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Assessing Terrestrial Water Storage Change Since the 1980s

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Abstract

Water availability for societies and ecosystems depends upon Terrestrial Water Storage (TWS), yet global, spatially resolved measurements are largely unavailable before the advent of the Gravity Recovery and Climate Experiment (GRACE) gravimetric measurements in 2002. By exploiting a larger set of model and observations-based datasets than previously considered, along with statistical and machine learning techniques, we advance understanding of TWS changes since the 1980s, including accounting for human water management (HWM).

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A decline in TWS during 2002-2019 is identified for three global hydrologic models with HWM and bias-corrected precipitation forcing (-0.91 to -0.06 mm yr^{-1}) with only one showing larger decreases than observed by GRACE observations (-0.80 mm y^{-1}). We further identify a longer-term decline in TWS during 1980-2019 in these models, linked with regional precipitation decreases and the net effects of HWM through TWS drawdowns over northern India, southwest U.S. and northeastern China, yet the amplitude of the global land trends remains poorly quantified, ranging from -0.72 to +0.04 mm y^{-1}. Statistical / Machine Learning (ML) reconstructions are found to match GRACE variability but their fidelity in the pre-GRACE/FO period remains unknown.

A stronger decline in TWS since 1980 in the European Centre for Medium-range Weather Forecasts 5th generation reanalysis (ERA5) enhanced land component (ERA5-Land) is linked to an artificial drop in precipitation around 2000-2002 in ERA5 that is most pronounced over equatorial central Africa, northeastern China and the northern Argentina / La Plata region. Our findings urge caution in inferring changes in hydroclimate variables from ERA5-Land and other reanalyses due to inhomogeneities in the assimilated observational data. Continued emphasis on bias corrections to hydrometeorological data and better modeling of HWM are crucial to improving all retrospective analyses of changes in land surface hydrology and terrestrial water stores.

1 Introduction

The global distribution and temporal evolution of Terrestrial Water Storage (TWS)[1] have profound consequences for human society. Access to water for irrigation, human health (consumption, sanitation), power generation, manufacturing, sustainable development and a supply resilient to climate change each demand improved assays of historical water distribution, availability and projections for the future (Vorosmarty et al, 2000; Wada and Bierkens, 2014; Rodell et al, 2018; Deng et al, 2025). TWS is also physically linked to freshwater discharge to the global oceans and, thus, Global Mean Sea-Level (GMSL) change (Pokhrel et al, 2012; Boening et al, 2012; Wada et al, 2017; Rodell et al, 2024; Chandanpurkar et al, 2025). TWS evolves as the net effect of precipitation (P), evapotranspiration (ET), runoff or discharge (RO), and the collection of human

[1] Appendix A contains a full list of acronyms

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influences we refer to here as Human Water Management (HWM). In a stationary climate, changes in TWS would largely vanish annually; this assumption, valid to first order on multi-annual timescales, has underpinned the success of Budyko's (1974) relationships in analyzing hydrologic behavior over differing climate regimes. But with significant natural climate variability, changing climate forcing that alters near-surface hydrometeorology, as well as the related growth of human activities altering vegetation, land, and water use, TWS variations and trends constitute important but poorly determined parts of the evolving terrestrial water balance.

Strategies for measuring TWS and its change have improved radically in recent decades. Satellite LASER Ranging (SLR) sensors provided the first spaceborne measurements of gravity changes at global and continental scale extending back to 1993 (Sośnica et al, 2015; Löcher and Kusche, 2020; Flechtner et al., 2021; Rodell et al, 2024; Nie et al, 2025); however, the coarse spatial resolution and larger uncertainties early in the period present notable limitations. GRACE (NASA's Gravity Recovery and Climate Experiment, Tapley et al., 2019) and its follow-on satellite mission GRACE-FO (Landerer et al., 2020), hereafter referred together as GRACE/FO, have provided the first regionally detailed measurements of water mass changes over land, ocean, ice sheets, and glaciers since early 2002. Advances in detailing TWS changes since that date (Rodell and Reager, 2023) have enabled much greater precision in quantifying the components of climate variability (Boening et al, 2012; Phillips et al, 2012; Ni et al, 2018; Tapley et al., 2019), irrigation and groundwater depletion (Rodell et al, 2009; Adams et al., 2022; Scanlon et al, 2023; Dharpure et al, 2025), and warming-induced cryospheric mass loss (Jacob et al., 2012; Velicogna et al., 2014, 2020; Loomis et al., 2019b). Quantifying these contributing processes has provided a valuable measurement and understanding of the mass related component of GMSL change, complementary to the altimetric measurements of total sea level rise that also includes thermal expansion of warmer oceans (Church et al., 2013).

The societal dependence on water availability demands a larger historical context for TWS changes that extends into the decades before space-based gravimetry. Numerical models, which differ in terms of the physical and biogeochemical processes and human interventions they emphasize, are valuable tools for inferring TWS behavior prior to the GRACE/FO era. Bierkens (2015) offered a genealogy of the various approaches, identifying four types: (i) Land Surface Models (LSMs) that emphasize energy and water exchange at the soil-vegetation-atmosphere interface, (ii) Land Earth

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System Models (LESMs) that typically include plant phenology and carbon cycling in addition to more in-depth hydrology, (iii) Dynamic Vegetation Models (DVMs) that emphasize biome evolution, but typically at the expense of hydrologic rigor, and (iv) Global Hydrology and Water Resource Models (GHMs) that incorporate water use and which may be constrained by measurements of HWM. Of course, these boundaries are not rigid. In the present analysis we will include models from each of these categories. One approach to extending the TWS record has been the use of offline versions of these global models driven with historical meteorological and radiative forcing data (e.g., Rodell et al., 2004; Sheffield and Wood, 2007; Li et al., 2019; Cáceres et al., 2020), or similar products taken from global atmospheric reanalyses (Reichle et al., 2012; Muñoz-Sabater et al., 2021). A commonality of these efforts is that the results are sensitive to the accuracy of meteorological forcing, model parameters, assumed soil and vegetation characteristics, and uncertainties in water resource data. (Wheedon et al., 2011, 2014).

Another approach to inferring past TWS changes differs fundamentally from physical modeling in that it involves various statistical techniques such as regression, principal component analysis or machine learning (ML) which are used to replicate the GRACE/FO TWS record and then to extend these empirically based estimates back prior to 2002. Among these efforts are data sets produced by Humphrey and Gudmundsson, (2019), Li et al. (2021), Chandanpurkar et al. (2022) and Yin et al. (2023). Some initial assessments of their accuracy are becoming available (Deng et al, 2023; Hacker and Kusche, 2024). As with the physical models, the accuracy of input training data is crucial with precipitation being of primary importance.

In this study we offer a benchmark of current capabilities in estimating TWS changes in the two decades before GRACE launched, focusing particularly on trends and interannual variations over the satellite era, nominally 1980 to near present. GRACE/FO retrievals of TWS are available only from 2002 onward, but they constitute an important tool to judge the various TWS estimates after that date, specifically in replicating pattern structure and amplitude. Our analysis centers primarily, but not exclusively, on the behavior of the ERA5-Land reanalysis (Muñoz-Sabater et al., 2021) because it supports a substantial fraction of land surface hydrology studies and serves as a key input to many TWS reanalyses and reconstructions. It relies on the ERA5 atmospheric reanalyses and thus, like other reanalyses, is subject to time dependent biases induced by assimilation of an ever changing mix of observing systems, most critically, the discrete sequence

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of satellite system changes. Further, the consequences of such biases on ERA5-Land are likely to be mirrored in other ERA5 driven reanalyses. In particular, number of investigations have noted likely artifacts in ERA5's hydrologic cycle stemming from these assimilation issues (Hersbach et al., 2019; Nogueira et al., 2020; Gleixner et al., 2020; Cleeland et al., 2024; Rodell et al., 2024; Wang et al., 2026). We review results from a number of GHM and LSM modeling efforts from the Inter-Sectoral Impact Model Inter-comparison Project, ISIMIP3a (Gosling et al., 2025) whose atmospheric forcing, including precipitation, benefits from attempts to reduce time-dependent biases. HWM contributions in three different ISIMIP3a models are considered, contrasting their TWS variations with those of ISIMIP3a LSMs that don't account for these effects. A surprising result, given that ERA5-Land does not account for HWM, is that downward TWS trends from ERA5-Land over the 1980-2019 period are as large or larger than those of the two GHMs. Given that the ERA5-Land formulation is essentially an LESM, we investigate the potential role of differences in forcing datasets used by ERA5-Land and ISIMIP3a models, principally the precipitation forcing. The additional perspective of three statistical TWS reconstructions is also considered as we compare their trend patterns and interannual signals to modeling results, ERA5-Land behavior and to GRACE/FO. Our analysis addresses global mean trends and variability but we also examine regional patterns of TWS and P that comprise global values.

2 Methods and Data Sets

This study uses six types of data in monthly mean, gridded form: (i) the ERA5-Land reanalysis, (ii) TWS retrievals from GRACE/FO, (iii) Global Satellite LASER Ranging (SLR) based TWS estimates, (iv) Model data including input precipitation and output TWS from the Inter-Sectoral Impact Model Inter-comparison Project, ISIMIP3a (Warszawski et al., 2013), (v) Three statistical TWS reconstructions based on training hydrometeorological predictors on the GRACE/FO record, and (vi) Gridded precipitation data sets from the Global Precipitation Climatology Centre (GPCC), the Global Precipitation Climatology Project, GPCP v3.2, and CRUJRA 2.2, a gridded time series meteorological variables produced by the Climatic Research Unit (CRU) at the University of East Anglia (UEA) (https://catalogue.ceda.ac.uk/uuid/10d2c73e5a7d46f4ada08b0a26302ef7).

2.1 ERA5-Land

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ERA5-Land (Muñoz-Sabater et al., 2021) is a continuing land surface reanalysis describing the water and energy balance globally at 9km daily resolution covering the period 1950 to near present. The assimilating model is the Carbon Hydrology-Tiled Scheme for Surface Exchanges over Land (CHTESSEL; Boussetta et al., 2021). In its ERA5-Land configuration there are four soil layers (7, 21, 72 and 189 cm thick) with a total depth of 2.89m. Recent improvements to CHTESSEL include incorporation of dynamic vegetation, an updated snow scheme, treatment of lake fractions, and treatment of urban land attributes. ERA5-Land was produced in separate, overlapping streams starting in 2001 and streams 2 and 3 initiated in 1980 and 1950. Three years of spin-up was used in the overlap period. ERA5-Land is driven by hourly ERA5 atmospheric reanalysis near surface meteorology, radiation and precipitation. One notable aspect of the surface evaporation calculation is that potential evapotranspiration is calculated assuming crop-type vegetation with no moisture stress but that the overlying atmosphere is not affected by this artificial surface condition.

