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Regional environment risk assessment over space and time: A case of China --Manuscript Draft--

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Regional environment risk assessment over space and time: A case of China

Abstract:

In order to better understand the environment quality of a country, it is necessary to make a correct quantitative evaluation on the effect of the policy to lay the foundation for further relevant policies and actions in the future. To this end, this paper constructs a composite environment risk index, and uses relevant socio-economic and environmental data of China's provincial regions to quantitatively analyze their environment risks. Furthermore, this paper constructs a panel data model to empirically test the key factors that lead to the environment risks. The study finds that, at least at this stage, the environment risks in various provincial regions in China are still relatively high, and the key factors that lead to the risks are economic growth, urbanization development, secondary industry growth and green policy. Therefore, China has to adopt more stringent environment protection policies and actions in the future.

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JEL Classifications:

1. Introduction

To implement the Paris Agreement reached by the 193 member states of the United Nations in 2015 and achieve the Sustainable Development Goals (SDGs) by 2030, China has been actively taking comprehensive environmental protection actions to improve the environment at national and regional levels (United Nations, 2015a; 2015b). However, due to differences in environmental resources and development conditions, different ecological and environmental states may occur even if stricter environmental protection measures are adopted in each region. This requires a scientific assessment of the environment risk. The spatial-temporal analysis of regional environment status can help the regions recognize the existing problems, so as to further adopt corresponding policies and measures towards the realization of the SDGs (Liu et al., 2021; United Nations, 2021).

The environment quality of a region is determined by many factors such as natural resources (especially water resources), natural disasters, waste discharge and pollution treatment (Afridi et al., 2021; Bryan et al., 2018; Xu et al., 2020). In a certain period of time, if these factors change significantly or drastically, it indicates that the environment is at greater risk. In order to extract effective information from multi-dimensional environment indicators, it is necessary to construct a composite environment risk index to quantify environment risks. Because the index is a composite of multiple environment indicators, it involves two specific problems. One is the definition and standardization of the risk index of a single indicator, because it involves the homogeneity and comparability of different indicators. Another is the determination of the weight of each single indicator in the total composite index, because it needs to consider the dual effects of time and space.

At present, some literature has constructed composite indexes, such as the Bertelsmann Index (Lafortune et al., 2018; Miola and Schiltz, 2019; Sachs et al., 2018; Sachs et al., 2021) and the Distance Measure Index (OECD, 2017), while the literature that uses multi-dimensional indicators (e.g., SDG Index) to calculate the composite index and conduct empirical analysis are also increasing with good research results (Halkos and Argyropoulou, 2022). However, the existing methods only perform general non-dimensionalization (such as range standardization and non-dimensionalization) of variable's indicators, but they do not solve the heterogeneity problem of variable's indicators (Li, 2021; Liu et al., 2019). Moreover, when synthesizing different index of variables, the weights of different indices need to be determined first, but the usual method (e.g., simple average method, subjective scoring method, and fuzzy decision method) has greater subjectivity, which affects the reliability of the measurement (Dhiman and Deb, 2020; Ervural et al., 2018; Palczewski and Sałabun, 2019).

In order to improve the reliability of the measurement, this paper makes improvements from three aspects. First, the relative distance between individuals and their mean is used to define the risks. The mean here contains the dual information of a specific indicator at different times and different individuals. This method can not only realize the dimensionlessness of

indices of the variables, but also enhance the comparability of measurement results over time and space.

Second, the paper unitizes the risk variables defined above to ensure that the calculated values of each relative risk index are within the range of 0 and 1. This method can not only realize the homogeneity, comparability and synthesizing of data, but also reduce possible divergence and instability problems (Dou, 2022).

Finally, the paper uses the unitized index data to calculate the weights. Because the homogeneity of the unitized data, it may realize the scientific determination of the weights in the calculation of the composite index when they are used to determine the weight. It solves the uncertainty of weight determination in traditional multi-standard decision analysis such as simple average method, subjective scoring method and fuzzy decision method.

The research shows that the composite risk index proposed here is suitable for the evaluation of complex system objects such as natural ecological and environmental system. Moreover, it can also be applied to more complex cases and more broad fields such as society, economy, finance, management, technology, and so on.

This paper addresses three questions. First of all, how has the actual status of the environment (risks) in each region. Second, how has the dynamic evolution process and trend of the environment (risks) in each region over time. Third, the paper empirically analyses the key factors that lead to the environment risks in various regions and their nature of action.

The study finds that the environment quality of each province-level region is quite unstable during the selected sample period, and most regions are at risk or high-risk situation in recent years. The empirical results indicate that the key factors leading to environmental risks are economic growth, urbanization development, secondary industry growth and green policies. Generally, economic growth, secondary industry growth, and green policies are conducive to reducing environmental risks, while urbanization will exacerbate environmental risks.

The remainder of the paper is structured as follows. The second section elaborates environmental risk measurement and evaluation. The third section is an empirical analysis of the determinants of regional environmental risks.

Section 4 is a dynamic test of regional environment system. The last is the conclusion.

2. Measurement and evaluation of regional environment risk

2.1 Method

We first consider the case of general two-level indicator system here. We use $CI_{.t}^{(i)}$ to represent the composite index of specific individual i ($i=1,2,\dots, I$), and $I_{j.t}^{(i)}$ ($j=1,2,\dots, J$) to represent for the first level index, and $I_{jk.t}^{(i)}$ ($k=1,2,\dots, K$) to represent the second level index (the lowest level index). Suppose that each second-level indicator ($I_{jk.t}^{(i)}$) contains sample data $X_{jk.t}^{(i)}$ ($j=1,2,\dots, J$; $k=1,2,\dots, K$; $t=1,2,\dots, T$). Thus, we can get $CI_{.t}^{(i)} = (I_{1.t}^{(i)} I_{2.t}^{(i)} \dots I_{j.t}^{(i)} \dots I_{J.t}^{(i)})'$, $I_{j.t}^{(i)} = (I_{j1.t}^{(i)} I_{j2.t}^{(i)} \dots I_{jk.t}^{(i)} \dots I_{jK.t}^{(i)})'$, and $I_{jk.t}^{(i)} = (X_{j1.t}^{(i)} X_{j2.t}^{(i)} \dots X_{jk.t}^{(i)} \dots X_{jK.t}^{(i)})$.

Our goal is to perform a weighted average of the variable values ($X_{jk.t}^{(i)}$) of different second-level indicators in each period to obtain the composite index value of their corresponding upper-level indicators (indicators of level 1) ($I_{j.t}^{(i)}$). The formula is as follows:

$$I_{j.t}^{(i)} = \sum_{k=1}^K w_{jk.t}^{(i)} I_{jk.t}^{(i)} = \sum_{k=1}^K w_{jk.t}^{(i)} X_{jk.t}^{(i)} \quad (1)$$

where $w_{jk.t}^{(i)}$ represents the weight corresponding to $X_{jk.t}^{(i)}$.

Similarly, the calculated first-level comprehensive indicators ($I_{j.t}^{(i)}$) are averaged with the corresponding weights to obtain the environmental risk index ($CI_{.t}^{(i)}$) of individual i in period t . Thus, the formula is as follows:

$$CI_{.t}^{(i)} = \sum_{j=1}^J w_{j.t}^{(i)} I_{j.t}^{(i)} \quad (2)$$

where $w_{j.t}^{(i)}$ represents the weight corresponding to $I_{j.t}^{(i)}$.

