Coupling between the layout pattern of green space and the function of urban wetland biomes in the context of urbanisation

Abstract: Accelerated global urbanisation has led to a sharp decrease in the area of natural wetlands and degradation of biological functions, and the morphological heterogeneity of urban green space layout has become a key variable affecting the sustainability of wetland ecological services. Based on the multi-source data fusion of satellite remote sensing (Landsat-8, Sentinel-2), biometric sensor network (infrared camera, acoustic recorder, eDNA) and microclimate hydrological monitoring, we constructed a machine learning-driven coupled model of morphology-function, and analyzed the nonlinear response mechanism of the green space layout parameters and wetland biological communities. We constructed a machine learning-driven 'form-function' coupled model to analyse the nonlinear response mechanism between green space layout parameters and wetland biological communities. Empirical evidence shows that the density of green space patches in the core area (27.4 patches/km^2) is 3.4 times higher than that in the suburban area, but the connectivity index (0.15) is less than 1/4 of that in the suburban area, which leads to a 58% reduction of heron nesting area; the insect diversity in the area of nighttime light intensity >50 lux decreases by 63%, and the 'ecological blind zone' revealed by the sensor data accounts for The 'ecological blind zone' revealed by sensor data accounted for 78% of the built-up area-wetland interface zone. The prediction accuracy of the random forest model (R^2 =0.83) was significantly better than that of the traditional method, and the connectivity index (32.7% contribution) and water proximity (28.5%) were identified as the key driving factors. The study proposes a 'multi-centre + corridor' resilience planning framework, which improves the success rate of biotic migration by 57% and delays the peak of stormwater runoff by 0.8 hours through the implantation of 1-3 ha greenbelt nodes and 30-metre ecological corridors. The results provide dynamic assessment tools and spatial intervention targets for ecological restoration in high-density cities, and promote the transformation of urban planning from form-fitting to process synergy.

Keywords: Urban Wetland Biocommunity Function, Green Space Configuration, Urbanization Ecological Effects, Biometric Monitoring Technology, Ecological Function Coupling Model.

I. INTRODUCTION

With the acceleration of global urbanisation, urban wetlands, as a scarce ecological resource in high-density built-up areas, are facing serious challenges such as habitat fragmentation and plummeting biodiversity. For example, in mega urban agglomerations such as the Yangtze River Delta and the Pearl River Delta in China, more than 60% of natural wetlands have been converted into construction land or artificial waters in the past 20 years, and the average area of the remaining wetland patches has shrunk to less than 30% of the original size, which has led to the decline of more than 50% in the population size of benthic fauna, migratory waterbirds, and other key species [1-2]. At the same time, the urban green space layout shows a significant 'centre-edge' differentiation: the core urban area is dominated by scattered small green spaces with less than 15% vegetation coverage, while the suburban wetland parks have an ecological base, but they are cut off from the urban functional blocks, making it difficult to form an effective ecological service network. Existing studies have shown that the maintenance of wetland biological community functions (e.g. carbon and nitrogen cycling, pollutant degradation) is highly dependent on the structural connectivity of the green space. The dispersal radius of indicator species, such as dragonflies, is limited by the vegetation cover corridor within 300 metres, while the reproductive success of amphibians is positively correlated with the connectivity of water bodies within the 500-metre buffer zone [3-5]. However, traditional planning mostly focuses on static indicators such as green space rate, ignoring the dynamic coupling mechanism between spatial form and biological behaviour. The current monitoring of wetland ecological processes still relies on manual sampling with low spatial and temporal resolution, which makes it difficult to capture sudden ecological threshold mutations in the process of urbanisation in a timely manner [6]. The study aims to analyse the green space pattern and wetland biological function response mechanism supported by high-precision biometrics, and to construct a spatial optimization decision-making framework by integrating multi-source remote sensing data, biosensor networks and machine learning models. For the first time, the study applies biometrics technologies, such as bird voiceprint recognition and insect tracking, to wetland ecological diagnosis, breaking through the bottleneck of data granularity in traditional monitoring, and providing quantifiable dynamic assessment tools for smart city ecological planning.

II. Research Methodology and Technical Framework

A. *Multi-source data collection and processing*

By integrating three types of heterogeneous data, namely satellite remote sensing, biometric sensor network and microclimate and hydrological monitoring of urban wetlands, the study constructs a multidimensional data collection and analysis framework to support the study of the coupling mechanism between green space layout patterns and wetland biomes. Satellite remote sensing data are dominated by Landsat-8 Operational Land Imager (OLI) and Sentinel-2 Multispectral Instrument (MSI) imagery, covering the time-series imagery of the study area from 2015 to 2023. The radiometric correction was used to eliminate the effect of atmospheric scattering, and the Random Forest (RF) algorithm was used to classify the Land Use and Land Cover (LULC), which classified the land surface into six categories, namely, building land, roads, tree woodland, shrub grassland, water bodies and bare land, and the classification accuracy was verified to be 89.3% by the field sampling. In response to the dynamic change characteristics of the wetland water body boundary, the Normalised Difference Water Index (NDWI) was introduced, and the seasonal inundation area range was extracted by the sliding window method, with the temporal resolution increased to 8 days, and the spatial resolution reached 30 m (Landsat-8) and 10 m (Sentinel-2), respectively. The spatial resolution reached 30 m (Landsat-8) and 10 m (Sentinel-2) respectively. The technical parameters of the remote sensing data cover sensor type, spatial and temporal resolution, core processing algorithms and data usage, which provide the basis for the subsequent landscape pattern analysis. The technical parameters and processing flow of satellite remote sensing data are shown in Table 1.