2.2. GRACE and GRACE-FO

GRACE (2002-2017) and GRACE-FO (2018-present) are twin satellite systems that infer time varying mass distributions over the globe based on precise measurements of intersatellite range (distance). These systems resolve gravity variations due to various geophysical processes, among them being changes in liquid and frozen water on and under the land surface. We use an average of three different Level III liquid water equivalent GRACE solutions, each at 0.5 degree resolution: (i) the GSFC mass concentration blocks (mascons) product GSFC.glb.200204_202501_RL06v2.0_OBP-ICE6GD_HALFDEGREE.nc, (Loomis et al., 2019a) which contains monthly estimates of time-variable gravity in units of cm equivalent water height, (ii) JPL TELLUS_GRAC-GRFO_MASCON_CRI_GRID_RL06.3_V4; http://grace.jpl.nasa.gov/data/get-data/jpl_global_mascons/, (Wiese et al., 2018), and (iii) the University of Texas Center for Space Research CSR_GRACE_GRACE-FO_RL0603_Mascons_all-corrections.nc, https://www2.csr.utexas.edu/grace/ (Save et al., 2016). Though we regrid these product to a 1.0 lat / lon grid for commonality with other data, the inherent resolution of GRACE/FO mascon determination is no better than 10^5 km^2 or roughly 3 degrees latitude / longitude (Wiese et al., 2018).

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2.3. Satellite LASER Ranging Data

Prior to GRACE, space based gravimetry was accomplished by satellite laser ranging (SLR) from Earth's surface to mirrored, passive geodetic satellites. After 1993, there were enough laser ranging satellites in orbit to derive mass change time series using the mass concentration (mascon) approach (Rowlands et al. 2005) with sub-continental scale resolution. Herein we use TWS mascon data derived from SLR observations from 5-7 geodetic satellites (Loomis et al. 2019a). The solution time series was adaptively de-seasoned using the Ensemble Empirical Mode Decomposition (Wu and Huang 2009). Mass trends were calibrated by GSFC to match GRACE/FO over a common span to mitigate impacts of parameter correlations, due to internal tests by GSFC that demonstrated that the recovered SLR inter-annual signals are not dependent on the background gravity model, but that the recovered trends are.

2.4. ISIMIP Models

The Inter-sectoral Impact Model Intercomparison Project, ISIMIP, is an international community-driven initiative that provides a consistent framework for multi-model climate-impact simulations across sectors such as water, agriculture, ecosystems, health, and infrastructure and many others (Warszawski et al., 2013; Rosenzweig et al., 2017; Frieler et al., 2024). It does this by establishing protocols for experiments designed to ensure comparability across the multiple sectors and scales. One subset of the most recent modeling efforts is ISIMIP3a and the sector Water_Global. A subset of these model experiments uses historical atmospheric forcing data sets to drive GHMs and LSMs (Gosling et al., 2025). Here we employ TWS data from five models: WaterGAP 2.2e, PCR-GLOBW 2, LPJmL5-7-10-fire, H08 and JULES. Data from three sets of forcing data sets are used. The GSWP3-W5E5 (Cucchi et al., 2020; Lange et al., 2022) adopts ERA5 near-surface meteorology, 1979-2019 over land, with CRU TS4.03 adjustments to two-meter air temperature, T_{2m}, net downward shortwave radiation, SW_d, number of wet days, and GPCC2018 monthly precipitation totals which have been adjusted for bias undercatch. GSWP3 (https://doi.org/10.48364/ISIMIP.982724.1) is a bias adjusted version of the Twentieth Century Reanalysis v2 (Kim, 2017; Compo et al., 2011) that has been harmonized to reduce biases relative to W5E5 over the 1978-1979 period. The GSWP3-W5E5 forcing has also been used at GSFC to produce a companion experiment with the Global Land Data Assimilation System (GLDAS; Rodell et al., 2004) driving the Noah land surface model. Finally, the ISIMIP3a protocol also

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makes available a set of experiments to compare the differences between ERA5 and W5E5 forcing: 20CRv3-W5E5 and 20CRv3-ERA5. These experiments use the version 3 of the NOAA 20th Century Reanalysis before 1979 (Slivinski et al., 2019), hence the different nomenclature, but they too are bias corrected to either ERA5 or W5E5. Since we confine our analysis to the post 1979 period, these bias corrections do not impact our results. We explore differences in these two analysis versions with WaterGAP, LPJ and H08 to quantify these different forcings on TWS evolution. Finally, we note that some of the GSWP3-W5E5 model experiments have additional versions where HWM has been disabled in the models, rendering them "LSM-like". We use these WaterGAP and LPJ experiment versions. Further details of the ISIMIP3a models used in this study and their formulation are found in Table 1.

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ISIMIP Model	Configuration	Hydrology	Human Water Management	Documentation
WaterGAP2.2e	GWHM 0.5 x 0.5 deg res; daily time step 20CRv3_W5E5, 20CRv3_ERA5 used	Canopy, vegetation, snow; single soil layer. Lake, reservoir and river modeling Runoff calibrated against observed streamflow Groundwater recharge, extraction and linear storage / outflow depletion.	Irrigation, domestic use, thermal & manufacturing, livestock Also run with no water management.	Döll et al., 2003 Müller Schmied et al., 2021, 2023. http://watergap.de/
PCR-GLOBWB-2	GWHM 5 arcmin (9 km); daily time step	2 soil, 1 groundwater layers. 4 landcover, soil types, climatologically varying phenology Runoff routing: kinematic wave enabling floodplain inundation Groundwater recharge, capillary rise, riverbed infiltration, linear storage / outflow depletion	Irrigation, domestic, livestock Simple reservoir management	van Beek et al., 2011 Sutanudajaja et al., 2018 http://globalhydrology.nl
LPJmL5-7-10-fire-Fire	DGVM Experiments used are 20CRv3_W5E5, 20CRv3_ERA5 forcing	5 soil layers: 20, 30, 50, 100, 100 cm Dynamic simulation of growth and productivity (prescribed spatial distribution of crops and pasture) Runoff routing: Continuity equation derived from linear reservoir model	Irrigation determined endogenously. Simple reservoir modeling, industry, domestic uses, prescribed water consumption provided by ISIMIP. Also run as LSM with no water management.	Sitch et al., 2003 Wirth et al., 2024
H08	GWHM 0.50.5 deg res; daily time step 20CRv3_W5E5, 20CRv3_ERA5 used	Single layer climate variable depth. Represents dominant veg for climate zones TRIP-based runoff routing	Abstraction & return flow for river, reservoir, renewable and non-renewable groundwater	Hanasaki et al., 2018. https://h08.nies.go.jp/
JULES-W2	LSM 0.5 x 0.5 deg res; daily time step	4 soil layers, 10, 25, 65, 200 cm Penman-Montieth ET TRIP-based runoff routing Fixed plant types but CO2 fertilization accounting	None	Best et al., 2011 https://jules.jchmr.org/ Oki and Sud, 1998
GLDAS/Noah	Noah LSM 1.0 x 1.0 deg res; 3-hourly time step	4 soil layers, $0^{-1}0$, 10-40, $40^{-1}00$, 100-200 cm Seasonally varying green vegetation fraction with constant Leaf area Index	None	Ek et al., 2003 Rodell et al. 2004 https://ldas.gsfc.nasa.gov/gldas

Table 1: Attributes of models using ISIMIP3a forcings.

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2.5. Statistical / Machine Learning TWS Reconstructions

To supplement our comparison of different modeling strategies we appeal to recently developed empirical / statistical methods for TWS estimates. Our analysis considers three statistical TWS reconstructions: (i) Humphrey and Gudmundsson, (2019), (ii) Li et al. (2021) and (iii) Yin et al. (2023). We refer to these as HG19, Li21 and Yin23, respectively. These statistical strategies vary in complexity and the number of input variables, but each trains against GRACE/FO TWS mascon data. HG19 is the simplest, principally relying on precipitation. Details of these approaches and reference information are provided in Table 2. While none of these reconstructions explicitly represent HWM, some implicit sensitivity to these factors is present in both Li21 and Yin23.

Dataset	Methodology	Input Data Sets	Comments	References
HG19	Linear water store model with spatial autoregressive modeling. Only IA components are modeled. JPL and GSFC mascons	ERA5, GSWP3, MSWEP2.2 precipitation and 2m temperature	Trend, seasonal cycles removed before training; yield is monthly anomalies Trends due to input precip only	Humphrey et al. (2017) Humphrey and Gudmundsson (2019)
Li21	Regionally determined. PCA-like decomposition of predictors. Seasonal, IA, trend components modeled. CSR RL06 GRACE mascons	2m T, NOAA CPC Precip, SST, 17 climate indices	Trained for seasonal cycle and anomalies. Trend pattern is specified from GRACE	Li et al. (2020, 2021)
Yin23	Trained with five different ML models x eight input data combinations JPL, GSFC and CSR mascons	ERA5 hydrometeorological variables + LAI, LULC	Reconstruction extends back to 1940	Yin et al. (2023)

Table 2: Significant attributes of three statistical methods for TWS reconstruction.

HG19 produced three different reconstructions using precipitation from either ERA5, the Multi-Source Weighted-Ensemble Precipitation dataset (MSWEP v2.2; Beck et al. 2017, 2019) or from the GSWP3 forcing data (Kim, 2017); the GSWP3 dataset has been used to bias correct the 20th Century Reanalysis (20CR) v2c. HG19 removed trends and seasonality in training against

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GRACE. Thus, trends in the reconstructed TWS are due solely to trends in input forcing precipitation on which the reconstruction is built. GSWPv3 data extend only through 2014. We exclude the MSWEP-based TWS reconstruction since its precipitation has an unrealistic upward trend compared to GPCC and other precipitation data sets. Using a more complex strategy, Li21 first resolve input predictors and GRACE/FO data into 26 river basins. Input predictors are then decomposed using data compression tools (e.g., principal component analysis). GRACE/FO are resolved into seasonal, interannual, residual and trend components and then reconstructed from the predictor data using various ML approaches yielding twelve different estimates. The GRACE trend is enforced in the reconstructions. Selection of the best estimate is done on a regional basis. Yin23 use five different ML approaches but a much larger set of predictors almost exclusively from the ERA5 reanalysis. These predictors are disaggregated into eight different combinations. In sequential fashion, the best performing ML scheme and the best of the eight input configurations in reproducing GRACE/FO TWS is selected. This process is repeated for three GRACE/FO mascon data sets: JPL, CSR and GSFC. Here, we have averaged the three reconstructions.

