Skills in sub-seasonal to seasonal terrestrial water storage forecasting: insights from the FEWS NET land data assimilation system

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Abstract. Accurate prediction of terrestrial water storage (TWS), the sum of soil moisture, groundwater, snow/ice, and surface water, is critical for informing water resource management and disaster responses. In this study, we evaluated subseasonal to seasonal (S2S) TWS forecasts~~,~~ produced by the Famine Early Warning Systems Network (FEWS NET) land data assimilation system (FLDAS)~~,~~ over Africa using observations from the Gravity Recover and Climate Experiment (GRACE) and its Follow-On (GRACE/FO) mission. FLDAS consists of two advanced land surface models, Noah-MP and the NASA Catchment Land Surface Model (CLSM), both of which simulate key TWS components including groundwater. Results show that CLSM generally outperformed ~~is more skillful in forecasting TWS anomalies at S2S scales than~~ Noah-MP, with ~~with >0.6~~ relative operating characteristics (ROC) scores exceeding 0.6 (the threshold for predictive skill) for tercile forecasts over >50%~~more than half~~ of the study domain across the 1-6 months lead times, and ~~. CLSM forecasts also maintain stronger~~ stronger correlations with GRACE/FO data~~ than Noah-MP, particularly at longer lead times, owing to more skillful reanalysis-based initial conditions and stronger persistence in simulated TWS~~. ~~In contrast, Noah-MP forecasts show weaker skill, especially in central Africa where the skill also declines rapidly with lead time.~~

The superior performance of CLSM is largely attributed to its reanalysis-based initial conditions, which more accurately captured interannual annual variability observed in GRACE/FO observations (correlation of 0.72 vs 0.56 for Noah-MP for domain averaged TWS). CLSM also simulates strong TWS temporal variability and thus persistence, enabling skillful initial conditions to propagate across forecast lead times. Accurate representation of interannual variability is essential for S2S forecasts because TWS is a long memory process and interannual variability also directly affects climatology used to determine anomalies. ~~Evaluation results show that accuracy of TWS forecasts is strongly influenced by precipitation interannual variability: forecasts driven by precipitation products with lower precipitation interannual variability are generally more~~

~~accurate than those driven by higher precipitation variability.~~ The performance gap between Noah-MP and CLSM is also more pronounced in regions with higher precipitation variability such as central Africa. ~~This sensitivity arises because TWS often exhibits strong multi-year variability in responses to interannual precipitation, making realistic simulation of long-term variability critical for skillful TWS forecasts. The superior performance of CLSM is attributed to its strong representation of upward groundwater movement, especially during prolonged droughts, which enhances TWS interannual variability. In contrast, the weak representation of capillary rise in Noah-MP limits its ability to capture effects of long-term precipitation variability on TWS. Both models exhibit lower correlation and higher RMSEs when evaluated against GRACE/FO data than relative to reanalysis, further underscoring substantial uncertainty in model physics.~~

~~Both models exhibit lower correlation and higher RMSEs when evaluated against GRACE/FO data than relative to reanalysis, further underscoring substantial uncertainty in model physics. Autocorrelation analyses show that TWS persistence is closely linked to groundwater persistence. CLSM groundwater exhibits stronger persistence than that of Noah-MP, owing to its ability to simulate groundwater responses to long-term precipitation variability~~. Although ~~While~~ persistence provides an important source of predictability, ~~our results also show that~~ this study also shows that inaccurate persistence, ~~such as that~~ such as that associated with anthropogenic~~ally-induced~~ trends and ~~changes in~~misrepresented precipitation variability,~~that are often inadequately captured by land surface models,~~ can degrade forecast skill. TWS forecasts from both models are highly sensitive to precipitation interannual variability, achieving higher TWS forecast skill when driven by precipitation forecasts with lower interannual variability. These findings underscore strong impacts~~the importance~~ of model physics and the critical role of~~using~~ independent observations~~datasets~~ such as GRACE/FO ~~observations to~~ for evaluating and improving~~e~~ TWS forecasts.

1 Introduction

Changes in terrestrial water storage (TWS), the sum of soil moisture, groundwater, snow/ice and surface water, reflects cumulated impacts of precipitation and evapotranspiration over weeks to months (Humphrey et al., 2016). As such, it provides unique insight into hydrological extremes (floods and droughts) and their responses to climate variability and climate change (Zhao et al., 2017; Rodell & Li, 2023; Li & Rodell, 2023; B. Li et al., 2025). Skillful TWS forecasts at subseasonal to seasonal (S2S) scales are therefore of great value for providing early warnings on water shortage and crop failure, especially in Africa, where persistent food and water insecurity faced by many communities are often exacerbated by frequent floods and droughts (~~Scanlon et al., 2020;~~ Ngcamu & Chari, 2020; Cook et al., 2021; Scanlon et al., 2022; WMO, 2025).

Thus far, most studies have focused on evaluating TWS forecasting skills by climate models at decadal scales (e.g., Jensen et al., 2019~~20~~; Yuan and Zhu, 2018; Zhu et al., 2019). These evaluations typically compare initialized forecasts, where initial conditions are derived from model simulation driven by observation or reanalysis-based atmospheric forcing data, with uninitialized ones to obtain skill scores. Initial conditions have been found to provide more skill than dynamical climate forecasts alone in 1-4 years lead time, suggesting persistence of TWS as a key source of predictability (Zhu et al, 2019). However, since most climate models do not simulate groundwater, the reported persistence mainly reflects that of soil moisture. More importantly, ~~in the absence of independent observational datasets, such~~ evaluations using simulated TWS as reference mask impacts of model physics and thus ~~–~~are unable to assess uncertainties in model physics and may even ~~may overestimate~~mischaracterize ~~the role of~~ persistence and its role in TWS forecast~~ce as they fail to account for uncertainties in land surface model physics and meteorological forecasts~~.

Groundwater, located in the deeper subsurface, has longer memory than other near surface processes such as soil moisture~~,~~ and its long-term~~making~~ temporal variability~~it~~ may ~~a~~ contribute to~~potential source of~~ TWS predictability~~y for TWS forecasting~~ (Eltahir and Yeh, 1999; Li et al., 2015). However, modeling groundwater is subject to greater uncertainty due to lack of information on hydrogeological properties and observational data to constrain simulation of deep subsurface processes (Xia et al., 2017). As a result, reanalysis-based groundwater estimates, when used as initial conditions, may not deliver correct persistence or memory for enhancing forecast skill. Furthermore, because of its long memory, groundwater is more sensitive to errors~~biases~~ in the meteorological forecasts that drive TWS forecasts. Previous studies have shown biases in S2S precipitation forecasts vary depending on climate conditions and terrains (Shukla et al., 2019; Slater et al., 2019; Zhang et al., 2021; Levey and Sankarasubramanian, 2024; Phakula et la., 2024). However, examining groundwater responses to meteorological forecasts and associated uncertainties is hindered by the scarcity of in situ groundwater observations at the continental to global scales (Jasechko et al., 2024).

TWS observations from the Gravity Recovery and Climate Experiment (GRACE) and its Follow On (hereafter GRACE/FO, Landerer et al., 2020) mission provide a unique opportunity to evaluate S2S TWS forecasts. Representing vertically integrated water storage changes, GRACE/FO data exhibits strong temporal variabilities from subseasonal to interannual scales, reflecting~~depending on~~ climate variability~~conditions~~ (Humphrey et al., 2016). While sub-seasonal variability is essential for assessing S2S forecast skill, interannual variability is equally important for evaluating~~establishing robust~~ climatology ~~needed~~used for forecasting TWS anomalies. GRACE/FO data have been widely used to validate reanalysis estimates and to identify deficiencies in model physics in large-scale hydrological models (e.g., Döll et al., 2014; Scanlon et al., 2018; Bonsor et al., 2018; Li et al., 2019a). In recent years, the record has also been leveraged to train machine learning models for forecasting TWS (e.g., F. Li et al., 2024 & 2025). However, few studies have used GRACE/FO data to evaluate operational S2S TWS forecasts by land surface models. Cook et al. (2021) assessed TWS forecast skill over Africa using a reconstructed GRACE product. With more than two decades of nearly continuous observations, GRACE/FO observations are ideal for objectively assessing S2S TWS forecast skill and ~~explor~~examining factors influencing TWS predictability.

The hydrological forecasting system~~,~~ implemented in the Famine Early Warning Systems Network (FEWS NET) l~~L~~and d~~D~~ata a~~A~~ssimilation ~~S~~system ~~Forecast~~ (FLDAS-Forecast)~~,~~ was developed to provide early warnings on droughts and floods across

Africa (Arsenault et al., 2020; Hazra et al., 2023). FLDAS-Forecast is a custom instance of the NASA Land Information System (LIS), an advanced computing framework that supports land surface modeling and data assimilation (Kumar et al., 2006). FLDAS-Forecast comprises two advanced land surface models, Noah-MP and the NASA Catchment Land Surface Model (CLSM), both of which simulate major TWS components including groundwater. FLDAS-Forecast issues TWS forecasts using~~ingests~~ precipitation forecasts from the full North American Multi-Model Ensemble (NMME, Kirtman et al., 2014)~~ which has shown to improve soil moisture forecasts in southern Africa, compared to forecasts based on a single NMME model (Hazra et al., 2023)~~ and non-precipitation meteorological forecasts from the Goddard Earth Observing System (GEOS, Borovikov et al., 2019).

The primary goal of this study is to provide an objective evaluation of the skill of S2S TWS forecasts~~hindcasts~~ ~~from FLDAS~~from FLDAS-Forecast~~,~~ using GRACE/FO observations. To this end, we analyze TWS hindcasts for the historical period 2003-2020. The hindcasts were generated using the same set of NMME models employed in the operational FLDAS forecasts (2021-present), except that one of the NMME models used a reduced number of ensemble members (Hazra et al., 2023). Initial conditions for the hindcasts are derived from model simulations forced by observation and reanalysis-based meteorological forcing fields. Consequently, TWS hindcast skill reflects the combined influence of land surface model physics, meteorological hindcasts, and the reanalysis-based initial conditions.

By leveraging the multi-model framework of FLDAS-Forecast, including two land surface models and a full ensemble of NMME precipitation~~meteorological~~ forecast models~~s~~, the evaluation aims to improve understanding of how model physics employed by land surface models influence TWS forecast skill and how they interact with precipitation~~meteorological~~ forecasts. In addition to GRACE/FO observations, ~~To isolate the impact of model physics from those of initial conditions and meteorological forecasts,~~ TWS hindcasts were ~~also~~ evaluated against~~using~~ reanalysis~~ based~~ TWS to isolate the impact of model physics from those of meteorological forecasts~~estimates, which are used as initial conditions for TWS forecasts~~. Unlike past studies where S2S forecasts were evaluated by the season~~s~~ when they were issued (e.g., Shukla et al., 2019; Hazra et al., 2023), statistics analyses are performed over the entire study period (2003-2020) in this study to better examine the role of long-term variability in precipitation and ~~and persistence of~~ simulated TWS processes in influencing TWS forecast skill~~s~~. Autocorrelation analysis is performed for simulated~~different~~ TWS processes and GRACE/FO observations to examine the role of temporal persistence on forecast skill and to assess the relative contribution of individual~~each~~ processes to overall TWS persistence.

2 Data and evaluation metrics

2.1 Observational and reanalysis-based meteorological input

Precipitation from the Climate Hazards Infrared Precipitation with Stations (CHIRPS, Funk et al., 2015) and other meteorological fields from the Modern-Era Retrospective Analysis for Research and Applications, Version 2 (MERRA-2, Gelaro et al., 2017) are used to drive model simulation by Noah-MP and CLSM from 1982 to present. The output of these simulation runs~~-~~, referred as the reanalysis, is then used as initial conditions for issuing TWS hindcasts (Hazra et al., 2023).

