

Article

Spatiotemporal Evolution of Groundwater System Sustainability in Northeast China's Transboundary River Basins Under Agricultural Expansion and Climate Variability: Insights from GRACE Satellite Observations

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Abstract

Groundwater is a critical strategic resource supporting agricultural production and ecological security in the transboundary river basins of Northeast China. However, intensified climate variability and rapid agricultural expansion over the past two decades have imposed increasing pressure on regional groundwater systems. In this study, we integrated GRACE-derived terrestrial water storage anomalies, GLDAS land surface data, meteorological datasets, land-use information, and agricultural statistics to construct a comprehensive assessment framework consisting of groundwater storage anomalies (ΔGWS), the GRACE Groundwater Drought Index (GGDI), and sustainability indicators—REL (Reliability), RES (Resilience), VUL (Vulnerability), and SI (Sustainability Index). By integrating GRACE-derived groundwater dynamics with sustainability indicators (REL, RES, VUL, and SI), enabling a basin-scale, long-term assessment of groundwater sustainability across Northeast China's transboundary basins, and clarifying the relative roles of climatic variability and intensive human water use. We systematically examined the spatiotemporal evolution of groundwater conditions in the Heilongjiang, Suifen, Tumen, and Yalu River basins from 2002 to 2022, and quantified the relative roles of climatic and anthropogenic drivers. The results indicate that groundwater storage exhibited pronounced seasonal fluctuations alongside a persistent downward trend, with GGDI remaining predominantly negative after 2018, reflecting the development of structural groundwater drought. The SI declined markedly from 0.32 to 0.06, and areas with extremely low sustainability accounted for more than 90% of the study region in recent years. MIC-based dependence analysis showed that sown area (MIC = 0.98) and nighttime light intensity (MIC = 0.92) were the dominant drivers of groundwater degradation, exerting far greater influence than precipitation or potential evapotranspiration. These patterns highlight that policy-driven agricultural expansion and increased irrigation demand have surpassed natural recharge capacity, becoming the fundamental cause of long-term groundwater depletion. This study underscores the urgency of promoting agricultural green transformation, optimizing crop planting structures, improving irrigation efficiency, and enhancing ecological conservation to rebuild groundwater resilience. Moreover, coordinated cross-border groundwater monitoring and management will be essential for ensuring the sustainable use of water resources in Northeast Asia's transboundary river basins.



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Keywords: Northeast China; groundwater sustainability; agricultural expansion; GRACE; policy drivers

1. Introduction

With the intensification of global climate change and the continuous expansion of agricultural production, freshwater scarcity has become increasingly prominent worldwide [1]. As a critical water source supporting agricultural irrigation, ecosystem stability, and domestic water supply, groundwater is experiencing persistent depletion in many regions [2]. Numerous studies have shown that under enhanced climate variability and intensive human interference, the recharge–discharge balance of groundwater systems is disrupted, leading to groundwater storage decline, more frequent droughts, and elevated regional ecological risks [3]. Meanwhile, groundwater sustainability has emerged as a key issue in international water resources management [4]. However, in most regions, systematic understanding of the long-term evolution mechanisms of groundwater systems, the interactions among different driving factors, and the level of sustainable utilization remains limited, particularly in areas where the combined effects of climate change and human activities are pronounced [5].

The transboundary region of Northeast China, encompassing the Heilongjiang (Amur), Yalu, Suifen, and Tumen River basins, is located on the eastern margin of the Eurasian continent and represents a typical area with dense transboundary river systems. It is also an important grain production base and ecological barrier in China [6]. Influenced jointly by the natural conditions and socio-economic patterns of China, Russia, North Korea, and Mongolia, this region is characterized by a pronounced monsoonal climate, rapid land-use change, high agricultural irrigation demand, and accelerated urbanization, resulting in complex and sensitive hydrological processes [7]. Adjustments in agricultural planting structure, expansion of sown areas, and increasing population activities have further reinforced the importance of groundwater for regional food production and ecological security [8]. In addition, the absence of unified water resources management mechanisms in transboundary regions, together with inconsistent monitoring systems and divergent policy measures among countries, increases the uncertainty and management difficulty associated with groundwater system changes [9]. Therefore, conducting long-term assessments of groundwater system dynamics and sustainability in this region is of significant scientific importance and practical relevance [10].

Although previous studies have demonstrated the considerable potential of GRACE/GRACE-FO for monitoring large-scale groundwater storage (GWS) variations and groundwater-related drought conditions, substantial challenges remain in conducting regional groundwater sustainability assessments in cold and transboundary basins. Due to the influence of snow-related hydrological processes and the relatively coarse spatial resolution of satellite products, GRACE-based groundwater estimates may involve greater uncertainties in cold regions. Meanwhile, most existing studies have focused on individual basins or administrative units, and comprehensive assessments spanning multiple transboundary basins are still limited, making it difficult to systematically characterize long-term groundwater evolution across national boundaries [11]. To date, GRACE data have been widely applied to investigate groundwater changes in regions such as the North China Plain, the black soil region, and the Songnen Plain; however, integrated studies targeting the four major transboundary basins in Northeast China remain scarce [12–14]. In addition, the combined effects of multiple driving factors—including agricultural expansion, land-use change, urbanization, and climate variability (precipitation and evapotranspiration)—have

not yet been systematically evaluated, and attribution analyses in some studies still rely primarily on linear correlation approaches, which may be insufficient to capture the complex and nonlinear interactions between climatic and anthropogenic influences [15–18]. Moreover, most existing groundwater sustainability assessment methods emphasize surface water–groundwater interactions, irrigation water demand, or drought indices, and therefore have limited capability to provide an integrated interpretation of groundwater system conditions in terms of resilience, vulnerability, and long-term risk [19–21]. Overall, significant research gaps remain in “integrated transboundary assessment,” “identification of compound driving mechanisms,” and “development of comprehensive sustainability frameworks,” highlighting the need for an integrated analytical framework that can support the characterization of spatiotemporal groundwater dynamics and the interpretation of sustainability implications [22].

To address these limitations, this study focuses on the Heilongjiang, Yalu, Suifen, and Tumen River basins as the study area and integrates multi-source datasets, including GRACE/GRACE-FO, GLDAS, meteorological observations, land-use data, nighttime light intensity data, and agricultural statistics, to construct a comprehensive research framework consisting of groundwater storage inversion, groundwater sustainability assessment, and driving factor analysis [23]. Using this framework, the spatiotemporal evolution characteristics of groundwater in the transboundary basins of Northeast China during 2002–2022 and their primary influencing mechanisms are systematically revealed [24]. The main innovations of this study are threefold: (1) adopting an integrated transboundary basin perspective to establish a unified-scale analytical framework and comprehensively characterize the long-term changes in the groundwater system of Northeast China; (2) integrating multi-source data and multiple indicators to jointly investigate the dominant driving factors of groundwater change from both climate variability and human activities; and (3) introducing sustainability indices and groundwater drought indicators to comprehensively evaluate the recovery capacity, vulnerability, and long-term risks of the groundwater system, thereby providing quantitative references for regional water resources management. The findings of this study can offer scientific support for agricultural water-use regulation, water security assurance, and cooperative governance of transboundary water resources in Northeast China [25].

2. Materials and Methods

2.1. Study Area

The transboundary river basins of Northeast China are located in the border regions of China, Russia, and North Korea, encompassing four major international rivers: the Heilongjiang (Amur), Suifen, Tumen, and Yalu Rivers (Figure 1) [26]. The total area of the study region is approximately 2.18×10^6 km², accounting for about 35% of the total area of Northeast China [27]. The region exhibits diverse geomorphological features, including mountainous and hilly terrains such as the Greater Khingan Mountains and the Changbai Mountains, as well as extensive agricultural plains such as the Songnen Plain, where surface water–groundwater interactions are closely coupled [28]. The study area is located within one of the world’s three major black soil belts, characterized by fertile soils and moderate accumulated temperature, and represents a core grain-producing region in China, often referred to as the “Golden Corn Belt” and the “Golden Rice Belt” [29]. Major crops include maize, rice, and soybean [30].

Marked differences in agricultural development levels and management systems among countries result in pronounced gradients of human activities across the region. Agriculture in Northeast China is highly intensive with substantial irrigation demand; the Russian Far East is relatively less developed, with sparse population; and the northern parts

of North Korea are characterized by smaller-scale agriculture and limited water conservancy infrastructure [31–33]. The climate is dominated by a temperate continental monsoon regime, with mean annual precipitation ranging from approximately 450 to 850 mm and strong seasonal variability, of which more than 60% occurs during June–September [34]. Spatially, the northwest is relatively dry while the southeast is more humid, and the uneven distribution of water and heat conditions leads to long-term dependence on groundwater irrigation in certain areas [35]. Aquifer systems mainly include unconsolidated porous aquifers, carbonate fractured aquifers, and bedrock fractured aquifers, with groundwater depths ranging from approximately 5 to 150 m, resulting in complex hydrogeological settings [36].

