

Dynamic Monitoring Study on Water Area in High Groundwater Level Coalfield: A Case Study of Yanzhou Coalfield

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Abstract: To reveal the spatiotemporal evolution characteristics of surface water bodies in the eastern high groundwater level mining areas, this paper takes Yanzhou Coalfield as the research area. Four commonly used water extraction methods, including the modified normalized difference water index (MNDWI) method, single-band threshold method, spectral relationship method, and K-T transformation method, were compared in terms of extraction accuracy and advantages and disadvantages. Based on the comparison results, the MNDWI method based on threshold segmentation was selected to extract water body information from 2015 to 2022, and its spatiotemporal variation characteristics were analyzed. The results show that the water body area generally increased from 2015 to 2019 with a total increase of 7.397 km² and an average annual growth of 1.849 km², reaching a maximum of 20.936 km² in 2019. The water area decreased by 0.449 km² in 2020 compared with 2019, with an annual decline rate of 2.1%. The fastest growth occurred from 2021 to 2022, with an annual growth rate of 30.7%. The expansion of water bodies in the study area was mainly concentrated in Xinglongzhuang Coal Mine, Nantun Coal Mine, and Baodian Coal Mine. Pearson correlation analysis revealed that the change in water body characteristics was mainly related to the cumulative coal mining volume. This study dynamically monitors the changes of surface water bodies in coal mining areas and analyzes the causes, which is helpful for objectively and quantitatively evaluating the impact of coal mining on ecosystems.

Keywords: Yanzhou Coalfield; coal mining subsidence; modified normalized difference water index (MNDWI); water area dynamic monitoring; driving force analysis

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I. INTRODUCTION

Coal is the primary energy source in China, serving as the material basis for the sustainable development of the national economy and environment, and an important guarantee for promoting social and economic sustainable development. Coal mining and utilization are indispensable components of China's social development and economic construction, playing a crucial role in driving the rapid development of the national economy. However, with the intensification of coal mining, the development and utilization of coal resources have brought a series of ecological and environmental problems to mining areas while providing impetus for China's high-speed economic development. In particular, large-scale ground subsidence in mining areas has caused great harm to the people in mining areas and restricted their sustainable development.

The eastern mining areas in China are typical high groundwater level coal mining areas, characterized by high groundwater levels and dense rivers and lakes. Long-term coal resource exploitation, especially coal seam group mining, has led to large subsidence areas, deep water accumulation, and long dynamic subsidence time, resulting in serious disorder of surface water systems and water areas, aggravated water pollution, and deteriorated water quality. A large amount of cultivated land is lost due to soil erosion, leading to a significant reduction in cultivated land resources. Villages are severely damaged, causing large-scale migration or relocation, which highlights social contradictions. These issues have a significant impact on China's food, energy, and ecological security, as well as regional social stability^[1].

The eastern coal mining areas in China are dominated by plains, which are typical grain-coal composite areas with fertile land and a large population. The grain output accounts for 34.18% of the national total, and the population density is 3.73 times the national average. It is estimated that the final subsidence area caused by coal mining in high groundwater level mining areas in China will reach 3.18×10⁶ hm², of which the final water accumulation area will exceed 1.91×10⁶ hm²^[1]. Ground subsidence and water accumulation caused by coal mining are one of the important characteristics of soil ecological environment changes in high groundwater level plain coal mining areas in eastern China. Surface water is an important part of the regional ecosystem. In-depth research

on the change characteristics of surface water under the influence of coal mining can provide a scientific basis for the quantitative evaluation of the comprehensive impact of coal mining on land, ecology, and society.

Remote sensing technology has become the main means of large-scale water extraction due to its wide coverage and high efficiency. Landsat series satellites, with their stable spectral performance and suitable spatial resolution, have been widely used in surface water monitoring. Early water body extraction mainly relied on manual visual interpretation, which was time-consuming and labor-intensive and could not meet the requirements of large-scale research areas. With the development of remote sensing technology, various quantitative analysis methods have been formed, which can be generally divided into linear spectral analysis, nonlinear index calculation, and supervised classification methods.

