DATA-DRIVEN MULTI-CRITERIA DECISION ANALYSIS FOR SOCIO-ENVIRONMENTAL RISK ASSESSMENT: A CASE STUDY OF ECOSYSTEM ENGINEERING IN POYANG LAKE, CHINA

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Abstract. This study assesses socio-environmental risks in the Poyang Lake Ecological Zone, China's largest freshwater lake system, under increasing pressures from large-scale ecosystem engineering and rapid land use change. A data-driven framework integrates Multi-Criteria Decision Analysis with Coupling Coordination Degree Modeling, using geospatial indicators such as NDVI degradation, land use change intensity, population density, and infrastructure proximity to construct a composite spatial risk index. Between 2012 and 2024, high-risk zones expanded across urban fringes and infrastructure corridors, where over 60 percent of grid cells exhibited poor coordination between environmental exposure and social vulnerability. While overall coordination improved modestly during the study period, significant regional disparities remain. Tobit regression analysis identifies ecological compensation coverage, government investment, and infrastructure accessibility as positive contributors to coordination, while vegetation degradation and land conversion exert negative effects. Dagum Gini decomposition shows that inter-regional variation accounts for 46 percent of coordination inequality, underscoring the influence of functional zoning. Results highlight the need for spatially adaptive planning, enhanced ecological incentives, and integrated monitoring systems to mitigate uneven risk distributions. This approach offers a scalable framework for socio-environmental risk assessment in ecologically sensitive development regions.
Keywords: *spatial heterogeneity, environmental exposure, social vulnerability, functional zoning, remote sensing, Tobit regression, coupling coordination model*

Introduction

Large-scale ecosystem engineering projects have emerged as critical tools for achieving regional development objectives and ecological restoration goals in the face of intensifying environmental and socio-economic pressures. These projects, ranging from wetland reclamation and infrastructure corridor expansion to hydrological regulation, inevitably alter landscape configurations and disrupt existing socio-ecological dynamics. Such transformations often exacerbate socio-environmental risks, particularly in ecologically sensitive yet development-prone regions where population density, land use intensity, and infrastructure expansion intersect with fragile ecological baselines. As highlighted by Cacciuttolo et al., the interaction between anthropogenic land alteration and ecological system vulnerability poses persistent threats to both environmental integrity and human health, necessitating robust frameworks for risk assessment and management (Cacciuttolo et al., 2023).

The complexity of socio-environmental risks lies in their multi dimensionality and spatial heterogeneity. Risks are not evenly distributed but instead emerge through the convergence of biophysical exposure and social vulnerability, as seen in agricultural systems subjected to climate variability and soil degradation (Faye and Braun, 2022). Furthermore, the interdependencies between environmental degradation and socio-economic marginalization are often mediated by land use practices and governance configurations, such as those observed in peri-urban agricultural zones where inadequate environmental safeguards expose communities to heightened health risks (Falcone et al.,

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2023). These dynamics underscore the necessity of integrative frameworks that transcend traditional siloed approaches to risk assessment and instead adopt spatially explicit, multi-criteria paradigms.

Recent studies have emphasized that socio-environmental crises are increasingly financialized, with risk shifting from material landscapes to investment portfolios, often leaving local populations exposed to the residual impacts (Cohen et al., 2021). In such contexts, decision-making must be informed by comprehensive assessments that can capture the multifaceted nature of risk, account for trade-offs among competing objectives, and support sustainable governance responses. Multi-Criteria Decision Analysis has gained traction as a suitable methodological paradigm for tackling these challenges due to its capacity to integrate diverse data types, stakeholder preferences, and spatial variability (Abdullah et al., 2021; Islam et al., 2024). Its applications span domains including flood risk management, energy planning, and agricultural zoning, where it facilitates evidence-based prioritization and spatial optimization (Ustaoglu et al., 2021; Ransikarbum et al., 2023).

However, while MCDA has seen widespread application in environmental planning, its integration with spatially continuous datasets and coupling coordination frameworks remains underdeveloped. There is a growing recognition of the need to incorporate spatially differentiated indicators, such as NDVI degradation, land conversion patterns, and infrastructure accessibility, into MCDA-based risk modeling to enhance resolution and policy relevance. Moreover, coupling coordination degree models have proven effective in analyzing the interplay between dual or multiple subsystems, such as urbanization and air quality, or ecological construction and socio-economic development (Zuo et al., 2021; Dong et al., 2023). These models provide a quantitative basis for diagnosing systemic misalignments and identifying opportunities for synergistic development. Nonetheless, methodological critiques have pointed to limitations in current coupling frameworks, including model misuse and insufficient treatment of spatial heterogeneity, thereby calling for refined applications that are context-specific and data-driven (Wang et al., 2021).

In this regard, the present study introduces a data-integrated MCDA framework combined with coupling coordination analysis to evaluate socio-environmental risk in the Poyang Lake Ecological Zone, China's largest freshwater lake system and a critical ecological node in the Yangtze River basin. The region exemplifies the development-ecology paradox: it is both ecologically indispensable and subject to escalating infrastructure development, land use intensification, and hydrological modification (Li et al., 2022; Qi et al., 2022). Addressing such paradoxes requires not only a granular understanding of environmental exposure and social vulnerability, but also insights into the degree of systemic coordination between these domains. Through the application of the Dagum Gini coefficient decomposition and Tobit regression modeling, this study aims to construct a spatially explicit socio-environmental risk index; analyze the coupling coordination dynamics between environmental and social risk subsystems; and identify the key factors influencing risk disparities and integration outcomes across functionally zoned landscapes.

By advancing the integration of spatial MCDA and coordination modeling, this research responds to a growing methodological demand for multi-dimensional, data-driven frameworks capable of informing adaptive policy interventions in ecosystem engineering projects. In doing so, it contributes not only to the theoretical discourse on

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socio-environmental risk but also to the practical domain of regional environmental governance and sustainable infrastructure planning.

Related works

Ecosystem engineering and risk tradeoffs

Ecosystem engineering has emerged as a critical paradigm in environmental management, offering both restorative potential and new sources of risk. Brazier et al. (2021) characterized beavers as natural ecosystem engineers, capable of reshaping hydrological regimes and enhancing wetland resilience. In agricultural systems, Josephrajkumar et al. (2022) described ecological engineering techniques for pest control through habitat modification. Similarly, Kristensen et al. (2022) emphasized the role of large herbivores in maintaining ecosystem carbon persistence under anthropogenic pressure. These examples highlight how intentional or unintentional landscape modification, whether by species or infrastructure, can generate tradeoffs between ecological stability and development objectives. This duality underscores the relevance of evaluating socio-environmental risk in engineered ecological systems such as the Poyang Lake region.

