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RESEARCH ARTICLE

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Hydrologic Implications of GNSS Vertical Displacements in Cold Regions: Insights From Northeast China



Key Points:

- Ground-based Global Navigation Satellite System (GNSS) vertical displacement provides an independent data source for terrestrial water storage (TWS) estimates
- GNSS captures the regional and interannual variations in TWS, whereas its agreement with GRACE estimates degrades during winter
- Uncertainty in GNSS observation error is quantified for future data assimilation work to improve estimated TWS

Supporting Information:

Supporting Information may be found in the online version of this article.

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Abstract Ground-based Global Navigation Satellite System (GNSS) vertical displacements are increasingly used to infer terrestrial water storage (TWS) variations, but their applicability remains uncertain where weak hydrological signals coexist with non-hydrological deformation processes. This study evaluates the potential of GNSS-derived vertical displacements to capture TWS variability in Northeast China (NEC), a representative cold region characterized by weak hydrologic variability, a sparse GNSS network, and widespread freeze-thaw processes. Vertical displacements from GNSS, GRACE, and the Noah land surface model during 2012–2023 were compared. At the regional scale, network-mean GNSS displacements calculated using all examined stations were moderately correlated with GRACE- and Noah-based estimates ($R = 0.61$ and 0.68 , respectively). At the station scale, GNSS captured long-term and interannual TWS variations at most stations, but its seasonal cycle differed markedly from GRACE and Noah. Agreement between GNSS and GRACE degraded substantially in winter ($R = 0.30$), possibly due in part to non-elastic deformation associated with freeze-thaw processes. Regional-average snow water equivalent was weakly correlated with station-mean vertical displacements from GNSS ($R = 0.10$), GRACE ($R = 0.28$), and Noah ($R = -0.21$), while correlations between TWS anomalies and vertical displacements were -0.60 , -0.88 , and -0.91 , respectively. These results suggest that snow mass alone does not dominate seasonal TWS variability in NEC. Overall, GNSS vertical displacements capture regional and interannual TWS variations in cold regions, highlighting their potential for large-scale hydrological monitoring. However, possible non-elastic deformation associated with freeze-thaw processes requires further investigation to improve GNSS-based hydrological applications in complex cold-region environments.

Plain Language Summary Terrestrial water storage (TWS) includes all forms of water on land, such as snow and ice, surface water, soil moisture, groundwater, and water intercepted by vegetation. Monitoring TWS variation is essential for effective water resource management and hazard prevention. The Gravity Recovery and Climate Experiment (GRACE) and GRACE Follow-on (GRACE-FO) satellite missions provide valuable global-scale observations of TWS changes. However, their coarse spatial resolution (~ 300 km) limits their application for studies at sub-regional and local scales. This study investigates the potential of using geodetic measurements of surface deformation, specifically from ground-based Global Navigation Satellite System (GNSS) vertical displacements, to infer TWS changes at finer spatial scales. By removing non-hydrological effects from GNSS vertical displacements, the remaining signals are interpreted as TWS variation. We applied this approach in a cold, snow-dominated region of Northeast China. The results show that processed GNSS vertical displacements effectively capture regional and long-term trends in TWS variations. However, human activities such as irrigation, groundwater pumping, and reservoir regulation, along with permafrost and seasonal frost, may contribute to larger differences between GNSS-derived signals and those from GRACE.

1. Introduction

Terrestrial water storage (TWS) encompasses all water stored on land, including snow and ice, soil moisture, groundwater, surface water, and biomass (Tapley et al., 2004). Changes in TWS reflect the net effect of climate and anthropogenic activities on the water cycle, making it a key indicator of water resources (Deng et al., 2023; Zhong et al., 2024). Thus, TWS has been adopted as an official essential climate variable (ECV) by the Global Climate Observing System (GCOS, 2022).

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The Gravity Recovery and Climate Experiment (GRACE) and GRACE Follow-on (GRACE-FO) satellite missions have achieved unprecedented success in global monitoring of TWS variations, providing valuable information for studies in floods and droughts (Bai et al., 2021; Long et al., 2013; Reager & Famiglietti, 2009; Yin & Park, 2021), groundwater depletion (Dharpure et al., 2025; Long et al., 2020; Rodell et al., 2009; Scanlon et al., 2012), and water budget analysis (Bringeland & Fotopoulos, 2025; Gao et al., 2010; Landerer et al., 2010; Lehmann et al., 2022). Nevertheless, the coarse spatiotemporal resolution of GRACE TWS retrieval constrains its ability to resolve sub-monthly TWS variations at local scales. Land surface models (LSMs) and global hydrological models (GHMs) offer an alternative for estimating TWS variations at finer resolution (Felfelani et al., 2017; Hu et al., 2021; Long et al., 2017; Trautmann et al., 2023). However, limited understanding and representation of physical processes, together with uncertainties in model parameters and boundary conditions, lead to evident discrepancies among model outputs (Deng et al., 2023; Long et al., 2017; Wood et al., 2011).

Ground-based Global Navigation Satellite System (GNSS) observations have increasingly been used to investigate TWS variation. Vertical displacement measured by GNSS reflects water mass redistribution through crustal elastic effects (Farrell, 1972). Previous studies have compared GNSS-derived vertical displacements with estimates from GRACE and LSMs, demonstrating that GNSS can reliably capture TWS variations at both local and regional scales after correcting for non-hydrological signals (Fu et al., 2012; Van Dam et al., 2001; Yin et al., 2020). Beyond comparison in the displacement domain, GNSS observations have also been inverted to estimate TWS variations, primarily using Green's functions in the spatial domain (Argus et al., 2014; Mielke et al., 2025) or Slepian basis functions in the spectral domain (Han & Razeghi, 2017; Jiang et al., 2021; Longuevergne et al., 2010). More recently, joint inversion frameworks integrating GNSS and GRACE observations have been developed to further improve TWS estimates (Adusumilli et al., 2019; Carlson et al., 2022, 2024; Li et al., 2023).

The rapid expansion of the global GNSS network has transformed GNSS from sparse point-based observations into increasingly interconnected networks, enhancing its potential for hydrological applications (Adams et al., 2022). To date, however, most GNSS-based hydrological studies have focused on regions with strong water signals and dense station coverage, such as the western United States (Argus et al., 2017; Borsa et al., 2014; Hammond et al., 2016), the Amazon Basin (Ferreira et al., 2021; Knowles et al., 2020; Moreira et al., 2016), and Southeast China (Hu et al., 2022; Jiang et al., 2017; Zhan et al., 2017). Despite the emerging paradigm of dense GNSS arrays, large portions of the globe remain sparsely instrumented and exhibit relatively weak hydrological loading signals, posing persistent challenges for GNSS-based TWS estimation.

Our previous study (Yin et al., 2021) demonstrated that assimilating GNSS-derived vertical displacements into an advanced LSM can substantially improve TWS estimates and reduce uncertainties, even in data-sparse regions. Building on this work, the present study evaluates the applicability of GNSS-derived vertical displacements for TWS monitoring in cold regions characterized by weak hydrological variability, sparse GNSS station coverage, and widespread freeze-thaw processes. Under these conditions, non-hydrological deformation may become comparable to, or even exceed, the hydrological signal, complicating the interpretation of GNSS-based vertical displacements in terms of TWS variations. Using Northeast China (NEC) as a natural testbed, this study assesses the consistency among GNSS, GRACE, and LSM-derived vertical displacements and investigates the potential factors influencing their agreement and discrepancies. The findings provide new insights into the applicability and limitations of GNSS for hydrological monitoring in cold regions and also support future dual-assimilation frameworks that integrate GNSS and GRACE observations into LSMs to advance regional hydrological simulations.

The remaining sections of this study are organized as follows: Section 2 introduces the data sets and data processing procedures, as well as the evaluation methods. Sections 3.1 to 3.3 compare the vertical displacements from GNSS, GRACE, and a land surface model across multiple spatiotemporal scales. Section 3.4 investigates the elastic response of vertical displacements to hydrological loading. Section 3.5 explores the discrepancies among the data sets, and Section 3.6 analyzes their uncertainties. Section 4 summarizes the findings of the study.

2. Data and Methods

2.1. Study Area

Northeast China (NEC) is located in the mid-to-high latitudes (~38°N–53°N) of the East Asian monsoon region, covering approximately 1.24 million km² and encompassing Heilongjiang, Jilin, and Liaoning Provinces, as well

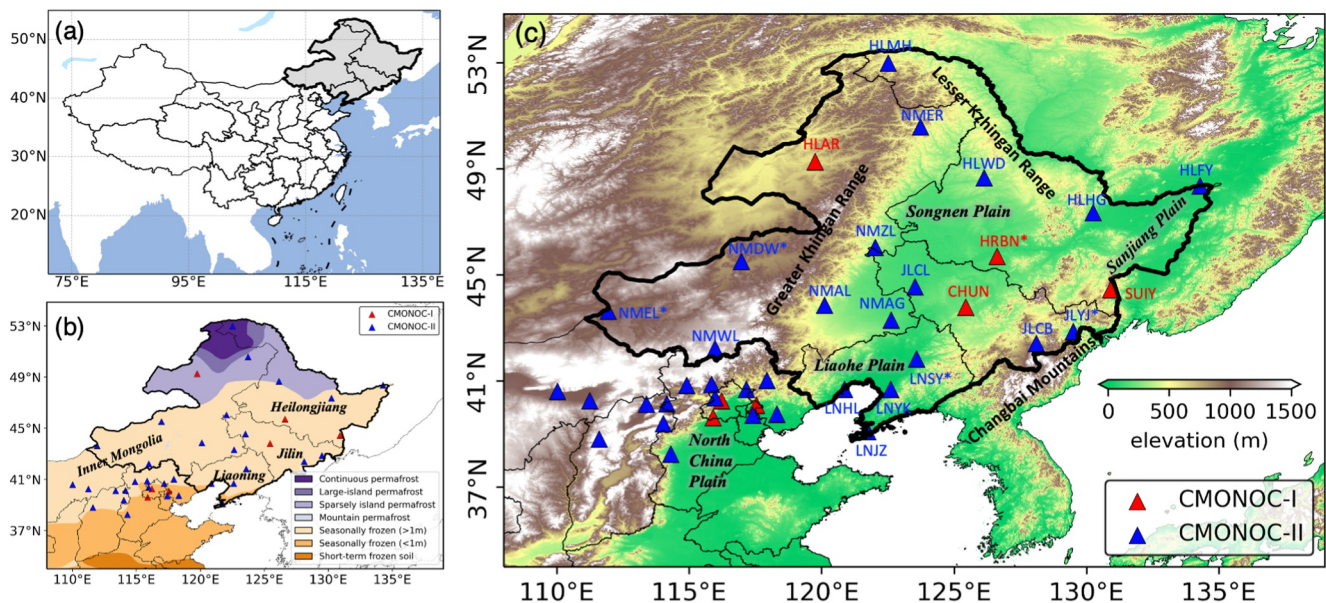


Figure 1. (a) Location of Northeast China (NEC), (b) geocryological regionalization map of the frozen soil in and near NEC, and (c) distribution of permanent GNSS stations (triangles) from the Crustal Movement Observation Network of China (CMONOC). Red and blue triangles represent stations established during the first-phase network (CMONOC-I, around 1999) and second-phase network (CMONOC-II, around 2010), respectively. Stations located within NEC are labeled with station IDs, and stations installed on soil layers are marked with asterisks.

