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Spatiotemporal Disparities and Key Drivers of Urban Sustainability Capacity in China

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Abstract

China's rapid urbanization has driven a pronounced east–west sustainability schism, where affluent coastal corridors face cumulative pollution pressures, while interior regions grapple with ecological fragility and comparatively weaker governance capacity. To diagnose this divergence, we establish the Environmental Stressor Regulatory Capacity (ESRC) framework, integrating indicators across industrial emissions, resource intensity, economic innovation, and institutional resilience. Leveraging Chinese spatiotemporal data from 283 prefecture-level cities from 2003 to 2021, our multi-method analysis reveals three core findings: Dagum Gini decomposition indicates intensifying interregional inequality. Kernel density estimation identifies four distinct transition archetypes: eastern high-base consolidation, central relay diffusion, western polarization–correction, and northeastern asymmetric revitalization. Crucially, random forest regression highlights the high predictive salience of Regulatory Capacity for ESRC variation. These findings are consistent with institutional asymmetry as the key explanatory factor for why some Western regions remain locked in spatial traps. These results may inform targeted ecological compensation for critical zones to support SDG advancement with regional equity.

Keywords: urban sustainability capacity; spatiotemporal disparities; Dagum Gini decomposition; kernel density estimation; random forest model

1. Introduction

Urbanization epitomizes a core paradox of the Anthropocene era, simultaneously driving socioeconomic advancement while intensifying environmental degradation. Global urban centers occupy merely 3% of terrestrial surfaces yet account for 80% of total energy consumption and 75% of carbon emissions, crystallizing the critical tension between developmental imperatives and planetary boundaries [1]. This crisis escalates in rapidly industrializing nations, where urban expansion routinely breaches ecological carrying capacity, with China's unprecedented urbanization trajectory serving as a critical proving ground. China's urban population share increased by 24.3 percentage points between 2003 and 2021, coinciding with severe environmental externalities [2]. In East Asia, 143 cities recorded annual PM_{2.5} concentrations at least seven times the 2021 WHO guideline, and all of these cities were in China [3]. Groundwater stress also intensified, with accelerated depletion documented in 30% of the world's regional aquifers over the past

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four decades [4]. Crucially, these stressors exhibit profound spatial heterogeneity, crystallizing into an east–west sustainability schism wherein affluent coastal corridors confront self-reinforcing pollution cascades while interior regions struggle with ecological fragility amplified by developmental deficits [5,6].

Currently, diagnostic research on environmental disparities still has serious limitations in analytical methods. Many studies only adopt a single environmental indicator, such as a single air quality index, a single water quality indicator, or the total carbon footprint, which cannot reflect the complex nonlinear dynamic change laws of the human–nature coupled system. Furthermore, static assessments obscure critical path dependencies, neglecting how historical industrialization patterns propagate contemporary ecological risks and lock in unsustainable trajectories. Perhaps more critically, the persistent disciplinary divide between environmental science and regional economics impedes a mechanistic understanding of spatial disparities.

Building on this motivation, we develop and operationalize an integrated Environmental Stressor-Regulatory Capacity (ESRC) framework that synthesizes 12 indicators spanning environmental pressures and governance capacity. Using panel data for 283 Chinese prefecture-level cities from 2003 to 2021, we combine CRITIC-AHP weighting with spatial diagnostics (Moran’s I and LISA), distributional analysis (Dagum Gini decomposition and kernel density estimation), and random forest regression with permutation importance to capture nonlinearities and heterogeneous associations. The primary contribution of this paper is the ESRC framework as a unified, city-level diagnostic that jointly measures environmental stressors and governance capacity; the institutional-asymmetry interpretation and the transition archetypes are analytic insights enabled by this diagnostic.

2. Literature Review

Urban sustainability governance is increasingly understood as a multi-level, multi-actor challenge in which cities must reconcile economic development with reductions in resource use and environmental burdens under heterogeneous institutional conditions. In rapidly urbanizing contexts, spatially uneven institutions interact with uneven environmental pressures, producing divergent sustainability trajectories that are further reinforced by spillovers and cross-jurisdictional externalities [7]. To clarify why such gradients persist, this review synthesizes evidence on cross-domain stressor dynamics, governance capacity beyond enforcement, and spatial dependence in regional divergence.

(i) How environmental stressors operate and interact

Urban environmental burdens operate as coupled systems rather than isolated pollutants. Prior studies indicate that environmental stressors can respond nonlinearly to interventions and that comparable abatement efforts can yield heterogeneous outcomes across locations and regimes [8,9]. Compound and climate-linked stress dynamics further complicate diagnosis based on single drivers, as meteorological variability and drought conditions can exacerbate PM_{2.5}–O₃ co-pollution and alter the effectiveness of control strategies [10]. Accordingly, fine particulate exposure has been used as a core pressure proxy in SDG-oriented urban assessments because it captures population-relevant air-quality burdens of urbanization [11]. Beyond air pollution, multi-indicator water-quality research underscores that risk typically reflects coexisting contaminants and trade-offs across indicators, strengthening the case for multi-index evaluation to avoid single-metric bias [12]. Land-development research similarly highlights that development patterns alter imperviousness and runoff regimes, with implications for water quality and broader system resilience [13].

Overall, this evidence shows that urban stressors are multi-domain and often nonlinear, making single-metric diagnostics insufficient. Yet stressor measures remain largely domain-specific, limiting cross-city comparability and obscuring how stressor configurations interact with governance responses. This motivates a parsimonious, multi-domain Environmental Stressors axis in ESRC.

(ii) What constitutes effective governance capacity beyond enforcement stringency

A second stream of literature emphasizes that transitions are shaped by interacting instruments and complementary institutions [14]. In global mitigation assessments, the institutional capability to deliver infrastructure, finance, and coordinated action is highlighted as a prerequisite for durable urban mitigation outcomes [8]. In China, finance-enabled governance instruments provide evidence of “capacity” operating through resource mobilization: the green credit policy has been associated with reductions in industrial emission intensity, consistent with capital allocation affecting the feasibility and speed of abatement [15]. At the sectoral level, ultra-low-emission retrofits in coal-fired power plants demonstrate how implementation capability and technological upgrading translate policy intent into measurable pollutant reductions [16]. Conservation and ecological governance studies likewise suggest that outcomes hinge on governance arrangements and coordination capacity, including mechanisms that integrate local livelihoods and institutional collaboration [17]. Fiscal foundations are another enabling condition: cross-country evidence shows that subnational governments finance a large share of climate-related public expenditure and investment, underscoring how stable revenue and expenditure capacity sustain policy commitments over time [18].

Taken together, this literature implies that regulatory capacity extends beyond enforcement stringency to include resource mobilization, implementation capability, and risk buffering. However, empirical proxies remain fragmented across finance, expenditure, innovation, and resilience, weakening comparability and synthesis at the city level. We therefore integrate observable indicators capturing these functions into a unified Regulatory Capacity axis for spatial diagnosis.

(iii) Why spatial gradients persist despite policy effort

A third stream of research documents that sustainability transitions are spatially interdependent. Environmental pressures and governance responses spill across jurisdictional boundaries, such that isolated local actions may be insufficient without broader coordination [19,20]. Empirically, archetypal spatial gradient patterns have been observed in the economy–population–air-quality nexus, implying that divergence is embedded in structured development gradients rather than driven only by idiosyncratic local shocks [21]. These regularities can be reinforced when stressor dynamics interact with uneven response capacity. In such contexts, clustering of high pressure may coincide with clusters of low capacity, sustaining “spatial traps” in which lagging regions face higher marginal abatement costs and weaker institutional learning channels. Evidence on institutional openness and governance foundations further indicates that institutional heterogeneity is closely linked to the ability to achieve synergistic reductions in air and carbon pollution [22,23] and to sustain environmental expenditure effort [24,25].

Despite robust evidence on spillovers and structured gradients, few studies disentangle how stressor intensity and governance capacity jointly sustain regional divergence under spatial dependence. Moreover, sustainability inequality is often reported descriptively rather than decomposed into within- and between-region components and their evolution over time. These considerations support adopting a unified diagnostic that separates stressor intensity from regulatory capacity and combining ESRC with spatial diagnostics, inequality decomposition, and distributional dynamics in this study.