Spatial heterogeneity and environmental indicators

Spatial heterogeneity is central to understanding risk in dynamic ecological landscapes. Gao et al. (2022) employed geographically weighted regression to show how urban heat island effects vary with block morphology, while Wang et al. (2021) demonstrated that spatial differences in human capital structure influence regional green productivity. Mishra et al. (2021) modeled spatial variation in permafrost carbon stocks based on environmental predictors, and Sun et al. (2021) used single-cell RNA sequencing to reveal intra-tumor variation as a key determinant in cancer immunology. Though diverse in domain, these studies converge on a common insight: spatial differentiation matters. This provides strong justification for incorporating high-resolution, spatially explicit indicators such as NDVI degradation, land use conversion intensity, and infrastructure accessibility into socio-environmental risk frameworks.

Multi-criteria decision analysis and coupling models

Multi-Criteria Decision Analysis (MCDA) has become a widely adopted methodology in environmental decision-making, enabling integration of heterogeneous indicators and stakeholder priorities. Abdullah et al. (2021) reviewed two decades of MCDA use in water-related disaster management, while Islam et al. (2024) applied MCDA with GIS to identify solar power plant locations in Bangladesh. Ustaoglu et al. (2021) used similar techniques to evaluate agricultural land suitability. Ransikarbum et al. (2023) combined MCDA with supply chain modeling to assess hydrogen logistics under uncertainty. Complementary to MCDA, Coupling Coordination Degree Models (CCDMs) provide quantitative assessments of synergy or misalignment between interrelated subsystems. Dong et al. (2023) applied CCDMs to evaluate the link between urbanization and air quality, and Zuo et al. (2021) used similar models to assess ecological construction progress. However, Wang et al. (2021) noted frequent methodological misuse of CCDMs in Chinese studies, particularly the neglect of spatial heterogeneity. This issue is directly addressed in the present study through functional zoning and Dagum Gini decomposition.

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Institutional drivers and coordination mechanisms

Socio-environmental risk is not only a function of ecological and spatial dynamics but also of institutional capacity and governance strategies. Understanding coordination performance requires identifying the systemic drivers behind it. Tobit regression models are especially well-suited for analyzing bounded dependent variables, as shown by Haralayya and Aithal (2021) in evaluating financial performance in the banking sector. While the present study focuses on environmental coordination rather than economics, the modeling principles are transferrable. By applying Tobit regression to coordination scores constrained between 0 and 1, this research identifies key explanatory factors such as ecological compensation, infrastructure access, urbanization pressure, and vegetation degradation. In doing so, it responds to prior calls for empirically grounded, spatially differentiated institutional diagnostics within risk modeling frameworks.

Methodology and data sources

This study proposes a data-driven Multi-Criteria Decision Analysis framework to evaluate socio-environmental risk in the Poyang Lake Ecological Zone. The methodology integrates geospatial indicators, statistical modeling, and spatial heterogeneity diagnostics to construct a composite risk index, analyze subsystem coordination, and identify key driving forces. The overall analytical workflow is presented in *Figure 1*, which outlines five major stages: data acquisition and pre-processing, indicator normalization, risk scoring, coupling coordination computation, and regression-based driver identification.

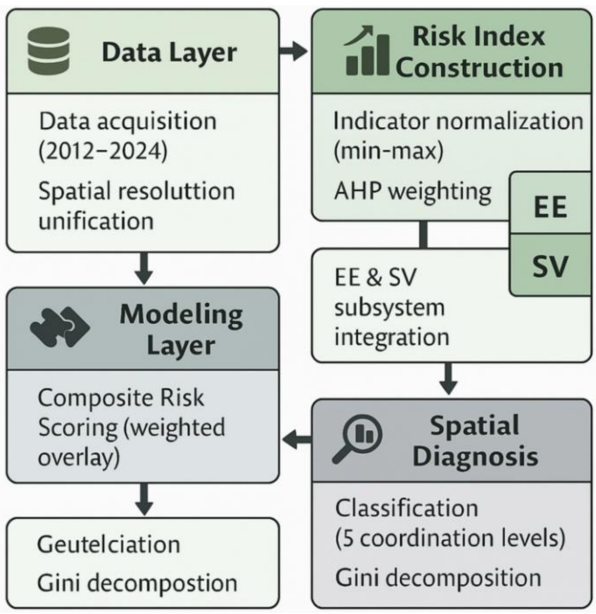

Figure 1. *Methodological framework of socio-environmental risk assessment*

Study area and spatial typology

The Poyang Lake region, located in southeastern China, encompasses over 16,000 km² and includes diverse ecological and development zones. To account for landscape

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function and anthropogenic pressure, the area is subdivided into four functional sub-regions: Wetland Core Protection Zone (WCPZ), Agricultural Transition Belt (ATB), Urban Expansion Fringe (UEF), and Infrastructure-Corridor Region (ICR) (see *Figure 2*), a classification that reflects ecological zoning practices and protection boundaries as documented in previous studies of the Poyang Lake wetland system (Li et al., 2022). This typology allows for zone-specific risk differentiation and spatial disaggregation in later analyses.

