Study on the Changes in Arable Land Resources and Driving Forces in the Three Northeastern Provinces of China Based on Urbanization

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Abstract: Urbanization, as a complex interdisciplinary social phenomenon, spans across sociology, economics, and geography, with its core manifestation being the large-scale aggregation and migration of populations from rural to urban areas. This study focuses on the northeastern region of China, specifically Liaoning, Jilin, and Heilongjiang provinces, covering the period from 2000 to 2021. The objective is to examine the impact of urbanization on the quantity of arable land resources and to explore its relationship with socio-economic development. Firstly, a comprehensive and detailed analysis of the effects of urbanization on arable land resources is conducted. Secondly, quantitative methods such as Principal Component Analysis (PCA) and Multiple Linear Regression (MLR) are employed to systematically investigate the driving factors behind the changes in arable land resources, revealing the underlying patterns within the urbanization process. The findings of this research not only provide theoretical support for advancing new urbanization planning in the three northeastern provinces, promoting urbanization processes, and protecting arable land resources, but also hold practical significance for guiding related policy formulation and implementation.

1 INTRODUCTION

This study focuses on the three northeastern provinces of China and employs quantitative research methods, including Principal Component Analysis (PCA) and Multiple Linear Regression (MLR), to thoroughly examine 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 of various factors in the alteration of arable land resources (YU et al., 2022).

2 STUDY AREA OVERVIEW

Liaoning Province, located to the east of the Bohai Sea, is a significant coastal region. Its geographic environment is diverse, featuring both plains and mountainous areas along with a coastline. Jilin Province, adjacent to Russia and bordered by North Korea to the east, holds a strategically important position. Heilongjiang Province, situated to the east of Northeast Asia and Russia, boasts abundant natural resources and a varied topography (ZHANG et al., 2022).

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3 DATA AND METHODS

3.1 Data Sources

This study employs a systematic scientific approach to ensure the research's rigor, feasibility, and adherence to data acquisition principles. We extensively utilized multidimensional data resources provided by the "Liaoning Statistical Yearbook," the "Jilin Statistical Yearbook," and the "Heilongjiang Statistical Yearbook," encompassing a range of data including population, economic indicators, and arable land. These data sources are highly reliable and authoritative, providing a solid foundation for the study and ensuring the accuracy and credibility of the results (WANG et al., 2021).

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. Through PCA, correlation analysis, and regression analysis, we will thoroughly elucidate the mechanisms driving changes in arable land quantity (YE et al., 2019). This research will quantitatively examine indicators such as population growth, economic development, and social progress, as detailed in Table 1.

4 RESULTS AND ANALYSIS

4.1 Changes in Arable Land Resources

Over the past 21 years (2000 to 2021), the total arable land resources in Northeast China—comprising Liaoning Province, Jilin Province, and Heilongjiang Province—have exhibited a consistent upward trend. According to the research data, from 2000 to 2021, the total arable land in Liaoning Province increased from 4.0821 million hectares in 2000 to 5.1594 million hectares in 2021, with an average annual increase of 51,300 hectares, representing a 26.39% growth compared to the total arable land at the beginning of the study period. In Jilin Province, arable land resources grew from 5.0833 million hectares in 2000 to 7.4985 million hectares in 2021, with an average annual increase of 115,000 hectares, reflecting a 47.51% increase relative to the total arable land at the start of the period (HOU et al., 2023). Heilongjiang Province saw its arable land resources rise from 11.7731 million hectares to 17.1660 million hectares, with an average annual growth of 256,800 hectares, demonstrating a notable growth trend and a 45.80% increase from the beginning of the study period (Figure 1).

