

Article

From Spatial Siphoning to Green Spillovers: Dynamic Effects and Distance-Decay Boundaries of the Digital Economy on Green Land Use Efficiency

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Abstract

Improving green land use efficiency is an important approach to reconciling urban development with resource and environmental constraints. Using panel data from 280 cities at the prefecture level and above in China from 2011 to 2024, this study employs a dynamic spatial Durbin model to examine the effects of the digital economy on green land use efficiency, focusing on temporal dynamics, spatial spillover effects, distance-decay boundaries, moderating mechanisms, and urban heterogeneity. The results show that the digital economy significantly improves local green land use efficiency. Its spatial externalities exhibit a pronounced dynamic transition from the spatial siphoning effect in the short term to the green spillover effect in the long term. The short-term spatial siphoning effect is mainly concentrated within approximately 200 km, whereas the long-term green spillover effect extends to approximately 250 km, indicating a clear distance-decay pattern. Green technological innovation and industrial upgrading mitigate short-term spatial siphoning and strengthen the long-term green spillover effect, whereas factor misallocation intensifies short-term spatial siphoning and weakens the long-term green spillover effect. The green-enabling effect of the digital economy is stronger in cities in eastern China, resource-based cities, high-tier cities, and cities with stricter environmental regulation. These findings underscore the importance of coordinating digital economy development with cross-regional green land governance, while strengthening regional absorptive capacity and improving factor allocation efficiency.

Keywords: digital economy; green land use efficiency; dynamic spatial externalities; spatial siphoning effect; green spillover effect; distance-decay boundaries

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1. Introduction

Rapid urbanization and industrialization have been accompanied by the continuous expansion of urban construction land. While this process has stimulated economic growth, it has also resulted in the excessive consumption of land resources, the contraction of ecological space, and increasing environmental pollution [1]. The conventional development model, which relies heavily on factor inputs and the extensive expansion of land, can no longer meet the practical need to coordinate economic growth with ecological protection. Against this background, improving green land use efficiency has become an important means of alleviating land-resource constraints and advancing the low-carbon

transformation of cities. Green land use efficiency emphasizes not only maximizing economic output while minimizing land inputs, but also balancing the social and ecological benefits arising from land use [2]. Therefore, how emerging production factors and technological change can improve green land use efficiency has become an important research question.

As a new economic form driven by data, digital technologies, and digital platforms, the digital economy is reshaping traditional production modes and the spatial organization of regional economies [3]. On the one hand, digital technologies can reduce information-search and transaction costs, improve the allocation efficiency of land, capital, labor, and other production factors, and reduce resource consumption and pollutant emissions per unit of land through digital management and precise environmental monitoring [4]. The digital economy can also promote green technological innovation and industrial upgrading, thereby facilitating the transition of urban land use from extensive expansion toward intensive, low-carbon, and efficient utilization [5]. On the other hand, data, knowledge, and technology are characterized by high mobility and strong network externalities. Unlike traditional production factors, whose spatial movement is constrained by physical scarcity and transportation costs, data are non-rival and highly replicable. Their spatial circulation depends mainly on digital infrastructure and local absorptive capacity rather than on physical relocation. This distinctive flow mechanism may generate both spatial concentration and spatial diffusion. In the short term, cities with stronger digital foundations can attract complementary production factors. In the long term, the repeated use of data can promote knowledge diffusion and green spillovers. Consequently, the effects of the digital economy extend beyond local boundaries to spatially connected cities through knowledge diffusion, industrial linkages, and factor mobility [6]. Examining only the direct local effects of the digital economy on green land use efficiency is therefore insufficient to fully reveal its influence on regional land use patterns.

A substantial body of research has examined the relationship between the digital economy and green land use. Existing studies mainly focus on local effects and generally find that the digital economy improves urban green land use efficiency [7–9]. Building on this, scholars have further examined the pathways linking the digital economy to green land use outcomes. Most studies suggest that the digital economy is associated with improvements in resource allocation efficiency, cleaner production, green technological innovation, and industrial upgrading, thereby providing sustained momentum for improvements in green land use efficiency [10–12]. However, as data, technology, and knowledge increasingly flow across regions, the effects of the digital economy are no longer confined to local areas, and its spatial externalities have attracted growing scholarly attention. Nevertheless, no consensus has yet been reached regarding the direction of the digital economy's effects on the green development of spatially connected cities. Drawing on the theories of network externalities and knowledge spillovers, some studies argue that the digital economy reduces the costs of information transmission and regional cooperation, transcends conventional geographical and administrative boundaries, and facilitates the cross-regional diffusion of green technologies and production factors, thereby generating positive spatial spillover effects and promoting coordinated green development in spatially connected cities [13–15]. By contrast, other studies emphasize the digital divide, core-periphery structures, and competition for production factors, suggesting that the early stages of digital development are often characterized by pronounced spatial concentration of production factors. Owing to superior digital infrastructure and higher returns to production factors, cities with first-mover advantages tend to attract capital, technology, and highly skilled labor from surrounding areas, thereby generating a spatial siphoning effect on peripheral cities [16–18]. Meanwhile, some energy-intensive, highly polluting, and low-value-added industries relocated or phased out by central cities

may shift to peripheral regions, further intensifying factor misallocation, environmental pressures, and spatial constraints on land use in neighboring areas [19].

The divergence among these findings may be attributed to insufficient attention to the dynamic transition of spatial externalities. During the early stages of digital economy development, the concentration of high-quality production factors in central cities may exert a spatial siphoning effect on peripheral regions. However, most existing studies rely on static spatial models and are therefore unable to identify this intertemporal transformation. Moreover, the spatial influence of the digital economy does not extend indefinitely. Although digital information can be transmitted rapidly, the absorption of tacit knowledge, industrial relocation, and cross-regional governance remain constrained by geographical distance, industrial linkages, and administrative boundaries. The associated spatial externalities therefore weaken as geographical distance increases and eventually become statistically insignificant [20]. Existing research has yet to provide precise quantitative evidence regarding the effective geographical ranges and distance-decay boundaries of the short-term spatial siphoning effect and the long-term green spillover effect.

This study uses panel data for 280 prefecture-level and above cities in China from 2011 to 2024 and develops a dynamic spatial Durbin model. By decomposing the effects of the digital economy into short-term and long-term direct and indirect effects, the study identifies the dynamic transition of its spatial externalities from the short-term spatial siphoning effect to the long-term green spillover effect. Spatial weight matrices based on different distance thresholds are further constructed to examine how the spatial externalities of the digital economy decay with geographical distance and to identify their effective boundaries. In addition, the moderating mechanisms are examined by introducing interaction terms between the digital economy and green technological innovation, industrial upgrading, and factor misallocation. Heterogeneity is also examined by geographical location, resource endowment, administrative hierarchy, and environmental regulation.

Compared with the existing literature, this study makes three main contributions. First, this study advances research on the dynamic spatial externalities of the digital economy. Rather than using a dynamic spatial model merely to account for temporal persistence and spatial dependence, it combines the dynamic spatial Durbin model with partial-derivative decomposition to distinguish short- and long-term direct and indirect effects. This approach identifies a directional transition from the short-term spatial siphoning effect to the long-term green spillover effect, thereby providing an intertemporal explanation for the coexistence of negative and positive spatial effects reported in previous studies. Second, this study integrates dynamic spatial-effect decomposition with distance-decay analysis. Previous dynamic spatial studies have mainly examined the temporal accumulation and average magnitude of spatial spillovers, whereas the geographical ranges of short-term and long-term effects have received relatively limited attention. By constructing spatial weight matrices based on successive distance bands, this study further examines whether the short-term spatial siphoning effect and the long-term green spillover effect exhibit different geographical ranges and decay patterns. This extends the analysis of spatial externalities from temporal dynamics to the joint consideration of temporal evolution and geographical scope. Third, this study improves the analytical framework for understanding how the digital economy affects green land use efficiency. From the perspectives of technological diffusion, industrial relocation and local absorption, and resource allocation, it examines the moderating roles of green technological innovation, industrial upgrading, and factor misallocation in the dynamic transformation of spatial externalities, revealing that the former two mitigate short-term siphoning while the latter intensifies it. By further identifying heterogeneity across geographical location, resource endowment, administrative hierarchy, and environmental regulation, the study provides

empirical evidence for differentiated strategies integrating digital development with green land governance.

2. Theoretical Analysis and Research Hypotheses

2.1. *Dynamic Spatial Externalities and Distance-Decay Boundaries of the Digital Economy*

The digital economy is driven by data as a key production factor and supported by digital infrastructure [21]. Unlike traditional production factors such as land and labor, data are non-rival and highly replicable. Their spatial circulation relies mainly on digital networks rather than physical relocation, which reduces marginal transmission costs and enables repeated use across regions. According to network externality theory, the value of data increases as the scale of digital connections expands. However, the realization of this value depends on digital infrastructure and local absorptive capacity. The uneven distribution of these complementary conditions gives the spatial circulation of data a dual character: it may reinforce the concentration of digital activities in some cities while also creating conditions for cross-regional diffusion.

This dual mechanism implies that the spatial externalities of the digital economy may evolve over time. During the early stage of digital economy development, core-periphery theory suggests that cities with stronger digital foundations and higher expected returns are more likely to acquire first-mover advantages. These cities attract digital industries and complementary production factors from surrounding areas, thereby reinforcing cumulative agglomeration and generating a short-term spatial siphoning effect [22]. As digital networks expand and the absorptive capacity of peripheral cities improves, the repeated use of data reduces knowledge transmission and regional coordination costs. The spatial influence of the digital economy then gradually shifts from factor concentration toward knowledge diffusion, providing a theoretical basis for the emergence of the long-term green spillover effect.

For peripheral cities, the persistent outflow of high-quality production factors may weaken their capacity for technological innovation and industrial upgrading, making them more likely to maintain resource-intensive and highly polluting land use patterns. Meanwhile, as central cities restructure their industries, some highly polluting and low-value-added industries may be relocated to peripheral regions, further increasing resource and environmental pressures in spatially connected cities. Consequently, during the early stages of digital economy development, the digital expansion of central cities may generate a pronounced spatial siphoning effect on surrounding cities and reduce their green land use efficiency.

As digitalization deepens, however, the spatial transmission mechanism of the digital economy gradually shifts from factor agglomeration toward knowledge diffusion and regional cooperation. On the one hand, digital platforms can substantially reduce the costs of information transmission, technology transactions, and cross-regional collaboration, thereby facilitating the cross-regional diffusion of green technologies [23]. On the other hand, rising land prices and increasing environmental carrying pressures in central cities may encourage some industrial activities to relocate to surrounding areas. Through the absorption of relocated industries and talent exchange, peripheral cities can gradually transform the digital technologies and green knowledge transferred from central cities into local productive capacity.

At the same time, the expansion of digital networks can strengthen industrial linkages among cities, gradually transforming spatial relationships based primarily on one-way factor attraction into those characterized by knowledge sharing, industrial coordination, and the diffusion of green development benefits. The effect of the digital economy on spatially connected cities therefore shifts from a spatial siphoning effect in the short

term to the green spillover effect in the long term. Based on the above analysis, the following hypothesis is proposed:

Hypothesis 1a. *The digital economy improves local green land use efficiency in both the short and long term.*

Hypothesis 1b. *The spatial externalities of the digital economy on green land use efficiency exhibit an intertemporal transition from the short-term spatial siphoning effect to the long-term green spillover effect.*

The spatial externalities of the digital economy not only vary over time but are also constrained by geographical distance. According to Tobler's First Law of Geography, the strength of spatial interactions generally decreases as geographical distance increases [24]. Although digital information can be transmitted rapidly through the Internet, information transmission does not necessarily translate into technological absorption or the local implementation of industrial activities. First, green technologies often involve substantial tacit knowledge, whose diffusion and application depend heavily on talent interactions and interfirm collaboration and therefore exhibit a strong dependence on geographical proximity. Second, industrial relocation and supply-chain collaboration remain constrained by transportation costs and cannot extend indefinitely across geographical space [25]. Finally, cross-regional land governance is also affected by administrative boundaries, local protectionism, and differences in environmental regulation.

The short-term and long-term spatial externalities of the digital economy may operate over different geographical ranges because the two effects rely on different transmission mechanisms. The short-term spatial siphoning effect is driven mainly by competition for mobile complementary factors among geographically proximate cities. Factor mobility and industrial relocation remain constrained by relocation costs and geographical proximity. Consequently, the capacity of central cities to attract production factors from surrounding cities weakens rapidly as intercity distance increases.

The long-term green spillover effect relies more strongly on digital knowledge diffusion and network-based regional cooperation. The replicability of data and the expansion of digital connections reduce spatial transmission costs, allowing green knowledge to reach a wider range of cities. However, the absorption of tacit knowledge still requires geographical proximity, while regional cooperation remains subject to coordination costs. The long-term green spillover effect therefore extends farther than the short-term spatial siphoning effect but still operates within a finite geographical range. The exact effective ranges cannot be derived directly from theory and must be identified empirically through successive distance bands. Based on the above analysis, the following hypothesis is proposed:

Hypothesis 2. *The spatial externalities of the digital economy on green land use efficiency exhibit a clear distance-decay pattern, and both the short-term spatial siphoning effect and the long-term green spillover effect operate within finite geographical ranges.*

2.2. Moderating Mechanisms Shaping the Dynamic Spatial Externalities of the Digital Economy

The transition in the spatial externalities of the digital economy from the short-term spatial siphoning effect to the long-term green spillover effect is not driven by digital technologies alone. Rather, its direction and magnitude are jointly shaped by cities' green innovation capacity, industrial structure, and factor allocation efficiency. To further explain

the conditions underlying this dynamic transition, this study focuses on three conditioning factors that moderate the dynamic spatial externalities of the digital economy: green technological innovation, industrial upgrading, and factor misallocation.

2.2.1. Moderating Role of Green Technological Innovation

Green technological innovation constitutes an important moderating condition shaping the extent to which the digital economy improves green land use efficiency and transforms its spatial externalities. Digital technologies can alleviate information asymmetry among innovation actors, reduce the costs of technological research and development and the commercialization of research outcomes, and facilitate cross-regional innovation collaboration between enterprises and research institutions through digital platforms [26].