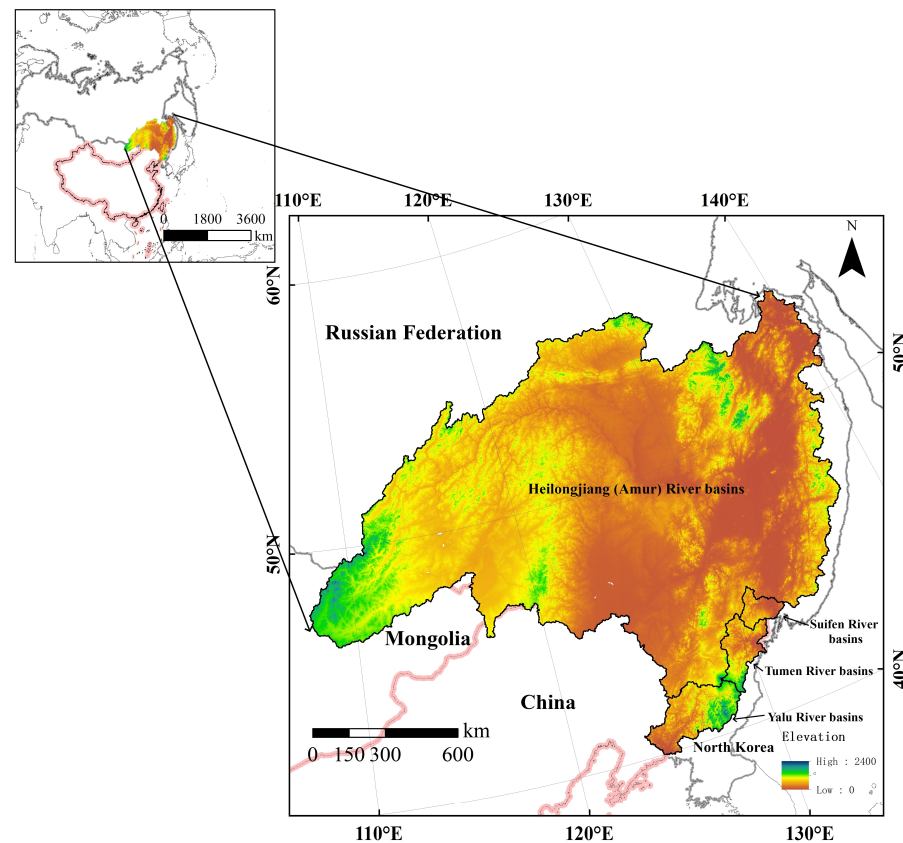


Figure 1. Overview map of the study area.

Overall, the transboundary river basins of Northeast China play a critical role in maintaining regional ecological security and food production, but they are simultaneously confronted with sustainability risks such as groundwater level decline, wetland degradation, and groundwater overexploitation [37].

2.2. Data Sources

This study integrates multi-source datasets, including gravity satellite observations, land surface process models, meteorological observations, land-use data, nighttime light intensity data, and agricultural statistics, to support groundwater storage inversion, sustainability assessment, and driving factor analysis. The sources, spatial and temporal resolutions, and specific applications of each dataset are systematically summarized in Table 1, while only their key functions are briefly described in the text.

Table 1. Datasets used in this study.

Data Category	Dataset Name and Source	Spatial/Temporal Resolution	Time Span	Purpose
Satellite gravimetry data	GRACE/GRACE-FO Mascon RL06 (CSR)	$0.25^{\circ} \times 0.25^{\circ}$	April 2002–December 2022 (249 months)	Retrieval of terrestrial water storage anomalies (TWSA) and estimation of groundwater storage changes (Δ GWS)
Terrestrial water data	GLDAS Noah (NASA GSFC, and NCEP)	$0.25^{\circ} \times 0.25^{\circ}$	2002–2022 (monthly)	Acquisition of soil moisture, snow water equivalent, and canopy water storage, used to estimate groundwater storage
Meteorological data	GPCC Monitoring Product (precipitation, PRE)	$1.0^{\circ} \times 1.0^{\circ}$	2002–2022	Assessment of precipitation variability and its relationship with groundwater changes
	MODIS MOD16A3 (potential evapotranspiration, PET)	500 m	2002–2022	Evaluation of the impact of evapotranspiration changes on groundwater storage
Land use data	Copernicus Global Land Cover	300 m	1992–present	Long-term monitoring of cropland, forest, wetland, and built-up land changes
Nighttime light intensity data	Global Annual Simulated VIIRS Nighttime Light intensity	500 m	1992–2023	Representation of regional human activity intensity
Agricultural statistics data	FAOSTAT (FAO) crop harvested area	National statistics	2002–2022	Analysis of agricultural scale and its temporal variation
	SPAM v3.0 (IFPRI) crop production maps	Multi-scale (≈ 10 km)	2000, 2010, 2020	Provision of the spatial distribution of crops and supplementary information on agricultural intensity

GRACE/GRACE-FO gravity satellite data were obtained from the Mascon RL06 product released by the Center for Space Research (CSR), University of Texas, and were used to derive terrestrial water storage variations [38]. The mascon solution has advantages in reducing signal leakage and minimizing dependence on post-processing filters, and it has been widely applied in regional-scale studies of terrestrial water storage variations and groundwater estimation. This product effectively corrects signal leakage caused by filtering through a mass concentration inversion approach and provides relatively high accuracy in terrestrial water storage anomaly (TWSA) analysis [39]. Its applicability in Northeast China has been validated by multiple studies, showing good consistency with in situ groundwater observations [40].

To isolate groundwater storage variations, land surface water storage components were derived from the Global Land Data Assimilation System (GLDAS) Noah land surface model [41,42]. This dataset provides key hydrological variables, including canopy water storage, snow water equivalent, and multilayer soil moisture, and has been widely applied in groundwater change studies [43]. In this study, GRACE anomalies (TWSA) were calculated relative to the 2004–2009 baseline period. To ensure consistency with the GRACE processing, the same 2004–2009 baseline was also applied to the non-water-balance components derived from GLDAS (e.g., soil moisture, snow, and canopy water storage)

when converting them to anomalies, thereby improving the consistency and reproducibility of the water-balance decomposition.

Regarding climatic driving factors, precipitation data were obtained from the GPCC Monitoring Product to characterize regional precipitation variability [44]. Potential evapotranspiration data were obtained from the MODIS MOD16A3 annual product (MOD16; NASA, Washington, DC, USA) to quantify the influence of evapotranspiration on groundwater recharge and depletion. This product has demonstrated high reliability in hydrological and climate-related studies [45,46].

Monthly precipitation data were obtained from the gridded product provided by the Global Precipitation Climatology Center (GPCC), with a spatial resolution of $1.0^{\circ} \times 1.0^{\circ}$. To derive basin-scale precipitation series, basin boundaries of each transboundary river basin were used as masks, and zonal statistics were applied to the GPCC precipitation grids. The mean value of all valid pixels within each basin (excluding NoData pixels) was calculated to construct a monthly basin-averaged precipitation time series for each basin.

Land-use change information was obtained from the global annual land cover dataset provided by the Copernicus Climate Data Store (CDS), which was used to characterize the long-term evolution of cropland, forest, wetland, and built-up land areas [47].

Human activity intensity and agricultural expansion were jointly characterized using nighttime light intensity data and agricultural statistics. Nighttime light intensity data were derived from the global annual simulated VIIRS nighttime light intensity dataset [48], which was used to reflect regional human activity intensity. Information on agricultural production scale was obtained from the FAOSTAT database [49] and further complemented by the Spatial Production Allocation Model (SPAM) gridded dataset released by the International Food Policy Research Institute (IFPRI) to characterize the spatial distribution patterns of crop cultivation [50,51].

2.3. Methods

Figure 2 summarizes the workflow of this study. GRACE/GRACE-FO TWSA, GLDAS components, climate variables (PRE and PET), land-use information, and basin boundaries were first collected and harmonized at a monthly scale. Basin masking and preprocessing were then performed to generate consistent basin-averaged time series and handle missing observations. Groundwater storage anomalies were estimated by subtracting non-groundwater water storage components from GRACE-based TWSA. Finally, groundwater sustainability was assessed, and the potential climatic and anthropogenic drivers were examined using both linear (Pearson) and nonlinear (MIC) analyses.

2.3.1. SSA Interpolation Method

Due to factors such as satellite maintenance, the CSR Mascon dataset contains 33 months of missing data during the study period. Consequently, the original dataset includes only 216 monthly records. Numerous studies have proposed the use of Singular Spectrum Analysis (SSA) for data gap filling [52,53]. This method has the advantage of stably identifying and enhancing periodic signals, and previous analyses have demonstrated its high reliability in filling terrestrial water storage datasets [54,55].

Therefore, to improve the temporal continuity and completeness of the CSR Mascon data, this study employed publicly available software packages to perform SSA-based missing-data reconstruction on the gridded GRACE-derived TWSA time series. The window length was set to $M = 48$, and the number of reconstructed components (RCs) was set to $K = 8$ [56]. The basic procedure of SSA interpolation is described as follows.