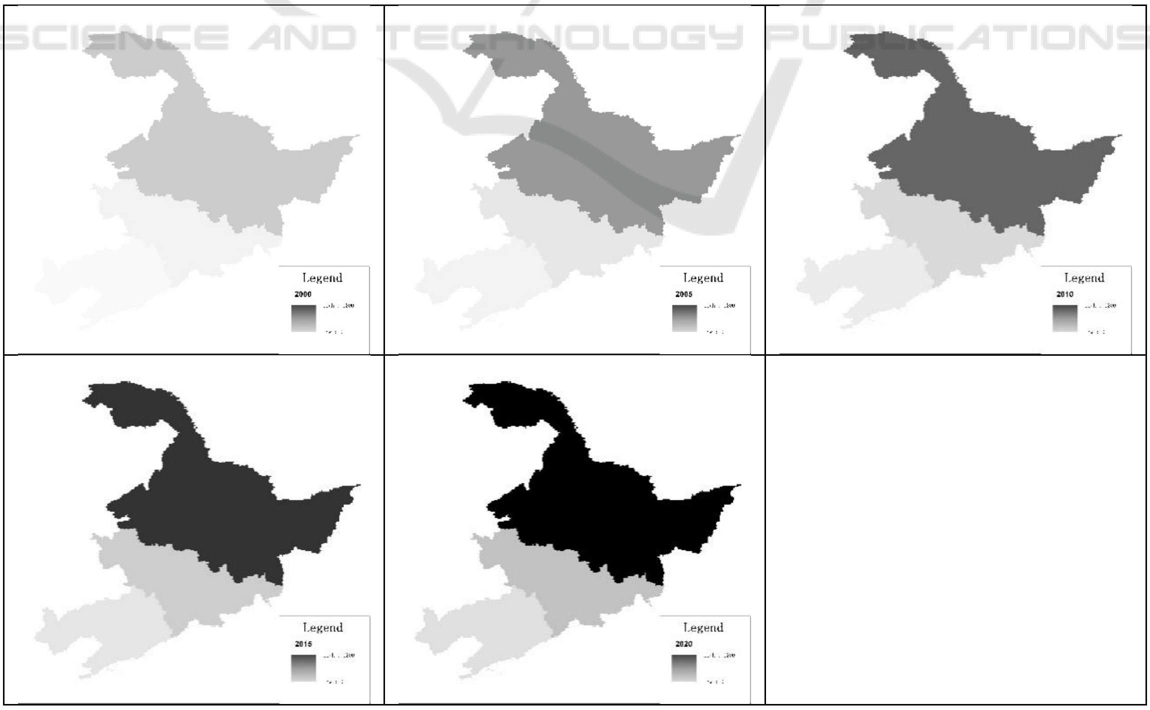


Figure 1: Changes in Arable Land Resources in the Three Northeastern Provinces (2000-2021).

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}

4.2 Drivers of Changes in Arable Land Resources

4.2.1 Indicators and Evaluation

(a) Correlation Test of Initial Variables

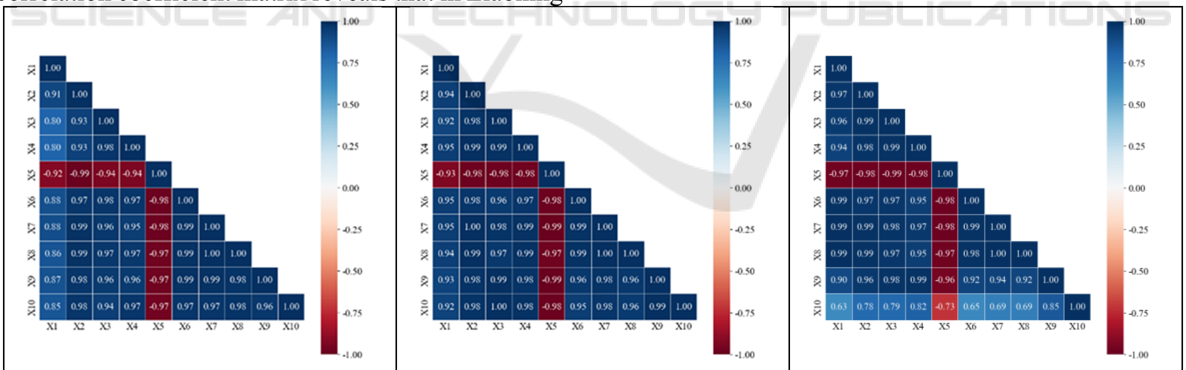
Figure 2 presents the correlation coefficient matrix for the ten indicators affecting arable land resources. This study aims to analyze the interrelationships among these indicators to uncover their intrinsic network of relationships (XIE et al., 2023). The correlation coefficient matrix reveals that in Liaoning Province, the indicators generally exhibit correlations above 0.80, in Jilin Province above 0.90, and in Heilongjiang Province above 0.60, highlighting a significant degree of correlation among the provinces in Northeast China.