Mcfeeters constructed the Normalized Difference Water Index (NDWI) using green and near-infrared bands, which effectively suppressed vegetation information and weakened the influence of soil, buildings, and shadows^[2]. However, NDWI is not suitable for all practical situations due to the influence of different image background information. Frazier et al. conducted in-depth research on the single-band threshold method, which has a simple principle but is prone to omission and misclassification when there is a transition zone between water and non-water bodies^[3]. Xu Hanqiu proposed the Modified Normalized Difference Water Index (MNDWI) based on NDWI, replacing the near-infrared band with the short-wave infrared band to reduce the interference of buildings and vegetation, significantly improving the extraction accuracy of water bodies in urban areas.

In the field of remote sensing monitoring of ground disturbance in high groundwater level mining areas, accurate and rapid acquisition of the spatiotemporal laws of surface water accumulation is crucial. Li Jing et al. took Yanzhou Coalfield from 1990 to 2014 as an example, compared four water extraction methods, and found that the MNDWI method had higher extraction accuracy and spatiotemporal adaptability, which could better avoid noise interference such as building shadows^[15]. However, most existing studies on dynamic monitoring of water body changes are based on images from a few periods for dual-temporal comparison, which makes it difficult to objectively reflect the change process. In terms of driving force analysis, existing studies have not comprehensively considered the combined effects of interannual precipitation differences and human factors such as coal mining.

To address the above problems, this study selects Yanzhou Coalfield as the research area, compares the accuracy and advantages/disadvantages of four different water extraction methods, extracts surface water body information for 8 periods from 2015 to 2022, analyzes their temporal and spatial distribution characteristics, and explores the driving factors from three aspects: precipitation, temperature, and coal mining.

II. STUDY AREA AND DATA SOURCES

Yanzhou Coalfield is located in the southwestern part of Shandong Province, between 116°10′–117°00′ E and 35°10′–35°40′ N, at the junction of Zoucheng, Qufu, and Yanzhou cities. It is a typical high-groundwater-level grain-coal composite area in eastern China. The total area of Yanzhou Coalfield is more than 3400 square kilometers, with proven coal reserves of 9.1 billion tons. It contains several mines such as Yangcun Coal Mine, Xinglongzhuang Coal Mine, Dongtan Coal Mine, Baodian Coal Mine, Beisu Coal Mine, and Nantun Coal Mine, with a minefield area of about 258 km²[15]. The 258 km² minefield spans the administrative boundaries of Yanzhou City, Qufu City and Zoucheng City. In terms of spatial distribution, Xinglongzhuang Coal Mine is located in the northeastern part of the minefield, adjacent to Qufu City; Yangcun Coal Mine is in the northwestern part, bordering Yanzhou City; Dongtan Coal Mine lies in the central-eastern region; Baodian Coal Mine is situated in the central-southern part; Nantun Coal Mine and Beisu Coal Mine are in the southern part, adjacent to Zoucheng City.

Yanzhou Coalfield has a warm temperate monsoon climate. Precipitation is concentrated in summer and autumn, with less precipitation in winter and spring, and alternating drought and flood. The annual average temperature is 12-15°C, and the annual average precipitation is about 800-1000 mm. The coldest month is January, with an average temperature of -3°C to 2°C, and the hottest month is July, with an average temperature of 24°C to 28°C. Meteorological data show that from 2015 to 2022, the annual average rainfall in the study area was 794.7 mm, with the maximum annual rainfall of 1071.8 mm in 2021 and the minimum of 550 mm in 2019. The annual average temperature in the study area was 14.84°C, with the highest annual average temperature of 15.4°C in 2022 and the lowest of 14.2°C in 2015.