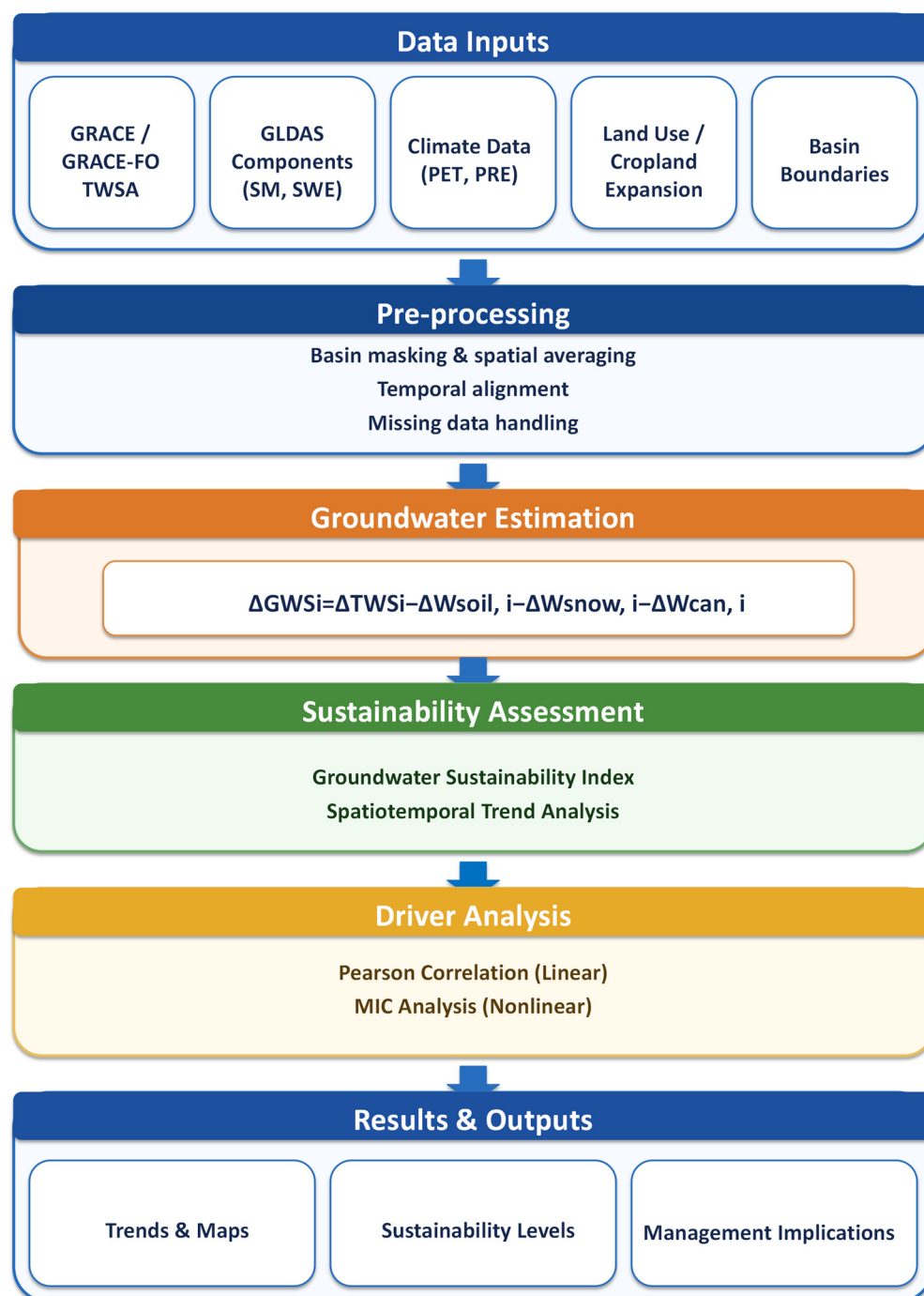


Figure 2. Methodological framework (flowchart).

Converting time series $X = [x_1, x_2, \dots, x_N]$ into a trajectory matrix [57]:

$$Y = \begin{bmatrix} x_1 & x_2 & \dots & x_L \\ x_2 & x_3 & \dots & x_{L+1} \\ \vdots & \vdots & \ddots & \vdots \\ x_M & x_{M+1} & \dots & x_N \end{bmatrix} \quad (1)$$

In the formula, the number of columns $L = N + 1 - M$, where N is the length of the time series, and M is the window length.

Use matrix Y to form the lagged covariance matrix YY' . Let $\lambda_1, \lambda_2, \dots, \lambda_m$ be the eigenvalues of YY' . The corresponding feature vectors are denoted by $U_1, U_2, \dots, U_m$, and it is assumed that $k = \text{rank}(Y)$.

$$Y = X_1 + X_2 + \dots + X_k \quad (2)$$

Therefore, the original series G is reconstructed by performing diagonal averaging on the matrix Y , as expressed below [58]:

$$G_i = \begin{cases} \frac{1}{i} \sum_{m=1}^i Z_{m, i-m+1}^*, 1 \leq i < M^* \\ \frac{1}{M^*} \sum_{m=1}^{M^*} Z_{m, i-m+1}^*, M^* \leq i < L^* \\ \frac{1}{N-i+1} \sum_{m=i-L^*+1}^{N-L^*+1} Z_{m, i-m+1}^*, L^* \leq i < N \end{cases} \quad (3)$$

G represents the time series interpolated at a given location using the SSA method, with the dataset completed to a total length of 249 months.

2.3.2. Inversion of Groundwater Storage Anomalies (ΔGWS)

Based on the water balance relationship, groundwater storage changes were isolated by combining GRACE-derived TWSA with GLDAS water storage components through a residual-based decomposition approach. This framework has been widely adopted in regional-scale groundwater change studies and provides an effective means to characterize long-term trends and relative variations in groundwater dynamics in regions where dense in situ monitoring data are limited or unavailable [59].

$$\Delta GWS_i = \Delta TWS_i - \Delta W_{soil, i} - \Delta W_{snow, i} - \Delta W_{can, i} \quad (4)$$

In this equation, ΔGWS_i represents the monthly mean groundwater storage change, ΔTWS_i denotes the monthly mean terrestrial water storage change, $\Delta W_{soil, i}$ represents the monthly mean soil water storage change, $\Delta W_{snow, i}$ denotes the monthly mean snow water equivalent change, and $\Delta W_{can, i}$ represents the monthly mean canopy water storage change. To ensure consistency in the water balance decomposition, both GRACE-derived TWSA and the non-groundwater component anomalies from GLDAS were converted to anomalies using the multi-year mean over the common reference period of 2004–2009.

2.3.3. GRACE Groundwater Drought Index (GGDI)

The first step is to calculate the monthly climatological mean of the GRACE-derived groundwater storage anomaly (C_i) (i.e., the mean seasonal cycle for each calendar month). The calculation is as follows [60]:

$$C_i = \frac{\sum_1^{n_i} \Delta GWS_{i,j}}{n_i}, i = 1, 2, \dots, 12 \quad (5)$$

where i ($i = 1, 2, \dots, 12$) denotes the calendar month, and $\Delta GWS_{i,j}$ represents the GRACE-derived groundwater storage anomaly in month i for the j -th year. n_i is the number of available observations for month i over the study period (i.e., the sample size of month i after excluding missing months). It should be noted that the removal of the monthly climatology (i.e., the mean seasonal cycle) is used to remove seasonality and highlight anomalous variations, whereas the subsequent standardization is applied to place the index on a comparable, dimensionless scale (e.g., for comparison with other drought indices). However, such standardization does not eliminate structural differences arising

from different GRACE products or auxiliary data/model combinations, and thus product-dependent biases may still propagate into GGDI.

The groundwater storage deviation (GSD) is obtained by removing the monthly climatological component from the GRACE-derived groundwater storage anomaly series, thereby isolating the non-seasonal groundwater drought signal.

The groundwater storage deviation (GSD) was calculated as:

$$GSD_t = \Delta GWSt - Cim(t). \quad (6)$$

where GSD_t is the groundwater storage deviation at time t , $\Delta GWSt$ is the GRACE-derived groundwater storage anomaly at time t , and $Cim(t)$ is the monthly climatic component corresponding to the calendar month m of time t ($m = 1-12$).

The final step is to standardize the GSD series by subtracting its mean and dividing by its standard deviation to obtain GGDI, as follows [61]:

$$GGDI = \frac{(GSD_t - \overline{GSD})}{S_{GSD}} \quad (7)$$

In the above equation, GSD_t represents the groundwater storage deviation, which is calculated by removing the monthly climatological (seasonal-cycle) component from the groundwater storage change derived from GRACE (Gravity Recovery and Climate Experiment) observations. GSD is further defined as the mean value of GSD_t , while S_{GSD} denotes the standard deviation of GSD_t .

2.3.4. Groundwater Sustainability Assessment (SI)

The sustainability index (SI) was constructed using the method proposed by Loucks and Sandoval-Solis [62]:

$$SI = REL \times RES \times (1 - VUL) \quad (8)$$

REL (Reliability): is defined as the historical probability of aquifer storage being below normal conditions, i.e., the percentage of GGDI at reliable levels.

$$REL = \frac{n_{GGDI > 0}}{n} \quad (9)$$

RES (Resilience): indicates the likelihood of the groundwater system recovering from a deficit state to a surplus state, i.e., the probability of the GGDI shifting from negative to positive values

$$RES = \frac{n_{GGDI < 0 \rightarrow GGDI > 0}}{n} \quad (10)$$

VUL (Vulnerability): is defined as the probability of drought occurring in a groundwater system, i.e., the ratio of negative GGDI values.

$$VUL = \frac{n_{GGDI < 0}}{n} \quad (11)$$

In this equation, $n_{GGDI > 0}$ denotes the number of occurrences in which the GRACE Groundwater Drought Index (GGDI) is greater than 0, $n_{GGDI < 0 \rightarrow GGDI > 0}$ represents the number of transitions of GGDI from values less than 0 to values greater than 0, and $n_{GGDI < 0}$ indicates the number of occurrences in which GGDI is less than 0 [63], where n is the total number of monthly GGDI observations within the selected period, and $n > 0$ denotes the number of months with GGDI > 0.

The above indices were classified and evaluated according to previous studies, and the assessment results are presented in Table 2 [64].

Table 2. Classification criteria for REL, RES, VUL, and SI.

Grade	Range			
	REL	RES	VUL	SI
Extremely low	0–0.25	0–0.20	0–0.10	0–0.20
Low	0.25–0.40	0.20–0.30	0.10–0.40	0.20–0.30
Moderate	0.40–0.60	0.30–0.50	0.40–0.60	0.30–0.50
High	0.60–0.75	0.50–0.75	0.60–0.75	0.50–0.75
Extremely high	0.75–1	0.75–1	0.75–1	0.75–1

Notes: REL (Reliability), RES (Resilience), VUL (Vulnerability), and SI (Sustainability Index).

2.3.5. Driving Factor Analysis

To more accurately identify the dominant driving factors of changes in groundwater sustainability, this study constructed an integrated diagnostic framework by jointly applying the MIC and Pearson correlation analysis methods [65]. The Pearson correlation coefficient was mainly used to determine the direction and strength of linear relationships between groundwater sustainability (SI) and various climatic and human activity factors. In contrast, MIC can characterize more complex dependency structures, including both linear and nonlinear relationships, and can be used to compare the relative importance of different driving factors [66]. The combined use of these two methods allows the driving mechanisms to be examined from complementary perspectives, thereby improving the robustness and comprehensiveness of the analysis and providing a solid basis for understanding groundwater system dynamics under the combined influences of agricultural expansion and urbanization [67].

