The Impacts of the Geographic Distribution of Manufacturing Plants on Groundwater Withdrawal in China

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Abstract

The overexploitation of groundwater in China has raised concern as it has caused a series of environmental and ecological problems. However, far too little attention has been paid to the relationship between groundwater use and the spatial distribution of water users, especially that of manufacturing factories. This study proposed a factory scatter index (FSI) that incorporates the latitude and longitude of each plant and calculates the distance between factories to characterize the degree to which manufacturing plants are scattered in China. It is found that counties and border areas between neighboring provinces registered the highest FSI increase. It seems that the degree of scattering of manufacturing plants is closely related to land planning and management of local governments. Further non-spatial and spatial regression models using 205 provincial-level secondary river basins in China from 2016 show that the scattered distribution of manufacturing plants played a key role in groundwater withdrawal in China, especially in fragile ecological-environment areas. The scattered distribution of manufacturing plants raises the cost of tap water transmission, makes monitoring and supervision more difficult, and increases the possibility of surface water pollution, thereby intensifying groundwater withdrawal. A reasonable spatial adjustment of manufacturing industry through planning and management can reduce groundwater withdrawal and realize the protection of groundwater. Our study may provide a basis for water-demand management through spatial adjustment in areas with high water scarcity and fragile ecological environment.

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Key Points:

- Manufacturing plants are more scattered in China's counties and bordering areas.
- The scattering of manufacturing plants has a significant impact on groundwater withdrawal, especially in ecologically fragile areas.
- Reasonable spatial adjustment of the spatial distribution of manufacturing plants can reduce groundwater withdrawal.

Abstract

The overexploitation of groundwater in China has raised concern as it has caused a series of environmental and ecological problems. However, far too little attention has been paid to the relationship between groundwater use and the spatial distribution of water users, especially that of manufacturing factories. This study proposed a factory scatter index (FSI) that incorporates the latitude and longitude of each plant and calculates the distance between factories to characterize the degree to which manufacturing plants are scattered in China. It is found that counties and border areas between neighboring provinces registered the highest FSI increase. It seems that the degree of scattering of manufacturing plants is closely related to land planning and management of local governments. Further non-spatial and spatial regression models using 205 provincial-level secondary river basins in China from 2016 show that the scattered distribution of manufacturing plants played a key role in groundwater withdrawal in China, especially in fragile ecological-environment areas. The scattered distribution of manufacturing plants raises the cost of tap water transmission, makes monitoring and supervision more difficult, and increases the possibility of surface water pollution, thereby intensifying groundwater withdrawal. A reasonable spatial adjustment of manufacturing industry through planning and management can reduce groundwater withdrawal and realize the protection of groundwater. Our study may provide a basis for water-demand management through spatial adjustment in areas with high water scarcity and fragile ecological environment.

1. Introduction

Groundwater is the world's largest freshwater resource and accounts for 33% of the annual global freshwater withdrawal. Globally, groundwater supplies drinking water to more than 2 billion people and provides more than half of the irrigation water (Giordano, 2009; de Graaf et al., 2019; Olea-Olea et al., 2020). In recent years, the increase in the global population, urbanization, and rising demands from the industrial and agricultural sectors have led to the excessive abstraction of groundwater, which in turn has led to an extreme lowering of water tables. The overexploitation of groundwater has caused a series of environmental and ecological problems, such as ground subsidence, seawater intrusion, and groundwater pollution (Braadbaart, O. & Braadbaart, F., 1997; Koncagül, 2015; de Graaf et al., 2019; Shah et al., 2000). Water demand must be managed to reduce groundwater consumption and hence to control ecological and environmental risks caused by the overexploitation of groundwater. As well as generic water-demand management measures such as developmental and technical measures, market-based measures have been reported in the broader literature (Hamdy et al., 2003; Yang et al., 2003; Gilg & Barr, 2006; Chang et al., 2017). However, the spatial distribution of water users is rarely incorporated into water-demand management measures.

By using GIS and statistical models to analyze single-family residential water withdrawal, Chang et al. (2010) found that the water withdrawal of communities with a high degree of aggregation was less than that of scattered communities. Shandas and Parandvash (2010) studied the relationship between land-withdrawal zoning and development-induced water withdrawal in Portland, Oregon, USA. They argued that the coordination between land-withdrawal planning and water demand management should be improved. Additionally, Sanchez et al. (2018) found that the agglomeration patterns of water users have the potential to improve water withdrawal efficiency. These authors showed that the spatial distribution of water users has an important impact on water consumption. However, far too little attention has been paid to the relationship between groundwater use and the spatial distribution of water users.

Groundwater is a vital source of industrial water. In North China, 50% of industrial water consumption is supplied by groundwater (Chinese Ministry of Environmental Protection, 2011). China's manufacturing industries are considered to be characterized by scattered distribution, which is mostly based on qualitatively studies of its status, forming mechanisms, or background of political institutions (Zhu & Guo, 2014; Zhu, 2017; Zhang et al., 2018). As has been found in this study, this scattered distribution often lead to more usage of groundwater, not only because of the difficulties to lay water pipelines, but also because it can lead to severe contamination of surface water and people have to shift to using more groundwater (Brown & Halweil, 1998). However, what is the degree of scattering of China's manufacturing industry? This issue has rarely been quantitatively measured, which limits our ability to study the impacts of manufacturing plants distribution on groundwater.

Zheng et al. (2019) investigated the relationship between the dispersion of manufacturing factories and groundwater withdrawal in Hebei Province in the North China Plain. They revealed that, in Hebei Province, the manufacturing industry is relatively dispersed, and the greater the dispersion of the manufacturing industry the greater the groundwater withdrawal. However, it is unclear whether the same relationship exists at the national level, and this research gap limits the planning of groundwater resource demand management.

In this paper, we quantitatively characterize the distribution of manufacturing plants and examine the relationship between the spatial distribution of the manufacturing industry and groundwater withdrawal in 205 provincial-level secondary river basins in China. The remainder of this paper is organized as follows: Section 2 describes the methodology; Section 3 presents the spatial distribution of manufacturing plants in China and empirically analyzes the relationship between the distribution of manufacturing plants and groundwater withdrawal; Section 4 discusses the results; and Section 5 presents the conclusions.

2. Materials and Methods

2.1. Factory Scatter Index (FSI)

Based on the address of each manufacturing factory in China derived from the Chinese Industrial Enterprises Database, the address resolution method was used to determine the latitude and longitude of each factory (Zheng et al., 2018). Then, using the spatial location of the manufacturing factories, an index named the factory scatter index (FSI) was designed to measure the degree of scattering of the manufacturing factories (Zheng et al., 2019). The FSI was calculated as follows: using the geographic location information for each manufacturing plant, grids were created with cell size d around factory j at the center of a square, as shown in Figure 1.

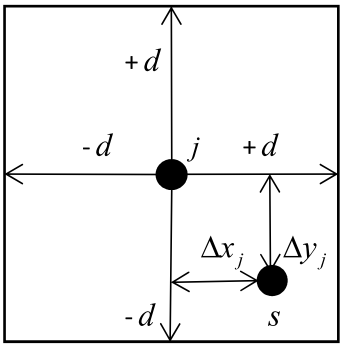


Figure 1. The calculation of the average distance between factory j and factory s.

The average distances between factories in each unit were calculated as follows to quantify the extent to which factories were scattered.

$$d_j = \frac{\sum_{s=1}^{m_j} \sqrt{\Delta x_s^2 + \Delta y_s^2}}{m_j} \tag{1}$$

where d_j is the average distance between factory j and all other factories in a study unit; j represents a factory; Δx_s and Δy_s are the differences in latitude and longitude between factory j and factory s, respectively; and m_j represents the number of factories that satisfy the conditions $j \in i$ and –6 km $\leq \Delta x_j,\ \Delta y_j \leq$ +6 km.