Yanzhou City is located in the Huaihe River Basin of Nansi Lake, with 14 first-class tributaries and 4 second-class tributaries within its territory. In addition, there are many rivers, reservoirs, and lakes such as Wulong Lake and Yihe Reservoir, which provide important domestic water and agricultural irrigation water sources for local residents, and are also important places for tourism and aquaculture.

Taking the Yishan Fault as the boundary, the eastern and northeastern parts of Yanzhou Coalfield are low mountain and hilly areas, belonging to the Taiyi Mountain System, mostly trending southeast-northwest. There are 43 mountain peaks with elevations ranging from +450 m to +648 m, mainly distributed in the east of

Zoucheng City and Qufu City. The interior of the coalfield is flat, gradually decreasing from northeast to southwest, with ground elevations ranging from +36 m to +72 m.

All mine fields in Yanzhou Coalfield are fully concealed coal fields dominated by the Taiyuan Formation and Shanxi Formation of the Carboniferous-Permian, with high coal content. The minable coal measure strata mainly include 3 (3 upper, 3 lower), 6 lower, 10 lower, 12 lower, 15 upper, 16 upper, and 17 coal seams. The main minable coal seams are 3 (3 upper, 3 lower), 16 upper, and 17, which are stable with an average thickness of about 10.39 meters, accounting for 72.91% of the minable coal seams. The locally minable coal seams are 3 upper, 6, 10 lower, 15 upper, and 18 upper, which are gently inclined coal seams. The coal mine has a history of more than 50 years since its opening, and was intensively developed from the late 1980s to the early 1990s, mainly mined by Yanzhou Coal Mining Co., Ltd.

The Landsat series satellites are the longest-running land observation program in existence. Since the launch of the first Landsat satellite in 1972, they have been continuously collecting surface images and providing uninterrupted data, which is of great help for government and relevant units to make rational decisions on the management of the earth's natural resources^[4]. This study uses Landsat data as the data source. During the research period, available Landsat data include Landsat TM, Landsat ETM+, and Landsat OLI satellite image data. Landsat OLI satellite was launched in February 2013 and is currently in good operating condition, providing high-quality ground observation images. Therefore, Landsat OLI image data were selected for the study period.

This study uses 8 Landsat images from 2015 to 2022, all provided by the United States Geological Survey (USGS). The downloaded image data are surface reflectance data with path number 122, row number 035, and spatial resolution of 30 m. The imaging dates are October 2, 2015, September 2, 2016, June 17, 2017, September 24, 2018, May 22, 2019, April 22, 2020, May 27, 2021, and May 30, 2022.

Meteorological data required for the study, including rainfall, temperature, and average humidity, were downloaded from the "National Meteorological Science Data Sharing Service Platform" (<http://data.cma.cn/site/index.html>), which provides complete ground meteorological observation data for the study area. The coal mining volume data of each mine in Yanzhou Coalfield were obtained from the annual reports of Yankuang Energy Group Co., Ltd. (<http://www.yanzhoucoal.com.cn/>) and publicly available statistical materials. The Jining Municipal Bureau of Statistics website was temporarily inaccessible during data collection, so supplementary data were obtained from industry reports and academic literature. In this study, temperature and precipitation refer to the annual average values corresponding to the image acquisition time; cumulative coal mining volume refers to the cumulative coal mining volume of major mines in the same observation year.

III. RESULTS AND ANALYSIS

This study aims to extract surface water bodies in the study area and reveal their spatiotemporal evolution characteristics. Based on the spectral characteristics of water bodies, the extraction effects and accuracy of four commonly used water extraction methods were compared to select the most suitable method for the study area. The selected method was used to extract water body information from multi-year Landsat OLI images, then dynamically analyze the change characteristics of water bodies in the study area, and analyze the correlation between driving factors (coal mining, rainfall, temperature) and water body changes to determine the dominant factors affecting water body changes in the study area.

