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ORIGINAL ARTICLE

Modeling groundwater depletion in Hungary through GRACE and GLDAS observations analyzed with ensemble machine learning models

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Abstract

Regional modeling of groundwater storage dynamic requires extensive parameterization and conceptualization, often relying on in-situ data collected from monitoring networks. However, the sparse spatial coverage and uneven distribution of these networks can limit the representativeness of such models. The use of remote sensing has greatly enhanced groundwater modeling by providing consistent and spatially comprehensive datasets. Satellite-based Earth observation systems, such as the Gravity Recovery and Climate Experiment (GRACE) and its follow-on mission (GRACE-FO), have significantly improved the ability to monitor water resources across broad spatial and temporal domains, thereby overcoming many of the limitations of traditional monitoring. In this study, groundwater storage (GWS) changes across Hungary, which is underlain predominantly by transboundary aquifers, were quantified by combining GRACE-derived Terrestrial Water Storage (TWS) anomalies with land surface components from the Global Land Data Assimilation System (GLDAS). To address data gaps in the GRACE time series, a Random Forest (RF) machine learning model was applied to impute missing TWS values. Subsequently, GWS anomalies were estimated by subtracting the GLDAS-based surface water components from the completed TWS records. Future GWS dynamics were further forecasted using a bootstrapped RF ensemble, which produced both point predictions and 95% confidence intervals. A Seasonal-Trend decomposition (STL) analysis indicated continued groundwater depletion in Hungary (-0.0375 to -0.0516 mm/year) with the long-term trend accounted for the majority of GWS variability, while seasonal fluctuations contributed approximately 10–20% of the total variance. The study concluded that under current climatic and usage patterns, several aquifers are at risk of reaching critical depletion levels. This underscores the urgent need for region-specific groundwater management strategies aimed at regulating extraction and promoting sustainable use to safeguard future water security.

Keywords Transboundary aquifer · GRACE satellite · GLDAS · Terrestrial water storage · Groundwater storage · Random forest · Uncertainty analysis

Introduction

Groundwater resources constitute one of the most critical components of the global hydrological cycle, providing freshwater as the primary source for drinking water supply and irrigation purposes for approximately two billion people worldwide (Famiglietti 2014). The sustainable management of groundwater resources has become increasingly challenging due to growing anthropogenic pressures, climate variability, and the inherent difficulty of monitoring groundwater storage changes across large spatial scales (Rodell et al. 2018). Groundwater monitoring approaches rely heavily on in-situ well measurements, which, while providing

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high temporal resolution and accuracy at point locations, are spatially limited and often inadequate for characterizing regional-scale groundwater dynamics (Rodell et al. 2007; Condon et al. 2021; Jasechko et al. 2024). The sparse distribution of monitoring wells, particularly in remote or economically disadvantaged regions, creates significant gaps in understanding groundwater storage variations and limits the effectiveness of water resource management strategies (Masood et al. 2022).

The advent of satellite gravimetry has provided the opportunity to directly measure water storage changes through observations of changes in Earth's gravity field (Tapley et al. 2019). Among these missions, the Gravity Recovery and Climate Experiment (GRACE) and its follow-on mission (GRACE-FO), have fundamentally contributed to understanding global water cycle dynamics by providing quantitative measures of terrestrial water storage (TWS) changes (Moudgil and Rao 2023). This enabled to investigate water depletion, seasonal storage variations, and long-term hydrological trends (Li et al. 2019; Mohamed et al. 2024b). However, TWS encompasses the total vertically integrated water content regardless of the storage reservoir. This necessitates the decomposition of GRACE-observed TWS signals into constituent components to isolate groundwater storage changes effectively (Li et al. 2024). The Global Land Data Assimilation System (GLDAS) is one of several auxiliary datasets used within the water balance framework (Rodell et al. 2004; Mohamed et al. 2024a). The fundamental principle underlying this approach involves calculating groundwater storage changes as the residual between GRACE-derived total water storage variations and land surface model-simulated surface water storage components, such as soil moisture, snow water equivalent, canopy water storage, and surface water storage (Sun et al. 2012).

Despite significant advances in satellite-based groundwater monitoring, modeling of future groundwater storage changes remains critical challenges for water resource planning (Graf et al. 2025). Traditional hydrogeological modeling approaches, while theoretically sound, often require extensive parameterization and may struggle to capture complex nonlinear relationships between climatic variables, surface processes, and groundwater dynamics (Boo et al. 2024). The emergence of machine learning techniques has opened new possibilities for groundwater modeling, offering data-driven approaches that can identify complex patterns and relationships within large datasets without requiring explicit knowledge of underlying physical processes (Ibrahem et al. 2022; Mohammed et al. 2025b). Recent studies have demonstrated the effectiveness of various algorithms including Random Forest, Support Vector Machines, Artificial Neural Networks, and ensemble methods for groundwater storage prediction across different temporal and spatial scales (Yin et al. 2021; Soltani and Azari 2022; Li et al. 2024; Eftekhari and Khashei-Siuki 2025). These studies have successfully demonstrated the exceptional effectiveness of machine learning models due to their ability to capture complex, nonlinear relationships and manage high-dimensional datasets. However, most documented studies focus primarily on maximizing predictive accuracy, often overlooking the systematic quantification and communication of uncertainty associated with model outputs (Nourani et al. 2022; Mohammed et al. 2025a). This omission can lead to overconfidence in predictions and limit their applicability in water resource management.

The hydrogeological setting of Hungary is highly complex and heterogeneous, shaped by diverse aquifer systems that vary widely in responses to climatic and anthropogenic influences (Tóth and Almási 2001; Mohammed et al. 2024a). This diversity poses significant challenges for monitoring groundwater storage changes, particularly under limited monitoring networks. GRACE and GRACE-FO observations have an effective spatial resolution of approximately 100,000 km^2 (Scanlon et al. 2016). However, its sensitivity depends primarily on the magnitude of mass change rather than basin size alone. Previous studies have shown that GRACE can detect groundwater-related storage variations in basins smaller than its nominal footprint when temporal mass changes are sufficiently large (Swenson and Wahr 2009; Becker et al. 2010; Wang et al. 2011; Longuevergne et al. 2013). This supports the use of GRACE data for assessing regional groundwater trends in smaller basins. In this study, groundwater storage changes are evaluated over three major hydrogeological regions in Hungary including the Transdanubian region, the Northern Hungarian karstic mountains, and the Great Hungarian Plain. These regions are largely transboundary (Szűcs et al. 2013), and their surrounding areas are included to capture the full groundwater dynamics.

Against this backdrop, the primary objectives of this study are threefold: (i) to quantify groundwater storage anomaly changes in Hungary through the integration of GRACE terrestrial water storage observations with GLDAS land surface model outputs; (ii) to analyze the spatial and temporal patterns of groundwater storage anomaly variations across the country; and (iii) to develop and evaluate ensemble machine learning model for forecasting future groundwater storage anomaly changes based on historical relationships between climatic variables, satellite observations, and groundwater dynamics. In doing so, this research addresses a critical gap by incorporating systematic uncertainty quantification into the forecasting framework, thereby enhancing the robustness and reliability of the predictions. To the best of our knowledge, this represents the first study in Hungary to integrate satellite gravimetry for groundwater storage assessment. The methodological framework developed here offers a transferable approach that can be adapted to other regional studies, supporting improved groundwater management strategies under growing water security challenges.

Characteristics of the study area

Hungary is located in southeastern Central Europe, covering a land area of 93,030 km^2 (Fig. 1) (Kovács and Jakab 2021). The physiographic characteristics of Hungary are shaped by its position within the Carpathian Basin, which represents one of the most significant sedimentary basins in Central Europe. The topography in Hungary is predominantly characterized by low-lying plains and gentle hills, with approximately two-thirds of the territory lying below 300 m above sea level (Haas 2012). The Great Hungarian Plain dominates the eastern and southeastern portions of the country and represents one of the most extensive lowland areas in Europe. This vast alluvial plain, formed by the sedimentary deposits of the Danube and Tisza rivers and their tributaries. Hungary has a continental climate, with a mean annual temperature of approximately 9.7 °C (Gavrilov et al. 2020). The country experiences a temperate seasonal climate, with generally warm summers with low overall humidity levels but frequent rain showers and cold snowy winters. Annual precipitation typically ranges from 500 to 800 mm. The seasonal distribution shows a pronounced peak during the late spring and early summer months (May-July), followed by a secondary maximum during autumn (NATéR 2023).

Hungary sits in the Pannonian Basin, creating diverse groundwater conditions across the country. The Great Hungarian Plain in the east contains large, porous aquifers made of Neogene-Quaternary sediments (Tóth and Almási 2001; Mohammed et al. 2024a). These contrast sharply with the fractured rock aquifers found in the surrounding uplands, which include volcanic, metamorphic, and carbonate rocks. In the eastern and southeastern regions (Great Plain), groundwater flows through layered sand and gravel deposits separated by clay layers. These deposits form multiple aquifer levels, ranging from unconfined near the surface to confined at greater depth (Buday et al. 2015). This layered structure creates strong vertical differences that control water storage and movement between layers. Moving west and north, the landscape changes to carbonate mountains (Transdanubian Range, Bükk Mountains) that contain productive karst aquifers with both conduit and matrix flow systems, along with thermal waters. The Neogene volcanic areas and metamorphic rock blocks provide fracture-controlled aquifers with variable water transmission properties (Miklós et al. 2020).