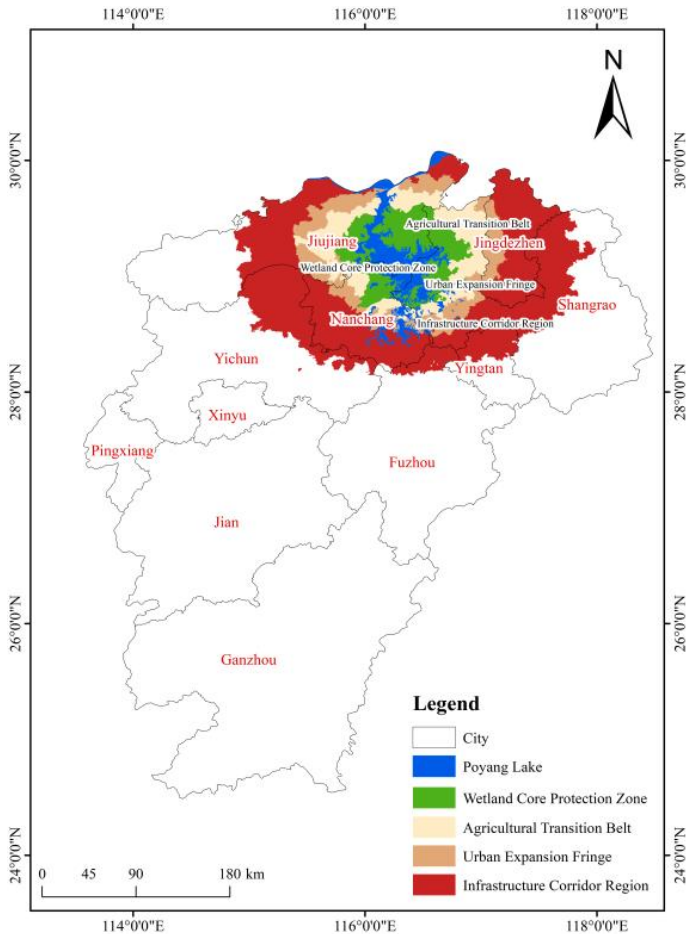

Figure 2. *Location of the Poyang Lake Ecological Zone and spatial distribution of the four functional sub-regions: Wetland Core Protection Zone (WCPZ), Agricultural Transition Belt (ATB), Urban Expansion Fringe (UEF), and Infrastructure Corridor Region (ICR).*

Data sources and indicator construction

The socio-environmental risk model is structured around two primary dimensions: Environmental Exposure and Social Vulnerability. Seven indicators are selected based on ecological relevance, spatial accessibility, and precedent in environmental modeling literature (Abdullah et al., 2021; Mishra et al., 2021; Wang et al., 2021; Ustaoglu et al., 2021; Gao et al., 2022; Kristensen et al., 2022). *Table 1* summarizes the indicators, data sources, spatial resolution, temporal coverage, and processing methods.

Environmental Exposure and Social Vulnerability were assessed through a multi-dimensional geospatial framework. EE incorporates land use change intensity derived

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from GlobeLand30 (2000–2024) via categorical transition matrices, NDVI degradation quantified through pixel-level linear regression of MODIS MOD13Q1 (Fleming et al., 2002), slope gradient calculated from SRTM DEM using Horn's algorithm, and proximity to flood-prone zones measured as Euclidean distance to historical inundation boundaries. SV integrates population density, night-time light intensity, and infrastructure accessibility. Although the flood risk data used to derive proximity to inundation areas were only available up to 2020, this indicator was retained throughout the 2012–2024 period due to the low temporal variability of floodplain boundaries in the Poyang Lake region. The area's geomorphological stability and ongoing hydrological regulation contribute to relatively stable spatial patterns of flood exposure.

Table 1. *Description of socio-environmental risk indicators and data sources*

Dimension	Indicator	Description	Data Source	Resolution	Time Span	Processing Method
Environmental Exposure	land use Change Intensity	Categorical transitions across time points	GlobeLand30	30 m	2000–2024	Classification diff maps; resampled to 100 m
Environmental Exposure	NDVI Degradation	Vegetation health trend (pixel-based regression)	MODIS MOD13Q1	250 m	2012–2024	Annual mean NDVI; linear trend
Environmental Exposure	Slope Gradient	Terrain-based erosion sensitivity	SRTM DEM	30 m	Static	Horn algorithm(Podani, 1994); reclassified into 6 risk levels
Environmental Exposure	Proximity to Flood Zones	Distance from inundation areas	MWR Flood Risk Maps	Vector	2008–2020	Euclidean distance raster
Social Vulnerability	Population Density	Proxy for exposure to social risk	WorldPop	100 m	2020–2024	Smoothed 3×3 filter; z-score normalized
Social Vulnerability	Night-Time Lights	Urban pressure proxy	VIIRS DNB Composites	500 m	2012–2024	Log-transformed and normalized
Social Vulnerability	Distance to Infrastructure	Proximity to roads, rail, dikes	OpenStreetMap + Baidu	Vector	Static	Rasterized distance; inverse normalized

All indicators are resampled to a unified 100 m resolution, directionally standardized so that higher values represent greater risk, and normalized using min-max scaling. As shown in *Equation (1)*:

$$x'_{ij} = \frac{x_{ij} - min(x_j)}{max(x_j) - min(x_j)} \quad \text{(Eq.1)}$$

where x'_{ij} is the normalized value of indicator j for spatial unit i; x_{ij} is the original value; $min(x_j)$ and $max(x_j)$ are the minimum and maximum values of indicator j across all spatial units, respectively.

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Risk scoring via weighted overlay

To integrate multi-dimensional risk information, we implement a weighted overlay model, assigning relative importance to each indicator via the Analytic Hierarchy Process (Saaty, 1980). The consistency ratio (CR) is computed to validate judgment matrices, with CR < 0.1 indicating acceptable consistency. The overall socio-environmental risk index for grid cell i is given by *Equation (2)*:

$$R_i = \sum_{j=1}^{n} w_j \cdot x'_{ij} \tag{Eq.2}$$

where R_i is the composite risk score, w_j is the AHP-derived weight for indicator j, and x'_{ij} is the normalized value.

Coupling Coordination Degree Model (CCDM)

To assess systemic interactions between EE and SV subsystems, the Coupling Coordination Degree Model is employed. First, the subsystem indices are aggregated as shown in *Equation (3)*:

$$U_{EE} = \sum_{k=1}^{m} w_k^{EE} \cdot x_{ik}, U_{SV} = \sum_{l=1}^{n} w_l^{SV} \cdot x_{il} \tag{Eq.3}$$

where U_{EE} and U_{SV} are the composite scores for Environmental Exposure and Social Vulnerability, respectively; w_k^{EE} and w_l^{SV} are the weights of the k-th and l-th indicators in EE and SV; x_{ik} and x_{il} are the normalized values of the k-th and l-th indicators for spatial unit i; mmm and nnn denote the number of indicators in EE and SV, respectively.

The coupling degree C reflects the interaction between subsystems. As shown in *Equation (4)*:

$$C = \frac{2\sqrt{U_{EE} \cdot U_{SV}}}{U_{EE} + U_{SV}} \tag{Eq.4}$$

where C represents the coupling degree between the Environmental Exposure (EE) and Social Vulnerability (SV) subsystems; U_{EE} and U_{SV} are the composite scores of the respective subsystems, as calculated in Equation (3). A higher C value indicates stronger interaction or synchronization between the two subsystems.