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

The statistical results distinctly indicate the significance of both the KMO test and Bartlett's test of sphericity, thereby affirming the suitability of principal component analysis (Ma et al., 2023). Consequently, it can be concluded that the dataset demonstrates reliability for principal component analysis, with the potential to effectively extract the principal factors (Table 2).

4.2.2 Eigenvalues and Contribution Rates

The results of the principal component analysis reveal the underlying structure of the ten variables and their associated data (GUAN et al., 2023). Notably, the cumulative contribution rates of the first two principal components are as high as 98.294% for Liaoning Province, 98.689% for Jilin Province, and 98.815% for Heilongjiang Province, all significantly exceeding the recommended statistical threshold. This indicates that the primary factors can be effectively represented by the first two principal components (YE et al., 2023), F_1 and F_2 (Table 3).



Liaoning Province | Jilin Province | Heilongjiang Province

Figure 2: Correlation Coefficient Matrix of Variables.

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

		Liaoning Province	Jilin Province	Heilongjiang Province
KMO Measure of Sampling Adequacy		0.813	0.862	0.87
Bartlett's Test of Sphericity	Approximate Chi-Square	637.807	715.654	674.224
	Degrees of Freedom	45	45	45
	Significance	0	0	0

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
Liaoning Province	F_1	9.554	95.541	95.541	9.554	95.541	95.541	6.049	60.489	60.489
	F_2	0.275	2.753	98.294	0.275	2.753	98.294	3.78	37.805	98.294
	F_3	0.065	0.647	98.942						
Jilin Province	F_1	9.747	97.467	97.467	9.747	97.467	97.467	5.4	53.998	53.998
	F_2	0.122	1.223	98.689	0.122	1.223	98.689	4.469	44.692	98.689
	F_3	0.067	0.668	99.358						
Heilongjiang Province	F_1	9.344	93.438	93.438	9.344	93.438	93.438	6.838	68.38	68.38
	F_2	0.538	5.376	98.815	0.538	5.376	98.815	3.043	30.434	98.815
	F_3	0.069	0.686	99.5						

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

	Liaoning Province				Jilin Province				Heilongjiang Province			
	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	0.448	0.888	-0.875	1.276	0.539	0.828	-1.309	1.588	0.938	0.335	0.303	-0.286
x_2	0.731	0.672	-0.099	0.296	0.741	0.664	0.109	0.031	0.848	0.525	0.098	0.045
x_3	0.877	0.45	0.491	-0.465	0.817	0.571	0.768	-0.695	0.831	0.549	0.069	0.09
x_4	0.884	0.443	0.513	-0.493	0.741	0.664	0.11	0.031	0.791	0.6	0.004	0.192
x_5	-0.726	-0.677	0.113	-0.314	-0.763	-0.633	-0.315	0.196	-0.873	-0.47	-0.157	0.051
x_6	0.806	0.583	0.162	-0.038	0.666	0.732	-0.445	0.64	0.928	0.361	0.277	-0.243
x_7	0.788	0.607	0.095	0.047	0.72	0.69	-0.071	0.23	0.908	0.413	0.224	-0.157
x_8	0.819	0.565	0.21	-0.1	0.695	0.706	-0.232	0.407	0.906	0.406	0.228	-0.164
x_9	0.795	0.588	0.137	-0.007	0.805	0.584	0.672	-0.59	0.738	0.656	-0.072	0.309
x_{10}	0.813	0.556	0.218	-0.112	0.818	0.568	0.784	-0.713	0.334	0.937	-0.539	1.012

