A STUDY OF THE IMPACT OF LAND USE CHANGE AND THE DIGITAL ECONOMY ON GREEN INNOVATION IN 30 CHINESE PROVINCES, 2013-2022

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Abstract. Green Innovation (GI) is an inevitable choice to achieve sustainable development under the dual carbon target. In the context of the "dual-carbon" strategy, there is an urgent need to clarify how the digital economy and land-use change can synergize to drive green innovation in order to break the dual dilemma of unbalanced regional development and resource and environmental constraints. This study utilizes the Super-SBM (Super-Slack-Based Measure) model to assess green innovation (GI) from 2013 to 2022. Using the Spatial Durbin Model, it reveals the impact of digital economy and land use on GI, and draws the following conclusions: (1) China's regional average GI index is at a low to medium level, but it shows a gradual upward trend with obvious regional differences. There is a decreasing trend from southeast to northwest. (2) The GI of each region shows obvious agglomeration, and some regions show polarization and return effects. (3) The spatial conduction effect is significant. Land use change has obvious direct negative effect on GI, and indirect effect offsets part of the direct effect, resulting in the overall effect is not significant. Digital economy has an obvious direct positive effect on GI, but the indirect negative effect is stronger, resulting in a negative overall effect and a more obvious interregional spatial spillover effect.
Keywords: *empirical analysis, time-space evolution, decomposition of spillover effects, spatial measurement, sustainable development*

Introduction

In the context of global climate change, green innovation has become a keyway to achieve sustainable development (Xiao and Zhang, 2019). GI involves not only technological innovation, but also management innovation, business model innovation, and many other dimensions, and its core objective is to promote economic growth while reducing negative impacts on the environment. In this context, land use change and digital economy, as two important factors affecting GI, have received widespread attention. Currently, the level of GI development in China is low, and the average level of most regions is in the middle and lower reaches, with more space for optimization and promotion (Zhang et al., 2023). Comprehensively upgrading the level of green innovation and development needs to be addressed urgently today.

Land use change is gradually becoming an important material vehicle for the new phase in economic development Land use change is closely linked to GI, and the optimization of land use is capable of enhancing the carbon sink function of the ecosystem and reduce carbon emissions, which is crucial to achieving the global carbon neutrality goal. Secondly, with the transformation of land use, ecosystem services can be enhanced, providing a good ecological environment base for the innovation of green technology. Optimizing land conversion, improving land utilization, and is a significant means of injecting GI and development vitality (Hao et al., 2023). Land use change is directly related to the protection and rational use of natural resources, and is a critical material

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basis for fulfilling green development. With the acceleration of urbanization, the efficient use of land resources becomes particularly important.

The digital economy with its high efficiency and cleanliness, provides a new impetus and platform for GI (Rosário and Dias, 2023). The digital economy makes a positive difference to GI by promoting the efficiency of information flow, optimizing resource allocation, and improving remote collaboration and intelligent production. It reduces the resource consumption and environmental impact of traditional industries, while providing new tools and platforms for research and promotion of green technologies. Digital technologies enabled enterprises to monitor and manage energy use more effectively, promoting the circular economy. Moreover, the digital economy has facilitated consumer awareness and acceptance of environmental services and green products, enhancing the market dynamics of GI through channels such as e-commerce and social media. However, the digital economy itself faces environmental issues such as energy consumption and e-waste disposal, which requires that while promoting the development of digital technologies, attention should also be paid to their environmental impacts in order to achieve truly green and sustainable development. The widespread promotion of digital technology will not only optimize the allocation of resources, but also promote the public's awareness of green lifestyles. In today's context of simultaneous economic development and environmental protection, taking the dual-carbon goal as the principle and green innovation as the goal, and giving full consideration to the two basic elements of land-use change and the digital economy, it will be possible to point out the way forward for the formation of a synergy of GI and development. GI is not only a national strategy, but also a realistic requirement (Song et al., 2021).

The purpose of the paper is to explore how land use change and the digital economy affect GI and how this effect varies across regions. By constructing a scientific indicator system and applying methods such as global entropy value-Topsis method and Dagum Gini coefficient, it estimates the national GI level from 2013 to 2022, and analyzes the spatial impacts of land-use change and digital economy on GI by using spatial measurement model (SDM) (Zhang and Wang, 2021). The paper will provide useful reference for promoting the popularization and progress of GI and narrowing the differences in the development of GI inputs between various regions, which will help to better promote sustainable development and high-quality development. Together, we will promote the green transformation and circular development of the economy, the rationalization of land use and the in-depth implementation of digital transformation.

Literature review

Connotation and estimation of GI

The concept of GI has not been fully harmonized in academia, but it is universally acknowledged that it involves technological innovation or process innovation that reduces resource consumption and environmental pollution in the production. Takalo and Tooranloo (2021) defined GI as new product development beneficial to the environment. While Chen (2008) proposed the concept of green core competence, which suggests that a firm's GI capability is positively related to its GI performance and green image. According to the connotation of GI, Song and Yu (2018) constructed a theoretical framework for understanding GI strategies. On the other hand, Aguilera-Caracuel and Ortiz-de-Mandojana (2013) explored the impact of GI on firms' financial status from an institutional perspective, pointing out that environmental regulation and environmental

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norms have an important impact on GI. Zhang and Zhang (2011) systematically sorted out GI from environmental economics and other aspects, emphasizing the impact of environmental regulation on corporate GI behavior. Li and Xiao (2020) explored the impact of pollution discharge fees and environmental protection subsidies on enterprises GI from the aspect of heterogeneous environmental regulatory tools, and found that sewage charges can "force" the enhancement of corporate GI capacity. Wang and Li (2019) analyzed and evaluated GI systematically by constructing GI performance evaluation index system. They point out that GI is a balance between improving economic efficiency and reducing damage to resources and the environment. GI metrics mostly rely on indicators such as patent data, R&D investment, and environmental investment. For example, Qi et al. (2018) studied the impact of environmental equity trading market on firms' GI using Chinese listed companies' green patent data and a triple difference approach. They found that the environmental equity trading market can induce GI activities of enterprises. Wang and Wang (2021) found that green credit-restricted industries had more active GI performance after the enforcement of the Green Credit Guidelines.

Impact of land use change on GI

As a significant production factor, land resources have an important influence on green technological innovation. In the process of urbanization, the transformation of land use not only affects the urban spatial structure and ecological environment, but also directly or indirectly contributes to the development of GI activities and the increase of innovation efficiency. Nowadays academics study the intrinsic link between land use change and GI, and although the relevant studies are still relatively limited and not comprehensive enough, the existing studies have provided a preliminary perspective for us to understand this complex relationship. Jin et al. (2023) found that land use changes, especially the increase of construction land, contributed to the increase of carbon emissions by affecting energy consumption, while the development of green technology could reduce this effect. This suggests that land use change has an indirect effect on GI through energy consumption. Zhao et al. (2023) pointed out that rational land use planning can effectively protect and enhance urban green space, which in turn promotes the value of ecosystem services. Shi (2020) found that the mismatch of land resources has a hindering effect on green technological innovation, and there is a threshold effect for this effect.

Impact of the digital economy on GI

The relationship between GI and the digital economy has been widely explored by academics, and it is generally recognized that the digital economy is beneficial to promoting GI. Research has generally focused on how the digital economy can lead to the development of GI through technological advances, financial support and the policy environment. Li et al. (2024) found that the digital economy improved GI, emphasizing the important role of data resources in promoting GI. Van It et al. (2024) also supported digital economy promoting green economy. Wei et al. (2022) indicated that the digital economy provides funding for GI by optimizing the financial structure. Ye and Zhang (2024) explored the influence of digital economy on urban GI from the aspect of heterogeneity and found that there are differences in promoting GI by the digital economy under different levels of environmental regulation intensity and intellectual property protection. Spatial effects are also an important aspect of the study. He et al. (2025) shows

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that digital economy not only promotes local GI, but also has positive spatial spillover effects on neighboring cities.

Through literature combing, the current study on the influence of digital economy and land use change on GI is relatively few, still in the exploratory stage, and the direction of the conclusion is not clear. There are two main deficiencies in the current study: first, there is not concerned enough about land use change, domestic and foreign research is mainly from the land use planning, land resource allocation and other aspects of the study, the influence of land use change on GI research is very scarce, but the existing studies have shown that land use change through a variety of ways to influence the development of GI. Secondly, the study on the influence of combining land use change and digital economy on GI is still insufficient, but the existing studies have proved that land use change has a certain impact on GI and digital economy on GI. In view of this, this paper firstly estimates the national GI from 2013 to 2022 by using the global entropy value-Topsis method, and secondly analyzes the difference status of development by using the Dagum Gini coefficient, and meanwhile innovatively reveals the spatial influences of land use change and digital economy on GI by using the SDM model.

Methodology

Research questions and hypotheses

This study centers on the central question of how land use change and digital economy development affect green innovation in China, aiming to reveal the direct effects of both on green innovation and the differences in their spatial effects across regions. To this end, this paper puts forward the following research hypotheses: First, although land use change can indirectly promote green innovation by optimizing resource allocation and ecosystem services, its direct effect may be negative due to ecological damage and resource mismatch, and the overall effect is not significant. Second, the development of digital economy can directly promote green innovation by improving information efficiency, green financial support and industrial intelligence, but its negative spatial spillover between regions may offset local benefits due to resource siphoning effect, resulting in a negative overall effect. Third, green innovation shows significant positive autocorrelation and agglomeration characteristics in space, and the intensity of the effects of land use change and the digital economy is heterogeneous across regions, which needs to be identified in the context of regional development stages and resource endowments. Furthermore, the study covers the period 2013–2022, during which data for 30 Chinese provinces were collected and analyzed.

Space estimation

In studying the influences of land use change and the digital economy on GI, this paper adopts spatial econometrics because of its ability to effectively capture and analyze the correlation and interaction of spatial data. Spatial econometric modeling can help us understand how different regions interact with each other and how their interactions affect economic activity. This can be very helpful in studying changes in land use and what causes them. At the same time, spatial econometric methods can be used to identify the spatial heterogeneity of the influence of the digital economy on GI, and interactions and synergies between different regions in GI.

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Spatial autocorrelation analysis

The Moran Index was used to estimate the spatial relevance of the level of GI development in urban agglomerations and was calculated to reveal its spatial relevance and its trend over time (Chen, 2013). In *Eq. 1*, n is the number of all spatial units, where x_i and x_j are the values of specific attributes of the ith and jth spatial units, respectively, x denotes the average of the level of development of GI in all provinces, and w_{ij} denotes the spatial weighting coefficients. The Moran Index has a value between -1 and 1. If the Moran index is greater than 0, then the level of GI development of city clusters shows positive spatial correlation; if the Moran index is less than 0, then it shows negative spatial correlation; and if the Moran index is close to 0, then it demonstrates that there is no obvious spatial correlation.

Global spatial autocorrelation estimates spatial dependence within an overall spatial context, and Moran's I is a common estimate of this autocorrelation. Using Moran's scatterplot, we can classify regions into four categories: the first category is "high high", i.e., both the region and its neighboring areas have high attribute levels with little spatial variation; the second category is "high low", i.e., the region has high attribute levels but its neighboring areas have low attribute levels with high spatial variation; the third category is "low low", i.e., the region has high attribute levels with low spatial variation; and the third category is "low low". The third category is "Low-Low", and the fourth category is "Low-High". By observing whether the "high-high" and "low-low" types are dominant, we can determine whether a region has obvious spatial autocorrelation, i.e., whether there is a spatial aggregation phenomenon (Chen, 2013).

Local spatial autocorrelation focuses on the similarity between individual spatial units and their neighbors, which reflects the consistency of the local unit with the overall trend, including the direction and strength of the trend, and reveals spatial heterogeneity, i.e., how spatial dependence varies according to location. Local Moran's I is a commonly used metric for measuring local spatial autocorrelation. It classifies patterns of spatial correlation into four types: positive spatial correlation includes "high-high correlation" (regions with above-average attribute values are surrounded by neighboring regions that are also above-average) and "low-low correlation"; negative spatial correlation includes Negative spatial correlations include "high low correlations" and "low high correlations".

$$I = \frac{n\sum_{i=1}^{n}\Sigma_{j=1}^{n} w_{ij}(x_i - \bar{x})\left(x_j - \bar{x}\right)}{\Sigma_{i=1}^{n}\Sigma_{j=1}^{n} w_{ij}\Sigma_{i=1}^{n}(x_i - \bar{x})^2} \quad \text{(Eq.1)}$$

In *Eq.1*, I denotes the global Moran's I statistic that estimates overall spatial autocorrelation; n is the number of spatial units in the sample; x_i and x_j represent the observed values of the study variable for spatial units i and j; $\bar{x} = n^{-1}\sum_{i=1}^{n} x_i$ is the arithmetic mean of that variable across all units; w_{ij} is the element in the spatial weight matrix W capturing the spatial proximity or contiguity between units i and j (with $w_{ii} = 0$ and W typically row-standardized or binary); and $S_0 = \sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}$ is the sum of all spatial weights that serves as a scaling factor in the statistic.

In this study, the spatial weight matrix was set up with geographic accessibility in mind, and instead of using a 0-1 matrix, the inverse of the distance between individual spatial units was used as the spatial weights.

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$$w_{ij} = \frac{1}{d_{ij}} \quad \text{(Eq.2)}$$

In *Eq. 2*, *d* is a pre-given distance threshold, *i* denotes the ith spatial unit, and *j* denotes the jth spatial unit.

Spatial estimation models

If there are spatial dependencies between variables, traditional statistical models may not be able to effectively deal with the issues raised by such dependencies. To avoid this situation, researchers need to consider using spatial econometric models (Mur and Angulo, 2006). This study aims to investigate the “proximity effect” of the level of green innovation development, in which the spatial dependence of the variables becomes a key consideration. Therefore, this section will attempt to construct an appropriate spatial econometric model.