To capture the extent of harmonious development, the coordination degree D is defined as *Equation (5)*:

$$T = \alpha \cdot U_{EE} + \beta \cdot U_{SV}, D = \sqrt{C \cdot T} \tag{Eq.5}$$

where α and β are subsystem weights (set to 0.5 each in this study). Based on Jenks natural breaks classification, D is categorized into five levels: severe disorder (D < 0.2), low coordination (0.2 ≤ D < 0.4), moderate coordination (0.4 ≤ D < 0.6), good coordination (0.6 ≤ D < 0.8), and high coordination (D ≥ 0.8). As shown in *Figure 3*.

Spatial inequality: Dagum Gini coefficient decomposition

To identify the sources of spatial disparity in coordination outcomes, the Dagum Gini coefficient (Dagum, 1997) is decomposed into three components: intra-group disparity

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(G_w), inter-group disparity (G_b), and transvariation intensity (G_t). The total Gini index G for the regional system is given by *Equation (6)*:

$$G = G_w + G_b + G_t \quad \text{(Eq.6)}$$

where G is the total Dagum Gini coefficient reflecting overall spatial inequality in coordination performance; G_w represents the intra-regional inequality component; G_b denotes inter-regional inequality; and G_t captures the transvariation intensity caused by distributional overlap across regions.

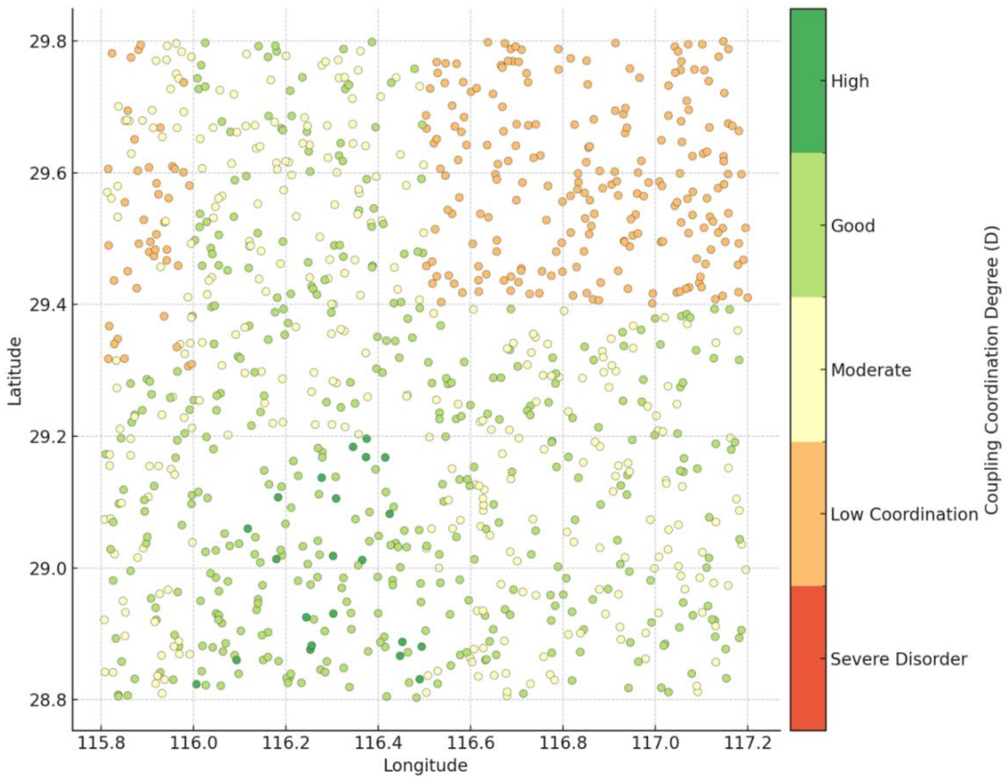

Figure 3. *Spatial distribution of coupling coordination levels*

The decomposition enables attribution of inequality to functional sub-zones (e.g., UEF vs. WCPZ), revealing whether coordination gaps stem primarily from structural or overlapping differences.

Tobit regression for driving factor analysis

To examine the determinants of coordination performance, a Tobit regression model (Haralayya and Aithal, 2021) is applied due to the bounded nature of the dependent variable ($0 \leq D \leq 1$). The model is specified as *Equations (7) and (8)*:

$$D_i^* = \beta_0 + \sum_{k=1}^{p} \beta_k X_{ik} + \varepsilon_i \quad \text{(Eq.7)}$$

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$$D_i = \begin{cases} 0, if D_i^* \leq 0 \\ D_i^*, if 0 < D_i^* < 1 \\ 1, if D_i^* \geq 1 \end{cases} \quad \text{(Eq.8)}$$

where D_i^* is the latent coordination score, X_{ik} are the explanatory variables (e.g., land use intensity, policy investment, infrastructure density). Description of Variables in Tobit Regression Model is shown as *Table 2*.

Table 2. *Description of variables in Tobit regression model*

Variable Name	Description	Type	Expected Sign
Coordination Degree (D)	Coupling coordination index between EE and SV	Dependent	–
Government Investment Index	Environmental investment intensity (per capita basis)	Continuous	+
Urbanization Rate	Proportion of urban land in total area	Continuous	+
Ecological Compensation Index	Share of region under policy incentive coverage	Continuous	+
Land Use Conversion Intensity	Rate of wetland, forest, or agri-land conversion	Continuous	–
NDVI Degradation Rate	Pixel-wise trend of vegetation loss	Continuous	–
Infrastructure Accessibility	Inverse mean distance to road/rail networks	Continuous	+

Data sources: Government investment data from Jiangxi Provincial Statistical Yearbooks (2012–2024); land use data from GlobeLand30; NDVI from MODIS MOD13Q1; infrastructure from OpenStreetMap and Baidu Maps; population from WorldPop; urban land use from GlobeLand30; ecological compensation coverage from Ministry of Ecology and Environment of China

Results and analysis

Spatial pattern of composite socio-environmental risk

The spatial distribution of composite socio-environmental risk across the Poyang Lake Ecological Zone reveals substantial regional heterogeneity. The composite risk index was generated based on AHP-derived weights assigned to seven indicators, reflecting their relative importance in the multi-dimensional risk framework. These weights and the AHP consistency ratio (CR = 0.067) are summarized in *Figure 4*.