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 three northeastern provinces are derived as follows (Fa represents Liaoning Province, F_b represents Jilin Province, and Fc represents Heilongjiang Province) (Li et al., 2023):

$$F_{a1}=-0.875x_1-0.099x_2+0.491x_3+0.513x_4+0.113x_5+0.162x_6+0.095x_7+0.210x_8+0.137x_9+0.218x_{10} \quad (1)$$

$$F_{a2}=1.276x_1+0.296x_2-0.465x_3-0.493x_4-0.314x_5-0.038x_6+0.047x_7-0.100x_8-0.007x_9-0.112x_{10} \quad (2)$$

$$F_{b1}=-1.309x_1+0.109x_2+0.768x_3+0.110x_4-0.315x_5-0.445x_6-0.071x_7-0.232x_8+0.672x_9+0.784x_{10} \quad (3)$$

$$F_{b2}=1.588x_1+0.031x_2-0.695x_3+0.031x_4+0.196x_5+0.640x_6+0.230x_7+0.407x_8-0.590x_9-0.713x_{10} \quad (4)$$

$$F_{c1}=0.303x_1+0.098x_2+0.069x_3+0.004x_4-0.157x_5+0.277x_6+0.224x_7+0.228x_8-0.072x_9-0.539x_{10} \quad (5)$$

$$F_{c2}=-0.286x_1+0.045x_2+0.090x_3+0.192x_4+0.051x_5-0.243x_6-0.157x_7-0.164x_8+0.309x_9+1.012x_{10} \quad (6)$$

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 (Zhang et al., 2022):

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

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

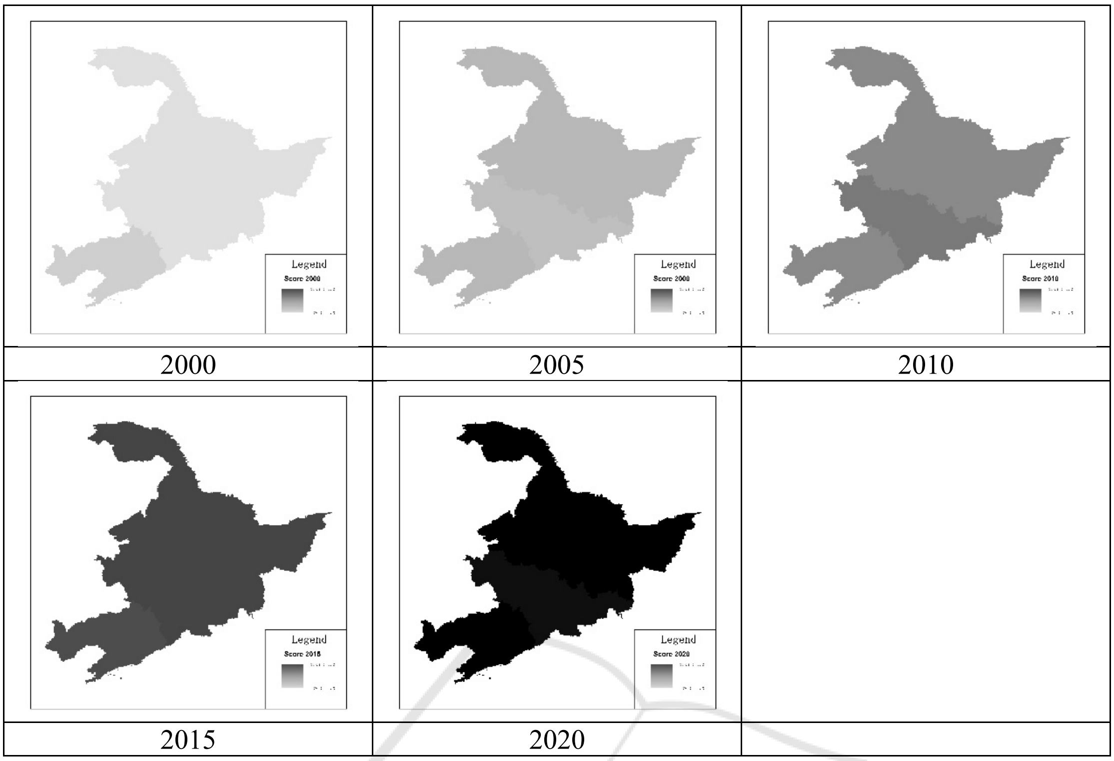


Figure 3: Changes in the Comprehensive Driving Force Score for Arable Land Resources in the Three Northeastern Provinces.