The main spatial econometric models include the Spatial Lag Model (SLM), the Spatial Error Model (SEM), and the Spatial Durbin Model (SDM) (Mur and Angulo, 2006). The SLM is usually recommended if the dependent variable shows spatial correlation.

The specific form of the SLM is

$$\ln GI_{it} = \rho \sum_{j=1}^{N} w_{ij} GI_{it} + \beta_i X_{it} + \gamma_i + \mu_t + \varepsilon_{it} \quad \text{(Eq.3)}$$

where, ρ represents the spatial lag parameter; N represents the total number of spatial units; X_{it} represents the vector consisting of the explanatory variables, β_i represents the estimated coefficients of the explanatory variables, while γ_i and μ_t represent the spatial fixed effects and time fixed effects, respectively.

If the model needs to take into account the spatial correlation of the residuals, then the SEM should be used. The expression for this model is given below:

$$\ln GI_{it} = \tau \sum_{j=1}^{N} w_{ij} \varphi_{ij} + \beta_i X_{it} + \gamma_i + \mu_t + \varepsilon_{it} \quad \text{(Eq.4)}$$

In a spatial econometric model, φ_{ij} is the spatially autocorrelated error term, while τ is the spatial autocorrelation coefficient of this error term. The other variables have the same meaning as in *Eq. 3*.

If both the dependent and independent variables show spatial dependence, then the SDM should be used. The SDM has the following form:

$$\ln GI_{it} = \rho \sum_{j=1}^{N} w_{ij} GI_{it} + \sum_{j=1}^{N} w_{ij} x_{jt} + \beta_i X_{it} + \gamma_i + \mu_t + \varepsilon_{it} \quad \text{(Eq.5)}$$

In this paper, in order to determine the most suitable model to analyze the correlation and interaction of spatial data, we will select a specific spatial econometric model by using tests such as the LM test, Hausman test, Wald test and LR test.

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Variable selection and data sources

Explained variables

Green innovation (GI): the results of GI are obtained by referring to a large number of literatures such as Wang et al. (2018), Bai et al. (2024), using the global entropy-Topsis method to estimate GI index (*Table 1*).

Table 1. *Green Innovation (GI) indicator system*

Variant	Level 1 indicators	Secondary indicators	Tertiary indicators	Forward/ Reverse	Weights
Explanatory variable	Degree of development of Green innovation (GI)	Capacity to access innovative resources	Full-time equivalents of R&D personnel in industrial enterprises above large scale (person-years)	+	0.1533
			Employment in urban units of scientific research and technical services (10,000 persons)	+	0.0681
			Number of R&D projects of industrial enterprises above designated size (items)	+	0.1716
			Expenditures on environmental protection in local finances (billions of yuan)	+	0.0377
		Green innovation absorptive capacity	Non-hazardous treatment rate of domestic waste	+	0.0009
			Investment in fixed assets in the electricity, heat, gas and water production and supply sector (excluding farms), year-on-year growth (%)	-	0.0088
			Number of innovative product projects of industrial enterprises above designated size (items)	+	0.183
		Capacity to translate innovation into results	Innovative green coverage in built-up areas (%)	+	0.0008
			Number of industrial pollution control projects completed this year (number)	+	0.0821
			Number of non-hazardous treatment plants (number)	+	0.0434
			Number of effective invention patents of industrial enterprises above designated size (pieces)	+	0.2146
		Capacity to utilize innovations	Growth rate of energy consumption (equivalent value) per unit of GDP (%)	-	0.0116
			Petroleum emissions (tons)	-	0.0088
			Electricity generation from conventional fossil energy sources	-	0.0153

Explanatory variables

Land use change (LUC). Land use change refers to changes in land-use patterns and types of coverage caused by the development and utilization of land resources by human activities, which involves many aspects such as ecological environment, economic development and social needs (Zhu, 2003). Technological breakthroughs in GI are closely linked to land use changes, which significantly impact GI development. Land use changes influence factors such as ecological quality, resource availability, policies, socio-economic structure, and public awareness, driving the demand for sustainable resources

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and green products. Public concern about environmental issues further accelerates GI progress. In this paper, we use the raster calculation-transfer matrix method to estimate integrated land use dynamics alongside GI development.

In this paper, we first use the raster calculator in ArcGIS software to estimate the land use area of the raster data of land use types in 30 provinces in China at 30-meter resolution, and then organize the calculated data into a land use transfer matrix through EXCEL software, and finally estimate the land use changes of 30 provinces in China from 2013 to 2022 by using the formula of the integrated land use change. The significance of the dynamic attitude index is that it can characterize the degree of regional land use change, and it is also suitable for comparing the local area with the whole region, as well as comparing the land use change between regions.

The transfer matrix (Zhu, 2003) can comprehensively and specifically portray the structural characteristics of regional land use change and the direction of change of each land use type, the method comes from the quantitative description of the system state and state transfer in the system analysis, and the mathematical form of the transfer matrix (*Eq. 6*) is:

$$L_{ij} = \begin{vmatrix} L_{11} & L_{12} & L_{13} & \cdots & L_{1n} \\ L_{21} & L_{22} & L_{23} & \cdots & L_{2n} \\ L_{31} & L_{32} & L_{33} & \cdots & L_{3n} \\ \cdots & \cdots & \cdots & \cdots & \cdots \\ L_{n1} & L_{n2} & L_{n3} & \cdots & L_{nn} \end{vmatrix} \tag{Eq.6}$$

where: L represents the area; n represents the number of land use types; i, j represent the land use types at the beginning and at the end of the study period, respectively. In specific applications, the matrix is usually presented in tabular form.

The comprehensive land use attitude index (Zhu, 2003) takes into account the transfer between land use types during the study period, focusing on the process of change rather than the result of change, and its significance is to reflect the intensity of regional land use change, so as to facilitate the identification of hotspot areas of land use change at different spatial scales. Comprehensive land use dynamic attitude index (*Eq. 7*) is calculated as follows:

$$LC_T = \left(\frac{\sum_{i=1}^{n} \Delta LU_{ij}}{\sum_{i=1}^{n} LU_i} \right) \times 100\% \tag{Eq.7}$$

where: LU_i is the area of class i land use type at the beginning of the study period; ΔLU_{ij} is the area of class i land use type converted to non-class i (class j, j = 1,2,3,…,n) land use type during the study period; T is the study period, and the model result is the annual comprehensive rate of change of land use of the region at this time when it is expressed in years.

Digital Economy (DE). The digital economy plays a key role in advancing GI by enhancing resource allocation, driving innovation, and optimizing industrial structures. It also reduces transaction costs and resource consumption by better matching supply and

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demand. However, its growth presents challenges, particularly in energy consumption and carbon emissions from data centers and digital infrastructure. Drawing on the paper of Lin et al. (2024), this study utilizes the global entropy-Topsis method to simultaneously estimate the digital economy and examine its impact on GI (*Table 2*).

Table 2. *Digital Economy (DE) indicator system*

Variant	Level 1 indicators	Secondary indicators	Tertiary indicators	Forward/ Reverse	Weights
Core explanatory variables	Digital Economy (DE)	Number of mobile Internet users	Average number of cell phones per 100 households at the end of the year (units)	+	0.0067
		Digital Finance for Inclusive Development	The Peking University Digital Financial Inclusion Index of China	+	0.0553
		Internet penetration	Mobile Internet subscribers (million)	+	0.2829
		Average compensation of Internet-related workers	Average wage of persons employed in urban units in the information transmission, computer services and software industry (yuan)	+	0.1174
		Internet-related outputs	Total telecommunications business (billion yuan)/year-end resident population (10,000 people)	+	0.5378

Control variables

Regional Gross Domestic Product (RGDP). More economically developed regions tend to have more resources and capital to invest in GI, which helps to promote the research and application of cleaner technologies and the transformation of industrial structure towards a more environmentally friendly and sustainable direction. Meanwhile, GI can also improve the efficiency of resource use, reduce environmental pollution, and bring new growth drivers and competitive advantages for economic development. This study adopts per capita gross regional product (yuan per person) as an indicator to estimate this variable.

Industrial Structure (IS). The restructuring and upgrading of industries have had a significant effect on GI. With economic growth, traditional industries have developed new competitive advantages by implementing green transformation measures, such as energy-saving, carbon-reducing and cleaner production technologies, which have improved energy utilization efficiency. The combined transformation of digitization and greening has facilitated the development of industries with the application of big data. These transformations have not only given rise to GI, but also provided policy support and market demand for GI, further promoting the transformation of industrial structure in a more environmentally friendly and sustainable direction. This study refers to the rationalization of Chunhui Gan’s Terre Index (Gan and Zheng, 2010) measure to explain this variable.

Human Capital (HC). Human capital has a multidimensional impact on GI. Firstly, human capital enhances the ability of firms to innovate in green products and processes by enhancing the green skills and knowledge of employees. Education and training increase employees’ awareness of environmental protection and their ability to apply

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green technologies, which helps promote the implementation of GI. In addition, the enhancement of human capital is often accompanied by an increase in the acceptance of new technologies and concepts, and this "externality effect" helps to support emission reduction and promote the development of GI. In addition, the concentration and spillover effects of human capital can promote inter-regional GI exchanges and cooperation, enhance the dissemination of green technology among enterprises, and improve the overall efficiency of GI. This study adopts average years of education as an indicator of this control variable.

The control variables are described in *Table 3* below.

Table 3. *Control variables indicator system*

Variant	Level 1 indicators	Secondary indicators	Tertiary indicators	Forward/ Reverse	Weights
Control variable	Regional Gross Domestic Product (RGDP)	GDP per capita	Gross regional product per capita (yuan per person)	+	/
	Industrial Structure (IS)	Rationalization of industrial structure	Rationalization of the estimation of Chunhui Gan's Terrell Index	-	/
	Human Capital (HC)	Average years of schooling	Average years of schooling = [number of people not attending school *0 + number of elementary school *6 + number of junior high schools *9 + number of senior high schools *12 + (colleges + universities + graduate schools) *16]/number of people aged 6 years and over	+	/

Descriptive statistics of variables

As shown in *Table 4*, the descriptive statistics for each variable are presented (with 300 observations corresponding to 30 province-level regions over the 10-year period 2013–2022).

Table 4. *Descriptive statistics of variables*

Variable	Observation	Mean	Standard Deviation	Minimum	Maximum
GI	300	11.98	12.34	3.330	93.08
LUC	300	0.0116	0.00625	0.00139	0.0393
DE	300	0.236	0.150	0.0389	0.795
RGDP	300	62715	31118	22089	190313
IS	300	0.159	0.112	0.00748	0.544
HC	300	9.251	0.922	7.165	12.77

GI = Green Innovation; LUC = Land Use Change; DE = Digital Economy; RGDP = Regional Gross Domestic Product; IS = Industrial Structure; HC = Human Capital

Data source

The data sources involved in the calculation of all variables in this paper are shown in *Table 5* below.

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Table 5. *Data source*

Variable	Definition / Estimation	Data Source
Green Innovation (GI)	Composite index of regional green innovation, estimated via a multi-indicator entropy-TOPSIS method (e.g. capacity to access innovative resources, green innovation absorptive capacity, etc., see Table. 1 for details)	Derived from official statistics in China Statistical Yearbooks (2013–2022) and provincial yearbooks (National Bureau of Statistics of China).
Land Use Change (LUC)	Comprehensive land use change (index) – reflects land use intensity by combining land use categories. Calculated using a land use transfer matrix and the formula for comprehensive land use degree. Higher values indicate more intensive land use.	30m Land Cover Dataset for China (annual land use raster data) from Wuhan University. We utilized the China Land Cover Dataset (CLCD) 1985–2022 released in 2024 by Wuhan University (Yang and Huang, 2021) essd.copernicus.org. Data were accessed via the Zenodo repository (DOI: 10.5281/zenodo.4417810) and processed with ArcGIS.
Digital Economy (DE)	Composite index of digital economy development, constructed via entropy-TOPSIS using indicators such as: number of mobile internet users per 100 households, digital finance inclusion level, internet penetration, average ICT sector wages, and telecom business per capita. Higher index values mean a more developed digital economy.	National Telecommunications Reports (Ministry of Industry and IT) for internet users and telecom data; Peking University Digital Financial Inclusion Index (PKU–DFIIC) for digital finance levelsen.idf.pku.edu.cn; and China Statistical Yearbooks (2013–2022) for ICT sector employment and wage data. All indicator data were compiled annually at the provincial level from these sources.
Regional Gross Domestic Product (RGDP)	Economic development level, estimated as real GDP per capita (yuan per person).	China Statistical Yearbooks (2013–2022) – Provincial GDP and population figures from the National Bureau of Statistics of China (NBS) were used to calculate per capita GDP each year. (NBS Yearbook portal).
Industrial Structure (IS)	Index of industrial structure rationalization. We use the Terrell index (modified from Gan & Zheng, 2010) to quantify the structure of the economy – values closer to 0 indicate more optimal (rational) industrial structure.	Calculated by authors using sectoral value-added data from China Statistical Yearbooks and provincial statistical bulletins (2013–2022). Primary, secondary, and tertiary industry output data (NBS) were input into the Terrell index formula (Gan and Zheng, 2010) to derive this index for each province-year.
Human Capital (HC)	Human capital level, estimated as the average years of schooling of the population (age ≥6). Higher values mean a more educated workforce.	China Population Census and Sample Survey Data – Educational attainment data were obtained from the 2010 & 2020 Population Census and yearly population sample surveys (NBS and Ministry of Education). We computed average schooling years using the formula given in the paper (see Table 3) based on the population shares of each education level.

GI = Green Innovation; LUC = Land Use Change; DE = Digital Economy; RGDP = Regional Gross Domestic Product; IS = Industrial Structure; HC = Human Capital

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Regional analysis method

In the field of economics and sociology, the estimation of income inequality or regional development differences is an important indicator for assessing social equity and economic development. Among them, the Thiel index (Conceição and Ferreira, 2000) and the Dagum Gini coefficient (Dagum, 1997) are the most common estimation tools.