2.6. Precipitation

The evolution of TWS is strongly related to that of precipitation and its space-time variability (Li et al., 2019; Zhang et al., 2019). In the ISIMIP3a model products examined here, the bias correction of precipitation (e.g. Cucchi et al., 2020) employs monthly means of gridded, gauge-based data from the Global Precipitation Climatology Center (GPCC). In contrast, the ERA5-Land meteorological forcing uses the precipitation generated by the ERA5 atmospheric reanalysis. To assess this influence on the evolution of ERA5-Land TWS we use the GPCC precipitation product GPCC Full 2020 (Schneider et al. 2014), an objectively analyzed gauge-only product gridded to 1.0 degree resolution.

Our precipitation analysis is supplemented by two other estimates. The Global Precipitation Climatology Project product GPCPv3.2 (Huffman et al. 2023; https://doi.org/10.5067/MEASURES/GPCP/DATA304) merged product blends precipitation estimates from low-orbit satellite microwave data, geosynchronous-orbit satellite infrared data, and sounder-based estimates. Calibration is by GPCC gauge measurements with under / over catch corrections applied. The CRUJRA v2.0 time precipitation analysis (Harris et al. 2021; Kobayashi et al. 2015) is similar in principle to that of W5E5 but instead it adjusts the JRA-55 forcing

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variables, T_{2m}, q_{2m}, SW_d, P and wet days, to aligned over land to CRU TS (v4.03) data. Here we adopt the resulting precipitation data.

Data sets have been re-gridded to 1.0 degree latitude x longitude resolution at monthly time steps and over a domain extending from 60S to 70N. GrADS software was used with box averaging for finer resolutions and bilinear interpolation for coarser resolution datasets. Glaciated grid points are masked, including the Himalayan region, southern South America, coastal portions of the Alaskan / Canadian coast, northern islands of Canada and Greenland. This facilitates comparisons to GRACE/FO by ensuring that we are excluding trends associated with melting ice sheets and glaciers that none of the models simulate. Monthly anomalies are calculated as departures from monthly varying climatologies over the period 2002 to 2019. This period was selected to facilitate comparisons with the GRACE and GRACE-FO products. Given the intrinsic resolution of GRACE/FO of approximately 10^5 km^2, for comparisons of TWS spatial structure to GRACE products the 1.0 degree model data sets have been smoothed with two applications of a nine-point spatial filter to yield a comparable spatial resolution.

3 Results

3.1 Global aspects of TWS changes

3.1.1 Area-average time series

Global mean TWS anomaly time series show striking diversity prior to 2001, yet reasonably consistent agreement thereafter for large interannual signals (Fig. 1). Long-term trends are smallest for the LSMs, which contain no HWM processes (Table 3). This contrasts with the GHMs but should not be surprising given the systematic omission of water use processes in LSMs. However, the relatively close trend agreement between ERA5-Land (-0.80 mm y^{-1}) and WaterGAP (-0.72 mm y^{-1}) over 1980-2019 is surprising given that ERA5-Land contains none of the HWM budget mechanisms contained in WaterGAP (or PCR-GLOBWB). Because the ERA5-Land surface model functions essentially as an LESM, the question then is what drives its large long-term trend? PCR-GLOBWB exhibits an intermediate long-term trend (-0.42 mm y^{-1}), roughly half that of WaterGAP. H08 has a weakly positive TWS trend over the longer period (0.04 mm y^{-1}).

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Since all of the GHMs are driven by the same meteorological forcing, these differences indicate uncertainty of TWS changes in the face of GHM model physics differences and their treatment of HWM processes.

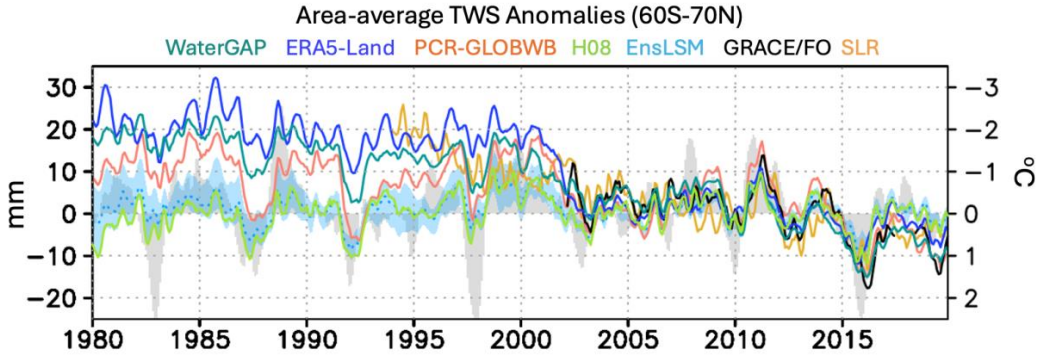

Figure 1: Time series of global area-averaged (60S-70N) Terrestrial Water Storage (TWS) anomalies (mm) from ERA5-Land, GRACE/FO, SLR, three Global Hydrologic Models: WaterGAP, PCR-GLOBWB and H08, an ensemble spread of Land Surface Models: JULES, LPJ, WaterGAP (with HWM disabled), and GLDAS/Noah. The LSM mean is shown as a dotted line. Anomalies are departures from monthly resolved climatologies over the period 2002-2019. A 3-month boxcar smoothing has been applied. Nino3.4 SST anomalies, ºC, are plotted as gray. The SST scale is inverted to emphasize the tendency for relationship between anomalously warm (cold) SST and depressed (elevated) precipitation over land.

In addition to the trend variations, there are strong coherent interannual signals that relate in large part to El Niño Southern Oscillation (ENSO) variability; TWS standard deviations (S.D.s) of order 3.5 to 4.5 mm around the trends are typical. PCR-GLOBWB, with three soil layers, has the largest value of 6.0 mm. Only PCR-GLOBWB approximates the GRACE/FO S.D. value of 4.7 mm during 2002-2019. Sensitivity studies have shown that adding more soil storage capacity notably increases variability and trends (Döll, personal communication). In the development of ENSO warm events (1987, 1992, 1997, 2015) significant TWS decreases are observed, reflecting decreased moisture transport to land and precipitation during warm SST episodes (Trenberth and Shea, 2005; Miralles et al., 2014; Robertson et al., 2016; Bosilovich et al., 2020). The strong La Niña SST cooling in 2010 is matched by large TWS increases, behavior consistent with the

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previously reported dramatic global mean sea level fall of 5 mm in 2011 (Boening et al, 2012). Relaxation of the strong SST cooling during 2000-2002 that followed the intense 1997/1998 El Niño is accompanied by strong TWS decreases in ERA5-Land, WaterGAP and PCR-GLOBWB; it is also present to a lesser extent in the LSMs. However, this 2000-2002 period of significant change in SSTs and associated TWS decreases also coincides with significant changes in satellite remote sensing that can bias reanalyses. Precipitation changes over this period in ERA5, which drives ERA5-Land, have been noted by Wang et al. (2026).

		GHMs			LSMs (No Water Management)				
	GRACE/FO	WaterGAP	PCR-GLOBWB	H08	ERA5-Land	JULES	LPJ NWM	WaterGAP NWM	GLDAS /Noah
Trend 1980-2019	---	-0.72	-0.42	0.04	-0.80	-0.23	0.36	0.05	-0.05
(2002-2019)	(-0.80)	(-0.91)	(-0.49)	(-0.06)	(-0.40)	(-0.09)	(0.50)	(-0.06)	(-0.01)
S.D. 1980-2019	---	4.19	5.98	4.24	5.07	4.49	3.34	4.25	3.48
(2002-2019)	(4.68)	(3.86)	(5.76)	(3.78)	(3.39)	(4.03)	(3.57)	(3.76)	(3.29)
Trend Pattern Correlation with GRACE/FO 2002-2019		0.36	0.36	0.25	0.30	0.22	0.27	0.24	0.20
Mean 2002-2019 Anomaly Correlation with GRACE/FO		0.55	0.53	0.47	0.63	0.62	0.55	0.25	0.57

Table 3: Various statistics summarizing TWS trends and variability. Trends (mm y^{-1}) and standard deviations (S.D., mm) of TWS time series are made with monthly data without the temporal smoothing in Fig. 1. Calculations are over the 1980-2019 period with values for the 2002-2019 period in parentheses. Anomaly correlations are time means of area-averaged

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(60S-70N) monthly correlation maps. For both trend pattern and anomaly correlations, two applications of a 9-point spatial filter have been applied to model TWS to approximate the intrinsic spatial resolution of GRACE/FO. All anomalies use a monthly resolved climatology of 2002-2019.

In contrast to the trend pattern correlations, in which the GHMs are systematically closer to GRACE/FO, the GHM anomaly correlations (just above 0.50) are even lower than for most of the LSMs. Two factors may contribute to these lower correlations. First, the time-integrated effects of water management on trends are likely better modeled than monthly variations of those processes. Second, TWS response to P, ET and RO at 1.0 degree gridpoints is noisy on a monthly time scale, equally affecting GHMs and LSMs. ERA5-Land shows closest agreement with GRACE/FO (r = 0.63), the highest of the LSMs, which is confirmation of the consistency of the ERA5 4D-Var assimilation system.

3.1.2 Spatial structure of TWS trends

Though our primary interest is in TWS change over the recent 40-year period, GRACE/FO data extend only from April 2002 onward. For the ISIMIP3a 1980-2019 experiment period this amounts to approximately 17 years. Examining spatial structure of trends over each of these periods (Fig. 2) provides a fuller context of TWS behavior differences resulting from the various modeling strategies. GRACE/FO TWS decreases (Fig. 2a) dominate much of the arid world including the Middle East, Western Russia, but also extending through Europe and North Africa. Focused areas of loss over northern India, northeast China, and the south central U.S. are present where groundwater depletion has been widely documented (Wada et al., 2010; Rodell et al., 2018; Gleeson et al., 2020). TWS declines over southeast Brazil adjacent to gains over the Amazon basin suggest ENSO influence that is unrectified in such a short period; but it may also reflect longer term changing precipitation patterns connected to Atlantic meridional SST gradients (Nobre and Shukla, 1996; Marengo et al., 2017; de Souza Santos et al., 2024) as well as long-term drying from land / ocean warming contrast (Wainwright et al. 2022). Prominent TWS gains over the Sahel and along the Rift Valley southwestward into Angola / Namibia dominate the African continent.

