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Research on the impact of China's new urbanization on industrial water utilization efficiency – based on spatial spillover effects and threshold characteristics

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ABSTRACT

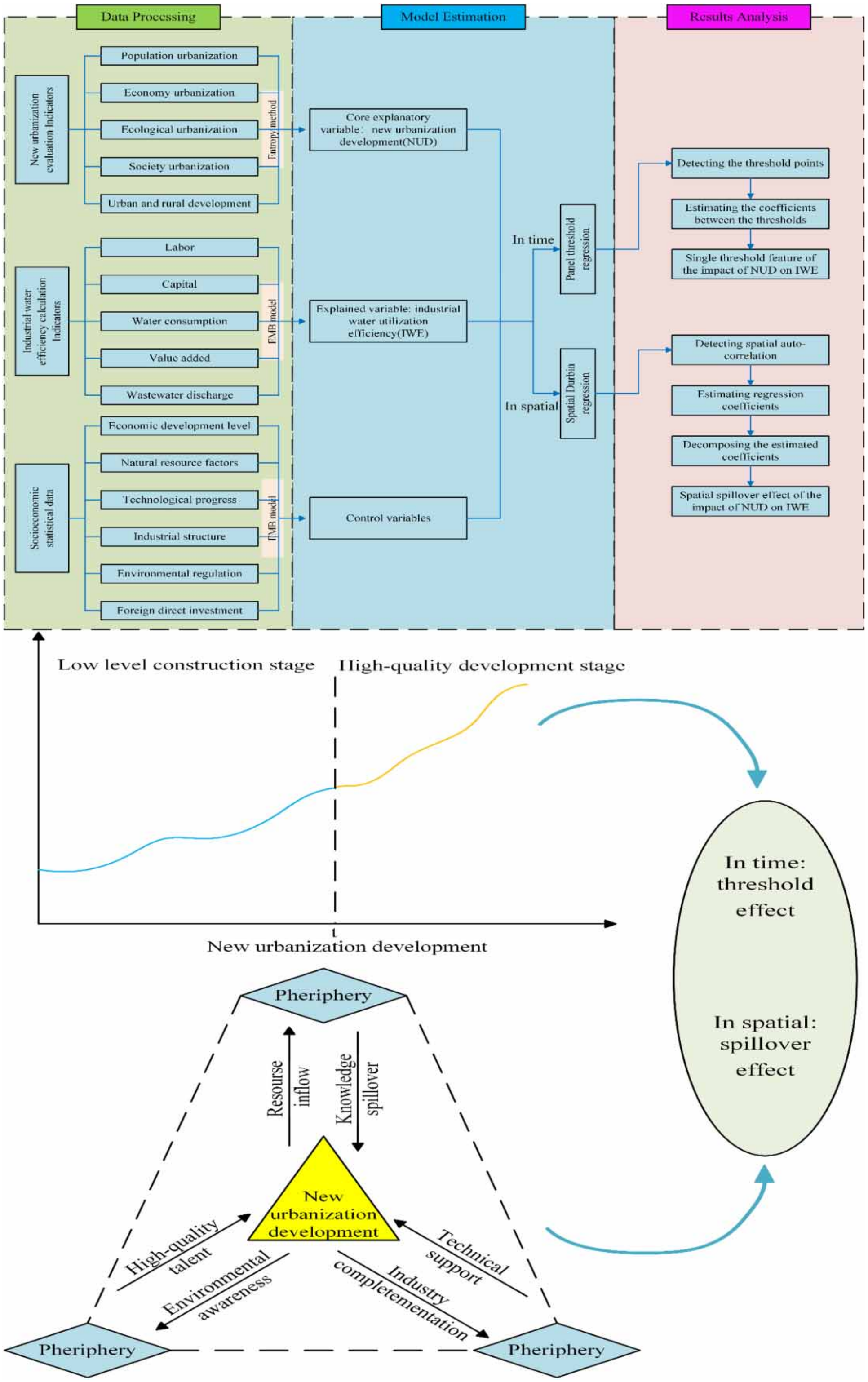
To explore the impact of new urbanization development on industrial water utilization efficiency, the epsilon-based measure model and the entropy method were used to calculate the industrial water utilization efficiency and the development of new urbanization based on the panel data of 30 provincial cities in China from 2011 to 2020. Then the spatial Durbin and the panel threshold models were constructed to explore the spatial spillover and threshold effects of new urbanization development on industrial water utilization efficiency. The results show that there are large regional differences in the development of new urbanization and industrial water utilization efficiency. New urbanization development has a positive spillover effects on the improvement of industrial water efficiency. The promotion effect of new urbanization development on industrial water efficiency is affected by the level of new urbanization development, thus showing different results. According to the findings, it is recommended that local governments at all levels should increase their efforts to build new urbanization. And boost high-level and high-quality development of towns and cities while promoting the rationalization of industrial structure and optimizing resource allocation, thereby improving the efficiency of industrial water utilization.

Key words: industrial water utilization efficiency, new urbanization development, regional diversity, spatial spillover effect, threshold feature

HIGHLIGHTS

- The evaluation index system is constructed from five dimensions to analyze the differences in the development of new urbanization.
- Using industrial wastewater discharge as unexpected output, the epsilon-based measure model is used to calculate the industrial water efficiency.
- The analysis of the dynamic development by kernel density estimation.
- The spatial Durbin and threshold models are used to analyze spatial spillover and nonlinear effects.

GRAPHICAL ABSTRACT



1. INTRODUCTION

China's urbanization has attracted global attention (Chen *et al.* 2016). First, although China's urbanization has grown rapidly over the past few decades, it only reached the world average in 2012 (Figure 1), so there is still much room for improvement compared to developed countries. However, as the world's most populous country, China's urbanization process will have a profound impact on the world. Second, the institutional arrangement of the government is the fundamental driving force of China's urbanization, and the role of the government in urbanization is much greater than that of the market, which is very different from the urbanization development model of the developed Western countries (Chen *et al.* 2018). Therefore, the previous models of urbanization development cannot be fully applied to China. Finally, as the world's second-largest economy, China consumes a huge amount of water resources, but it is a country with scarce water resources. Furthermore, it is currently at the peak of rapid industrialization and resource consumption, with even greater water consumption (Wang *et al.* 2019). Therefore, studying the impact of urbanization on industrial water utilization efficiency (IWE) provides experiences and insights for China to achieve sustainable development and resolve the conflict between water supply and demand. Meanwhile, research shows that improving IWE is an inherent requirement to promote the transformation of industrial water utilization from crude and inefficient to economical and efficient, and it is an important way to ensure water security in China, with urbanization being an important factor affecting IWE. In 2014, the Chinese government released the 'National New Urbanization Plan (2014–2020)' to vigorously promote the construction of new urbanization. Compared with traditional urbanization, the new urbanization is 'people oriented' and emphasizes the transformation from 'township' to 'city' in terms of industrial support, living environment, social security, and lifestyle to achieve urban–rural integration and sustainable development. Therefore, the new urbanization development (NUD) is an important tool to promote the improvement of IWE. This article first theoretically explained the mechanism of the influence of NUD on IWE, then the spatial Durbin model (SDM) and the panel threshold model (PTM) were constructed to empirically test the spatial spillover and threshold effects of NUD on IWE, and finally, the corresponding policy implications were derived from the findings.

The research in this article focuses on the following two aspects: first, the existing studies on the relationship between NUD and IWE have not established a complete theoretical framework, resulting in a lack of theoretical support for related re-examination. Therefore, this article constructed a theoretical framework between NUD and IWE under the premise of considering spatial spillover effects and threshold effects. Second, the existing literature mainly has adopted linear analysis to explore the impact of social and economic factors on IWE, but lacked a nonlinear perspective to analyze the impact of NUD on IWE. In addition, due to the differences in the levels of NUD and IWE in different regions of China, the hypothesis of spatial homogeneity in previous studies has been interpreted differently for the effects of NUD. Therefore, this article attempted to analyze the impact of NUD on IWE from the perspective of nonlinear and spatial spillover characteristics on the basis of existing research findings, so as to provide experiences and insights for promoting regional cooperation and achieving sustainable development.

The rest of this article can be divided into five sections. Section 2 presents the literature review. Section 3 presents the theoretical framework. Section 4 introduces the models along with the selection of variables and data sources. Section 5 presents the empirical analysis of the threshold effect and spatial spillover effect of NUD on IWE. Section 6 presents the conclusions and policy recommendations.

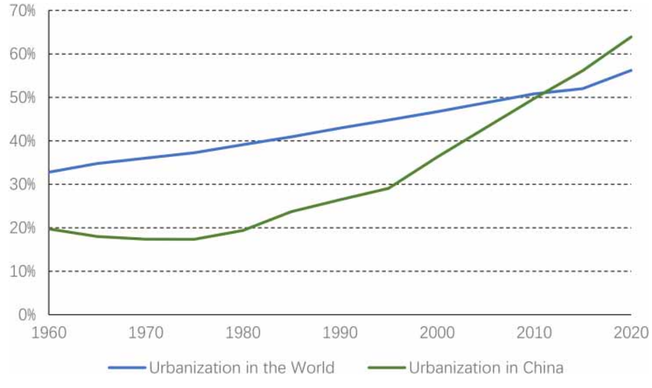


Figure 1 | Trends of urbanization over 1960–2020. *Note*: Data from the World Bank.