CHIRPS integrates satellite-based precipitation estimates with station data to produce global precipitation time series at 0.05° spatial resolution and a 6-hour interval. MERRA-2, which has 0.5° in latitude by 0.625° in longitude resolution, is an atmospheric reanalysis product based on the ~~Goddard Earth Observing System (~~GEOS~~)~~ model, featuring assimilation of various atmospheric observations such as radiances, surface winds, temperature, and aerosol and improved representation of stratosphere and cryosphere processes (Gelaro et al., 2017). While CHIRPS precipitation was interpolated to 0.25° for this study by the data develop group, MERRA-2 forcing fields were interpolated to 0.25° using LIS built-in functions for model simulation. Temporal disaggregation was also performed within LIS.

2.2 Meteorological hindcasts

To generate TWS hindcasts, atmospheric forcing fields must be obtained from hindcast products to properly represent forecast uncertainty, as reanalysis products cannot predict future weather events. Unlike reanalysis fields which are constrained by observations, meteorological hindcasts are produced by climate models alone and therefore, are subject to larger uncertainties. FLDAS-Forecast employs a suite of NMME ~~FLDAS-Forecast uses~~ models~~precipitation hindcasts from a suite of NMME models~~ developed by multiple institutions to provide S2S precipitation (and temperature which is not currently used by FLDAS-Forecast) forecasts (Table 1). The ensemble approach not only enables uncertainty quantification but also generally yields higher predictive skill than any single model (Wood et al., 2002; Kirtman et al., 2014).

Since the NMME suite does not provide the full set of meteorological forcing fields needed to drive land surface models, ~~and~~ non-precipitation fields, such as radiation and winds, are obtained from the GEOS ensemble hindcasts~~-~~ (Borovikov et al., 2019) ~~to generate S2S TWS hindcasts~~. Given that~~Since~~ GEOS ~~has~~ only includes four ~~fewer~~ ensemble members, ~~than NMME models, GEOS~~ non-precipitation fields~~ensemble members~~ from ~~are~~ randomly selected GEOS ensemble members are ~~to~~ paired with ~~the~~ NMME precipitation hindcasts~~models~~ to~~for generating~~ produce TWS hindcasts~~forecasts~~ (see details in Hazra et al., 2023). ~~NMME hindcasts are provided as monthly data on a 1° resolution global grid and~~ NMME precipitation hindcasts are ~~bias-corrected and~~ spatially downscaled to ~~the~~ 0.25° resolution using the ~~al~~CHIRPS 0.25° product, whereas GEOS non-precipitation fields were first downscaled to MERRA-2 resolution and then to 0.25° using LIS built-in functions ~~gorithms implemented in FLDAS-Forecast using higher-resolution precipitation data from CHIRPS~~ (Arsenault et al., 2020; Hazra et al., 2023). The spatial downscaling also includes bias-correction using the respected reanalysis and observation fields. Both NMME and GEOS forecasts are further temporally downscaled to sub-daily for model simulation using the procedures described in Hazra et al. (2023). ~~Monthly hindcasts are first downscaled to daily values using daily GEOS data and further downscaled to 6-hour intervals using MERRA-2 sub-daily climatology (Arsenault et al., 2020).~~ For simplicity, the combined NMME precipitation and GEOS non-precipitation ~~meteorological~~ hindcasts are referred to as NMME hindcast models in the following sections.

Table 1. NMME precipitation hindcast specifications~~model specifies used in FLDAS-Forecast~~. CFS: Climate Forecast System; CESM: Community Earth System Model; CanESM: Canadian Earth System Model; GFDL: Geophysical Fluid Dynamics Laboratory; GEM: Global Environmental Multiscale; NEMO: Nucleus for European Modeling of the Ocean; NCEP: National Centers for Environmental Prediction; NCAR: National Center for Atmospheric Research; GMAO: Global Modeling and Assimilation Office.

Models	Centers	ensemble members
CFSv2	NOAA/NCEP	12
CESM1	NCAR	10
CanESM5(CSM5)	Environmental Canada	10
GEOSv2	NASA/GMAO	4
GFDL	NOAA/GFDL	15
GEM5.2-NEMO(GNEMO5.2)	Environmental Canada	10

2.3 Land surface models and TWS reanalysis and hindcasts

Both Noah-MP and CLSM simulate key components of TWS, soil moisture, groundwater storage and snow water equivalent (SWE), based on water and energy balance equations. However, they differ considerably in model physics, particularly in modeling subsurface water flows (see Table 1 of Xia et al., 2017 for model configuration and descriptions).

Noah-MP simulates soil moisture dynamics in four unsaturated soil layers based on Richards' equation (Niu et al., 2011). Groundwater storage in FLDAS-Forecast/Noah-MP is represented by a linear reservoir scheme that computes groundwater storage changes based on net water exchanges between the lowest soil layer and the aquifer (Niu et al., 2011). Although the scheme simulates capillary rise, the upward water movement from the aquifer to the upper unsaturated soil~~, is~~ has been shown to be minimal, resulting in small seasonal variations in simulated groundwater in some regions (Xia et al., 2017; Li et al., 2021).

In contrast, CLSM~~MS~~ simulates subsurface water storage changes at three~~ water storage~~ layers: a 2 cm surface layer, a 1 m root zone and the total profile (Koster et al., 2000). The depth of the soil profile is determined by a spatially varying bedrock depth parameter (see Fig.10 of Li et al., 2019b for the spatial map). Water flows among these layers are governed by empirically derived time constants that actively redistribute water, mov~~transferr~~ing water downward during precipitation events, and upward during the dry months to sustain ET. This strong coupling between surface and deep layers results in pronounced seasonal variations in CLSM simulated groundwater and TWS, even in dry climates (Xia et al., 2017; Li et al., 2019b). Although ~~While it~~CLSM does not explicitly model groundwater, groundwater variation is included in the total profile soil moisture; thus, CLSM groundwater storage is~~can be~~ obtained by subtracting water storage in the root zone from that of the total soil ~~soil~~ profile, following previous studies (e.g., Li et al., 2019b). Compared to Noah-MP, CLSM groundwater contains soil moisture from the 1-m depth to the implicit water table. Despite this diagnostic approximation, CLSM groundwater has been shown to compare well with in situ groundwater in different climates (Xia et al., 2017; Li et al., 2019b).

The two models also employ different physics for ET estimates which, along with precipitation, exerts~~are~~ major controls on the temporal variability of groundwater in unconfined aquifers (Eltahir and Yeh, 1999; Li et al., 2015; Li et al., 2019b; Ascott et al., 2020). Previous studies have shown that CLSM tends to simulate higher ET than other land surface models, primarily due to its strong coupling among soil layers and the specific ET algorithms it employs (Xu et al., 2019). For instance, bare soil evaporation is computed as a nonlinear function of soil moisture in Noah-MP, but a linear function in CLSM (Niu et al., 2011; Koster and Suarez, 1996). Although both models employ the TOPMODEL concept to simulate surface and subsurface (baseflow) runoff, discrepancies in simulating ET and profile moisture lead to different runoff estimates~~ by the two models~~ (Xia et al., 2017).

Neither model simulates surface water, which is detected by GRACE/FO satellites. However, surface water contribution to TWS is generally smaller compared to other TWS components, except in areas with large surface water bodies ~~such as African Great Lakes, the Kariba reservoir and other reservoirs along the Nile~~ (Rodell & Famiglietti~~et al.~~, 2001~~2~~; Getirana et al., 2017; Deggim et al., 2021). Implications of neglecting surface water storage for the evaluation results are discussed in section 3. In addition, both models do not simulate water storage changes in confined aquifers which are also detected by GRACE/FO satellites. ~~Additionally, b~~Because snow is negligible in Africa, simulated TWS in this study is thus represented as the sum of soil moisture in the unsaturated zone, 2 m for Noah-MP and 1m for CLSM, and groundwater storage.

Model simulations were first performed by driving Noah-MP and CLSM ~~driven by~~with CHIRPS precipitation and non-precipitation fields from MERRA-2. ~~. Since~~ Because MERRA-2 is a reanalysis product, these simulations are collectively referred to ~~are referred to~~ ~~as~~ the reanalysis~~ in the following sections.~~ TWS hindcasts with lead times of 1 to 6 months were then generated by forcing Noah-MP and CLSM with the NMME hindcasts described above~~, . As discussed above,~~ using the corresponding reanalysis output as initial conditions~~ for each hindcast~~. Since CHIRPS and MERRA-2 are constrained by hydrological and atmospheric observations, initializing hindcasts with the reanalysis, rather than modeled states driven solely by NMME meteorological hindcasts, helps reduce uncertainty in TWS hindcasts. ~~at any month are obtained from the corresponding model simulation driven by CHIRPS precipitation and non-precipitation fields from MERRA-2. Since~~

~~MERRA-2 is a reanalysis product, these simulations are referred to as reanalysis in the following sections.~~ In section 3, we evaluate both the ensemble mean TWS hindcasts of individual NMME models and those of all NMME models.

2.4 GRACE/FO TWS observations

GRACE/FO data used in this study were developed by the Center for Space Research (CSR) at the University of Texas based on the mass concentration (mascon) approach (Save et al., 2016). The mascon approach utilizes time-variable constraints to constrain the inversion of satellite ranging data to gravity fields at each mascon block. This~~e mascon~~ approach eliminates the need for postprocessing as with the spherical harmonical approach and thus better preserves signals related to TWS changes (Landerer & Swenson, 2012; Save et al., 2016).

CSR GRACE TWS observations are provided as monthly anomalies relative to the 2004-2009 temporal mean, at a 0.25° spatial resolution. However, the effective resolution remains relatively coarse, approximately 150,000 km^2 at mid-latitudes (Tapley et al., 2004). There are 34 months with missing data, including the 11-month gap between the two missions. Missing data were filled using linear interpolation, except for the 11-month gap. We found filling the gap had no noticeable impact on the statistical results.

2.5 Data processing and study domain

To ensure consistency with GRACE/FO data, we first removed the temporal mean of simulated TWS for ~~over~~ 2004-2009 ~~was removed~~ at each grid cell to align the model's mean period with that of GRACE/FO. W~~Next,~~ e then computed non-seasonal TWS anomalies by subtracting the monthly mean (climatology), one for each calendar month,~~, was removed~~ from the ~~to obtain TWS anomalies for both~~ simulated TWS and GRACE/FO time series~~data. For evaluation, TWS time series~~ for their overlapping period~~ between TWS hindcasts and GRACE/FO data~~, 2003-2020. Unless otherwise noticed, all results presented in section 3 are based on the non-seasonal TWS anomalies. ~~, were extracted from both the reanalysis and the hindcasts at 2-,4- and 6-month lead times at each grid cell.~~

For identifying severity of extreme conditions, percentiles, P, of TWS hindcasts (anomalies relative to monthly climatology) are calculated by ranking the anomalies against the climatology of the corresponding month:

$$P = k*100/N \quad (1)$$

where k is the rank of the TWS hindcast respect to the climatology, and N is the number of monthly anomalies in the climatology which are sorted in ascending order. Lower percentiles indicate drier conditions, while higher percentiles indicate wetter conditions.

