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Spatiotemporal Groundwater Dynamics and Relative Risk Assessment in the West Liao River Basin, China (2019–2024)

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Abstract

Groundwater is a critical water source in the semi-arid West Liao River Basin (WLRB). Based on daily observations from 117 monitoring wells distributed across the basin during 2019–2024, this study analyzed interannual and seasonal groundwater-level dynamics and identified areas of relative groundwater stress using groundwater level elevation (WLE) and depth to water (DTW). The Mann–Kendall test, Sen’s slope estimator, ordinary kriging, and a composite risk index were applied to quantify temporal trends, map spatial patterns, and classify groundwater risk. Regional WLE showed weak interannual variability but a distinct seasonal cycle, with positive anomalies from January to April and negative anomalies from June to September. At the well scale, 51 wells (43.59%) exhibited significant increases, whereas 36 wells (30.77%) showed significant decreases. Sen’s slope ranged from -2.75 to 0.61 m/year, indicating that the strongest local changes were associated with groundwater-level decline. Spatially, WLE was generally higher in the southwest and lower toward the northeast. Areas with WLE decline were concentrated in the central-western and southern sectors, whereas relative WLE increases occurred in parts of the northern and eastern sectors. The low-, medium-, and high-risk classes included 39, 38, and 39 wells, accounting for 33.62%, 32.76%, and 33.62% of the wells retained for the risk assessment, respectively. High-risk wells clustered in the central-western and southern areas, while low-risk wells dominated the northern and eastern sectors. These results highlight the importance of well-scale monitoring for identifying priority areas of groundwater stress. The proposed framework provides a practical basis for screening priority monitoring areas and supporting spatially differentiated groundwater management in semi-arid basins. However, this study is limited by the relatively short monitoring period (2019–2024) and the lack of quantitative driver attribution; therefore, the findings reflect recent groundwater dynamics rather than long-term secular trends.



Received: 20 May 2026

Revised: 7 July 2026

Accepted: 10 July 2026

Published: 12 July 2026

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Keywords: West Liao River Basin; groundwater level elevation; depth to water; spatial heterogeneity; trend analysis; groundwater risk

1. Introduction

Groundwater is a fundamental component of water-resource systems in semi-arid and agro-pastoral transitional regions [1–5]. In these regions, surface water is often limited,

unevenly distributed, and strongly seasonal. Groundwater therefore plays a central role in sustaining agricultural production, domestic water supply, and groundwater-dependent ecological functions [6–8]. Globally, groundwater overextraction has triggered a “hidden crisis” of depletion, leading to persistent water table decline and land subsidence [9–11]. Similar problems have been reported in major irrigated aquifer systems, such as the High Plains and Central Valley aquifers in the United States, where long-term groundwater use has produced spatially uneven depletion and sustainability concerns [12]. Recent global syntheses have also shown that rapid groundwater-level decline and localized water-level rise can coexist across different aquifer systems under different pumping, recharge, and management settings [9,13–15]. These examples indicate that groundwater change is often spatially heterogeneous, highlighting the need for well-scale observations to identify localized groundwater-level decline or relative water-level rise in semi-arid basins such as the WLRB. The WLRB in northern China is both a water-limited basin and an important agricultural production region [16–20]. Its groundwater system is subject to increasing stress from climatic water deficit, concentrated seasonal precipitation, and long-term dependence on groundwater resources. Recent studies indicate that groundwater storage depletion in the WLRB is closely linked to intensified agricultural pumping for maize irrigation. Moreover, groundwater-level decline may threaten irrigation security, regional water supply, and groundwater-dependent vegetation by reducing groundwater accessibility and weakening shallow groundwater support. Marked groundwater-level fluctuations may also reduce the basin’s resilience to future hydrological change [21–24]. A clear understanding of recent groundwater dynamics in the WLRB is therefore essential for supporting spatially differentiated groundwater management.

Groundwater changes in the WLRB and other semi-arid basins have been widely linked to both climate variability and human activities [1,22,24–26]. Previous studies have used monitoring-well observations, statistical trend analysis, numerical simulation, and remote sensing methods to examine these changes. GRACE satellite data have been applied to groundwater storage depletion, while deep learning models and flow field evolution analysis have been used to predict fluctuations under intensive pumping [22–24,27–32]. These studies have helped identify long-term groundwater decline, spatial differences in depletion intensity, and the influence of agricultural water demand [9,33,34]. Despite these advances, groundwater drought and its agricultural impacts remain important challenges in the WLRB, and the response of groundwater levels to multi-year climate variability remains complex [35–37].

Several issues remain unresolved. First, broad-scale assessments can obscure the behavior of individual monitoring wells [12,13,38,39]. A basin may appear relatively stable in terms of its regional groundwater surface, even when localized stress persists in specific sectors. Second, temporal and spatial variations are often treated separately. Interannual variability, seasonal fluctuation, and well-scale trends have rarely been considered within a single analytical framework [40,41]. Spatial interpolation and comparative studies of interpolation methods are needed to better characterize groundwater-level patterns [42–44]. Third, assessments based on a single indicator may not adequately represent groundwater stress. WLE reflects the groundwater–surface configuration, whereas DTW more directly describes groundwater accessibility and management-related risk [45,46]. Their combined use, integrated through multi-indicator risk systems, can provide a more informative basis for groundwater management [47]. In this study, groundwater risk is used in a relative sense to describe groundwater-level stress within the monitoring network. It is indicated by deeper DTW, increasing DTW, declining WLE, and stronger intra-annual groundwater-level fluctuations.

The WLRB offers a suitable setting for examining these issues. The basin is characterized by highly seasonal and unevenly distributed precipitation, limited surface-water availability, and marked spatial differences in topography and hydrogeological conditions. Recent policy shifts, such as the “Regulations on Groundwater Management” implemented in 2021, have further altered the exploitation landscape by strengthening control over groundwater abstraction, groundwater-level targets, restricted or prohibited abstraction zones, and over-exploitation treatment [48]. Under these conditions, groundwater responses are unlikely to be spatially uniform. Local WLE decline and relative WLE increase may occur simultaneously in different parts of the basin [14,15,38,45,49]. Monitoring-well observations are therefore needed to evaluate groundwater dynamics at both regional and local scales.

In this study, groundwater dynamics in the WLRB during 2019–2024 were examined using monitoring data from 117 wells. The six-year daily record enabled the analysis of interannual variability, seasonal fluctuations, and well-scale monthly trends within a consistent basin-wide monitoring framework. The specific objectives were to: (1) characterize the interannual and seasonal variability of WLE; (2) identify well-scale groundwater trends and representative dynamic patterns; (3) reveal the spatial distribution of annual mean WLE and its net changes during the study period; and (4) develop a WLE–DTW-based relative groundwater risk index to identify wells with deeper groundwater, declining water levels, and stronger intra-annual fluctuations. By combining temporal variability, well-scale trend analysis, spatial mapping, and risk classification, this study supports spatially differentiated groundwater monitoring and management in semi-arid basins.