Urbanization is defined as the share of the urban population in the total population.

2. LITERATURE REVIEW

2.1. Measurement of IWE

In recent years, with the growing prominent conflict between water supply and demand, water resources have become the major bottleneck limiting sustainable economic development. As the second largest user of water resources in China, industrial water consumption is under the pressure of water shortage and will increase during the '14th Five-Year Plan' period as the number and scale of industrial enterprises continue to increase. Therefore, the issue of IWE is not only of great concern to the government but also of increasing interest to the academic community. The existing studies on IWE in the literature focus on two aspects: first, the measurement of IWE; and second, the influencing factors of IWE.

Data envelopment analysis (DEA) and the stochastic frontier analysis (SFA) have been chosen by most researchers to measure IWE. The DEA model was proposed by Charnes and has been widely used to calculate the efficiency of resource utilization. Cabrera *et al.* (2018) calculated the efficiency of 194 water utilities in Portugal by using the DEA model and provided recommendations for inefficient DMUs (decision making units). Chen *et al.* (2021) measured IWE in 31 Chinese provinces from 2005 to 2015 by using the self-sampling DEA method. Although the DEA model can measure the efficiency of 'multi-input' and 'multi-output', it ignores the effect of random errors. However, the SFA model takes into account the effect of the presence of random errors on the results, making the calculation more accurate. Lei *et al.* (2017) measured the IWE by using the SFA model on the basis of 31 provinces of China from 2004 to 2014. Zheng *et al.* (2018) introduced the shepherd water distance function to construct the total factor water efficiency index and then calculated the efficiency index by using the SFA model. The SFA model considers the effect of the presence of random errors on the results, but it may cause structural bias due to the misconfiguration of the production function. Therefore, some more advanced models such as the slack-based model (SBM) were proposed based on traditional models to solve the problem of inaccurate calculation results due to the shortcomings of traditional efficiency methods. The SBM model addressed the issue of how to deal with undesirable outputs, which allows scholars to conduct more in-depth research. Ding *et al.* (2019) measured the IWE of the Yangtze River Economic Belt by using the improved super-efficient DEA model. Liu *et al.* (2020) measured IWE in China by using the SBM model based on undesirable outputs. However, the SBM model lacks information on the ratio of input or output target values to actual values, so the epsilon-based measure (EBM) model proposed by Tone and Tsutsui (Tone & Tsutsui 2010) addressed this problem. The EBM model includes both radial and nonradial slack variables, which makes the calculated efficiency values closer to the actual situation and has been adopted by most scholars in efficiency calculations (Wang *et al.* 2017; Liu & Peng 2020).

It can be found that existing studies have mostly used radial distance functions such as CCR (A. Charnes, W.W. Cooper and E. Rhodes) and BCC (Banker, Charnes, and Cooper) or nonradial distance functions such as SBM, but they all have shortcomings. The EBM model is a hybrid model that integrates both radial and nonradial distance functions, and it not only accounts for slack variables but also solves the problem of losing the original scale information of the projected value of the efficiency frontier, thus making the calculation results more accurate.

2.2. Urbanization and IWE

There are many relevant studies on the relationship between urbanization and IWE, but the results are quite different. From the perspective of linear analysis, most scholars believe that urbanization can improve IWE. Zhao *et al.* (2022) concluded that the increasing level of urbanization has a promotion effect on improving the water environment by using 43 prefectural units in the Yellow River Basin of China as the research area. Li *et al.* (2019) found a positive effect of urbanization on IWE using data from 31 Chinese provinces as a sample. Zheng *et al.* (2018) and Bao *et al.* (2016) investigated the relationship between urbanization and IWE and came to similar conclusions. Some scholars also argue that urbanization inhibits IWE. Ding *et al.* (2019) found that both population and land urbanization have a negative impact on IWE using a sample of provinces in China's Yangtze River Economic Belt. Hai *et al.* (2018) found that urbanization has a negative impact on IWE by analyzing the relationship between urbanization quality and IWE from different urbanization perspectives, such as population, economy, society, and land. Other scholars believe that urbanization has different impacts on IWE in different regions due to regional differences (Ma *et al.* 2018; Liu *et al.* 2019).

From the perspective of nonlinear analysis, as many economic variables in reality have structural mutation problems, especially for large samples and panel data, thus the PTM has been widely adopted by scholars to find structural mutation points for nonlinear studies. The PTM was proposed by Hansen (1999), in which the static PTM has been used to study the relationship between variables. Guo *et al.* (2022), Huo *et al.* (2022), Li *et al.* (2020), Luo & Zhang (2021), and Wu *et al.* (2021) investigated the threshold effects between green economy or innovation efficiency and its influencing factors by using the static PTM. Yang *et al.* (2019) and Zhang *et al.* (2019) studied the threshold effects between eco-efficiency and its influencing factors. It can be seen that there is a lack of nonlinear studies on the impact of urbanization on IWE, but some scholars have studied the nonlinear relationship between urbanization and water resources. Wang *et al.* (2022) studied the threshold effects of urbanization and industrial structure change on water stress by using the PTM. Zhang *et al.* (2011) found a complex quadratic curve relationship between urbanization and water use in Urumqi.

From the perspective of spatial spillovers, the spatial panel data models were used by scholars to study spatial characteristics, with application areas ranging from regional economics to real estate economics and financial geography, etc. (Zhang 2016; Wang & Guan 2017; Iwata *et al.* 2019). Not only that but also the traditional fields of labor economics (Azorin & de la Vega 2015), energy economics (Zhang *et al.* 2017; Pan *et al.* 2018; Kiziltan 2021), environmental economics (Huang *et al.* 2020; Karahasan & Pinar 2022), international trade (Metulini *et al.* 2018), and other aspects of research have risen to the spatial level. Although the spatial spillover effects of urbanization on IWE are relatively scarce, Zhang *et al.* (2020) found that urbanization has spatial spillover effects on water utilization efficiency and a negative effect on agricultural water utilization efficiency. Lu *et al.* (2022) constructed the dynamic spatial econometric model, and the spatial decomposition results showed that urbanization has a short-term positive effect on agricultural water utilization efficiency in the region and surrounding areas. We found no consensus among scholars regarding the spatial impact of urbanization on water utilization efficiency.

The choice of empirical research method has a great influence on the research results. Existing studies only have analyzed the impact of urbanization on IWE from a single aspect of spatial spillover effects or threshold effects, which may lead to bias in the estimation results. Therefore, this article integrated the research findings of spatial spillover effects and threshold effects and systematically analyzed the impact of NUD on IWE.

3. THEORETICAL HYPOTHESIS

New urbanization is a comprehensive development process, which involves economic development, ecological environmental protection, social governance, and other aspects. Moreover, new urbanization, as a complex economic variable, is likely to have structural abrupt points in its development process, and thus, its impact on IWE may be nonlinear. Therefore, this article studied the threshold effects of NUD on IWE from the following aspects.

The NUD can affect IWE through the pooling of production factors such as population and resources. (1) The NUD causes a large number of people to move from rural to urban areas, increasing the population density and expanding the size of cities. Moreover, the population tends to move to areas with higher levels of economic development and more opportunities in the process of population transfer (Feng *et al.* 2022). The influx of high-tech talents continuously improves the level of science and technology, thereby enhancing regional innovation capabilities, reducing industrial water consumption, and improving industrial water resource reuse and IWE. However, excessive population gathering may also lead to urban development problems, such as a sharp increase in domestic water consumption and pollution of the water environment, thus resulting in inadequate and inefficient industrial water utilization. (2) The NUD optimizes resource allocation and improves industrial productivity and IWE by providing favorable conditions for the pooling of various production resources (Fujita & Mori 1997).

The NUD can affect IWE by increasing the demands of residents on the living environment and strengthening the management and control of industrial enterprises. (1) The industrial enterprises have to transform and upgrade their production methods and purchase more advanced wastewater purification equipment to meet the government requirements for pollution control and reduction of wastewater discharge, which lead to an increase in production costs (Bo 2021). Meanwhile, industrial enterprises carry out innovation of production technology to save costs, that is, to make the benefits by implementing technological innovation offset the increased costs of enterprises, thereby improving IWE. (2) In terms of lifestyle, the NUD makes residents more aware of environmental protection and therefore a higher demand for urban environmental quality, thus forcing enterprises to reduce the discharge of wastewater and sewage and improving IWE. In addition, a series of environmental protection measures by industrial enterprises improve the urban environment and attract more talents to settle down and therefore help increase labor productivity and IWE. However, the improvement of living standards and changes in lifestyles caused by NUD make residents increase their demand for service industries, while leading to the rapid development of the tertiary industries, thus resulting in affecting the optimization and upgrading of industrial structure and hindering the improvement of IWE (Fox 2012).

The NUD can affect IWE by optimizing the water use structure of industrial enterprises and adjusting the industrial structure. (1) The new urbanization advocates environmental protection and resource conservation. Therefore, industrial enterprises improve the reuse rate of water through cooling water recycling, sewage reuse, and other methods to reduce the consumption of fresh water and then optimize the structure of water use. (2) The new urbanization requires the efficient and economical utilization of resources, which promotes industrial enterprises to vigorously develop water-saving intensive industries and abandon water-intensive industries that use water in a sloppy manner, thus making the industrial structure optimized and helping to improve IWE.