The FSI of a study unit can then be defined as the average value of dj as follows:

$$D_i = \frac{\sum_{j=1}^{t_i} d_j}{t_i} \tag{2}$$

where D_i is the average distance between factories, i denotes a study unit, and t_i is the number of factories in study unit i.

According to the calculation of Zheng et al. (2019), the optimal value of d that most accurately characterizes the degree to which plants are scattered is 6 km. Areas within 6 km of development are assumed to be hotspots for settlement (Zhang et al., 2009). Therefore, considering that it is difficult to obtain a uniform d value nationwide, we also chose 6 km as the cell size for this study.

2.2. Models and Variables

We used the following three models to study the influencing factors of groundwater withdrawal. The first model was the ordinary least squares (OLS), which uses all variables to fit a single linear regression. Its expression formula is:

$$ln y_i = \beta_0 + \sum \beta_i x_i + \varepsilon_i \quad 3)$$

where $\ln y_i$ is the dependent variable, x_i is the independent variables, and ε_i is the random error.

It was found that there were areas where the groundwater withdrawal was 0. So Tobit model was used to eliminate the influence of zero value. Its expression formula is the same as that of the OLS regression.

To further examine the relationship between independent variables and the dependent variable with the consideration of their spatial variations, Geographically Weighted Regression (GWR) model was also used to integrate the geographic coordinates of each observation into the linear regression model. The expression formula of the GWR model is:

$$ln y_i = \beta_{0(u_i, v_i)} + \sum \beta_{k(u_i, v_i)} x_{ik} + \varepsilon_i$$

4)

where $\ln y_i$ is the dependent variable, β_0 is a constant term, (u_i, v_i) is the spatial position of the sampling point i, $\beta_{k(u_i,v_i)}$ is the correlation coefficient between variables at point (u_i, v_i), x_{ik} is the independent variables, and ε_i is the random error.

In all models, the logarithm of groundwater withdrawal was taken as the dependent variable and the FSI of the same basin as the target independent variable. Since the groundwater withdrawal data at the district and county level is not available, we take 205 provincial-level secondary river basins in China as samples.

Based on related literature, we considered both the natural and social-economic factors as independent variables to examine their influence on groundwater withdrawal. In China, the main types of water use are agricultural water, industrial water and residential water. Among them, agriculture is the largest user of groundwater in China (Zhang et al., 2013). Since the amount of water used in agriculture is closely related to the area irrigated, we characterized it by the area of actual irrigated land. According to the results of a national water conservancy census in 2011, in that year, high-water-consumption industries accounted for 3/4 of China's total industrial water consumption. So we used the number of high-water-consumption factories and the proportion of high-water-consumption factories to the total number of factories to represent the industrial water usage. Residential water use is closely related to population size and level of urbanization, so we adopted total population and urbanization rate. At the same time, economic efficiency and water use efficiency can also affect water consumption, so we chose GDP per capita and water withdrawal per GDP as indicators. In addition, for natural factors, the average rainfall per year was used to control for the effect of possible increased surface water, and the average temperature per year was used to control for the effect of possible increased water demand. Moreover, considering the differences in factors such as hydrology and climate between North China and South China, provinces were divided into northern provinces and southern provinces according to the perspective of economic geography of Sheng et al. (2018). Exactly, Beijing, Tianjin, Hebei, Shanxi, Shaanxi, Heilongjiang, Jilin, Liaoning, Inner Mongolia, Ningxia, Gansu, Xinjiang, and Qinghai were included in the northern region, and the remaining 18 provinces and cities (excluding Hong Kong, Macao, and Taiwan) were included in the southern region. Based on that, a dummy variable was constructed, namely whether the provincial-level secondary river basin is in South China.

Groundwater withdrawal data, agricultural irrigation data, water use efficiency data and annual average rainfall data were all collected from the Chinese Water Resources Bulletin (2016) and were assigned to provincial-level secondary river basins based on certain rules. Factory location and the number and proportion of high-water-consumption factories were all obtained from the Chinese Industrial Enterprise Database. Since the Chinese Industrial Enterprise Database is only updated to 2013, we use the latest 2013 enterprise data. For population and urbanization data, we believe that census data is more comprehensive and accurate than sample data. Therefore, we collected them from the latest China Population Census in 2010. Data on GDP per capita was taken from China’s County and City Economic

Statistics Yearbook for 2016. The annual average temperature data was acquired from the Climatic Research Unit Global Climate Dataset (version 4.03).

Table 1 reports the basic characteristics of each variable. Due to the differences in the units of each variable, we normalized all the original data. Table S1 reports the correlation coefficients between the independent variables (after normalization). Although there was a high correlation between temperature and rainfall, they did not affect the target variable. Additionally, the calculated variance inflation factor was less than 5. Therefore, there were no serious multicollinearity existing among independent variables.

Table 1

Variable Summary Statistics

Variable	Observations	Mean	SD	Max	Min
Groundwater withdrawal (10^4 m^3)	205	5.1560	11.848	0.000	89.220
Factory scatter index (FSI) (km)	179	2.2330	1.165	0.000	5.065
Area of actual irrigated land (10^4 m^2)	205	425.6320	832.676	0.000	6840.100
Number of high-water-consumption plants	175	526.4630	1080.326	1.000	6457.000
Proportion of high-water-consumption plants (%)	175	30.7850	17.000	0.000	100.000
Total population (x 10^4)	205	673.7730	1078.268	0.000	6663.180
Urbanization rate (%)	190	44.1540	20.668	0.000	95.667
GDP per capita (10^4 yuan/person)	190	4.4080	2.985	0.000	17.387
Water withdrawal per GDP (yuan/m^3)	181	0.0129	0.016	0.001	0.123
Rainfall (mm)	204	815.7960	555.906	0.000	2540.349
Temperature (°C)	204	8.9610	8.023	–20.494	22.798

Note. we used the factories above the designated size in China in the thermal power industry and other high-water-consumption industries as high-water-consumption factories. Among them, industrial enterprises above a designated size in China refer to the enterprises whose annual revenue of main business is more than 20 million yuan according to the National Bureau of Statistics of China.

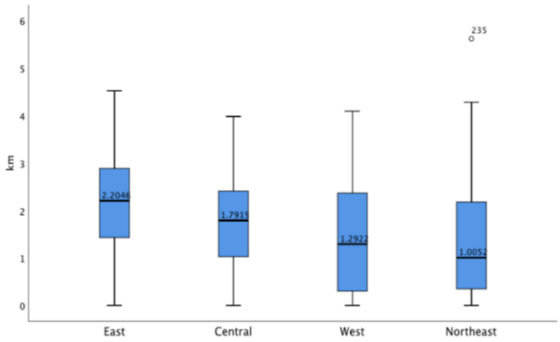
3. Results

3.1. General Characteristics of the Distribution of Manufacturing Plants in China

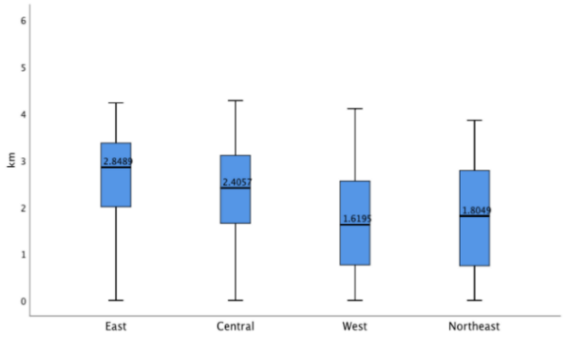
In order to determine the general characteristics of the distribution of manufacturing plants in China, we calculated the number of manufacturing plants and the FSIs in the four geographic regions of East China, Central China, West China, and Northeast China, respectively, and subdivided areas in the four regions into districts and counties—which were classified based on the administrative division of China in 2015—in order to compare the differences between urban and non-urban areas.