as the eastern Inner Mongolia Autonomous Region (Figure 1). The region is bounded by the Greater Khingan Range in the west, the Lesser Khingan Range in the north, and the Changbai Mountains in the east. Nestled between these ranges, the Northeast China Plain (including the Songnen Plain, Liaohe Plain, and the Sanjiang Plain) forms a fertile basin that makes NEC one of the most important grain-producing regions in China, contributing about 18%, 34%, and 49% of national rice, maize, and soybean production, respectively (National Bureau of Statistics of China, 2024).

NEC lies within a transitional climate zone, ranging from warm-temperate conditions in the south to cold-temperate conditions in the north (Yang et al., 2018). The region experiences distinct seasonality, with short humid summers and long cold winters. Its cryospheric environment is complex, featuring widespread seasonal frost, sporadic to discontinuous permafrost in the north and high-altitude areas (Figure 1b; Li et al., 2008), and seasonal snow cover that strongly influences regional water and energy cycles (Qi et al., 2020; Ran et al., 2012; Zhan et al., 2022). Soil freeze-thaw dynamics regulate hydrological and ecological processes, while the spatial heterogeneity of permafrost and snowpack makes NEC particularly sensitive to climate change.

Over recent decades, NEC has emerged as one of the most pronounced warming regions in China (Ministry of Ecology and Environment, 2022). Rising temperatures have enhanced evapotranspiration, shifted the regional climate toward warmer and drier conditions, and made NEC a hotspot for flash drought (Sun et al., 2024). Concurrently, warming has increased the frequency of extreme precipitation, leading to more severe summer floods (Qi et al., 2021; Xie et al., 2024; Yin et al., 2024). These changes have also accelerated wetland degradation and increased the vulnerability of permafrost and snow cover (Ministry of Ecology and Environment, 2022). High-resolution monitoring of TWS variation is therefore essential for improving flood and drought resilience, safeguarding food security, maintaining ecosystem stability, and supporting climate adaptation strategies.

2.2. Data Sets

2.2.1. GNSS Data

Daily GNSS vertical displacements from the Crustal Movement Observation Network of China (CMONOC) were used in the study. The CMONOC network comprises two stages (CMONOC-I and CMONOC-II) with stations mostly established around 1999 and 2010, respectively. The data are archived at the National Earthquake Data Center (https://www.eqdsc.com/eastern/report.shtml?PAGEID=sharedata_station&parid=10&type=sjxl),

and the time series were processed by the GAMIT/GLOBK software. The study used records from 39 stations from February 2012 to January 2023, including 22 stations in the NEC region and 17 nearby stations (Figure 1). Among the 22 NEC stations, five are installed on soil layers, which may be more susceptible to freeze-thaw processes. Detailed information on all GNSS stations is provided in Table S1 in Supporting Information S1. The nearby stations also facilitate comparisons of vertical displacement characteristics inside and outside NEC, as the surrounding regions generally experience shorter winters and warmer summers, with stronger anthropogenic activities, particularly groundwater pumping and water diversion in the North China Plain (Lu et al., 2021; Xiong et al., 2023). Additionally, these nearby stations provide improved spatial constraints for future inversion of regional water mass variations.

Following previous studies (Li et al., 2023; Yin et al., 2020), post-processing was performed to remove non-hydrologic loading effects from the vertical displacement measurements. First, offsets caused by earthquakes, antenna changes, or other disturbances were removed using metadata provided by the China Earthquake Administration. Next, outliers were identified and removed using a three-sigma threshold relative to the mean of each time series. Atmospheric and non-tidal ocean loading effects were corrected using the Atmosphere and Ocean De-Aliasing (AOD) model (Bettadpur, 2018), and the thermal expansion effects were removed following Yan et al. (2009). Previous studies (Chew & Small, 2014; Han, 2017) have shown that removing a linear trend can effectively suppress secular deformation signals without materially affecting the analysis of seasonal and interannual hydrological variability. Therefore, a linear detrending procedure was applied to the GNSS time series to reduce the influence of long-term non-hydrological deformation signals, primarily associated with glacial isostatic adjustment and tectonic effects. Finally, the processed daily vertical displacements were converted to monthly data using a simple arithmetic mean to ensure temporal consistency with GRACE TWS retrievals. Details of the GNSS data post-processing are provided in Text S1 in Supporting Information S1. The resulting monthly GNSS vertical displacements were used to evaluate their capability to represent regional and local water mass variations.

2.2.2. GRACE Data

GRACE Level 3 Release 06.3 mass concentration (mascon) product from the Center for Space Research (CSR, https://www2.csr.utexas.edu/grace/RL06_mascons.html) was used as a reference data to examine the capability of GNSS vertical displacement to infer water mass variations. The CSR mascon product provides monthly terrestrial water storage anomalies (TWSA) from April 2002 to the present on a 0.25° grid, derived from a native 1° × 1° equal-area geodesic grid at the equator (Save et al., 2016). For consistency with GNSS data, GRACE TWSA from February 2012 to January 2023 was selected, and the long-term mean was removed from the time series.

For comparison with GNSS vertical displacements, GRACE TWSA-derived vertical displacements at each GNSS station location were calculated using the Green's function approach (Farrell, 1972). Assuming a disk loading with angular radius α , the vertical displacement can be expressed as a function of angular distance λ from the disk center as:

$$dr = \sum_{l=0}^{\infty} h_l' \Gamma_l \frac{4\pi GR}{g(2l+1)} P_l(\cos \lambda)$$

$$\Gamma_l = \frac{1}{2} [P_{l-1}(\cos \alpha) - P_{l+1}(\cos \alpha)] \quad l > 0$$

$$\Gamma_0 = \frac{1}{2} (1 - \cos \alpha)$$
(1)

where P_l is the Legendre polynomials of degree l , G is Newton's gravitational constant, g is the gravitational acceleration at the Earth's surface, R is the average Earth radius, and h_l' are the elastic load Love numbers. By aggregating TWS-induced deformation from all grid cells, GRACE-based vertical displacement was obtained and compared with GNSS-based vertical displacement at each station location. Further details of the conversion from gridded TWSA to point-scale vertical displacement can be found in Yin et al. (2020).

2.2.3. Land Surface Model

The NASA Global Land Data Assimilation System (GLDAS) provides optimal estimates of land surface states and fluxes by integrating satellite- and ground-based observations with advanced land surface models via data assimilation techniques (Rodell et al., 2004). The study used GLDAS-2.1 Noah LSM outputs at 0.25° spatial and 3-hourly temporal resolutions (available at <https://disc.gsfc.nasa.gov/datasets?keywords=GLDAS>). Noah-based TWS was computed as the sum of soil moisture in all layers, snow water equivalent, and canopy water storage following previous studies (Cai et al., 2014; Scanlon et al., 2019; Sun et al., 2021). For consistency with GNSS data, the anomaly (i.e., Noah TWSA) was calculated by removing the long-term mean for 2012–2023. The resulting Noah-based TWSA were then converted to vertical displacement at each GNSS station location following the same procedure applied to the GRACE data.

2.2.4. Precipitation Data

Precipitation data from the Integrated Multi-Satellite Retrievals for the Global Precipitation Measurement mission (IMERG) were used to examine the response of vertical displacements to precipitation. IMERG provides near real-time, global gridded multi-satellite precipitation estimates at a spatial resolution of 0.1° and a temporal resolution of up to 30 min (Huffman et al., 2020). The study used the IMERG Version 7 Final Run daily precipitation product (<https://gpm.nasa.gov/data/directory>). The daily data were accumulated to monthly totals to be consistent with the processed monthly vertical displacement data.

2.2.5. Snow Water Equivalent Data

The European Space Agency (ESA) Snow Climate Change Initiative (snow_cci) data set was used to examine snow water equivalent (SWE) variations. The SWE product is derived using the GlobSnow algorithm, which combines passive microwave observations with in situ snow depth measurements via a Bayesian non-linear iterative assimilation framework (Luo et al., 2025). The data set provides daily SWE estimates for the Northern Hemisphere winter seasons from 1979 to 2023. In this study, the Climate Research Data Package (CRDP) version 4.0 with a spatial resolution of 0.1° was used (<https://data.ceda.ac.uk/neodc/esacci/snow/data/swe/MERGED/v4.0/>). Daily SWE data were converted to monthly values using a simple arithmetic mean to ensure consistency with the monthly vertical displacement time series.