In order to achieve comparability over time and space, different individuals and times of the same index (including primary and secondary indicators) use the same weight. That is:

$$w_{jk.t}^{(i)} = w_{jk} \quad (3)$$

$$w_{j.t}^{(i)} = w_j \quad (4)$$

The above is a general solution idea. In order to measure the environment risk, let us redefine the value of the variable X. For the sake of simplicity, we here use the absolute value of the relative deviation to measure the risk, and it is calculated as follows:

$$x_{jk,t}^{(i)} = d(X_{jk,t}^{(i)}, \bar{X}_{jk}^{(i)}) = |X_{jk,t}^{(i)} - \bar{X}_{jk}^{(i)}| / \bar{X}_{jk}^{(i)} \quad (5)$$

where $\bar{X}_{jk}^{(i)} = \sum_{t=1}^T X_{jk,t}^{(i)} / T$, and it is the mean of the variables of sub-indicator k in the second layer (the last layer) of individual i for period t.

However, due to the different orders of magnitude of different indicators including the first and second levels, the difference in the risk values are often large and lack comparability, which brings difficulties to the determination of the weights. It has puzzled the academia in the construction of the composite index of multidimensional indicators for a long time.

Traditional methods of weight determination are often subjective, which reduces the credibility of research results. In order to solve this problem, we will unitize (process through logistic function conversion) the risk value ($x_{jk,t}^{(i)}$) calculated by formula (5) (Kramer, 1991) as follows:

$$U_{jk,t}^{(i)} = 1 / (1 + \exp(-x_{jk,t}^{(i)})) \quad (6)$$

where $U_{jk,t}^{(i)}$ represents the risk value after unitization processing.

For the variable value ($U_{jk,t}^{(i)}$) of the sub-indicator k of the index j of the specific object i (sub-index k in the last layer), we first obtain their time mean ($\bar{U}_{jk}^{(i)}$). Then, we averaged the time averages ($\bar{U}_{jk}^{(i)}$) of sub-indicator k of different individual i between different individuals again. Therefore, we will perform the following operations:

$$\bar{\bar{U}}_{jk} = \frac{1}{I} \frac{1}{T} \sum_{i=1}^M \sum_{t=1}^T U_{jk,t}^{(i)} \quad (7)$$

where $\bar{\bar{U}}_{jk}$ means the average of the unitized risk value ($U_{jk,t}^{(i)}$) at different times and in different individuals.

The weight of the corresponding second-level index ($I_{jk,t}^{(i)}$) can be calculated from equation (7) as follows:

$$w_{jk.t}^{(i)} = w_{jk} = \overline{\overline{U}}_{jk} / \sum_{k=1}^K \overline{\overline{U}}_{jk} \quad (8)$$

where $w_{jk.t}^{(i)}$ represents the weight of sub-indicator k in the second-level index ($I_{jk.t}^{(i)}$) of the index j ($I_{j.t}^{(i)}$) of the individual i the period t . For the same secondary index, because the differences between individuals and between times are not considered here, the same weights (w_{jk}) are used for the risk values ($U_{jk.t}^{(i)}$) of the same period and all individuals. Therefore, we can get $w_{jk.t}^{(i)} = w_{jk}$.

The unit risk composite index ($CU_{j.t}^{(i)}$) of the corresponding first-level index ($I_{j.t}^{(i)}$) of each individual i can be calculated in different periods from formula (6) and formula (8) as follows:

$$CU_{j.t}^{(i)} = \sum_{k=1}^K w_{jk} U_{jk.t}^{(i)} \quad (9)$$

Similarly, we can calculate the weight ($w_{j.t}^{(i)}$) of the index j of the first layer ($I_{j.t}^{(i)}$) using the result calculated by formula (9) as follows:

$$\overline{\overline{CU}}_j = \frac{1}{M} \frac{1}{T} \sum_{i=1}^M \sum_{t=1}^T CU_{j.t}^{(i)} \quad (10)$$

$$w_{j.t}^{(i)} = w_j = \overline{\overline{CU}}_j / \sum_{j=1}^J \overline{\overline{CU}}_j \quad (11)$$

where $\overline{\overline{CU}}_j$ represents the average of the first-level index composite index ($CU_{j.t}^{(i)}$), and $w_{j.t}^{(i)}$ represents the weight of the index j in the first-level index system of individual i in period t . For the same first-level indicator, because the differences over space and time are not considered here, the same weights (w_j) are used for the risk values ($CU_{j.t}^{(i)}$) of all individuals and the same period. Therefore, we can get $w_{j.t}^{(i)} = w_j$.

We can calculate the final unit risk index ($UERI$) of each individual i in different periods from formulas (9) and (11) as follows:

$$UERI_t^{(i)} = \sum_{j=1}^J w_j CU_{j.t}^{(i)} \quad (12)$$

The unit risk index ($UERI$) is de-unitized and multiplied by 100 to obtain the composite risk index (ERI) for different periods as follows:

$$ERI_t^{(i)} = \ln\left(\frac{1}{UERI_t^i} - 1\right)^{-1} \times 100 \quad (13)$$

2.2 Indicator and data

Considering the availability of data, the conciseness of research and the comparability of results, this paper sets indicators from four dimensions, for example, water resources, natural disasters, waste discharge and environmental governance investment. Furthermore, the indicator of the water resources has three sub-indicators such as surface water, groundwater and other water resources (unit: 100 million cubic meters).

The indicators of natural disaster have four sub-indicators, including flood, drought, wind and hail disaster and freezing disaster (unit: thousand hectares). The indicators of waste discharge has three sub-indicators, e.g., wastewater, waste gas and garbage (unit: 10,000 tons). The indicators of environmental governance investment includes six sub-indicators such as waste water, waste gas, solid waste, noise, other governance, and forestry project investment (unit: ten thousand yuan) (Dou 2015; Dou, 2016; Gonzalez-Gonzalez et al., 2021; Noori et al., 2021; Shi et al., 2021).

This paper uses annual data from 31 provincial administrative regions in China. The raw data come from China's National Bureau of Statistic (2021). In order to improve the reliability of the measurement results, we have performed statistical processing on individual missing or abnormal data.

2.3 Descriptive statistical analysis

Fig. 1 shows the descriptive statistics of the environment risks of 31 provincial administrative regions in China. We can find that almost all the provincial regions show a skewed distribution. Clearly, Shanxi, Liaoning, Jiangxi, Shandong, Hubei and Shaanxi show significant left-skewed distributions, but other regions show right-skewed distributions. This indicates that the environment risks in most areas are relatively high.

In terms of maximum value, Beijing has the highest maximum value, and Xizang is in second place. Moreover, the maximum value of Tianjin, Hainan and Chongqing is significantly higher than other regions. In terms of minimum values, Shaanxi and Anhui have the same and the lowest minimum, and Gansu has the second minimum. In addition, Shandong, Guangdong, Inner Mongolia, and Shaanxi have the minimum values that are relatively

close and slightly higher than Gansu.

As for mean value, Xizang has the largest mean value, Hainan's mean value is second and closer to Xizang, and Gansu's mean value is the smallest. This result is closely related to the special natural and socio-economic conditions of each region.