3. ESRC Framework Construction and Methodology

3.1. Conceptualizing the ESRC Framework

Traditional sustainability assessment is confronted with persistent methodological limitations, characterized by simplified environmental indicators, static analysis that ignores historical path dependence, and disciplinary fragmentation in the ecological and socio-economic fields. To address these limitations, this study proposes a novel dual-axis Environmental Stressor-Regulatory Capacity (ESRC) framework (Table 1). This integrated construct quantifies anthropogenic pressures on natural systems (Environmental Stressors) alongside societal capacities to mitigate such pressures (Regulatory Capacity), explicitly aligning with the United Nations Sustainable Development Goals [26], while accommodating China's unique urbanization challenges.

In this study, Environmental Stressors (ES) denote measurable anthropogenic pressures arising from urban production and consumption activities. Correspondingly, Regulatory Capacity (RC) is conceptualized as urban governance capacity to mitigate and adapt to environmental stressors, rather than a direct measure of regulatory stringency. RC is operationalized through three complementary components, Resource Mobilization, Policy Implementation, and Risk Buffering, which together reflect a city's capacity to mobilize resources, implement policy actions, and buffer shocks to sustain long-term resilience. Accordingly, the green-finance index is used as an observable proxy for resource mobilization, while environmental governance investment proxies implementation effort in environmental management.

This framework adheres to three fundamental design principles to ensure the robustness and policy relevance of the methodology: The first is the principle of SDG localization, which transforms global goals into an indicator system that suits specific national conditions. For example, the framework incorporates SDG 11.6 on urban air quality by using widely applied air-quality indicators and threshold-based assessments in China, and introduces the industrial pollution index to quantify regional industrialization differences. The second is the principle of dimensional hierarchy, which builds an analytical framework by establishing theoretical linkages. The environmental secondary dimensions, especially resource efficiency and pollution control, are directly related to Sustainable Development Goals 12–13. Regulatory sub-dimensions connect to socioeconomic targets spanning innovation (SDGs 8–9) and institutional resilience (SDGs 10–11). The third is the principle of Policy Responsiveness, which integrates China's national strategies, notably the Dual Carbon Goals and New Urbanization Policy, through forward-looking indicators [27,28]. Representative metrics such as the Green Financial Index and Environmental Governance Investment Ratio enable dynamic monitoring of strategic implementation over time [29]. Guided by the above principles, indicators were selected using four criteria, theoretical relevance, data comparability, policy interpretability, and non-redundancy, to retain a parsimonious yet multi-dimensional representation of ES and RC. Taken together, the above conceptualization and design principles position ESRC as a complement to existing sustainability indices, which often emphasize outcome metrics or single-sided diagnostics focusing solely on pressures or capacities.

As a robustness note, the key spatial ranking patterns and regional gradients of ESRC are unlikely to be associated with a single indicator grouping or weighting choice and are expected to remain qualitatively stable under reasonable alternative specifications.

Table 1. Environmental stressor regulatory capacity (ESRC) framework.

Dimension	Sub-Dimension	Measurement	Rationale
Environmental Stressors	Pollution Load	Industrial Pollution Index (Synthesized via entropy weighting of SO ₂ emissions, wastewater discharge, and industrial smoke/dust emissions)	Captures composite industrial pollution pressure across major emissions [30].
		Air Quality Stress (Daily max AQI based on SO ₂ , NO ₂ , PM _{2.5} , etc.; aggregated annually)	Captures acute, population-exposed atmospheric pollution pressure [31].
	Resource Intensity	Energy Pressure (Total energy consumption/Real GDP)	Measures energy intensity, reflecting resource-use efficiency and decarbonization constraints [32].
		Land Development Intensity (Proportion of built-up land area)	Proxy for built-up expansion and habitat conversion [33].
	Resource Mobilization	Green Finance Level (EWM composite of seven indicators)	Proxy for the city's capacity to mobilize and allocate capital toward green transition and pollution control [34].
		Industrial Upgrading Efficacy (Industrial structure upgrading index = $\sum (\text{Share of industry } i \times i)$)	Captures structural reallocation capacity toward less pollution-intensive and higher value-added activities [35].
Regulatory Capacity	Policy Implementation	Economic Density Management (GDP/Administrative land area)	Reflects spatial efficiency and compact development capacity [36].
		Environmental R&D Intensity (Patent grants per 10,000 people)	Proxies technological innovation output and adoption capacity supporting environmental policy implementation [37].
		Environmental Governance Investment (% of GDP allocated to pollution control)	Represents fiscal commitment and administrative execution capacity for pollution control and ecological restoration [38].
	Risk Buffering	Social Risk Coverage (Pension + medical + unemployment insurance participation rate)	Captures institutional buffering mechanisms that protect livelihoods and maintain stability under environmental and economic shocks [39].
		Trade Flow Resilience (Total imports & exports/GDP (%))	Proxy for external shock absorption and supply-chain connectivity that supports sustained transition capacity [40].
		Logistics System Efficiency (Total highway freight volume [10 k tons])	Proxies logistics throughput relevant to supply-chain resilience [41].

3.2. Measurement Methods and Data Sources

1. Integrated Weighting Methodology

To overcome limitations of subjective weighting and static assumptions in conventional approaches, this study employs an integrated CRITIC-AHP framework to quantify urban sustainable development levels. A purely data-driven method such as the entropy weight method (EWM) assigns weights largely according to dispersion, which may overemphasize highly variable indicators while underweighting theoretically central but less dispersed ones. In contrast, CRITIC provides an objective baseline by jointly considering indicator variability and inter-indicator conflict, which is well suited to multi-dimensional constructs. AHP is then introduced as a constrained expert-judgment layer to ensure consistency with the ESRC conceptual structure and policy interpretability.

Standardized values (z_{ij}) are first obtained via min–max normalization:

The formula for standardizing the positive indicators is

$$z_{ij} = [x_{ij} - \min(x_j)] / [\max(x_j) - \min(x_j)] \quad (i = 1, 2, \dots, n; j = 1, 2, \dots, m), \quad (1)$$

The formula for normalizing the inverse indicator is

$$z_{ij} = [\max(x_j) - x_{ij}] / [\max(x_j) - \min(x_j)] \quad (i = 1, 2, \dots, n; j = 1, 2, \dots, m), \quad (2)$$

Subsequently, contrast intensity (σ_j) and conflict (R_j) are calculated as

$$\sigma_j = \sqrt{\sum_{i=1}^n (Z_{ij} - \bar{z}_j)^2 / n - 1} \quad R_j = \sum_{k=1}^m (1 - \rho_{jk}), \quad (3)$$

where ρ_{jk} denotes the Pearson correlation coefficient between indicators j and k . The objective weight w'_j is then computed as

$$w' = \sigma_j R_j / \sum_{k=1}^m \sigma_k R_k, \quad (4)$$

Complementarily, the Analytic Hierarchy Process (AHP) establishes subjective weights w'_j through expert-calibrated pairwise comparisons using Saaty's 1–9 scale. The AHP judgments were provided independently by three experts with complementary expertise: Expert A has extensive experience in national and environmental–economic accounting, including service in national statistical administration; Expert B is trained in economic statistics and econometrics, with project experience in industrial upgrading and fiscal/financial policy evaluation; and Expert C contributes domain expertise in green finance and urban sustainability governance.

Individual judgments were aggregated using the geometric mean, and all comparison matrices satisfied the AHP consistency criterion ($CR < 0.10$). Finally, the combined weight w_j integrates both approaches through importance coefficients α_i and β_i :

$$\alpha_i = w'_i / (w'_i + w''_i) \quad \beta_i = w''_i / (w'_i + w''_i), \quad (5)$$

$$w_i = \alpha_i w'_i + \beta_i w''_i / \sum_{i=1}^n (\alpha_i w'_i + \beta_i w''_i), \quad (6)$$

This synthesis mitigates methodological biases while preserving contextual relevance to China's sustainability challenges.