TABLE I. SATELLITE REMOTE SENSING DATA TECHNICAL PARAMETERS AND PROCESSING WORKFLOW

Data Type	Data Source	Spatial Resolution	Temporal Resolution	Core Processing Algorithm	Data Application
Multispectral Imagery	Landsat-8 OLI	30 meters	16 days	Random Forest Classification	Land Use Classification
High-Resolution Imagery	Sentinel-2 MSI	10 meters	5 days	NDWI Time Series Analysis	Wetland Water Dynamics Monitoring
Thermal Infrared Data	Landsat-8 TIRS	100 meters	16 days	Land Surface Temperature Retrieval	Urban Heat Island Effect Assessment
Radar Data	Sentinel-1 C-SAR	20 meters	12 days	Interferometric Synthetic Aperture Radar (InSAR)	Surface Deformation Monitoring
Elevation Data	ALOS World 3D	30 meters	Static	Digital Elevation Model Generation	Terrain Slope and Watershed Delineation
Nighttime Light Data	Suomi NPP VIIRS	500 meters	Daily	Radiometric Calibration and Denoising	Human Activity Intensity Quantification

The biometric sensor network was deployed using a stratified sampling strategy, with 32 fixed monitoring nodes in the wetland core area, transition zone and urban greenfield edge zone. Each node integrates an infrared camera (Bushnell Aggressor series), a broadband acoustic recorder (Wildlife

Acoustics SM4) and an environmental DNA (eDNA) sampling device to synchronise the capture of species diversity, activity trajectories and genetic information. The infrared camera operates in passive infrared triggering mode with a time interval of 5 minutes and an effective detection range of 30 m, recording the diurnal rhythms of mammals, birds and amphibians; the acoustic recorder with a sampling rate of 48 kHz continuously captures the wing beating of insects, bird calls and frog courtship vocal patterns [7-8]; the eDNA sampling is performed through a filter membrane (0.45 μm aperture) that enriches the exfoliated cells of the water column, combined with macro barcoding technology (0.45 μm) and a micro barcoding technology (0.45 μm pore size) that allows for simultaneous capture of species diversity and genetic information. The eDNA samples were collected by filter membrane (0.45 μm pore size) to enrich the detached cells in the water column, and then combined with macro-barcoding technology (COI gene fragment amplification) to analyse the composition of zooplankton and benthos. After denoising and feature extraction, a Convolutional Neural Network (CNN) was used for automatic species identification. The model training set covered 12,800 acoustic samples and 9,450 infrared images from East Asia, with a cross-validation accuracy of 92.1%. The biometric sensor network deployment scheme, as shown in Table 2.

TABLE II. BIOSENSOR NETWORK DEPLOYMENT PLAN

Monitoring Level	Sensor Type	Deployment Density (units/km²)	Core Monitoring Objective	Data Fusion Strategy	Spatial Coverage Range
Wetland Core Area	Infrared Camera, eDNA Sampler	4.2	Waterbird Habitats, Benthic Community Structure	Spatial Hotspot Clustering Analysis	50-meter Radius Buffer Zone
Transition Zone	Acoustic Recorder, Micro Weather Station	3.8	Insect Pollination Paths, Amphibian Migration	Time Series Cross-Correlation	100-meter Belt Area
Urban Fringe Zone	Multi-Parameter Water Quality Sensor, Anemometer	2.5	Non-Point Source Pollution Input, Wetland-Urban Interaction	Gradient Diffusion Model Coupling	0-200 meters from Urban Boundary
Vegetation Corridor	Photosynthetically Active Radiation (PAR) Sensor	1.2	Canopy Light Transmittance, Microclimate	Spatial Interpolation Integration	±10 meters from Corridor Axis
Water Surface Layer	Plankton Sampler	0.8	Zooplankton Density, Algal Biomass	Vertical Profile Data Integration	0-0.5 meters Below Water Surface
Wetland Bottom Layer	Sediment Oxygen Probe	0.6	Benthic Habitat Environmental Quality	Time Lag Effect Analysis	0-10 cm Below Sediment Surface

Urban wetland microclimate and hydrological data are collected in real time through distributed IoT nodes, covering 14 parameters such as air temperature, relative humidity, wind speed, light intensity, water pH, dissolved oxygen (DO), conductivity and turbidity. The meteorological station (HOBO U30 series) was installed at a height of 1.5 metres from the ground, and the recording interval was set at 10 minutes to avoid the influence of vegetation shading on the integrity of the data; hydrological sensors (YSI EXO2 multi-parameter water quality meter) were deployed in the surface layer (0.5 metres in depth) and the bottom layer (1.2 metres in depth) of the wetland water body to monitor the change of vertical gradient simultaneously. The data were pre-processed using a sliding average method to eliminate transient noise and Kriging Interpolation to generate a spatially continuous field. For equipment drift errors, on-site calibration was performed once a month, using standard buffers (pH 4.01, 7.00, 10.01) to calibrate the pH probe, and the conductivity meter calibrant covering the range of 0-100 mS/cm, to ensure that the measurement error was controlled within ±2%.

Spatio-temporal alignment of multi-source data is a key technical aspect of this study. Firstly, based on the unified geographic coordinate system (WGS84 UTM Zone 50N), the spatial alignment of remote sensing images, sensor points and microclimate raster data was carried out using the ArcGIS platform, and the maximum residuals were controlled within 0.5 image elements. Secondly, Dynamic Time Warping (DTW) algorithm was used to match the data streams with different sampling frequencies, for example, to synchronise the minute-level meteorological data with the hourly biological activity records. Finally, we extracted the correlation characteristics between green spatial morphological indices (e.g., patch density, edge curvature, landscape connectivity) and biofunctional indices (e.g., species richness, trophic energy flow) by dimensionality reduction through Principal Component Analysis (PCA), which provided input variables for the construction of the subsequent coupled model.

B. *Quantitative Modelling of Green Space Layout Patterns*

The quantification of green spatial layout should take into account both static structure and dynamic functional characteristics. In this study, the synergistic framework of landscape pattern index and spatial syntax analysis is used to construct a multi-scale evaluation system, which covers the geometric characteristics of patches, spatial topological relationships, and the effects of anthropogenic disturbances, and provides quantifiable morphology parameters for the subsequent coupled model.

The landscape pattern indices were selected based on the ecological process response mechanism, including Patch Density (PD), Edge Density (ED), Aggregation Index (AI), Connectivity Index (CONNECT), Shannon's Diversity Index (Shannon's Diversity Index) and the Shannon's Diversity Index (Shannon's Diversity Index). Index (SHDI) and Water Proximity (WP). Patch density reflects the degree of green space fragmentation and is defined as the number of independent patches per square kilometre; the connectivity index is calculated by weighting the minimum Euclidean distance between patches and characterises the potential path resistance of species migration. For the ecological characteristics of wetlands, the spatial interaction effect between water body proximity metrics and wetlands was calculated using a Gaussian decay function to simulate the pattern of biological dispersal over distance, and the radius of decay was set to 500 m to match the activity range of amphibians. The landscape pattern index system and ecological interpretation, as shown in Table 3.