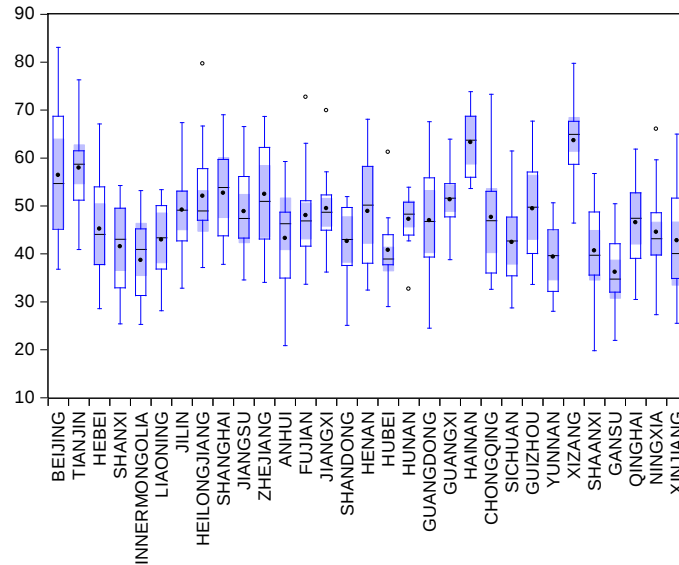


Fig. 1. Box plot of the ecological risk index of each provincial region

2.4 Change in environment risks

Our research indicates that, the environment of 31 provincial regions in mainland China has shown an unstable state during the sample period. Moreover, most of the provincial-level regions have large fluctuations. We find through in-depth analysis that the environment status of China's provincial regions has the following characteristics.

First of all, the time trend of environment changes in most areas is not significant, and it does not show significantly and relatively stable phase characteristics. Secondly, the environment in most regions shows divergent changes without significant convergence. Finally, although the environmental protection policies and measures of the national and various regions have become increasingly strict in recent years, the phenomenon of tail-lifting is still prominent (Fig. 2).

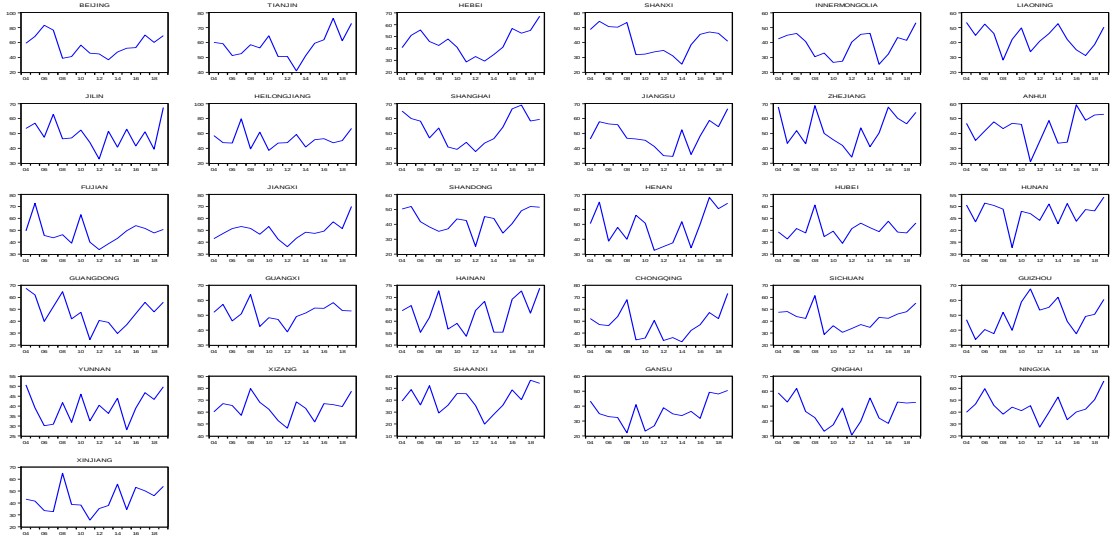


Fig. 2. Changes in environment risks in provincial regions

2.5 Environment risk assessment

For the sake of intuitive analysis, we divide the environmental risk index from 0 to 100 into five levels: (0, 20], (20, 40], (40, 60], (60, 80], and (80, 100]. They represent no-risk, low-risk, risk, high-risk, and extreme risk, respectively. Correspondingly, we use dark green, light green, yellow, blue, and red squares to represent them, respectively. Then, we draw a Dashboard graph according to the various provincial regions in different years (Fig. 3) (Schmidt-Traub et al., 2017).

Fig. 3 shows that most of the province-level regions in China have relatively high environmental risks, and they have been in a risky or high-risk state in recent years. It is worth noting that the environmental risks in Beijing are relatively high in the early stage, which has improved slightly after governance, but become serious in the later stage. This shows that the environmental pressure on Beijing, the capital of China, is increasing. Tianjin, Shanghai and Zhejiang have similar situations to Beijing, but to a lesser degree.

Among the 31 provincial-level regions, Xizang has the most prominent environmental problems with 12 blue and 4 yellow in the sample period, which is significantly at risk and high risk. Followed by Hainan, there are 10 blue and 6 yellow in the sample period, which is also at risk and high risk. This may be closely related to the special conditions of the two provincial

regions.

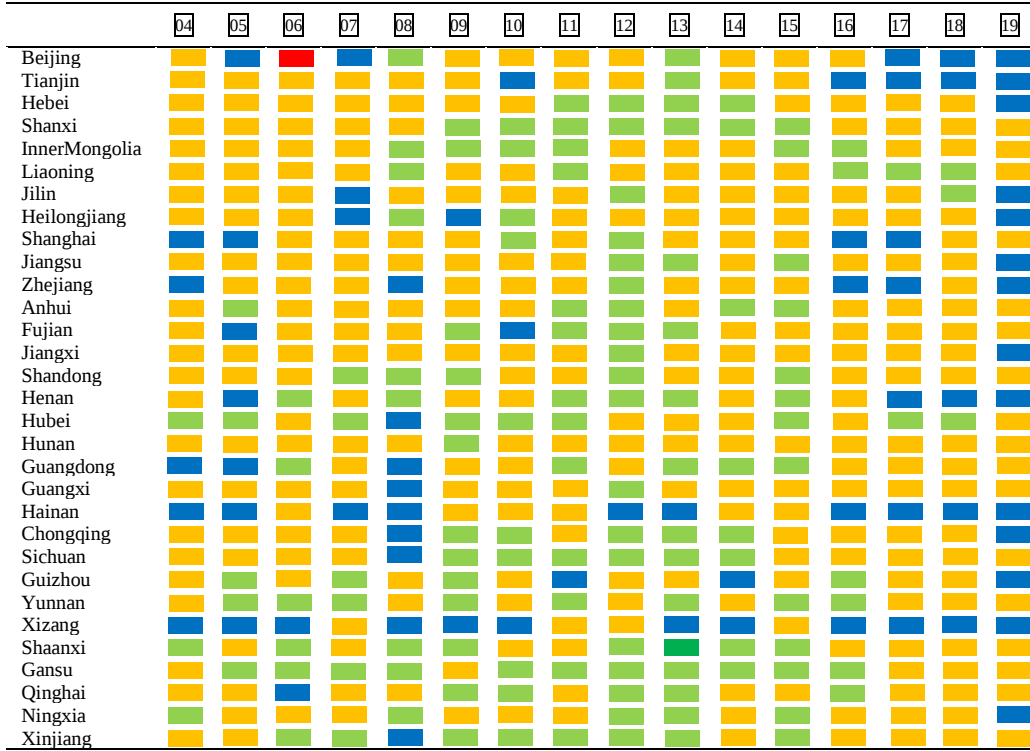


Fig. 3. SDG Dashboards 2004-2016. We divide the environment risk index from 0 to 100 into five levels: (0, 20], (20, 40], (40, 60), (60, 80], and (80, 100). They respectively indicate no risk, low risk, risk, high risk and extreme risk. Correspondingly, we use dark green (■), light green (■), yellow (■), blue (■) and red (■) squares to represent them, respectively.