2. Spatial Autocorrelation Analysis

Spatial spillovers are intrinsic to urban sustainability transitions yet neglected in aspatial models. We employ Global and Local Moran's I [42] with inverse-distance weights w to:

Diagnose nationwide clustering patterns:

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

where n denotes the number of cities, x_i is the sustainability score of city i , and s^2 is the sample variance. For local clustering diagnostics, LISA is computed as

$$I_i = (x_i - \bar{x}) \sum_{j \neq i}^n w_{ij} (x_j - \bar{x}) / S^2, \quad (8)$$

3. Dagum Gini Decomposition Framework

Traditional inequality metrics fail to disentangle intra-regional, inter-regional, and overlap components. Spatial heterogeneity is dissected through the Dagum Gini coefficient, which partitions total inequality (G) into intra-regional (G_w), inter-regional (G_{nb}), and transvariation (G_t) components. For k regions:

$$G = G_w + G_{nb} + G_t = \sum_{j=1}^k \sum_{h=1}^k \sum_{i=1}^{n_j} \sum_{r=1}^{n_h} |y_{ij} - y_{hr}| / 2n^2 \bar{Y}, \quad (9)$$

The decomposition formalizes as

$$G_w = \sum_{j=1}^k G_{jj} p_j s_j, \quad (10)$$

$$G_{nb} = \sum_{j=2}^k \sum_{h=1}^{j-1} G_{jh} (p_j s_h + p_h s_j) D_{jh}, \quad (11)$$

$$G_t = \sum_{j=2}^k \sum_{h=1}^{j-1} G_{jh} (p_j s_h + p_h s_j) (1 - D_{jh}), \quad (12)$$

Here, $p_j = n_j/n$, $s_j = n_j \bar{y}_j / n \bar{y}$ ($j=1, 2, \dots, k$) and is the relative affluence between regions j and h .

4. Dynamic Distribution Estimation via Kernel Density

Static inequality measures obscure distributional dynamics. Nonparametric kernel density estimation [43] captures the temporal evolution of sustainability distributions.

The density function $\hat{f}(y)$ at sustainability score y is:

$$\hat{f}(y) = \frac{1}{n} \sum_{i=1}^n \frac{K\left(\frac{y-Y_i}{h_i}\right)}{h_i}, \quad (13)$$

where n is the sample size, h is the bandwidth optimized via cross-validation, Y_i is the observed scores, and $K(\cdot)$ is the Gaussian kernel.

5. Quantitative Feature Importance Assessment

Sustainable transition processes involve complex nonlinear threshold effects and cross-dimensional feedback mechanisms. Conventional linear models struggle to capture such intricate relationships due to fixed parametric assumptions and collinearity blindness. Random forest regression helps summarize the relative predictive importance of candidate drivers. Feature-importance scores are interpreted as indicators of predictive contribution within the model, rather than as causal effects. The mean decrease impurity (MDI) method and Mean Decrease Accuracy (MDA) were used for comprehensive verification:

Mean Decrease Impurity: The importance of feature j is quantified as the mean MSE reduction across all nodes splitting on j :

$$MDI_j = \frac{1}{T} \sum_{t=1}^T \sum_{s \in S_{j,t}} \frac{N_s}{N} [I(s) - \frac{N_L}{N_s} I(L) - \frac{N_R}{N_s} I(R)], \quad (14)$$

where T denotes the number of trees in the forest, $I(\cdot)$ represents the impurity measure for the regression tree, N_s is the number of samples reaching node s , N is the total number of samples, and L and R denote the left and right child nodes, respectively.

$$MDA_j = \frac{1}{R} \sum_{r=1}^R \left[\frac{1}{I_{OOB}} \sum_{i \in I_{OOB}} (\ell(y_i, \hat{y}_{i,OOB}(j, \pi_r)) - \ell(y_i, \hat{y}_{i,OOB})) \right], \quad (15)$$

where $\hat{y}_{i,OOB}$ denotes the out-of-bag prediction of the random forest, $\hat{y}_{i,OOB}(j, \pi_r)$ is obtained after performing R independent permutations of the j feature, $I_{OOB} = \bigcup_{b=1}^T O_b$ represents the union of OOB samples across all trees, and $\ell(y_i, \hat{y}_i)$ is the loss function, i is the number of trees in the forest, and denotes the set of OOB samples for the b -th tree.

3.3. Subjects of the Study and Data Sources

This research employs a longitudinal panel dataset encompassing 283 prefecture-level cities in China from 2003 to 2021, yielding 5378 valid observations. Air quality metrics were sourced from the China National Environmental Monitoring Centre (CNEMC) real-time monitoring platform. Patent authorization records originate from the China National Intellectual Property Administration (CNIPA). Within the ESRC framework, the green finance level indicator is incorporated as a pre-composite, entropy-weighted index, integrating seven sub-indicators: green credit scale (environmental project loan balance/total loan balance); green investment intensity (environmental pollution control investment/GDP); green insurance penetration (environmental liability insurance premiums/total property insurance premiums); green bond issuance volume (green bond issuance/total bond issuance); green fiscal support (environmental protection fiscal expendi-

ture/general public budget expenditure); green fund coverage (green fund market capitalization/total fund market value); and green equity trading volume ([carbon emissions + energy use rights + pollution discharge rights] trading volume/total equity market trading volume). This synthesized green finance level indicator is then treated as a single variable within the ESRC framework and assigned its weight using the integrated CRITIC-AHP method described in Section 3.2. Data for these sub-indicators were compiled from the China Financial Yearbook, China Banking and Insurance Regulatory Commission (CBIRC) regional statistical reports, Wind Financial Terminal, and provincial/municipal Statistical Bulletins on National Economic and Social Development. Remaining socioeconomic, land-use, and environmental governance variables were directly extracted or calculated from the China City Statistical Yearbook, CSMAR database, and Wind Database.

3.4. Weight Calculation and Measurement Results

The CRITIC-AHP weighted analysis has clarified the structural hierarchy of sustainability drivers in the urban systems of China (Table 2). The division of weights has different implications for the governance of environmental stressors. The industrial pollution index and air quality pressure are the main influencing factors. Energy pressure offers a higher AHP than CRITIC weighting. Among the drivers of institutional capacity, economic density management and the level of green finance emerge as prominent predictors in the weighted index structure. It is worth noting that the CRITIC weight of green finance level is significantly greater than the AHP weight, indicating that its objective intercity dispersion far exceeds expert-based expectations. Environmental Governance Investment indicates institutional mechanisms as pivotal regulatory tools, aligning with SDG implementation priorities through balanced CRITIC-AHP weighting. The weights of industrial upgrading efficiency and logistics system efficiency in both evaluation methods have shown a systematic decline.

As a robustness check, we recalculated the ESRC index using the entropy-weight method to examine whether the CRITIC-AHP-based composite scores exhibit potential systematic bias. We then compared the entropy-weight ESRC with the baseline CRITIC-AHP ESRC across the full city-year sample. The two series exhibit very high consistency (Pearson $r = 0.972$; Spearman $\rho = 0.979$), indicating that the relative ranking and spatial patterns of ESRC are robust to alternative weighting specifications.

Table 2. CRITIC-AHP integrated weights for ESRC indicators.

Indicator	CRITIC Weight	AHP Weight	Composite Weight
Industrial Pollution Index	0.11818	0.07692	0.08944
Air Quality Stress	0.11731	0.03419	0.08649
Energy Pressure	0.05556	0.13072	0.09504
Land Development Intensity	0.06572	0.09150	0.07084
Green Finance Level	0.18034	0.09846	0.13289
Industrial Upgrading Efficacy	0.06853	0.02462	0.04995
Economic Density Management	0.04428	0.19692	0.14822
Environmental R&D Intensity	0.05843	0.10667	0.07863
Environmental Governance Investment	0.17606	0.10667	0.13153
Social Risk Coverage	0.02703	0.05333	0.03904
Trade Flow Resilience	0.06550	0.04174	0.04937
Logistics System Efficiency	0.02307	0.03826	0.02856

4. Empirical Analysis

To improve traceability, we present the results around three guiding questions. First, we document whether ESRC exhibits systematic spatiotemporal gradients and spatial clustering (Sections 4.1 and 4.2). Second, we characterize the evolution of regional disparities and decompose the sources of inequality (Sections 4.3 and 4.4). Third, we assess the model-based importance rankings of ESRC indicators and their temporal shifts using random forest diagnostics (Section 4.5).

4.1. Spatiotemporal Distribution Patterns

Spatiotemporal analysis of Environmental Stressor Regulatory Capacity (ESRC) scores across 283 Chinese prefectures reveals a sustained national improvement from 2003 to 2021 (Figure 1). The average index gradually rose from 0.386 to 0.467, with faster growth in later years than in earlier periods. Across the full sample, 98.9% of cities showed growth in ESRC, while only 1.1% of cities experienced marginal regression. Regional disparities persist. In 2021, the hierarchy remained as follows, Eastern > Northeastern > Central > Western, reinforcing the deeply entrenched East–West development gradient. The eastern region of China has maintained its dominant position through a high-speed growth trajectory, while the northeastern region has achieved high-base growth, which coincides with the later acceleration stage of strengthening environmental governance after China's carbon peak commitment in 2015.