Consistent with previous evaluations of modeled TWS (Scanlon et al., 2018; Tiwari et al., 2025), none of the GHMs or LSMs can satisfactorily replicate GRACE trend patterns or magnitudes over

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the 2002-2019 period; nor does ERA5-Land. WaterGAP and PCR-GLOBWB achieve the largest trend pattern correlation with GRACE (0.36), but this agreement is quite low (Table 2). ERA5-Land is slightly lower (0.30), marginally stronger than the LSMs. Strongest agreement of the two GHMs with GRACE/FO is in regions where groundwater extraction is prominent (Fig. 2 c,d; much of the Middle East, northern India, northeastern China and the U.S. southern plains). Here the GHMs benefit from water use simulations supporting irrigation, industry and human consumption. To the point, the trend pattern for the WaterGAP experiment with no water management (WaterGAP NWM; not shown) looks very close to the LSM mean in Fig. 2e. These effects are not modeled by ERA-Land nor any of the LSMs we examined, thus it's no surprise that these local maxima of TWS depletion are essentially missing in these models. An exception might be for ERA5-Land in TWS-depleted northeast China. This may be due in part to the practice in ERA5-Land of actual evaporation being set to the potential rate in irrigated areas, thus drawing down soil moisture. HWM trends in WaterGAP and PCR-GLOBWB are also prominent in the pre-GRACE period (Fig. 2g, h). These patterns are consistent with the gridded water use patterns assembled by Huang et al. (2018). However, to recover local detail in their analysis these authors made use of patterns of water management derived from previous model integrations of the HWMs examined here to extend country wide water use data.

Over central equatorial Africa and the Congo Basin a noticeable downward TWS trend in ERA5-Land contrasts with GRACE/FO and any of the GHMs or LSMs (Figs. 2 b, f). As discussed by many studies (Washington et al., 2012; Nicholson et al., 2014; Maidment et al., 2015; Rodell et al., 2024; Su et al., 2026) this region is poorly sampled by meteorological sensors and rain gauges, making it sensitive to changes in assimilated satellite data on which it must more heavily rely. In terms of the entire 1980-2019 period, this difference between ERA5-Land and the other models becomes more pronounced. Other regions (e.g., northeast China, the east-west band across central Asia, and northern Argentina) also exhibit much stronger TWS depletion in ERA5-Land than either WaterGAP, PCR-GLOBWB, or especially the collection of LSMs. Although some of the large TWS trends may relate to ERA5-Land allowing ET at the potential rate for irrigated crop

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areas, this cannot explain the drying trends in central Africa, central China or eastern Asia.

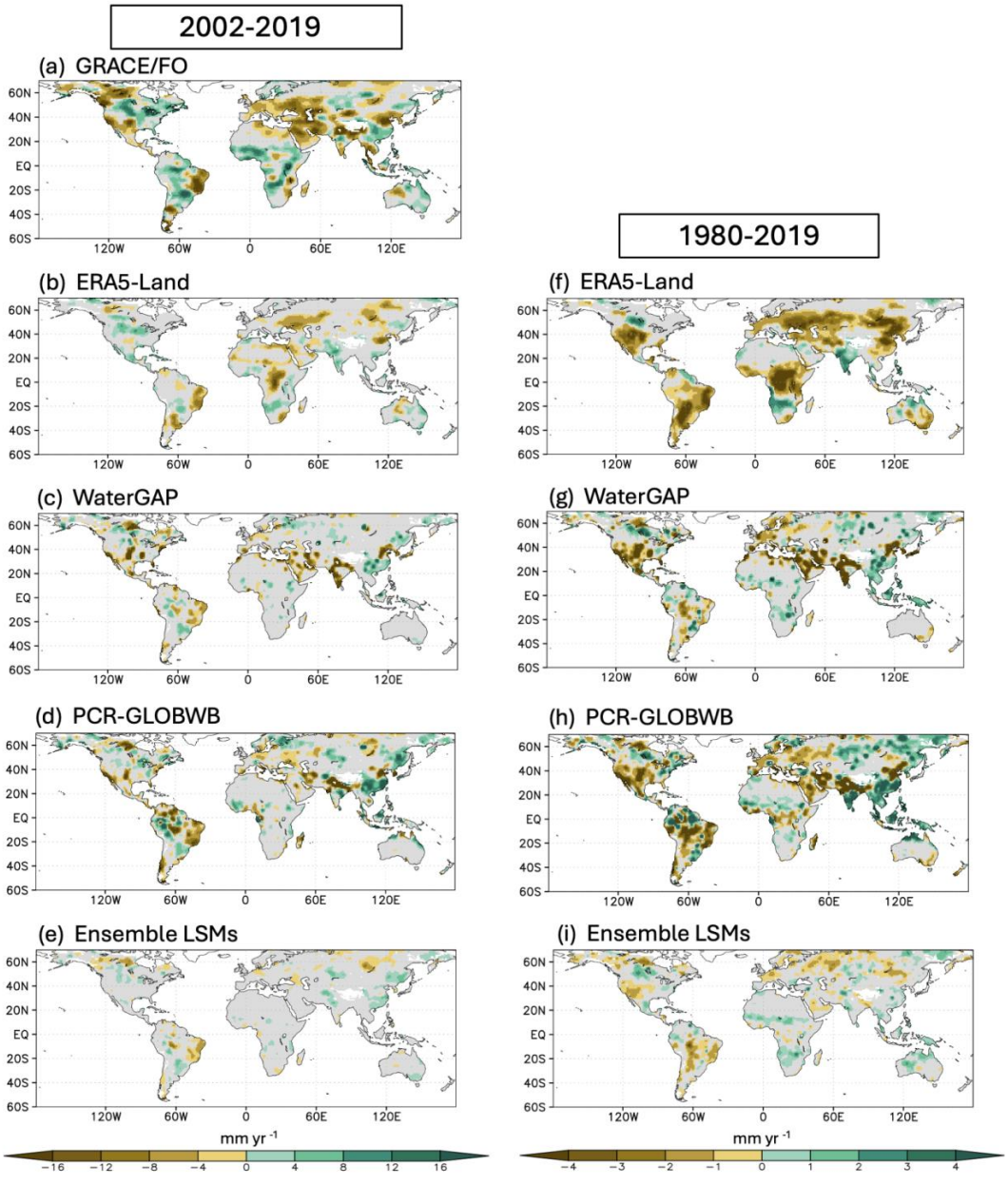

Figure 2: Linear trends of TWS (mm y^{-1}) over the periods 2002-2019 (left) and 1980-2019 (right). Note the factor of four difference in the color bar scale for the two periods. Ensemble

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LSMs include JULES, LPJ, WaterGAP (with HWM disabled), and GLDAS/Noah. Given the intrinsic resolution of GRACE/FO data of approximately 10^5 sq km, about 3.0 degrees in middle latitudes, the 1.0 degree resolution model data sets have been smoothed with two applications of a nine-point spatial filter to yield a comparable spatial resolution.

3.2 Regional Time Series

The strong regional structure of the TWS trends among the different models and ERA5-Land motivates examining time series of TWS anomalies in several key regions (Fig. 3). None of the models captures the amplitude of GRACE/FO or SLR variability over central Africa (Fig. 3a) with two large minima in 2004-2005 and 2010-2011; nor can they replicate its upward trend with time. Between the late 1990s and 2002 there was a precipitous decline in ERA5-Land TWS not seen in other models and coinciding with multiple satellite system changes (Selva et al., 2017; Dinz and Toddling, 2020; Hersbach et al., 2020; Wang et al., 2026). A subsequent smaller drop also appears after 2014.

Over the Indian subcontinent (Fig. 3b) the initial rise in GRACE/FO TWS and its decline after 2014 is well captured only by PCR-GLOBWB. ERA5-Land interannual variability does match that of PCR-GLOBWB but does not capture the elevated TWS in the GHMs prior to 2002. WaterGAP has a much stronger TWS decline but has relatively weak interannual signals.

The northern Argentina and La Plata Basin region (Fig. 3c) is heavily influenced by ENSO (Ropelewski and Halpert, 1987; Barros et al., 2000; Costa et al., 2024). Coherence of TWS changes at interannual scales among all the model simulations is striking and closely follows GRACE/FO except after 2015. The LSMs agree with the GHMs, suggesting dominance of natural variability. Though ERA5's steep decline in TWS near 2002-2003 is consistent with GRACE/FO and PCR-GLOBWB, it clearly defines a shift between two different epochs in terms of the range of variability of TWS that is not seen in the other models. This TWS decline does not cleanly align with that noted over central Africa in 2000-2002, perhaps due to ENSO influence and other factors such as south Atlantic SST variability (Barros et al., 2000; Kayano et al., 2013).

The southwestern U.S. (Fig. 3d) has endured recurring droughts over past decades and has depended heavily upon irrigation to sustain agriculture (Elias et al, 2016). A resulting drawdown

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in TWS is seen in the GRACE/FO data and is matched closely during that period by WaterGAP and PCR-GLOBWB. Those two models simulate comparable rates over the full 40-year period. ERA5-Land and the LSMs indicate a much more modest decline. Given the dense surface and upper air meteorological observational network over North America, the impact of shifts in satellite observing systems used in ERA5 should be muted in ERA5-land.

Western Eurasia (Fig. 3e) and areas southward into northern Africa and the Middle East (Fig. 3f) are regions in which all models replicate drawdown of TWS during the GRACE/FO record to varying degrees. Still, none fully capture the amplitude; ERA5-Land and PCR-GLOBWB perform best. There are important differences between the northern and southern halves of this region, which extends from 20S to 60N. Strong interannual variability and an associated downward trend in GRACE TWS characterizes the northern half of the region. A number of studies have examined the recurrence of hydrometeorological drought in this region (Cherenkova et al., 2015; Semenova and Slizhe, 2020 and Semenova and Vicente-Serrano, 2024) and the role of atmospheric warm season blocking episodes, i.e., stationary atmospheric Rossby waves. Of special note are the 2007 and 2010 events as evidenced by the Palmer (1965) and Standardized Precipitation and Evapotranspiration Index (SPEI), https://spei.csic.es/database.html) drought indices. In the southern half of the region GRACE/FO still shows a strong TWS decline but with a more dramatic decline in 2007 (Fig. 3f). In this region, none of the models adequately capture interannual signals or the associated trend. WaterGAP and PCR-GLOBWB do have long-term downward trends absent in ERA5-Land and the LSMs. We suspect that modeled groundwater depletion, however incomplete and uncertain in these models, may explain the difference. Joodaki et al. (2014) used a combination of GRACE and land surface model estimates of soil, snow, canopy and river water to argue that groundwater depletion dominates during 2003-2014 in this region, centered specifically in Iran. Using a similar strategy, Chao et al. (2017) also reported extraction as the explanation for groundwater depletion within the Tigris-Euphrates Basin over a similar period.

