



Twenty-Five Years of Groundwater Depletion and Recharge across North America

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Abstract. Groundwater and lakes supply water for human activities, support ecosystems, and influence local and continental climate. Despite this, monthly to interannual-scale impacts of changing climate on continental-scale groundwater and lake water storage are poorly understood. We bridge this gap by simulating the North American climate-driven changing water table at monthly frequency from 2000 to 2025. We find an overall decline in storage, with depletion rates in some areas reaching 10 cm/yr while other areas undergo slow but steady recharge. Over 57.6% of land area experienced an overall decline in water table depth, and total continent-wide storage decreased by 566.20 km³ or 1.57 mm sea-level equivalent. Most depletion occurred between 2005 and 2015, driven by widespread droughts and increased evapotranspiration, which was followed by partial recovery after 2015. Water table changes occurred predominantly in groundwater storage, while lake storage remained relatively steady, and declining water tables preferentially affected human population centers, with 63.25% of the continent showing groundwater responses consistent with land-cover vulnerability patterns. Our results show that climate forcing alone can drive substantial continental-scale groundwater loss and emphasize the growing vulnerability of the North American groundwater system, establish a baseline for assessing future climatic impacts on continental water resource availability, and highlight the urgent need for adaptive water management under intensifying climatic stress.

1 Introduction

Groundwater is the largest store of accessible freshwater on Earth and supplies substantial drinking water and irrigation across North America (Famiglietti, 2014; Taylor et al., 2013). Water table levels can vary significantly over short periods due to both natural climate variability and anthropogenic activities (Fan et al., 2024; Huo et al., 2024). Understanding these fluctuations is critical for water resource management under climate change conditions (Herman et al., 2020). Water table variations play essential roles in ecosystem sustainability, wetland health (Zhong et al., 2020), and water availability (Ma et al., 2026). However, the high-resolution temporal patterns and immediate ecological impacts of these fluctuations remain largely unknown due to limited monthly data (Wunsch et al., 2022). This gap makes it challenging to differentiate trends in climate-influenced water level from changes caused by human withdrawal (Liu et al., 2024; Cooley et al., 2021). Recent limited observations indicate large monthly fluctuations in water table levels in North America due to climate change, particularly changes in precipitation and evaporation (Lall et al., 2024; Yao et al., 2023). These human-driven changes have not been restricted to the groundwater



25 system: surface water and lake levels also underwent rapid monthly changes due to higher temperatures during the late 20th
century, with increased evaporation and changed precipitation intensity accentuating the variability in hydrological systems
(Ahmed et al., 2013; Famiglietti, 2014). Frequent droughts, attributable to climate change, have contributed to rapid lake level
declines and wetland shrinkage, especially within the western United States (Cook et al., 2015). Although satellite-based obser-
30 vations from the Gravity Recovery and Climate Experiment (GRACE) (Rodell et al., 2018; Rodell and Reager, 2023) provide
significant data around changing terrestrial water distribution over the recent historical period, these observations are limited
from 2002 to present and cannot directly reveal the causes of changing water distribution.

Large-scale simulations can fill this gap, enabling causal exploration of the role of changing climate on water table fluc-
tuations. Simulation of continental-scale water table dynamics requires models capable of representing large-scale surface
water-groundwater interactions (Wada et al., 2014; de Graaf et al., 2015; Barthel and Banzhaf, 2016). While several large-scale
35 integrated hydrology models and deep learning approaches exist (Kollet and Maxwell, 2008; Döll et al., 2003; Müller Schmied
et al., 2021; Fan et al., 2013a; Wunsch et al., 2022; Liu et al., 2022; Hoch et al., 2023; Schulze et al., 2024), these can be
computationally costly, or lack the ability to produce kilometer-resolution multi-decadal transient simulations at continental
scales (McMillan et al., 2025; Schaperow et al., 2021). We bridge this gap by simulating changing water tables across North
America at a monthly resolution from 2000 to 2025 using the Water Table Model (WTM) (Callaghan et al., 2025). The WTM
40 is a physics-based model that uses climate and land surface input data to simulate changing water table levels at large scales
(Callaghan et al., 2025). The ability of the WTM to simulate long-term transient change based on historical, present and future
climate variables makes it particularly suitable for monthly to decadal and longer simulations of water table dynamics. North
America is an ideal focus for understanding water table dynamics at these timescales because of its wide range of climatic
zones, major unconfined aquifer systems (Famiglietti, 2014), and more extensive data availability compared to other regions
45 (Taylor et al., 2013). By simulating transient behavior, the WTM reproduces seasonal and interannual fluctuations in water
table levels driven primarily by variations in precipitation and evaporation. Because direct human influences such as pumping
are excluded, our simulation isolates the natural and climatic signal of groundwater variability, including human impacts on the
climate signal, providing a baseline to assess how anthropogenic stress accelerates depletion. Understanding this benchmark
is essential for quantifying the magnitude and rate of ongoing groundwater decline, evaluating regional vulnerability to future
50 droughts, and guiding the development of sustainable groundwater management and recharge strategies (Scanlon et al., 2017).

2 Methods

2.1 The Water Table Model (WTM)

The Water Table Model is a specialized hydrological model intended for the simulation of water table level dynamics at
large spatial scales and temporal scales ranging from months to millennia. It integrates simulation of groundwater flow with
55 a dynamic approach to changing lake area and storage volume. The WTM moves groundwater cell-to-cell by solving the 2D
groundwater flow equation for a heterogeneous (nonuniform), horizontally isotropic medium, using non-linear equation solvers
provided by the high-performance SNES component from PETSc (Balay et al., 2025; Callaghan et al., 2025). The WTM can



solve both transient and steady-state groundwater conditions, allowing us to understand the impacts of large-scale climate and topographic change on water table dynamics. The dynamic lake component of the WTM, Fill-Spill-Merge, (Barnes et al., 2020) is used to model the distribution of surface water into depressions, forming lakes, which are able to interact with the groundwater system. Unlike many groundwater models that neglect lakes or treat them as static or isolated, the WTM calculates changes in lake volumes and extents, and allows for both seepage and groundwater exfiltration. This approach allows the WTM to bridge gaps in hydrological modeling frameworks, particularly for continental and millennial-scale studies, by providing insight into the spatio-temporal variability of water table levels across different environmental conditions (Callaghan et al., 2025). In this study, we initialized our simulation from a 0 CE water table, which had previously been transiently simulated from 21,000 calendar years before present (Callaghan et al, in review). We then ran the WTM transiently from January 0 CE to December 2025, including a temporal spin-up period prior to our targeted twenty-five year study. Detailed descriptions of the model configuration, baseline selection, transient setup, and spin-up strategy are provided in the Supplementary Information (Fig. S1).

The WTM focuses on groundwater and surface-water dynamics and does not explicitly simulate soil moisture as a separate storage compartment. Instead, changing soil water content is implicitly represented through the land-surface forcing terms, precipitation and evapotranspiration, that drive recharge to the water table. This simplification is appropriate for continental-scale, multi-decadal simulations where the primary hydrological response is groundwater storage change, but it implies that short-term soil moisture variability is not resolved, and that our results conflate water-table and soil moisture storage variability. We also note that although the WTM does not include an explicit pumping or irrigation scheme, the effects of anthropogenic water consumption are partly embedded in the forcing: the evapotranspiration (and, to a lesser extent, precipitation) fields are derived from observation-based land-surface products in which irrigation-enhanced evapotranspiration and the redistribution of pumped water are already implicitly represented.

2.2 Model Spin-up

The simulation was initialized using a previously simulated transient result at 0 CE (Callaghan et al., 2025), and Callaghan et al. (2026) under review. This result was simulated at 500-year temporal resolution starting 21,000 calendar years before present. In order to be able to make interpretations at a final temporal scale, we performed a temporal model spin-up. To do so, we ran our simulation in decadal time steps from 0 CE to 1000 CE, annual time steps from 1000 CE to 1900 CE, and then monthly time steps from 1900 CE to 2025 CE. At the initial phase of the this model, for each temporal resolution, we conducted an independent spin-up under constant 0 CE climate forcings (Supplementary Fig. S1) to evaluate the time taken for the model to equilibrate before initiating the transient runs (Zhou and Qin, 2022; Masse-Dufresne et al., 2020). Based on this, simulations required a 1450-year spin-up to permit slow, deep aquifer adjustments and stabilization under hydrological forcing. For this equilibration test, the climatological inputs were held constant (Jerez et al., 2020), and the water table outputs were monitored until successive model cycles generated average depth changes of less than 0.01 m/year, signaling a steady state (Ma et al., 2020). This equilibration testing procedure minimized initial condition artifacts and ensured that our transient analyses correctly represent groundwater responses to future and past climate change (Zhan et al., 2024; Roy et al., 2024). It



also showed how long the model needed to fully adjust to its starting groundwater conditions (about 1450 years). Once we confirmed this adjustment time, we then began the transient run with spin-up from 0 CE using time-varying climate input.

2.3 Data (model input) Sources and Preprocessing

95 The WTM requires several climate and land surface datasets as inputs. The required climate variables are precipitation, evapo-
transpiration, winter temperature, and open-water evaporation. For the period between 0 CE and 1990 CE, we used the TraCE-
21ka (transient GCM output) dataset (Otto-Bliesner and Rosenbloom, 2021) for these climate variables (<https://gdex.ucar.edu/datasets/d651050/dataaccess/#>); and from 1990 to 2025 we used the Climate Data Store (CMIP6)(CESM2 ESM)(Eyring
et al., 2016) dataset (<https://cds.climate.copernicus.eu/datasets/projections-cmip6?tab=download>). These datasets were cor-
100 rected through Bias Correction and Spatial Downscaling (BCSD). For bias correction, we used the Quantile Delta Mapping
method, with additive correction for temperature and multiplicative correction for precipitation and evapotranspiration, based
on a 30-year reference period (Tong et al., 2021). We used the higher-resolution Terraclimate (Abatzoglou et al., 2018) dataset
(<https://www.climatologylab.org/terraclimate.html>), to correct and downscale the data, and resampled all inputs to a spatial
resolution of 30 arc-seconds. This spatial resolution was selected to balance computational requirements with the finer spatial
105 resolution required to resolve surface-water bodies and the coarser resolution of input climate data.