2. Materials and Methods

2.1. Study Area

The WLRB is located in Northeast China, approximately between 116°36′–124°01′ E and 41°05′–45°20′ N, and covers approximately 136,000 km² (Figure 1) [24,50]. The basin lies in the agro-pastoral transitional zone of northern China [24]. Its terrain gradually descends from the southern Greater Khingan Mountains and the northern Yanshan Mountains toward the broad alluvial plains in the central and southern parts of the basin, where most agricultural activities are concentrated. The WLRB has a temperate semi-arid continental monsoon climate, with strong seasonal contrasts in precipitation and temperature. Mean annual precipitation increases from about 350 mm in the northwest to about 450 mm in the southeast, and more than 70% of the annual rainfall occurs between June and September. Mean annual temperature ranges from 4 °C to 8 °C. Potential evapotranspiration commonly exceeds 1000 mm yr^{−1}, resulting in a persistent climatic water deficit [50,51]. The main aquifer system consists of unconsolidated Quaternary alluvial–proluvial deposits. In the central plain, these deposits locally exceed 200 m in thickness and form the principal groundwater-bearing strata. They are generally underlain by less permeable Tertiary or Cretaceous bedrock [51]. These lithological conditions imply spatial differences in hydraulic conductivity, transmissivity, specific yield, and vertical or horizontal connectivity across the basin. Cultivated land dominates the basin [52], particularly in the central and southern plains, with maize as the main crop. Groundwater is the primary source of irrigation water, and abstraction is closely associated with seasonal agricultural water demand [24,51]. Because surface-water resources are limited and unevenly distributed, groundwater use is spatially intensive but uneven across the basin [24]. Groundwater occurrence and exploitation pressure therefore vary markedly from place to place.

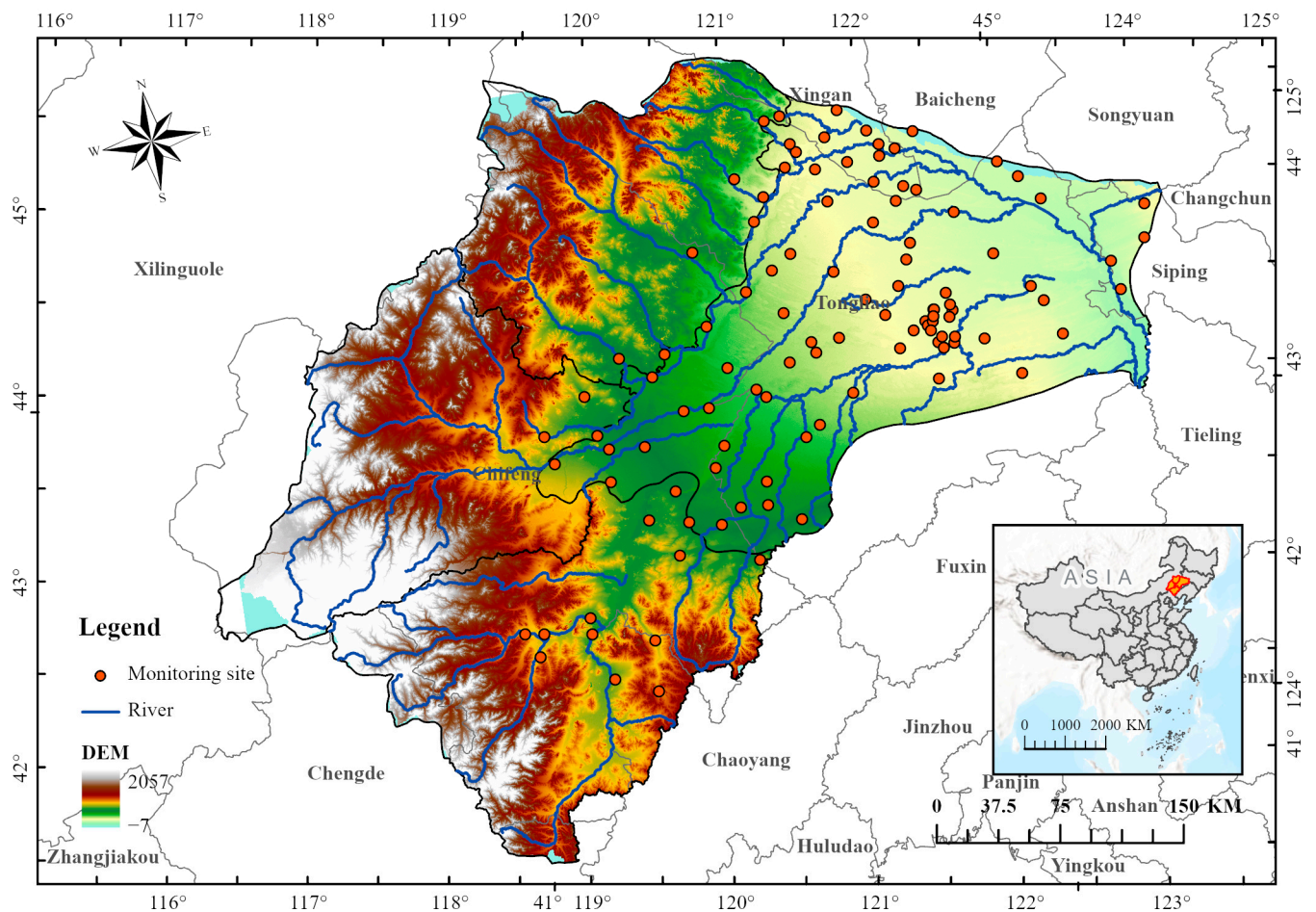


Figure 1. Spatial distribution of groundwater monitoring wells in the West Liao River Basin.

2.2. Data and Methods

Groundwater observations from 117 monitoring wells in the West Liao River Basin were used to examine groundwater dynamics from January 2019 to December 2024. These records were obtained from the national groundwater monitoring program operated by the China Institute of Geo-Environment Monitoring. After quality control, WLE and DTW were retained as the two basic variables. WLE was used to describe groundwater-level conditions and changes in the groundwater surface, whereas DTW was used to indicate groundwater accessibility and potential groundwater stress. The analysis focused on four aspects: interannual and seasonal variability, well-scale trends, spatial groundwater-level patterns, and integrated groundwater risk. The data-processing procedures and analytical methods are described below. All data preprocessing, statistical analyses, sensitivity analyses, and statistical figure preparation were performed using R version 4.5.1.

2.2.1. Data Preprocessing and Calculation of WLE and DTW

Daily groundwater monitoring records from 117 wells were compiled for the period from January 2019 to December 2024. The dataset included WLE and DTW. Before further analysis, invalid entries were removed and abnormal values were screened. Outliers were identified for each well using the median absolute deviation (MAD), which is less sensitive to extreme values than the standard deviation. For a given well, an observation x_i was treated as an outlier when:

$$|x_i - \tilde{x}| > k \times 1.4826 \times MAD \quad (1)$$

where $\tilde{x}$ is the median of the time series, $MAD = \text{median}(|x_i - \tilde{x}|)$, and $k = 3$. The factor 1.4826 was used to make the MAD comparable to the standard deviation under an approximately normal distribution. Observations deviating from the well-specific median by more than three robust standard deviations were treated as outliers and replaced with missing values. The screening was applied independently to WLE and DTW so that abnormal values in one variable did not affect the screening of the other.

