Study on the Changes in Arable Land Resources and Driving Forces in the North China Region Based on Urbanization

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Abstract: Urbanization is a multifaceted and interdisciplinary social phenomenon, encompassing a broad range of research fields including, but not limited to, sociology, economics, and geography. The fundamental characteristic of urbanization is the large-scale migration and concentration of populations from rural to urban areas. As the urbanization process continues to deepen, its impact on the quantity of arable land resources and its interaction with socio-economic development have emerged as focal points of concern for both academia and policymakers. This study selects Hebei Province as a case study, aiming to explore the effects of urbanization on arable land resource quantity and to analyze the intrinsic connections between these changes and socio-economic development by examining time series data from 2000 to 2021. Initially, a comprehensive qualitative analysis is conducted to assess the potential impacts of urbanization on arable land resources. Subsequently, quantitative research methods such as Principal Component Analysis (PCA) and Multiple Linear Regression (MLR) are employed to systematically identify and quantify the key driving factors influencing variations in arable land resources.

1 INTRODUCTION

This study focuses on the North China region, encompassing Hebei Province, Beijing, and Tianjin, and employs quantitative research methods such as Principal Component Analysis (PCA) and Multiple Linear Regression (MLR) to comprehensively investigate the dynamic driving factors behind changes in arable land resources from 2000 to 2021. By delving deeply into statistical data, the research reveals the complex and diverse roles played by various factors in the fluctuations of arable land resources (Yu, 2022; Zhang, 2022; Wang, 2021; Ye, 2019; Hou, 2023).

2 STUDY AREA OVERVIEW

Hebei Province is situated in the North China Plain, bordered by the Bohai Sea to the east, Henan Province to the south, Shanxi Province to the west, and the Inner Mongolia Autonomous Region to the north, with Hebei Province to the northeast. The province features a complex and diverse topography that includes expansive plains, mountainous regions, plateaus, and basins. Beijing, located in northern China, occupies a position of significant geopolitical importance. It lies in the northern part of the North China Plain and serves as the political, cultural, and transportation center of the nation. Tianjin, one of China's directly administered municipalities, is located in the northeastern part of the North China Plain, bordering the Bohai Sea to the east, the Yanshan Mountains to the north, Hebei Province to

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the south, and Beijing to the west. Tianjin is a critical industrial base and commercial hub in China, boasting advanced sectors such as manufacturing, petrochemicals, shipping, and more, while also being a key center for finance, education, and research in northern China.

3 DATA AND METHODS

3.1 Data Sources

This study adheres to a rigorous scientific research methodology, aiming to ensure the scientific integrity of the research design, the feasibility of empirical analysis, and the standardization of the data collection process. The research team utilized the multidimensional data resources provided by the "Statistical Yearbook of Hebei Province," the "Statistical Yearbook of Beijing," and the "Statistical Yearbook of Tianjin," thereby establishing a robust data foundation for the investigation.

3.2 Research Content and Methods

The study will employ Principal Component Analysis (PCA) to develop a model of the driving factors behind changes in arable land resources in the research area (Xie, 2023; Ma, 2023; Guan, 2023; Ye, 2023; Li, 2023). Through PCA, correlation analysis, and regression analysis, we will thoroughly elucidate the mechanisms driving changes in arable land quantity (Zhang, 2022; Xu, 2023). This research will quantitatively examine indicators such as population growth, economic development, and social progress, as detailed in Table 1.

Table 1: Indicator System for Driving Forces of Arable Land Resource Changes.

Indicator	Variable
Urban Population Proportion	x_1
Per Capita GDP	x_2
Fixed Asset Investment in Secondary Industry	x_3
Fixed Asset Investment in Tertiary Industry	x_4
Secondary Industry Output Ratio	x_5
Tertiary Industry Output Ratio	x_6
Disposable Income of Urban Residents	x_7
Per Capita Net Income of Rural Residents	x_8
Built-up Area	x_9
Real Estate Development Investment	x_{10}

4 RESULTS AND ANALYSIS

4.1 Changes in Arable Land Resources

During the extensive research period from 2000 to 2021, significant reductions in agricultural land resources were observed in Hebei Province, Beijing, and Tianjin. The analysis reveals that the total area of arable land in Hebei Province decreased from 6.88326 million hectares in 2000 to 5.90144 million hectares in 2021, indicating an average annual reduction rate of 46,700 hectares. In Beijing, the total area of arable land markedly diminished from 329,000 hectares in 2000 to 127,860 hectares in 2021. Similarly, Tianjin's arable land area declined from 483,430 hectares in 2000 to 366,250 hectares in 2021, reflecting a significant contraction. Moreover, further statistical analysis indicates that, compared to the initial year of the study period, Hebei Province experienced a total decline of 0.67% in arable land resources, while Beijing's annual average reduction was approximately 9,570 hectares, and Tianjin's average annual reduction rate was about 5,580 hectares.