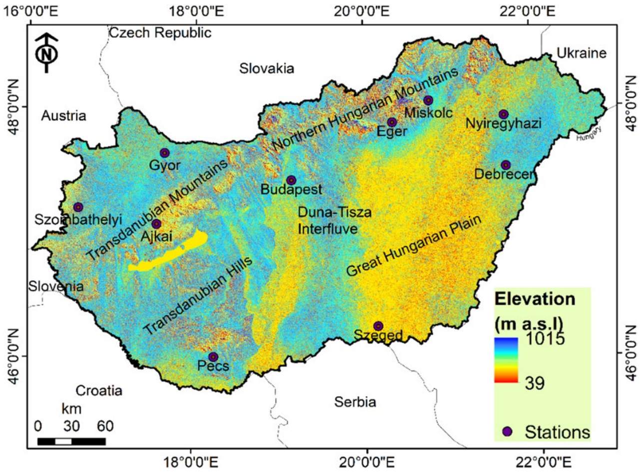


Fig. 1 Geographical location of Hungary and its main physiographic features

At the regional scale, groundwater flows through two main systems (Mohammed et al. 2024b). Shallow systems follow surface topography, where water infiltrates at high elevations and discharges in lowlands, river valleys, and wetlands. Deep systems contain pressurized saline and thermal waters formed by sediment compaction, tectonic forces, and heat-driven density differences (Tóth and Almási 2001). The Danube-Tisza Interfluve area provides a classic example of this dual flow system (Csondor et al. 2020). In karst areas, buoyancy effects and thermal convection create more complex flow patterns. Water recharge occurs through different pathways depending on the local geology (Tóth and Almási 2001). Carbonate highlands receive direct infiltration and focused recharge through sinkholes. Mountain-front areas provide recharge from uplands to adjacent basins. The Danube and Tisza River systems contribute through bank infiltration and losing stream reaches that feed shallow porous aquifers. Isotope and groundwater age studies show that young, shallow waters overlie older, slower-moving deep groundwater (Szőcs et al. 2024).

Datasets and methods

The workflow adopted in this study (Fig. 2) begins with the acquisition of GRACE satellite observations for terrestrial water storage (TWS) anomalies and GLDAS land surface model outputs for surface water components. Missing values in the GRACE TWS time series are addressed using Random Forest (RF)-based imputation to ensure a continuous record. Groundwater storage (GWS) is then derived from the completed TWS dataset and subsequently modeled and forecasted using a bootstrapped RF framework. Finally, long-term trends in GWS are assessed through statistical trend analysis.

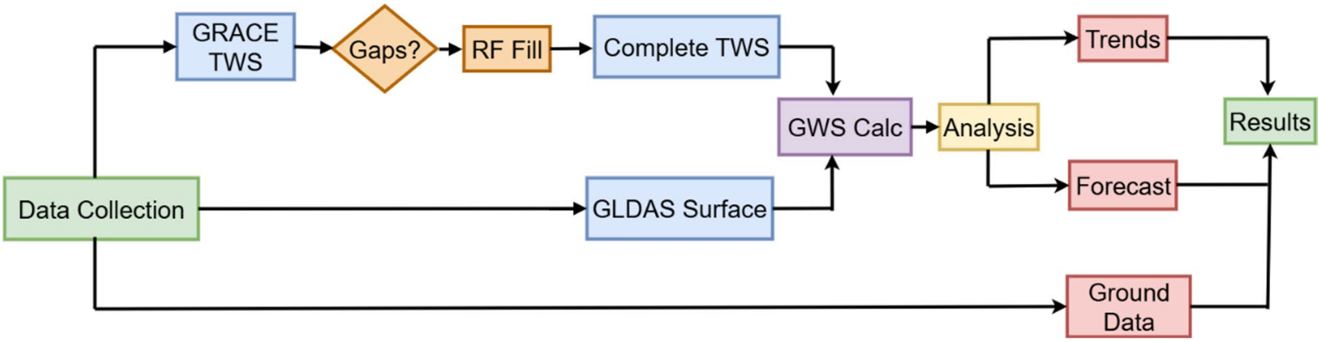


Fig. 2 The workflow of the study

CSR-based GRACE/GRACE-FO

Satellite-based gravity observations from the GRACE mission and its successor, GRACE-FO have substantially advanced our understanding of global water storage dynamics (Tapley et al. 2004). Operating through a partnership between NASA and Germany's GFZ research institute, these satellites detect shifts in Earth's gravitational pull over time, revealing how mass redistributes throughout our planet's systems. Among the most valuable datasets generated from these observations are Terrestrial Water Storage (TWS) anomalies, which capture variations in all forms of water present from the surface down through subsurface layers, including aquifers, soil moisture, rivers and lakes, along with frozen water in snow and ice.

Several institutions serve as primary processing centers for GRACE and GRACE-FO mission data, most notably the Center for Space Research (CSR) at the University of Texas at Austin, the Jet Propulsion Laboratory (JPL), and the German Research Centre for Geosciences (GFZ). Each center independently processes satellite observations using distinct methodological frameworks (Scanlon et al. 2016). Although both JPL and CSR provide mascon-based GRACE solutions, the native effective spatial resolution of the JPL RL06.3 product over Hungary is lower due to its coarser 3° × 3° mascon geometry. In contrast, the CSR RL06.03 mascon dataset is estimated on 0.25°× 0.25° grid, allowing improved spatial representation of groundwater storage variability. For this reason, the CSR mascon product was selected as the primary GRACE input in this study. However, global studies showed high correlations between these two solutions with no significant difference in TWS (Scanlon et al. 2016; Jing et al. 2019).

The sixth-generation release (RL06) produced by CSR incorporates substantial advances in data processing algorithms, background model corrections, and validation procedures (Save 2020). This processing framework employs enhanced atmospheric and oceanic correction models that filter out transient gravitational fluctuations, yielding more reliable monthly estimates (Dobslaw et al. 2013). To make these gravity measurements more accessible for research applications, CSR distributes Level 3 mascon products that convert complex mathematical representations into user-friendly gridded formats at 0.5° grid format. These mascon datasets preserve the detailed spatial information from raw observations while presenting water storage changes in a more straightforward format. The comprehensive CSR RL06.3 mascon time series extends from April 2002 through current operations, though an interruption occurred between July 2017 and May 2018 when missions transitioned.

GLDAS dataset

The Global Land Data Assimilation System (GLDAS) provides widely used auxiliary land-surface datasets that support the partitioning and interpretation of water storage variations observed by GRACE missions (Rodell et al. 2004). GLDAS incorporates multiple land-surface modeling frameworks (NOAH, Community Land Model (CLM), and Variable Infiltration Capacity (VIC) that provide realizations of land-surface processes. The system delivers outputs at spatial resolutions ranging from 0.25° to 1° and across multiple temporal scales. Key variables include multilayer soil moisture, evapotranspiration, surface and near-surface water storage, land-surface temperature, snow-water equivalent, and energy balance components.

The GLDAS system has undergone continuous development, with major releases including version 2.0 (spanning 1948–2014), followed by versions 2.1 and the current version 2.2, which incorporates improved forcing datasets, enhanced data assimilation techniques, and near–real-time updates (Wang et al. 2016). In this study, four GLDAS-NOAH monthly datasets from 2002 to 2025 were employed: multilayer soil moisture, surface water storage, snow-water equivalent, and vegetation canopy water. The soil moisture product measures water content across stratified depth intervals. Soil moisture was represented by the average of the upper GLDAS-NOAH layers (0–10 cm, 10–40 cm, and

40–100 cm). This prevents underestimation of groundwater contributions in the water balance. Surface water storage represents water temporarily retained on the land surface when precipitation exceeds infiltration capacity. Snow storage was represented using the snow water equivalent (SWE) output from the GLDAS-NOAH model. SWE quantifies the amount of water stored as snowpack and is simulated based on precipitation phase, temperature, and energy balance processes. Vegetation canopy storage quantifies intercepted precipitation that evaporates before reaching the ground, a relatively small but seasonally important component, especially in densely vegetated regions.

Estimation of groundwater storage anomalies

Groundwater storage (GWS) variations were estimated using a water balance approach that links GRACE-derived total water storage (TWS) anomalies with individual land surface water components simulated by GLDAS-NOAH. GWS changes were computed as the difference between TWS (Fig. 3) and the sum of modeled surface water components, expressed as $\mathrm{GWS_A} = \mathrm{TWS_A} - (\mathrm{CWS_A} + \mathrm{SWE_A} + \mathrm{SMS_A} + \mathrm{SWS_A})$, where CWS represents canopy water storage, SWE is snow water equivalent, SMS denotes soil moisture storage, SWS corresponds to surface water storage, and subscript $_\mathrm{A}$ denotes anomalies. The water balance equation was applied to storage anomalies, in which $\mathrm{TWS_A}$ were obtained from GRACE by removing the long-term mean over the 2004–2009 baseline period. To ensure consistency across water storage components, all non-groundwater variables derived from GLDAS were converted to anomalies using the same 2004–2009 baseline.

The analysis was conducted over Hungary and its surrounding areas, focusing on three major hydrogeological regions (Fig. 1) represented by 10 stations. These regions include Transdanubian region (~45,000 km^2), Northern Hungarian karstic mountains (~18,000 km^2), and Great Hungarian Plain (~70,000 km^2). Surrounding transboundary areas were included to capture the full dynamics of the aquifers, as these groundwater systems extend beyond Hungary's political boundaries. The spatial extents reported here correspond to the main portions of each hydrogeological body within the study domain and align with previous regional hydrogeological assessments (Szűcs et al. 2021). GRACE-derived groundwater storage anomalies were spatially averaged over these hydrogeologically defined regions, which helps reduce local noise and partially mitigate signal leakage and attenuation.