The Theil index, also known as the Theil diversity index, was originally used in ecology and later introduced into economics to estimate equality in income distribution and developmental disparities (Conceição and Ferreira, 2000). The Theil index can be decomposed into within and between-group inequality, which provides more detailed information on the sources of inequality. Compared to the Dagum Gini coefficient, the Thiel index has advantages when dealing with multiple data sets, but its sensitivity to income transfers and errors in the analysis of developmental disparities may lead to an overestimation of inequality.

Dagum (1997) proposed a new formula to decompose the Gini coefficient, a method that can reveal the source of variation in a given index. As a result, the overall regional variation can be decomposed into three components: intra-regional variation, inter-regional variation, and hypervariance density, which makes an in-depth analysis of the sources of regional variation much clearer. Initially, Dagum's Gini coefficient analysis method was mainly used to analyze income disparity and economic development disparity, but some studies have also applied it to analyze the regional differences in market-oriented allocation of factors and the regional differences in China's carbon emission intensity, etc. (Zhang et al., 2022).

This study will use the Dagum Gini coefficient decomposition technique to analyze the spatial differences in the level of GI development in different regions. Based on Dagum's proposed method of decomposing the Gini coefficient by subgroups, we can define the Gini coefficient of China's GI development level *(Eq. 8)* as follows:

$$G=\sum_{j=1}^{k}\sum_{h=1}^{k}\sum_{i=1}^{n_j}\sum_{r=1}^{n_h}\frac{|\,y_{ji}-y_{hr}|}{2n^2\overline{y}} \tag{Eq.8}$$

Here: G is Gini coefficient, this method divides the country into k regions and n provinces. n_j (n_h) is the number of provinces in region j(h), y_{ji} (y_{hr}) denotes the degree of GI development of any province in region *j(h)*, and $\overline{y}$ denotes the average degree of GI development of each province, j ,h = 1,2,3,...,k; . n_j ,n_h = 1,2,3..., n_j (n_h).

Before decomposing the level of green innovation development, it is also necessary to calculate the mean value of the level of green innovation development in each region separately and rank it as (*Eq. 9*):

$$\bar{Y}_l \leqslant \cdots \leqslant \bar{Y}_h \leqslant \cdots \leqslant \bar{Y}_k \tag{Eq.9}$$

As a result, the Gini coefficient G of the degree of GI development, which is the overall variation, can be further decomposed into a component contributed by intra-regional variation G_w the component contributed by inter-regional differences in net G_{nb}, and the hypervariance density G_t. The relationship (*Eq. 10*) between them is satisfied:

$$G=G_w+G_{nb}+G_t \tag{Eq.10}$$

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Here, the hypervariance density represents the variance caused by the overlapping parts between different regions. Following the Gini coefficient decomposition method, we can decompose the overall variation into the following components. *Eq. 11* shows the Gini coefficient of per capita consumption in region j, G_{ji}; *Eq. 12* represents the contribution of intra-regional variation in the region to the overall variation, G_w; *Eq. 13* shows the inter-regional Gini coefficient between region j and region h, G_{jh}; *Eq. 14* is the contribution of the net inter-regional variation to the overall variation, G_{nb}; and *Eq. 15* depicts the contribution of hypervariance density G_t.

$$G_{ij} = \frac{\frac{1}{2\overline{Y}_j}\sum_{i=1}^{n_j}\sum_{r=1}^{n_j}|y_{ji} - y_{hr}|}{n_j^2} \quad \text{(Eq.11)}$$

$$G_w = \sum_{j=1}^{k} G_{jj} p_j s_j \quad \text{(Eq.12)}$$

$$G_{jh} = \frac{\sum_{i=1}^{n_j}\sum_{r=1}^{n_j}|y_{ji} - y_{hr}|}{n_j n_h\left(\overline{Y}_j + \overline{Y}_h\right)} \quad \text{(Eq.13)}$$

$$G_{nb} = \sum_{j=2}^{k}\sum_{h=1}^{j-1} G_{jh}(p_j s_h + p_h s_j) D_{jh} \quad \text{(Eq.14)}$$

$$G_t = \sum_{j=2}^{k}\sum_{h=1}^{j-1} G_{jh}(p_j s_h + p_h s_j)(1 - D_{jh}) \quad \text{(Eq.15)}$$

Among other things, $p_j = n_j\bar{Y}, s_j = \frac{n_j\bar{Y}_j}{n\bar{Y}}, j = 1,2,3,\cdots,k$. Also, D_{jh} is the interaction between the indicators of region j and region h, and d_{jh} is the difference in the degree of GI development between these two regions, i.e., it is the expected value of all sample values in these two regions that satisfy the $y_{jh} - y_{ji} > 0$ conditions of all sample values summed up to the expectation. Similarly, the p_{jh} is the difference between the indicators of the two regions, i.e., the expectation of the sum of all the sample values in the two regions that satisfy the conditions.$y_{hr} - y_{ji} > 0$ the expectation of the sum of all the sample values in the two regions j and h that satisfy the conditions.D_{jh} , the d_{jh} and p_{jh} The defining equations are given by *Eq. 16*, *Eq. 17*, and *Eq. 18*, respectively:

$$D_{jh} = \frac{d_{jh} - p_{jh}}{d_{jh} + p_{jh}} \quad \text{(Eq.16)}$$

$$d_{jh} = \int_0^{\infty} \mathrm{d}F_j(y)\int_0^{y}(y - x)\mathrm{d}F_h(x) \quad \text{(Eq.17)}$$

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$$p_{jh} = \int_0^{\infty} \mathrm{d}F_h(y) \int_0^{y} (y-x)\mathrm{d}F_j(x) \quad \text{(Eq.18)}$$

where $F_j(F_h)$ is the cumulative distribution function of j(h) region.

Therefore, $y_{ji}(y_{hr})$ can be used to represent the degree of GI development in each province of China respectively, and to decompose its regional gap and sources.

Results

Estimation results

Results of GI estimation

This paper divides the country into eastern, central, western and northeastern regions according to the level of regional economic development, the degree of land use and other factors (Yu et al., 2025).

This paper estimated GI using the global entropy value-Topsis method, and the results are in *Table 6* and *Fig. 1* below, which can summarize the following characteristics of the GI score: spatially and temporally, the east is better than the west, and the GI index decreases from east to west; typologically, the GI index of the old industrial provinces such as Liaoning, Heilongjiang, and Tianjin is lower, and the GI index of the new industrial provinces like Jiangsu, Zhejiang, and Guangdong is higher. In terms of type, old industrial provinces like Liaoning, Heilongjiang and Tianjin have lower GI indexes, while developed provinces with emerging industries such as Jiangsu, Zhejiang and Guangdong have higher GI indexes. To summarize, the level of GI development varies among provinces nationwide, and the overall development situation is relatively positive.

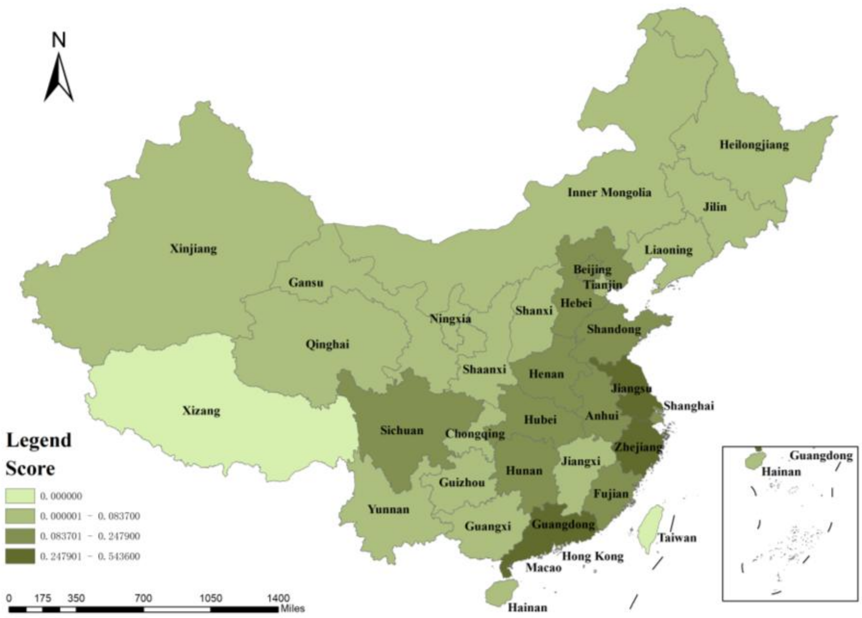

Figure 1. *Distribution of average Green Innovation (GI) Development Index values across 30 provinces in China over the decade 2013-2022*

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Table 6. *Green Innovation (GI) development index for 30 provinces in China, 2013-2022*

Region	Year Province	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022	mean value	Sort by mean
Eastern region	Beijing	0.1500	0.1516	0.1539	0.1736	0.1833	0.1830	0.1780	0.1606	0.1732	0.1811	0.1688	5
	Tianjin	0.0680	0.0734	0.0716	0.0732	0.0732	0.0692	0.0778	0.0734	0.0775	0.0811	0.0738	18
	Hebei	0.0776	0.0850	0.0942	0.0983	0.1064	0.1144	0.1255	0.1361	0.1333	0.1434	0.1114	11
	Shanghai	0.0872	0.0942	0.0911	0.0976	0.1070	0.1129	0.1289	0.1306	0.1398	0.1582	0.1148	9
	Jiangsu	0.2495	0.2727	0.2785	0.3077	0.3332	0.3704	0.4186	0.4642	0.5054	0.5613	0.3762	2
	Zhejiang	0.2057	0.2186	0.2340	0.2518	0.2774	0.3133	0.3697	0.4187	0.4651	0.5187	0.3273	3
	Fujian	0.0777	0.0997	0.0838	0.0991	0.0951	0.1110	0.1159	0.1335	0.1481	0.1710	0.1135	10
	Shandong	0.1863	0.1931	0.1924	0.2046	0.2223	0.2312	0.2325	0.2738	0.3438	0.3993	0.2479	4
	Guangdong	0.2721	0.2908	0.3140	0.3817	0.4776	0.5508	0.6451	0.7303	0.8425	0.9308	0.5436	1
	Hainan	0.0354	0.0357	0.0363	0.0367	0.0368	0.0376	0.0386	0.0409	0.0420	0.0418	0.0382	29
Central region	Shanxi	0.0645	0.0651	0.0654	0.0670	0.0688	0.0711	0.0760	0.0801	0.0785	0.0761	0.0713	19
	Anhui	0.0777	0.0818	0.0856	0.0946	0.1119	0.1156	0.1346	0.1488	0.1672	0.1881	0.1206	6
	Jiangxi	0.0522	0.0524	0.0531	0.0586	0.0667	0.0777	0.0906	0.1026	0.1120	0.1281	0.0794	15
	Henan	0.0903	0.0955	0.0983	0.1028	0.1079	0.1178	0.1311	0.1346	0.1456	0.1591	0.1183	7
	Hubei	0.0757	0.0795	0.0814	0.0867	0.0897	0.0995	0.1149	0.1247	0.1367	0.1541	0.1043	13
	Hunan	0.0724	0.0773	0.0760	0.0810	0.0858	0.0981	0.1159	0.1265	0.1522	0.1812	0.1066	12
Western Region	Inner Mongolia	0.0455	0.0471	0.0505	0.0526	0.0504	0.0506	0.0502	0.0498	0.0505	0.0507	0.0498	25
	Guangxi	0.0598	0.0625	0.0635	0.0640	0.0635	0.0618	0.0626	0.0653	0.0713	0.0766	0.0651	21
	Chongqing	0.0561	0.0603	0.0614	0.0645	0.0706	0.0750	0.0779	0.0846	0.0935	0.1031	0.0747	16
	Sichuan	0.0967	0.1029	0.0988	0.1024	0.1128	0.1153	0.1221	0.1338	0.1452	0.1515	0.1182	8
	Guizhou	0.0479	0.0514	0.0546	0.0569	0.0579	0.0605	0.0630	0.0645	0.0693	0.0728	0.0599	22
	Yunnan	0.0744	0.0766	0.0796	0.0829	0.0851	0.0848	0.0895	0.0882	0.0878	0.0883	0.0837	14
	Shaanxi	0.0630	0.0656	0.0662	0.0659	0.0708	0.0706	0.0735	0.0732	0.0776	0.0788	0.0705	20
	Gansu	0.0421	0.0476	0.0460	0.0519	0.0501	0.0549	0.0504	0.0530	0.0499	0.0504	0.0496	26
	Qinghai	0.0364	0.0372	0.0415	0.0426	0.0422	0.0416	0.0413	0.0431	0.0456	0.0465	0.0418	28
	Ningxia	0.0353	0.0353	0.0358	0.0367	0.0368	0.0388	0.0389	0.0333	0.0369	0.0357	0.0364	30
	Xinjiang	0.0353	0.0373	0.0405	0.0421	0.0429	0.0460	0.0453	0.0450	0.0502	0.0484	0.0433	27
Northeast region	Liaoning	0.0677	0.0708	0.0660	0.0657	0.0689	0.0702	0.0737	0.0804	0.0856	0.0927	0.0742	17
	Jilin	0.0544	0.0546	0.0569	0.0533	0.0479	0.0510	0.0565	0.0543	0.0550	0.0536	0.0538	24
	Heilongjiang	0.0528	0.0536	0.0580	0.0558	0.0604	0.0558	0.0622	0.0647	0.0596	0.0621	0.0585	23

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The GI development index reflects to a certain extent the level of GI development in the whole country, and the higher the development index, the better the degree of GI development in the region and the higher the development potential. From a macro viewpoint, with 0.05 as the basic standard score, more than 90% of the thirty provinces in the country have a ten-year average GI score of 0.05 or above. Among them, the scores of Jiangsu, Zhejiang and Guangdong Province show two peaks of 0.35 and 0.543, respectively, while the northwest regions such as Gansu, Qinghai and Ningxia have a lower degree of GI development. The correlation between the estimation results and geographic location is strong, with the eastern coastal region having developed science and education and investing more in GI and environmental economy, while the northwestern region has a complex geographic environment and harsh natural climate, and has invested more in infrastructure construction and less in GI. The trend line of the score shows a regional downward trend from east to west, and the overall level of GI development is at a low to medium level. A graph of GI score trends and a bar chart of averages are shown in *Fig. 2* below.