In 2011, Reshef et al. [67] proposed the Maximal Information Coefficient (MIC), which can be used to identify potential relationships between two variables and to quantify both linear and nonlinear associations.

The basic expression of MIC is as follows:

$$MIC(X, Y) = \max_{m, n \leq B(N)} \frac{I^*(m, n)}{\log(\min(m, n))} \quad (12)$$

$I^*(m, n)$ denotes the maximal mutual information under an $m \times n$ grid partition; $B(N)$ is a constraint function related to the sample size and is generally set to 0.6. The MIC ranges from 0 to 1, with values closer to 1 indicating stronger dependence between variables.

Pearson correlation analysis is a traditional and widely used statistical method for describing the strength and direction of linear relationships between two continuous variables [68].

The Pearson correlation coefficient R is calculated as follows:

$$R = \frac{\sum_{i=1}^n (x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^n (x_i - \bar{x})^2 \cdot \sum_{i=1}^n (y_i - \bar{y})^2}} \quad (13)$$

where x_i and y_i are the sample values of the two variables, $\bar{x}$ and $\bar{y}$ denote their respective sample means, and $R \in [-1, 1]$, with values closer to ± 1 indicating stronger linear correlation [69].

For driving-factor analysis, monthly SI (and climatic variables) were aggregated to annual means to match the annual SA/NTL/PET series before MIC and Pearson analyses.

2.3.6. Time-Series Robustness Analysis (RAPS and ITA)

To strengthen the robustness of time-series interpretation and to capture possible irregular behaviors beyond monotonic trend tests, we additionally applied Rescaled Adjusted

Partial Sums (RAPS) [70] and Innovative Trend Analysis (ITA) [71] to the key hydrological outcomes and their drivers. For a time series x_i ($i = 1, 2, \dots, n$), the standardized anomaly is computed as follows:

$$z_i = \frac{x_i - \bar{x}}{s} \quad (14)$$

where $\bar{x}$ and s are the mean and standard deviation, respectively. The RAPS curve is defined as:

$$RAPS_k = \sum_{i=1}^k \frac{x_i - \bar{x}}{s} \quad (15)$$

and changes in its slope indicate potential regime shifts. ITA divides the series into two equal halves, sorts each half, and plots the sorted first-half values against the sorted second-half values; points mainly above (below) the 1:1 line indicate an increasing (decreasing) tendency, while larger scatter suggests stronger variability. RAPS/ITA were used for GGDI (and ΔGWS when appropriate) and for PRE, PET, SA, and NTL to support the interpretation of stage-wise evolution and potential decoupling patterns [72].

3. Results

3.1. Spatiotemporal Anomaly Characteristics of Groundwater Storage

Figure 3 illustrates the spatiotemporal distribution characteristics of groundwater storage anomalies (ΔGWS) in the four major transboundary river basins of Northeast China during 2002–2022. Overall, groundwater storage in the study area exhibits pronounced variability at the monthly scale, with substantial differences in monthly mean values across different months: the highest regional mean value occurs in July (4.766 cm), while the lowest regional mean value is observed in February (-0.305 cm). This pronounced seasonal variation is closely associated with factors such as the concentration of regional precipitation in summer, winter freezing conditions, and increased irrigation demand during spring.

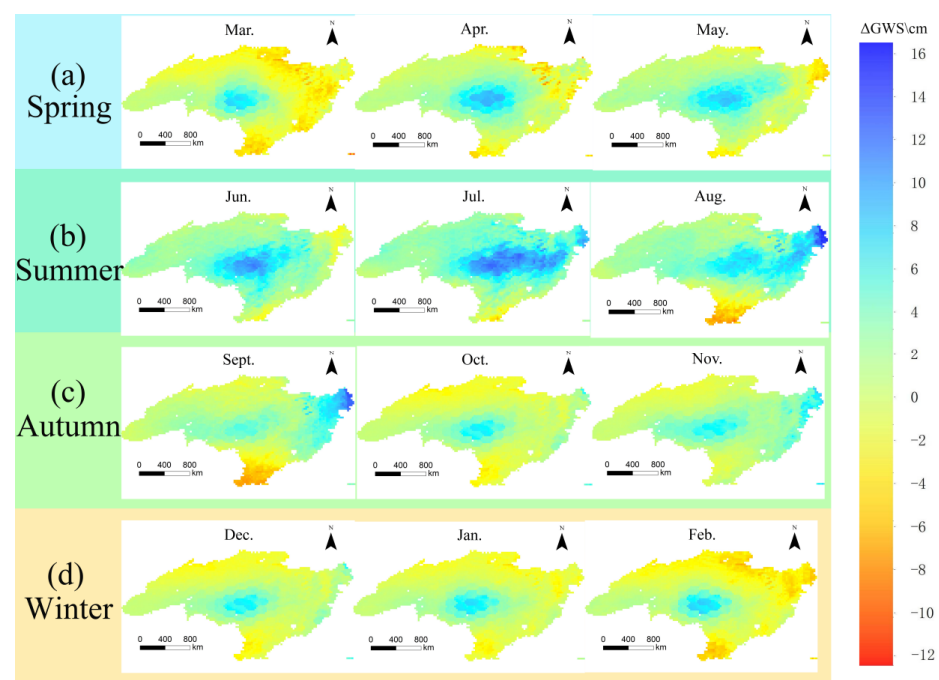


Figure 3. Multiyear monthly mean groundwater storage anomalies (ΔGWS , cm) in the transboundary river basins of Northeast China during 2002–2022. (a) Spring (Mar–May): Mar., Apr., May. (b) Summer (Jun–Aug): Jun., Jul., Aug. (c) Autumn (Sep–Nov): Sep., Oct., Nov. (d) Winter (Dec–Feb): Dec., Jan., Feb.

In terms of spatial distribution, ΔGWS also exhibits pronounced regional heterogeneity. The maximum ΔGWS reaches 15.826 cm in the northeastern part of the Heilongjiang (Amur) River basin, indicating a relatively strong water surplus capacity. In contrast, the minimum ΔGWS value of -8.97 cm occurs in the southern part of the Yalu River basin, reflecting weak groundwater recharge capacity or relatively high consumption pressure in this area. Overall, the Heilongjiang (Amur) River basin, where agricultural areas are densely distributed, shows more pronounced groundwater storage fluctuations, whereas mountainous and hilly regions (e.g., the Tumen and Yalu River basins) exhibit smaller variations and are less influenced by human activities.

3.2. Spatiotemporal Variations of GGDI

Figure 4 illustrates the temporal evolution of GGDI. From 2002 to December 2009, groundwater storage alternated between surplus and deficit conditions. During the period from January 2010 to May 2015, groundwater storage was generally in a deficit state. From June 2015 to May 2018, groundwater storage was predominantly characterized by surplus conditions, except for June–July 2016 and March–June 2017. From June 2018 to December 2022, GGDI entered a persistent and pronounced deficit phase, with only brief recoveries observed during September–October 2020 and March–April 2021.

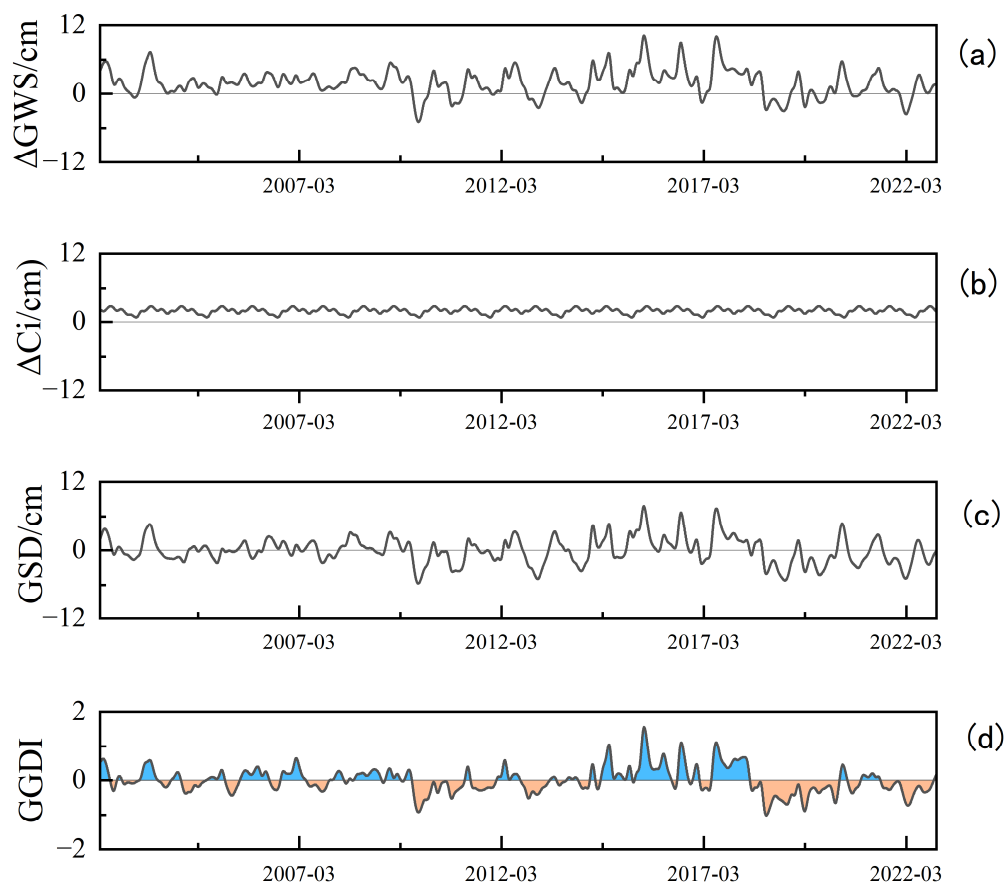


Figure 4. Time series of (a) ΔGWS , (b) C_i , (c) GSD , and (d) $GGDI$. In (d), blue and orange shaded areas indicate positive and negative $GGDI$ values, respectively.