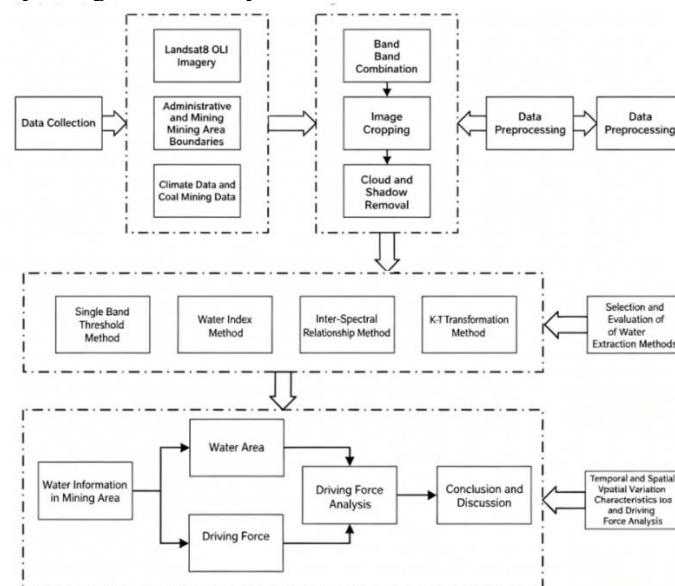


Fig. 1 Technical flow chart of the study

Remote sensing technology processes and analyzes electromagnetic signals reflected and emitted by the earth's surface to extract surface feature information and invert remote sensing parameters. During remote sensing imaging, factors such as satellite platforms, sensors themselves, atmospheric factors, the earth's own properties, random errors, and solar altitude angles will cause a large amount of noise in the actual image grayscale, making it impossible to invert the true electromagnetic radiation energy of the target. Therefore, data preprocessing is required before using remote sensing images to eliminate the influence of the above factors, mainly including radiometric calibration, atmospheric correction, and geometric correction.

The remote sensing data used in this study are surface reflectance data products processed by Landsat Surface Reflectance Code (LaSRC), which have undergone systematic atmospheric correction, geometric correction, and radiometric calibration. Therefore, the above preprocessing operations are not required. The preprocessing work for remote sensing images in this study mainly includes band synthesis, study area boundary cropping, and cloud and shadow masking.

In nature, all ground objects can reflect, emit, and absorb electromagnetic waves. Different types of objects have different internal molecular structures and molecular and atomic motion forms, so they emit light of different frequencies. The physical basis for the development of remote sensing technology is the electromagnetic wave characteristics of objects.

When sunlight irradiates, water bodies absorb most of the incident solar radiation energy, showing low reflectance characteristics in most spectral ranges of remote sensing images, and the reflectance gradually decreases with the increase of wavelength. Before the red band in the visible spectrum, water bodies absorb less and have low reflectance, with a large amount of incident light transmitted, and the reflectance of water bodies is about 5%. The reflectance of red light is only 2% to 3%. In the near-infrared and short-wave infrared regions, there are strong absorption zones, and the reflectance is close to zero. Therefore, in remote sensing images, especially near-infrared images, water bodies appear obviously black, which is the fundamental difference between water bodies and other ground objects.

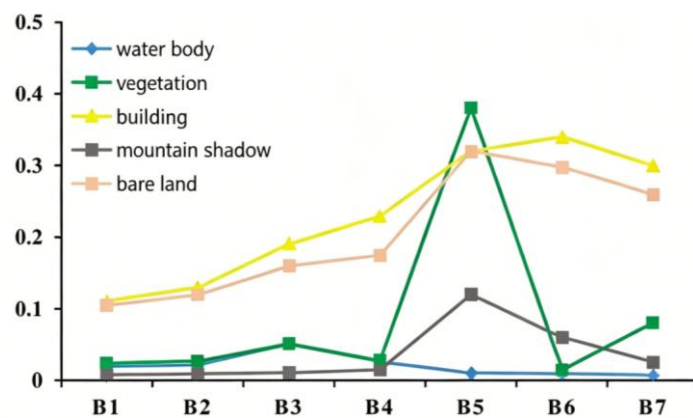


Fig. 2 Spectral reflectance curves of typical land cover types in Landsat OLI bands