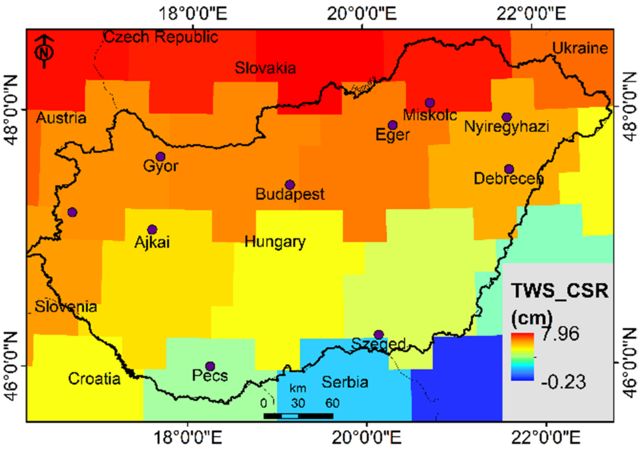


Fig. 3 Example of distribution of terrestrial water storage change obtained from GRACE/GRACE-FO CSR in April 2002

Random forest

This research applied Random Forest (RF) regression methodology as a powerful machine learning framework for two purposes: filling gaps in terrestrial water storage (TWS) and projecting future groundwater storage (GWS) variations. RF operates as an ensemble technique that develops numerous decision tree models throughout the training phase, then combines their individual predictions through averaging to yield precise and consistent outcomes (Breiman 2001). Each individual tree undergoes training using a distinct resampled portion of the input data, while node-level divisions consider only a randomly chosen group of input features. This twofold randomization strategy applied to both data sampling and variable selection minimizes overfitting tendencies and strengthens the model's ability to generalize beyond training data. When applied to hydrological temporal datasets, RF demonstrates several notable strengths: it successfully identifies intricate, non-linear connections among variables without necessitating manual feature engineering, manages intercorrelated predictors effectively, and shows considerable resilience to data noise and hyperparameter choices relative to alternative ensemble approaches (Jing et al. 2020).

Bootstrap resampling method

Bootstrap resampling is defined as a statistical method through which the reliability of predictions can be assessed (Davison and Hinkley 1997). The technique is implemented by creating multiple versions of the original dataset, where data points are randomly selected and the same points can be chosen more than once. This means some observations are included multiple times in a new dataset while others are excluded entirely. This approach is employed in the study to measure the uncertainty associated with Random Forest predictions. The process is executed as follows: Many different datasets are generated through this random selection process. For each new dataset, a separate Random Forest model is trained. Through this procedure, a collection of models is developed, with each model learning slightly different patterns from its particular version of the data. When a prediction is required, it is processed through all these models. By each model, its own answer is provided, creating a range of possible predictions rather than a single value.

Development of the bootstrapped RF model

Within the bootstrapped RF framework (Fig. 4), a comprehensive modeling approach was implemented to ensure both accurate predictions and reliable uncertainty estimates. Each modeling iteration was configured with an ensemble of 100 decision trees, which were used to capture complex patterns in the data. To enhance model robustness and enable rigorous uncertainty quantification, 50 bootstrap samples were systematically generated from the training dataset. This bootstrap resampling process created multiple variations of the training data, allowing the model to learn from different perspectives of the same underlying information.

Prior to model training, all input features and target variables were normalized using the MinMaxScaler transformation technique. Through this normalization process, all values were rescaled to a standardized range of [0, 1], which ensured consistent feature scaling and prevented any single variable from dominating the learning process due to its original measurement scale. The predictor set was carefully designed to capture multiple dimensions of temporal variability in groundwater storage. Temporal descriptors, including year and month were incorporated to account for cyclical and seasonal patterns. Additionally, lag features were included to capture the influence of previous time steps on current conditions (Barzegar et al. 2025), recognizing that groundwater storage exhibits memory effects. Rolling statistics, specifically 7-day rolling mean and standard deviation, were computed and added as features to identify short-term trends and variability patterns. Together, these features enabled the model to capture both long-term seasonal patterns and short-term temporal dependencies inherent in groundwater storage dynamics. To preserve the chronological structure essential for time series analysis, a temporal train–test split strategy was applied rather than random splitting. This approach respected the sequential nature of the data by allocating the first 80% of the chronologically ordered dataset for model training, while the most recent 20% was reserved for independent testing. This configuration ensured that the model was evaluated on future data it had never encountered during training, mimicking real-world forecasting scenarios.

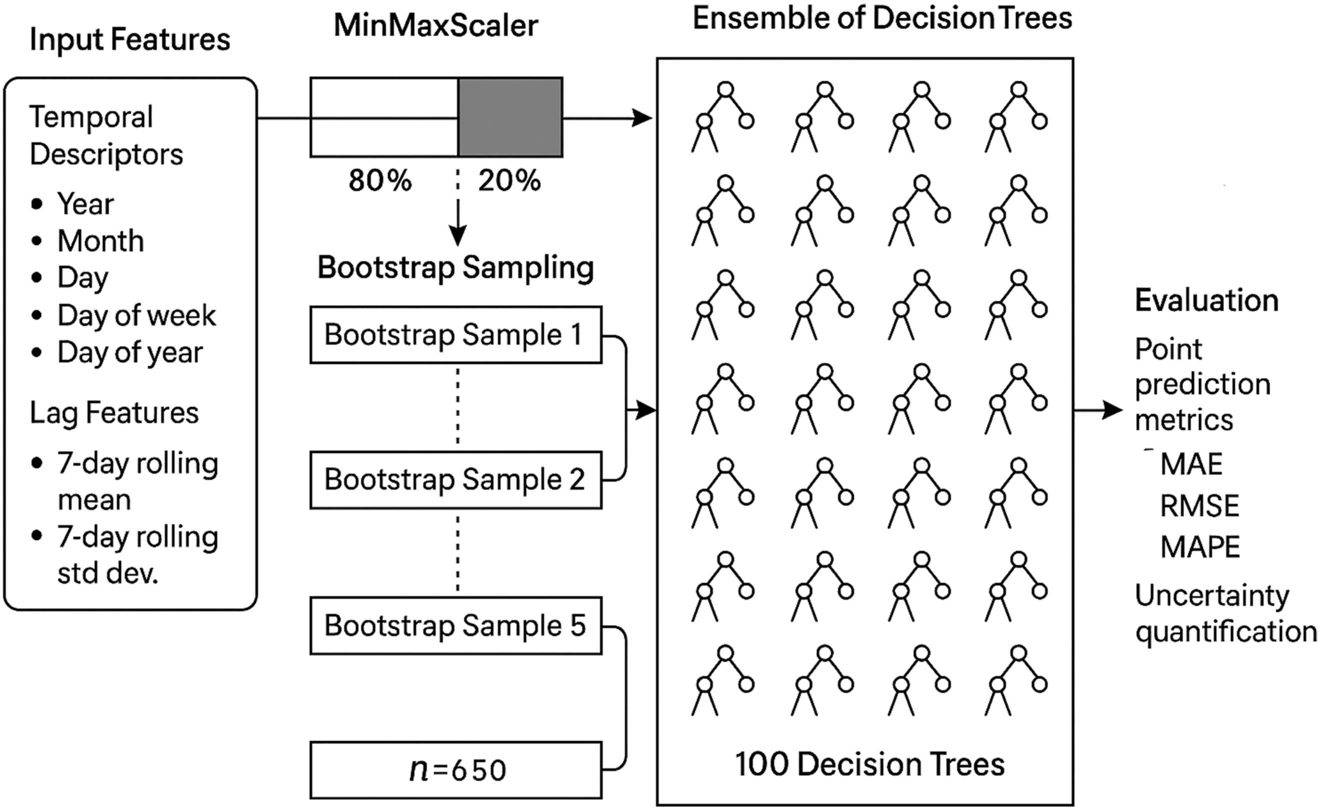


Fig. 4 The structure of the development bootstrapped random forest model

Model performance was comprehensively assessed through multiple evaluation metrics. Point prediction accuracy was measured using three standard metrics: Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and the coefficient of determination (R^2). Beyond point predictions, uncertainty quantification was derived by analyzing the variability across all 50 bootstrap iterations. This approach produced prediction intervals and confidence bounds that reflected the inherent uncertainty in the model's forecasts.

Trend analysis

Seasonal–Trend decomposition using Loess (STL) was applied to monthly groundwater storage anomaly time series to separate long-term trends, seasonal variability, and residual components (Cleveland et al. 1990). The analysis was performed using the STL implementation in the *statsmodels* Python library, with a fixed seasonal period of 12 months to represent the dominant annual hydrological cycle. The *robust* option was enabled to reduce sensitivity to outliers and short-term anomalies commonly present in GRACE-derived time series. Default LOESS smoothing parameters were adopted to provide a balanced decomposition without overfitting short-term variability or excessively constraining interannual seasonal changes.

The magnitude of the long-term tendency was quantified using Sen's slope estimator (Sen 1968), a non-parametric approach that determines the median rate of change from all possible pairwise slopes in the record. Because this technique relies on medians rather than means, it is resilient to noise and extreme values, making it suitable for hydrological trend assessment. To map the spatial variation in groundwater trends, Sen's slope values from individual sites were interpolated using inverse distance weighting (IDW), in which estimates at unsampled locations are computed from nearby observations with distance-based weighting (Shepard 1968).

Results and discussion

Reconstruction of TWS data

To reconstruct missing values in the TWS time series, a Random Forest (RF) model was employed to generate imputed estimates for all Hungarian monitoring locations. Model performance was assessed using a mask-and-reconstruct validation procedure: selected observed values were temporarily withheld, predicted using the RF model, and then compared with the true measurements. This approach allowed for direct evaluation of the model's ability to recover realistic temporal behavior. The validation results show consistently strong performance across the study area (Fig. 5). Coefficients of determination (R^2) ranged from 0.89 to 0.97, meaning that the RF model accounted for 89–97% of the variability in the observed TWS records. This high predictive capacity demonstrates that the model successfully reproduces both long-term variations and seasonal cycles in the GRACE-derived storage anomalies. Error statistics were similarly encouraging: RMSE values fell between 0.71 cm and 1.12 cm, and MAE values ranged from 0.56 cm to 0.97 cm. These small errors are noteworthy given that typical TWS anomalies span approximately ± 10 cm, underscoring the model's reliability for gap-filling and subsequent groundwater storage analysis.