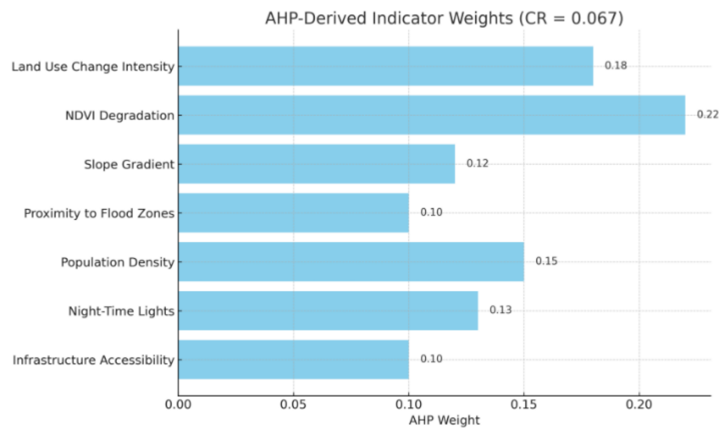

Figure 4. *AHP-derived indicator weights and consistency ratio*

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As shown in *Figure 5*, high-risk zones are predominantly clustered along the Urban Expansion Fringe and sections of the Infrastructure-Corridor Region (ICR), particularly in areas intersected by transportation networks and exhibiting strong night-time light signals. These zones exhibit concurrent high values in both Environmental Exposure and Social Vulnerability, driven by rapid land use conversion, population concentration, and ecological fragmentation.

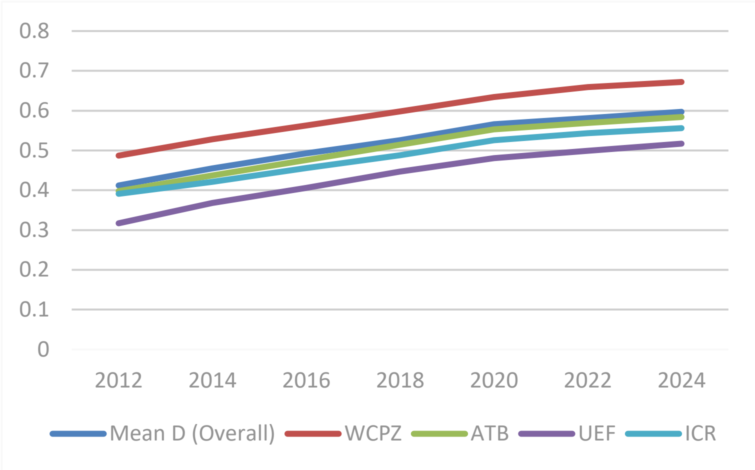

Figure 5. *Spatial distribution of composite socio-environmental risk (2012–2024)*

In contrast, the Wetland Core Protection Zone shows predominantly low to moderate composite risk, largely attributable to regulatory constraints and reduced anthropogenic activity. The Agricultural Transition Belt presents a mixed risk profile, with moderate values resulting from gradual cropland expansion and periodic hydrological stress.

Composite socio-environmental risk index derived from weighted MCDA integration of seven indicators. High-risk zones concentrate in urban fringe and infrastructure corridors.

As shown in *Figure 6*, Ramsar-designated wetlands (orange) are concentrated within the Wetland Core Protection Zone (WCPZ) in the central and southern portion of the Poyang Lake Ecological Zone, predominantly surrounding the main water body and key wetland habitats. These areas are largely encircled by open water (blue) and buffered from high-intensity human activities by agricultural transition belts and urban fringes. The spatial containment of Ramsar sites within the WCPZ reflects the alignment between international conservation designations and domestic functional zoning. Their geographic positioning away from major infrastructure corridors and high-density population clusters contributes to the observed low composite risk scores and high coupling coordination levels in this zone (see *Table 3*). This spatial configuration underscores the effectiveness of legal protection and ecological compensation measures in maintaining ecological integrity within internationally recognized wetlands.

The zonal summary in *Table 3* confirms these spatial patterns. The UEF records the highest mean risk score (0.713), followed by the ICR (0.662). Meanwhile, the WCPZ exhibits the lowest mean value (0.391), reflecting successful ecological protection interventions in wetland core areas.

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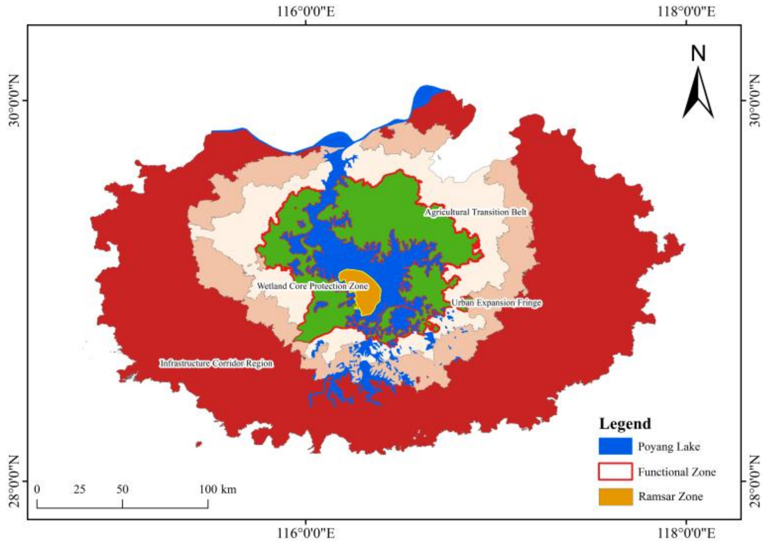

Figure 6. *Functional zoning of the Poyang Lake Ecological Zone and spatial distribution of Ramsar-designated wetlands*

Table 3. *Zonal summary statistics of composite risk scores*

Sub-region	Mean Risk Score	Std. Dev.	Max	Min
WCPZ	0.391	0.084	0.572	0.217
ATB	0.544	0.097	0.712	0.302
UEF	0.713	0.103	0.887	0.456
ICR	0.662	0.089	0.803	0.412

To better understand the spatial structure of individual indicators contributing to composite risk, *Figure 7* visualizes the geospatial distribution of five key socio-environmental risk variables, including NDVI degradation, land conversion intensity, terrain sensitivity, population density, and infrastructure accessibility.

