SYNERGISTIC EFFECTS OF GREEN AND DIGITAL POLICIES ON URBAN ECOLOGICAL RESILIENCE: EVIDENCE FROM CHINA'S LOW-CARBON AND BROADBAND PILOT CITIES

LIU, R.[1*] – YANG, S.[2] – SONG, Z. C.[3]

[1]*School of Mathematics and Statistics, Chongqing Technology and Business University, Chongqing 400067, China*

[2]*School of Mechanical Engineering, Chongqing Technology and Business University, Chongqing 400067, China*

[3]*Institute for Chengdu-Chongqing Economic Zone Development, Chongqing Technology and Business University, Chongqing 400067, China*

**Corresponding author*
e-mail: liurong24@ctbu.edu.cn

(Received 15th Oct 2025; accepted 6th Jan 2026)

Abstract. Amid intensifying climate change, mounting resource and environmental constraints, and accelerating digital transformation, enhancing urban ecological resilience (UER) has become critical for sustainable development and governance. As China advances its dual strategies of Carbon Peak Carbon Neutrality and Digital China, it has established a synergistic policy framework represented by the dual pilots of Low Carbon City (LC) and Broadband China (BC), requiring assessment of their combined impacts on urban ecosystem stability and adaptability. Grounded in Social Ecological Technological Systems (SETS) theory, this study develops an analytical framework for UER. Using panel data from 280 prefecture level and above cities from 2011 to 2021, we combine Double Machine Learning (DML) with mediation effect models to examine how green and digital policy synergies (GD) shape UER. Results show that GD significantly enhances UER, with dual pilot cities outperforming single policy and non-pilot cities. The effects operate through green technological innovation, digital infrastructure capability, public ecological awareness, and factor allocation efficiency, with public ecological awareness the most salient channel. The GD effect is stronger in economically advanced regions, non-traditional industrial bases, and resource-based cities, highlighting the role of institutional capacity and structural conditions in policy performance.
Keywords: *social-ecological-technological systems (SETS), double machine learning (DML). mediation analysis, public ecological awareness, factor allocation efficiency*

Abbreviations: UER, Urban Ecological Resilience; LC, Low-Carbon (pilot initiative); BC, Broadband China (pilot initiative); SETS, Social-Ecological-Technological Systems; DML, Double Machine Learning; GD, Green-Digital policy overlap/synergy (joint implementation of LC and BC); OECD, Organisation for Economic Co-operation and Development; IPCC, Intergovernmental Panel on Climate Change; NDRC, National Development and Reform Commission (China); GTI, Green Technological Innovation; DIC, Digital Infrastructure Capability; PEA, Public Ecological Awareness; FAE, Factor Allocation Efficiency; DID, Difference-in-Differences; R&D, Research and Development; ED, Economic Development Level; OP, Openness to the Outside World; IND, Level of Industrialization; INF, Infrastructure Level; FIN, Financial Scale; GDP, Gross Domestic Product; PM2.5, Particulate matter with aerodynamic diameter ≤ 2.5 μm; SO_2, Sulfur dioxide

Introduction

In recent years, urban ecological resilience (UER) has emerged as a key indicator for assessing the capacity of urban systems to maintain functional stability and achieve self-adjustment in response to environmental shocks and resource pressures, attracting

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN 1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2401_17931816

growing global attention in the context of sustainable governance. The United Nations' Sustainable Development Goals explicitly call for a systematic enhancement of cities' integrated response capabilities to climate change, resource depletion, and pollution risks. International organizations, such as the Organisation for Economic Co-operation and Development (OECD) (2024) and Intergovernmental Panel on Climate Change (IPCC) (2023), have similarly underscored the need to synergistically build the structural robustness, functional redundancy, and adaptive feedback mechanisms of urban ecological systems through green transition, technological empowerment, and institutional innovation. Against this backdrop, developed economies in Europe and North America have widely implemented policy toolkits aimed at "systemic resilience enhancement," centered on the coordinated advancement of green technologies and digital infrastructure (Artmann et al., 2019; Martin et al., 2018).

In China, the construction of urban ecological resilience (UER) has progressively shifted from an environmental performance-oriented governance tool toward a broader objective embedded in national governance modernization. This shift is driven not only by high level strategic goals but also by concrete city level policy instruments that restructure local governance priorities and capacities. In this context, the Low Carbon City Pilot (LC) and the Broadband China Pilot (BC) are two representative initiatives that operationalize, respectively, green transition governance and digital infrastructure upgrading, and their staggered rollout provides a policy setting in which potential synergy can be empirically examined.

The LC pilot was initiated by the National Development and Reform Commission (NDRC) as part of China's climate governance and low carbon development agenda. In August 2010, the NDRC issued an official notice to launch pilot work for low carbon provinces and low carbon cities, requiring pilot jurisdictions to integrate climate change mitigation into local planning, formulate low carbon development plans, explore supportive institutional arrangements, and promote measures such as industrial structure adjustment, energy structure optimization, energy saving, efficiency improvement, and carbon sink enhancement. The pilot scheme was subsequently expanded through additional batches, including the second batch announced in 2012, which further broadened the coverage of pilot provinces and cities and reinforced the policy objective of embedding low carbon transition into local governance systems.

In contrast, the BC pilot originates from China's national broadband development strategy. In August 2013, the State Council issued the "Broadband China" Strategy and its Implementation Scheme, which set out a government led plan to accelerate broadband network construction and improve access capability, speed, and coverage. Building on this strategic framework, relevant central authorities organized the selection of "Broadband China" demonstration cities or city clusters in multiple rounds. For example, the Ministry of Industry and Information Technology and the NDRC released official announcements for demonstration city lists, including the 2016 round, as part of the national effort to promote broadband upgrading and connectivity as a foundational condition for digitalization.

A key point for this study is that LC and BC were introduced under different national objectives and led by different policy logics. In their initial design stages, the two pilots were largely developed as separate policy streams, and systematic pre decision integration of green and digital policy goals was limited. However, as both initiatives expanded and diffused across cities, they generated substantial spatial and temporal overlap. In many cities, low carbon transition objectives coexisted with accelerated broadband deployment,

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN 1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2401_17931816

creating a governance environment in which digital infrastructure could plausibly strengthen the implementation of low carbon policies through improved monitoring, coordination, information transparency, and technology diffusion, while low carbon governance could stimulate demand for digital solutions in emissions accounting, energy management, and smart environmental regulation. This evolution from parallel policy deployment to increasing coexistence and potential complementarity provides a clear institutional background for analyzing whether, and through which mechanisms, the joint coverage of LC and BC enhances UER.

Existing literature has extensively examined the individual impacts of green policies (e.g., LC) and digital policies (e.g., BC) on environmental performance and urban green development, with a primary focus on outcome variables such as carbon emission control, green technological innovation, and pollution abatement efficiency (Cheng et al., 2019; Ding et al., 2024; Yu and Zhang, 2021). However, limited attention has been paid to how such institutional interventions enhance UER by reshaping the structural capacities of urban systems. Moreover, most studies rely on constructed interaction terms to identify policy synergy effects without empirically leveraging the real-world institutional setting of "dual-policy pilot cities." In addition, the identification framework concerning how policies jointly shape ecological system capacities through multidimensional mechanisms-such as institutional innovation, technological responses, structural factor optimization, and public cognitive mobilization-remains underdeveloped and warrants further theoretical and empirical exploration.

To address the aforementioned research gaps, this study introduces the Social-Ecological-Technological Systems (SETS) theory as its analytical framework. This theoretical lens underscores that UER derives not only from the self-organizing capacity of ecosystems themselves but also from the synergistic integration of institutional governance, technological infrastructure, social cognition, and factor allocation efficiency (McPhearson et al., 2022; Sharifi, 2023). Within this framework, the coordinated implementation of green institutions represented by the LC and digital infrastructure represented by the BC constitutes a critical institutional environment for enhancing the structural robustness, responsiveness, and adaptive capacity of urban ecosystems. This study posits that the synergy between green and digital policies (GD) influences UER through four key mechanisms: green technological innovation (GTI), digital infrastructure capacity (DIC), public ecological awareness (PEA), and factor allocation efficiency (FAE), as illustrated in *Figure 1* (Branny et al., 2022).

This study makes four key contributions. First, from a theoretical perspective, it embeds the synergy of green and digital policies into the logic of UER formation based on the SETS framework. It constructs a four-dimensional mechanism pathway consisting of institutional constraint, technological empowerment, social feedback, and resource coordination, thereby enriching the conceptual expansion of the SETS framework with respect to system capability building. Second, in terms of methodology, this study takes China's dual pilots of LC and BC as a natural institutional experiment and innovatively integrates Double Machine Learning (DML) with mediation effect models to enhance the precision of causal inference, addressing specification biases inherent in conventional interaction-term-based identification strategies. Third, empirically, using panel data on 280 Chinese prefecture-level cities from 2011 to 2021, this study systematically quantifies the differential impacts and transmission pathways of policy synergy across multiple dimensions of UER, including robustness, adaptability, and transformability. It further identifies how contextual factors, such as institutional capacity and industrial

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN 1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2401_17931816

structure, moderate these effects. Fourth, in terms of policy implications, the study reveals significant heterogeneity in the "amplification effect" of GD across different types of cities, highlighting the decisive role of institutional capacity and complementary governance frameworks in shaping the marginal effects of policy synergy. These findings offer both theoretical support and empirical evidence for building more adaptive and resilient urban governance systems.

