

Article

Coupled Impacts of Climate Variability and Landscape Transformation on Terrestrial Water Storage in the Yiluo River Basin, China

Yingying Liu ^{1,2}, Xiwang Lian ³, Songliang Chen ^{1,2} and Hongyan Li ^{1,2,*}

¹ Key Laboratory of Groundwater Resources and Environment, Ministry of Education, Jilin University, Changchun 130021, China; liuyy21@mail.jlu.edu.cn (Y.L.)

² Jilin Provincial Key Laboratory of Water Resources and Environment, Jilin University, Changchun 130021, China

³ Jilin Provincial General Station of Water Conservancy and Hydropower Survey and Design Review, Changchun 130021, China

* Correspondence: lihongyan@jlu.edu.cn

Abstract

Terrestrial water storage in semi-arid basins is increasingly affected by the combined pressures of climate variability, land use change and intensive human activities. However, how landscape composition and configuration interact with climatic forcing to shape basin-scale terrestrial water storage anomalies (TWSA) remains insufficiently understood, particularly in rapidly urbanising tributary basins of the Yellow River. This study integrates GRACE/GRACE-FO-derived TWSA, meteorological observations and multi-period land use data to examine the coupled relationships among climate variability, landscape patterns and water storage in the human-dominated Yiluo River Basin. The results show that basin-averaged TWSA experienced a significant long-term decline during the GRACE/GRACE-FO period (-4.47 mm yr^{-1}), with a statistically detectable transition around 2012 and stronger depletion in the northern and eastern parts of the basin. Precipitation exhibited a cumulative and delayed relationship with TWSA, with the strongest raw association occurring under a six-month accumulation and one-month lag (Pearson's $r = 0.44$, $p < 0.001$, $n = 134$). After removing the seasonal cycle, the relationship remained significant but weaker ($r = 0.30$, $p = 0.001$, $n = 129$), indicating that precipitation explains part, but not all, of the interannual variability in water storage. Landscape composition showed stronger associations with TWSA than landscape configuration. Construction land was negatively associated with water storage, whereas cultivated land and grassland showed positive associations, suggesting that impervious surface expansion and the loss of permeable land may weaken the basin's water retention capacity. These findings indicate that water storage change in the Yiluo River Basin is shaped by both climatic forcing and human-induced land surface transformation. Basin management should therefore prioritise the control of urban impervious surface expansion, the protection of permeable agricultural and ecological land, and the integration of land use planning with adaptive water resource regulation.

Keywords: climate variability; GRACE TWSA; hydrological response and lag effects; Yiluo River Basin; ecohydrology

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1. Introduction

Climate variability and intensified human activities are reshaping terrestrial hydrological processes and landscape patterns across many river basins [1,2]. Rising temperatures, altered precipitation regimes and more frequent hydroclimatic extremes affect evapotranspiration, soil moisture, groundwater recharge and surface water availability, while urban expansion, agricultural adjustment and infrastructure development modify infiltration, runoff generation and ecological connectivity [3,4]. These changes are particularly important in semi-arid and transitional climatic regions, where limited water availability makes ecosystems and human water use highly sensitive to both climatic fluctuations and land surface transformation [5–8]. Understanding how climate variability and landscape evolution jointly influence basin-scale water storage is therefore essential for water resource security, ecological restoration and land use regulation [9,10].

As an essential ecological shield and economic zone of China, the Yellow River Basin is highly sensitive to climatic fluctuations and human disturbance [11,12]. The 18,881 km² Yiluo River Basin is a semi-arid tributary with pronounced relief, limited water availability and dense settlement [13]. Between 1985 and 2020, construction land expanded from 488.25 to 1365.12 km² (+179.6%), while cultivated land decreased by 12.1% and grassland by 51.4%. The basin is characterised by pronounced topographic relief, scarce water resources, and dense population, which make its responses to climate change and human activities particularly complex and prominent. Previous studies and the multi-period land use data used in this study indicate substantial landscape transformation in the Yiluo River Basin, characterised particularly by forest and construction land expansion and reductions in cultivated land and grassland [11,12]. These changes have resulted in declining ecosystem service functions and increasing landscape fragmentation [13,14].

Traditional studies on the driving mechanisms of landscape patterns have primarily relied on meteorological indicators such as precipitation and temperature. While these indicators effectively reveal the direct climatic influences on ecosystems, they fall short of characterising the integrated state of the hydrological system [15,16]. In arid and semi-arid regions, high precipitation variability coupled with intensive groundwater extraction often renders changes in terrestrial water storage a more immediate constraint on landscape pattern evolution than individual climatic factors [17–19].

The Gravity Recovery and Climate Experiment (GRACE) and its successor, GRACE Follow-On (GRACE-FO), provide global estimates of Terrestrial Water Storage Anomaly (TWSA) [20–22]. This dataset comprehensively integrates variations in key hydrological components—such as precipitation, evapotranspiration, surface water, and groundwater [23–25]. It has been extensively applied to monitor groundwater depletion, glacial melt, drought assessment, and water cycle studies [22]. Compared to conventional meteorological data, GRACE TWSA offers a more holistic characterisation of regional hydrological conditions, directly manifesting the combined effects of climate and human activities [26]. Therefore, integrating GRACE TWSA into landscape ecology research helps transcend the limitations of previous studies that relied solely on singular meteorological factors like precipitation and temperature [27].

Recent years have witnessed a growing body of research leveraging GRACE data to disentangle the driving mechanisms of climate change and human activities on water storage, yielding significant findings [22,28]. Some researchers have combined GRACE data with GLDAS simulations to partition the contributions of climate forcing and anthropogenic water use to groundwater changes, whereas others have utilised GRACE to monitor drought processes and elucidate their impacts on vegetation dynamics [29,30]. Most of these efforts, however, remain focused on water resource attribution and drought assessment, with scant attention paid to the relationship between terrestrial water storage anomalies and the evolution of landscape patterns. In typical river basins, fluctuations in water

storage not only constrain vegetation restoration and land use transformation but also indirectly regulate regional ecological functioning by altering landscape connectivity and diversity [31–34].

Against this backdrop, we hypothesised that (H1) basin-scale TWSA responds to precipitation cumulatively and with a hydrologically plausible delay, and (H2) landscape composition has stronger basin-scale associations with TWSA than landscape configuration because GRACE integrates storage over a footprint much larger than individual patches. We therefore aimed to: (1) characterise the long-term trend, regime shift and spatial heterogeneity of GRACE/GRACE-FO-derived TWSA; (2) quantify the cumulative and lagged association between precipitation and TWSA; (3) separate the associations of landscape composition and configuration with TWSA; and (4) derive implications for land use regulation and adaptive water resource management. This framework links climatic forcing, land surface transformation and integrated water storage while retaining explicit scale and attribution limits.

2. Materials and Methods

2.1. Study Area

The Yiluo River, a primary tributary of the Yellow River, flows through Shaanxi and Henan Provinces. It originates in Bayuan Township, Lantian County of Shaanxi, and converges into the Yellow River at Shenbei Village, Gongyi City in Henan (Figure 1). The basin (33°33′–35°05′ N, 109°35′–113°06′ E) encompasses a total area of 18,881 km². Its river system is primarily composed of the main stem, the Luo River (446.9 km in length), and a major tributary, the Yi River (264.8 km in length) [12].

Located in a transitional zone between the subtropical and warm temperate climates, the basin experiences a typical continental monsoon pattern, characterised by cold, dry winters and hot, rainy summers with pronounced precipitation seasonality. The mean annual precipitation ranges from 710 to 930 mm, and the mean annual air temperature varies between 7.8 and 13.9 °C. Recorded temperature extremes range from 37.0–40.8 °C in summer to −21.6–−11.8 °C in winter. The mean annual runoff is approximately 3.422 billion m³. Intensive summer rainfall frequently leads to rapid increases in river discharge, elevating flood risks in the lower reaches.