In the short term, the attraction of capital, technology, and talent by central cities may lead to the outflow of innovation factors from peripheral regions. However, cities with stronger green technological innovation capacity generally possess greater knowledge absorptive capacity. On the one hand, accumulated local green technological capabilities can partially offset the loss of technological and human capital resources, thereby mitigating the adverse effects of factor outflows on green land use. On the other hand, stronger innovation capacity enables peripheral cities to absorb and apply digital technologies more effectively, thereby cushioning the negative effects associated with the agglomeration and expansion of central cities [27]. Green technological innovation can therefore weaken the short-term spatial siphoning effect.

In the long term, digital networks reduce the costs of the cross-regional diffusion of green knowledge, allowing green patents, environmentally friendly production processes, and management practices developed in central cities to spread to surrounding areas. Through technological imitation, collaborative research and development, and talent exchange, peripheral cities can transform external knowledge into local green productive capacity, reduce resource consumption and pollutant emissions per unit of land, and thereby strengthen the long-term green spillover effect of the digital economy. Based on the above analysis, the following hypothesis is proposed:

Hypothesis 3. *Green technological innovation positively moderates the spatial externalities of the digital economy on green land use efficiency, weakening the short-term spatial siphoning effect and strengthening the long-term green spillover effect.*

2.2.2. Moderating Role of Industrial Upgrading

The spatial externalities of the digital economy on green land use efficiency are conditioned by the transformation of the real economy. A more advanced industrial structure can improve a city's capacity to absorb digital technologies and translate them into intensive, low-carbon, and efficient land use outcomes [28]. The transformation of the industrial structure from dominance by traditional industries toward the coordinated development of advanced manufacturing and modern services can reduce economic growth's dependence on land expansion and increase economic output per unit of land.

During the early stages of digitalization, industrial upgrading can enhance the ability of peripheral cities to withstand factor siphoning. Cities with more advanced industrial structures generally possess more complete industrial systems, which can reduce the risk of excessive resource outflows to central cities and decrease dependence on energy-intensive and highly polluting industries. Industrial upgrading can therefore alleviate the short-term spatial siphoning effect of central cities on green land use in peripheral regions.

Over the long term, the digital economy transforms regional industrial specialization from simple competition for production factors into coordinated cooperation. Central cit-

ies can concentrate on technology-intensive industries, while surrounding cities can leverage their advantages in costs, location, and industrial foundations to absorb suitable green manufacturing activities and supporting industries [29]. Through the gradual relocation of industries across regions, the overall regional industrial structure can be optimized, and land use in surrounding cities can shift from extensive expansion toward greener utilization, thereby sustaining the release of positive spatial spillover effects. Based on the above analysis, the following hypothesis is proposed:

Hypothesis 4. *Industrial upgrading positively moderates the spatial externalities of the digital economy on green land use efficiency, weakening the short-term spatial siphoning effect and strengthening the long-term green spillover effect.*

2.2.3. Moderating Role of Factor Misallocation

The realization of the spatial externalities of the digital economy also depends on whether production factors, including capital, labor, and land, can be efficiently allocated according to their marginal productivity. Under conditions of market segmentation, production factors may be unable to move smoothly across regions and industries and may consequently become locked into inefficient, energy-intensive, and highly polluting industries. Factor misallocation not only reduces local production efficiency but also weakens cities' capacity to absorb and transform digital technologies.

In the short term, factor misallocation can amplify the spatial siphoning effect of the digital economy. When peripheral cities experience severe capital and labor misallocation, distorted factor returns reduce their ability to retain highly skilled workers, innovation capital, and digital firms, making these factors more likely to flow toward central cities [30]. At the same time, the lock-in of local capital and labor in inefficient industries weakens cities' ability to restructure their industries and respond to external competition for production factors. Factor misallocation therefore not only accelerates the outflow of high-quality factors but also reinforces peripheral cities' dependence on resource-intensive and highly polluting land use patterns, thereby intensifying the spatial siphoning effect during the early stages of digital economy development.

In the long term, although digital platforms can facilitate the cross-regional diffusion of green technologies, such external knowledge can be transformed into actual green productive capacity only when it is effectively matched with the local industrial foundation. When factor markets are severely distorted, capital cannot flow efficiently toward high-productivity green industries, while labor cannot enter sectors that match its skills, resulting in a mismatch between external digital knowledge and local production factors [31]. Consequently, even when central cities continuously transmit digital technologies and green knowledge to surrounding areas, peripheral cities may be unable to translate these external benefits into resource conservation and improvements in green land use efficiency, thereby weakening the long-term green spillover effect. Factor misallocation may further become an endogenous barrier to the continued diffusion of digital dividends. Based on the above analysis, the following hypothesis is proposed:

Hypothesis 5. *Factor misallocation negatively moderates the spatial externalities of the digital economy on green land use efficiency, intensifying the short-term spatial siphoning effect and weakening the long-term green spillover effect.*

2.3. Heterogeneity in the Effects of the Digital Economy on Green Land Use Efficiency

2.3.1. Heterogeneity by Geographical Location

Geographical location affects not only the level of urban digital infrastructure but also the degree of market integration, the concentration of innovation resources, and the

capacity for regional cooperation [32]. Cities in eastern China generally have stronger economic foundations, more developed digital infrastructure, higher levels of marketization and openness, and denser industrial networks. These conditions facilitate the intercity flow of data, technology, and knowledge and improve the efficiency with which digital technologies are translated into green production and intensive land use.

By contrast, cities in central and western China tend to be relatively disadvantaged in terms of digital infrastructure, skilled technical personnel, and innovation platforms, which may constrain their capacity to absorb and apply digital technologies. Moreover, during the early stages of digitalization, these cities are more vulnerable to the siphoning of production factors by more developed regions. Consequently, the effect of the digital economy on green land use efficiency may be more uncertain in central and western China. The green effect of the digital economy may therefore vary substantially across geographical locations.

2.3.2. Heterogeneity by Resource Endowment

Resource endowment shapes a city's existing industrial structure, modes of production, and land use pattern [33]. Resource-based cities generally depend heavily on resource extraction, have relatively undiversified industrial structures, and experience high levels of energy consumption and pollutant emissions in the land use process. Digital technologies can optimize production processes and facilitate the digital and green transformation of resource-based industries, thereby improving green land use efficiency.

However, resource-based cities may also exhibit strong path dependence. When traditional industries account for an excessively large share of the local economy and technological absorptive capacity remains limited, the green transformation effect of the digital economy may be constrained. Non-resource-based cities generally have more diversified industrial structures and more favorable conditions for absorbing and applying digital technologies. Nevertheless, because their initial land use efficiency may already be relatively high, the scope for further marginal improvement generated by the digital economy may be limited. The effect of the digital economy may therefore differ according to cities' resource endowments.

2.3.3. Heterogeneity by Administrative Hierarchy

Within China's urban governance system, administrative hierarchy affects the allocation of fiscal resources, infrastructure investment, and innovation factors [34]. High-tier cities, including provincial capitals and sub-provincial cities, generally possess stronger resource-mobilization capacities and are more likely to receive priority support for digital infrastructure construction, technological innovation, and green development policies. These advantages can improve the efficiency of digital technology adoption and strengthen the positive effect of the digital economy on green land use efficiency.

At the same time, high-tier cities may face agglomeration diseconomies arising from excessive factor concentration, rising land costs, and increasing pressure on environmental carrying capacity. Although ordinary cities have relatively limited policy resources, they may obtain latecomer advantages from digitalization by absorbing relocated industries, exploiting cost advantages, and integrating into regional industrial chains. Administrative hierarchy may therefore not only reinforce the digital empowerment advantages of high-tier cities but also generate differentiated benefits for ordinary cities through regional specialization and industrial relocation.

2.3.4. Heterogeneity by Environmental Regulation

Environmental regulation provides both external constraints and policy incentives for realizing the green effects of the digital economy [35]. More stringent environmental

regulation raises the production costs of energy-intensive and highly polluting firms, encouraging them to adopt digital technologies to optimize production processes and reduce resource consumption and pollutant emissions. Environmental policies may also stimulate green technological research and development through the innovation compensation effect and promote coordination between digital infrastructure construction and low-carbon development objectives.

However, the effect of environmental regulation also depends on how it is implemented. Moderate and appropriately enforced regulation can facilitate the integration of digital technologies with green production, whereas poorly designed or improperly implemented regulation may increase firms' operating costs and crowd out investment in digital transformation and technological innovation. In cities with less stringent environmental regulation, digital technologies may be used primarily to expand production rather than improve environmental efficiency. Environmental regulation therefore alters the actual effect of the digital economy on green land use efficiency.

Based on the above analysis, the following hypothesis is proposed:

Hypothesis 6. *The effect of the digital economy on green land use efficiency exhibits significant urban heterogeneity and varies across geographical location, resource endowment, administrative hierarchy, and environmental regulation.*

The conceptual framework of these moderating mechanisms is illustrated in Figure 1.

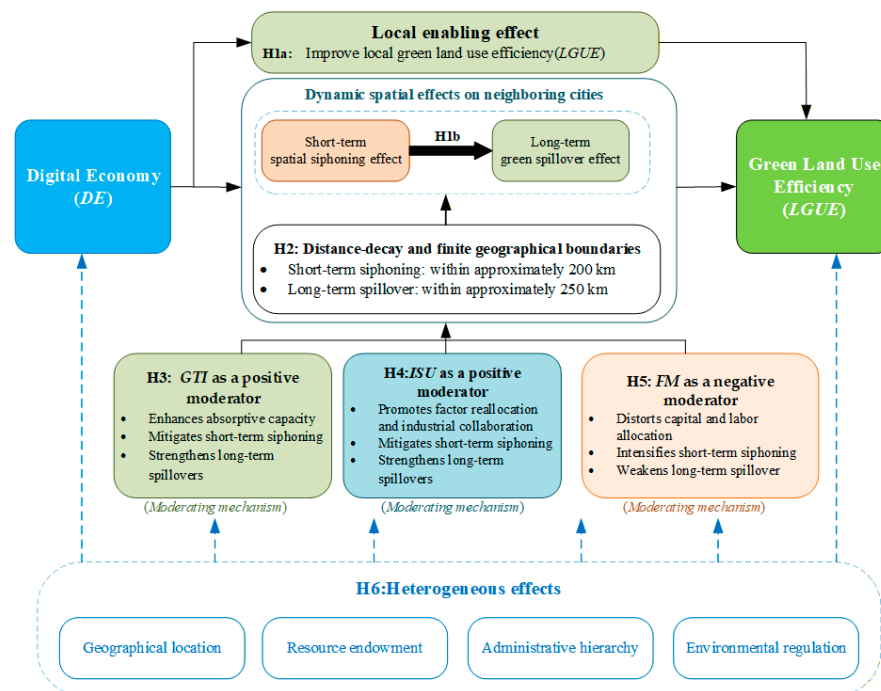


Figure 1. Research framework. Note: Solid arrows indicate the hypothesized direct and transmission relationships, whereas dashed arrows indicate the dimensions used for the heterogeneity analysis.

3. Materials and Methods

3.1. Model Specification

3.1.1. Spatial Weight Matrices

Identifying the spatial externalities of the digital economy on green land use efficiency first requires the specification of appropriate spatial weight matrices. Because intercity linkages are shaped not only by geographical distance but also by differences in economic development, this study constructs a geographical distance matrix, an economic distance matrix, and an economic–geographical nested matrix. These matrices capture spatial dependence among cities from different perspectives and are also used to assess the robustness of the empirical results.

1. Geographical distance matrix (W_{geo}). According to Tobler's First Law of Geography, spatial interactions among cities generally weaken as geographical distance increases. Based on the longitude and latitude coordinates of each city, this study calculates the spherical distance (d_{ij}) between city i and city j and constructs the geographical distance matrix using the inverse squared distance:

$$W_{geo,ij} = \begin{cases} \frac{1}{d_{ij}^2}, & i \neq j \\ 0, & i = j \end{cases} \quad (1)$$

2. Economic distance matrix (W_{eco}). Cities with similar levels of economic development tend to have more comparable industrial structures, market demand, and technological conditions, which may facilitate factor mobility and knowledge diffusion. Accordingly, the economic distance matrix is constructed using the inverse of the absolute difference in average per capita GDP between two cities over the sample period:

$$W_{eco,ij} = \begin{cases} \frac{1}{1 + |\ln \bar{Y}_i - \ln \bar{Y}_j|}, & i \neq j \\ 0, & i = j \end{cases} \quad (2)$$

where $\bar{Y}_i$ and $\bar{Y}_j$ denote the average per capita GDP of city i and city j , respectively, over the sample period.

3. Economic–geographical nested matrix ($W_{eco-geo}$). In practice, spatial influence is often asymmetric. Economically more developed central cities generally exert stronger effects on peripheral cities than peripheral cities exert on central cities. To account simultaneously for geographical proximity and differences in economic influence, this study incorporates an economic-development-level weight into the geographical distance matrix and constructs the economic–geographical nested matrix as follows:

$$W_{eco-geo,ij} = \begin{cases} W_{geo,ij} \times W_{eco,ij}, & i \neq j \\ 0, & i = j \end{cases} \quad (3)$$

where $\bar{Y}$ denotes the average per capita GDP of all sample cities. This matrix captures both geographical distance constraints and the asymmetric spatial influence associated with differences in urban economic development levels.

All spatial weight matrices are row-standardized before estimation to ensure comparability and facilitate the interpretation of spatial externalities.

3.1.2. Dynamic Spatial Durbin Model

Green land use efficiency is characterized by a dynamic transition process with pronounced path dependence, indicating that its current level is strongly influenced by historical accumulation. Meanwhile, regional economic interactions generate substantial spatial dependence in green land use efficiency across cities. Conventional static panel models that ignore temporal persistence and spatial dependence may therefore suffer

from endogeneity and model misspecification. Accordingly, this study extends the conventional spatial Durbin model by incorporating both the temporal and spatial lag terms of the dependent variable and constructs a dynamic spatial Durbin model with two-way fixed effects:

$$LGUE_{it} = \alpha + \tau LGUE_{i,t-1} + \rho WLGUE_{it} + \eta WLGUE_{i,t-1} + \beta DE_{it} + \theta WDE_{it} + \gamma Control_{it} + \vartheta WControl_{it} + \mu_i + \lambda_t + \varepsilon_{it} \quad (4)$$

where $LGUE_{it}$ denotes green land use efficiency in city i in year t ; DE_{it} represents the level of digital economy development in city i in year t ; $LGUE_{i,t-1}$ is the one-period lagged term of green land use efficiency; W denotes the spatial weight matrix; $WLGUE_{it}$ is the spatial lag term of the dependent variable; ρ is the spatial autoregressive coefficient; τ is the coefficient of the temporal lag term; β is the coefficient of the core explanatory variable; WDE_{it} denotes the spatial lag term of the core explanatory variable; θ is the spatial Durbin coefficient; $Control_{it}$ denotes the set of control variables; $WControl_{it}$ represents the spatial lag terms of the control variables; η captures the spatiotemporal dependence of green land use efficiency across spatially connected cities; γ , and ϑ denote the corresponding coefficients; μ_i and λ_t represent city fixed effects and year fixed effects, respectively; ε_{it} is the random disturbance term; and α is the constant term.