This study employs Principal Component Analysis (PCA) to systematically investigate the underlying causes of changes in arable land resources in Liaoning, Jilin, and Heilongjiang provinces. By aggregating the weighted coefficients of the primary influencing factors, data from 2000 to 2021 were analyzed. The overall trend indicates that from 2000 to 2021 (Xu et al., 2023), the driving forces behind changes in arable land resources in the three northeastern provinces exhibited a continuous upward trajectory. Prior to 2011, the comprehensive driving force scores were negative; starting in 2012, these scores gradually became positive, suggesting an increasing influence of factors affecting the variation in arable land resources in these provinces from 2012 to 2021 (Figure 3).

4.3 Evaluation of Driving Factors for Changes in Arable Land Resources in the Three Northeastern Provinces

The study reveals that the variation in arable land resources across the three northeastern provinces 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 Liaoning, Jilin, and Heilongjiang are 0.906, 0.922, and 0.923, respectively. This indicates that the two principal component factors included in the regression model account for 90.6%, 92.2%, and 92.3% of the variance in the dependent variable, demonstrating an excellent fit of the model. This model proves highly valuable for evaluating changes in arable land resources across the three northeastern provinces. The principal component regression equations established in this study are as follows (Table 5):

$$Y_a=428.712+31.562x_1+5.766x_2 \quad (8)$$

$$Y_b=620.823+71.683x_1+59.162x_2 \quad (9)$$

$$Y_c=1396.729+183.609x_1+115.355x_2 \quad (10)$$

Table 5: Regression Analysis Results of Principal Components.

		Unstandardized Coefficients		Standardized Coefficients	t-Statistic	Sig
		Coefficient	Standard Error			
Liaoning	Constant	428.712	2.311		185.549	0
	F_1	31.562	2.365	0.937	13.346	0
	F_2	5.766	2.365	0.171	2.438	0.025
	R^2	0.906				
Jilin	Constant	620.823	6.046		102.675	0
	F_1	71.683	6.189	0.741	11.583	0
	F_2	59.162	6.189	0.611	9.56	0
	R^2	0.922				
Heilongjiang	Constant	1396.729	14.043		99.463	0
	F_1	183.609	14.373	0.813	12.774	0
	F_2	115.355	14.373	0.511	8.026	0
	R^2	0.923				

Table 6: Regression Coefficients for Each Original Variable.

	Liaoning					*Jilin*					*Heilongjiang*				
	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	-0.875	-27.616	1.276	7.358	-20.258	-1.309	-93.836	1.588	93.962	0.127	0.303	55.682	-0.286	-32.986	22.696
x_2	-0.099	-3.131	0.296	1.706	-1.425	0.109	7.847	0.031	1.849	9.696	0.098	17.99	0.045	5.155	23.144
x_3	0.491	15.485	-0.465	-2.679	12.806	0.768	55.049	-0.695	-41.13	13.919	0.069	12.718	0.09	10.374	23.092
x_4	0.513	16.178	-0.493	-2.841	13.337	0.11	7.89	0.031	1.81	9.7	0.004	0.777	0.192	22.121	22.897
x_5	0.113	3.582	-0.314	-1.811	1.771	-0.315	-22.593	0.196	11.602	-10.992	-0.157	-28.871	0.051	5.867	-23.004
x_6	0.162	5.103	-0.038	-0.22	4.883	-0.445	-31.875	0.64	37.886	6.011	0.277	50.895	-0.243	-28.082	22.813
x_7	0.095	3.004	0.047	0.272	3.276	-0.071	-5.076	0.23	13.62	8.544	0.224	41.093	-0.157	-18.068	23.026
x_8	0.21	6.626	-0.1	-0.578	6.048	-0.232	-16.623	0.407	24.05	7.427	0.228	41.868	-0.164	-18.964	22.903
x_9	0.137	4.31	-0.007	-0.04	4.271	0.672	48.205	-0.59	-34.905	13.301	-0.072	-13.159	0.309	35.641	22.482
x_{10}	0.218	6.876	-0.112	-0.647	6.229	0.784	56.215	-0.713	-42.203	14.012	-0.539	-98.993	1.012	116.717	17.724