The single-band threshold method is based on the characteristic that water bodies strongly absorb incident light energy in the near-infrared and short-wave infrared bands, while other ground objects such as plants and soil have strong reflectivity in these bands^[3]. Water body information is extracted by setting corresponding thresholds. The appropriate threshold selection directly affects the extraction results; too high or too low thresholds will cause confusion of water samples. This method is computationally efficient but difficult to distinguish between water bodies and shadows, resulting in high misclassification rates.

The water index method extracts surface water body information by performing difference operations on the reflectance of different bands of the image, making specific ground objects easier to identify on the difference image. Xu Hanqiu proposed the MNDWI based on NDWI, replacing the near-infrared band with the short-wave infrared band. This is because buildings often have high reflectance in the short-wave infrared band, while water bodies have low reflectance, which can better distinguish buildings from water bodies and reduce the degree of confusion between them. In addition, MNDWI can separate shadows from other ground objects, fully considering factors such as soil, artificial ground objects, and shadows, and taking into account the spectral characteristic differences of different land cover types, making the extraction results closer to the actual ground object conditions^[12].

The calculation formula of MNDWI is: $MNDWI = (Green - MIR)/(Green + MIR)$ where Green and MIR refer to the 3rd and 6th bands of Landsat OLI data, which are the green band and short-wave infrared band, respectively.

In water extraction, threshold selection is very important and directly affects the extraction accuracy. In this study, the maximum inter-class variance method was used to calculate the segmentation threshold. This method maximizes the inter-class variance between the background and the target to obtain the optimal segmentation threshold.

The spectral relationship method is a multi-band method that uses the difference in spectral values between different bands to distinguish water bodies from other ground objects. This method can well extract mountain shadows, so it is suitable for extracting water bodies in mountainous areas, but the extraction results are prone to misclassify residential areas as water bodies^[8].

K-T transformation, also known as tasseled cap transformation, is an empirical linear orthogonal transformation performed on images based on the spatial distribution characteristics of information such as vegetation and soil in multi-spectral remote sensing images^[8]. It can effectively eliminate the inter-correlation between spectra and identify water and non-water information. This method can not only eliminate the influence of clouds and shadows but also improve the extraction accuracy of surface water bodies.

Statistical analysis and spatial analysis methods were used to analyze the spatiotemporal changes of water bodies in the study area. The dynamic changes of water body information are not only reflected in the water area but also in the changes of spatial distribution and different types of transfer processes. The water area of each image was counted to obtain the interannual area changes and growth rates, and the spatial distribution characteristics of water bodies and the information of spatial changes of surface water bodies were analyzed.

The causes of surface water body changes in the study area are mainly divided into natural factors and human factors. In this study, qualitative and quantitative analysis methods were combined to explore the internal relationship between influencing factors such as coal production, annual precipitation, and average temperature and the dynamic changes of water areas, and to reveal the dominant factors affecting water body changes. Pearson correlation coefficient was used for driving force analysis, which is a statistical indicator that reflects the degree of linear relationship between two variables, with values ranging from -1 to +1. A positive value indicates a positive correlation, a negative value indicates a negative correlation, and the larger the absolute value, the stronger the linear correlation.

Taking the Landsat OLI image of 2021 as an example, four methods (single-band threshold method, MNDWI method, spectral relationship method, and K-T transformation method) were used to extract water body information, and their accuracy was compared to select the most suitable water extraction method.

