixel level. Subsequently, the CA based on Multiple Random Seeds (CARS) module integrates these Random Forest-derived development probabilities, dynamic neighborhood effects, and scenario-specific spatial constraints to iteratively allocate the land-use quantities predicted by the MC model into precise spatial configurations.

$$P_{d,k}^i(x) = \frac{1}{M} \sum_{m=1}^M I(h_i^m(x) = d) \quad (2)$$

where $P_{d,k}^i(x)$ represents the probability that sample unit x is classified into land use type d ; $I(h_i(x) = d)$ is a binary indicator function that takes the value of 1 when $h_i(x) = d$ (indicating that the i -th decision tree classifies the unit as type d), and 0 otherwise; $h_i(x)$ denotes the final classification result of the i -th decision tree for unit x ; and M represents the total number of decision trees in the random forest.

$$OP_{i,k}^{d=1,t} = P_{i,k}^{d-1} \times \Omega_{i,k}^t \times D_k^t, \quad (3)$$

where $OP_{i,k}^{d=1,t}$ represents the overall probability of cell i within neighborhood k transitioning from other land use types to type d at time t ; $P_{i,k}^{d,t-1}$ denotes the probability of this cell transitioning from other types to type d at the previous time step; $\Omega_{i,k}^t$ represents the neighborhood effect, specifically the proportion of surrounding cells belonging to type d within neighborhood k ; and D_k^t is the adaptive driving coefficient, reflecting the deviation between the macroscopic scenario target and the current simulated state.



(a)

Figure 5. Cont.

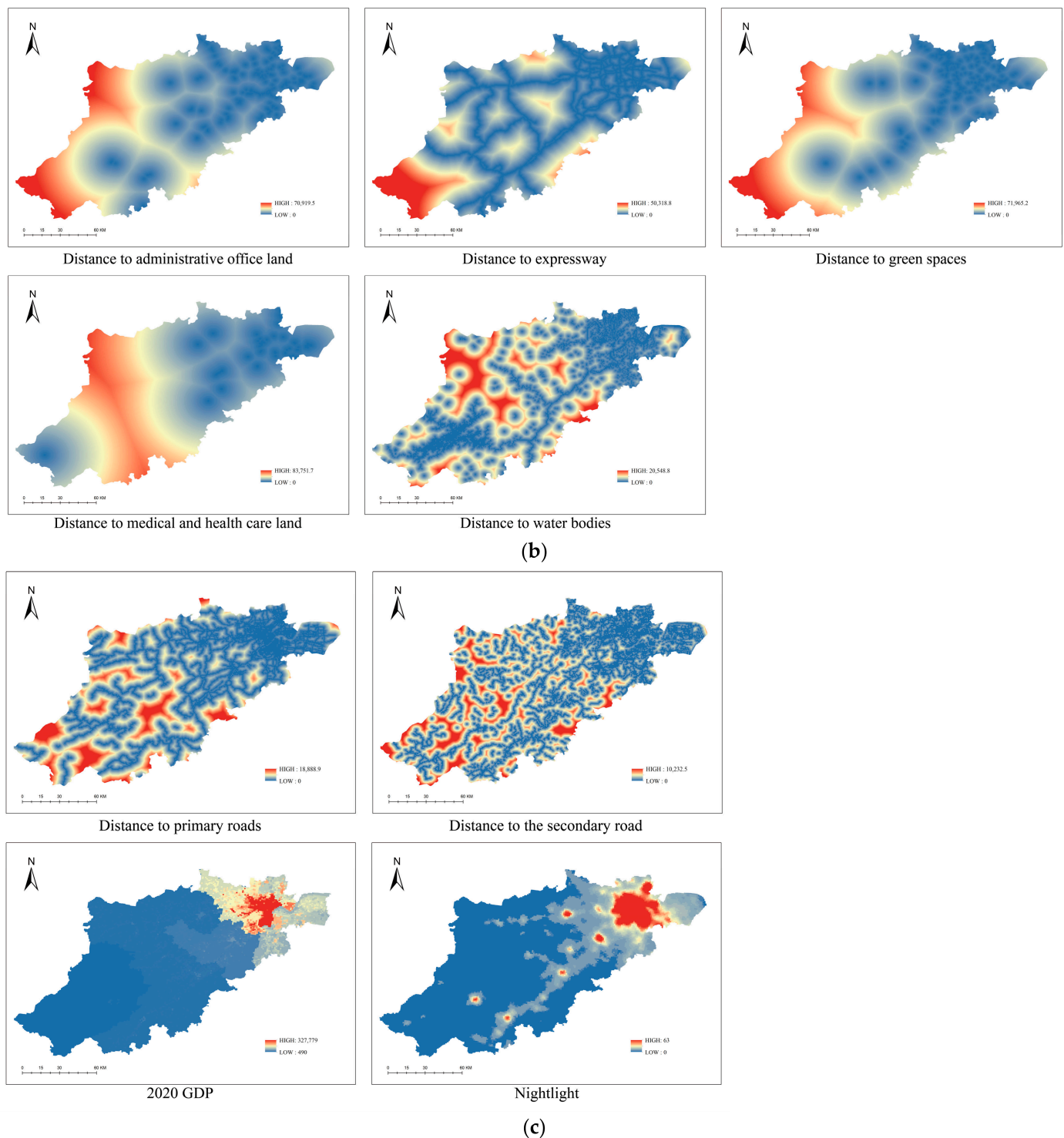


Figure 5. Driving factors of (a) natural factors, (b) social factors, (c) economic factors for the PLUS model.

2.3.2. Forest-Dominated Ecological Network Construction Based on MSPA-MCR

Based on MSPA, the landscape is classified into structural units such as core, edge, bridge, and loop. To define the core ecological sources tailored to a “forest-dominated” network in Hangzhou’s highly fragmented urban landscape, specific thresholds were established. Patches were designated as core sources only if their area exceeded 16 km², a study-specific threshold set to retain sufficiently large forest patches under Hangzhou’s intense urban fragmentation and thermal-edge pressures [44,45], while dPC and dIIC

values greater than 1 were used to identify patches making non-trivial contributions to overall landscape connectivity.

The Probability of Connectivity (PC) (Equation (4)) and the Integral Index of Connectivity (IIC) (Equation (5)) are defined as follows [46,47]:

$$PC = \frac{\sum_{i=1}^n \sum_{j=1}^n S_i S_j p_{ij}}{S^2} \quad (4)$$

where PC represents the PC index; n represents the number of landscape elements; S_i and S_j represent the areas of ecological sources i and j , respectively; S^2 represents the total area of the regional landscape; p_{ij} represents the maximum product of probabilities of all possible paths between ecological sources i and j .

$$IIC = \frac{\sum_{i=1}^n \sum_{j=1}^n \frac{a_i \times a_j}{1 + nl_{ij}}}{A_L^2} \quad (5)$$

where IIC represents the IIC index; n represents the total number of patches; a_i and a_j represent the areas of patch i and patch j , respectively; nl_{ij} represents the number of links between patch i and patch j ; and A_L represents the total landscape area.

During the network linkage phase, the Minimum Cumulative Resistance (MCR) model was applied (Equation (6)) [10]. It should be emphasized that the outputs of the MCR model represent potential structural corridors within the forest-dominated ecological network, rather than directly verified biological flows or empirically confirmed cooling transport pathways. Following previous studies [48,49], resistance values were assigned to different land-cover types to reflect the extent to which each surface type impedes species movement and broader ecological processes. Forest was assigned the lowest resistance value (3) as the most favorable matrix for ecological flow; grassland and cropland were assigned medium resistance values (30 and 100, respectively) because they may act as semi-permeable buffers; transportation infrastructure, water bodies, and unutilized land were assigned relatively high resistance values (600, 900, and 700, respectively); and construction land was assigned the highest resistance value (1000) because of its strong impermeable and barrier effects. Based on these settings, the MCR model was implemented following the minimum-cost path principle, whereby species or ecological processes are assumed to preferentially disperse along pathways with the lowest cumulative resistance and minimum energy expenditure [50,51]. The resulting outputs were then used to identify the most likely structural linkages among ecological sources and to map the spatial distribution and connectivity pattern of potential ecological corridors.

$$MCR = f_{min} \sum_{j=n}^{i=m} (D_{ij} \times R_i) \quad (6)$$

where f is a positive correlation function reflecting the relationship between the minimum resistance of any point in space and its distance to all other points across the baseline landscape characteristics. D_{ij} is the spatial distance of a species traveling from point j to a specific point crossing landscape i ; R_i is the resistance value of landscape i .

2.3.3. Multi-Scenario Overlay Analysis of the Forest-Dominated Ecological Network

To better characterize the spatial organization of the forest-dominated ecological network under different land-use scenarios, this study overlaid the identified ecological sources with the potential structural corridors derived from the MSPA-MCR framework. The purpose of this analysis was not to infer confirmed ecological flows or verified cooling

transport, but rather to identify the spatial coincidence, continuity, and structural interaction among key ecological elements under different development trajectories. In this sense, the overlay analysis provides a scenario-based assessment of potential ecological connectivity and the relative stability of the network structure.

Specifically, the analysis focused on three aspects: (1) the spatial aggregation and persistence of core ecological source areas across scenarios; (2) the continuity, interruption, and redistribution of potential corridor pathways; and (3) the degree of spatial coupling between source patches and corridor axes. Through this overlay, areas with persistent source–corridor associations were identified as priority ecological conservation structures, because they are more likely to contribute to long-term landscape connectivity and ecological security. By contrast, areas showing corridor contraction, source isolation, or weakened source–corridor coupling under urban expansion scenarios were interpreted as structurally vulnerable zones requiring enhanced planning attention.

It should be emphasized that the resulting corridor patterns represent potential structural ecological corridors inferred from landscape resistance and least-cost relationships, rather than directly observed functional corridors for species movement or empirically validated cooling pathways. Therefore, the overlay results are interpreted as a spatial basis for comparative planning analysis and conservation prioritization, rather than definitive evidence of realized ecological or thermal processes. On this basis, the study further delineates core conservation structures under multiple scenarios and provides quantitative support for priority zoning, ecological restoration, and urban ecological governance.

2.3.4. Machine Learning-Based Analysis of LST Mechanisms and Scenario Prediction

To overcome the limitations of conventional linear models in capturing spatially heterogeneous thermal responses, this study developed an analytical framework integrating a Random Forest (RF) regressor with the SHAP (SHapley Additive exPlanations) method. The framework was designed to link present-day thermal mechanisms with future spatial predictions (Figure 6). It should be noted that the LST data used in this analysis represent the mean land surface temperature during the summer of 2020 (June–August), rather than single-date or daily observations.