As shown in Figure 5, the RAPS curve of $GGDI$ exhibits a clear multi-stage cumulative behavior with several slope transitions over the study period, indicating pronounced regime shifts rather than a single stable evolution. Persistent declining segments of RAPS correspond to sustained negative $GGDI$ departures (deficit-dominated conditions), whereas recovery segments reflect a relative improvement in groundwater sustainability. This

objective diagnosis is consistent with the stage-wise interpretation in Figure 4, thereby strengthening the reliability of the results. The ITA scatter plot further shows an overall downward shift from the first half to the second half of the record, with most points located below the 1:1 reference line, implying generally lower GGDI levels and intensified groundwater stress in the later period. Moreover, the dispersion of points around the 1:1 line suggests notable temporal variability and potential irregular fluctuations, supporting the adoption of a stage-wise framework to interpret groundwater-system evolution.

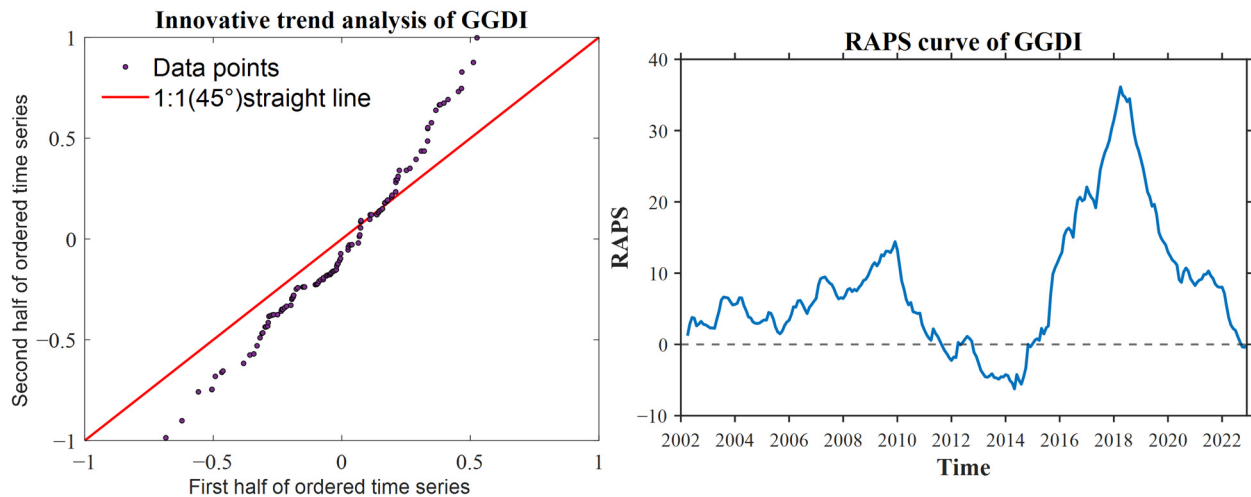


Figure 5. RAPS and ITA Diagnostics of GGDI.

3.3. Groundwater Sustainability Assessment in the Transboundary River Basins of Northeast China

To facilitate interpretation of the long-term evolution of groundwater sustainability, the study period (April 2002–December 2022) was divided into four multi-year stages: 2002–2007, 2008–2012, 2013–2017, and 2018–2022. This segmentation was designed for the following goals: (1) to ensure comparable time-window lengths with sufficient observations for robust estimation of reliability (REL), resilience (RES), vulnerability (VUL), and the sustainability index (SI); (2) to reflect major stage-wise shifts in groundwater conditions identified from the Δ GWS and GGDI time series.

This study evaluated the sustainability of the groundwater system in the transboundary river basins of Northeast China from April 2002 to December 2022. From a temporal perspective, groundwater sustainability in the study area exhibits an overall declining trend. In 2002, the sustainability level was relatively high ($SI = 0.56$). After 2003, sustainability rapidly decreased to a moderate level and further declined to a low level in 2004. Since 2008, groundwater sustainability in the transboundary river basins of Northeast China has continuously deteriorated, eventually reaching an extremely low level.

Figure 6 illustrates the spatial distributions of reliability (REL), resilience (RES), vulnerability (VUL), and the sustainability index (SI) of the groundwater system in the transboundary river basins of Northeast China during four periods: 2002–2007, 2008–2012, 2013–2017, and 2018–2022. During 2002–2007, most plain areas and the eastern part of the Heilongjiang (Amur) River basin exhibited poor sustainability ($SI < 0.2$), whereas the western part of the basin showed extremely high sustainability ($SI > 0.9$). During 2008–2012, the overall condition deteriorated markedly, with extremely low sustainability ($SI < 0.1$) observed in the central and western regions, and the area of low sustainability in the eastern Heilongjiang (Amur) River basin further expanded. During 2013–2017, sustainability declined across the entire region ($SI < 0.2$). During 2018–2022, groundwater sustainability

decreased substantially, with SI values below 0.2 across nearly the entire basin, indicating an extremely low sustainability state.

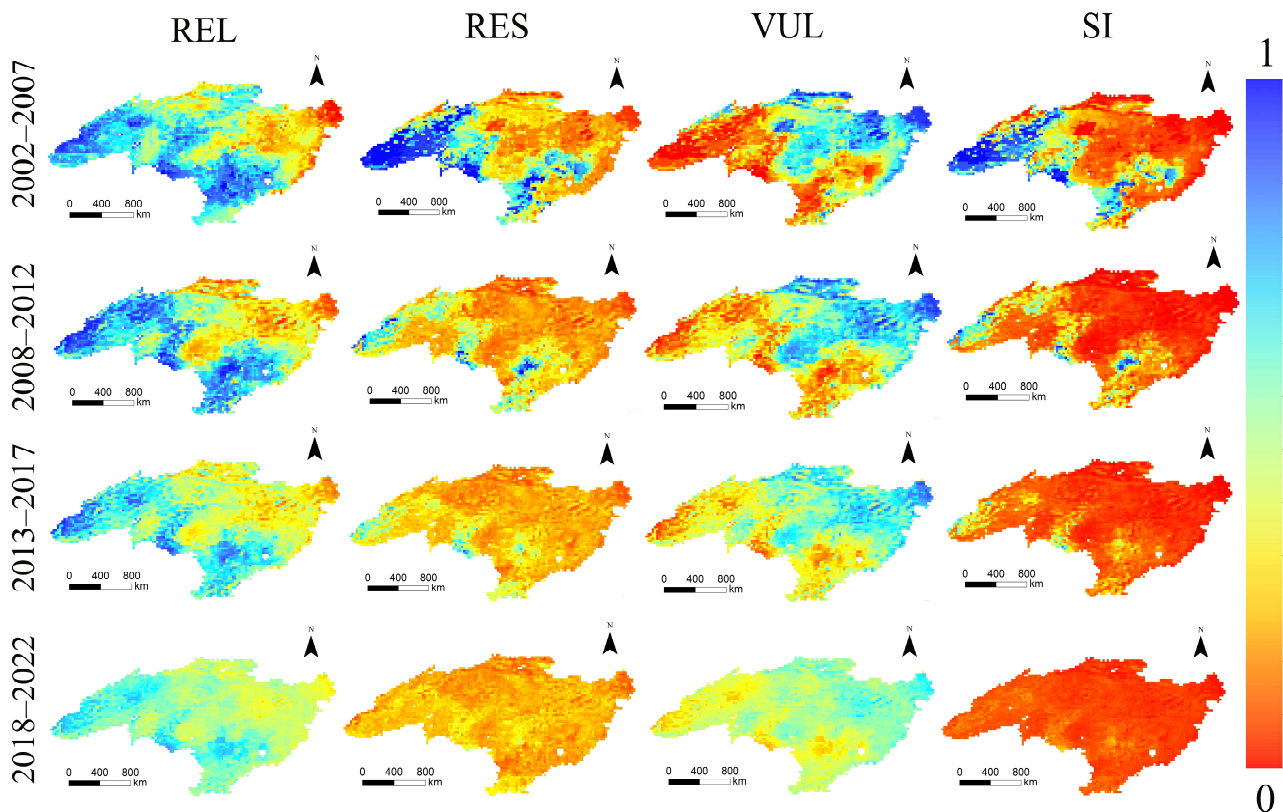


Figure 6. Spatial distribution of groundwater REL (Reliability), RES (Resilience), VUL (Vulnerability), and SI (Sustainability Index) in the transboundary river basins of Northeast China during different periods.

As shown in Figures 6 and 7, groundwater sustainability has declined markedly since 2002. During 2002–2007, areas with extremely low sustainability accounted for 51.6% of the region. Overall groundwater sustainability was classified as moderate, with an average sustainability index (SI) of 0.32. During 2008–2012, the proportion of extremely low sustainability areas increased to 76.8%, while the proportions of high and very high sustainability areas declined to 4.4% and 1.6%, respectively. The proportion of moderately sustainable areas remained relatively stable, resulting in an overall decline in groundwater sustainability to a low level, with an average SI of 0.14. During 2013–2017, the proportion of extremely low sustainability areas continued to increase, whereas the proportions of moderate and high sustainability areas consistently decreased. Overall sustainability remained on a downward trajectory, with an average SI of 0.09. During 2018–2022, groundwater system conditions further deteriorated, presenting a concerning situation. Nearly all areas exhibited extremely low or low sustainability levels, accounting for 99.6% and 0.4% of the region, respectively, with an average SI of 0.06. These results indicate that the groundwater system has entered a highly vulnerable state.