4.2 Drivers of Changes in Arable Land Resources

4.2.1 Indicators and Evaluation

(a) Correlation Test of Initial Variables

Figure 2 presents the correlation coefficient matrix of ten initial explanatory variables influencing the quantity of arable land resources. This study aims to conduct a thorough analysis of the interactions among these variables and the intricate network of relationships they form. The correlation coefficient matrix reveals a pervasive correlation exceeding 0.95 among these indicators in Hebei Province, above 0.80 in Beijing, and greater than 0.80 in Tianjin, underscoring a degree of interrelatedness among the provinces in North China, which may result in partial information redundancy.

(b) KMO Test and Bartlett's Test of Sphericity

To assess the suitability of the dataset for Principal Component Analysis (PCA), this study employed the Kaiser-Meyer-Olkin (KMO) test and Bartlett's Test of Sphericity as statistical tools. The statistical results presented in Table 2 clearly indicate the significance of both the KMO test and Bartlett's test, thereby further validating the appropriateness of conducting PCA. Consequently, it can be concluded

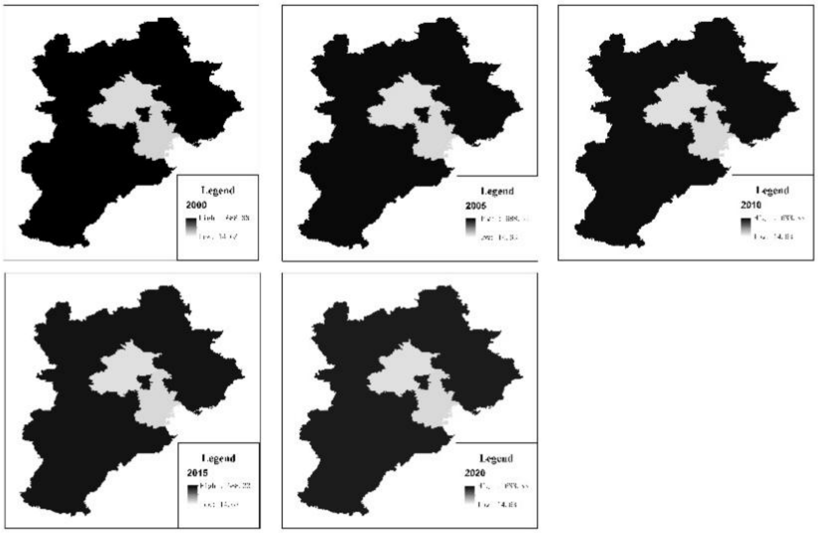
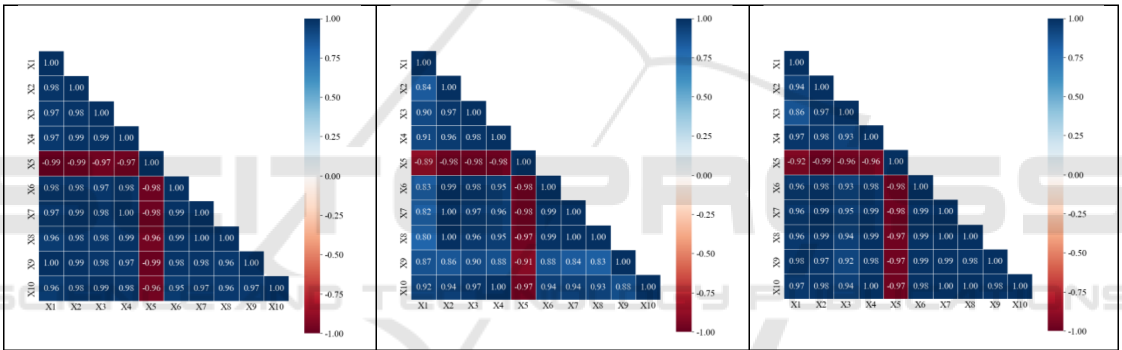


Figure 1: Changes in the Quantity of Arable Land Resources in North China.



Hebei	Beijing	Tianjin

Figure 2: Correlation Coefficient Matrix of Variables.

Table 2: KMO and Bartlett's Test for Arable Land Resources.