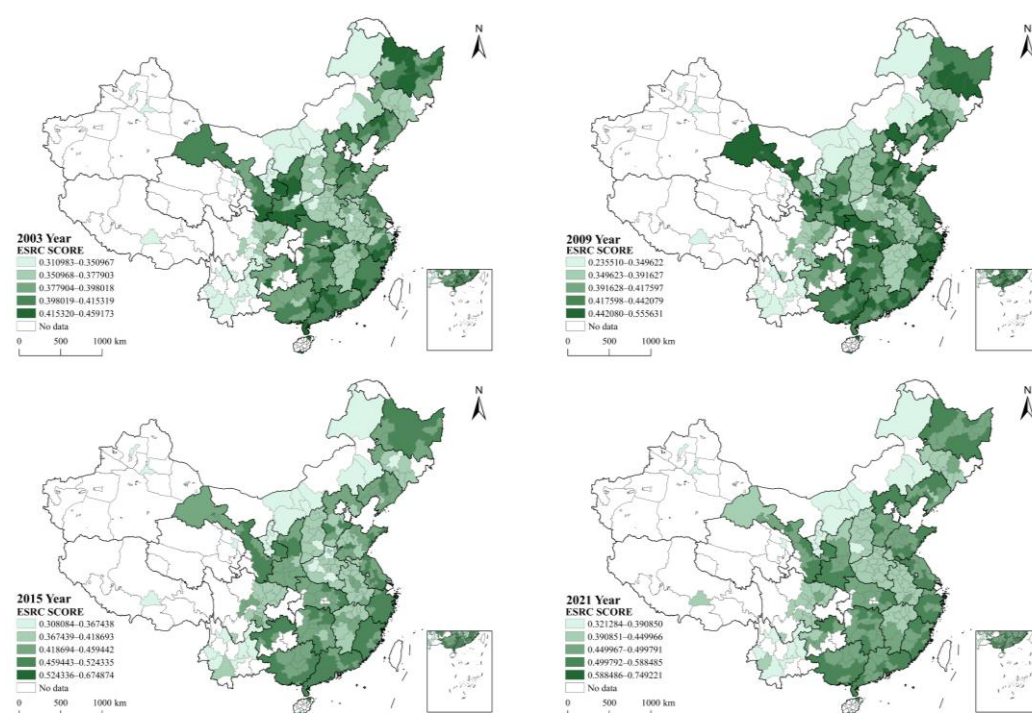


Figure 1. Spatiotemporal evolution of urban sustainability levels.

The spatial concentration of high ESRC values mainly occurs in two major corridors: one is the continuous coastal belt that runs through the Liaodong Peninsula, the Bohai Bay, the Shandong Peninsula, the Yangtze River Delta, the west coast of the Taiwan Strait and the Pearl River Delta. The other one is the Yangtze River Economic Belt, which integrates the Chengdu–Chongqing metropolitan area, the Wuhan–Changsha–Nanchong urban agglomeration and the Jiangsu–Zhejiang–Shanghai urban agglomeration. The regional development trajectories show significant differences: Core cities maintain a strong

development momentum in the Beijing–Tianjin–Hebei region and the Bohai Bay area, while Hebei and the western part of Inner Mongolia show an unbalanced development trend. Central accelerated post-2009, attaining sustained medium-high levels by 2015–2021. The Chengdu–Chongqing region showed pronounced late-phase intensification, emerging as western China’s dominant growth pole with radial diffusion toward Panzhihua and southern Sichuan. Northeast China underwent selective revitalization during 2015–2021, during which the Liaodong Peninsula and Harbin–Changchun hubs substantially outperformed peripheries. Despite isolated high-value nodes in the Hexi Corridor and the Yellow River basin, Northwest China and the Tibetan Plateau retained structural constraints.

4.2. Spatial Autocorrelation Characteristics

1. Global Autocorrelation Assessment

Global Moran’s I analysis for 283 Chinese cities indicates persistent positive spatial autocorrelation in ESRC scores (Figure 2), indicating significant clustering of cities with comparable sustainability performance. The temporal trajectory exhibits a clear inflection point: Moran’s I fluctuates between 0.135 and 0.172 before 2013, and stabilizes at a higher level thereafter, suggesting stronger and more persistent spatial clustering in later periods.

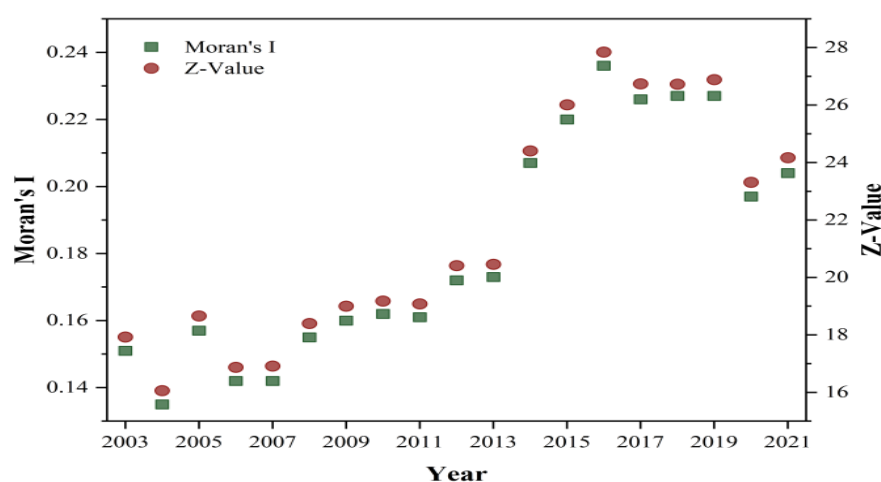


Figure 2. Global spatial autocorrelation trajectory.

2. Spatiotemporal Evolution of LISA Clusters

Figure 3 presents a spatial analysis using local indicators of spatial association (LISA). The 2003 distribution exhibited a bipolar spatial structure characterized by high–high (HH) clusters concentrated along the southeastern coastal corridor with secondary nuclei in Northeast China’s industrial cores, while extensive low–low (LL) zones dominated the Loess Plateau–North China Plain. Evolutionary trajectories subsequently diverged regionally. By 2009, the high-voltage system clusters along the coast had gradually merged and spread inland to strategic river basins, while the high-voltage systems in the northeast contracted towards gateway cities. The pattern in 2015 indicated that the coastal HH zone strengthened, and the inland interface witnessed the formation of a high–low (HL) transition, marking the initial stage of sustainable diffusion. By 2021, the Southeast Corridor had solidified into a continuous high-pressure belt. The Northeast region showed a spatially concentrated recovery trend at the hub of the Liaodong Peninsula. High- and low-pressure areas persisted in the central and western regions. The high- and low-pressure values that emerged along the periphery of the high values indicated a potential spillover effect. Notably, isolated high- and low-pressure (LH) enclaves appear within otherwise high-performing corridors, indicating local discontinuities relative to surrounding neighborhoods.

Regionally, Eastern China was characterized by the expansion and consolidation of coastal HH clusters. The Northeast shifted from a more dispersed pattern in 2003 to a more concentrated high-value core by 2021. Central China remained relatively fragmented, with several provincial capitals appearing as HL local configurations relative to surrounding lower-value areas. Western China showed the greatest persistence of LL clustering, with only limited and spatially discontinuous high-value pockets.

Overall, ESRC exhibits persistent positive spatial autocorrelation and an increasingly consolidated clustering structure, with stable high–high corridors and persistent low–low interiors across the study period.