First, qualitative analysis was carried out using visual interpretation. The results show that the MNDWI method and single-band threshold method have better extraction effects, followed by the K-T transformation method. The single-band threshold method is difficult to distinguish small water bodies and shadows mixed in water bodies, resulting in misclassification and omission. The spectral relationship method has the worst extraction effect, with more omitted water body information. Local effect analysis in Xinglongzhuang Coal Mine shows that the MNDWI method has a good effect in extracting small-area water bodies, while the single-band threshold method is prone to misclassify shadows in water bodies as water bodies. The spectral relationship method and K-T transformation method have poor extraction effects, failing to completely extract water body boundaries and having more omitted water body information.

Quantitative accuracy verification was carried out using 300 random verification points selected from Google Earth images, including 100 water body sample points and 200 non-water body sample points. The results show that the MNDWI method has the highest overall accuracy (94.7%) and Kappa coefficient (0.891)^{[12][15]}, followed by the single-band threshold method with an overall accuracy of 93.2% and Kappa coefficient of 0.863. The K-T transformation method ranks third with an overall accuracy of 83.1%, and the spectral relationship method has the lowest overall accuracy of 78.8%. All four methods have omission phenomena, with the spectral relationship method being the most serious (40.2%), followed by the K-T transformation method (33.8%). Based on the accuracy verification results, the MNDWI method was selected for water body change information extraction in this study because of its highest overall accuracy and Kappa coefficient, and low commission and omission errors.

The water area of each year was counted based on the extraction results of the MNDWI method. In 2015, the water body area in the study area was 13.539 km², which increased to 15.263 km² in 2016 and 17.603 km² in 2017. In 2018, the area decreased slightly to 17.150 km², then rose sharply to 20.936 km² in 2019, reaching the first peak. In 2020, the area decreased to 20.487 km², remained basically stable at 20.546 km² in 2021, and then increased rapidly to 26.846 km² in 2022.

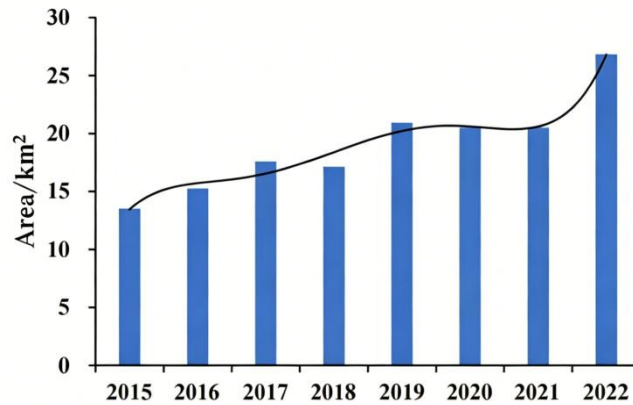


Fig. 3 Interannual variation trend of water body area in Yanzhou Coalfield from 2015 to 2022

From 2015 to 2022, the water body area in the study area generally showed a significant growth trend, with a total increase of 13.307 km². According to the growth rate, the observation period can be divided into three stages: slow growth stage (2015-2019), where the water body area increased slowly by 7.397 km², with an average annual growth of 1.849 km²; stable fluctuation stage (2019-2021), where the water body area decreased slightly, with an average annual decrease of 0.195 km², reaching a minimum of 20.487 km² in 2020; rapid growth stage (2021-2022), where the water body area increased rapidly by 6.3 km², with an average annual growth rate of 30.7%.

The spatial distribution changes of water bodies were analyzed based on the interannual water body position change maps.