In Budapest, the RF model achieved an R^2 of 0.95, an RMSE of 3 cm, and an MAE of 2.36 cm, indicating excellent performance in an urbanized and hydrologically moderate setting. Similarly, in Debrecen and Szeged, R^2 values of 0.94 and 0.91, respectively, were accompanied by RMSEs of 2.23 cm and 3.09 cm, and MAEs of 1.74 cm and 2.32 cm. Slightly lower performance was observed in a few areas such as Gyor, Pecs, and Szombathely, where R^2 values approached 0.8, and RMSE and MAE values were marginally higher. These differences are likely to be due to stronger seasonal amplitude and more abrupt fluctuations in the original TWS data, which pose greater challenges for purely data-driven models. The imputed values are statistically

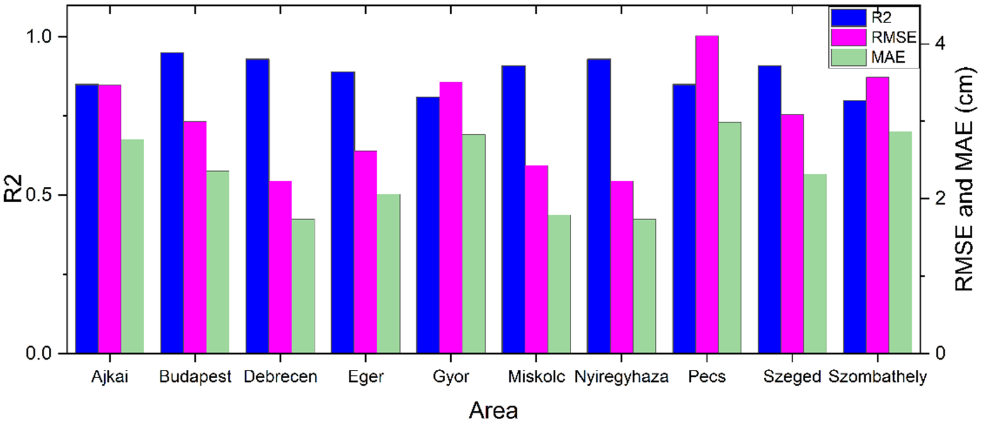


Fig. 5 Performance of the RF model in filling the missing TWS

plausible but may not fully capture subtle physical inconsistencies, particularly during extreme hydrological events. Furthermore, the model's performance is inherently tied to the range and quality of the observed training data, limiting its ability to accurately impute values during periods with hydrological conditions not represented in the training set (Jing et al. 2020).

Previous investigations have shown that Random Forest models generally outperform approaches such as multiple linear regression and neural networks when reconstructing basin-scale TWS variations (Jing et al. 2020). Their advantage largely arises from the ensemble structure of RF, which mitigates overfitting and enhances predictive robustness (Tang et al. 2021). Nonetheless, the accuracy of any RF application is closely tied to the completeness and reliability of its input variables; substantial data gaps or persistent biases can degrade model skill (Mo et al. 2022). In this study, although performance varied among individual sites, the overall accuracy remained well within acceptable bounds for hydrological analyses. A comparison between measured and RF-imputed TWS series (Fig. 6) further supports the model's suitability: the reconstructed values reproduce observed temporal behavior smoothly, without generating unrealistic jumps or artificial noise.

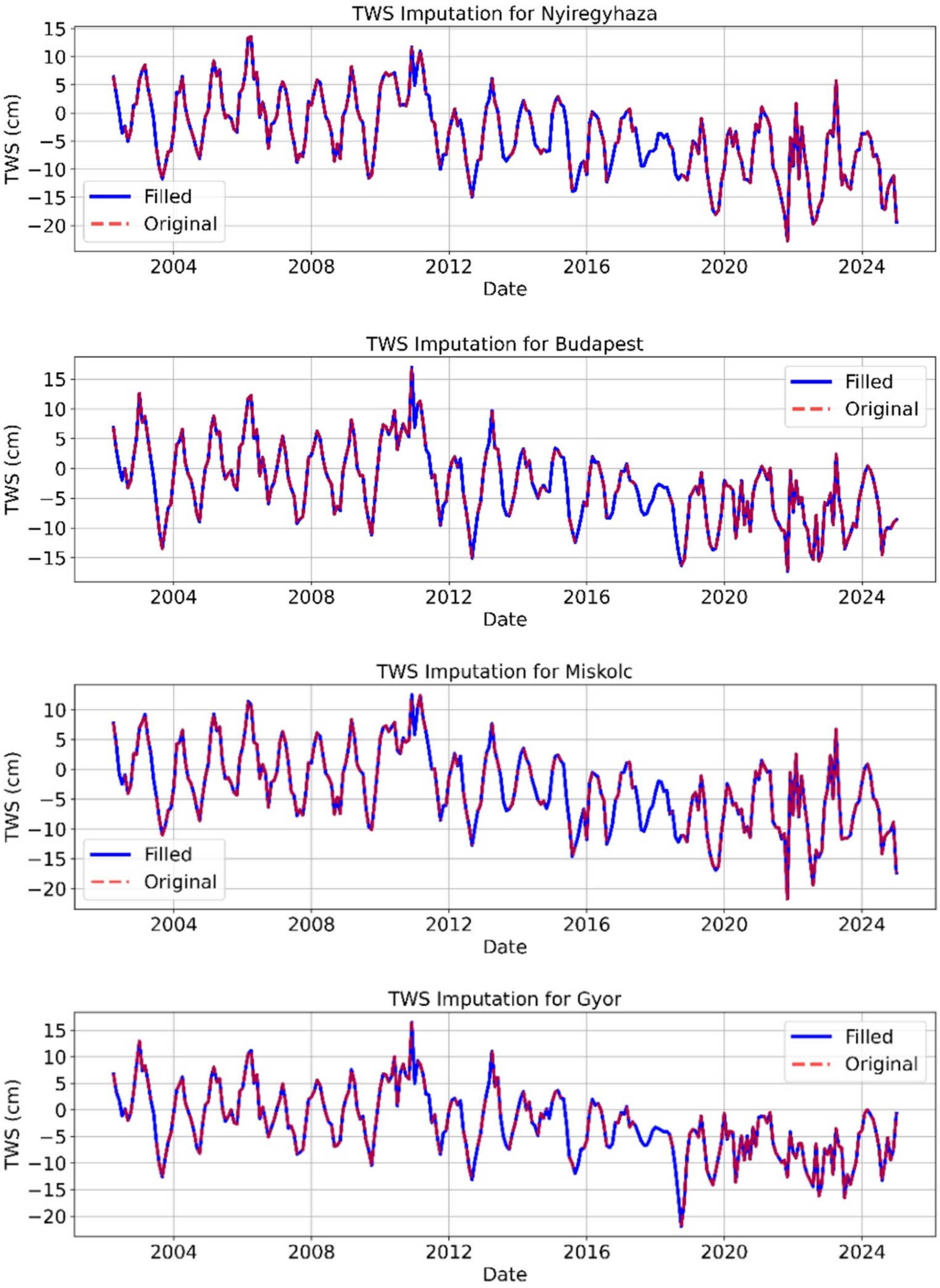


Fig. 6 Example for the imputed TWS using RF model in Nyíregyháza, Budapest, Miskolc, and Gyor

Groundwater storage change

The GLDAS time series showed clear but regionally distinct seasonality across parameters (Fig. 7). Soil moisture storage (SMS) shows the most consistent annual cycle, peaking in late winter–early spring (monthly climatology maxima in February) and reaching minima in late summer (August). The largest seasonal amplitudes occur in Nyíregyháza, Eger, and Miskolc, while Budapest exhibits the smallest range; Győr is moderate rather than among the highest. This pattern is consistent with Central European hydroclimate, where cool-season precipitation and reduced evapotranspiration recharge soils, followed by summer drawdown (and a recently documented mid-spring drying tendency in the region) (Ionita et al. 2020; Silvestri et al. 2025). Snow water equivalent (SWE) is confined to the cold season (maxima in February) and is most pronounced in Eger, Miskolc, Nyíregyháza, Ajka, and Szombathely, while Szeged shows the weakest signal, consistent with Hungary's low-elevation, southern plains experiencing milder winters; observed spatial patterns and recent analyses of snow/icing risk gradients support this north–west emphasis (Somfalvi-Tóth and Simon 2023).

Surface water storage (SWS) exhibits episodic peaks with high interannual variability; the largest seasonal ranges occur in Miskolc, Szombathely, Eger, and Nyíregyháza, whereas Szeged is comparatively muted. This aligns with established hydrologic responses whereby steeper terrain and impervious cover amplify water storage and diminish infiltration-driven recharge (Jacobson 2011). The Budapest and Ákjai exhibited notable anomalies in water storage patterns, which can be attributed to the influence of perennial streams and major water bodies in the region, including the Danube River and Lake Balaton. Canopy water storage (CWS) is small in magnitude but seasonally variable, with stronger signals in the more vegetated northern and western areas (e.g., Miskolc, Eger, Nyíregyháza) and weaker signals in the drier southern lowlands.