The FLDAS-Forecast domain encompasses the African continent and a large portion of the Middle East (Supplementary Fig.S1). Northern Africa and parts of the Middle East have experienced long-term TWS declines associated with extensive groundwater withdrawals for irrigation (Gossel et al. 2004; Rodell et al., 2018; Frappart et al.,2020; Scanlon et al., 2018~~20~~). Since FLDAS-Forecast does not simulate these anthropogenic effects, these regions were excluded from the evaluation using the groundwater depletion masks provided by Rodell et al. (2018).

~~For drought and flood monitoring, percentiles are obtained by ranking forecasts against climatology derived from hindcasts for 2003-2020 for each NMME model. Average percentiles across all NMME models are then used to produce percentile maps. In addition, probabilities are computed for tercile forecasts, below normal (< 33%), normal (33% - 67%) and above normal (>67%), across all ensemble members at each grid cell (see details in Hazra et al, 2023).~~

2.6 Evaluation metrics

The root mean square error (RMSE) and Pearson correlation are used to evaluate the performance of TWS forecasts~~anomalies, with respect to GRACE/FO TWS anomalies~~. Additionally, skill in forecasting terciles is assessed using the relative operating characteristic (ROC) score, a commonly used metric for evaluating forecasts that measures ~~representing~~ the ratio of hit rates to false alarm rates~~, is used to assess tercile-based TWS hindcasts~~ (Met Office). A ROC score of 1 indicates a perfect forecast.~~,~~ ROC ~~while s~~scores below 0.5 suggest no ~~skill~~ skill, while scores above 0.6 indicate predictive skill (Met Office). High ROC scores and strong correlation are commonly interpreted as indication of skillful forecasts (e.g., Yuan and Zhu, 2018).

3 Results

As indicated earlier, ~~The skill of TWS forecasts is influenced by three factors, initial conditions, meteorological forecasts and physics employed by the land surface model. To isolate contribution of each factor, we first examine temporal variability of reanalysis of TWS processes. We then evaluate hindcasts at different lead times using GRACE/FO data to explore different controls on TWS accuracy. To isolate the impact of model physics, we further compare TWS hindcasts with the reanalysis. Finally, we analyze TWS persistence and explore its role in influencing TWS forecast skill.~~

skill of TWS hindcasts is influenced by several factors, including initial conditions, meteorological hindcasts, and the underlying land surface model physics which affect both the reanalysis-based initial conditions and TWS hindcasts. Because these influences are interrelated, fully isolating their individual contribution to hindcast skill is inherently challenging. To address this, we conduct a series of complementary evaluations using both GRACE/FO data and the reanalysis as reference.

We begin by examining the temporal variability of reanalysis soil moisture and groundwater, which are used as initial conditions for TWS hindcasts, to assess their relative contribution to temporal variability and accuracy of TWS (section 3.1). We then evaluate TWS hindcasts and the corresponding reanalysis using GRACE/FO observations to quantify forecast skill for each land surface model and NMME forcing model, and accuracy of initial conditions (section 3.2). Since TWS hindcasts differ from the reanalysis TWS only in their meteorological forcing fields, evaluating TWS hindcasts using the reanalysis as reference helps isolate uncertainties in NMME hindcasts. Differences between evaluation metrics computed relative to GRACE/FO and to the reanalysis, in turn, reveal impacts of land surface model physics that are masked when the reanalysis is used as reference (section 3.3). To quantify hydrological memory, an important source of predictability, we conduct autocorrelation analyses of simulated TWS processes and GRACE/FO observations at three lags relevant to S2S hindcasts (section 3.4). Finally, we present a case study to demonstrate the relevance of TWS forecasts for predicting hydrological extremes (section 3.5).

3.1 Evaluation of reanalysis TWS processes

To understand how soil moisture and groundwater contribute to TWS variability, we decompose TWS time series from the reanalysis and GRACE/FO into seasonal and non-seasonal components and summarize the domain average results in Fig.1. ~~Domain average estimates of reanalysis show l~~Large discrepancies are observed between the two models at both seasonal and non-seasonal timescales~~ (Fig.1)~~. Noah-MP, with a 2 m soil depth, simulates greater soil moisture variability than CLSM which has a 1 m soil depth. In contrast, CLSM simulates much stronger groundwater variations than Noah-MP across both seasonal and non-seasonal scales (Figs.1c,d), with the seasonal amplitude and temporal standard deviation of non-seasonal groundwater~~TWS~~ being nearly five times larger than those of Noah-MP (Figs.1e,f).

As a result of the strong groundwater temporal variability, non-seasonal CLSM TWS estimates also show strong temporal variation and ~~that contributed to stronger~~ correlate more strongly~~ion~~ (0.72) with GRACE/FO data than those of Noah-MP~~ TWS~~ (0.57; Fig.1f). Non-seasonal CLSM TWS also exhibits smaller (1.04 cm) RMSEs than that of Noah-MP (1.16 cm). ~~In addition to year-to-year variation, non-seasonal GRACE/FO data exhibit multi-year variability, such as an increasing trend from 2006 to 2010 and a decreasing trend from 2013 to 2017. These interannual variations reflect combined influences of large-scale oceanic drivers such as the El Niño Southern Oscillation (ENSO) and the Indian Ocean Dipole, which strongly affect precipitation in parts of Africa (Mason & Goddard, 2001; Nicholson, 2017). Accurately capturing these climate-driven responses remains challenging due to deficiencies in land surface model physics as shown here and limitations in seasonal weather forecasts (Willians et al., 2023).~~

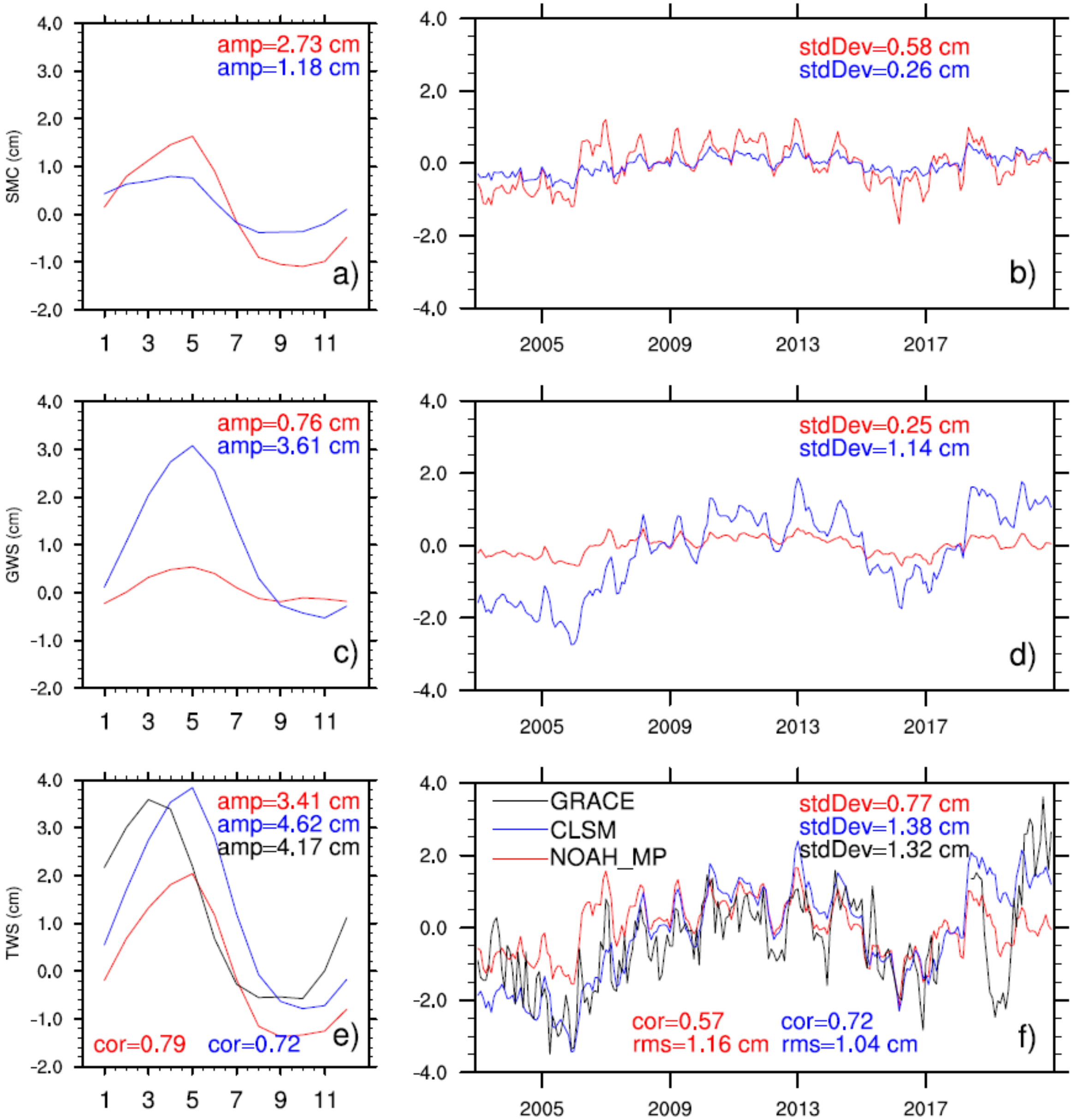


Fig.1 Domain-averaged seasonal and non-seasonal components of soil moisture of the unsaturated soil (a, b), groundwater storage (c, d) and TWS (e, f) from the Noah-MP (red lines) and CLSM (blue lines) reanalysis and GRACE/FO data (black lines). Amplitudes of mean seasonal cycles, temporal standard deviations of non-seasonal components, RMSEs and correlations between the reanalysis and GRACE/FO data are shown~~provided~~ in matching colors of the corresponding time series.

The strong correlation between CLSM TWS and GRACE/FO data is also contributed by the presence of statistically significant secular trends in the two time series ~~which are statistically significant~~(*p* <0.01 based on the Mann-Kendall test; Yue et al., 2002), ~~at~~ 0.014 ~~cm~~m ~~/~~month^{-1} for CLSM and~~,~~ 0.007 ~~cm~~m ~~/~~month^{-1} for GRACE/FO~~, respectively~~. In contrast, Noah-MP TWS time series did not show a statistically significant trend. ~~Large discrepancies are observed in 2019 when GRACE/FO data show substantially lower anomalies than either model. The low anomalies in GRACE/FO data may reflect anthropogenic effects such as groundwater withdrawals during droughts which are not simulated by the models.~~

CLSM ~~also better~~also better captured the seasonal amplitude of TWS changes as observed in GRACE data (Fig.1e). Although seasonal variations simulated by both models show >0.7 correlations with GRACE/FO data, their seasonal maxima ~~lags~~lag that of GRACE/FO data by two months, likely due to deficiencies in model physics and errors in the meteorological forcing fields. ~~Because droughts and floods are relative to the climatological mean, evaluations in the following sections focus on non-seasonal TWS, i.e., TWS anomalies relative to monthly means.~~

To further evaluate the performance of reanalysis TWS, we examine temporal variability of TWS time series for the six largest river basins in Africa (see Supplementary Fig.S1a for basin delineations). Seasonal TWS for both models show high correlations (generally >0.7) with GRACE/FO data in most basins, indicating that the timing of the seasonal cycle is well captured by the models (Fig.2, left column). Noah-MP often exhibits slightly higher seasonal correlations than CLSM (e.g., in Congo, Niger, Zambezi, and Chad); however, its performance degrades substantially in Orange, where the correlation with GRACE/FO data is near zero (Fig.2g). This low correlation is attributed to the misalignment in the timing of the annual minimum TWS, with Noah-MP reaching its seasonal low in February, whereas GRACE/FO observations (and CLSM) reach their seasonal low in November.