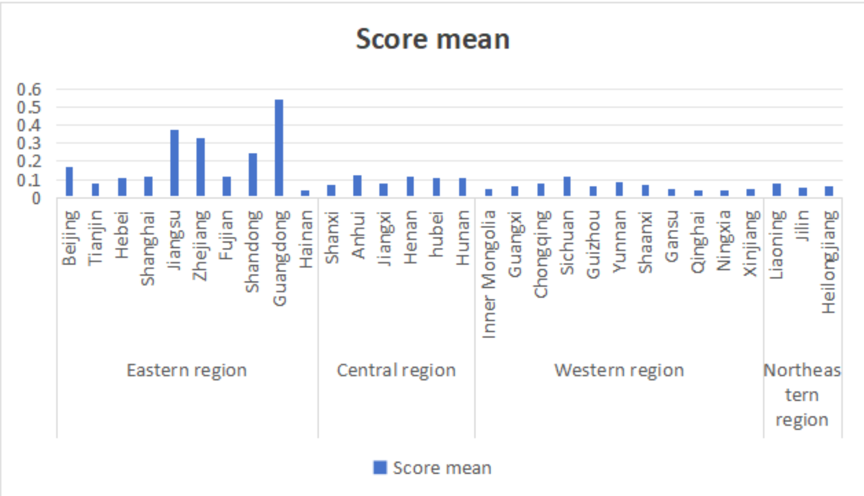

Figure 2. *Average Green Innovation (GI) development index for eastern, central, western, and northeastern China over the 10-year period 2013-2022*

Digital economy estimation results

After measuring GI as a whole, this paper then estimates the digital economy and land use separately. The Digital Economy Index reflects the level of development of the digital economy in the country, and the higher the development index indicates that the degree of development of the digital economy in the region is better, and the development potential is greater. Macro view, with 0.15 as the basic standard score, the ten-year average digital economy score of thirty provinces in the country reaches 0.15 or more than 95% of the region. Spatially and temporally, the eastern and central regions are better than the western region, and the northeast region has the lowest degree of development of the digital economy, and the whole shows a decreasing degree of development of the digital economy from the southeast coast to the northwest inland in turn, and the northeast region is characterized by slow development; type of view, Beijing, Chongqing, Hainan and other regional nodes of the digital economy development degree of the province (city, district) The degree of digital economy development in Beijing, Chongqing, Hainan and

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other regional node provinces (cities and districts) is in a leading position in the country, while the degree of development in Henan, Guangxi, Shandong and other regions is lower due to geographic environmental factors or other impediments in society caused by the large population base. The results of digital economy estimation are in *Table 7* and *Fig. 3* below.

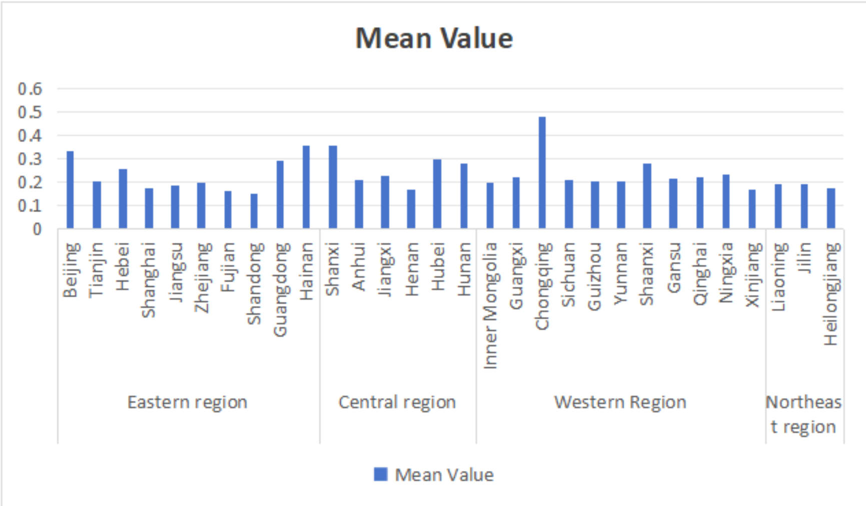

Figure 3. *Average Digital Economy (DE) Development index for eastern, central, western, and northeastern China over the 10-year period 2013-2022*

As shown in *Fig. 4* below, the provinces with high levels of regional digital economy development are Shanxi, Chongqing and Hainan. Among them, a high-level digital economy development belt is formed from Beijing-Tianjin-Hebei to the Hubei-Guangzhou region to the Hengqin-Guangdong-Macao Greater Bay Area. The agglomeration effect of a developed digital economy region leads to the growing digital economy in the surrounding areas, but unrestricted development may cause the region to exceed the take-off stage, and it will have a self-development ability, constantly accumulating favorable factors to create favorable conditions for its own further development, which is likely to be transformed into a polarization effect under the spontaneous action of the market mechanism (see the section of the regional disparity estimations below). All in all, China's digital economy has good prospects for more even development, with no obvious polarization effect. (The values for Tibet and Hong Kong, Macao and Taiwan are zero, and the data are temporarily missing).

Results of land-use change estimations

In this study, we use ArcGIS software to import the 30-meter precision raster data released by Wuhan University (Yang and Huang, 2021) in August 2024, which is divided into nine land cover categories, namely, Cropland, Forest, Shrub, Grassland, Water, Snow/Ice, Barren, Impervious and Wetland, and then we use the raster calculator that comes with the ArcGIS software to calculate the overlap of the various categories and then import it into excel to use pivot tables to transfer the matrix. Finally, the formula is used to calculate (i.e. the above formula for comprehensive land utilization rate). Comprehensive land use rate shows the degree of land use of economic indicators.

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Table 7. *Digital Economy (DE) development index for 30 provinces in China, 2013-2022*

Region	**Year Province**	**2013**	**2014**	**2015**	**2016**	**2017**	**2018**	**2019**	**2020**	**2021**	**2022**	**mean value**	**Sort by mean**
Eastern region	Beijing	0.1897	0.2020	0.2577	0.2132	0.2855	0.4301	0.5771	0.6333	0.2682	0.2674	0.3324	4
	Tianjin	0.0775	0.0937	0.1198	0.1090	0.1470	0.2710	0.4112	0.5056	0.1464	0.1544	0.2036	19
	Hebei	0.1254	0.1438	0.1676	0.1948	0.2211	0.2932	0.4043	0.4759	0.2633	0.2702	0.2560	9
	Shanghai	0.0635	0.0738	0.0903	0.0926	0.1294	0.2208	0.3484	0.4357	0.1415	0.1407	0.1737	26
	Jiangsu	0.0640	0.0738	0.0911	0.0825	0.1250	0.2700	0.4147	0.4934	0.1318	0.1303	0.1877	24
	Zhejiang	0.0992	0.1123	0.1348	0.1357	0.1704	0.2497	0.3500	0.4161	0.1654	0.1664	0.2000	21
	Fujian	0.0578	0.0663	0.0816	0.0804	0.1206	0.2270	0.3538	0.4201	0.1141	0.1156	0.1637	29
	Shandong	0.0770	0.0760	0.0860	0.0925	0.1265	0.1911	0.2779	0.3369	0.1275	0.1327	0.1524	30
	Guangdong	0.1653	0.1819	0.2158	0.1926	0.2350	0.3472	0.4756	0.5614	0.2785	0.2843	0.2938	6
	Hainan	0.2297	0.2292	0.2570	0.2645	0.3371	0.4138	0.5535	0.6303	0.3185	0.3168	0.3550	3
Central region	Shanxi	0.1985	0.2124	0.2495	0.2482	0.3108	0.4347	0.6046	0.6772	0.3171	0.3246	0.3578	2
	Anhui	0.0686	0.0948	0.1338	0.1458	0.1720	0.2457	0.3699	0.4465	0.1993	0.2101	0.2087	15
	Jiangxi	0.1213	0.1292	0.1482	0.1370	0.1695	0.2850	0.4136	0.4779	0.1866	0.1982	0.2267	11
	Henan	0.0600	0.0687	0.0875	0.0967	0.1270	0.2114	0.3337	0.4020	0.1570	0.1656	0.1710	27
	Hubei	0.1763	0.1918	0.2129	0.2441	0.2863	0.3398	0.4239	0.4758	0.3077	0.3180	0.2977	5
	Hunan	0.1269	0.1520	0.1866	0.2108	0.2579	0.3322	0.4186	0.5142	0.2979	0.3086	0.2806	8
Western Region	Inner Mongolia	0.0916	0.1060	0.1279	0.1338	0.1615	0.2398	0.3326	0.4065	0.1983	0.2092	0.2007	20
	Guangxi	0.1033	0.1132	0.1334	0.1519	0.1814	0.2629	0.3764	0.4722	0.2197	0.2289	0.2243	12
	Chongqing	0.3330	0.3493	0.3781	0.3696	0.4530	0.5587	0.6953	0.7946	0.4486	0.4626	0.4843	1
	Sichuan	0.0834	0.0935	0.1110	0.1169	0.1500	0.2535	0.3925	0.4932	0.1912	0.1983	0.2084	16
	Guizhou	0.0608	0.0665	0.1065	0.0851	0.1449	0.2839	0.4043	0.4947	0.1920	0.2045	0.2043	17
	Yunnan	0.0737	0.0891	0.1128	0.1113	0.1472	0.2689	0.4130	0.4828	0.1669	0.1713	0.2037	18
	Shaanxi	0.1606	0.1756	0.1965	0.2154	0.2437	0.3259	0.4123	0.5313	0.2817	0.2893	0.2832	7
	Gansu	0.0664	0.0777	0.0958	0.0967	0.1493	0.3096	0.4862	0.5788	0.1609	0.1650	0.2186	14
	Qinghai	0.0786	0.0926	0.1186	0.1224	0.1734	0.2952	0.4457	0.5537	0.1651	0.1726	0.2218	13
	Ningxia	0.0941	0.1122	0.1357	0.1438	0.1798	0.3191	0.4461	0.5200	0.2028	0.2099	0.2364	10
	Xinjiang	0.0613	0.0625	0.0757	0.0693	0.1075	0.2417	0.3776	0.4680	0.1175	0.1168	0.1698	28
Northeast region	Liaoning	0.0389	0.0530	0.0796	0.0541	0.1314	0.3328	0.4653	0.5482	0.1168	0.1160	0.1936	22
	Jilin	0.0460	0.0588	0.0855	0.0690	0.1431	0.3086	0.4535	0.5251	0.1156	0.1111	0.1916	23
	Heilongjiang	0.0631	0.0730	0.0886	0.0765	0.0995	0.1845	0.3806	0.5257	0.1340	0.1305	0.1756	25

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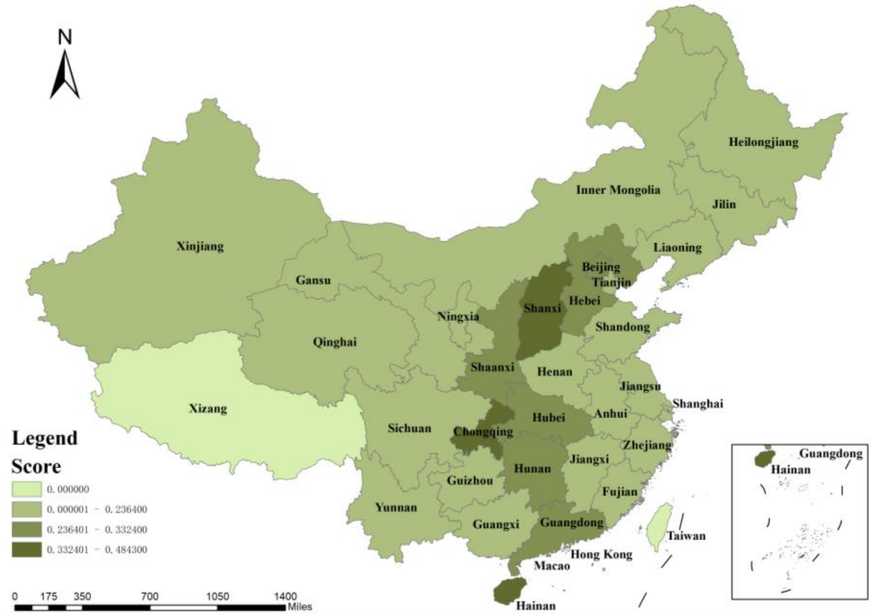

Figure 4. *Distribution of average Digital Economy (DE) development index values across 30 provinces in China over the decade 2013-2022*

Usually, under different types of areas, different land conditions, different natural environmental factors and socio-economic conditions, the comprehensive land utilization rate varies greatly. Even under the same natural conditions, land productivity varies due to different material inputs, scientific and technological levels and management levels. The results of land use change estimation are shown in the *Table 8* below.

From a macroscopic perspective, China's comprehensive land utilization degree has obvious geographical characteristics and agglomeration characteristics (*Fig. 5*). Among them, the phenomenon of agglomeration is most obvious in Yunnan, Guizhou and Sichuan, with the highest degree of comprehensive land utilization in the three provinces reaching 1.58%, 1.91% and 1.54% respectively.