3.4. Analysis of Factors Influencing Groundwater Sustainability

As shown in Figure 8, precipitation (PRE), potential evapotranspiration (PET), sown area (SA), and nighttime light intensity (NTL) all exhibit clear temporal trends. The Mann–Kendall (MK) trend test results indicate that PRE, PET, NTL, and SA have all increased significantly. RAPS and ITA results show distinct evolution patterns among PRE, PET, SA, and NTL, with PET, SA, and NTL exhibiting cumulative tendencies consistent

with their overall increases, whereas PRE displays stronger interannual variability. These findings further support the trend-test results and suggest potential short-term oscillations and regime shifts under long-term change. To comprehensively evaluate the impacts of these factors on groundwater sustainability (SI), this study did not exclude other potential influencing variables but instead employed a combined approach using maximal information coefficient (MIC) analysis and Pearson correlation analysis to examine the relationships between these four indicators and SI. The results show that sown area exhibits the highest MIC value and the largest absolute Pearson correlation coefficient ($|R|$) among the four indicators (Table 3), indicating that sown area is the most significant factor affecting groundwater sustainability.

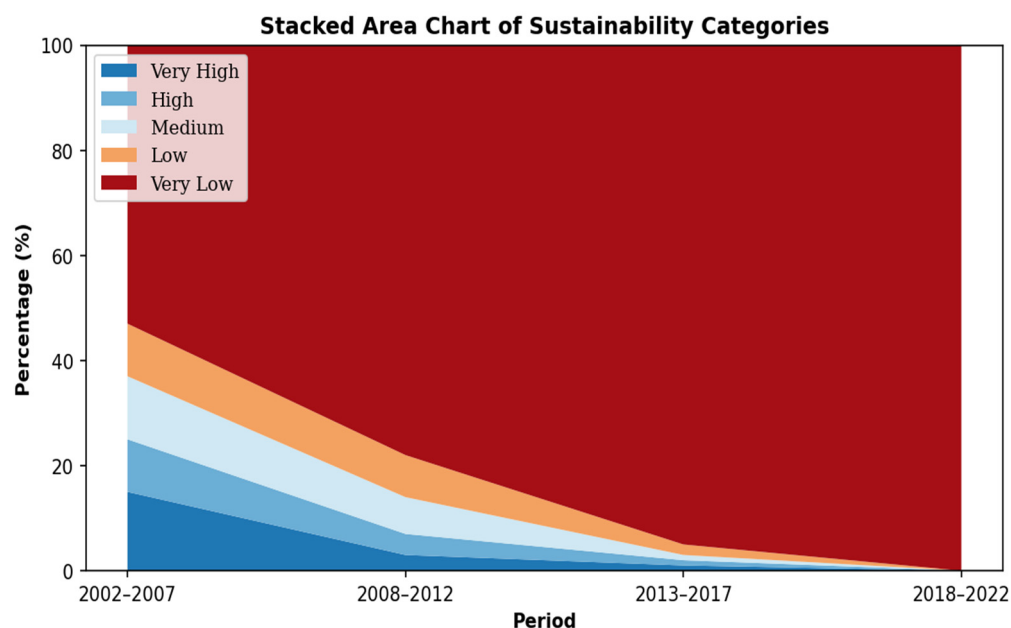


Figure 7. Proportions of different groundwater sustainability levels in the study area during different periods.

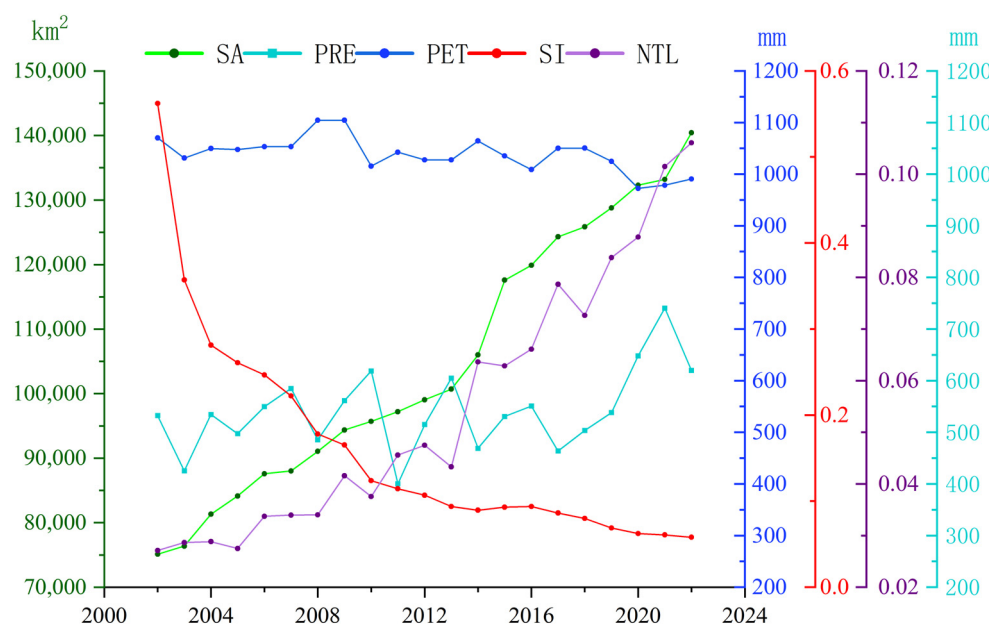


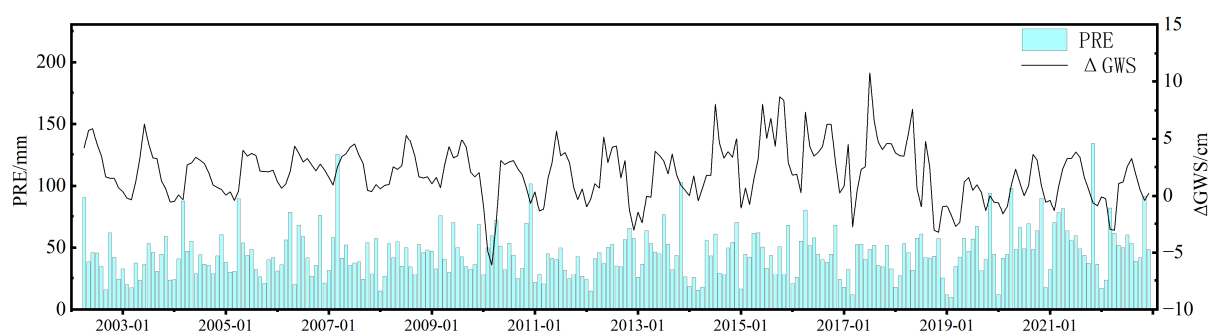
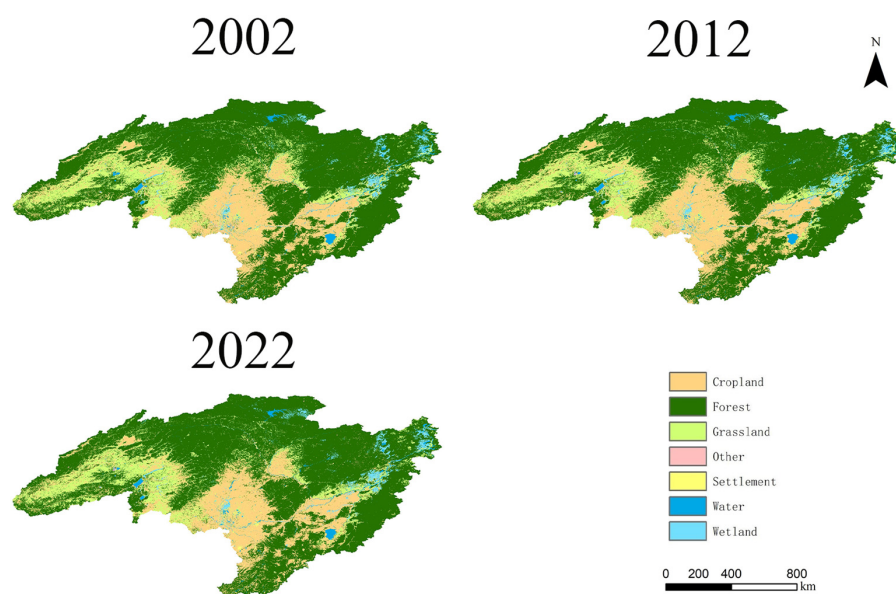
Figure 8. Temporal variations of factors influencing groundwater sustainability. The time series of various sustainability metrics, with the left y-axis representing SA (km^2) in green, and the right y-axis representing PRE (mm), SI, NTL, and PET (mm) in blue, red, purple and cyan, respectively.

Table 3. Responses of multiple variables to MIC and Pearson correlation coefficients.

	SA	PRE	PET	NTL
MIC	0.98	0.38	0.44	0.92
R	−0.79	−0.27	−0.43	−0.70

3.4.1. Relationship Between Precipitation and Δ GWS

Figure 9 shows that there is a certain degree of correlation between groundwater storage changes (Δ GWS) and precipitation in the transboundary river basins of Northeast China; however, the Pearson correlation coefficients are low, indicating a weak linear relationship (Table 3). Overall, GWS and precipitation variations exhibit relatively high consistency, with both showing closely related periodic fluctuations. During 2009–2015, both precipitation and GWS declined to varying degrees. After 2016, precipitation remained relatively stable, whereas groundwater storage continued to show a declining trend. Furthermore, ITA comparison indicates that the magnitude shift in PRE between the two halves of the record is weaker than that in Δ GWS, and when combined with their RAPS behaviors, this provides additional evidence that groundwater variations are not fully controlled by precipitation fluctuations. Under the relatively limited precipitation changes in the later period, intensified anthropogenic impacts may have driven continued groundwater depletion, leading to inconsistent responses of groundwater storage to precipitation changes.