In contrast, the non-seasonal component of reanalysis TWS exhibits notably lower correlations with GRACE/FO (Fig.2, right column), reflecting greater challenges in simulating interannual TWS variability. CLSM generally achieves higher correlations than Noah-MP in the central and northcentral basins (Congo, Nile and Zambezi), whereas Noah-MP performs better in the northwestern basins (Niger and Chad). RMSEs are lower for each model in three of the six basins. Consistent with the domain averaged analysis (Fig.1), CLSM simulates larger seasonal variability and stronger interannual variability than Noah-MP, both of which are in closer agreement with GRACE/FO data in most cases (Table 2).

Non-seasonal TWS often exhibits strong interannual variability, reflecting both climate variability and anthropogenic effects. For instance, TWS reached maxima in the Zambezi and Orange basins in 2011 in association with the La Niña event (Figs.2h,j), which typically brings wetter conditions to southern Africa (Mason and Goddard, 2001; Scanlon et al., 2022;). Similarly, the strong TWS increases in the Nile basin in 2019, evident in GRACE/FO data (Fig.2f), is linked to a strong positive phase of the Indian Ocean Dipole (Scanlon et al., 2022) and enhanced precipitation variability in the East African Rift (Boergens et al., 2024). In the Niger basin (Fig.2d), GRACE/FO shows a strong persistent increasing trend (0.048 cm month^{-1}) that has been linked to conversion of shrubs to crops (Favreau et al., 2009) and corroborated by well data (Scanlon et al., 2022). Since the models do not represent land cover change, the reanalysis TWS exhibits smaller trends (0.019 cm month^{-1} for Noah-MP and 0.016 cm month^{-1} for CLSM with p <0.01 for all three trends). Discrepancies are also observed in the Congo and Chad basins during multi-year periods (Figs.2b,l), which may be linked to deforestation and are discussed in more detail in section 3.2. Overall, the reanalysis TWS captures interannual variability observed by GRACE/FO but tends to underestimate strong anomalies such as the 2019 elevated TWS in the Nile basin and the 2016 and 2019 lows in the Zambezi basin, reflecting deficiencies in land surface model physics and uncertainties in the reanalysis forcing data. Because droughts and floods are relative to the climatological mean, evaluations in the following sections focus on non-seasonal TWS forecasts, i.e., TWS anomalies relative to monthly means.

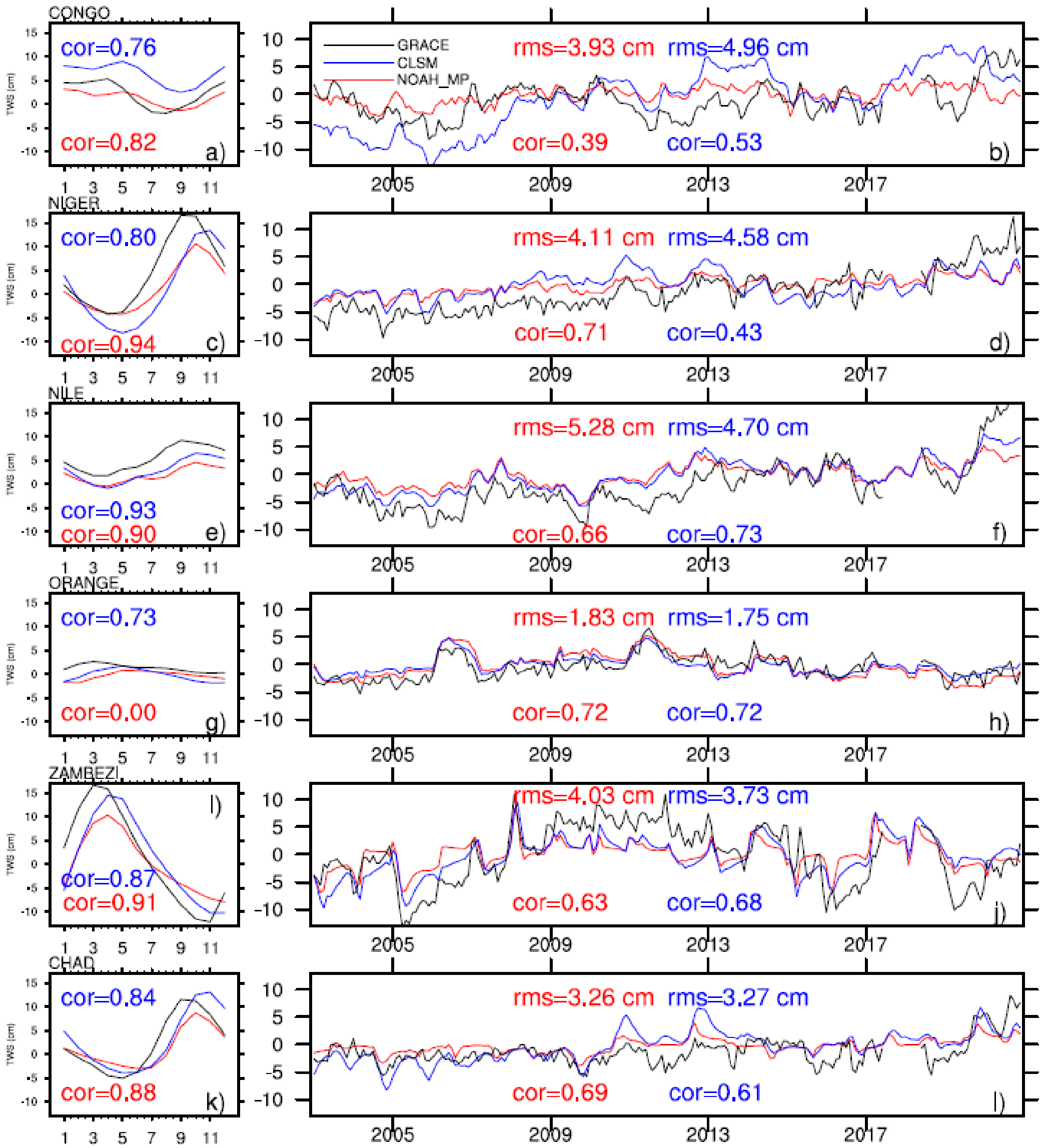


Fig.2 Average seasonal (left column) and non-seasonal (right column) components of TWS from the Noah-MP (red lines) and CLSM (blue lines) reanalysis and GRACE/FO data (black lines) for the six largest river basins in Africa (Basin delineations are shown in Supplementary Fig.S1a). RMSEs and correlations with respect to GRACE/FO are shown in matching colors of corresponding time series.

Table 2. Amplitudes of mean seasonal TWS changes and temporal standard deviations of non-seasonal TWS over the six largest river basins in Africa (see Supplementary Fig.S1a for basin delineations).

	Amplitude (cm)			Temporal Std (cm)		
	Noah-MP	CLSM	GRACE/FO	Noah-MP	CLSM	GRACE/FO
Congo	4.51	6.52	7.21	1.53	5.56	3.23
Niger	14.83	21.64	20.81	1.54	2.29	3.85
Nile	5.05	7.41	7.43	2.13	2.98	4.71
Orange	2.66	3.58	2.44	2.30	1.68	2.16
Zambezi	18.27	24.76	28.87	2.55	3.54	5.37
Chad	11.74	16.97	16.62	1.31	2.70	2.49

3.2 Evaluation of TWS hindcasts using GRACE/FO

RMSEs of the ensemble mean TWS hindcasts of all NMME models, with respect to GRACE/FO data, exhibit distinct spatial patterns (Fig.3). Large RMSEs are observed in the interior western Sahel, a large region across Lake Victoria~~, and~~ Lake Tanganyika, and Lake Volta as well as ~~and~~ southern Zambia and Angola, for both models ~~(Fig.2)~~. As the models do not simulate surface water which is detected by GRACE/FO satellites, unresolved surface water dynamics and water management activities may have contributed to errors in lake areas. In addition, uncertainties in precipitation forcing data, from both reanalysis and hindcasts may further amplify errors in simulated TWS. As discussed earlier, the East African Rift region, which includes Lake Victoria, has seen increased precipitation variability (Boergens et al., 2024); similarly, Southern Africa including southern Angola has been experiencing erratic precipitation patterns and more severe meteorological droughts in recent years (Trisos et al., 2022; Correia et al., 2025). However, considering that the reanalysis exhibits similar spatial patterns and magnitudes of RMSEs as the hindcasts (Figs.3a,e), these results suggest that deficiencies in model physics are the dominant contributor to RMSEs in TWS hindcasts.

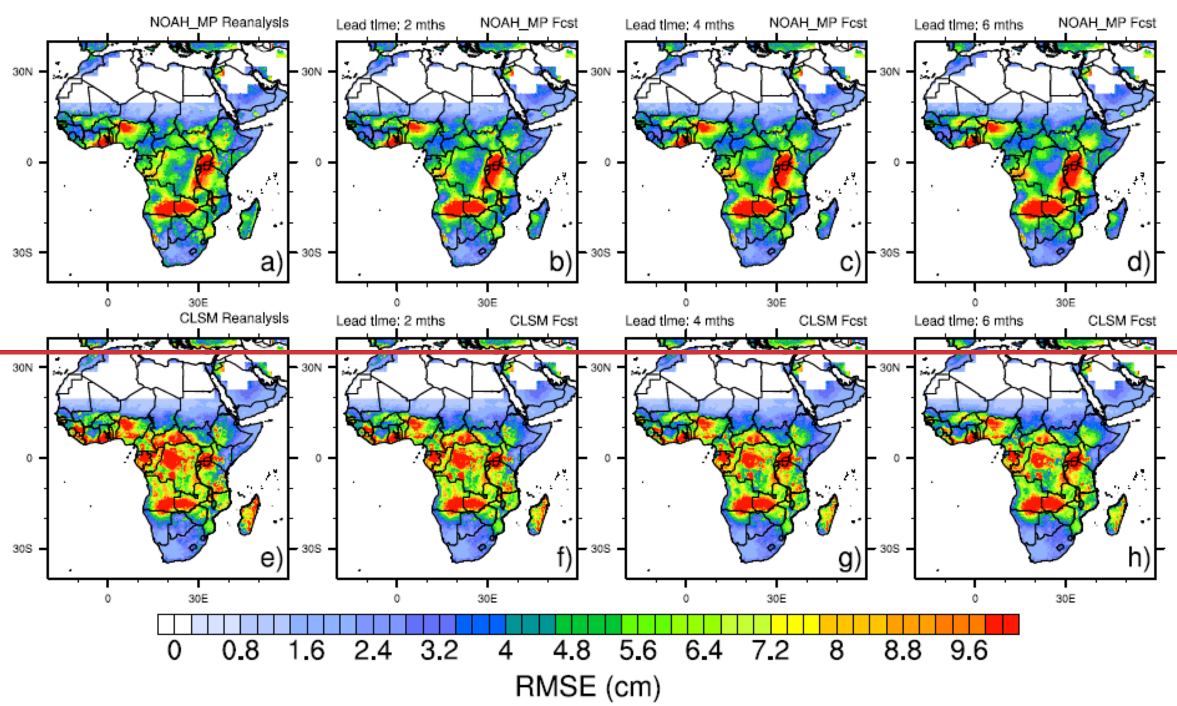
CLSM forecasts show larger RMSEs than Noah-MP in Gabon, Central African Republic (CAR) and Democratic Republic of the Congo (DRC) where mean annual precipitation is among the highest ~~, as indicated by both CHIRPS and NMME models, and where NMME models disagree considerably in interannual variability of precipitation~~ (Supplementary Figs. S1a~~,2~~). This result suggests that CLSM is more sensitive to precipitation and its associated uncertainty, likely due to strong interannual variability in its groundwater and TWS. ~~This result suggests that CLSM is more sensitive to precipitation uncertainties, due to its simulated long memory in groundwater and TWS which allow errors in precipitation and other forcing data to persist and grow over time.~~