The NUD can affect IWE by increasing the number of industrial enterprises. The degree of industrialization is becoming higher and higher to adapt to the rapid development of new urbanization, which makes the number of industrial enterprises continue to increase and expand the scale of production, thereby increasing the consumption of industrial water and inhibiting the improvement of IWE (Balland *et al.* 2020). But the expansion of regional production scale may also reduce production costs and help to improve IWE.

Accordingly, this article proposed research hypothesis 1: the NUD has threshold effects on IWE.

The aforementioned analysis showed that the NUD has an impact on the local IWE, so will NUD also have an impact on IWE in the surrounding areas? Compared with traditional urbanization, new urbanization pays more attention to the coordinated development of urban and rural areas, environmental protection, and efficient utilization of resources, and aims to achieve healthy and high-quality development of urbanization. Therefore, this article believes that cities with better development of new urbanization have an impact on IWE of surrounding areas from the following aspects (Figure 2).

The NUD creates a platform for the inflow of various resources. The rapid development of new urbanization in the region attracts a large inflow of capital, advanced technology, and talents, which lays the foundation for innovation and therefore improves the IWE in the region (Lahr 2009). Meanwhile, the labor force in the surrounding areas flows into the city on a large scale due to the profit-seeking psychology, and various production factors from the surrounding areas also keep flowing in, thus weakening the ability of the surrounding areas to improve IWE. On the other hand, technological innovation in this region can generate knowledge spillovers and spread to the surrounding areas, so the surrounding areas can make technological changes through imitation and secondary innovation to improve IWE.

The NUD promotes the development of water-saving intensive industries, and high-efficiency enterprises cluster in cities due to the selection effects, so water-intensive and low-efficiency enterprises with sloppy water consumption are pushed out to the surrounding areas. Then the high-efficiency enterprises clustered in cities can continuously reduce production costs due to the scale effects, exacerbating the gap with surrounding areas (Yuan *et al.* 2022), that is to say, it is not conducive

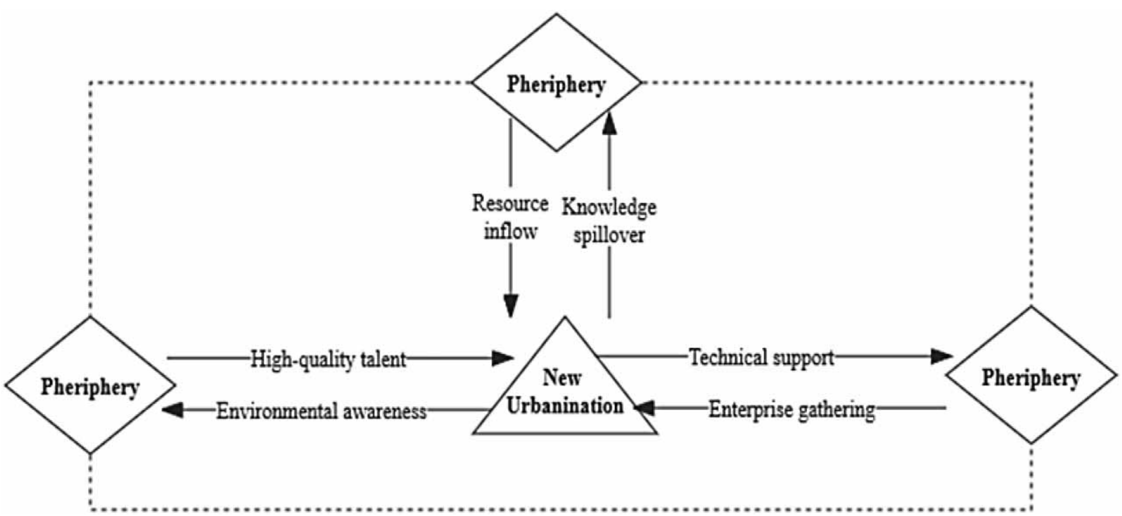


Figure 2 | The spatial spillover effects of NUD on IWE.

to the improvement of IWE in the surrounding areas. On the other hand, the NUD focuses on regional coordinated and balanced development. Neighboring cities can generate complementary industrial clusters through the division of labor and cooperative production and share advanced production technologies, which can improve IWE in the surrounding areas.

Since the purpose is 'people oriented', the new urbanization focuses on the construction of infrastructure such as culture, education, medical care, and transportation, which improves the convenience and welfare of residents and attracts the inflow of capital and talents. Then the influx of innovative talents can improve the productivity of enterprises and expand the advantages of the region, without taking advantage of the improvement of IWE in the surrounding areas. On the other side, neighboring areas can form close-knit city clusters due to the improvement of transportation, communication, and other infrastructures, which is conducive to accelerating knowledge dissemination and information sharing (Qin 2017) and the development of the surrounding areas. In addition, the NUD of the region promotes the environmental awareness of residents in the surrounding areas by influencing their lifestyles (Liddle 2004), thus forcing industrial enterprises to upgrade their technology and helping to improve IWE.

Accordingly, this article proposed hypothesis 2: NUD has spatial spillover effects on IWE.

4. METHODOLOGY AND DATA

4.1. Model and method of estimation

4.1.1. EBM model

In this article, the EBM model was used to measure IWE. To summarize the literature, many scholars have widely used the CCR, BBC, and SBM models to measure the efficiency values, which cannot measure input–output relationships that include radial and nonradial characteristics. However, the EBM model can solve the aforementioned problems and make the calculation results more accurate. The equation of the EBM model is as follows:

$$\begin{aligned} &\gamma^{*} = \min_{\theta,\lambda,s^-} \theta - \varepsilon_x \sum_{i=1}^{M} w_i s_i^- / x_{ik} \\ &s.t.\ \theta x_{ik} - \sum_{j=1}^{N} x_{ij}\lambda_j - s_i^- = 0, i = 1, \ldots, M \\ &\sum_{j=1}^{N} y_{rj}\lambda_j \geq y_{rk}, r = 1, \ldots, s, \lambda_i \geq 0, s_i^- \geq 0 \end{aligned} \tag{1}$$

where γ^* is the efficiency value (IWE value); x_{ik} and y_{ik} are the ith input and rth output of the kth DMU, respectively; θ is the radial value of the efficiency; w_i is the weight value of each influencing factor; ε_x is the key parameter combining radial and nonradial; and s_i^- is the relaxation variable.

4.1.2. Entropy method

The entropy method was used to measure the NUD of 30 provincial cities in China. The advantage of the entropy method is that it is not influenced by subjective factors in determining the index weights, which makes the evaluation results more objective, accurate, and scientific. The specific steps of the entropy method are as follows: Z_{rji} is the ith indicator of the jth city in the rth year. First, the extremum method was used to standardize the indicators. The normalization of positive and negative indicators is shown in Equations (2) and (3). The normalized data are shifted to prevent the interference of zero values and is shown in Equation (4). The entropy value, coefficient of variation, and indicator weights are calculated using Equations (5)–(7). Finally, according to Equation (8), the composite score of NUD quality is calculated for each province.

$$P_{rji} = (Z_{rji} - Z_{\min})/(Z_{\max} - Z_{\min}) \tag{2}$$

$$P_{rji} = (Z_{rji} - Z_{\min})/(Z_{\max} - Z_{\min}) \tag{3}$$

$$K_{rji} = P_{rji} + 1e - 09 \tag{4}$$

$$E_j = -\sum_n \sum_s K_{rji} \ln K_{rji} / [\ln (n \times s)] \tag{5}$$

$$F_j = 1 - E_j \tag{6}$$

$$W_j = F_j / \sum_j F_j \tag{7}$$

$$G_{yj} = \sum_j (W_j \times K_{rji}) \tag{8}$$

4.1.3. Panel threshold model

According to the theoretical analysis, there may be threshold effects between NUD and IWE. In this article, the NUD was used as a threshold variable to study the threshold characteristics. The PTM was proposed by Hansen (1999), which has the advantage of avoiding the subjectivity of other models in selecting the threshold values and finding the true threshold values through data simulation (Yang & Song 2019). The model is as follows:

$$\begin{aligned} \mathrm{IWE}_{it} = {} & \beta_{11}\mathrm{NUD}_{it} I(\mathrm{NUD}_{it} \leq \gamma_1) + \beta_{12}\mathrm{NUD}_{it} I(\gamma_1 < \mathrm{NUD}_{it} < \gamma_2) \\ & + \ldots + \beta_{1n}\mathrm{NUD}_{it} I(\gamma_{n-1} < \mathrm{NUD}_{it} \leq \gamma_n) + \beta_{1(n+1)}\mathrm{NUD}_{it} I(\mathrm{NUD}_{it} \geq \gamma_{n+1}) + \beta_1 \mathrm{PGDP}_{it} \\ & + \beta_2 \mathrm{PCWR}_{it} + \beta_3 \mathrm{TWR}_{it} + \beta_4 \mathrm{TP}_{it} + \beta_5 \mathrm{ISF}_{it} + \beta_6 \mathrm{ISS}_{it} + \beta_7 \mathrm{ER}_{it} + \beta_8 \mathrm{FDI}_{it} \end{aligned} \tag{9}$$

IWE_{it} is the industrial water efficiency of the ith region in the t year; NUD_{it} is the NUD of the ith region in the t year; PGDP, PCWR, TWR, TP, ISF, ISS, ER, and FDI are the control variables of this articles; the specific description is shown in Table 3; γ_1–γ_{n+1} are the threshold value; β_{11}–$\beta_{1(n+1)}$ are the regression estimation coefficients of different threshold intervals; and I (*) is the indicative function.