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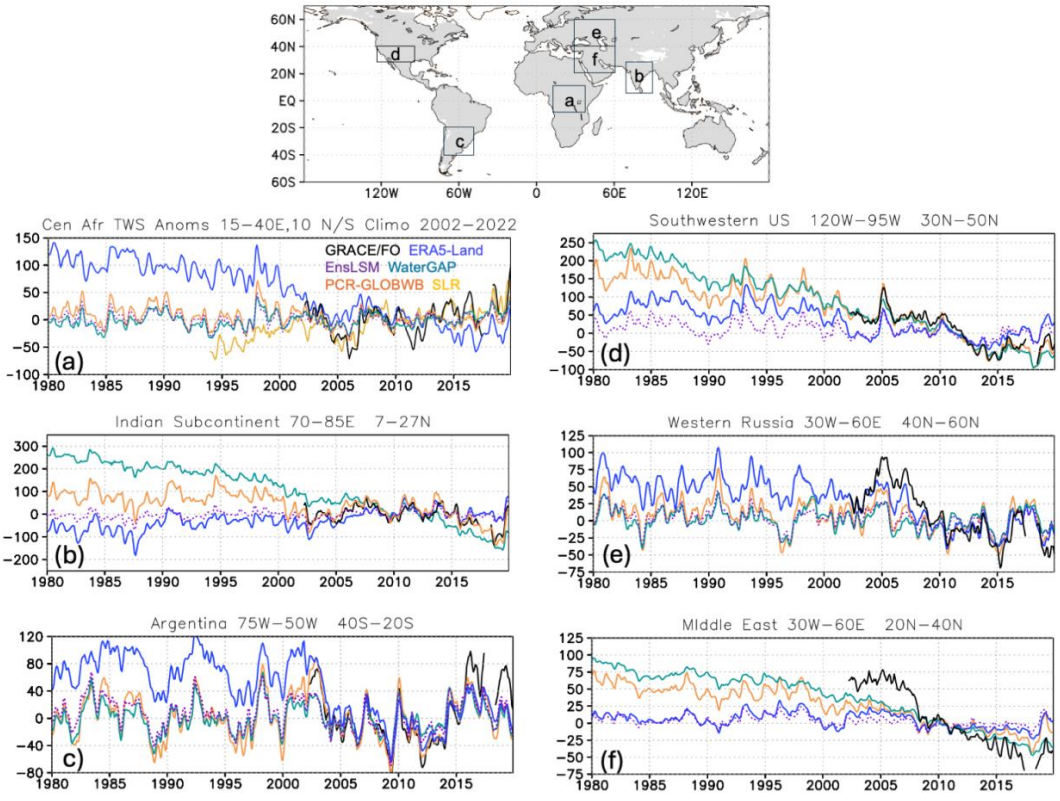

Figure 3: Regional area-averages of TWS time series anomalies (mm) for ERA5-Land, WaterGAP and PCR-GLOBWB with ensemble LSMs shown as dotted purple lines. GRACE/FO and satellite laser ranging (SLR; global only) based TWS time series are also plotted. Geographic extent of regions is shown in map at top. Anomalies were computed relative to a baseline period of 2002-2019.

Collectively, these different regional views show that relationships between the GHMs, GRACE/FO and LSMs are not uniform and depend on the hydroclimate of the region (strong ENSO signals over Argentina; stationary Rossby wave effects over European Russia), the precipitation gauge density (e.g. Congo basin) and the degree of HWM, especially groundwater extraction (India and parts of the Middle East). There are, however, systematic differences in the TWS behavior of the GHMs and ERA5-Land pre- and post-2000/2002. The Congo Basin and northern Argentina are the most prominent examples. There is evidence, too, over the

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southwestern U.S., where ERA5-Land and the ensemble LSM TWS signals diverge during the 2000-2002 period.

3.3 Precipitation Differences

The systematic differences between ERA5-Land, GRACE/FO, and model TWS behavior (Figs. 2, 3) leads us to investigate the differences in atmospheric forcing, especially precipitation, compared to observation based estimates. Time series of global land area-average ERA5-Land and GRACE/FO anomalies in TWS tendency (dTWS/dt), and ERA5-Land P, ET, and RO are shown in Figs. (4a,b). P variations have the largest amplitude followed by those of RO. Phasing of these two quantities is anticorrelated with variations in Nino3.4 SST anomalies, suggesting that SST variations control moisture transport between land and ocean (Trenberth and Shea, 2005; Ropelewski and Halpert, 1987; Robertson et al., 2020). Notably, ERA5-Land P and RO anomalies exhibit significant declines during the 2000-2002 period. These declines do coincide with a transition of cold to warm SSTs in Nino3.4. What is apparent though is that this juncture marks a change in ERA5-Land P and RO behavior before and after this period; both variables are systematically elevated before 2000 compared to the period 2002-2019 (which was used as a baseline for computing anomalies). An important aspect, too, is a strong annual signal in P, RO and dTWS/dt anomalies that emerges before this time. This suggests that the climatology of ERA5-Land, at least its hydrological quantities, differs between these two epochs as is noted in Wang etal. (2026).

A defining characteristic of satellite remote sensing from 1980 to the present is the jump in the number of observations, their spectral diversity, spatial resolution and accuracy, especially during the middle of this period (Gelaro et al., 2017; Hersbach et al., 2020). We suspect that the transition from TOVS to ATOVS sounders during 1998-2002 as well as the subsequent availability of AIRS profiles in 2002 enabled improved assimilated temperature and moisture data that systematically changed the ERA5 hydrology (Fig. 4a,b). Just as important is improved temporal coverage of passive microwave imagers in the late 1990s relative to measurements that began in late 1987. In effect, more frequent and better data allowed a stronger, more accurate correction, via data assimilation, of physics biases in the ERA5 model. ERA5-Land inherits the shifting biases in near surface meteorology, precipitation and radiation. A direct goal of W5E5 adjustments was to mitigate these biases where possible using in situ observations (Cucchi et al., 2020).

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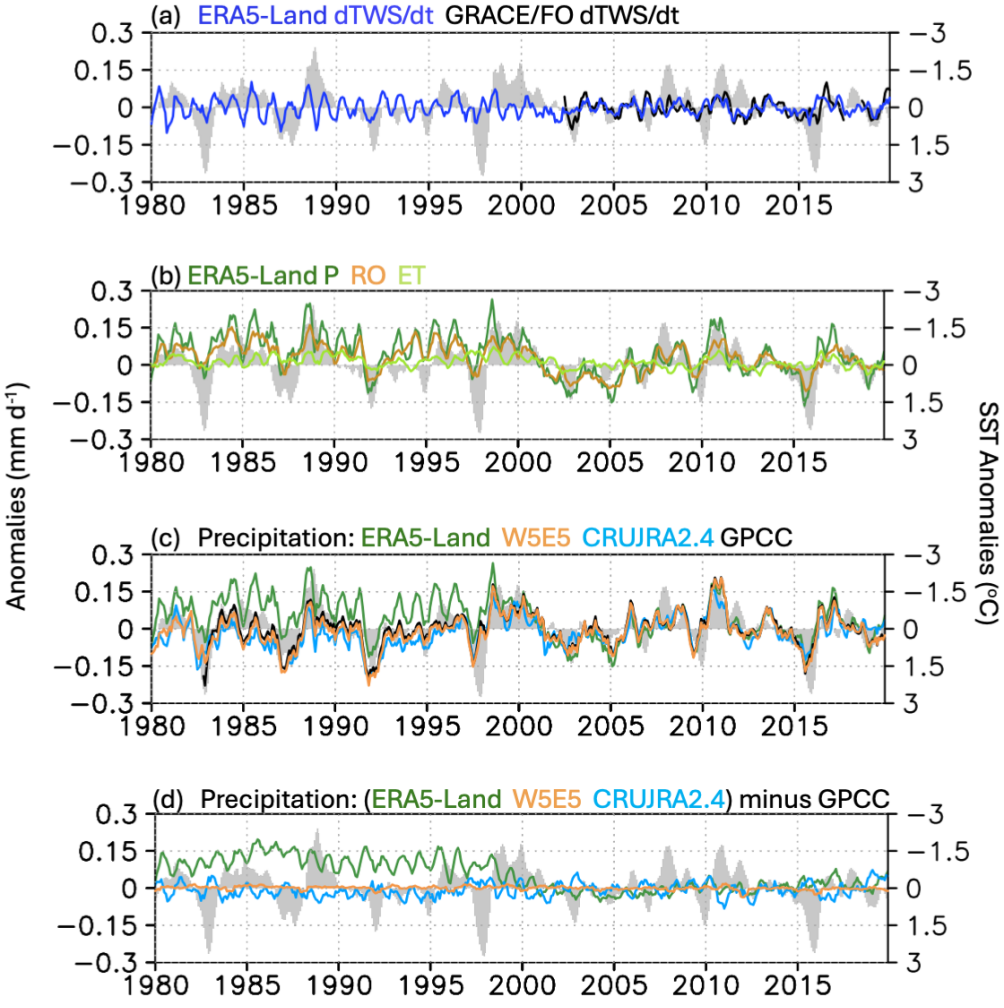

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489 **Figure 4: Time series of various global area-average (60S-70N) quantities, units mm d^{-1}: (a)**
490 **ERA5 and GRACE/FO TWS tendencies, (b) ERA5-Land P, RO and ET, (c) Precipitation**
491 **for ERA5-Land, W5E5, CRUJRA2.4 and GPCC gauge amounts, (d) Same as in (c) but as**
492 **differences from GPCC. Nino3.4 SST anomalies, °C, are plotted as gray. The SST scale is**
493 **inverted to emphasize the tendency for relationship between anomalously warm (cold) SST**
494 **and depressed (elevated) precipitation over land. A 5-month smoother has been applied to**
495 **the data. Anomalies were computed relative to a baseline period of 2002-2019.**

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Evidence of these turn-of-century changes is seen in time series of global mean (60S / 70N Land) monthly precipitation from ERA5 (which are used as inputs to ERA5-Land), the GEWEX Soil Wetness Project-WATCH Forcing Data-ERA5 (GSWP3-W5E5), [https://doi.org/10.5194/essd-12-2097-2020]), and CRUJRA 2.2 (https://www.nature.com/articles/s41597-020-0453-3) (Fig. 4c). ERA5 P values that are elevated relative to the best observationally constrained, bias-corrected estimates are prominent before the late 1990s. Figure 4d shows this clearly, plotting the differences between GPCC gauge precipitation and ERA5, W5E5 and CRUJRA2.4. Note that the latter two precipitation data sets are heavily anchored to GPCC.