2.3. Evaluation Methods

2.3.1. Time Series Decomposition

The Seasonal Trend Decomposition using Loess (STL) method is a filtering procedure that uses locally weighted regression to decompose a time series into trend, seasonal, and remainder components (Cleveland et al., 1990), which facilitates time series analysis, anomaly detection, and forecasting (Wen et al., 2020). STL has been widely used to characterize GRACE TWSA variations across multiple temporal scales (Humphrey et al., 2016; Li et al., 2024; Scanlon et al., 2021). In the study, the STL method was used to decompose vertical displacement time series derived from ground-based GNSS, satellite-based GRACE, and model-based Noah at each GNSS station location. Each time series was separated into long-term, seasonal, and residual components (Equation 2). The long-term component represents the slowly varying nonseasonal variability in the time series. The long-term and seasonal components across data sets were compared to assess the capability of GNSS vertical displacement to detect TWSA variations at different time scales.

$$dr_{\text{total}} = dr_{\text{long-term}} + dr_{\text{seasonal}} + dr_{\text{residual}} \quad (2)$$

2.3.2. Triple Collocation Method

Triple collocation (TC) analysis is a method for estimating the random error variances of three collocated data sets of the same geophysical variable without requiring the ground truth (Gruber et al., 2016; Stoffelen, 1998). TC has been widely used in data uncertainty analysis for various hydrometeorological states and fluxes, such as soil moisture (Crow et al., 2015; Scipal et al., 2010; Yilmaz et al., 2012), precipitation (Chen et al., 2022; Lyu et al., 2021; Yin et al., 2024), and TWSA (Hasan & Tarhule, 2021; Yin & Park, 2021). With collocated vertical displacements derived from GNSS, GRACE, and Noah, TC was used to quantify random error standard

deviations of the input data sets. The analysis helps improve the understanding of data error characteristics and provides observation error estimates for future assimilation of GNSS vertical displacements into land surface models.

A linear relationship is assumed between the true and estimated vertical displacements induced by water mass variations:

$$S_i = \alpha_i + \beta_i S_t + \varepsilon_i \quad (3)$$

where S_i ($i = 1, 2, 3$) represents the three collocated vertical displacements from GNSS, GRACE, and Noah, respectively; α_i and β_i are the linear regression coefficients between the estimates S_i and the true state S_t ; ε_i is the random error with a mean of zero and an error standard deviation of σ_{ε_i} . As the long-term mean has been removed from the vertical displacements, α_i is simplified as zero:

$$S_i = \beta_i S_t + \varepsilon_i \quad (4)$$

The unscaled error standard deviation σ_{ε_i} for each input data set can be calculated as:

$$\begin{aligned} \sigma_{\varepsilon_1} &= \sqrt{\sigma_1^2 - \frac{\sigma_{12}\sigma_{13}}{\sigma_{23}}} \\ \sigma_{\varepsilon_2} &= \sqrt{\sigma_2^2 - \frac{\sigma_{21}\sigma_{23}}{\sigma_{13}}} \\ \sigma_{\varepsilon_3} &= \sqrt{\sigma_3^2 - \frac{\sigma_{31}\sigma_{32}}{\sigma_{12}}} \end{aligned} \quad (5)$$

where σ_i^2 and σ_{ij} denote the data variance and covariance, with $i, j \in \{1, 2, 3\}$ and $i \neq j$. More details on the TC analysis can be found in Gruber et al. (2016).

2.3.3. Evaluation Metrics

To analyze the agreements among vertical displacements derived from ground-based GNSS, satellite-based GRACE, and model-based Noah, Pearson's correlation coefficients (R) were computed to represent the linear correlation between two time series. The weighted root mean square (RMS) reduction, computed as the normalized variance reduction resulting from subtracting one time series from another (Equation 6), was used to quantify the agreement between two time series. A large positive RMS reduction value represents good agreement between two time series in both phase and amplitude.

$$\text{RMS}_{\text{reduction}} = \frac{\text{RMS}_A - \text{RMS}_{A-B}}{\text{RMS}_A} \times 100\% \quad (6)$$

where RMS_A is the variance of data set A (i.e., GNSS), RMS_{A-B} is the variance of the time series after subtracting data set B from A where data set B is either GRACE- or Noah-based monthly vertical displacements in the study.

To further characterize temporal similarity beyond linear correlation, dynamic time warping (DTW) was applied to account for potential shifts and nonlinear time alignments between vertical displacements from different data sets. The DTW distance was originally used for speech recognition (Vidal Ruiz et al., 1985) and has been widely applied to time series classification and clustering across various fields (Ouyang et al., 2010; Rinderer et al., 2017; Wang et al., 2020). In the study, the similarity of vertical displacements among GNSS, GRACE, and Noah data sets at the long-term and seasonal scales was analyzed using STL-decomposed time series. To mitigate the effects of differing data dynamic across station locations, the decomposed time series were standardized using z-score normalization (i.e., subtracting the mean and dividing by the standard deviation) prior to DTW. Eventually, the normalized DTW (nDTW) was used for similarity analysis in Sections 3.2 and 3.3. A small nDTW distance indicates that the two time series exhibit similar temporal patterns.

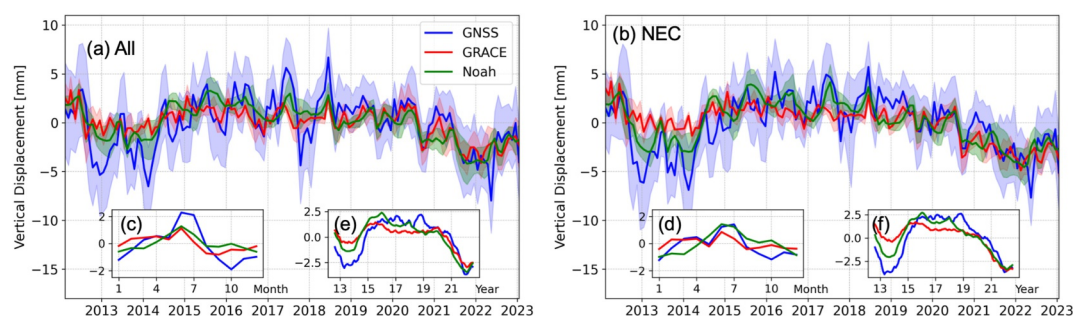


Figure 2. Network-wide mean vertical displacements derived from GNSS (blue), GRACE (red), and Noah (green) for (a) all stations and (b) stations within the NEC region. Shaded areas indicate ± 1 standard deviation for each data set. Inset panels (c) and (d) show the mean seasonal cycles, and inset panels (e) and (f) show the 13-month moving-average time series of the network-wide mean vertical displacements.

3. Results and Discussion

3.1. Monthly Vertical Displacement Analysis

Monthly vertical displacements derived from GNSS, GRACE, and Noah were compared at each GNSS station (example stations shown in Figure S1 in Supporting Information S1). For each data set, the regional signal was defined as the network-wide mean vertical displacement sampled at the GNSS stations. The mean time series were calculated separately using all stations (Figure 2a) and only those stations located within the NEC region (Figure 2b). GNSS-derived vertical displacements generally show larger magnitudes of variation than those from GRACE or Noah. Such differences may be associated with the limited spatial resolution and residual leakage of the GRACE Mascon product (Wiese et al., 2016), structural limitations of the Noah model (Yin et al., 2020), and local hydrological variability that may not be fully represented in GRACE- and model-derived estimates (Gu et al., 2017; Tregoning et al., 2009). Correlation analysis indicates the strongest agreement between GRACE and Noah, with R values of 0.82 for all stations and 0.79 for NEC stations. The consistency between GNSS and GRACE is lower ($R = 0.61$ and 0.58 , respectively). The agreement between GNSS and Noah is higher for NEC stations ($R = 0.74$) than for all stations ($R = 0.68$).

The network-wide mean vertical displacements from all three data sets exhibit relatively weak seasonal cycles. The mean seasonal cycles (i.e., the multiyear average for each month; Figures 2c and 2d) derived from GNSS, GRACE, and Noah show peak vertical displacements in June or July, corresponding to periods of minimum TWSA. GNSS exhibits a minimum displacement in October at the regional scale, while such troughs are not evident in GRACE- or Noah-based vertical displacements. It is also noteworthy that the seasonal variations in mean vertical displacement are weaker when considering only NEC stations compared to all stations, suggesting reduced seasonal TWSA variability in the NEC region. A 13-month moving average was applied to the network-wide mean vertical displacements (Figures 2e and 2f) to examine interannual variability. All three data sets exhibit consistent interannual behavior, with pronounced negative displacements in 2013–2014, relatively stable conditions during 2015–2020, and a rapid decline after 2020.

To further examine the spatial variability of data consistency, the pairwise correlation coefficients and RMS reductions are shown in Figure 3. Consistent with the regional analysis, the correlations between GNSS and GRACE are notably lower, particularly for stations within the NEC region ($R_{\text{all}} = 0.46$ and $R_{\text{NEC}} = 0.44$). Across all comparisons, stations in the central plain with flat, low-elevation terrain exhibit relatively higher R values. In contrast, some stations in the southwest show inferior R values in all comparison cases, reflecting substantial discrepancies among the three data sets. Additionally, Noah-based vertical displacements show weaker agreement with either GRACE or GNSS for stations outside the NEC region, suggesting potential missing physics in the Noah model.