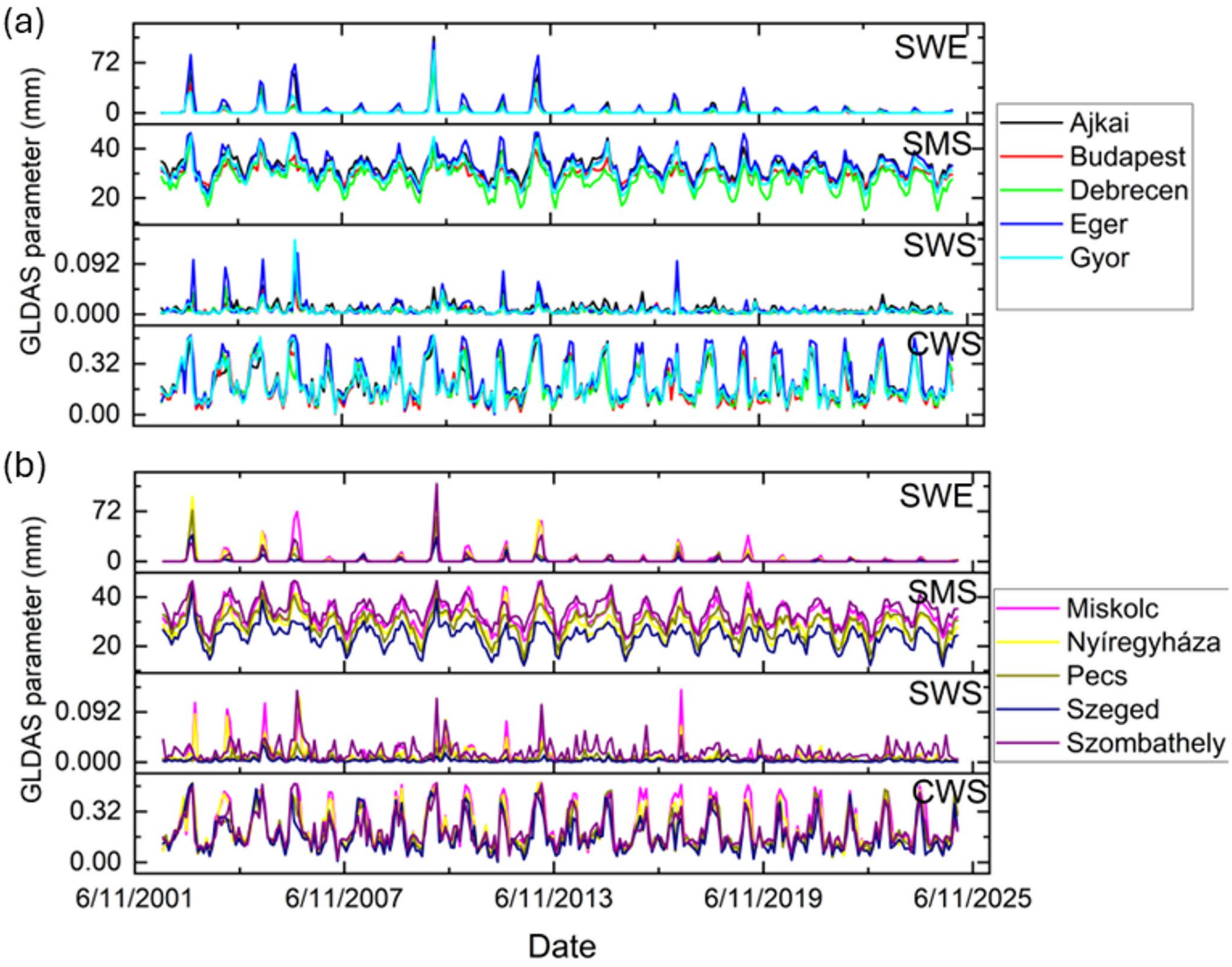


Fig. 7 The temporal change of GLDAS parameters between 2002 and 2025 in (**a**) Ajkai, Budapest, Debrecen, Eger, and Gyor, and (**b**) Miskolc, Nyiregyhaza, Pecs, Szeged, and Szombathely

Analysis of GRACE-derived TWS and GWS anomalies from 2002 to 2025 across the study area reveals distinct spatiotemporal patterns (Fig. 8). TWS and GWS exhibit strong seasonal cycles superimposed on long-term trends. In the Great Hungarian Plain, Szeged exhibits moderate GWS fluctuations, with values ranging from −12.34 cm to +5.45 cm. Szeged shows a long-term decline. This was previously indicated by (Farsang et al. 2017) in which greater association between groundwater level and the surrounding surface water sources is observed. Eastern parts, represented by Debrecen and Nyíregyháza, show more pronounced seasonal and interannual declines. Debrecen reached −13.67 cm during a multi-year drought, with declines attributed to overexploitation of the Quaternary aquifers for municipal supply and agriculture. Nyíregyháza shows post-2010 declines with partial recovery in wetter years, highlighting the responsiveness of aquifers to meteorological variability but also their vulnerability to droughts and pumping (Timár et al. 2024).

Budapest shows similar moderate GWS variability, with fluctuations influenced by river–aquifer interactions and seasonal recharge events. While groundwater levels in Budapest have benefited from episodic wet years, they remain susceptible to localized over-abstraction and reduced recharge during dry spells (Fehér and Rakonczai 2019). In Transdanubia, karst regions such as Pécs record sharper and more episodic GWS variability, reaching −21.43 cm. Karst aquifers have rapid recharge–discharge dynamics but low storage capacity, making them sensitive to short-term rainfall deficits (Szűcs et al. 2021). Pécs also experiences persistent declines due to low recharge and high dependence on groundwater resources. Northern fractured rock systems, such as Miskolc, display smaller amplitude changes, benefiting from upland recharge and higher precipitation, resulting in stable long-term GWS trends (Miklós et al. 2020). Similarly, Eger and Győr maintain stable trends with seasonal synchronization between TWS and GWS, suggesting minimal anthropogenic disturbance.

Across the study area, TWS and GWS generally exhibit parallel variations over the study period. However, in recent years, a marked divergence has emerged, characterized by high TWS values coinciding with lower-than-expected

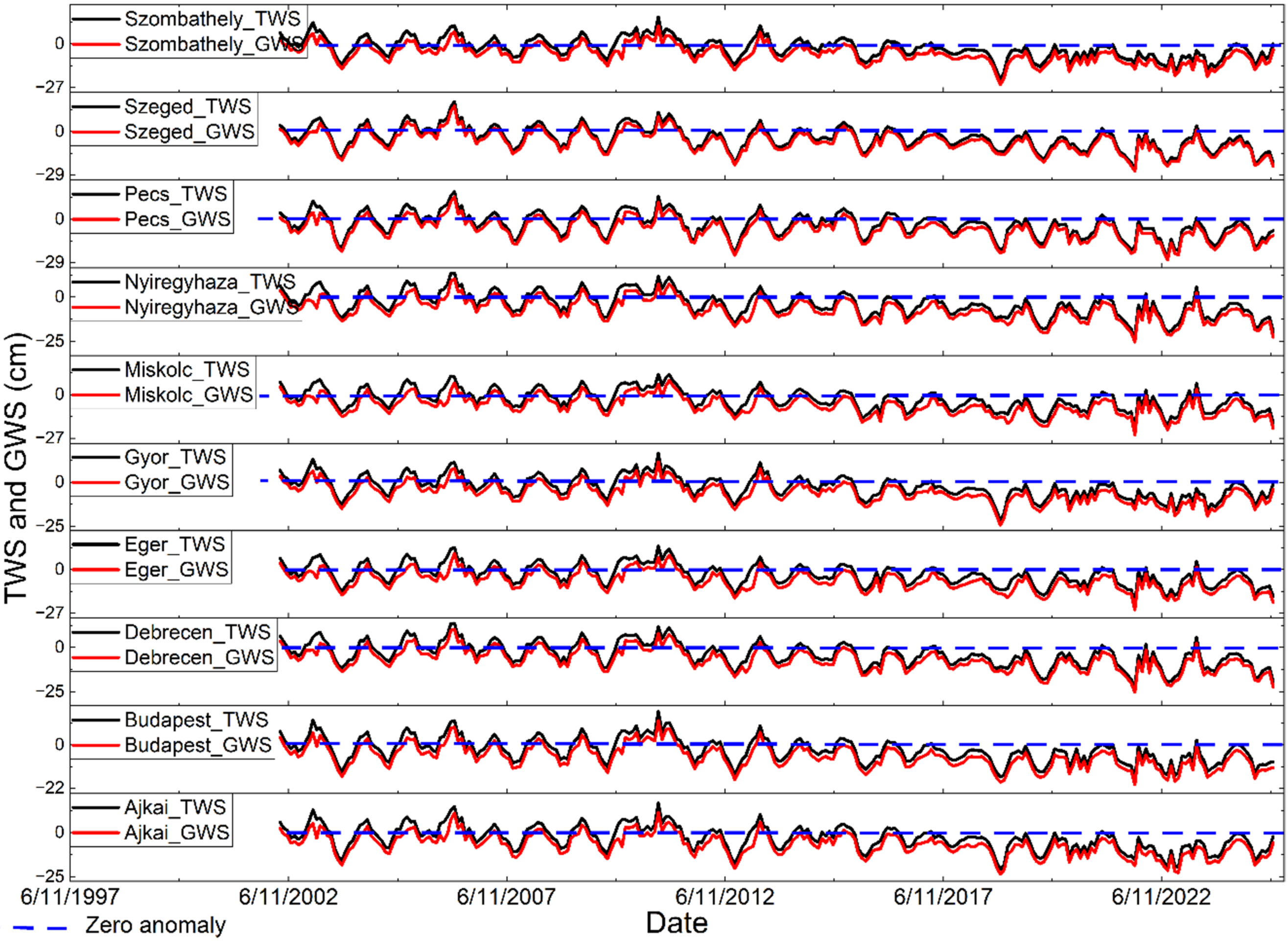


Fig. 8 Comparison between the groundwater storage change and terrestrial water storage in different zones in Hungary

GWS levels. This pattern suggests that while surface and near-surface water components have increased during certain wet periods, groundwater recharge has lagged, likely due to limited infiltration, increased water storage, or intensified abstraction. The magnitude of this divergence varies spatially. It is less pronounced in Ajka and Szombathely, where climatic conditions and aquifer characteristics promote more effective translation of TWS gains into GWS recovery. In contrast, southern and eastern regions show a greater disconnect between TWS and GWS, reflecting the complex interactions between climate variability and groundwater abstraction.

