WEP Warwick Evans Publishing

International Journal of Natural Resources and Environmental Studies

ISSN: 3006-2012 (Print), ISSN: 3006-0834 (Online)
Volume 8, Number 8, Year 2026
DOI: https://doi.org/10.62051/ijnres.v8n8.01

Downscaling of Groundwater Reserves in Henan Province Based on Xgboost

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ABSTRACT

Addressing the challenge posed by the relatively low spatial resolution of gravity satellite data, which hampers the fine monitoring of groundwater in provincial regions, this study focuses on Henan Province and develops a method utilizing eXtreme Gradient Boosting (XGBoost) for statistical downscaling of Groundwater Storage Anomaly (GWSA). Initially, the land water storage anomaly was derived from the GRACE/Grace-FO Mascon product provided by CSR. This was combined with surface water storage components, including soil moisture, snow water equivalent, and canopy water, as modeled in the GLDAS Noah land surface model, to calculate the groundwater storage anomaly. Subsequently, multiple source factors—such as precipitation, air temperature, relative humidity, surface temperature, evapotranspiration, normalized vegetation index, and elevation—were standardized to a 0.01° grid. This facilitated the establishment of a nonlinear mapping relationship between the coarse-resolution GWSA and high-resolution environmental factors, ultimately generating groundwater reserve anomaly products at a 0.01° resolution for Henan Province. The model results were validated through coarse-scale aggregation consistency tests, time series comparisons of monitoring wells, and error index evaluations. The findings indicate that XGBoost effectively preserves the spatiotemporal variation characteristics of the original GRACE results. After aggregation to 0.25°, a strong correlation with the original GWSA is observed. The downscaling results generally align with the variation trends observed in the monitoring wells. This research offers a high spatial resolution data foundation for the dynamic monitoring of groundwater resources, agricultural irrigation management, and regional water security assessments in Henan Province.

KEYWORDS

XGBoost; Groundwater Storage Anomaly; Spatial Downscaling

1. INTRODUCTION

Groundwater serves as a vital resource for agricultural irrigation, urban and rural livelihoods, and industrial production. It is also crucial for sustaining the base flow of rivers, supporting wetland ecosystems, and facilitating the terrestrial water cycle. In recent years, the interplay of population growth, the expansion of agricultural irrigation, and extreme climate events has disrupted the balance between groundwater recharge and extraction in numerous regions. Henan Province, situated in the heart of the Huang-Huai-Hai Plain, is a significant grain-producing area in China, where agricultural water use heavily relies on groundwater. Concurrently, urbanization, industrial development, and local mineral resource extraction have intensified pressure on the groundwater system. A precise understanding of regional disparities and long-term trends in groundwater reserves is essential for effective water resource allocation, the management of groundwater over-exploitation, and the assurance of food security.

Traditional groundwater monitoring primarily depends on monitoring wells, hydrological stations, and hydrogeological models. Monitoring wells offer continuous water level data at specific locations; however, their limited spatial density, high maintenance costs, and lack of spatial representativeness hinder their ability to capture overall changes in groundwater reserves across extensive areas. While hydrological models can elucidate processes, they depend on numerous parameters and boundary conditions, leading to significant uncertainty in regions with inadequate data. The GRACE mission, which measures variations in terrestrial water storage by observing the Earth's time-varying gravitational field, presents a novel technical approach for large-scale and continuous monitoring of the terrestrial water cycle [1-2]. Previous studies have demonstrated that GRACE can detect groundwater depletion signals in areas such as North China and exhibits strong consistency with surface observations [3].

The spatial resolution of GRACE's original products typically spans several hundred kilometers, with each grid representing the average quality variation over a broad area. This limitation hinders precise comparisons among agricultural, urban, and ecological regions within a province. The fundamental approach to spatial downscaling involves establishing statistical relationships using high-resolution environmental factors, thereby restoring regional spatial details while adhering to the large-scale constraints imposed by GRACE. Early studies primarily employed linear regression, empirical statistics, and scale factor methods [4-5]. In recent years, techniques such as random forests, enhanced regression trees, and deep learning have been utilized to downscale GRACE's groundwater reserves, yielding promising verification results [6-8].In contrast to traditional linear models, XGBoost effectively manages nonlinear relationships, variable interactions, and missing values while mitigating overfitting through regularization. This approach is well-suited for modeling groundwater responses influenced by the interplay of meteorological, vegetation, and topographic factors.

