Spatial Spillover Effect of Green Innovation on Eco-environmental Quality: an Empirical Study in Eastern Yangtze River Delta Area of China

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Abstract. Green innovation is the critical driving force behand the coordinated development of ecological environment and economy. The article utilizes the panel data of 25 cities located in the typical Yangtze River delta area of East China from 2012 to 2020 as a sample, and employs the Spatial Dubin Model to explore the local effect and spatial spillover effect of green innovation on eco-environmental quality. The findings indicate that the eco-environment status index of cities in East China fluctuates and rises as a whole, but there are significant differences between the cities. Furthermore, it shows obvious spatial aggregation characteristics. There is a remarkably positive spatial spillover effect on eco-environmental quality. Green innovation and the urbanization rate contribute to the enhancement of the eco-environmental quality with conspicuous spatial spillover effects. Population density and industrial structure have significant inhibitory consequences on the ecological environment. Science and technology expenditure is not beneficial for the ecological environment index improvement in the area, while its influence on neighboring regions is insignificant.

Keywords: green innovation • eco-environmental quality • spatial spillover effect •Yangtze River Delta area

1 Introduction

China has achieved remarkable success in rapid economic growth, which has, however, led to a host of significant ecological and environmental issues that cannot be overlooked [1]. Regional economic growth has unlimited demand for natural resources, but the supply capacity of resources is limited, especially in the cities of east China. Facing the dual challenges of economy development and environmental conservation, it is essential to rely on sustainable development to break the deadlock between economic gain and the depletion of resources and environmental degradation [2]. The improvement of environmental quality requires good economic foundation support, and the carrying capacity of the environment affect the sustainable economic development of a region. In order to completely solve the serious and unsustainable problems such as

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high emissions, high energy consumption and high pollution behind the rapid economic growth, promoting green development is a necessary way to accelerate the construction of ecological civilization. Owing to its dual characteristics of innovation-driven nature and green development, green innovation plays a considerable role in sustainable development [3].

Green innovation represents an environmentally-conscious innovation activity that mitigates environmental impacts. Specifically, it involves the development, application, and introduction of novel concepts, behaviors, products, and procedures that help reducing the environmental burden of a business or achieving ecologically specific sustainability goals [4]. A number of studies on green innovation have focused on ascertaining whether it is beneficial for enhancing environmental quality [5, 6]. Empirical studies indicated that green innovation can enable a company to reduce waste [7], decrease its adverse ecological effects [8]. Nevertheless, it is uncertain how green innovation to impact eco-environmental quality, especially in from a spatial perspective [9]. Differences in natural conditions, economic foundations, industrial structures, and other aspects among cities have given rise to significant variations in the impact of green innovation on the ecological environment [10]. The relationship between green innovation and eco-environmental quality from a spatial perspective is becoming an emerging research field.

The relationship between the coordinated development of economy and environmental governance under green innovation is mainly manifested in three dimensions. Firstly, green innovation injects new impetus into economic development, which accelerates the greening of the production process, promotes in-depth research and development in related fields, enriches the effective supply of ecological and improves environmental protection products. Secondly, the positive externalities brought by economic development reduce the production costs of enterprises, and the knowledge spillover between industries promotes enterprise innovation, which benefits to reduce the production energy consumption of enterprises, achieve better matching of production factors, improve resource use efficiency, and enhances the competitiveness of enterprises. Lastly, environmental governance has an optimization and promoting effect on economic development. Based on the government annual report, it was shown that the cost of environmental control increased by 1%, the R&D investment intensity, the number of patents granted and the sales revenue of new products increased by 0.12%, 0.30% and 0.22%, respectively. In short, economy, innovation and environment owns a relationship of mutual influence and mutual constraint, which also has internal consistency. Not only innovation is an important factor in the improvement of resources and environment, but also environmental improvement and economic development can provide driving force for innovation and development. The investment of innovative factors can improve the utilization rate of resources and improve the level of environmental management, and also it can provide economic entities with a green economic development environment and achieve sustainable development of environmental economy.

This research is intended to analyze the spatial effect of green innovation on eco-environment quality at the city level in a typical Yangtze River Delta (YRD) area of east China. In comparison with the current studies in this domain, this research fills the following research voids. To begin with, the study provides new evidences to illustrate the spatial effect of green innovation on eco-environment quality by utilizing a panel data of 25 cities in China's YRD eastern region. Furthermore, it is firstly attempts to use eco-environment status index to assess urban eco-environmental quality comprehensively.