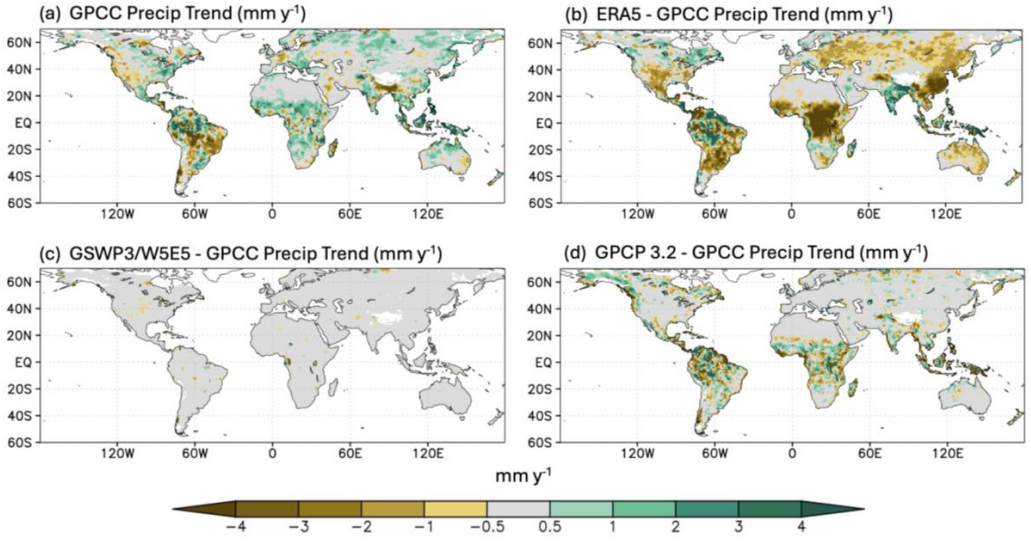

Figure 5: GPCC precipitation trend (a), mm yr $^{-1}$, and differences from (b)ERA5, (c) W5E5, and (d) GPCP v3.2. Trends are computed over the 1980-2019 period.

The spatial structure of these differences from GPCC precipitation, especially the resulting trend pattern, strongly resembles the ERA5-Land TWS trend itself (Fig. 5b vs Fig. 2f). Stronger ERA5 precipitation declines are prominent over central Africa and southeast China, but they are also seen over parts of Asia, the western U.S. and much of South America. Excessive precipitation gains over India also correspond to excessive TWS increases. Weaker correspondence is present across much of Asia and over N. America. The GSWP3-W5E5 precipitation forcing for ISIMIP model experiments differs negligibly from GPCC by construction. The resulting GPCPv3.2 - GPCC trend difference pattern has more structure than W5E5 - GPCC but much less than in the case of

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ERA5-Land. CRUJRA2.2 differences from GPCC (not shown) are similarly small. These comparisons indicate that the systematic differences between ERA5-Land and other model simulated TWS declines are linked to the precipitation forcing sources.

3.4 ERA5 vs W5E5 Hydrological Forcing

The impact on TWS of the large, seemingly unrealistic decline in ERA5-Land precipitation around 2001-2003 is confirmed by comparing the means of three different ISIMIP3a models (Fig. 6a). Shading denotes the three-model spread of TWS around the means. While there are differences among the models, the systematic increase in TWS decline resulting from ERA5 compared with W5E5 forcing is apparent. WaterGAP, LPJ and H08 have anomaly differences between the pre- and post-2000 periods of approximately 10 mm. These results are consistent with the changes in precipitation forcing in ERA5 relative to the ISIMIP3a precipitation, the latter of which employs GPCC gauges to bias-corrected ERA5 precipitation (Fig. 4c,d; Fig 5b).

The regional expression of the global mean time series is seen in an ensemble of the ERA5 minus ISIMIP forced TWS trends (Fig. 6b). The ensemble mean difference map of TWS trends shows prominent discrepancies over central Africa and eastern China with weaker systematic variations over Asia and the Americas. These patterns align with the precipitation differences between the two forcing data sets (Fig. 5b) as well as with the 1980-2019 ERA5-Land TWS trends in Fig. 2f.

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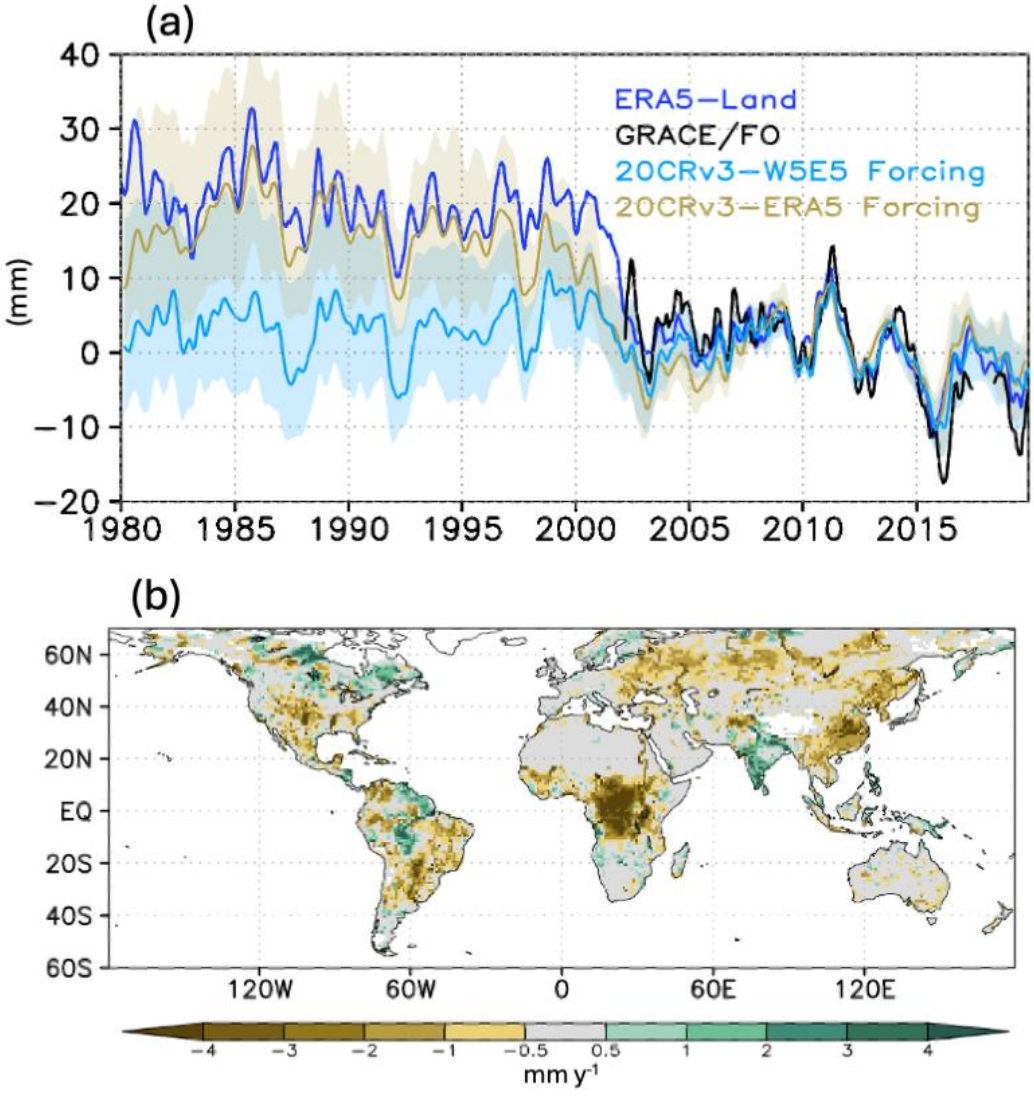

Figure 6: (a) TWS time series for two ensembles of three GHMs (WaterGAP, H08 and LPJ) but each ensemble under different forcing. The light blue line indicates forcing by the W5E5 data during 1979-2019 which is based on 20CRv3-W5E5, the observational bias correction of ERA5 meteorology. The tan line is for models run with 20CRv3-ERA5 meteorological forcing. Shading indicates the spread of the three GHMs. A 5-month smoother has been applied to the data. See text for additional discussion. (b) 1980-2019 TWS trend difference (mm yr $^{-1}$) for the ensemble GHMs, ERA5 minus W5E5 forcing.

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3.5. Statistical / Machine Learning TWS Reconstructions

Statistical reconstructions take advantage of covariant relationships between hydrometeorological state and flux variables so as to replicate GRACE/FO TWS and therefore serve as a basis for reconstructing TWS in the pre-GRACE/FO era. Global mean TWS time series from this approach are shown in Fig. 7. Trends, S.Ds. of anomalies, and anomaly correlations with respect to the detrended time series are given in Table 4.

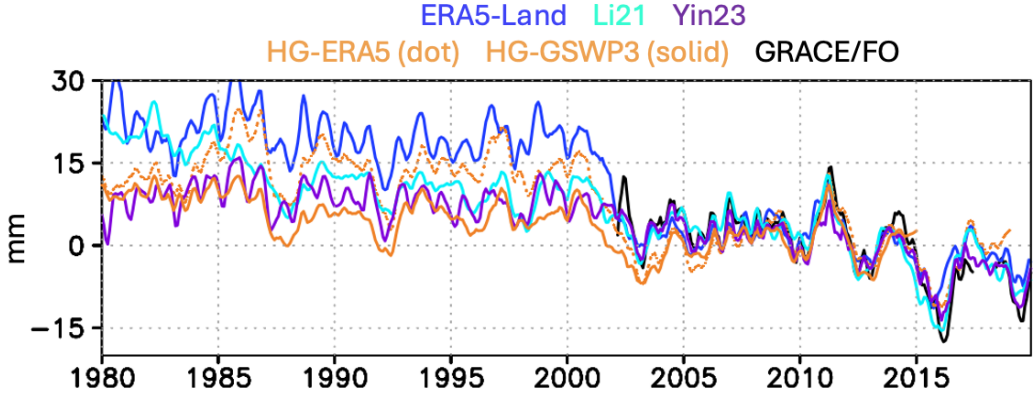

Figure 7: Time series of globally averaged TWS estimates from various statistical reconstructions. ERA5-Land, SLR and GRACE/FO are shown for reference.