As shown in Table S2, from 2000 to 2010, the number of manufacturing plants in China increased by nearly two times. Among the four regions, East China had the largest number of manufacturing plants and the fastest growth rate of 223%. From the comparison of counties and districts, in East China and North China, the number of manufacturing plants in districts was found to be more than that in counties, both in 2000 and 2010; meanwhile, in Central China and West China, the number of manufacturing plants in districts was always less than that in counties. Additionally, in East, Central, and Northeast China, the growth rate of the number of manufacturing plants in counties was higher than that in districts.

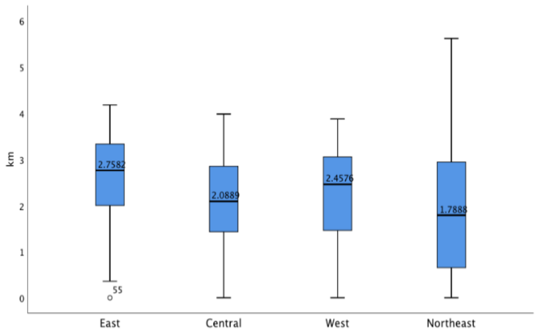
Figure 2 displays the FSIs in different regions of China in 2000 and 2010, and further shows the FSIs by district and county. As shown in Figure 2(a) and Figure 2(b), in each region, the FSIs increased from 2000 to 2010. Among them, the FSIs in East China and Central China had relatively higher average values and shorter box lengths, which indicates that the FSIs in these two regions are concentrated at higher average values. In other words, the distribution of manufacturing plants is more scattered in these two regions than in other regions. In terms of districts and counties, it can be seen that in 2000 and 2010, the FSIs in districts were higher than those in counties and the average FSIs in districts in different regions of China were similar. Additionally, from 2000 to 2010, the average FSIs in counties increased more than those in districts.



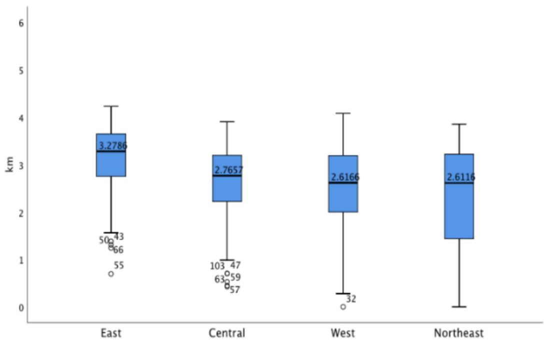
(**a**) FSI in four regions in 2000



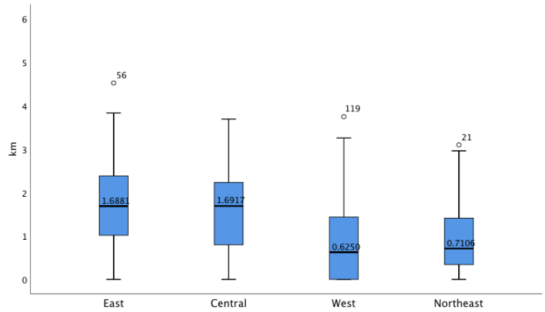
(**b**) FSI in four regions in 2010



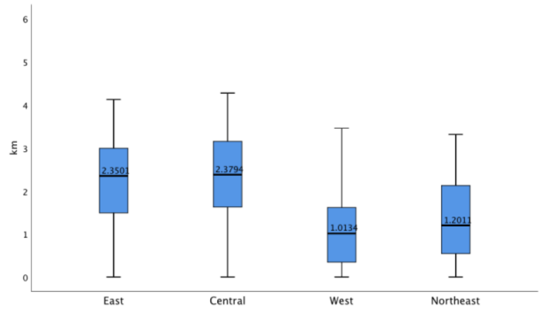
(**c**) FSI in districts in 2000



(**d**) FSI in districts in 2010



(**e**) FSI in counties in 2000



(**f**) FSI in counties in 2010

Figure 2. a Values of the FSI in four regions of China in 2000. **b** Values of the FSI in four regions of China in 2010. **c** Values of the FSI in districts in four regions of China in 2000. **d** Values of the FSI in districts in four regions of China in 2010 (unit: km). **e** Values of the FSI in counties in four regions of China in 2000. **f** Values of the FSI in counties in four regions of China in 2010.

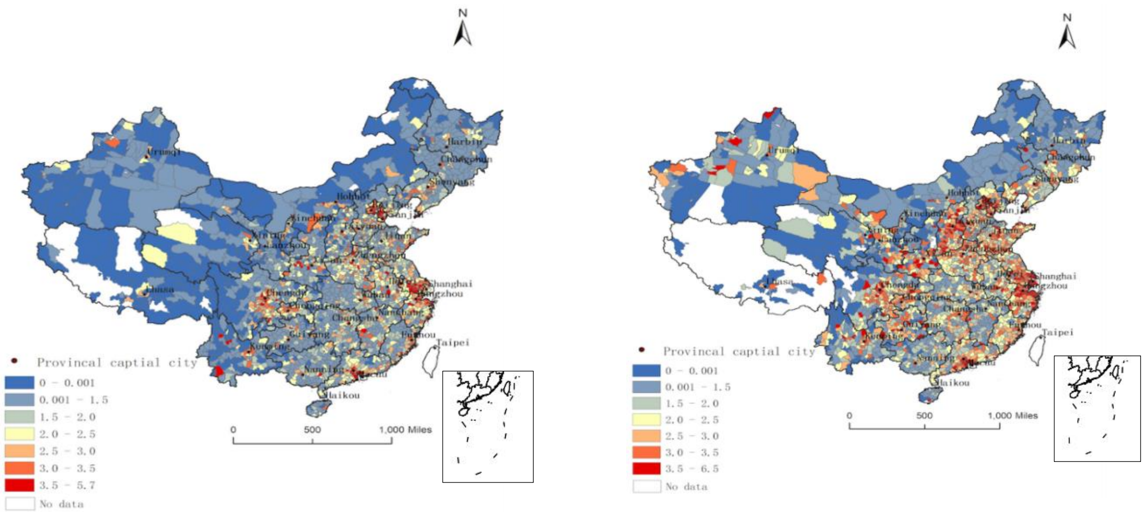
Finally, in order to present the distribution of manufacturing plants in different regions of China with different FSIs more intuitively, we calculated the FSIs by province and displayed the distribution of manufacturing plants in the four provinces with the highest FSIs in 2000 and 2010, respectively, as shown in Figure S1.

3.2. The Evolution of the Spatial Distribution of Manufacturing Plants in China

Figure S2 shows the spatial distribution of manufacturing plants in China in 2000 and 2010, respectively. It was found that, between 2000 and 2010, the manufacturing industry began to shift to Central and West China while continuing to develop in East China. Specifically, in 2000, a large number of manufacturing plants were concentrated in the Yangtze River Delta, Pearl River Delta, Shandong Peninsula, and other eastern coastal areas (see Figure

S2(a)); meanwhile, by 2010, the number of manufacturing plants in the coastal areas of East China had increased significantly, and some areas in Central and West China, such as eastern Hunan, eastern Hubei, Chengdu, and Chongqing, had also seen an intense growth in the number of manufacturing plants (see Figure S2(b)).