TABLE III. LANDSCAPE PATTERN INDEX SYSTEM AND ECOLOGICAL INTERPRETATION

Index Name	Abbreviation	Spatial Scale	Ecological Significance	Data Source	Calculation Software	Sensitivity Threshold
Patch Density	PD	Patch Level	Fragmentation Degree Assessment	Sentinel-2 Classification Results	Fragstats 4.2	PD > 15 patches/km² indicates high fragmentation
Edge Density	ED	Patch Level	Habitat Boundary Effect Intensity	Land Use Vector Data	ArcGIS 10.8	ED > 120 m/ha indicates strong edge disturbance
Aggregation Index	AI	Landscape Level	Spatial Aggregation Quantification	Landscape Pattern Raster	GuidosToolbox	AI < 40% indicates discrete distribution
Connectivity Index	CONNECT	Landscape Level	Species Migration Path Accessibility	Least-Cost Path Model	Conefor Sensinode	CONNECT < 0.3 indicates low connectivity

Index Name	Abbreviation	Spatial Scale	Ecological Significance	Data Source	Calculation Software	Sensitivity Threshold
Shannon Diversity Index	SHDI	Landscape Level	Spatial Heterogeneity Characterization	Multispectral Image Classification	ENVI 5.3	SHDI > 1.5 indicates high heterogeneity
Water Proximity	WP	Patch Level	Wetland-Green Space Interaction Effect	Wetland Boundary Buffer Analysis	QGIS 3.22	WP < 200 m indicates strong association zone

Space Syntax Analysis (SSA) focuses on the assessment of service effectiveness of green space, and analyses the accessibility and ecological radiation capacity from the perspective of topological network [9-10]. Based on the urban road network and green space entrance data, a dual network model was constructed at the pedestrian scale (500 m radius) and ecological scale (2000 m radius), and the Normalised Depth Value (NDV), Weighted Integration (WINT) and Ecological Service Radius (ESR) were calculated. Ecological Service Radius (ESR). Normalised Depth Value (NDV) reflects the topological accessibility of nodes in the network, and is normalised to eliminate scale effects; Weighted Integration (WINT) incorporates pedestrian density data to quantify the centrality of green spaces in urban activities. The ecological service radius is solved by coupling the noise attenuation model with 3D visual field analysis, with constraints including safe flight height for birds (>15 m) and human noise interference threshold (<55 dB). Spatial syntactic analysis parameters and functions were defined, as shown in Table 4.

TABLE IV. SPACE SYNTAX ANALYSIS PARAMETERS AND FUNCTIONAL DEFINITIONS

Parameter Name	Abbreviation	Spatial Scale	Functional Definition	Data Source	Calculation Tool	Core Constraints
Normalized Depth Value	NDV	Community Level (500 m)	Topological Accessibility Assessment	Road Network Topology Model	Depthmap X	Walking Speed ≤ 1.2 m/s
Weighted Integration	WINT	City Level (2000 m)	Spatial Centrality Quantification	Mobile Signaling Heatmap	Axwoman 9.0	Population Density Weight Calibration
Ecological Service Radius	ESR	Regional Level (5 km)	Ecological Radiation Range Definition	3D Terrain Model	ArcGIS 3D Analyst	Noise < 55 dB, Flight Height ≥ 15 m
Visual Graph Analysis	VGA	Patch Level	Visual Permeability Effect Assessment	LiDAR Point Cloud Data	Viewshed Analysis Module	Viewpoint Height 1.5 m, View Angle 120°
Topological Penetration	TPA	Road Network Level	Path Usage Efficiency Quantification	Traffic Flow Monitoring Data	sDNA Plugin	Path Flow/Length Ratio
3D Green Volume Index	3DGI	Building Cluster Level	3D Ecological Capacity Measurement	Airborne LiDAR	CloudCompare	Point Cloud Density ≥ 8 points/m²

The computation of spatial syntactic parameters relies on topological network modelling and physical environment constraints. As an example, the normalised depth value is calculated based on the number of shortest path steps between network nodes, and the elimination of quantitative differences needs to be shown in equation (1).

$$NDV = (DV - \mu) / \sigma \quad (1)$$

In equation (1), μ and σ are the mean and standard deviation of the depth values, respectively. The weighted integration degree, on the other hand, introduces the logarithmic transformed value of crowd density as a weighting factor, as shown in Equation (2).

$$WINT = INT \times \log(P_d) \quad (2)$$

In Eq. (2), P_d is the value of population density based on the inversion of mobile phone signalling data. The calculation of the ecological service radius needs to be coupled with the acoustic attenuation model as shown in equation (3), which can be analysed with the 3D buffer zone of flight height.

$$D_{noise} = 10^{(L0-Lt)/(20\alpha)} \quad (3)$$

In equation (3), $L0$ is the noise source intensity, Lt is the target threshold, and α is the atmospheric absorption coefficient.

In the model construction, the fusion of landscape pattern indices and spatial syntactic parameters is achieved through spatial superposition and machine learning. For example, the spatial coupling of patch density (PD) and weighted integration (WINT) can identify highly fragmented-low accessibility areas; the interaction of water body proximity (WP) and ecological service radius (ESR) can quantify the functional synergistic effects of wetlands and green spaces [11-12]. The XGBoost algorithm was used to filter 10 sensitivity indicators from 32 initial parameters, including aggregation index (AI), three-dimensional green volume index (3DGI) and normalised depth value (NDV), to ensure the streamlining and explanatory power of the model input variables.

The model validation adopted a spatial cross-validation strategy by dividing the study area into 1km × 1km grid cells, randomly selecting 70% of the cells as the training set and the remaining 30% as the test set. The prediction accuracy was assessed by root mean square error (RMSE) and coefficient of determination (R^2) to ensure the generalisation ability of the model in heterogeneous regions.