The topography is predominantly mountainous and hilly, with plains mainly distributed along the lower reaches of the Luo and Yi Rivers. Brown earths (cinnamon soils) constitute the dominant soil type, while Shajiang black soils are sporadically found in low-lying areas. The northern part of the basin borders the Loess Plateau, where loose soil structures and low vegetation coverage result in severe soil erosion during the flood season, further exacerbating ecological vulnerability [35].

Cropland is the predominant land use type, followed by forestland, with scattered distributions of grassland and constructed areas. Intensive agricultural activities and significant urban expansion have made the regional hydrological processes and landscape patterns particularly sensitive to climate change and human disturbances.

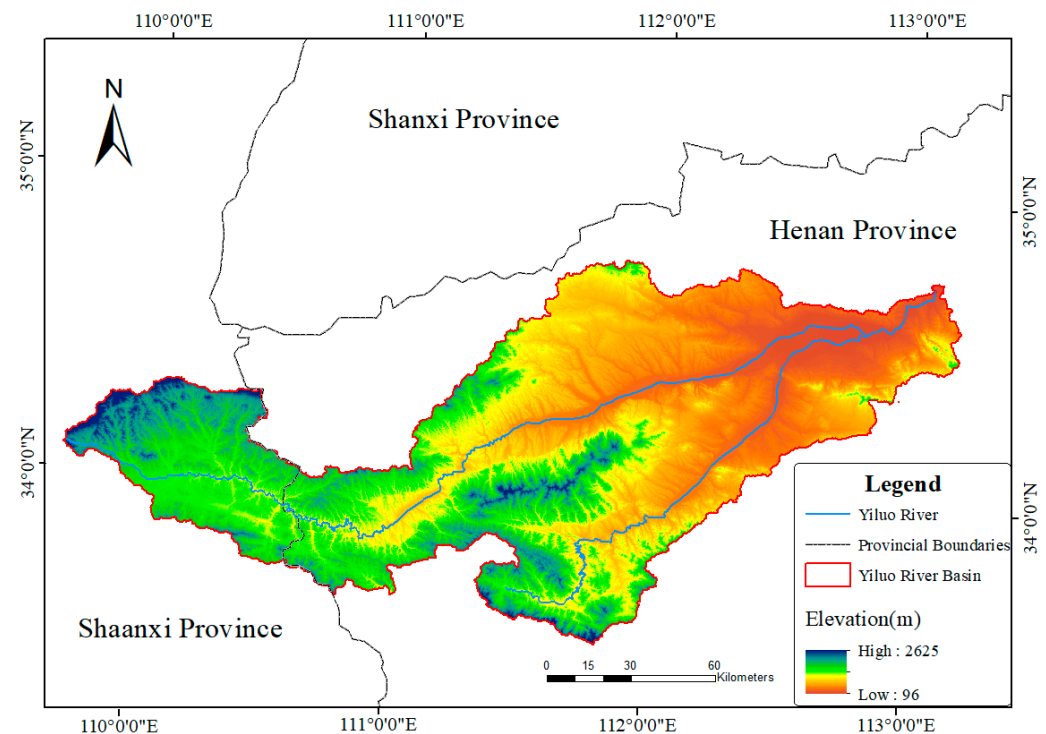


Figure 1. Yiluo River Basin Map.

2.2. Data Sources

This study used four main categories of data: meteorological data, GRACE/GRACE-FO terrestrial water storage anomaly (TWSA) products, land-use/land-cover (LUCC) data, and auxiliary spatial data including the basin boundary and digital elevation model (DEM). All spatial datasets were projected to a consistent coordinate system and clipped to the boundary of the Yiluo River Basin before analysis. Temporal aggregation was conducted at monthly or annual scales depending on the analytical objective.

Monthly precipitation totals and monthly mean air temperature were used as the meteorological variables. For the lag analysis, monthly precipitation was aggregated over candidate accumulation windows and aligned with the monthly GRACE/GRACE-FO series after applying the specified lag. For the climate–landscape analysis, annual precipitation totals and annual mean temperatures were matched to the eight LUCC observation years (1985–2020). Basin means were calculated consistently for all time steps before statistical analysis.

TWSA data were sourced from the latest GRACE/GRACE-FO Mascon product (Release 06.3 Version 04, RL06.3Mv04) released by the Jet Propulsion Laboratory (JPL), NASA [36]. This dataset employs Coastline Resolution Improvement (CRI) filtering to effectively reduce leakage errors near land–ocean boundaries, making it highly suitable for terrestrial hydrological studies. The product provides monthly data at a spatial resolution of $0.5^\circ \times 0.5^\circ$, representing equivalent water thickness anomalies relative to a long-term baseline. The study period spans both the GRACE mission (2002–2017) and the GRACE-FO mission (2018–2025), a monthly series based on all available observations.

For the Yiluo River Basin, the JPL Mascon grids were clipped using the basin boundary, and basin-averaged TWSA was calculated using an area-weighted method. The weight assigned to each grid cell accounted for the proportion of the cell overlapping the basin and the variation in grid cell area with latitude through a $\cos(\varphi)$ correction. This approach ensured that each valid grid cell contributed to the basin mean according to its effective surface area. The resulting monthly TWSA series was aligned to a month-start

timestamp. Duplicate records and invalid values were removed before subsequent analysis.

Seasonal components were removed to distinguish interannual variability from the regular annual cycle. For each calendar month, the long-term monthly climatological mean was calculated from all valid observations and subtracted from the corresponding monthly TWSA values. Both raw and deseasonalised TWSA series were retained: the raw series was used to examine total storage variability, while the deseasonalised series was used to test whether precipitation–TWSA relationships remained significant after removing shared seasonality. Missing GRACE/GRACE-FO months were not gap-filled in the main analysis. Isolated missing months were treated as unavailable observations and excluded from correlation, trend and regression calculations. Periods with insufficient valid samples were excluded from seasonal trend assessment. The monthly availability of valid GRACE/GRACE-FO observations is provided in Table 1.

Several limitations of GRACE/GRACE-FO data were considered in the interpretation. Although the JPL Mascon product is provided on a 0.5° grid, its effective spatial resolution is substantially coarser because of the nature of satellite gravimetry and the regularisation used in mass concentration solutions. Spatial leakage and signal attenuation can be reduced but not fully eliminated by CRI filtering. These limitations are particularly relevant for relatively small basins such as the Yiluo River Basin. Therefore, pixel-scale GRACE results were interpreted as broad regional patterns, while the basin-averaged TWSA series was treated as the primary basis for temporal analysis. The results should be understood as integrated storage signals rather than direct measurements of groundwater or surface-water changes.

Table 1. Monthly Availability of Valid GRACE/GRACE-FO Observations.

Month	Jan.	Feb.	Mar.	Apr.	May	Jun.	Jul.	Aug.	Sept.	Oct.	Nov.	Dec.
Sample counts	21	20	21	22	21	20	20	20	19	19	21	20
Coverage rate (%)	91.3	87.0	91.3	91.6	87.5	83.3	87.0	87.0	82.6	82.6	91.3	87.0

LUCC data were obtained from Wuhan University for eight time points: 1985, 1990, 1995, 2000, 2005, 2010, 2015 and 2020. The dataset has a spatial resolution of 30 m. Following the land use classification system of the Chinese Academy of Sciences, the original categories were reclassified into six major types: forest, grassland, cultivated land, water bodies, construction land and unutilised land. The reported overall classification accuracy is approximately 79%, which is acceptable for basin-scale landscape analysis but introduces uncertainty into land use area estimation and landscape metric calculation. Several limitations of GRACE/GRACE-FO data were explicitly considered. Although the JPL Mascon product is distributed on a 0.5° grid, this sampling interval is not its independent resolving power: satellite gravimetry and mascon regularisation yield a substantially coarser effective spatial resolution.