The WTM also requires topography data as an input. We use the GEBCO_2020 (GEBCO Bathymetric Compilation Group,
2020) (<https://download.gebco.net/>) grid to represent modern-day topography, resampled to 30 arcseconds and modified to
include lake bathymetries from FLake (Choulga et al., 2014) (<http://www.flake.igb-berlin.de/site/download>). We further modify
the topography as a result of ongoing Glacial Isostatic Adjustment (GIA) during the spin-up and simulation periods. To do
110 so, we spliced together an ice history combining the Lambeck et al (Lambeck et al., 2014; Creel et al., 2024) and ICE-6G
reconstructions (Peltier et al., 2015; Dendy et al., 2017; Abe-Ouchi et al., 2013) with ice-sheet projections from the ISMIP6
framework using the SICOPOLIS ice-sheet model (experiments exp05 and exp10), which provide transient ice thickness and
extent simulations under CMIP6 climate forcing (Nowicki et al., 2016; Goelzer et al., 2020). We simulated the changes in
relative sea level (RSL) that would result from this ice history using a gravitationally self-consistent formulation of the sea-
115 level equation (Mitrovica and Milne, 2003; Kendall et al., 2005; Austermann and Mitrovica, 2015). We used a spherically
symmetric Earth viscosity structure with an elastic lithospheric thickness of 96 km, an upper-mantle viscosity of 0.5×10^{21} Pa
s, and a lower-mantle viscosity of 20×10^{21} Pa s. The changing RSL through time was applied to the topographic grid, which
was then linearly interpolated to the monthly time-scale used in our simulations. Topographic slope was calculated for each
time step based on these topography inputs. The model also requires porosity and hydraulic conductivity input data. These
120 were derived from the soil textures provided by the hybrid State Soil Geographic–Food and Agriculture Organization soil
texture database (<https://ral.ucar.edu/solutions/products/wrf-noah-noah-mp-modeling-system>), and were converted to porosity
and hydraulic conductivity using representative values (Clapp and Hornberger, 1978; Fan et al., 2007; Earle, 2015).

Simulation results were validated using observational datasets. For groundwater, we used the USGS groundwater ob-
servation dataset from 2000 to 2024 (<https://www.usgs.gov/apps/ngwmn/index.jsp>); for lake depth observations we used
125 the FLake dataset as a global Lake dataset (<http://www.flake.igb-berlin.de/>), and for lake extent we used the Freshwater



Ecosystems Explorer dataset (<https://www.sdg661.app/downloads>). The observational datasets were converted to raster format and resampled to a common spatial resolution of 30 arcseconds to ensure they were temporally and spatially consistent with the model output. For watershed-level analyses, we used the level 2 North America watershed boundaries obtained from the Commission for Environmental Cooperation (CEC) North American Environmental Atlas (<https://www.cec.org/north-american-environmental-atlas/watersheds/>).

To evaluate large-scale terrestrial water storage variability, and the differences between our simulations and the reality that includes direct anthropogenic impacts on the water cycle, we used three independently processed GRACE and GRACE-FO mascon solutions (Monthly anomalies are deseasonalized by subtracting the mean climatology of each calendar month, and detrended by removing a least-squares linear fit): (1) the NASA JPL Mascon RL06.3Mv04 terrestrial water storage anomaly dataset (GRACE-FO, D. N. W., 2024) (<https://www.earthdata.nasa.gov/data/catalog/pocloud-tellus-grac-grfo-mascon-grid-rl06.3-v4-rl06.3mv04>), (2) the CSR GRACE/GRACE-FO RL06 Mascon Solutions from the Center for Space Research at the University of Texas at Austin (Save et al., 2016) (https://www2.csr.utexas.edu/grace/RL06_mascons.html), and (3) the GSFC GRACE/GRACE-FO RL06 Mascon Solutions from NASA Goddard Space Flight Center (Luthcke et al., 2013) (<https://earth.gsfc.nasa.gov/geo/data/grace-mascons>), all for the period 2002–2025. All three terrestrial water storage anomaly products were processed relative to the 2004–2009 baseline period and compared against simulated water-table depth anomalies from the WTM to assess the differences between modeled and GRACE-derived large-scale temporal groundwater and lake storage variability across North America. The use of three independent mascon solutions allows us to quantify processing-related uncertainty in the GRACE signal and ensures that the agreement with simulated water storage changes is robust across different gravity field solutions. We isolated the groundwater and surface water components from the GRACE terrestrial water storage anomalies using snow water equivalent data obtained from the GLDAS Noah Land Surface Model L4 monthly $0.25^\circ \times 0.25^\circ$ V2.1 dataset (GLDAS_NOAH025_M), available from the NASA Goddard Earth Sciences Data and Information Services Center (GES DISC) at https://disc.gsfc.nasa.gov/datasets/GLDAS_NOAH025_M_2.1/summary (Beaudoing et al., 2020; Rodell et al., 2004). For comparison with the WTM, monthly column-integrated snow water equivalent from GLDAS Noah v2.1 were subtracted from each GRACE terrestrial water storage anomaly to isolate the combined groundwater-plus-surface-water signal (GW+SW = TWSA - snow). The isolated GRACE anomalies were referenced to the same 2004–2009 baseline, resampled to a common grid, and correlated (Pearson r) with simulated water-table depth anomalies at both continental and Level-2 watershed scales, for monthly and annual aggregations.

2.4 Validation

The WTM results were validated against observed surface water (Choulga et al., 2014; Pekel et al., 2016) and groundwater level monitoring (Teeple et al., 2025). We validated at a monthly time-scale for groundwater for year 2024 and year 2015 for surface water to determine the model accuracy in reproducing water table fluctuations at different times and under varying environmental conditions. The validation results showed adequate performance of the WTM, emphasizing the reliability of the model in simulating water table dynamics at a monthly scale and thus acting as a helpful tool in understanding the historical trend for the prediction of water table levels. To validate the performance of the model, the coefficient of determination (R^2) and



160 Nash-Sutcliffe Efficiency (NSE) were used as statistical metrics. The R^2 value represents the strength of the linear relationship between observed (O) and simulated (S) data. We computed R^2 as the square of the Pearson correlation coefficient between observed (O) and simulated (S) values (Gupta et al., 2009; Chicco et al., 2021). The NSE is the measure of predictive skill of the model that relates the sum of squared deviations between observed and simulated values to variance of observed data. Higher values of R^2 and NSE assure better agreement between observed and simulated results. In addition, spatial validation
165 of simulated surface-water extent was conducted by identifying grid cells where simulated water-table depth exceeded 0 m (representing standing water conditions). These modeled surface-water areas were compared against observed lake extents using pixel-wise classification metrics. Model skill was quantified using Precision (Powers, 2020; Hastie et al., 2009), Recall (Powers, 2020), F1-score (Powers, 2020), Intersection-over-Union (IoU) (Wang et al., 2020), and overall Accuracy (Hastie et al., 2009). (See more details in the Supplementary material: Validation section).

170 2.5 Computation of Climate Drought Indices

To evaluate the climatic drivers of groundwater variability, we calculated standardized monthly precipitation index (SPI) (Liu et al., 2021), and standardized precipitation–evapotranspiration index (SPEI) (Kamruzzaman et al., 2022) for 2000–2025 using the same downscaled climate fields that force the WTM. A SPI index was obtained by first forming multi-year rolling sums of P (here using a 1-year accumulation window) and then standardizing the resulting time series with a z -score transformation
175 over the full record (Liu et al., 2021). Positive SPI values therefore indicate wetter than average years, whereas negative values indicate persistent moisture deficits (Liu et al., 2021). An SPEI field was computed in a similar way but was spatially normalized: for a selected year, we calculated $P - ET$ for each grid cell and the resulting map over all land pixels, yielding a spatial anomaly field in which positive values mark wetter than average locations and negative values highlight spatial drought patterns. To link these climate indices to groundwater dynamics, we extracted annual mean water table depth time series. The
180 SPEI series and WTD series were aligned in time and we computed the Pearson correlation coefficient r between them as a function of lag L (0–5 years), where a positive lag denotes the WTD response occurring L years after the climate anomaly (Majd et al., 2025). We also estimated a simple linear sensitivity by fitting an ordinary least squares regression (Crossett et al., 2020) of WTD against the SPEI index at the best lag (the lag with maximum $|r|$). Supplementary Fig. S4 illustrates this procedure for a representative example of North America, showing the SPEI spatial pattern for a single year, the paired SPEI
185 and WTD time series, the lag–correlation curve, and the regression between WTD and the SPEI at the best lag. To characterize the spatial variability of hydroclimatic extremes, we computed the interquartile range (IQR) of standardized water-balance anomalies (Netzel and Cywicka, 2025) across North America for each year from 2001 to 2025. Monthly precipitation (P) and evapotranspiration (ET) were aggregated to a 12-month rolling water balance ($WB = P - ET$) and standardized at each grid cell using z -scores relative to a baseline period (year 2000 CE). For each calendar year, the IQR (75th–25th percentile) of the
190 standardized WB time series was calculated at the pixel scale, providing a robust measure of intra-annual variability that is insensitive to outliers.



3 Results

3.1 Changing Water Table Over Twenty-Five Years

Over the twenty-five years simulated (2000 to 2025), we see notable trends in WTD evolution and response to climatic forcing (Fig. 1). At the monthly scale, our simulation captures strong seasonal variability (Fig. 1a), whereas the annual aggregation smooths much of the intra-annual variability in WTD change and highlights long-term trends (Fig. 1b). During 2000–2005 (Fig. 1c), approximately 60.9% of the continent experienced an increase in simulated water table levels, showing recharge across northern and central regions. This trend was reversed in 2005–2010 (Fig. 1d), when 69.2% of the area experienced a simulated decline, particularly in the arid and semi-arid areas, such as southwestern United States, northern Mexico, and the Caribbean. Simulated depletion was even more spatially extensive during the 2010–2015 period (Fig. 1e) with WTD declines across 70.3% of the land surface, resulting from large-scale moisture deficits during this time. A partial recovery was simulated between 2015 and 2020 (Fig. 1f), when the proportion of regions with water-table rise increased to 56%, followed by 53.2% of the continent experiencing rising simulated WTD from 2020 to 2025 (Fig. 1g).