TWS in each of the four reconstructions trend downward over the 1980-2019 period and with magnitudes less than that of ERA5-Land. By design Li21 assumes the GRACE/FO trend pattern which, as noted by the authors, is likely inaccurate for longer periods of time where climate is non-stationary and HWM also changes. Yin23 is the only reconstruction that specifically tries to match the full GRACE/FO variability including the trend, but its input data are almost exclusively from ERA5. HG19 provides two contrasting TWS realizations, each constrained by precipitation input. When developed using ERA5 precipitation (HG-ERA5), the 2002-2018 trend (-0.81 mm y^{-1}) nearly replicates GRACE/FO. HG19 using GSWP3 precipitation (HG-GSWP3) is actually positive (0.29 mm y^{-1}) over the GRACE/FO period, but this reflects the fact that GSWP3 ends in 2014, hence HG19-GSWP3 lacks the strong downturn in TWS after 2014 seen in the models and other reconstructions. The trend changes to -0.30 mm y^{-1} over the longer period. None of the reconstructions have trends as large as ERA5-Land over the 1980-2019 period. The HG19 reconstructions also show the weakest interannual signals over both periods. Though Yin23 has

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arguably the most complex methodology and the largest number of input predictors, it also exhibits weak interannual changes compared to GRACE/FO. The reconstructions are consistently better correlated with GRACE/FO than are the models. It's important to keep in mind that this is by construction. As Li21 notes, enforcing a strong fit to GRACE/FO trend data prior to 2002 carries significant uncertainty and a stationary trend pattern is unlikely.

	HG19 GSWP3*	HG19 ERA5	Li21	Yin23	ERA5-Land	GRACE/FO
Global Mean Trend 1980-2019 (2002-2019)	-0.30 (0.29)*	-0.53 (-0.81)	-0.63 (-0.67)	-0.40 (-0.63)	-0.80 (-0.40)	--- (-0.80)
S.D. 1980-2019 (2002-2019)	3.18 (2.86)*	5.27 (3.39)	3.89 (4.50)	3.50 (3.22)	5.07 (3.39)	--- (4.68)
Trend Pattern Correlation with GRACE/FO 2002-2019	0.26*	0.36	0.92	0.95	0.30	
Mean 2002-2019 Anomaly Correlation with GRACE/FO	0.68*	0.78	0.80	0.94	0.63	

* GSWPv3 only extends through 2014, thus limiting the training to GRACE during 2002-2014 and failing to sample the lower TWS values and strong variability present 2015-2019.

Table 4: Same as in Table 2 except for statistically-based TWS reconstructions. Trends are mm y^{-1} and standard deviations, S.D., are mm. ERA5-Land and GRACE/FO values are also reproduced from Table 2.

Figure 8 maps reconstructed TWS trends over 2002-2019, with ERA5-Land and GRACE/FO included for comparison. Li21 trends are not shown since by construction they are essentially identical to those of GRACE/FO (Fig 8a). Yin23 successfully matches the full GRACE/FO variability and, thus, also matches its pattern closely (0.95; Table 4). The slightly lower correlation for Li21 (0.92) may be due to their training with a single data set, CSR GRACE TWS, while our GRACE data is the average of GSFC, JPL and CSR versions, the same combination used by Yin23. To the extent that HWM explains trend structure, it is implicitly

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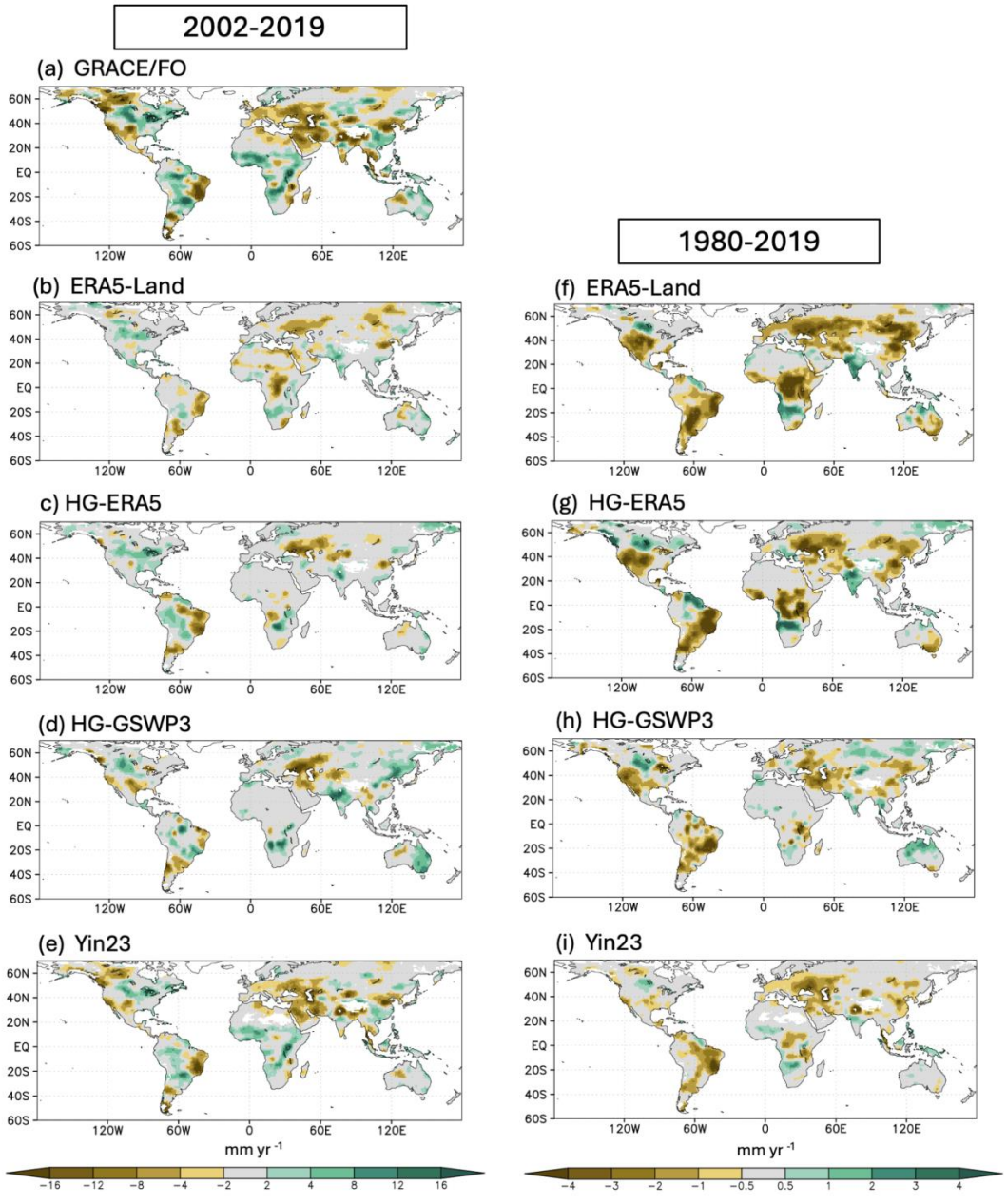

Figure 8: Linear trends of TWS (mm y^{-1}) over the periods 2002-2019 (left) and 1980-2019 (right) for various statistical reconstructions. ERA5-Land and GRACE/FO are shown for reference. Note the factor of four difference in the color bar scale for the two periods. Given the intrinsic resolution of GRACE/FO data of approximately 10^5 sq km, about 3.0 degrees

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in middle latitudes, the 1.0 degree resolution model data sets have been smoothed with two applications of a nine-point spatial filter to yield a comparable spatial resolution.

captured in these two reconstructions (e.g., strong TWS declines over northwest India; Fig. 8e,i). In contrast, trend structure in the two HG estimates represent precipitation effects alone. Though many large-scale trend features are similar for these reconstructions (e.g., TWS declines over western Russia, the Middle East, eastern Brazil, northeastern China), significant differences from GRACE/FO regional details are present. Not surprisingly, HG-ERA5 indicates a generally negative TWS trend over central Africa while HG-GSWP3 captures at least some of the largely positive trends detected by GRACE/FO.

Over the 1980-2019 period HG-ERA5 replicates much of the large amplitude trend structure seen in ERA5-Land, attesting to the primacy of precipitation forcing. HG-GSWP3 and Yin23 agree in the much weaker decreases over central Africa, Argentina and northeastern China compared to ERA5. However, only Yin23 weakens the TWS losses over southwest North America.

4 Discussion and Conclusions

Our analysis has considered a range of physical modeling and statistical approaches to reconstructing TWS in the pre-GRACE/FO era: GHMs, LSMs, the ERA5-Land reanalysis and statistical / ML methods. The bulk of these estimates support a continued global drawdown of TWS since the 1980s. However, the range of resulting trend estimates from near zero to -0.9 mm yr^{-1} (Tables 3, 4) and their differences in spatial structure (Figs. 5,8) are substantial. These results highlight the challenges inherent in quantifying TWS variability before routine GRACE/FO gravimetric measurements became available. To summarize our findings:

1. ERA5 is affected by a stepwise change in the observing system producing an unrealistic decline in precipitation from before to after 2000-2002, which was implied by earlier work (Hersbach et al. 2020; Allan 2023; Wang et al. 2026). This is evidenced by comparison of ERA5 and the GSWP3-W5E5 precipitation and confirmed by ISIMIP3a GHM models forced by ERA5 versus ISIMIP3a W5E5 meteorology; for three ISIMIP3a models ERA5 forcing leads to global mean TWS being at least 15 mm higher prior to 2000. These artifacts are small and largely unimportant for many applications of ERA5-Land which focus on short time scales (i.e., days to months) but

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they are of comparable size to many climate variability and change signals. Numerous investigations have demonstrated that ERA5 and ERA5-Land are significant improvements over previous reanalysis efforts (Muños-Sabater et al., 2021; Wang et al., 2022). ERA5-Land supports an ever wider variety of investigations of land surface hydrology (e.g., Liu et al., 2020; Clelland et al., 2024; Wang et al., 2026). All reanalyses contend with physics biases and assimilate observations whose quality and coverage varies with time. Our results here clarify aspects of TWS behavior in ERA5-Land of which users studying multi-decadal variability must be aware.