C. *Biome function assessment system*

The assessment of biotope function needs to take into account the ecological roles and ecosystem service values of species functional groups. In this study, we constructed a multi-dimensional assessment framework through the quantitative model of species classification and ecological processes driven by biometrics technology. The system breaks through the limitations of traditional biomass or diversity indicators, and analyses the comprehensive effectiveness of wetland biomes from the dual perspectives of dynamic interactions of functional groups and spatial heterogeneity of ecological services.

Based on the ecological niche theory and the morphological characteristics, behavioural patterns and trophic relationships of species, the biotope of wetland biotopes is divided into Pollinator, Decomposer, Seed Disperser and Primary Producer, Predator and Ecosystem Engineer [13-15]. The definition of the functional groups relies on multiple sources of biometric data: infrared cameras to capture feeding behaviour of mammals and birds, acoustic recorders to analyse the correlation between insect wing beat frequency and plant pollination, and environmental DNA (eDNA) macro-barcoding to identify the trophic status of benthic organisms. For example, the pollinator functional group includes bees, butterflies and some beetles, whose activity trajectories are tracked by Radio Frequency Identification (RFID) tags and pollination efficiency is quantified in relation to the amount of pollen attached; the decomposer functional group includes oligochaetes, nematodes and fungi, and the rate of organic matter degradation is assessed by metabolite spectroscopy (e.g., chitinase activity) [16-17]. The decomposer functional group covers oligochaetes and nematodes as well as fungi. The classification system and monitoring methods of wetland biofunctional groups are shown in Table 5.

TABLE V. WETLAND BIOLOGICAL FUNCTIONAL GROUP CLASSIFICATION SYSTEM AND MONITORING METHODS

Functional Group Name	Representative Species	Biomonitoring Technology	Functional Contribution Indicators	Ecological Service Type	Data Collection Equipment	Spatial Resolution
Pollinators	Chinese Honeybee, Jade Butterfly	RFID Tracking, Pollen Counter	Daily Pollination Count, Pollen Load	Plant Reproduction Support	Micro RFID Tags, Microscopic Imaging	Individual Activity Trajectories
Decomposers	Tubifex, White Rot Fungi	eDNA Metabolite Analysis	Cellulose Degradation Rate, Enzyme Activity	Organic Matter Mineralization	High-Throughput Sequencer, Spectrometer	Sediment Sampling Points
Seed Dispersers	Light-vented Bulbul, Brown Rat	Infrared Camera Behavioral Sequence Analysis	Seed Dispersal Distance, Germination Success Rate	Vegetation Community Renewal	Thermal Imaging Camera, GPS Collars	50-meter Grid
Primary Producers	Reed, Pondweed	Chlorophyll Fluorescence Imaging	Net Primary Productivity (NPP)	Carbon Sequestration, Oxygen Release	Photosynthesis Measurement System	Canopy Scale
Predators	Grey Heron, Ricefield Eel	Acoustic Predation Event Detection	Prey Consumption, Trophic Level Position	Food Web Stability Maintenance	Underwater Sonar, Stomach Content Analysis	Water Column Monitoring
Ecosystem Engineers	Freshwater Clam, Mole Cricket	3D Burrow Structure Scanning	Substrate Porosity, Water Flow Disturbance Intensity	Habitat Structure Modification	CT Tomography, Flow Velocity Sensor	Microhabitat Scale

The quantification of the value of ecological services is based on a combination of process modelling and the market value approach, covering three core services: carbon sinks, water purification and habitat quality. The carbon sink assessment is based on vegetation biomass and soil organic carbon pool measurements, as shown in equation (4).

$$C_{seq} = \sum(B_i \times CF_i) + SOC \times D \times A \quad (4)$$

In equation (4), B_i is the biomass of vegetation in category i (kg/m^2), CF_i is the carbon content coefficient (e.g., 0.5 for trees and 0.45 for herbs), SOC is the organic carbon content of soil (g/kg), D is the soil depth (m), and A is the area (ha) [18-19]. Water purification capacity is accounted for by pollutant removal, calculated as shown in equation (5).

$$W_p = \sum(C_{in} - C_{out}) \times Q \times V_p \quad (5)$$

In Eq. (5), C_{in} and C_{out} are the concentrations of ammonia nitrogen and total phosphorus at the inlet and outlet (mg/L), respectively, Q is the hydrological flux (m^3 /day), and V_p is the cost of treating the pollutants per unit (yuan/kg). Habitat quality was assessed by Habitat Suitability Index (HSI), integrating parameters such as vegetation cover, disturbance intensity and food resource abundance, and the calculation formula was shown in Equation (6).

$$HSI = \prod_{i=1}^{n} S_i^{w_i} \quad (6)$$

In equation (6), S_i is the suitability of the ith habitat factor (0-1), and w_i is the weight [20]. The parameters and data sources for quantifying the value of ecological services are shown in Table 6.

TABLE VI. ECOLOGICAL SERVICE VALUE QUANTIFICATION PARAMETERS AND DATA SOURCES

Service Type	Quantification Indicator	Data Source	Spatial Scale	Temporal Resolution	Calculation Model	Value Conversion Coefficient
Carbon Sequestration	Vegetation Biomass, Soil Organic Carbon	Airborne LiDAR, Soil Core Sampling	Patch Level	Annual	InVEST Carbon Module	Carbon Trading Price (¥/t)
Water Purification	Ammonia Nitrogen, Total Phosphorus Removal	Automatic Water Quality Monitoring Stations	Watershed Level	Daily	SWAT Hydrological Model	Wastewater Treatment Cost
Habitat Quality	Habitat Suitability Index (HSI)	Species Distribution Model	Landscape Level	Quarterly	MaxEnt Algorithm	Habitat Restoration Cost
Pollination Service	Crop Yield Increase Ratio	Farm Yield Statistics	Regional Level	Growing Season	Pollen Limitation Model	Agricultural Market Price
Biological Control	Pest Predation Rate	Trap Monitoring Data	Field Level	Weekly	Predator-Prey Dynamics Model	Pesticide Replacement Cost
Cultural Services	Recreational Visits	Mobile Signaling Location Data	City Level	Real-Time	Travel Cost Method	Per Capita Consumption Expenditure

The spatial heterogeneity analysis of ecological services relies on the Geographic Information System (GIS) platform to standardise and weight the carbon sink, water purification and habitat quality indicators. The weights were assigned using the Analytic Hierarchy Process (AHP), and 15 experts in the fields of ecology and urban planning were invited to compare the importance of each service, and the Consistency Ratio (CR) was controlled within 0.1. For example, the weight of carbon sink service was set to 0.35, water purification to 0.30, habitat quality to 0.25, and cultural service to 0.10, reflecting the difference in the priority of wetland ecological functions.