Over the full twenty-five year period from 2000 to 2025 (Fig. 1h), 57.6% of the continent experienced declining simulated WTD while 42.4% experienced rising simulated WTD, confirming that groundwater depletion remains the decadal-scale trend. In general, our simulation shows stronger and longer depletion periods followed by short recharge periods, with significant spatial heterogeneity (Fig. 1). The pronounced decreases between 2005 and 2015 reflect the combined impacts of intensified drought conditions in warm and arid regions, particularly in the central and southern United States, Mexico, and Central America. The trend towards recovery after 2015 suggests transient recharge in northern basins such as Mackenzie (b), Hudson Bay (c), and the Great Lakes region (e). Overall, the 25-year simulation points to a growing spatial disparity in groundwater declines across lower latitudes versus sustained or increasing storage in northern watersheds. This pattern highlights the cumulative impact of climate forcing on groundwater systems and shows increasing hydrologic stress under ongoing warming and precipitation variability.

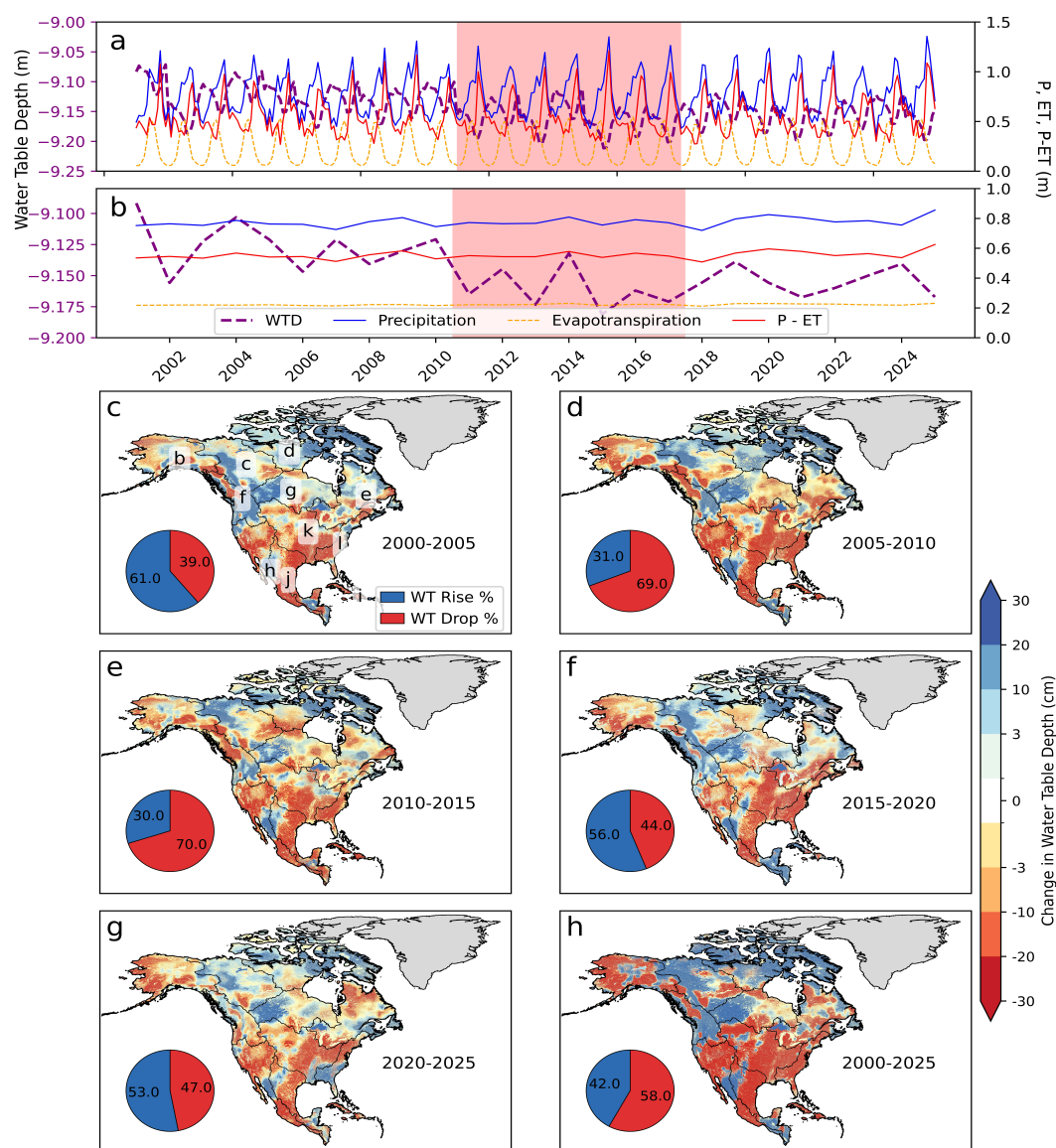


Figure 1. Spatial and temporal evolution of WTD change across North America. (a) Monthly and (b) annual averaged time series of WTD, precipitation, evapotranspiration, and P-ET. (c–h) Change in mean WTD during (c) 2000–2005, (d) 2005–2010, (e) 2010–2015, (f) 2015–2020, (g) 2020–2025, and (h) 2000 to 2025. Blue areas represent rising water table, while red areas indicate water-table decline. Pie charts summarize the percentage of the total area that experienced water-table rise (blue) and drop (red).

3.1.1 Water-table depth and hydroclimatic forcing

215 To confirm that these groundwater changes are consistent with large-scale hydroclimatic forcing, we computed standardized monthly precipitation (SPI) and precipitation–evapotranspiration (SPEI) indices for 2000–2025 using the same climate fields



that force the WTM (Supplementary Fig. S2-S3). Both indices show a prolonged negative phase between about 2005 and 2015, followed by more frequent positive anomalies after 2015, mirroring the timing of the strongest simulated groundwater depletion and subsequent partial recovery. SPEI exhibits more persistent and stronger negative excursions during major drought periods than SPI, reflecting the additional influence of evaporative demand on regional moisture variability.

To illustrate how these climate anomalies translate into local groundwater responses, we also examined the linkage between SPEI and simulated water table depth (Supplementary Fig. S4). We standardized SPEI over space to produce a per-pixel drought map (Supplementary Fig. S4a) which represents the distribution of climatic water-balance anomalies across North America. Positive anomalies (blue) indicate wetter-than-average conditions and are primarily concentrated in parts of eastern Canada and the northeastern United States, whereas negative anomalies (red) indicate drier-than-average conditions and dominate much of the western, central, and southern United States, including northern Mexico. These spatial contrasts highlight the regional heterogeneity of hydroclimatic forcing during the analyzed period. We then created a time series of mean annual SPEI based on multi-year accumulated P-ET and the corresponding mean water table depth (Supplementary Fig. S4b). Both SPEI and water table depth show wet and dry phases, with positive index anomalies generally associated with shallower groundwater. This agreement indicates that interannual groundwater variability is strongly controlled by climatic water-balance conditions.

To quantify the temporal relationship between climatic variability and groundwater response, we performed a lagged correlation analysis between SPEI and WTD (Supplementary Fig. S4c). The analysis shows that the strongest positive correlation occurs at short lags (0–5 years), with a pronounced peak around year 2 (Supplementary Fig. S4c), indicating that groundwater variations respond most strongly to climatic forcing within a few years. The strong correlation at year 2 also emphasizes the importance of multi-year transient simulations of changing water table, because of the long memory that changing water table has of P-ET anomalies (Zhou et al., 2021; Bevacqua et al., 2024). To quantify the strength of the climate–groundwater relationship, we performed a linear regression between SPEI and WTD at the lag corresponding to the maximum correlation (Supplementary Fig. S4d). The regression shows a strong positive linear relationship, with WTD varying proportionally with SPEI, indicating that groundwater depth responds systematically to climatic water-balance anomalies (for more information, see supplementary table S1).

3.1.2 Changing water-table depth and human and natural systems

To evaluate the impacts of climate-driven groundwater change across human and natural systems, we classified land-cover types into three categories representing strong human influence, mixed human–climate effects, and predominantly climate-driven systems (Fig. 2a-c, and more detail see the supplementary section 5) Foley et al. (2005); Cuthbert et al. (2019); Latifovic et al. (2016).

