

Groundwater Storage Dynamics and Lagged Responses to Precipitation in the Qinling Mountains (2004–2021)

Jiajun Shan*

School of Tourism and School of Artificial Intelligence, Xi'an Foreign Studies University, Xi'an 710128, Shaanxi, China

*Corresponding Author: Jiajun Shan

ABSTRACT

Addressing the challenges of sparse hydrological stations and limited groundwater monitoring in the complex terrain of the Qinling Mountains, this study integrated multi-source datasets from 2004 to 2021, including GRACE satellite observations and ERA5 meteorological reanalysis. An extreme gradient boosting (XGBoost) machine learning model was developed to estimate groundwater storage (GWS), followed by a systematic investigation of its spatiotemporal evolution and lagged responses to precipitation. The results demonstrate that: ① The XGBoost model achieved high retrieval accuracy on the test dataset ($R^2=0.9549$, $RMSE=15.07$ mm); ② Over the past 18 years, GWS across the Qinling Mountains exhibited a significant declining trend (-33.8 mm/a), with the rate of depletion following the spatial pattern of Central (-3.34 mm/a) > Southern (-2.98 mm/a) > Northern (-2.00 mm/a); ③ The response of GWS to precipitation revealed pronounced spatial heterogeneity and lag effects—the southern region responded rapidly with a 0-month lag, whereas the northern and central regions, buffered by thick soils and human disturbance, exhibited lag times of 8 and 9 months, respectively. These findings elucidate the modulation of groundwater recharge mechanisms by complex mountainous topography and anthropogenic activities.

KEYWORDS

Qinling Mountains; Groundwater Storage (GWS); Multi-Source Remote Sensing; Xgboost; Spatiotemporal Evolution; Precipitation Response

1. INTRODUCTION

As a natural geographic and climatic boundary between northern and southern China, the Qinling Mountains serve not only as a pivotal water conservation zone for both the Yangtze and Yellow River basins, but also as the primary headwater catchment for the Middle Route of the South-to-North Water Diversion Project. They play a strategic role in maintaining national ecological security and regional water balance[1]. However, influenced by intense tectonic deformation and severe erosional dissection, the mountainous terrain of the Qinling region is extremely rugged, resulting in highly heterogeneous groundwater occurrence conditions. Owing to complex topography and financial constraints, the density of in-situ groundwater monitoring wells across this alpine area is sparse, which severely limits spatial representativeness and impedes the accurate understanding of regional groundwater storage dynamics.

The Gravity Recovery and Climate Experiment (GRACE) satellite mission has revolutionized terrestrial hydrology by enabling the continuous quantification of terrestrial water storage anomalies (TWSA) at regional and global scales, effectively overcoming the spatial constraints of conventional ground-based observations[2-3]. Nonetheless, the native spatial resolution of GRACE gravity

products is coarse (typically $\sim 1^\circ \times 1^\circ$ or roughly 100 km), which hinders their direct utility in capturing the micro-topographical and micro-climatic hydrologic heterogeneity inside complex mountain ranges. In recent years, ensemble machine learning algorithms, notably Random Forest (RF) and Extreme Gradient Boosting (XGBoost), have gained widespread prominence in satellite remote sensing. They facilitate effective spatial downscaling and high-precision temporal reconstruction by integrating coarse gravity data with high-resolution meteorology (ERA5), vegetation indices (NDVI), and topography (DEM) [4-5].

To overcome the observational limitations in the Qinling Mountains, this study integrates multi-source datasets spanning 2004 to 2021, including GRACE RL06 mascon data, the GLDAS hydrological model, and ERA5-Land reanalysis. An XGBoost retrieval model was established based on the terrestrial water budget equation to reconstruct high-resolution, long-term groundwater equivalent water thickness (GWSA) series. Subsequently, the Theil-Sen estimator, Mann-Kendall test, and Cross-Correlation Function (CCF) were employed to characterize the spatiotemporal evolution of groundwater storage and reveal its sensitivity and time-lag response to precipitation across the southern, central, and northern sub-regions. This study provides scientific references for water resource vulnerability assessment and ecological redline management in mountainous environments.