This paper investigates the "Downscaling of Groundwater Reserves in Henan Province Based on XGBoost." The research encompasses several key components: the construction of a GRACE/GLDAS groundwater reserve anomaly dataset; the integration of multi-source high-resolution environmental factors; and the establishment of an XGBoost statistical downscaling model. The downscaling results are evaluated from two perspectives: coarse-scale consistency and monitoring well consistency, and the applicability of these results for groundwater monitoring in Henan Province is discussed.

2. OVERVIEW AND DATA OF THE STUDY AREA

2.1. Overview of the Study Area

Henan Province is situated in the central and eastern regions of China, encompassing a geographical range of approximately 31°23' - 36°22'N and 110°21' - 116°39'E. The province's terrain is characterized by higher elevations in the west and lower elevations in the east. The western and southwestern areas are predominantly mountainous and hilly, while the central and eastern regions consist of extensive plains. The climate varies from a warm temperate zone in the north to a north subtropical zone in the south. Precipitation is unevenly distributed throughout the year, with a concentration of rainfall during the summer months. The plain areas feature contiguous cultivated land and a significant demand for irrigation, leading to challenges such as groundwater extraction and land subsidence. In contrast, the precipitation, topography, and vegetation conditions in the south and west are relatively favorable, resulting in a more pronounced connection between groundwater fluctuations and precipitation recharge.

2.2. Data Sources and Preprocessing

The study utilized monthly scale data spanning from April 2002 to December 2024. Following quality inspection, temporal alignment, and spatial resampling of various data types, a regular grid with a resolution of 0.01° was established. The CSR GRACE/Grace-FO RL06 Mascon v02 product was employed to derive terrestrial water storage anomalies. The GLDAS-2.1 Noah product supplied data on soil water, snow water equivalent, and canopy water. Precipitation, temperature, relative humidity, and air pressure data were obtained from ChinaMet. MODIS products contributed information on NDVI, day/night surface temperature, and evapotranspiration. Elevation data were sourced from SRTM, while monitoring well data were utilized for independent trend verification.

Data preprocessing involves three key steps. First, the time labels from different data sources are unified, all variables are converted to a monthly scale, and outliers are calculated using a consistent base period. Second, the spatial grid is aligned; the high-resolution factor is resampled to the target grid of 0.01° while preserving effective pixels within the administrative boundary. Finally, quality control is performed to address missing measurements and outliers. For invalid pixels in remote sensing products, information from neighboring pixels or adjacent months is utilized for completion, while pixels with prolonged missing measurements are excluded from model training. This process minimizes discrepancies among various data sources regarding time frequency, coordinate systems, and spatial support scales.

The monitoring well data are predominantly located in the northern and northeastern plain regions of Henan Province, whereas well points in the western, southern, and southeastern areas are relatively sparse. This uneven distribution of well points indicates that the verification results are more representative of the northern plain, necessitating a cautious interpretation for other regions. The spatial distribution of the monitoring wells is illustrated in Figure 1.