2.6 Regional comparative analysis

In order to better examine the particularities of each region, we used systematic cluster analysis to classify the environmental risks of China's 31 provincial administrative regions (Fig. 4). According to Fig. 4 and our research purpose, we here divide them into 7 types.

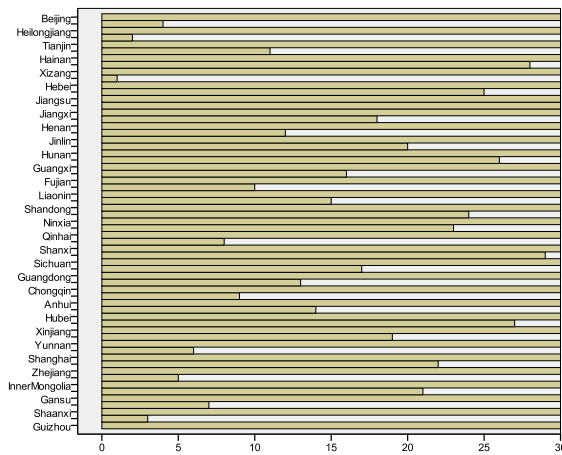


Fig. 4. The ice chart of hierarchical cluster analysis

Among the 7 types, Beijing (Type I), Heilongjiang (Type II) and Guizhou (Type VII) becomes a separate category, which shows that they are quite different from other regions and have their own environment and socio-economic characteristics. Beijing, as the capital of China, despite its huge investment in environmental protection, the excessive accumulation of population and economic resources has led to greater risks to the environment. Heilongjiang is located in the northernmost part of China, and it is one of the three northeastern provinces that are lagging behind in development at this stage. Although its ecological conditions are relatively good, its socio-economic conditions are relatively weak. Guizhou is one of the most underdeveloped regions in China, and it has a relatively special natural environment as well as a relatively backward social economy.

Type III includes three regions of Tianjin, Hainan and Xizang. Tianjin is one of the most developed regions in China's society and economy, but water resources are scarce and the natural environment is highly volatile. Hainan is an independent island with rich tropical biological resources, but due to large-scale development in recent years, the environmental and socio-economic conditions have changed significantly. Xizang is an area with rich ecological resources but the most fragile natural ecosystem in China, so it is greatly affected by climate change. The high environmental risks of Hainan Province and Xizang Autonomous Region are inseparable from their own special environment and climatic conditions. Natural disasters occur frequently in Hainan Province, while the ecological environment of the Xizang Autonomous Region is fragile and natural disasters occur frequently. Therefore, the environment management in these special areas is quite difficult.

Shanghai and Zhejiang are Type V regions. They are all social and economically developed areas in China and geographically adjacent, but the area of jurisdiction is relatively small. Because of their excessive concentration of population and economic resources, they have similar ecological and environmental risks.

InnerMongolia, Gansu and Shaanxi in Type VI are located in the

northwestern region of China, and their environment has certain similarities. Inner Mongolia is one of the most developed areas of animal husbandry in China, but due to pasture degradation and extreme climate change, the environment is still at a relatively high risk. Both Gansu and Shaanxi have serious water shortage and drought problems, which has led to serious soil desertification and soil erosion. Therefore, their environment risks are very prominent.

Except for the above six types of regions, the rest of the regions belong to Type IV, which covers 20 provincial administrative regions. For example, Hebei, Shanxi, Liaoning, Jilin, Jiangsu, Anhui, Fujian, Jiangxi, Shandong, Henan, Hubei, Hunan, Guangdong, Guangxi, Chongqing, Sichuan, Yunnan, Qinghai, Ningxia, and Xinjiang. Among these 20 provincial administrative regions, Fujian and Guangdong belong to the economically developed areas along the coast. Although Jiangsu and Shandong are coastal areas, their economies are at a medium level. The rest are located in the northwest (Qinghai, Ningxia and Xinjiang), the southwest (Guangxi, Sichuan and Yunnan) and the central inland areas. The environment risks in these areas are either caused by the environment governance lagging behind the socio-economic development, or caused by the shortage of water resources and climate change, or caused by the combination of the two.

3. Determinants of regional environmental risks

3.1 Model and data

In order to investigate the influencing factors of environment changes, we here construct a panel data econometric model. The environment risk of a region is determined by many of factors. However, for China at this stage, the influence of several key socio-economic factors is very important. The first is the impact of economic growth on the environment. On the one hand, economic growth has a negative impact on the environment; on the other hand, economic growth has increased the fiscal revenue of various regional governments, and the increase in fiscal revenue will help the government to increase investment in environmental governance, which is conducive to the improvement of the environment (Li et al., 2021; Shi et al., 2020).

The growth of the secondary industry has both favorable and unfavorable effects like economic growth, too. At this stage, as the secondary

industry occupies a large proportion of GDP, so its development can significantly promote economic growth. At the same time, since the secondary industry has the characteristics of high inputs, high energy consumption, high outputs and high emissions, so it has an adverse impact on the environment. The final result depends on the strength of the both (Chen et al., 2020; Zhang and Liu, 2021).

In recent years, China's urbanization has developed rapidly, but the impact of urbanization on the environment is significant. First of all, the development of urbanization (especially the development of small cities) directly erode the environment resources such as land resources, forest resources, and water resources, and this impact is irreversible. Secondly, although urbanization has a resource agglomeration effect, the city itself needs to consume a lot of resources and produce a lot of waste, which has a significant adverse impact on the environment (Ahmed et al., 2020; Yao et al., 2021).

Green policies play an important role in improving environment. China has not only adopted strict environmental protection policies, but has also continuously increased its investment in environmental governance. In terms of industrial policies, the state has been investing large amounts of financial funds in recent years to transform traditional high-energy-consumption and high-pollution industries, and actively supporting the development of green and low-carbon industries. At present, the national and local governments have formulated and implemented a complete set of green policies, which has fundamentally improved the environment (Cao et al., 2021; Qin et al., 2021; Yang et al., 2021).

According to the above theoretical analysis and considering the reality of China's economic development and environment changes at this stage, this paper selects the key factors of economic growth, secondary industry growth, urbanization development and green policy for empirical analysis. The equation is set as follows.

$$LnERI_{it} = \beta_0 + \beta_1 LnED_{it} + \beta_2 LnGP_{it} + \beta_3 LnIR_{it} + \beta_4 LnUR_{it} + \varepsilon_{it} \quad (14)$$

where ERI stands for environment risk, ED stands for economic growth, GP stands for green policy, IR stands for secondary industry growth, UR stands

for urbanization development, i represents cross-sectional individual, t means time, and ε is white noise series.

Because the socioeconomic development and the natural environment of different regions are different, the environment risks of various regions in China are also quite different. In order to clarify the real situation of the environment in various regions, this paper takes 31 provincial administrative regions in mainland China as the research object, and the sample period is from 2004 to 2019. All data come from the yearbook of the National Bureau of Statistics (2021).