All LUCC datasets were checked for spatial consistency, clipped to the Yiluo River Basin boundary and converted to a unified classification scheme before area calculation. The area of each land use type was calculated for each available year. Landscape metrics were then derived from the classified LUCC maps using Fragstats 4.2. The analysis included both compositional indicators, represented by the area of each land use type, and configurational indicators, including number of patches, patch density, mean patch area, mean fractal dimension index and Shannon’s diversity index. Because LUCC data were available only for eight discrete years, the statistical associations between landscape

variables and TWSA were interpreted cautiously as indicative relationships rather than deterministic causal effects.

All spatial analyses were conducted in ArcGIS 10.8, while time series processing, statistical analysis and visualisation were performed using MATLAB 2024b and Python 3.12. To reduce temporal inconsistency among datasets, monthly climate and TWSA records were aggregated or matched to the corresponding annual LUCC years when analysing climate–landscape and landscape–TWSA relationships.

2.3. M-K Test

The M-K test is a convenient non-parametric test used in this study for identifying hydrological variable change points. The M-K test can handle non-normal distribution data and is not affected by outliers, making it widely used in hydrology, meteorology, and other fields. The M-K equation is shown below:

$$S = \sum_{i=1}^{n-1} \sum_{j=i+1}^n \text{sgn}(X_j - X_i) \quad (1)$$

$$\text{sgn}(\theta) = \begin{cases} 0 & \theta \leq 0 \\ 1 & \theta > 0 \end{cases} \quad (2)$$

where X_i and X_j represent the data values, and n represents the length of the time series.

The formulas for calculating the variance and mean of the sequence are shown below:

$$\text{Var}(S) = n \times (n-1) \times \frac{(2n+5)}{72} \quad (3)$$

$$E(S) = n \times \frac{n-1}{4} \quad (4)$$

Normalise S to:

$$U_n = \frac{S - E(S)}{\sqrt{\text{Var}(S)}} \quad (5)$$

If $U_n > 0$, the sequence has an upward trend, and vice versa, if it has a downward trend. With a given significance level α , if $|U_n| > U_\alpha$, the change in the trend of the sequence is significant.

2.4. Calculation of Landscape Indices

Landscape patterns represent both the outcome of interacting disturbances and a factor influencing regional ecological processes. The analysis of these patterns serves as an effective approach to reveal the state and spatial heterogeneity of a regional ecosystem. Building on previous research, this study adopted the following landscape-level metrics: mean patch area (AREA_MN), mean fractal dimension index (FRAC_MN), number of patches (NP), patch density (PD), and Shannon's diversity index (SHDI). These landscape indices were computed for the entire study area as well as within individual sampling grids using Fragstats 4.2. The mathematical expressions for each metric are provided below (Table 2).

Table 2. Landscape indices and their mathematical expression.

landscape Indices	Mathematical Expression
NP	$NP = N$
	N is the total number of patches
PD	$PD = N/A$
	A is the total area of patches
SHDI	$SHDI = - \sum_{i=1}^m (P_i \times \ln P_i)$
	P_i is proportion of the landscape occupied by patch type i , m is the number of patch types in the present landscape

AREA_MN

FRAC_MN

$$\text{AREA_MN} = A/N$$

$$\sum_{i=j}^m \sum_{j=1}^n 2\ln(0.25P_{ij})/\ln(A_{ij})$$

P_{ij} is the perimeter of patch ij ; A_{ij} is area of patch ij and $1 \leq \text{FRAC_MN} \leq 2$

2.5. EOF Analysis of TWSA Fields

To characterise the dominant modes of spatio-temporal variability in terrestrial water storage, an empirical orthogonal function (EOF) analysis was applied to the GRACE/GRACE-FO TWSA fields over the Yiluo River Basin. Monthly TWSA anomalies at the native $0.5^\circ \times 0.5^\circ$ resolution were first deseasonalised as described in Section 2.1, so that the EOFs primarily represent interannual variability rather than the repeating seasonal cycle. Only grid cells located within the basin and with sufficient valid observations over 2002–2023 were retained for the analysis.

Let $X(x_i, t_j)$ denote the deseasonalised TWSA anomaly at grid cell i and time step j . The anomalies were arranged into a two-dimensional matrix X of size $T \times M$, where T is the number of time steps and M is the number of grid cells. For each grid cell, the temporal mean was removed so that the EOFs describe deviations from the long-term mean state. A covariance-based EOF decomposition was then performed using singular value decomposition. The anomaly field can be expressed as:

$$X(x_i, t_j) = \sum_{k=1}^K PC_k(t_j) EOF_k(x_i) \quad (6)$$

where $EOF_k(x_i)$ are the spatial loading patterns (EOFs) and $PC_k(t_j)$ are the corresponding principal component time series. The EOFs are orthonormal in space, and the PCs are mutually uncorrelated in time. The associated eigenvalues provide the fraction of total variance explained by each mode, which was used to order the EOFs. In this study, interpretation focuses on the first three modes, which together explain most of the variance in the TWSA anomaly field (see Section 3.2).

2.6. Data Analysis and Robustness Assessment

This study adopted a multi-step analytical framework to examine the coupled relationships among climate variability, landscape patterns and terrestrial water storage changes. First, the temporal and spatial characteristics of GRACE/GRACE-FO-derived TWSA were analysed using trend detection, change-point analysis and EOF decomposition. Second, the cumulative and lagged responses of TWSA to precipitation and temperature were examined at monthly to seasonal time scales. Third, landscape variables were separated into compositional indicators, represented by the area of major land use types, and configurational indicators, represented by patch-based landscape metrics. This distinction allowed the analysis to evaluate whether basin-scale water storage was more closely associated with land cover proportions or with the spatial arrangement of landscape patches.

The robustness of the main statistical relationships was assessed through consistency checks across complementary methods and variable treatments. For TWSA trends, Theil–Sen slope estimation, Mann–Kendall testing and Pettitt change-point detection were jointly used to reduce reliance on a single trend indicator. In the spatial analysis, false discovery rate correction was applied to limit the overinterpretation of multiple pixel-wise significance tests. For the precipitation–TWSA relationship, both raw and deseasonalised TWSA series were analysed to determine whether the relationship persisted after removing the common seasonal cycle. Pearson and Spearman correlations were also compared to examine whether the identified relationships were consistent under both linear and rank-based measures.

The accumulation and lag windows were not assumed in advance. The optimum was also assessed against neighbouring combinations rather than as an isolated maximum: elevated raw correlations formed a broad response zone around 6–8 months of accumulation and 0–2 months of lag. The selected 6-month/1-month combination therefore represents the centre of a hydrologically coherent response region, while the 12-month/0-month maximum after deseasonalisation indicates longer interannual precipitation memory.

All hypothesis tests were two-sided and used a nominal significance level of $\alpha = 0.05$. For pixel-wise and within-month multiple testing, statistical significance was assessed after false discovery rate correction at $q < 0.05$. Exact p values and effective sample sizes are reported with the principal correlation results. Correlation and regression analyses indicate association rather than deterministic causality; interpretation therefore combined statistical evidence with hydrological reasoning and explicitly considered GRACE resolution and leakage, LUCC classification uncertainty, meteorological data uncertainty and the absence of direct records of groundwater abstraction, irrigation and reservoir regulation.