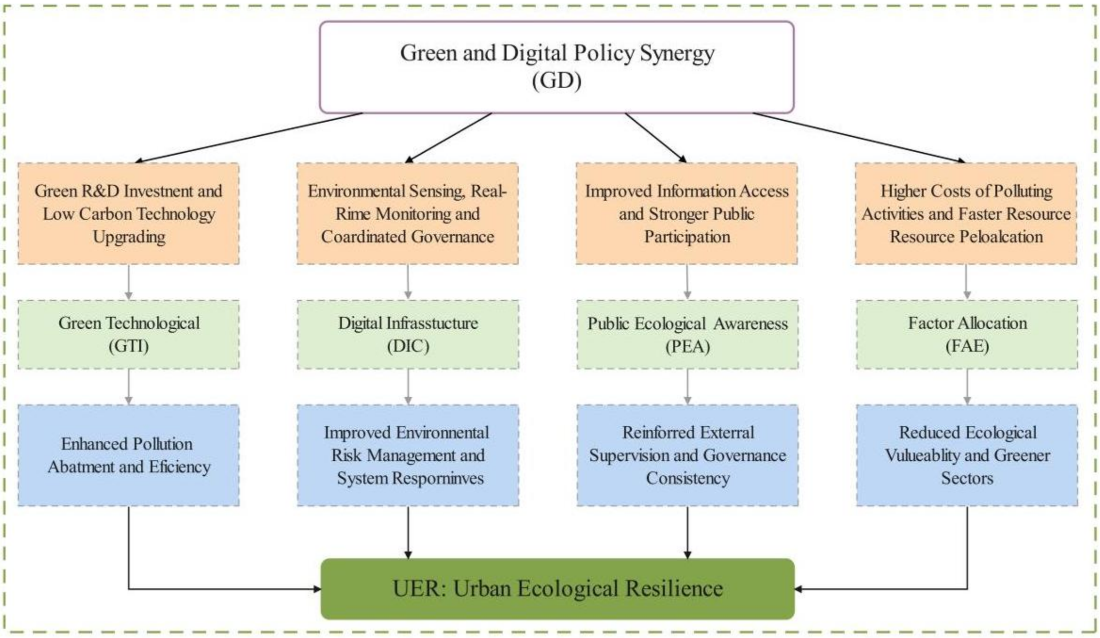


Figure 1. *Machine diagram*

Literature review

Driving mechanisms of urban ecological resilience

Ecological resilience, defined as a critical system's capacity to absorb external shocks, maintain functional stability, and achieve structural transformation, has increasingly been understood as shaped not only by natural attributes but also by structural factors such as institutions, technology, and social feedback (Spears et al., 2015; Zhou et al., 2021). The existing literature generally identifies four co-evolving dimensions within complex systems as the core drivers of UER: institutional capacity, technological foundation, resource allocation, and public feedback.

Specifically, institutional governance capacity provides the regulatory architecture and resource mobilization foundation essential for enhancing system stability and recovery (Beunen et al., 2017; Elmqvist et al., 2019; Young, 2010). Technological infrastructure-particularly in the domains of environmental monitoring, smart sensing, and digital platforms-plays a pivotal role in improving cities' responsiveness to environmental disturbances and enhancing governance precision (Keeler et al., 2019; Kitchin and Moore-Cherry, 2021). Meanwhile, ecological awareness and public participation serve as critical downstream mechanisms for policy implementation and governance feedback, strengthening institutional compliance and regulatory rigidity through behavioral alignment and public opinion pressure (Galli et al., 2020). The efficiency of resource and factor allocation determines the structural robustness and functional redundancy of the

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN 1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2401_17931816

system, constituting a key economic mechanism for achieving system adaptability and transformative potential (Zhao, 2024).

To systematically integrate these multidimensional structural elements, the SETS framework has emerged as a central analytical paradigm in UER research. This framework emphasizes the feedback-coupling relationships among institutional systems, ecological foundations, and technological structures. It argues that system adaptability depends not merely on the strength of any single subsystem but, more importantly, on the degree of coupling, feedback sensitivity, and structural redundancy across the three systems (Krueger et al., 2022; McPhearson et al., 2016).

Limitations in identifying the effects of single policies

Green and digital policies have become central instruments in contemporary urban sustainable governance. A growing body of research has demonstrated that the LC program significantly facilitates reductions in carbon intensity (Feng et al., 2021), improvements in energy efficiency (Wang et al., 2023c), and increases in green innovation outputs (Liu et al., 2025). Meanwhile, digital infrastructure policies such as the BC initiative have substantially enhanced urban information-sensing capacities, elevated the level of intelligence in environmental monitoring, pollution source tracing, and emergency response (Li et al., 2015; Wang et al., 2023a), and have to some extent promoted green production efficiency and digital-green integration (Song et al., 2024).

Despite these achievements in performance evaluation, most studies remain focused on outcome variables-such as carbon emissions, energy intensity, and green total factor productivity-while lacking analytical perspectives on system-level capabilities. Mainstream identification methods, such as Difference-in-Differences (DID) and Propensity Score Matching, are effective for estimating average treatment effects; however, they offer limited insights into how institutional and technological pathways shape structural capabilities, including system resilience, responsiveness, and adaptability. Moreover, the identification of multi-policy interaction mechanisms within complex urban systems remains insufficient, particularly in terms of empirical investigation and theoretical clarification of how GD restructures the capacity architecture of UER.

The impact of policy synergy on urban ecological resilience

Amid increasingly multifaceted system transition goals, policy synergy has become a critical approach for enhancing institutional efficiency and governance capacity (Ben Yahia et al., 2021; Howlett and Rayner, 2007). Green and digital policies are highly complementary in terms of their functional objectives and governance instruments. Their coordinated implementation is considered conducive to fostering green innovation (Yin and Yu, 2022), improving environmental information transparency and regulatory effectiveness (Dwivedi et al., 2022), and advancing the sustainability of urban systems (Luo et al., 2023). Some studies have employed interaction-term models to identify the synergistic effects of green and digital policies, confirming their enhancing impacts on green total factor productivity (Wang et al., 2023b) and the carbon peaking process (Wei et al., 2022).

However, existing research has yet to develop a systematic framework for revealing how GD enhance UER, and the underlying mechanisms remain theoretically fragmented and empirically underexplored. More importantly, the "capacity-building" function of policy synergy has not received sufficient scholarly attention.

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN 1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2401_17931816

Research gaps

As shown in *Figure 2* of the above literature review, this paper finds three key research gaps. First, there is insufficient identification of how synergistic policies affect UER as a systemic capacity variable. Most current research emphasizes the performance outcomes of GD but lacks a systematic analysis of how these policies shape the structural and functional synergies of urban ecosystems. Second, the mechanism identification for UER remains theoretically fragmented. Although some studies have explored green technological innovation (Lan et al., 2025), digital infrastructure capacity (Agboola and Tunay, 2023), public ecological awareness (Soares et al., 2021), and factor allocation efficiency (Gao et al., 2023), an integrated conceptual framework is still lacking. Third, current approaches to identifying policy synergy have not sufficiently leveraged the institutional features of China's "dual pilot" system. In practice, a large number of cities have already implemented overlapping LC and BC initiatives, forming a natural experimental setting for policy synergy-yet this institutional overlap has not been effectively utilized as a synergy variable in empirical analysis.

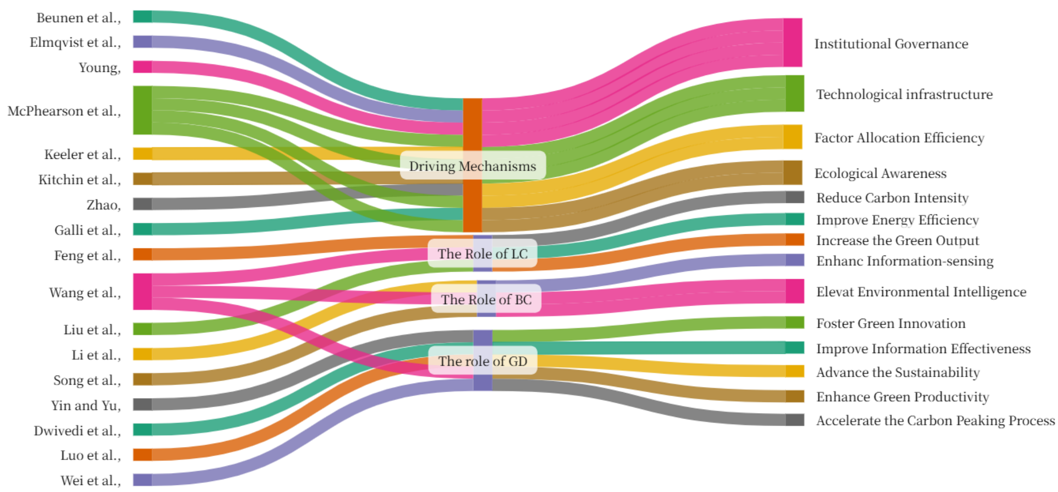


***Figure 2.** Literature review diagram*

Theoretical framework and research hypotheses

Direct effects of green and digital policy synergy on urban ecological resilience

UER is a system-level outcome that emerges from the dynamic interaction among social institutions, technological capabilities, and ecological processes. The SETS framework provides an appropriate analytical lens for examining how policy interventions reshape these interactions and, in turn, alter urban resilience trajectories (McPhearson et al., 2022). A central implication of SETS theory is that improvements within isolated subsystems are insufficient to induce sustained resilience gains. Instead, resilience enhancement depends on whether policy interventions reconfigure cross-system coupling mechanisms and feedback structures. Social institutions determine regulatory constraints and incentive structures governing environmental behavior; technological systems shape information availability, monitoring capacity, and coordination efficiency; and ecological systems generate feedback signals that condition institutional and technological adjustments.