- (1) Spatial feature extraction: Spatial explanatory variables were extracted at a 30 m resolution, including target land-use/land-cover (LULC), nearest-corridor LULC, and Euclidean distance to the nearest corridor. To capture local thermal context and edge-related interactions, an 11×11 pixel moving window (approximately 330×330 m) was used to calculate neighborhood LULC fractions, thereby balancing the representation of local heterogeneity with noise reduction. Boundary bias was reduced through mask-based exclusion.
- (2) Estimation of corridor-cooling distance decay: To quantify the cooling gradient associated with ecological corridors, the LST difference (Δ LST) was calculated between each pixel and a background reference zone located more than 1000 m from the nearest corridor. Using this baseline, a distance–decay relationship was established to identify the effective attenuation range of corridor-related cooling.
- (3) RF-SHAP analysis: An RF model was constructed to predict the mean summer LST as a function of the extracted spatial variables. The model was implemented using the scikit-learn library in Python 3.9. To ensure optimal predictive performance, hyperparameters were determined through grid-search optimization, resulting in 100 trees and a maximum depth of 20. A random sample of 100,000 pixels was drawn from the valid raster data for model training, while 1500 samples were reserved for SHAP interpretation. Model performance was validated using the in-sample coefficient of determination (R^2). Subsequently, SHAP values were calculated via the

shap library to quantify the relative importance, direction of influence, and non-linear effects of the spatial predictors on LST variation.

- (4) Future scenario prediction: The validated RF model was subsequently applied in a feed-forward manner to the 2030 LULC scenarios simulated by the MC-PLUS model, including the Business-as-Usual, Economic Development, and Ecological Conservation scenarios. By coupling projected LULC patterns with the learned present-day thermal response relationships, high-resolution LST prediction surfaces were generated for each scenario. These spatially explicit estimates of relative thermal risk and cooling potential provide scientific support for urban climate adaptation and ecological network planning.

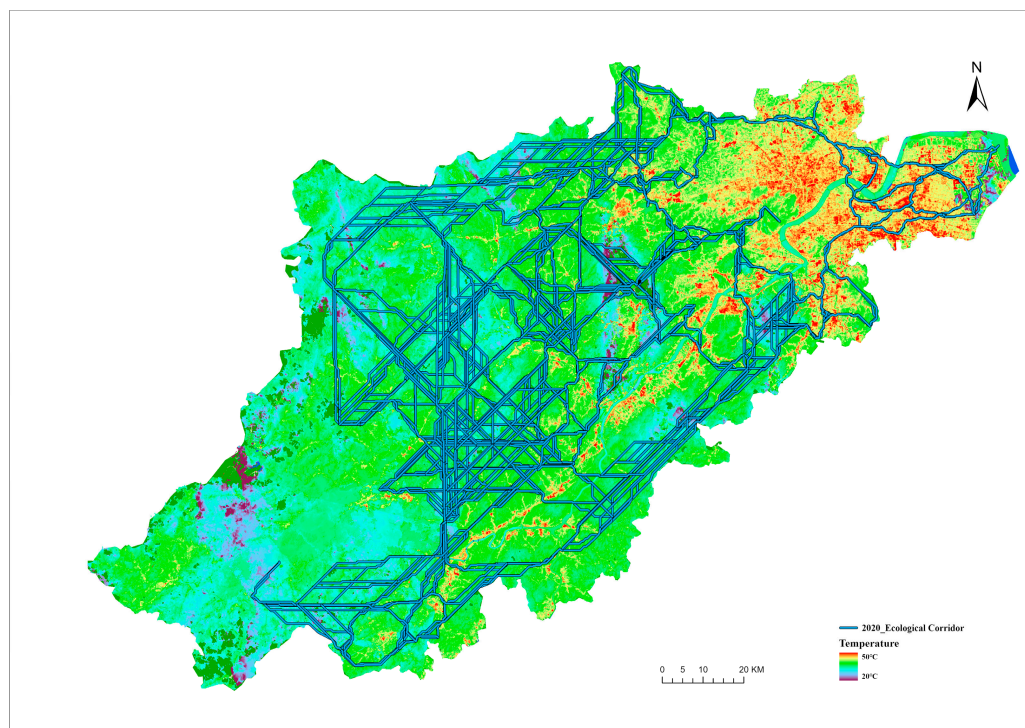


Figure 6. Spatial relationship between potential ecological corridors and the mean summer (June–August) LST pattern in Hangzhou in 2020.

3. Results

3.1. Quantitative Prediction of Land Use and Forest Cover Under Multiple Scenarios

As detailed in Table 3, the three 2030 scenarios exhibit distinct land-use trajectories. The Business-as-Usual (BAU) scenario follows historical trends, characterized by construction land expansion at the expense of forests, grasslands, and water bodies, alongside a modest increase in cropland. The Economic Development (ED) scenario presents the most aggressive urban growth, with construction land expanding from 1497.56 km² in 2020 to 1964.71 km² in 2030. This rapid expansion intensifies spatial competition, leading to the most severe degradation of agricultural and ecologically sensitive surfaces. Conversely, the Ecological Conservation (EC) scenario effectively restrains disorderly sprawl, demonstrating the lowest construction land growth, the highest net increase in cropland, and the strongest mitigation of forest loss. Overall, the intensity of construction land expansion follows the order ED > BAU > EC. Although the absolute differences in subsequent scenario-based thermal indicators are relatively small, their practical implications and associated model uncertainties are further addressed in Section 4.

Table 3. Hangzhou’s 2020 land use and land demand forecast for 2030.

Land Use Type	2020 (Base)	BAU Scenario			ED Scenario			EC Scenario		
	Area (km ²)	Area (km ²)	CR (%)	CCR (%)	Area (km ²)	CR (%)	CCR (%)	Area (km ²)	CR (%)	CCR (%)
Cropland	2690.99	2759.53	2.6	7.5	2692.86	0.1	0.0	2826.96	5.1	15.1
Forest	11,894.68	11,516.04	−3.2	41.2	11,507.16	−3.3	52.1	11,524.43	−3.1	41.1
Grassland	1.65	1.21	−26.7	0.1	1.06	−35.8	15.9	1.36	−17.6	0.0
Construction land	1497.56	1888.42	26.1	42.5	1964.71	31.2	4.3	1812.14	21.0	34.9
Unutilized land	0.27	0.29	7.4	0.0	0.28	3.7	15.9	0.3	11.1	0.0
Water bodies	785.59	705.25	−10.2	8.7	704.66	−10.3	11.8	705.57	−10.2	8.9

Note: CR = Change Rate; CCR = Contribution to Change Rate.

3.2. Spatial Distribution of Forest and Land Use Under Multiple Scenarios

Figure 5 presents a multi-scale comparison of the simulated land use/land cover (LULC) spatial patterns in the study area for 2030 under the BAU, ED, and EC scenarios. The left column shows the full-domain simulation maps, the middle column displays the corresponding locally enlarged views, and the right column provides further zoomed-in details of patch distribution around the urban built-up areas.

Under the BAU scenario (Figure 7a), urban expansion exhibits a relatively dispersed and multi-directional outward pattern. Construction land extends into peri-urban spaces across multiple districts, forming several detached growth patches, particularly evident at the urban fringe and near-water development zones. Cropland remains relatively continuous in some outer areas and forms transitional belts between urban and forest spaces; however, this transitional pattern also contributes to increased fragmentation of adjacent forest patches. The middle enlarged view clearly illustrates the intermixed distribution of built-up areas with surrounding cropland and forest, while the right detailed panel further reveals the dispersed and irregular morphology of patches as well as the fragmentation at forest edges.

In contrast, the ED scenario (Figure 7b) is characterized by a more continuous and intensive pattern of built-up expansion. Construction land extends in broader and more spatially connected belts along existing urban edges and development axes, significantly intensifying the fragmentation of surrounding forest and agricultural land. Compared with the BAU scenario, this scenario exerts stronger pressure on the continuity of peri-urban forest and green spaces, while the contraction of cropland further amplifies spatial differentiation and ecological compression at the urban fringe. The middle enlarged view highlights the contiguous development trend of construction land, and the right detailed panel emphasizes the more finely dissected nature of forest patches.

By comparison, the EC scenario (Figure 7c), constrained by ecological protection, displays a more compact urban form. Construction land is more concentrated around existing built-up cores, while peri-urban forest areas are better preserved. Cropland forms relatively continuous buffer zones around the urban expansion boundary, resulting in an overall spatial pattern that can be summarized as “core concentration with edge protection.” This configuration effectively reduces disorderly encroachment into ecologically sensitive forest landscapes and helps maintain regional ecological security. The middle enlarged view shows more regular boundaries of built-up areas, and the right detailed panel clearly demonstrates the smoother transitions among forest, cropland, and construction land, along with a lower degree of fragmentation.

Overall, the multi-scale comparison indicates that the EC scenario is the most effective in maintaining forest-dominated landscape integrity and mitigating urbanization-induced fragmentation.

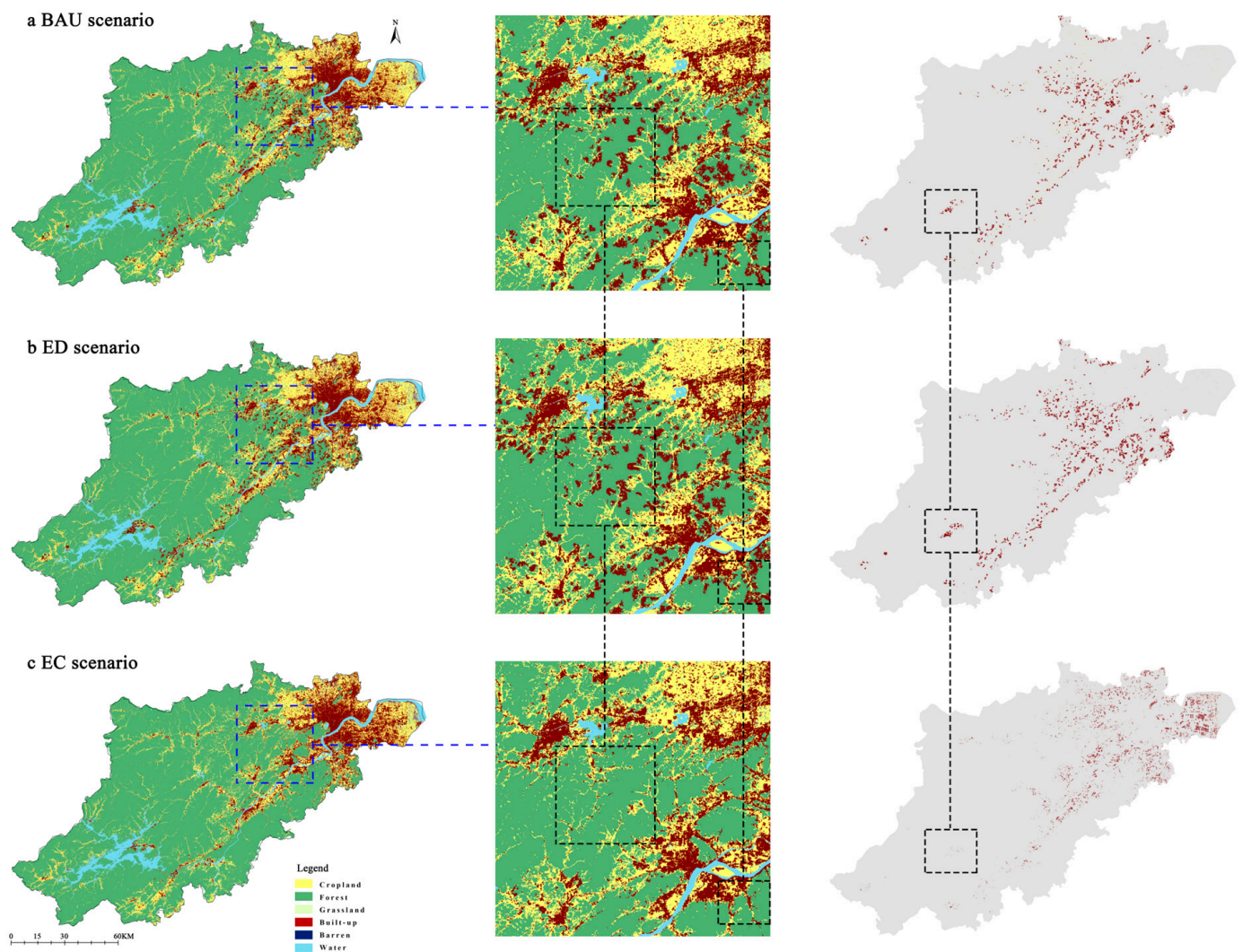


Figure 7. Simulated land use maps for 2030 under different scenarios.