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:

$$Y_a=428.712-20.258x_1-1.425x_2+12.806x_3+13.337x_4+1.771x_5+4.883x_6+3.276x_7+6.048x_8+4.271x_9+6.229x_{10} \quad (11)$$

$$Y_b=620.823+0.127x_1+9.696x_2+13.919x_3+9.700x_4-10.992x_5+6.011x_6+8.544x_7+7.427x_8+13.301x_9+14.012x_{10} \quad (12)$$

$$Y_c=1396.729+22.696x_1+23.144x_2+23.092x_3+22.897x_4-23.004x_5+22.813x_6+23.026x_7+22.903x_8+22.482x_9+17.724x_{10} \quad (13)$$

5 CONCLUSION

Between 2000 and 2021, the quantity of arable land resources in the three northeastern provinces exhibited a gradual upward trend, influenced by a confluence of interacting factors. Research indicates that the driving force behind the changes in arable land resources in these provinces has progressively strengthened. Specifically, the composite score for the northeastern provinces remained negative until 2011, but began to turn positive from 2012 onwards, indicating a significant intensification of the forces driving changes in arable land resources during this period.

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REFERENCES

Yu Y. 2022. Applications of 3 D laser scanning technology in the extraction of vegetation parameters , *Journal of Henan Polytechnic University (Natural Science)*, 41(04): 51-57. DOI: 10.16186/j.cnki.1673-9787.2020090105.

Zhang Z Q. 2022. The evolution pattern and influence of human activities of landslide driving factors in Wulong section of the Three Gorges Reservoir area, The Chinese Journal of Geological Hazard and Control, 33(03): 39-50. DOI: 10.16031/j.cnki.issn.1003-8035.2022.03-05.

Wang N. 2021. Mine Environment Investigation and Research Based on Remote Sensing Technology:A Case Study of the Jidong Iron Mine, Metal Mine, (10): 192-198. DOI:10.19614/j.cnki.jsks.202110026.

YE S S. 2019. Ecological Environmental Cost Accounting of Mining Area Based on the Green Mine: A Case from a Mining Area in the North China Plain , Metal Mine, (04): 168-174. DOI: 10.19614/j.cnki.jsks.201904031.

Hou J W. 2023. Discourse on scientific advancements in mining ecological restoration, Mining Safety & Environmental Protection, 50(06): 1-6, 15. DOI:10.19835/j.issn.1008-4495.2023.06.001.

Xie Y. 2023. Analysis of land use change and influencing factors based on GIS and RS:A case of Hefei, Natural Resources Informatization, (04): 18-23. DOI: 10.3969/j.issn.1674-3695.2023.04.003

Ma J X. 2023. Spatio-temporal change characteristics of water conservation function in the Zhang-Cheng district based on the InVEST model, Hydrogeology & Engineering Geology, 50(03): 54-64. DOI:10.16030/j.cnki.issn.1000-3665.202208084.

Guan D J. 2023. Study on the Spatial-temporal Coupling Relationship between New Urbanization and Logistics Industry: Based on the Panel Data of Anhui Province , Journal of Cangzhou Normal University, 39(01): 51-55. DOI:10.13834/j.cnki.czsfxyxb.2023.01.012.

Ye S S. 2023. Comprehensive Management of Ecological Protection and Restoration Funds, Finance and Accounting for International Commerce, (20): 54-58. DOI: 10.3969/j.issn.1673-8594.2023.20.009

Li X L. 2023. Theoretical analysis and engineering practice of dynamic pre-reclamation in coal mining subsidence area, Mining Safety & Environmental Protection, 50(01): 86-91. DOI: 10.19835/j.issn.1008-4495.2023.01.015.

Zhang Y. 2022. Selection of pioneer plants for repairing limestone high and steep slopes in North China, The Chinese Journal of Geological Hazard and Control, 33(05): 109-118. DOI: 10.16031/j.cnki.issn.1003-8035.202110012.

Xu L. 2023. Carbon Storage Change in Xishuangbanna Based on PLUS and InVEST Model , Ecology and Environmental Monitoring of Three Gorges, 8(02): 75-87. DOI: 10.19478/j.cnki.2096-2347.2023.02.10.