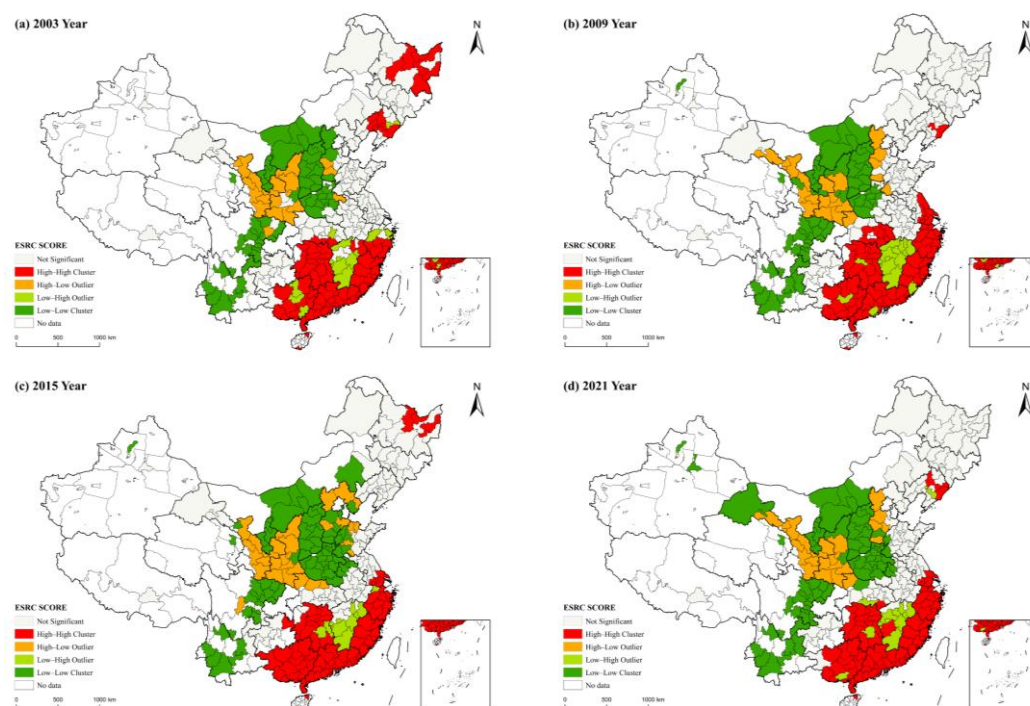


Figure 3. LISA cluster typology evolution.

4.3. Regional Disparity Decomposition

4.3.1. Intra-Regional Inequality Trends

China's national sustainability inequality, measured by the Dagum Gini coefficient followed a two-stage ascent, rose 56.1% from 0.041 in 2003 to 0.064 in 2021 (Figure 4). The initial acceleration stage from 2003 to 2009 was observed during decentralized regulatory capacity building in the early stage of the environmental governance transformation. Meanwhile, despite the absolute growth across the country, the situation has remained stable at a relatively high level since 2010. The eastern region presented an inverted U-shaped curve, reaching a peak of 0.036 in 2015, consistent with the initial polarization accompanied by aggregation, followed by convergence coinciding with coordination after 2016. The western region experienced significant fluctuations. In 2015, it reached 0.075 alongside the growth of resource endowments, but later dropped to 0.045 in 2021 after the ecological red line policy. Although the Northeast region maintained a leading position in total volume, the disparity between high and low adjacent areas in spatial distribution intensified, and the degree of inequality reached its peak in 2021. The Central region remains moderate overall, with a temporary rise around 2013 followed by stabilization in subsequent years.

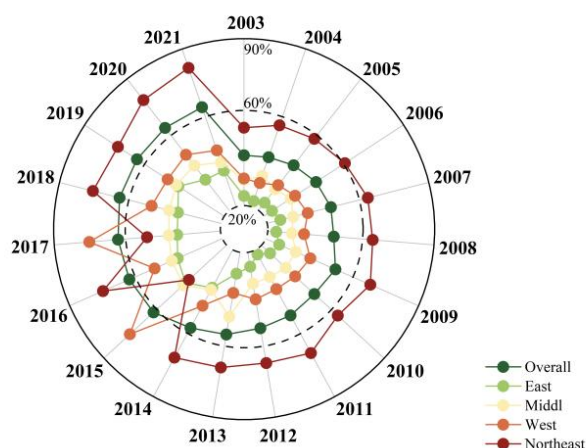


Figure 4. Intra-regional inequality dynamics.

4.3.2. Inter-Regional Disparity Patterns and Drivers

The 2021 disparity landscape reveals entrenched sustainability divides, with the East–Northeast gap constituting the most severe fracture, followed by East–West and Central–Northeast differentials (Figure 5). The degree of separation in coastal areas far exceeds that of all other regional combinations. Crucially, the gap between the eastern and central regions is slight. Longitudinal analysis shows that during the period from 2003 to 2021, the gaps between the northeastern and eastern regions and between the eastern and western regions were the main drivers of absolute inequality growth, and the widening disparities between the central and western regions and the northeastern region further strengthened this trend. The long-standing gap between the east and the west highlights the sharp contrast between the highly regulated balance mechanism in the coastal areas and the institutional vulnerability in the west. The widening divide between the north–Middle East and the west further indicates a gap in capacity diffusion, which contrasts sharply with the cross-jurisdictional coordination mechanism demonstrated by the east–central region, which shows strong resilience.

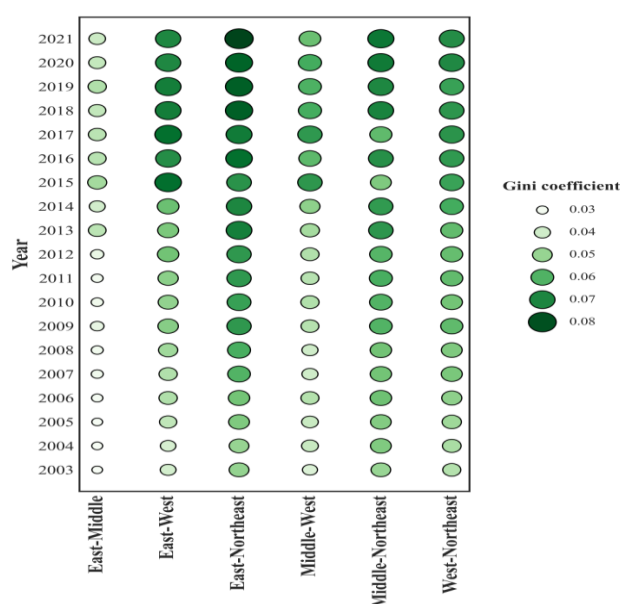


Figure 5. Inter-regional disparity drivers.

4.3.3. Dagum Gini Decomposition Results

Employing the Dagum Gini decomposition framework (Figure 6), China's urban sustainability heterogeneity is deconstructed into three components: intraregional disparity (Gw), interregional disparity (Gnb), and transvariation density (Gt). Inequality among regions has gradually become the dominant and continuously intensifying force, with its proportion rising from 42.96% in 2003 to 51.46% in 2021. This structural expansion is consistent with the stable decline in intra-regional contributions and cross-variability density, thereby confirming the position of Gnb as a major driver of national inequality, while reducing distribution overlap and indicating deep-rooted club-type divisions. Dynamic evolution has gone through four stages: In the first stage (2003–2007), transitional differentiation characteristics were presented. The differences between regions increased moderately while the cross-variability density was relatively high. The second stage (2008–2013) accelerated the differentiation process, with the inter-regional differences surging to 52.52%. In the third stage (2014–2016), there was a temporary reversal. The inter-regional differences shrank to 44.20–44.95%, and the cross-variability density rebounded to 31.54–31.96%, reflecting that policy intervention measures weakened regional barriers. In the fourth stage (2017–2021), the trend of differentiation was consolidated through the recovery of inter-regional differences to 51.46% and the reduction in cross-variability density to 26.08%, forming a more consolidated pattern of clusters of high sustainability along the coast and low sustainability inland.

In sum, ESRC inequality follows a rising trajectory with clear regional heterogeneity, and the widening gaps are concentrated in comparisons involving the coastal macro-region, which motivates the subsequent attribution analysis of key correlates.

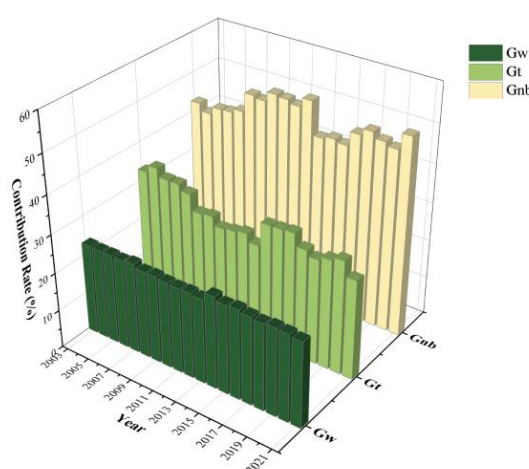


Figure 6. Structural decomposition of spatial heterogeneity.