3.2 Baseline model estimation

Table 1 reports the estimation results of Eq. (14). It can be seen that economic growth (ED), urbanization development (UR), secondary industry growth (IR) and green policies (GP) have all a significant impact on the environment. The empirical results show that the faster the economic growth of a region, the smaller the environmental risk in the region. This is because the central and local governments have attached great importance to environment protection in recent years, which has forced local governments to increase their financial investment in environmental governance as much as possible, while economic growth has laid the financial foundation for the government to increase financial investment. In addition, strict ecological and environmental protection policies have also reduced the impact of social and economic development on the environment.

In theory, the development of the secondary industry may make an adverse impact on the environment. However, the empirical results here show that it is beneficial to reduce the environmental risks (Table 1). One possible explanation is that the key secondary industries in all regions are concentrated in cities, and the government has implemented strict environmental protection policies for industrial enterprises with high energy consumption, high emissions and high pollution, which has prompted enterprises to improve efficiency (Chen et al., 2020), thereby minimizing the adverse effects of the development of the secondary industry on the environment. Moreover, since the secondary industry accounts for a large proportion of GDP at this stage, so the better the development of the secondary industry in a region, the faster the economic growth, which is conducive to improving the environment.

The implementation of the green policy is important to the improvement of the environment, as it helps to significantly reduce the environment risk. The role of the green policy is that it not only increases the financial investment of the central government and various regional governments in the governance of the environment, but also strictly restricts the economic behavior of economic agents that may deteriorate the environment. In recent years, the breadth and depth of the implementation of green policies in all regions have been continuously increasing, effectively reversing the continuous deterioration of the environment in the early stages of reform and opening up (Kahn et al., 2022).

The empirical results show that the development of urbanization will exacerbate the environment risks. China's urbanization is characterized by extensive and rapid progress. The first is that all regions have been making great effort to promote urbanization, which not only encroaches on a large amount of land, forests and other ecological resources, but also the excessive expansion of the city in the short term, resulting in large population agglomeration and industrial development, has caused the growth of urban wastes to make great pressure on the environment. Secondly, the development of some small and medium-sized cities lacks scientific planning and strict governance, resulting in a comprehensive and irreversible impact on the local environment.

Table 1
The estimation result of the Eq. (14)

Variable	Coefficient	Std. Error	T-Statistic	Prob.
LnED	-0.057002	0.027252	2.0916770	0.0370
LnGP	-0.072095	0.029318	2.459047	0.0143
LnIR	-0.454376	0.068073	6.674796	0.0000
LnUR	0.198607	0.091151	2.178884	0.0298
C	5.411459	0.372432	14.53004	0.0000

3.3 Analysis of individual differences

Fig. 5 reports the differences between the individuals. We can find that the environmental risks of provincial administrative regions in China are different. From the perspective of individual differences, Beijing, Inner

Mongolia, Yunnan and Gansu have the environment risk level below 5.3. Nine areas, including Liaoning, Jilin, and Jilin, Shanghai, Anhui, Shandong, Hubei, Sichuan, Shaanxi and Xinjiang, are between 5.3 and 5.4. Twelve areas, such as Hebei, Shanxi, Heilongjiang, Fujian, Hunan, Guangdong, Guangxi, Hainan, Chongqing, Guizhou, Qinghai and Ningxia, are between 5.4 and 5.5. Five areas, including Tianjin, Jiangsu, Zhejiang, Jiangxi and Henan, are between 5.5 and 5.6. Only Xizang is above 5.6.

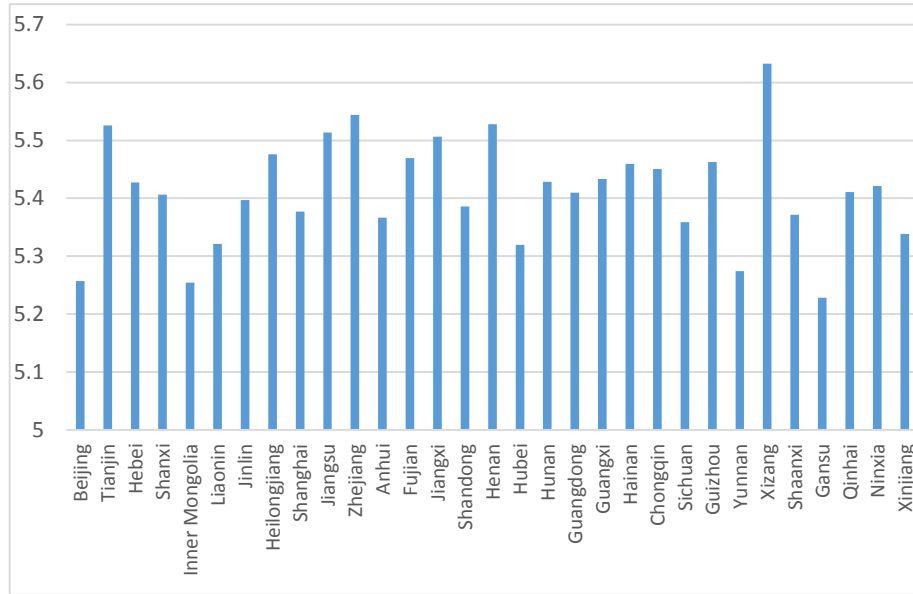


Fig. 5. Differences between individuals

The individual differences between different provincial administrative regions are caused by the differences in the endowment of environment resources, the level of social and economic development, and the degree of environmental protection and governance in each region, and the environment of a region is jointly determined by these key factors. However, due to the large differences in these factors and conditions in different provincial administrative regions in China at this stage, the emergence of individual differences is inevitable. This shows that the environment protection and governance of various regions in China must adopt corresponding policies in accordance with their own actual conditions in the future.

3.4 Robustness test

In order to test the reliability of the estimation results of the equation, we reduce the scope of the sample to re-estimate the Eq. (14). Table 2 reports the estimation results. It shows that the influence of all explanatory variables is

still statistically significant, the sign of each coefficient has not changed, and the value of the coefficient only has a small change compared with Table 1. This demonstrates that the estimation results of the Eq. (14) are reliable.

Table 2

The results of robustness test

Variable	Coefficient	Std. Error	T-Statistic	Prob.
LnED	-0.083484	0.372960	3.035746	0.0025
LnGP	-0.094507	0.030156	3.133923	0.0018
LnIR	-0.403176	0.069595	5.793209	0.0000
LnUR	0.182875	0.090697	2.016334	0.0443
C	5.563155	0.372696	14.92680	0.0000

4. Dynamic test of regional environment system

This study applies the SVAR model to investigate how various factors affect the dynamic changes of the ecological environment system. We specify the model as follows:

$$B_0 y_t = \Gamma_0 + \Gamma_1 y_{t-1} + \Gamma_2 y_{t-2} + \Gamma_3 y_{t-3} + \Gamma_p y_{t-p} + u_t \quad (15)$$

Where B_0 represents the coefficient matrix of the current period, Γ_0 represents the constant term, Γ_i ($i=1,2,\dots,p$) represents the coefficient matrix of the lag period, y represents the variable matrix in the system and $y=(\text{ERI}, \text{ED}, \text{GP}, \text{IR}, \text{UR})'$, u is white noise series, and t is time ($t=1,2,\dots,n$).

The SVAR model can not only describe the current relationship between various variables in the system, but also describe the structural relationship of each period compared with the VAR model. Therefore, it can better characterize the dynamic influence between variables in the system.