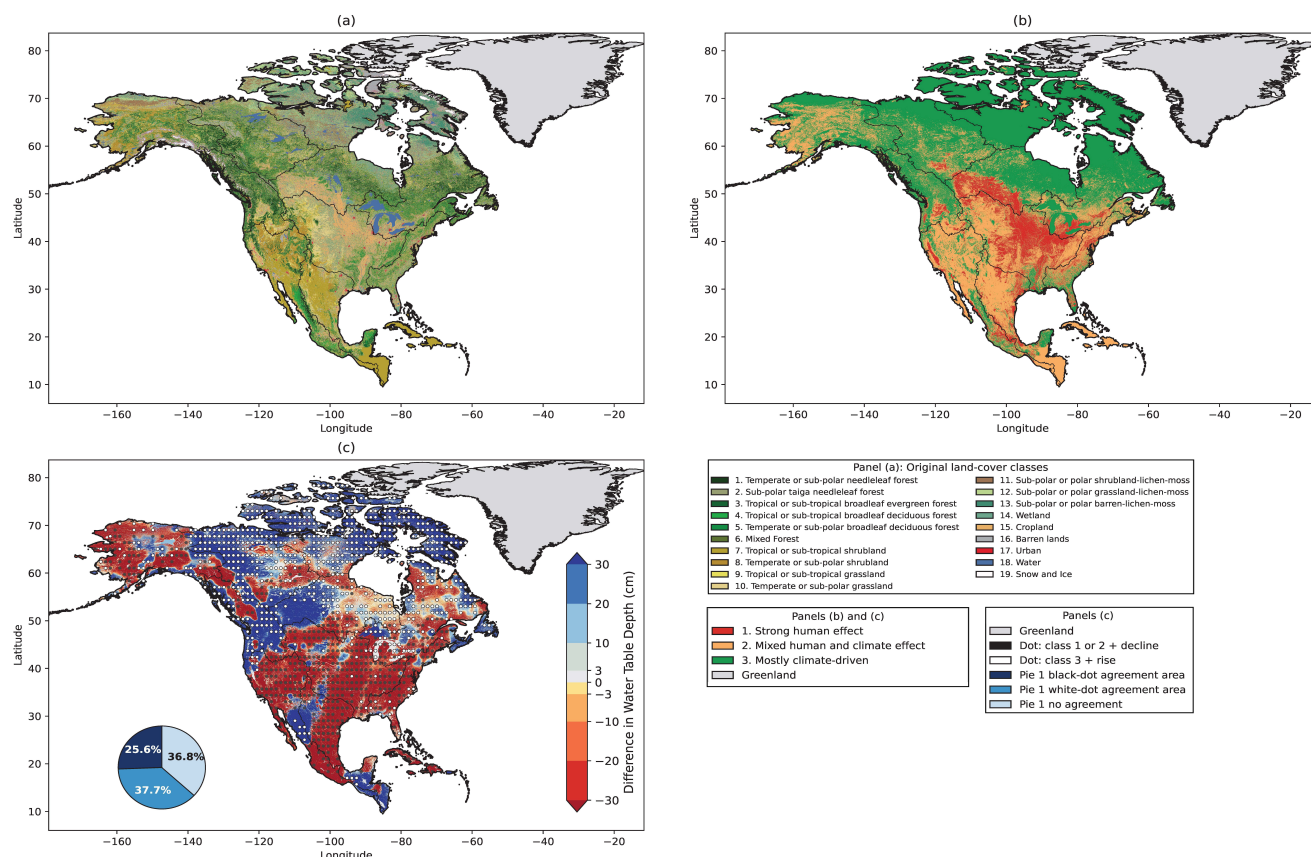


Figure 2. Link between land-cover-based human influence and water-table-depth change across North America (2000–2025). (a) Original land-cover map showing the 19 vegetation and surface classes used in the analysis (Latifovic et al., 2016). (b) Land-cover classes aggregated into three categories: strong human effect (red), mixed human and climate effect (orange), and mostly climate-driven regions (green). (c) Simulated change in water-table depth between 2000 and 2025 (in cm). Negative values indicate water-table decline, whereas positive values indicate a rise in water table. Black dots mark systematic grid locations where regions classified as strong or mixed human influence (classes 1 and 2) coincide with declining water tables, whereas white dots indicate climate-driven regions (class 3) associated with rising water tables. The pie chart shows the proportion of decline in human-influenced regions, rise in climate-driven regions, and areas with no correspondence.

Regions with strong and mixed human influence, particularly across the central and southern United States, northern Mexico, and parts of Central America, show larger water-table declines, indicating more climate-driven drying (25.57% of North American land area shows both WTD decline and strong to mixed human influence). Meanwhile, 37.68% of land area shows both WTD rise and a predominantly climate-driven system, for a total of 63.25% of North American land area showing consistency between land classification and groundwater response. The remaining 36.75% shows no agreement. This indicates that humans tend to live in regions that are disproportionately drying within North America, and that our vulnerability to declining water tables is higher than continental averages may show. This comparison is intended to assess whether climate forcing alone



produces groundwater responses that spatially align with regions known to be vulnerable to human pressure, rather than to represent direct anthropogenic impacts (For more detail, see Supplementary Section 5)

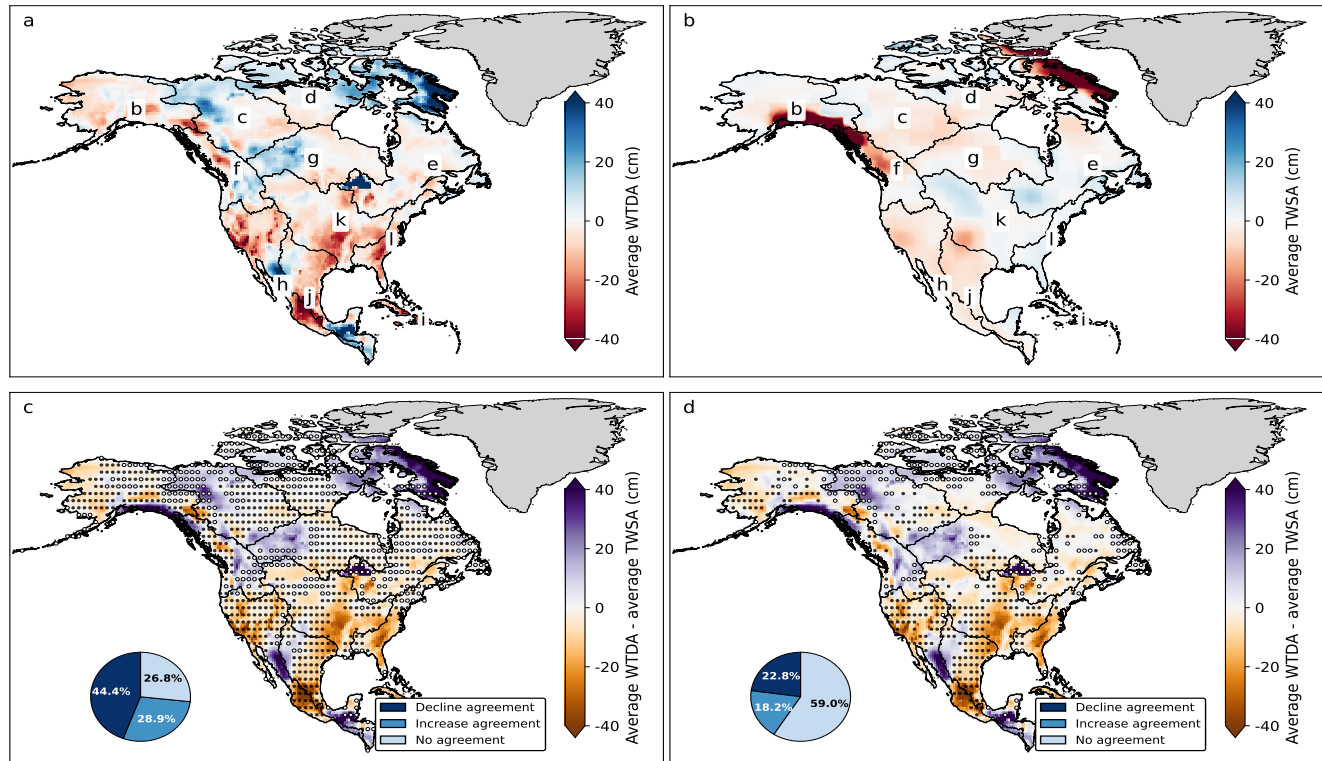


Figure 3. Comparison of simulated water table anomalies with GRACE-derived terrestrial water storage. (a) Mean water table depth anomaly (WTDA; cm) simulated by the Water Table Model, referenced to the 2004–2009 baseline period. Positive values (blue) indicate rising water tables and negative values (red) indicate water table decline. (b) Mean terrestrial water storage anomaly (TWSA; cm), computed as the ensemble mean of three GRACE and GRACE-FO mascon solutions (JPL, CSR, and GSFC) and referenced to the same 2004–2009 baseline. This is the raw TWSA signal, with snow retained; it is therefore the total column storage rather than the isolated groundwater signal used in Fig. S5. (c) Spatial difference between WTDA and TWSA (background map; WTDA – TWSA). Dots mark locations where the two datasets share the same anomaly sign, or where their absolute difference falls within a 20 cm tolerance ($|WTDA - TWSA| \leq 20$ cm), so that pixels with opposite signs but near-zero magnitudes are not misclassified as disagreement. Black dots denote co-occurring negative anomalies (decline agreement) and white dots denote co-occurring positive anomalies (increase agreement); for pixels within the tolerance band, the sign of the mean of WTDA and TWSA determines the dot category. (d) The same WTDA – TWSA difference map and 20 cm tolerance criterion as in panel (c), but with agreement further constrained by land-cover classification (Fig. 2b). Black dots denote co-occurring negative anomalies in human- and mixed-influenced regions (classes 1 and 2), and white dots denote co-occurring positive anomalies in climate-driven regions (class 3). Pie charts summarize the fractional area of decline agreement, increase agreement, and no agreement across the North American domain.



255 Furthermore, to evaluate whether simulated groundwater dynamics are consistent with large-scale observational constraints, we compared water table depth anomalies (WTDA) (Fig. 3a) with terrestrial water storage anomalies (TWSA) (GRACE-FO, D. N. W., 2024; Chandanpurkar et al., 2025) derived from the ensemble mean of three GRACE mascon solutions (JPL, CSR, and GSFC; Fig. 3b). Agreement maps (Fig. 3c,d), defined based on the sign of anomalies, quantify the spatial consistency between datasets. In Fig. 3c, which shows sign agreement between the two anomaly fields, 44.4% of the domain corresponds to co-
260 occurring negative anomalies, 28.9% to co-occurring positive anomalies, and 26.8% shows no agreement, yielding an overall agreement of 72.0%. In Fig. 3d, which incorporates land-cover classification (Fig. 2b) together with the spatial difference between WTDA and TWSA, 22.8% of the domain corresponds to co-occurring decline in human- and mixed-influenced regions (classes 1 and 2), 18.2% to co-occurring increase in climate-driven regions (class 3), and 59.0% shows no agreement, yielding an overall agreement of 40.4%. The regions of disagreement reveal locations where WTDA and TWSA measure different
265 things: because the WTM excludes human pumping, areas of intensive groundwater extraction show stronger observed TWSA declines than the climate-driven model, while snow, ice, and surface-water storage that contribute to GRACE but are not represented as groundwater in the WTM drive further mismatch at high latitudes. The spatial disagreement therefore reflects differences in what the datasets capture rather than model error alone. Removing the snow component from the GRACE signal leaves this agreement essentially unchanged (Supplementary Fig. S5): the sign-based comparison yields an overall agreement
270 of 73.4% (43.8% co-occurring decline, 29.6% co-occurring increase, 26.7% no agreement), and the land-cover-constrained comparison yields 41.6% (22.8% co-occurring decline, 18.8% co-occurring increase, 58.4% no agreement), indicating that the consistency between the datasets is not an artifact of the snow term in terrestrial water storage.

Time series comparisons further demonstrate coherent long-term variability between WTDA and all three GRACE products across the continent and individual watersheds (Fig. 4). At the continental scale, both the monthly and annual anomalies
275 are strongly correlated with each GRACE product, with the monthly series showing the closest agreement (JPL $r = 0.87$, CSR $r = 0.87$, GSFC $r = 0.89$) and the annual anomalies remaining robustly correlated (JPL $r = 0.77$, CSR $r = 0.75$, GSFC $r = 0.80$). The high monthly correlations reflect the strong shared seasonal cycle in total water storage, while the annual comparison, being less sensitive to seasonal phasing, provides a more conservative measure of long-term agreement. The consistency of the correlation across three independent mascon solutions indicates the result is not sensitive to the choice of
280 GRACE product. Isolating the groundwater signal by removing snow (Supplementary Fig. S6) lowers the monthly correlations (JPL $r = 0.60$, CSR $r = 0.60$, GSFC $r = 0.68$) because it suppresses part of the shared seasonal signal and amplifies the relative contribution of surface-water storage, while the annual correlations remain comparably strong (JPL $r = 0.81$, CSR $r = 0.82$, GSFC $r = 0.86$). The spread among the three GRACE products reflects observational uncertainty and provides a useful benchmark for model evaluation.