**Figure 9.** Variations in Δ GWS and precipitation during 2002–2022.**Figure 10.** Changes in land-use types in the study area between 2002 and 2022.

3.4.2. Land-Use Change

Figure 10 illustrates the changes in land-use types in the transboundary river basins of Northeast China during 2002–2022. Overall, cropland and forest land exhibit relatively small changes, with cropland area increasing by only 0.96% and forest land slightly decreasing by 0.16%. Grassland area declined by 5.05%. In contrast, the areas of water bodies and wetlands expanded markedly, increasing by 6.05% and 12.17%, respectively. Other land-use types decreased by 10.24%, whereas Settlement (built-up) increased substantially, with a growth rate as high as 75.07%.

4. Discussion

4.1. Effects of Climatic Factors on Groundwater Sustainability

It should be noted that the climatic influence on groundwater sustainability may be obscured by other controlling factors, which helps explain the seemingly inconsistent evidence among different figures and tables. Figure 3 mainly reflects seasonal variability and generally supports the role of precipitation in regulating short-term groundwater storage fluctuations. However, the stage-based results in Figure 8 and Table 3 represent integrated sustainability conditions, where the direct statistical relationship with precipitation becomes weaker. In theory, both precipitation (as the main input) and potential evapotranspiration (PET, as a proxy of atmospheric water demand) should affect groundwater recharge and storage. Nevertheless, in cropland-dominated sub-regions, intensive human water use (e.g., seasonal irrigation pumping and water management practices) can disrupt the natural balance between climatic inputs and losses, thereby weakening the apparent correlations of precipitation and PET with groundwater sustainability indicators. Therefore, our results suggest that climate factors contribute to the seasonal groundwater signal, while long-term sustainability patterns are jointly shaped by evapotranspiration demand and human water withdrawal, particularly in agricultural hotspots.

The results indicate that the impacts of climatic factors on groundwater storage and sustainability exhibit pronounced seasonal and regional characteristics [73]. The relationship between precipitation (PRE) and groundwater is relatively complex. On the one hand, precipitation is the primary source of groundwater recharge, and abundant rainfall during the summer wet season can temporarily increase ΔGWS values, leading to short-term recovery in some areas. On the other hand, at the interannual scale, precipitation shows considerable variability, and slight increases in precipitation are insufficient to offset the long-term groundwater depletion caused by human activities. The MIC results show that the correlation between PRE and groundwater sustainability is relatively low (MIC = 0.382), indicating that precipitation variability has limited explanatory power for changes in groundwater sustainability [74].

Potential evapotranspiration (PET) exhibits an increasing trend, implying enhanced evaporative losses and reduced effective infiltration. This effect is particularly evident during the early stages of crop growth in spring and during periods of high summer temperatures, when elevated PET further weakens groundwater recharge capacity. The moderate correlation of PET (MIC = 0.4401) suggests that it has become an important climatic factor influencing groundwater recovery rates [75]. In the cold temperate regions of Northeast China, permafrost and seasonal frozen soil exert strong controls on hydrological processes: winter freezing reduces soil permeability, nearly interrupting recharge during winter and early spring, while concentrated runoff during the spring thaw is unfavorable for infiltration. Consequently, groundwater systems exhibit delayed and nonlinear responses to climatic variability [76]. Overall, although climatic factors play a certain role, they are insufficient to explain the continuously intensifying groundwater deficits observed over the past two decades.

4.2. Effects of Human Activities on Groundwater Sustainability

Compared with climatic factors, human activities exert more direct and stronger impacts on groundwater systems. The MIC results indicate that the correlation between sown area (SA) and the groundwater sustainability index (SI) is as high as 0.98, approaching an almost perfectly consistent variation pattern, which demonstrates that agricultural expansion is the dominant driver of the decline in groundwater sustainability [77].

As shown in Figure 10 and Table 4, although the areal extent of cropland in the study region changed only slightly during 2002–2022, FAOSTAT data indicate a substantial intensification of agricultural production over the past two decades. Specifically, the sown area increased from 75,104 km² to 140,427 km², representing a growth of 86.97%, while total grain production increased by 114.93%. It should be noted that land-cover data (Table 4) mainly reflect changes in cropland extent at the basin scale, which may remain relatively stable, and therefore may not fully capture the intensification of agricultural activities. In contrast, FAOSTAT indicators (e.g., sown area and crop production) better characterize changes in cultivation intensity, cropping structure, and associated water demand. Consequently, even when the proportion of cropland exhibits only slight variation, increased agricultural intensity and seasonal irrigation withdrawals can still impose substantial pressure on groundwater systems. Along with the expansion and intensification of agriculture, irrigation water withdrawals increased rapidly, and in many areas groundwater abstraction exceeded natural recharge capacity, leading to a continuous decline in GGDI and a persistent deterioration of SI [78].

Table 4. Characteristics of land-use type changes in the transboundary river basins of Northeast China during 2002, 2012, and 2022.

Year	Land Use Types (km ²)						
	Cropland	Forest	Grassland	Other	Settlement	Water	Wetland
2002	452,584.33 (20.73%)	1,361,235.43 (62.35%)	289,055.71 (13.24%)	4922.95 (0.23%)	8570.58 (0.39%)	29,084.44 (1.33%)	37,626.05 (1.72%)
2012	456,727.60 (20.92%)	1,361,216.01 (62.35%)	280,980.51 (12.87%)	4321.00 (0.20%)	11,660.00 (0.53%)	29,766.24 (1.36%)	38,410.82 (1.76%)
2022	456,953.84 (20.93%)	1,359,058.91 (62.25%)	274,464.70 (12.57%)	4418.88 (0.20%)	15,005.00 (0.69%)	30,975.20 (1.42%)	42,205.64 (1.93%)

The high correlation of nighttime light intensity (NTL) (MIC = 0.92) reveals another important mechanism associated with urbanization and economic activities. On the one hand, built-up land increased by 75.07%, indicating that population growth and economic expansion have significantly raised domestic and industrial water demand. On the other hand, large-scale urbanization has altered land surface infiltration conditions, further reduced natural recharge, thereby exacerbating groundwater depletion [79]. In addition, increasing levels of agricultural mechanization, changes in cropping structure (e.g., the expansion of water-intensive crops such as maize, rice, and soybean), and infrastructure development in rural areas have collectively imposed sustained pressure on groundwater systems [80]. Overall, the intensification of human activities has disrupted the natural equilibrium of regional groundwater systems and represents the fundamental driving force behind the transition from episodic groundwater fluctuations to structural groundwater drought.

4.3. Impacts of Agricultural and Regional Development Policies on Groundwater Systems

The results indicate that policy-driven intensification of human activities constitutes an important institutional driver of the continuous decline in groundwater sustainability in the study region. Agricultural support policies centered on food security have, to some extent,

promoted cropland expansion and increases in sown area, thereby intensifying irrigation water demand and representing a key pathway through which groundwater changes are influenced. Although recent climate warming has led to increased snowmelt and slightly improved precipitation conditions, partially alleviating surface water shortages in some areas, such enhancement of natural recharge remains insufficient to offset the sustained water demand associated with large-scale agricultural production. Consequently, groundwater systems have long remained in an imbalanced state characterized by “high consumption–low recharge,” ultimately manifested as persistently negative GGDI values and a continuous decline in SI [81].

It should be noted that, within the context of large transboundary river basins, groundwater changes are not the outcome of a single agricultural policy, but rather the integrated result of multiple policy influences. In addition to agricultural development policies, regional economic revitalization strategies, infrastructure construction, urbanization processes, and water resources allocation and management regimes also exert long-term impacts on groundwater systems by altering land-use structures, water demand patterns, and recharge conditions. The correspondence between sown area expansion, changes in groundwater sustainability, and key policy milestones illustrated in Figure 11 reflects the cumulative effects of policy interventions on groundwater systems at different stages.

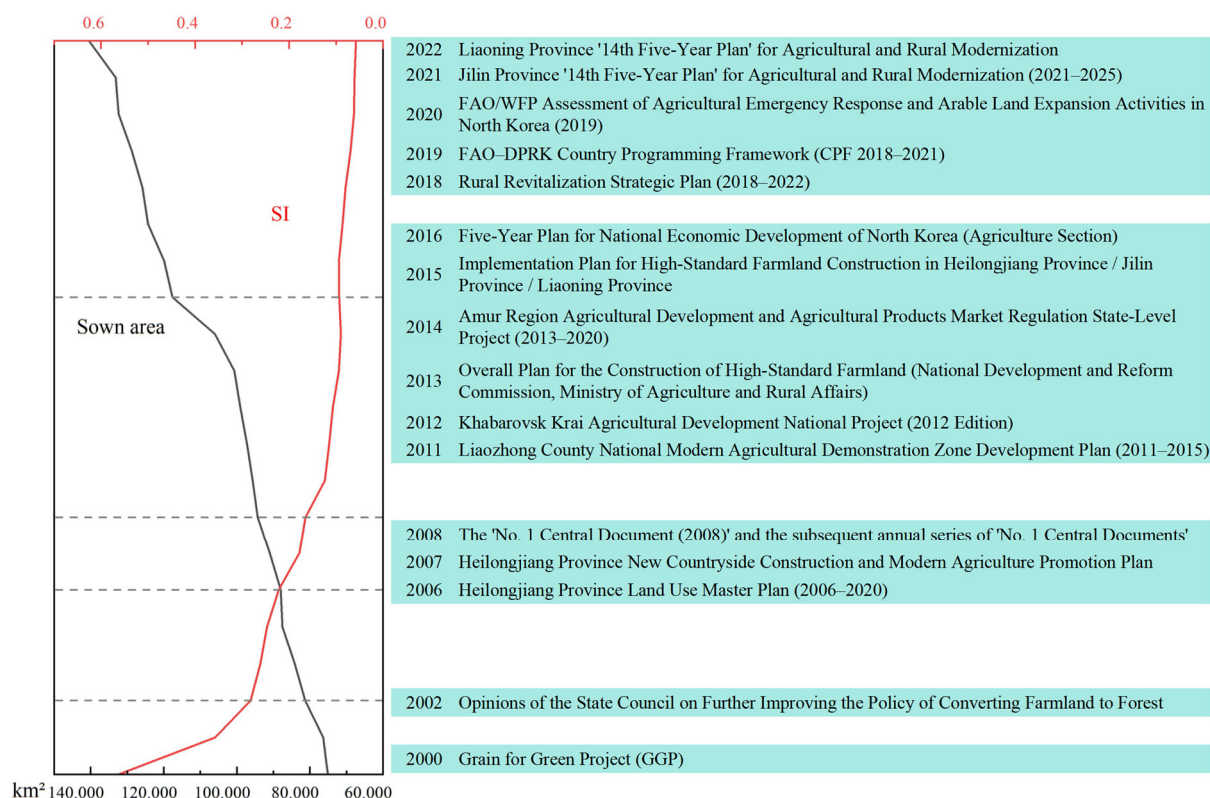


Figure 11. Changes in sown area, groundwater sustainability, and major policy events in selected areas of the study region during 2000–2022.