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN 1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2401_17931816

In China's urban governance context, the LC initiative and the BC initiative intervene in distinct but interdependent subsystems. LC primarily operates through the social subsystem by strengthening environmental regulations and green governance rules, while BC intervenes through the technological subsystem by expanding digital infrastructure and data-processing capacity. When implemented independently, each policy faces structural limitations: institutional constraints may suffer from enforcement frictions, and digital infrastructure may lack clear environmental orientation. When LC and BC are implemented simultaneously within the same city, policy instruments across the social and technological subsystems become mutually reinforcing. Institutional constraints introduced by LC establish binding environmental objectives, while digital capabilities enabled by BC reduce information asymmetry, lower enforcement costs, and enhance feedback efficiency. This cross-system alignment alters the incentive–constraint configuration faced by governments, firms, and the public, thereby weakening path dependence embedded in existing production structures and governance routines.

Through this mechanism, GD reshapes the functional architecture of the urban SETS and enhances system flexibility and adaptive capacity. Based on this theoretical reasoning, the following hypothesis is proposed.

H1: The GD enhances UER.

Transmission mechanisms of green and digital policy synergy

Under the SETS framework, GD strengthens UER by aligning LC-induced institutional constraints with BC-enabled digital capabilities, thereby improving governance incentives, feedback efficiency, and structural adjustment. Accordingly, we propose four mediating mechanisms, namely GTI, DIC, PEA, and FAE, through which GD enhances UER.

First, GTI reflects the innovation response induced by the constraint–incentive configuration under GD. LC raizes regulatory stringency and clarifies low-carbon governance objectives, while BC improves monitoring, evaluation, and coordination efficiency by enabling data-driven governance. The joint presence of stronger constraints and lower information frictions increases the credibility of policy signals faced by local governments and firms, encouraging higher investment in green R&D and faster upgrading of low-carbon technologies. Such innovation upgrading improves pollution abatement capacity and energy-use efficiency, thereby strengthening the ecological subsystem's resilience.

Second, DIC captures the technological pathway through which GD improves environmental risk governance. By expanding digital infrastructure and data-processing capabilities, BC enhances environmental sensing, real-time monitoring, and cross-departmental collaboration. When combined with the governance objectives embedded in LC, these digital capabilities are more likely to be oriented toward environmental management tasks, reducing response delays and coordination costs in risk identification and mitigation. As a result, the urban system becomes more responsive and more capable of recovery under external shocks.

Third, PEA represents the social feedback mechanism that supports effective ecological governance under GD. Digital connectivity facilitated by BC reduces information frictions and broadens access to environmental information, while the regulatory orientation of LC provides clear targets for public scrutiny. This combination increases public attention and participation in environmental affairs, intensifies external supervision pressure, and strengthens enforcement credibility, thereby improving the

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN 1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2401_17931816

consistency and sustainability of ecological governance and contributing to resilience enhancement.

Fourth, FAE reflects the structural adjustment channel through which GD weakens path dependence in urban production and resource allocation. LC increases the relative costs of "high energy consumption–high pollution–high capital intensity" activities through regulatory constraints and compliance requirements, while BC reduces transaction costs and improves matching efficiency in factor markets by facilitating information diffusion and coordination. Together, these forces promote the reallocation of capital and other factors away from polluting sectors toward greener and more productive activities, thereby reducing systemic ecological vulnerability and providing a structural foundation for the improvement of UER.

In summary, GTI, DIC, PEA, and FAE constitute four complementary mediation pathways through which GD translates the joint effects of LC and BC into resilience gains. Based on this theoretical reasoning, the following hypothesis is proposed:

H2: GD enhances UER indirectly through the mediating effects of GTI, DIC, PEA, and FAE.

Heterogeneous effects of green and digital policy synergy

While GD can, in principle, integrate regulatory constraints and incentive mechanisms and thereby improve policy transmission, its effectiveness is unlikely to be uniform across cities. In the SETS framework, cities are open systems in which the UER trajectory depends not only on policy inputs but also on initial conditions such as institutional capacity, resource dependence, and industrial structure. Cross-city differences in absorptive capacity, technology adaptation, and social responsiveness therefore condition the strength of GD effects.

Specifically, economically advanced cities typically possess stronger governance capacity, greater allocation efficiency, and higher responsiveness, which improves the translation of LC-induced constraints and BC-enabled digital capabilities into effective environmental governance. As a result, the impact of GD on UER is expected to be stronger in these cities. Resource-based cities, by contrast, tend to rely more heavily on high-emission and primary sectors, making green transition more dependent on external regulatory and technological shocks. In this context, GD may generate larger marginal gains by tightening constraints while lowering information and coordination frictions. Moreover, non-old industrial cities often exhibit greater structural flexibility and institutional adaptability, making it easier for GD to form a reinforcing cycle linking institutional embedding, technological upgrading, and societal response. Old industrial bases, however, may face stronger path dependence and structural rigidity, which can dampen the realized effects of GD. Based on this reasoning, we propose:

H3: The effect of GD on UER is heterogeneous and is more pronounced in economically advanced cities, resource-based cities, and non-old industrial cities.

Materials and methods

Research methodology

A growing body of empirical research has examined the joint effects of GD initiatives using quasi-natural experiments based on the BC and LC (Zeng et al., 2025). Such studies provide important evidence on policy synergy, but they also imply that estimated effects

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN 1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2401_17931816

may depend on the study period and the empirical strategy adopted, as policy implementation intensity, enforcement capacity, and digital adoption evolve over time, and treatment effects may be heterogeneous across cities. Consequently, conclusions drawn from conventional specifications can be sensitive to modelling choices, particularly when confounding factors are complex. In this context, traditional regression models often face limitations in variable selection, nonlinear structure recognition, and the evaluation of high-dimensional interactions when assessing the impact of GD on UER. These challenges are especially pronounced in city-level policy evaluation, where policy effects are embedded in intertwined socioeconomic, environmental, and governance systems. Model misspecification under such conditions may lead to biased or inefficient estimates, making it difficult to assess whether the hypothesized relationships are robust to alternative research designs.

To address these concerns and improve both robustness and causal interpretability, this study adopts DML as a complement to conventional econometric analysis. The DML framework combines flexible machine learning techniques with orthogonalized estimation, thereby mitigating biases arising from high-dimensional controls and nonlinear relationships. In implementation, Random Forest is employed to model the nuisance components in both the outcome and treatment equations, given its ability to capture nonlinearities, interaction effects, and heterogeneous patterns without imposing strong parametric assumptions. By residualizing the outcome and treatment variables with respect to a rich set of covariates and applying cross-fitting to avoid overfitting, the DML procedure yields estimates of the GD effect that are more stable to modelling choices and remain interpretable within a causal inference framework.

To enhance transparency and reproducibility, this study explicitly reports the software used for empirical estimation and visualization. Baseline econometric estimations and robustness checks are implemented in Stata. The double machine learning procedure based on Random Forest is carried out in Python using standard libraries. Conceptual diagrams and mechanism pathway figures are produced using Microsoft Visio, and spatial visualizations of policy implementation and urban ecological resilience are generated in ArcGIS.

The double machine learning model

This study builds on the DML approach proposed by Chernozhukov et al. (2022) and integrates city-level panel data to specify the following baseline model:

$$UER_{i,t} = \theta_0 GD_{i,t} + g(X_{i,t}) + U_{i,t}, E(U_{i,t} \mid GD_{i,t}, X_{i,t}) = 0 \qquad \text{(Eq.1)}$$

where i denotes the city and t denotes the year; $UER_{i,t}$ represents the level of the energy transition and $GD_{i,t}$ is the policy synergy variable representing the joint implementation of the LC and the BC; $U_{i,t}$ is the error term with a conditional expectation of 0; $X_{i,t}$ is the set of high-dimensional control variables, and the functional form $g(X_{i,t})$ is estimated using machine learning algorithms, denoted as $\hat{g}(X_{i,t})$. The coefficient estimator can be derived based on *Equation 2*:

$$\hat{\theta}_0 = \left(\frac{1}{n}\sum_{i\in I, t\in T} GD_{i,t}^2\right)^{-1} \frac{1}{n}\sum_{i\in I, t\in T} GD_{i,t}(UER_{i,t} - \hat{g}(X_{i,t})) \qquad \text{(Eq.2)}$$

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN 1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2401_17931816

To ensure the coefficient estimator remains unbiased in small samples, the following auxiliary regression is constructed:

$$GD_{i,t} = m(X_{i,t}) + V_{i,t}, E(V_{i,t} \mid X_{i,t}) = 0 \quad \text{(Eq.3)}$$

where $m(X_{i,t})$ denotes the regression function of the core explanatory variable on the high-dimensional control variables, with its specific form estimated via machine learning algorithms. $V_{i,t}$ represents the error term, whose conditional mean is 0. The specific procedure is as follows:

Regress *Equation 3* to obtain the residual $V_{i,t} = GD_{i,t} - m(X_{i,t})$; then use $V_{i,t}$ as an instrumental variable for $GD_{i,t}$ in a subsequent regression to obtain an unbiased coefficient estimator:

$$\hat{\theta}_0 = \left(\frac{1}{n} \Sigma_{i \in I, t \in T} \hat{V}_{i,t} GD_{i,t} \right)^{-1} \frac{1}{n} \Sigma_{i \in I, t \in T} \hat{V}_{i,t} (UER_{i,t} - \hat{g}(X_{i,t})) \quad \text{(Eq.4)}$$

The mediation model

To identify the transmission pathways through which GD enhances UER, this study employs a multiple mediation model. It assesses whether GTI, DIC, PEA, and FAE mediate the relationship between GD and UER. The mediation effects are estimated as follows:

$$M = \beta_0 + \beta_1 GD + X_{i,t} + \varepsilon_{i,t} \quad \text{(Eq.5)}$$

$$ER_{it} = \gamma_0 + \gamma_1 M + X_{i,t} + \varepsilon_{i,t} \quad \text{(Eq.6)}$$

The mediating variable *M* represents GTI, DIC, PEA, and FAE. *Equation 5* primarily tests the impact of the independent variable on the mediating variable, where β_1 indicates the direct effect of the independent variable on the mediator *M*. *Equation 6* examines the impact of the mediating variable on the dependent variable, where γ_1 denotes the direct effect of the mediator on the dependent variable.

Variable description and data sources

Variable definitions

The dependent variable. The dependent variable in this study is the Urban Ecological Resilience (UER) Index, which captures a city's capacity to maintain core functions, recover from environmental disturbances, and achieve adaptive structural transformation under shocks. Grounded in the SETS framework and informed by established approaches to resilience measurement (Elmqvist et al., 2019), we construct a multidimensional composite index with four primary dimensions, as reported in *Table 1*.

Specifically, resource supply and environmental carrying capacity characterize the foundational conditions that support urban functioning and ecological stability. Ecosystem pressure measures the intensity of external disturbances arising from pollution emissions and resource consumption associated with economic activity and population concentration. Green space and ecological buffering capacity captures the extent to which ecological space can absorb shocks, regulate environmental processes, and facilitate recovery. Adaptive and governance capacity reflects the institutional ability to identify risks, respond through policy action, and enable structural adjustment. Together, these dimensions form a closed-loop framework that maps onto the resilience process from baseline support, to shock exposure, to buffering and recovery, and finally to governance-led adaptation. This structure helps avoid a partial characterization of UER that would result from focusing solely on ecological conditions or governance inputs.

All indicators are standardized according to their positive or negative attributes, and weights are assigned using the entropy method to reduce subjectivity in weighting. The weighted indicators are then aggregated to obtain the composite UER Index. The underlying data are primarily drawn from authoritative official sources, including the China City Statistical Yearbook, the China Statistical Yearbook, provincial and municipal statistical yearbooks and statistical bulletins, and environmental statistics and annual reports released by ecological and environmental authorities.

Table 1. *Urban ecological resilience indicator system*

Primary indicator	Secondary indicator	Unit	Attribute
Resource supply and environmental carrying capacity	Per capita water resources	Cubic meters/person	Positive
	Per capita urban park green space	Hectares per 10,000 people	Positive
Ecological system pressure	Per capita industrial wastewater discharge	Tons/person	Negative
	Per capita industrial SO_2 emissions	Tons/person	Negative
	Per capita industrial smoke and dust emissions	Tons/person	Negative
	Per capita carbon emissions	Tons/person	Negative
	Annual average PM2.5 concentration	μg/m³	Negative
Green space and buffering capacity	Green coverage rate in built-up areas	%	Positive
	Industrial sulfur dioxide removal rate	%	Positive
	Industrial smoke and dust removal rate	%	Positive
Adaptive and governance capacity	Harmless treatment rate of household waste	%	Positive
	Centralized treatment rate of sewage plants	%	Positive
	Comprehensive utilization rate of industrial solid waste	%	Positive

Explanatory Variable. The policy synergy variable for the LC and the BC, denoted as $GD_{i,t}$, serves as the core explanatory variable in this study. It is defined as the interaction term between the city-level dummy variable $Treat_i$ and the time dummy variable $Post_{i,t}$. Specifically, for $Treat_i$, cities simultaneously designated as pilots for both the LC and BC initiatives are assigned to the treatment group ($Treat_i = 1$), while cities not involved in either pilot constitute the control group (Treati = 0). Regarding the time dummy $Post_{i,t}$, the value is set to 1 for the first year and subsequent years in which both policies are concurrently implemented and 0 for all other years. The identification strategy for the individual policy variables-LC and BC-is constructed using the same logic.

Mediating Variables. To identify how the GD influences UER, this study constructs four mechanism variables based on an extended SETS system framework. These variables correspond to four dimensions: institutional incentives, technological support, social feedback, and structural coordination. Green technological innovation (*GTI*) is measured by the number of green invention patent applications in each city, capturing the effect of institutional incentives on guiding technological pathways for green transition. Digital infrastructure capacity (*DIC*) is proxied by the density of industrial robot

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN 1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2401_17931816

installations, reflecting the technological system's ability to perceive and respond to ecological governance demands. Public ecological awareness (*PEA*) is measured using the annual average city-level search intensity for the keyword "environment" from the Baidu Index, which indicates the public's feedback and participation capacity within the social system. Factor allocation efficiency (*FAE*) is measured inversely by the degree of capital market distortion, revealing the role of institutions and technologies in optimizing resource allocation structures. Together, these four variables form the transmission channels through which GD enhances UER, thereby representing a mechanism-level extension of the SETS theoretical framework.

Control Variables. To ensure the accuracy of policy effect estimation, this study incorporates several control variables that may influence UER: (1) Economic Development Level (*ED*), measured by the logarithm of regional GDP; (2) Openness to the Outside World (*OP*), proxied by the ratio of foreign direct investment to regional GDP; (3) Level of Industrialization (*IND*), represented by the ratio of industrial value added to regional GDP; (4) Infrastructure Level (*INF*), measured by Per capita road freight volume; (5) Financial Scale (*FIN*), indicated by the ratio of the year-end balance of financial institutions' deposits and loans to regional GDP.

Data sources

The data used in this study are mainly drawn from the China City Statistical Yearbook, provincial statistical yearbooks, provincial energy statistical yearbooks, the official databases of the National Bureau of Statistics of China, government-issued policy documents and official pilot city lists, and the Baidu Index. The sample covers 280 prefecture-level cities and above in mainland China. The study period spans 2011 to 2021, yielding a balanced panel dataset. *Table 2* reports descriptive statistics for all variables used in the empirical analysis.

Table 2. *Descriptive statistics*

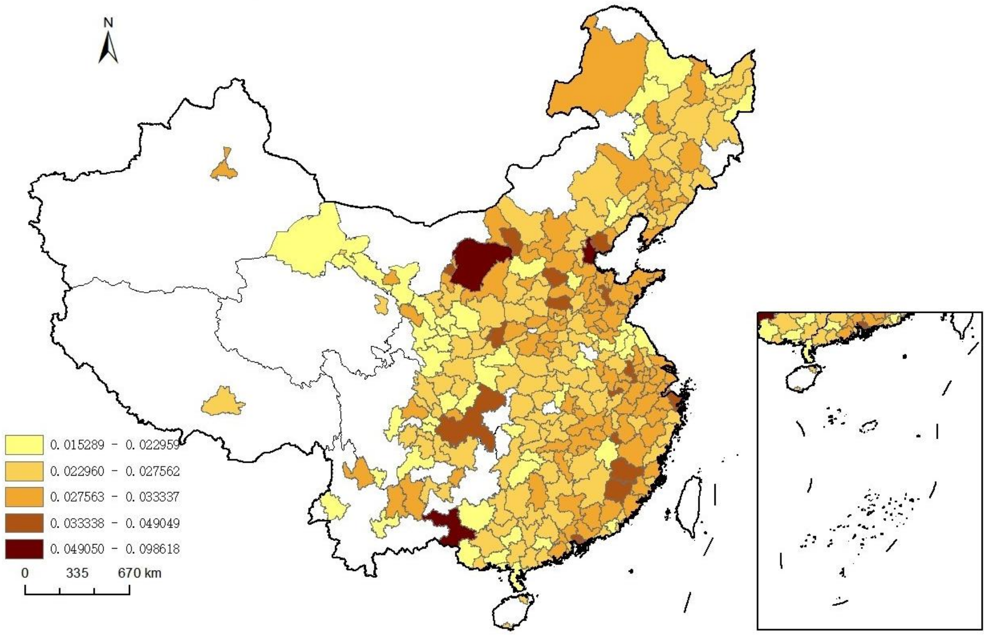
Variable	Mean	SD	Min	Max	N
UER	0.0000	1.0000	-1.7279	1.7392	3080
GD	0.0747	0.2629	0.0000	1.0000	3080
GTI	0.0704	0.2056	0.0000	3.1964	3080
DIC	5.2632	4.2783	0.0000	25.9109	3080
PEA	23.4808	26.6382	0.0000	164.5069	3080
FAE	0.0223	0.0226	0.0014	0.2320	3080
ED	16.6391	0.9392	14.1063	19.8843	3080
OP	0.0536	0.0685	0.0000	0.9038	3080
IND	0.3746	0.1321	-0.3960	0.9907	3080
INF	31.2249	68.3213	1.0000	3041.7290	3080
FIN	3.2649	3.4952	0.1682	111.9150	3080