Estimation strategy. The baseline dynamic spatial Durbin model is estimated using the bias-corrected quasi-maximum likelihood estimator implemented through the `xsmle` command in Stata 17.0 (StataCorp LLC, College Station, TX, USA) [36]. For dynamic spatial autoregressive and spatial Durbin models with fixed effects, this estimator first obtains the initial quasi-maximum likelihood estimates and then applies analytical bias corrections to the model coefficients [37]. This procedure mitigates the incidental-parameter and Nickell-type bias associated with the inclusion of the temporally lagged and spatiotemporally lagged dependent variables. City and year fixed effects are included throughout the estimation. The estimation is conditional on the observed initial values of green land use efficiency. Specifically, the observations for 2011 are used to construct $LGUE_{i,t-1}$ and $WLGUE_{i,t-1}$, while the effective estimation period is 2012–2024.

To ensure that the dynamic spatial process converges to a stable equilibrium, this study further examines the stability of the dynamic transition matrix. After rearranging Equation (4), the transition matrix of the lagged dependent variable can be expressed as $A = (I - \rho W)^{-1}(\tau I + \eta W)$. The dynamic spatial Durbin model is stable when the spectral radius of A is smaller than one. This condition ensures that temporal and spatial feedback effects gradually decay rather than accumulate indefinitely.

3.1.3. Decomposition of Short-Term and Long-Term Spatial Externalities

Because the dynamic spatial Durbin model simultaneously incorporates the spatial lag of the dependent variable $\rho WLGUE_{it}$, its temporal lag $\tau LGUE_{i,t-1}$, and its spatiotemporal lag $\eta WLGUE_{i,t-1}$, the estimated coefficients β and θ on the digital economy variable and its spatial lag represent only point estimates from the model and cannot be directly interpreted as the true marginal effects of the digital economy. To obtain effect estimates with clear economic interpretations, this study applies the partial-derivative decomposition approach to decompose the overall spatial effects of the digital economy on green land use efficiency into direct and indirect effects and to further distinguish between short-term and long-term effects.

In the dynamic spatial Durbin model, the short term refers to the contemporaneous response of green land use efficiency to a change in the digital economy in period t , before the temporal feedback generated by the lagged dependent variables is fully accumulated. The short-term effect is therefore calculated using Equation (5). The long term refers to the cumulative equilibrium response after temporal persistence and spatial feedback have

been fully transmitted through the dynamic system. The long-term effect is calculated using Equation (6). Accordingly, the distinction between the short term and the long term is model-based rather than calendar-based. The empirical results do not identify a specific year in which the spatial effect changes direction. Instead, the effect decomposition identifies whether the direction and magnitude of spatial externalities differ between the contemporaneous horizon and the cumulative equilibrium horizon.

The short-term partial-derivative matrix is expressed as:

$$S^{SR} = (I - \rho W)^{-1}(\beta I + \theta W) \quad (5)$$

The average of the diagonal elements of the matrix represents the short-term direct effect, whereas the average row sum of its off-diagonal elements represents the short-term indirect effect.

The long-term partial-derivative matrix is expressed as:

$$S^{LR} = [(1 - \tau)I - (\rho + \eta)W]^{-1}(\beta I + \theta W) \quad (6)$$

The average of the main diagonal elements of the matrix represents the long-term direct effect, whereas the average row sum of its off-diagonal elements represents the long-term indirect effect. This model is used to test Hypotheses 1a and 1b.

3.1.4. Distance-Decay Boundary Identification

To identify the distance-decay pattern of the spatial externalities of the digital economy, this study divides intercity geographical distances into consecutive 50 km bands, including 0–50 km, 50–100 km, 100–150 km, and 150–200 km, continuing up to 750–800 km, and constructs a corresponding distance-band spatial weight matrix for each interval. A 50 km interval is selected to balance spatial resolution and estimation reliability. Narrower distance bands may result in sparse intercity connections and an insufficient number of city pairs within individual bands, thereby increasing sampling variability and reducing the stability of the row-standardized spatial weight matrices. Conversely, wider distance bands may obscure the gradual weakening of spatial externalities and reduce the precision with which their effective geographical ranges can be identified. Therefore, the 50 km specification provides a reasonable compromise between maintaining sufficient intercity observations within each distance band and capturing the distance-decay pattern in a sufficiently fine-grained manner. The estimated distance ranges should consequently be interpreted as approximate effective geographical ranges rather than exact cut-off points.

For any given distance band $(D_{k-1}, D_k]$, the matrix element is assigned a value of 1 if the geographical distance between city i and city j falls within that interval and 0 otherwise. All diagonal elements are set to 0. By comparing the direction, magnitude, and statistical significance of the short-term and long-term indirect effects of the digital economy across different distance bands, this study identifies the distance-decay patterns and effective geographical boundaries of the short-term spatial siphoning effect and the long-term green spillover effect. This approach is used to test Hypothesis 2.

3.1.5. Model for Testing Moderating Mechanisms Shaping the Dynamic Spatial Externalities

To examine how green technological innovation, industrial upgrading, and factor misallocation moderate the dynamic spatial externalities of the digital economy, this study extends the baseline dynamic spatial Durbin model by incorporating interaction terms between the digital economy and each moderating variable. The model is specified as follows:

$$LGUE_{it} = \alpha + \tau LGUE_{i,t-1} + \rho WLGUE_{it} + \eta WLGUE_{i,t-1} + \beta_1 DE_{it} + \beta_2 M_{it} + \beta_3 (DE_{it} \times M_{it}) + \theta_1 WDE_{it} + \theta_2 WM_{it} + \theta_3 W(DE_{it} \times M_{it}) + \gamma Control_{it} + \vartheta WControl_{it} + \mu_i + \lambda_t + \varepsilon_{it} \quad (7)$$

where M_{it} denotes the moderating variables, including green technological innovation (GTI), industrial upgrading (ISU), and factor misallocation (FM), respectively. This model is used to test Hypotheses 3, 4, and 5.

3.1.6. Heterogeneity Analysis Strategy

To examine city-level differences in the effects of the digital economy on green land use efficiency, this study conducts subgroup estimations according to geographical location, resource endowment, administrative hierarchy, and environmental regulation.

First, based on the official regional classification, the sample cities are divided into cities in eastern China, cities in central China, and cities in western China to examine whether differences in digital infrastructure, marketization, and innovation conditions lead to heterogeneous effects across regions. Second, according to the classification criteria for resource-based cities issued by the State Council of China, the sample is divided into resource-based and non-resource-based cities to identify differences associated with resource dependence and the need for industrial transformation. Third, based on administrative hierarchy, the sample is divided into high-tier and ordinary cities. High-tier cities include municipalities directly under the central government, provincial capitals, and sub-provincial cities, while the remaining cities are classified as ordinary cities. This classification is used to examine the influence of cities' capacity to mobilize and allocate administrative resources. Fourth, the intensity of environmental regulation is measured by the proportion of local fiscal expenditure on energy conservation and environmental protection in total general public budget expenditure. This indicator reflects the fiscal resources allocated by local governments to environmental governance and pollution control. To maintain consistent city classifications throughout the sample period, the annual environmental regulation indicator is first averaged for each city over the sample period. Cities with an average value above the sample median are classified as cities with stricter environmental regulation, whereas the remaining cities are classified as cities with less stringent environmental regulation.

By comparing the direction, magnitude, and statistical significance of the estimated effects of the digital economy across different groups, this study determines whether its impact on green land use efficiency exhibits significant urban heterogeneity, thereby testing Hypothesis 6.

3.2. Measurement of Variables

3.2.1. Dependent Variable: Green Land Use Efficiency (LGUE)

Green land use efficiency (LGUE) reflects a city's comprehensive capacity to increase desirable economic, social, and ecological outputs while reducing undesirable outputs, such as pollutant emissions, under constraints imposed by inputs of land, capital, labor, science and technology, and energy. Unlike conventional land use efficiency, which focuses primarily on economic output, green land use efficiency simultaneously considers economic development, social welfare, and ecological improvement. It emphasizes achieving higher-quality land use outcomes with fewer resource inputs and lower environmental costs.

Following Tan et al. [38], this study employs a super-efficiency slack-based measure (SBM) model incorporating undesirable outputs to estimate urban green land use efficiency. An evaluation index system is constructed from three dimensions: inputs, desirable outputs, and undesirable outputs, as shown in Table 1. The input indicators include

land, capital, labor, science and technology, and energy inputs. The desirable outputs comprise economic, social, and ecological benefits, whereas the undesirable outputs mainly include industrial wastewater, sulfur dioxide, and industrial smoke and dust emissions. To measure social benefits, this study applies the entropy-weight method to construct a social development index based on population development, economic income, employment, medical resources, investment in science and education, and technological innovation. The detailed indicators are presented in Table 2.

Table 1. Construction of the indicator system for *LGUE*.

Indicator Type	Element	Indicator Description
Input	Land	Area of production and living land (km ²)
	Capital	Fixed asset investment (10 ⁴ CNY)
	Labor	Total employment (10 ⁴ persons)
	Technology	Proportion of science and technology expenditure in GDP (%)
	Energy	Total energy consumption (10 ⁴ tons of SCE)
Desirable Output	Economic benefit	Gross regional product minus resource depletion costs and environmental pollution losses (10 ⁴ CNY)
	Social benefit	Social development index
	Ecological benefit	Greening coverage rate of built-up areas (%)
Undesirable Output	Negative ecological effect	Industrial wastewater emissions per unit of land area (10 ⁴ tons/km ²)
		Sulfur dioxide emissions per unit of land area (10 ⁴ tons/km ²)
		Industrial smoke and dust emissions per unit of land area (10 ⁴ tons/km ²)

Table 2. Construction of the indicator system for the social development index.

Variable	Indicator	Indicator Description	Direction
Social development index	Natural population growth rate	Ratio of the natural increase in population to the total population (%)	Positive
	Consumption level	Per capita retail sales of consumer goods (10 ⁴ CNY/person)	Positive
	Per capita disposable income	Ratio of total regional disposable income to the total population (10 ⁴ CNY/person)	Positive
	Unemployment rate	Proportion of the registered unemployed population to the total labor force (%)	Negative
	Medical resources	Number of hospital beds per 10,000 persons	Positive
	Government support for science and education	Proportion of science and education expenditure to total local general public budget expenditure (%)	Positive
	Level of innovation output	Sales revenue from new products of industrial enterprises above designated size per unit of land area (10 ⁴ CNY/km ²)	Positive

3.2.2. Independent Variable: Digital Economy (DE)

The digital economy (*DE*) is a comprehensive concept encompassing the development of digital industries, the application of digital technologies, and the digital transformation of the real economy. This study constructs an evaluation index system from five dimensions: digital product manufacturing, digital product services, digital technology applications, digital factor-driven development, and digital efficiency improvement.

To eliminate differences in measurement units and orders of magnitude across the original panel data, this study first applies min–max normalization to transform the underlying indicators into dimensionless values. The objective entropy-weight method is then employed to determine the weight of each indicator. Finally, the standardized value of each indicator is multiplied by its corresponding entropy weight and aggregated to obtain the composite digital economy development index *DE* for each city and year. The detailed evaluation index system is presented in Table 3.

Table 3. Construction of the indicator system for *DE*.

Variable	Indicator	Indicator Description
Digital economy	Digital product manufacturing	Logarithm of the output of integrated circuits
		Mobile phone penetration rate
		Proportion of fixed asset investment in the computer services and software industry to total fixed asset investment
	Digital product services	Logarithm of software product revenue
		Logarithm of total telecom business volume
	Digital technology application	Logarithm of the number of domain names
		Logarithm of the number of Internet users
		Logarithm of information technology service revenue
	Digital factor-driven development	Number of Internet broadband access subscribers per 100 persons
		Logarithm of e-commerce transaction volume
		Logarithm of the number of industrial Internet patent grants
	Digital efficiency improvement	Payment usage sub-index of the Digital Financial Inclusion Index
		Insurance usage sub-index of the Digital Financial Inclusion Index
		Installation density of industrial robots

3.2.3. Moderating Mechanism Variables

1. Green technological innovation (*GTI*). Following Johnstone et al. [39], this study measures urban green technological innovation using the number of green patent applications per 10,000 inhabitants. Patent applications are employed rather than patent grants because application data are less affected by administrative approval lags and can therefore capture a city's current green innovation capacity in a more timely manner. Green patent applications are identified by matching the patent-level International Patent Classification (IPC) codes obtained from the China National Intellectual Property Administration with the technology categories and corresponding IPC codes listed in the World Intellectual Property Organization (WIPO) IPC Green Inventory. The identified applications are then aggregated at the prefecture-level city level. To smooth the distribution and accommodate zero values, the natural logarithm of the number of green patent applications per 10,000 inhabitants plus one is used.
2. Industrial upgrading (*ISU*). This study measures the level of urban industrial upgrading using the industrial structure hierarchy coefficient. This method assigns progressively higher weights to the primary, secondary, and tertiary sectors to reflect the advancement of the industrial structure. The index is calculated as follows:

$$ISU_{it} = \sum_{m=1}^3 y_{i,m,t} \times m \quad (8)$$

where $y_{i,m,t}$ denotes the share of value added generated by industry m in the gross regional product of city i in year t .