2 Materials and Methods

2.1 Samples and Variables

The research investigates panel data of 25 cities (Jiangsu Province, Zhejiang Province and Shanghai) in China's typical (YRD) region to find out the spatiotemporal evolution patterns and also the impact of green innovations on eco-environment quality from 2012 to 2020. Yangtze River Delta integration development is one of most important national development strategies in China. While, Yangtze River Delta eco-green integrated development is the most important part of the regional integration development [11]. By fully taking the advantages of the YRD region in terms of population, economy, science and technology, etc., it is urgent to promote green innovation and take the lead in achieving the sustainable development goal [12]. Therefore, taking the typical area of YRD Region (Jiangsu Province, Zhejiang Province and Shanghai) as the research sample is representative.

The variable that this study depends on is the quality of the eco-environment, which is represented by an eco-environment status index (EI) to depict the overall condition of the regional ecological and environmental quality [13]. The eco-environment status index is drived from the "Technical Criterion for Ecosystem Status Evaluation". According to the Technical Criterion, the ecological environment index weighted by biological abundance index (BI), vegetation cover index (VI), water network density index (WI), land stress index (LI) and pollution load index (PI) was used as the ecological environment evaluation index, that is,

$$EI=0.35\times BI+0.25\times VI+0.15\times WI+0.15\times(100-LI)+0.1\times(100-PI) \tag{1}$$

The data of the EI is derived from the governmental environmental status bulletin of each city, such as Jiangsu Province Environmental Status Report, Zhejiang Province Ecological Environment Status Assessment Report and the municipal environmental protection bureaus.

The key independent variable is green innovation. Since the statistical data of green patents mainly reflect the innovation, application and promotion of technologies such as resource conservation, energy efficiency improvement, pollution abatement and prevention, and the realization of cleaner production, compared with other analysis methods, the level and scale of green innovation activities in a region can be measured more intuitively [14]. Hence, this article employs the logarithm of green patent data applications to indicate urban green innovation level [15]. The data is obtained based on all patent application details disclosured by the State Intellectual Property Office and in conjunction with the green patents ISC codes in the green patent list furnished by the World Intellectual Property Organization.

The quality of ecological environment is closely related to the level of regional economic development and regional innovation ability. First of all, economic development has become an important financial foundation of the ecological environment, and the high-quality development of the economy can also effectively protect the ecological environment and improve the eco-environmental quality. Meanwhile, the improvement of ecological environment quality can reduce the cost of economic development and provide important support for economic development. Secondly, there is an inextricable link between the ability of regional technological innovation and the ecological environment. With the advancement of ecological civilization construction, green innovation has become an important way to protect the ecological environment. With the support of green innovations such as new energy applications with relatively high scientific and technological content, energy saving, safety, environmental protection and balanced energy consumption, green innovation greatly affect the ecological environment. Therefore, the following five control variables are selected: population density (Des), economic development level (GDP), science and technology expenditure (Govte), industrial structure (Ins) and urbanization level (Urb). Population density is indicated by the population per unit area. Economic development level is measured by GDP per capital of each city. Science and technology expenditure is calculated by the proportion of science and technology expenditure to public financial expenditure. Infrastructure level is measured by the road area per capita. Urbanization level is determined by the urban population proportion. Opening-up level is calculated by the ratio of FDI to GDP. The data of control variables are collected from the China Statistical Yearbook, China Urban Statistical Yearbook, China Statistical Yearbook on Science and Technology. Some of missing data are sourced from the municipal statistical yearbook.

2.2 Spatial Auto-correlation Analysis

Global spatial autocorrelation is capable for reflecting the overall traits of spatial correlation. It is generally measured by global Moran's I index, which can be calculated as:

$$\text{Moran's } I = \frac{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}(x_i-\bar{x})(x_j-\bar{x})}{S^2\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}} \tag{2}$$

where, $S^2 = \frac{\sum_{i=1}^{n}(x_i-\bar{x})^2}{n}$ is the sample variance, x_i is the observed value of region i, n is the number of regions; w_{ij} denotes the spatial weight matrix. This study measured the spatial weight matrix by geographic distance weight matrix and geographic adjacency weight matrix, respectively.