		Hebei	Beijing	Tianjin
KMO Measure of Sampling Adequacy		0.774	0.873	0.857
Bartlett's Test of Sphericity	Approximate Chi-Square	782.514	658.461	729.733
	Degrees of Freedom	45	45	45
	Significance	0	0	0

that the dataset exhibits reliability for PCA, demonstrating the potential to effectively extract principal factors (Figure 1).

4.2.2 Eigenvalues and Contribution Rates

In this study, the results of the Principal Component Analysis (PCA) presented in Table 3 reveal the underlying structure of the observed variable set. The cumulative contribution rate of the first two principal components in Hebei Province reaches an impressive 99.025%, while in Beijing, it is 97.552%, and in Tianjin, it stands at 98.048%. All these figures significantly exceed the recommended statistical threshold, indicating that the analysis effectively captures the variance through the first two principal components, F1 and F2.

Table 3: Principal Component Analysis.

province	Component	Initial Eigenvalues			Extracted Sum of Squares Loadings			Rotated Sum of Squares Loadings		
		Total	Contribution Rate	Cumulative Contribution Rate	Total	Contribution Rate	Cumulative Contribution Rate	Total	Contribution Rate	Cumulative Contribution Rate
Hebei	F_1	9.811	98.111	98.111	9.811	98.111	98.111	5.109	51.095	51.095
	F_2	0.091	0.914	99.025	0.091	0.914	99.025	4.793	47.931	99.025
	F_3	0.064	0.644	99.670						
Beijing	F_1	9.406	94.055	94.055	9.406	94.055	94.055	5.534	55.342	55.342
	F_2	0.350	3.497	97.552	0.350	3.497	97.552	4.221	42.211	97.552
	F_3	0.154	1.536	99.088						
Tianjin	F_1	9.732	97.320	97.320	9.732	97.320	97.320	5.203	52.033	52.033
	F_2	0.173	1.728	99.048	0.173	1.728	99.048	4.701	47.015	99.048
	F_3	0.047	0.475	99.523						

Table 4: Rotated Component Loadings and Component Score Coefficients Matrix.

	Hebei				Beijing				Tianjin			
	Rotated Component Matrix		Component Score Coefficients Matrix		Rotated Component Matrix		Component Score Coefficients Matrix		Rotated Component Matrix		Component Score Coefficients Matrix	
	1	2	1	2	1	2	1	2	1	2	1	2
x_1	0.603	0.797	-1.091	1.272	0.439	0.874	-0.627	0.872	0.868	0.490	1.036	-0.948
x_2	0.718	0.691	0.097	0.046	0.848	0.524	0.375	-0.274	0.654	0.753	-0.307	0.472
x_3	0.771	0.628	0.717	-0.596	0.743	0.658	0.057	0.095	0.502	0.859	-1.033	1.232
x_4	0.778	0.626	0.767	-0.647	0.717	0.679	-0.004	0.165	0.764	0.635	0.332	-0.202
x_5	-0.633	-0.770	0.788	-0.959	-0.765	-0.637	-0.114	-0.030	-0.633	-0.762	0.391	-0.559
x_6	0.679	0.723	-0.288	0.443	0.836	0.539	0.339	-0.232	0.741	0.661	0.195	-0.058
x_7	0.747	0.660	0.419	-0.287	0.867	0.496	0.437	-0.346	0.726	0.686	0.082	0.063
x_8	0.773	0.621	0.770	-0.651	0.883	0.468	0.496	-0.415	0.740	0.668	0.174	-0.034
x_9	0.630	0.774	-0.823	0.996	0.518	0.795	-0.419	0.633	0.779	0.617	0.425	-0.300
x_{10}	0.785	0.601	0.945	-0.832	0.687	0.705	-0.078	0.250	0.745	0.662	0.203	-0.066

4.2.3 Establishment of Principal Component Linear Models

Based on the principal component score coefficient tables (Table 4), the final principal component score formulas for the North China Region are derived as follows(Fa represents Hebei Province, F_b represents Beijing, and Fc represents Tianjin):

$$F_{a1}=-1.091x_1+0.097x_2+0.717x_3+0.767x_4+0.788x_5-0.288x_6+0.419x_7+0.770x_8-0.823x_9+0.945x_{10} \quad (1)$$

$$F_{a2}=1.272x_1+0.046x_2-0.596x_3-0.647x_4-0.959x_5+0.443x_6-0.287x_7-0.651x_8+0.996x_9-0.832x_{10} \quad (2)$$

$$F_{b1}=-0.627x_1+0.375x_2+0.057x_3-0.004x_4-0.114x_5+0.339x_6+0.437x_7+0.496x_8-0.419x_9-0.078x_{10} \quad (3)$$