3. Factor misallocation (*FM*). This study measures the degree of factor misallocation based on the classic theoretical framework proposed by Zhang et al. [40]. First, the output elasticities of capital and labor for each city are estimated using a Cobb–Douglas (C–D) production function. The capital misallocation index (τK) and labor misallocation index (τL) are then calculated by comparing the marginal products of the respective factors with their actual factor prices. Finally, a composite factor misallocation index is constructed as follows:

$$FM_{it} = \sqrt{\tau K_{it}^2 + \tau L_{it}^2} \quad (9)$$

3.2.4. Control Variables

To mitigate omitted-variable bias, this study includes the following control variables:

1. Urbanization level (*URB*). This variable is measured as the proportion of the urban resident population in the total resident population. Urbanization can improve land use intensity and public service efficiency through population agglomeration and infrastructure sharing, whereas excessive urban expansion may also increase pressure on land resources and the ecological environment.
2. Degree of openness (*Fdi*). This variable is measured as the ratio of actually utilized foreign direct investment to gross regional product. Foreign direct investment may introduce green technologies and advanced management practices, but it may also lead to the relocation of polluting industries.
3. Government intervention (*Gov*). This variable is measured as the ratio of local general public budget expenditure to gross regional product. Local governments can influence land use patterns through fiscal expenditure, industrial policies, and environmental governance.
4. Population density (*Pop*). This variable is measured as the ratio of the year-end population to the administrative land area. Population agglomeration may improve the utilization efficiency of land and public facilities, whereas excessive agglomeration may increase resource and environmental pressures.
5. Human capital (*Human*). This variable is measured as the ratio of students enrolled in regular higher education institutions to the annual average population. Higher levels of human capital facilitate the absorption of digital technologies, green innovation, and industrial upgrading.
6. Industrialization level (*Industry*). This variable is measured as the share of industrial value added in gross regional product. A higher proportion of traditional industry may increase land occupation, energy consumption, and pollutant emissions.

3.3. Data Sources

This study constructs a panel dataset covering 280 prefecture-level and above cities in China from 2011 to 2024. The raw data on macroeconomic conditions and the ecological environment are primarily obtained from the *China Statistical Yearbook*, *China Environmental Statistical Yearbook*, *China City Statistical Yearbook*, *China Regional Economic Statistical Yearbook*, and the CSMAR database, supplemented by the statistical bulletins on national economic and social development issued by provincial and municipal governments. For a small number of isolated missing observations within the sample period, linear interpolation is used to impute the missing values. Selected continuous variables with highly skewed distributions are transformed using natural logarithms to reduce skewness and mitigate potential heteroskedasticity. Definitions and descriptive statistics of the main variables are presented in Table 4. Although the original dataset covers 280 cities from 2011 to 2024, the inclusion of the one-period lagged dependent variable in the dynamic spatial Durbin model reduces the effective estimation period to 2012–2024. Therefore, the baseline regression sample contains 3640 city-year observations. The base map was obtained from the Standard Map Service website of the Ministry of Natural Resources, using the standard map with approval number GS (2024) 0650. No modifications were made to the base map.

Table 4. Definition and expression of variables.

Variable Type	Variable	Symbol	Mean	Standard Deviation
Dependent variable	Green land use efficiency	<i>LGUE</i>	0.806	0.120
Independent variable	Digital economy	<i>DE</i>	0.326	0.167

Moderating mechanism variables	Green technological innovation	<i>GTI</i>	1.284	0.936
	Industrial upgrading	<i>ISU</i>	2.356	0.184
	Factor misallocation	<i>FM</i>	0.427	0.286
Control variables	Urbanization level	<i>URB</i>	0.606	0.148
	Degree of openness	<i>Fdi</i>	0.021	0.026
	Government intervention	<i>Gov</i>	0.183	0.092
	Population density	<i>Pop</i>	0.061	0.073
	Human capital	<i>Human</i>	0.023	0.019
	Industrialization level	<i>Industry</i>	0.346	0.112

4. Results

4.1. Spatiotemporal Evolution of DE and LGUE

4.1.1. Temporal Distribution Dynamics

To examine the temporal dynamics of the digital economy (*DE*) and green land use efficiency (*LGUE*), three-dimensional kernel density estimation (KDE) plots are generated using MATLAB R2023a (The MathWorks, Inc., Natick, MA, USA). Figure 2a presents the three-dimensional KDE results for China's *DE* from 2011 to 2024. In terms of distribution location, the main peak of the KDE curve shifts gradually toward higher values over time, indicating an overall upward trend in the level of digital economy development. Regarding distribution shape, the height of the main peak declines steadily, while its width gradually expands, suggesting that data dispersion has increased, and that intercity disparities in *DE* development have gradually widened. In terms of tail behavior and polarization, the right tail on the high-value side becomes increasingly elongated, and the initially unimodal distribution gradually evolves into a multimodal pattern. This indicates that the number of cities with relatively high levels of *DE* has increased, while a differentiated regional gradient has gradually emerged.

Figure 2b presents the three-dimensional KDE results for China's *LGUE* from 2011 to 2024. In terms of distribution location, the main peak of the KDE curve also shifts continuously toward higher values, indicating a significant overall improvement in *LGUE*. Regarding distribution shape, the height of the main peak shows a slight declining trend with fluctuations, accompanied by a slight broadening of the distribution, suggesting that intercity disparities in *LGUE* have widened gradually. In terms of polarization, the right tail on the high-value side becomes noticeably longer over time, while a small secondary peak emerges in the extremely high-value range. This pattern suggests that a small number of cities have entered a relatively high-efficiency range, leading to increasing spatial polarization.

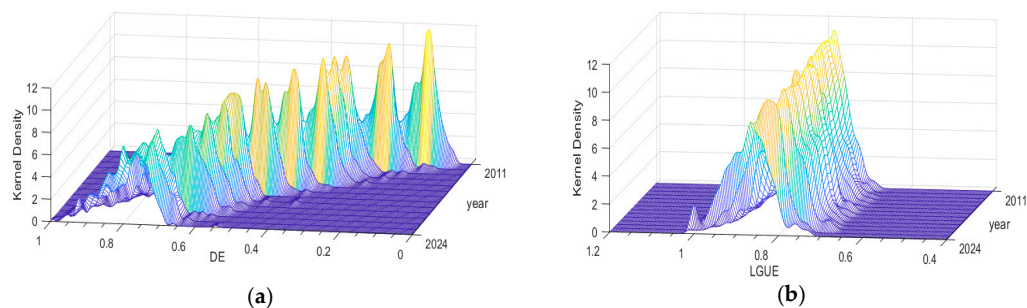


Figure 2. Three-dimensional KDE of *DE* and *LGUE* from 2011 to 2024: (a) *DE*; (b) *LGUE*. Note: Colors correspond to the magnitude of the kernel density values, with dark blue indicating lower density and yellow indicating higher density.

4.1.2. Spatial Distribution Patterns

To investigate the spatial evolution characteristics of *DE* and *LGUE*, this study selects measured results for four periods including 2011, 2015, 2019 and 2024, and adopts ArcGIS 10.8 (Esri, Redlands, CA, USA) to conduct spatial visualization analysis on the two indicators in the four years.

As shown in Figure 3, the spatial distribution of *DE* exhibits a pronounced east–west gradient. In 2011, most cities remained in the low-value range, while only a small number of eastern coastal cities displayed an initial advantage. From 2015 to 2019, *DE* developed rapidly, and high-value areas gradually expanded from isolated coastal growth poles toward surrounding cities. By 2024, relatively high levels of *DE* had formed contiguous clusters along the eastern coast. Meanwhile, several regional central cities in central and western China also experienced rapid catch-up growth. Overall, the spatial distribution of *DE* evolved from isolated high-value areas to more spatially connected clusters, while maintaining a general pattern of higher levels in the east and lower levels in the west.

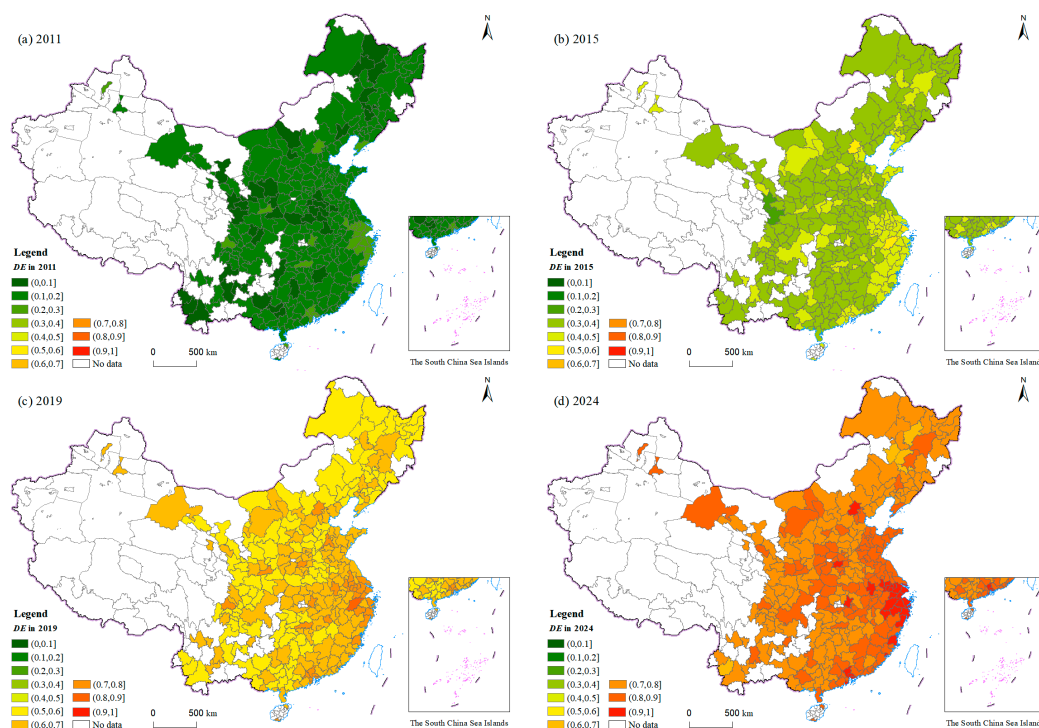


Figure 3. Spatial distribution of *DE* in 2011, 2015, 2019, and 2024.

Figure 4 presents the spatial evolution of *LGUE*. In 2011, most cities were concentrated in the low- and medium-value ranges, and high-efficiency cities were scattered across space. By 2024, the overall level of *LGUE* had increased considerably, while high-value areas had gradually evolved from isolated points into more contiguous clusters. This spatial transformation suggests that improvements in *LGUE* were accompanied by increasingly evident spatial agglomeration. From 2011 to 2024, both *DE* and *LGUE* displayed clear upward trends and increasingly clustered spatial distributions. The consistent temporal and spatial evolution of *DE* and *LGUE* provides preliminary descriptive evidence of a potential correlation between digital economy development and green land use efficiency. Nevertheless, whether *DE* significantly affects *LGUE*, whether this effect generates spatial externalities, and whether these spatial effects are conditioned by green technological innovation, industrial upgrading, and factor misallocation require further econometric investigation.

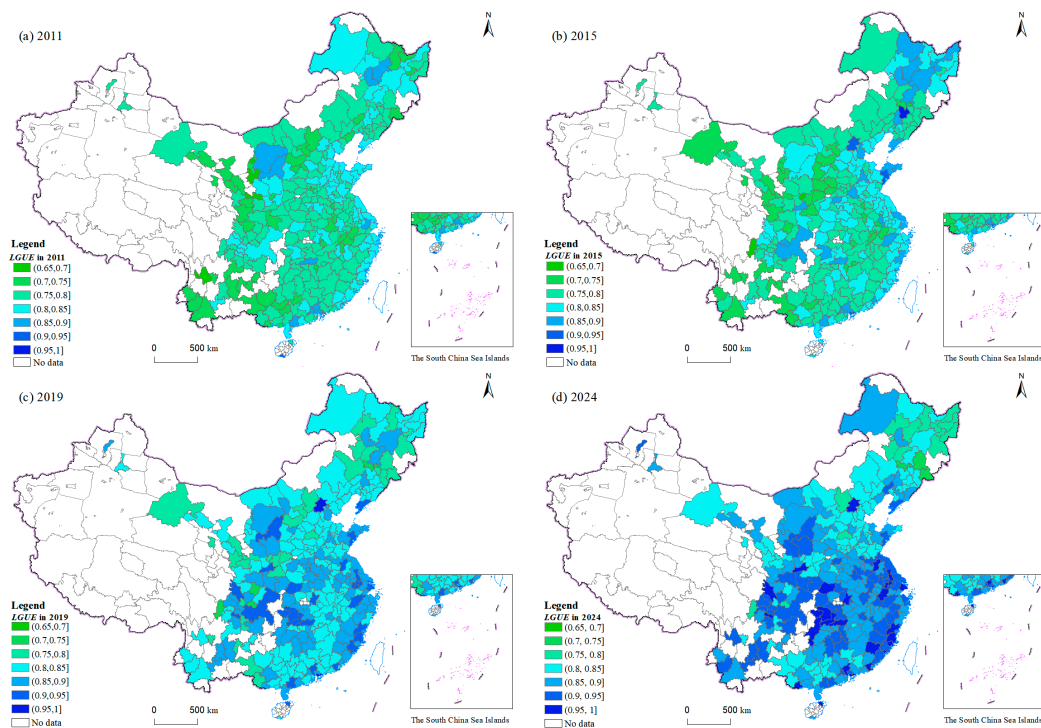


Figure 4. Spatial distribution of *LGUE* in 2011, 2015, 2019, and 2024.

4.2. Spatial Autocorrelation Test

4.2.1. Global Spatial Autocorrelation

To examine whether the digital economy (*DE*) and green land use efficiency (*LGUE*) exhibit significant spatial dependence, this study calculates their global Moran's *I* statistics for the period 2011–2024 using the geographical distance matrix. The results are reported in Table 5. Throughout the sample period, the Moran's *I* statistics of both *DE* and *LGUE* are positive, and the corresponding Z-statistics are statistically significant. All reported Moran's *I* statistics are statistically significant at the 1% level, with the exception of *LGUE* in 2016, which remains significant at the 5% level. These findings indicate that *DE* and *LGUE* are not randomly distributed across space but exhibit significant positive spatial autocorrelation. Specifically, cities with relatively high values tend to be located near other high-value cities, while cities with relatively low values are also more likely to form spatial clusters.

From a temporal perspective, the Moran's *I* statistic of *DE* shows an overall upward trend with some fluctuations, increasing from 0.304 in 2011 to 0.502 in 2024. This pattern indicates an overall increasing trend in spatial clustering of *DE*. Although the Moran's *I* statistic of *LGUE* declined from 0.260 in 2011 to 0.098 in 2016, it generally increased thereafter and reached 0.497 in 2024, indicating that the positive spatial association of *LGUE* became notably stronger in the later sample period. Overall, both *DE* and *LGUE* exhibit significant positive spatial dependence, although the temporal evolution of *LGUE* is characterized by noticeable fluctuations.

Table 5. Global Moran's *I*.