After quality control, daily records were aggregated to monthly and annual time scales. Monthly mean values were calculated only when at least 20 valid daily observations were available in a given well-month. This threshold was used to ensure that each monthly value represented most of the month, following the general principle that monthly means should satisfy data-completeness requirements before being used in temporal analysis [53]. Annual mean WLE for well i in year y was calculated as:

$$\overline{WLE}_{i,y} = \frac{1}{n_{i,y}} \sum_{d=1}^{n_{i,y}} WLE_{i,y,d} \quad (2)$$

where $WLE_{i,y,d}$ is the valid daily WLE observation for well i on day d in year y , and $n_{i,y}$ is the number of valid daily observations in that year. For spatial interpolation, only well-year records with a valid daily ratio of at least 75% were retained. This threshold was adopted to obtain representative annual mean WLE estimates and to reduce bias from uneven seasonal data coverage, as interpolated annual groundwater-level surfaces are sensitive to seasonal gaps in the underlying observations. In the subsequent analyses, WLE served as the primary indicator of groundwater-level condition and groundwater–surface change, while DTW provided complementary information on groundwater stress.

2.2.2. Analysis of Interannual and Seasonal Variability

Interannual variability was evaluated using the annual mean WLE series of individual wells. For each year from 2019 to 2024, annual mean WLE values from all available wells were summarized at the regional scale. The median, interquartile range, and full range were used to describe the central tendency and spread of the annual WLE distribution. These statistics allowed year-to-year differences in groundwater-level conditions to be compared without relying only on regional mean values.

Seasonal variability was examined using monthly WLE anomalies rather than raw WLE values. This treatment was adopted because absolute WLE differs substantially among wells due to topographic and hydrogeological differences. For each well, the multi-year mean WLE for a given calendar month was first calculated as:

$$WLE_{i,m}^{\text{clim}} = \frac{1}{N_{i,m}} \sum_{y=1}^{N_{i,m}} \overline{WLE}_{i,y,m} \quad (3)$$

where $\overline{WLE}_{i,y,m}$ is the monthly mean WLE of well i in year y and month m , and $N_{i,m}$ is the number of years with valid monthly means for that month at well i . The overall mean WLE of each well was then calculated from all valid monthly means:

$$\overline{WLE}_i = \frac{1}{N_i} \sum_{y,m} \overline{WLE}_{i,y,m} \quad (4)$$

where N_i is the number of valid monthly means for well i . The seasonal anomaly for month m at well i was defined as:

$$A_{i,m} = WLE_{i,m}^{\text{clim}} - \overline{WLE}_i \quad (5)$$

For each calendar month, the mean, minimum, maximum, and interquartile range of $A_{i,m}$ were summarized across wells.

2.2.3. Trend Analysis at the Well Scale

Well-scale trends were analyzed from the monthly mean WLE series. Only wells with valid monthly observations for at least 70% of the full study period were retained. This threshold was adopted to maintain sufficient temporal representativeness for Mann–Kendall and Sen’s slope analyses while allowing minor gaps in the monitoring records. For well i , the valid monthly ratio was defined as:

$$R_i = \frac{n_i^{\text{valid}}}{72} \quad (6)$$

where n_i^{valid} is the number of months with valid monthly mean WLE during 2019–2024. The denominator 72 represents the total number of months in the six-year study period. Wells were retained for trend analysis when $R_i \geq 0.70$.

For each retained well, the Mann–Kendall test was used to determine whether a monotonic trend was present. Sen’s slope estimator was applied to quantify the rate of groundwater-level change. For a monthly WLE series, the pairwise slope between two valid observations was calculated as:

$$Q_{jk} = \frac{x_k - x_j}{t_k - t_j}, 1 \leq j < k \leq n \quad (7)$$

where x_j and x_k are monthly mean WLE values at times t_j and t_k , respectively. Sen’s slope is the median of all Q_{jk} :

$$Q_{\text{Sen}} = \text{median}(Q_{jk}) \quad (8)$$

Because Q_{Sen} represents the monthly rate of WLE change, it was converted to an annual rate as:

$$Q_{\text{year}} = 12 \times Q_{\text{Sen}} \quad (9)$$

Trend classes were assigned using both the Mann–Kendall significance test and the annual Sen’s slope Q_{year} . A trend was considered statistically significant when $p < 0.05$. The classification rules were defined as follows:

$$\left\{ \begin{array}{ll} p < 0.05 \text{ and } Q_{\text{year}} < 0, & \text{significant decrease} \\ p < 0.05 \text{ and } Q_{\text{year}} > 0, & \text{significant increase} \\ p \geq 0.05 \text{ and } |Q_{\text{year}}| < 0.02 \text{ m/year}, & \text{stable} \\ p \geq 0.05, |Q_{\text{year}}| \geq 0.02 \text{ m/year, and } Q_{\text{year}} < 0, & \text{non-significant decrease} \\ p \geq 0.05, |Q_{\text{year}}| \geq 0.02 \text{ m/year, and } Q_{\text{year}} > 0, & \text{non-significant increase} \end{array} \right. \quad (10)$$

This classification separates statistically significant groundwater-level changes from non-significant changes. Among statistically non-significant trends, wells with an absolute Sen’s slope below 0.02 m/year were classified as stable. This near-zero threshold was used only to subclassify non-significant trends and did not affect the identification of significant increases or decreases. The sensitivity of this threshold was further examined using alternative values of 0.01 and 0.05 m/year. Fluctuation intensity was described using the amplitude of monthly mean WLE:

$$\text{Amp}_i = \max(\overline{\text{WLE}}_{i,t}) - \min(\overline{\text{WLE}}_{i,t}) \quad (11)$$

where $\overline{WLE}_{i,t}$ is the monthly mean WLE for well i at time t . Representative hydrographs were selected to illustrate typical groundwater dynamic patterns, including declining, seasonal fluctuation, fluctuating increase, and relatively stable types.

2.2.4. Spatial Interpolation of WLE

Annual mean WLE in 2019, 2022, and 2024 was spatially interpolated to characterize the regional groundwater–surface pattern and its recent evolution. Well coordinates were projected from WGS84 to UTM Zone 50N. The basin boundary was transformed to the same coordinate system, and a 1000 m resolution grid was generated within the basin. Coordinate transformation, spatial interpolation, raster processing, and map production were performed using ArcGIS Pro version 3.1.

Inverse distance weighting (IDW) and ordinary kriging were evaluated using leave-one-out cross-validation. Each monitoring well was removed in turn, and its WLE was predicted from the remaining wells. Prediction errors were summarized using mean error (ME), mean absolute error (MAE), and root mean square error (RMSE). Ordinary kriging was selected for the final interpolation because it showed better cross-validation performance than IDW in the selected years (Table 1). This method estimates values at unsampled locations by assigning weights to nearby observations according to the spatial autocorrelation structure described by a fitted semivariogram. For an unsampled location x_0 , the ordinary kriging estimate was calculated as:

$$\hat{Z}(x_0) = \sum_{i=1}^n \lambda_i(x_0) Z(x_i), \sum_{i=1}^n \lambda_i(x_0) = 1 \quad (12)$$

where $Z(x_0)$ is the predicted WLE at location x_0 , $Z(x_i)$ is the observed WLE at monitoring well i , n is the number of wells used for interpolation, and $\lambda_i(x_0)$ is the kriging weight assigned to well i .

Table 1. Leave-one-out cross-validation results for IDW and ordinary kriging interpolation of annual mean WLE.