4.1.4. Moran index

The global Moran's I was used to study the spatial autocorrelation of NUD and IWE, which is a method to reveal spatial relationships (Long *et al.* 2020). If $I > 0$, it means that there is a positive spatial correlation between NUD and IWE; if $I < 0$, it means that there is a negative spatial correlation; if $I = 0$, it means that there is no spatial correlation. The formula is as follows:

$$\text{Moran's } I = \frac{\sum_{i=1}^{n} \sum_{j=1}^{n} w_{ij}(x_i - \overline{x})}{\sum_{i=1}^{n} (x_i - \overline{x}) / n \sum_{i=1}^{n} \sum_{j=1}^{n} w_{ij}} \tag{10}$$

where x_i is the attribute value of element I and w_{ij} is the spatial adjacency matrix. The spatial adjacency matrix sets the weight according to whether it is geographically adjacent, the adjacent area is set to 1, and the nonadjacent area is set to 0, as shown in Equation (10). To test the robustness of the regression results, a geographical distance matrix was also used as a proxy, and the matrix formula is expressed as follows:

$$w_1 = \begin{cases} 1 & i = j \\ 0 & i \neq j \end{cases} \tag{11}$$

$$w_2 = \begin{cases} 1/d_{ij}^2 & i = j \\ 0 & i \neq j \end{cases} \tag{12}$$

where $i = j$ means that the area i and j are adjacent, $i \neq j$ means that the area i and j are not adjacent, d_{ij} is the geographic distance between area i and j.

4.1.5. Spatial Durbin model

The aforementioned theoretical analysis found that the NUD may have spatial spillover effects on IWE. Therefore, to avoid the bias in the regression results caused by neglecting the spatial effects, the SDM was used to investigate the spatial spillover effects of NUD on IWE. The SDM controls for the spatial correlation of the explained variables and the spatial correlation of the explanatory variables with the error term (Xie *et al.* 2021). If the lagged effect of the explanatory variables does not exist, then the SDM degenerates into the spatial lag model (SAR), and if the lagged effect of the explained variables does not exist, then the SDM degenerates into spatial error model (SEM) (Yang 2013). The model is shown as follows:

$$\begin{aligned}\mathrm{IWE}_{it} =& \beta_0 + \beta_1\mathrm{NUD}_{it} + \beta_2\mathrm{PGDP}_{it} + \beta_3\mathrm{PCWR}_{it} + \beta_4\mathrm{TWR}_{it} + \beta_5\mathrm{TP}_{it} + \beta_6\mathrm{ISF}_{it} + \beta_7\mathrm{ISS}_{it}\\ &+ \beta_8\mathrm{ER}_{it} + \beta_9\mathrm{FDI}_{it} + \theta_1 W(\mathrm{NUD}_{it}) + \theta_2 W(\mathrm{PGDP}_{it}) + \theta_3 W(\mathrm{PCWR}_{it}) + \theta_4 W(\mathrm{TWR}_{it})\\ &+ \theta_5 W(\mathrm{TP}_{it}) + \theta_6 W(\mathrm{ISF}_{it}) + \theta_7 W(\mathrm{ISS}_{it}) + \theta_8 W(\mathrm{ER}_{it}) + \theta_9 W(\mathrm{FDI}_{it}) + \rho\sum_{i=1}^{n} w_{ij}\mathrm{IWE}_{it} + \varepsilon_{it}\end{aligned} \tag{13}$$

where ρ is the spatial regression correlation coefficient, w_{ij} is the spatial adjacency matrix, β is the estimated regression coefficient for each explanatory variable, ε_{it} is the random term, $W(*)$ is the spatial lag term of each variable, θ_1–θ_9 are the spatial regression coefficients of each explanatory variable, and other variables are defined as earlier.

Existing studies suggest that there are feedback effects in the spatial econometric model, that is, changes in the NUD of this region can be fed back by affecting NUD of neighboring areas. Therefore, the partial differential decomposition method was used to decompose the estimated coefficients of the SDM with reference to the study by Li & Li (2020). We organized the SDM displacement into general form, and the equation is expressed as follows:

$$\mathrm{IWE}_{it} = (I-\rho W)^{-1}Al_n + (I-\rho W)^{-1}(X\beta + WX\theta) + (I-\rho W)^{-1}\varepsilon \tag{14}$$

The matrix of partial differential equations for the explanatory variable IWE about the kth explanatory variable is shown in Equation (15):

$$\left[\frac{\partial \mathrm{IWE}}{\partial X_{1K}} \cdots \frac{\partial \mathrm{IWE}}{\partial X_{NK}}\right] = (I-\rho W)^{-1}\begin{pmatrix} \beta_k & W_{12} & \cdots & W_{1N}\theta_K \\ W_{21}\theta_K & \beta_K & & W_{2N}\theta_K \\ \vdots & & \ddots & \vdots \\ W_{N1}\theta_K & W_{N2}\theta_K & \cdots & \varphi\beta_K \end{pmatrix} \tag{15}$$

where W is the spatial adjacency matrix, I is a matrix of order n, A is a constant term, l_n is an $n \times 1$ order identity matrix, n is the number of provinces, X is the observed value of the explanatory variable, and other variables are defined as earlier.

4.2. Variables

4.2.1. The explained variable: IWE

The EBM model was used to measure IWE. On the basis of the existing literature (Zheng *et al.* 2020), the industrial fixed assets, industrial employment, and industrial water consumption of 30 provinces (cities and autonomous regions) in China were selected as input indicators, and industrial added value (expressed at constant prices in 2011) and industrial wastewater discharge are indicators of desirable and undesirable outputs, respectively. The indicator system is shown in Table 1.

Table 1 | Calculation index system of industrial water utilization efficiency

Primary indicator	Secondary indicator	Tertiary indicator	Specific description
Input indicator	Input of social resources	Labor	End-of-year employment in mining, manufacturing, electricity, gas and water production, and supply
		Capital	Total fixed assets of industrial enterprises above designated size
	Input of natural resource	Water consumption	Industrial water consumption
Output indicator	Desired output	Value added	Industrial output value added
	Undesirable output	Wastewater discharge	Industrial wastewater discharge

In this article, the kernel density estimation method was used to study the dynamic distribution of IWE. As shown in Figure 3, the distribution curves of IWE in 2011, 2015, and 2020 are plotted. From the perspective of the distribution position, there is no significant change in the curve position, indicating that the IWE is not greatly improved. From the perspective of distribution shape, the peak height first decreases and then rises, but the overall trend is down and the width gradually increases, indicating that the gap of IWE between provinces increases. In terms of distribution polarization, the multipeak is obvious, indicating a bifurcation of IWE.

4.2.2. The explanatory variable: NUD

The core explanatory variable is NUD, which was measured by the entropy method. Referring to the existing literature (Wu *et al.* 2019; Ma *et al.* 2021), a comprehensive evaluation system of NUD composite indicators was established from the five aspects of population, economy, ecology, society, and urban and rural development, which was composed of 14 specific indicators, as shown in Table 2.

Based on the measurement of the level of NUD by using the entropy method, the kernel density estimation method was also used to study the dynamic distribution of NUD. As shown in Figure 4, the distribution curve of NUD shifts to the right during the study period, indicating that the overall level of NUD gradually improves. In terms of distribution shape,

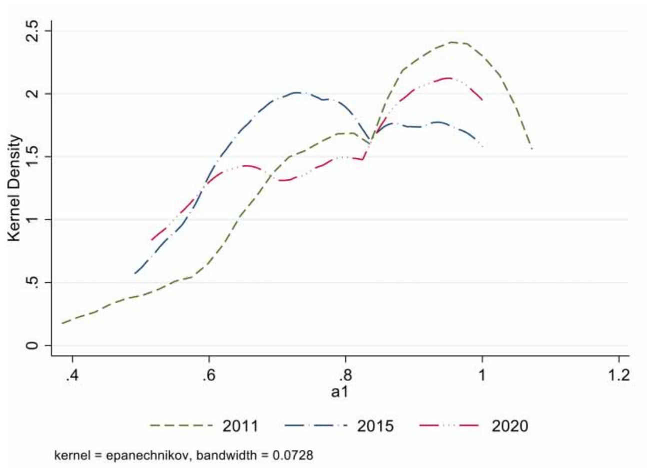


Figure 3 | Distribution curve of IWE.