3. Results

3.1. TWSA Analysis

The basin-averaged GRACE/GRACE-FO TWSA series from April 2002 to June 2025 shows an overall declining tendency in the Yiluo River Basin (Figure 2). The Mann–Kendall test indicates a significant monotonic decrease, and the Theil–Sen slope is estimated at approximately -4.47 mm yr^{-1} . The Pettitt change-point test identifies a statistically detectable shift around late 2012, with the raw TWSA series indicating a breakpoint in November 2012 and the deseasonalised series indicating a similar transition in September 2012. Although this transition is not visually abrupt in all months in Figure 2, the statistical tests and segmented trend analysis suggest that the basin entered a lower-storage stage after 2012. The mean TWSA decreased from approximately $+2.1 \text{ cm}$ before the breakpoint to -1.8 cm after the breakpoint, while the fitted declining trend became steeper in the post-break period. The estimated post-break slope was approximately -5.2 mm yr^{-1} , compared with -3.1 mm yr^{-1} before the breakpoint. These results indicate a persistent reduction in basin-scale terrestrial water storage, with the 2012 transition representing a statistically supported shift rather than a visually abrupt discontinuity.

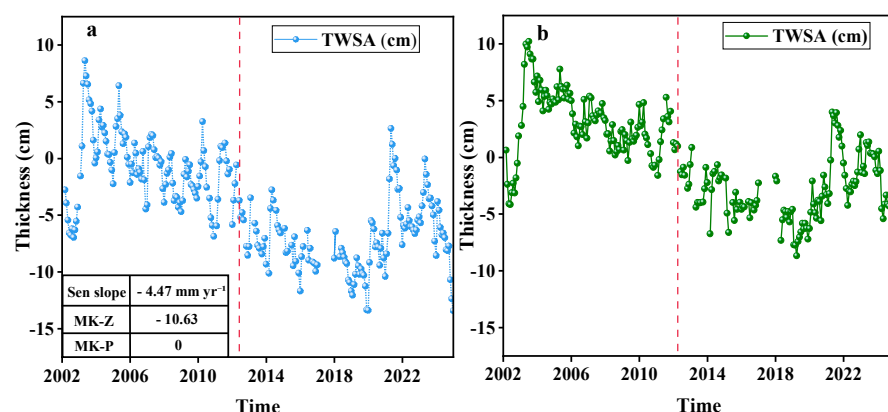


Figure 2. Basin-averaged GRACE/GRACE-FO TWSA series. (a) raw TWSA series; (b) deseasoned TWSA series.

Seasonal decomposition further reveals that the long-term decline was not uniform across months. The within-month Sen slopes (Figure 3) show negative trends for most calendar months, but the magnitude of decline was stronger during the dry season

months, with several months exceeding -6 mm yr^{-1} . After controlling for multiple testing using the false discovery rate correction ($q < 0.05$), these dry season declines remained statistically significant. By contrast, some wet season months, particularly September and October, showed weaker or non-significant trends. This seasonal asymmetry suggests that the long-term reduction in TWSA was more strongly expressed during months with limited precipitation recharge and higher dependence on stored water. The pattern may be related to the combined effects of seasonal water demand, evapotranspiration and delayed recharge, although the GRACE-derived TWSA signal alone cannot separate the individual contributions of groundwater, soil moisture and surface water storage.

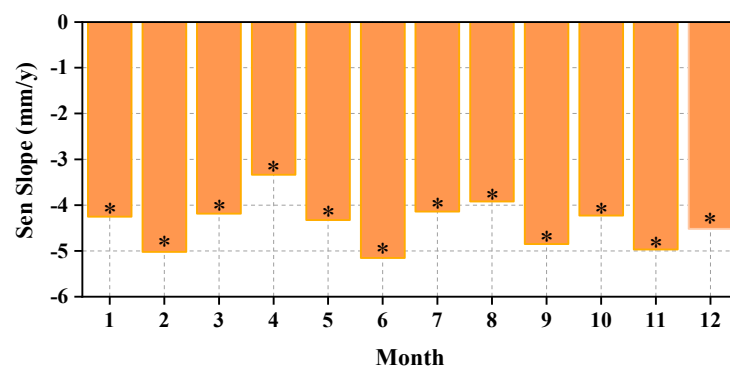


Figure 3. TWSA Within-month trends with FDR significance (* $q < 0.05$).

3.2. Spatio-Temporal Patterns of TWSA

Having characterised the basin-averaged temporal dynamics of TWSA, the analysis was extended to the spatial domain to examine whether the storage decline was spatially uniform or concentrated in specific parts of the basin. Pixel-wise trend estimation and change-point detection were applied to the GRACE/GRACE-FO TWSA fields for 2002–2023, and the results were interpreted as broad regional patterns because of the coarse effective spatial resolution of GRACE observations.

Figure 4a shows the spatial distribution of Theil–Sen slopes of TWSA over the Yiluo River Basin, with FDR-corrected significant pixels marked. The results indicate that most parts of the basin experienced negative TWSA trends during the study period, confirming that the basin-scale decline identified in Section 3.1 was also reflected in the spatial fields. The strongest negative trends were mainly located in the middle, eastern and northern parts of the basin, with local slopes approaching approximately -20 mm yr^{-1} . In contrast, weaker negative trends or locally positive values occurred in parts of the southwestern basin. This spatial contrast suggests that terrestrial water storage depletion was not evenly distributed, but showed clear sub-regional heterogeneity.

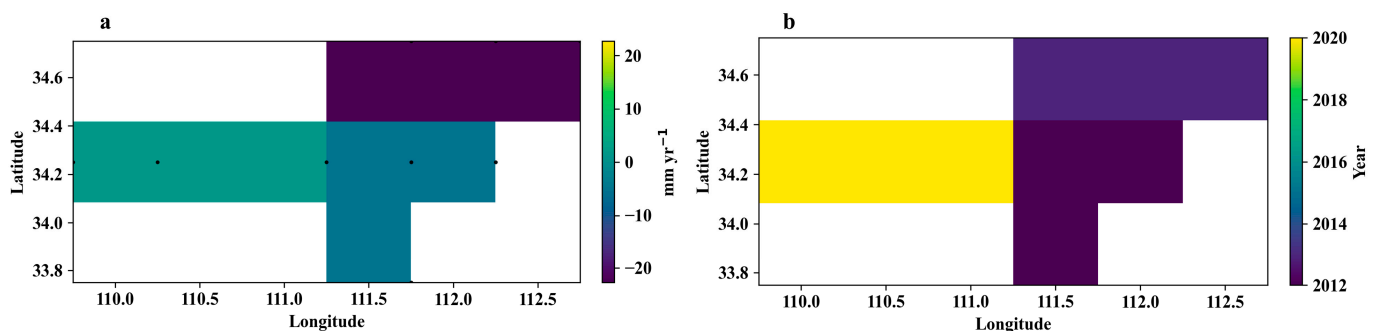


Figure 4. Basin-scale GRACE/GRACE-FO TWSA trends. (a) Theil–Sen slope (mm yr^{-1}) with FDR ($q < 0.05$) significance indicated by black dots. (b) Pettitt break year per pixel.

The pixel-wise Pettitt test identified change points concentrated mainly around 2012 and 2020 (Figure 4b). Change points around 2012 were more evident in the middle and eastern parts of the basin and were broadly consistent with the change point identified from the basin-averaged series in Section 3.1. Change points around 2020 were more spatially fragmented.