Year	Interpolation Method	ME (m)	MAE (m)	RMSE (m)
2019	IDW	−9.650	17.285	30.717
	Ordinary kriging	−0.313	17.138	24.945
2022	IDW	−9.630	18.504	35.035
	Ordinary kriging	−5.601	22.050	33.921
2024	IDW	−10.165	18.278	34.831
	Ordinary kriging	−2.359	19.491	29.874

The interpolated surfaces were clipped to the basin boundary. Net change in groundwater level was calculated as:

$$\Delta WLE = WLE_{2024} - WLE_{2019} \quad (13)$$

Positive values indicate groundwater-level rise, whereas negative values indicate groundwater-level decline. The interpolated annual WLE surfaces were used to compare the regional groundwater–surface pattern among the selected years, and the net-change surface was used to locate areas of decline and increase.

2.2.5. Groundwater Risk Index Construction and Classification

In this study, groundwater risk refers to relative groundwater stress within the monitoring network and was evaluated at the well scale by combining four indicators: mean

DTW, DTW trend, risk-oriented WLE trend, and mean annual amplitude. These indicators represent three aspects of groundwater stress. Mean DTW describes the current groundwater-depth condition, DTW and WLE trends reflect the direction of groundwater-level change, and annual amplitude represents the intensity of intra-annual fluctuation. Mean DTW for well i was calculated as:

$$\overline{DTW}_i = \frac{1}{N_i} \sum_{t=1}^{N_i} DTW_{i,t} \quad (14)$$

where $DTW_{i,t}$ is the valid monthly mean DTW of well i at time t , and N_i is the number of valid monthly DTW records. The trends of DTW and WLE were quantified using Sen's slope and expressed in m/year. A positive DTW trend indicates increasing DTW and therefore greater groundwater stress. By contrast, a negative WLE trend indicates groundwater-level decline. To make the WLE trend consistent with the risk direction of the other indicators, it was multiplied by -1 :

$$T_{WLE,i}^{risk} = -T_{WLE,i} \quad (15)$$

where $T_{WLE,i}$ is the annual Sen's slope of WLE for well i , and a larger $T_{WLE,i}^{risk}$ value indicates stronger groundwater-level decline. Mean annual amplitude was used to describe the magnitude of seasonal groundwater-level fluctuation. For well i in year y , annual amplitude was calculated as:

$$Amp_{i,y} = \max(\overline{WLE}_{i,y,m}) - \min(\overline{WLE}_{i,y,m}) \quad (16)$$

The mean annual amplitude of each well was then obtained by averaging across all valid years:

$$\overline{Amp}_i = \frac{1}{N_{y,i}} \sum_{y=1}^{N_{y,i}} Amp_{i,y} \quad (17)$$

where $N_{y,i}$ is the number of valid years used for amplitude calculation. Only wells with valid monthly WLE and DTW records for at least 70% of the study period and sufficient data to calculate all four risk indicators were retained for risk analysis. After data-completeness screening, 116 of the 117 monitoring wells were retained for the relative groundwater risk assessment.

All indicators were standardized to a 0–1 range using min–max normalization:

$$Z_{i,k} = \frac{X_{i,k} - X_{k,\min}}{X_{k,\max} - X_{k,\min}} \quad (18)$$

where $X_{i,k}$ is the original value of indicator k for well i , $X_{k,\min}$ and $X_{k,\max}$ are the minimum and maximum values of that indicator across all retained wells, and $Z_{i,k}$ is the normalized value. Because all indicators were oriented so that larger values represent greater groundwater stress, larger normalized values correspond to higher risk.

The equal-weight scheme was used as the baseline risk index because the four indicators describe complementary dimensions of groundwater stress. It assigned the same weight to the four normalized indicators:

$$Risk_i^{equal} = 0.25Z_{\overline{DTW},i} + 0.25Z_{T_{DTW},i} + 0.25Z_{T_{WLE,i}^{risk}} + 0.25Z_{\overline{Amp},i} \quad (19)$$

An empirical-weight scheme was also tested by assigning a larger weight to mean DTW and a lower weight to annual amplitude:

$$Risk_i^{emp} = 0.35Z_{\overline{DTW},i} + 0.25Z_{T_{DTW},i} + 0.25Z_{T_{WLE,i}^{risk}} + 0.15Z_{\overline{Amp},i} \quad (20)$$

where $Z_{\overline{DTW},i}$, $Z_{T_{DTW},i}$, $Z_{T_{WLE}^{risk},i}$, and $Z_{\overline{Amp},i}$ are the normalized values of mean DTW, DTW trend, risk-oriented WLE trend, and mean annual amplitude, respectively. In addition to the empirical-weight scheme, two further weighting schemes were examined in the sensitivity analysis: a DTW-dominant scheme and a trend-dominant scheme. These alternative schemes were used to test whether the relative risk classification was sensitive to the weighting assigned to groundwater-depth conditions, directional trends, and intra-annual fluctuation.

Composite risk scores were classified into low-, medium-, and high-risk categories using tercile-based thresholds derived from the 33.33rd and 66.67th percentiles of the baseline risk-score distribution. The three classes therefore describe relative groundwater risk within the monitoring network, rather than absolute risk thresholds. The equal-weight and tercile-based scheme was adopted for the final risk assessment, and the robustness of the classification was further evaluated using alternative weighting schemes, normalization methods, and classification thresholds, as described in Section 2.2.6.

2.2.6. Method Robustness and Sensitivity Checks

Method robustness was assessed through interpolation cross-validation and sensitivity tests of the relative groundwater risk classification. For spatial interpolation, leave-one-out cross-validation was used to compare IDW and ordinary kriging for annual mean WLE in 2019, 2022, and 2024. Prediction errors were summarized using mean error (ME), mean absolute error (MAE), and root mean square error (RMSE). The method with better overall cross-validation performance was used to generate the final annual WLE surfaces and the net-change map.

The sensitivity of the relative groundwater risk classification was then examined by changing the main methodological settings. The baseline index was based on min–max normalization, equal weighting, and tercile-based classification. Three alternative weighting schemes were tested, including empirical, DTW-dominant, and trend-dominant schemes. Rank-based normalization was used as an alternative to min–max normalization, and quartile-based classification and Jenks natural breaks were compared with the baseline tercile classification. Each alternative setting was compared with the baseline using classification agreement, high-risk well overlap, and Spearman’s rank correlation.

The near-zero slope threshold used in trend classification was also tested. In addition to the baseline threshold of 0.02 m/year, thresholds of 0.01 and 0.05 m/year were examined. This test evaluated whether the subdivision of statistically non-significant trends into stable, non-significant increase, and non-significant decrease classes depended on the selected threshold. The near-zero slope threshold was applied only to statistically non-significant trends; therefore, it did not affect the identification of significant increasing or decreasing trends.

3. Results

3.1. Interannual and Seasonal Variations in WLE

WLE displayed limited interannual variation but a clear seasonal signal during 2019–2024 (Figure 2). The annual mean WLE distributions were similar among the six years, with only small changes in the median, interquartile range, and overall spread (Figure 2a). The median annual mean WLE remained close to 192 m throughout the study period. It increased slightly between 2019 and 2020 and then stayed relatively stable from 2021 onward. The lower quartiles were consistently around 168–170 m, whereas the upper quartiles ranged approximately from 287 to 345 m. No consistent basin-wide increasing or decreasing tendency was evident from the annual distributions.