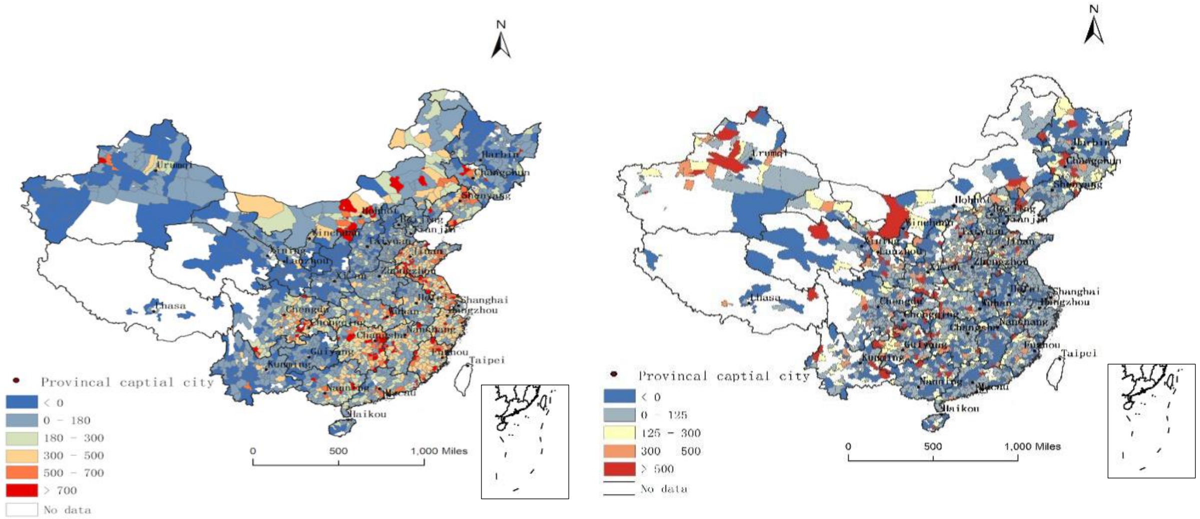
Figure 3 shows the spatial distribution of FSIs in China in 2000 and 2010, respectively. It was found that the scattering of manufacturing plants is relatively high in China, and that the value of FSIs increased from 2000 to 2010, with the degree of scattering being highest in 2010.



(**a**)2000 (**b**)2010

Figure 3. Values of the FSIs in districts and counties of China in 2000 and 2010.

Figure 4 shows the spatial distribution of the change rate of the number of manufacturing plants and FSIs in China between 2000 and 2010. It can be seen that the counties or districts with the largest increase in the number of plants were not necessarily those with the largest increase in FSIs. For example, Jiangsu and Zhejiang provinces in East China and Jiangxi provinces in Central China all had relatively large growth rates of the number of manufacturing plants and relatively lower rates of change of FSIs. Among them, the FSIs of most districts and counties in Jiangxi Province showed a negative growth trend. Additionally, a very prominent feature is that the districts and counties with the largest growth rates of FSIs appeared at the boundary between adjacent provinces.



(**a**) (**b**)

Figure 4. The change rate of the number of manufacturing plants (a) and FSI values (b) in districts and counties of China between 2000 and 2010.

In order to more clearly compare the degree of scattering of manufacturing plants in various regions, we calculated the change rate of FSIs and the number of manufacturing plants and its change rate in each province of China (Table 2). As shown in Table 2, the national average change rate of FSIs from 2000 to 2010 was 33%. Among the 26 studied provinces, 11 had FSI change rates that were higher than the national average. By comparing the change rate of the number of manufacturing plants and the change rate of FSIs, it was found that the provinces with the largest increase in the number of manufacturing plants were not necessarily those with the largest change rate of FSIs. In other words, the increase in the number of manufacturing plants does not necessarily lead to the spatial scattering of manufacturing plants, which is consistent with the above conclusion.

Table 2

The Change Rate of the Number of Manufacturing Plants and the Change Rate of FSIs in Different Provinces from 2000 to 2010.

Province	Manufacturing plants in 2000	Rank	Manufacturing plants in 2010	Rank	Change rate of the number of manufacturing plants (%)	Rank	Change rate of FSIs (%)	Rank
National average	5887	11	17,293	9	147	13	33	12
Jiangsu	16,201	2	74,809	1	361.76	2	9.65	26
Zhengjiang	14,720	3	62,084	3	321.77	3	13.05	25
Beijing	4803	13	6404	18	33.33	22	14.3	24
Fujiang	6010	8	24,533	5	308.2	4	17.88	22
Guangdong	18,697	1	64,486	2	244.9	6	25.8	15
Hebei	7282	7	10,806	14	48.39	19	27.38	14
Shanghai	8771	6	15,102	11	72.18	18	37.51	11
Hainan	505	26	906	26	79.41	17	43.1	8
Tianjing	5313	12	6348	19	19.48	25	46.12	7
Shandong	11,670	4	38,062	4	226.15	8	58.79	3
Jiangxi	3598	17	12,077	13	235.66	7	9.17	27
Anhui	3685	16	8034	16	118.02	14	18.31	21
Henan	9856	5	19,588	7	98.74	15	24.08	17
Hunan	4687	14	21,896	6	367.16	1	37.84	10
Hubei	5919	10	17,618	8	197.65	10	41.66	9
Shanxi	3179	19	4477	20	40.83	21	65.51	2
Chongqing	1955	25	7974	17	307.88	5	17.88	23
Shanxi	2665	22	3366	22	26.3	23	18.38	20
Sichuan	4411	15	13,281	12	201.09	9	23.33	19
Guanxi	3246	18	8690	15	167.71	12	24.62	16
Ningxia	407	27	736	27	80.84	16	29.74	13
Guizhou	1984	24	2240	25	12.9	27	52.61	5
Yunan	2154	23	2694	24	25.07	24	54.96	4
Liaoning	5925	9	16,413	10	177.01	11	23.68	18

Heilongjian	2695	21	3045	23	12.99	26	46.61	6
Jilin	2736	20	3937	21	43.9	20	88.73	1

Note. due to the incompleteness of the information about the plants in districts and counties of the provinces of Xinjiang, Tibet, Inner Mongolia, Gansu, and Qinghai, these areas are not discussed.

3.3. Empirical Results

Taking groundwater withdrawal as the dependent variable and FSIs as the target independent variable, OLS regression, Tobit regression, and GWR were carried out in turn to examine the relationship between the degree of scattering of manufacturing plants and groundwater withdrawal.

As shown in Table 3, of all the OLS regression results, column (4) performed best, explaining 52.2% of the groundwater withdrawal. Among them, the FSI showed a relatively high importance in the model, accounting for 17.85% of the groundwater withdrawal, ranking third among all the influencing factors (see Figure 5). Generally, the coefficients of FSI in all models were significantly positive, indicating that the degree of scattering of manufacturing plants had a significant impact on groundwater withdrawal. Additionally, the coefficients of the total population and the area of actual irrigated land were also significantly positive in all the models, which is consistent with reality. Furthermore, the urbanization rate was found to be significantly positively correlated with the groundwater withdrawal, meaning that the increase of the urbanization rate will aggravate groundwater withdrawal. Finally, there was a positive relationship between groundwater consumption and water withdrawal per GDP, which indicates that the lower the water withdrawal efficiency, the more groundwater is used.

Furthermore, the regression results of the Tobit model were basically consistent with those of the OLS model (see Table 3, column (5)-(8)); therefore, no further explanation of the results of this model were given. Table 4 shows the results of the GWR. The coefficient of FSI was stable to positive in all results of the GWR, with a minimum value of 0.1043 and a maximum value of 0.3782, confirming that the more scattered the spatial distribution of manufacturing plants, the greater the groundwater withdrawal.

Across all models, GWR outperformed OLS, as indicated by lower AIC values and higher global R-squared values (Table S3). The GWR model explained 60% of the variation in groundwater withdrawal. The important improvement in performance of the GWR relative to the OLS regression indicates spatial non-stationarity in statistical relationships across the study area. Therefore, we provided an in-depth analysis of spatial heterogeneity as represented by the GWR model. As shown in Figure A4, local R-squared values varied from 0.474 to 0.7267 (Figure 6(a)) and the standard error varied from 0.0107 to 0.1471 (Figure 6(b)). We can also see that GWR coefficients varied significantly between different regions of China (Figure 7). Specifically, the coefficients of the FSI were relatively small in Hebei, Tianjin, Beijing, and Inner Mongolia, while large in West China which is ecologically fragile the most.