RMS reduction values are generally positive across the comparison cases, with negative values occurring at a few stations (Figures 3d and 3e). When GRACE or Noah signals are removed from the GNSS time series, negative RMS reduction values are mainly observed in the northern part of the study domain. When removing Noah-derived vertical displacements from the GRACE time series, stations in the central plain exhibit reductions

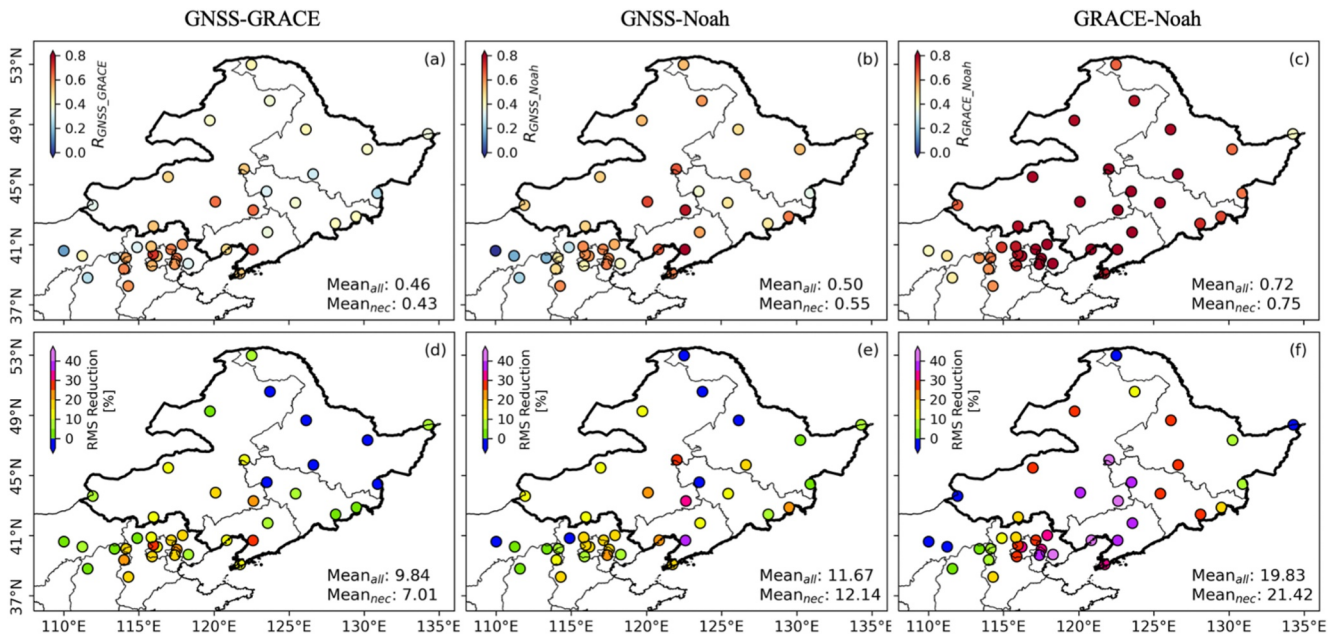


Figure 3. (a–c) Correlation coefficient maps of vertical displacements between GNSS and GRACE, GNSS and Noah, and GRACE and Noah, respectively. (d–f) Root-mean-square (RMS) reduction maps of vertical displacements after removing GRACE from the GNSS time series, Noah from the GNSS time series, and Noah from the GRACE time series, respectively.

exceeding 40%, whereas negative values mostly appear along the regional boundaries. These patterns are consistent with the regional analysis and indicate larger discrepancies between GNSS-based vertical displacements and those from GRACE or Noah at specific locations within the NEC region.

3.2. Long-Term Variation Analysis

Vertical displacements derived from GNSS, GRACE, and Noah at each station were decomposed using the STL method to obtain the long-term and seasonal components. The long-term variabilities extracted from the three data sets are compared in this section. Figure 4 shows the correlation coefficients and nDTW distances for the long-term time series derived from GNSS, GRACE, and Noah. The correlations between the long-term components are substantially higher than those of the original time series, with approximately 86%, 92%, and 94% of stations showing increased R values for GNSS versus GRACE, GNSS versus Noah, and GRACE versus Noah, respectively. The corresponding station-averaged R values also increased to 0.57, 0.66, and 0.75 for all stations. A pronounced improvement in the GNSS-GRACE correlation is observed along the Changbai Mountains region. The improved correlation suggests that GNSS captures the interannual TWSA variations well, and that the low R values in the original time series are likely influenced by short-term fluctuations. However, the southwestern stations located outside NEC that show low R values in the original time series continue to exhibit weak correlations across all comparison cases.

To account for potential time misalignment among data sets, the nDTW distance was calculated to quantify the shape similarity between two long-term time series (Figures 4d–4f). The spatial pattern of nDTW distances is broadly consistent with the correlation results. Stations with relatively low R values generally exhibit large nDTW distances, indicating poor agreement in interannual variability between GNSS and GRACE or Noah. An exception is observed for the GNSS-GRACE comparison, where some southwestern stations show low R values but do not exhibit correspondingly large nDTW distances. A closer inspection of these stations revealed that GNSS- and GRACE-derived long-term components share similar overall rising and falling patterns, but are temporally offset. In such cases, nDTW remains sensitive to similarities in overall long-term shape, whereas the correlation coefficient becomes weak because the peaks and troughs are shifted in time.

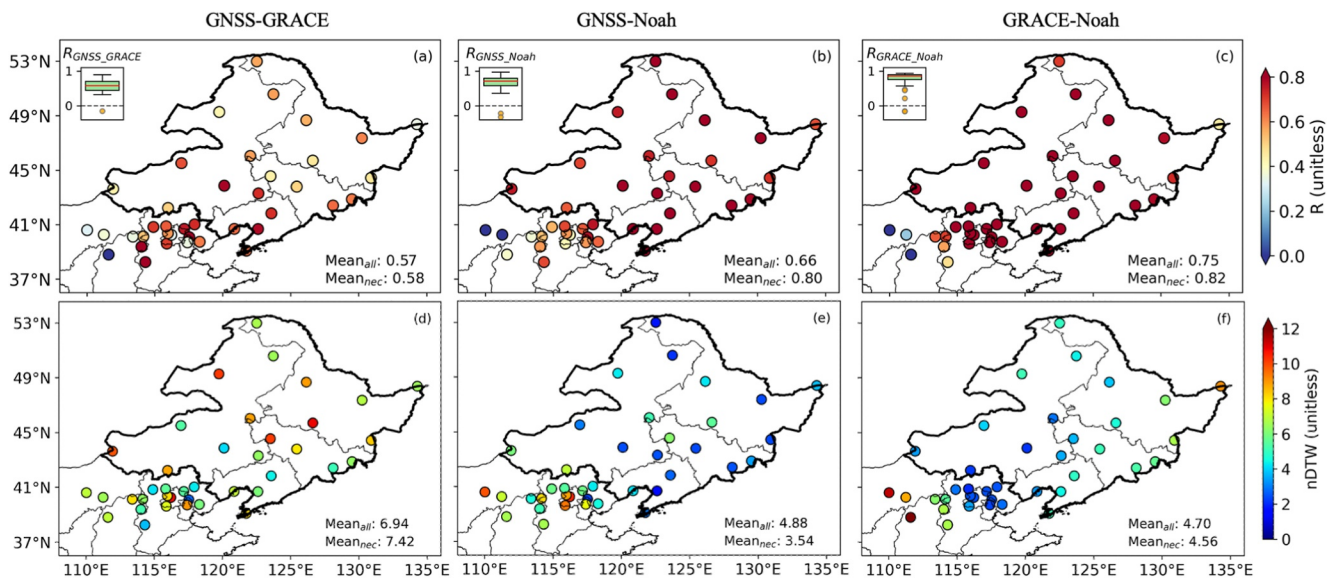


Figure 4. (a–c) Correlation coefficients for STL-derived long-term components of vertical displacement between GNSS and GRACE, GNSS and Noah, and GRACE and Noah, respectively. The distributions of correlation coefficients across all stations are shown in the upper-left inset of each subplot. (d–f) Corresponding normalized Dynamic Time Warping (nDTW) distances for the same pairs of STL-derived long-term components.

3.3. Seasonal Variation Analysis

The seasonal components of vertical displacement from GNSS, GRACE, and Noah were also examined (Figure 5). In contrast to the long-term analysis, correlations between the seasonal components are generally weak. Compared to the original time series, lower R values are detected at about 77%, 85%, and 77% of stations for GNSS versus GRACE, GNSS versus Noah, and GRACE versus Noah, respectively. The R values are evidently different between stations located within and outside the NEC boundary. For NEC stations, the average R values are 0.14, 0.24, and 0.45 for GNSS-GRACE, GNSS-Noah, and GRACE-Noah comparisons, respectively, whereas the corresponding values for stations outside the NEC increase to 0.45, 0.35, and 0.64. Among these comparisons, GNSS-GRACE exhibits the weakest seasonal agreement within NEC, with about 68% (13 out of 22) of stations showing R values below 0.3.

The nDTW distances were calculated for seasonal components to account for temporal misalignment. Both GNSS-GRACE and GRACE-Noah comparisons show larger nDTW distances for NEC stations, which is consistent with the correlation results. In the central plain, GRACE-Noah correlations are higher than those for GNSS-Noah, whereas the corresponding nDTW distances are also larger. This contrast indicates that the seasonal components of GRACE and Noah may exhibit notable phase shifts, amplitude differences, or shape mismatches in this area.

The timing of peak vertical displacement was further analyzed by computing the multiyear-average seasonal cycles and identifying the dominant phase via a Fourier transform. GRACE- and Noah-based peaks occur earlier in the northern region and exhibit a progressive southward delay (Figures 5h and 5i), reflecting earlier onset of the dry season in the north. More specifically, GRACE peaks typically occur in April–May in the north and September–October in the south, one to 2 months earlier than the corresponding Noah peaks in the north and about 1 month later in the south (Figure S2 in Supporting Information S1). In contrast, GNSS-derived seasonal phase does not exhibit a clear north–south gradient in peak timing. Within NEC, GNSS peak timing aligns more closely with Noah, which may partially contribute to the lower GNSS-Noah nDTW distances, although nDTW reflects the overall similarity of the seasonal cycle beyond peak timing alone. Outside NEC, GNSS peaks occur one to 3 months earlier on average relative to GRACE and Noah.