Local Moran's I is used to examine whether similar or dissimilar observed values cluster in local regions. Local Moran's I is calculated as:

$$I_i = \frac{\sum_{i=1}^{n} W_{ij}(X_i-\bar{X})(X_j-\bar{X})}{S^2} \tag{3}$$

2.3 The Spatial Econometric Model

Since the spatial durbin model contains both the spatial lag terms of independent variables and dependent variables, which can comprehensively reflect exogenous and endogenous spatial effects and eliminate the problem of parameter estimation losing meaning due to error terms, making it more general and universal. The SDM can generally be formulated as below:

$$Y=\rho WY_{it} + X_{it}\beta+\theta WX_{it} + \mu_i + \mu_t + \varepsilon_{it} \quad (4)$$

where, Y_{it} is the explained variable; X_{it} represents the explanatory variable; ρ and θ denote the spatial regressive coefficients; μ_i and μ_t denote the spatial effect and time effect, ε_{it} represents random error. W is the spatial weight matrix. And the specific spatial econometric model can be expressed as:

$$EI_{it} = \alpha_0 + \alpha_1 Gp_{it} + \alpha_2 X_{it} + \mu_i + \mu_t + \varepsilon_{it} \quad (5)$$

where, EI_{it} represents the eco-environmental quality of the city i at year t; Gp_{it} represents the green patents of city i; α_1 represents the spatial spillover coefficient; X_{it} denotes the control variables.

3 Results and Discussion

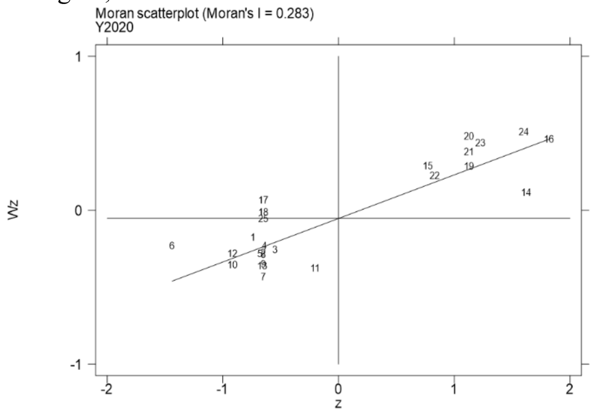
3.1 Analysis of Spatial Autocorrelation

The results of Global Moran's I value of eco-environmental quality are shown in Table 1, which are calculated under the conditions of two spatial weight matrixes by STATA 16. The results demonstrate that all the global Moran's I of EI passed the significance test at the 1% significance level. This implies that eco-environmental quality of cities in China's YRD eastern region has not been randomly distributed over these years. The global Moran's I of each year is positive, indicating that eco-environmental quality has a significant positive spatial autocorrelation. As depicted in Table 1, the spatial dependence of eco-environmental quality has shown a significant increase.

Table 1. Moran's I value of EI

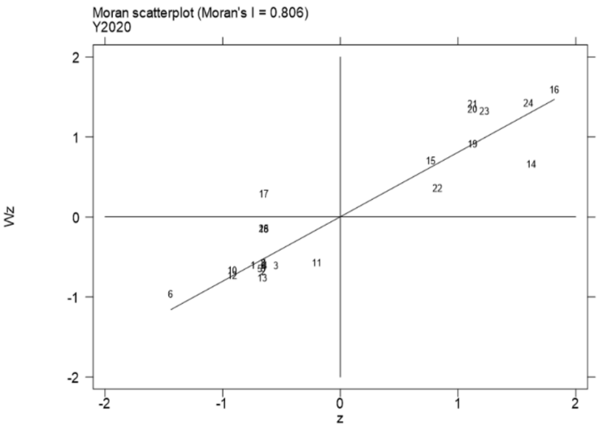
Year	Geographic distance matrix			Geographic adjacency matrix		
	Moran's I	Z value	P value	Moran's I	Z value	P value
2012	0.239	6.87	0	0.658	5.989	0
2013	0.218	6.399	0	0.652	5.971	0
2014	0.231	6.687	0	0.683	6.215	0
2015	0.245	7.005	0	0.752	6.774	0
2016	0.248	7.054	0	0.727	6.546	0
2017	0.254	7.153	0	0.741	6.622	0
2018	0.261	7.312	0	0.741	6.606	0
2019	0.250	7.088	0	0.735	6.589	0
2020	0.283	7.887	0	0.806	7.192	0

Local spatial autocorrelation test results of eco-environmental quality based on geographical matrix and the adjacent matrix of 25 cities in Jiangsu, Zhejiang and Shanghai area are shown in Figure 1 and Figure 2, respectively. From both of Figure 1 and Figure 2, it can be found that most of cities are located in the third and first quadrants. The first quadrant includes cities which own high eco-environmental quality and are surrounded by the cities with high eco-environmental quality, such as, Jiaxing, Zhoushan and Hangzhou, etc. The third quadrant includes low-low clustering type cities, such as Nantong, Zhenjiang, Nanjing, etc. This finding further demonstrates that there is a significant positive spatial autocorrelation of eco-environmental quality in China's eastern YRD region, which is also in accordance with the results of Global Moran's I.