4.4. Dynamic Transition Trajectories

Nonparametric kernel density estimation reveals distinct spatiotemporal patterns in China's urban sustainability capacity across macroregions (Figure 7). All regions exhibited rightward distributional shifts, confirming nationwide progress. East demonstrated sustained high-performance advancement as its primary density peak migrated from 0.40–0.45 to 0.50–0.55. Initial distribution widening during the 2009–2015 transitioned to post-2016 narrowing, reflecting coordinated governance maturation. Central China achieved incremental catch-up with peaks advancing from 0.35–0.40 to 0.43–0.47. Between 2012 and 2015, the distribution exhibited transient multimodality, followed by subsequent smoothing as industrial chains became more integrated. Western regions showed moder-

ate rightward shifts but pronounced multi-peak broadening during 2013–2016, later converging post-2017 through enhanced diffusion mechanisms. Northeast regions registered the most pronounced rightward shift during 2015–2021; after 2016, they paradoxically broadened, reflecting asymmetric revitalization despite aggregate growth. These transformations define regional archetypes: high-base consolidation (East), relay diffusion (Middle), polarization–correction cycles (West), and asymmetric revitalization (Northeast). Distribution narrowing in the East aligns with intraregional convergence, while Western regions’ multi-peak distributions correspond to earlier polarization extremes. Northeastern regions’ simultaneous broadening explains rising intraregional inequality and their expanding gap with advanced coastal regions. In summary, inequality in ESRC has increased over time and is dominated by between-region disparities, with the largest gaps concentrated in comparisons involving the coastal macro-region.

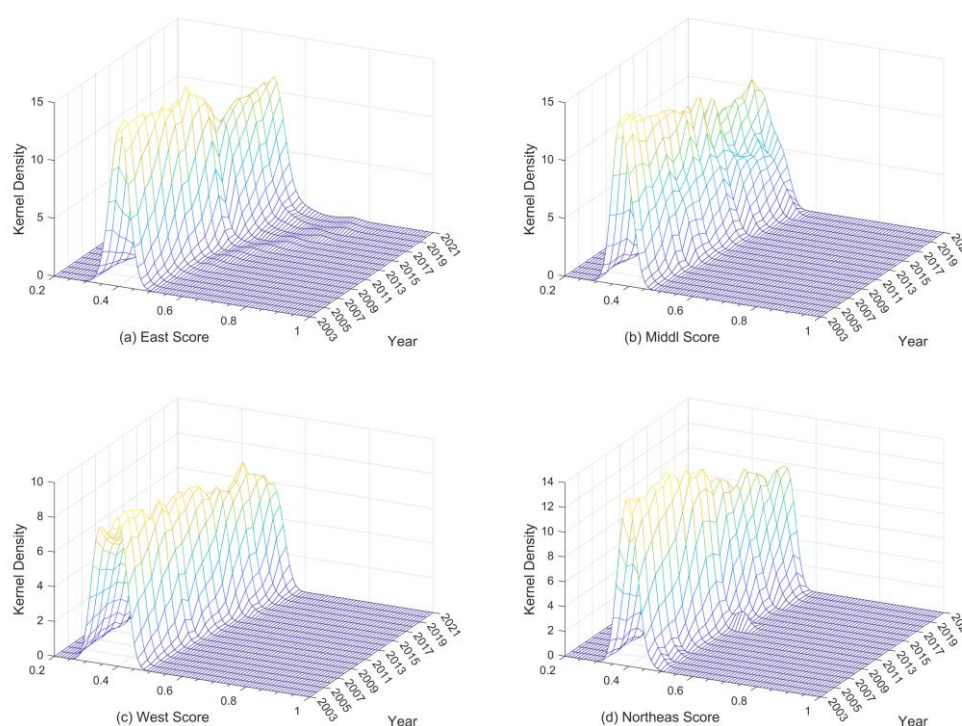


Figure 7. Regional transition trajectories via kernel density estimation.

4.5. Dominant Driver Identification

A CART-based random forest was fitted year by year to capture nonlinear sustainability drivers under small cross-sections (Figure 8) ($N = 283$ observations per year; $p = 12$ predictors). The model demonstrated exceptional predictive accuracy across 2003–2021, with OOB R^2 ranging from 0.785 to 0.842, mean 0.815, and OOB_MAE of 0.0102. Minimal generalization gaps were observed, with the mean R^2 disparity between training and OOB validation at 0.039, well below critical thresholds for longitudinal policy analysis. Annual OOB R^2 consistently exceeded 0.78, while peak train–test divergence remained constrained to 0.048. Temporal stability was evidenced by MAE_OOB averaging only 18% above training errors, confirming reliable extrapolation capacity. Detailed implementation procedures and reproducibility settings for the random forest models are provided in Appendix C.

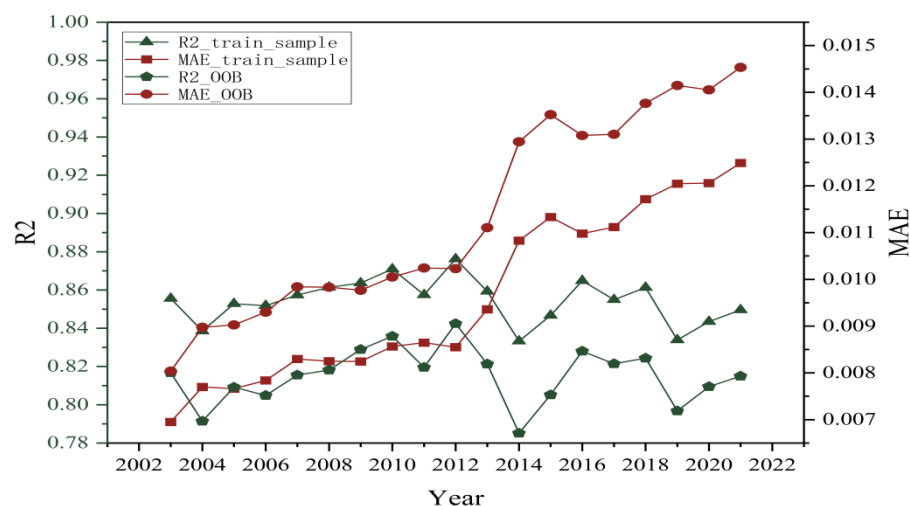


Figure 8. Random forest model validation metrics.

The complete temporal evolution of feature importance distributions is visualized (Figure 9). Across years, regulatory-capacity indicators consistently rank at the top of the random forest importance profile. Under the mean decrease impurity (MDI) metric, green finance level and environmental governance investment together account for 72.5% of aggregate importance. A notable indicator transition is evident: industrial pollution intensity fell from 0.091 in 2003 to 0.009 in 2021 and was progressively superseded by air-quality stress and energy pressure. Air-quality stress reached peak influence in 2015, coinciding with China's air-pollution crisis, while energy pressure rose from 0.046 to 0.062 during 2017 to 2018.

Complementary drivers show distinct trajectories. Environmental research-and-development intensity increased from 0.050 to 0.069 during 2012 to 2013, then stabilized at around 0.04 to 0.05. Trade-flow resilience rose steadily after 2015, reaching 0.057 to 0.060 by 2017–2018, signaling the growing role of globalization. Economic-density management remained consistently relevant. Logistics efficiency, land-development intensity, social-risk coverage, and industrial-upgrading efficacy displayed episodic significance.

Governance priorities evolved through five phases. The foundational period from 2003 to 2008 showed heightened predictive salience of regulatory capacity. The subsequent innovation-and-opening transition from 2009 to 2013 featured sharp increases in the importance of R&D and trade-flow resilience by 82% and 59%, respectively. During the air-quality constraint phase from 2014 to 2016, air-quality stress became the third-ranked driver at 0.079, aligned with the implementation of the "Atmosphere Ten Measures." The energy-chain interdependence phase in 2017 and 2018 was characterized by concurrent maxima in energy pressure and trade-flow resilience. The institutional re-consolidation phase from 2019 to 2021 restored regulatory dominance and stabilized environmental pressures. Full annual MDI scores for all features are reported in Appendix A. Robustness validation using permutation importance (MDA) yields a consistent feature ranking, again placing regulatory-capacity indicators at the top; green finance level and environmental governance investment contribute a combined 85.6% in Appendix B.