4.1 Dynamics of Type I areas

Fig. 6 reports the dynamics of ecosystems in Type I regions. The self-shock impact caused by changes in ecological risk (ERI) has the characteristics of significant convergence and periodic changes. It decreases sharply in the second period, decreases rapidly in the third to sixth period, and stabilizes and converges to the mean value after the sixth period. This shows that although the ecological risk variable (ERI) has a certain degree of self-perturbation, it tends to be gradually stable over time.

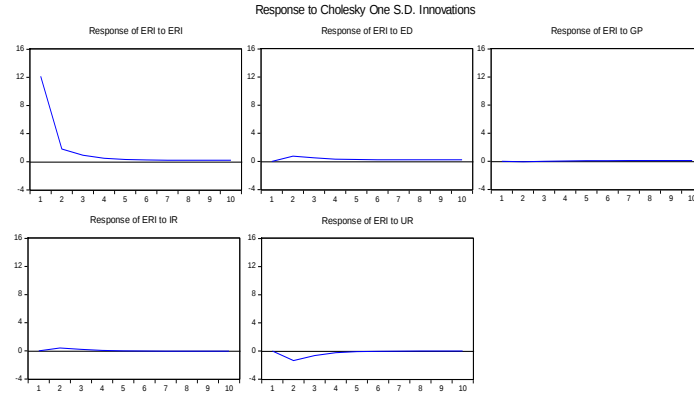


Fig. 6. Impulsive response of ERI to other variables in type I

The change in economic growth (ED) has a certain positive impact on the ecological environment (ERI), but the impact is relatively small. The disturbance caused by it is relatively large from the first period to the fifth period, and it is in a relatively stable state of change after the sixth period. However, the disturbance it causes does not converge to the mean.

The change in green policy (GP) has relatively little disruption to ecosystem. From the first period to the fourth period, it has almost no effect. It produces a certain disturbance after the fifth period, but the impact is small (almost converges to the mean value) and shows a stable state.

The development of the secondary industry (IR) has a certain impact on the ecological environment (ERI) as a whole, and there is a phenomenon of alternating positive and negative impacts. It has a positive effect in periods 1 to 4, but has little effect in periods 4 to 7. However, it has a negative effect after the 7th period, and this effect is small and shows a stable trend.

Urbanization development (UR) has a disturbing effect on the ecological environment (ERI). It leads to a significant negative change in the ecological environment (ERI) during the 1st to 5th period, while the change caused by it is significantly smaller and shows a stable state from the 5th to the 8th period. However, it converges to its mean after period 8 (see Fig. 6).

4.2 Dynamics of Type II areas

In Type II areas, the self-shock effects caused by changes in ecological risk (ERI) are complex. During periods 1 to 2, the effect it caused drops sharply and goes from positive to negative. The negative volatility it causes becomes smaller after period 2, but it has a small positive volatility and

converges to its mean in period 3. After period 6, it has another slight negative swing, but the swing is smaller (see Fig. 7).

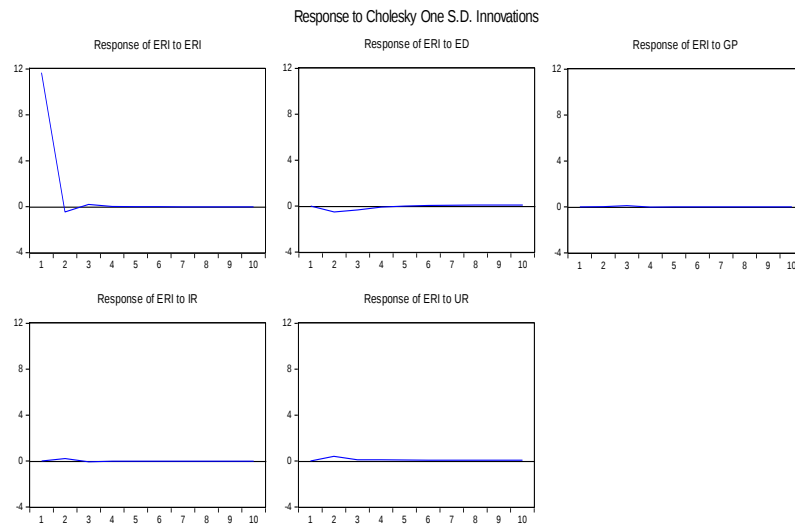


Fig. 7. Impulsive response of ERI to other variables in type II

The disturbing effects of changes in economic growth (ED) on the ecosystem (ERI) are complex. From the first period to the fourth period, it has a significant negative disturbance effect, and the disturbance effect gradually becomes larger from the first period to the second period, but becomes smaller from the third period. After the 4th period, its perturbation converges to the mean and continues until the 7th period. After period 7, it produces positive disturbances, but the fluctuations are small and relatively stable (see Fig. 7).

Fig. 7 shows that the change in green policy (GP) has less perturbation effect on the ecosystem (ERI). It converges to its mean value in all other periods except for a slight positive perturbation in periods 2 to 4. Therefore, green policies are conducive to improving the ecological environment.

For Type II regions, the disturbance of the secondary industry development (IR) on the ecological environment (ERI) is small. Except for a slight positive perturbation in periods 1 to 3, it converges to the mean in all other periods (Fig. 7).

Urbanization development (UR) has always a positive disturbance effect on the ecological environment (ERI). In the first to third period, the positive

change caused by it is significant. But after the 3rd period, the change it caused is significantly smaller and shows a stable state (Fig. 7).

4.3 Dynamics of Type III areas

In Type III regions, the self-shock impacts of changes in ecological risk (ERI) are complex. During periods 1 to 2, it results in a positive effect with a sharp decline. After period 2, its positive volatility gradually becomes smaller. It converges to its mean during periods 3 to 4. After period 4, it has a slight negative swing and has been trending steadily (Fig. 8).

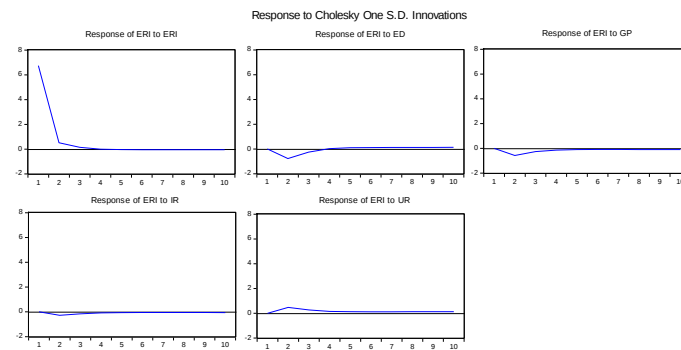


Fig. 8. Impulsive response of ERI to other variables in type III

The disturbing effects of changes in economic growth (ED) on the ecosystem (ERI) are complex. It has a significant negative perturbation effect from the first period to the fourth period, and its perturbation effect gradually becomes larger during the first period to the second period, but it becomes smaller after the third period. After the 4th period, it produces a positive disturbance effect, and its disturbance effect becomes slightly larger and shows a relatively stable state from the 5th period (see Fig. 8).

The disturbances caused by green policy (GP) changes to the ecosystem (ERI) have always shown negative changes. It produces a significant negative perturbation effect during the period 1 to 4. However, its negative perturbation effect begins to become smaller and shows a relatively stable state after the 4th period (Fig. 8).

Fig. 8 shows that the development of the secondary industry (IR) has always a negative disturbing effect on the ecological environment system (ERI). The negative disturbance generated by it is relatively large from the

first period to the fourth period, and then becomes smaller and shows a relatively stable state.