3.3. Construction of Ecological Networks Under Multiple Scenarios

3.3.1. Identification of Forest-Dominated Ecological Sources

Using the screening criteria defined in Section 2.3.2—namely, $dIIC > 1$, $dPC > 1$, and patch area $> 16 \text{ km}^2$ —a set of core forest-dominated ecological sources was identified for each scenario (Figure 8). Based on these criteria, 50 core source patches were identified for 2020, compared with 48 under the BAU scenario, 47 under the ED scenario, and 45 under the EC scenario. Among these, 19 patches met the criteria under all four temporal/scenario conditions and were therefore regarded as highly persistent source areas with long-term strategic importance.

In spatial terms, the identified ecological sources exhibit an overall pattern of “western concentration with peripheral dispersion.” Large mountainous forest areas in the western, southwestern, and northwestern parts of Hangzhou form the structural backbone of the ecological network and provide the main support for habitat maintenance, biodiversity conservation, and canopy-related ecological regulation. Typical high-value source areas include Dongming Mountain, Qiandao Lake, Tianmu Mountain, and Lingshan. By contrast, source patches located in eastern and peri-urban areas are generally smaller and structurally less connected; however, they still play important complementary roles in supporting urban green infrastructure, enhancing landscape resilience, and supplying localized ecosystem services.

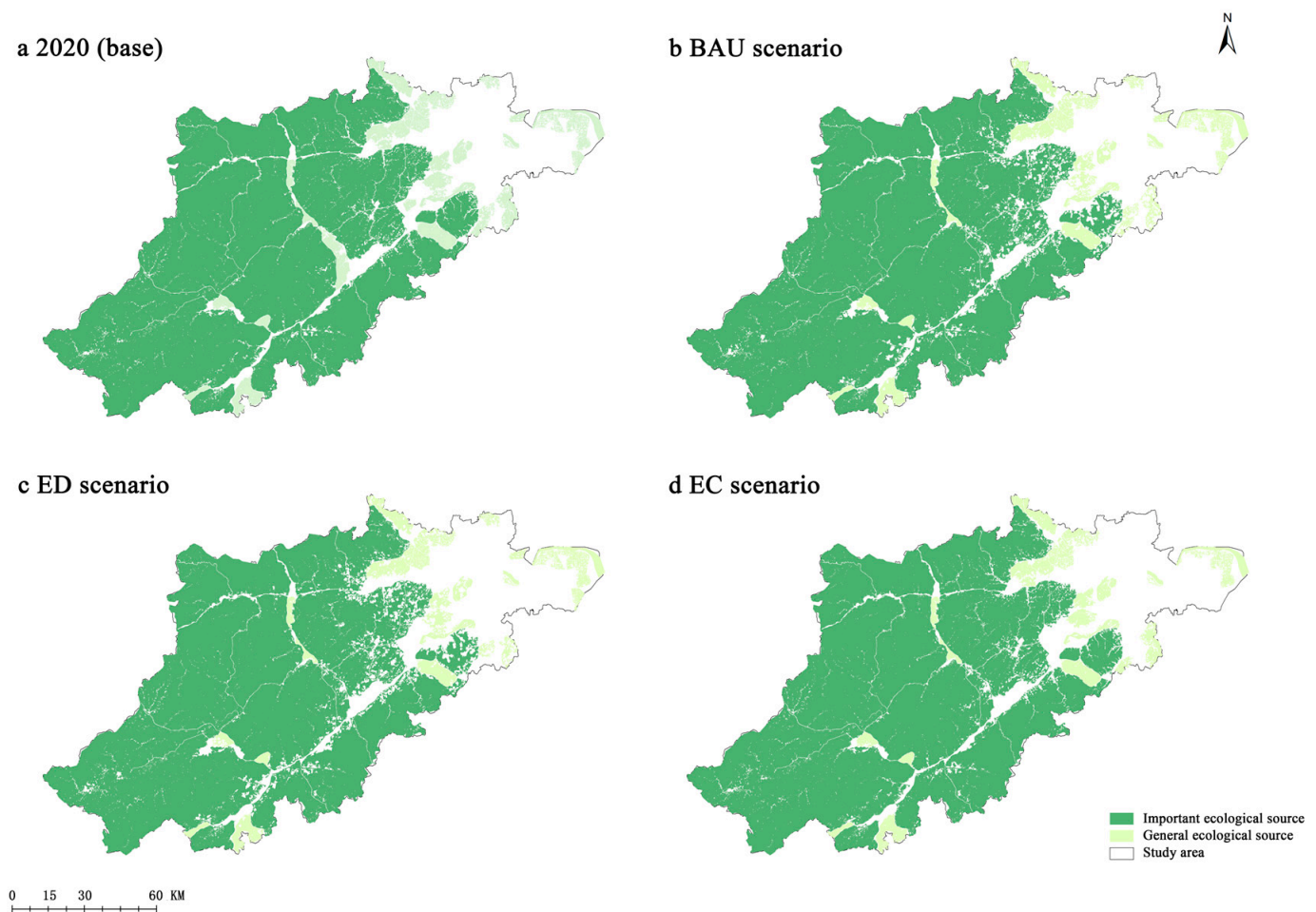


Figure 8. Distribution of ecological source areas under multiple scenarios.

In the city–mountain transition zone, remnant forest areas such as Wuchao Mountain and Longmen retain important buffering functions despite increasing anthropogenic disturbance. Meanwhile, urban and near-urban vegetated patches such as West Lake, Xianghu Lake, and Liangzhu remain significant for maintaining local canopy cover and improving the urban microclimate, even though their structural connectivity is weaker than that of the major mountainous sources.

It should be noted that the decline in the number of identified source patches under future scenarios does not necessarily imply an equivalent decline in ecological function. In particular, under the EC scenario, a smaller number of sources may partly result from patch amalgamation, expansion of core forest areas, and reduced edge fragmentation. Therefore, source number should be interpreted together with source size, spatial continuity, and structural role within the network, rather than as a stand-alone indicator of ecological quality.

3.3.2. Construction of Potential Forest-Dominated Ecological Corridors Based on the MCR Model

Based on the MCR model, the potential forest-dominated ecological corridors of Hangzhou were extracted for 2020 and for the three 2030 scenarios (Figure 9). These corridors represent potential structural pathways inferred from cumulative resistance surfaces, rather than empirically verified habitat movement routes or directly measured urban cooling channels. Therefore, the following analysis focuses on the comparative structural properties of the corridor network across scenarios.

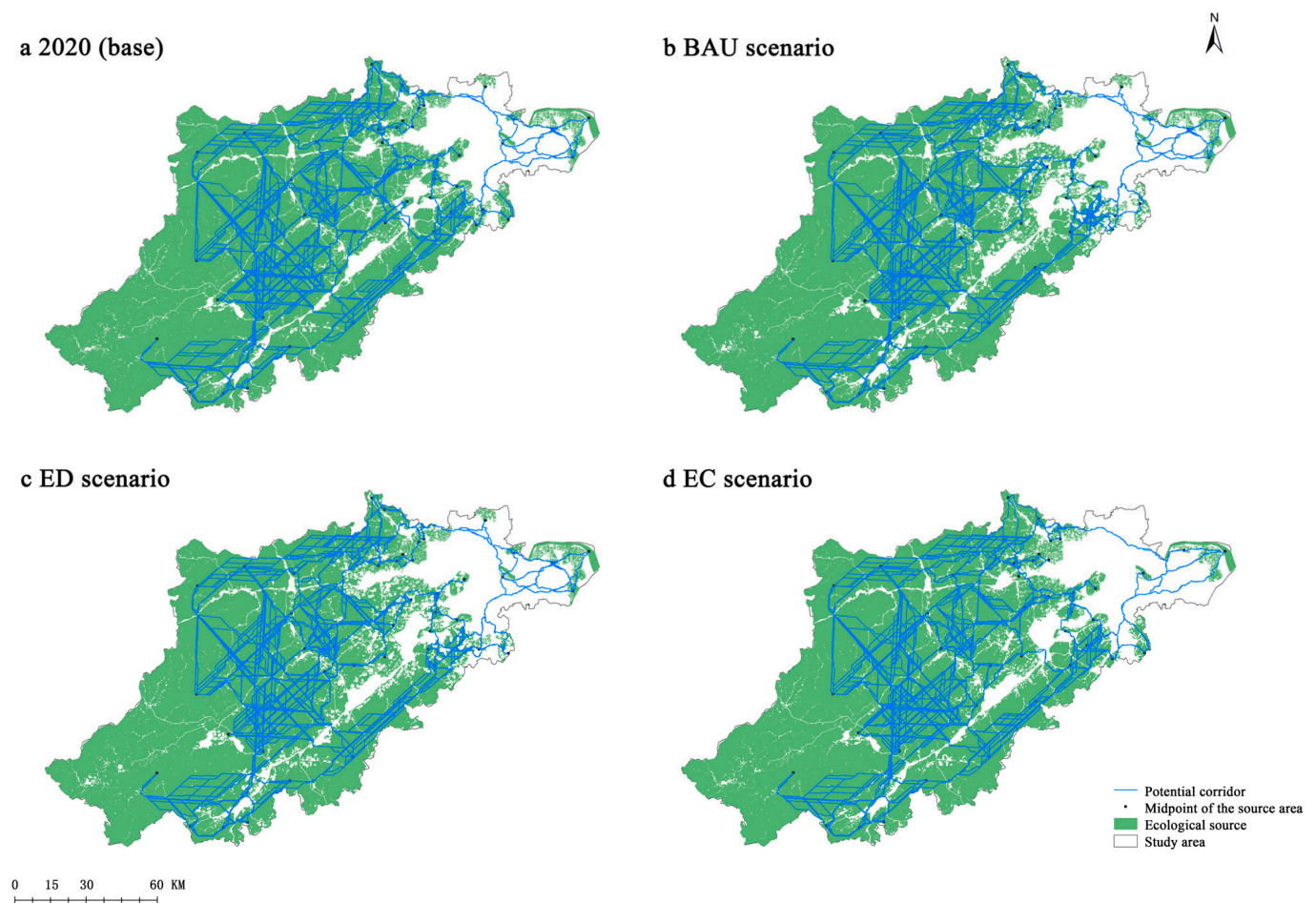


Figure 9. Ecological corridors distribution map under multiple scenarios.

At the regional scale, the potential ecological network of Hangzhou exhibits a differentiated spatial pattern, with stronger corridor concentration in some central and eastern sectors and weaker cross-regional connectivity in other parts of the metropolitan area. In particular, the main urban core and some western urbanized sectors show a relative lack of continuous cross-city green linkages, which constrains structural vegetation connectivity. By contrast, some eastern areas retain relatively denser corridor distributions, likely reflecting the stronger persistence of natural or semi-natural landscape elements in those zones.