The northern region generally has a high comprehensive land utilization rate, basically reaching a utilization degree of more than 1%. Taking the Hu Huanyong line (demographic distribution demarcation line) as the boundary, the west part of the line and the northeast region have better performance in terms of comprehensive land utilization rate, i.e., the land utilization change is more active; while the middle and lower reaches of the Yangtze River provinces, which are east of the line, have a lower land utilization rate. (0 represents missing data.)

The changes of the national comprehensive land utilization degree in the ten-year study period show a mostly fluctuating decreasing trend, among which the northwest region and Beijing-Tianjin-Hebei region show the most obvious decrease in the comprehensive land utilization rate, which indicates that the effect of returning farmland to forests and lakes and the natural ecological protection project is better in the above mentioned regions in the study period (*Fig. 6*).

In the following, this paper selects four regional representative provinces in the eastern, central, western and northeastern regions of China to analyze the land use transfer matrix for the period of 2013-2022.

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Table 8. *Land use changes (LUC) for 30 provinces in China, 2013-2022*

Region	Year Province	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022	Mean value	Sort by mean
Eastern region	Beijing	1.55%	0.65%	0.66%	0.63%	0.77%	0.70%	0.67%	0.53%	0.20%	0.69%	0.71%	28
	Tianjin	2.36%	0.81%	1.03%	1.11%	1%	0.65%	0.82%	1.30%	0.24%	1.18%	1.05%	15
	Hebei	2.34%	1.66%	2.15%	1.78%	2.05%	1.93%	1.91%	2%	1.28%	2.16%	1.93%	2
	Shanghai	2.02%	1.07%	1.55%	1.34%	1.72%	1.72%	2.02%	1.75%	0.84%	2.34%	1.64%	5
	Jiangsu	1.58%	0.67%	1.13%	1.01%	1.15%	0.94%	0.87%	1.14%	0.46%	1.90%	1.08%	14
	Zhejiang	1.36%	0.57%	0.76%	0.69%	0.60%	0.70%	0.69%	0.57%	0.34%	1.28%	0.76%	24
	Fujian	1.63%	0.68%	0.74%	0.86%	0.91%	0.79%	0.76%	0.72%	0.50%	1.56%	0.92%	21
	Shandong	1.62%	0.55%	0.57%	0.67%	0.63%	0.59%	0.70%	0.51%	0.28%	1.42%	0.75%	25
	Guangdong	1.25%	0.73%	0.68%	0.64%	0.70%	0.76%	0.54%	0.46%	0.14%	1.02%	0.69%	29
	Hainan	1.64%	0.75%	0.78%	0.70%	0.62%	0.79%	0.72%	0.77%	0.28%	1.18%	0.82%	22
Central region	Shanxi	1.59%	0.63%	0.72%	0.80%	0.69%	0.80%	0.69%	0.75%	0.28%	0.95%	0.79%	23
	Anhui	1.30%	0.48%	0.68%	0.76%	0.59%	0.68%	0.64%	0.61%	0.27%	0.91%	0.69%	30
	Jiangxi	1.25%	0.67%	0.68%	0.68%	0.64%	0.64%	0.66%	0.81%	0.27%	0.80%	0.71%	27
	Henan	1.58%	0.75%	1.11%	1.19%	0.89%	0.95%	0.89%	0.89%	0.47%	1.72%	1.04%	16
	Hubei	1.46%	0.76%	0.92%	0.80%	0.91%	0.75%	0.78%	1.61%	0.31%	0.99%	0.93%	20
	Hunan	1.23%	0.51%	0.78%	0.73%	0.71%	0.75%	0.88%	0.60%	0.29%	0.96%	0.74%	26
Western Region	Inner Mongolia	2.02%	0.68%	1%	1.14%	1%	0.92%	0.76%	0.73%	0.37%	1.30%	0.99%	19
	Guangxi	1.90%	0.71%	1.18%	1.25%	1.09%	1.08%	0.94%	0.91%	0.48%	1.65%	1.12%	12
	Chongqing	1.95%	0.82%	1.07%	1.28%	1.19%	1.19%	1.04%	1.15%	0.52%	1.64%	1.19%	11
	Sichuan	2.39%	0.95%	1.42%	1.81%	1.36%	1.25%	1.36%	1.38%	0.71%	2.75%	1.54%	7
	Guizhou	3.39%	1.77%	1.77%	1.53%	2.11%	1.90%	1.70%	1.68%	0.69%	2.62%	1.91%	3
	Yunnan	3.46%	0.78%	1.14%	2.09%	1.27%	1.16%	1.76%	1.38%	0.63%	2.13%	1.58%	6
	Shaanxi	1.86%	0.64%	0.79%	1.06%	0.79%	0.91%	1%	0.87%	0.43%	1.76%	1.01%	17
	Gansu	3.34%	1.18%	1.72%	2.09%	1.54%	1.61%	1.91%	1.73%	0.81%	2.34%	1.83%	4
	Qinghai	2.44%	1.09%	1.21%	1.31%	1.24%	1.42%	1.20%	1.16%	0.64%	1.98%	1.37%	8
	Ningxia	2.08%	0.89%	1.30%	1.23%	1.28%	1.12%	1.19%	1.11%	0.54%	2.42%	1.32%	10
	Xinjiang	1.95%	0.82%	1.19%	1.15%	1.45%	1.22%	1.24%	1.29%	0.56%	2.64%	1.35%	9
Northeast region	Liaoning	1.30%	0.66%	0.82%	0.72%	0.82%	1.17%	1.03%	0.87%	0.52%	2.11%	1%	18
	Jilin	3.60%	1.13%	1.94%	2.20%	2.26%	2.09%	1.78%	2.10%	0.68%	3.93%	2.17%	1
	Heilongjiang	1.65%	0.67%	0.96%	0.88%	0.76%	1.18%	1%	0.80%	0.44%	2.51%	1.09%	13

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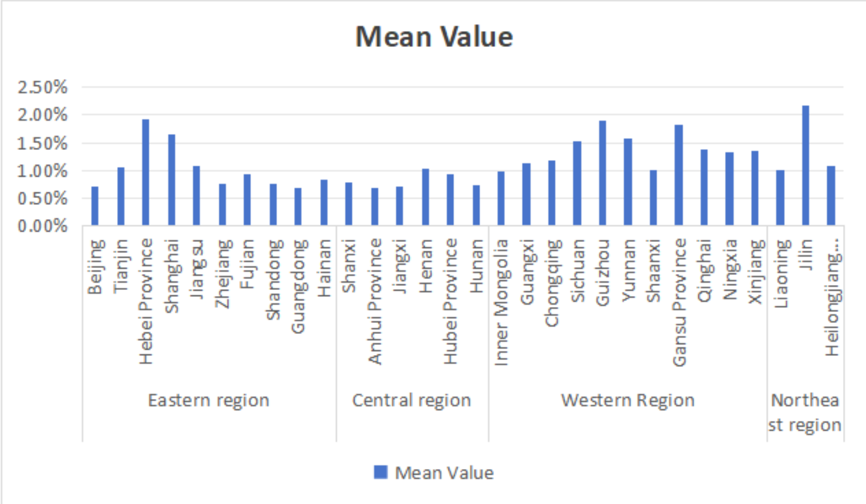

Figure 5. *Average Land Use Change (LUC) development index for eastern, central, western, and northeastern China over the 10-year period 2013-2022*

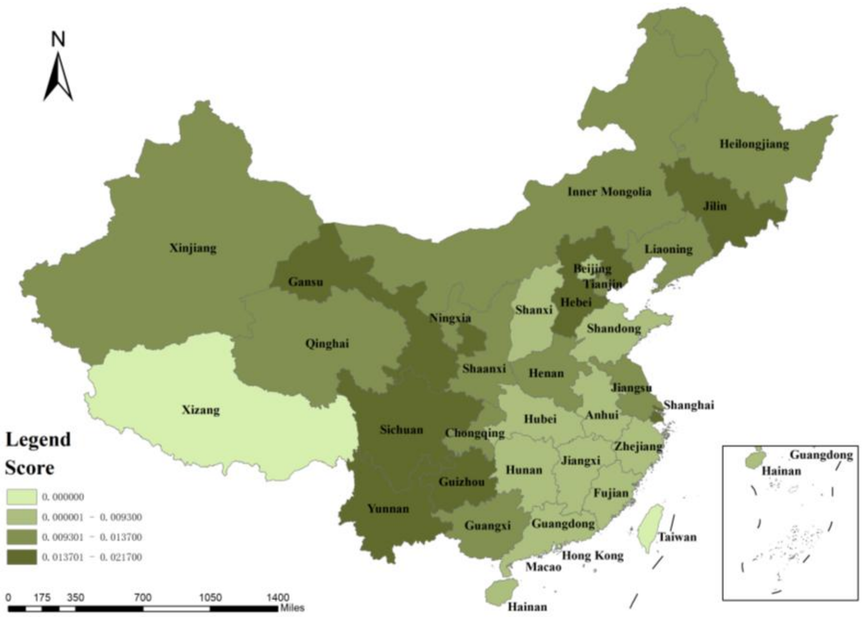

Figure 6. *Distribution of average Land Use Change (LUC) development index values across 30 provinces in China over the decade 2013-2022*

The land use transfer matrix can quantitatively and intuitively present the direction and amount of mutual transformation of different land types during the study period, which helps to reveal the internal process of land use change. Based on this method, we selected the provinces with the median land use change rate in the four regions of the East, Central, West and Northeast as representatives to avoid the interference of extreme values and reflect the typical change characteristics of each region. Shanghai, a highly urbanized city, is selected in the eastern region to represent the developed coastal area; Shanxi, a resource-based province, is selected in the central region to reflect the inland provincial situation dominated by energy industry; Xinjiang, a vast province, is selected in the west

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to reflect the land development and ecological changes in the arid frontier; and Heilongjiang, a large agricultural province, is selected in the northeast to represent the human-land pattern in the high-latitude agroforestry composite area. The development stages and natural endowments of different regions have led to different directions of land-use transformation: arable land in rapidly urbanizing areas has been converted to construction land in large quantities, large areas of arable land in key ecological restoration zones have been returned to forests and grasslands, and there has been an expansion of arable land reclamation in the Three Rivers Plain of the North-East China and in the northern part of Xinjiang.

The 2013-2022 land use transfer matrix of Shanghai shows significant urbanization characteristics: the proportion of arable land transferred to construction land is obvious (*Table 9*). About 5.6% of the initial arable land has been transferred to construction land in 9 years, covering 241.65 square kilometers, reflecting the continuous occupation of arable land by the construction of mega-cities. Meanwhile, the arable land retention rate is about 94% (4074/4334), indicating a relatively limited decline in the total amount of arable land under the strict arable land protection policy. Forest land is small and fragmented, with only 47% of forest land remaining unchanged (about 5.48/11.65 km^2), and a small amount of the remaining portion converted to cropland and construction land, reflecting the pressure of encroachment on green space by urban expansion. It is worth noting that Shanghai has realized the replenishment of arable land through land enclosure and reduced reclamation of construction land, a phenomenon reflected in the matrix by the conversion of waters into arable land (about 140.46 km^2), showing that the loss of arable land has been compensated to a certain extent by the enclosure of mudflats and the restructuring of agriculture. Shanghai is located in the coastal area, where land resources are extremely scarce. The high degree of industrialization and service sector development has led to the expansion of construction land much higher than the national average, and arable land has been mainly replaced by urban construction. At the same time, due to the emphasis on ecological functions, Shanghai has promoted the reduction of low utility land and ecological restoration in recent years, adding new forested land and increasing the proportion of natural land such as forested land and watersheds. Under the combined effect of geographic location and economic drive, Shanghai's land transfer structure reflects a unique pattern of mainly converting arable land to construction land, with reclaimed land supplementing arable land.

Table 9. *Shanghai land use transfer matrix for the period 2013-2022 (square kilometer)*

	Cropland	**Forest**	**Grassland**	**Water**	**Barren**	**Impervious**	**Total**
Cropland	4074.189	3.0825	0.0819	14.922	0.0081	241.6527	4333.937
Forest	6.0669	5.4819	0	0.0162	0	0.0891	11.6541
Grassland	0.0153	0	0.0396	0	0.0477	0.468	0.5706
Water	140.4639	0.0315	0	1156.994	0.0828	14.5089	1312.081
Barren	0.0081	0	0.0036	0	0.1269	0.1368	0.2754
Impervious	0.513	0	0	4.0131	0.0036	2288.757	2293.286
Total	4221.257	8.5959	0.1251	1175.945	0.2691	2545.612	7951.804

The land use transfer matrix of Shanxi from 2013 to 2022 reflects the coexistence of agricultural development and ecological restoration (*Table 10*). Cultivated land shows a net increase of about 3,081 km^2 to 58,833.41 km^2 from the initial total of 55,752.02 km^2, indicating an increase in the total amount of cultivated land. This increase stems mainly

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from the large-scale reclamation of grassland into cropland (13.0% of the initial grassland, or about 7,020.45 square kilometers), reflecting the development of agriculturally desirable grassland driven by food security in recent years. During the same period, some arable land was withdrawn from production and converted into grassland (about 3,308.57 square kilometers) and forest land (419.13 square kilometers), reflecting the implementation of the policy of “returning farmland to forest/grassland” in the Loess Plateau region. The matrix shows a net increase of about 3,367 square kilometers of forested land (from 38,045 to 41,413 square kilometers), mainly due to the conversion of large areas of grassland to forested land (about 3,604.83 square kilometers) and the renewal of shrubs to forested land, which verifies the effectiveness of Shanxi's “Returning Farmland to Forests” project. The forest land retention rate is very high (about 97.6% of the forest land remains unchanged), indicating that the forest resources are generally stable and slightly increasing under the policy of natural forest protection and artificial forestation. Grassland, on the other hand, has suffered a net decrease of about 7,315 square kilometers, most of which has been converted into cropland and forest land, showing that the conversion of land use between cropland, forest land, and grassland has been the most active in the agricultural and animal husbandry intertwined areas. The expansion of construction land is faster, with the area increasing from 7085.13 to 8240.60 square kilometers (an increase of about 16%), of which 869.30 square kilometers of arable land is converted to construction land, accounting for a large proportion of the amount of arable land converted out. This is directly related to urbanization and industrial land expansion under the resource-based economy of Shanxi. On the other hand, land disturbance caused by industrial activities such as mining is also reflected in the matrix: the net increase of bare land area is about 3.57 square kilometers, and there is the phenomenon of arable land and grassland being converted to bare land, showing the impact of mining land and collapsed areas on the land pattern. In summary, the land transfer characteristics of Shanxi reflect the development logic of “one increase and one decrease”: on the one hand, under the requirements of food production and red line of arable land, actively reclaiming and organizing the land (converting grassland to arable land), and on the other hand, under the guidance of ecological policy, withdrawing from the agricultural land in the fragile areas (retiring the arable land to forest and grassland). Overlaying its high per capita arable land but uneven spatial and temporal distribution of water resources and other natural conditions, Shanxi is striving to achieve the balance of arable land through the reclamation of industrial and mining wasteland and other measures, while consolidating the results of returning farmland to forests, and coordinating economic development and ecological protection in the process of energy-based industrial transformation.