Urbanization development (UR) has always a positive disturbance effect on the ecological environment (ERI). However, the positive change caused by it is relatively significant during periods 1 to 4, and then becomes smaller and relatively stable (Fig. 8).

4.4 Dynamics of Type IV areas

Fig. 9 reports the dynamics of ecological environment (ERI) system in the Type IV areas. The self-shock impacts caused by changes in ecological risk (ERI) have the characteristics of stages. It shows a positive effect and declines sharply during periods 1 to 2. However, its positive volatility gradually becomes smaller from period 2 to period 4. Further, it converges to its mean during periods 4 to 6, and it has a slight negative fluctuation and has been showing a stable trend after the 6th period (Fig. 9).

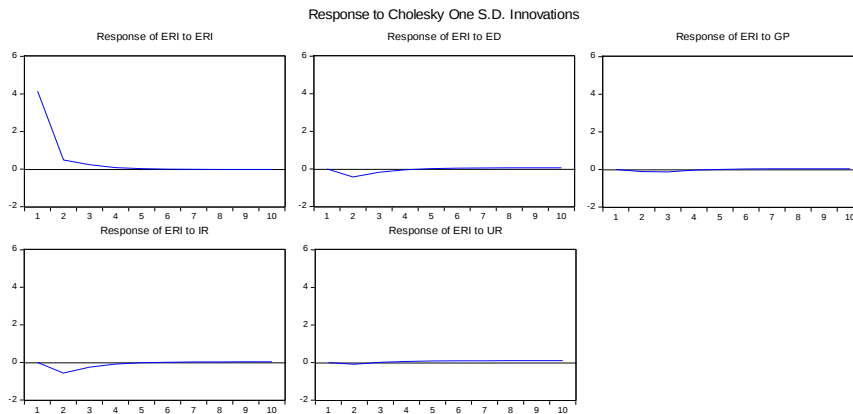


Fig. 9. Impulsive response of ERI to other variables in type IV

The disturbing effects of changes in economic growth (ED) on the ecosystem (ERI) are complex. It has a significant negative perturbation effect from the 1st to the 4th period, and its perturbation effect gradually becomes larger during the 1st to the 2nd period, but it becomes smaller from the 3rd period. Furthermore, it converges to its mean during periods 4 to 6, and it produces relatively small positive disturbance and shows a relatively stable state after the 6th period (Fig. 9).

The disturbance caused by green policy (GP) changes to the ecosystem (ERI) is not particularly significant, but its disturbance presents three changes:

negative, convergent and positive. It produces a negative perturbation effect from period 1 to period 4, but the fluctuation range is relatively small. Further, it converges to its mean during period 4 to 5. However, it produces a relatively small positive disturbance and shows a relatively stable state after the 5th period (Fig. 9).

Fig. 9 shows that the development of the secondary industry (IR) has a negative disturbing effect on the ecological environment system (ERI) from the first period to the fifth period. Among them, the negative disturbance effect caused by it shows a trend of increasing from the first period to the second period, and the negative disturbance effect that it produces gradually becomes smaller from the second period to the fifth period. Then, its effect is insignificant and has been converging to its mean after period 5.

The disturbance effect of urbanization development (UR) on the ecological environment (ERI) presents a state of alternating negative and positive changes, but the magnitude of the change is relatively small. It shows a small change from negative to positive during the 1st to 4th period, but it has been showing a relatively small and stable positive change after period 4 (Fig. 9).

4.5 Dynamics of Type V areas

The self-shock impact caused by the change of ecological risk (ERI) presents the characteristics of positive change. It shows a positive impact and decreases sharply from period 1 to 2, but its positive volatility gradually decreases from period 2 to period 4. Then, it has a small positive fluctuation and has been showing a stable trend after the 4th period (Fig. 10).

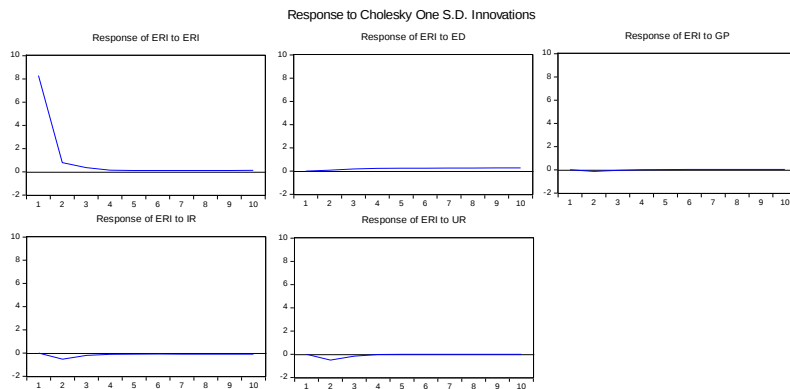


Fig. 10. Impulsive response of ERI to other variables in type V

The disturbance effect of economic growth (ED) changes on the ecosystem (ERI) shows a positive divergent trend. It has a smaller positive perturbation effect in the 1st to 3rd period, but its perturbation effect becomes larger during the 3rd to the 7th period and becomes larger after the 7th period. Although it produces a relatively small positive disturbance and presents a relatively stable state in stages, it exhibits divergence (Fig. 10).

Ecosystem (ERI) disturbances caused by green policy (GP) changes are not significant. It produces a slight negative perturbation effect from period 1 to period 4, and it always converges to its mean starting from period 4 (Fig. 10).

The development of the secondary industry (IR) has always a negative disturbing effect on the ecological environment system (ERI). Its negative perturbation effect tends to increase from the 1st to the 2nd period, while the negative perturbation effect that it produces gradually becomes smaller in the 2nd to the 4th period. Further, its negative perturbation effect is small after the fifth period, and it has been showing a stable trend (Fig. 10).

The disturbance effect of urbanization development (UR) on the ecological environment (ERI) shows a gradually increasing negative change state from the first to the second period, but its negative change gradually becomes smaller after the second period. But since period 3, it has been converging to its mean (Fig. 10).

4.6 Dynamics of Type VI areas

In the Type VI areas, the self-shock impact caused by the change of ecological risk (ERI) presents the characteristics of positive and negative alternating changes. It shows a positive effect and decreases sharply from period 1 to 2, but the positive fluctuation gradually decreases from period 2 to period 4. It starts to fluctuate from positive to negative after period 4, but the magnitude of negative fluctuation is smaller and it has been showing a stable trend (Fig. 11).

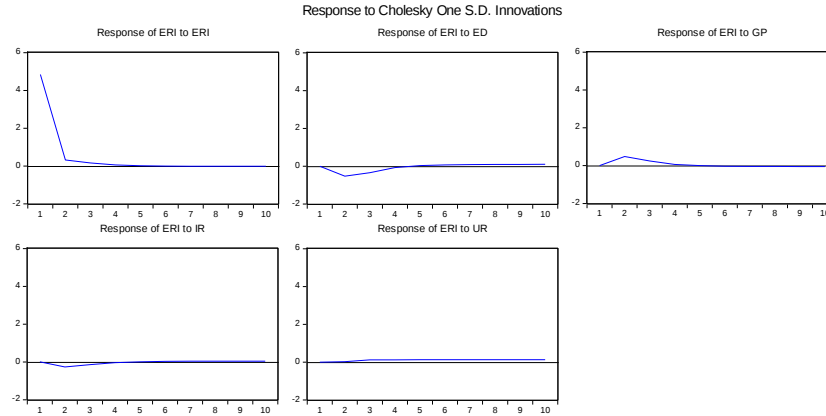


Fig. 11. Impulsive response of ERI to other variables in type VI

The disturbance effect of economic growth (ED) changes on the ecosystem (ERI) presents alternately negative and positive features. It shows a gradually increasing trend of negative perturbation in the 1st to 2nd period, but its negative perturbation effect gradually becomes smaller in the 2nd to 4th period. Then, the disturbance effect that it produces changes from negative to positive from the fourth period, and has a gradually increasing trend. However, its positive perturbation effect appears to be relatively stable after the sixth period (Fig. 11).