2. STUDY AREA AND METHODOLOGY

2.1. Study Area Overview

The Qinling Mountains span east-west across central China, situated primarily within southern Shaanxi Province, extending from Gansu in the west to Henan in the east ($32^\circ 40' - 34^\circ 35' \text{ N}$, $105^\circ 30' - 111^\circ 03' \text{ E}$), covering an area of approximately $6.19 \times 10^4 \text{ km}^2$. The terrain features dramatic relief, with elevations gradually descending from the central ridges toward the northern and southern valleys, reaching a maximum elevation of 3767 m at Mount Taibai.

The mountain range serves as an ecoclimatic transition zone between the northern subtropical monsoon and the warm-temperate continental monsoon zones, exhibiting pronounced north-south differentiation[6-7]. The southern slope is warm and humid, receiving over 800 mm of annual precipitation, characterized by dense forest canopy and frequent storm-runoff processes. Conversely, the northern slope is sheltered by continental air masses, with annual precipitation ranging from 500 to 700 mm, exhibiting a semi-arid climate. The high-altitude central ridge serves as the core water conservation hub. Controlled by lithology and complex structural barriers, groundwater in the basin occurs as fractured bedrock aquifers, clastic porous-fissure aquifers, and valley alluvial pore-water aquifers, characterized by complex recharge-discharge dynamics.

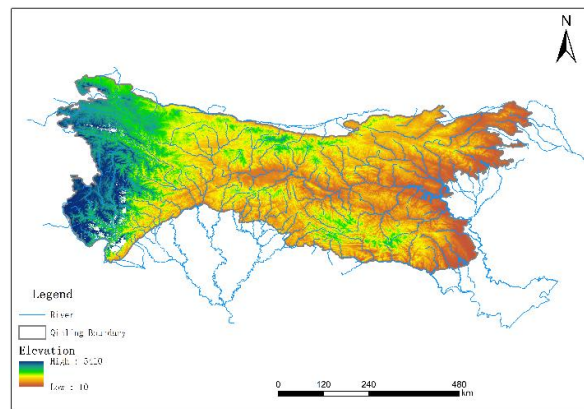


Figure 1. Geographic location, topographical relief, and digital elevation model (DEM) of the Qinling Mountains.

2.2. Data Sources and Preprocessing

Multi-source hydrometeorological and remote sensing datasets covering January 2004 to December 2021 were compiled. All gridded fields were resampled to a standardized spatial resolution of $0.25^\circ \times 0.25^\circ$ with a monthly time step:

GRACE Gravimetry Data: Monthly RL06 Mascon solutions derived from the Center for Space Research (CSR), University of Texas, were utilized to obtain TWSA[8], with the 2004–2009 baseline mean subtracted;

GLDAS Hydrological Model Data: Soil moisture anomalies (SMS, 0–200 cm), snow water equivalent (SWE), and canopy water storage (CWS) were derived from the GLDAS Noah Land Surface Model;

ERA5-Land Reanalysis: Monthly precipitation (TP), 2m surface temperature (TEM), and potential evapotranspiration (PET) were sourced from the European Centre for Medium-Range Weather Forecasts (ECMWF);

Surface Characterization Data: The MODIS Normalized Difference Vegetation Index (NDVI) product (MOD13A2) and the SRTM 90m Digital Elevation Model (DEM) were integrated;

In-situ Well Observations: Continuous water level time series from groundwater monitoring wells provided by the Shaanxi Hydrology and Water Resources Survey Center were collected for independent model validation.