Table 2 | Evaluation index system of new urbanization development level

Primary indicator	Quantitative indicator	Attribute	Weight
Population urbanization	The proportion of urban population (%)	Positive	0.081
	Urban population density (person/km²)	Positive	0.088
Economy urbanization	GDP per capita (yuan)	Positive	0.118
	The proportion of the total output value of secondary and tertiary industries in GDP (%)	Positive	0.044
Ecological urbanization	Urban sewage treatment rate (%)	Positive	0.033
	Industrial SO_2 emissions (ton)	Negative	0.040
	Harmless treatment rate of municipal solid waste (%)	Positive	0.034
	Green coverage area of built districts (%)	Positive	0.042
Society urbanization	Per capita area of roads (m^2)	Positive	0.063
	Per capita public library collection (volume)	Positive	0.207
	Number of doctors per 10,000 people (person)	Positive	0.065
	Urban gas penetration rate (%)	Positive	0.033
Urban and rural development	Ratio of rural per capita net income to urban per capita disposable income (ratio)	Positive	0.084
	Ratio of per capita consumption of rural and urban residents (ratio)	Positive	0.067

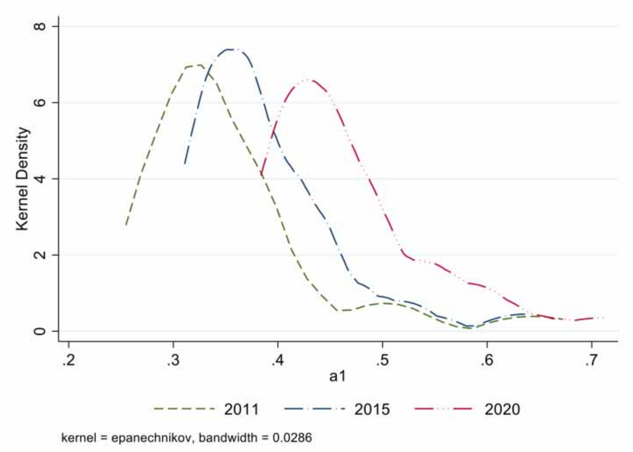


Figure 4 | Distribution curve of NUD.

the height of the distribution curve decreases slightly, indicating that NUD in different provinces becomes more diverse. From the perspective of distribution ductility, the right tail becomes longer, indicating that the number of provinces with a high level of NUD is gradually increasing.

4.2.3. Control variables

(1) Economic development level, measured by GDP per capita. (2) Natural resource factors, measured by water resources per capita (water endowment) and total water resources. (3) Technological progress, measured by the number of domestic patent applications granted. (4) Industrial structure, measured by the tertiary industry as a share of the output value of the secondary industry and the share of tertiary industry output in GDP. (5) Environmental regulation, measured by completed an investment in industrial wastewater treatment. (6) Foreign direct investment. Since GDP per capita, completed investment in industrial wastewater treatment and foreign direct investment have an exponential growth trend, they are treated as logarithms.

4.3. Data source

In this study, 30 provincial-level cities in China were selected as research objects. Due to the lack of data in Hong Kong, Macau, Taiwan, and Tibet, this study does not include the aforementioned four cities for the time being. The research period range is 2011–2020. The data in this article come from *China Statistical Yearbook*, *China Environmental Statistical Yearbook*, and *China Industrial Statistical Yearbook*. Explanations of specific indicators and statistical analysis of the data are shown in Table 3.

Table 4 shows the correlation matrix of the variables. It can be seen that most of the variables are correlated at the 1% significance level. Moreover, the correlation coefficient between the explained variable IWE and the core explanatory variable NUD is 0.328, which is significantly positive at the 1% level, indicating that a high level of NUD is conducive to improving IWE.

5. RESULTS

5.1. Regional difference analysis

The IWE of China from 2011 to 2020 was calculated by using the EBM model, and then a radar map of the IWE in 2011, 2015, and 2020 was made. As shown in Figure 5. Overall, there are obvious regional differences in IWE, with the eastern region having the highest efficiency values and being higher than the national average, and the central and western regions having relatively lower efficiency. We also found that there is an obvious trend of agglomeration among regions, as reflected in the gradual spread of regions with higher IWE from the eastern region to the central and western regions. From the perspective of the average efficiency, the efficiency values of six provinces – Beijing, Hebei, Zhejiang, Fujian, Guangdong, and Shaanxi – all reach 1; moreover, we found that all provinces except Shaanxi belong to the eastern region, indicating that the IWE in the eastern region is relatively high and the water utilization is more reasonable. But the efficiency values of Qinghai, Jilin, Gansu, Jilin, and Heilongjiang are all lower than 0.6, and all of the above provinces belong to the central and western

Table 3 | Specific explanation of indicators and descriptive statistics

Variable	Symbol	Variable description	Mean	Std. Dev	Min.	Max.
Industrial water efficiency	IWE	–	0.828	0.166	0.343	1
New urbanization development	NUD	–	0.407	0.083	0.283	0.722
Economic development level	PGDP	GDP per capita	10.743	0.413	9.706	0.722
Natural resource factors	PCWR	Per capita water resources (water resources endowment)	0.218	0.261	0.006	1.706
	TWR	Total water resources	802.725	726.679	8.100	3,237.3
Technological progress	TP	The number of domestic patent applications authorized	58.602	89.367	0.502	709.725
Industrial structure	ISF	The share of tertiary industry output in GDP	49.162	8.976	32.656	83.732
	ISS	The tertiary industry as a share of the output value of the secondary industry	121.925	69.597	51.803	529.682
Environmental regulation	ER	Completed investment in industrial wastewater treatment	9.670	1.393	3.751	12.597
Foreign direct investment	FDI	–	5.449	1.728	−1.287	7.811

regions, which means that there may be water wastage in terms of industrial water use. In addition, the efficiency values of most provinces in the central and western regions are lower than 0.7 in 2020, so there is still much room for improvement.

The comprehensive quality score of NUD in 30 provinces (cities and autonomous regions) in China from 2011 to 2020 was measured by the entropy method. Then ArcGIS10.3 was used to visualize the level of NUD in 2011, 2015, and 2020. As shown in Figure 6, overall, the level of NUD in China is gradually improving. The number of cities with a comprehensive quality score of NUD above 0.5 increases significantly, while the number of cities with a score of below 0.4 decreases from 26 in 2011 to 6 in 2020. From the regional perspective, the cities with a score of above 0.5 in 2020 are all located in the eastern coastal area except for Ningxia, so we can see that the level of NUD in the eastern region is higher than that in the central and western regions. Furthermore, Beijing, Tianjin, and Shanghai rank among the top three cities in China in terms of efficiency value, with scores above 0.5, while Sichuan, Guangxi, and Guizhou rank in the bottom three. While the western region is constrained by reasons such as geographic situation, economic growth, and natural conditions, the eastern region has significant advantages and the level of NUD exhibits high agglomeration characteristics. In conclusion, although there is diversity in the level of NUD in each region, the overall trend is steadily increasing.

5.2. Estimation results of panel threshold regression

According to the threshold effect results (Table 5), the NUD passed the single threshold test at the 10% significance level, but not the double threshold test, that is, it has a single threshold effect on the IWE. Table 6 presents the single threshold

Table 4 | Correlation matrix

Variable	IWE	NUD	PGDP	PTWR	TWR	TP	ISF	ISS	ER	FDI
IWE	1.000									
NUD	0.328***	1.000								
PGDP	0.477***	0.833***	1.000							
PTWR	− 0.399***	− 0.268***	− 0.311***	1.000						
TWR	0.069	− 0.305***	− 0.275***	0.419***	1.000					
TP	0.362***	0.424***	0.525***	− 0.202***	0.141**	1.000				
ISF	0.041	0.724***	0.608***	− 0.122**	− 0.252***	0.217***	1.000			
ISS	0.024	0.554***	0.440***	− 0.127**	− 0.215***	0.125**	0.873***	1.000		
ER	0.341***	− 0.133**	− 0.029	− 0.160***	0.210***	0.294***	− 0.466***	− 0.485***	1.000	
FDI	0.638***	0.307***	0.537***	− 0.524***	0.055	0.485***	0.08	0.074	0.324***	1.000

$^{**}p < 0.05$, $^{***}p < 0.01$.

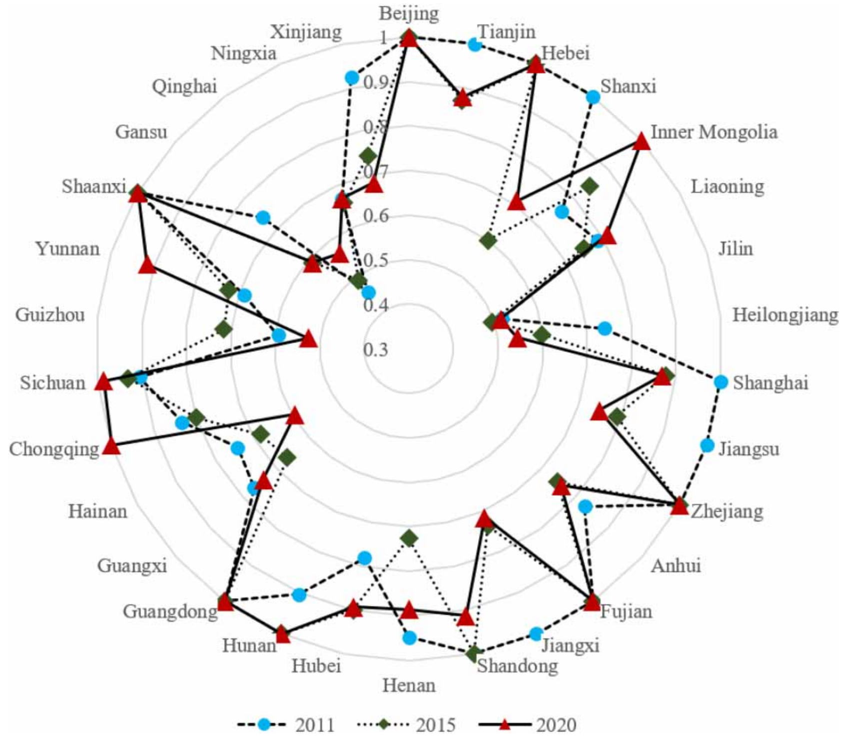


Figure 5 | Radar map of industrial water utilization efficiency in 2011, 2015, and 2020.