To investigate the cause of the weak agreement in the seasonal components between GNSS and GRACE or Noah, correlations were calculated separately for each season (Figure 6). GNSS-GRACE correlations vary across both seasons and regions. For all stations, the lowest mean correlation occurs in autumn ($R_{\text{SON}} = 0.36$), although winter (DJF) also exhibits relatively weak correlations ($R_{\text{DJF}} = 0.38$) and greater variability among stations. For NEC

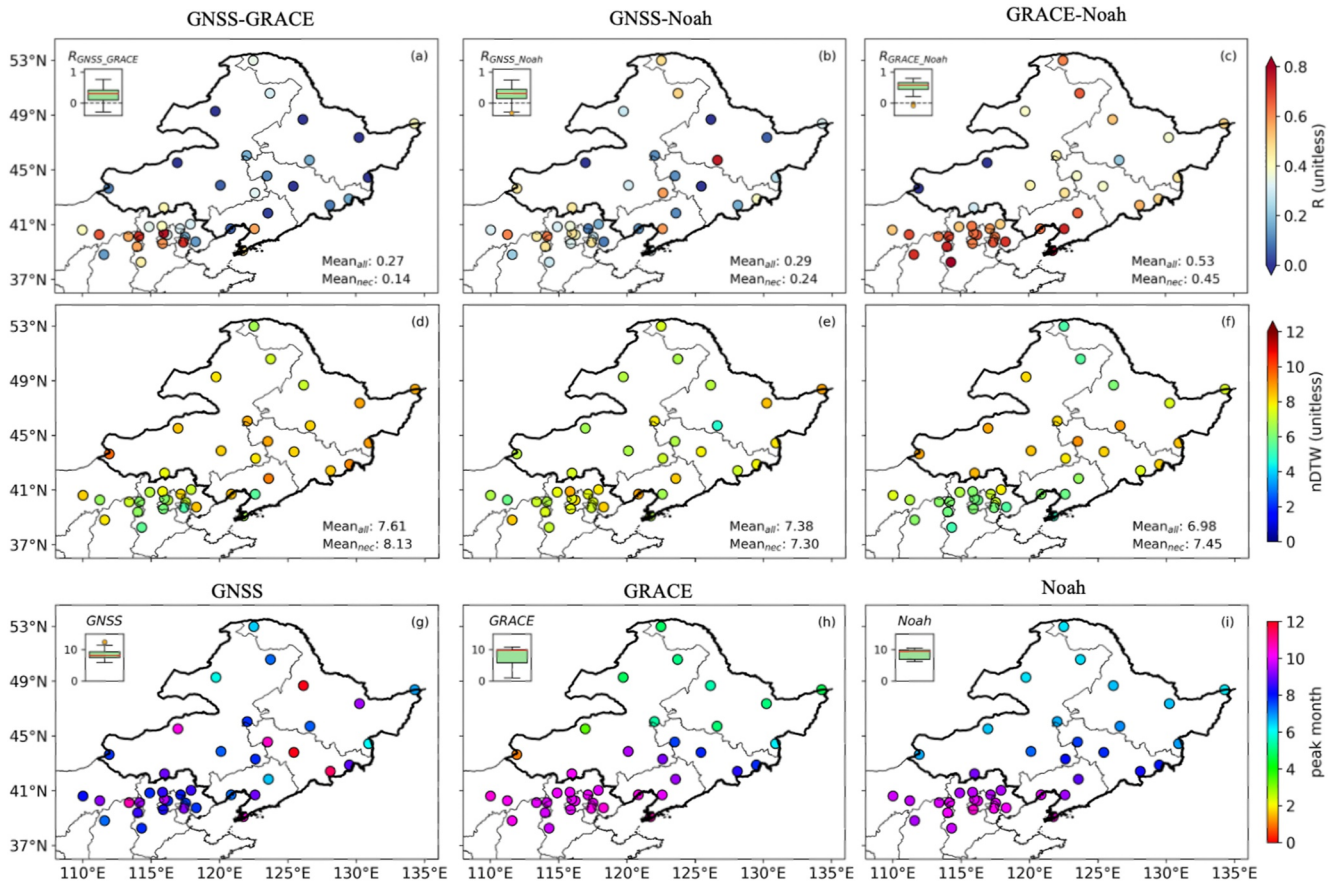


Figure 5. Spatial distribution of (a–c) correlation coefficients and (d–f) normalized Dynamic Time Warping (nDTW) distances between the STL-decomposed seasonal components of vertical displacement from GNSS, GRACE, and Noah. Panels (g–i) show the peak month of the seasonal cycle derived from GNSS, GRACE, and Noah, respectively. Insets in (a–c) and (g–i) present the distributions of correlation coefficients and peak months across all stations.

stations, the lowest mean correlation occurs in winter. The large spread observed for all stations during the winter mainly reflects the contrasting performance between stations within NEC (mean $R = 0.30$) and those outside NEC (mean $R = 0.49$). In comparison, GRACE-Noah correlations are more stable across seasons, with a larger spread among stations in winter. These seasonal discrepancies may arise from different sources of uncertainty in the three data sets. GRACE- and Noah-based displacements both reflect elastic loading responses to large-scale TWS

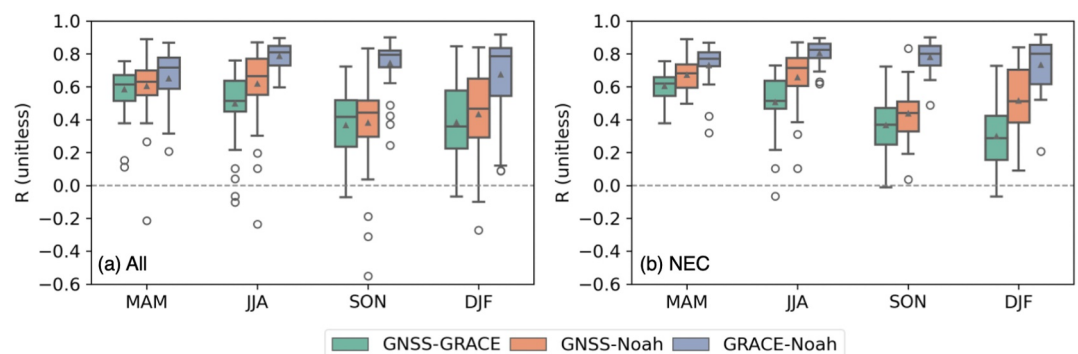


Figure 6. Seasonal correlation coefficients between GNSS and GRACE, GNSS and Noah, and GRACE and Noah for (a) all stations and (b) stations within the NEC region. The central line and triangular mark indicate the median and mean, respectively; the box represents the interquartile range (25th–75th percentiles), and the whiskers extend to the most extreme values within 1.5 times the interquartile range.

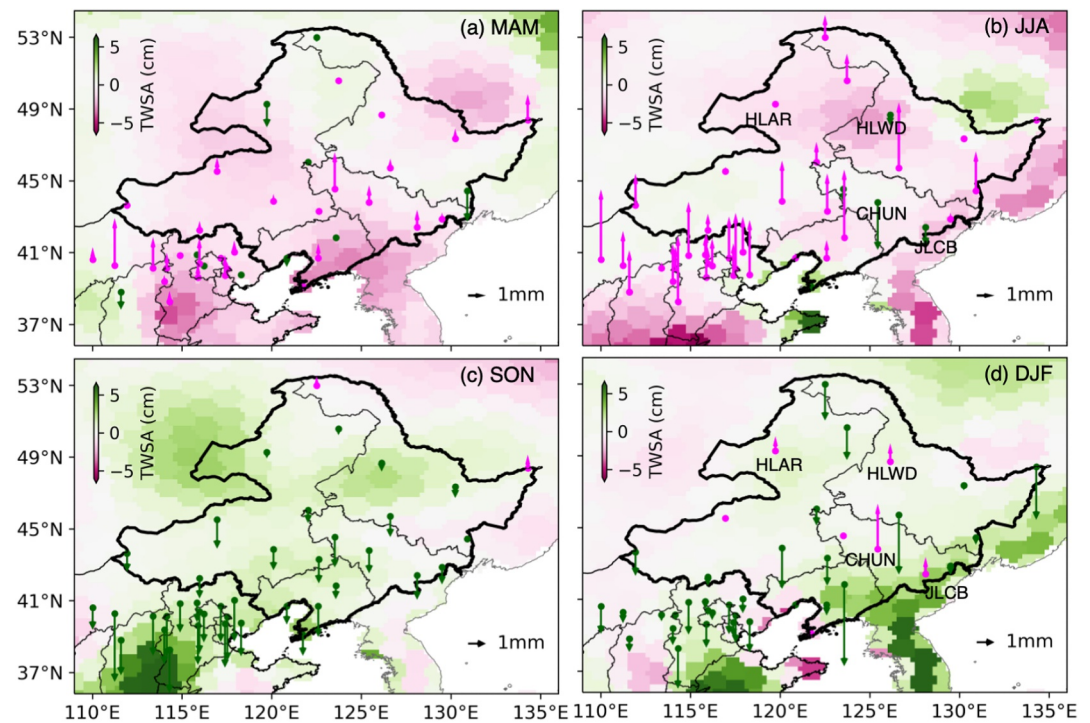


Figure 7. Seasonal average vertical displacement from GNSS overlaid on GRACE-based seasonal TWSA from 2012 to 2023.

variations, whereas GNSS observations may additionally be affected by local loading effects and site-specific conditions (e.g., freeze-thaw processes). These factors may contribute to the stronger seasonal variability observed in GNSS-related correlations. Further discussion of the discrepancies among the three data sets is provided in Section 3.5.

3.4. Response of Vertical Displacement to Hydrological Loading

Previous studies found strong responses of GNSS vertical displacement to hydroclimate variables, such as precipitation, snow water equivalent, and teleconnection indices, in different regions at multiple temporal scales (Knapp et al., 2019; Yin et al., 2020). Therefore, this study explored such responses of GNSS displacements to hydrological loading in NEC.

3.4.1. Vertical Displacement and TWSA

The seasonal mean GNSS vertical displacements at individual GNSS stations were compared with seasonal GRACE TWSA (Figure 7). During the study period of 2012–2023, GRACE shows higher TWSA during autumn (SON) and winter (DJF), and lower water storage during spring (MAM) and summer (JJA). The same seasonal variation of TWSA is observed in Noah-based TWSA, though with slightly different spatial patterns (Figure S3 in Supporting Information S1). This seasonal behavior indicates that winter snowfall exerts a great influence on regional water storage dynamics.