Groundwater Level Elevation Variations during 2019–2024

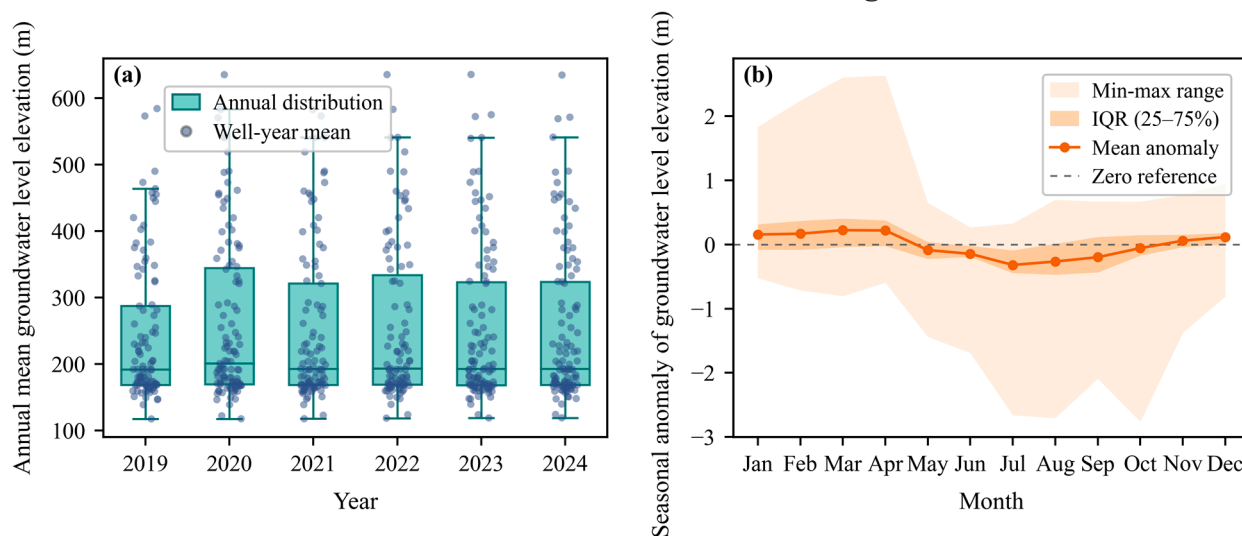


Figure 2. WLE during 2019–2024: (a) interannual distribution of annual mean WLE and (b) seasonal anomaly of WLE.

Differences among wells were much larger than differences among years. Most wells were concentrated between approximately 160 and 250 m, whereas several high-elevation wells consistently exceeded 500 m, with maximum values above 630 m in multiple years (Figure 2a). The persistent spread indicates that spatial contrasts in WLE were much greater than the corresponding interannual differences. The relatively stable number of wells included in the annual statistics also suggests that year-to-year comparisons were not strongly affected by changes in data availability.

Monthly WLE anomalies revealed a more pronounced seasonal pattern (Figure 2b). Monthly WLE anomalies showed a seasonal range of approximately 0.54 m, from a minimum of about -0.32 m in July to maxima of about $+0.22$ m in March and April (Figure 2b). Mean anomalies were positive from January to April, became negative in May, and remained negative from June to September. After September, the negative anomaly gradually weakened, and slightly positive values reappeared in November and December. The seasonal cycle therefore reflects higher-than-average groundwater levels in the early part of the year, a decline during summer, and gradual rebound toward the end of the year.

The shaded envelope in Figure 2b shows that the magnitude of seasonal anomalies differed substantially among wells. Even so, the mean anomaly curve indicates a consistent seasonal tendency across the monitoring network. The summer low-water period was especially clear from June to September, when the mean anomaly remained negative. During 2019–2024, WLE dynamics in the WLRB were therefore marked by limited interannual variability and a recurrent seasonal cycle.

3.2. Well-Scale Trends in WLE

Well-scale trends were analyzed using monthly WLE records from 117 monitoring wells during 2019–2024 (Figure 3). In total, 51 wells (43.59%) had significant increases, whereas 36 wells (30.77%) had significant decreases. The remaining wells were classified as non-significant increase, non-significant decrease, or stable. Increasing trends were more frequent than decreasing trends at the monitoring-well scale, but declining wells still accounted for a substantial proportion of the network, and persistent local WLE decline remained evident.

Trend Characteristics of Groundwater Level Elevation

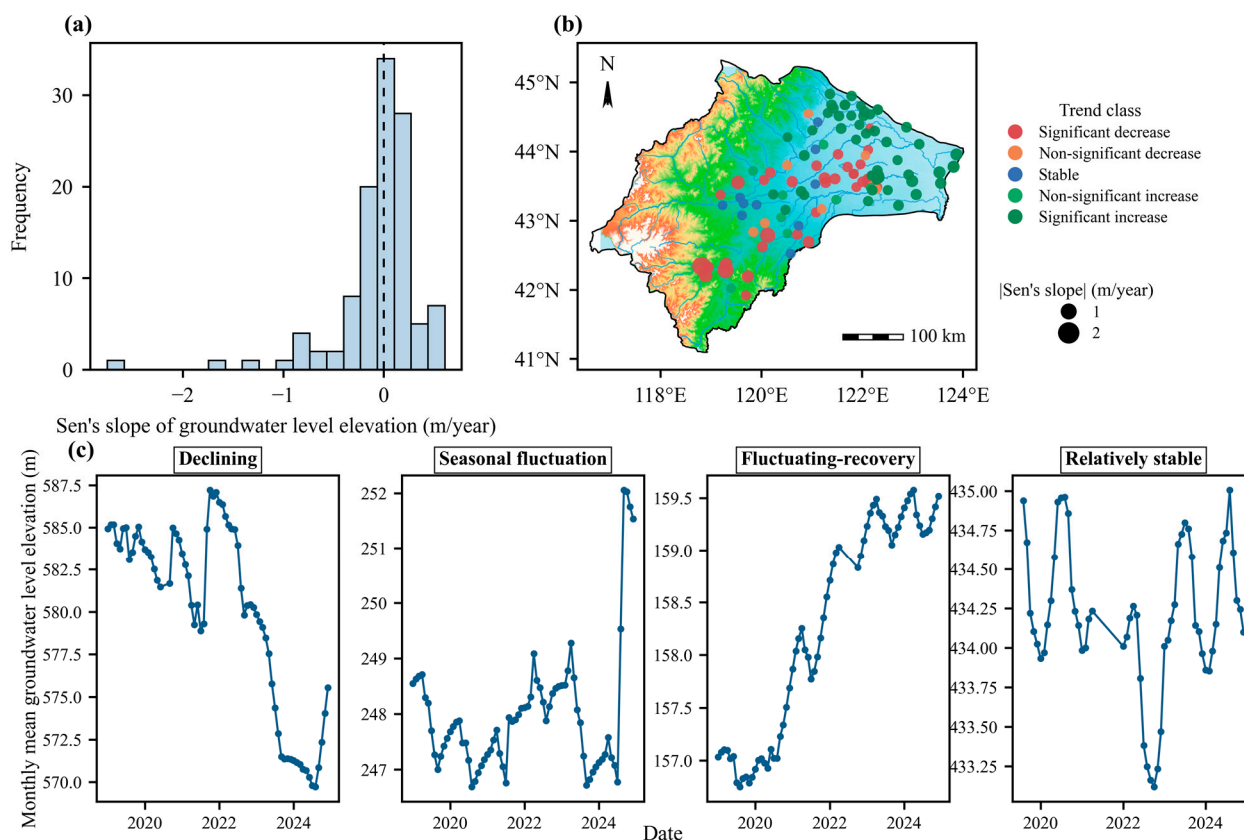


Figure 3. Trend characteristics of WLE at the monitoring-well scale during 2019–2024: (a) distribution of Sen's slope, (b) spatial distribution of trend classes, and (c) representative hydrographs of typical dynamic patterns.