$$F_{b2}=0.872x_1-0.274x_2+0.095x_3+0.165x_4-0.030x_5-0.232x_6-0.346x_7-0.415x_8+0.633x_9+0.250x_{10} \quad (4)$$

$$F_{c1}=1.036x_1-0.307x_2-1.033x_3+0.332x_4+0.391x_5+0.195x_6+0.082x_7+0.174x_8+0.425x_9+0.203x_{10} \quad (5)$$

$$F_{c2}=-0.948x_1+0.472x_2+1.232x_3-0.202x_4-0.559x_5-0.058x_6+0.063x_7-0.034x_8-0.300x_9-0.066x_{10} \quad (6)$$

4.2.4 Comprehensive Score

Based on the findings of this study, the comprehensive evaluation model for principal components is calculated using the proportion of each principal component's eigenvalue relative to the sum of the eigenvalues of the extracted principal components as weights:

$$F=\sum_{k=1}^{n}\lambda_k F_k = \lambda_1 F_1 + \lambda_2 F_2 \quad (7)$$

In the equation above, F represents the comprehensive score for the variation in arable land resources across the north China Region; λ_k denotes the eigenvalue of the k-th principal component (where k=1,2).

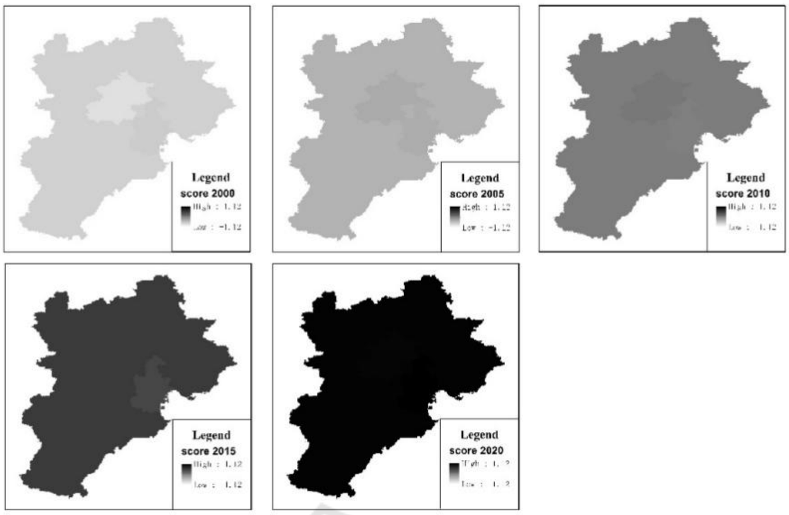


Figure 3: Changes in the composite driving force score of arable land resource quantity in North China.

This research team adopted Principal Component Analysis (PCA) as a quantitative methodology to investigate the underlying dynamics of changes in arable land resources in Hebei Province, Beijing, and Tianjin. By constructing a weighted coefficient matrix, the PCA method provided a comprehensive analysis of time series data from 2000 to 2021. This integrated assessment model elucidated the overall trend in changes to arable land resources over this period. Notably, prior to 2012, the composite driving force score was negative, indicating that arable land resources were predominantly influenced by constraining factors. However, beginning in 2012, the score shifted to positive, suggesting a trend of positive enhancement in the factors affecting arable land resources in subsequent years (Figure 3).

4.3 Evaluation of Driving Factors for Changes in Arable Land Resources in the North China Region

The study reveals that the variation in arable land resources across the North China Region is correlated with several selected factors. These factors include the proportion of urban population (x_1), per capita GDP (x_2), fixed asset investment in the secondary industry (x_3), fixed asset investment in the tertiary industry (x_4), output value ratio of the secondary industry (x_5), output value ratio of the tertiary industry (x_6), disposable income of urban residents (x_7), per capita net income of rural residents (x_8), built-up area (x_9), and investment in real estate development (x_{10}).