In terms of network composition, the number of core source patches decreases slightly from 2020 to the three simulated scenarios, but this reduction translates into a more pronounced decline in the theoretical maximum number of source-to-source corridor connections. According to the combinatorial relation $N = n(n - 1)/2$, where n is the number of source nodes, the theoretical maximum numbers of potential corridors are 1225, 1128, 1081, and 990 for 2020, BAU, ED, and EC, respectively. This result indicates that even a modest reduction in the number of ecological sources can lead to a disproportionately faster loss of potential structural linkages, because redundant alternative pathways decline simultaneously as source patches are reduced or merged.

However, the quantitative decline in corridor number should be interpreted cautiously. A lower number of potential corridors does not necessarily mean a weaker ecological network in functional terms. For example, under the EC scenario, the reduction in source number and theoretical corridor count may partly reflect source consolidation, growth of core forest area, and reduced edge dissection, rather than simple ecological deterioration. In

this sense, the EC scenario may produce a more compact and structurally efficient network, even if the number of discrete source–corridor elements appears smaller.

3.4. Overlay Analysis

3.4.1. Overlay Analysis of Forest-Dominated Ecological Sources

Compared to the 2020 baseline, the three 2030 scenarios exhibit relative quantitative stability in the total number of core ecological sources but marked structural divergence in spatial configuration, fragmentation, and source–corridor coupling (Figure 10). These discrepancies are predominantly concentrated in ecologically sensitive zones, particularly urban fringes and built-up/forest interfaces.

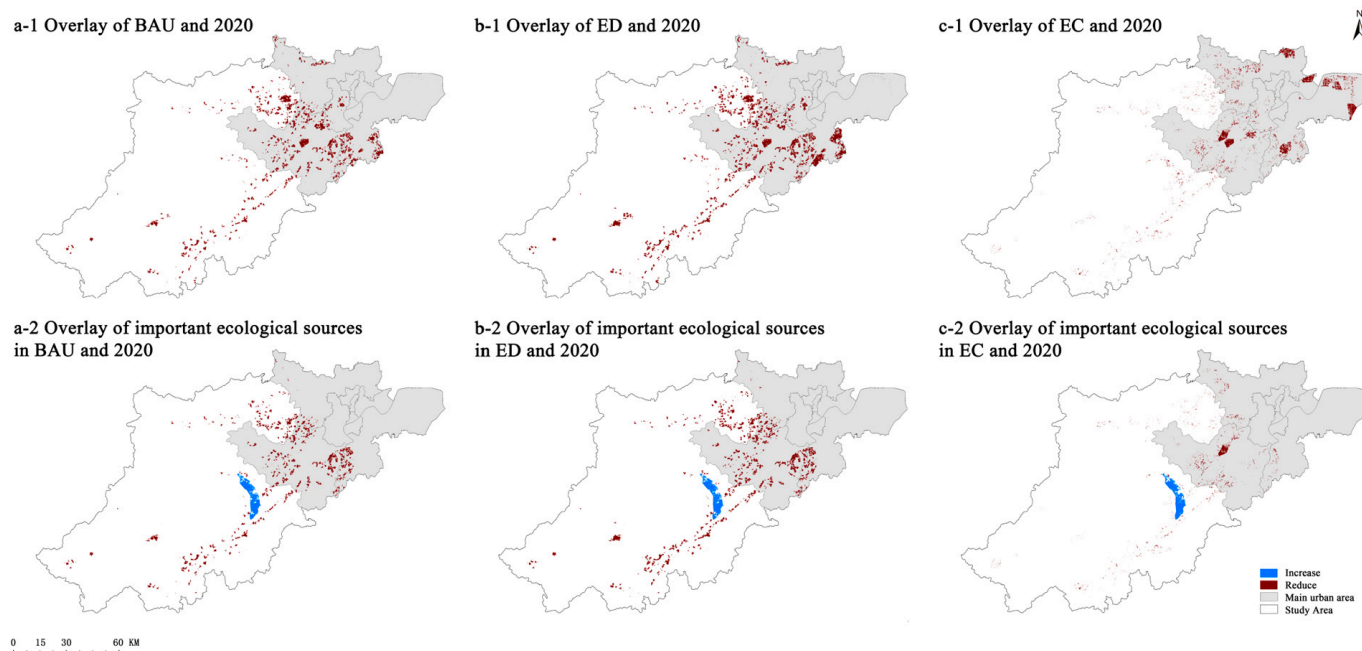


Figure 10. Spatial overlay of ecological source under multiple scenarios.

Under the BAU scenario, continuous urban expansion isolates smaller, morphologically complex patches, thereby reducing spatial continuity and network redundancy. The ED scenario demonstrates the most severe structural fragmentation. Intensive development compresses and segments sources, converting former stepping-stone connectors into isolated, terminal nodes. Consequently, the ED network becomes disproportionately dependent on a few large core sources, significantly increasing its vulnerability to external disturbances.

Conversely, the EC scenario achieves the highest structural stability. Regulated by strict development constraints, source integrity is preserved and spatial isolation is minimized. Notably, the nominally lower source count under the EC scenario reflects structural consolidation—driven by patch amalgamation, reduced edge fragmentation, and improved compactness—rather than ecological deterioration.

Overall, similar source quantities across the scenarios conceal profound differences in the internal organization, structural connectivity, and ecological resilience of the network.

3.4.2. Overlay Analysis of Potential Forest-Dominated Ecological Corridors

Compared to the 2020 baseline, the MCR-derived network undergoes significant reorganization (e.g., alignment shifts, rerouting, and density changes) due to scenario-driven alterations in ecological sources and resistance surfaces (Figure 11).

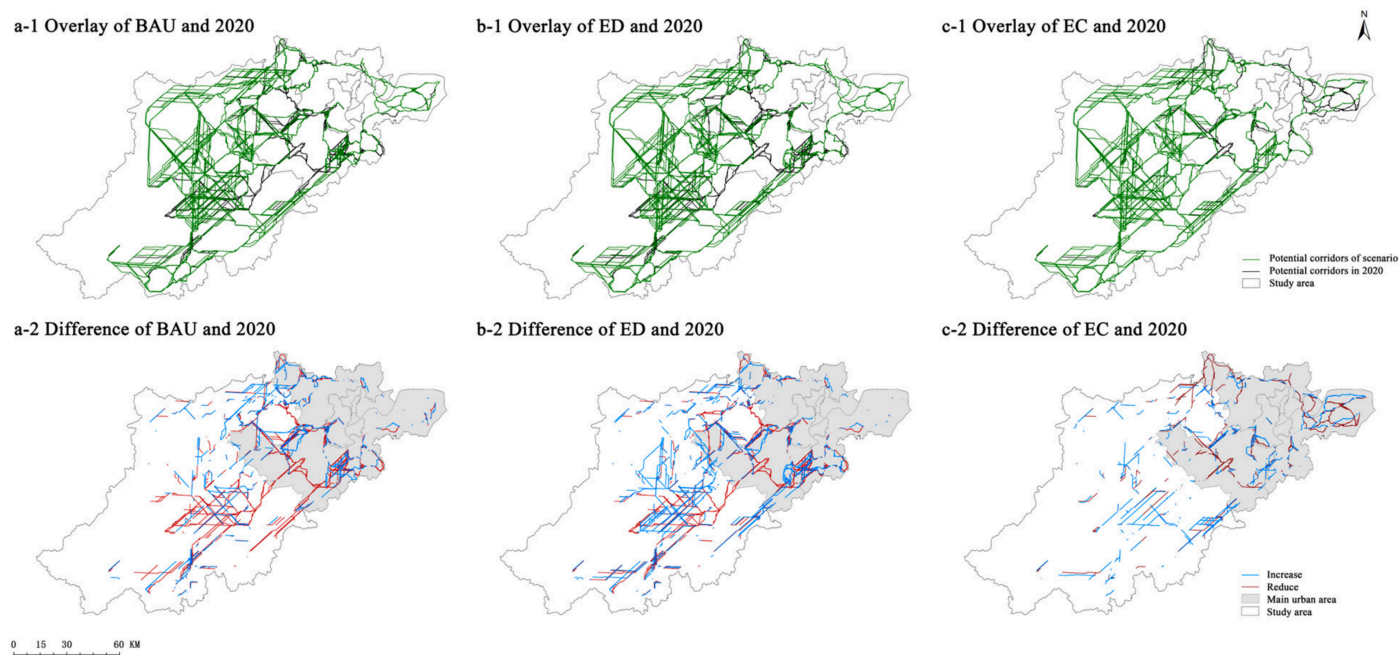


Figure 11. Spatial overlay of ecological corridor under multiple scenarios.

Under the BAU scenario, moderate development pressure at urban fringes causes local pathway realignments and slightly reduces network redundancy. The ED scenario exhibits severe reorganization; intense built-up expansion eliminates parallel pathways, significantly increasing bottleneck risks and compromising overall structural robustness. Conversely, the EC scenario maintains high spatial stability and continuity, with structural adjustments largely confined to short-distance alignment optimizations. Notably, these pathways represent structural potentials inferred from resistance modeling to compare scenario impacts, rather than empirically validated ecological or thermal flows.

Quantitatively (Table 4), the EC scenario forms the most cooling-effective configuration. Despite a lower total corridor length, it features the shortest mean length (7957.93), highest length coefficient of variation ($CV = 1.6283$), largest network scale (2639 nodes; 3835 edges), and maximum network diameter (341). These topological metrics indicate a dense hierarchy of short, localized corridors optimally structured to connect ecological sources and facilitate the spatial diffusion of cooling benefits.

Table 4. Comparison of network structure metrics under the BAU, ED, and EC scenarios.

Metric	BAU	ED	EC
Nodes	904	1181	2639
Edges	1515	1963	3835
Diameter	98	174	341
Total corridor length	64,729,951.46	64,481,907.59	56,954,923.96
Mean corridor length	12,827.97	12,268.25	7957.93
Corridor length CV	1.0853	1.0987	1.6283

3.4.3. Overlay Analysis of Ecological Breakpoints

To further evaluate structural vulnerability within the ecological network, Kernel Density Estimation (KDE) was applied to ecological breakpoints—locations where potential corridors are structurally interrupted or compressed (Figure 12). The KDE is calculated as:

$$f(s) = \sum_{i=1}^n \frac{1}{h^2} k\left(\frac{s - c_i}{h}\right) \quad (7)$$

where $f(s)$ is the calculated kernel density function at location s ; c_i is the event point; h is the distance threshold; k is the spatial decay function, wherein the kernel density value drops to 0 when the distance to the core c_i reaches the threshold h ; and n is the number of sample points whose distance to location s is less than or equal to h .