The EOF decomposition further supports the interpretation of a dominant basin-wide TWSA signal with secondary spatial heterogeneity (Figure 5). EOF1 explains 83.0% of the total variance and shows a spatially coherent loading pattern across most of the basin. Its corresponding principal component displays a long-term declining tendency with interannual fluctuations, indicating that the leading mode mainly represents basin-wide water storage loss. EOF2 and EOF3 explain 14.8% and 2.2% of the variance, respectively, and capture weaker sub-regional differences. These secondary modes suggest that localised deviations from the basin-wide trend exist, but they are much less important than the dominant coherent decline represented by EOF1.

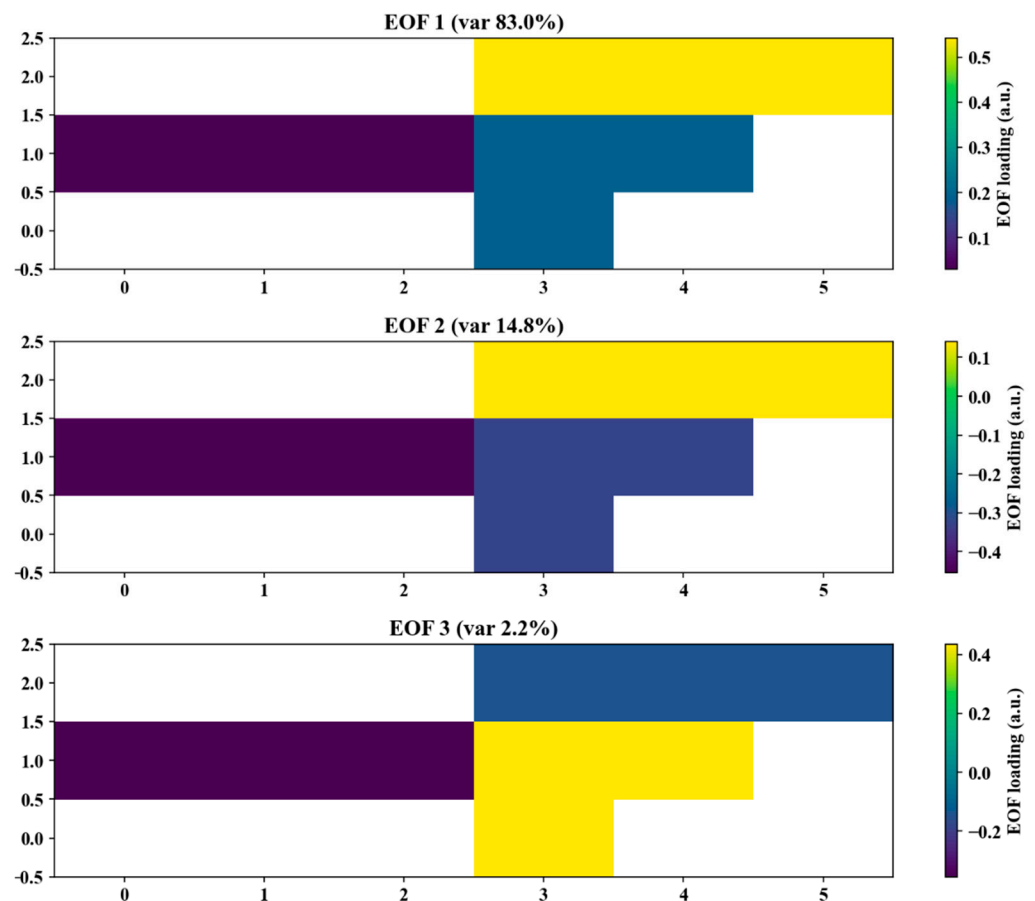


Figure 5. Spatial patterns and principal components from EOF analysis.

The Hovmöller diagrams provide an additional view of the spatio-temporal evolution of TWSA anomalies along latitude and longitude (Figure 6). Both cross-sections show a transition from predominantly positive anomalies in the early 2000s to more persistent negative anomalies after approximately 2012. The negative anomalies were more pronounced in the northern and eastern sectors, consistent with the pixel-wise trend results. Together, the spatial trend, change-point, EOF and Hovmöller analyses indicate that the

decline in TWSA was a basin-wide phenomenon, but its magnitude and timing varied among sub-regions. This spatial heterogeneity provides important context for interpreting the subsequent climate and landscape analyses.

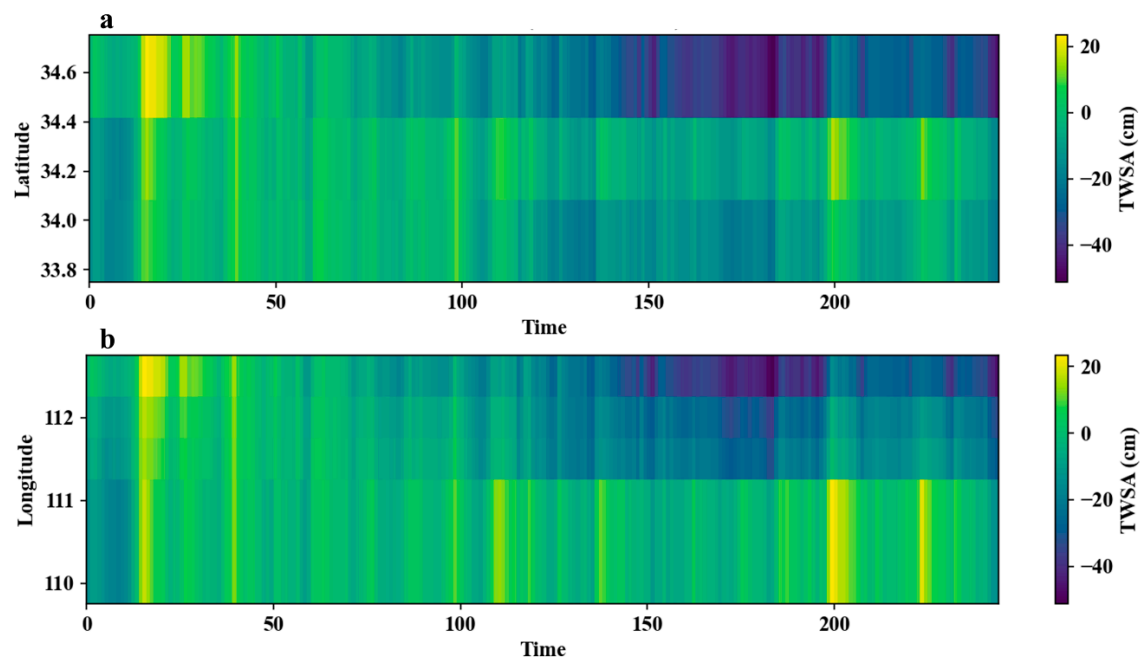


Figure 6. Hovmöller diagrams of GRACE/GRACE-FO TWSA anomalies (cm) averaged by (a) latitude and (b) longitude across the Yiluo River Basin.

3.3. Lagged Response of TWSA to Precipitation

The relationship between precipitation and TWSA was examined for the overlapping period from April 2004 to December 2017. Rather than assuming a fixed response time, multiple precipitation accumulation windows and lag periods were compared to identify the time scale at which precipitation showed the strongest association with basin-scale water storage. The correlation heatmap based on the raw TWSA series (Figure 7) shows that short accumulation windows of 1–3 months generally produced weak correlations, indicating that monthly or short-term rainfall variations were not sufficient to explain basin-scale TWSA variability. Correlations increased when longer accumulation windows were used, particularly for 6–8 months, suggesting that TWSA responds to the integrated effect of precipitation over seasonal time scales.