The estimated Groundwater storage anomalies are subject to uncertainties related to both GRACE-TWS products and auxiliary datasets. Differences among GRACE solutions produced by various processing centers and methodologies can introduce variability in groundwater anomaly estimates, while reliance on a single land surface model to represent non-groundwater components may lead to structural and parameterization biases (Saxe et al. 2021; Akl and Thomas 2024). Inconsistencies in model-derived surface water and soil moisture representations can further affect the partitioning of total water storage into groundwater components (Akl et al. 2025; Getirana et al. 2025). Nevertheless, previous studies have reported strong correlations among different GRACE-TWS products despite differences in magnitudes (Scanlon et al. 2016), indicating that GRACE data provide a reliable basis for assessing long-term groundwater trends even when product-specific uncertainties exist. These considerations suggest that while absolute groundwater storage changes should be interpreted cautiously, GRACE-based analyses remain robust for identifying regional-scale groundwater depletion patterns.

Forecasting and uncertainty analysis

This study employed a bootstrapped RF modeling framework to predict and forecast GWS changes, demonstrating variable performance across study areas that reflect the influence of hydrogeological characteristics, climate variability, and anthropogenic pressures on GWS dynamics (Fig. 9). The model achieves exceptional performance at western Transdanubian regions, with Győr showing the highest accuracy (MAE: 0.43 cm, RMSE: 0.62 cm, R^2: 0.98) and Szombathely demonstrating similarly strong results (MAE: 0.55 cm, RMSE: 0.75 cm, R^2: 0.97). Northern and transitional areas including Eger (MAE: 0.92 cm, R^2: 0.91) and Ajkai (MAE: 0.90 cm, R^2: 0.94) also exhibit robust performance, suggesting that areas with consistent climate-groundwater interactions provide favorable conditions for machine learning algorithms regardless of specific hydrogeological settings.

In contrast, areas in highly stressed aquifer systems present greater prediction challenges, particularly Szeged with the poorest performance metrics (MAE: 2.06 cm, RMSE: 2.96 cm, R^2: 0.80), reflecting the complex dynamics of southern Great Plain aquifers where intensive agricultural extraction and limited recharge create highly non-linear groundwater responses. Regions with mixed hydrogeological characteristics show intermediate accuracy, as evidenced by Budapest's moderate performance (MAE: 1.12 cm, R^2: 0.89) and Miskolc's elevated errors (MAE: 1.75 cm, R^2: 0.85) despite its stable northern location. The MAPE values reveal that areas with extreme groundwater fluctuations, such as Miskolc (30.60%) and Budapest (23.83%), exhibit higher percentage errors while maintaining acceptable absolute metrics. Model validation demonstrates excellent calibration, with scatter plots showing tight clustering around the 1:1 line for actual versus predicted GWS values (Fig. 10), and the uncertainty analysis confirming that more than 93% of actual values fell within the 95% confidence intervals derived from bootstrap ensembles, affirming the reliability of the prediction intervals across diverse Hungarian hydrogeological settings.

The forecasted GWS values were compared against the predicted GWS range, defined as the 2.5th to 97.5th percentile of past observations. The distinction between prediction and forecasting phases was evident (Fig. 11). Prediction uncertainties, based on training and validation, exhibited a tight near-normal distribution with a mean standard deviation of 0.58 cm and a spread of 0.32 cm, with most values between 0.3 and 0.8 cm. This distribution demonstrates the consistent and stable performance of the model across diverse hydrogeological settings. In contrast, forecast uncertainties were broader and right skewed, with a mean standard deviation of 1.14 cm and greater variability of 0.73 cm. Most forecast uncertainties fell between 0.5 and 1.5 cm, but values occasionally extended up to 5.0 cm for certain station–time combinations.

The forecasting results revealed distinct spatial differences in confidence interval (CI) widths that reflect the hydrogeological and climatic diversity of aquifers (Supplementary materials and Fig. 12). Eastern parts such as Debrecen and Nyíregyháza exhibited the narrowest intervals (± 5–8%), despite historical groundwater stress. This reliability stems from the predictable seasonal cycles and gradual long-term trends of the Quaternary aquifers in the Great Hungarian Plain. In contrast, the Transdanubian karst system represented by Pécs showed the widest intervals (± 15–20%), which capture the episodic fluctuations associated with rapid recharge–discharge dynamics and strong sensitivity to climatic variability. Northern areas such as Miskolc and Eger displayed moderately narrow intervals (± 7–12%), although intervals widened slightly during transitional

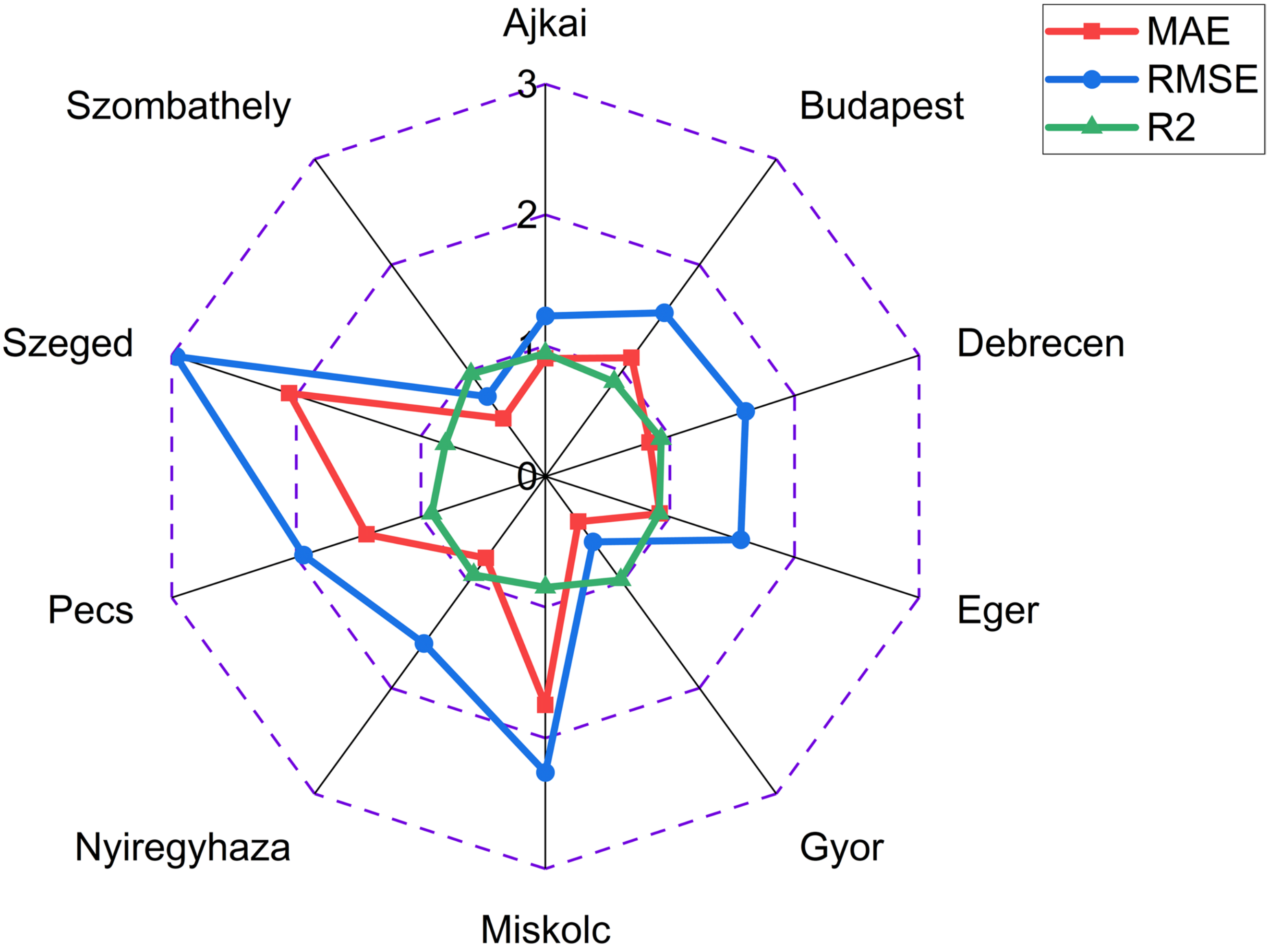


Fig. 9 Perfoemance of the bootstrapped random forest model in predicting groundwater storage changes in the Hungary. The coefficient of determination (R^2) is unitless, while the RMSE and MAE are expressed in in centimeters (cm)

periods affected by variable rainfall. The remaining parts, including Budapest, Szeged, Győr, Ajka, and Szombathely, exhibited moderately wide intervals (± 10–15%) shaped by moderate variability in GWS. In general time intervals with higher forecasted GWS values than their historical baselines showed wider CIs, while those within historical ranges had narrower ones. This means the model increases uncertainty when predicting recovery or changes from past trends but is more confident when continuing established patterns.

The results demonstrate that the bootstrapped Random Forest model effectively reconstructed and projected groundwater storage (GWS) anomalies across Hungary. The model accurately captured historical GWS fluctuations and produced forecasts accompanied by 95% confidence intervals. This dynamic uncertainty quantification demonstrates the robustness of the approach for both deterministic prediction and probabilistic forecasting. The findings are in line with recent applications of machine learning for GRACE-based groundwater forecasting. Studies employing XGBoost models (Shilengwe et al. 2024) have shown skill in capturing seasonal cycles but often underestimate nonlinear long-term changes, while deep learning approaches such as LSTMs (Yin et al. 2021) have demonstrated strength in modeling temporal dependencies but time consuming and require large datasets. The bootstrapped RF ensemble assumes that the relationships between hydrological predictors and groundwater storage remain stationary over the forecast period. This assumption may not hold under changing climate conditions, altered water use, or abrupt hydrological events, potentially leading to underestimation of extremes or accelerated depletion/recovery phases (Jing et al. 2020). Therefore, the forecasts should be interpreted primarily as indicators of relative trends and variability rather than precise volumetric predictions.