285 The continental-scale monthly time series Fig. 4 Panel A shows that WTDA closely tracks the interannual and seasonal variability captured by all three GRACE-derived TWSA products. The annual anomalies (Panel a) further highlight the decadal-scale consistency between simulated groundwater and satellite-observed total water storage. Across watersheds (Panels b–l), agreement remains high in large basins dominated by groundwater and surface-water storage (Panels b, c, e, h), but weakens or



reverses in high-latitude, snow-dominated, or small coastal watersheds (Panels d, j, k, l), where residual snow and surface-water
290 signals, GRACE's coarse mascon resolution, and leakage across small basins limit the comparison.

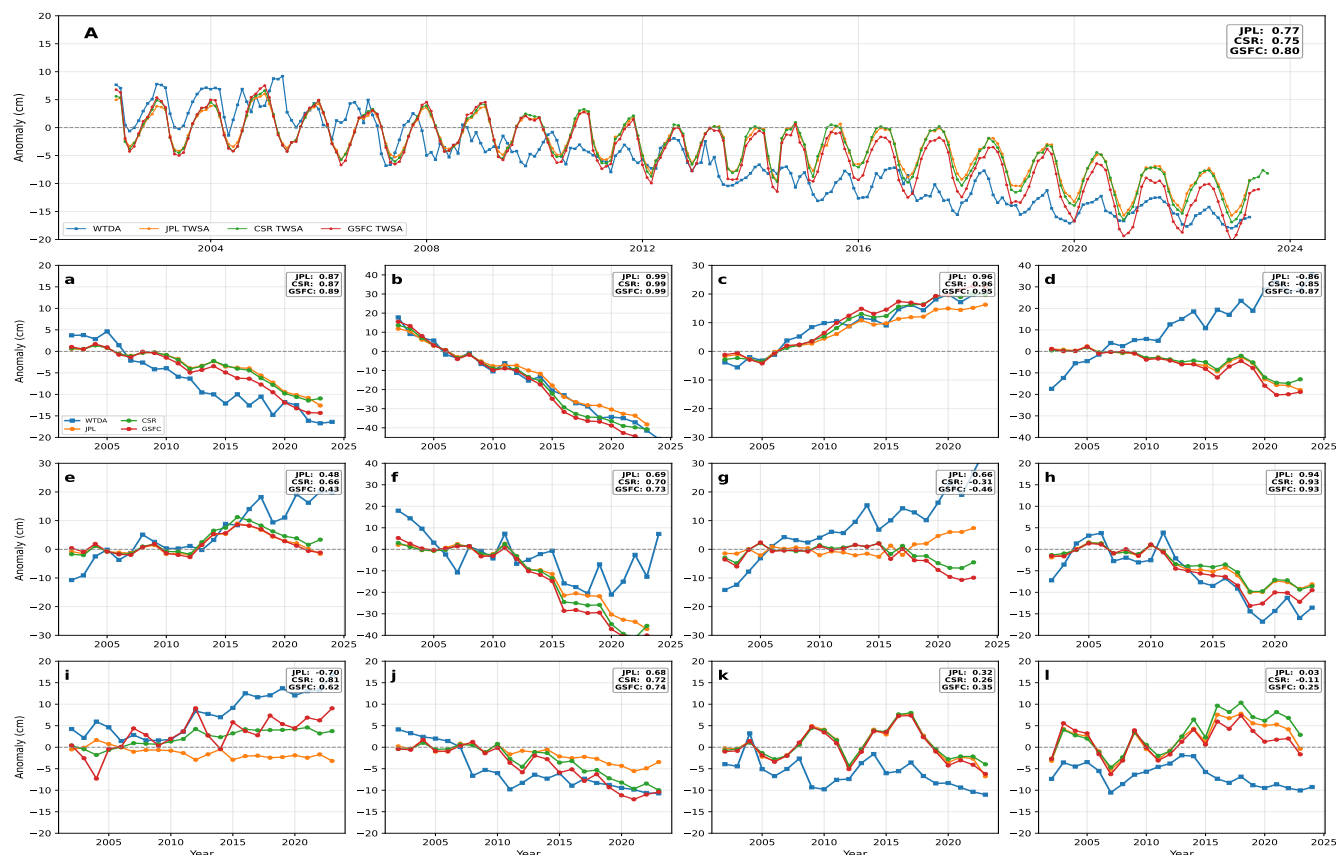


Figure 4. Temporal comparison of simulated groundwater anomalies with three GRACE-derived terrestrial water storage products across North America. Panel A shows the monthly mean water-table depth anomaly (WTDA; blue) and terrestrial water storage anomaly (TWSA) from three independent GRACE and GRACE-FO mascon solutions – JPL (orange), CSR (green), and GSFC (red) – averaged across North America from 2002 to 2025. Panel a shows the corresponding annual mean anomalies for North America, and panels b–l show annual mean WTDA and TWSA for individual Level-2 watershed regions. All anomalies are expressed in centimeters relative to the 2004–2009 baseline period. WTDA is derived from Water Table Model simulations, and TWSA from the JPL, CSR, and GSFC mascon products. Pearson correlation coefficients between WTDA and each GRACE product are annotated in each panel. The close correspondence between simulated groundwater variability and all three satellite-derived storage products across most watersheds highlights the model's ability to capture large-scale hydroclimatic fluctuations, while the spread among the three GRACE solutions provides a measure of observational uncertainty.

3.1.3 Water table depletion rates

The overall magnitude of water-table depletion rate over the 2000–2025 period (Fig. 5) ranges from approximately –10 to +10 cm/yr, revealing strong spatial contrasts in both the directionality and intensity of groundwater change. The most persistent



depletion (often exceeding -5 cm/yr) occurs across southern and southwestern regions, including northern Mexico, the U.S. Southwest, Central America (j), and parts of the Southeastern (l) and Mississippi (k) basins, consistent with the strong negative phases during 2005–2015 shown in Fig. 1. In contrast, northern high-latitude regions such as Alaska, the Mackenzie Basin (b), and Hudson Bay (c) show positive trends of $+1$ to $+8$ cm/yr, reflecting sustained recharge under cold and moisture-rich climates.

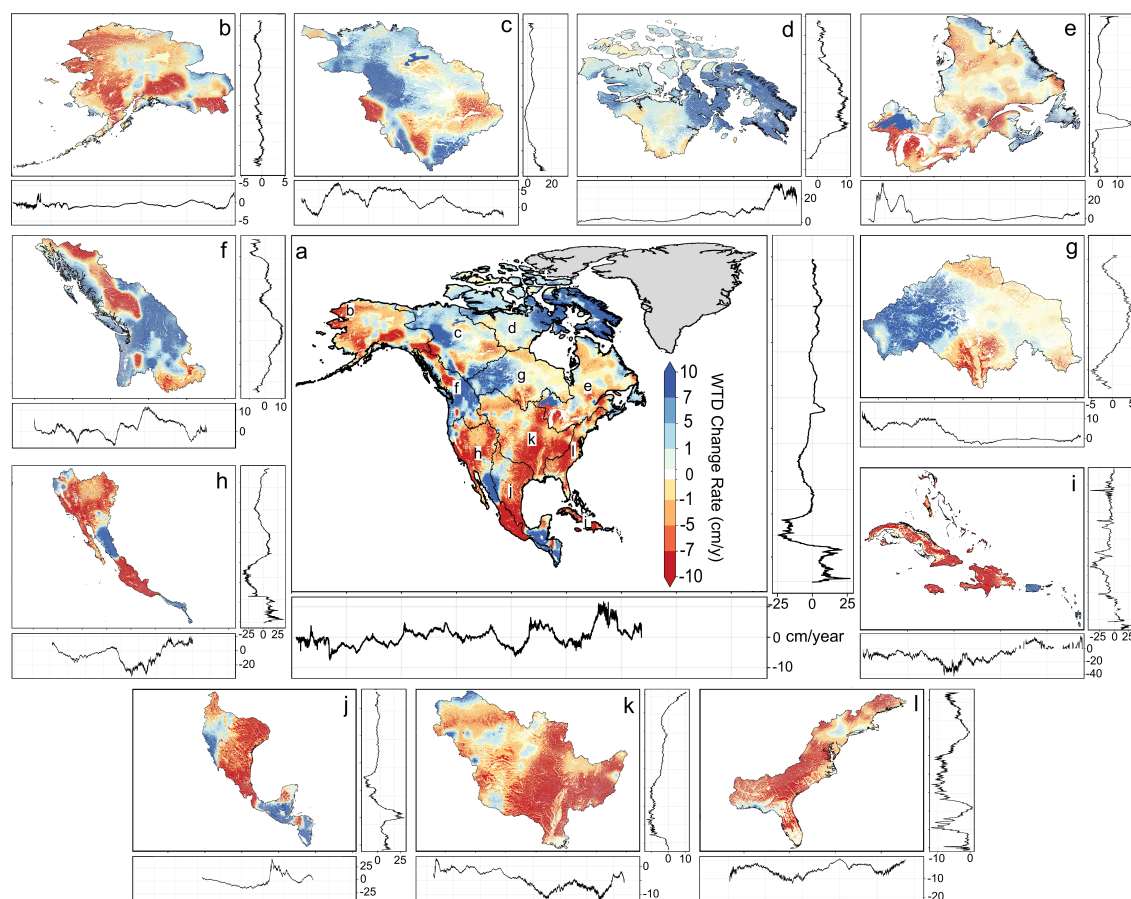


Figure 5. Spatial distribution of long-term water-table depletion and recharge rates (cm/yr) across North America and its major watersheds from 2000 to 2025. Panel (a) shows the continent-wide mean annual rate of water-table change, with red indicating water-table depletion and blue indicating recharge. Panels (b–l) present corresponding depletion-rate patterns for individual Level-2 watersheds. Each subplot includes zonal (latitude) and meridional (longitude) averages of depletion rate (cm/yr), highlighting regional contrasts in the direction and intensity of groundwater trends. The maps reveal pronounced long-term declines across southern and eastern regions, balanced by localized recharge zones in northern and mountainous areas.