The strongest raw relationship was obtained under a six-month precipitation accumulation and a one-month lag, with Pearson's $r = 0.44$ ($p < 0.001$, $n = 134$) and Spearman's $\rho = 0.44$. The consistency between Pearson and Spearman correlations indicates that the relationship was not only linear but also stable under a rank-based measure. This result suggests that precipitation affects TWSA through a delayed and cumulative process, rather than through an immediate same-month response.

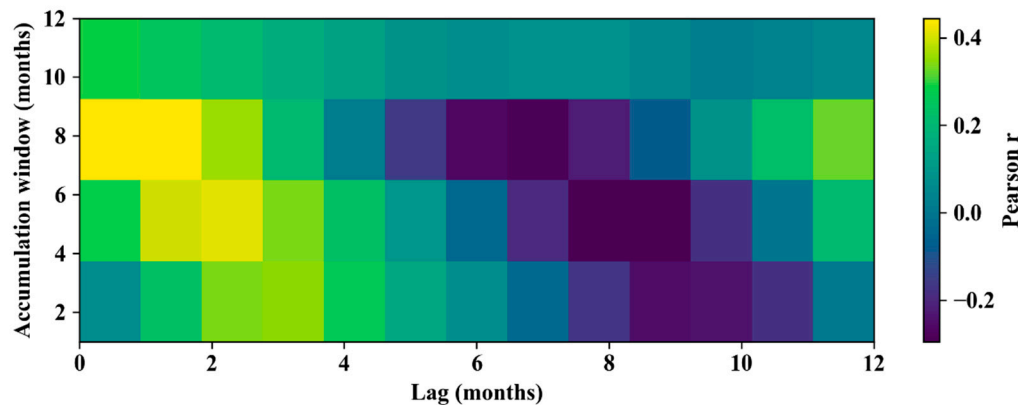


Figure 7. TWSA vs. precipitation: correlation heatmap (raw TWSA).

The scatter plot for the best raw correlation (Figure 8) illustrates a clear upward trend, showing that higher accumulated precipitation generally corresponds to larger TWSA. However, the dispersion of data points also highlights the role of additional processes such as groundwater abstraction, which can modulate the storage response. The time series comparison between TWSA and 3-month accumulated precipitation (Figure 9) further supports this finding, with both series exhibiting synchronous fluctuations at interannual scales. Pronounced declines, such as in 2009–2010, coincide with regional drought conditions, while the recovery in 2012 matches a period of above-average rainfall.

To test whether the observed relationship was mainly controlled by the common seasonal cycle, the precipitation–TWSA correlation analysis was repeated using the deseasonalised TWSA series. After removing the seasonal component, the maximum correlation decreased compared with the raw series. The strongest deseasonalised relationship was found under a 12-month accumulation window with no lag, with Pearson’s $r = 0.30$ ($p = 0.001$, $n = 129$) and Spearman’s $\rho = 0.27$ ($p = 0.002$) (Figure 10). Although weaker than the raw correlation, the relationship remained statistically significant, indicating that precipitation still contributed to interannual TWSA variability after the seasonal cycle was removed. The shift from a six-month window in the raw series to a 12-month window in the deseasonalised series further suggests that seasonal storage variations are partly controlled by medium-term precipitation accumulation, whereas interannual storage anomalies are more closely associated with longer-term precipitation memory.

The precipitation–TWSA analysis indicates that water storage in the Yiluo River Basin responds to precipitation through both cumulative and delayed processes. The strongest relationship in the raw series reflects the seasonal integration of precipitation inputs, while the weaker but significant deseasonalised relationship shows that precipitation continues to influence TWSA at interannual time scales. However, the moderate correlation coefficients also indicate that precipitation is only one component of TWSA variability. Human water use, land surface change and storage regulation are likely to contribute to the remaining unexplained variability, which is further examined through the landscape analysis in the following section.

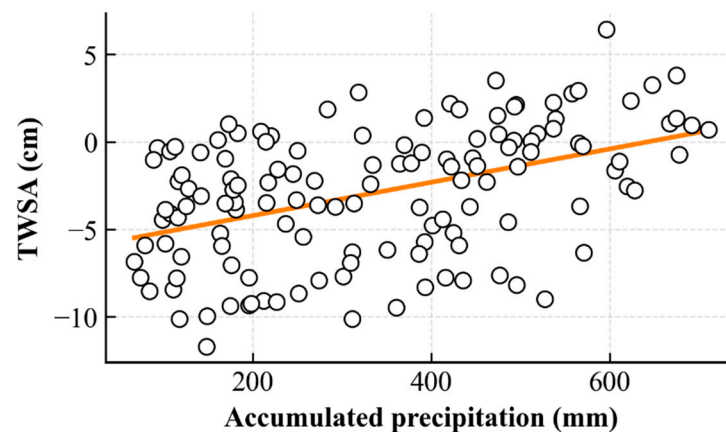


Figure 8. Relationship between TWSA and the best-performing accumulated precipitation predictor ($r = 0.44$, $p < 0.001$, $n = 134$; 6-month accumulation, 1-month lag).

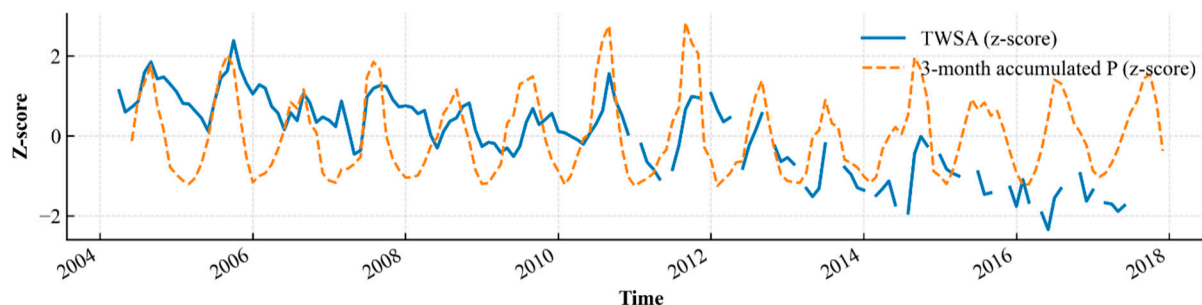


Figure 9. Standardised TWSA and 3-month accumulated precipitation during the overlapping observation period.

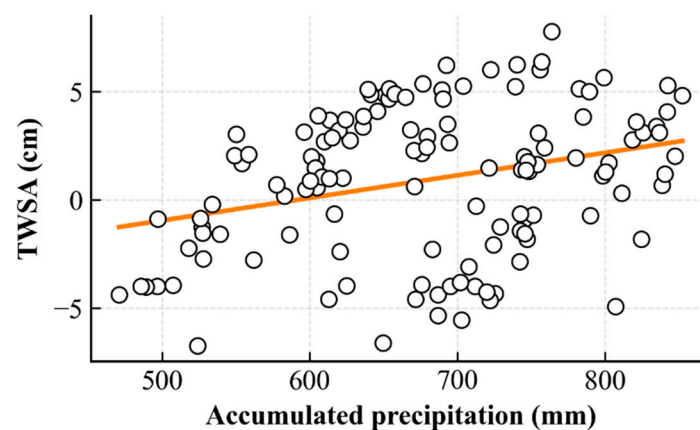


Figure 10. Relationship between deseasonalised TWSA and the best-performing accumulated precipitation predictor ($r = 0.30$, $p = 0.001$, $n = 129$; 12-month accumulation, no additional lag).