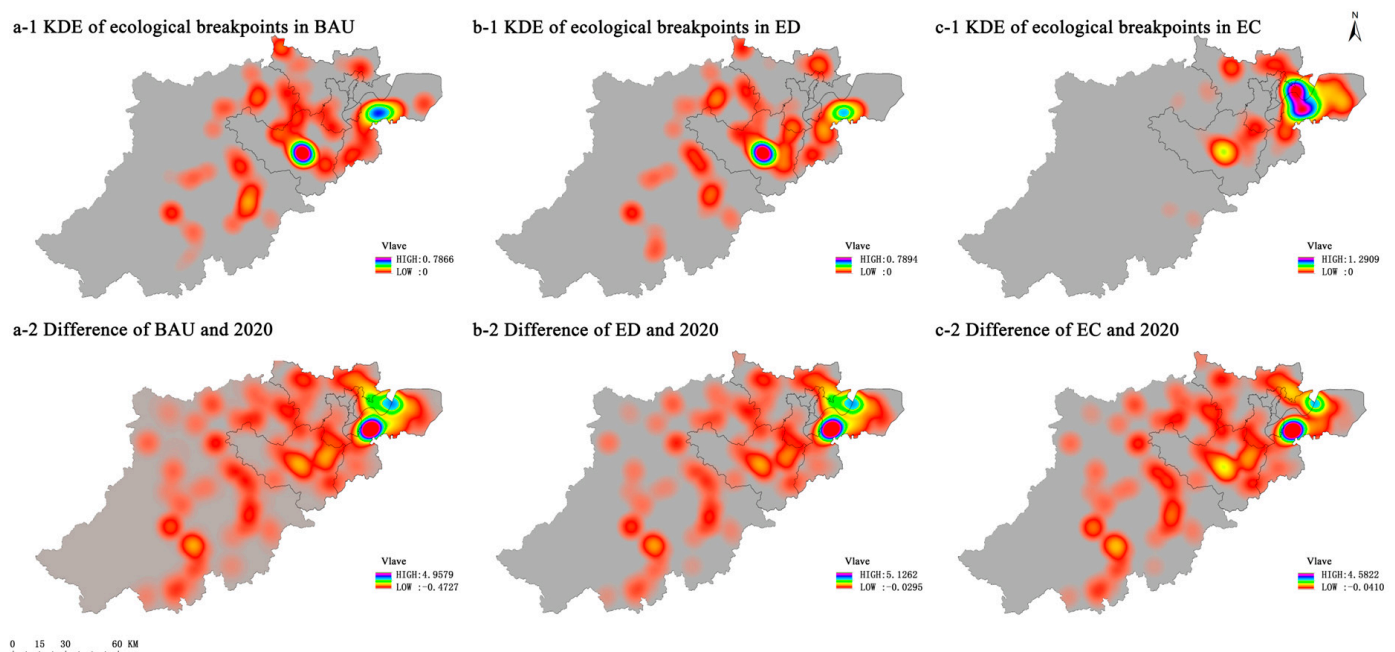


Figure 12. KDE of Ecological Breakpoints under Multiple Scenarios.

The KDE results reveal distinct scenario-dependent evolutionary trajectories of spatial breakpoints compared to the 2020 baseline:

- (1) BAU (Continued accumulation and peripheral expansion): Breakpoint hotspots cluster at built-up/ecological interfaces (e.g., Linping, Qiantang, Xiaoshan, and Fuyang districts), forming belt-like interruption zones driven by development inertia.
- (2) ED (Intensification and spatial diffusion): High-density hotspots broadly expand along the city's main development axis. This intense development not only exacerbates local rupture risks but also widens the spatial range of corridor instability, complicating localized management.
- (3) EC (Overall contraction and localized concentration): Both the number and density of breakpoints decrease significantly. The remaining hotspots are tightly confined to specific edge-contact areas (e.g., the Qiantang–Xiaoshan fringe), highlighting the efficacy of ecological policies in suppressing structural ruptures and maintaining network integrity.

Ultimately, these variations demonstrate that scenario differences lie in internal structural stability as much as in ecological land quantity. While these modeled KDE hotspots represent elevated structural fragmentation risks rather than empirically validated ecological failures, they provide spatially explicit targets for urban ecological governance and priority corridor restoration.

3.5. Evolution of Urban Thermal Environment (LST) Effects Based on Ecological Networks

3.5.1. Baseline Land Surface Temperature Patterns and Edge-Related Thermal Context

Based on the 2020 remotely sensed LST dataset, clear thermal differentiation was observed among major land use/land cover (LULC) types (Figure 13a). Built-up land and barren land exhibited the highest surface temperatures, with mean LST values of 45.41 °C

and 45.31 °C, respectively, indicating pronounced surface heat accumulation. In contrast, water bodies and forest land represented the coolest land-cover categories, with mean LST values of 31.99 °C and 32.41 °C, respectively. These results are consistent with the expected thermal buffering roles of water surfaces and tree-covered areas in urban landscapes.

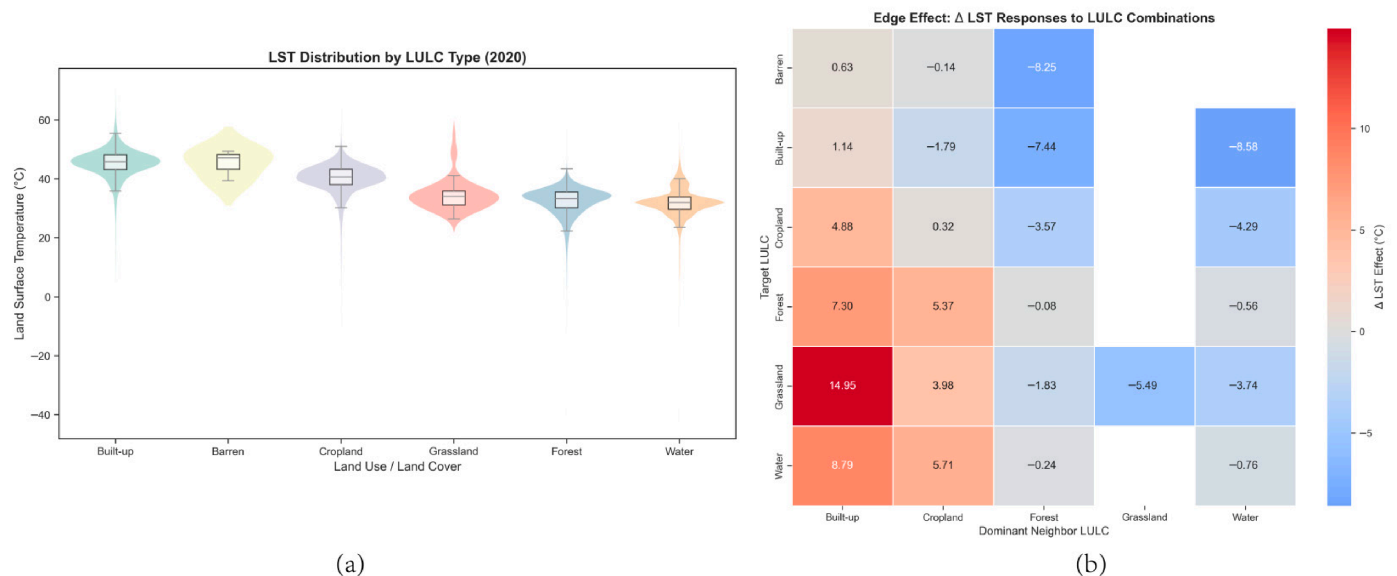


Figure 13. (a) LST Distribution of Different Land Use Types and (b) the Adjacency Thermal Effect Matrix in 2020.

While these baseline differences confirm strong thermal contrasts among LULC types, the comparison of median and distributional characteristics reveals that the LST of grassland and forest do not differ sharply. This similarity in median LST can be attributed to several factors. Biophysically, urban grasslands during summer often maintain high soil moisture and intense evapotranspiration—frequently supplemented by artificial irrigation—which can cool surface temperatures to levels comparable to forest canopies. Furthermore, at the 30 m spatial resolution of the LULC data, mixed pixels containing sparse trees and grass are common, potentially blurring the thermal boundary between low-density forests and open grasslands. This suggests that local thermal behavior is not controlled solely by broad land-cover classifications, but is shaped by internal structural characteristics (e.g., canopy density), local moisture conditions, and the surrounding spatial context. Therefore, the thermal role of urban vegetation should be interpreted as context-dependent rather than as a fixed attribute of a land-cover class.

To further explore this context dependence, adjacency fractions between neighboring land-cover combinations were extracted and summarized in the thermal adjacency matrix (Figure 13b). The matrix shows that local LST is strongly associated with adjacent land-cover composition. On the one hand, built-up land adjacent to cooler surfaces such as water and forest exhibits markedly lower surface temperature than built-up land embedded in more artificial surroundings: the mean temperature shift reaches -8.58 °C when adjacent to water and -7.44 °C when adjacent to forest. On the other hand, forest and grassland located within strongly built-up contexts display substantially higher temperatures than their baseline category averages, with positive shifts of 7.30 °C and 14.95 °C, respectively.

These patterns are compatible with a process of edge-related thermal erosion in which artificial surfaces weaken the thermal buffering capacity of adjacent vegetated patches. However, the present data demonstrate spatial associations among neighboring land-use combinations rather than a fully isolated physical mechanism. Therefore, throughout this study, the term “thermal erosion” is used in a cautious sense to describe patterns consistent

with edge-related warming effects, rather than as direct proof of the full causal process. Taken together, the results suggest that urban heat mitigation should focus not only on the total quantity of green space but also on the spatial configuration, edge integrity, and adjacency context of urban forests and other cooling surfaces.

3.5.2. Distance–Decay Pattern and Spillover Cooling of Forest-Dominated Ecological Corridors

Potential ecological corridors may contribute to thermal mitigation by maintaining continuous vegetated structures across urban space. To examine this possibility, the study quantified the spatial relationship between LST and distance from the nearest potential forest-dominated ecological corridor. Rather than using machine-learning partial dependence, this curve was derived through direct spatial buffering. Specifically, the Euclidean distance from each raster pixel to the nearest corridor boundary was calculated, and the pixels were sequentially grouped into 50 m distance intervals. Using the mean LST of areas located beyond 1000 m from the corridor as the background reference [31], a corridor-related cooling gradient (ΔLST) was calculated for each interval and summarized as a distance–decay curve (Figure 14a).

The results show a clear distance–decay pattern. Mean absolute LST increases gradually with increasing distance from the nearest corridor, from 33.53 °C within the 0–50 m band to 35.29 °C in the 900–950 m band. The corresponding cooling effect is strongest in the immediate corridor vicinity, with a mean ΔLST ranging from approximately -1.77 °C to -1.90 °C within the first 100 m, and remains detectable up to approximately 300 m from the corridor edge. These results indicate that corridor-associated cooling is strongest at short range and weakens progressively with distance.

Further stratification by corridor type and neighboring land-use context reveals substantial heterogeneity in the magnitude of this effect (Figure 14b,c). Corridors dominated by forest land exhibit stronger and more persistent cooling signals than less densely vegetated or thermally mixed corridor contexts. Built-up land located near forest-dominated corridors receives the most pronounced relative cooling benefit. For example, built-up pixels immediately adjacent to the corridor boundary show a temperature reduction of up to -8.04 °C, while the cooling effect remains evident at 30 m (-3.93 °C) and 120 m (-2.98 °C) from the corridor.