The coupling between functional groups and ecological services was realised by Structural Equation Modeling (SEM). Pollinator abundance was assumed to positively influence vegetation productivity (path coefficient β 1), decomposer activity to drive carbon sink capacity (β 2), and predator numbers to regulate pest control services (β 3), and green space morphological parameters (e.g., patch density, connectivity index) were introduced as exogenous variables. Model fitting was performed by maximum likelihood estimation, and the fitness was assessed by chi-square test (χ^2 /df<3) and Comparative Fit Index (CFI>0.9) to ensure the scientific validity of the theoretical framework.

III. COUPLED ANALYSIS OF LAYOUT PATTERNS AND BIOLOGICAL FUNCTIONS

A. Characteristics of green space distribution under urbanisation gradient

The differences in green space distribution in the core, edge and suburban areas of the study area significantly affect the continuity of wetland biological community functions. Based on the landscape pattern index and biological activity monitoring data, the green space distribution under the urbanisation gradient is characterised by increasing patch fragmentation, decaying functional connectivity and imbalance of ecological service supply and demand. The average density of green space patches in the core area (within a radius of 5 km) is 27.4 patches/km², 3.4 times higher than that in the suburbs (8.1

patches/km²), but the average patch area is only 0.26 hectares, which is less than 1/6 of that in the suburbs (Table 7). The high fragmentation characteristics led to an Edge Density (ED) of 192.3 m/ha and a patch Shape Index (SI) of 4.7 in the core area, indicating that the complexity of habitat boundaries disturbed by human activities far exceeded the natural wetland threshold. The comparison of green space morphological parameters under different urbanisation gradients is shown in Table 7.

TABLE VII. COMPARISON OF GREEN SPACE MORPHOLOGICAL PARAMETERS ACROSS URBANIZATION GRADIENTS

Region Type	Patch Density (patches/km²)	Mean Patch Area (ha)	Edge Density (m/ha)	Connectivity Index	Water Proximity (m)	Aggregation Index (%)
Core Urban Area	27.4	0.26	192.3	0.15	368.9	39.6
Urban Fringe	16.2	0.82	130.7	0.31	225.4	52.1
Suburban Area	8.1	1.61	86.5	0.63	142.8	69.3
Wetland Core Protected Area	5.3	2.34	58.2	0.78	65.7	76.8
Along Transportation Corridors	21.5	0.33	160.8	0.19	302.1	43.9
Industrial Development Zone	29.8	0.18	210.4	0.09	418.5	35.2

In Table 7, the patch density and edge density of the core area are significantly higher than those of other areas, but the connectivity index (0.15) is only 19.2% of that of the wetland core reserve, indicating that the green space in the city centre is highly fragmented and ecological flow is impeded. Although the average patch area of green space in the fringe area (0.82 ha) is larger than that in the core area, its connectivity index (0.31) is still lower than that in the suburbs (0.63), which is mainly due to the fact that the green space in the fringe area is mostly distributed in a narrow strip along the roads or rivers, and the node breaks (such as bridges and overpasses across the rivers) lead to the interruption of the paths of organisms' migratory paths by 2.8 times. The aggregation index (76.8%) of the wetland core reserve is much higher than that of the built-up area, which confirms the spatial integrity of the natural wetland and the biological shelter function.

The blocking effect of high-density built-up areas (>70% coverage) on wetland connectivity was spatially cumulative and non-linear. When the coverage rate of built-up area increases from 30% to 70%, the number of effective ecological corridors decreases sharply from 9.2 to 2.1, and the average width of corridors is compressed from 41.7 to 14.6 metres. Take an urban wetland as an example, the new residential area (plot ratio 3.2) on the east side of the wetland reduced the number of corridors connecting the wetland with the mountain green space from 6 to 1, and the remaining corridor width was less than 20 metres, resulting in a 62% reduction of heron's nesting area. The blocking effect was further amplified by artificial lighting (>50 lux) and traffic noise (>70 dB) at night, and the insect diversity within 0-200 m of the wetland edge decreased by 58%, which directly affected the foraging efficiency of birds (e.g. night herons). The effects of different built-up densities on wetland connectivity are shown in Table 8.

TABLE VIII. IMPACT OF BUILT-UP DENSITY ON WETLAND CONNECTIVITY

Built-Up Area Coverage (%)	Effective Corridor Count	Average Corridor Width (m)	Minimum Interruption Distance (m)	Biological Migration Success Rate (%)	Noise Level (dB)	Light Intensity (lux)
<30	9.2	41.7	505	80.3	47.5	11.8
30-50	6.4	31.9	272	61.7	56.9	23.5

Built-Up Area Coverage (%)	Effective Corridor Count	Average Corridor Width (m)	Minimum Interruption Distance (m)	Biological Migration Success Rate (%)	Noise Level (dB)	Light Intensity (lux)
50-70	3.5	20.1	135	40.9	64.3	37.2
>70	2.1	14.6	68	25.4	71.8	49.6
Around Transportation Hubs	1.3	8.7	30	13.8	79.5	65.3
Around Industrial Areas	0.6	5.9	15	7.5	86.7	87.1

In Table 8, when built-up area coverage exceeded 50 per cent, biological migration success (40.9 per cent) decreased by nearly 50 per cent compared to the low-density area (80.3 per cent), and noise levels (64.3 dB) and light intensity (37.2 lux) approached wetland biological tolerance thresholds. The effective corridor width in the area around the transport hub is only 8.7 metres, with a minimum interruption distance of 30 metres, forcing small and medium-sized mammals (e.g. ferrets and badgers) to extend their migration paths by a factor of 3.2. The light intensity of 87.1 lux around the industrial site caused nocturnal insects (e.g. moths) to retreat 1.5 km to the wetland core area, exacerbating intraspecific competition among predators (e.g. bats) in the core area.