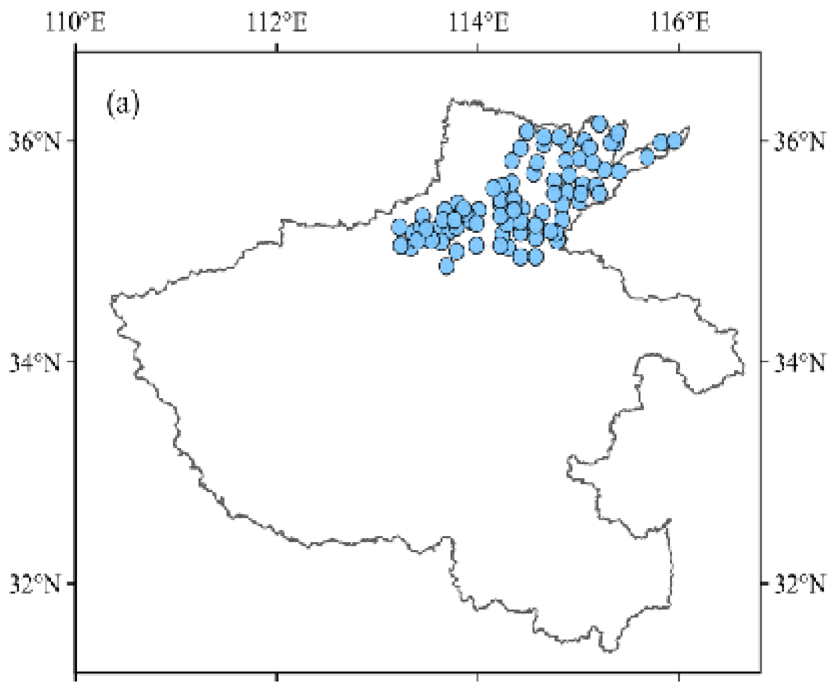

Figure 1 Spatial distribution of Groundwater monitoring Wells in Henan Province

3. RESEARCH METHODS

3.1. Abnormal Calculation of Groundwater Reserves

The total terrestrial water storage anomaly (TWSA) observed by GRACE encompasses surface water, soil water, groundwater, snow cover, and canopy water. First, the GRACE/Grace-FO products are restricted to the geographic extent of Henan Province and converted to equivalent water height. Subsequently, four layers of soil water, snow water equivalent, and canopy water are extracted from the GLDAS Noah product to compute the anomalous surface water storage (SMSA). Abnormal groundwater reserves are calculated using the following formula:

$$GWSA(t) = TWSA(t) - SMSA(t) \tag{1}$$

In the formula, t denotes the month, and the units for GWSA, TWSA, and SMSA are all measured in millimeters. Due to the interruption in observations between the GRACE and GRACE-FO missions, this paper implements time unification and processes missing data within the monthly sequence. Additionally, outlier checks are conducted on each input variable prior to model training.

3.2. Construction of Multi-source Factors

The input variables for the downscaling model comprise both dynamic and static factors. The dynamic factors include monthly precipitation, air temperature, relative humidity, air pressure, daytime surface temperature, nighttime surface temperature, evapotranspiration, and NDVI. In contrast, the static factor is elevation. The dynamic factors are aggregated to a consistent monthly time scale and subsequently resampled to a resolution of 0.01°. For remote sensing products such as NDVI and evapotranspiration, quality control is conducted initially; invalid pixels are removed before calculating the monthly average values. The elevation data, which remained constant throughout the study period, serves to represent the spatial background influence of topography on precipitation distribution, runoff convergence, and groundwater recharge conditions.

3.3. XGBoost downscaling model

XGBoost is an ensemble learning algorithm that utilizes gradient boosting trees. Its fundamental principle involves incrementally constructing a regression tree and fitting the residuals from the preceding model in each iteration. The integration of multiple weak learners enhances the model's fitting capability compared to a solitary decision tree. Unlike traditional linear regression, the tree model does not necessitate a linear relationship between the input variables and the target variable. The objective function of the model is:

$$Obj = \Sigma_i L(y_i, \hat{y}_i) + \Sigma_k \Omega(f_k) \tag{2}$$

$$\Omega(f_k) = \gamma T_k + ½\lambda ||w_k||^2 \tag{3}$$

In this context, L denotes the loss function that quantifies the discrepancy between predicted and observed values, while f represents the KTH regression tree. T indicates the number of leaf nodes, w refers to the weights assigned to these leaf nodes, and γ and λ are the regularization parameters. This study employs 0.25° GWSA as the supervisory objective and 0.01° multi-source factors as the features. Through the training process, a nonlinear mapping is established between environmental factors and abnormal groundwater reserves. The training samples are categorized into a training set, validation set, and test set based on temporal and spatial considerations. Cross-validation is utilized to optimize parameters such as tree depth, learning rate, sub-sampling ratio, and the number of trees, while an early stopping strategy is implemented to mitigate the risk of model overfitting.

For sample organization, the monthly scale GWSA of each coarse-resolution pixel serves as the supervisory label, while the corresponding 0.01° environmental factors for the same month are compiled into feature vectors. To mitigate the overestimation resulting from spatial autocorrelation, the training, validation, and test samples are categorized based on time periods and spatial units, ensuring complete independence of the samples during the testing phase. The model output undergoes boundary masking, preserving only the valid grids within the administrative boundaries of Henan Province.

3.4. Result Aggregation and Accuracy Evaluation

To ensure compatibility of the downscaling results with GRACE observations at a large scale, the 0.01° prediction results are area-weighted and aggregated to 0.25°, followed by a comparison with the original GWSA. The model's accuracy is assessed using the Pearson correlation coefficient (R), mean absolute error (MAE), and root mean square error (RMSE).