These findings suggest that the thermal benefits of ecological corridors are not spatially uniform, but depend on both corridor attributes and the thermal properties of surrounding land uses. At the same time, this analysis should be interpreted cautiously. The MCR-derived corridors used here are potential structural corridors, not empirically validated airflow channels or directly observed cooling conduits. Accordingly, the observed distance–decay relationship is interpreted as a corridor-related thermal pattern, rather than conclusive proof that the corridor itself physically transports cooling. Nevertheless, the results are compatible with the idea that preserving or strengthening forest-dominated corridor structures around dense built-up areas may enhance local heat mitigation capacity.

3.5.3. Contributions of Spatial Drivers to the Thermal Environment Based on the RF-SHAP Model

To clarify how different spatial variables jointly influence the thermal environment, a Random Forest (RF) regression model combined with SHAP interpretation was applied (Figure 15a). The model achieved an R^2 of 0.768, indicating acceptable predictive performance for capturing nonlinear thermal variation across heterogeneous urban landscapes. However, this accuracy should be interpreted as evidence of a useful explanatory-predictive model rather than a complete representation of all thermal processes.

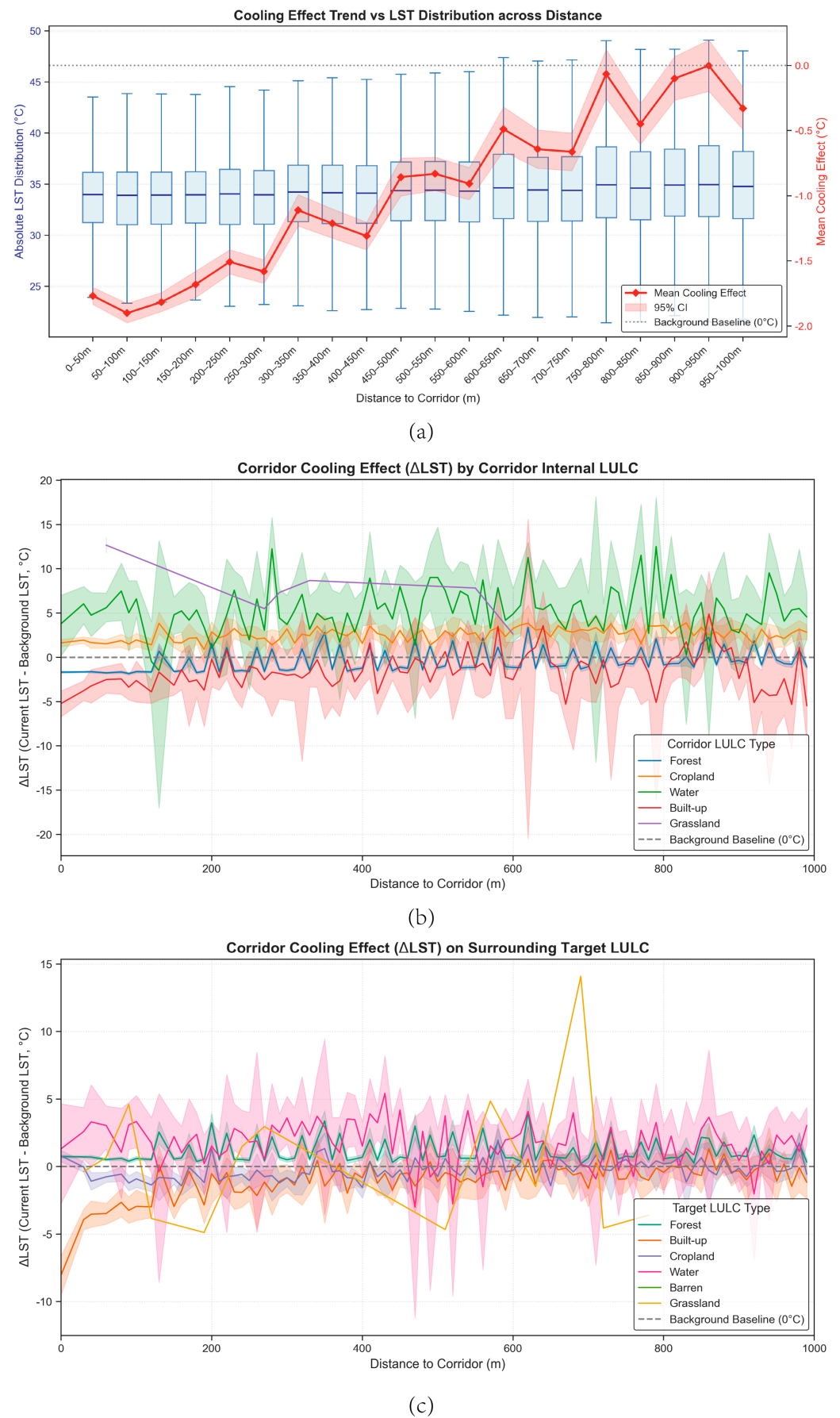


Figure 14. (a) Distance decay curve and dual-axis trend plot of the cooling effect of ecological corridors (b) by corridor internal LULC and (c) on surrounding target LULC.

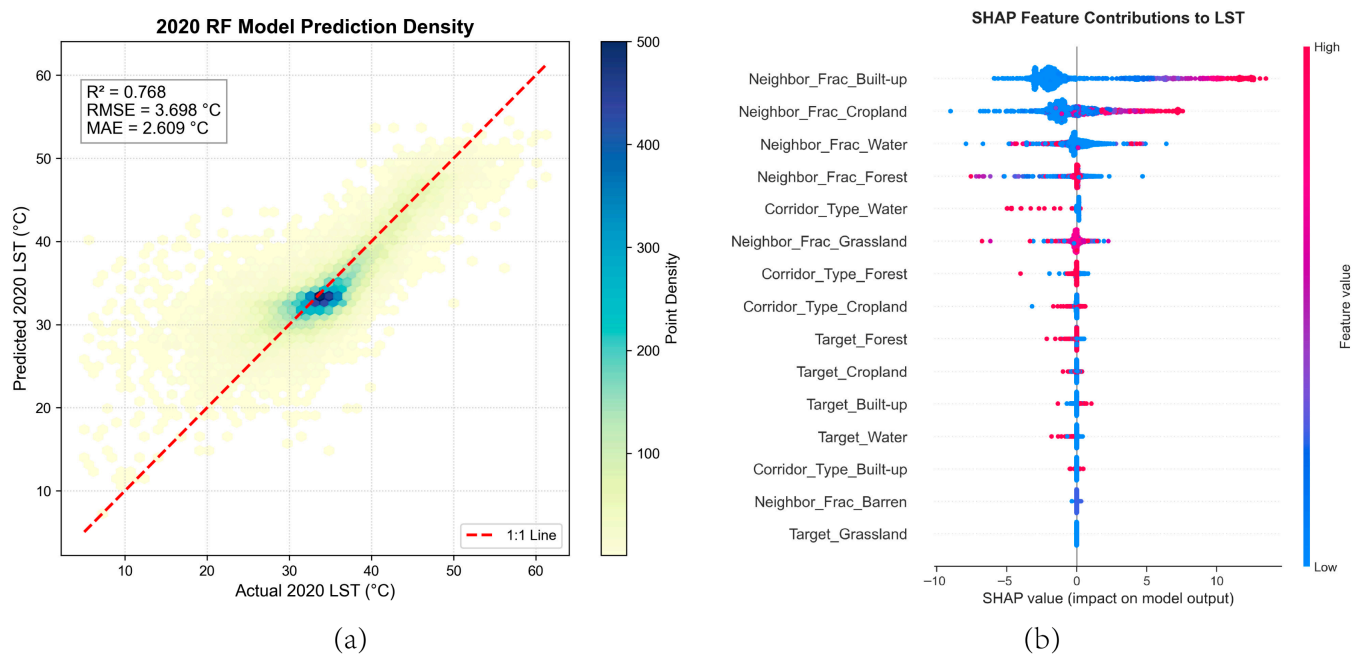


Figure 15. (a) Predictive performance evaluation of the RF model and (b) SHAP-based global feature contributions of LST driving factors.

The SHAP-based global importance ranking (Figure 15b) shows that local LST is strongly shaped by the spatial context effect of surrounding land-cover composition. Among all predictors, Neighbor_Frac_Built-up has the highest average absolute SHAP value (3.2943), indicating that the proportion of built-up land in the neighborhood is the dominant factor associated with local temperature increase. By contrast, adjacency to forest and water contributes negatively to predicted LST, reflecting their cooling association within the model.

These results support the interpretation that urban thermal conditions are controlled not only by the land-cover type of a focal pixel, but also by the structure of the surrounding landscape matrix. In particular, compact clusters of built-up land amplify local heat accumulation, whereas nearby cooling surfaces such as forests and water moderate thermal intensity. Therefore, the mitigation of urban thermal stress depends not simply on increasing green area in isolated patches, but on coordinated spatial optimization of built-up intensity, forest distribution, and water-green network configuration.

To ensure transparency and reproducibility, the detailed RF-SHAP modelling settings are provided in Appendix A, including the full names, units, and definitions of all predictor variables. In this study, the Random Forest model was trained using a random sample of up to 100,000 observations from the full valid dataset, and SHAP values were calculated from a further random subsample of up to 1500 observations (random_state = 42). Model performance was assessed using the in-sample R^2 between observed and fitted LST values, as no explicit training–testing split was applied in the current workflow. These details provide the basis for reproducing the modelling procedure and for interpreting the relative contribution of individual predictors more rigorously.

3.5.4. Multi-Scenario Simulation of the Thermal Environment for 2030

The Random Forest (RF) model, which demonstrated robust predictive accuracy during the 2020 calibration phase with an in-sample R^2 of 0.768, served as the diagnostic engine for future thermal projections. Following the principle of space-for-time substitution, we applied the learned thermal response relationships to the three 2030 land-use scenarios gen-

erated by the MC-PLUS framework: Natural Development (ND), Economic Development (ED), and Ecological Conservation (EC).

To ensure predictive consistency, the 2030 LST surfaces were simulated by integrating scenario-specific structural variables—including updated land-use patterns, recalculated neighborhood composition fractions (within an 11×11 window), and Euclidean distances to the newly configured ecological corridors—while maintaining physical indices (NDVI, NDBI, and NDWI) as baseline environmental constraints. Subsequently, scenario-based cooling gradients were derived by calculating the pixel-level temperature deviation (ΔLST) relative to the unaffected background temperature (defined by the 1000 m threshold identified in Section 4.3). These outputs (Figures 16–18) provide a spatially explicit basis for comparing the efficacy of alternative ecological network designs in mitigating future urban heat stress and inform climate-adaptive spatial planning.

The results indicate that the ED and BAU scenarios are associated with higher background thermal conditions than the EC scenario. In the distal reference zone located 950–1000 m from the nearest corridor, the predicted mean LST reaches 35.44 °C under ED and 35.41 °C under BAU, compared with 35.00 °C under EC. Although the absolute differences among scenarios are moderate, they are spatially systematic and coincide with major differences in urban expansion intensity, forest edge preservation, and corridor continuity.