GNSS-derived vertical displacements generally correspond well with TWSA, with positive TWSA leading to surface subsidence and negative TWSA producing uplift. This elastic response is particularly evident in MAM, JJA, and SON, while more deviations occur in winter. Stations such as HLWD, CHUN, and JLCB exhibit subsidence during negative-TWSA seasons and uplift during positive-TWSA seasons. The apparent reversed responses in winter are unexpected given the presence of prolonged snow cover, which has been shown to produce persistent subsidence signals through snow loading (Zheng et al., 2025). Combined with the reduced consistency between GNSS- and GRACE-derived vertical displacements during winter (Section 3.3), these results suggest deviations from the ideal elastic loading relationship between GNSS-derived vertical displacements and TWSA. Considering the widespread freeze-thaw processes in NEC, the non-elastic deformation associated

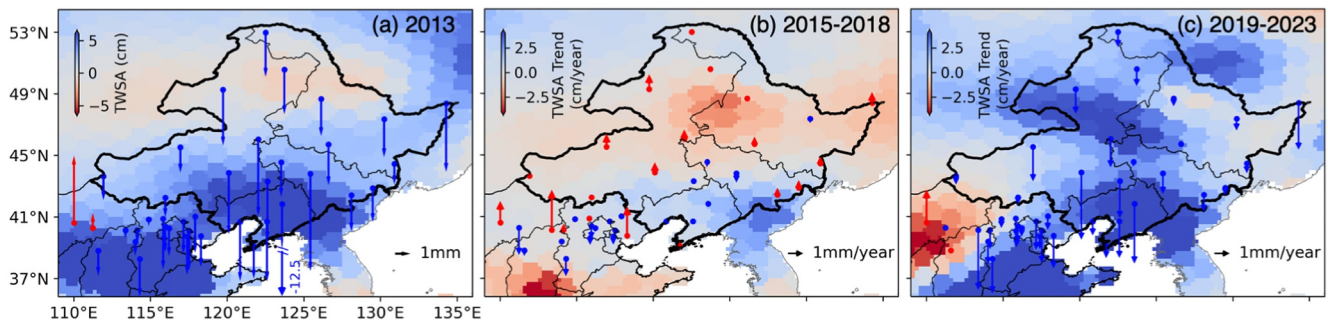


Figure 8. (a) Spatial pattern of average GNSS vertical displacement overlaid on GRACE TWSA in 2013. Panels (b) and (c) show linear trends of GRACE-based TWSA for 2015–2018 and 2019–2023, respectively.

with frozen soil processes likely contributes to the observed winter vertical displacements in GNSS. More detailed discussion of potential freeze-thaw effects on GNSS vertical displacements is provided in Section 3.5.

The GNSS network-wide mean vertical displacement (Figure 2) showed distinct interannual features, including a pronounced trough in 2013, a relatively stable period during 2015–2018, and a declining phase after 2019. To evaluate the consistency between GNSS-derived vertical displacements and GRACE TWSA, spatial patterns were analyzed for 2013, while linear trends were computed for 2015–2018 and 2019–2023 due to their multi-year duration (Figure 8). In 2013, GRACE showed positive TWSA across most of the domain, particularly in the south. GNSS-based vertical displacements matched this pattern with widespread subsidence except at two stations (NMBT and NMTK) in the southwest. During 2015–2018, GRACE exhibited decreasing TWSA in the northern Songnen Plain and North China Plain, and increasing TWSA in the Liaohe Plain and along the Changbai Mountains. GNSS vertical displacements generally exhibited an elastic response to TWS variations, but several stations deviated from this behavior, likely due to the small fluctuations and spatial heterogeneity of TWSA trends, as well as the spatial resolution mismatch between GNSS and GRACE. During 2019–2023, strong increases in TWSA occurred across most of the domain, accompanied by large subsidence trends in GNSS vertical displacements.

Scatterplots of GNSS vertical displacement trends and TWSA trends at collocated grid cells (Figures 9a and 9b) show that most stations lie in the second and fourth quadrants, with positive (negative) vertical displacement trends corresponding to decreasing (increasing) TWSA, suggesting an elastic response of vertical displacement to hydrologic loading variations. The elastic response is more pronounced in 2019–2023 than in 2015–2018 for both GRACE- and Noah-based TWSA. The weaker response during 2015–2018 can be explained by the smaller water mass variations, as reflected by the reduced range of values compared to those shown in Figure 9b. More specifically, when hydrological loading signals in GNSS are weak, errors in non-hydrological loading corrections can become comparable to, or even exceed the hydrologic signal, thereby increasing uncertainty in the post-processed vertical displacements. Moreover, small-magnitude and spatially heterogeneous TWSA variations may cancel out within the relatively coarse spatial footprints of GRACE mascons and Noah grid cells, causing GNSS to reflect more localized hydrological loading signals than can be captured by GRACE or Noah. Except for GNSS-related characteristics, Noah-based TWSA is subject to uncertainties in model structure, initial conditions, and boundary conditions. Additionally, the 2015–2018 period covers the end of the GRACE mission, when noise in the observation and processing chain increased, substantially elevating relative uncertainty in GRACE TWSA, particularly in regions or periods with weak hydrological signals or limited spatial sampling (Boergens et al., 2022; Chen et al., 2021).

3.4.2. Vertical Displacement and Precipitation

Precipitation is the primary driver of TWS variations, making it a critical variable for understanding hydrological loading signals captured by GNSS vertical displacements. NEC-average precipitation from IMERG was calculated (Figure 10a). The seasonal cycle (Figure 10b) was removed to obtain deseasonalized precipitation, followed by the application of a 13-month moving average to highlight interannual variability (Figure 10c). Unlike TWSA, NEC precipitation showed a strong seasonal pattern, peaking in summer and dipping in winter. Interannual variations showed below-average precipitation during 2014–2018, while precipitation increased markedly after

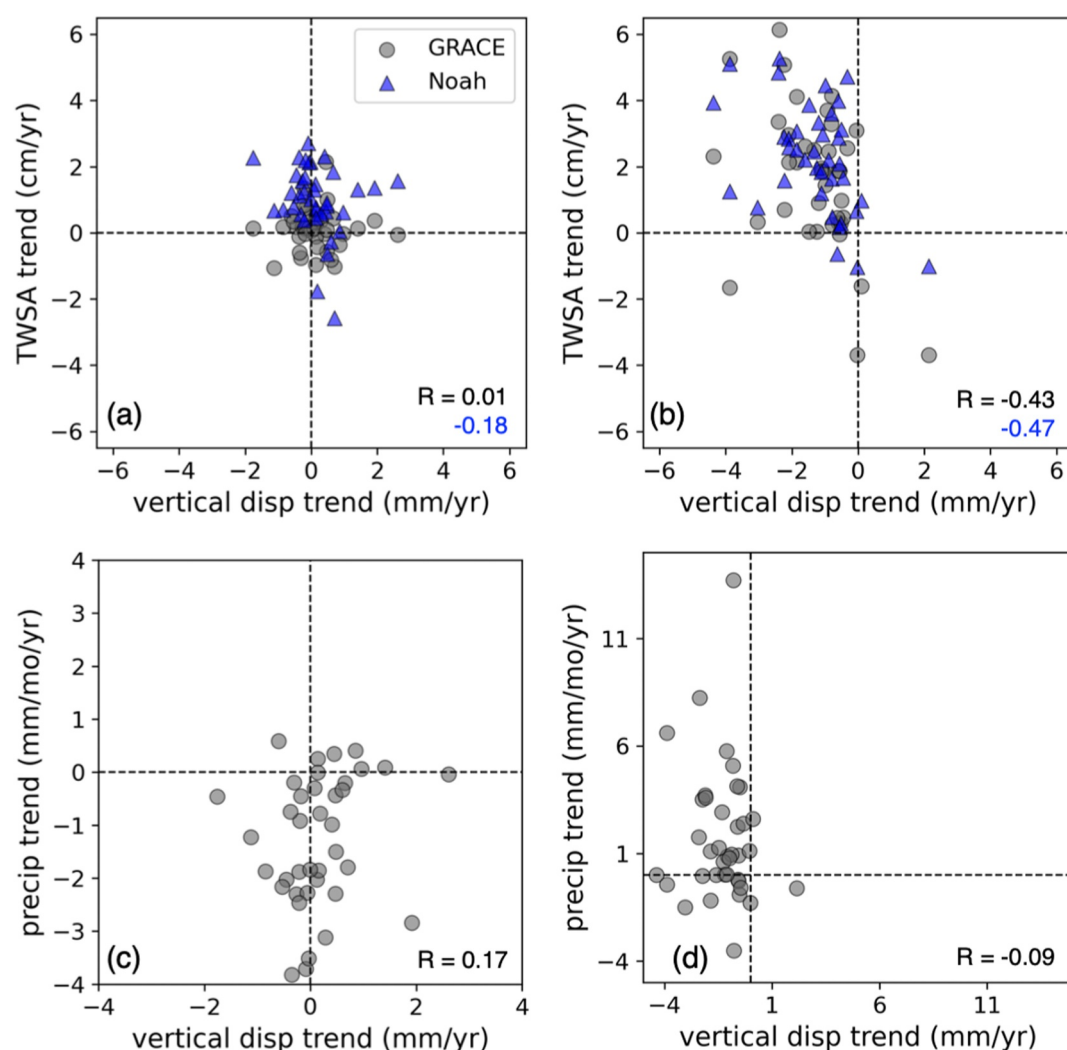


Figure 9. Scatterplots of GNSS vertical displacement trends versus collocated TWSA from GRACE and Noah for (a) 2015–2018 and (b) 2019–2023. Panels (c) and (d) show scatterplots of GNSS vertical displacement trends versus collocated precipitation for the same periods.

2019. The post-2019 increase in precipitation aligns with the increasing GRACE-derived TWSA and more negative network-mean GNSS vertical displacements, suggesting that GNSS-derived vertical displacements can capture regional water mass changes at interannual timescales.

To be consistent with the TWSA analysis, precipitation trends during 2015–2018 and 2019–2023 were computed. Although precipitation trends (Figures 10d and 10e) and TWSA trends (Figures 8b and 8c) broadly show similar spatial patterns, regional discrepancies exist. For example, during 2015–2018, precipitation decreased across most areas of NEC, particularly in the Liaohe Plain and along the Changbai Mountains (locations shown in Figure 1), where TWSA showed an increasing trend. During 2019–2023, increases in TWSA in these regions correspond closely with elevated precipitation. Meanwhile, the northern Songnen Plain (around 47°N, 123°E) experienced a pronounced TWSA increase during 2019–2023 despite no significant precipitation trend.