Table 10. *Shanxi land use transfer matrix for the period 2013-2022 (square kilometer)*

	Cropland	Forest	Shrub	Grassland	Water	Barren	Impervious	Total
Cropland	51101.7	419.1309	0.621	3308.57	51.8652	0.8352	869.2974	55752.02
Forest	634.8213	37126.27	217.8864	46.9746	0.1476	0.0009	19.0332	38045.13
Shrub	7.4106	262.0512	573.1119	357.1713	0	0.0279	0.0324	1199.805
Grassland	7020.448	3604.827	116.352	43082.22	5.8059	8.1459	277.4529	54115.25
Water	65.4966	0.432	0	2.4363	480.2292	0.5868	30.3858	579.5667
Barren	0.6219	0	0	2.4354	1.2204	1.7748	1.7559	7.8084
Impervious	2.9169	0.0045	0	0.0864	39.4731	0.009	7042.638	7085.128
Total	58833.41	41412.71	907.9713	46799.89	578.7414	11.3805	8240.595	156784.7

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The 2013-2022 land-use transfer matrix for Xinjiang is ambitious, with a total land area of more than 1.63 million square kilometers, demonstrating the coexistence of reclamation expansion and ecological evolution (*Table 11*). The initial area of arable land is 83,491.79 square kilometers, with a net increase of about 3,290 square kilometers to 86,781.55 square kilometers by 2022 after large-scale development. The matrix shows that grassland and bare land are the main sources of arable land expansion: about 9,322.07 square kilometers of grassland (2.4% of the initial grassland) and 1,991.40 square kilometers of bare land have been reclaimed as arable land, reflecting the sustainable use of land resources under the "large-scale development" strategy of the western frontier. During this period, Xinjiang made great efforts to improve farmland water conservancy facilities and promote water-saving irrigation, enabling the reclamation of desert edges that used to have poor soil and water conditions into farmland. In contrast, some 7,680.72 square kilometers of arable land was withdrawn from cultivation and degraded/restored to grassland, indicating that estimates such as "returning farmland to grassland" were implemented in ecologically fragile areas, with farmland that was not sustainable returned to grassland in order to prevent land desertification. The total area of grassland, on the other hand, decreased significantly by nearly 9,745 km^2 (from 382,433 to 372,688 km^2), mainly due to the conversion of large areas of grassland to cropland (2.4%) and bare land (about 34,302 km^2, or 9% of the initial grassland). The conversion of grassland to bare land reflects the trend of pasture degradation and desertification, with large areas of grassland vegetation degraded to desert bare land under the effect of arid climate and overgrazing. The total area of bare land (unutilized land) has increased by a net of about 5,960 square kilometers to 1,103,300 square kilometers, accounting for the bulk of Xinjiang's land. This stems from the aforementioned degradation of grasslands on the one hand, and the impact of glacier ablation on the other: the matrix shows that about 5,338.07 square kilometers of glacier ice and snow melted and were converted into bare land. In the same period, the area of permanent snow and ice decreased by about 1,641 square kilometers (5.2%), which is consistent with the trend of glacier retreat in the Tian Shan and Kunlun Mountains in the context of global warming. The water area decreased slightly (a net decrease of 368 square kilometers), and the recession of some alpine snow and ice meltwater may have led to the shrinkage of lakes. Construction land also increased significantly in Xinjiang, from 3639.93 to 5,292.14 km^2 (an increase of about 45%), with grassland and cropland converted to construction land of about 868.0 and 304.6 km^2, respectively, reflecting the expansion of towns and villages and industrial and mining land, driven by population growth and urbanization in the oasis region.

The land use transfer matrix of Heilongjiang for 2013-2022 reflects the equal importance of agricultural expansion and ecological protection (*Table 12*). The total land area of Heilongjiang province is about 452,500 km^2, of which forest land and cropland are the main land categories, accounting for about 48% and 35% of the province's area, respectively. The results of the matrix indicate a slight net increase in cropland over the study period: initial cropland of 201677.38 km^2 increased to 204307.58 km^2 by 2022 (a net increase of about 2630 km^2). Part of this increase stems from the reclamation of wetlands and grasslands: about 202.50 km^2 of wetlands and 2,556.68 km^2 of grasslands were converted to cropland. However, this has come at an ecological cost - the wetland area has decreased significantly by about 197.8 km^2 (a 36% decrease, from 543.91 to 346.08 km^2), reflecting the fact that there are still some swampy wetlands in places such as the Three Rivers Plain that have been converted into paddy field cultivation areas.

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Table 11. *Xinjiang land use transfer matrix for the period 2013-2022 (square kilometer)*

	Cropland	Forest	Shrub	Grassland	Water	Snow/Ice	Barren	Impervious	Wetland	Total
Cropland	75236.51	44.9406	0.2943	7680.721	75.5019	0	148.653	304.6365	0.5265	83491.79
Forest	116.8551	17467.55	0.6984	18.8649	0.5157	0	0	2.9214	0	17607.41
Shrub	0	0.0135	0.0405	0.0162	0	0	0	0	0	0.0702
Grassland	9322.066	946.2843	5.0436	336370	244.4301	280.5156	34301.84	867.9771	94.9626	382433.1
Water	108.2556	5.5035	0.0162	406.575	7931.23	10.9674	1045.578	110.2239	0.1026	9618.452
Snow/Ice	0.0036	5.8122	0.0009	235.6515	160.1343	31448.18	5338.068	0.8721	0	37188.72
Barren	1991.405	4.8663	0.0666	27863.79	807.1686	3808.309	1062503	403.1415	0.1197	1097382
Impervious	0.4491	0	0	1.917	30.9204	0	4.2894	3602.359	0	3639.935
Wetland	6.0012	0.0009	0	110.7837	1.0728	0	0.0612	0.0045	246.2562	364.1805
Total	86781.55	18474.97	6.1605	372688.4	9250.974	35547.97	1103341	5292.136	341.9676	1631725

Table 12. *Heilongjiang land use transfer matrix for the period 2013-2022 (square kilometer)*

	Cropland	Forest	Shrub	Grassland	Water	Snow/Ice	Barren	Impervious	Wetland	Total
Cropland	194323.4	3074.848	0.4986	2483.285	354.321	0.0153	6.1227	1423.498	11.4147	201677.4
Forest	6775.797	215627.7	16.6698	149.3154	18.7407	0	0.0162	104.4036	0.1431	222692.8
Shrub	0	0	0.0009	0	0	0	0	0	0	0.0009
Grassland	2556.683	203.3334	0.0387	3857.536	54.3816	0.0171	81.1773	266.0022	14.9661	7034.135
Water	386.2035	20.6073	0.0495	23.7519	6786.139	0.0027	52.3863	141.0192	0.0171	7410.176
Snow/Ice	0	0	0	0	0.0027	0.0027	0	0	0	0.0054
Barren	58.1598	0.2556	0	56.0358	31.7079	0.0018	250.3674	41.508	0.0009	438.0372
Impervious	4.8555	0.0171	0	0.6309	200.3436	0	1.3626	12540.61	0	12747.82
Wetland	202.5009	7.9398	0.0108	8.4582	5.3091	0	0.0126	0.1341	319.5396	543.9051
Total	204307.6	218934.7	17.2683	6579.014	7450.945	0.0396	391.4451	14517.18	346.0815	452544.2

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In fact, the scale of conversion of ecological land to cropland in the Northeast had been 3.11 times that of conversion of cropland back to ecological land, and the conversion of forest and grassland to cropland was quite active around 2000. In the northern border area of Heilongjiang, the area of forest land decreased by 3,585 km^2 and the net increase of cropland was 5,507 km^2 from 2000 to 2015, and the conversion of forest land to cropland was the main source of land change in the region. This indicates that forest resources were once eroded under the pressure of agricultural development. However, during the study period, forest land still dominates in Heilongjiang, with an area of 218,934.67 km^2 in 2022, a slight decrease of about 3,758 km^2 compared with 2013, but the main flow of forest land out of forest land is cultivated land reclamation (about 6,775.80 km^2) and a small amount of land for construction, while at the same time 3,074.85 km^2 of cultivated land is restored through "Returning farmland to forests" has restored forest land, which has offset the loss of forest land to a certain extent. Under the influence of the national natural forest protection project and the long-term logging ban policy, deforestation in key forest areas such as the Great and Small Hinggan Mountains has been completely stopped, and it is expected that forest land will remain stable in the future. Grassland accounts for a small proportion (~1.5%) in Heilongjiang, and the matrix shows a net reduction of grassland of about 455 square kilometers, mainly converted to cropland (2,556.68 square kilometers) and forested land, with a portion of the fragmented pastureland being reclaimed by agriculture or utilized for afforestation. Construction land, on the other hand, grew slowly with urbanization, increasing from 12,747.82 to 14,517.18 square kilometers (a 13.8% increase), with about 1,423.50 square kilometers of cropland converted to construction land, reflecting the demand for land for the agglomeration of population to the cities and for industrial development. Of concern is the phenomenon of abandonment and ecological recovery of some arable land in Heilongjiang: about 2,483.29 square kilometers of arable land were converted back to grassland in the matrix, indicating that due to population exodus and low economic efficiency, some arable land in remote areas was withdrawn from cultivation and naturally succeeded to grassland or scrub. The study showed that about 4202.40 square kilometers of arable land were returned to forests and grasslands in the black soil area of Heilongjiang in the past 20 years, accounting for 5.29% of the total arable land, which improved the ecological environment; however, 3017.37 square kilometers of arable land were deserted as a result of occupancy or abandonment by development and construction, accounting for 3.80% of the arable land, which had an unfavorable ecological impact.

To sum up, the sustainable development of GI can only be realized by rationally utilizing the limited land while maintaining innovative technology, paying attention to the green ecology and the red line of arable land without wavering, and other principle issues.

Results of the analysis of regional differences in GI

After completing the estimation work, the paper proceeds to the analysis of regional differences. Generally speaking, 0.4 is the "warning line" for development disparity, and when it is exceeded, the increase in regional disparity is more likely to cause social problems (Barbieri et al., 2025). *Table 13* below presents a summary of the Gini coefficient.

The *Fig. 7* illustrates the Gini coefficient of GI for the entire nation. The overall Gini coefficient for the period from 2013 to 2022 is between 0.3 and 0.7, which is reasonable and the magnitude of macro changes is not large. As China's economy is in a phase of

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rapid development, the difference in the overall GI index is gradually widening, and the overall difference between 2017 and 2022 will continue to widen at a slower rate than that between 2015 and 2017, with the difference curve in the ten-year period showing a gradual upward trend. the Lorenz curve is more reasonable.

Table 13. *Results of Dagum's Gini coefficient decomposition of green innovation (GI) development levels from the eastern, central, western, and northeastern regions, 2013-2022*

Year		2013	2014	2015	2016	2017	2018	2019	2020	2021	2022
Overall Gini coefficient		0.33	0.34	0.34	0.36	0.39	0.40	0.42	0.44	0.46	0.48
Intra-regional Gini coefficient	eastern	0.31	0.31	0.33	0.34	0.37	0.39	0.41	0.42	0.44	0.44
	central	0.09	0.10	0.11	0.11	0.11	0.10	0.10	0.10	0.12	0.14
	western	0.18	0.18	0.17	0.16	0.18	0.18	0.19	0.21	0.22	0.23
	northwest	0.06	0.06	0.03	0.05	0.08	0.07	0.06	0.09	0.10	0.13
Inter-regional Gini coefficient	East-Central	0.37	0.38	0.39	0.40	0.42	0.43	0.42	0.43	0.45	0.45
	East-West	0.47	0.48	0.48	0.51	0.54	0.56	0.59	0.61	0.63	0.65
	East-Northeast	0.44	0.46	0.46	0.51	0.55	0.58	0.59	0.61	0.64	0.66
	Central-Western	0.19	0.19	0.19	0.19	0.21	0.23	0.28	0.30	0.32	0.36
	Central-North-East	0.12	0.14	0.14	0.17	0.20	0.24	0.27	0.29	0.33	0.37
	West-Northeast	0.15	0.15	0.13	0.12	0.15	0.14	0.15	0.17	0.18	0.20
Contribution (%)	regional	22.75	22.42	22.89	22.67	23.25	23.15	23.26	23.41	23.38	23.09
	interregional	68.93	69.35	69.13	70.44	69.85	70.69	70.55	70.34	70.37	70.45
	hypervariable density	8.31	8.23	7.98	6.89	6.90	6.16	6.20	6.25	6.24	6.46

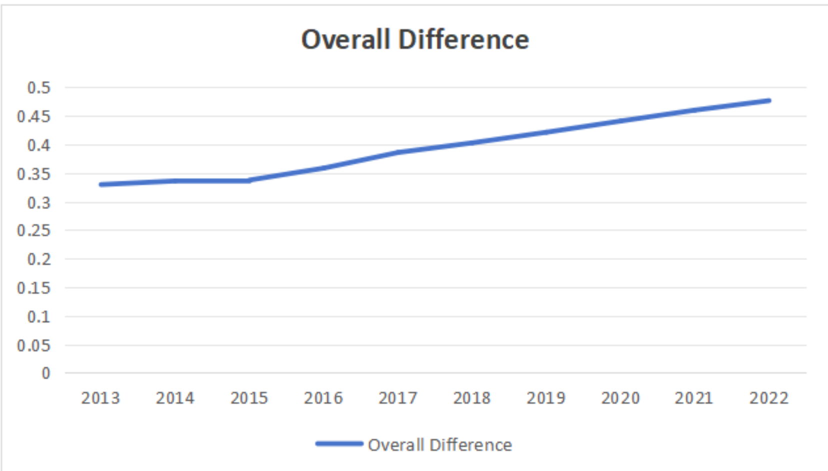

Figure 7. *Trends in overall Gini coefficients for China's 30 provinces over the period 2013-2022*

After comparing the contribution rates, the study found that the inter-regional contribution rate is significantly higher than the other two types of contribution rates. It shows that the main factor contributing to the gradual expansion of the overall Gini coefficient is the large inter-subgroup differences between regions. Therefore, it can be concluded that the key to reducing the overall differences or slowing down the expansion of the overall differences is to reduce the interaction obstacles between provinces and to narrow the development differences.