The distribution of Sen's slope suggests that most wells changed only moderately during the study period (Figure 3a). Sen's slope values were mainly concentrated between -0.5 and 0.5 m/year, with a median of 0.034 m/year. The full range extended from -2.75 to 0.61 m/year. This asymmetric range shows that, although significant increases were more numerous, the strongest local changes were associated with groundwater-level decline. A small number of wells therefore contributed disproportionately to the negative tail of the slope distribution. The spatial pattern of trend classes was not random (Figure 3b). Wells with significant decreases were mainly located in the west-central, southwestern, and south-central parts of the study area. Significantly increasing wells were more common in the northern, northeastern, and eastern sectors. This distribution points to a clear spatial contrast: groundwater-level decline was concentrated mainly in the central-southern part of the basin, whereas increasing WLE signals were more evident toward the north and northeast.

The representative hydrographs in Figure 3c illustrate how these trends developed through time. The declining well had a persistent downward shift, with WLE in the later stage clearly lower than that in the earlier stage. The seasonal fluctuation well had repeated intra-annual oscillations but no obvious long-term displacement, indicating a recurrent seasonal pattern. The fluctuating-increase well had a gradual rise after a relatively low early stage, although short-term fluctuations remain visible. The relatively stable well maintained a narrow range of variation, with no clear long-term increase or decrease.

The well-scale results indicate that groundwater evolution in the WLRB cannot be represented by a single regional trend. Increasing WLE trends were widespread, but local decline persisted and was stronger in magnitude at several wells. The contrast among trend classes, spatial locations, and hydrograph shapes shows that recent groundwater-level change was spatially differentiated, with WLE increases and declines occurring simultaneously in different parts of the basin.

3.3. Spatial Distribution and Net Changes in WLE

Leave-one-out cross-validation showed that ordinary kriging generally performed better than IDW for annual mean WLE interpolation (Table 1). Therefore, ordinary kriging was used to generate the final annual WLE surfaces and the net-change map. The interpolated annual mean WLE surfaces for 2019, 2022, and 2024 displayed a similar large-scale spatial pattern across the study area (Figure 4a–c). WLE was generally higher in the southwestern part of the basin and gradually decreased toward the northeast. The highest values occurred in the southwestern sector, where local WLE exceeded 600 m. Much lower values were found in the northeastern and eastern sectors, mostly within the range of 200–300 m. This southwest–northeast gradient remained visible in all three selected years, suggesting little change in the regional groundwater–surface configuration during 2019–2024.

Annual Mean Groundwater Level Elevation Estimated by Ordinary Kriging

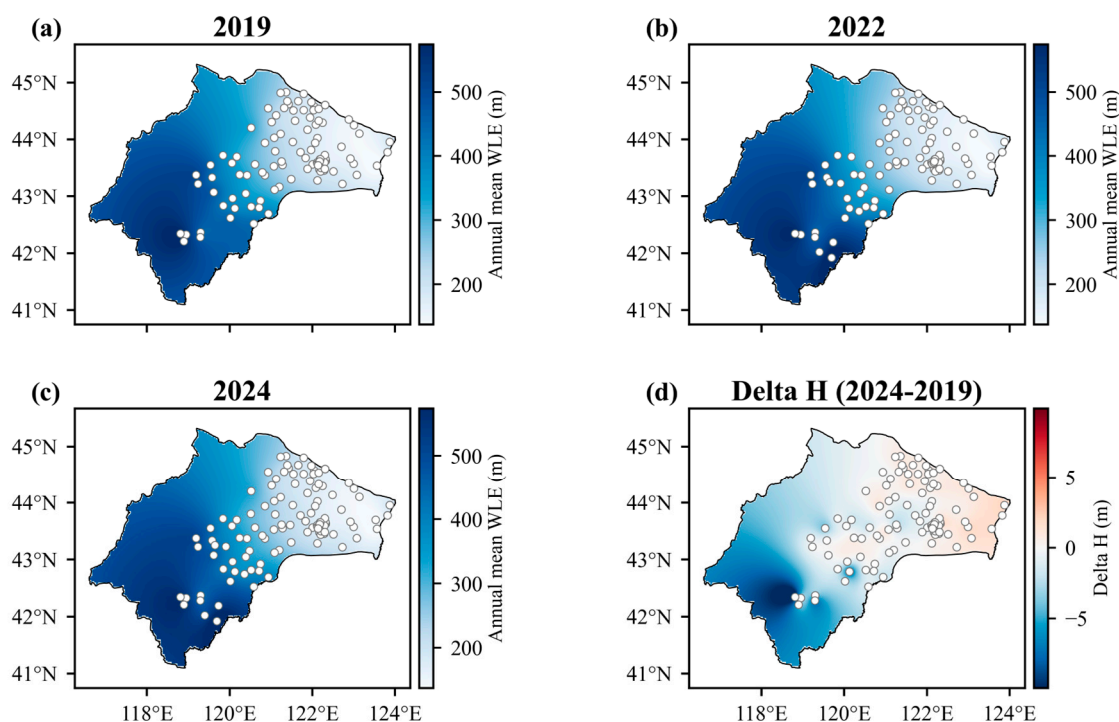


Figure 4. Spatial patterns of annual mean WLE estimated by ordinary kriging: (a) 2019, (b) 2022, (c) 2024, and (d) net change between 2019 and 2024.

The net-change map showed localized variations that were less evident from the annual WLE surfaces alone (Figure 4d). The strongest decline occurred in the southwestern part of the basin, where WLE decreased by up to about 10 m between 2019 and 2024. Smaller decline patches were also present in the central part of the study area. Positive changes were mainly distributed in parts of the eastern and northeastern sectors, indicating localized WLE increase.

The decline areas identified from the net-change map were generally consistent with the distribution of decreasing wells in the well-scale trend analysis, particularly in the southwestern and south-central parts of the basin. Areas with modest WLE increase corresponded broadly to sectors where increasing trends were more common. The interpolated surfaces support the well-scale results: recent groundwater change in the WLRB was spatially uneven, with localized decline and limited water-level rise occurring against a relatively stable regional groundwater–surface background.

3.4. Groundwater Risk Identification Based on WLE and Depth-to-Water Indicators

Groundwater risk was evaluated using four indicators: mean DTW, DTW trend, risk-oriented WLE trend, and mean annual amplitude. In the baseline scheme, the four indicators were normalized using min–max normalization, assigned equal weights, and classified into low-, medium-, and high-risk classes using tercile thresholds. The first and second tercile thresholds of the baseline risk score were 0.112 and 0.188, respectively. Based on these thresholds, 39 wells were classified as low risk, 38 as medium risk, and 39 as high risk, accounting for 33.62%, 32.76%, and 33.62% of the retained monitoring wells, respectively (Table 2). Sensitivity analysis indicated that the risk ranking and high-risk well identification were generally robust to alternative weighting schemes and normalization methods. Compared with the baseline scheme, the empirical, DTW-dominant, and trend-dominant weighting schemes produced classification agreement rates of 93.10%, 89.66%, and 84.48%, respectively, with high-risk well overlaps of 97.44%, 94.87%, and 89.74%. Rank-based normalization also produced a similar risk ranking, with a classification agreement of 84.48%, a high-risk overlap of 84.62%, and a Spearman rank correlation of 0.966. However, the discrete low-, medium-, and high-risk labels were affected by the selected risk-class threshold, especially under Jenks natural breaks. Therefore, the risk classes should be interpreted as relative categories within the monitoring network rather than absolute groundwater-risk thresholds. The equal-weight and tercile-based scheme was used for the final risk zoning (Figure 5).