The distribution of green space in the core area was highly coupled with the intensity of land development. In high-rise building density areas with plot ratios >3.0, 68% of green space patches are road green belts or rooftop gardens, and patch spacing is generally less than 40 m. However, functional connectivity is severely disturbed by vibration from traffic (frequency 20-50 Hz) and light reflection from glass curtain walls. For example, the theoretical migration path between adjacent green space patches in a commercial area is 90 m, but infrared camera monitoring shows that the actual migration success rate of amphibians (e.g., the Chinese giant toad) is only 12%, which is mainly due to the hard road segregation and the interference of night-time lighting. Although the green space in the fringe area has banded continuity, its ecological function has been weakened by artificial management - 63% of the river green space has been converted into hard barge, the cover of aquatic plants has been reduced from 72% to 19%, and the biomass of benthic animals (e.g. snails) has been reduced by 81%.

The morphological integrity of suburban green spaces is high, but ecological functions are implicitly eroded by agricultural activities and recreational facilities. In large suburban wetland parks (>50 ha), 55% of the water body shoreline was hardened by walkways and hydrophilic platforms, resulting in a decrease in submerged plant (e.g., tunicates) cover from 68% to 14%, and the benthic fauna diversity index (Shannon-Wiener) from 2.4 to 1.1. In addition, pesticide dispersal exceeded the pyrethroid concentration in the water bodies of the suburban wetland by a factor of 1.8, which directly suppressed dragonfly larval plumage rates (down 43%). Nevertheless, some ecological springboards (e.g., woodland patches of 1-2 ha in size) were still retained in the suburban area, and their spacing was mostly less than 150 m, which provided migration paths for small mammals (e.g., hedgehogs), and the migration success rate was 5.3 times higher than that in the core area.

The wetland-built-up area interface zone (0-500 m range) is the transition zone with the most drastic degradation of ecological functions. The average density of green space patches in the interface zone is 19.8 patches/km^2, but the connectivity index is only 0.21, and 81% of the patches are cut off by car parks and fitness facilities. Acoustic monitoring data shows that the frequency of bird calls in the interface zone is 79% lower than that of natural wetlands, and the Acoustic Diversity Index (ADI) has dropped from 0.75 to 0.26. At the same time, the artificial light at night in the interface zone causes 83% of nocturnal insects to migrate to the interior of the wetland, forcing the density of insects in the core area of the wetland to increase by 2.4 times and further breaking the balance of the original food chain.

The above results show that the green space distribution characteristics under the urbanisation gradient is not only the result of planning decisions, but also a dynamic game between biological behavioural responses and human activities' coercion.

B. *Biometrics-driven functional response*

The spatial matching characteristics of species diversity hotspots and green space nodes revealed by biometrics provide high-precision evidence for resolving the coupling mechanism between layout patterns and ecological functions. Multi-source data fusion based on infrared camera, acoustic recorder and Environmental DNA (eDNA) macro-barcoding technology showed that the functional response of urban wetland biomes had significant spatial heterogeneity and scale dependence. The mean value of species diversity index (Shannon-Wiener, H') within 50 m of the edge of the wetland in the core area was only 1.2, which was significantly lower than that of 2.7 in the suburban wetland, but the combined effect of artificial light intensity (>45 lux) and traffic noise (>65 dB) at night led to the formation of unique "artificial-natural" transitional biological communities in the core area. The combination of nighttime artificial light intensity (>45 lux) and traffic noise (>65 dB) resulted in the formation of a unique 'artificial-natural' transitional community in the core area. For example, tolerant species (e.g., house sparrows, brown house mice) accounted for 78% of the wetlands in the core area, while sensitive species (e.g., herons, dragonflies) accounted for only 12%, and their ranges were compressed to isolated patches less than 0.5 ha in size. The match between species diversity hotspots and green space nodes in different regions is shown in Table 9.

TABLE IX. SPECIES DIVERSITY HOTSPOT AND GREEN SPACE NODE MATCHING IN DIFFERENT REGIONS

Region Type	Species Diversity Index (H')	Hotspot Density (individuals/km²)	Number of Green Space Nodes	Node-Hotspot Matching Rate (%)	Proportion of Sensitive Species (%)	Proportion of Tolerant Species (%)
Core Area Wetland Edge	1.2	3.5	8	22.4	12	78
Edge Area River Corridor	2.1	6.8	15	48.7	34	59
Suburban Natural Wetland	2.7	11.4	23	72.9	58	35
Traffic Green Space Nodes	0.9	1.2	3	8.6	5	91
Industrial Zone Greenbelt	0.7	0.8	2	4.3	2	94
Ecological Restoration Demo Area	2.5	9.7	18	65.2	49	42

In Table 9, the node-hotspot matching rate of natural wetlands in the suburban area (72.9%) was 3.3 times higher than that of the wetland edge in the core area (22.4%), confirming the key role of green space morphological integrity in biodiversity maintenance. Although the river corridor in the fringe area had a high density of hotspots (6.8/km²), the percentage of sensitive species (34%) was still significantly lower than that in the suburban area (58%), which was mainly due to the loss of aquatic insect habitats caused by hard barge renovation. The species diversity index (0.7) and matching rate (4.3%) of the isolated green belt in the industrial area were the lowest, indicating that green spaces relying solely on visual amenity could not support ecological functions.

The sensor network data further revealed the prevalence of 'ecological blind zones' in urban wetlands. In the border zone between built-up areas and wetlands (0-200m range), the frequency of bird calls detected by acoustic recorders was 89% lower than that in the core area of natural wetlands, and the Acoustic Diversity Index (ADI) dropped from 0.81 to 0.19. Infrared camera monitoring showed that the frequency of nocturnal mammals (e.g., hedgehogs) in the blind zones dropped by 76%, and their migration paths were blocked by car parks and fences. Their migration paths were forcibly shifted by more than 1.2 km by facilities such as car parks and fences. eDNA analysis showed that the zooplankton biomass in the water body of the blind zone was only 14% of that of the natural wetland, and the proportion of fouling-tolerant species (e.g., trembling earthworms) was as high as 93%, reflecting the cascading destruction of the ecological chain caused by the implicit environmental stresses. Comparison of sensor monitoring data in typical ecological blind zones is shown in Table 10.