Year	<i>DE</i>			<i>LGUE</i>		
	Moran's <i>I</i>	Z Value	<i>p</i> Value	Moran's <i>I</i>	Z Value	<i>p</i> Value
2011	0.304	7.631	0.000	0.260	6.542	0.000
2012	0.329	8.264	0.000	0.232	5.840	0.000

2013	0.344	8.616	0.000	0.183	4.633	0.000
2014	0.321	8.064	0.000	0.152	3.861	0.000
2015	0.286	7.175	0.000	0.150	3.825	0.000
2016	0.309	7.755	0.000	0.098	2.524	0.012
2017	0.293	7.364	0.000	0.262	6.601	0.000
2018	0.340	8.524	0.000	0.298	7.481	0.000
2019	0.418	10.461	0.000	0.331	8.304	0.000
2020	0.438	10.969	0.000	0.313	7.853	0.000
2021	0.463	11.583	0.000	0.335	8.406	0.000
2022	0.484	12.108	0.000	0.329	8.241	0.000
2023	0.501	12.516	0.000	0.294	7.393	0.000
2024	0.502	12.539	0.000	0.497	12.407	0.000

4.2.2. Local Spatial Clustering

To further characterize the local spatial clustering patterns of the digital economy (*DE*) and green land use efficiency (*LGUE*) during the study period, this study constructs LISA cluster maps for both variables, as shown in Figure 5. The sample cities are classified into four types: high–high clusters, low–low clusters, high–low spatial outliers, and low–high spatial outliers.

Overall, the local spatial distributions of both *DE* and *LGUE* are dominated by high–high and low–low clusters, indicating pronounced spatial agglomeration and polarization. Over time, the spatial continuity of the high–high and low–low clusters increases, and the pattern of local spatial differentiation becomes increasingly distinct.

Specifically, the high–high clusters of *DE* are concentrated primarily in the eastern coastal region, and their spatial coverage expands markedly into more contiguous areas over time, indicating a strong spatial clustering and diffusion pattern. By contrast, the low–low clusters are concentrated in contiguous areas of central, western, and northeastern China, reflecting a pronounced spatial lock-in of low *DE* levels.

The local spatial clustering pattern of *LGUE* broadly resembles that of *DE*. Its high–high clusters are mainly distributed in the eastern coastal region and in several urban agglomerations with relatively strong economic foundations, evolving from an initially scattered distribution into more contiguous clusters. Low–low clusters are concentrated primarily in parts of northeastern China and the inland areas of central and western China. The spatial overlap between the high-value clusters of *DE* and *LGUE* suggests that regions with relatively advanced digital economy development also tend to exhibit higher levels of green land use efficiency.

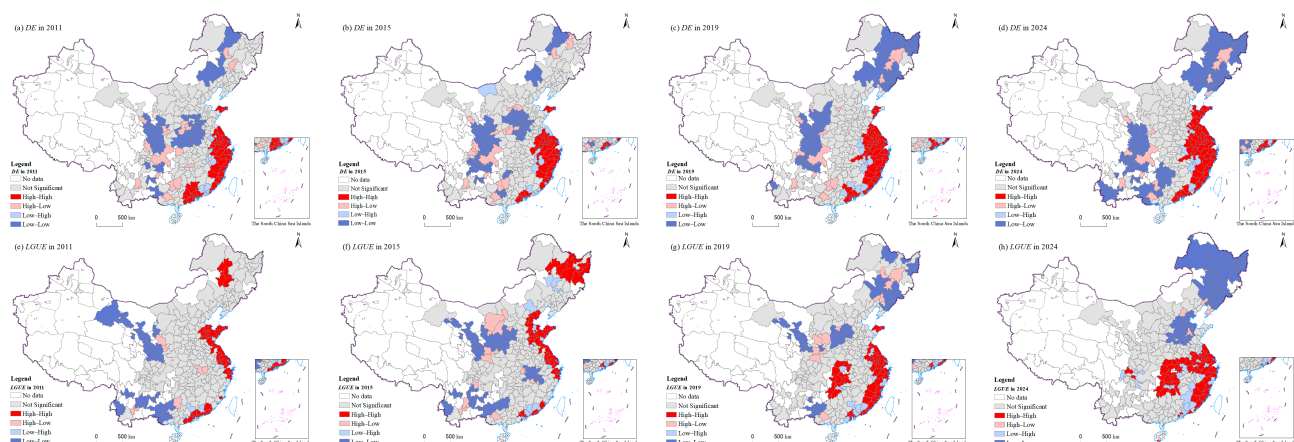


Figure 5. LISA cluster maps of *DE* and *LGUE*.

4.3. Selection of Spatial Model

To identify the appropriate spatial econometric specification for examining the effect of the digital economy on green land use efficiency, this study conducts a series of diagnostic tests, including the Lagrange Multiplier (LM) test, robust LM test, Wald test, likelihood-ratio (LR) test, and Hausman test. The Akaike information criterion (AIC) and Bayesian information criterion (BIC) are further used to determine the appropriate fixed-effects specification. The results are reported in Tables 6 and 7.

First, the LM-Error, LM-Lag, Robust LM-Error, and Robust LM-Lag statistics are 1187.960, 17.860, 1153.657, and 12.704, respectively, and all corresponding p -values are below 0.01. These results indicate the presence of both spatial lag dependence and spatial error dependence. Therefore, neither a spatial autoregressive model that considers only the spatial lag of the dependent variable nor a spatial error model that accounts only for spatial correlation in the error term can fully capture the complex spatial relationship between the digital economy and green land use efficiency. Accordingly, the spatial Durbin model, which incorporates the spatial lags of both the dependent and explanatory variables, is preferred.

Second, the Wald-SAR and Wald-SEM statistics are 58.560 and 46.670, respectively, and both are significant at the 1% level. Similarly, the LR-SAR and LR-SEM statistics are 58.010 and 47.510, respectively, and are also significant at the 1% level. These results jointly reject the null hypotheses that the spatial Durbin model can be simplified to either a spatial autoregressive model or a spatial error model, supporting the use of the full spatial Durbin specification.

Third, the Hausman test statistic is 273.570 and is significant at the 1% level, leading to the rejection of the null hypothesis in favor of the fixed-effects model. This indicates that a fixed-effects specification is more appropriate for the panel data.

Finally, Akaike information criterion (AIC) and Bayesian information criterion (BIC) are further employed to compare alternative fixed-effects specifications. The two-way fixed-effects model yields an AIC of $-18,891.390$ and a BIC of $-18,745.120$, both of which are lower than those of the city fixed-effects and year fixed-effects models. This indicates that the two-way fixed-effects specification provides the best model fit.

Based on these diagnostic tests, the spatial Durbin specification is preferred over SAR and SEM specifications. Given the strong intertemporal persistence of *LGUE*, the model is further extended by incorporating the temporal lag and spatiotemporal lag of the dependent variable, resulting in the dynamic spatial Durbin model used in the baseline estimation.

Table 6. Results of LM, Wald, LR, and Hausman tests.

Test Type	Statistic	p Value
LM-Error	1187.960	0.000
LM-Lag	17.860	0.000
Robust LM-Error	1153.657	0.000
Robust LM-Lag	12.704	0.000
Wald test-SAR	58.560	0.000
Wald test-SEM	46.670	0.000
LR test-SAR	58.010	0.000
LR test-SEM	47.510	0.000
Hausman test	273.570	0.000

Table 7. Results of AIC and BIC tests.

Test Type	Statistic
AIC for city fixed effect	−18,354.530
AIC for time fixed effect	−16,137.480
AIC for two-way fixed effects	−18,891.390
BIC for city fixed effect	−18,194.040
BIC for time fixed effect	−16,014.840
BIC for two-way fixed effects	−18,745.120

4.4. Baseline Regression Results

4.4.1. Estimation Results of the Dynamic Spatial Durbin Model

Table 8 reports the estimation results of the dynamic spatial Durbin model based on three spatial weight matrices (W_{geo} , W_{eco} , and $W_{eco-geo}$). The spectral radii of the dynamic transition matrices are 0.931, 0.804, and 0.740 under the geographical distance matrix, economic distance matrix, and economic–geographical nested matrix, respectively. All values are below one, indicating that the dynamic spatial processes satisfy the stability condition and converge to stable equilibria. The relatively large spectral radius under W_{geo} also suggests that green land use efficiency exhibits stronger dynamic persistence when spatial linkages are defined primarily by geographical proximity.

The coefficients of the temporally lagged green land use efficiency term ($L.LGUE$) are 0.383, 0.392, and 0.418, while the coefficients of the spatiotemporally lagged term ($L.WLGUE$) are 0.345, 0.191, and 0.114. All coefficients are positive and statistically significant at the 1% level. These results indicate that the evolution of green land use efficiency exhibits both temporal path dependence and spatiotemporal dependence. Improvements in green land use efficiency therefore constitute a cumulative and dynamically persistent process rather than an outcome that can be achieved instantaneously.

The estimated spatial autoregressive coefficients ρ are 0.218, 0.275, and 0.281 under the three spatial weight matrices, respectively, and all are significantly positive at the 1% level. This result confirms the existence of significant positive spatial dependence in urban green land use efficiency. A city's green land use efficiency is influenced not only by its own socioeconomic and environmental conditions but also by the green land use performance of spatially connected cities.

The coefficients of the digital economy are 0.073, 0.119, and 0.136, respectively, and are all positive and statistically significant at the 1% level. This finding indicates that digital economy development is positively associated with local green land use efficiency. By contrast, the coefficients of the spatially lagged digital economy term (WDE) are −0.063, −0.083, and −0.082, respectively, and are all significantly negative at the 1% level. The negative coefficients provide preliminary evidence that digital economy development may generate a negative contemporaneous spatial transmission effect on spatially connected cities, potentially reflecting the cross-regional concentration of capital, technology, and high-skilled labor.

However, because the dynamic spatial Durbin model simultaneously incorporates spatial feedback, temporal accumulation, and spatiotemporal interaction effects, the point estimates of DE and WDE cannot be directly interpreted as the true direct and spatial spillover effects of the digital economy. Therefore, the partial-derivative decomposition approach is subsequently employed to calculate the short-term and long-term direct and indirect effects.

Table 8. Baseline estimation results of the dynamic spatial Durbin model.

Variables	(1) W_{geo}	(2) W_{eco}	(3) $W_{eco-geo}$
<i>L.LGUE</i>	0.383 *** (0.015)	0.392 *** (0.013)	0.418 *** (0.013)
<i>L.WLGUE</i>	0.345 *** (0.034)	0.191 *** (0.028)	0.114 *** (0.041)
<i>DE</i>	0.073 *** (0.020)	0.119 *** (0.031)	0.136 *** (0.035)
<i>URB</i>	0.017 *** (0.006)	0.071 *** (0.013)	0.092 *** (0.013)
<i>Fdi</i>	0.025 *** (0.009)	0.009 (0.009)	0.040 *** (0.009)
<i>Gov</i>	0.019 *** (0.003)	0.002 (0.003)	0.010 *** (0.003)
<i>Pop</i>	−0.144 ** (0.073)	−0.305 *** (0.074)	−0.430 *** (0.074)
<i>Human</i>	0.108 *** (0.033)	0.214 *** (0.033)	0.073 ** (0.033)
<i>Industry</i>	−0.292 *** (0.044)	−0.332 *** (0.044)	−0.430 *** (0.043)
<i>WDE</i>	−0.063 *** (0.009)	−0.083 *** (0.011)	−0.082 *** (0.011)
<i>Spatial ρ</i>	0.218 *** (0.021)	0.275 *** (0.026)	0.281 *** (0.024)
<i>WControl</i>	YES	YES	YES
City fixed effect	YES	YES	YES
Time fixed effect	YES	YES	YES
<i>N</i>	3640	3640	3640
overall R^2	0.337	0.361	0.396
Spectral radius of <i>A</i>	0.931	0.804	0.740

Note: Standard errors are in parentheses; ** $p < 0.05$, and *** $p < 0.01$.

4.4.2. Short-Term and Long-Term Spatial Externalities Decomposition

Given the complex spatial interaction and feedback mechanisms embedded in the spatial Durbin model, relying solely on point estimates cannot accurately capture the true marginal effects of the explanatory variables. Following the approach commonly adopted in the literature, this study applies the partial-derivative decomposition method to decompose the effects of the digital economy into short-term and long-term direct and indirect effects, as reported in Table 9.

From the perspective of short-term effects, the direct effect of *DE* is significantly positive under all three spatial weight matrices, indicating that digital economy development can improve local green land use efficiency (*LGUE*) within a relatively short period. By contrast, the short-term indirect effect of *DE* is significantly negative under all three spatial weight matrices, suggesting that the digital economy generates a pronounced spatial siphoning effect on other spatially connected cities during the early stages of development. A possible explanation is that digital infrastructure, innovation capital, highly skilled labor, and high-value-added industries tend to agglomerate first in central cities with stronger economic foundations and higher levels of digitalization. Consequently, surrounding cities may experience an outflow of high-quality production factors, weakened innovation capacity, and constraints on industrial upgrading, thereby adversely affecting their *LGUE*. From the perspective of long-term effects, the long-term direct effect of *DE* is significantly positive under all three spatial weight matrices, indicating that as digital technologies become increasingly embedded in urban production systems, their positive impact on local *LGUE* is gradually released and accumulated. The significantly positive short- and long-term direct effects support Hypothesis 1a.

The long-term indirect effects are 0.065, 0.043, and 0.046, respectively. The estimates are positive and statistically significant at the 1% level under W_{geo} and $W_{eco-geo}$, and at the 5% level under W_{eco} . The shift from significantly negative short-term indirect effects to significantly positive long-term indirect effects demonstrates that the spatial influence of the digital economy on spatially connected cities gradually shifts from the short-term spatial siphoning effect to the long-term green spillover effect.

This intertemporal transition reveals the pronounced dynamic nature of the spatial externalities of the digital economy. In the short term, cities with stronger economic foundations and higher levels of digitalization may attract capital, talent, and technology from spatially connected cities, thereby generating a spatial siphoning effect. Over time, however, digital networks continue to improve, the cost of knowledge transmission declines, and green technology diffusion, industrial cooperation, and regional specialization gradually deepen. spatially connected cities may gradually transform externally diffused digital resources into local green productive capacity through technological imitation, the absorption of relocated industries, and talent exchange, thereby promoting a shift in spatial externalities from siphoning to the green spillover effect.

The directions of the estimated effects are broadly consistent across the three spatial weight matrices, indicating that the dynamic transition from the short-term spatial siphoning effect to the long-term green spillover effect is robust across alternative definitions of spatial connectivity. The transition from a negative short-term indirect effect to a positive long-term indirect effect supports Hypothesis 1b.