The risk map displays a distinct spatial pattern (Figure 5a). High-risk wells were mainly clustered in the central-western and southern parts of the study area, with additional high-risk wells in the central-southern sector. Medium-risk wells were distributed more widely and commonly appeared around the high-risk clusters or in transitional areas. Low-risk wells were concentrated mainly in the northern, northeastern, and eastern sectors. This distribution suggests a general decrease in relative groundwater risk from the central-southern part of the basin toward the northeast. Areas with stronger groundwater-level decline and increasing DTW were more likely to fall into the high-risk class, whereas areas with increasing WLE or weaker groundwater-level stress were more often classified as low risk.

The relationship between risk level and groundwater dynamic type is shown in Figure 5b. Type I wells, corresponding to the declining pattern, were all assigned to medium- or high-risk classes, and 54.55% of them were classified as high risk. Type II wells, representing moderate water-level rise, were mainly medium risk (50.00%), followed by low risk (36.84%). Type III wells, characterized by fluctuating increase, were dominated by the low-risk class, which accounted for 87.50% of this group. This contrast indicates that the risk index separates wells with persistent decline from those showing increasing or lower-stress water-level behavior.

The distributions of the four individual indicators further explain the separation among risk classes (Figure 5c). Median mean DTW increased from 3.27 m in the low-risk group to 8.20 m in the medium-risk group and 14.58 m in the high-risk group. DTW trend followed a similar upward shift across the three classes. The risk-oriented WLE trend was

highest in the high-risk group, indicating stronger groundwater-level decline in these wells. Mean annual amplitude also increased toward the high-risk class, suggesting that high-risk wells were associated not only with deeper groundwater and declining levels, but also with stronger intra-annual fluctuations.

Groundwater Risk Identification

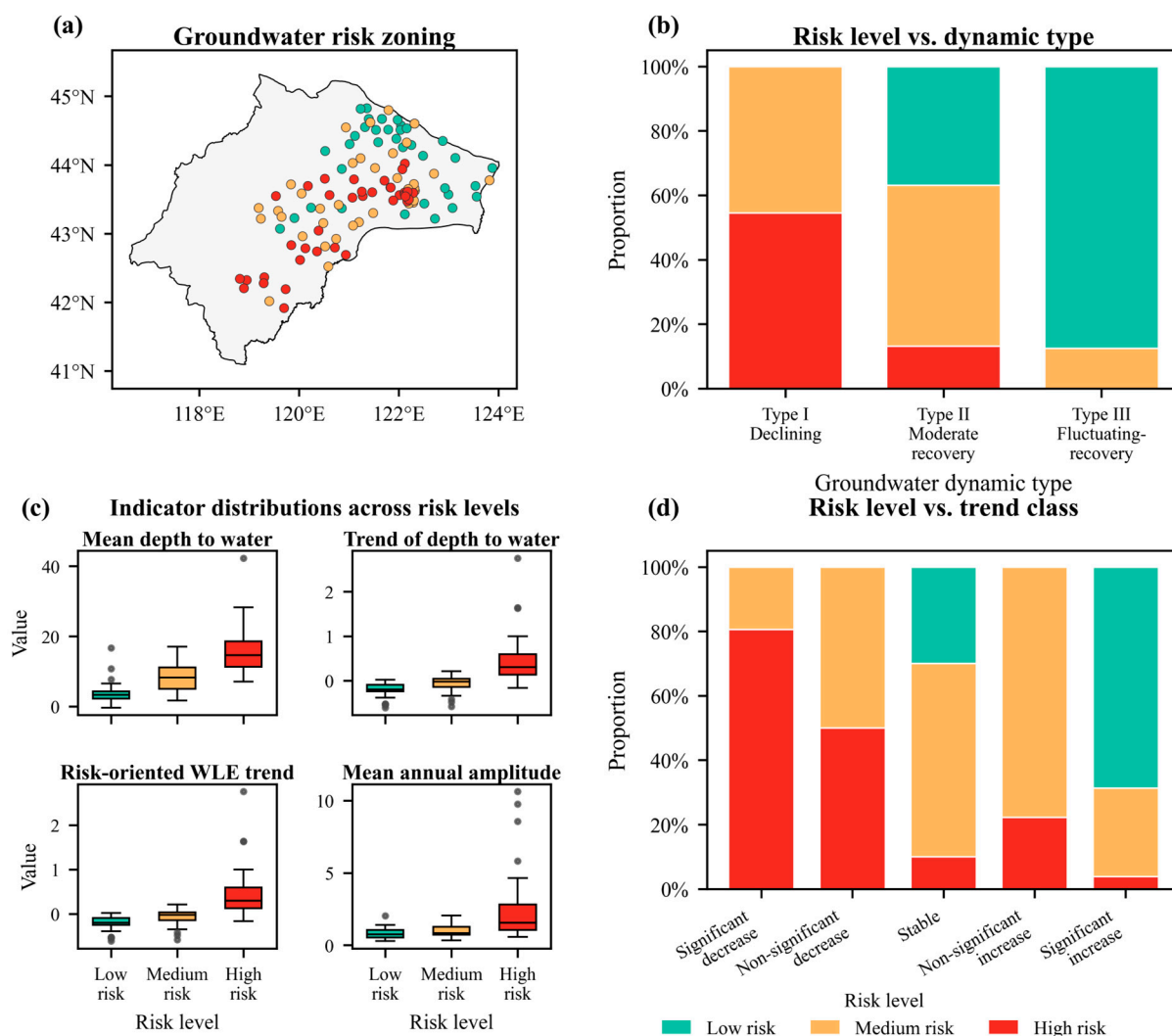


Figure 5. Relative groundwater risk identification based on WLE and depth-to-water indicators in the West Liao River Basin: (a) spatial distribution of risk classes, (b) relationship between risk class and groundwater dynamic type, (c) distributions of individual risk indicators among risk classes, and (d) relationship between risk class and trend class.

Risk level also varied systematically among trend classes (Figure 5d). In the significant decrease group, 80.56% of wells were classified as high risk, and the remaining wells were medium risk. In the Non-significant decrease group, medium- and high-risk wells each accounted for 50.00%. In contrast, the significant increase group was dominated by low-risk wells (68.63%), followed by medium-risk wells (27.45%), with only 3.92% classified as high risk. Stable wells were mainly medium risk (60.00%), and Non-significant increase wells were also dominated by the medium-risk class (77.78%). These proportions show that declining trends were closely associated with higher risk levels, while increasing trends generally corresponded to lower risk.

Table 2. Sensitivity analysis and threshold information for relative groundwater risk and trend classification.