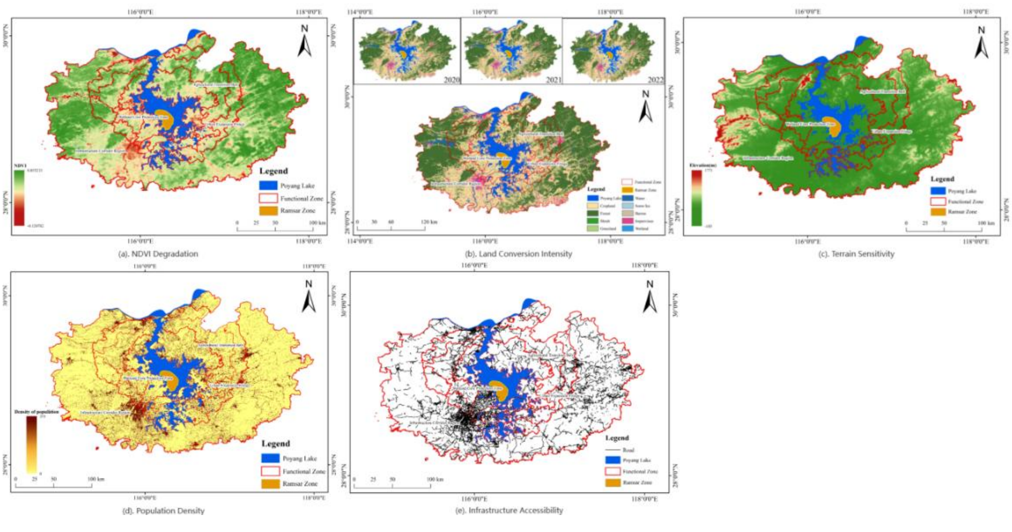

Figure 7. *Spatial distribution of socio-environmental risk indicators in the Poyang Lake Region (a). NDVI Degradation; (b). Land Conversion Intensity; (c). Terrain Sensitivity; (d). Population Density; (e). Infrastructure Accessibility*

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Coupling coordination degree dynamics

The temporal evolution of the Coupling Coordination Degree (CCD) between EE and SV subsystems from 2012 to 2024 illustrates an overall trend of gradual improvement. As shown in *Figure 8*, the mean CCD value increased from 0.412 in 2012 (moderate imbalance) to 0.597 in 2024 (near-moderate coordination), reflecting incremental progress in aligning ecological protection with socio-economic planning.

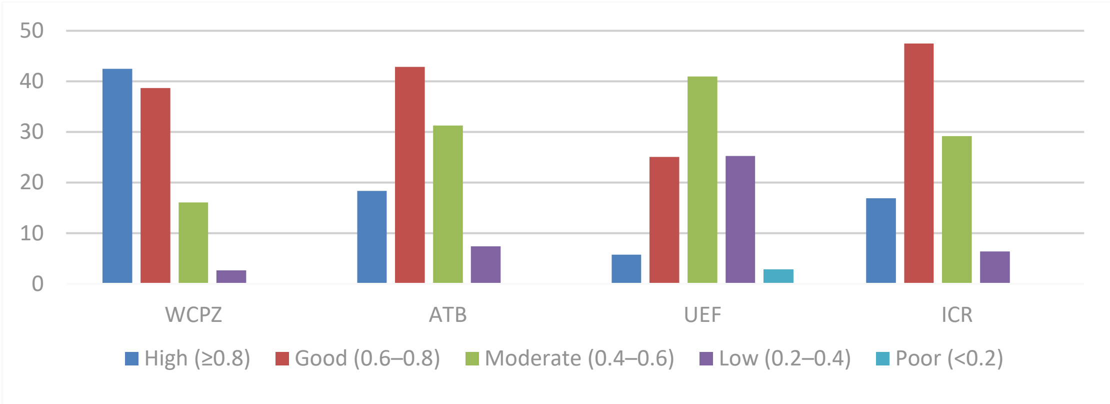

Figure 8. *Temporal trend of coupling coordination degree (2012–2024)*

However, the coordination improvement is not uniformly distributed. The UEF demonstrates persistent underperformance, with over 60% of grid cells classified in the "low coordination" category even in 2024. This study further examined the spatial distribution of coordination changes between 2012 and 2024 across the four functional sub-regions. Notably, the WCPZ showed a clear upward shift in coordination scores, suggesting that ecological protection measures in Ramsar-designated wetlands have had a stabilizing effect. In contrast, limited improvement was observed in the UEF, indicating that current policies may not be sufficiently mitigating the socio-environmental pressures in rapidly urbanizing zones. These spatially disaggregated temporal trends help clarify the differentiated effectiveness of ecological compensation and land use control policies across zones. By contrast, the WCPZ achieved "high coordination" levels in over 40% of its area, due to stable ecological indicators and limited exposure to social pressure.

To further examine the relationship between risk intensity and systemic coordination, a scatter analysis was conducted between composite socio-environmental risk scores and coupling coordination degree values. As shown in *Figure 9*, a negative linear trend is observed, suggesting that areas with higher composite risk tend to exhibit lower coordination levels between environmental and social subsystems. Each point represents a spatial grid cell in the Poyang Lake Ecological Zone. The negative correlation ($R^2 \approx 0.51$) indicates that higher composite risk is generally associated with lower levels of systemic coordination.

Temporal evolution of coupling coordination degree across the Poyang Lake region. Moderate improvement is observed overall, but sub-regional divergence persists. As shown in *Table 4*.