Table 3

The Results of Ordinary Least Squares (OLS) Regression and Tobit Regression

	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
Variable	OLS 1	OLS 2	OLS 3	OLS 4	Tobit 1	Tobit 2	Tobit 3	Tobit 4
FSI	0.471***	0.168**	0.235**	0.233**	0.455***	0.179*	0.236***	0.234***
	(0.078)	(0.0848)	(0.0903)	(0.0904)	(0.0723)	(0.0721)	(0.0764)	(0.0764)
Area of actual irrigated land		0.643**	0.586*	0.582*		0.642***	0.573***	0.570***

		(0.32)	(0.302)	(0.311)		(0.143)	(0.145)	(0.146)
Number of high-water-consumption plants		-0.122	-0.123	-0.123		-0.125	-0.121	-0.12
		(0.11)	(0.123)	(0.126)		(0.104)	(0.107)	(0.107)
Proportion of high-water-consumption plants		-0.0987	-0.131	-0.14		-0.0864	-0.117	-0.124
		(0.109)	(0.12)	(0.128)		(0.0882)	(0.094)	(0.0951)
Total population		0.318	0.381*	0.384*		0.296**	0.364**	0.366**
		(0.202)	(0.207)	(0.208)		(0.14)	(0.141)	(0.141)
Urbanization rate		0.250***	0.212**	0.208**		0.213***	0.184**	0.181*
		(0.0852)	(0.0933)	(0.0933)		(0.0741)	(0.0912)	(0.0918)
GDP per capita			0.0207	0.0206			0.00793	0.00715
			(0.0935)	(0.0962)			(0.0999)	(0.1)
Water withdrawal per GDP			0.321*	0.317*			0.357**	0.352**
			(0.174)	(0.175)			(0.167)	(0.17)
Rainfall				-0.0749				-0.0517
				(0.15)				(0.111)
Temperature				0.0679				0.0518
				(0.127)				(0.113)
dummy	0.179***	0.160***	0.174***	0.168***	0.174***	0.150***	0.163***	0.159***
	(0.032)	(0.027)	(0.0276)	(0.0394)	(0.0335)	(0.027)	(0.0274)	(0.0356)
Intercept	0.260***	0.254***	0.208***	0.196*	0.276***	0.278***	0.233***	0.221***
	(0.0408)	(0.0655)	(0.0793)	(0.104)	(0.0419)	(0.0556)	(0.0645)	(0.084)
N	182	160	153	153	182	160	153	153
R^2	0.229	0.52	0.521	0.522				

Note. standard errors are in parentheses, * p < 0.1, ** p < 0.05, *** p < 0.01.

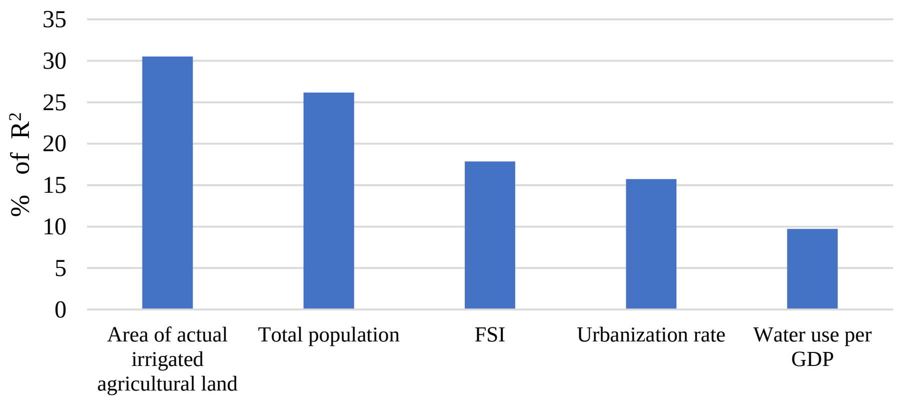
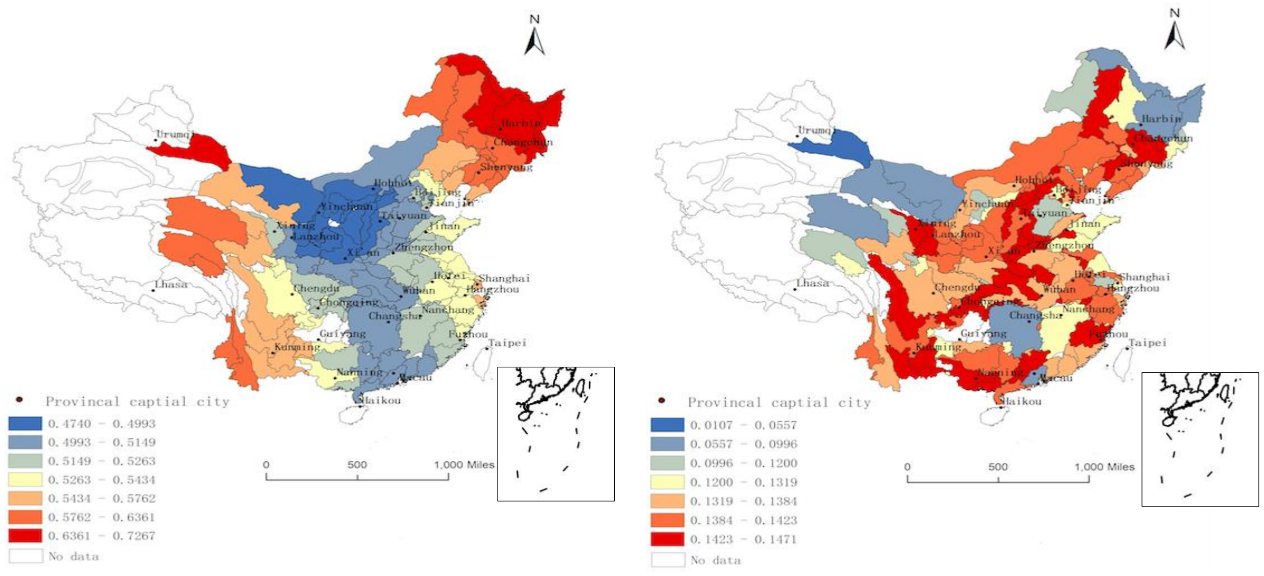


Figure 5. Measures of relative importance for ordinary least squares (OLS) regression influencing factors of groundwater withdrawal.

Table 4

The Results of Geographically Weighted Regression (GWR).

Variable	Min	Q(1/4)	Q(1/2)	Q(3/4)	Max
FSI	0.104	0.133	0.177	0.218	0.378
Area of irrigated land	0.264	1.088	1.281	1.391	1.532
Number of high-water-consumption plants	-0.354	-0.218	-0.178	-0.137	0.097
Proportion of high-water-consumption plants	-0.287	-0.247	-0.181	-0.046	0.137
Total population	-0.160	-0.070	-0.004	0.057	0.453
Urbanization rate	0.130	0.187	0.228	0.334	0.597
GDP per capita	-0.143	-0.019	0.065	0.127	0.193
Water withdrawal per GDP	-0.781	-0.585	-0.432	-0.020	0.490
Rainfall	-0.988	-0.398	-0.284	-0.115	0.098
Temperature	-0.307	-0.126	-0.012	0.059	0.611
Intercept	0.089	0.346	0.451	0.539	0.632



(a) **local R-squared** (b) **standard error**

Figure 6. The spatial distribution of the local R-squared (a) and standard error (b) in the Geographically Weighted Regression (GWR) results.