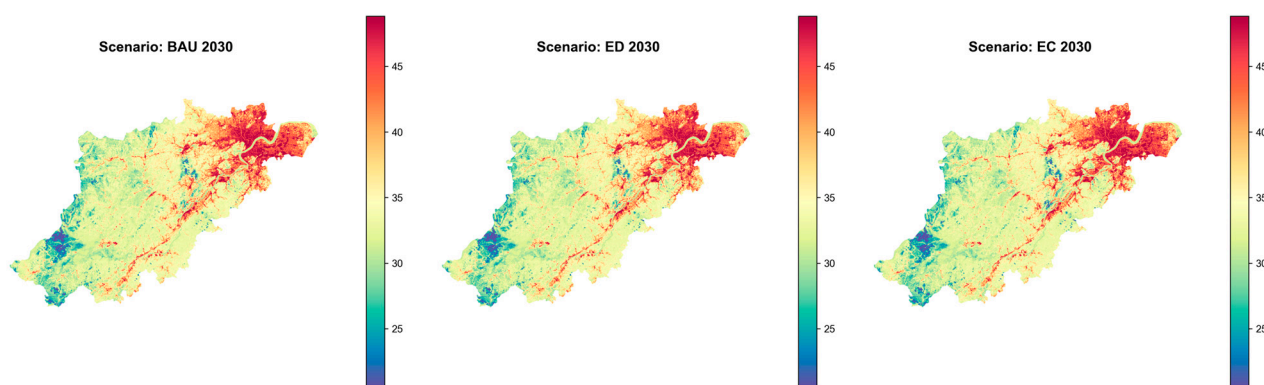


Figure 16. Spatial overlay of LST map for 2030 under Multiple Scenarios.

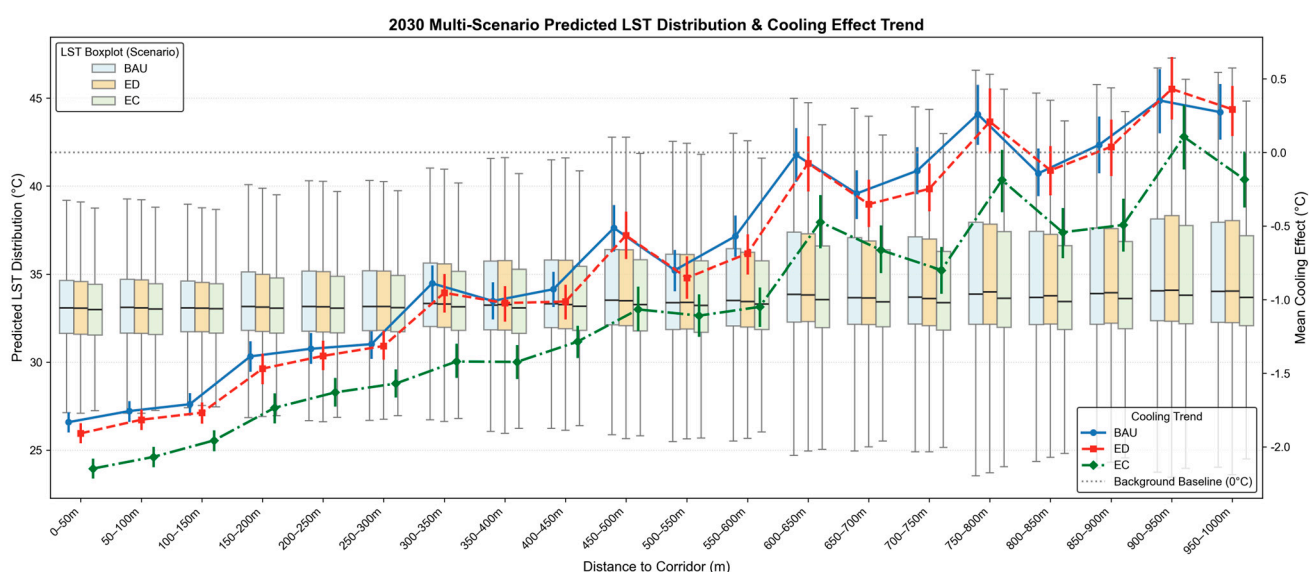


Figure 17. Dual-axis trend plot of cooling effect for 2030 under Multiple Scenarios.

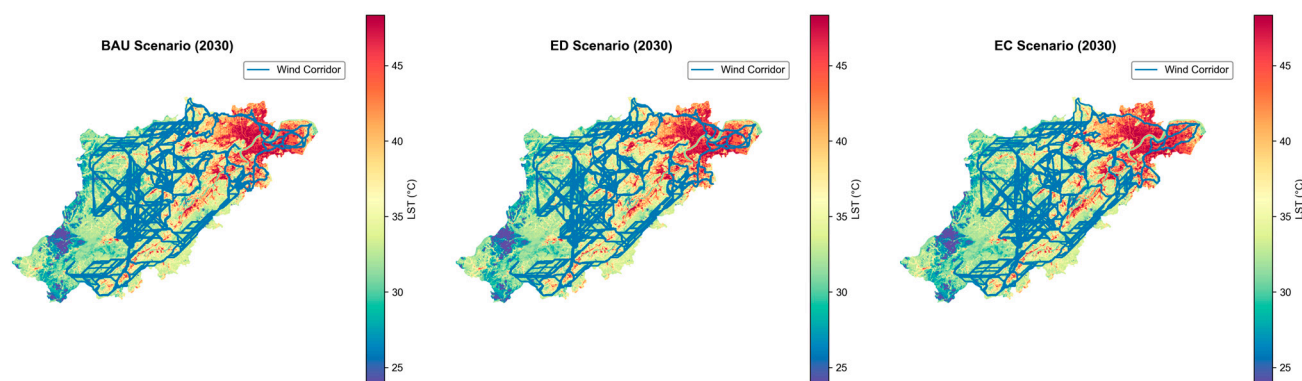


Figure 18. Spatial overlay of ecological corridor on LST map for 2030 under Multiple Scenarios.

The distance–decay curves further illustrate how these scenarios differ in maintaining corridor-related cooling gradients (Figure 17). Under the EC scenario, the strongest cooling effect occurs in the immediate corridor buffer (0–50 m), where the mean Δ LST reaches approximately -2.15°C . As distance increases, the cooling signal under BAU and ED weakens more rapidly and becomes negligible near 900–950 m, whereas the EC scenario retains a detectable negative thermal difference over a longer distance, persisting to approximately 850–900 m. This suggests that the EC scenario is more favorable for preserving the spatial continuity and persistence of corridor-related thermal mitigation.

Nevertheless, the practical relevance of these scenario differences should be interpreted with caution. Some contrasts in background temperature are relatively small in absolute terms, and their planning significance depends on the broader context of model uncertainty, spatial consistency, and cumulative heat exposure across the landscape. For this reason, the scenario results are best understood as comparative spatial tendencies, rather than exact deterministic forecasts of future surface temperature.

From a spatial planning perspective, the results indicate that fragmented increases in green space alone are unlikely to offset the systemic warming associated with dispersed urban expansion. Instead, preserving the structural integrity of connected forest–water corridor systems appears more effective for sustaining background cooling gradients and reducing thermal exposure in adjacent built-up areas. Accordingly, future planning should prioritize the protection of key corridor skeletons, forest edges, and associated buffer zones, especially in locations where urban expansion would otherwise sever cooling-supportive landscape continuity.

3.5.5. Planning and Governance Implications for Urban Forest Optimization

By integrating the multi-scenario evolution of ecological network structure with the nonlinear spatial drivers of LST, this study suggests that fragmented and isolated increases in green space are insufficient to counteract the combined ecological and thermal pressures associated with high-intensity urban development. Instead, urban climate adaptation and ecological governance should move from area-based greening alone toward a more integrated spatial strategy that simultaneously considers source conservation, corridor continuity, and hotspot intervention.

Accordingly, the EC scenario provides the most favorable planning orientation among the three scenarios examined here, not because it completely eliminates warming or fragmentation, but because it better preserves the structural conditions associated with ecological stability and corridor-related cooling persistence. Based on these findings, a planning framework can be proposed at three spatial levels:

(1) Area level: safeguard core forest sources and reduce edge-related warming pressure

Ecological source areas with high persistence and structural importance—such as major mountainous forests and key urban forest complexes—should be incorporated into strict protection or high-priority conservation zones. In these areas, planning should focus not only on preventing direct land conversion but also on reducing edge exposure to dense artificial surfaces. Functional transition zones and ecological buffers should be established around major forest sources to reduce edge-related warming pressure and support the restoration of degraded peri-forest landscapes.

(2) Line level: strengthen connected forest-water corridor systems

Given the limited continuity of green linkages in parts of the main urban area, urban planning should prioritize the maintenance and reinforcement of connected forest-water corridor structures. Particular attention should be given to corridor sections adjoining high-density built-up land, where corridor-related cooling benefits appear strongest. Rather than treating all green space as equivalent, planning should emphasize connectivity, width, continuity, and buffer integrity in corridor design, while preserving the effective cooling zone identified in the near-corridor range, especially within approximately 0–300 m, where thermal mitigation is most apparent in the present analysis.

(3) Point level: target ecological breakpoints and thermal vulnerability hotspots

At the urban expansion front and in structurally fragile transition zones, localized ecological interventions should be used to repair network discontinuities and reduce thermal vulnerability. Such interventions may include stepping-stone vegetation patches, small urban forests, pocket parks, and other forms of targeted greening, depending on local land availability and landscape context. In areas with recurrent ecological breakpoints, dynamic monitoring of canopy continuity, land conversion pressure, and local thermal conditions should be incorporated into fine-scale urban forestry governance.

These recommendations should be understood as scenario-informed planning implications, rather than direct prescriptions derived from experimentally verified thermal transport processes. Even so, they indicate that urban forest optimization is likely to be most effective when ecological network planning and heat mitigation planning are addressed jointly, rather than as separate policy domains.

4. Discussion

4.1. From Extensive Urban Expansion to Structure-Based Forest–Thermal Synergy

The results indicate that, in Hangzhou, differences among future scenarios are expressed less by simple changes in the total amount of ecological land than by changes in spatial configuration, edge integrity, and source–corridor continuity. This finding is consistent with graph-based connectivity research showing that habitat amount alone does not adequately represent ecological availability, because connectivity depends on both patch attributes and the way patches are linked within the landscape [46]. It also agrees with recent MSPA-MCR studies showing that urban ecological security is strongly shaped by the joint organization of sources, corridors, and resistance surfaces rather than by area totals alone [52,53]. In this sense, the present study supports a transition from area-oriented planning logic toward a structure-oriented planning logic, in which the thermal and ecological consequences of urban growth are mediated by where development occurs and how it alters the continuity of wooded land.

This interpretation is also supported by the thermal results. Previous studies have shown that urban forest cooling is influenced not only by forest presence, but also by patch structure, crown closure, leaf area, neighboring greenspace, and spatial location relative to buildings and water. Ren et al. [54], for example, found that urban cool island

intensity varied with forest structural attributes and location, with important distance-related thresholds relative to surrounding built form. Xu et al. (2024) likewise showed that the cooling effect of forest vegetation is generally stronger than that of grassland and that the relationship between forest pattern and LST is scale-dependent [55]. The present results extend this line of evidence by showing that built-up expansion into forest edges is associated with stronger local warming and that the cooling value of forest land depends heavily on adjacency context. Accordingly, urban thermal mitigation should not rely only on increasing green coverage in aggregate; it should focus on preserving compact, connected, and edge-protected forest structures, especially where wooded land interfaces with dense built-up land.