Table 9. Decomposition of the short-term and long-term effects of *DE*.

Effect	W_{geo}	W_{eco}	$W_{eco-geo}$
Short-term direct effect	0.059 *** (0.017)	0.101 *** (0.016)	0.131 *** (0.017)
Short-term indirect effect	−0.046 *** (0.012)	−0.052 *** (0.010)	−0.056 *** (0.013)
Long-term direct effect	0.120 *** (0.021)	0.211 *** (0.023)	0.243 *** (0.024)
Long-term indirect effect	0.065 *** (0.017)	0.043 ** (0.017)	0.046 *** (0.016)

Note: Standard errors are in parentheses; ** $p < 0.05$, and *** $p < 0.01$.

4.5. Robustness Checks

To ensure the reliability of the empirical results obtained from the dynamic spatial Durbin model, this study conducts a series of robustness checks, including endogeneity-related tests as follows.

1. Lagged explanatory variables. Considering the potential reverse causality between the digital economy (*DE*) and green land use efficiency (*LGUE*), all core explanatory variables and control variables are lagged by one period and reintroduced into the baseline model. This lag structure not only helps mitigate contemporaneous bidirectional causality but also accounts for the potential time-lagged effects of the digital economy on *LGUE*. As shown in Column (1) of Table 10, the coefficient of the lagged *DE* remains positive and statistically significant at the 10% level, which broadly supports the robustness of the baseline results.
2. Auxiliary IV-GS2SLS estimation. The IV-GS2SLS specification is employed only as a separate auxiliary test of the potential endogeneity of the digital economy and is not used as an alternative estimator of the full dynamic spatial Durbin model. Accordingly, the IV-GS2SLS column reports the digital economy, its spatial lag, and the spatial autoregressive parameter, together with the corresponding identification and weak-instrument diagnostics. Short-term and long-term effect decompositions are not reported for this auxiliary specification. The instrumental variable is constructed as the interaction between the postal and telecommunications business volume per 10,000 people in each city in 1984 and the lagged national growth rate of internet broadband access users. The relevance of the instrument arises from the persistent influence of historical communication infrastructure on subsequent digital development. The postal and telecommunications business volume in 1984 reflects a city's initial communication foundation and its capacity to adopt emerging information technologies. When national internet use expands, cities with stronger historical communication foundations are generally better able to absorb the common technological

shock and develop digital industries. The interaction term therefore captures the heterogeneous responses of cities to the same national internet expansion and is expected to be closely correlated with current digital economy development. The under-identification and weak-instrument tests are further employed to assess this relevance empirically. The plausibility of the exclusion restriction rests on the predetermined nature of the historical communication variable and the fixed-effects structure of the panel model. The postal and telecommunications business volume in 1984 predates the sample period by several decades and therefore cannot be affected by current green land use efficiency. City fixed effects absorb the time-invariant influence of historical communication conditions, while year fixed effects absorb national internet expansion and other common macroeconomic shocks. Although the national growth rate itself is absorbed by year fixed effects, its interaction with the city-specific historical communication variable varies across cities and years and therefore provides the identifying variation. As reported in Column (2) of Table 10, the under-identification test rejects the null hypothesis of under-identification, while the weak-instrument statistic exceeds the corresponding critical value, supporting the relevance of the instrument. After accounting for potential endogeneity, the IV-GS2SLS estimates remain broadly consistent with the baseline results, providing auxiliary evidence that the main findings are not driven by the potential endogeneity of the digital economy.

3. Winsorization. Considering possible fluctuations in macro-statistical data due to changes in statistical calibration in certain years, all variables are winsorized at the 1% and 99% levels to mitigate the influence of extreme observations. As shown in Column (3) of Table 10, the signs and statistical significance of the key coefficients remain consistent with the baseline results, indicating that extreme outliers do not drive the main conclusions.
4. Alternative measurement of the dependent variable. In the baseline model, green land use efficiency (*LGUE*) is measured using a super-efficiency SBM model with undesirable outputs. To address potential measurement bias in efficiency estimation, this study re-estimates green land use efficiency using the EBM (Epsilon-Based Measure) model, which integrates both radial and non-radial distance functions and better captures the joint presence of proportional and slack-based inefficiencies in land use systems. After replacing the dependent variable with the EBM-based measure, the dynamic spatial Durbin model and the corresponding effect decomposition are re-estimated. As reported in Column (4) of Table 10, the short-term direct effect remains significantly positive, whereas the short-term indirect effect remains significantly negative. In the long term, both the direct and indirect effects remain significantly positive. These results confirm that the transition from the short-term spatial siphoning effect to the long-term green spillover effect is robust to the alternative measurement of green land use efficiency.
5. Alternative measurement of the independent variable. In the baseline model, *DE* is constructed using the objective entropy-weight method. Although this method reduces the influence of subjective weighting, the empirical results may still be sensitive to the specific weighting scheme used to construct the composite index. To address this potential measurement bias, this study reconstructs *DE* using principal component analysis based on the same underlying indicators reported in Table 3. Specifically, all indicators are first standardized, after which the principal components are extracted and weighted according to their respective variance contribution rates. The weighted principal component scores are then aggregated and normalized to obtain the PCA-based *DE* index. After replacing the baseline *DE* index with the PCA-based *DE* index, the dynamic spatial Durbin model is re-estimated. As reported

in Column (5) of Table 10, the directions and statistical significance of the estimated effects remain broadly consistent with the baseline results. The transition from the short-term spatial siphoning effect to the long-term green spillover effect also remains unchanged, indicating that the main conclusions are not driven by the specific weighting method used to construct *DE*.

6. Sample adjustment. Considering that municipalities directly under the central government typically enjoy stronger policy support and exhibit atypically high levels of digital infrastructure and land-use efficiency, which may bias the estimation results, this study excludes these cities for robustness checks. As shown in Column (6) of Table 10, after removing these potentially extreme high-value observations, the coefficient of *DE* remains significantly positive, further confirming the generalizability of the baseline findings.
7. Alternative spatial weight matrix. To further examine whether the empirical results are sensitive to the specification of spatial linkages, this study replaces the baseline spatial weight matrices with a binary geographical contiguity matrix. Specifically, the element of the matrix is assigned a value of 1 when city *i* and city *j* share a common administrative boundary and 0 otherwise. The diagonal elements are set to 0, and the matrix is row-standardized before estimation. Compared with the baseline matrices, which assign continuous weights according to geographical distance or economic proximity, the binary contiguity matrix defines intercity spatial dependence solely on the basis of geographical adjacency. As reported in Column (7) of Table 10, the short-term direct effect remains positive, whereas the short-term indirect effect remains negative. In the long term, both the direct and indirect effects remain positive. The transition from the short-term spatial siphoning effect to the long-term green spillover effect therefore remains unchanged. In addition, the spectral radius of the dynamic transition matrix is below one, indicating that the model satisfies the dynamic stability condition under the alternative spatial specification. These results confirm that the main conclusions are not driven by a particular spatial weight matrix.

Table 10. Results of robustness tests.

Variables	(1) Lagged Variables	(2) GS2SLS	(3) Winsorization	(4) EBM-Based <i>LGUE</i>	(5) PCA-Based <i>DE</i>	(6) Sample Adjustment	(7) W_{0-1}
<i>L.LGUE</i>	0.321 *** (0.014)	—	0.246 *** (0.013)	0.238 *** (0.008)	0.267 *** (0.013)	0.254 *** (0.015)	0.301 *** (0.016)
<i>L.WLGUE</i>	0.312 *** (0.030)	—	0.308 *** (0.029)	0.323 *** (0.015)	0.310 *** (0.026)	0.304 *** (0.031)	0.277 *** (0.028)
<i>DE</i>	0.054 * (0.028)	0.026 ** (0.012)	0.070 *** (0.020)	0.059 *** (0.008)	0.065 *** (0.014)	0.044 * (0.024)	0.058 *** (0.011)
<i>WDE</i>	−0.037 ** (0.015)	−0.023 ** (0.011)	−0.042 *** (0.011)	−0.037 ** (0.016)	−0.043 *** (0.011)	−0.028 ** (0.012)	−0.039 *** (0.010)
<i>DE</i> Short-term Direct Effect	0.048 * (0.027)	—	0.069 *** (0.021)	0.051 *** (0.008)	0.064 *** (0.014)	0.041 * (0.023)	0.056 *** (0.011)
<i>DE</i> Short-term Indirect Effect	−0.027 * (0.015)	—	−0.035 ** (0.016)	−0.024 *** (0.007)	−0.036 *** (0.012)	−0.021 * (0.012)	−0.032 *** (0.012)
<i>DE</i> Long-term Direct Effect	0.088 *** (0.025)	—	0.100 *** (0.023)	0.080 *** (0.017)	0.091 *** (0.028)	0.060 ** (0.029)	0.084 *** (0.031)
<i>DE</i> Long-term Indirect Effect	0.004 ** (0.002)	—	0.003 *** (0.001)	0.011 ** (0.005)	0.009 *** (0.002)	0.002 ** (0.001)	0.007 *** (0.001)
<i>Spatial ρ</i>	0.183 *** (0.022)	0.256 *** (0.022)	0.175 *** (0.019)	0.198 *** (0.029)	0.202 *** (0.020)	0.182 *** (0.020)	0.214 *** (0.022)

Kleibergen-Paap rk LM		113.341 ***					
Kleibergen-Paap Wald F		234.132					
Stock-Yogo		16.38					
WControl	YES	YES	YES	YES	YES	YES	YES
Control variables	YES	YES	YES	YES	YES	YES	YES
City fixed effect	YES	YES	YES	YES	YES	YES	YES
Time fixed effect	YES	YES	YES	YES	YES	YES	YES
Spatial weight matrix	W_{geo}	W_{geo}	W_{geo}	W_{geo}	W_{geo}	W_{geo}	W_{0-1}
N	3360	3640	3640	3640	3640	3588	3640
Overall R ²	0.345	0.331	0.461	0.385	0.418	0.376	0.352
Spectral radius of A	0.775	—	0.672	0.700	0.723	0.682	0.735

Note: Standard errors are in parentheses; * $p < 0.1$, ** $p < 0.05$, and *** $p < 0.01$.

4.6. Distance-Decay Characteristics and Effective Geographical Boundaries

4.6.1. Distance-Decay Characteristics

The preceding analysis demonstrates that the digital economy exerts a significant short-term spatial siphoning effect and a long-term green spillover effect on green land use efficiency. To further examine how these spatial externalities decay with geographical distance, this study constructs distance-band spatial weight matrices at 50 km intervals and separately estimates the short-term and long-term indirect effects of the digital economy across different distance bands. The results are presented in Figure 6.

From a short-term perspective, the indirect effect of the digital economy on spatially connected cities is significantly negative within relatively short distances, indicating a pronounced spatial siphoning effect. As the geographical distance between cities increases, the absolute magnitude of the short-term negative indirect effect generally declines, suggesting that the short-term spatial siphoning effect of the digital economy exhibits a clear distance-decay pattern. When the distance exceeds approximately 200 km, the 95% confidence interval includes zero, indicating that the short-term negative indirect effect is no longer statistically significant.

From a long-term perspective, the indirect effect of the digital economy becomes significantly positive and gradually weakens as geographical distance increases. When the distance exceeds approximately 250 km, the 95% confidence interval of the long-term indirect effect begins to cross the zero line, indicating that the positive effect is no longer statistically significant.

Overall, the spatial externalities of the digital economy are highly distance-sensitive and operate within a distance-decay pattern. The short-term spatial siphoning effect remains statistically significant within a distance of approximately 200 km, after which its magnitude declines and becomes statistically insignificant. In contrast, the long-term green spillover effect persists up to approximately 250 km before gradually converging toward zero and losing statistical significance. The broader geographical range of the long-term effect indicates that the spatial transmission mechanism of the digital economy gradually shifts over time from factor competition among spatially connected cities toward wider-ranging knowledge diffusion, industrial collaboration, and the dissemination of green technologies. These results confirm a clear distance-decay pattern in the spatial externalities of the digital economy and support Hypothesis 2.

The 200 km and 250 km values denote the upper endpoints of the first distance bands in which the short-term and long-term indirect effects are no longer statistically detectable, respectively. They should therefore be interpreted as approximate and sample-dependent ranges of statistical detectability. The relatively limited range of the short-term spatial siphoning effect reflects the localized nature of factor competition. Central cities

are more likely to attract mobile complementary factors from nearby cities because relocation frictions increase with geographical distance. By contrast, the long-term green spillover effect is transmitted mainly through digital networks and knowledge diffusion. The replicability of data allows digital knowledge to reach cities located beyond the immediate neighboring area. Nevertheless, tacit knowledge absorption and regional coordination remain sensitive to geographical distance, preventing the long-term green spillover effect from extending indefinitely. The difference between the two estimated ranges is therefore consistent with a transition from geographically localized factor competition to broader but still finite knowledge diffusion.

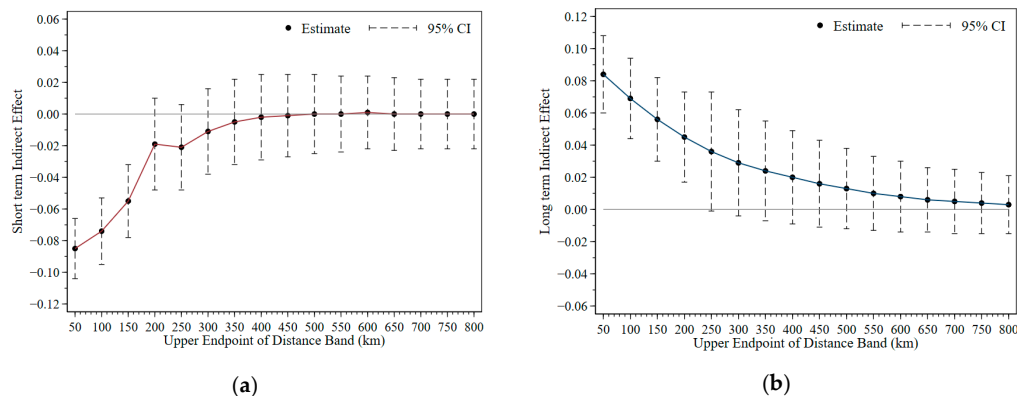


Figure 6. Distance-decay patterns of the indirect effects of *DE*: (a) short-term indirect effect; (b) long-term indirect effect. Notes: Horizontal gray line represents the zero reference line. Horizontal-axis values denote the upper endpoints of mutually exclusive 50 km distance bands. Thus, 50 km represents the 0–50 km band, 100 km represents the 50–100 km band, and subsequent bands are defined analogously.