Component	Setting or Criterion	Result
Baseline risk classification	Low risk: Risk ≤ 0.112	39 wells; 33.62%
	Medium risk: $0.112 < \text{Risk} \leq 0.188$	38 wells; 32.76%
	High risk: Risk > 0.188	39 wells; 33.62%
Weighting-scheme sensitivity	Empirical weight	Agreement = 93.10%; high-risk overlap = 97.44%; Spearman's $\rho = 0.989$
	DTW-dominant weight	Agreement = 89.66%; high-risk overlap = 94.87%; Spearman's $\rho = 0.981$
	Trend-dominant weight	Agreement = 84.48%; high-risk overlap = 89.74%; Spearman's $\rho = 0.963$
Normalization-method sensitivity	Rank-based normalization	Agreement = 84.48%; high-risk overlap = 84.62%; Spearman's $\rho = 0.966$
Risk-class threshold sensitivity	Quartile-based classification	Agreement = 82.76%; high-risk overlap = 74.36%; Spearman's $\rho = 1.000$
	Jenks natural breaks	Agreement = 41.38%; high-risk overlap = 17.95%; Spearman's $\rho = 1.000$
Trend-threshold sensitivity	Near-zero slope threshold = 0.01 m/year	Significant increase = 51; significant decrease = 36; stable wells = 4
	Near-zero slope threshold = 0.02 m/year	Significant increase = 51; significant decrease = 36; stable wells = 12
	Near-zero slope threshold = 0.05 m/year	Significant increase = 51; significant decrease = 36; stable wells = 20

Note: The baseline risk classification was based on min–max normalization, equal weighting, and tercile-based classification. Agreement indicates the percentage of wells assigned to the same risk class as in the baseline scheme. High-risk overlap indicates the proportion of baseline high-risk wells that remained high risk under the alternative setting. For the risk-class threshold tests, Spearman's ρ equals 1.000 because the underlying risk scores were unchanged and only the class thresholds were modified. The trend-threshold sensitivity test evaluates how alternative near-zero slope thresholds affect the subdivision of statistically non-significant trends.

In summary, high-risk wells were generally characterized by larger DTW, continued DTW increase, stronger WLE decline, and greater annual amplitude. Low-risk wells, by contrast, tended to have shallower groundwater, more stable or increasing WLE behavior, and weaker fluctuations.

4. Discussion

The results indicate that recent groundwater-level change in the WLRB cannot be characterized by a single uniform basin-wide tendency. Regional WLE distributions and the overall groundwater–surface pattern remained broadly stable during 2019–2024, whereas individual monitoring wells showed both declining and increasing trends. This pattern is consistent with previous studies showing that groundwater depletion and localized water-level rise may coexist within aquifer systems where recharge conditions, groundwater use, and management histories differ spatially [9,13–15,41]. Similar local heterogeneity has been reported in intensively irrigated aquifers, including the High Plains and Central Valley aquifers [12]. For the WLRB, earlier GRACE-based, modelling, and broader-scale studies have emphasized groundwater storage depletion and the role of agricultural water demand [22–24]. The present study complements these studies by providing well-scale evidence that recent groundwater dynamics are locally heterogeneous even under a relatively stable regional background.

The observed seasonal pattern is broadly consistent with the semi-arid agricultural setting of the basin, where precipitation, evapotranspiration, and irrigation demand are strongly seasonal [53,54]. However, the present analysis did not separate the effects of rainfall, pumping, evapotranspiration, and recharge. The seasonal WLE signal should

therefore be treated as an observed groundwater-level response, rather than as evidence for a specific controlling process.

The WLE–DTW-based index provides a practical screening approach for relative groundwater stress. By combining groundwater-depth condition, recent trend direction, and intra-annual fluctuation, the index identifies wells where unfavorable groundwater conditions tend to occur together. The agreement among risk classes, trend classes, and groundwater dynamic types suggests that the index reflects meaningful differences in water-level behavior, not merely a ranking based on one variable. Nevertheless, the low-, medium-, and high-risk classes are relative categories within the WLRB monitoring network. They should not be interpreted as absolute groundwater-sustainability thresholds or transferred directly to other basins.

The spatial patterns identified here should not be interpreted as a quantitative attribution of drivers. Previous studies have pointed to agricultural pumping, climatic variability, land-use change, and groundwater regulation as possible controls on groundwater change in northern China and the WLRB [7,22–26,48]. These factors provide plausible context for the observed heterogeneity, but they were not explicitly included in this study. Therefore, groundwater-level decline, increase, and relative risk are used here as descriptive terms for monitoring-based water-level behavior, not as proof of exploitation effects, management-induced recovery, or policy outcomes.

From a management perspective, the proposed framework is most useful as an initial screening tool. High-risk wells indicate locations where deeper groundwater, adverse trends, and stronger fluctuations co-occur, and these sites should be prioritized for further monitoring and local investigation [55]. Future work should combine longer groundwater-level records with precipitation, evapotranspiration, abstraction, irrigation intensity, land-use change, recharge estimates, aquifer properties, and policy-implementation data [56]. With these data, lagged correlation analysis, regression-based methods, geographically weighted models, machine-learning approaches, or process-based groundwater modelling could be used to move from relative risk identification toward quantitative driver attribution and mechanism-based groundwater management [57].

5. Conclusions

This study examined recent groundwater dynamics and relative groundwater risk in the WLRB using daily records from 117 monitoring wells during 2019–2024. Regional WLE remained broadly stable, with a median annual value of approximately 192 m, while the seasonal anomaly showed an intra-annual range of about 0.54 m. At the well scale, 51 wells showed significant increases and 36 wells showed significant decreases, with Sen's slopes ranging from -2.75 to 0.61 m/year. These results demonstrate that the recent groundwater-level changes were strongly differentiated at the monitoring-well scale.

The four objectives of the study were addressed by quantifying interannual and seasonal WLE variability, identifying well-scale trends, mapping spatial groundwater-level changes, and constructing a WLE–DTW-based relative risk index. Trend analysis and spatial interpolation consistently showed that recent groundwater evolution did not follow a uniform basin-wide pattern. The risk index classified 39, 38, and 39 wells as low, medium, and high risk, respectively, and captured observed differences in groundwater-level behavior by integrating groundwater depth, trend direction, and fluctuation intensity.

From a management perspective, high-risk wells should be prioritized for enhanced monitoring and local verification of groundwater abstraction, recharge conditions, and irrigation use. The proposed framework provides a practical basis for screening groundwater stress in spatially heterogeneous semi-arid basins. However, the 2019–2024 study period is relatively short for assessing long-term groundwater trends, and the analysis did not quan-

titatively attribute groundwater-level changes to pumping, recharge, or climatic variability. Future work should extend the time series and incorporate climatic and anthropogenic drivers to support more mechanistic groundwater management.

Author Contributions: F.Y. mainly participated in the data resources, interpretation of results, and manuscript revision. Q.R. mainly participated in methodology development, data processing, statistical and spatial analyses, visualization, and manuscript drafting. J.Q. and X.L. contributed to supervision and manuscript review. W.L., Y.Z., J.W. and L.W. contributed to data compilation, data checking, and technical support. All authors have read and agreed to the published version of the manuscript.

Funding: This research was supported by the China Geological Survey (Grant No. DD202605101501).

Data Availability Statement: The data presented in this study are available from the corresponding author upon reasonable request. The data are not publicly available due to restrictions on regional groundwater monitoring data management.

Conflicts of Interest: The authors declare no conflicts of interest.

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