2.3. Groundwater Storage Estimation and Model Construction

2.3.1. Water Balance Principle

According to the principle of terrestrial hydrologic conservation, terrestrial water storage anomalies (Δ_{TWSA}) comprise changes in soil moisture (Δ_{SMS}), snow water equivalent (Δ_{SWE}), canopy water storage (Δ_{CWS}), and groundwater storage anomalies (Δ_{GWSA}). By isolating the surface hydrologic components, groundwater storage variations are computed as:

$$\Delta_{GWSA} = \Delta_{TWSA} - \Delta_{SMS} - \Delta_{SWE} - \Delta_{CWS} \quad (1)$$

2.3.2. XGBoost Retrieval Model

The Extreme Gradient Boosting (XGBoost) algorithm[9] was deployed to model the non-linear relationship between high-resolution surface predictors and groundwater storage. Input features included ERA5 precipitation (with 1–3 month lags), temperature, PET, NDVI, DEM, slope, and soil moisture components. The water-balance derived coarse GWSA served as the learning target. Hyperparameters were tuned via grid search combined with 5-fold cross-validation (learning rate $\eta = 0.05$, maximum depth $max_depth = 6$, L2 regularization $\lambda = 1.0$). The 2004–2021 dataset was partitioned into training (80%) and testing (20%) subsets to reconstruct continuous high-resolution GWSA series across the Qinling region.

2.4. Trend Detection and Lag Analysis Methods

Theil-Sen Estimator and Mann-Kendall Test: The non-parametric Theil-Sen estimator was applied to quantify the decadal rate of change in groundwater storage (Slope, mm/a), while the Mann-Kendall (M-K) test was employed to verify the statistical significance of monotonic trends at a significance level of $\alpha = 0.05$

Cross-Correlation Analysis (CCF): Cross-Correlation Functions were computed to examine dynamic couplings between precipitation variations and GWSA. Correlation coefficients $R(k)$ across delay times of $k = 0, 1, 2, \dots, 12$ months were evaluated. The lag time corresponding to the maximum

absolute correlation coefficient was identified as the optimum response period, characterizing the agility of groundwater recharge across the study area.

3. RESULTS AND ANALYSIS

3.1. Model Retrieval Accuracy and Spatial Consistency

To assess the reliability of the XGBoost-based groundwater storage retrieval model, independent cross-validation was conducted using a 20% testing dataset excluded from training, alongside in-situ groundwater monitoring records. The results demonstrated robust non-linear fitting and generalization capabilities of the XGBoost model, achieving a coefficient of determination (R^2) of 0.9549, a Root Mean Square Error (RMSE) of 15.0651 mm, and a Mean Absolute Error (MAE) of 10.9986 mm on the testing set.

Regarding spatial continuity, the downscaled groundwater storage anomalies (GWSA) exhibited high consistency with the original GRACE water-balance estimates, with absolute residuals across most pixels constrained within ± 5 mm. The reconstructed fields not only preserved the macroscopic terrestrial water gradients captured by GRACE, but also effectively eliminated high-frequency stripe errors and spatial smoothing artifacts, clearly resolving fine-scale hydrological heterogeneity along major river valleys and intermontane basins.

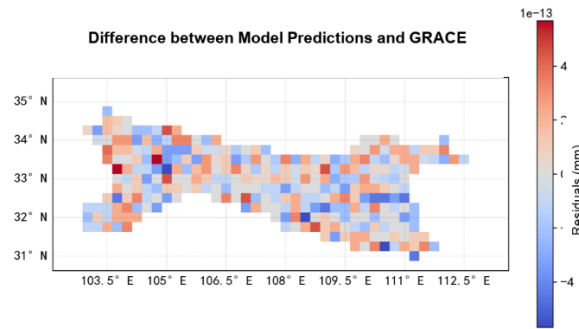


Figure 2. Spatial distribution of residuals between XGBoost model predictions and GRACE-derived estimates.