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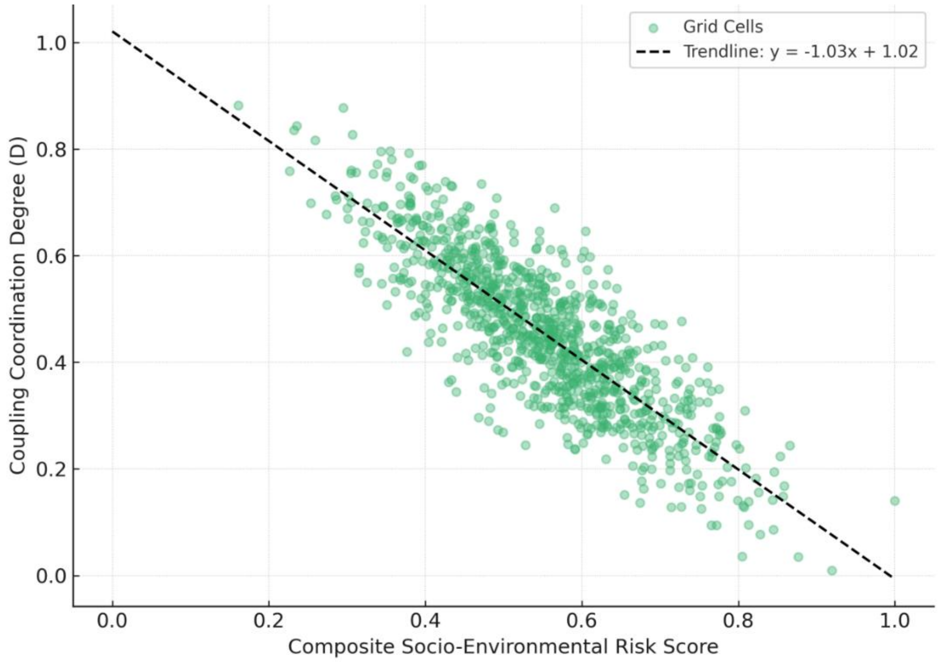

Figure 9. *Relationship between composite socio-environmental risk score and coupling coordination degree (D)*

Table 4. *Area distribution by coupling coordination levels and sub-region (2024)*

Sub-region	High (≥0.8)	Moderate (0.6–0.8)	Low (0.4–0.6)	Poor (<0.4)
WCPZ	42.5%	38.7%	16.1%	2.7%
ATB	18.4%	42.9%	31.3%	7.4%
UEF	5.8%	25.1%	41.0%	28.1%
ICR	16.9%	47.5%	29.2%	6.4%

Spatial inequality decomposition

To further interrogate coordination disparities across the functional landscape, the Dagum Gini coefficient was decomposed into three components. The overall Gini index in 2024 is 0.274, indicating moderate spatial inequality in coordination performance. As illustrated in *Table 5*, inter-regional differences (G_b= 0.126) are the dominant source of inequality, followed by overlapping risk distributions (G_t= 0.091). Within-region differences (G_w= 0.057) contribute the least, suggesting that functional zoning explains much of the disparity.

Table 5. *Dagum Gini coefficient decomposition for coordination degree (2024)*

Component	Value	Contribution (%)
G_w (Intra-zone)	0.057	20.8%
G_b(Inter-zone)	0.126	46.0%
G_t (Overlap)	0.091	33.2%
Total Gini	0.274	100%

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These findings underscore the structural importance of functional zones in shaping coordination outcomes, and suggest that targeted interventions, especially in UEF and ATB, are necessary to close systemic gaps.

The proportional contributions of the three Gini components are further visualized in *Figure 10*. Inter-zone disparity accounts for the largest share (46.0%), highlighting the fact that spatial inequality in coordination is primarily driven by structural regional differences, rather than random or local inconsistencies. The total coordination inequality (Gini = 0.274) is decomposed into inter-zone differences (0.126, 46.0%), overlap effects (0.091, 33.2%), and intra-zone variation (0.057, 20.8%). Results highlight the dominant role of regional structural disparities in shaping coordination performance across the Poyang Lake Ecological Zone.

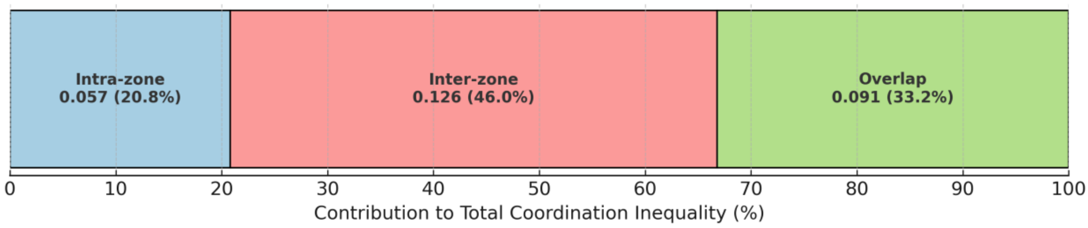

Figure 10. *Dagum Gini decomposition of coordination inequality (2024)*

Driving factors of risk coordination: Tobit regression results

The Tobit regression model identifies several significant drivers of the coordination degree, as summarized in *Table 6*. Government environmental investment intensity ($p < 0.01$), urbanization rate ($p < 0.05$), and ecological compensation policy coverage ($p < 0.05$) are positively associated with higher coordination, reinforcing the role of institutional support in integrated risk management. Conversely, land use conversion intensity and NDVI degradation rate are negatively correlated with coordination outcomes ($p < 0.01$), indicating that uncontrolled ecological disruption hampers systemic integration.

Table 6. *Tobit regression results for coordination degree (dependent variable: D)*

Variable	Coefficient	Std. Error	p-value
Government Investment Index	+0.219	0.045	0.000
Urbanization Rate	+0.132	0.061	0.032
Ecological Compensation Index	+0.178	0.074	0.017
Land Use Conversion Intensity	–0.267	0.054	0.000
NDVI Degradation Rate	–0.195	0.048	0.001
Infrastructure Accessibility	+0.088	0.039	0.027
Constant	0.411	0.093	0.000

These results emphasize the dual need to mitigate environmental degradation and intensify socio-political alignment to improve overall risk coordination. The evidence supports differentiated policy prescriptions based on spatial function and ecological sensitivity. The relative strength and direction of explanatory variables are summarized in *Figure 11*. Government investment, ecological compensation, and urbanization rate

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exhibit positive associations with coordination degree, whereas NDVI degradation and land use conversion intensity exert strong negative influences.