The corridor-related results point in the same direction. The EC scenario does not simply preserve more “green space”; it preserves a more coherent forest–water structural skeleton, which is associated with lower background LST and a more persistent cooling gradient. This is consistent with broader urban greening literature showing that cooling effects are sensitive to measurement method, spatial scale, and buffer definition, and that remotely sensed LST studies should be interpreted as spatial thermal patterns rather than direct substitutes for canopy-layer thermal comfort [56]. Recent synthesis work has also emphasized that surface temperature and air temperature may diverge substantially, which is important when translating landscape metrics into planning implications [57]. For this reason, the contribution of this study is not that it proves a fully observed physical cooling transport mechanism, but that it identifies a set of spatial patterns compatible with stronger forest-related thermal buffering under a conservation-oriented development pathway.

From a planning perspective, this means that mature urbanization should be managed through spatial restructuring rather than continued outward land conversion. In practical terms, policy should prioritize the control of built-up encroachment into forest edges, the maintenance of corridor continuity in peri-urban transition zones, and the reinforcement of forest–water linkages in high-heat-risk sectors [58]. Such a strategy is more consistent with resilient urban development than a conventional approach centered only on meeting greening quotas.

4.2. The Planning Value of Coupling Multi-Scenario Ecological Networks with Interpretable Machine Learning

A key methodological contribution of this study is the integration of multi-scenario land-use simulation, forest-dominated ecological networks, and interpretable machine learning. While earlier MSPA-MCR studies primarily focused on static landscape connectivity [13] and recent thermal analyses have utilized ML (e.g., Random Forest, XGBoost, SHAP) to uncover nonlinear LST relationships [59,60], our framework synergizes these approaches. By linking future scenario-based land allocations with network structures, this coupling enables the simultaneous interpretation of spatial LST drivers and plausible future trajectories, significantly enhancing policy relevance.

The RF-SHAP results strongly reinforce the spatial context of urban thermal outcomes. Consistent with interpretable ML literature showing that vegetation mitigates heat while imperviousness drives nonlinear thermal amplification [54], our results identify the neighborhood built-up fraction as the dominant warming driver and proximity to forest/water as key cooling factors. This underscores that ecological planning and urban heat mitigation are fundamentally inseparable: spatial decisions governing patch isolation, edge exposure, and corridor continuity directly dictate the urban thermal behavior.

Furthermore, this coupled framework enhances the resolution of decision support. By identifying structural elements that remain resilient across alternative development pathways (e.g., the preserved core forests and persistent cooling gradients in the EC scenario), it transcends the limitations of purely static network assessments and retrospective

heat-island analyses. Consequently, it provides a practical, spatially explicit basis for prioritizing ecological redlines, corridor protection, and restoration in zones where structural and thermal benefits overlap.

Although MCR identifies potential structural pathways rather than empirical ecological flows, and RF provides scenario-based thermal estimates rather than absolute microclimate forecasts, this integrated approach remains highly operational. It equips planners to transparently evaluate the compounded structural and thermal consequences of diverse land-use strategies, substantially outperforming isolated connectivity or thermal modeling.

4.3. Limitations and Prospects for a Structure–Function–Oriented Forest Evaluation Framework

While this study provides a novel framework for forest evaluation, several limitations remain to be addressed in future research:

(1) Parameter sensitivity and thresholding in connectivity models:

Connectivity metrics (e.g., IIC, PC, and MSPA-MCR) are inherently sensitive to spatial resolution, resistance assignments, and distance thresholds. For instance, the observed reduction in corridor counts in the EC scenario may indicate a functional amalgamation of the network rather than a loss of connectivity. This suggests that future evaluations should prioritize functional performance (e.g., flow volume or ecological flux) over the mere quantification of structural components.

(2) Spatial scale and thresholds for microclimate analysis:

The 1000 m range used to define “unaffected background temperature” for ΔLST calculation was chosen based on reported cooling distances for urban green infrastructure. However, this threshold is an analytical simplification. Urban thermal environments are highly heterogeneous; a 2000 m range might better capture macro-scale cooling in sparse urban fabric but risks introducing noise from distal land-use types. Future work should employ multi-scale sensitivity analyses to determine if optimal cooling buffers vary across different urban functional zones.

(3) Discrepancies between surface and canopy-layer thermal dynamics:

This framework relies on Land Surface Temperature (LST), which effectively captures lateral spatial patterns but may overestimate heat stress compared to ambient air temperature. LST does not account for vertical canopy-layer airflow or the physiological mechanisms of human thermal comfort. Integrating satellite-derived LST with high-density in situ meteorological sensors and urban canopy models (UCMs) remains essential for a more granular understanding of forest-driven cooling.

(4) Integration of 3D urban morphology:

The current 2D model overlooks vertical urban complexity (e.g., building height, Sky View Factor, and building density). Given that microclimates at scales below 100 m are non-linearly influenced by shading and local radiative geometry, next-generation frameworks must couple 2D forest metrics with 3D morphological parameters to provide more accurate climate-adaptive design recommendations.

(5) Resolution limits in forest categorization and canopy structure:

The current macro-level framework relies on a generalized “forest” category derived from 30 m LULC datasets. Consequently, the internal structural heterogeneity of urban forests—such as variations between high-stocked forest stands and low-density tree cover—is not explicitly differentiated. While topological and area-based criteria (e.g., patch area > 16 km²) effectively screen core ecological network sources at a regional scale, they

cannot capture intra-class canopy variations. Future meso-to-micro scale assessments must integrate high-resolution canopy masks and LiDAR-derived volumetric metrics to construct a refined urban forest typology, thereby clarifying how specific stand characteristics influence thermal regulation.

5. Conclusions

This study integrated multi-scenario land-use simulation, forest-dominated ecological network modeling, and interpretable machine learning (RF-SHAP) to explore the synergistic evolution of urban structural connectivity and the thermal environment in Hangzhou. The multi-scenario projections for 2030 reveal that the resilience of the urban ecological network depends less on the total quantity of forest patches than on their spatial configuration, edge integrity, and structural continuity. Under the Economic Development (ED) and Business-as-Usual (BAU) scenarios, multi-centric and continuous outward sprawl of built-up land intensifies the fragmentation of forest habitats. This development inertia not only disrupts potential structural corridors across peri-urban transition zones but also elevates the density of network breakpoints, substantially weakening the overall structural robustness of the ecological network.

Furthermore, the thermodynamic analysis confirms that local Land Surface Temperature (LST) is primarily governed by the “spatial context” of macro-landscape components. The RF-SHAP model identifies neighborhood built-up fraction as the dominant driver of localized warming. The intensive encroachment of artificial surfaces into forest borders triggers significant edge-related warming, compromising the natural cooling baseline of wooded patches. In contrast, spatially continuous forest-dominated corridors demonstrate a pronounced thermal buffering capacity. Spatial distance–decay analysis reveals that built-up areas immediately adjacent to these corridors experience significant relative LST reductions, with the most effective cooling patterns concentrated within a 300 m proximity.

Crucially, the Ecological Conservation (EC) scenario demonstrates that mitigating urban heat and ecological fragmentation does not strictly require massive increases in total green space area. By enforcing ecological redlines and promoting a compact urban form, the EC scenario achieves a higher quality of structural consolidation. Despite a slight reduction in the absolute number of isolated patches, the network’s structural integrity is enhanced through patch amalgamation and reduced breakpoint density. Consequently, this structurally optimized network effectively suppresses the diffuse expansion of extreme heat islands and maintains a persistent temperature buffering gradient up to 850–900 m in background areas. Ultimately, these findings indicate that future urban forestry and climate adaptation strategies must transition from an area-based quota system toward a structure-oriented paradigm. Planning should prioritize the protection of core forest-water structural skeletons, strictly control the disordered adjacency of high-density built-up land near ecological borders, and focus on suturing structural breakpoints to sustain both ecological connectivity and microclimate resilience.

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Abbreviations

The following abbreviations are used in this manuscript:

BAU	Business-as-Usual
EC	Ecological Conservation
ED	Economic Development
CA	cellular automata
CARS	CA based on Multiple Random Seeds
CCR	Contribution to Change Rate
CLUE-S	Conversion of Land Use and its Effects at Small regional extent
CR	Change Rate
dIIC	delta Integral Index of Connectivity
dPC	delta Probability of Connectivity
DEM	Digital Elevation Model
FLUS	Future Land Use Simulation
IIC	Integral Index of Connectivity
KDE	Kernel Density Estimation
LEAS	Land Expansion Analysis Strategy
LST	Land Surface Temperature
LULC	land use/land cover
MC	Markov Chain
MC-PLUS	Markov Chain coupled with PLUS
MCR	Minimum Cumulative Resistance
MSPA	Morphological Spatial Pattern Analysis
PC	Probability of Connectivity
PLUS	Patch-generating Land Use Simulation
RF	Random Forest
SHAP	SHapley Additive exPlanations
TIRS	Thermal Infrared Sensor
UHI	Urban Heat Island

Appendix A

Table A1. Definitions of predictor variables used in the SHAP analysis.

Variable	Full Name	Category	Definition
Neighbor_Frac_Cropland	Neighborhood fraction of cropland	Neighborhood composition	Proportion of cropland within the 11×11 neighborhood window
Neighbor_Frac_Forest	Neighborhood fraction of forest	Neighborhood composition	Proportion of forest within the 11×11 neighborhood window
Neighbor_Frac_Grassland	Neighborhood fraction of grassland	Neighborhood composition	Proportion of grassland within the 11×11 neighborhood window
Neighbor_Frac_Built-up	Neighborhood fraction of built-up land	Neighborhood composition	Proportion of built-up land within the 11×11 neighborhood window

Table A1. Cont.

Variable	Full Name	Category	Definition
Neighbor_Frac_Barren	Neighborhood fraction of barren land	Neighborhood composition	Proportion of barren land within the 11×11 neighborhood window
Neighbor_Frac_Water	Neighborhood fraction of water body	Neighborhood composition	Proportion of water body within the 11×11 neighborhood window
Target_Cropland	Target pixel land-use type: cropland	Target LULC type	Indicates whether the target pixel is cropland
Target_Forest	Target pixel land-use type: forest	Target LULC type	Indicates whether the target pixel is forest
Target_Grassland	Target pixel land-use type: grassland	Target LULC type	Indicates whether the target pixel is grassland
Target_Built-up	Target pixel land-use type: built-up land	Target LULC type	Indicates whether the target pixel is built-up land
Target_Barren	Target pixel land-use type: barren land	Target LULC type	Indicates whether the target pixel is barren land
Target_Water	Target pixel land-use type: water body	Target LULC type	Indicates whether the target pixel is water body
Corridor_Type_Cropland	Nearest corridor internal land-use type: cropland	Corridor internal LULC type	Indicates whether the nearest corridor pixel is cropland
Corridor_Type_Forest	Nearest corridor internal land-use type: forest	Corridor internal LULC type	Indicates whether the nearest corridor pixel is forest
Corridor_Type_Grassland	Nearest corridor internal land-use type: grassland	Corridor internal LULC type	Indicates whether the nearest corridor pixel is grassland
Corridor_Type_Built-up	Nearest corridor internal land-use type: built-up land	Corridor internal LULC type	Indicates whether the nearest corridor pixel is built-up land
Corridor_Type_Barren	Nearest corridor internal land-use type: barren land	Corridor internal LULC type	Indicates whether the nearest corridor pixel is barren land
Corridor_Type_Water	Nearest corridor internal land-use type: water body	Corridor internal LULC type	Indicates whether the nearest corridor pixel is water body

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