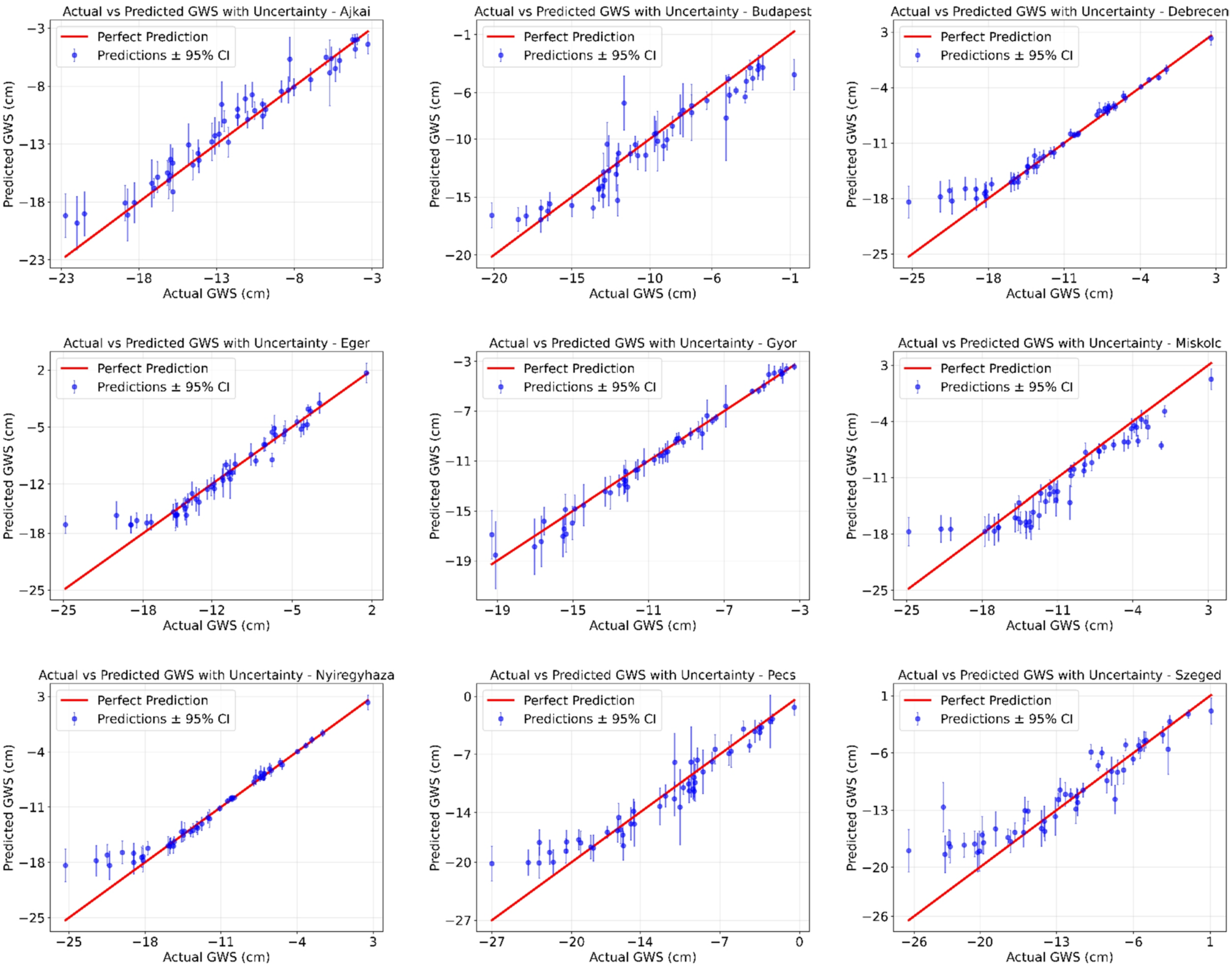


Fig. 10 Scatter plots showing the correlation between the actual and predicted groundwater storage changes with uncertainties

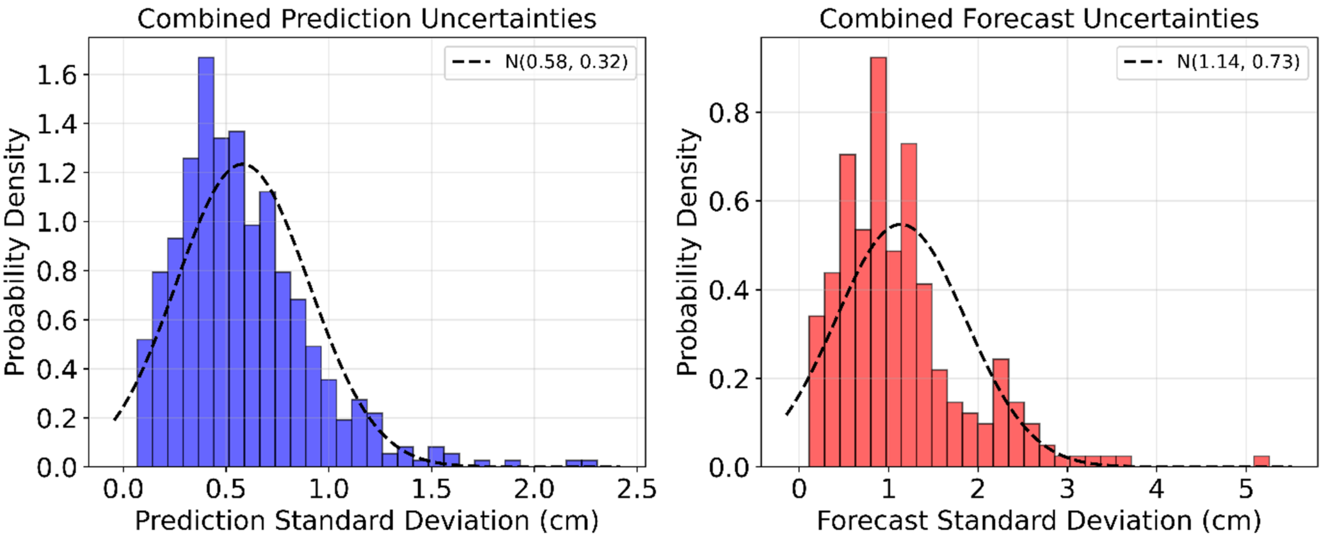
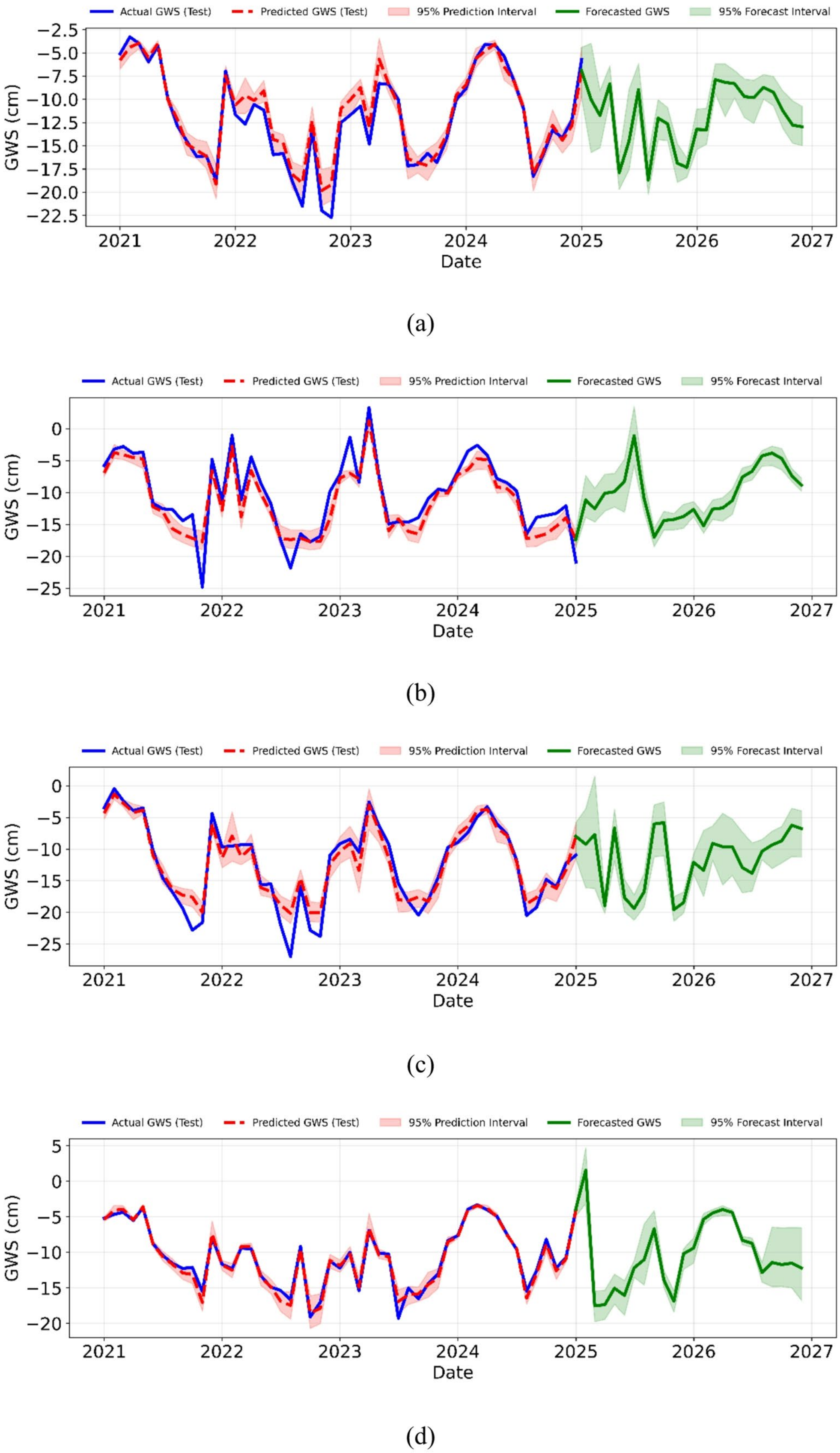