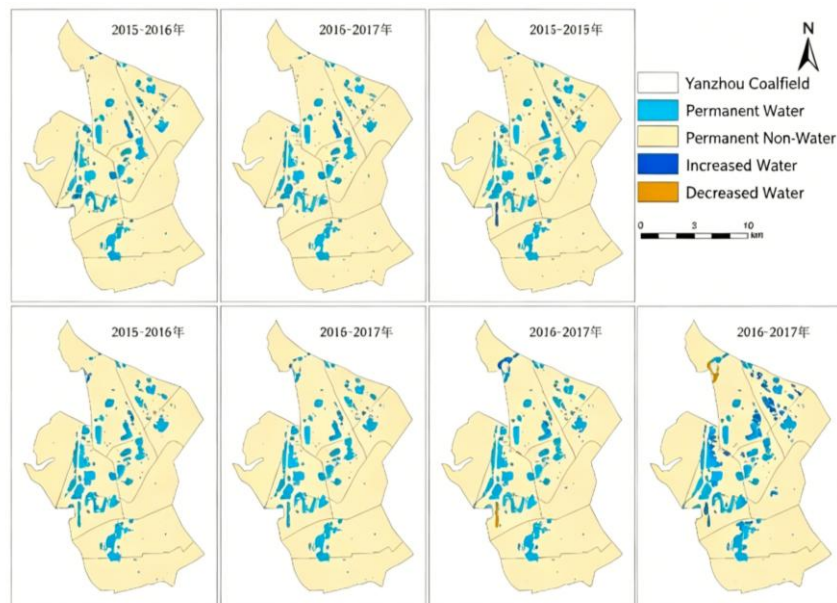


Fig. 4 Interannual spatial transfer map of surface water bodies in Yanzhou Coalfield (2015-2022)

From 2015 to 2017, the water bodies in the study area showed an overall growth trend, mainly distributed at the edges of subsidence water accumulation areas in Xinglongzhuang Coal Mine and Dongtan Coal Mine. From 2017 to 2018, the increased and decreased water bodies were basically the same, mainly distributed in Xinglongzhuang Coal Mine and Baodian Coal Mine. From 2018 to 2019, the water body growth area reached 4.048 km², with the most obvious expansion in Baodian Coal Mine, and the water body decrease area was only 0.265 km². From 2019 to 2020, the water body area decreased compared with the previous year, and both the decreased and increased water bodies were mainly distributed in Xinglongzhuang Coal Mine. From 2020 to 2021, the increased and decreased water bodies were basically the same, mainly distributed in Baodian Coal Mine and Xinglongzhuang Coal Mine. From 2021 to 2022, the water body area increased by 7.587 km², with a decrease area of only 1.290 km², and the water body expansion was more obvious, mainly distributed in Baodian Coal Mine, Xinglongzhuang Coal Mine, and Nantun Coal Mine.

Pearson correlation coefficient was used to analyze the relationship between driving factors (average temperature, precipitation, cumulative coal mining volume) and water body area changes.