4. Discussion

4.1. Regional Differences in the Degree of Scattering of Manufacturing Plants

As shown in Figure 2, the FSIs in districts were higher than those in counties and the average FSIs in districts in different regions of China were similar, suggesting that factories within a district are generally farther apart from each other. High land rents owing to high levels of urban services and infrastructure in the districts often push manufacturing to the fringes, where the distance between manufacturing plants are often far apart.

Additionally, from 2000 to 2010, the average FSIs in counties increased more than those in districts. So recently, it was the counties, with relatively low land prices and weak environmental management regulations, that have taken over most of the manufacturing plants. In China, counties usually have fierce competition in attracting investment. Therefore, local governments, especially those in less developed areas, are more supportive than regulated to manufacturing plants. For example, when Foxconn moved to Jincheng, Shanxi province, the local government provided the most favorable policies for land, labor recruitment, water and electricity supply, and tax breaks (Geng & Lin, 2014). As a result, the lack of planning in site selection often leads to a spatially dispersed distribution of regional manufacturing (Fan et al., 2009).

Some researchers may argue that an increase in the distance between plants (i.e. FSI value) is inevitable, especially when a large number of manufacturing plants enter with rapid industrial development. However, our results found that the districts or counties with the largest increase in the number of manufacturing plants are not necessarily those with the largest increase in FSI values. In Jiangsu Province, the number of manufacturing plants increased greatly between 2000 and 2010, but the growth rate of FSI during this period was small, which means that the average distance between factories did not increase much. It seems that the spatial pattern of plants can be adjusted by local government's planning and management (Fan, 1996). The FSI index can reflect the extent to which local government’s planning and management plays a role in formatting an appropriate spatial structure.

Interestingly, districts or counties with the largest increase in the scattering degree of manufacturing plants appeared at the boundary between neighboring provinces. Plants located there can often easily escape punishment for polluting because their emissions often affect neighboring provinces. Disputes over pollution need to be reported to higher-level government, which makes management more difficult. So, people there often choose to close an eye on and local governments tend to implement loose land planning and management in border areas (Duvivier & Xiong, 2013). Therefore, the plants there often located according to their own requirements, e.g. large areas of single-story plants, which lead to a dispersed distribution of manufacturing plants there.

4.2. Effects of the Scattering of Manufacturing Plants on Groundwater Withdrawal

The results of this study suggest that the degree of scattering of manufacturing plants has a significant impact on groundwater withdrawal, that is, the more scattered the manufacturing plants are, the larger the groundwater withdrawal. In China, areas of enterprise clusters (such as industrial parks) are usually equipped with complete municipal waterworks and facilities (Zhao et al., 2013). So, it is convenient to monitor and charge for the water consumption of manufacturing plants, and it is also easier for local water resources department to supervise water use in the cluster area. Since strict management can lead to the increase of cost, manufacturing plants have to reduce their cost by improving the resource utilization efficiency, such as saving water or upgrading technology (Wang et al., 2018). Therefore, the manufacturing plants in the cluster area tend to reduce the use of groundwater.

However, scattered distribution of manufacturing plants increases the cost of pipeline laying, making municipal works difficult. In addition, due to advances in water drilling technology, scattered factories usually choose to drill on-site, especially when China did not restrict well drilling in previous years (e.g., there were 58 counties with more than 10,000 wells and 6 counties with more than 100,000 wells in Hebei Province in 2011) (Zheng et al., 2019). Manufacturing plants scattered in rural areas may also share wells with villagers. In such cases, the amount of water used by factories cannot be assessed quantitatively, and strict monitoring cannot be performed (Zhang et al., 2014). The cost of water for scattered factories is relatively low; factories that share wells with villagers usually pay only a small fee to the local village.

Therefore, with convenient well drilling and low water costs, manufacturing plants have weak awareness of water conservation, and groundwater over-extraction and waste occur frequently.

Moreover, in the absence of environmental regulation, scattered manufacturing plants, especially polluting ones, usually discharge more heavily (Schnaiberg, 1986; Cohen, 1997). The discharge of sewage into local rivers leads to surface water contamination, leaving no available clean surface water, which in turn causes the entire region to rely on groundwater (Brown & Halweil, 1998). The discharge of wastewater has an important indirect but non-negligible impact on the increase of groundwater use throughout China.

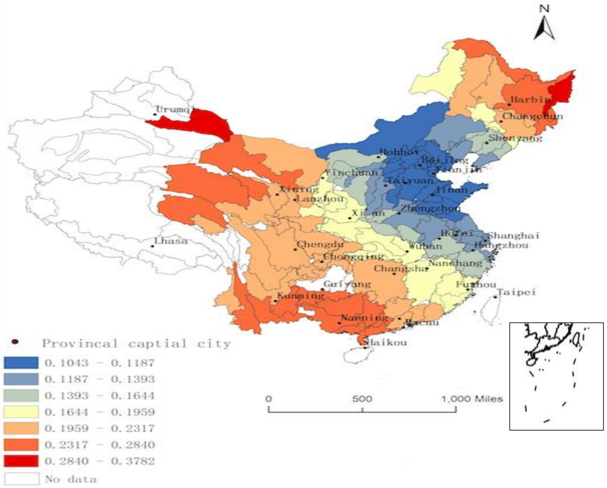
It is clear that the scattering of manufacturing plants and the corresponding water management play an exceptionally significant role in groundwater withdrawal, which deserves much attention.

4.3. Regional Differences in the Effects of the Scattering of Manufacturing Plants on Groundwater Withdrawal

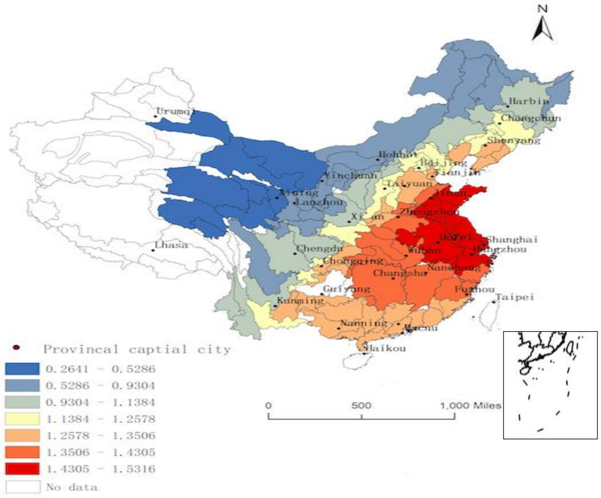
The regression results of the GWR model (Figure 7) show that the impact of the degree of scattering of manufacturing plants on groundwater withdrawal varies in different regions of China. As such, when planning efficient water resources development, it may be more useful to adopt different water conservation strategies in different regions according to the spatially varying trends in groundwater withdrawal than to adopt a "one size fits all" strategy.

It is noted that the spatial scattering of manufacturing plants is not the most important factor affecting groundwater withdrawal in North China (Figure 7(a)). The actual irrigated agricultural area is the main variable affecting groundwater consumption there (Figure 7(b)). This is consistent with the results of Tian et al. (2016), who found that agricultural irrigation is the main factor affecting groundwater withdrawal in the North China Plain, and the greater the dependence of agricultural irrigation water on groundwater, the more serious the groundwater withdrawal is.