Notes: 1=Nanjing; 2=Wuxi; 3=Xuzhou; 4=Changzhou; 5=Suzhou; 6=Nantong; 7=Lianyungang; 8=Huai'an; 9=Yancheng; 10=Yangzhou; 11=Zhenjiang; 12=Taizhou of Jiangsu Provice; 13=Suqian; 14=Hangzhou; 15=Huzhou; 16=Jiaxing; 17=Jinhua; 18=Lishui; 19=Ningbo; 20=Quzhou; 21=Shaoxing; 22=Taizhou of Zhejiang Province; 23=Wenzhou; 24=Zhoushan; 25=Shanghai.

Fig. 1. Local spatial autocorrelation test of EI under geographic distance matrix



Notes: 1=Nanjing; 2=Wuxi; 3=Xuzhou; 4=Changzhou; 5=Suzhou; 6=Nantong; 7=Lianyungang; 8=Huai'an; 9=Yancheng; 10=Yangzhou; 11=Zhenjiang; 12=Taizhou of Jiangsu Provice; 13=Suqian; 14=Hangzhou; 15=Huzhou; 16=Jiaxing; 17=Jinhua; 18=Lishui; 19=Ningbo; 20=Quzhou; 21=Shaoxing; 22=Taizhou of Zhejiang Province; 23=Wenzhou; 24=Zhoushan; 25=Shanghai.

Fig. 2. Local spatial autocorrelation test of EI under Geographic adjacency matrix

3.2 Analysis of Spatial Econometric Model Regression

The results of LM test, robust LM test and Wald test are shown in Table 2. As shown in Table 2, all results rejected the null hypothesis at 1% significance level. Thus, the

SDM is best suitable for this study. Additionally, the Hausman test was used to identify whether a fixed-effect or random-effect model was chosen. In this study, Hausman test results indicate that it rejects the null hypothesis and passed the significance test at 1% level of confidence. Thus, fixed-effect model is adopted for analyzing the spatial spill-over effect of green innovation on eco-environmental quality.

Table 2. The results of LM test, robust LM test and Wald test

Statistical tests	SLM		SEM	
	Z-value	P-value	Z-value	P-value
LM test_	2.130	0.034	14. 865	0.000
Robust LM	3.849	0.000	17.202	0.000
LR test	15.18	0.013	1051.01	0.000

The spatial econometric regression results are presented in Table 3. As presented in Table 3, under the geographic distance matrix, the estimated parameter of Gp is 3.723 and significant at the 1% level. It implies that green innovation contributes to the optimization and improvement of eco-environmental quality. Additionally, the coefficient of W×Gp is 17.996 and is significant at the 1% level, implying that green innovation in local cities is also essential for improving the eco-environmental quality in neighboring cities. Under the adjacency matrix, the estimated parameter of Gp is not significant, and the coefficient of W×Gp is 5.772 and is significant at the 1% level. To sum up, under the national policies and systems that encourage green innovation, the ecological environment can be effectively improved.

According to Table 3, it is evident from the significant negative coefficients of direct and indirect effects of population density that the pressure of population on the eco-environmental quality is still mainly reflected in the rise of the number of people per unit area, and the high per capita consumption level in Jiangsu, Zhejiang and Shanghai is more likely to cause ecological imbalance, so it brings negative effects. The level of economic development exerts a negative impact on the EI. Although the negative effect on the eco-environmental quality of the region itself is not pronounced, it has a substantially negative impact on the eco-environmental quality of the surrounding cities. Simultaneously, it can be seen that the industrial structure has a significant negative impact on the EI. The reason is that the government's economic development level still mainly depends on industry and manufacturing, etc., and the pollution emissions have a negative effect on the EI in the region. Furthermore, with the intensification of ecological environment regulation in the region, relevant polluting enterprises will transfer to neighboring areas, thereby bringing inhibitory effects to the eco-environmental quality of these areas.