Additionally, the downscaling results were extracted at the monitoring well locations, and a Pearson correlation analysis was performed with the anomalous sequences of groundwater levels at these points. Given the variations in feed water quality and aquifer thickness across different well locations, this study primarily assesses the trends and temporal consistency of the data, rather than converting the water levels at the well points to the equivalent satellite water height in absolute terms.

R indicates the consistency of change direction and phase, while MAE measures the average deviation amplitude. RMSE, on the other hand, is more sensitive to a small number of larger errors. Utilizing these three types of indicators in conjunction can prevent the erroneous conclusion that a model's absolute accuracy is adequate based solely on a relatively high correlation coefficient. Additionally, for spatial results, it is essential to assess whether the predicted field exhibits significant boundary breaks, abnormal patches, or extreme values that surpass reasonable limits.

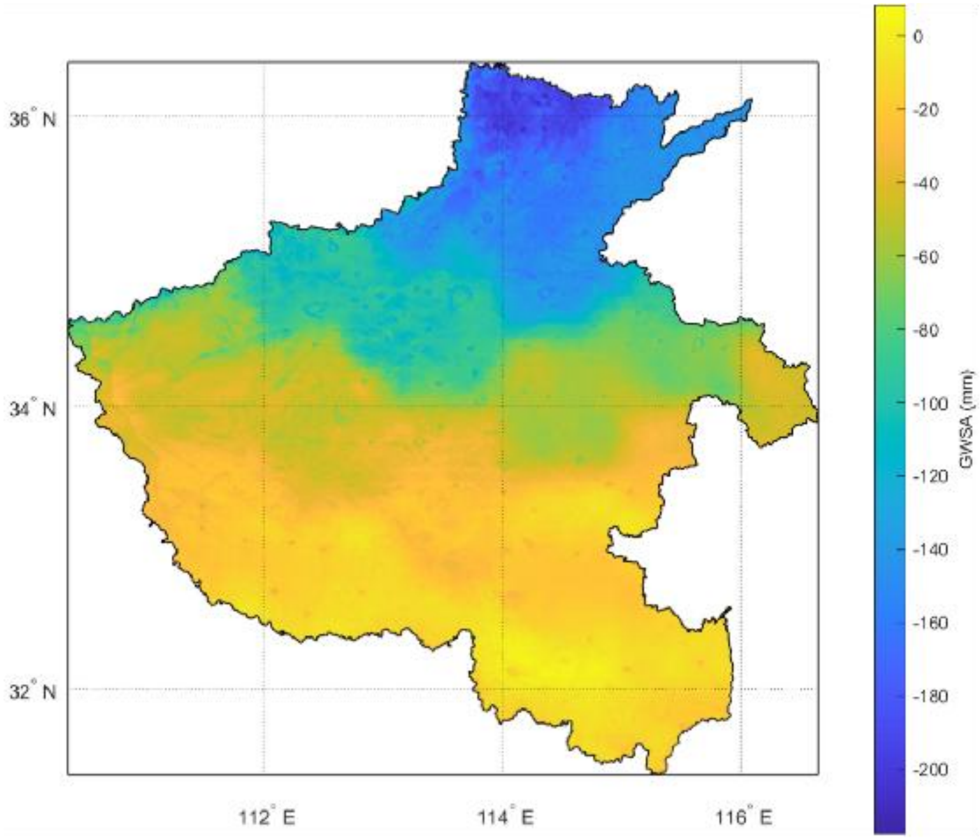

Figure 2 shows the abnormal spatial distribution of groundwater reserves in Henan Province based on XGBoost