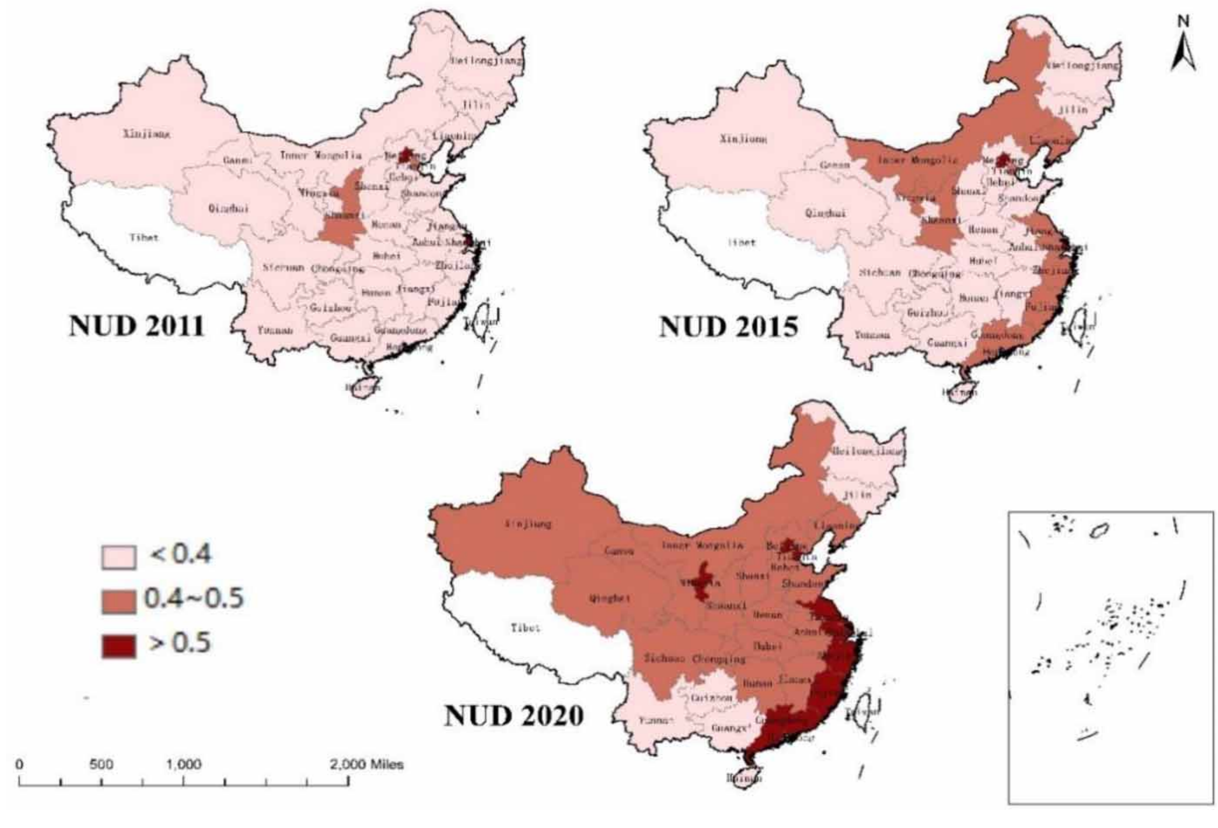


Figure 6 | The spatial distribution pattern of new urbanization development level in 2011, 2015, and 2020.

Table 5 | Threshold effect test

Variable	Threshold	*F*-value	*P*-value	10%	5%	1%
NUD	Single threshold	17.94	0.0633	14.0526	19.0467	25.4020
	Double threshold	7.75	0.4400	12.8598	16.4949	22.1338

Table 6 | Threshold regression estimation result

Variable	Type	Threshold estimate	Confidence interval
NUD	Single	0.3137	[0.3101, 0.3138]

estimation value and its 95% confidence interval with NUD as the threshold variable, and we can see that the threshold value is 0.3137, which is in the interval [0.3101, 0.3138]. The likelihood ratio (LR) trend charts of the single threshold and double threshold are shown in Figure 7.

The regression results of the PTM are shown in Table 7. The linear estimation results of the ordinary least squares (OLS) are also given for the purpose of comparative analysis. As shown in column (1) of Table 7, the estimated coefficient of NUD by OLS is significantly positive, indicating that the NUD is beneficial for improving IWE. According to column (2) of Table 7, we found that the NUD has a significant single threshold effect on IWE, that is, when the level of NUD is lower than 0.3137, it has a positive but not significant effect on IWE, and when the level of NUD is higher than 0.3137, its regression estimated coefficient is 0.540 and is significantly positive at the 5% level. The possible explanation is that there is a bottleneck in the NUD, and the improvement effect of the lower level of NUD on IWE is not significant, while with the improvement of the level of NUD, the industry actively carries out technological transformation and industrial structure upgrading and pays more attention to resource protection and coordinated development of industry and ecological environment in the production process, so that the negative externalities caused by 'urban disease' are gradually alleviated, which is conducive to the improvement of IWE. In conclusion, the linear model does not fully reveal the effect of NUD on IWE, so hypothesis 1 was confirmed.

From the perspective of the control variables, the rise of PGDP is conducive to the improvement of IWE, while ISF has a negative inhibitory impact on IWE. From the regression coefficients, the coefficient of PGDP is the largest, which indicates that it has the most obvious impact on IWE, so improving the level of economic development can significantly promote the improvement of IWE.

The aforementioned analysis showed that the impact of NUD on IWE is nonlinear. To further analyze the relative threshold distribution of NUD during the study period, the samples were divided into 'low-level' and 'high-level' groups according to whether they crossed the threshold value. The results of the group are shown in Figure 8. There are 18 out of 30 provinces in the 'high-level' group in 2011, and most of which belong to the eastern coastal cities. With the rapid

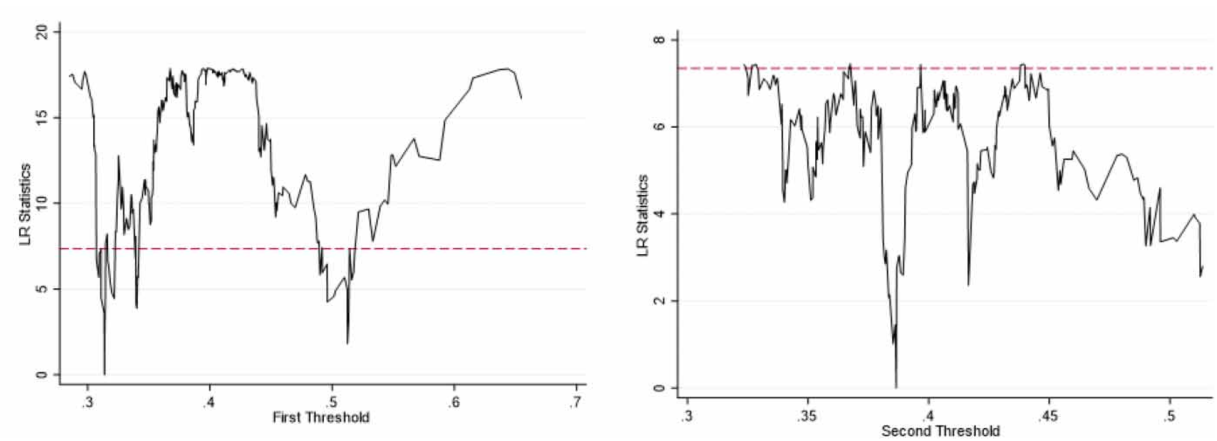


Figure 7 | Single threshold and double threshold LR statistics.

Table 7 | Regression results of threshold effect

Variable	OLS (1)	PTM (2)
NUD	0.292* (1.66)	
NUD $\leq$ 0.3137		0.304 (1.27)
NUD>0.3137		0.540** (2.43)
PGDP	0.164*** (4.23)	0.099* (2.42)
PTWR	−0.130*** (−3.47)	−0.066 (−0.73)
TWR	5.19×10^{-5}*** (4.09)	-1.92×10^{-5} (−0.66)
TP	-2.04×10^{-4}** (−2.01)	6.26×10^{-5} (0.59)
ISF	−0.006*** (−2.98)	−0.015*** (−7.55)
ISS	3.41×10^{-4} (1.60)	1.59×10^{-4} (0.67)
ER	0.018*** (2.69)	−0.002 (−0.3)
FDI	0.027*** (3.99)	−0.019** (−2.11)

*$p < 0.10$, **$p < 0.05$, ***$p < 0.01$; *t*-test values in parentheses.

development of new urbanization, we found that provinces in the 'low-level' group shift to the 'high-level' group in 2016, and all provinces cross the threshold value to achieve high-quality development of new urbanization.