As shown in Supplementary Tables S2–S3 and Supplementary Figs. S7, S8, S9, and S10, mean groundwater depth across North America (a) declined from approximately -12.42 m in 2000 to -12.52 m in 2025 (-10 cm), corresponding to a negative



tive trend of about -0.004 m/yr. Strong depletion trends are observed in the Caribbean (i, -0.121 m/yr), Central America (j, -0.051 m/yr), Great Lakes–St. Lawrence (e, -0.064 m/yr), and Southeastern U.S. (l, -0.048 m/yr) watersheds, whereas the Arctic (d) exhibits a positive trend ($+0.054$ m/yr). In contrast, mean surface-water depth increased continent-wide from 13.35 m to 13.89 m ($+0.022$ m/yr), with the largest increases occurring in the Rocky Mountain–Prairie (g, $+0.061$ m/yr) and Mississippi (k, $+0.060$ m/yr) watersheds, while the Caribbean (i) shows a declining trend (-0.022 m/yr) and the Arctic (d) displays a slight decrease (-0.002 m/yr). Monthly wet–dry dominance patterns derived from the P–ET balance reveal pronounced seasonal and interannual variability across North America. Consistent with these patterns (Supplementary Fig. S11), the simulated water-table depth shows coherent declines during prolonged dry phases (2005–2015), highlighting the strong coupling between climatic water balance and groundwater dynamics. Spatial hydroclimatic variability was assessed using the interquartile range (IQR) of standardized 12-month water balance (WB12 = P–ET) (Supplementary Fig. S12). Regions with high WB12 IQR, indicating strong hydroclimatic variability, are concentrated mainly across western and central North America (Supplementary Fig. S12). These same regions exhibit the largest simulated water-table fluctuations, as shown by the similar spatial distribution of WTD IQR (Supplementary Fig. S13). This spatial coherence indicates that groundwater variability is strongest where climatic water-balance fluctuations are most pronounced, supporting climate as the primary driver of simulated water-table dynamics.

3.1.4 Validation of water-table depth

Independent validation of simulated water tables against USGS groundwater wells, observed lake depth and lake-extent datasets demonstrates model performance at both monthly and annual scales. Direct point-wise comparison between simulated and observed water-table depths shows consistently reasonable skill (monthly $R^2 = 0.92$; NSE = 0.91; Table S4). The spatial distribution of the simulation–observation residuals (Supplementary Fig. S14) confirms that there are differences between the simulations and observations, but with larger deviations confined to regions of complex topography and localized human influence. Spatial overlap analysis of modeled versus observed surface-water extent for year 2024 further confirms realistic surface dynamics (Precision = 0.40, Recall = 0.54, F1 = 0.46, IoU = 0.30; Supplementary Fig. S15). The comparatively weaker groundwater agreement reflects spatial bias in the distribution of USGS monitoring wells, the influence of localized human pumping that alters observed water-table changes at most wells in ways not represented in the model, and the averaging of fine-scale topography and subsurface heterogeneity over simulation cell sizes, which can obscure local water-table dynamics. These results demonstrate that simulated groundwater depletion and recovery patterns arise from physically coherent hydroclimatic responses.

3.2 Present-Day Continental Water Table Patterns and Seasonal Variability

We show an example of the simulated North American water table depth for 2024 in Fig. 6. In general, WTD is shallower in the wetter northern regions (Canada and the northern United States) and deeper in the arid southwest. The simulation successfully produces the Great Lakes and other important surface-water bodies. Spatial trends in WTD reflect underlying climatic, topographic, and soil property controls on recharge and groundwater movement. Flat, humid regions maintain higher



groundwater levels, while drier, steeper terrains tend towards deeper water tables. As shown in Fig. 6, the water table depth for the year 2024 reflects strong spatial variability across North America. The mean simulated 5 cm decrease in WTD (Fig. 7) is attributable to climate variability (primarily precipitation) in the absence of pumping. This change is spatially variable: some regions in the western U.S. are enduring a multi-year drought and experience ongoing water table decline, while other regions with consistent or above-average precipitation show stable or rising water tables. These changes are mostly driven by changes in precipitation-minus-evapotranspiration (P-ET), showing that changing climate conditions are a dominant control over local groundwater resources (Richey et al., 2015).

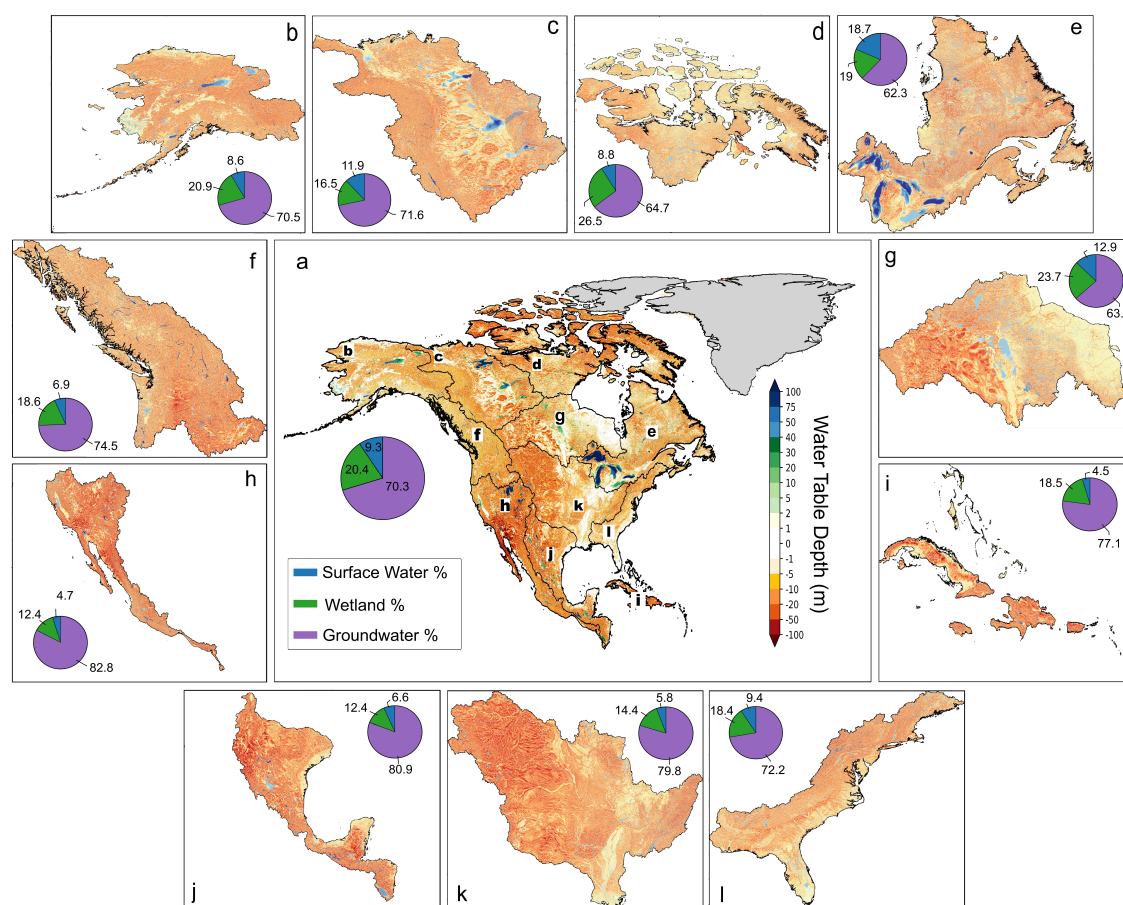


Figure 6. Spatial distribution of simulated water-table depth (m) across North America and its major watersheds for the year 2024.

Panel (a) shows the continental-scale pattern of water-table depth, where negative values indicate regions where the water table lies below the land surface (deeper groundwater) and positive values correspond to areas where the water table is above the surface (saturated or surface-water-dominated zones). Panels (b-l) display the corresponding maps for each Level-2 watershed. Pie charts illustrate the relative proportions of groundwater (purple), wetlands (green), and surface water (blue) within each watershed, revealing the dominant storage component of each region.



The heterogeneous impact of climatic variables on the North American water table are also seen in seasonal water table depth fluctuations, which are clearly evident in the model outputs and correspond closely to precipitation and evaporation cycles. Fig. 7 illustrates the change in WTD from January to December 2024 across North America (see also Supplementary Fig. S16 for month-to-month changes). Northern and northeastern regions show positive WTD anomalies during spring and early summer, whereas southern and western regions, including the U.S. Southwest and northern Mexico, exhibit negative anomalies during mid- to late summer. The strongest declines occur between July and September, followed by partial recovery in late fall, reflecting seasonal contrasts in precipitation and evapotranspiration across humid and arid regions. The most depletion occurs in regions with strong seasonal precipitation regimes, such as the Midwestern United States, as well as parts of the southern U.S.. In these areas, groundwater levels rise and fall in step with wet and dry seasons. For example, spring and early summer precipitation in the Midwest lead to a rise in the water table, whereas late summer drier conditions cause a drop of groundwater by early fall.

During 2024, the Mackenzie (b), Hudson Bay (c), Arctic Archipelago (excluded glacier ice) (d), and Rocky Mountain-Prairie (g) watersheds predominantly experience rising WTD (more than 70% of the land area within each watershed experienced a rising water table); in contrast, the Caribbean (i), Baja California (h), Pacific Coastal (f), Mississippi (k), Great Lakes–St. Lawrence (e), Southeastern U.S. (l), and Central America (j) watersheds exhibit mainly decreases in WTD (more than 60% of the land area within each watershed experienced a drop in water table), indicating continuous depletion likely tied to evapotranspiration intensification and reduced recharge. The continental average (a) is fairly balanced in terms of land area, with 52% of the continent experiencing rising water table and 48% experiencing depletion. However, the latitudinal line chart reveals pronounced fluctuations around the arid–humid transition, where opposing hydrologic regimes meet (Fig. 7). Sharper peaks and troughs in watersheds shown in panels e, k and l highlight localized water table rise and drop, while smoother profiles in northern watersheds (b–d) suggest stable conditions. Overall, these results delineate a clear north–south hydrologic gradient: groundwater tables are generally rising in high-latitude cold regions and declining sharply in low-latitude warm basins, reflecting continental scale climate–groundwater coupling.