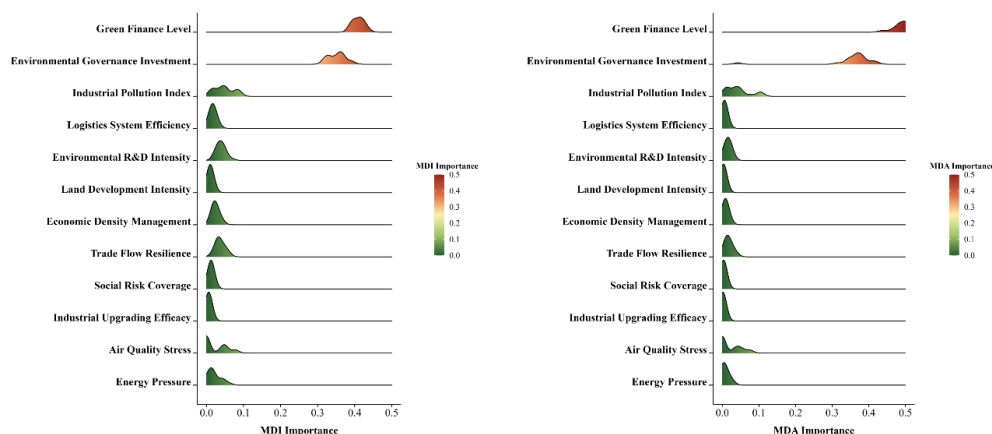


Figure 9. Dominant driver importance distribution.

5. Discussion and Conclusions

5.1. Discussion

We highlight three empirical regularities. ESRC shows persistent and strengthening spatial dependence, with high- and low-performing cities forming contiguous clusters. Inequality decomposition indicates that between-region disparity becomes increasingly salient over time. Random forest diagnostics consistently rank regulatory-capacity indicators among the top features, alongside time-varying stressor-related indicators, motivating an institutional-asymmetry interpretation of the observed gradients. These patterns are broadly consistent with strands of prior work emphasizing (i) nonlinear and compound stressor dynamics in urban environmental systems, (ii) governance capacity as an enabling condition beyond enforcement intensity, and (iii) spatial spillovers that make sustainability transitions inherently interdependent across jurisdictions.

This study interprets China's east–west sustainability divide through an institutional-asymmetry lens, highlighting how cross-regional differences in governance capacity may be associated with divergent ESRC profiles. Dagum Gini decomposition indicates intensifying interregional inequality, suggesting a growing between-region component of divergence. This divergence is plausibly accompanied by coastal governance advantages that accelerate capability accumulation, while interior regions face compounding institutional constraints. In practical terms, stronger resource mobilization and implementation commitment reduce the effective cost of abatement and speed up policy learning and capability accumulation. Over time, high-capacity cities can convert fiscal and administrative slack into sustained improvements, whereas low-capacity areas face higher marginal costs and slower adjustment, thereby widening regional gaps. These dynamics are most visible in Western China's persistent low–low clusters and the Northeastern “revitalization paradox,” where aggregate recovery coexists with widening intraregional dispersion under uneven institutional reconstruction. Consistent with this interpretation, random forest feature-importance results show that regulatory-capacity indicators—particularly green finance and environmental governance investment—rank highly in explaining ESRC variation under both mean decrease impurity and permutation-based Mean Decrease Accuracy. These feature-importance patterns capture predictive relevance in our data rather than causal effects and should be interpreted alongside the spatial and inequality evidence as convergent descriptive support for the institutional-asymmetry interpretation.

The identified transition archetypes offer mechanistic explanations for divergent regional development pathways. Eastern China's high-base consolidation is characterized

by an inverted-U trajectory in regional inequality, followed by post-2016 convergence evident in narrowing kernel density distributions. This pattern demonstrates how mature institutional coordination effectively mitigated the diseconomies stemming from excessive agglomeration. Central China's relay diffusion pathway aligns with a pulsed evolution in inequality metrics, where initial developmental leapfrogging by provincial capitals preceded the subsequent phase of broader industrial chain integration across the region. Western China exhibits a distinct polarization–correction cycle, reflecting the moderating influence of strict ecological redline enforcement. This policy intervention has successfully contracted areas of persistent low sustainability, despite the continued presence of underlying spatial anomalies. Northeastern revitalization presents a broadening paradox; while achieving leading aggregate growth rates, this process has exposed fundamental institutional incompleteness, resulting in the simultaneous expansion of both development hotspots and disadvantaged enclaves.

Methodologically, the Environmental Stressor-Regulatory Capacity framework advances sustainability assessment through three key innovations. It resolves disciplinary fragmentation by integrating stressor-specific thresholds with institutional resilience metrics, capturing critical inflection points such as air quality stress peaking during pollution crises. Temporal feature importance transitions successfully decode policy regime shifts, notably documenting the obsolescence of point-source control as industrial pollution intensity declines. Spatialized machine learning further reveals context-dependent leverage points, identifying industrial upgrading efficacy as critical for disrupting eastern pollution-resilience lock-ins, while corridor-based logistics optimization proves essential for western diffusion barriers.

Policy intervention efficacy follows a demonstrable three-tiered hierarchy. Primary leverage requires scaling green finance instruments and maintaining environmental expenditure at a stable share of GDP allocation. Secondary leverage necessitates targeted industrial abatement in pressure-intensive hubs, exemplified by ultra-low emission retrofits for cities with higher industrial pollution intensity. Tertiary pathways should strategically embed spatial-capability factors through coordinated initiatives like the Yangtze Economic Belt integration and cross-jurisdictional innovation corridors.

Several considerations for methodological refinement merit attention. The current prefecture-level analysis may benefit from future integration of district-scale environmental monitoring to capture intra-city heterogeneity. The framework could be strengthened through the incorporation of climate resilience metrics to better address escalating extreme weather impacts. Machine learning explainability might be enhanced via causal forest approaches to more precisely disentangle institutional feedback loops. These potential refinements represent natural extensions rather than fundamental limitations, offering pathways to advance spatially explicit sustainability transition theory.

5.2. Conclusions

This study systematically examines the institutional and spatial patterns of China's urban sustainability transition across 283 prefecture-level cities, documenting persistent east–west gradients and spatial clustering in ESRC outcomes. Random forest attribution further indicates that regulatory-capacity indicators are consistently among the most salient predictors of ESRC variation, accounting for a dominant share of total feature importance. Interregional inequality remains the dominant component of overall disparity, with systematically higher ESRC levels in coastal regions and persistent low-level clusters in parts of the interior.

Methodologically, the ESRC framework integrates multidimensional environmental stressors with governance-capacity indicators and combines spatial autocorrelation, ine-

quality decomposition, distribution dynamics, and random forest models to profile spatio-temporal heterogeneity. The analysis identifies four transition archetypes, eastern high-base consolidation, central relay diffusion, western polarization–correction, and northeastern asymmetric revitalization, providing a comparable typology for cross-region diagnosis.

Empirically, the archetype patterns and the concentration of low- and high-cluster regions imply that intervention priorities are likely to be region-specific rather than uniform across China. From a policy perspective, this motivates differentiated portfolios across macro-regions. For eastern industrial corridors, scaling ultra-low emission retrofits in top-decile industrial pollution hubs may help to weaken pollution-resilience lock-ins. Western critical zones could prioritize cross-jurisdictional ecological compensation mechanisms coupled with logistics corridor optimization to reduce diffusion barriers. Nationally, maintaining environmental governance expenditure effort and expanding green-finance channels are plausible leverage points suggested by the model-based attribution, while regional coordination platforms can support cross-jurisdiction implementations.

The main novelty lies in the ESRC framework as a comparable stressor–capacity diagnostic at the prefecture-city scale. Building on this measurement, the analysis (i) interprets persistent gradients through an institutional-asymmetry lens and (ii) proposes a transferable archetype typology for heterogeneous transition trajectories. The ESRC diagnostic logic is transferable, but cross-country generalization of the empirical patterns requires context-specific validation.

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Data Availability Statement: The data presented in this study are openly available in FigShare [10.6084/m9.figshare.31098310] [31098310].

Conflicts of Interest: The authors declare no conflict of interest.