To enhance groundwater sustainability in the future, it is necessary to promote multi-objective, coordinated regulation at the policy level. On the one hand, direct pressure from agricultural activities on groundwater can be alleviated by optimizing cropping structures, reducing the proportion of water-intensive crops, promoting water-saving irrigation technologies, and improving farmland water-use efficiency. On the other hand, strengthened coordination among land-use regulation, water resources management institutions, and ecological protection policies is required to protect wetlands and groundwater recharge

zones and to enhance the overall resilience of the regional water cycle. For transboundary river basins, differences among countries in agricultural development stages, land-use policies, and water resources governance frameworks further highlight the importance of transboundary monitoring, data sharing, and ecological compensation mechanisms, which will be critical pathways for achieving long-term sustainable management of regional groundwater systems [82].

4.4. Spatial Heterogeneity of Groundwater Sustainability and Implications for Transboundary Water Resources Management

Groundwater sustainability exhibits pronounced spatial heterogeneity across the study region, jointly determined by natural conditions, the intensity of human activities, and land-use structure. The Heilongjiang (Amur) River basin concentrates most of the regional cropland and grain production, characterized by large-scale agriculture and high irrigation demand. As a result, groundwater has long been subjected to high extraction pressure, leading to the most pronounced decline in SI and significant deterioration of the REL and VUL indicators. In contrast, the Tumen and Yalu River basins are dominated by mountainous and hilly terrain, with limited agricultural activity, high vegetation coverage, and abundant precipitation, which provide favorable recharge conditions and result in a relatively slower decline in SI. The Suifen River basin is influenced by a humid maritime climate and exhibits both intensive agricultural activities and strong natural recharge, making groundwater more sensitive to short-term climatic variability [83].

The groundwater storage decrease observed in the southern part of the study area in August can be interpreted by considering both hydroclimatic processes and agricultural water use. Although August is within the regional flood season, precipitation does not necessarily translate into immediate groundwater recharge because a considerable fraction may contribute to surface runoff or remain in shallow soil storage, while groundwater replenishment often occurs with a time lag. In addition, southern sub-regions (e.g., Jilin Province) are characterized by intensive cropland distribution and high seasonal water demand. August–September corresponds to the peak growing season of major crops such as maize, during which supplemental irrigation and associated groundwater pumping may increase and locally offset effective recharge, leading to temporary groundwater decline. The alleviation from October to January is consistent with reduced irrigation withdrawal after harvest, lower evapotranspiration, and delayed infiltration recharge. By contrast, northern mountainous and forested areas with limited cropland and irrigation pressure tend to show more stable groundwater signals.

From a transboundary governance perspective, substantial differences among China, Russia, and North Korea in economic development levels, agricultural structures, water-use policies, and management capacities increase the complexity of groundwater system management. Groundwater stress in the Heilongjiang (Amur) River basin may be transmitted downstream toward Russia, implying that unilateral measures are unlikely to achieve basin-wide effectiveness. Future efforts should focus on establishing coordinated transboundary mechanisms, including the promotion of water-saving agriculture, adjustment of water-use structures, development of transboundary monitoring systems, data sharing, and ecological compensation mechanisms. These measures would facilitate a shift from “passive adaptation” to “active regulation,” thereby safeguarding food security, ecological security, and long-term socio-economic sustainability in transboundary river basins [84].

4.5. Methodological Uncertainties and Limitations

It should be noted that groundwater storage anomalies (GWSA) derived from the GRACE residual approach are subject to several sources of uncertainty. First, differences among GRACE processing centers and inversion strategies may lead to discrepancies in

the magnitude of terrestrial water storage anomalies (TWSA) [85]. Second, the estimation of non-groundwater components relies on a single land surface model (GLDAS-Noah), which may introduce structural and parameterization-related errors [86]. Third, due to the lack of long-term and consistent observations of surface water storage, surface water variations were not explicitly separated in this study; therefore, the residual term may contain a certain contribution from surface water signals in some local areas [87]. For these reasons, our results are mainly intended to characterize the long-term trends and spatial patterns of groundwater variations rather than to provide highly accurate estimates of absolute magnitudes.

It should also be noted that potential biases in GRACE-derived GWSA may propagate into GGDI, and the standardization procedure in GGDI mainly removes seasonal variability but cannot eliminate structural differences among GRACE–groundwater products derived from different models and processing strategies [88].

In addition, groundwater systems may exhibit a lagged response to precipitation, and such time-lag effects can influence the apparent correlations between precipitation and GRACE-derived groundwater signals. Given that this study primarily focuses on long-term trends and spatial pattern interpretation, future work will further incorporate approaches such as cross-correlation analysis to quantitatively identify basin-specific lag time scales, thereby improving the physical interpretability of the inferred groundwater–climate relationships.

5. Conclusions

Based on GRACE gravity satellite observations combined with GLDAS products, meteorological records, land-use data, and agricultural statistics, this study provides an integrated and long-term assessment of groundwater storage dynamics, drought evolution, and system sustainability across the four major transboundary river basins of Northeast China (2002–2022). By linking groundwater drought indicators with sustainability metrics and multi-source drivers, the analysis clarifies the relative influences of climatic variability and intensive human activities on regional groundwater decline and associated risks. These findings offer a scientific basis for sustainable groundwater management and transboundary water-resource governance. The main conclusions are summarized as follows:

- (1) Continuous groundwater storage decline, intensifying drought conditions, and pronounced spatial heterogeneity. During 2002–2022, Δ GWS in the study area exhibited a fluctuating downward trend, with the highest values occurring in July and the lowest in February. The upper reaches of the Heilongjiang (Amur) River basin showed relative water surplus conditions, whereas the southern Yalu River basin experienced persistent deficits. GGDI results indicate that groundwater drought has continuously intensified since 2018, with agriculturally intensive regions such as the Songnen Plain and the San Jiang Plain emerging as core areas of long-term structural groundwater drought.
- (2) Persistent decline in groundwater sustainability, characterized by reduced reliability and resilience and increasing system vulnerability. Groundwater sustainability consistently deteriorated over the study period, manifested by weakened reliability, reduced recovery capacity, and heightened sensitivity to external disturbances. The SI values for the four successive stages were 0.32, 0.14, 0.09, and 0.06, respectively, while the proportion of areas with extremely low sustainability increased from 51.6% to 99.6%, covering nearly the entire basin. Notably, although precipitation exhibited an increasing trend during the same period, groundwater conditions did not improve and instead continued to deteriorate. In contrast, sown area (MIC = 0.98) and nighttime light intensity (MIC = 0.92) showed much stronger synchronicity with groundwater

sustainability changes. This indicates that groundwater dynamics are no longer primarily controlled by natural recharge, but are increasingly dominated by agricultural expansion and urban development. The evolution of REL, RES, and VUL further corroborates this shift, highlighting a transition from natural regulation to human water-use dominance and a marked increase in regional groundwater security risks.

- (3) Agricultural expansion and human activities are the primary drivers of declining groundwater sustainability, with policy factors as the underlying causes. MIC analysis reveals that sown area (SA) exerts the strongest influence on SI (0.98), followed by nighttime light intensity (NTL, 0.92), both substantially exceeding the impacts of climatic factors. During 2002–2022, cropland area increased by 0.96%, built-up land by 75.07%, and sown area by 86.97%. Policy orientations such as “high-standard farmland construction,” “grain yield enhancement,” and “rural revitalization” have promoted agricultural intensification well beyond natural recharge capacity, constituting a key institutional driver of long-term groundwater depletion.
- (4) Enhancing groundwater sustainability requires integrated efforts in agricultural restructuring, water-saving technologies, and transboundary cooperative governance. Given the difficulty of reversing natural drivers in the short term, priority should be given to reducing the proportion of water-intensive crops, optimizing cropland spatial allocation, strengthening wetland protection, and expanding the application of water-saving irrigation technologies. Moreover, considering the substantial policy differences among China, Russia, and North Korea, enhanced data sharing, joint monitoring, and coordinated governance across transboundary river basins will be critical pathways toward achieving long-term, sustainable utilization of regional water resources.

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Data Availability Statement: The data used in this study are derived from publicly available datasets, including GRACE/GRACE-FO, GLDAS, GPCC, MODIS, FAOSTAT, SPAM, and global nighttime light intensity products. Detailed data sources are provided in the references. Further processed data are available from the corresponding author upon reasonable request.

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

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