Figure 3 reveals pronounced spatiotemporal heterogeneity in UER. Overall, the national level of UER has shown a steady upward trend, indicating a continuous strengthening of urban systems' structural capacities to cope with environmental disturbances and resource constraints. However, from a spatial perspective, resilience levels remain unevenly distributed, displaying a "high in the east, low in the west" pattern,

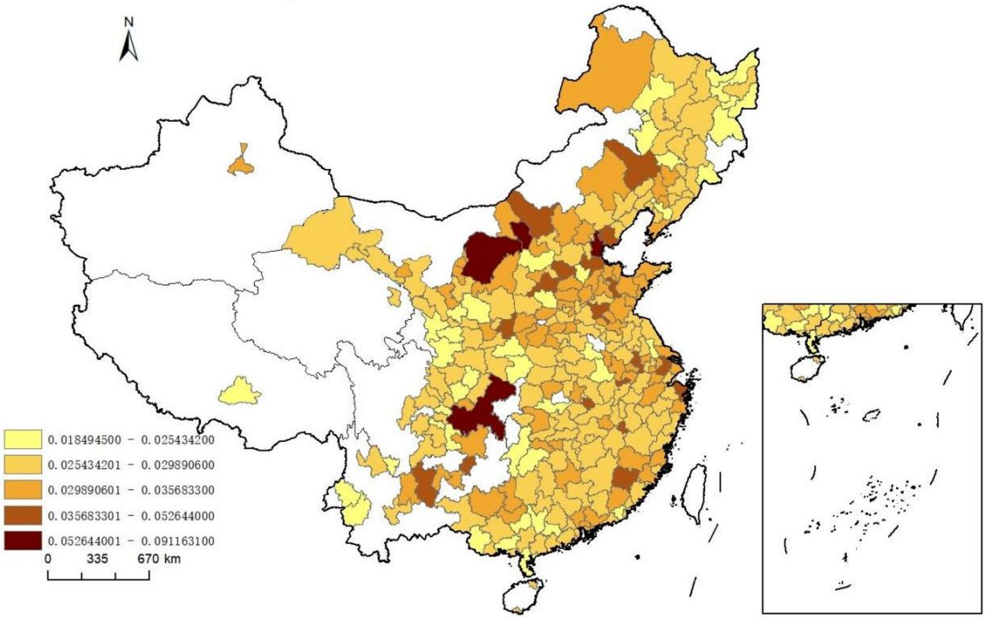
http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN 1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2401_17931816

which underscores disparities in policy implementation outcomes and institutional response capacities. Notably, this pattern largely corresponds to underlying institutional differences in the coordinated advancement of green and digital policies. Certain "dual-pilot" cities, such as Tianjin and Chongqing, have demonstrated early-mover advantages in areas like green technology adoption, digital infrastructure development, and ecological governance capacity. These cities have consistently ranked among the top in terms of UER, suggesting that integrating green and digital policies may yield synergistic effects in enhancing systemic robustness and adaptability. Preliminary evidence suggests that GD has the potential to reshape the structural foundations of UER. However, whether it generates significant marginal gains requires further empirical investigation to uncover its underlying mechanisms and transmission pathways.

Ecological resilience of Chinese cities in 2011



Ecological resilience of Chinese cities in 2015



http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN 1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2401_17931816

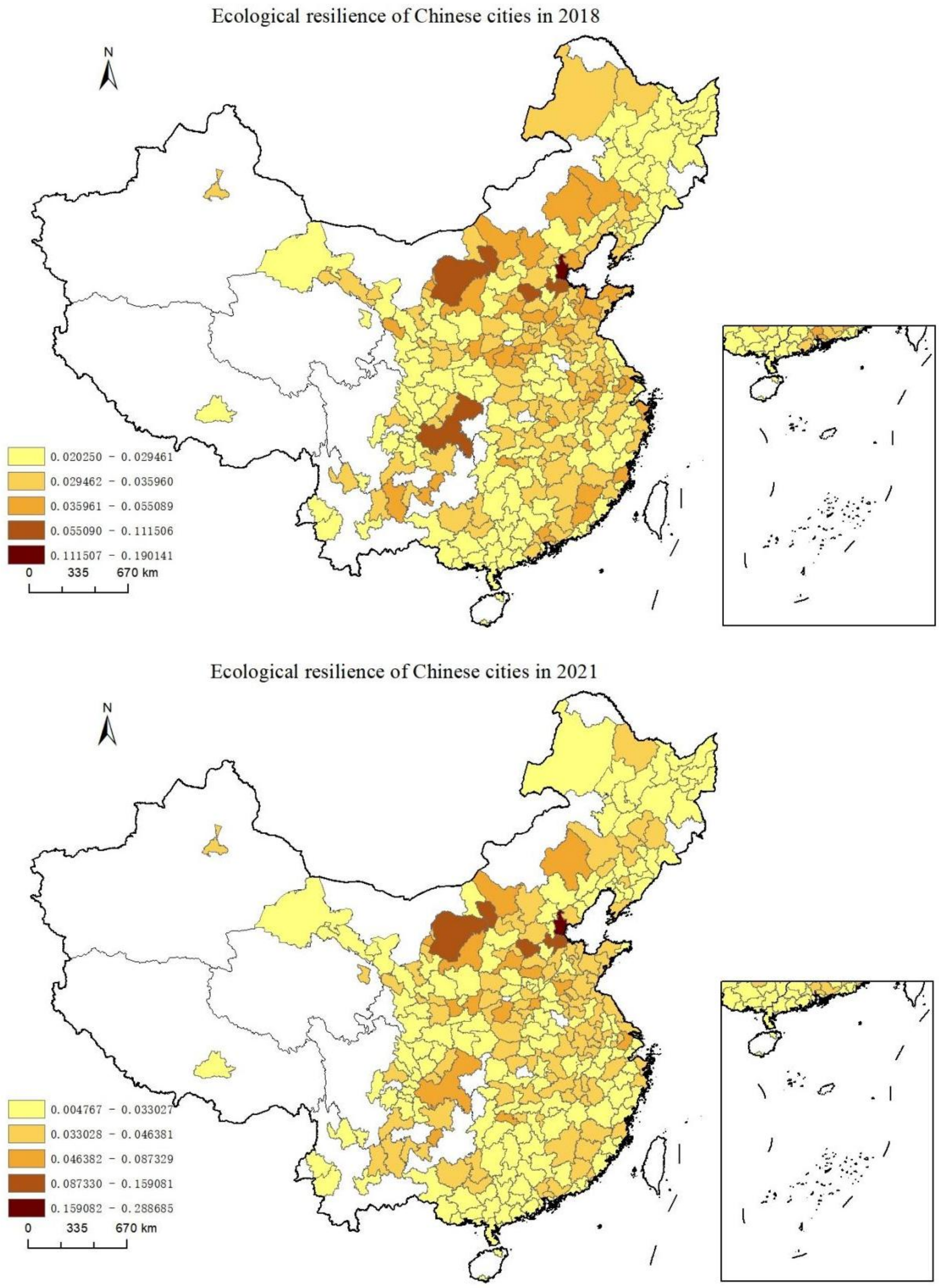


Figure 3. *Spatial distribution of urban ecological resilience*

Empirical results

Baseline regression

This study prioritizes the use of the Random Forest algorithm due to its strong robustness and fault tolerance. It effectively identifies variable importance and mitigates multicollinearity, making it well-suited for uncovering complex variable structures and nonlinear policy interactions in ecological resilience mechanisms. The results are presented in *Table 3*. Columns (1)-(2), (3)-(4), and (5)-(6) report estimation results based

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN 1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2401_17931816

on sample splitting ratios of 1:2, 1:4, and 1:6, respectively. It is evident that the estimation performance is optimal when the sample split ratio is 1:6; thus, all subsequent empirical analyses adopt the 1:6 split configuration. Based on the results in Column (5), after including the first-order terms of the control variables as well as city and time fixed effects, the regression coefficient of policy synergy on UER is significantly positive at the 1% level. Column (6) presents the estimation results with the inclusion of the second-order terms of the control variables, where the coefficient remains significantly positive. This suggests that policy synergy has a significant impact on UER. The findings in Columns (1)-(2) and (3)-(4) are consistent with those in Columns (5)-(6), thereby providing empirical support for H1.