For Type VI regions, the disturbance to the ecosystem (ERI) caused by green policy (GP) changes is complex. It produces a progressively larger positive disturbance during period 1 to 2, but the positive disturbance it produces begins to decrease from period 2 to 4. Then, its perturbation effect changes from positive to negative starting from period 4 and shows a divergent trend (Fig. 11).

The disturbance effect of the development of the secondary industry (IR) on the ecological environment system (ERI) presents a state of alternating negative and positive changes. It produces a gradually increasing negative perturbation effect during the period 1 to 2, but its negative perturbation effect gradually becomes smaller in the period 2 to 4. However, its perturbation effect changes from negative to positive after the fourth period, and has been showing a stable trend after the fifth period (Fig. 11).

The disturbance effect of urbanization development (UR) on the ecological environment (ERI) is always in a positive state. Its positive fluctuation range is not significant from the first period to the second period,

but its positive change is more significant after the second period, and shows a relatively stable trend (Fig. 11).

4.7 Dynamics of Type VII areas

In the Type VII areas, the self-shock impact caused by the change of ecological risk (ERI) presents a positive disturbance. Its positive fluctuation decreases sharply in periods 1 to 2, but gradually decreases in periods 2 to 3. However, its positive perturbation amplitude becomes very small after the third period, and has been showing a stable trend (Fig. 12).

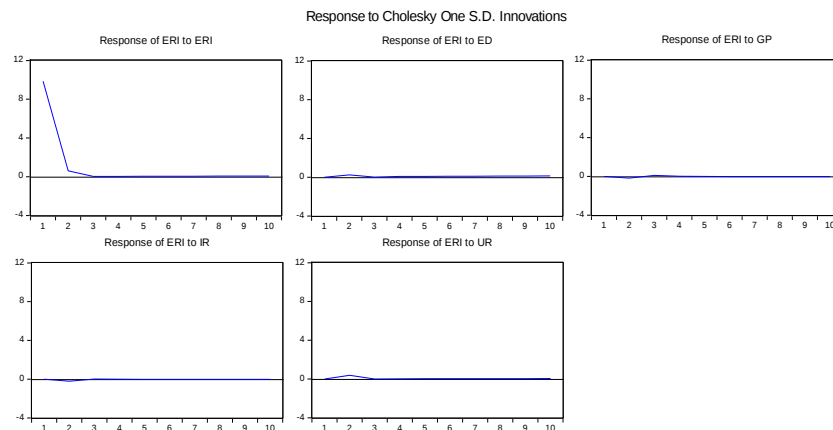


Fig. 12. Impulsive response of ERI to other variables in type VII

Change in economic growth (ED) has a positive disturbing effect on the ecosystem (ERI). Its positive perturbation effect is relatively large in the first to second period, but its positive perturbation effect is not significant during the second to third period. From the third period onwards, the positive perturbation effect it produces slightly increases and shows a relatively stable state (Fig.12).

The disturbances caused by green policy (GP) changes to the ecosystem (ERI) alternate negatively and positively. It produces a small negative perturbation effect from period 1 to period 2, but it produces an insignificant positive perturbation effect from period 2 and almost converges to its mean (Fig. 12).

The disturbance of the secondary industry development (IR) to the ecological environment system (ERI) is relatively small. It produces a relatively significant negative perturbation effect from period 1 to period 2, but the negative perturbation effect it causes is small from period 2 and

almost converges to its mean (Fig.12) . This can be related to the industrial backwardness of the region.

The disturbance effect of urbanization development (UR) on the ecological environment (ERI) is in a positive state. Its positive fluctuation range is relatively large from period 1 to period 2, but its positive change is not significant after period 2 and almost converges to its mean value (Fig. 12).

5. Conclusion

The goal of this paper is to construct an environment risk index to measure and evaluate the environment risks of regions in mainland China. The study finds that the environment risk index of each region shows significant and unstable changes during the 2004-2019 sample period selected, which indicates that the environment of these regions is at a greater risk. Further, we find that the environment of each province-level region in China has the following characteristics of changes. First of all, the environment changes in most regions does not show significant and relatively stable phased-characteristics. Secondly, the environment of most regions shows divergent changes. Finally, although the environmental protection policies and measures of the national and all regions have become stricter in recent years, the environment risks have not been significantly improved.

This paper empirically tests the impact of four key economic variables including economic growth, urbanization development, secondary industry growth and green policy on the environment on the basis of environment risk measurement and evaluation. The study finds that economic growth, secondary industry growth and green policies have a negative correlation with the environment risk index, while there is a positive correlation between urbanization development and the environment risk, which is in line with the actual situation in China. Although economic growth and the growth of the secondary industry have certain adverse effects on the environment, China has been implementing strict environmental protection policies in recent years and at the same time continuously increasing investment in environmental governance, thereby reducing the negative impact on the environment. Because the goal of green policy implementation is to improve the environment, it has a positive impact on the environment. On the other

hand, because China's urbanization development is large-scale, rapid and extensive, it has a direct negative impact on the environment.

The research results of this paper show that although China's regional environment risks are still relatively large at this stage, China's regional environmental risks will be controlled within a reasonable range with China's social and economic development and the continuous implementation of environmental protection policies. The future regional environment governance should focus on the following aspects on the premise of solving social and economic problems and regional imbalances.

(1) Full implementation of green policy. Because green policy has direct and significant effects in improving the environment, China must implement more stringent green policies in all areas of consumption, product and energy production, circulation, urban infrastructure construction in the future (Yang et al., 2022).

(2) Significantly to increase capital investment in water resources and watershed management, biodiversity protection, and environment infrastructure (Crist et al., 2017; Moffette et al., 2021). The first is to increase financial investment in environment governance. Because the environment has the attributes of public goods, the central and local governments must bear the corresponding governance and protection responsibilities. The second is to encourage social capitals to participate in the governance and protection of the environment through financial and fiscal policies to make up for the lack of fiscal funds. With the increasing environmental awareness of the public and enterprises, the potentials of social capitals are huge.

(3) Comprehensively to promote the development of high-quality urbanization. At this stage, China's urbanization has achieved a large-scale quantitative expansion, and has already possessed a stage of transition from a quantitative development to a qualitative development. Therefore, China must promote the high-quality development of cities in a timely manner. This is not only a requirement for the management and protection of the environment, but also an inevitable requirement for improving the efficiency of urban development and operation.

The research provides a multi-index and comprehensive environment risk assessment method. The advantage of this method is that it can not only

perform multi-index and multi-scale evaluation, but also extract the spatial and temporal effects of different objects evaluated. Therefore, the results measured by such a method are conducive to objective evaluation from the vertical and horizontal dimensions. In addition, this method provides a methodological basis for risk measurement and evaluation of more complex systems, subsystems and larger index systems.

Declaration of Competing Interest

The authors declare that there are no any competing financial interests or personal relationships that could influence the work reported in this paper.

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