2. Our analysis also shows that GHMs, even when driven with state of the art, bias corrected meteorology can yield global TWS trends and associated regional structures that differ systematically from those observed by GRACE/FO. We reaffirm the results of Scanlon et al. (2018) and Tiwari et al. (2025) that GHMs have difficulty capturing the amplitudes of trends seen by GRACE/FO. The spread of global mean trends in just three GHMs, from -0.06 to -0.91 during the GRACE/FO period and 0.04 to -0.80 mm y^{-1} over 1980 to 2019, attest to the remaining challenges. The degree to which this is due to internal model physics and parameters (e.g., depth of the saturated zone and soil storage capacity, the still rudimentary treatment of groundwater, landcover / land use changes) or the (lack of) treatment of HWM remains unknown.

3. The incorporation of HWM does make crucial contributions in many regions (e.g., northern India, northeast China and southern Great Plains). Without accounting for HWM, WaterGAP global TWS trends over 2002-2019 change from -0.40 mm y^{-1}, roughly half the GRACE/FO value, to -0.06 mm y^{-1}. We have used only a subset of the full range of ISIMIP3a models, and examining details of their relevant process representations would be a valuable next step. Telteu et al. (2021) and Muller-Schmied et al. (2025) offer a needed framework for consistency in defining model physics and comparing GHM output that allows experiments to isolate model shortcomings.

4. Finally, we considered a third methodology of TWS estimation that involves training statistical models to replicate TWS variability seen in the GRACE/FO record and then projecting these statistical reconstructions back before 2002. To varying degrees these reconstructions are able to capture the global imprint of interannual variability associated with ENSO. In terms of TWS trends, the input data sets have some issues. Li21 only models seasonal and interannual TWS signals and just embeds the linear trend taken from GRACE/FO. The fidelity of this assumption encompassing the entire 1980-2019 period is questionable. Yin23 use by far the largest set of

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predictors but virtually all are taken from the ERA5 reanalysis without any recourse to bias correction. Nevertheless, the prominent decline in ERA5-Land TWS during the 2000-2002 period is damped in Yin23. Since the precipitation input is the same in these two products, it is not clear what factors, training algorithm strategy or data input, produce this behavior. The HG-GSWP3 reconstruction does not take advantage of the full GRACE/FO record. Yet, it does indicate that precipitation forcing by itself produces a downward trend over the 1980-2019 period. Common to all these methods, though, is that no direct accounting of HWM is present. While to some degree these effects are present implicitly in Li21 and Yin23, this is a distinct limitation of all present statistical TWS reconstructions.

Taken as a whole, all three methodologies, the ERA5-Land reanalysis, GHMs and statistical approaches, strongly support continued drawdown of TWS in many regions over the full 40-year period starting in 1980: the dry lands of western Russia, the Middle East, northern India, southeastern Brazil, and parts of the southwestern U.S. Of these methods we argue that the ERA5-Land regional amplitudes and global trend are unrealistically large, likely due to non-physical ERA5 precipitation changes, although we cannot estimate the amount accurately. Furthermore, since ERA5-Land does not account directly for HWM, these effects might restore a large trend were they included in an experiment with bias-corrected forcing. WaterGAP and PCR-GLOBWB each produce TWS declines, most likely determined by HWM effects. It is noteworthy that the HG-GSWP3 and Yin23 statistical / machine learning reconstructions also produced downward trends, -0.30 and -0.40 mm y^{-1}, respectively; the former is from precipitation forcing only while the latter implicitly includes at least some HWM effect. For all these estimates it should be emphasized that interannual variability and longer term decadal processes likely influence trends on this scale substantially. Ultimately a process understanding behind any trend estimates needed to make them useful for planning.

Some recommendations for the future as a result of this study include:

(i) Continued refinement and improvement of bias correction for model forcing. This study has illustrated how diversity of reconstructed global mean TWS trends and their constituent regional contributions is sensitive to forcing data, most notably precipitation. The ISIMIP3a experiments contrasting ERA5 versus the bias corrected W5E5 (Fig. 6) clearly point to this issue. The hydroclimate community has expended substantial effort developing methods to minimize bias in

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forcing data sets (Sheffield and Wood, 2007; Wheedon et al., 2011, 2014; Cucchi et al., 2020). The rapid maturation of passive microwave imaging, the transition from TOVS to ATOVS sounding and increased aircraft reports all challenge bias-correction efforts. The reliance of assimilation systems on temporally inconsistent observations to correct model physics biases is a perennial problem.

(ii) An especially important component of bias correction is precipitation. All gridded forcing data for models, whether model or satellite sensor based, are ultimately calibrated based on in situ gauge records, which are widely known to have issues with heterogeneity of geographic coverage, inconsistent and ephemeral temporal coverage and access restrictions stemming from geopolitical issues (Famiglietti et al., 2015). Improved access to data records has been made through "data archaeology" (e.g. Nicholson et al., 2014; Thorne et al., 2017; Chimani et al., 2022). Efforts like these to bolster poorly sampled regions and countries need more emphasis.

(iii) Improved fidelity of HWM simulations in GHMs. Despite efforts to accommodate groundwater storage and its governing processes in GHMs, the treatment remains simplistic and suffers from sparse measurement density needed to sample different hydroclimate regimes. Other HWM aspects such as reservoir and river flow management, changes in local lakes with drought and inundation with drought are all needing improvement. But this attention to HWM must be supported by improved GHM physics such as biophysical processes, soil properties and layer structure. The methodology for standardizing model process definitions for archival (Telteu et al., 2021) is a contribution that will greatly facilitate model intercomparison and improvement. Extending and improving regional details of water use and groundwater extraction (Huang et al., 2018) for validating models is crucial.

(iv) While differing in concept from physical modeling, statistical ML, AI and deep learning methods will likely advance these efforts. As the GRACE/FO record lengthens and samples more modes of TWS variability these methods could offer insight on how various hydrometeorological inputs contribute to TWS variability, contingent of course on adequate bias treatment of training data.

In summary, our findings indicate that previously documented TWS decline since 2002 extend back over the past four decades and are explained by coincident decline in regional precipitation combined with a growing influence of HWM, though the magnitude of this global and regional

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drying is poorly quantified. We urge caution in interpreting reanalyses, model produced data sets, or any reconstructed estimates that have not used bias corrected forcing data. The present study is just a snapshot of current efforts to extend understanding of TWS variability to years before space-based gravimetry began to make definitive measurements of water stores and their evolution. Though all reconstruction techniques are just estimates, prospects for narrowing their uncertainties and improving the historical understanding of this component of the global water cycle are encouraging and important to water resource and ecosystem management.

Appendix A List of Acronyms

Acronym	Full Form
AIRS	Atmospheric Infrared Sounder
ATOVS	Advanced Tiros Operational Vertical Sounder
CRUJRA	Climatic Research Unit Japanese Reanalysis
CSR	Center for Space Research
DVM	Dynamic Vegetation Model
ENSO	El Niño–Southern Oscillation
ERA5	Fifth generation ECMWF atmospheric reanalysis
ERA5-Land	Land component of ERA5 reanalysis
GHM	Global Hydrology and Water Resource Model
GLDAS	Global Land Data Assimilation System
GPCC	Global Precipitation Climatology Centre
GPCP	Global Precipitation Climatology Project
GRACE	Gravity Recovery and Climate Experiment
GRACE-FO	Gravity Recovery and Climate Experiment – Follow-On
GSFC	Goddard Space Flight Center
HCTESSEL	Carbon Hydrology-Tiled Scheme for Surface Exchanges over Land
HWM	Human Water Management
IA	Interannual
ISIMIP	Inter-sectoral Impact Model Intercomparison Project
ISIMIP3a	Third round of ISIMIP experiments (phase a)

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JPL	Jet Propulsion Laboratory
LSM	Land Surface Model
LESM	Land Earth System Model
LULC	Land Use / Land Cover
ML	Machine Learning
SLR	Satellite Laser Ranging
SPEI	Standardized Precipitation and Evapotranspiration Index
SST	Sea Surface Temperature
TOVS	Tiros Operational Vertical Sounder
TWS	Terrestrial Water Storage
UEA	University of East Anglia
WATCH	Water and Global Change initiative
W5E5	WATCH de-biasing methodology applied using ERA5 data over land and ERA5 data over ocean

Code and Data Availability

ISIMIP3a model experiment output,
https://data.isimip.org/search/tree/ISIMIP3a/OutputData/water_global/
PCR-GLOBWB 2 model experiment output, contact edwin.sutanudaja@uu.nl
http://globalhydrology.nl
ERA5_Land Reanalysis
https://cds.climate.copernicus.eu/datasets/reanalysis-era5-land?tab=overview
Precipitation:
GPCC Full 2020: https://psl.noaa.gov/data/gridded/data.gpcc.html,
GPCPv3.2, https://doi.org/10.5067/MEASURES/GPCP/DATA304;
CRUJRA, https://catalogue.ceda.ac.uk/uuid/10d2c73e5a7d46f4ada08b0a26302ef7
GRACE Mascon TWS:
GSFC, https://earth.gsfc.nasa.gov/geo/data/grace-mascons
JPL http://grace.jpl.nasa.gov/data/get-data/jpl_global_mascons/
CSR https://www2.csr.utexas.edu/grace/
SLR Mascon TWS: https://earth.gsfc.nasa.gov/geo, contact bryant.d.loomis@nasa.gov

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GRACE-Like TWS Reconstructions

Humphprey and Gudmundsson (2019): https://doi.org/10.6084/m9.figshare.7670849

Li et al. (2021): https://datadryad.org/dataset/doi:10.5061/dryad.z612jm6bt

Yin et al.(2023): https://doi.org/10.5281/zenodo.10040927

GLDAS-Noah Experiment with W5E5 Forcing: https://ldas.gsfc.nasa.gov/gldas, contact hiroko.beaudoing@nasa.gov

Author Contributions

FRR conceptualized the study in consultation with all other authors, produced and executed the analysis code, and produced the initial draft. MGB helped develop Grads analysis and graphics code. MR led analysis of GRACE diagnostics. RPA led in critical structuring of paper, JM-S analyzed and critiqued ERA5-Land diagnostics, BL developed the SLR TWS retrievals. HB produced the Noah-GLDAS experiment data, JBR assisted in discussion of ML techniques. All authors contributed substantially to writing the manuscript, providing critical feedback and approving the final draft.

Competing Interests

The contact author has declared that none of the authors has any competing interests.

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