~~Several factors likely contributed to these large errors. First, CHIRPS precipitation shows wetting trends in the western Sahel and the Lake Victoria and Lake Tanganyika area (Supplementary Fig.S1) which may be difficult for NMME precipitation forecasts to capture accurately, thus resulting in elevated errors. Second, in southern Zambia and Angola, strong precipitation~~

~~interannual variability and the discrepancies among NMME models (Supplementary Figs.S1,2), may have contributed to inaccurate forecasts. Strong interannual variability in precipitation often leads to large errors in TWS simulation due to the challenge to accurately model long-term memory in TWS (see Fig.2 of Li et al., 2019b). Third, since the models do not simulate surface water which is detected by GRACE/FO satellites, unresolved surface water dynamics and water management activities in Lake Victoria and Tanganyika, and Lake Kariba in southern Zambia may have contributed the large errors.~~

~~CLSM forecasts show larger RMSEs than Noah-MP in Gabon, Central African Republic (CAR) and Democratic Republic of the Congo (DRC) where mean annual precipitation is among the highest, as indicated by both CHIRPS and NMME models, and where NMME models disagree considerably in interannual variability of precipitation (Supplementary Figs. S1,2). This result suggests that CLSM is more sensitive to precipitation uncertainties, due to its simulated long memory in groundwater and TWS which allow errors in precipitation and other forcing data to persist and grow over time.~~

~~For both models, the spatial pattern and magnitudes of RMSEs remain stable between reanalysis and hindcasts of different lead times, suggesting uncertainty in model physics, which remain the same for reanalysis and hindcast, play a strong role affecting accuracy of TWS forecasts.~~



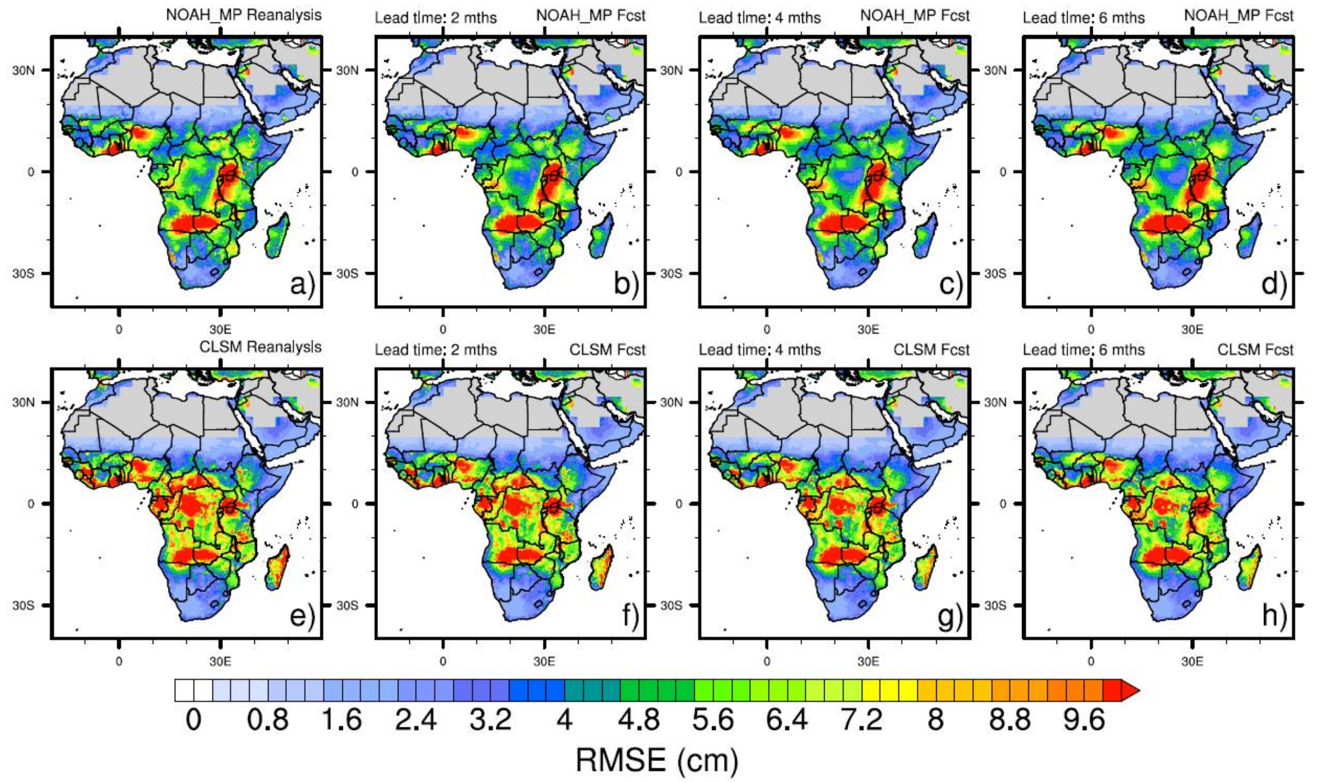
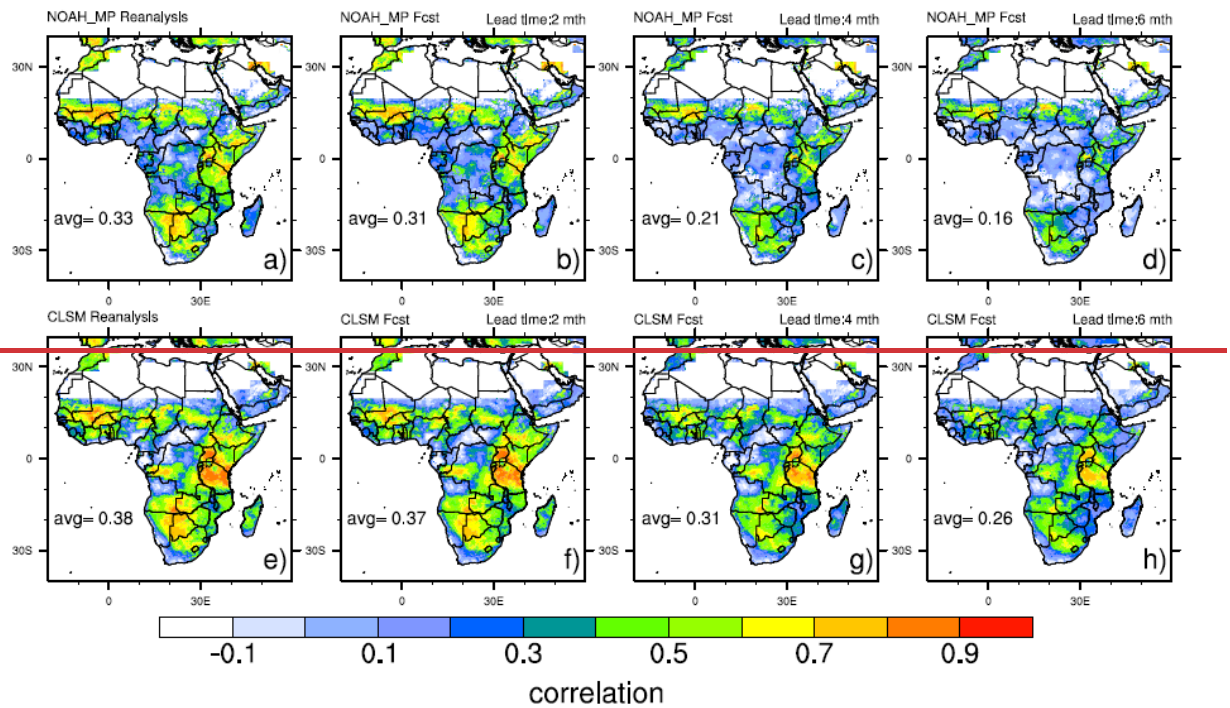


Fig.3~~2~~ RMSEs of non-seasonal reanalysis TWS, ensemble mean TWS forecasts of all NMME models with respect to GRACE/FO data for Noah-MP (top row) and CLSM (bottom row) at three lead times.

C~~The c~~orrelation between the ensemble mean TWS forecasts of all NMME models and GRACE/FO data exhibits similar spatial patterns between Noah-MP and CLSM (Fig.4~~3~~), suggesting precipitation~~ forecasts~~ ~~likely~~ plays a stronger role ~~on~~in correlation than model physics. However, the strength of those correlations differs notably between the two models, especially at long lead times with higher average correlation for CLSM. Correlations decrease with lead time for both models, but more rapidly for Noah-MP which, on average, decreased by 48% from the 2- to 6-month lead time, compared to the 27% decrease with CLSM. Most of the deterioration in correlation is observed in central Africa where mean annual precipitation is the largest (Supplementary Fig.S1a), reflecting larger precipitation uncertainty in wet regions and the model's response to such uncertainty.

Similar to RMSEs, correlations of the reanalysis exhibit spatial patterns comparable to those of hindcasts but with higher values, owing to the use of more accurate meteorological forcing fields (Figs.4a,e). On spatial average, the CLSM reanalysis shows higher correlations with GRACE/FO data than Noah-MP, contributing to the higher forecast skill of CLSM (Fig.4). Note that strong performance in one metric does not necessarily imply similar performance in another; in some cases, the metrics may even indicate opposite behavior. For instance, both higher correlation and larger RMSEs are observed in southern Zambia and Angola and Lake Victoria, reflecting different controls on these metrics. ~~Similar with RMSEs, spatial patterns of correlation are consistent between reanalysis and hindcasts,~~

~~indicating strong control of initial conditions on forecast skill. On average, CLSM reanalysis shows higher correlations with GRACE/FO data than that of Noah-MP, contributing to the higher forecast skill of CLSM (Fig.3).~~