Appendix A. Temporal Evolution of Random Forest Feature Importance (MDI Metrics)

Indicator	Green Finance Level	Environmental Governance Investment	Industrial Pollution Index	Logistics System Efficiency	Environmental R&D Intensity	Land Development Intensity	Economic Density Management	Trade Flow Resilience	Social Risk Coverage	Industrial Upgrading Efficiency	Air Quality Stress	Energy Pressure
2003	0.39903	0.39350	0.09098	0.02493	0.02090	0.01630	0.01561	0.01516	0.01372	0.00987	0.00000	0.00000
2004	0.41512	0.36024	0.08120	0.02414	0.02567	0.01486	0.02664	0.02884	0.01293	0.01035	0.00000	0.00000
2005	0.41234	0.36545	0.08765	0.01937	0.02934	0.01377	0.01896	0.02706	0.01502	0.01104	0.00000	0.00000
2006	0.38942	0.38961	0.08117	0.02486	0.02505	0.00988	0.01699	0.03094	0.00986	0.00644	0.00000	0.01578
2007	0.42109	0.37275	0.05703	0.02081	0.02860	0.01107	0.01960	0.03163	0.01138	0.00614	0.00000	0.01991
2008	0.43787	0.35809	0.04742	0.02019	0.03422	0.00930	0.02207	0.03385	0.01233	0.00743	0.00000	0.01722

2009	0.41668	0.36828	0.03675	0.03346	0.03251	0.00975	0.01839	0.04116	0.01818	0.00453	0.00000	0.02033
2010	0.42954	0.36675	0.04212	0.02100	0.03535	0.00824	0.01928	0.04357	0.01326	0.00599	0.00000	0.01487
2011	0.42518	0.35935	0.05546	0.01409	0.03831	0.01018	0.02469	0.03287	0.01255	0.00472	0.00000	0.02261
2012	0.42093	0.36129	0.05108	0.01635	0.05041	0.00813	0.03066	0.02865	0.01744	0.00439	0.00000	0.01067
2013	0.41184	0.35028	0.04508	0.01435	0.06939	0.01433	0.03697	0.02717	0.01463	0.00525	0.00000	0.01070
2014	0.40489	0.31932	0.07770	0.01825	0.04470	0.00725	0.02014	0.03102	0.01216	0.00612	0.04857	0.00988
2015	0.39768	0.33233	0.04465	0.01212	0.03804	0.00631	0.02238	0.04397	0.01192	0.00373	0.07920	0.00767
2016	0.39197	0.33854	0.02950	0.01157	0.04854	0.00830	0.01805	0.05038	0.00953	0.00389	0.07713	0.01261
2017	0.38754	0.32596	0.02310	0.00875	0.05135	0.00945	0.02907	0.05655	0.00949	0.00244	0.05030	0.04597
2018	0.39101	0.32141	0.01545	0.00684	0.04118	0.00870	0.02422	0.05980	0.01213	0.00535	0.05168	0.06222
2019	0.39728	0.31863	0.01353	0.01049	0.04845	0.01698	0.04206	0.05365	0.00970	0.00651	0.03648	0.04624
2020	0.42340	0.34735	0.01578	0.01581	0.03648	0.00574	0.02035	0.02987	0.00825	0.00872	0.04858	0.03968
2021	0.40914	0.33324	0.00896	0.01295	0.04435	0.01103	0.03931	0.03582	0.01250	0.00551	0.04667	0.04052

Appendix B. Robustness Validation of Driver Importance (MDA Permutation Results)

Indicator	Green Finance Level	Environmental Governance Investment	Industrial Pollution Index	Logistics System Efficiency	Environmental R&D Intensity	Land Development Intensity	Economic Density Management	Trade Flow Resilience	Social Risk Coverage	Industrial Upgrading Efficiency	Air Quality Stress	Energy Pressure
2003	0.43424	0.42214	0.10805	0.00821	0.00490	0.00600	0.00507	0.00473	0.00437	0.00229	0.00000	0.00000
2004	0.48641	0.36529	0.10113	0.00831	0.00791	0.00528	0.00893	0.01069	0.00370	0.00236	0.00000	0.00000
2005	0.92574	0.04238	0.01667	0.00276	0.00251	0.00150	0.00198	0.00428	0.00122	0.00096	0.00000	0.00000
2006	0.47753	0.37693	0.10429	0.00680	0.00727	0.00642	0.00324	0.01067	0.00362	0.00323	0.00000	0.00000
2007	0.49298	0.40191	0.05638	0.00875	0.00933	0.00453	0.00572	0.00978	0.00325	0.00136	0.00000	0.00600
2008	0.53518	0.36175	0.04645	0.00696	0.01264	0.00330	0.00843	0.01363	0.00366	0.00197	0.00000	0.00601
2009	0.49101	0.41239	0.03341	0.01121	0.01118	0.00343	0.00555	0.01755	0.00626	0.00096	0.00000	0.00705
2010	0.52023	0.38552	0.03613	0.00623	0.01374	0.00236	0.00657	0.01838	0.00379	0.00211	0.00000	0.00494
2011	0.51655	0.37925	0.04678	0.00388	0.01580	0.00322	0.00800	0.01387	0.00362	0.00148	0.00000	0.00755
2012	0.51033	0.37896	0.04892	0.00583	0.01966	0.00196	0.01265	0.01129	0.00626	0.00113	0.00000	0.00302
2013	0.50774	0.38569	0.03577	0.00462	0.02930	0.00413	0.01458	0.00897	0.00445	0.00153	0.00000	0.00321
2014	0.49169	0.31477	0.07752	0.00768	0.01696	0.00296	0.00670	0.01731	0.00441	0.00210	0.05545	0.00245
2015	0.47168	0.35349	0.04069	0.00437	0.01611	0.00242	0.00789	0.02587	0.00323	0.00079	0.07216	0.00131
2016	0.45732	0.36648	0.02380	0.00508	0.02464	0.00317	0.00628	0.02817	0.00216	0.00100	0.07799	0.00389
2017	0.49322	0.34015	0.01698	0.00535	0.02211	0.00267	0.01148	0.03361	0.00324	0.00098	0.04723	0.02298
2018	0.47839	0.34584	0.00905	0.00369	0.02175	0.00256	0.01131	0.03934	0.00495	0.00305	0.04966	0.03041
2019	0.50533	0.34329	0.00690	0.00624	0.02411	0.00533	0.01966	0.02653	0.00291	0.00243	0.03554	0.02173
2020	0.52364	0.36931	0.00703	0.00470	0.01391	0.00142	0.00837	0.01337	0.00207	0.00351	0.03647	0.01619
2021	0.50555	0.36655	0.00562	0.00388	0.02056	0.00344	0.01801	0.01686	0.00474	0.00188	0.03615	0.01677

Appendix C. Random Forest (Python v3.14.2) Specification and Reproducibility

To identify potentially nonlinear sustainability drivers under small annual cross-sections, we fitted a CART-based random forest separately for each year. Each annual model used $N = 283$ city observations and $p = 12$ predictors.

1. Model Class and Training Protocol

All models were implemented in Python (scikit-learn) using a RandomForestRegressor with CART-style decision trees. Models were fitted year-by-year to accommodate time-varying driver structures.

2. Hyperparameter Settings

Hyperparameters were tuned to balance fidelity and generalization, prioritizing leaf-based regularization:

```

max_features =  $\sqrt{p}$  (i.e., square-root feature subsampling);
max_depth = 8;
min_samples_split = 28;
min_samples_leaf = 12.

```

To avoid underfitting at this sample scale, cost-complexity pruning was kept minimal ($ccp_alpha \leq 1 \times 10^{-4}$). Larger values substantially pruned informative splits in our setting.

3. Ensemble Size, Bootstrap, and Parallelization

We trained 100 trees with bootstrap aggregation (`bootstrap = True`) and full-core parallelization (`n_jobs = -1`). The ensemble size was selected at the plateau of the out-of-bag (OOB) learning curve.

4. Model Validation and Performance Metrics

Model robustness was evaluated using OOB estimation, reporting OOB-based R^2 and MAE. Given the limited cross-sectional sample size per year, OOB validation was used to reduce dependence on a dedicated holdout set while retaining an internal generalization check.

5. Feature Importance Reporting

Unless otherwise stated, reported feature contributions are based on mean decrease in impurity (MDI) aggregated over trees. As a robustness check, permutation importance can be computed on the OOB predictions (not required for the main results, but included as an optional validation step).

6. Reproducibility Settings

All annual models were run with a fixed random seed to ensure reproducibility (`random_state = 42`, unless otherwise specified). Predictor preprocessing followed the main-text pipeline; no leakage occurs because each year is trained independently.

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