3.2. Spatiotemporal Evolution Patterns of Groundwater Storage

3.2.1. Temporal Evolution Trend

From 2004 to 2021, regional groundwater storage across the Qinling Mountains exhibited a pronounced fluctuating depletion trend. Based on the Theil-Sen estimator and Mann-Kendall test, the 18-year GWSA series underwent a statistically significant decline ($p < 0.01$) at an average rate of -33.80 mm/a. Regional storage remained in a dynamic equilibrium state between 2004 and 2010; however, depletion accelerated markedly post-2011, with sharp troughs coinciding with severe drought anomalies in 2013 and 2015.

3.2.2. Spatial Differentiation and Sub-regional Trends

Spatially, the equivalent water thickness of groundwater exhibited a distinct "high in the south, low in the north" distribution. Elevated values were concentrated in the upper Hanjiang River basin and densely vegetated southern slopes, while lower values occurred in the transition belt adjacent to the Weihe Valley on the northern slopes.

Zonal trend analysis across northern, central, and southern latitudinal zones (Table 1) revealed distinct sub-regional dynamics:

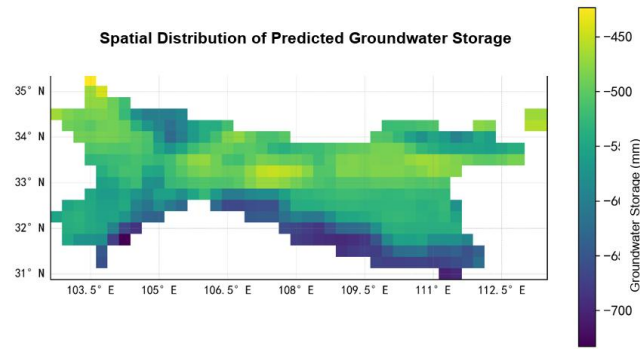


Figure 3. Spatial distribution pattern of mean groundwater storage anomalies (GWSA) across the Qinling Mountains.

Central Sub-region: Exhibited the most severe groundwater depletion, declining at -3.34 mm/a ($Z = -3.85, p < 0.01$), indicating an extremely significant downward trend;

Southern Sub-region: Showed the second fastest depletion rate at -2.98 mm/a ($Z = -3.42, p < 0.01$);

Northern Sub-region: Displayed a comparatively moderate decline rate of -2.00 mm/a ($Z = -2.15, p < 0.05$), suggesting that northern deep groundwater is less sensitive to interannual hydroclimatic fluctuations.

Table 1. Statistical trends of groundwater storage across Qinling sub-regions (2004–2021)

Region	Linear Rate (Slope / $\text{mm} \cdot \text{a}^{-1}$)	M-K Statistic (Z)	Significance Level (p)	Trend Characteristic
Northern Sub-region	-2.00	-2.15	< 0.05	Significant decline
Central Sub-region	-3.34	-3.85	< 0.01	Highly significant decline
Southern Sub-region	-2.98	-3.42	< 0.01	Highly significant decline
Whole Region	-33.80	-4.12	< 0.01	Highly significant decline

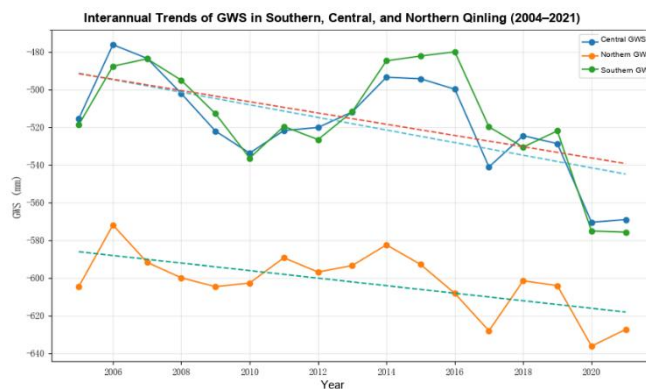


Figure 4. Interannual variation trends of groundwater storage in northern, central, and southern Qinling from 2004 to 2021.