Consistent with these spatial patterns, monthly water-table dynamics are strongest in regions driven by greater seasonal precipitation variability (Fan et al., 2021) (supplementary Fig. S16). The northern and eastern regions generally experience positive anomalies, indicating net water gains sufficient for groundwater recharge, particularly in spring and early summer. Negative anomalies dominated the southern and western regions, which coincided with peak evaporation and diminished precipitation. Monthly-scale changes in WTD (supplementary Fig. S16) were dramatic, especially in regions with a strong seasonal variation in precipitation. The monthly interaction between water-table depth, precipitation, evapotranspiration, and the precipitation minus evapotranspiration balance ($P-ET$) across North America for 2023 to 2025 (supplementary Fig. S18), and for 25 years (2000–2025, Fig. 1a) shows that groundwater levels closely follow climatic variations with clear recharge during wet months and depletion during dry periods. A notable feature is the temporal lag between precipitation and groundwater response, typically three to five months, (Nott et al., 2024) indicating the time needed for groundwater to move to nearby areas and affect the regional water table. As shown in Supplementary Fig. S16, positive anomalies (relative to January), indicating rising water tables, dominate in the northern and central regions, matching well with periods of heavy precipitation and reduced evapotran-



380 spiration (Wittenberg et al., 2019). Negative anomalies indicate declining water table levels in the main areas mostly during dry or/and drought periods (Hunter et al., 2024). Such negative anomalies were particularly prevalent in summer, heavily displaying climatic conditions of limited precipitation and high evapotranspiration levels. This assessment gives good evidence of the extreme sensitivity and reactivity of water table systems to climatic conditions, as well as regional differences in groundwater susceptibility to drought (Nygren et al., 2022).

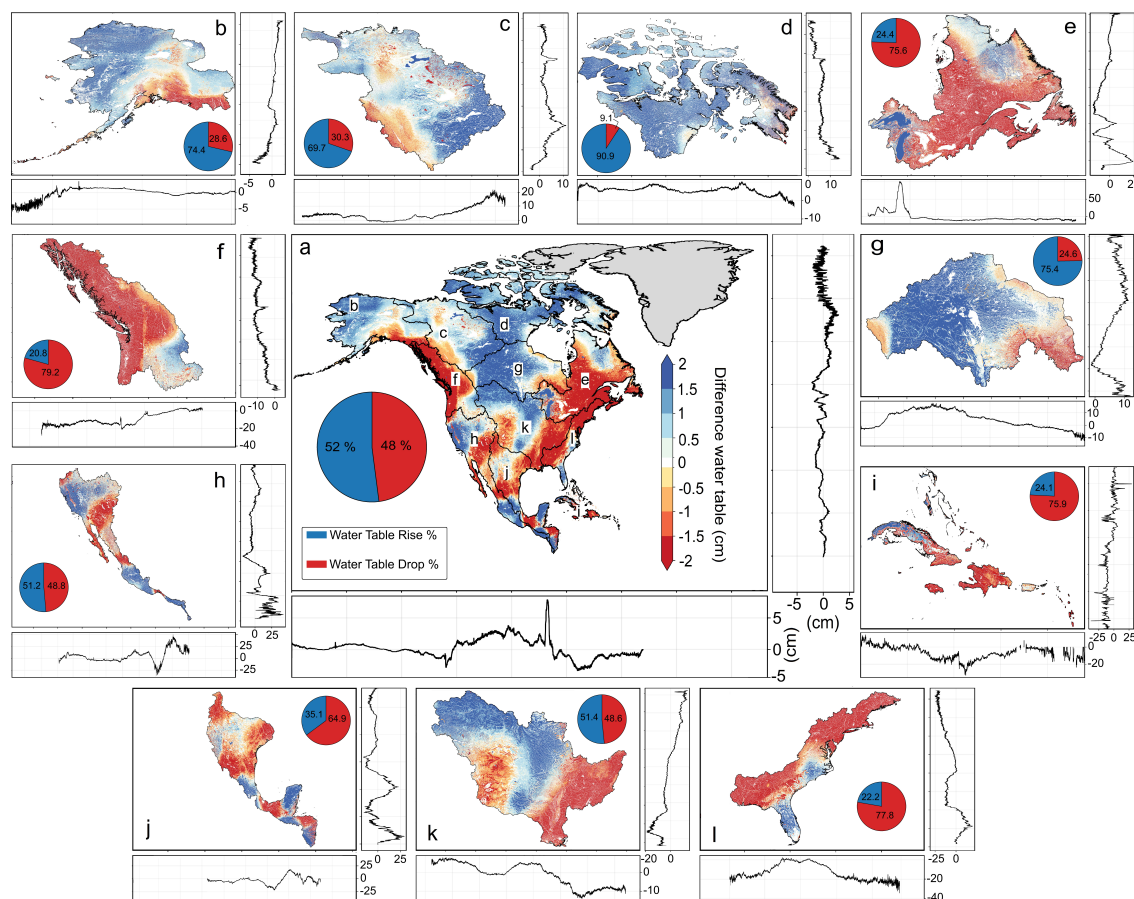


Figure 7. Spatial distribution of water table depth change from January to December 2024 across North America and its major watersheds. Panel (a) shows the continental-scale difference in monthly mean water-table depth (December minus January 2024), where blue indicates a water-table rise and red a decline. The accompanying pie chart summarizes the percentage of total area experiencing water-table rise (blue) versus drop (red) across the continent. Panels (b–l) present the corresponding results for individual Level-2 watersheds. For each watershed, the color map illustrates local groundwater change, the pie chart quantifies the proportion of rising and declining areas, and the two adjacent line plots depict the zonal (latitude) and meridional (longitude) averages of water table change (in cm). Together, these panels highlight distinct spatial patterns of seasonal groundwater storage dynamics and reveal contrasting regional responses to climatic forcing across North America.



3.3 Seasonal and Long-Term Sea-Level Equivalent (SLE) Dynamics

Here, we examine the total magnitude of volume change in continent-wide groundwater and lake storage as Sea-Level Equivalent (SLE), which represents the amount by which sea level would change if the volume of water from changed storage were evenly spread across the entire modern ocean surface (Fig. 8). We use this as a useful measure of volume when considering continental-scale changes in water storage. Strong seasonality and over-annual change is seen in recharge and discharge.

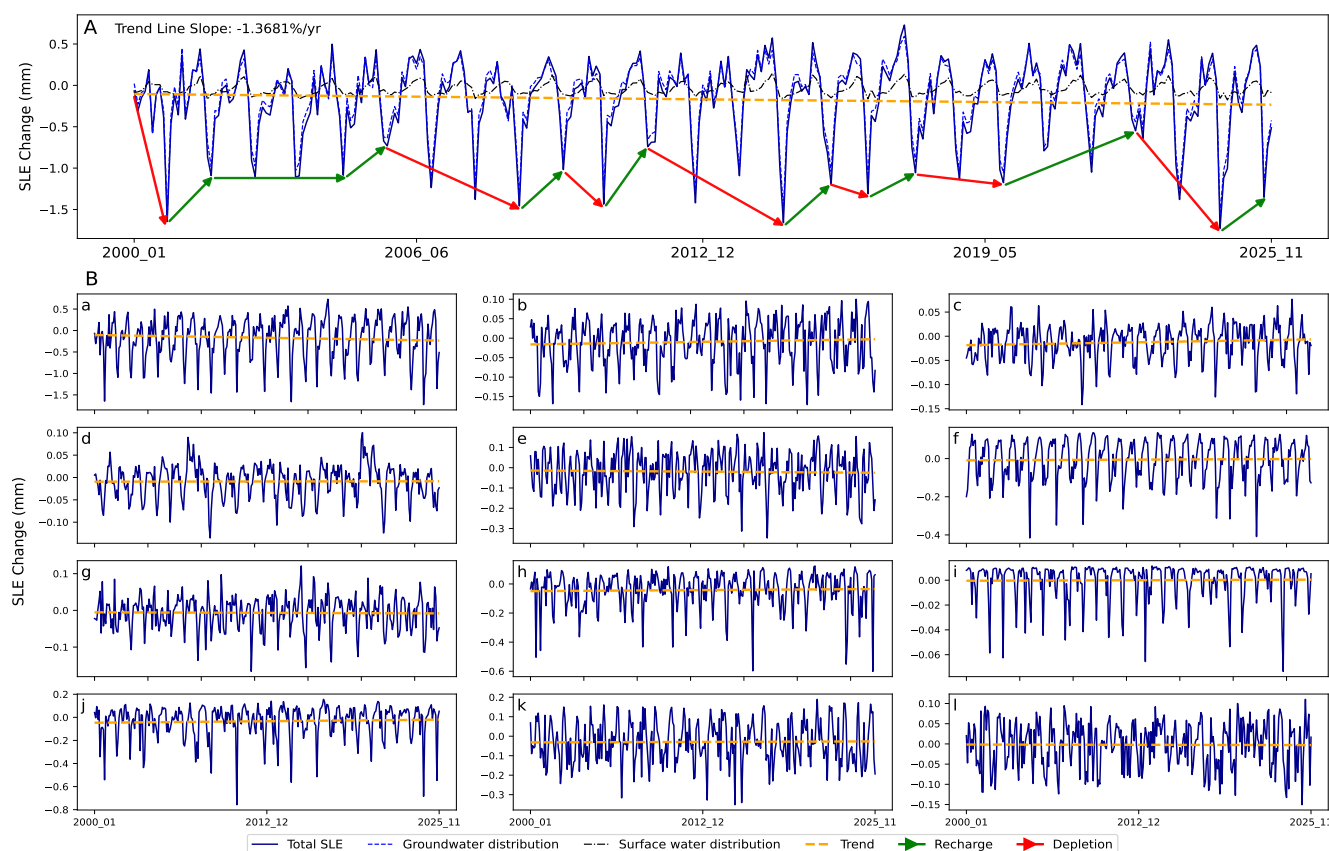


Figure 8. Temporal variations in simulated volume of stored water as Sea-Level Equivalent (SLE), derived from monthly continental-scale groundwater and surface water storage dynamics between 2000 and 2025. (A) Time series of total volume change as SLE (dark blue), groundwater contribution (blue dashed), surface water contribution (black dashed), and the trend line (orange dashed) for the entire North American domain. The red and green arrows highlight major discharge (water loss) and recharge (water gain) periods, respectively, emphasizing the alternating cycles of groundwater depletion and recovery through time. (B) Corresponding total volume change components as SLE for each Level-2 watershed (panels a–l), showing regional variability in the magnitude and timing of changing water storage volume. Positive values indicate a rise in continental water storage (reducing sea level), while negative values reflect continental storage loss (increasing sea level).