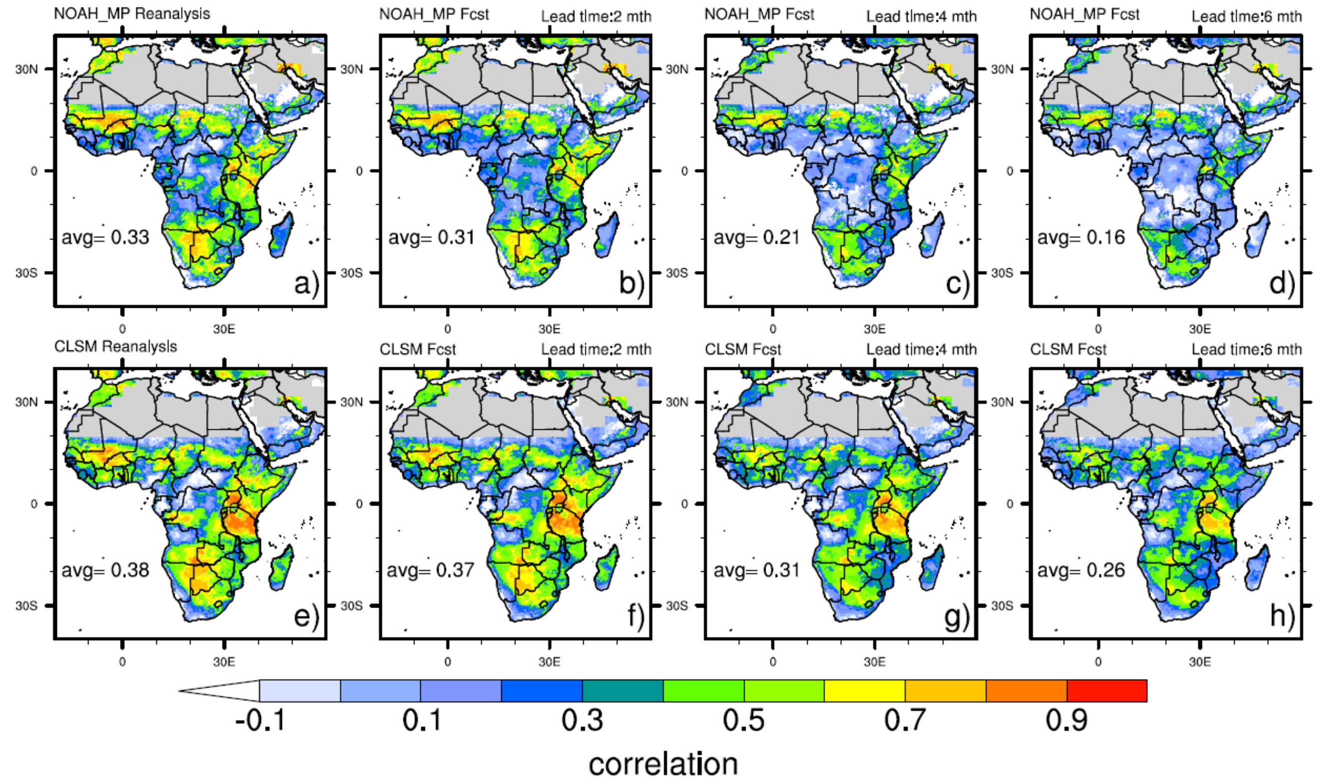


Fig.4~~3~~ Correlation between non-seasonal reanalysis TWS and ensemble mean TWS forecasts of all NMME models at three lead times, and GRACE/FO ~~TWS~~ observations for Noah-MP (top row) and CLSM (bottom row). Domain average correlations are shown~~provided~~ in inset text.

In CAR and South Sudan, TWS hindc~~forec~~asts from both models show near and below ~~-~~zero correlations with GRACE/FO data likely due to the opposite trends between reanalysis TWS and GRACE/FO data in that region (Supplementary Fig.S2~~3~~). The negative trends in GRACE/FO data (Supplementary Fig.S2c) may reflect the impacts of deforestation, which alter the partitioning of precipitation with~~by~~ increas~~es~~~~ing~~ in surface runoff and decreas~~es in~~~~ing~~ soil infiltration~~ and TWS~~. Although deforestation can also reduce evapotranspiration and thus increase TWS, this effect ~~on TWS~~ is likely minor because of reduced soil infiltration. According to the Global Forest Watch, CAR and South Sudan lost more than 20% of its primary forests during 2000-2024. Since neither Noah-MP nor CLSM accounts for land cover change, they simulated increases in TWS (Supplementary Figs.S2a,b) in response to increases in annual precipitation in that region (Supplementary Fig.S1c). Because the reanalysis is used as initial conditions for each forecast issued, inaccuracy in long-term trends inevitably affected climatology and the associated anomalies.

~~To further explore the role of model physics and meteorological forecasts, we computed RMSEs and correlation of TWS hindcasts with respect to reanalysis (Supplementary Figs.S4,5). As expected, using reanalysis as reference results in~~

~~substantially lower RMSEs and higher correlations. RMSEs show clear increases with lead time which is not obvious when evaluated against GRACE/FO data. In addition, the spatial pattern of RMSEs differs from that with respect to GRACE/FO data. These results suggest that model physics, which are not evaluated when compared to reanalysis, have a strong impact on forecast accuracy. In contrast to evaluation relative to GRACE/FO data, CLSM forecasts show strong correlation with reanalysis in CAR across all leads due to its ability to capture interannual variability in precipitation. On the other hand, correlation for Noah-MP forecasts decreased rapidly in this region, reflecting its inability to simulate long-term TWS variability. This outcome underscores the importance of using independent data to evaluate TWS forecasts.~~

RMSEs of TWS forecasts by individual NMME models exhibit contrasting behaviors with respect to lead time between Noah-MP and CLSM (Figs.5a, b). RMSEs of TWS forecasts increase with lead time for Noah-MP, reflecting growing uncertainty in meteorological forecasts~~ (Fig.4a)~~. In contrast, RMSEs of CLSM forecasts decrease with lead time, except for forecasts~~those~~ driven by GEOSv2~~ (Fig.4b)~~. ~~This behavior likely reflects CLSM's tendency to overestimate TWS interannual variability, compared to GRACE/FO data, especially in regions with pronounced precipitation interannual variability including central Africa (see Fig.2 of Li et al., 2019b).~~ As shown in previous studies (e.g., Li et al., 2019b), CLSM has the tendency to overestimate TWS dynamic ranges. Because~~As~~ interannual variability of NMME precipitation forecasts generally decreases with increasing lead time (Supplementary Fig.S3~~2~~), this ~~the~~ overestimation~~dynamic ranges~~ ~~of simulated TWS~~ is~~are~~ progressively damped~~suppressed~~, leading to reduced RMSEs at longer lead times.~~ This explains why largest RMSEs are observed in hindcasts by~~ On the other hand, GEOSv2 precipitation exhibits substantially larger interannual variability than other NMME products, which remains strong across all leads and leads to slightly increasing RMSEs with lead times ~~which also increase with lead time, owing to its largest precipitation interannual variability~~ (Supplementary Fig.S3~~2~~). ~~. These results again suggest that model physics may have stronger influences on accuracy of TWS forecasts than meteorological forecasts.~~

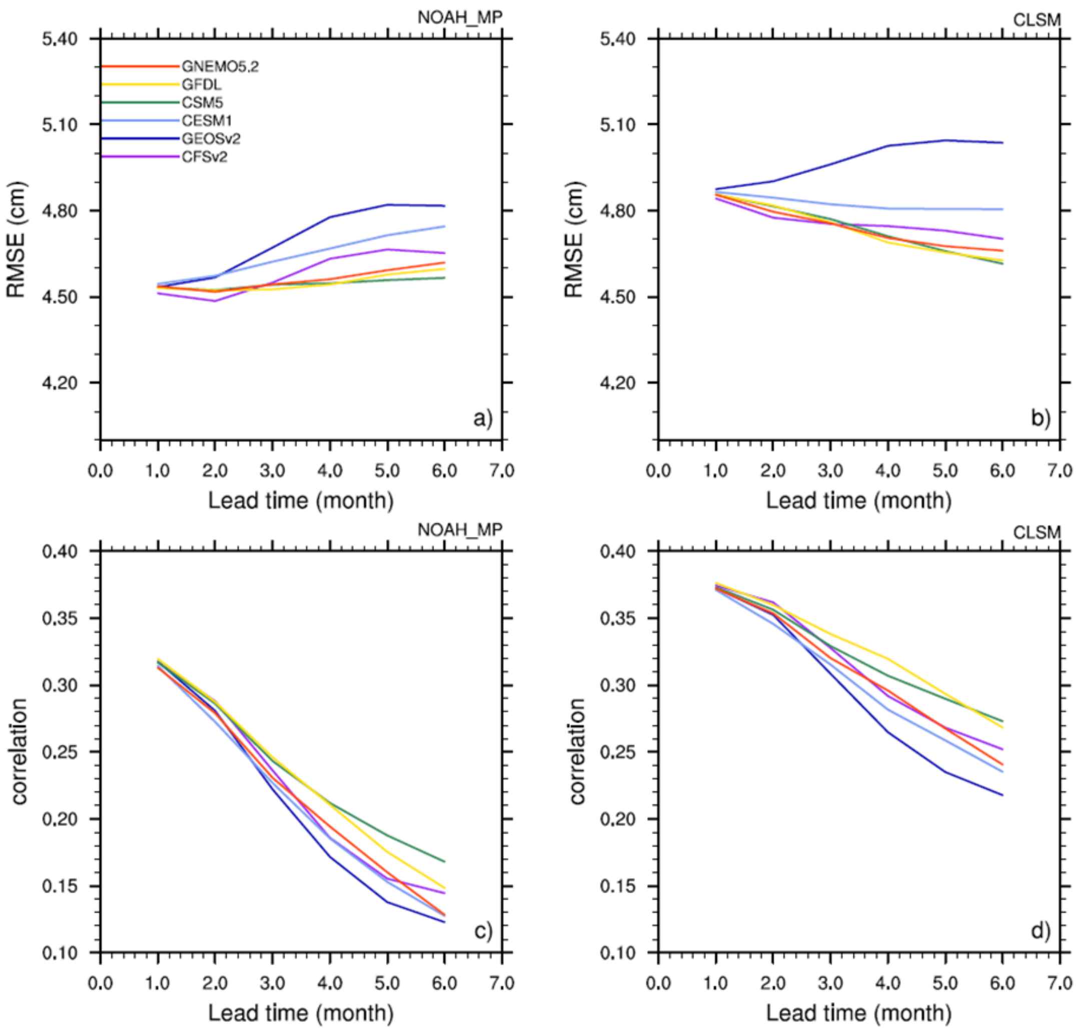


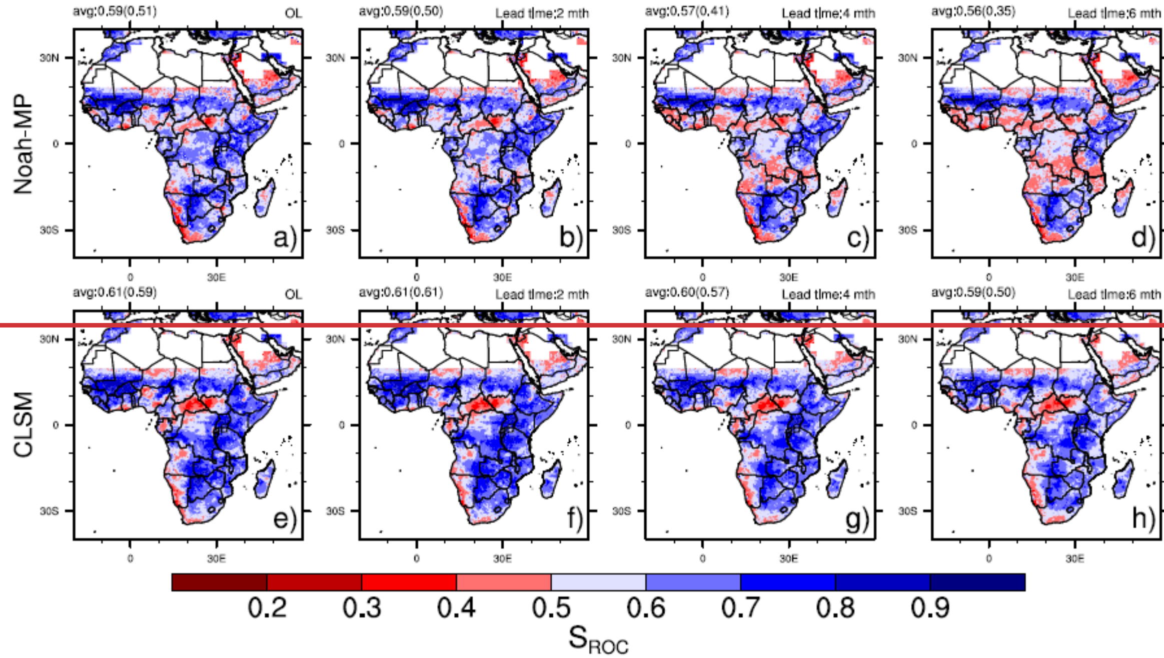
Fig.5~~4~~ Average RMSEs (top row) and correlations (bottom row) of ensemble mean TWS forecasts of individual NMME models relative to GRACE/FO data for Noah-MP (left column) and CLSM (right column) as a function of lead time.