Table 3. *Results of benchmark regression*

Variables	Kfolfs = 3		Kfolfs = 5		Kfolfs = 7	
	(1) *UER*	(2) *UER*	(3) *UER*	(4) *UER*	(5) *UER*	(6) *UER*
GD	0.286^{***} (4.18)	0.282^{***} (3.93)	0.256^{***} (3.17)	0.261^{***} (3.16)	0.305^{***} (3.98)	0.312^{***} (4.09)
Control variable	Yes	Yes	Yes	Yes	Yes	Yes
Control variables squared terms	No	Yes	No	Yes	No	Yes
Fixed city time	Yes	Yes	Yes	Yes	Yes	Yes
N	3080	3080	3080	3080	3080	3080

Robustness tests

To ensure the robustness of the main findings, a series of sensitivity analyses are conducted, and the results are shown in *Table 4*. First, the dependent variable, the UER index, is recalculated using principal component analysis. The results remain consistent with the baseline estimation. Second, the sample period is modified to cover the years from 2011 to 2019 to test the temporal stability of the findings, and the synergistic effects of green and digital policies continue to show statistical significance. Third, alternative machine learning algorithms-specifically Lassocv, Gradboost and Ridgecv-are used in place of the originally applied Random Forest within the double machine learning framework. The core results remain robust under these different algorithmic settings. Finally, to address potential confounding from overlapping environmental initiatives, two additional policy variables are introduced: the Emissions Trading Scheme pilot and the Key Air Pollution Control Zones. Even after accounting for these concurrent policies, the positive impact of GD on UER remains significant. Overall, these robustness checks confirm the consistency and credibility of the empirical findings.

Endogeneity test

To address potential endogeneity concerns arising from reverse causality, where improvements in UER may increase the likelihood of a city being selected for either LC or BC, this study employs an instrumental variable strategy. The shortest distance from each prefecture-level city to the nearest provincial boundary is selected as the

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN 1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2401_17931816

instrument for GD. This choice is grounded in the empirical observation that cities located farther from provincial borders are more likely to benefit from stronger administrative coordination and more efficient public service delivery, thereby increasing their chances of being designated as dual-policy pilot cities. This characteristic ensures the instrument's relevance. To capture variation over time and mitigate potential skewness, the instrument is constructed as the natural logarithm of the product between the distance to the provincial boundary and a linear time trend. As shown in Column (1) of *Table 5,* the estimation using the instrumental variable approach confirms the robustness of the baseline results, with the positive effect of GD on UER remaining statistically significant.

Table 4. *Robustness tests*

Variables	*UER*	*UER*	*UER*	*UER*	*UER*	*UER*	*UER*	*UER*
GD	0.3295*** (3.79)	0.1625** (2.39)	0.1709*** (2.71)	0.1240* (1.69)	0.1310*** (2.90)	0.2820*** (4.17)	0.2840*** (4.14)	0.2890*** (4.35)
Control variable	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Control variables squared terms	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fixed city time	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	3080	2520	3080	3080	3080	3080	3080	3080

Table 5. *Endogeneity test*

Variables	**(1)** ***UER***	**(2)** ***UER***
Distance	7.8200*** (5.35)	
Random		0.1830*** (2.75)
Control variable	Yes	Yes
Control variables squared terms	Yes	Yes
Fixed city time	Yes	Yes
N	3080	3080

Additionally, the selection of cities for LC and BC pilot status is not random. Inherent characteristics, such as geographic location, economic development level, and environmental constraints, often influence it. To account for potential selection bias, this study follows the approach proposed by Lu et al. (2017) and includes interaction terms between time trends and city-specific attributes as additional instruments. These attributes include whether a city is a special economic zone, designated as a pilot, or has notable topographic variation. As reported in Column (2) of *Table 5,* after controlling for these structural differences, the estimated coefficient for GD remains significantly positive, further confirming the validity and robustness of the main findings.

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN 1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2401_17931816

Synergy analysis

Net effects of single policies

Column (1) of *Table 6* presents the estimation results using the "LC only" group as the treatment group and the "non-pilot" group as the control group. The coefficient on the LC reflects its net effect on UER, yielding a value of 0.177, which is statistically significant. This suggests that the LC initiative effectively promotes UER. Similarly, Column (2) of *Table 6* reports the results with the "BC only" group as the treatment group and the "non-pilot" group as the control. The coefficient for the BC initiative is 0.0967 and statistically significant, indicating that the BC strategy also contributes positively to UER. These results collectively demonstrate that both single-pilots exert positive net effects on UER. However, the impact of the LC policy is greater than that of the BC initiative.

Comparison between single-policy and synergistic policy net effects

To examine whether the GD delivers superior policy performance compared to single-pilots, the analysis reconstructs the treatment and control groups by excluding all non-pilot cities. Specifically, cities simultaneously designated as both LC and BC are defined as the treatment group, while those with only one of the two pilot designations serve as the control group. Column (3) of *Table 6* reports the estimation results. It is evident that GD generates a more substantial positive impact on UER than single pilots.

Table 6. *Synergy tests*

Variables	**(1)** ***UER***	**(2)** ***UER***	**(3)** ***UER***
LC	0.0247^{***} (5.51)		
BC		0.0027^{***} (6.20)	
GD			0.0087^{***} (4.09)
Control variable	Yes	Yes	Yes
Control variables squared terms	Yes	Yes	Yes
Fixed city time	Yes	Yes	Yes
N	3080	3080	1086

Heterogeneity analysis

To explore the differentiated effects of GD on UER, this study conducts subgroup regression analyses based on economic development level, resource type, and industrial structure. Regarding economic development, as shown in Columns (1) and (2) of *Table 7,* the GD significantly enhances UER in economically advanced cities. At the same time, the effect is not statistically significant in cities with weaker economic foundations. Concerning resource endowment, Columns (3) and (4) of *Table 7* indicate that GD has a stronger positive effect on UER in resource-based cities. Although the effect remains significant in non-resource-based cities, the magnitude of the coefficient is comparatively lower. In terms of industrial structure, Columns (5) and (6) of *Table 7* reveal that the

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN 1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2401_17931816

positive impact of GD on UER is significant in non-traditional industrial cities, whereas the effect is not significant in traditional industrial bases. Taken together, these findings provide empirical support for H3.

Table 7. *Heterogeneity tests*

Variables	(1) *UER*	(2) *UER*	(3) *UER*	(4) *UER*	(5) *UER*	(6) *UER*
GD	0.2930*** (3.92)	0.1110 (0.98)	1.2110*** (4.63)	0.2660*** (3.79)	-0.0920 (-0.25)	0.2570*** (3.35)
Control variable	Yes	Yes	Yes	Yes	Yes	Yes
Control variables squared terms	Yes	Yes	Yes	Yes	Yes	Yes
Fixed city time	Yes	Yes	Yes	Yes	Yes	Yes
N	374	2706	1111	1969	1034	2046

Transmission mechanism analysis

The mediation regression results presented in Columns (1)–(4) of *Table 8* show that GD has significantly positive effects on GTI, DIC, PEA, and FAE. Among these, the impact on PEA is the most pronounced, suggesting that, within the multidimensional transmission pathways, the enhancement of PEA plays a pivotal role in advancing UER through GD.

Table 8. *Mediation mechanism tests*

Variables	(1) *GTI*	(2) *DIC*	(3) *PEA*	(4) *FAE*
GD	0.4310*** (5.14)	1.1760*** (3.02)	6.5800*** (3.02)	0.0047*** (3.43)
Control variable	Yes	Yes	Yes	Yes
Control variables squared terms	Yes	Yes	Yes	Yes
Fixed city time	Yes	Yes	Yes	Yes
N	3080	3080	3080	3080

Conclusion, discussion, and policy recommendations

Conclusion

This study takes the LC and the BC initiatives as its starting point and constructs an analytical framework for UER grounded in the SETS theory. It systematically evaluates both the direct effects of GD on UER and the multi-pathway mediating mechanisms, using panel data from Chinese prefecture-level cities and above, spanning the years 2011–2021.

The empirical findings reveal the following: First, the GD significantly enhances the level of UER. Compared with single-pilot or non-pilot cities, dual-pilot cities exhibit stronger improvements in UER, confirming a "1 + 1 > 2" effect of GD. Second, the mediation analysis shows that GD indirectly fosters UER through four transmission channels: GTI, DIC, PEA, and FAE. Among these, the transmission effect of PEA is the most pronounced, underscoring the critical role of societal responsiveness in resilience building. Third, heterogeneity analysis reveals that the positive impact of policy synergy is more pronounced in economically advanced regions, non-traditional industrial bases, and resource-based cities, underscoring the profound influence of institutional response capacity and governance fundamentals on policy effectiveness.

Discussion

Green and digital policy synergy empowering urban ecological resilience

This study finds that the GD significantly enhances UER. This result aligns with the theoretical framework proposed by Reyers et al. (2018), which suggests that polycentric institutional nesting strengthens the disturbance-coping capacity of social-ecological systems and complements the OECD (2024) empirical insight that integrating green governance and digital transformation enhances urban system resilience. Specifically, as a dual-pilot city, Beijing has developed an intelligent and low-carbon urban governance system by promoting green buildings, carbon trading mechanisms, and digital infrastructure interconnectivity. Since 2013, the city's annual average PM2.5 concentration has decreased by over 50%, while per capita green space has increased to 15.6 square meters, providing evidence of the amplifying effect of institutional overlap on ecological governance performance. In contrast, Tianjin, although also a dual-pilot city, has experienced periodic stagnation in its resilience enhancement process due to a lack of coordination between its green transition efforts and digital infrastructure deployment. This suggests that the actual effectiveness of policy synergy is still contingent on local institutional implementation capacity and the level of technological integration. Internationally, Amsterdam's implementation of a "Green City + Digital City" strategy parallel advancements in energy system optimization and digital monitoring platform construction—offers a compelling example. Its "City Data Commons" initiative has significantly improved the city's real-time response to climate risks and its capacity for ecological resource allocation. This case resonates strongly with the findings of this study, underscoring that GD has become a global policy direction for strengthening UER.