The coefficient of determination R^2 for Hebei Province, Beijing, and Tianjin in North China are 0.980, 0.830, and 0.785, respectively. These values indicate that the two independent variables included in the regression models account for 98.0%, 83.0%, and 78.5% of the variance in the dependent variable, demonstrating an excellent fit of the equations. This provides substantial reference value for assessing changes in arable land resources in North China. The principal component regression equations established in this study are as follows (Table 5):

$$Y_a=634.209-15.833x_1-21.000x_2 \quad (8)$$

$$Y_b=22.497-2.645x_1-2.877x_2 \quad (9)$$

$$Y_c=43.754-2.135x_1-1.765x_2 \quad (10)$$

Substitute the ten principal component factors into the principal component regression model to calculate the corresponding parameters in the original regression model (see Table 6), thereby obtaining the standard regression model that eliminates multicollinearity :

$$Y_a=634.209-9.433x_1-2.499x_2+1.155x_3+1.438x_4+7.663x_5-4.736x_6-0.606x_7+1.478x_8-7.876x_9+2.514x_{10} \quad (11)$$

$$Y_b=22.497-0.852x_1-0.204x_2-0.425x_3-0.464x_4+0.388x_5$$

$$-0.229x_6-0.160x_7-0.116x_8-0.713x_9-0.512x_{10} \quad (12)$$

$$Y_c=43.754-0.539x_1-0.177x_2+0.032x_3-0.353x_4+0.152x_5-0.315x_6-0.286x_7-0.310x_8-0.378x_9-0.318x_{10} \quad (13)$$

Table 5: Regression Analysis Results of Principal Components.

		Unstandardized Coefficients		Standardized Coefficients	t-Statistic	Sig
		Coefficient	Standard Error			
Hebei	Constant	634.209	0.848		748.182	0.000
	F_1	-15.833	0.868	-0.596	-18.249	0.000
	F_2	-21.000	0.868	-0.790	-24.205	0.000
	R^2	0.980				
Beijing	Constant	22.497	0.397		56.673	0.000
	F_1	-2.645	0.406	-0.616	-6.510	0.000
	F_2	-2.877	0.406	-0.671	-7.081	0.000
	R^2	0.830				
Tianjin	Constant	43.754	0.325		134.804	0.000
	F_1	-2.135	0.332	-0.683	-6.427	0.000
	F_2	-1.765	0.332	-0.565	-5.313	0.000
	R^2	0.785				

Table 6: Regression Coefficients for Each Original Variable.

	Hebei					*Beijing*					*Tianjin*				
	F_1	μ_1F_1	F_2	μ_2F_2	μ_nF_n	F_1	μ_1F_1	F_2	μ_2F_2	μ_nF_n	F_1	μ_1F_1	F_2	μ_2F_2	μ_nF_n
x_1	-1.091	1.272	17.270	-26.702	-9.433	-0.627	0.872	1.658	-2.509	-0.852	1.036	-0.948	-2.212	1.673	-0.539
x_2	0.097	0.046	-1.532	-0.966	-2.499	0.375	-0.274	-0.993	0.789	-0.204	-0.307	0.472	0.656	-0.833	-0.177
x_3	0.717	-0.596	-11.357	12.512	1.155	0.057	0.095	-0.151	-0.274	-0.425	-1.033	1.232	2.207	-2.174	0.032
x_4	0.767	-0.647	-12.148	13.586	1.438	-0.004	0.165	0.011	-0.475	-0.464	0.332	-0.202	-0.709	0.357	-0.353
x_5	0.788	-0.959	-12.469	20.131	7.663	-0.114	-0.030	0.302	0.086	0.388	0.391	-0.559	-0.834	0.986	0.152
x_6	-0.288	0.443	4.557	-9.293	-4.736	0.339	-0.232	-0.897	0.669	-0.229	0.195	-0.058	-0.417	0.102	-0.315
x_7	0.419	-0.287	-6.641	6.036	-0.606	0.437	-0.346	-1.156	0.997	-0.160	0.082	0.063	-0.174	-0.111	-0.286
x_8	0.770	-0.651	-12.196	13.674	1.478	0.496	-0.415	-1.311	1.195	-0.116	0.174	-0.034	-0.370	0.060	-0.310
x_9	-0.823	0.996	13.036	-20.912	-7.876	-0.419	0.633	1.107	-1.820	-0.713	0.425	-0.300	-0.908	0.530	-0.378
x_{10}	0.945	-0.832	-14.955	17.469	2.514	-0.078	0.250	0.207	-0.719	-0.512	0.203	-0.066	-0.434	0.116	-0.318

5 CONCLUSION

Between 2000 and 2021, the urbanization process in Hebei Province, Beijing, and Tianjin in North China exhibited a significant upward trend, a phenomenon resulting from the complex interplay of various factors. The findings indicate that prior to 2012, the composite impact score for arable land resources in North China was negative, suggesting that during this period, the quantity of arable land was predominantly influenced by inhibiting factors. After 2012, the composite score shifted to a positive value, indicating a gradual strengthening of the drivers affecting changes in the quantity of arable land resources in North China.

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