5.3. Estimation results of spatial econometric regression

5.3.1. Spatial autocorrelation test

The global Moran's I was used to examine the spatial autocorrelation of IWE and NUD. As shown in Table 8, the global Moran's I values of NUD from 2011 to 2020 show an overall upward trend from 0.241 in 2011 to 0.305 in 2020, and all are significant at the 1% level, indicating that it has a significant positive spatial autocorrelation. The global Moran's I values of IWE are positive from 2011 to 2020, and most of them are significant at the 10% level. Overall, the IWE has a positive spatial autocorrelation.

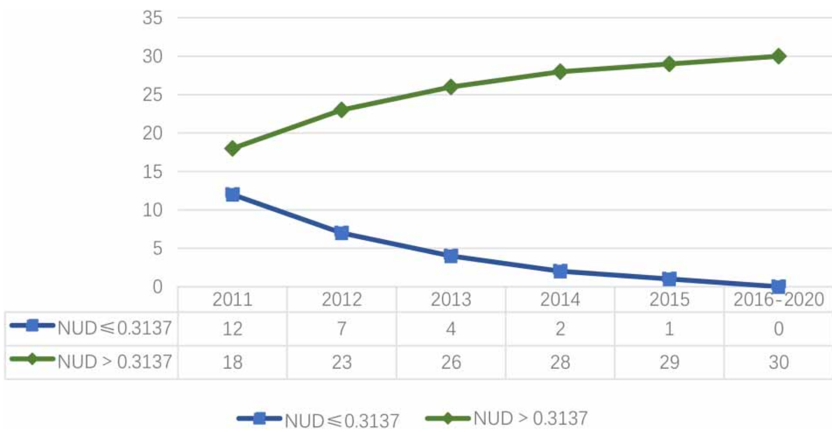


Figure 8 | Change trend of 30 NUD threshold.

Table 8 | Moran I of NUD and IWE

		2011	2012	2013	2014	2015	2016	2017	2018	2019	2020
NUD	Moran I	0.241	0.245	0.242	0.246	0.302	0.279	0.310	0.355	0.336	0.305
	Critical value Z	2.489	2.528	2.488	2.518	2.963	2.824	3.080	3.411	3.209	2.901
IWE	Moran I	0.307	0.274	0.191	0.164	0.109	0.148	0.239	0.035	0.110	0.019
	Critical value Z	2.783	2.503	1.824	1.604	1.148	1.461	2.211	0.566	1.166	0.425

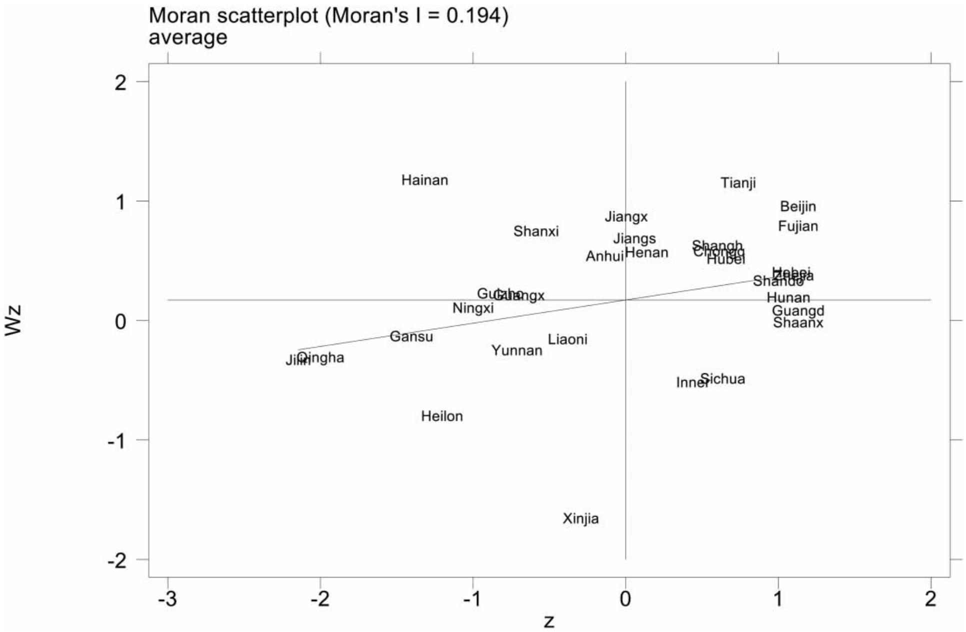


Figure 9 | Moran scatter plot of the mean values of IWE from 2011 to 2020.

According to the scatter plot of the mean values of NUD and IWE (Figures 9 and 10), it can be seen that most provinces are located in the first and third quadrants, indicating that the NUD and IWE of Chinese provinces show 'high-high' and 'low-low' agglomeration characteristics, and there is a strong spatial similarity among provinces.

5.3.2. Regression results analysis

The Hausman test was first performed and it passed the 1% significance test, so the fixed effect model was selected. Next, the Lagrangian multiplier test (LM test) was carried out, and the LM error, robust LM error, and robust LM lag all passed the 1%

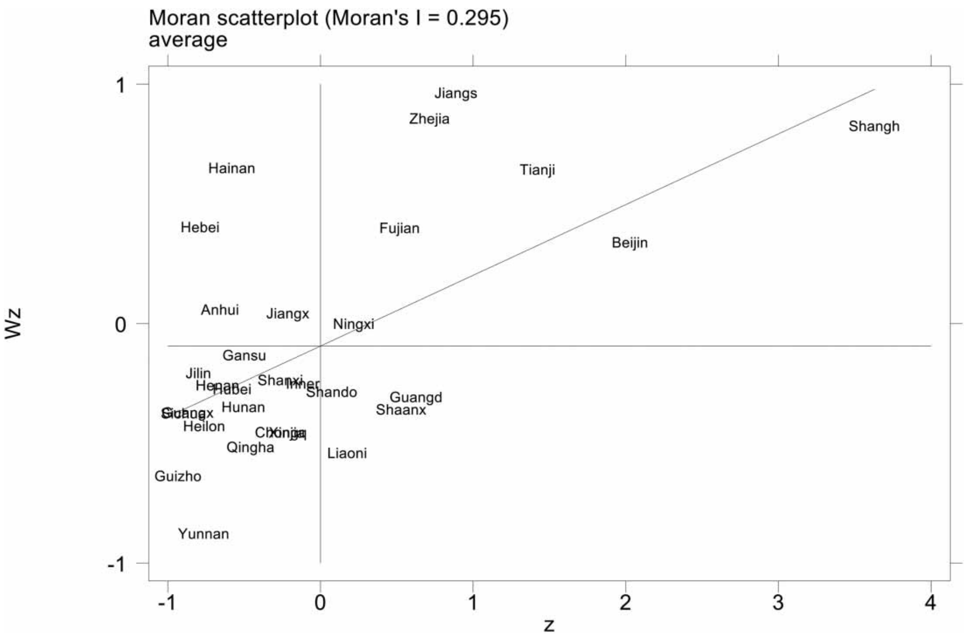


Figure 10 | Moran scatter plot of the mean values of NUD from 2011 to 2020.

Table 9 | LM, LR, Wald, and Hausman tests results

Test	Statistic	Test	Statistic
LM error	21.356***	LR error	31.05***
Robust LM error	27.694***	LR lag	46.22***
LM lag	2.779*	Wald error	29.78***
Robust LM lag	9.117***	Wald lag	22.95***
Hausman	22.30***		

*p<0.10, ***p<0.01.

significance test and the LM lag passed the 10% significance test, so the SDM of fixed effect was chosen. Finally, the LR test and Wald test were carried out, and both passed the 1% significance test, indicating that the SDM cannot degenerate into SAR or SEM. The results are shown in Table 9.