Identification of mediating mechanisms

The empirical analysis reveals that GD primarily influences UER through four mediating pathways: GTI, DIC, PEA, and FAE. These pathways correspond to four dimensions: institutional incentives, technological support, societal participation, and resource coordination, reflecting a multidimensional, interactive mechanism for enhancing UER. GTI, as an institutional incentive pathway, supports the argument by Murray et al. (2016) that "green regulation stimulates technological innovation to facilitate low-carbon transition." For example, under the impetus of dual-pilot policies, Shenzhen has consistently ranked among the top cities nationwide in green patent applications, contributing to both industrial green transformation and ecosystem restoration. The DIC pathway aligns with Yang et al. (2021) theory that "smart infrastructure enhances urban adaptability and feedback capacity." Hangzhou's "City Brain" initiative exemplifies this by enabling real-time monitoring of pollution, water resources, and ecological spaces, thus translating digital technologies into effective tools for environmental governance. The significance of the PEA pathway provides empirical support for the societal dimension's role in UER, echoing the conclusion of Galli et al. (2020) that "public cognitive structures shape the responsiveness of environmental

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN 1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2401_17931816

governance." Policy-induced shifts in environmental consciousness and behavioral norms have created positive feedback loops, particularly evident in cities like Beijing and Chengdu. Regarding the factor allocation pathway, the findings are consistent with the empirical analysis by Li et al. (2024), which suggests that "market distortions inhibit the efficiency of urban green transition." In Wuhan, the implementation of both low-carbon and digital pilot policies, coupled with state-owned enterprise reforms and capital market optimization, has led to sustained improvements in the efficiency of green factor allocation. Among the four pathways, this study finds that the mediating effect of PEA is the strongest result not yet fully emphasized in existing literature. This underscores the importance of institutionalizing public participation and social responsiveness mechanisms in future efforts to strengthen UER governance.

Urban heterogeneity in green and digital policy synergy

The heterogeneity analysis reveals that the effect of GD is more pronounced in cities with stronger economic foundations, non-traditional industrial bases, and resource-dependent economies. This finding aligns with Ricks and Doner (2021), who argue that "institutional transformation is constrained by institutional capacity." Additionally, it aligns with the conclusion by Li and Puppim de Oliveira (2021) that structural factors often influence green governance performance in developing countries. For instance, Suzhou, a non-traditional industrial city with a robust economic base, has rapidly established a green manufacturing and smart governance system under the dual support of GD, consistently ranking among the top in UER indices. In contrast, in traditional industrial cities such as Shenyang, path dependence and institutional inertia have impeded the realization of GD, confirming the decisive role of institutional implementation flexibility in determining policy effectiveness. In the context of resource-based cities, Ordos has leveraged the coordinated implementation of carbon reduction and broadband policies to restructure its energy system, promote the substitution of clean energy, and develop digital operation platforms. As a result, the UER index has significantly improved over the past five years, suggesting that even under resource constraints, GD can activate latent ecological governance potential. Internationally, the case of Katowice, Poland, exemplifies the challenges of a green transition when confronted with governance fragmentation and infrastructural deficits. Despite broad policy coverage, the city has seen limited recovery of its ecological systems, reinforcing the conclusion of this study that "institutional support capacity constrains the marginal effects of synergistic policies."

Policy recommendations

Promoting integrated design and coordinated implementation of green and digital policies

To avoid fragmentation and path divergence between green and digital policies, institutional integration should be reinforced at the level of top-level design. It is recommended to promote the strategic alignment of the "Carbon Peak and Carbon Neutrality" initiative with the "Digital China" strategy by establishing a dedicated interdepartmental policy synergy mechanism, thereby building an integrated green-digital urban governance system. At the policy implementation level, a pilot "dual-policy synergy checklist system" could be introduced to clarify responsibilities for ecological objectives and digital infrastructure deployment, thereby enhancing the coordinated execution capacity.

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN 1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2401_17931816

Constructing multidimensional resilience pathways centered on key mechanisms

Efforts should focus on strengthening four core dimensions: institutional incentives, technological support, social engagement, and resource coordination. This includes promoting incentive schemes for GTI, ensuring an equitable distribution of digital infrastructure, conducting environmental awareness campaigns, and implementing efficient factor market allocation mechanisms. At the city level, a "mechanism-nested policy toolbox" should be developed to facilitate the diversification and contextualization of ecological governance pathways, thereby enhancing multidimensional coordination capabilities.

Designing differentiated urban policy synergy pathways

Given the heterogeneity in economic foundations, industrial structures, and governance capacities across cities, a "type-response" matching mechanism is essential. In non-traditional industrial cities, emphasis should be placed on integrating green and digital industries, as well as applying resilient governance scenarios. Resource-based cities should prioritize clean energy substitution and intelligent operation and maintenance, while traditional industrial bases should focus on restructuring governance mechanisms and reforming institutional adaptability. Furthermore, cities may draw on the integrated policy experiences of domestic leaders, such as Shenzhen, and international pioneers, like Amsterdam, to foster context-specific innovation in their policy portfolios.

Establishing a dynamic evaluation and policy feedback mechanism for urban ecological resilience

It is advisable to establish a national-level dynamic monitoring indicator system for UER based on the logic of the SETS framework and to conduct regular resilience assessments at the city level. Local governments should be encouraged to develop big data-driven tools, such as "urban resilience profiles" and "governance feedback loops," to enable the dynamic identification of policy impacts, timely adjustments, and risk forecasting. This will improve the precision and foresight of policy regulation.

Funding. This research received no external funding.

Conflict of interests. The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

REFERENCES

[1] Agboola, O. P., Tunay, M. (2023): Urban resilience in the digital age: the influence of information-communication technology for sustainability. – Journal of Cleaner Production 428: 139304. https://doi.org/https://doi.org/10.1016/j.jclepro.2023.139304.

[2] Artmann, M., Kohler, M., Meinel, G., Gan, J., Ioja, I.-C. (2019): How smart growth and green infrastructure can mutually support each other—a conceptual framework for compact and green cities. – Ecological Indicators 96: 10-22. https://doi.org/https://doi.org/10.1016/j.ecolind.2017.07.001.

[3] Ben Yahia, N., Eljaoued, W., Bellamine Ben Saoud, N., Colomo-Palacios, R. (2021): Towards sustainable collaborative networks for smart cities co-governance. – International Journal of Information Management 56: 102037. https://doi.org/https://doi.org/10.1016/j.ijinfomgt.2019.11.005.

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN 1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2401_17931816

[4] Beunen, R., Patterson, J., Van Assche, K. (2017): Governing for resilience: the role of institutional work. – Current Opinion in Environmental Sustainability 28: 10-16. https://doi.org/https://doi.org/10.1016/j.cosust.2017.04.010.
[5] Branny, A., Møller, M. S., Korpilo, S., McPhearson, T., Gulsrud, N., Olafsson, A. S., et al. (2022): Smarter greener cities through a social-ecological-technological systems approach. – Current Opinion in Environmental Sustainability 55: 101168. https://doi.org/https://doi.org/10.1016/j.cosust.2022.101168.
[6] Cheng, J., Yi, J., Dai, S., Xiong, Y. (2019): Can low-carbon city construction facilitate green growth? Evidence from China's pilot low-carbon city initiative. – Journal of Cleaner Production 231: 1158-1170. https://doi.org/https://doi.org/10.1016/j.jclepro.2019.05.327.
[7] Chernozhukov, V., Newey, W. K., Singh, R. (2022): Automatic debiased machine learning of causal and structural effects. – Econometrica 90(3): 967-1027. https://doi.org/https://doi.org/10.3982/ECTA18515.
[8] Ding, C. J., Chen, H., Liu, Y., Hu, J., Hu, M., Chen, D., Irfan, M. (2024): Unleashing digital empowerment: pioneering low-carbon development through the broadband China strategy. – Energy 295: 131034. https://doi.org/https://doi.org/10.1016/j.energy.2024.131034.
[9] Dwivedi, Y. K., Hughes, L., Kar, A. K., Baabdullah, A. M., Grover, P., Abbas, R., et al. (2022): Climate change and COP26: Are digital technologies and information management part of the problem or the solution? An editorial reflection and call to action. – International Journal of Information Management 63: 102456. https://doi.org/https://doi.org/10.1016/j.ijinfomgt.2021.102456.
[10] Elmqvist, T., Andersson, E., Frantzeskaki, N., McPhearson, T., Olsson, P., Gaffney, O., et al. (2019): Sustainability and resilience for transformation in the urban century. – Nature Sustainability 2(4): 267-273. https://doi.org/10.1038/s41893-019-0250-1.
[11] Feng, T., Lin, Z., Du, H., Qiu, Y., Zuo, J. (2021): Does low-carbon pilot city program reduce carbon intensity? Evidence from Chinese cities. – Research in International Business and Finance 58: 101450. https://doi.org/https://doi.org/10.1016/j.ribaf.2021.101450.
[12] Galli, A., Iha, K., Moreno Pires, S., Mancini, M. S., Alves, A., Zokai, G., et al. (2020): Assessing the Ecological Footprint and biocapacity of Portuguese cities: critical results for environmental awareness and local management. – Cities 96: 102442. https://doi.org/https://doi.org/10.1016/j.cities.2019.102442.
[13] Gao, Q., Cheng, C., Sun, G. (2023): Big data application, factor allocation, and green innovation in Chinese manufacturing enterprises. – Technological Forecasting and Social Change 192: 122567. https://doi.org/https://doi.org/10.1016/j.techfore.2023.122567.
[14] Howlett, M., Rayner, J. (2007): Design principles for policy mixes: cohesion and coherence in 'new governance arrangements'. – Policy and Society 26(4): 1-18. https://doi.org/10.1016/S1449-4035(07)70118-2.
[15] Keeler, B. L., Hamel, P., McPhearson, T., Hamann, M. H., Donahue, M. L., Meza Prado, K. A., et al. (2019): Social-ecological and technological factors moderate the value of urban nature. – Nature Sustainability 2(1): 29-38. https://doi.org/10.1038/s41893-018-0202-1.
[16] Kitchin, R., and Moore-Cherry, N. (2021): Fragmented governance, the urban data ecosystem and smart city-regions: the case of Metropolitan Boston. – Regional Studies 55(12): 1913-1923. https://doi.org/10.1080/00343404.2020.1735627.
[17] Krueger, E. H., Constantino, S. M., Centeno, M. A., Elmqvist, T., Weber, E. U., Levin, S. A. (2022): Governing sustainable transformations of urban social-ecological-technological systems. – NPJ Urban Sustainability 2(1): 10. https://doi.org/10.1038/s42949-022-00053-1.
[18] Lan, C., Li, X., Peng, B., Li, X. (2025): Unlocking urban ecological resilience: the dual role of environmental regulation and green technology innovation. – Sustainable Cities and Society 128: 106466. https://doi.org/https://doi.org/10.1016/j.scs.2025.106466.
[19] Li, D., Cao, J., Yao, Y. (2015): Big data in smart city. – Science China Information Sciences 39. https://doi.org/10.1007/s11432-015-5396-5.