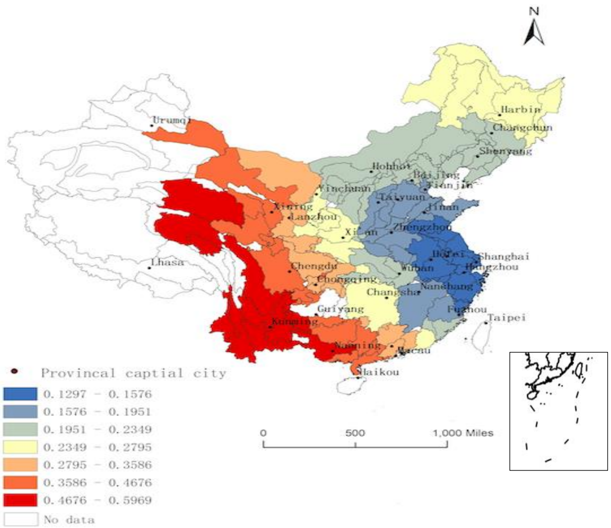
However, the spatial scattering of manufacturing plants has a great impact on groundwater withdrawal in West China, especially in fragile ecological-environment areas (Figure 7(a)). The reasons for this are as follows: First of all, groundwater is an important source for industrial, agricultural, and domestic usage in West China due to severe shortage of available surface water (Wu et al., 2020). Secondly, compared with East China, West China is geographically vast and sparsely populated, so the cost of tap water transmission caused by the scattered distribution of manufacturing plants is much higher. Additionally, the broad jurisdiction of district and county governments in West China makes it more difficult to regulate the use of water by scattered manufacturing plants. Therefore, in West China, factories often choose to use groundwater, which is more convenient and available, to save costs. Thirdly, due to the lack of unified water withdrawal planning in West China, the structure of water use and industry is irrational, resulting in the low efficiency of water withdrawal (Liu et al., 2016). The ecological environment of West China is extremely fragile, and groundwater withdrawal will aggravate this vulnerability, thus affecting local sustainable development (Zhou, 2015; Wang & Shao, 2016).



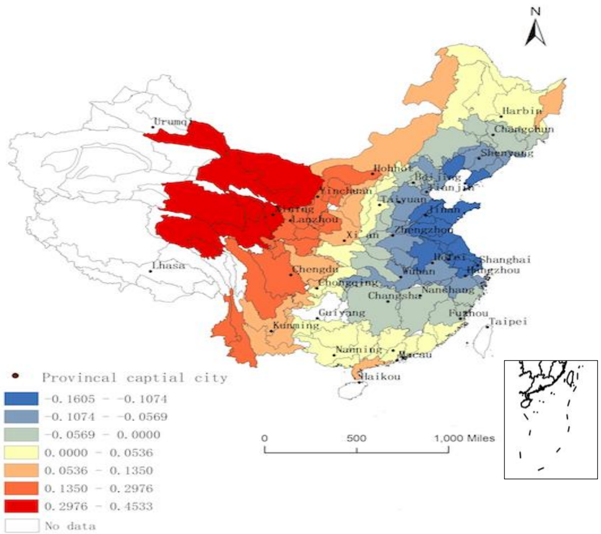
(a) FSI



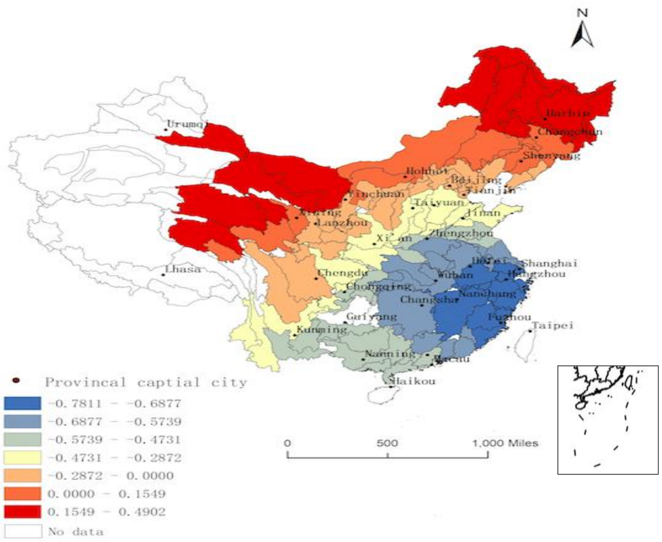
(b) Area of actual irrigated agricultural land



(c) Urbanization rate



(d) Total population



(e) Water withdrawal per GDP

Figure 7. The coefficients of some variables in the GWR model.

5. Conclusions

Our empirical research highlights the importance of introducing the distribution of manufacturing plants into the groundwater use analysis framework. We found that the scattered distribution of manufacturing plants played a key role in groundwater withdrawal in China, especially in fragile ecological-environment areas. The scattered distribution of manufacturing plants raises the cost of tap water transmission, makes monitoring and supervision more difficult, and increases the possibility of surface water pollution, thereby intensifying groundwater withdrawal. This indicates that it is particularly important to reduce groundwater withdrawal and realize the protection of groundwater through the reasonable adjustment of the spatial distribution of the manufacturing industry in areas with water shortage, high dependence on groundwater, and fragile ecology, so as to effectively alleviate the pressure on the regional ecological environment.

At present, China is in the middle stage of industrialization, and the scattering of manufacturing plants is relatively high. Under increasingly severe resource and environmental constraints, exploring the relationship between the spatial pattern of manufacturing development and resource utilization is of great significance for solving problems related to resources and the environment. As seen in this paper, planning and management can play a very important role in the spatial distribution of manufacturing plants. Our conclusions provide an important practical basis for the adjustment of the spatial distribution of manufacturing plants in areas with fragile ecological environment and a severely scattered distribution of factories.

However, given the data availability, the empirical part of this paper used only one year of provincial-level secondary river basin data. The lack of accurate data made it impossible for us to continue to measure the impact of the scattered distribution of manufacturing plants on groundwater withdrawal at the district and county scale. With the availability of various resource data in the future, we believe that we will be able to measure the impact of the FSI on resource consumption and environmental pollution in a more detailed way, which is our next research direction.

Acknowledgments

This research was supported by the National Key Research and Development Program of China (2017YFC1503002), the National Natural Science Foundation of China (41001094), the Important Science & Technology Specific Projects of Qinghai Province (2019-SF-A4-1) and the National Natural Science Foundation of Qinghai Province (2019-ZJ-7020), and Beijing Key Lab of Study on Sci-Tech Strategy for Urban Green Development, Beijing, China.

Data Availability Statement

Groundwater withdrawal data, agricultural irrigation data, water use efficiency data and annual average rainfall data were all collected from the Chinese Water Resources Bulletin (2016) （http://www.mwr.gov.cn/sj/tjgb/szygb/). Factory location and the number and proportion of high-water-consumption factories were all obtained from the Chinese Industrial Enterprise Database (http://microdata.sozdata.com/login.html). Population and urbanization data are collected them from the latest China Population Census in 2010 (http://www.stats.gov.cn/tjsj/pcsj/rkpc/6rp/indexch. htm). Data on GDP per capita was taken from China's County and City Economic Statistics Yearbook for 2016 (https://data.cnki.net/yearbook/Single/N2017050134). The annual average temperature data was acquired from the Climatic Research Unit Global Climate Dataset (version 4.03) (http://www.ipcc-data.org/observ/clim/cru_climatologies.html).

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AGU PUBLICATIONS

Water Resources Research

Supporting Information for

The Impacts of the Geographic Distribution of Manufacturing Plants on Groundwater Withdrawal in China

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Contents of this file

Introduction

This supporting information reports additional results of spatial and empirical analyses.

Figure S1 shows the FSIs by province and displays the distribution of manufacturing plants in the four provinces with the highest FSIs in 2000 and 2010, respectively.

Figure S2 displays the number of manufacturing plants in districts and counties of China in 2000 and 2010.

Table S1 reports the correlation coefficients between the independent variables (after normalization).

Table S2 shows the number of manufacturing plants in different regions of China.

Table S3 is a comparison of the regression results of the OLS and GWR models, which shows that GWR outperformed OLS across all models, as indicated by lower AIC values and higher global R-squared values.