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The country's thirty provinces are divided into eastern, central, western and northeastern parts by spatial distribution. (Data for Tibet, Hong Kong, Macao and Taiwan are not yet available) The study of Gini coefficients within provinces allows us to analyze the differences in development between provinces (cities and districts) within the region. As shown in the *Fig. 8*, the difference in GI within the eastern part is the largest and gradually expanding over the years; the difference within the central part remains dynamic and stable, basically maintained at the level of agreement within ten years; the northeast region shows a fluctuating slow increase; and the difference within the western part also demonstrates a downward trend with ups and downs and the difference in the value of the difference is lower than that of the other parts of the country.

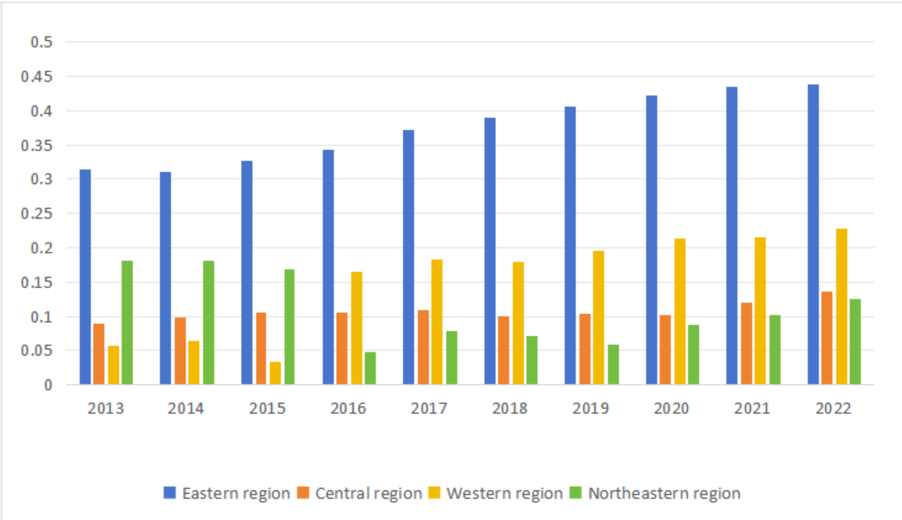

Figure 8. *Trends in Gini coefficients within the four major regions of China: eastern, central, western and northeastern regions, 2013-2022*

By comparing the Gini coefficients of the four regions, the Gini coefficients between the subgroups can be calculated. The coefficient is allocated between 0.12-0.66, in which the value of the Gini coefficient among regions bordering each other is mostly smaller and more reasonable; the Gini coefficient between the eastern part, the northwestern part and the northeastern part is low, that is, the difference in GI is very small, and the change in land use, status of scientific and technological development are the main imbalance factors; the eastern region and the western region and the northeastern region have the largest difference in GI differences are the largest, all of which reached more than 0.43 in ten years, and the only imbalance factor that initially caused this result was the state of scientific and technological development, which became an imbalance between GI inputs and the degree of land use before and after 2018.

In conclusion, GI varies greatly between regions, with different factors contributing to the variation, mainly focusing on land use and digital economy and technological innovation, and basically showing a trend of slow expansion annually. This indicates that the extent of imbalance in GI of new energy enterprises between regions in China is relatively obvious.

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Spatial estimation analysis

Spatial autocorrelation test

Based on the geographic distance matrix, the study calculates the Moran index of GI of 30 provinces (cities and districts) in China from 2013 to 2022 and conducts the significance test, and the results are demonstrated in the table (the P value in the table is the significance level). As shown in the *Table 14* below, the Moran indexes of 30 provinces (cities and districts) in China between 2013 and 2022 are all showed positive and passed the significance level test, indicating that there is a strong positive spatial correlation of GI among different parts of China, and the impact of land use status and digital economy on GI can be analyzed using spatial econometric models.

Table 14. *Moran's index and significance level on Green Innovation (GI) in 30 provinces in China, 2013-2022*

Particular year	I	P-value
2013	0.13	0.041
2014	0.139	0.031
2015	0.132	0.038
2016	0.132	0.038
2017	0.138	0.032
2018	0.142	0.027
2019	0.178	0.008
2020	0.186	0.006
2021	0.19	0.005
2022	0.209	0.003

Moran's I>0 means positive spatial correlation, as the years progress, the value of Moran's index continues to rise. the spatial correlation is getting more and more obvious. The P-value is in the study interval of 2013- 2018 values remain between 0.01-0.05, while in 2019-2022 they are below 0.01. The test was passed and the argument can be continued.

After understanding the relevance of global GI at the regional level in China, this paper further applies the Moran scatterplot study to intercept the Moran index scatterplot for the four years of 2013, 2016, 2019 and 2022 (*Fig. 9*). From a macro point of view, the provinces (cities and districts) in the country have been characterized by more "low-low" and "high-high" clusters than "high-low" and "low-high" clusters over the decade. Provinces (cities and districts) with a lower (higher) level of GI development are more likely to cluster spatially. From the point of view of differences, if there are more "low-low" and "high-high" types of districts and counties, it means that the spatial differences are smaller at this time. In accordance with the theory of technology diffusion, the study focuses on the high-high type (first quadrant HH) and low-low type (third quadrant LL) regions of the Moran scatter plot.

The Northeast and Western regions are mainly clustered in the "Low-Low" quadrant, while the Central part and the Eastern provinces (cities and districts) bordering the Central part are mostly in the "High-High" quadrant. It is apparent that most of the cities with strong GI capacity in the "High-High" quadrant (HH) are located in the eastern coastal economic activity agglomeration area as well as the core areas in the central and western city network system, which not only have high green technology innovation capacity, but also have obvious radiation-driven capacity to the neighboring areas. Gradually formed to the Yangtze River Delta, Shandong Peninsula and the West Coast of the Taiwan Strait City Cluster, the Central Plains Economic Belt, the main "multi-core" sea and land clustering pattern. On the other hand, the regionally developed provinces such as Beijing, Guangdong and Sichuan are mostly located in the "High-Low" (HL) quadrant. The small diffusion effect and the strong reflux effect are important reasons for the differences in technological innovation in their regions. Cities categorized in the "Low-Low" (LL) quadrant are predominantly found in the Northwest and Northeast parts, which are mostly inland resource-exhausted provinces and old industrial bases, and have long been dominated by the crude economic growth of expanding production, and lack of GI inputs for technological development. Through the preliminary analysis of the spatial data, the study found that the general trend of GI development level for each city is evident, additionally, there is a notable positive spatial correlation and clustering tendency; however, the progression of GI is significantly influenced by the phase of economic growth and the clustering effect.

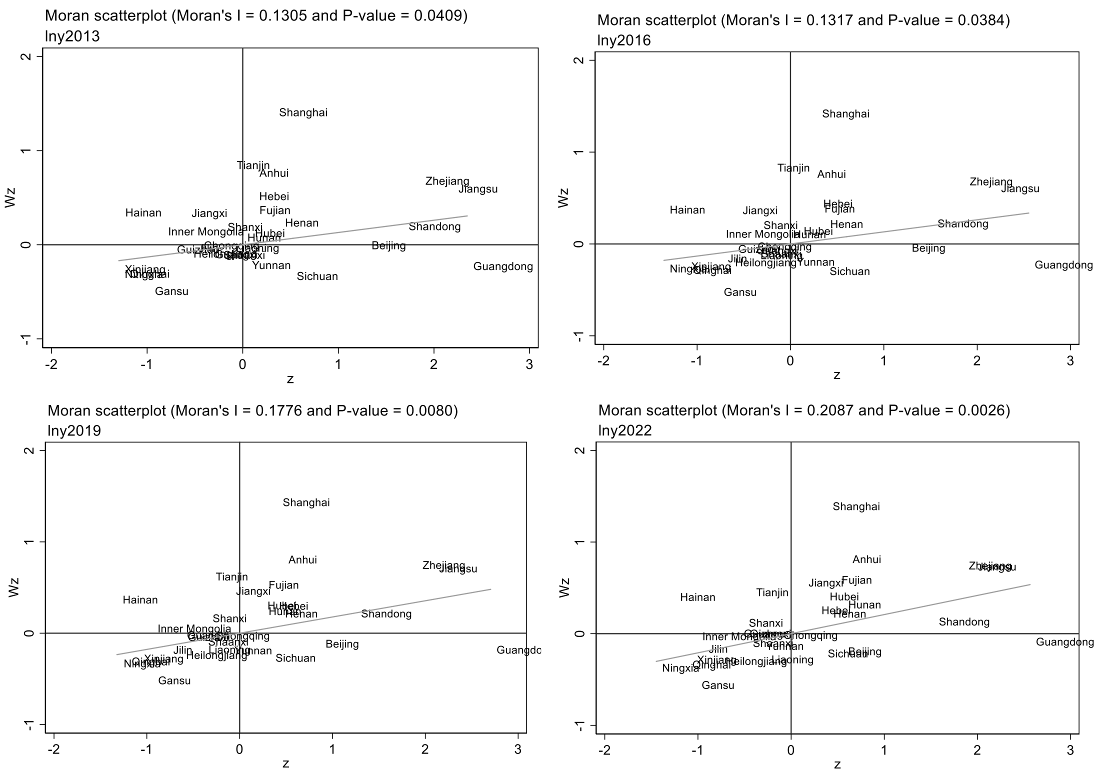

***Figure 9.** Moran scatterplot on Green Innovation (GI) in 30 Chinese provinces in 2013, 2016, 2019 and 2022*

Spatial estimation regression results

(1) Spatial model selection

After completing the spatial autocorrelation test, the paper then proceeds to perform the test in order to select an appropriate spatial model to explore. Before delving into the empirical examination of determinants influencing GI, this study initially conducted a series of diagnostic tests, including LM, Wald, LR, and Hausman tests, to ascertain the

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appropriate model specification. The findings, as depicted in the ensuing *Table 15*, reveal that the LM statistic met the criteria for significance, signifying the presence of spatial autocorrelation in the model's residuals. Consequently, the paper proceeded to refine the model selection through Wald and LR tests. The outcomes demonstrated that both the spatial lag and spatial error models' Wald and LR statistics failed to support the null hypothesis. This indicates that the spatial Durbin model (SDM) provides a more fitting analytical framework for this investigation, and it should not be directly reduced to either the spatial lag or spatial error model. Moreover, the Hausman test's results also dismissed the random effects model hypothesis. Hence, this study ultimately opted for the SDM with time-fixed effects to delve into the spatial spillover effects.

Table 15. *Results of each test for spatial model selection*

Testing Method	Statistic	P-value
LM (lag) test	23.536	0.000
Robust LM (lag) test	20.206	0.000
LM (error) test	3.541	0.060
Robust LM (error) test	0.21	0.646
Hausman test	-157.75	0.000
Wald_spatial_lag	93.18	0.000
LR_spatial_lag	101.23	0.000
Wald_spatial_error	106.32	0.000
LR_spatial_error	99.03	0.000

(2) Spatial Durbin model results

By the spatial autoregressive coefficient p-value of 0.060, which is significant at 10% level and its coefficient is positive, it indicates that GI possesses a beneficial spatial spillover impact on its own development (*Table 16*). From the statistical values in Main, both reached the 1% level of significance, the coefficient of land use change (LUC) is -11.103 and the coefficient of digital economy (DE) is 5.315, indicating that LUC has a negative effect on GI and DE has a positive effect on GI, and the research employs a semi-logarithmic linear model, which takes the following form: $\ln GI_{it} = \rho \sum_{j=1}^{N} w_{ij} GI_{it} + \sum_{j=1}^{N} w_{ij} x_{jt} + \beta_i X_{it} + \gamma_i + \mu_t + \varepsilon_{it}$, GI is taken logarithmic, while the explanatory variables etc. are not taken logarithmic. The coefficients β means the percentage of the average rate of change in GI when LUC changes by one unit. That is, the more frequent the alteration in land use and the higher the extent of utilization, the stronger the promotion of GI; the higher the extent of development of the digital economy is the stronger the promotion of the sustainable economy.