4. RESULTS AND ANALYSIS

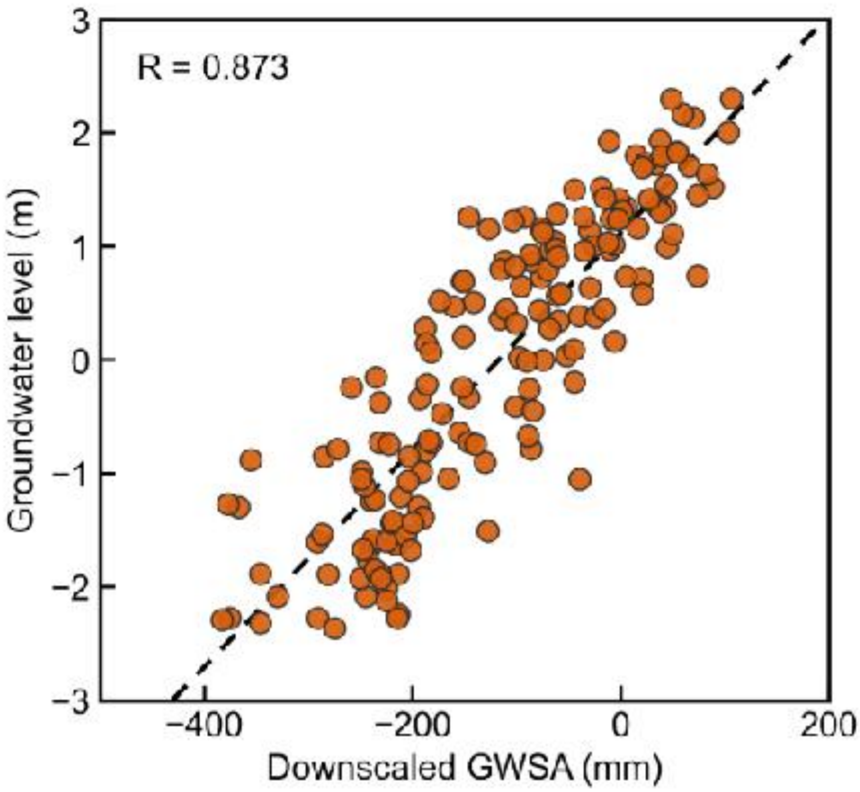

Figure 3 shows the correlation between downscaling GWSA and the groundwater level of monitoring Wells

4.1. Overall consistency of downscaling results

The XGBoost model produced a 0.01° monthly scale Groundwater Storage Anomaly (GWSA) sequence for Henan Province. In comparison to the original 0.25° product, the downscaling results reveal more pronounced regional spatial differences and effectively preserve the seasonal variations and long-term trends evident in the original GRACE observations over time. Upon aggregating the prediction results to a 0.25° scale, the model yielded evaluation metrics of R=0.964, MAE=53.594 mm, and RMSE=69.741 mm during the test period. These results indicate that high-resolution environmental factors provide a superior explanation for the primary changes in coarse-scale groundwater reserve anomalies. It is important to note that the consistency observed in aggregation primarily reflects the model's ability to retain the large-scale signals of GRACE, rather than serving as an independent validation of each 0.01° pixel measurement.

4.2. Spatial Distribution Characteristics of Groundwater Reserves

From the perspective of multi-year averages and spatial trend distribution, significant regional disparities exist in the changes of groundwater reserves in Henan Province. The northern and northeastern plain areas exhibit pronounced negative anomalies or downward trends, while the central region experiences moderate changes. In contrast, the southern and southwestern regions display relatively mild variations. This spatial pattern correlates well with regional precipitation conditions, land use practices, irrigation intensity, and the historical context of groundwater extraction. In the northern plain, where cultivated land is densely concentrated, the demand for irrigation during the crop growing season is high. Consequently, insufficient groundwater replenishment can lead to continuous losses. Conversely, the southern and southwestern regions benefit from relatively abundant precipitation. The undulating terrain and extensive river networks facilitate the exchange between surface water and groundwater, resulting in more stable fluctuations of groundwater reserves.

The downscaling results indicate that average provincial scale values obscure local variations. In some adjacent grids, anomalies manifest in opposing directions within the same month, a discrepancy attributed to local topography, vegetation coverage, and surface temperature. In contrast to directly applying spatial interpolation to the original GRACE grid, the XGBoost results leverage spatial information from environmental factors, thereby addressing the issue of smooth transitions and offering a more refined spatial reference for identifying critical loss areas and facilitating partition management.

Figure 2 illustrates the spatial distribution of XGBoost downscaling for groundwater surface area (GWSA). The northern region predominantly exhibits shades of blue to bluish blue, signifying abnormally low groundwater reserves. The central area transitions to light green, while the southern and southwestern regions are primarily yellow and yellowish green, indicating relatively weak anomalies. This color gradient reflects a regional pattern of diminishing intensity from north to south, aligning with the hydrological context characterized by high long-term irrigation water intake in the northern plain of Henan Province and comparatively favorable precipitation conditions in the south. It is important to note that Figure 2 depicts the spatial state for a specific period or statistic and should not be used in isolation to infer long-term trends. Long-term changes must be assessed in conjunction with monthly sequences and trend estimates.