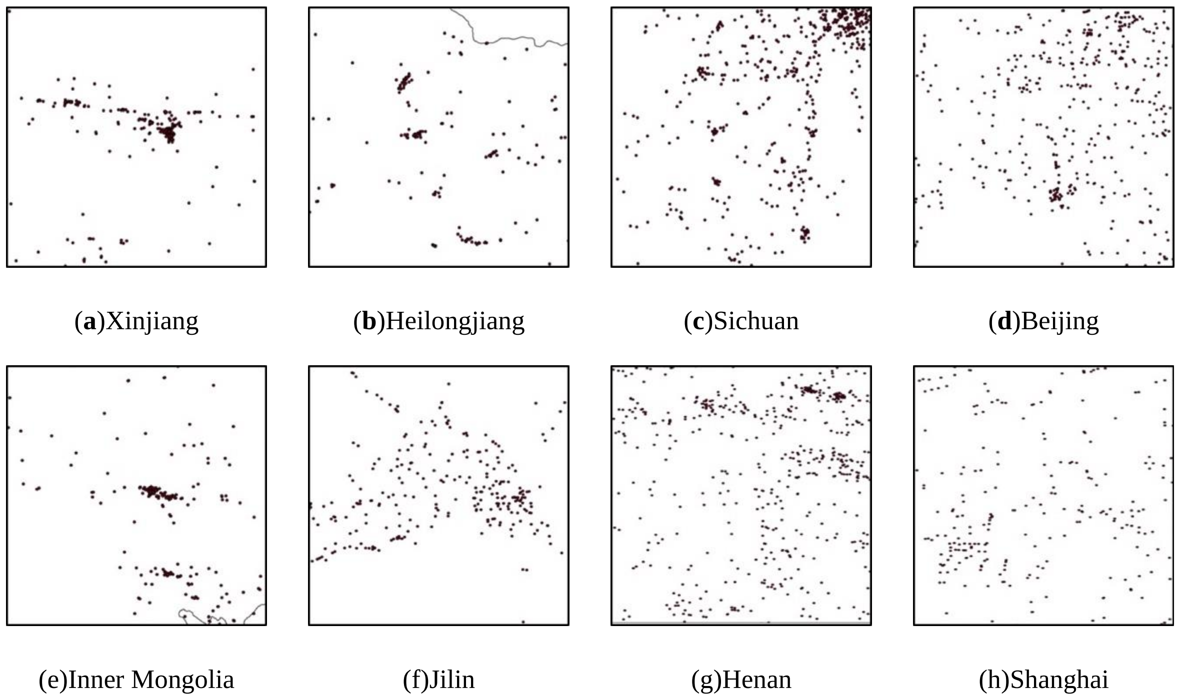
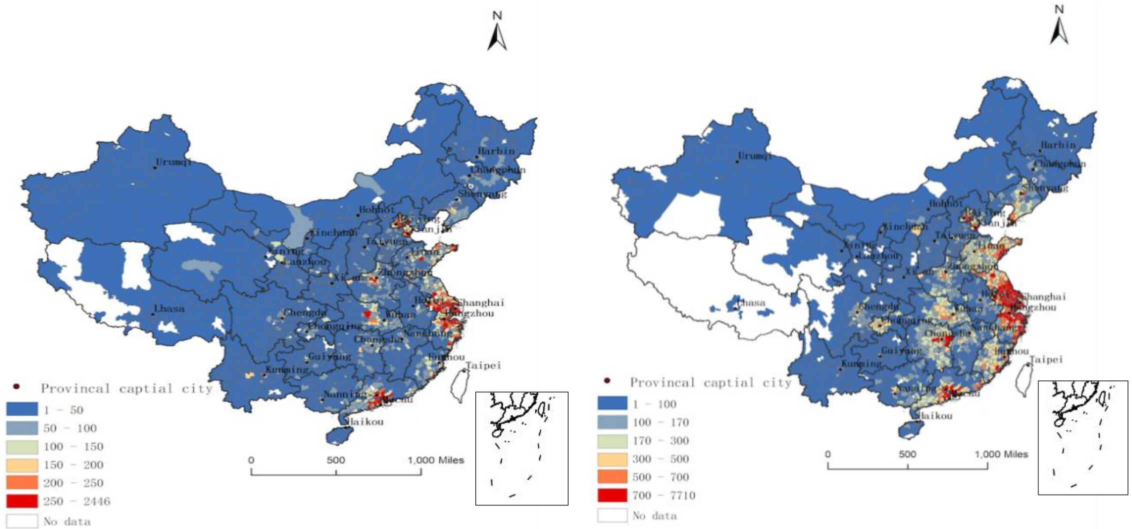


Figure S1. The distribution of manufacturing plants in Xinjiang (a), Heilongjiang (b), Sichuan (c), and Beijing (d) in 2000 (upper row) and in Inner Mongolia (e), Jilin (f), Henan (g), and Shanghai (h) in 2010 (lower row) (unit: km).



(**a**)2000 (**b**)2010

Figure S2. The number of manufacturing plants in districts and counties of China in 2000 and 2010.

	Log of groundwater withdrawal	**FSI**	**Number of high-water-consumption plants**	**Total population**	**Area of actual irrigated land**	**Proportion of high-water-consumption plants**	**Urbanization rate**	**GDP per capita**	**Water withdrawal per GDP**	**Rainfall**	**Temperature**
Log of groundwater withdrawal	1										
FSI	0.3424	1									
Number of high-water-consumption plants	0.2825	0.3959	1								
Total population	0.5058	0.3575	0.7042	1							
Area of irrigated land	0.5143	0.1643	0.4513	0.7561	1						
Proportion of high-water-consumption plants	-0.0429	-0.2284	-0.0838	-0.0618	0.0061	1					
Urbanization rate	0.521	0.4653	0.3629	0.3846	0.2129	-0.2442	1				

GDP per capita	0.3382	0.432	0.4192	0.3261	0.144	-0.0919	0.68	1			
Water withdrawal per GDP	-0.2375	-0.2001	-0.209	-0.2066	-0.0636	0.1351	-0.3529	-0.2687	1		
Rainfall	-0.0281	0.3312	0.2605	0.2629	0.1477	-0.0783	0.1646	0.2404	0.1175	1	
Temperature	-0.031	0.2712	0.2447	0.2215	0.1446	-0.0361	0.1249	0.2182	0.1836	0.8014	1

Table S1. Correlation matrix between the independent variables after normalization.

	TOTAL				
Region	East China	Central China	West China	Northeast China	China
Number of manufacturing plants in 2000	93,972	30,924	23,033	11,356	159,285
Number of manufacturing plants in 2010	303,540	83,690	46,127	23,395	456,752
Change rate (2000–2010) (%)	223.01	170.63	100.26	106.01	186.75
		Counties			
Region	East China	Central China	West China	Northeast China	China
Number of manufacturing plants in 2000	37,769	20,226	12,196	4525	74,716
Number of manufacturing plants in 2010	143,361	58,221	24,345	10,318	236,245
Change rate (2000–2010) (%)	279.57	187.85	99.61	128.02	216.19
		Districts			
Region	East China	Central China	West China	Northeast China	China
Number of manufacturing plants in 2000	56,203	10,698	10,837	6831	84,569
Number of manufacturing plants in 2010	160,179	25,469	21,782	13,077	220,507
Change rate (2000-2010) (%)	185.00	138.07	101.00	91.44	160.74

Table S2. The number of manufacturing plants in different regions of China.

Model	AIC	R^2	Adjusted R^2
OLS	-94.49802	0.5222	0.4849
GWR	-119.56729	0.6829	0.6045

Note. AIC: Akaike information criterion.

Table S3. A comparison of the regression results of the OLS and GWR models.