The coefficient of Wx is more indicative of spatial conduction effect than that of Main, by the p-value of LUC and DE is 0.992 and 0.000 respectively, which indicates that DE is significant at 1% level, and the coefficient is -10.274, it can be demonstrated that DE exerts an adverse spatial spillover impact, and that the neighboring areas have a negative conduction effect on the local area to take logarithmic down to get the GI. Therefore, and then concluded on the GI that plays a positive conduction role. That is, the high-speed development of DE in a region will have a positive impact on improving the development of domestic GI, and the sustained development of DE will form a certain geographical advantage, and the beneficial spatial spillover effect will propel the growth of the digital economy sector in adjacent areas, which will in turn radiate to the development of GI in neighboring parts.

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Table 16. *Spatial Durbin model regression results*

ln GI	Variable	Coef.
Main	LUC	-11.103***
	DE	5.315***
	RGDP	1.45E-06
	IS	-0.393*
	HC	-0.143***
Wx	LUC	0.112
	DE	-10.274***
	RGDP	1.97E-05***
	IS	-4.829***
	HC	-0.309***
	Spatial rho	0.209*
	Variance sigma2_e	0.076***

Note: *** indicate $p < 0.01$, ** indicate $p < 0.05$, * indicate $p < 0.1$. GI = Green Innovation; LUC = Land Use Change; DE = Digital Economy; RGDP = Regional Gross Domestic Product; IS = Industrial Structure; HC = Human Capital

Results of decomposition effects of spillovers

In their study, LeSage and Pace (2009) proposed a spatial econometric model with special emphasis on the concepts of direct and indirect effects. The direct impact denotes the consequence of a shift in a region's independent variable on its own dependent variable, whereas the indirect impact signifies the repercussions of that change on the dependent variable in other regions. Such indirect effects reflect spatial spillovers, i.e., how changes in one region affect other regions through spatial correlations. To estimate this effect, they suggest using averages to estimate direct, indirect, and total effects. Subsequently, Elhorst and Fréret (2009) further developed this theory by providing the corresponding statistical test estimates to validate these effects. In analyzing the spatial spillover effects, the direct and indirect effects of the variables were decomposed by means of a matrix of partial derivatives. This allows for a more detailed observation and analysis of the effects of different variables on complex phenomena such as GI, and a more accurate understanding of how key economic indicators such as land-use change and the digital economy interact and influence each other spatially, thus providing a more precise basis for policymaking and economic strategy.

Statistical analysis (*Table 17*) shows that land use change may have a hindering effect on green innovation (GI): its LR direct effect coefficient is -10.985, which is significantly negative, while its LR indirect effect coefficient is -2.061, which does not pass the test of significance; although land use change has a more significant direct negative effect on GI, the total effect is insignificant due to the non-significant indirect effect offsetting part of the direct effect, a finding that complements the study of Liang et al. (2019), who also explored the link between land use and green development and found that the green transformation of land constitutes a certain impediment to the development of GI, and that this change does not have a significant effect on the surrounding area's green development, and that such changes do not have a significant impact on the green development of neighboring regions, probably because frequent land use changes lead to ecological degradation, and large-scale, intensive, and disorderly land changes can drastically reduce the potential space for GI, but it seems that drastic changes in land use in one region do not have a significant spillover or return effect on neighboring regions.

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Table 17. *Results of decomposition effects of spatial spillovers for each variable*

Variable	LR Direct	LR Indirect	LR Total
LUC	-10.985***	-2.061	-13.046
DE	5.010***	-11.591***	-6.582***
RGDP	2.22E-06*	2.5E-05***	2.72E-05***
IS	-0.550**	-6.151***	-6.701***
HC	-0.156***	-0.418***	-0.575***

Note: *** indicate $p < 0.01$, ** indicate $p < 0.05$, * indicate $p < 0.1$. GI = Green Innovation; LUC = Land Use Change; DE = Digital Economy; RGDP = Regional Gross Domestic Product; IS = Industrial Structure; HC = Human Capital

The development of the digital economy can improve GI: its LR direct effect coefficient is 5.010, significantly positive, while its LR indirect effect coefficient is -11.591, significantly negative; the direct effect of the digital economy on GI is significantly positive, but the indirect effect is much more negative, thus the total effect is negative and equally significant; the development of the digital economy provides technical support for GI With the arrival of the digital workplace and big data era, economic interaction is no longer limited to the traditional flow of funds, the digital economy gradually eliminates the limitations of the traditional model of geographic conditions and decision-making errors, and also provides financial support and a relaxed environment for the new concepts of green finance, inclusive development, etc., and its obvious indirect effect will also lead to the development of the digital economy of the developed regions, and enhance the GI of the less developed neighboring regions. Its obvious indirect effect will also drive the development of digital economy in developed regions and enhance the GI of neighboring underdeveloped regions, thus forming a significant spatial spillover effect.

Discussion

This study systematically evaluates the development level of green innovation based on the panel data of 30 provinces in China from 2013 to 2022, and utilizes the spatial Durbin model to reveal the direct and spatial spillover effects of land use change and digital economy on green innovation. The study finds that the overall level of green innovation in China is still at a low to medium stage, with significant regional differences, showing a spatial pattern of “high in the east and low in the west”, and obvious spatial clustering and polarization phenomena, which verifies the unbalanced diffusion characteristics of green innovation among regions. The direct effect of land use change on green innovation is significantly negative, indicating that frequent land development and ecological disturbance may damage the ecosystem service function and inhibit the spatial carrier and resource base of green technological innovation, although its spatial spillover effect is not significant, but it does not effectively alleviate the local negative effect, reflecting the short-sightedness and fragmentation of the current land use policy in the green transformation. At the same time, the direct promotion effect of digital economy on green innovation is remarkable, indicating that digital technology effectively promotes the research and development and application of green technology by enhancing the efficiency of resource allocation, optimizing the industrial structure and reducing the cost of information; however, its negative spatial spillover effect is stronger, which may be attributed to the siphoning effect of the developed regions on the

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surrounding areas. However, its negative spatial spillover effect is stronger, probably due to the “siphoning effect” of developed regions on neighboring regions, i.e., the concentration of resources, talents and capitals in the digitalized highland, which in turn inhibits the green innovation capacity of neighboring regions, forming an unbalanced pattern of green innovation under the “digital divide”. In addition, the spatial autocorrelation of green innovation has been increasing year by year, indicating that the path dependence and institutional barriers to the diffusion of green technology between regions are intensifying, and the heterogeneity of regional development stages has further amplified the differences in the impacts of land use and the digital economy on green innovation. Therefore, future policy design should go beyond local perspectives, strengthen cross-regional synergistic governance, promote the green integration of land use planning and digital infrastructure construction, and build a green innovation community centered on ecological prioritization and digital empowerment, so as to achieve coordinated and sustainable regional development under the goal of “dual-carbon”.

Conclusions and recommendations

Conclusion

The paper estimated China's GI development using the global entropy-Topsis method and the Dagum Gini coefficient, with an examination period of 2013-2022, analyze its spatio-temporal evolutionary process and developmental differences, and at the same time, the SDM model has also been used to identify the spatial impacts of land use change and the digital economy on GI, and reached the following conclusions: The national average level of GI is low but shows an upward trend, and there is a significant difference between the eastern, central, western and northeastern parts, in which the eastern region performs the best, the northeastern and central parts are second, and the western region is relatively backward; meanwhile, the distribution of GI among the cities shows agglomeration characteristics and regional hierarchies, and the development of GI in one region can contribute to the enhancement of the surrounding regions, but there are also polarization phenomenon and return effect, in addition, the spatial conduction effect is significant, good land use change and digital economy development make positive difference to GI, although the direct effect of land use change about green and high-quality development is negative, however, the total effect is not significant, perhaps due to the positive elements of the indirect effect to offset part of the direct effect, and the digital economy has a considerable direct positive effect on GI, however, the indirect effect is stronger, resulting in a negative total effect, and the spatial spillovers between regions are more pronounced, meanwhile, the government's land use policy, natural geographic conditions and the development level of the digital economy have a profound effect on GI.

Recommendations

Improving the allocation of land resources to enhance the effectiveness of land use

Formulate all-encompassing land use plan, promote green building standards, adjust land tax policies to incentivize environmentally friendly development, improve land transfer mechanisms, increase urban greening, protect agricultural land, adhere to the "1.8 billion mu" of arable land, designate ecological protection zones, set up a market for

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the trading of land-use rights, strengthen land-use monitoring, and raise public awareness of land use and environmental protection. Relevant departments should enhance public awareness of land environmental protection, utilize advanced technologies such as geographic information systems (GIS) to improve management effectiveness, and at the same time strengthen collaboration among different departments to jointly promote efficient utilization of land resources, facilitating the process of GI.

Accelerating the cultivation of digital economy industries and tapping into the internal energy of new elements

Promoting regional GI, the application of the digital economy in the financial sector is particularly crucial, especially in green and science and technology finance, through blockchain technology, AI, big data integration and other cutting-edge technologies, big data analysis and mobile payment, to enhance the transparency and credibility of green finance, and thus expand its market influence. Commit to removing barriers in the field of GI and building an efficient and integrated science and technology financial service platform to serve innovative entities. Strive to build a diversified green financial framework to reduce the financial burden of GI through credit support and preferential policies. Continuously innovate science and technology financial products and service models to ensure adequate financial support for GI activities and open up more long-term financing avenues for low-carbon enterprises, while building an effective financial incentive system.

Be careful of reflux and polarization effects, rationally combine land use with the digital economy, form a joint force to improve the GI level and achieve balanced development

To promote the sustainable development of green innovatiion, a balanced regional development strategy should be implemented, ensuring equitable distribution of resources and avoiding polarization. Establishing regional cooperation mechanisms will foster resource sharing and reduce backflow effects. Land use planning must align with GI needs, protect the environment, and prevent disorderly development. Support for green technology innovation through R&D incentives, fiscal subsidies, and tax benefits is essential. Green financial policies, such as green credit and bonds, should direct funds to GI projects. Strict environmental supervision and public participation will ensure responsible development and social consensus. Furthermore, integrating land use with the digital economy using GIS, remote sensing, and AI will enhance planning, promote smart agriculture and cities, and optimize resource use while advancing GI development.

Guiding land and digital policies to synergistically drive green innovation

The findings of this study can be directly embedded in the preparation and evaluation of land spatial planning and digital China strategy: on the one hand, identifying the negative impacts of land use changes and their spatial boundaries can provide quantitative basis for governments at all levels to draw ecological protection red lines, formulate land use intensification indexes, and differentiate land supply policies, so as to avoid erosion of green innovation vectors by the “pie” type of expansion. On the other hand, revealing the promotion of local green innovation and the siphoning effect of digital economy on neighboring places can help embed the green finance and talent enclave mechanism in the layout of “East Counts, West Counts” hubs, new data centers and 5G base stations, and transform the positive externalities of the digital dividend into the positive

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externalities of the digital dividend through the trans-regional financial compensation and the trading of data elements. Through cross-regional financial compensation and data element trading, the positive externalities of digital dividend will be transformed into synergistic power of green innovation, and the spatial coupling and policy resonance of land use, digital infrastructure and green transformation will be realized eventually.

Shortcomings and prospects

Shortcomings

Although this paper has made some progress in green innovation estimation and identification of spatial effects, the following limitations still exist: firstly, although the green innovation index system covers multi-dimensional dimensions such as resource input, technology transformation and environmental performance, the availability of data on the quality of green patents, the diffusion paths of green technologies and the micro-behavior of enterprises is still limited, which may have underestimated the real level and dynamic evolution of green innovation; secondly, the green innovation index system is still limited in terms of the quality of green patents, the diffusion paths of green technologies and the micro-behavior of enterprises. Second, the estimation of land use change is mainly based on remote sensing raster data and transfer matrix, and has not yet fully incorporated institutional variables such as land policy intensity, land use efficiency and ecological restoration potential, which may have weakened the institutional regulation of land use policy on green innovation; Third, although the digital economy indicators cover core dimensions such as user scale, infrastructure and industrial output, they do not have a clear understanding of digital technology penetration and platform economic activity. Although the digital economy indicators cover core dimensions such as user scale, infrastructure and industrial output, they are not sufficiently involved in detailed indicators such as the penetration rate of digital technology, the activity of platform economy and the level of green digital governance, making it difficult to comprehensively reflect the complex mechanism of the digital economy's impact on green innovation; finally, although the spatial econometrics model can capture the spatial dependence of inter-regional green innovation, the identification of interactions among spatially heterogeneous factors such as institutional environments, market mechanisms and policy differences remains insufficient. In the future, multi-level models or machine learning algorithms should be introduced to improve the accuracy and robustness of causal identification.

Prospect

Future research can be deepened and expanded in the following aspects: first, to construct a green innovation database integrating macro and micro perspectives, integrating multi-source data such as green patents, green finance, corporate ESG performance and urban green governance, so as to improve the systematic and dynamic nature of green innovation estimation; second, to introduce institutional variables such as land use policy intensity, ecological compensation mechanism and green spatial planning, so as to construct a “land use policy intensity” and a “green spatial planning” model, so as to improve the accuracy and robustness of green innovation estimation. Secondly, we introduce institutional variables such as land use policy intensity, ecological compensation mechanism and green spatial planning to construct a “land use-ecosystem service-green innovation” conduction path model, revealing the long-term impact

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mechanism of land system change on green innovation; thirdly, we deepen the research on the non-linear relationship between digital economy and green innovation, and explore the relationship between digital infrastructure, green computing power center and green innovation. Thirdly, we will deepen the research on the non-linear relationship between digital economy and green innovation, explore the threshold effect and synergistic effect of digital infrastructure, green computing center and green financial platform on green innovation, and identify the optimal path for green transformation empowered by digital technology; fourthly, we will construct a framework for collaborative governance of cross-regional green innovation, and combine spatial measurements, complex networks and policy simulation to simulate the spatial evolution trend of green innovation under different policy scenarios, so as to contribute to the reduction of the gap of regional green innovation and the realization of “dual carbon”. This will provide a policy experiment platform and decision-making support tools for narrowing the regional green innovation gap and realizing regional coordination under the “dual-carbon” goal.

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