As observed in all-model ensemble mean, c~~C~~orrelations between ensemble mean TWS hindcasts of individual NMME models and GRACE/FO data ~~follow the similar pattern as those of all-model ensemble mean: correlations~~ decrease with increasing lead time (Figs.5~~4~~c,d). In addition, CLSM hind~~fore~~casts for each NMME model ~~, on average,~~ exhibit higher correlation than those of Noah-MP at all~~ll~~ lead times~~s~~.

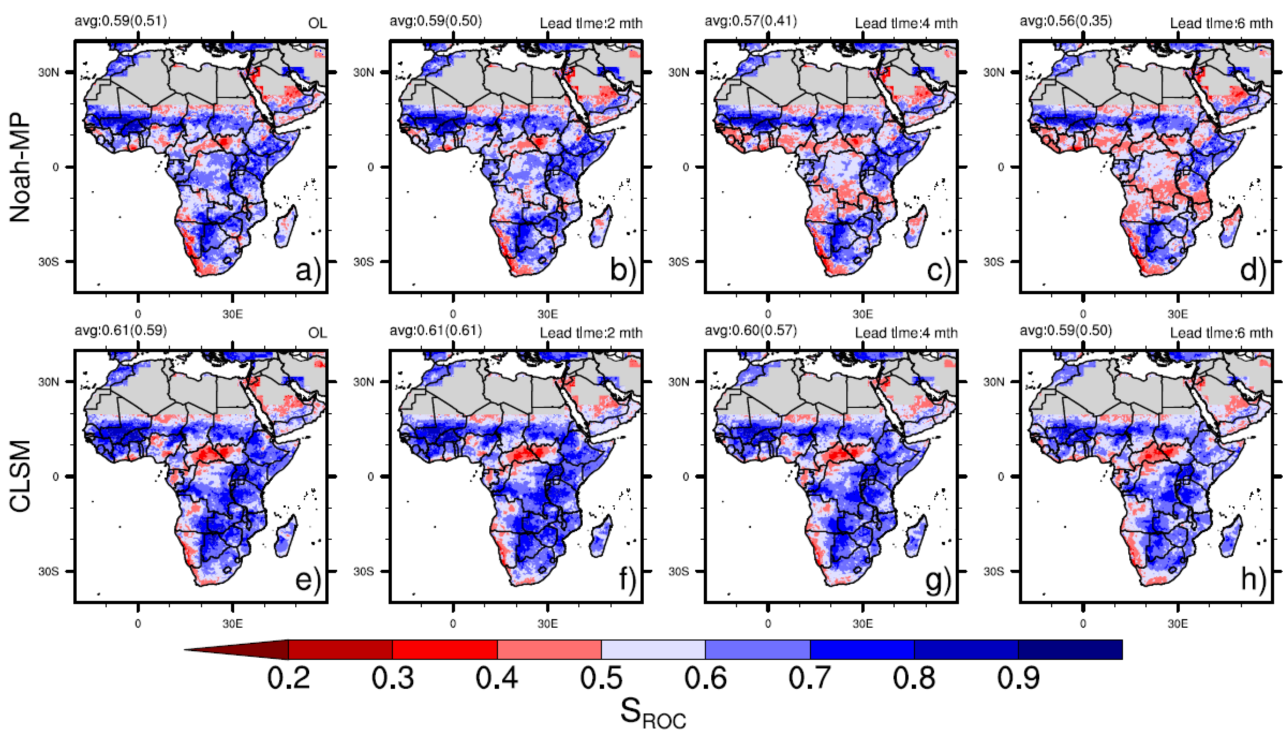
Among all NMME models, GFDL and CSM5, which exhibit the lowest precipitation interannual variability (Supplementary Fig.S3), produce the most accurate forecasts, with the lowest RMSEs and the highest correlations, whereas GEOSv2, with the highest interannual variability, produced the least accurate TWS forecasts, yielding the largest RMSEs and lowest correlations for both Noah-MP and CLSM~~ at all lead times~~. In addition to strong interannual variability~~ of GEOSv2 discussed above~~, previous studies showed that GEOS precipitation forecasts are less consistent within~~among~~ its ensemble members than other NMME models (Becker et al., 2014), indicating larger uncertainty in GEOS precipitation forecasts.

While RMSEs and correlation quantify the magnitude of discrepancies and the temporal consistency between two time series, they do not directly assess the ability to accurately forecast wetter and drier conditions. Therefore, we use ROC scores, which measure the hit rate relative to the false-alarm rate, to evaluate the performance of Noah-MP and CLSM in predicting terciles, corresponding to below-normal, near-normal and above-normal conditions. ROC scores for the lower tercile hind~~fore~~cast from the two models exhibit similar spatial patterns but differ in magnitude~~as correlations~~ (Fig.6~~5~~). Both models perform well in the Sahel (minus the northern edge), the Horn of Africa, and the eastern part of southern Africa~~ where trends in reanalysis TWS generally agree with those of GRACE/FO data (Supplementary Fig.S3)~~. B~~As expected, b~~oth models scored low ROC values in CAR and South Sudan, ~~due to the opposite TWS trends with GRACE/FO data as discussed previously.~~ consistent with correlations relative to GRACE/FO. ~~-~~CLSM shows more~~considerable~~ skills overall, achieving >0.6 ROC scores over ≥50% of the domain across all lead times. Note that ~~T~~the 0.6 threshold for predictive skill is based on the guideline by the Met Office (Met Office). In contrast, Noah-MP forecasts exhibit lower ROC scores, on average,~~overall~~ and the scores decrease quickly with increases in lead time, ~~especially in central Africa,~~ with only 35% of the domain~~areas~~ achieving >0.6 ROC scores at the 6-month lead time. The decreases is particularly noticeable in central Africa where annual precipitation is the largest (Supplementary Fig.S1a) ~~Both models perform well in the Sahel (minus the northern edge), the Horn of Africa, and the eastern part of southern Africa where trends in reanalysis TWS generally agree with those of GRACE/FO data (Supplementary Fig.S3). As expected, both models scored low ROC values in CAR and South Sudan, due to the opposite TWS trends with GRACE/FO data as discussed previously.~~

ROC scores for the upper tercile forecast show similar spatial patterns but with slightly higher values than those of ~~the~~ lower terciles (Supplementary Fig.S4~~6~~). This difference likely reflects the uneven occurrences of wet and dry anomalies over the relatively short study period (2003-2020). For both upper and lower terciles, the spatial patterns of ROC scores including their changes with lead time show broad agreement with those of correlations, suggesting a close relationship between the two metrices.



Noah-MP
CLSM
avg:0.59(0.51) OL
avg:0.59(0.50) Lead time:2 mth
avg:0.57(0.41) Lead time:4 mth
avg:0.56(0.35) Lead time:6 mth
avg:0.61(0.59) OL
avg:0.61(0.61) Lead time:2 mth
avg:0.60(0.57) Lead time:4 mth
avg:0.59(0.50) Lead time:6 mth
a) b) c) d) e) f) g) h)
30N 0 30S
0 30E
0.2 0.3 0.4 0.5 0.6 0.7 0.8 0.9
S_{ROC}



Noah-MP
CLSM
avg:0.59(0.51) OL
avg:0.59(0.50) Lead time:2 mth
avg:0.57(0.41) Lead time:4 mth
avg:0.56(0.35) Lead time:6 mth
avg:0.61(0.59) OL
avg:0.61(0.61) Lead time:2 mth
avg:0.60(0.57) Lead time:4 mth
avg:0.59(0.50) Lead time:6 mth
a) b) c) d) e) f) g) h)
30N 0 30S
0 30E
0.2 0.3 0.4 0.5 0.6 0.7 0.8 0.9
S_{ROC}

Fig.6~~5~~ ROC scores (S_{roc}) of lower terciles of ensemble mean TWS forecasts of all NMME models by Noah-MP (top row) and CLSM (bottom row) with respect to GRACE/FO data. The upper left text indicates average S_{roc} and the fraction of area (in parentheses) with S_{roc}>0.6.

3.3 Evaluation of TWS hindcasts using reanalysis

Since TWS hindcasts differ from the reanalysis only in the meteorological forcing data used, evaluating TWS forecasts against the reanalysis helps isolate impacts of NMME hindcasts from those of model physics. RMSEs relative to the reanalysis exhibit similar spatial patterns between the two models (Supplementary Fig.S5), with larger errors in wetter central Africa and smaller errors in drier northern and southern regions, highlighting mean annual precipitation and associated uncertainty as a main driver of TWS forecast errors when uncertainty in model physics is masked. As expected, these RMSEs are substantially lower than those relative to GRACE/FO and increase steadily with increasing lead time, reflecting growing discrepancies between NMME precipitation hindcasts and CHIRPS precipitation estimates.

Correlations evaluated relative to the reanalysis reveal contrasting patterns between the two models (Fig.S6). For Noah-MP, correlations relative to the reanalysis exhibit spatial patterns similar to those obtained using GRACE/FO as reference, with higher correlations in the drier northern and southern regions and lower correlations in central Africa. In contrast, when evaluated against the reanalysis, CLSM yields stronger correlations in central Africa through the 1–6-month lead times, in sharp contrast to the low skill inferred when GRACE/FO is used as reference. This region of strong correlations coincides with that of strong long-term TWS trends in CLSM (Supplementary Fig.S2b) which, as discussed in section 3.4, may induce strong persistence in simulated TWS and hence strong correlation. For both models, domain-averaged correlations relative to the reanalysis are more than twice those relative to GRACE/FO in most cases, underscoring substantial uncertainty in model physics that limit TWS forecast skill and the need to use independent data for evaluation.

3.4~~3~~ Persistence of TWS processes

Persistence refers to the tendency of a process or variable in retaining its past state (wet or dry conditions) and has been~~is~~ known to help enhance hydrological prediction skill. To ~~properly~~ examine~~examine~~ persistence, we computed the autocorrelation of TWS time series from the two re-analyses and GRACE/FO data at three lags (Fig.7~~6~~, top three rows). Autocorrelations for the two models exhibit distinct spatial patterns. Noah-MP simulates higher autocorrelation, suggesting stronger persistence, in the drier northern and southern Africa, whereas CLSM reanalysis~~TWS~~ exhibits higher autocorrelations ~~than Noah-MP~~ across the wetter central Africa.