3.4. Climate–Landscape and Landscape–TWSA Associations

The relationships between climatic variables and land use composition were first examined using the eight available LUCC observations from 1985 to 2020 ($n = 8$). Temperature showed stronger associations with land use change than precipitation. Forest area was strongly and positively correlated with temperature (Spearman's $\rho = 0.964$, $p = 0.0005$), whereas cultivated land and grassland were negatively correlated with temperature, with $\rho = -0.928$ ($p = 0.0002$) and $\rho = -0.857$ ($p = 0.013$), respectively. Water-body area and construction land were also positively correlated with temperature ($\rho = 0.820$, $p = 0.023$ for

both), while the relationship between temperature and unutilised land was weak and statistically non-significant ($q = 0.070$, $p = 0.869$).

These correlations indicate that warmer years coincided with larger areas of forest, water bodies and construction land, and with smaller areas of cultivated land and grassland. However, these relationships should not be interpreted as evidence that temperature directly caused the observed land use transitions. Both temperature and several land use categories exhibited pronounced long-term trends during the study period, and the LUCC dataset contained only eight temporal observations. The high correlation coefficients may therefore partly reflect common temporal evolution, together with the effects of ecological restoration, agricultural adjustment and urban expansion. The results are consequently interpreted as climate–landscape co-variation rather than direct climatic attribution.

Compared with temperature, precipitation showed weaker relationships with land use composition, and none of the correlations reached the 0.05 significance level. Forest area was moderately positively correlated with precipitation ($q = 0.600$, $p = 0.148$), whereas grassland and cultivated land both showed moderate negative correlations ($q = -0.500$, $p = 0.253$). Water-body area showed a weak-to-moderate positive relationship with precipitation ($q = 0.464$, $p = 0.294$), while construction land was only weakly correlated with precipitation ($q = 0.321$, $p = 0.482$). These results suggest that interannual precipitation variability was not the dominant statistical correlate of the long-term land use changes identified from the discrete LUCC observations.

The long-term changes in land use composition are summarised in Table 3. From 1985 to 2020, forest area increased from 7887.15 to 8818.56 km², while construction land expanded from 488.25 to 1365.12 km². In contrast, cultivated land decreased from 9250.65 to 8127.27 km², and grassland declined from 1385.64 to 673.29 km². Water-body area showed a comparatively small increase, whereas unutilised land remained limited throughout the study period. These changes indicate that the basin experienced simultaneous ecological restoration, agricultural land contraction and urban expansion.

The analysis was then extended to landscape patterns and basin-scale TWSA. Annual mean TWSA was matched to the four LUCC snapshots within the GRACE era (2005, 2010, 2015 and 2020; $n = 4$). Composition variables showed larger absolute Pearson correlations than configuration metrics. Construction land had the strongest negative association ($r = -1.00$, $p = 0.005$), followed by forest ($r = -0.94$, $p = 0.058$) and water-body area ($r = -0.92$). Cultivated land was positively associated with TWSA ($r = 0.97$), while grassland also showed a positive but weaker relationship ($r = 0.71$). Given $n = 4$, these coefficients are highly sensitive to individual years and are reported as descriptive, hypothesis-generating evidence rather than stable effect estimates.

Configuration metrics were weaker: number of patches and patch density each had $r = -0.51$, mean patch area and mean fractal dimension each had $r = 0.52$, and Shannon's diversity index had $r = -0.19$. None of these configuration relationships reached $\alpha = 0.05$. Quantitatively, the contrast in absolute correlation magnitude supports the interpretation that land cover proportions were more closely aligned with basin-scale TWSA than patch arrangement during the four overlapping years; it does not establish that configuration is hydrologically unimportant.

The four observations in Figure 11 visualise the contrasting composition relationships for forest and construction land. The construction land slope was stronger and statistically detectable ($r = -1.00$, $p = 0.005$, $n = 4$), whereas the forest relationship was slightly weaker and marginal ($r = -0.94$, $p = 0.058$, $n = 4$). These plots are diagnostic visualisations and not independent evidence of causal effects.

Overall, landscape composition exhibited stronger descriptive associations with TWSA than landscape configuration in the four overlapping GRACE–LUCC years. Expansion of construction land coincided with lower TWSA, whereas larger cultivated and

grassland areas coincided with higher TWSA. These directions are hydrologically consistent with contrasts in imperviousness, infiltration and soil-water retention, but the very small temporal sample precludes causal attribution.

The bivariate relationships shown in Figure 12 further illustrate the contrasting responses of forest and construction land. Both variables showed negative slopes with TWSA, but the relationship with construction land was more pronounced. Nevertheless, the small number of observations limits the statistical power of these fits, and individual years may exert considerable influence on the estimated slopes. These plots are therefore used as diagnostic visualisations of the observed relationships rather than as independent evidence of causal effects.

The results indicate that landscape composition was more strongly associated with TWSA than landscape configuration during the overlapping GRACE–LUCC period. In particular, the expansion of construction land coincided with lower TWSA, whereas larger cultivated and grassland areas coincided with higher TWSA. These relationships are consistent with potential differences in imperviousness, infiltration and soil-water retention among land cover types.

Table 3. Changes in the areas of major land use types in the Yiluo River Basin from 1985 to 2020 (km²).

Landscape Type	Area in 1985 (km ²)	Area in 1990 (km ²)	Area in 1995 (km ²)	Area in 2000 (km ²)	Area in 2005 (km ²)	Area in 2010 (km ²)	Area in 2015 (km ²)	Area in 2020 (km ²)
Unutilized land	0.27	0.27	0.09	0.09	0.09	0.18	0.27	0.18
Forest	7887.15	7886.16	7807.95	8046.09	8197.65	8223.21	8488.71	8818.56
Grassland	1385.64	1476.27	1308.06	1237.14	1036.08	1195.02	1037.34	673.29
Water bodies	70.38	72.27	61.47	68.22	85.86	92.34	100.44	97.92
Cultivated land	9250.65	9145.17	9268.83	8923.86	8854.38	8492.04	8182.8	8127.27
Construction land	488.25	502.2	638.73	806.94	908.28	1079.55	1272.78	1365.12

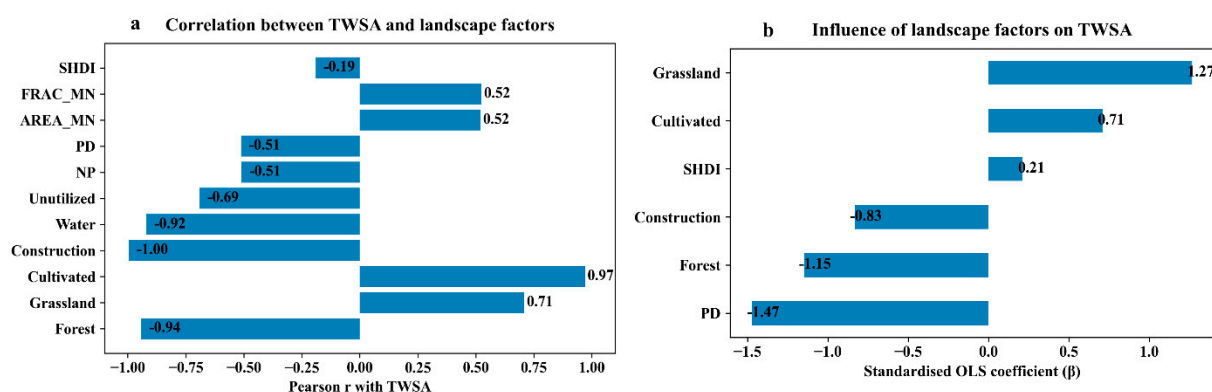


Figure 11. Relationship between TWSA and landscape factors. (a) Pearson correlation coefficients between annual TWSA and key landscape variables for the GRACE–LUCC overlapping years (2002–2020). (b) Standardised coefficients (β) from the multiple linear regression using TWSA as the response and the main landscape factors.