4.6.2. Spatial Visualization of Statistically Detectable Geographical Ranges

To provide a more intuitive representation of the spatial coverage of the short-term spatial siphoning effect and the long-term green spillover effect of the digital economy, this study identifies cities in the top 10% of the *DE* distribution in 2024. Based on the short-term and long-term effective geographical boundaries identified above, their spatial radiation ranges are visualized in Figure 7.

In the short term, the negative spatial externalities of core cities are mainly concentrated in their neighboring areas, and their spatial coverage is relatively limited. This pattern indicates that factor attraction and siphoning during the initial stage of digital economy development are strongly characterized by geographical proximity. By contrast, the spatial coverage of the long-term green spillover effect expands substantially, extending beyond the boundary of the short-term spatial siphoning effect and reaching a broader range of surrounding areas.

This asymmetry between the short-term and long-term spatial ranges suggests that, during the early stage of development, central cities primarily generate competitive effects on spatially connected cities through factor agglomeration. As digital technologies diffuse, regional industrial linkages deepen, and green knowledge spreads, the long-term spatial externalities gradually shift from localized siphoning toward broader green spillovers.

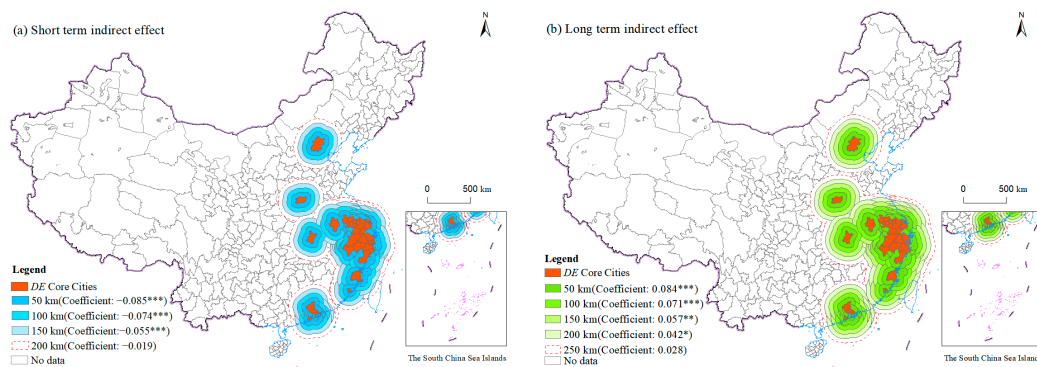


Figure 7. Spatial radiation ranges of *DE* core cities in 2024. Note: * $p < 0.1$, ** $p < 0.05$, and *** $p < 0.01$.

4.7. Moderating Mechanism Analysis Based on Interaction Effects

To further examine the conditional mechanisms that shape the dynamic transition of the digital economy's spatial externalities from the short-term spatial siphoning effect to the long-term green spillover effect, this study investigates three moderating mechanism variables: green technological innovation (*GTI*), industrial upgrading (*ISU*), and factor misallocation (*FM*). Interaction terms between the digital economy and each moderating variable are sequentially incorporated into the baseline dynamic spatial Durbin model, and the short-term and long-term direct and indirect effects of these interaction terms are subsequently decomposed. The results are reported in Table 11.

Table 11. Decomposition of the Direct and Indirect Effects in the Moderation Models.

Variables	Short-Term Direct	Short-Term Indirect	Long-Term Direct	Long-Term Indirect
Panel A. Moderating role of green technological innovation (<i>GTI</i>)				
<i>DE</i>	0.046 *** (0.010)	−0.012 ** (0.006)	0.033 ** (0.014)	0.013 *** (0.004)
<i>GTI</i>	0.031 *** (0.011)	0.020 * (0.011)	0.037 * (0.021)	0.032 ** (0.014)
<i>DE × GTI</i>	0.025 * (0.014)	0.051 ** (0.023)	0.041 ** (0.017)	0.062 ** (0.027)
Panel B. Moderating role of industrial upgrading (<i>ISU</i>)				
<i>DE</i>	0.051 *** (0.011)	−0.014 *** (0.004)	0.057 *** (0.021)	0.014 ** (0.006)
<i>ISU</i>	0.049 *** (0.018)	0.017 ** (0.007)	0.074 *** (0.017)	0.053 *** (0.009)
<i>DE × ISU</i>	0.028 * (0.015)	0.041 ** (0.020)	0.069 *** (0.019)	0.067 *** (0.007)
Panel C. Moderating role of factor misallocation (<i>FM</i>)				
<i>DE</i>	0.052 *** (0.008)	−0.016 ** (0.008)	0.062 *** (0.015)	0.011 * (0.006)
<i>FM</i>	−0.027 ** (0.012)	−0.007 ** (0.003)	−0.030 *** (0.010)	−0.039 *** (0.013)
<i>DE × FM</i>	−0.016 ** (0.007)	−0.043 *** (0.014)	−0.057 *** (0.015)	−0.062 *** (0.012)
Control variables	YES	YES	YES	YES
City fixed effect	YES	YES	YES	YES
Time fixed effect	YES	YES	YES	YES
<i>N</i>	3640	3640	3640	3640
Spatial weight matrix	$W_{eco-geo}$	$W_{eco-geo}$	$W_{eco-geo}$	$W_{eco-geo}$

Note: Standard errors are in parentheses; * $p < 0.1$, ** $p < 0.05$, and *** $p < 0.01$.

4.7.1. Empirical Evidence on the Moderating Role of Green Technological Innovation

Green technological innovation represents an important moderating condition that shapes how the digital economy facilitates the application and diffusion of green knowledge. Digital platforms can reduce the costs of cross-regional innovation collaboration and promote the diffusion of green production processes across cities. Meanwhile, stronger green innovation capacity can enhance a city's ability to absorb external digital knowledge, thereby altering the magnitude of the spatial externalities generated by the digital economy.

As shown in Table 11, the short-term indirect effect of the interaction term between the digital economy and green technological innovation ($DE \times GTI$) is positive, indicating that green technological innovation can mitigate the spatial siphoning effect exerted by the digital economy on spatially connected cities during the initial stage of development. This is because stronger green technological innovation capacity improves spatially connected cities' ability to retain innovation factors and absorb digital technologies, thereby reducing the adverse effects caused by the one-way concentration of capital, talent, and technology in core cities.

In addition, the long-term indirect effect of $DE \times GTI$ is significantly positive. This finding suggests that, as digital networks continue to improve, green technological innovation promotes knowledge diffusion, technological imitation, and cross-regional collaborative research and development. It thereby enables spatially connected cities to transform the digital and green knowledge released by core cities into local green productive capacity, strengthening the long-term green spillover effect of the digital economy. Therefore, green technological innovation not only weakens short-term spatial siphoning but also reinforces the long-term green spillover effect, supporting Hypothesis 3.

4.7.2. Empirical Evidence on the Moderating Role of Industrial Upgrading

Industrial upgrading represents an important moderating condition that determines how effectively digital technologies are translated into green land use outcomes. The widespread application of digital technologies can promote the green transformation of traditional industries and facilitate the reallocation of capital and labor from resource-intensive, land-intensive, and low-value-added sectors toward technology-intensive and high-value-added industries. This process reduces the dependence of economic growth on land expansion and intensive resource inputs.

As shown in Table 11, the short-term indirect effect of $DE \times ISU$ is positive, indicating that a higher level of industrial upgrading weakens the negative short-term indirect effect of the digital economy and alleviates the spatial siphoning effect on spatially connected cities. Cities with more advanced industrial structures generally possess more complete industrial systems and stronger factor-carrying capacity. These characteristics reduce the risk of sustained outflows of high-quality production factors and decrease dependence on energy-intensive and highly polluting industries.

From a long-term perspective, the indirect effect of $DE \times ISU$ is significantly positive, suggesting that industrial upgrading strengthens the long-term green spillover effect of the digital economy. As regional specialization deepens, core cities can increasingly undertake research and development functions, while spatially connected cities can draw on their own industrial foundations to absorb suitable green manufacturing and supporting industries. This process promotes cross-regional industrial coordination and facilitates the diffusion of digital dividends across a broader geographical range. Therefore, industrial upgrading mitigates the short-term spatial siphoning effect and reinforces the long-term green spillover effect, supporting Hypothesis 4.

4.7.3. Empirical Evidence on the Moderating Role of Factor Misallocation

Factor misallocation reflects the extent to which production factors, such as capital and labor, deviate from their optimal allocation. It represents a negative moderating condition that constrains the spatial diffusion of digital technologies and the conversion of their associated green benefits.

As shown in Table 11, the short-term indirect effect of $DE \times FM$ is negative, indicating that factor misallocation further intensifies the short-term spatial siphoning effect of the digital economy. On the one hand, severe capital and labor misallocation weakens spatially connected cities' ability to attract highly skilled workers, innovation capital, and digital firms, making high-quality factors more likely to flow toward core cities with more favorable market conditions. On the other hand, when production factors remain locked into inefficient and highly polluting industries, spatially connected cities become less capable of responding to external competition.

The long-term indirect effect of $DE \times FM$ is also negative, indicating that factor misallocation suppresses the realization of the long-term green spillover effect of the digital economy. Even when digital technologies and green knowledge can diffuse across regions, distorted factor allocation may prevent external knowledge from being effectively matched with local capital, labor, and industrial foundations, thereby reducing the efficiency with which such knowledge is transformed into green productive capacity. Therefore, factor misallocation not only intensifies the short-term spatial siphoning effect but also weakens the long-term green spillover effect, supporting Hypothesis 5.

4.7.4. Summary of the Moderating Mechanism Analysis

Taken together, the three moderating mechanism analyses indicate that the dynamic transition in the spatial externalities of the digital economy does not occur automatically but is jointly shaped by urban innovation capacity, industrial foundations, and factor allocation efficiency. Green technological innovation and industrial upgrading act as positive moderators by improving spatially connected cities' capacity to absorb digital knowledge, green technologies, and relocated industries. They therefore mitigate spatial siphoning during the initial stage of digital economy development and strengthen the long-term green spillover effect.

By contrast, factor misallocation acts as a negative moderator and constitutes a major barrier to the cross-regional transmission of digital dividends. It not only intensifies the adverse effects of short-term factor agglomeration on spatially connected cities but also hinders the transformation of digital knowledge and green technologies into actual productive efficiency over the long term. These findings further clarify the conditions under which the spatial externalities of the digital economy shift from the short-term spatial siphoning effect to the long-term green spillover effect.

4.8. Heterogeneity Analysis

The preceding results show that the digital economy significantly affects green land use efficiency. However, cities differ considerably in terms of digital infrastructure, resource endowments, and environmental conditions, which may lead to heterogeneous green effects of the digital economy. To further identify these differences across city characteristics, this study conducts subgroup estimations from four perspectives: geographical location, resource endowment, administrative hierarchy, and environmental regulation. The results are presented in Figure 8. The subgroup estimates are interpreted jointly with the formal cross-group equality tests reported in Appendix A Table A1.

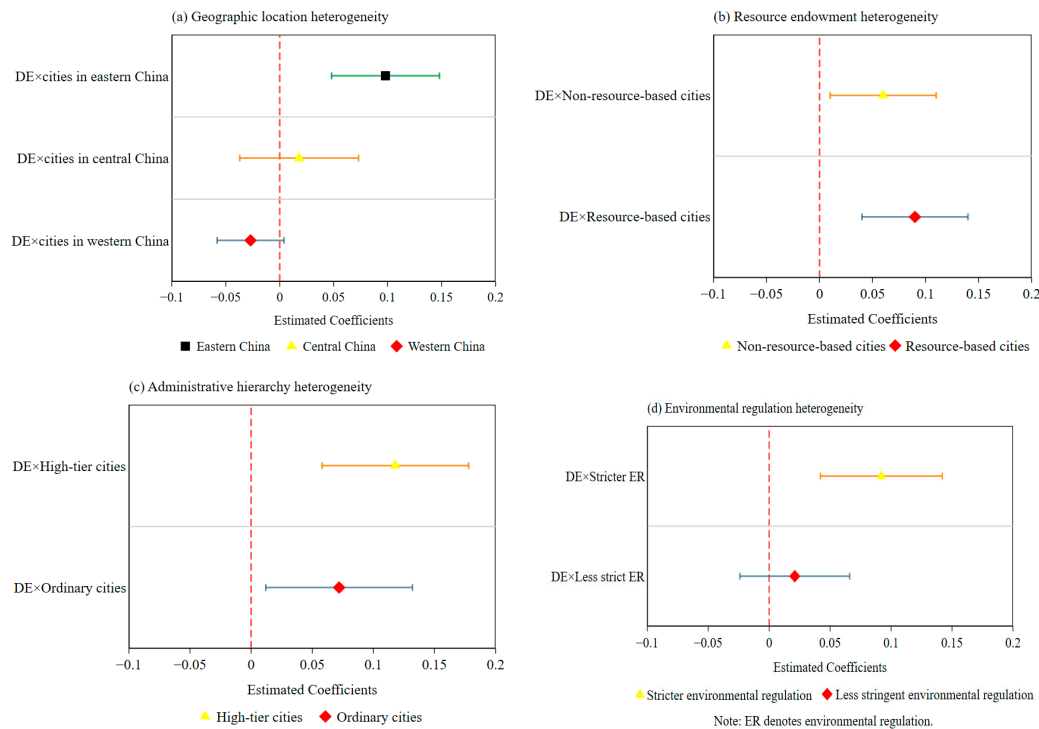


Figure 8. Heterogeneity effects of *DE* on *LGUE*. Note: The markers represent the estimated coefficients, the horizontal error bars represent the 95% confidence intervals, and the red dashed vertical lines indicate the zero-effect reference line.

4.8.1. Empirical Evidence on Heterogeneity by Geographical Location

Figure 8a presents the results of the geographic location heterogeneity analysis. The digital economy has a significantly positive effect on green land use efficiency in cities in eastern China. In contrast, the estimated effect is positive but statistically insignificant in cities in central China and negative but statistically insignificant in cities in western China. These results indicate that the green effects of the digital economy vary across cities in different regions.