Table 3. Spatial Dubin model quantitative regression results

	Y	Geographic distance matrix	Geographic adjacency matrix
Main	Gp	3.723*** (0.135)	-0.108 (0.200)
	Dens	-14.108*** (0.002)	-8.037*** (0.112)
	GDP	0.093 (0.732)	1.247*** (0.130)
	Govte	-172.23*** (0.001)	-102.433** (0.020)
	Ins	-29.254*** (0.008)	-38.834* ** (0.001)
	Urb	0.559*** (0.002)	0.137 (0.142)
Wx	Gp	17.996*** (0.001)	5.772*** (0.001)
	Dens	-79.337*** (0.001)	-1.809(0.441)
	GDP	-5.585*** (0.006)	-2.134*** (0.031)
	Govte	512.682** (0.031)	-32.386 (0.705)
	Ins	-27.934 (0.723)	22.744 (0.350)
	Urb	4.208*** (0.102)	0.357*** (0.064)
ρ		0.657***	0.751****
Adj-R^2		0.6212	0.3554
Log-likelihood		-673.636	-679.608

Note: ***, ** and * indicate significance at 1%, 5% and 10% level respectively.

Since these models incorporate a spatial lag term, the estimation results cannot directly represent the marginal effect of the variables. Consequently, the partial differential method is employed to assess the direct effect, indirect effect, and total effect under geographical weight matrix, with the outcomes presented in Table 4. The coefficient of green innovation is significantly positive and passed the test at the significance level of 1%. It indicates that a 1% increasement in green innovation can result in a 5.776 increasement in local eco-environmental quality. When it comes to the indirect effect, coefficient of green innovation is 61.357 and significant at 5%. Thus, enhancing green innovation in local areas will improve EI both in local regions and in adjacent cities. From the decomposition results of the control variables displayed in Table 4, the direct and indirect effect coefficients of urbanization rate are significantly positive, indicating a positive effect on the region and surrounding cities. It might be explained by that the government can protect the ecological environment by standardizing scientific urban planning and functional positioning, as well as policy support. Additionally, surrounding cities can benefit from the ecological advantages of the region, which will subsequently influence the relevant models of the region.

Table 4. Spatial effect of green innovation on EI under geographical weight matrix

	Direct effect	Indirect effect	Total effect
Gp	5.776***	61.357**	67.133**
Dens	-22.983*	-267.16***	-290.143***
GDP	-0.423	-16.285*	-16.707*
Govte	-135.748**	1190.394	1054.646
Ins	-34.582*	-156.45	-191.032
Urb	1.013*	13.729**	14.742**

Note: ***, ** and * indicate significance at 1%, 5% and 10% level respectively.

4 Conclusion

This study explores panel data of 25 cities in China's YRD eastern region during the period 2012-2020 to analyze the spatial spillover effects of green innovation on eco-environmental quality. The findings conclude that the eco-environmental quality of Jiangsu, Zhejiang and Shanghai urban agglomerations showed a fluctuating upward trend. From a sub-regional perspective, cities in Jiangsu Province showed a gradual upward trend, while Shanghai's eco-environmental quality rose low. The eco-environmental quality of Jiangsu, Zhejiang and Shanghai urban agglomerations is mainly located in the first and third quadrants spatially, showing a significant positive correlation. The SDM regression results reveal that green innovation has a significantly positive effect both on local eco-environmental quality and on its neighboring cities. Overall, green innovation makes a substantial contribution to improving the eco-environmental quality across the entire region. Moreover, the urbanization rate is beneficial for the enhancement of eco-environmental quality and exhibits obvious spatial spillover effects. Population density and industrial structure have a significant inhibitory effect on the eco-environmental quality. Science and technology expenditure is not advantageous for the improvement of the eco-environmental quality in the region, but the impact on neighbouring areas is not significant.

Based on the research, policy suggestions are put forward. Firstly, it is recommended to strengthen the transformation and application of green innovative technologies and strengthen the concept of green ecology. Under the strategy of green innovation and development, technological innovation will be closely integrated with the market based on the market demand. Furthermore, it is suggested to strengthen environmental protection and pollution control, make full use of technological innovation resources, optimize resource allocation, improve innovation output, improve green technology innovation, and achieve a mutual benefit. Secondly, all regions should pay attention to changing the traditional thinking of economic development, abandon the backward consciousness of unilaterally pursuing industrial indicators, actively promote the exchange of green innovation technology and technology cooperation, realize the sharing of advanced green technology and scientific management experience, reduce the cost of environmental pollution. Thirdly, it is recommended that inter-regional environmental policy coordination and cooperation are strengthened.

In sum, there are still some certain limitations in this study. Firstly, this study only examined the spatial spillover effect of green innovation on eco-environmental quality based on China's eastern Yangtze River Delta Region, which limits the universality of the conclusions to other regions with diverse industrial characteristics and natural environments. And future studies could investigate the longer-term effects between green innovations and eco-environmental quality. Thirdly, the impact mechanism and conduction pathway between green innovations and eco-environmental quality remains to be further studied.

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