The estimated results of the SDM are shown in Table 10. We found that the time fixed effect is most appropriate by comparing. According to the results, the autoregressive coefficient is 0.184 and is significant at the 5% level, which means that there is a significant positive spatial spillover effect on IWE. The regression estimation coefficient of the core explanatory variable NUD is 0.666 and is significant at the 1% level, indicating that NUD is conducive to the improvement of IWE. The possible explanation is that the construction of new urbanization has brought a large amount of resources to the cities, which are expanding in size while promoting economic development and technological progress, thus enabling industries to accelerate the transformation and upgrading of their industrial structure and technological innovation. Furthermore,

Table 10 | Regression results of SDM

	Spatial fixed effects		Time period fixed effects		Spatial and time period fixed effects	
Variable	Coefficients	*z* Values	Coefficients	*z* Values	Coefficients	*z* Values
NUD	0.236	0.93	0.666***	3.63	−0.347	−1.35
PGDP	−0.043	−0.77	0.141***	3.57	−0.072	−1.38
PTWR	−0.164*	−1.83	−0.129***	−3.38	−0.156*	−1.85
TWR	-4.74×10^{-6}	−0.15	1.92×10^{-5}	1.15	-2.15×10^{-5}	−0.74
TP	-2.23×10^{-5}	−0.22	-2.15×10^{-4}**	−2.09	-9.29×10^{-5}	−0.94
ISF	−0.019***	−8.10	−0.007***	−3.48	−0.019***	−7.70
ISS	1.05×10^{-4}	0.38	2.29×10^{-4}	0.95	-2.75×10^{-4}	−1.02
ER	−0.002	−0.34	0.012	1.58	−0.002	−0.35
FDI	−0.005	−0.62	0.040***	5.03	0.001	0.16
W*NUD	0.095	0.20	0.865**	2.07	−1.796***	−3.27
W*PGDP	0.174**	2.32	−0.275***	−3.93	0.121	1.63
W*PTWR	0.115	0.69	0.007	0.07	0.053	0.34
W*TWR	1.66×10^{-5}	0.37	4.72×10^{-5}*	1.84	2.98×10^{-5}	0.63
W*TP	-2.79×10^{-4}**	−2.54	-1.06×10^{-4}	−0.73	-4.10×10^{-4}***	−3.55
W*ISF	0.010**	2.49	0.007	1.62	0.004	0.76
W*ISS	-3.66×10^{-4}	−0.69	-8.33×10^{-4}	−1.54	−0.002***	−3.42
W*ER	−0.016*	−1.67	−0.050***	−2.85	−0.018*	−1.75
W*FDI	−0.007	−0.41	0.007	0.45	0.013	0.79
Spatial rho	0.090	1.10	0.184**	2.22	−0.166*	−1.84
R^2	0.004	12.24	0.011***	12.09	0.003***	12.21
Log-L	421.0348		254.0651		443.8927	

*$p < 0.10$, **$p < 0.05$, ***$p < 0.01$.

the policy changes brought about by the NUD have forced industrial enterprises to abandon water-intensive industries and vigorously develop water-saving industries. In addition, the construction of new urbanization has improved the quality of the population, enhanced awareness of water conservation and environmental protection among residents, and improved the construction of social infrastructure in terms of education, social functions, and environmental protection, thereby making industrial enterprises pay more attention to issues such as water recycling and wastewater discharge.

Since the regression estimation coefficients in the SDM cannot reflect the impact of NUD in the adjacent areas on the IWE of the region, this article decomposed the spatial effects. As shown in Table 11, we report the decomposition results of both the spatial adjacency matrix and the geographic distance matrix. We can see that the estimated coefficient of the direct effect of NUD is significantly positive at the 1% level, confirming that the NUD can indeed improve IWE by optimizing the industrial structure, rationally allocating resources, and strengthening technological innovation. The estimated coefficient of the indirect effect of NUD is 1.119, which is significant at the 5% level, confirming that there is a significant positive spatial spillover effect, that is, NUD can not only directly improve IWE in this region but also provide support for the improvement of IWE in this region by influencing NUD in the surrounding areas. In addition, from the perspective of the estimated coefficients, the estimated coefficient of the indirect effect of NUD is higher than the direct effect, which means that the positive driving effect of NUD on the improvement of IWE depends to a large extent on the spatial spillover effects. Hypothesis 2 was, therefore, verified.

From the perspective of control variables, we found that the direct effect of PGDP is significantly positive, and the indirect effect is significantly negative, which means that the increase of PGDP in this region is conducive to the improvement of IWE, but the increase of PGDP in surrounding areas has a negative impact on the IWE in this region. The indirect effect of ER is significantly negative, which is explained by the fact that the enhanced environmental regulations in the surrounding areas have led industrial enterprises to relocate high water-consuming and high-polluting industries to the region, thereby adversely affecting the improvement of IWE in the region. The direct effect of PCWR is significantly negative, that is to say, the abundance of natural resources has hampered the improvement of IWE, which is a typical phenomenon of the 'resource curse.' The direct effect of FDI is significantly positive, which is due to the fact that FDI has brought capital, technology, and advanced management concepts to industrial development and promotes the improvement of IWE. Since the direct and indirect effects of ISS are not significant, this article used ISF to represent the industrial structure for analysis. We can see

Table 11 | Decomposed spatial effects of SDM

	Spatial adjacency matrix			Geographic distance matrix		
Variable	**Direct effects**	**Indirect effects**	**Total effects**	**Direct effects**	**Indirect effects**	**Total effects**
NUD	0.708*** (3.78)	1.181** (2.34)	1.889*** (3.24)	0.661*** (3.27)	2.697*** (3.57)	3.358*** (3.86)
PGDP	0.127*** (3.78)	−0.292*** (−3.35)	−0.165* (−1.67)	0.107*** (2.99)	−0.016 (−0.11)	0.090 (0.54)
PCWR	−0.126*** (−3.10)	−0.014 (−0.11)	−0.140 (−0.94)	−0.232*** (−4.10)	−0.477** (−2.52)	−0.709*** (−3.05)
TWR	2.14×10^{-5} (1.18)	5.7×10^{-5}** (2.11)	7.85×10^{-5}*** (2.65)	7.89×10^{-5}*** (4.97)	1.78×10^{-4}*** (3.27)	2.57×10^{-4}*** (4.37)
TP	-2.39×10^{-4}** (−1.98)	-1.55×10^{-4} (−0.90)	-3.93×10^{-4} (−1.63)	-2.87×10^{-4}** (−2.39)	−0.001*** (−2.99)	−0.002*** (−3.23)
ISF	−0.007*** (−3.37)	0.006 (1.17)	-3.23×10^{-4} (−0.05)	−0.006*** (−3.05)	0.006 (0.77)	1.53×10^{-4} (0.02)
ISS	1.82×10^{-4} (0.79)	-9.05×10^{-4} (−1.37)	-7.23×10^{-4} (−0.90)	1.27×10^{-4} (0.50)	−0.001 (−1.32)	−0.001 (−0.98)
ER	0.009 (1.38)	−0.056*** (−2.67)	−0.047** (−2.07)	0.008 (1.08)	0.024 (0.83)	0.032 (1.00)
FDI	0.042*** (6.23)	0.017 (0.86)	0.059*** (3.01)	0.026*** (3.92)	−0.068** (−2.17)	−0.042 (−1.27)

*$p < 0.10$, **$p < 0.05$, ***$p < 0.01$; *t*-test values in parentheses.

that the direct effects of both ISF and TP are significantly negative, which is consistent with the research of Li *et al.* (2019), where there is a time lag in the implementation of scientific and technological innovation and the shortcomings of industrial structure, both of which reduce IWE.

6. CONCLUSIONS AND POLICY IMPLICATIONS

This study explored the mechanism of action between NUD and IWE. First, the EBM model and the entropy method were used to measure IWE and NUD. Second, the spatial spillover effects and threshold characteristics of NUD on IWE were discussed by using the SDM and the PTM. The following conclusions are drawn:

(1) The IWE and NUD are unbalanced in regional development and both show a spatial pattern that gradually decreases from east to west. The IWE in the eastern region is significantly higher than that in the central and western regions, and it shows a trend of spreading from the east to the central and western regions. The level of NUD is gradually improving, and cities with a high level of development are mainly distributed in the eastern region, while there is a large room for improvement in the central and western regions.
(2) The NUD has a significantly positive spatial spillover effect on IWE. Both the direct and the indirect effects of NUD are significant positive by using the partial differential method to decompose the total effect, that is, the NUD can not only improve IWE in this region but also promote IWE by influencing NUD in the surrounding areas. Furthermore, the spillover effects between regions are greater than the local effect within the region.
(3) There is an interval effect between NUD and IWE, and the structural change point is 0.3137. The results of the panel threshold regression model show that when the level of NUD is below the threshold value, the promotion effect of NUD on IWE is not significant; when NUD exceeds the threshold value, the driving effect is significantly increased.

On the basis of aforementioned conclusions, this article put forward the following policy recommendations:

First, the government should pay attention to regional differences to formulate policies and plans that are in line with local development according to local conditions. Beijing, Zhejiang, Guangdong, and other high-efficiency cities can maintain their current resource management policies and investments. Medium-efficiency and low-efficiency cities should actively develop their economies and strengthen water resources management. The government should try to reduce the number of high water-consuming and high-polluting enterprises in the industrial layout. Moreover, areas with slow development of new urbanization should pay attention to infrastructure construction and improve the quality of public services to make up for the shortcomings of development.

Second, we should strengthen the construction of new urbanization, vigorously improve the quality of urbanization development, and promote industrial development. The regions should cultivate a sense of cooperation, strengthen exchanges and cooperation between regions, and bring into play the demonstration and radiation role of urban agglomerations. Moreover, the regions should strengthen the deep integration of new urbanization and technological innovation to create a good environment for the full release of technological spillovers brought about by the development of new urbanization, so as to achieve an increase in the efficiency of industrial water utilization.

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DATA AVAILABILITY STATEMENT

All relevant data are included in the paper or its Supplementary Information.

CONFLICT OF INTEREST

The authors declare there is no conflict.

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