3.3. Climate Response and Precipitation Time-Lag Effects

Correlation analysis revealed a weak negative correlation between monthly regional GWSA and contemporaneous precipitation (TP) ($r = -0.33, p < 0.05$). This apparent inverse relationship primarily reflects the intra-annual phase mismatch between precipitation distribution and

evapotranspiration/runoff processes (summer peak precipitation is accompanied by intense latent heat vaporization and rapid surface runoff discharge).

Cross-Correlation Functions (CCF) were computed across delay times from 0 to 12 months, demonstrating pronounced spatial heterogeneity in precipitation response times (Table 2):

Southern Sub-region: The peak negative correlation occurred at a 0-month lag ($r = -0.537$), indicating instantaneous hydrologic response where rainfall pulses are rapidly evacuated as storm runoff over steep slopes;

Central Sub-region: The optimal lag interval extended to 9 months ($r = -0.280$);

Northern Sub-region: Exhibited an optimal lag period of 8 months ($r = -0.144$).

The extended lag times observed in the northern and central zones quantitatively verify the substantial "low-pass filtering" and buffering capacity exerted by thick unsaturated zones and soil moisture reservoirs during recharge migration[10].

Table 2. Optimal lag intervals and cross-correlations between precipitation and GWS

Evaluated Zone	Optimum Lag/ Months	Cross-Correlation (r)	Response Characteristic
Southern Sub-region	0	-0.537	Instantaneous response
Central Sub-region	9	-0.280	Substantial mid-to-long lag
Northern Sub-region	8	-0.144	Long-period buffered response

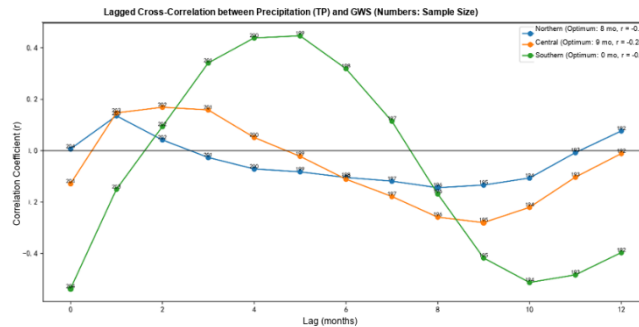


Figure 5. Lagged cross-correlation curves between precipitation (TP) and groundwater storage (GWS) across different sub-regions.

4. DISCUSSION AND DRIVING MECHANISMS

The spatiotemporal evolution of groundwater storage in the Qinling Mountains and its lagged responses to precipitation are jointly governed by climatic regimes, hydrogeological structures, and anthropogenic activities:

Southern "Fast Response–Runoff Depletion" Mechanism: Situated on the windward slope, the southern sector receives heavy rainfall. However, steep topographical gradients and impermeable crystalline/metamorphic bedrock restrict infiltration capacity. Most precipitation is rapidly discharged as surface runoff into the Hanjiang River. High thermal conditions and intense forest evapotranspiration further accelerate moisture losses within the same month (lag = 0), preventing sustained storage renewal and driving a steady decline of -2.98 mm/a

Northern "Deep Buffering–Extended Lag" Mechanism: The northern slope lies in a semi-arid rain-shadow belt mantled by thick loess deposits and piedmont alluvium, with vadose zones reaching dozens of meters in depth. Vertical percolation pathways are exceptionally long; the deep soil profile

acts as a regulatory buffer, resulting in an 8-month delay before rainfall anomalies perturb the water table.

Central "Anthropogenic Stress–Accelerated Depletion" Mechanism: The central corridor hosts concentrated agricultural irrigation, industrial centers, and diversion works. Intensive groundwater abstraction has disrupted natural equilibrium[11], making this zone the most depleted sub-region (-3.34 mm/a). Artificial groundwater withdrawal and surface flow regulation further perturb natural recharge pathways, prolonging the response cycle to 9 months.

In summary, these differentiated hydrogeological mechanisms highlight the necessity of implementing zoning-based water resource management to sustain the Qinling ecological security barrier[12].