These inconsistencies between precipitation and TWSA suggest additional effects that modulate water storage. For example, enhanced evapotranspiration and variations in soil moisture (Figure S4 in Supporting Information S1) indicate that land-surface water redistribution may partially offset the effects of precipitation anomalies. In addition, anthropogenic influences, such as irrigation practices, reservoir operations, and water diversion projects, may further contribute to the observed discrepancies. Trends in GNSS vertical displacements also show

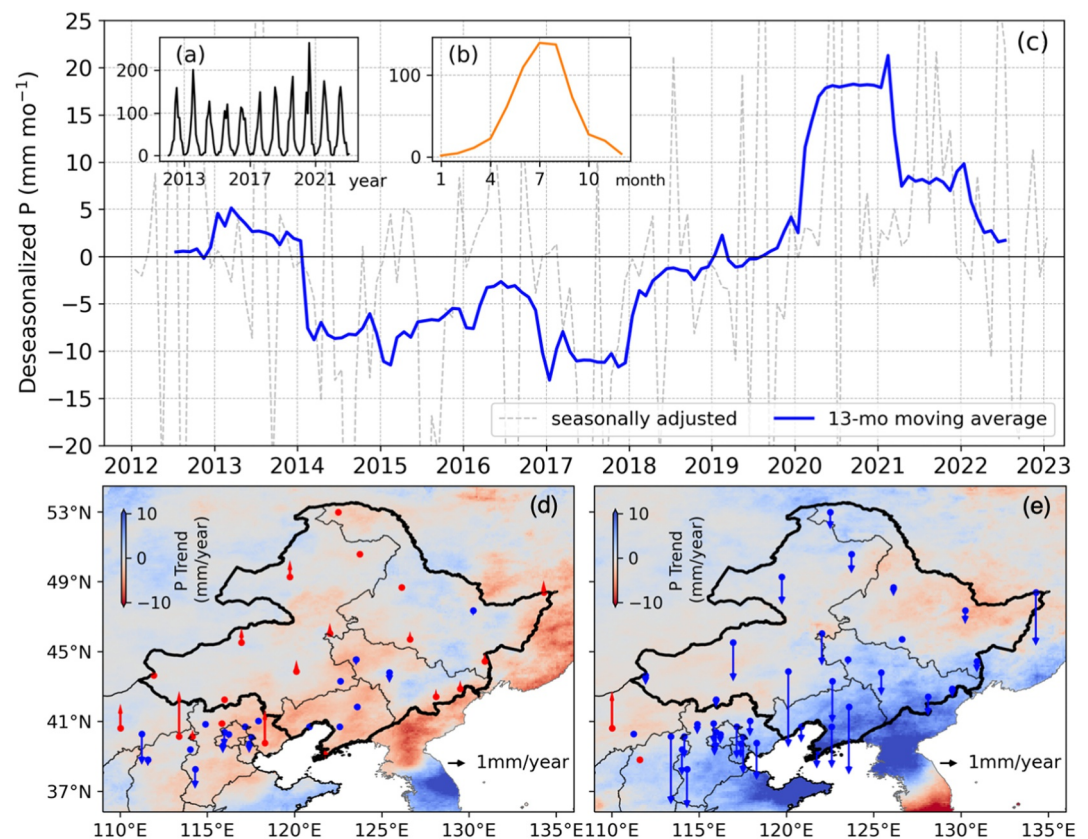


Figure 10. (a) Regional average monthly precipitation over NEC derived from IMERG (black line; mm month^{-1}). (b) Mean seasonal cycle of monthly precipitation during 2012–2023 (orange line; mm month^{-1}). (c) Seasonally adjusted precipitation (gray dashed line) and 13-month moving average representing interannual variation (blue line). Panels (d) and (e) show the precipitation trends for 2015 to 2018 and 2019 to 2023, respectively, with arrows indicating corresponding trends in GNSS vertical displacement at each station.

higher agreement with TWSA variations than with precipitation (Figures 9c and 9d), demonstrating that GNSS vertical displacements respond to the net water mass changes rather than to meteorological inputs alone.

3.4.3. Vertical Displacement and Snow Water Equivalent

Considering that seasonal snowpack acts as an important natural water reservoir during winter in NEC, snow variability is expected to exert a strong influence on vertical displacements. To evaluate this hypothesis, regional mean SWE was correlated with the network-mean vertical displacement derived from 22 stations located within NEC. The resulting correlations were weak, with R values of 0.10, 0.28, and -0.21 for GNSS-, GRACE-, and Noah-derived displacements, respectively. In contrast, substantially stronger correlations were obtained between the network-mean vertical displacements and GRACE-derived regional mean TWSA ($R = -0.60$, -0.88 , and -0.91 , respectively). These results suggest that SWE variability alone cannot explain the observed seasonal loading signal and that regional-scale seasonal TWS variability is governed by the combined contributions of multiple water storage components.

The spatial relationship between SWE and vertical displacement was further examined following Yin et al. (2020). The amplitudes derived from the ESA snow_cci SWE product were compared with the amplitudes of vertical displacements at individual stations (Figure 11). Annual amplitudes were estimated by fitting a harmonic function to each time series, with the amplitude representing half of the peak-to-trough variation of the fitted annual cycle. Larger SWE amplitudes are mainly concentrated in the surrounding mountain regions, whereas SWE amplitudes over the central plains are relatively smaller (~ 10 mm). Among the three displacement data sets, Noah-based displacement amplitudes exhibit higher spatial correspondence with SWE, providing a correlation coefficient of 0.50 between displacement amplitudes and SWE amplitudes at the corresponding station grids. In

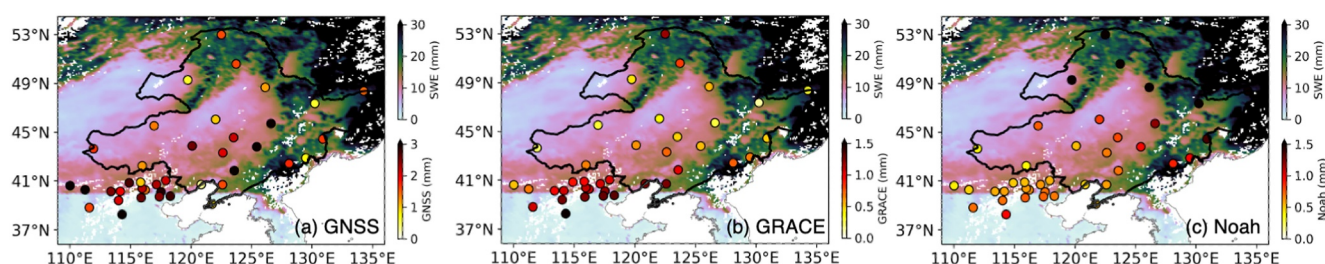


Figure 11. Spatial distribution of SWE amplitudes derived from the ESA snow_cci data set (background shading). White areas indicate masked regions, including mountainous areas and water bodies where SWE estimates are unavailable. Colored circles denote the amplitudes of vertical displacements derived from (a) GNSS, (b) GRACE, and (c) Noah.

contrast, GNSS- and GRACE-derived vertical displacement amplitudes show weaker spatial correlations with SWE amplitudes (-0.21 and -0.46 , respectively). GNSS amplitudes are largest along the northwestern foothills of the Changbai Mountains, while GRACE-based amplitudes are spatially smoother. Notably, both GNSS and GRACE reveal large amplitudes outside the NEC boundary, which are not observed in Noah.

It is noted that Noah-derived displacements are calculated from modeled TWSA composed of soil moisture, canopy water, and SWE, while groundwater and surface water variations are not represented. Therefore, Noah-based TWSA may be more directly linked to snow-related storage variability, particularly in mountain regions with more snow loading. In comparison, GNSS- and GRACE-derived vertical displacements integrate the effects of all water mass variations, including groundwater, surface water, and anthropogenic water redistribution processes such as irrigation and groundwater pumping, which are not explicitly represented in Noah. Consequently, the discrepancies between Noah and the observation-based estimates may reflect the influence of hydrological processes that are not fully captured by the model in the North China Plain where human-induced water storage changes are substantial (Wang et al., 2017; Xiong et al., 2023).

Despite uncertainties in satellite-based SWE estimates, the snow_cci product is generally capable of capturing large-scale snow variability. Overall, the weak temporal correlations and the spatial mismatch between SWE and observed vertical displacements suggest that snow contributes to seasonal mass loading, but it alone may not dominate TWS variations or vertical deformation in NEC. Multiple hydrological processes and anthropogenic water management likely contribute jointly to the observed TWS variations and associated surface deformation.

3.5. Discrepancies Among Data Sets

The comparison of vertical displacements from GNSS, GRACE, and Noah (Sections 3.1–3.3) reveals differences in the three data sets in both amplitude and phase. GNSS-derived displacements exhibit the largest annual amplitude (2.01 ± 0.95 mm), which is approximately 2.4 times larger than GRACE (0.85 ± 0.39 mm) and 2.2 times larger than Noah (0.92 ± 0.62 mm). The larger amplitudes observed by GNSS have also been reported in previous studies (Fu et al., 2012; Khan et al., 2010; Yin et al., 2020) and are generally attributed to the higher sensitivity of GNSS to short-wavelength, local hydrological loading that cannot be fully resolved by GRACE and Noah.

Unlike results reported for other regions (Knappe et al., 2019; Yin et al., 2020), GNSS-derived vertical displacements show only moderate agreement with GRACE- and Noah-based vertical displacements within NEC, which may be associated with the weak TWS variability in the study domain. The weak TWSA signals make the vertical displacements in NEC more sensitive to local hydrological loading variations, which can be observed by ground-based GNSS but cannot be captured by GRACE or Noah due to the coarse spatial resolution of their TWSA estimates. As discussed in Section 3.4.1, when the magnitude and spatial extent of TWS changes were greater during 2019–2023 than during 2015–2018, the response of GNSS vertical displacement to GRACE TWSA was more pronounced. The correlations of vertical displacements derived from GNSS and GRACE in 2019–2023 (station-average $R = 0.56$) are also higher than in 2015–2018 ($R = 0.14$).