4.3. Verification of monitoring Wells

The 0.01° downscaling results were compared with the anomalous groundwater levels observed in monitoring wells across Henan Province. The sequence of well points and the model outcomes exhibited generally synchronous seasonal variations and long-term declining trends, with a provincial average correlation coefficient of approximately 0.87. However, the correlation among certain well points was relatively low, potentially due to factors such as the type of aquifer, local pumping activities, variations in recharge rates, and GRACE signal leakage. Given that monitoring wells provide point-based observations while downscaling products reflect the average state of the grid, discrepancies in spatial scale and physical dimensions exist. Consequently, the verification results should be interpreted as evidence of trend consistency rather than a comprehensive assessment of the absolute error associated with individual pixels.

Figure 3 illustrates the relationship between the downscaled Groundwater Surface Altitude (GWSA) and the groundwater levels recorded at the monitoring well. The scattered points are predominantly aligned along the 1:1 reference line, suggesting that the model effectively captures the primary trends in groundwater fluctuations at the well locations. Nevertheless, there remains a notable degree of dispersion among the points, with deviations from the reference line observable in both high and low value intervals. This variability can be attributed, in part, to the differing physical quantities represented by the equivalent water height from the satellite and the water level at the well. Additionally, the well point reflects the specific response of the local aquifer, whereas the 0.01° grid represents an average condition over a broader area. The correlation coefficient of $R=0.873$ depicted in the figure indicates a strong linear consistency between the two data sets; however, this value should not be interpreted as implying uniform accuracy across all well points.

4.4. Sources of Error and Applicability

Model errors primarily arise from three sources: spatial smoothing observed by GRACE and signal leakage; the model dependence of GLDAS on soil water and canopy water simulations; and missing measurements, resampling errors, and inter-variable correlations among high-resolution meteorological and remote sensing variables. The statistical downscaling produces an empirical relationship between environmental factors and coarse-scale GWSA during the study period. This relationship may shift in response to significant changes in land use, pumping intensity, or climatic conditions. Consequently, the results should be utilized as supplementary data for monitoring and zonal management, in conjunction with groundwater levels, water intake and utilization, and hydrogeological surveys.

Furthermore, the feature importance derived from XGBoost can aid in elucidating the model; however, the significance attributed to the tree model does not necessarily imply a direct causal contribution. There exists a physical connection and a statistical correlation among precipitation, evapotranspiration, and surface temperature. The importance of an individual variable is influenced by the presence of other variables and the duration of the sample period. Consequently, this paper employs the model for spatial downscaling without attempting to establish a causal ranking of each driving factor, thereby avoiding the risk of over-interpreting the statistical relationships.

From an application perspective, the 0.01° product is better suited for identifying relative changes and delineating key areas of concern, rather than serving as a direct replacement for single-well observations or groundwater resource volume calculations. In high-intensity water-consuming regions, such as the northern plains, continuous negative anomalies, downward trends, and well point verification results can be integrated to establish a basis for zoned early warning systems. Conversely, in the western and southern regions, where well points are sparse, greater reliance should be placed on precipitation, river, and aquifer investigation data for cross-judgment. Additionally, the model results can serve as a benchmark for subsequent assessments of the effectiveness of groundwater pressure extraction. However, in policy evaluations, it is essential to clearly distinguish the impacts of climate fluctuations from those of anthropogenic water extraction.

5. CONCLUSION

(1)Utilizing GRACE/Grace-FO and GLDAS data, we can construct the abnormal sequence of groundwater reserves on a monthly scale in Henan Province. A crucial step in deriving groundwater storage anomalies (GWSA) involves subtracting soil moisture, snow water equivalent, and canopy water from the total terrestrial water storage.

(2)The XGBoost model, which incorporates precipitation, air temperature, relative humidity, surface temperature, evapotranspiration, NDVI, and elevation as inputs, establishes a nonlinear relationship between the coarse-resolution GWSA and the 0.01° high-resolution environmental factors. The aggregation test indicates that the model effectively preserves the regional variation information present in the original GRACE product.

(3) The downscaling results indicate significant spatial variations in groundwater reserve changes across Henan Province. The loss signal is particularly pronounced in the northern and northeastern plain regions, whereas it remains relatively stable in the southern and southwestern areas. A comparison with the monitoring well sequence demonstrates that the downscaling results accurately capture the primary temporal trend of groundwater fluctuations.

(4)The XGBoost downscaling results are effective for identifying and dynamically monitoring critical groundwater areas in Henan Province; however, their accuracy remains influenced by GRACE signal leakage, GLDAS model errors, the quality of input data, and the spatial representativeness of well points. In practical management applications, it is essential to conduct joint verification of multi-source data.

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