Fig. 11 The uncertainties of the predicted and forecasted groundwater storage change

Fig. 12 Forcasted groundwater storage change in (**a**) Ajkai, (**b**) Miskolc, (**c**) Pécs, and (**d**) Gyor using Boostrapped Random Forest model



(a)

(b)

(c)

(d)

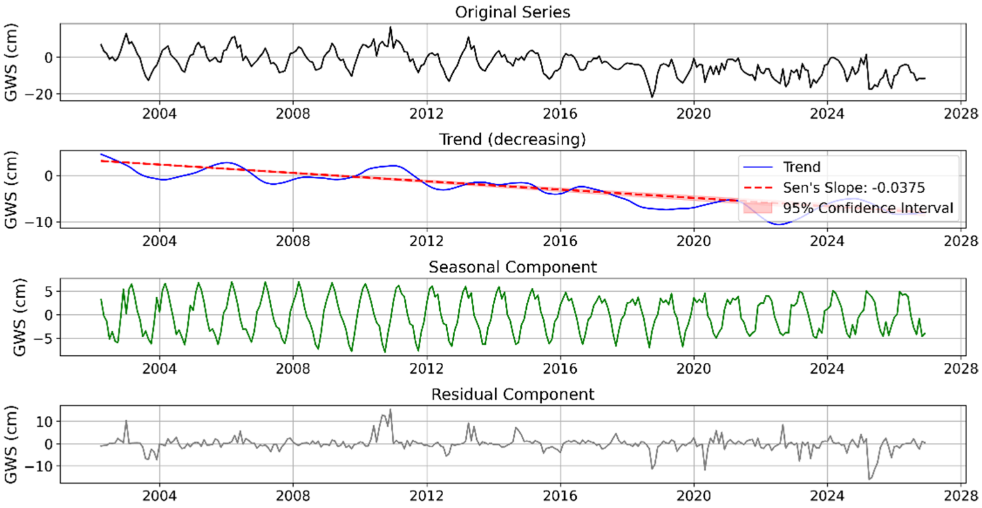
Trend analysis

Temporal decomposition analysis is conducted to reveal the underlying structure of groundwater storage dynamics by separating the time series into trend, seasonal, and residual components (Fig. 13). The extracted trend component shows smooth and monotonic decreases, confirming that groundwater depletion is a persistent, long-term phenomenon rather than short-term fluctuations. The seasonal component exhibits regular cyclical patterns representing 10–20% of the total signal variance. These seasonal fluctuations follow the expected hydrological cycle, with higher values during spring recharge periods and lower values during summer-autumn depletion phases. The residual component captures the remaining unexplained variability, including irregular events and measurement noise, and generally exhibits much smaller magnitudes compared to both trend and seasonal components. This decomposition structure indicates that while seasonal variations and random fluctuations occur, the underlying declining trend represents the dominant signal in groundwater storage changes across Hungary.

The trend analysis of the historical and future groundwater storage demonstrated a systematic reduction, with Sen’s slope values ranging from −0.038 cm/year in Győr to -0.052 cm/year in Nyíregyháza. The most severe declining trends were observed in Nyíregyháza (-0.052 cm/year), Szeged (-0.05 cm/year), and Debrecen (-0.049 cm/year), suggesting that these regions of Hungary experiencing the most pronounced groundwater stress. In contrast, Győr showed the smallest declining trend (-0.037 cm/year), though still representing a significant negative change. The results suggest that without intervention, all ten cities will face continued groundwater depletion at rates consistent with their historical trends. The spatial analysis revealed distinct regional patterns in groundwater storage depletion rates (Fig. 14). As indicated, the eastern and southeastern regions exhibited the most severe declining trends. The western and northwestern regions showed relatively lower depletion rates, the more moderate end of the decline spectrum. Despite these regional variations, the consistent negative trends indicate that groundwater depletion is a nationwide phenomenon in Hungary, with the magnitude of decline varying by approximately 27% between the most and least affected cities.

The results of the trend analysis have important implications for water resource management and sustainability in Hungary. Declining groundwater levels pose risks not only to water supply but also to ecosystem health, particularly in wetlands and riparian zones that depend on consistent groundwater discharge. Economic impacts are also likely, including reduced agricultural productivity, stress on industrial operations, and challenges for municipal water supply, especially in regions where persistent groundwater decline is observed. In the eastern part of Hungary, intensive abstraction has already resulted in aquifer compaction and associated land subsidence, as well as deterioration of groundwater quality (Szűcs et al. 2009). Addressing these challenges will require a suite of interventions. Areas exhibiting sustained negative trends may necessitate water use restrictions, expansion of groundwater monitoring networks, or the development of alternative water sources to ensure long-term sustainability. Enhanced recharge programs, public awareness campaigns, and incentive-based conservation measures could further contribute to mitigating depletion. Importantly, because many of Hungary’s aquifers are transboundary and hydraulically connected with neighboring countries, sustainable management cannot be achieved in isolation. Effective groundwater governance will therefore require regional cooperation, data sharing, and joint management strategies to balance extraction pressures and safeguard shared water resources (Szűcs et al. 2013). Integrating trend analysis with socio-economic data can provide information about the human dimensions of groundwater change and support both

Fig. 13 Example of STL decomposition of the historical and forecasted groundwater storage change in Gyor area



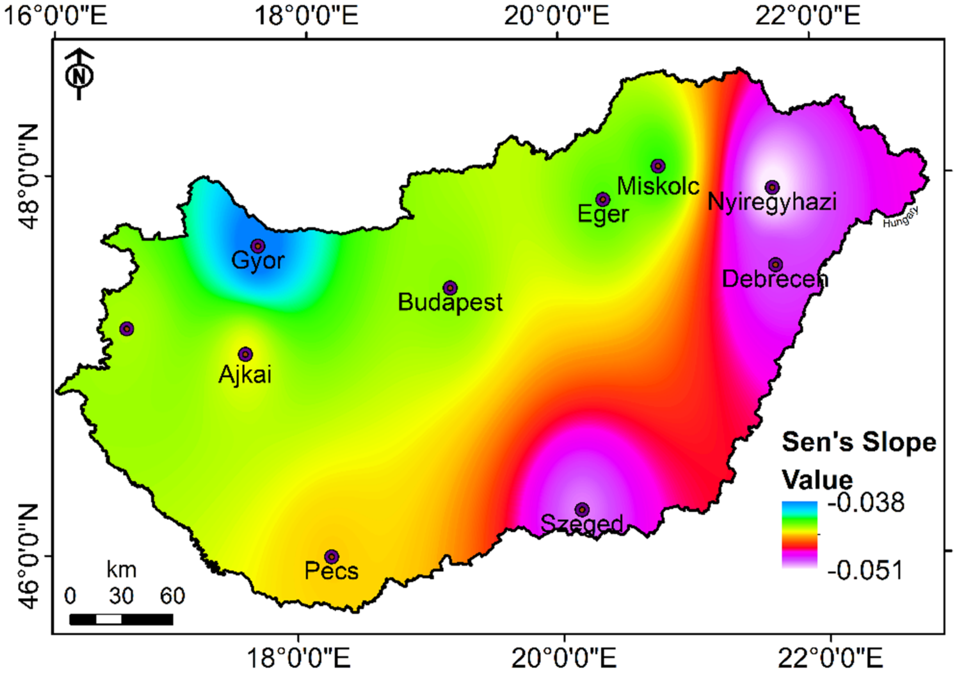


Fig. 14 Spatial distribution of the trend magnitude of groundwater storage change

national and cross-border management frameworks for securing future water security.

Conclusions

This study developed a data-driven framework to reconstruct and forecast groundwater storage (GWS) changes across Hungary by integrating GRACE/GRACE-FO terrestrial water storage (TWS) anomalies with GLDAS land-surface components and machine learning. Missing GRACE-TWS observations were reconstructed using a Random Forest–based imputation approach, ensuring temporal continuity of the storage anomaly series. A bootstrapped Random Forest ensemble was then applied to model historical GWS variability and generate probabilistic forecasts with 95% confidence intervals. The results indicate that long-term declining trends dominate groundwater storage dynamics, with estimated depletion rates ranging from −0.0375 to −0.0516 mm/year.

The coarse effective spatial resolution of GRACE (~ 100,000 km²) limits the interpretation of groundwater variations at sub-basin scales due to signal attenuation and leakage. Uncertainties in non-groundwater storage components derived from land-surface models may propagate into GWS estimates. Excluding the deepest GLDAS-NOAH soil moisture layer (100–200 cm) may underestimate soil moisture and lead to a slight overestimation of GWS magnitudes. In addition, the forecasting framework assumes relative stationarity and may not fully capture abrupt changes associated with climate extremes or rapid human interventions. Consequently, results are best interpreted in terms of relative trends and probabilistic ranges rather than exact volumetric values.

Despite these limitations, the framework demonstrates the utility of satellite gravimetry combined with probabilistic machine learning for regional groundwater assessment. The persistent depletion trends suggest that several major aquifer systems in Hungary face increasing risk under current climatic and water-use conditions, underscoring the need for improved monitoring and region-specific groundwater management strategies.

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Data availability The data that supports the findings of this study are available from the corresponding author upon request.

Declarations

Ethical approval The authors confirm that all the research meets ethical guidelines.

Consent to participate Not applicable.

Consent to publish The authors declare that this work does not contain any material from any individual.

Competing interests The authors declare no competing interests.

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