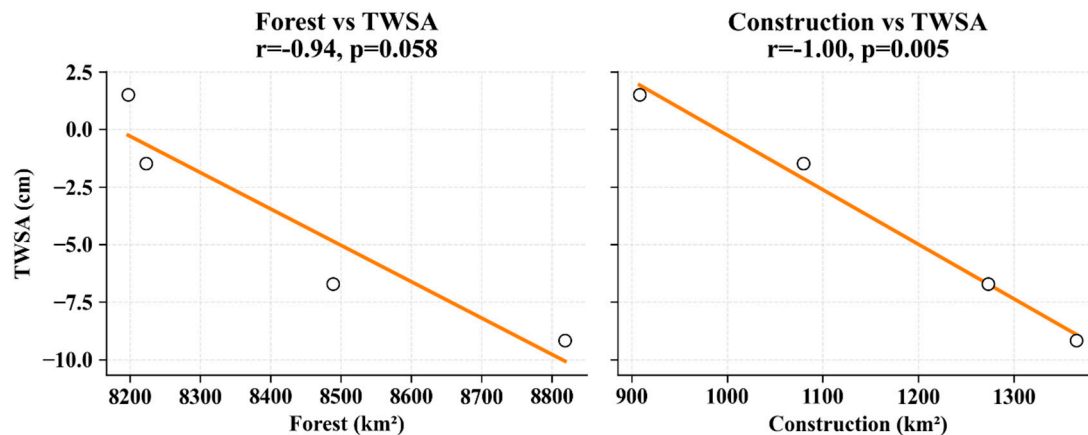


Figure 12. Bivariate relationships of TWSA with forest and construction land.

4. Discussion

The results indicate that landscape change in the Yiluo River Basin occurred under the combined influence of climatic variability and human land management. Temperature showed stronger statistical associations with long-term land use composition than precipitation, but these relationships should not be interpreted as direct climatic causation. Forest, water body and construction land areas increased over the study period, whereas cultivated land and grassland areas declined. These changes likely reflect the combined effects of ecological restoration, agricultural restructuring and urban expansion, rather than temperature change alone. In particular, the positive relationship between temperature and construction land mainly reflects common temporal development, while forest expansion may represent both vegetation restoration and increased vegetation water demand [37]. In semi-arid basins, vegetation recovery can improve soil stability and infiltration, but may also increase evapotranspiration and reduce water yield when water availability is limited. Similar trade-offs have been reported in the Loess Plateau, where vegetation restoration altered regional water yield through changes in evapotranspiration and land surface water balance [38].

The precipitation–TWSA analysis reveals a cumulative and delayed hydrological response. The strongest raw relationship occurred under a six-month precipitation accumulation and one-month lag, indicating that basin-scale water storage integrates rainfall inputs over seasonal time scales rather than responding only to same-month precipitation [39]. Short-term rainfall may be rapidly converted into runoff or evapotranspiration, whereas accumulated precipitation over several months is more likely to influence antecedent soil moisture, infiltration and groundwater recharge. After removing the seasonal cycle, the strongest relationship shifted to a 12-month accumulation window and became weaker, suggesting that part of the raw correlation was controlled by shared seasonality, while interannual TWSA variability retained a longer precipitation memory. Similar lagged relationships between precipitation and GRACE-derived TWSA have been reported across global river basins, with different water-storage components responding to precipitation forcing over different time scales [40]. Nevertheless, the moderate correlation coefficients indicate that precipitation explains only part of TWSA variability, and that evapotranspiration, groundwater abstraction, irrigation and reservoir regulation may also contribute to storage changes.

Landscape composition was more strongly associated with TWSA than configuration, although the evidence is based on only four overlapping years. Construction land showed the strongest negative relationship. Hydrologically, impervious expansion can reduce infiltration, accelerate runoff and alter groundwater recharge, while also acting as a proxy

for urban water demand. Cultivated and grassland areas showed positive associations, consistent with greater permeability and soil-water retention than built surfaces, although irrigation may offset this benefit through groundwater withdrawal. Forest area was negatively associated with TWSA, highlighting a possible evapotranspiration trade-off in a semi-arid setting. Configuration metrics describe patch arrangement, edge and diversity, which can influence runoff routing, flow-path continuity and ecological connectivity. Their weaker relationships here should therefore be interpreted in light of both the very small temporal sample and a scale mismatch: local patch processes are compared with a spatially integrated, coarse-resolution GRACE signal.

The findings support both structural and non-structural measures. In the middle, eastern and northern sub-regions, structural measures should include permeable pavements, rain gardens, infiltration trenches, detention facilities, blue–green corridors and upgrades that reduce leakage and improve reuse [41]. Agricultural infrastructure should prioritise efficient irrigation and soil-moisture monitoring, while ecological restoration should favour native, drought-tolerant species and stand densities compatible with hydrological carrying capacity. Non-structural measures should include impervious surface limits in land use approvals, groundwater abstraction licensing and metering, drought-stage allocation rules, reservoir–groundwater coordination, water use quotas and a shared monitoring system linking wells, reservoirs, meteorological observations and satellite TWSA. These measures address water quantity and retention directly; water quality protection additionally requires riparian buffers, erosion control, source pollution management and routine monitoring of agricultural, domestic and industrial discharges [42].

5. Limitations

Several limitations constrain interpretation. First, GRACE/GRACE-FO provides an integrated storage anomaly at a coarse effective resolution; leakage, attenuation and scaling uncertainty are consequential for a basin of this size, and groundwater, soil moisture, surface water, snow and vegetation water cannot be separated. Second, LUCC is represented by only eight snapshots, with just four overlapping the GRACE period. The landscape–TWSA correlations therefore have low power and high sensitivity to individual years; multivariable regression was not retained because the sample is insufficient for simultaneous estimation of multiple predictors. Third, approximately 79% LUCC classification accuracy propagates uncertainty into areas and landscape metrics. Finally, groundwater abstraction, irrigation, domestic and industrial use, reservoir operation and other interventions were not observed directly. The results are consequently mechanism-informed associations, not causal attribution. Future work should integrate well and reservoir records, water use statistics, higher-resolution storage proxies and process-based hydrological modelling, and should test alternative GRACE solutions and leakage/scaling treatments.

6. Conclusions

This study combined GRACE/GRACE-FO TWSA, meteorological observations and multi-period LUCC data to examine climate- and landscape-related water storage changes in the Yiluo River Basin. Basin-averaged TWSA declined significantly at approximately -4.47 mm yr^{-1} , with a transition around 2012 and stronger depletion in the middle, eastern and northern parts of the basin. TWSA was most strongly associated with precipitation accumulated over six months with a one-month lag. After deseasonalisation, a weaker but significant association remained over a 12-month accumulation period, indicating both seasonal and interannual precipitation memory.

Landscape composition showed stronger associations with TWSA than landscape configuration. Construction land was negatively associated with water storage, whereas cultivated land and grassland showed positive associations. Forest area was also negatively associated with TWSA, suggesting a potential water use trade-off under semi-arid conditions. These relationships indicate that TWSA change was associated with both climatic variability and land surface transformation, but they do not establish direct causality. Future basin management should combine impervious surface control, water-saving irrigation, hydrologically appropriate ecological restoration and coordinated monitoring of groundwater, reservoirs and satellite-derived TWSA.

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