5. CONCLUSIONS

By coupling GRACE gravity satellites, the GLDAS model, and ERA5 reanalysis, this study established an XGBoost framework to retrieve monthly groundwater storage anomalies (GWSA) across the Qinling Mountains from 2004 to 2021. The main findings are as follows:

High Model Fidelity: The XGBoost retrieval model showed excellent performance on the independent testing set ($R^2 = 0.9549$, $RMSE = 15.07 \text{ mm}$), effectively realizing continuous, high-resolution groundwater reconstruction in complex mountain terrain.

Persistent Storage Depletion: Over the past 18 years, Qinling groundwater storage has decreased significantly (-33.80 mm/a), exhibiting a "high in the south, low in the north" pattern. The annual depletion rates followed the order: Central (-3.34 mm/a) > Southern (-2.98 mm/a) > Northern (-2.00 mm/a).

Divergent Precipitation Lags: The response of groundwater to precipitation exhibited strong spatial divergence—the southern slopes responded instantaneously with a 0-month lag, whereas the northern and central zones exhibited buffered response times of 8 and 9 months, respectively, reflecting the combined controls of deep vadose zones and anthropogenic extraction.

REFERENCES

- [1] Rodell, M., Famiglietti, J. S., Wiese, D. N., et al. (2018). Emerging trends in global freshwater availability. *Nature*, 557(7707), 651–659.
- [2] Tapley, B. D., Watkins, M. M., Flechtner, F., et al. (2019). Contributions of GRACE to understanding climate change. *Nature Climate Change*, 9(5), 358–369.
- [3] Chen, J., Famiglietti, J. S., Scanlon, B. R., et al. (2016). Groundwater storage changes: present status and future opportunities. *Water Resources Research*, 52(4), 2532–2559.
- [4] Zhao, L., Xu, M., Zhang, Y., et al. (2021). High-resolution reconstruction of watershed groundwater storage based on multi-source remote sensing and machine learning. *Journal of Hydraulic Engineering*, 52(9), 1089–1100. (in Chinese)
- [5] Li, X., Dong, Z. Y., Wang, X. Q., et al. (2020). Downscaling of GRACE terrestrial water storage anomaly based on random forest. *National Remote Sensing Bulletin*, 24(7), 877–889. (in Chinese)
- [6] Zhang, M. L., Liu, C. M., & Sun, R. (2019). Spatiotemporal variation characteristics of precipitation and its influence on vegetation coverage across the north-south regions of the Qinling Mountains. *Acta Geographica Sinica*, 74(5), 875–888. (in Chinese)
- [7] Yao, Y. B., Wang, J. S., Feng, J. Y., et al. (2020). Transitional characteristics of the Qinling Mountains climatic boundary line and its response to climate warming. *Acta Ecologica Sinica*, 40(6), 2085–2097. (in Chinese)
- [8] Chen, T., & Guestrin, C. (2016). XGBoost: A scalable tree boosting system. In *Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining* (pp. 785–794). ACM.

- [9] Hou, J. M., Li, G. D., & Wang, X. J. (2021). Quantitative evaluation of impacts of climate change and human activities on water resources in the upper reaches of Hanjiang River. *Water Resources Protection*, 37(2), 45–52. (in Chinese)
- [10] Scanlon, B. R., Zhang, Z., Save, H., et al. (2016). Global evaluation of new GRACE mascon products for analyzing terrestrial water storage changes. *Water Resources Research*, 52(9), 6999–7012.
- [11] Sun, H., Kang, Y., & Song, S. B. (2022). Groundwater storage variations and lagged responses in the Loess Plateau based on GLDAS and GRACE. *Transactions of the Chinese Society of Agricultural Engineering*, 38(3), 120–128. (in Chinese)
- [12] Wang, X. F., Feng, X. M., Tu, Y., et al. (2021). Trade-offs and synergies among ecosystem services in the Qinling ecological security barrier. *Acta Ecologica Sinica*, 41(23), 9300–9314. (in Chinese)