TABLE X. COMPARISON OF SENSOR MONITORING DATA IN TYPICAL ECOLOGICAL BLIND SPOTS

Blind Spot Type	Location Characteristics	Sensor Type	Species Diversity Index (H')	Sensitive Species Activity Decline Rate (%)	Main Interference Type	Ecological Function Decline Rate (%)
Elevated Bridge Projection Area	Under the bridge, 0-50 meters	Acoustic Recorder + Infrared Camera	0.5	92	Noise (>75 dB)	84
Glass Curtain Wall Reflection Zone	50-100 meters south of building	Polarization Light Sensor	0.7	88	Light Pollution (>80 lux)	79
Hard Embankment Transition Zone	0-30 meters at river-road junction	eDNA Sampler	0.9	76	Hydrological Pulse	68
Night Lighting Intensive Area	Streetlight spacing < 20 meters	Spectrometer	0.6	95	Artificial Lighting (>50 lux)	87
Parking Lot Permeation Zone	0-100 meters at wetland boundary	Soil Moisture Probe	0.4	83	Oil Pollution Percolation	72
Fitness Trail Disturbance Zone	0-15 meters on both sides of the trail	Vibration Sensor	0.8	69	Human Footstep	61

In Table 10, the projected area of the viaduct has the highest rate of ecological function attenuation (84%) and the highest rate of sensitive species activity decline (92%), and its noise level (>75 dB) exceeds the auditory tolerance threshold of most bird species (<60 dB), resulting in the complete avoidance of species such as house swallows. The intensity of light pollution (>80 lux) in the reflective zone of the glass curtain wall triggered disruption of phototropic behaviour in insects, with 73% of individual nocturnal moths monitored to be dead on impact with the curtain wall, which directly cut down on the food supply for predators such as bats. The benthic community structure in the transition zone of the hard barge was homogenised by hydrological pulses (storm water runoff velocity >1.2 m/s), and the proportion of oligochaete biomass detected by eDNA increased from 42% in the natural state to 89%.

Biometrics also captured the 'spatial-temporal mismatch' phenomenon in green space nodes. The detection rate of birds in the arboreal woodland node (area >0.3 ha) of the artificial wetland park in the core area was only 0.3 birds/hour during the peak period of human activities in the daytime (10:00-16:00), and increased to 2.1 birds/hour in the early morning (5:00-7:00), suggesting fluctuation of ecological functions in the temporal dimension. The frequency of pollinator (e.g. honeybee) visits to green space nodes in the fringe zone was significantly out of phase with the flowering period of the vegetation - peak pollination was delayed by 14 days compared to the natural community in the cultivated beds, resulting in a 37% increase in pollen limitation.

Sensor data-driven recommendations for spatial optimisation showed that the addition of micro-corridors >20m wide between existing green space nodes increased amphibian migration success by 58%. A core wetland expanded the dispersal range of black-spotted frog populations by 1.8 times by implanting three shrub barrier strips (25 m in width). Among the ecological blind zones identified, 83% of them can be functionally restored through simple interventions (e.g., adjusting the wavelength of street lamps to below 590 nm and installing sound barriers), and the diversity of nocturnal insects can be rebuilt to 65% of its natural state.

These results show that biometrics not only accurately quantifies the coupling relationship between green space morphology and biological functions, but also reveals the hidden ecological stress mechanisms that are difficult to be captured by traditional survey methods.

C. *Coupling model construction and optimisation path*

The coupling model constructed based on machine learning algorithm and ecological resilience theory reveals the non-linear correlation law between green space layout pattern and wetland biological function, and provides a precise optimisation path for urban ecological restoration. The study uses three types of algorithms, namely Random Forest (RF), Gradient Boosting Decision Tree (GBDT) and Support Vector Machine (SVM), to compare and analyse the results, and the results show that the Random Forest model is very effective in predicting the responses of biological functions (e.g., species diversity, carbon sink efficiency). Species diversity and carbon sink efficiency), with a cross-validation coefficient of determination (R^2) of 0.83, significantly higher than that of GBDT (0.76) and SVM (0.68). Among the model input parameters, the green space connectivity index (CONNECT) and water proximity (WP) contributed 32.7% and 28.5%, respectively, while the negative effect weight of patch density (PD) was 19.3%, confirming that ecological flows are the core driver of biological functions. This confirms the central driving role of ecological flow continuity on biological functions. The predictive performance of the machine learning model with parameter sensitivity is shown in Table 11.

TABLE XI. MACHINE LEARNING MODEL PREDICTION PERFORMANCE AND PARAMETER SENSITIVITY

Model Type	Coefficient of Determination (R^2)	Root Mean Square Error (RMSE)	Run Efficiency (seconds/iteration)	Connectivity Index Contribution (%)	Water Proximity Contribution (%)	Patch Density Contribution (%)
Random Forest (RF)	0.83	0.12	45	32.7	28.5	19.3
Gradient Boosting Decision Tree (GBDT)	0.76	0.18	62	29.4	25.8	22.1
Support Vector Machine (SVM)	0.68	0.24	89	24.6	21.3	26.9
Artificial Neural Network (ANN)	0.79	0.15	105	31.2	27.1	18.7
Bayesian Regression	0.61	0.31	28	18.9	16.5	31.4

Model Type	Coefficient of Determination (R^2)	Root Mean Square Error (RMSE)	Run Efficiency (seconds/iteration)	Connectivity Index Contribution (%)	Water Proximity Contribution (%)	Patch Density Contribution (%)
(BR) Decision Tree (DT)	0.72	0.21	37	26.3	23.7	24.6

In Table 11, the random forest model performs the best in both the coefficient of determination (0.83) and the running efficiency (45 s/run), and its high accuracy stems from the ability to adaptively capture nonlinear relationships. The contribution of water body proximity (28.5%) indicates that the spatial interaction effect between wetland and green space is a key factor in the maintenance of biological functions, while the negative weight of the contribution of patch density (19.3%) corroborates the inhibitory effect of high fragmentation on ecological services. The Bayesian regression model's prediction accuracy (R^2 =0.61) was significantly lower than other algorithms due to its inability to handle high-dimensional interaction features, highlighting the advantages of machine learning in complex ecological modelling.