Cities in eastern China generally have more developed digital infrastructure, a higher concentration of innovation resources, and stronger technological absorptive capacity, which enable them to translate digital development more effectively into improvements in green land use efficiency. By contrast, cities in central China may still face constraints related to digital infrastructure and innovation capacity, limiting the realization of the green benefits of the digital economy. Cities in western China may additionally experience the outflow of capital, skilled labor, and other high-quality production factors toward more developed regions or regional central cities.

4.8.2. Empirical Evidence on Heterogeneity by Resource Endowment

Figure 8b reports the results of the resource-endowment heterogeneity analysis. The estimated coefficients of the digital economy are significantly positive in both resource-based and non-resource-based cities, with a slightly larger magnitude in resource-based cities. This result suggests that the digital economy generally improves green land use efficiency and exhibits a stronger marginal effect in resource-based cities. Non-resource-based cities typically have more diversified industrial structures and relatively mature market mechanisms. The digital economy can improve land use efficiency by optimizing resource allocation. Resource-based cities, by contrast, often depend heavily on resource

extraction and traditional heavy industries, resulting in relatively undiversified industrial structures, high energy consumption, and substantial environmental pressure. The application of digital technologies can improve the precision of energy use, facilitate the green transformation of traditional resource-based industries, and provide technological support for the cultivation of new industries and the replacement of old growth drivers with new ones.

4.8.3. Empirical Evidence on Heterogeneity by Administrative Hierarchy

Figure 8c presents the results of the administrative-hierarchy heterogeneity analysis. The digital economy has a significantly positive effect on green land use efficiency in both high-tier and ordinary cities, but the estimated coefficient is markedly larger for high-tier cities, indicating a stronger green enabling effect. High-tier cities possess clear advantages in administrative resources, digital infrastructure, highly skilled human capital, and application scenarios, allowing them to exploit the multiplier effect of data resources more efficiently. By comparison, ordinary cities face greater constraints in fiscal capacity, talent reserves, and industrial carrying capacity, resulting in a relatively lower efficiency in converting digital economy development into green benefits.

4.8.4. Empirical Evidence on Heterogeneity by Environmental Regulation

Figure 8d reports heterogeneity in the effect of the digital economy across cities with different levels of environmental regulation. Environmental regulation is measured by the share of local fiscal expenditure on energy conservation and environmental protection in total general public budget expenditure. Cities are classified as having stricter environmental regulation or less stringent environmental regulation according to whether their average environmental regulation intensity during the sample period is above or below the sample median. The results show that the digital economy significantly improves green land use efficiency in cities with stricter environmental regulation, whereas the positive effect in cities with less stringent environmental regulation is not statistically significant.

Stricter environmental regulation strengthens the incentives for local governments and firms to integrate digital technologies into environmental governance. Digital technologies can therefore be used more extensively in environmental monitoring, energy management, and cleaner production, thereby reducing resource consumption and pollutant emissions during land use. By contrast, in cities with less stringent environmental regulation, digital technologies may be used primarily to improve production efficiency and expand economic activity, while their contribution to resource conservation and pollution reduction remains limited. These findings indicate that environmental regulation provides an important institutional condition for translating digital economy development into improvements in green land use efficiency.

Overall, the effect of the digital economy on green land use efficiency varies significantly across geographical locations, resource endowments, administrative hierarchies, and environmental regulation. These findings support Hypothesis 6.

5. Discussion

5.1. Main Findings and Their Interpretation

This study finds that the spatial externalities of the digital economy on green land use efficiency exhibit a significant dynamic transformation. In the short term, the digital economy mainly generates a spatial siphoning effect on spatially connected cities, whereas in the long term, it shifts toward a positive green spillover effect. This finding supports the hypothesis that the spatial externalities of the digital economy vary over time and

suggests that these effects cannot be simply characterized as uniformly positive or uniformly negative.

During the early stage of digital economy development, digital infrastructure, innovation capital, highly skilled labor, and high-value-added industries tend to concentrate first in core cities with stronger development foundations. This concentration improves resource allocation efficiency in core cities but may weaken the innovation capacity and industrial transformation of spatially connected cities through the outflow of high-quality production factors, thereby generating the short-term spatial siphoning effect. As digital infrastructure gradually improves, the costs of information transmission, technology transactions, and regional cooperation decline. Green knowledge, digital technologies, and managerial experience consequently begin to diffuse to spatially connected cities, while regional industrial linkages gradually shift from factor competition toward specialized division of labor and coordinated development, ultimately generating the long-term green spillover effect.

This finding helps explain the inconsistent conclusions in previous studies regarding the spatial externalities of the digital economy. Some studies emphasize the network externalities and knowledge-diffusion effects of digital technologies and argue that the digital economy promotes coordinated regional green development. Other studies, drawing on the digital divide and core-periphery structure, suggest that digital development may induce factor siphoning. The findings of this study indicate that these two conclusions are not necessarily contradictory but may correspond to different stages in the evolution of the spatial externalities of the digital economy.

5.2. Distance-Decay Boundaries and Their Implications

The results show that the spatial externalities of the digital economy do not diffuse indefinitely but exhibit a clear distance-decay pattern. The effective geographical range of the short-term spatial siphoning effect is approximately 200 km, whereas the long-term green spillover effect extends to approximately 250 km. The broader range of the long-term effect indicates that the spatial transmission mechanism of the digital economy gradually shifts over time from direct factor competition under geographical proximity toward more extensive knowledge diffusion, technology dissemination, and industrial collaboration.

Although digital information can transcend conventional geographical constraints, green technologies often involve substantial tacit knowledge, whose absorption still depends on talent exchange, interfirm cooperation, and local industrial foundations. Industrial relocation and regional governance are also constrained by transportation costs, administrative boundaries, and institutional differences. The spatial externalities of the digital economy therefore continue to follow a distance-decay pattern. This finding advances the existing literature from examining whether spatial spillover effects exist to identifying how far such spillover effects can extend, thereby providing empirical evidence for determining an appropriate spatial scale for cross-regional digital governance and green land governance.

5.3. Moderating Mechanisms and Urban Heterogeneity

The moderating mechanism analysis further shows that the transformation of the spatial externalities of the digital economy from the short-term spatial siphoning effect to the long-term green spillover effect does not occur automatically. Instead, it is conditioned by cities' green innovation capacity, industrial structure, and factor allocation efficiency. Green technological innovation enhances cities' capacity to absorb and transform external digital knowledge, while industrial upgrading promotes regional industrial specialization and the diffusion of green production activities. Both positive moderators mitigate the

short-term spatial siphoning effect and strengthen the long-term green spillover effect. By contrast, factor misallocation acts as a negative moderator by weakening spatially connected cities' capacity to retain high-quality production factors and absorb digital technologies, thereby intensifying the short-term spatial siphoning effect and obstructing the transformation of long-term digital dividends into green productive capacity.

The heterogeneity analysis similarly indicates that the green effects of the digital economy are conditioned by urban development characteristics. Cities in eastern China, high-tier cities, and cities with stricter environmental regulation generally possess more developed digital infrastructure, richer innovation resources, and more favorable institutional environments, making it easier for them to transform digital technologies into improvements in green land use efficiency. Cities in central and western China and ordinary cities, by contrast, may be constrained by weaker digital foundations, talent outflows, and limited absorptive capacity. The relatively stronger positive effect observed in resource-based cities suggests that digital technologies provide greater marginal improvement potential for the intelligent and green transformation of traditional resource-based industries.

These findings demonstrate that the digital economy does not automatically generate equal green benefits across all cities. Its effects depend not only on digital investment itself but also on complementary conditions, including local innovation capacity, industrial structure, factor markets, and environmental regulation.

5.4. Theoretical and Policy Implications

The theoretical contribution of this study lies in providing a unified explanation, from a dynamic spatial perspective, for the coexistence of the short-term spatial siphoning effect and the long-term green spillover effect. It further identifies the distance-decay boundaries and realization conditions of the spatial externalities of the digital economy. In doing so, the study extends the analysis of spatial externalities from static directional judgments to temporal evolution, geographical boundaries, and moderating mechanisms, thereby providing a more comprehensive framework for understanding how digitalization reshapes regional patterns of green land use.

From a policy perspective, the coordination of the digital economy and green land governance should not be confined to individual municipal administrative boundaries. Metropolitan areas and urban agglomerations should instead serve as important units of coordination, with digital infrastructure, green technology cooperation, and regional industrial specialization jointly organized within the effective geographical range of approximately 200–250 km. At the same time, excessive concentration of high-quality production factors in core cities during the early stage of digitalization should be prevented. Regional innovation platforms, talent cooperation mechanisms, and technology-sharing arrangements should be established to strengthen the absorptive capacity of spatially connected cities.

For cities in central and western China, ordinary cities, and resource-based cities, policy priorities should include improving digital infrastructure, human capital, industrial absorption capacity, and factor allocation efficiency. Greater coordination should also be promoted among digital economy policies, low-carbon city development, environmental regulation, and green innovation policies.

5.5. Limitations and Future Research

This study also has several limitations.

- First, although the dynamic spatial Durbin model captures the temporal evolution and spatial spillovers of the digital economy, the analysis is conducted at the city level and cannot fully reveal micro-level behavioral mechanisms among firms,

households, and local governments. Future research could use firm-level or land-parcel-level data to examine how digital technologies reshape land use decisions more directly.

- Second, the empirical analysis relies primarily on secondary data obtained from statistical yearbooks, government statistical bulletins, and commercial databases. Although data from different sources were cross-checked, differences in statistical definitions and data quality across cities and years may still introduce measurement errors. Future research could combine official statistics with remote-sensing data, firm-level digitalization data, and land-parcel information to improve the accuracy and granularity of variable measurement.
- Third, future research could extend the analytical framework beyond China by constructing comparable city-level panel datasets for countries and regions with different levels of digital development, urban systems, and land-governance arrangements. After harmonizing the measurement of the digital economy and green land use efficiency, the same dynamic spatial Durbin model and distance-band analysis could be applied to examine whether the transition from the short-term spatial siphoning effect to the long-term green spillover effect also occurs in other contexts. Cross-country and cross-regional comparisons would further help identify how institutional conditions, digital infrastructure, and regional connectivity shape the direction and effective geographical ranges of spatial externalities.
- Fourth, although this study examines the moderating roles of green technological innovation, industrial upgrading, and factor misallocation, future research could further incorporate data-factor markets, intercity policy coordination, and digital infrastructure networks to provide a more refined explanation of how digital economy development reshapes regional green land use patterns.

6. Conclusions

Using panel data for 280 prefecture-level and above cities in China from 2011 to 2024, this study develops a dynamic spatial Durbin model to examine the local effects, dynamic spatial externalities, distance-decay boundaries, moderating mechanisms, and urban heterogeneity of the digital economy's impact on green land use efficiency. The main conclusions are as follows.

- First, the digital economy significantly improves local green land use efficiency. The development of digital infrastructure and the application of data resources and digital technologies reduce information and transaction costs, improve the allocation of land, capital, labor, and other production factors, and promote the transition of urban land use from extensive expansion toward more intensive, low-carbon, and efficient patterns.
- Second, the spatial externalities of the digital economy exhibit a clear dynamic transformation. In the short term, core cities attract capital, technology, and highly skilled labor through their advantages in digital infrastructure and factor returns, thereby generating a significant spatial siphoning effect on spatially connected cities. In the long term, as digital networks improve, knowledge diffusion accelerates, and regional industrial linkages deepen, these spatial externalities gradually shift toward the positive green spillover effect. Therefore, the short-term spatial siphoning effect and the long-term green spillover effect are not contradictory, but represent different stages in the evolution of the digital economy's spatial externalities.
- Third, the spatial externalities of the digital economy exhibit significant distance-decay and finite geographical boundaries. The short-term spatial siphoning effect is concentrated mainly within approximately 200 km, whereas the long-term green spillover effect extends to approximately 250 km. The broader range of the long-term

effect indicates that the spatial transmission mechanism gradually shifts from geographically proximate factor competition toward wider knowledge diffusion, technology dissemination, and industrial collaboration.

- Fourth, the dynamic transformation of these spatial externalities depends on cities' absorptive and transformative capacities. Green technological innovation and industrial upgrading mitigate the short-term spatial siphoning effect and strengthen the long-term green spillover effect, whereas factor misallocation intensifies the short-term spatial siphoning effect and restricts the transformation of long-term digital dividends into green productive capacity. Digital infrastructure investment must therefore be combined with improvements in innovation capacity, industrial upgrading, and factor-market reform to fully realize its green benefits.
- Fifth, the effect of the digital economy on green land use efficiency exhibits substantial urban heterogeneity. Its positive effect is more pronounced in cities in eastern China, high-tier cities, and cities with stricter environmental regulation. In cities in central and western China and ordinary cities, weaker digital foundations, talent outflows, and limited technological absorptive capacity may constrain the realization of digital benefits. The relatively strong effect in resource-based cities indicates that digital technologies provide substantial potential for the intelligent and green transformation of traditional resource-based industries.

Based on these findings, digital economy policies should be coordinated at the scale of metropolitan areas and urban agglomerations, particularly within the effective range of approximately 200–250 km. Policy efforts should focus on preventing excessive factor concentration in core cities, strengthening digital infrastructure and absorptive capacity in less-developed cities, promoting the digital and green transformation of resource-based industries, and improving factor-market efficiency. These measures can help transform digital dividends from localized concentration into broader regional green benefits.

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

Appendix A

Table A1. Heterogeneity Estimates and Cross-Group Difference Tests.

Group	Estimated Coefficient	95% Confidence Interval	Cross-Group Comparison	Coefficient Difference	Cross-Group Equality-Test <i>p</i> -Value
Panel A. Geographic location heterogeneity.					
Eastern China	0.098	[0.051, 0.145]	Eastern China—Central China	0.080	0.030
Central China	0.018	[−0.037, 0.073]	Eastern China—Western China	0.125	<0.001
Western China	−0.027	[−0.058, 0.004]	Central China—Western China	0.045	0.162
Panel B. Resource endowment heterogeneity.					
Non-resource-based cities	0.052	[0.012, 0.092]	Resource-based cities—Non-resource-based cities	0.029	0.064
Resource-based cities	0.081	[0.041, 0.121]			
Panel C. Administrative hierarchy heterogeneity.					
High-tier cities	0.118	[0.058, 0.178]	High-tier cities—Ordinary cities	0.046	0.088
Ordinary cities	0.072	[0.012, 0.132]			
Panel D. Environmental regulation heterogeneity.					
Stricter ER	0.092	[0.042, 0.142]	Stricter—Less stringent environmental regulation	0.071	0.039
Less strict ER	0.021	[−0.024, 0.066]			

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