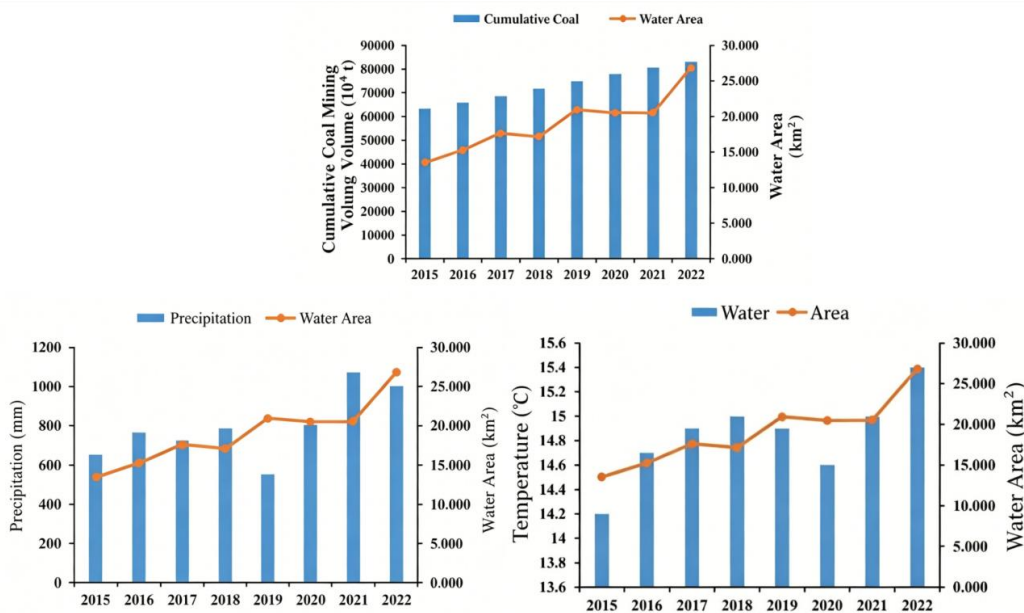


Fig. 5 Relationship between water body area and driving factors

The results show that the water body area has a strong positive correlation with the cumulative coal mining volume, with a correlation coefficient of 0.8573, significant at the 0.01 level. The correlation coefficient with the annual average temperature is 0.6323, also significant at the 0.01 level, while the correlation with annual precipitation is relatively weak, with a coefficient of only 0.2713. This indicates that the main driving factors of water body area changes are cumulative coal mining volume and average temperature, with cumulative coal mining volume being the dominant factor. The temperature showed an upward trend from 2015 to 2022, which was roughly consistent with the change trend of water bodies. The correlation between precipitation and water body area was low, mainly because precipitation had obvious dry and wet years, showing a fluctuating change with a large difference. The change trend of cumulative coal mining volume was consistent with that of water body area, with a high correlation coefficient, indicating that cumulative coal mining volume is the main driving factor of water body area changes.

IV. CONCLUSIONS AND PROSPECTS

This study takes Yanzhou Coalfield as an example, applies four commonly used water extraction methods to extract water body information from 8 remote sensing images from 2015 to 2022, and compares and analyzes the accuracy of each method. The spatiotemporal variation characteristics of surface water bodies in the study area were analyzed, and the driving factors of the changes were explored using Pearson correlation coefficient.

Through the comparison of four water extraction methods, the MNDWI method based on threshold segmentation has the best performance in water extraction accuracy and Kappa coefficient, with an overall accuracy of 94.7% and a Kappa coefficient of 0.891. It can effectively avoid noise interference such as building shadows and is suitable for long-term water body monitoring in high groundwater level coal mining areas.

From 2015 to 2022, the water body area in the study area generally showed an upward trend, with a total increase of 13.307 km². The change process can be divided into three stages: slow growth (2015-2019), stable fluctuation (2019-2021), and rapid growth (2021-2022). The water body expansion was mainly concentrated in Xinglongzhuang Coal Mine, Nantun Coal Mine, and Baodian Coal Mine.

The driving force analysis shows that the cumulative coal mining volume has the strongest positive correlation with the surface water body area, followed by the average temperature, while the correlation with annual precipitation is relatively weak. This indicates that coal mining is the main driving force leading to the change of water body area in Yanzhou Coalfield.

This study has achieved certain results in the dynamic monitoring of water bodies in high groundwater level coal mining areas, but there are still some limitations that need to be further improved in future research. In

this study, only one Landsat image was selected for each year, and the image dates are not completely consistent, which may lead to certain differences in the spatial distribution of water bodies in different years. In future research, multi-temporal images in the same season can be used to synthesize annual average water body information to improve the representativeness of the results.

This study only considered the driving factors of climate and coal mining, and did not take into account the influence of factors such as cultivated land changes, differences between dry and wet seasons, and ecological restoration policies. In future research, more driving factors can be included to improve the accuracy of the driving force analysis.

The traditional pixel-based classification method used in this study is prone to salt-and-pepper noise and has certain limitations in identifying small and fragmented water bodies. In future research, high-resolution remote sensing data can be introduced, and object-oriented classification methods or deep learning methods can be combined to further improve the extraction accuracy of water bodies^[8].

The driving force analysis model used in this study is a linear model, which cannot fully reflect the complex nonlinear relationship between driving factors. In future research, system analysis methods and machine learning models can be introduced to conduct more in-depth qualitative and quantitative research on the driving mechanism of water body changes.

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