Moreover, NEC is covered by seasonal frost over a large portion of the plains, and permafrost is mainly distributed across the Greater and Lesser Khingan Ranges (Figure 1b). The freeze-thaw dynamics cause frost heave during soil freezing and thaw subsidence during spring melt (Liu & Larson, 2018). These deformation

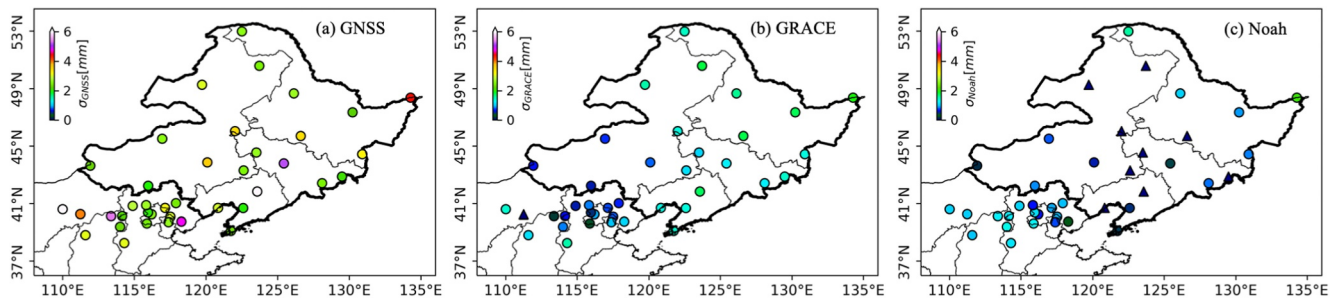


Figure 12. TC-based random error standard deviations of vertical displacements derived from (a) GNSS, (b) GRACE, and (c) Noah. Triangles indicate stations where TC-derived error variances are negative and were set to zero.

signals are not directly related to water mass loading and can contaminate GNSS-derived hydrological signals, particularly during winter and transition seasons. According to the foundation types of GNSS stations, NEC stations installed on soil foundations generally showed lower correlations than those anchored on bedrock (Table S2 in Supporting Information S1), with the inferior performance being more pronounced during winter ($R = 0.17$ for soil and 0.32 for bedrock) than in other seasons (e.g., 0.49 and 0.61, respectively, in summer).

However, because of the lack of detailed information on monument foundation conditions (e.g., anchoring depth) and site-specific frozen-ground characteristics, together with the absence of an established method to quantitatively separate freeze-thaw-induced deformation from GNSS observations, the contribution of freeze-thaw processes cannot be explicitly quantified in this study. Therefore, it is premature to attribute the reduced GNSS-GRACE consistency at soil-founded stations in winter solely to freeze-thaw processes. Additional field investigation and improved methods for quantifying freeze-thaw-induced deformation are required to further evaluate this hypothesis. In addition to the freeze-thaw processes, previous studies have shown that snow accretion on GNSS antenna radomes may introduce spurious subsidence signals (Heki & Jin, 2023; Zheng et al., 2025). Although a quality control procedure was applied in the study to reduce potential artifacts, such as outlier removal, such effects may still exist in the remaining observations.

Additionally, the plains are an important agricultural region with extensive anthropogenic activities, such as irrigation, groundwater withdrawal, reservoir regulation, and water diversion projects (Lu et al., 2021; Sun et al., 2022; Zhong et al., 2018). These activities may modify the natural TWS variability and are not explicitly represented in the Noah land surface model. Furthermore, GNSS stations above groundwater aquifers experiencing substantial groundwater depletion may also record a poroelastic response associated with aquifer compaction and land subsidence. However, the relative contribution of these processes to the discrepancies among GNSS-, GRACE-, and Noah-derived vertical displacements cannot be quantified with available observations. Future studies integrating independent observations of human water use will be important for improving the interpretation of GNSS observations in hydrological studies.

3.6. Data Uncertainty Analysis

To further assess uncertainties in each data set and to support future GNSS data assimilation, the TC method was applied to estimate the random error standard deviations of vertical displacements from GNSS, GRACE, and Noah (Figure 12). GNSS exhibits the largest random error standard deviation (3.19 ± 1.39 mm), which is consistent with its larger data variability. GRACE (1.13 ± 0.47 mm) and Noah (0.92 ± 0.38 mm, based on the 30 stations with positive error variances) generally have smaller uncertainty, with larger random error standard deviations in the north, whereas GNSS shows less spatial consistency, likely due to additional local non-hydrologic signals. Negative TC-derived error variances were obtained for Noah at 9 of the 39 stations, most of which were located in the central plains. Although these values were displayed as zero in Figure 12, they represent invalid TC results for which a physically meaningful error standard deviation could not be obtained, rather than zero uncertainty. These stations were excluded from the Noah uncertainty statistics. Such nonphysical negative error variance estimates may indicate potential violations of TC assumptions (Su et al., 2014). In this study, the Noah model does not explicitly simulate groundwater storage or anthropogenic management, whereas both GNSS and GRACE data reflect the integrated effects of total water storage changes. This issue is particularly

evident in the Songnen and Liaohe Plains, where groundwater usage and agricultural activities are relatively intensive (Deng et al., 2026; Yu et al., 2020).

Although the TC method requires mutually independent random errors among the input data sets, this assumption is often only approximately satisfied in real-world applications because geophysical data sets may share common forcing data or retrieval methodologies (McCormick et al., 2026; Wu et al., 2019; Yilmaz & Chow, 2014). In this study, for example, the same AOD1B product was used to remove atmospheric and oceanic loading effects from both GRACE and GNSS observations, which may introduce some degree of shared errors and potentially bias the estimated error standard deviations (Yilmaz & Chow, 2014). As a sensitivity analysis, a revisited version of the three-cornered hat (TCH) method was applied to quantify the error standard deviations of the three data sets while relaxing the strict independence assumption by allowing non-zero error cross-correlations (Long et al., 2017; Premoli & Tavella, 1993). The resulting error standard deviations were generally consistent with those estimated by TC (Figure S5 in Supporting Information S1), indicating that the overall uncertainty patterns were not highly sensitive to the treatment of error cross-correlations. Nevertheless, given the underlying assumptions of both methods and the occurrence of nonphysical negative error variances at some stations, these estimates should be interpreted as first-order uncertainty information rather than definitive error parameters. They may therefore provide a useful reference for specifying observation errors in future TWS inversion and data-assimilation applications.

4. Conclusions

The study assessed the potential of ground-based GNSS vertical displacements to infer TWS variations in NEC, a region characterized by complex cryospheric conditions and intensive human activities. After removing non-hydrological loading effects, GNSS-derived vertical displacements were compared with GRACE- and Noah-based vertical displacements at individual stations. The response of GNSS vertical displacements to hydrological loading was analyzed across multiple spatiotemporal scales.

The consistency between GNSS and both GRACE and Noah varied spatially and temporally. At the regional scale, network-wide mean vertical displacements show relatively strong agreement among GNSS, GRACE, and Noah, reflecting coherent large-scale hydrological loading signals. At the station scale, GNSS vertical displacements generally agree well with GRACE and Noah in terms of long-term variability, whereas substantial discrepancies emerge in the seasonal cycle. Particularly, the consistency between GNSS and GRACE weakens during winter, highlighting the sensitivity of GNSS observations to cold-region processes that differ from the large-scale mass loadings resolved by satellite gravimetry and land surface models.

The relatively weak and spatially heterogeneous TWSA variability in NEC causes GNSS to reflect more localized hydrologic signals than GRACE or Noah can resolve, contributing to the observed discrepancies. Despite the presence of prolonged snow cover during winter, snow mass alone does not appear to be the sole dominant driver of TWS variations and vertical deformation in the study region. Both anthropogenic activities, such as irrigation, groundwater pumping, and reservoir regulation, and cryospheric processes associated with permafrost and seasonally frozen ground dynamics may also contribute to GRACE-derived TWSA and GNSS vertical displacement signals. However, their relative contributions remain uncertain because of limited in situ observations and incomplete understanding of the underlying physical mechanisms. Improved approaches are needed to separate hydrological loading from possible non-hydrological deformation associated with freeze-thaw processes, thereby enhancing the interpretation of GNSS observations in cold-region environments.

Despite these discrepancies and challenges, the results demonstrate that GNSS vertical displacements are capable of capturing TWSA variations at regional and long-term scales. The local hydrological loading information embedded in GNSS observations provides valuable insights for fine-scale water storage dynamics. GNSS could potentially improve the characterization of regional land surface processes through future assimilation of GNSS observations, either independently or in combination with GRACE TWSA.

Conflict of Interest

The authors declare no conflicts of interest relevant to this study.

Availability Statement

The daily GNSS vertical displacements are available at the National Earthquake Data Center at https://www.eqdsc.com/eastern/report.shtml?PAGEID=sharedata_station&parid=10&type=sjxl (in Chinese). The GRACE mascon product are from the Center for Space Research at https://www2.csr.utexas.edu/grace/RL06_mascons.html (Save, 2020), the AOD data is available at <https://doi.org/10.5067/GRGAC-20C06> (Bettadpur, 2018), the Noah model estimates are available at <https://disc.gsfc.nasa.gov/datasets?keywords=GLDAS> (Beaudoin et al., 2020), the IMERG V7 final run daily precipitation data are acquired from <https://gpm.nasa.gov/data/directory> (Huffman et al., 2023), and the ESA snow_cci SWE estimates are acquired from <https://data.ceda.ac.uk/neodc/esacci/snow/data/swe/MERGED/v4.0/> (Luoju et al., 2025). The geocryological regionalization data is acquired from <https://www.tpdac.cn/zh-hans/data/15bf484c-e4bc-4990-b01b-c26da686e254/> (Zhou et al., 2011).

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