The overall SLE trend shows a long-term decrease in water stored on the continent, reflecting that discharge events tend to outweigh recharge over time. The total volume change during this twenty-five year period is -566.20 km^3 or -1.57 mm SLE. Again, the most significant decreases in storage occur between 2005–2015, consistent with the widespread water-table declines identified earlier (Fig. 8A). Partial recovery is evident after 2015, where recharge becomes more frequent. There is substantial spatial variability (Fig. 8B). Northern basins such as the Mackenzie (b), Hudson Bay (c), and Arctic (d) show relatively stable oscillations centered near equilibrium, with limited long-term drift. In contrast, mid-latitude and southern watersheds, especially the Mississippi (k), Southeastern U.S. (l), and Pacific Coastal (f), exhibit pronounced negative trends, reflecting continuous water storage depletion. The domain of seasonal variability also varies, with wetter regions showing stronger seasonal peaks and drier basins demonstrating muted but consistently negative anomalies.

The SLE patterns are indicative of the different hydrologic regimes across the continent. The consistent recharge-discharge cycling in northern watersheds reflects a balanced water budget dominated by climatic forcing, where precipitation replenishes groundwater and surface reservoirs annually. The stability of water storage in the Mackenzie (b) and Hudson Bay (c) watersheds shows long-term resilience under cold, moisture-rich conditions. Conversely, the persistent downward drift in water storage observed in the Mississippi (k), Great Lakes–St. Lawrence (e), and Southeastern U.S. (l) watersheds likely follows lower precipitation and higher evapotranspiration, droughts, and reduced effective recharge. The Pacific and Mexican basins (h,f,j) display the sharper declines and largest interannual variability, showing their heightened sensitivity to climatic extremes. Overall, the SLE time series emphasizes that while seasonal recharge cycles remain active, long-term water storage continues to decline in many mid- and low-latitude regions, indicating emerging groundwater stress and diminishing storage resilience under ongoing climatic variability.

4 Discussion

Our results show that climate forcing, including anthropogenic impacts on climate, alone is sufficient to drive substantial continental-scale groundwater loss across North America over the past twenty-five years, even in the absence of human pumping. This is a central point of this study: because the WTM excludes anthropogenic withdrawals, the depletion we simulate represents a climate-driven baseline rather than the combined climate-plus-extraction signal captured by observations such as GRACE (Rodell et al., 2018; Jasechko et al., 2024). The fact that 57.6% of the continent still experienced declining water tables under climate forcing alone indicates that a meaningful fraction of the groundwater decline observed across North America is attributable to hydroclimatic change, and that anthropogenic extraction acts on top of an already-declining system.

The strong spatial contrast we find is the persistent depletion across southern and mid-latitude basins versus sustained recharge in northern watersheds which reflects the underlying hydroclimatic gradient of the continent. Depletion is concentrated in arid and semi-arid regions where precipitation is low and evaporative demand is high, particularly the U.S. Southwest, northern Mexico, and Central America, whereas the cold, moisture-rich northern basins such as the Mackenzie, Hudson Bay, and Arctic maintain positive trends. This north–south divide is consistent with the spatial patterns of the SPI and SPEI indices, which show that the same regions experiencing the strongest moisture deficits also show the largest water-table declines. The



dominance of SPEI over SPI in explaining these patterns further emphasizes that evaporative demand, not precipitation alone,
420 governs where groundwater is most vulnerable, a distinction that becomes increasingly important under continued warming.

The multi-year lag between climatic anomalies and the groundwater response is one of the more important findings for
interpreting continental groundwater dynamics. The peak correlation between SPEI and WTD at a lag of approximately two
years demonstrates that groundwater systems integrate climatic signals over multiple years, buffering short-term variability
but also transmitting the cumulative effect of prolonged droughts. This hydrologic memory explains why the depletion during
425 2005–2015 was so pronounced and why the partial recovery after 2015 has been insufficient to offset it: recharge events are
short-lived relative to the timescale over which the system responds, so a sequence of dry years produces a decline that a few
wet years cannot reverse.

The agreement between our simulated water-table depth anomalies and terrestrial water storage anomalies from three in-
dependent GRACE mascon solutions (JPL, CSR, and GSFC) provides independent observational support for these trends.
430 The correspondence is strongest against the raw TWSA signal (annual $r = 0.87$ – 0.89) and remains high (0.81 – 0.86) once snow
is removed to isolate the groundwater-plus-surface-water component, confirming that the agreement reflects genuine storage
covariance rather than a shared seasonal signal. At the same time, the divergence in certain northern and coastal watersheds
is informative: where the three products themselves disagree, or where WTDA moves opposite to the GRACE signal, the
difference reflects storage components, snow, ice, and surface water, that contribute to GRACE but are not represented as
435 groundwater or lakes in the WTM. The larger simulated storage decline relative to GRACE in the southern watersheds (k and
l) may partly reflect the warm and dry summer biases that climate models exhibit over the central-southern Great Plains (Sun
and Liang, 2023), and reducing such biases would be expected to improve the accuracy of hydrological simulations like ours.

The correspondence between land-cover-based human influence and the pattern of groundwater decline carries a cautionary
implication. Because our simulation contains no human water use, the tendency for human-influenced regions to coincide
440 with declining water tables cannot be directly attributed to pumping in our model, though irrigation-related heightening of
evapotranspiration may play a role; rather, it shows that human populations in North America are concentrated in regions
that are disproportionately drying under climate forcing alone. This means that continental-average statistics understate the
exposure of the population to groundwater decline, and that the regions where people actually live are more vulnerable than
aggregate figures suggest. When anthropogenic withdrawals are superimposed on this natural drying signal (Jasechko et al.,
445 2024), the compounding effect in these same regions is likely to be severe.

Several limitations should be noted. The WTM does not represent human water use, so our results describe the climate-driven
component of change and should not be interpreted as total observed depletion. The exclusion of seasonal lake ice from the
evaporation scheme leads to overestimated evaporation and underestimated lake extent at high latitudes, which partly explains
the weaker surface-water validation metrics in northern regions. Point-scale validation against USGS wells is also affected by
450 the spatial bias of the monitoring network and by localized pumping that alters observed levels in ways the model does not
capture, which contributes to the comparatively lower groundwater agreement relative to lake levels. Finally, our analysis relies
on a single, physically consistent model configuration forced by bias-corrected climate data; residual differences between the
forcing and observed climate propagate into the simulated storage trends. Despite these limitations, the coherence between the



simulated patterns, the drought indices, and three independent satellite products indicates that the large-scale trends reported
455 here are robust and primarily controlled by climate forcing rather than model artifacts.

5 Conclusions

Our 25-year simulation of climate-driven transient monthly groundwater dynamics at high spatial and temporal resolution uncovers consistent patterns of depletion in southern and mid-latitude regions, contrasted by stable recharge in northern basins. The results show groundwater depletion rates reaching up to 10 cm/yr in areas such as the southwestern United States, northern
460 Mexico, and Central America, marking these regions as the hot-spot of accelerated hydrologic stress. The spatial depletion aligns with the climatic transition zones, reflecting interactions between precipitation and evapotranspiration. Temporal analysis over the period from 2000 to 2025 shows that while intermittent recharge phases occur, they are short-lived and insufficient to offset the cumulative losses from extended droughts and increased evaporation. Consequently, the continental water storage has dropped by 1.5 mm SLE, predominantly as a result of changing groundwater levels. Simulated water-table depth anomalies
465 show strong agreement with GRACE-derived terrestrial water storage anomalies, with a continent-wide correlation of 0.87 and consistent spatial-temporal variability across major North American basins, providing independent observational support for the simulated groundwater trends. This indicates that even in the absence of human extraction, climate-driven processes alone result in declines in continental-scale groundwater storage. The persistence and magnitude of simulated depletion provides a warning that North America's groundwater systems may become even more vulnerable into the future. This research establishes
470 a critical benchmark for understanding the pace and drivers of continental-scale groundwater change, emphasizing that the acceleration of depletion, if compounded by anthropogenic withdrawals (Jasechko et al., 2024), could push large portions of the continent toward long-term hydrologic instability and irreversible groundwater loss.

Code availability. The algorithms and program codes used in this study are publicly available at https://github.com/MHaghiri/Present_Water_Table_Level-PWTL and <https://doi.org/10.5281/zenodo.20417549>

475 *Data availability.* All datasets used in this study are publicly available: The climate forcing data used in this study are publicly available from the Earth System Grid Foundation (TraCE-21ka; <https://gdex.ucar.edu/datasets/d651050/dataaccess/#>) and the Copernicus Climate Data Store (CMIP6 CESM2; <https://cds.climate.copernicus.eu/datasets/projections-cmip6?tab=download>). TerraClimate data are available at http://thredds.northwestknowledge.net:8080/thredds/catalog/TERRACLIMATE_ALL/data/catalog.html. Topographic data are from GEBCO_2020 (GEBCO Bathymetric Compilation Group, 2020) and (<https://download.gebco.net/>). USGS groundwater observations are
480 available at <https://www.usgs.gov/apps/ngwmn/index.jsp>. GRACE and GRACE-FO mascon data are available at (<https://doi.org/10.5067/TEMSC-3MJ634>), (<https://earth.gsfc.nasa.gov/geo/data/grace-mascons>) and (https://www2.csr.utexas.edu/grace/RL06_mascons.html). Model output and processing codes are publicly available at <https://doi.org/10.5281/zenodo.20417549>. Hybrid State Soil Geographic–Food and Agriculture Organization soil texture database: <https://ral.ucar.edu/solutions/products/wrf-noah-noah-mp-modeling-system>. Level 2 North



America watershed boundaries: <https://www.cec.org/north-american-environmental-atlas/watersheds/>. FLake: <http://www.flake.igb-berlin.de/site/download>. Freshwater Ecosystems Explorer dataset: <https://www.sdg661.app/downloads>

Author contributions. Conceptualization: K.L. Callaghan and M. Haghiri Software: WTM: K.L. Callaghan with guidance from A.D. Wickert. Pre- and post-processing: M. Haghiri, K.L. Callaghan, and R. Creel. Validation: M. Haghiri. Formal analysis: all authors, led by M. Haghiri. Investigation: M. Haghiri. Resources: K.L. Callaghan. Writing - original draft: M. Haghiri. Writing - review and editing: all authors. Visualisation: M. Haghiri.

490 *Competing interests.* N/A

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