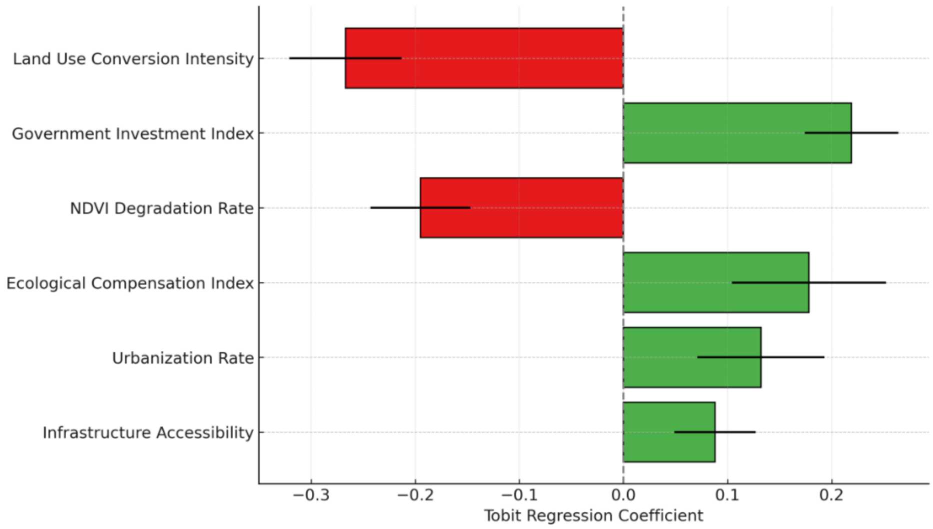

Figure 11. *Effects of explanatory variables on coupling coordination degree based on Tobit regression*

Discussion

The empirical findings from the Poyang Lake Ecological Zone underscore the multi-dimensional and spatially heterogeneous nature of socio-environmental risk in the context of large-scale ecosystem engineering. The observed divergence in risk levels and coordination degrees across functional sub-regions confirms prior assertions that ecological fragility and development intensity are not evenly distributed, but instead reflect deeper structural and spatial configurations of land use regimes, governance practices, and environmental exposure. For instance, the persistent high-risk levels in the Urban Expansion Fringe align with studies that emphasize the role of rapid urbanization, infrastructure clustering, and ecological simplification in amplifying systemic vulnerability (Huang et al., 2022; Li et al., 2023). The fact that coupling coordination has improved modestly over the 2012–2024 period, yet remains imbalanced in key zones, mirrors the wider tension observed in Chinese freshwater systems, where ecological management lags behind spatially diffuse development trajectories (Li et al., 2022).

This spatial unevenness finds conceptual parallels in the broader literature on environmental heterogeneity. Gao et al. (2022) and Mishra et al. (2021) have shown that physical landscape features and anthropogenic modifications jointly influence ecological function across scales. The present study extends this insight to socio-environmental interactions, showing that coordination is not solely a function of ecological condition or social pressure but rather a synthesis of both subsystems and their spatial interdependencies. The dominance of inter-regional differences in the Gini decomposition further corroborates Wang et al.'s (2021) findings that spatial heterogeneity in development capacity, such as human capital or infrastructure quality, can exacerbate uneven sustainability outcomes.

From a methodological perspective, the integration of MCDA with the coupling coordination degree model offers a useful analytic lens for evaluating system interactions

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in multi-risk environments. Previous research has applied coupling coordination frameworks to urban-air, land-energy, and hydrological-ecological systems; this study contributes by adapting the model to a socio-environmental domain and enriching it with high-resolution spatial data (Qi et al., 2022; Dong et al., 2023). The classification and quantification of coordination levels using remote sensing and functional zoning enhance the interpretability and actionability of risk metrics. However, critiques of the model's potential misuse, such as in assuming linear coordination trajectories or failing to account for overlapping boundaries, remain pertinent and suggest that CCDM should be continually refined and context-calibrated (Wang et al., 2021).

The role of institutional and economic drivers also emerged prominently in the Tobit regression analysis. Variables such as environmental investment intensity and ecological compensation coverage significantly contributed to improved coordination, validating arguments in the literature that targeted policy instruments can mitigate risk through financial and governance interventions (Kristensen et al., 2022). Conversely, the strong negative association between NDVI degradation and coordination highlights the ecological consequences of unchecked land conversion, echoing concerns raised by Kristensen et al. (2022) and Sun et al. (2021) regarding long-term ecological instability induced by anthropogenic pressures. These findings suggest that coordination is neither automatic nor neutral, it must be institutionally produced, spatially mediated, and ecologically sustained.

Finally, the use of remote sensing and AI-supported spatial models holds promise for advancing socio-environmental risk assessment. Emerging technologies such as foundation models (e.g., SpectralGPT, RemoteCLIP) offer unprecedented capacity for semantic scene understanding and spatial generalization (Liu et al., 2024; Hong et al., 2024). Future research should consider embedding these models within MCDA frameworks to improve indicator precision, automate classification tasks, and reduce data processing burdens. As Zhang et al. (2022) argue, intelligent sensing systems will become essential infrastructure for environmental governance in the era of ecosystem engineering.

Conclusion and policy implications

This study developed and validated a data-driven, multi-criteria decision analysis framework for assessing socio-environmental risk in large-scale ecosystem engineering projects, with an application to the Poyang Lake Ecological Zone. Through the integration of geospatial indicators, functional sub-regional zoning, and a coupling coordination degree model, the analysis revealed pronounced spatial heterogeneity in both risk intensity and coordination capacity. While ecological protection zones exhibited relatively stable conditions, areas under rapid urbanization and infrastructure expansion were characterized by persistent high risk and low coordination.

The coupling analysis indicated modest improvements in risk integration over the 2012–2024 period, yet structural disparities, especially between the Urban Expansion Fringe and other functional zones, remain substantial. Decomposition of spatial inequality using the Dagum Gini index highlighted inter-regional differences as the primary source of coordination disparity, while regression results pointed to both ecological degradation and institutional capacity as key determinants of systemic outcomes. These findings affirm the necessity of regionally differentiated strategies that are both ecologically grounded and governance-sensitive.

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Policy implications from this study include the need to: strengthen ecological compensation and incentive mechanisms in transitional zones; enforce spatially adaptive land use planning to mitigate the impact of infrastructure encroachment; and integrate real-time remote sensing systems with decision support platforms to enhance dynamic monitoring and policy responsiveness. Ecosystem engineering, if not accompanied by spatially nuanced and socially inclusive governance, risks deepening existing vulnerabilities rather than resolving them.

Future research should expand on this framework by incorporating machine learning for non-linear coordination modeling, developing participatory MCDA systems involving stakeholder input, and validating the model in other ecological regions. As China and other nations increasingly embrace ecological infrastructure as a pathway to sustainability, the integration of spatial analytics, coordination diagnostics, and institutional design will be critical for balancing ecological integrity with human development imperatives.

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