The planning framework of 'multi-centre + corridor' under the perspective of resilient city improves the disturbance resistance of wetland ecosystem through spatial reorganisation and functional optimisation. The polycentric layout refers to the implantation of green nodes with an area of >1 ha and a spacing of <500 m in the built-up area as stepping stones for biological dispersal, while the ecological corridors need to meet the requirements of the minimum effective width (30 m) and the heterogeneity of the vegetation cover (tree-shrub-grass ratio of 4:3:3). Simulation shows that after the implementation of the framework, the nesting area of wetland birds in the core area can be enlarged by 2.3 times, the pollination efficiency of insects can be increased by 41%, and the peak of storm water runoff can be delayed by 0.8 hours, reducing the risk of waterlogging. The planning path and implementation effect of 'multi-centre + corridor' are shown in Table 12.

TABLE XII. "MULTI-CENTER + CORRIDOR" PLANNING PATH AND IMPLEMENTATION EFFECT OPTIMIZATION PATH

Implementation Measure	Expected Ecological Gain (%)	Technical Support	Cost-Effectiveness (10,000 CNY/ha)	Key Constraints
Multi-Center Green Space Insertion	Add 1-3 ha of community parks, spacing <500 meters	Drone Site Selection Algorithm	120-150	Difficulty in integrating land ownership
Ecological Corridor Restoration	Widen corridor to 30 meters, plant multi-layered trees, shrubs, and grasses	LiDAR Terrain Modeling	80-100	Avoidance of existing infrastructure
Wetland Buffer Zone Reconstruction	Retreat hardened shoreline, restore 50 meters of submerged plant belt	Hydrological Connectivity Simulation	60-80	Property value loss in waterfront real estate
Ecological Renovation of Artificial Facilities	Replace glass curtain walls with ecological walls, reduce noise by 60%	Acoustic Material Performance Testing	200-250	High initial investment cost
Light Pollution Control	Replace LED wavelength to <590nm, reduce	Spectral Analysis & Smart Regulation System	30-50	Conflicts with municipal lighting standards

Implementation Measure	Expected Ecological Gain (%)	Technical Support	Cost-Effectiveness (10,000 CNY/ha)	Key Constraints
Stormwater Management Coordination	nighttime lighting Build permeable paving + rain garden system	SWMM Model Optimization	40-60	Underground pipeline renovation limits

In Table 12, the expected ecological gain (+57% migration success) and cost-effectiveness (RMB 800-1 million/ha) of ecological corridor restoration are combined optimally, and its technical support relies on LiDAR terrain modelling to accurately identify topographic relief and hydrological pathways. The ecological modification of artificial facilities is more costly (RMB 2-2.5 million/ha), but it can significantly increase the return rate of birds (+29%), which is especially suitable for high-density commercial areas. Light pollution regulation measures achieve rapid insect diversity recovery (+63%) at lower cost (300,000-500,000 RMB/ha), but require coordination of municipal lighting standards to avoid traffic safety risks.

Model-driven spatial optimisation suggests that adding 3-5 north-south ecological corridors >25 m wide to the current green space layout can reduce resistance to biotic migration between wetlands in the core area and the suburbs by 62%. For example, in one city, a network of corridors connecting wetland parks with peri-urban forest parks resulted in a 1.7-fold expansion of habitat area for medium-sized mammals (e.g., raccoon) and a 48% increase in the frequency of gene exchange. In addition, machine learning identified 'inefficient green spaces' (high morphological index but low functional contribution) that accounted for 23% of the total green space, and through micro-adaptation (e.g., increasing the shrub layer and installing ecological depressions), their carbon sink efficiency could be increased by 34%.

The implementation of the resilience planning framework needs to break through traditional land management barriers. It is recommended that ecological corridors be incorporated into the red line control system of urban roads, and that banded spaces with a width of >30 metres be mandatorily reserved; a land exchange mechanism for wetland buffer zones be established, allowing developers to balance the development intensity of waterfront areas through off-site eco-compensation; and an 'eco-banking' system be promoted to turn the ecological service value of greenfield nodes into tradable credits, attracting the participation of social capital. The system of 'eco-banking' is promoted, and the ecological service value of green space nodes is transformed into tradable credits to attract social capital participation. The integrated application of the above paths can significantly increase the resilience threshold of urban wetlands to cope with climate change and human interference.

IV. Conclusion

The sustainability of urban wetland biome function is deeply regulated by green space layout patterns, while traditional planning lacks quantitative constraints on the dynamic response of ecological processes. Aiming at the problems of blocked ecological flow and increased implicit stress in high-density urbanised areas, we integrate multi-source remote sensing data, biometric sensor networks and machine learning algorithms to construct a cross-scale coupled analysis framework. By analysing the green space gradient characteristics of mega urban agglomerations such as the Yangtze River Delta and Pearl River Delta, it is found that the fragmentation of green space in the core area (patch density >24 patches/km ^{2}) synergistically with the artificial light at night (>45 lux) leads to a decrease in the percentage of sensitive species to 12%, and the frequency of disruption of ecological flow in strip green space in the edge area due to the nodal fault zones increases by 2.8 times. The Random Forest model quantified the dominant effects of connectivity index and water proximity, with contributions of 32.7% and 28.5% respectively, providing data support for accurate identification of inefficient green spaces. The proposed 'multi-centre + corridor' planning pathway was simulated and verified, which can expand the wetland bird habitat by 2.3 times and increase the pollination efficiency of insects by 41%, confirming the significant benefits of morphological optimization on ecological function recovery.

The practical value of the study lies in the development of a dynamic assessment system based on the chain reaction of biological behaviours, which breaks through the limitations of the traditional static indicators in the characterization of complex ecological processes, and provides a quantitative basis for the design of ecological compensation mechanisms in urban regeneration. The limitations are that the data coverage is limited to the cities in the East Asian monsoon region, and the applicability to the cities in the arid and cold regions needs to be verified; and the prediction accuracy of the machine learning model for sudden disturbances (e.g., extreme rainfall, species invasion) needs to be further improved. In the future, we should strengthen the real-time monitoring capability of multi-sensor Internet of Things (IoT), integrate urban climate models with ecotoxicological data, and build a decision support system for the whole process of 'stress-response-adaptation'. Explore the replacement model of ecological restoration benefits and land economic value, promote the transformation of green space from 'cost burden' to 'asset value-added', and provide methodological innovations for the synergistic promotion of smart city and ecological civilisation construction.

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