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN 1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2401_17931816

[20] Li, K., Xu, C., Tang, L. (2024): The important of eliminating energy market distortions: the perspective of industrial green productivity. – Energy Economics 132: 107472. https://doi.org/https://doi.org/10.1016/j.eneco.2024.107472.
[21] Li, W., Puppim de Oliveira, J. A. (2021): Environmental governance for sustainable development in Asia. – Journal of environmental management 290: 112622. https://doi.org/https://doi.org/10.1016/j.jenvman.2021.112622.
[22] Liu, K., Huang, T., Xia, Z., Xia, X., Wu, R. (2025): The impact assessment of low-carbon city pilot policy on urban green innovation: a batch-time heterogeneity perspective. – Applied Energy 377: 124489. https://doi.org/https://doi.org/10.1016/j.apenergy.2024.124489.
[23] Lu, Y., Tao, Z., Zhu, L. (2017): Identifying FDI spillovers. – Journal of International Economics 107: 75-90. https://doi.org/https://doi.org/10.1016/j.jinteco.2017.01.006.
[24] Luo, S., Yimamu, N., Li, Y., Wu, H., Irfan, M., Hao, Y. (2023): Digitalization and sustainable development: How could digital economy development improve green innovation in China? – Business Strategy and the Environment 32(4): 1847-1871. https://doi.org/https://doi.org/10.1002/bse.3223.
[25] Martin, C. J., Evans, J., Karvonen, A. (2018): Smart and sustainable? Five tensions in the visions and practices of the smart-sustainable city in Europe and North America. – Technological Forecasting and Social Change 133: 269-278. https://doi.org/https://doi.org/10.1016/j.techfore.2018.01.005.
[26] McPhearson, T., Pickett, S. T. A., Grimm, N. B., Niemelä, J., Alberti, M., Elmqvist, T., et al. (2016): Advancing urban ecology toward a science of cities. – BioScience 66(3): 198-212. https://doi.org/10.1093/biosci/biw002.
[27] McPhearson, T., Cook, E. M., Berbés-Blázquez, M., Cheng, C., Grimm, N. B., Andersson, E., et al. (2022): A social-ecological-technological systems framework for urban ecosystem services. – One Earth 5(5): 505-518. https://doi.org/10.1016/j.oneear.2022.04.007.
[28] Murray, F., Aghion, P., Dewatripont, M., Kolev, J., Stern, S. (2016): Of mice and academics: examining the effect of openness on innovation. – American Economic Journal: Economic Policy 8(1): 212-252. https://doi.org/10.1257/pol.20140062.
[29] Reyers, B., Folke, C., Moore, M.-L., Biggs, R., Galaz, V. (2018): Social-ecological systems insights for navigating the dynamics of the anthropocene. – Annual Review of Environment and Resources 43(Volume 43: 2018): 267-289. https://doi.org/https://doi.org/10.1146/annurev-environ-110615-085349.
[30] Ricks, J. I., Doner, R. F. (2021): Getting institutions right: matching institutional capacities to developmental tasks. – World Development 139: 105334. https://doi.org/https://doi.org/10.1016/j.worlddev.2020.105334.
[31] Sharifi, A. (2023): Resilience of urban social-ecological-technological systems (SETS): a review. – Sustainable Cities and Society 99: 104910. https://doi.org/https://doi.org/10.1016/j.scs.2023.104910.
[32] Soares, J., Miguel, I., Venâncio, C., Lopes, I., Oliveira, M. (2021): Public views on plastic pollution: knowledge, perceived impacts, and pro-environmental behaviours. – Journal of Hazardous Materials 412: 125227. https://doi.org/https://doi.org/10.1016/j.jhazmat.2021.125227.
[33] Song, S., Wen, J., Li, Y., Li, L. (2024): How does digital economy affect green technological innovation in China? New evidence from the "Broadband China" policy. – Economic Analysis and Policy 81: 1093-1112. https://doi.org/https://doi.org/10.1016/j.eap.2024.01.008.
[34] Spears, B. M., Ives, S. C., Angeler, D. G., Allen, C. R., Birk, S., Carvalho, L., et al. (2015): FORUM: Effective management of ecological resilience—are we there yet? – Journal of Applied Ecology 52(5): 1311-1315. https://doi.org/https://doi.org/10.1111/1365-2664.12497.

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN 1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2401_17931816

[35] Wang, H., Zhou, J., Li, X., Ling, Q., Wei, H., Gao, L., et al. (2023a): Review on recent progress in on-line monitoring technology for atmospheric pollution source emissions in China. – Journal of Environmental Sciences 123: 367-386. https://doi.org/https://doi.org/10.1016/j.jes.2022.06.043.

[36] Wang, J., Liu, Y., Wang, W., Wu, H. (2023b): How does digital transformation drive green total factor productivity? Evidence from Chinese listed enterprises. – Journal of Cleaner Production 406: 136954. https://doi.org/https://doi.org/10.1016/j.jclepro.2023.136954.

[37] Wang, L., Shao, J., Ma, Y. (2023c): Does China's low-carbon city pilot policy improve energy efficiency? – Energy 283: 129048. https://doi.org/https://doi.org/10.1016/j.energy.2023.129048.

[38] Wei, Y.-M., Chen, K., Kang, J.-N., Chen, W., Wang, X.-Y., Zhang, X. (2022): Policy and management of carbon peaking and carbon neutrality: a literature review. – Engineering 14: 52-63. https://doi.org/https://doi.org/10.1016/j.eng.2021.12.018.

[39] Yang, F., Wen, X., Aziz, A., Luhach, A. K. (2021): The need for local adaptation of smart infrastructure for sustainable economic management. – Environmental Impact Assessment Review 88: 106565. https://doi.org/https://doi.org/10.1016/j.eiar.2021.106565.

[40] Yin, S., Yu, Y. (2022): An adoption-implementation framework of digital green knowledge to improve the performance of digital green innovation practices for industry 5.0. – Journal of Cleaner Production 363: 132608. https://doi.org/https://doi.org/10.1016/j.jclepro.2022.132608.

[41] Young, O. R. (2010): Institutional dynamics: resilience, vulnerability and adaptation in environmental and resource regimes. – Global Environmental Change 20(3): 378-385. https://doi.org/https://doi.org/10.1016/j.gloenvcha.2009.10.001.

[42] Yu, Y., Zhang, N. (2021): Low-carbon city pilot and carbon emission efficiency: quasi-experimental evidence from China. – Energy Economics 96: 105125. https://doi.org/https://doi.org/10.1016/j.eneco.2021.105125.

[43] Zeng, L., Wen, M., Li, C., Nie, Y., Wang, S. (2025): Impact of digital greening synergistic transformation on urban economic resilience in China: evidence from quasi-natural experiments. – Humanities and Social Sciences Communications 12(1): 85. https://doi.org/10.1057/s41599-025-04358-1.

[44] Zhao, J. (2024): How do innovation factor allocation and institutional environment affect high-quality economic development? Evidence from China. – Journal of Innovation & Knowledge 9(2): 100475. https://doi.org/https://doi.org/10.1016/j.jik.2024.100475.

[45] Zhou, Q., Zhu, M., Qiao, Y., Zhang, X., Chen, J. (2021): Achieving resilience through smart cities? Evidence from China. – Habitat International 111: 102348. https://doi.org/https://doi.org/10.1016/j.habitatint.2021.102348.