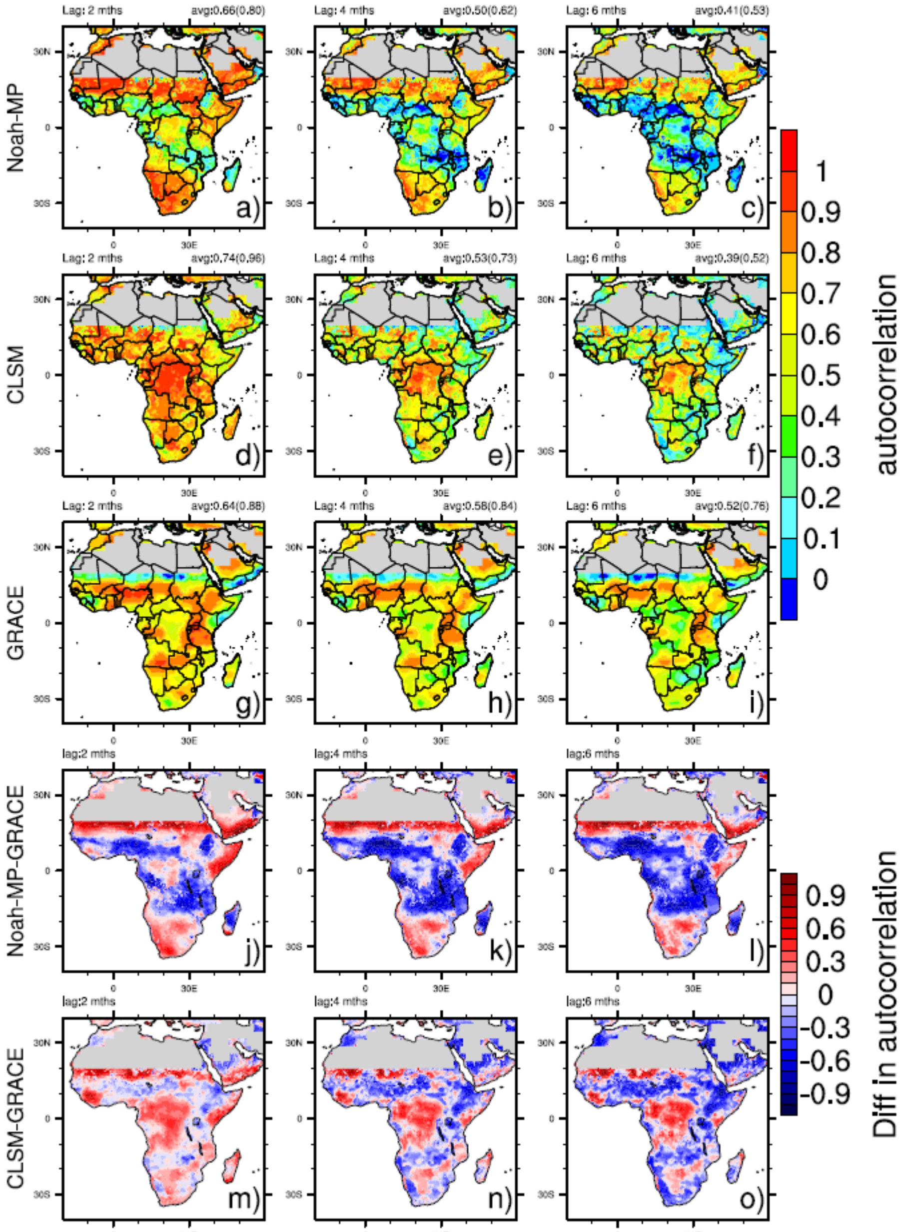
GRACE/FO observations exhibit different patterns of persistence with strong persistence in the interior Sahel, southern Africa and the large swath area encompassing Lake Victoria (Fig.7, third row) where they exhibit strong long-term trends (Supplementary Fig.S2). On average, GRACE/FO data shows lower persistence at the 2-month lag, but substantially higher autocorrelation at 4- and 6-month lags than the reanalysis. The area with >0.37 autocorrelation (representing the e-folding time) in GRACE/FO data remains high, above 75% even at the 6-month lag. These results suggest that persistence simulated by the model may not represent real-world persistence and thus may not help with enhancing forecast skill.

Differences between simulated and GRACE/FO TWS persistence exhibit spatial patterns similar to those of mean annual precipitation, reflecting the strong influence of mean annual precipitation and associated uncertainty on persistence (Fig.7, bottom two rows). However, the two models often exhibit contrasting performances. Compared to GRACE/FO, Noah-MP underestimates persistence in central Africa and overestimates it elsewhere. In contrast, CLSM overestimates persistence in central Africa while underestimating it in other regions, with the discrepancy steadily increasing with lags. In wetter central Africa, strong interannual variability in CLSM TWS helps retain past wetness conditions and contributes to its strong persistence. On the other hand, the underestimation of persistence by CLSM in drier regions may be linked to the model's tendency to overestimate ET, which acts as continuous disruption to soil moisture states, thus leading to low persistence. These results reflect strong impacts of model physics, especially their responses to precipitation variability, on simulated TWS variability. For both models, discrepancies between the reanalysis and GRACE/FO increase with lag (Fig.7, bottom two rows), reflecting the accumulation of differences from past states.

The spatial patterns of persistence resemble those of correlations using the reanalysis as the reference (Fig.S6), suggesting that persistence is a useful indicator of forecast skill primarily when uncertainty in model physics is minimal, as in the case of using the reanalysis as the reference. Moreover, the spatial patterns of persistence align well with those of correlations and ROC scores only for Noah-MP, suggesting that short-term persistence (1-6 months) may not be reliable indication of forecast skill for models that simulate strong interannual variability such as CLSM. ~~at all three lags, while Noah-MP simulates strong persistence in the drier northern and southern Africa.~~

~~GRACE/FO data reveals a different spatial pattern in persistence, with strong persistence in the interior Sahel and a large swath area across Lake Victoria, and Zambia and southern Angola.Compared to reanalysis, GRACE/FO data shows lower persistence at the 2-month lag, but substantially higher autocorrelation at 4- and 6-month lags. The area with >0.37 autocorrelation in GRACE/FO data remains high, above 75% even at the 6-month lag.~~

~~Regardless of data sources, strong persistence in TWS is generally associated with strong long-term trends in TWS (Supplementary Fig.S3). The positive trends in the western Sahel shown in GRACE/FO data have been linked to the northward shift of the northern African monsoon, which has led to increases in wet extremes in the region (Monerie et al., 2021; Rodell and Li, 2023). The increasing trend was better captured by the Noah-MP reanalysis than CLSM. On the other hand, CLSM reanalysis better reflected the wetting trends in the Lake Victoria region observed in GRACE/FO data. Note that while surface water is a major TWS component in Lake Victoria, the increasing trend in GRACE/FO data mainly reflected precipitation surpluses around 2020, not due to water management activities (Boergens et al., 2024). As discussed earlier, the strong persistence in CAR for CLSM reanalysis is associated with increases in precipitation.~~


Lag: 2 mths
avg:0.66(0.80)
Lag: 4 mths
avg:0.50(0.62)
Lag: 6 mths
avg:0.41(0.53)
Lag: 2 mths
avg:0.74(0.96)
Lag: 4 mths
avg:0.53(0.73)
Lag: 6 mths
avg:0.39(0.52)
Lag: 2 mths
avg:0.64(0.88)
Lag: 4 mths
avg:0.58(0.84)
Lag: 6 mths
avg:0.52(0.76)
lag:2 mths
lag:4 mths
lag:6 mths
lag:2 mths
lag:4 mths
lag:6 mths
Noah-MP
CLSM
GRACE
Noah-MP-GRACE
CLSM-GRACE
a)
b)
c)
d)
e)
f)
g)
h)
i)
j)
k)
l)
m)
n)
o)
30N
0
30S
0
30E
1
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0
autocorrelation
0.9
0.6
0.3
0
-0.3
-0.6
-0.9
Diff in autocorrelation

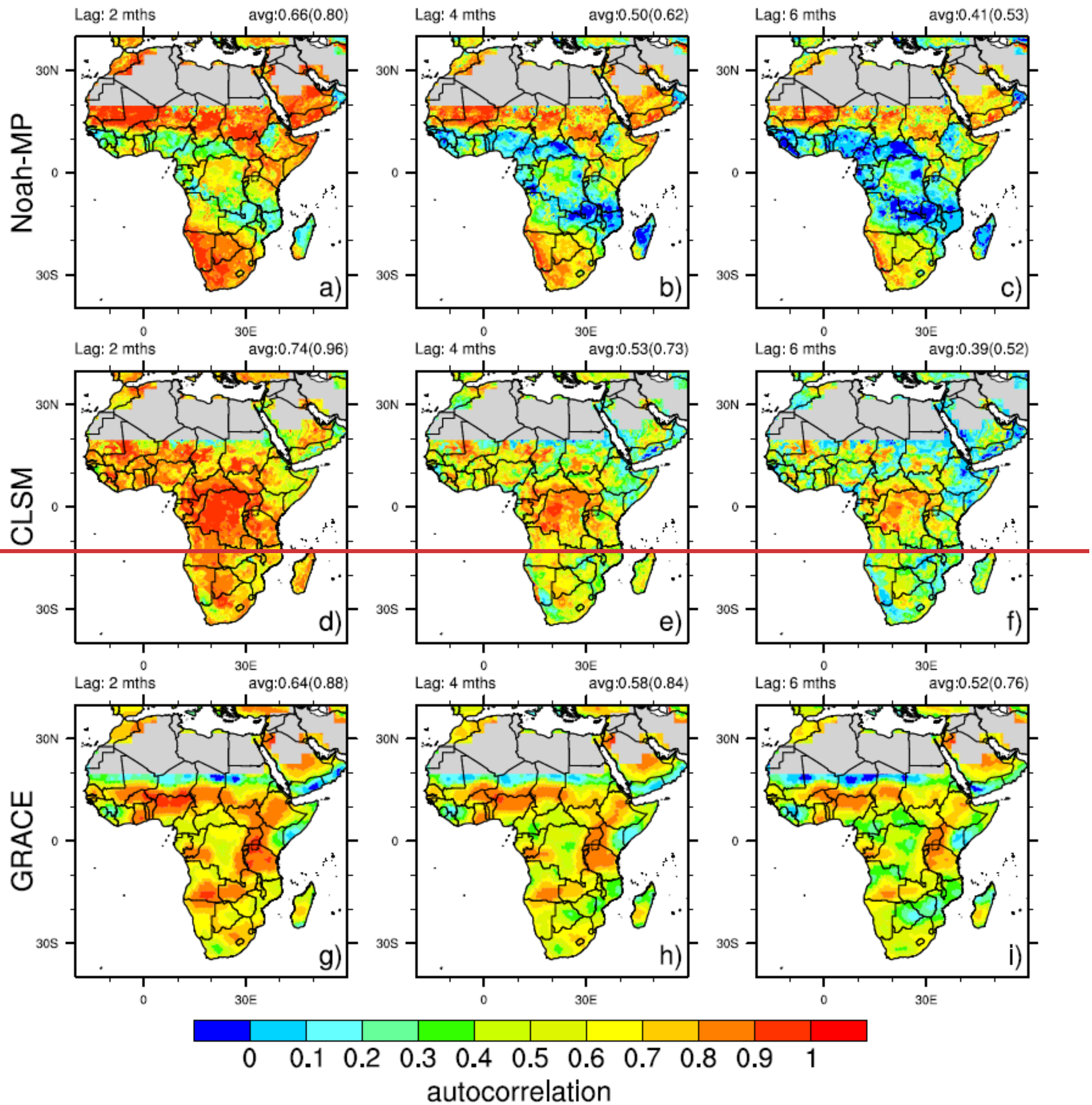


Fig.7~~6~~ Autocorrelation of ~~TWS time series for~~ Noah-MP~~ (top row)~~ and CLSM ~~(middle row) r~~reanalysis TWS (top two rows), and GRACE/FO data (third~~bottom~~ row) at three lags. The fourth and fifth rows show differences in autocorrelations between the reanalysis and GRACE/FO data. Upper right text in the top three rows show~~indicate~~s average autocorrelation and fraction of area with autocorrelation>0.37 (in parentheses).

~~On average, CLSM reanalysis shows stronger persistence than Noah-MP, with a larger fraction of the domain exhibiting >0.37 auto-correlation (representing e-folding time) at the 2- and 4-month lags. Compared to reanalysis, GRACE/FO data shows lower persistence at the 2-month lag, but substantially higher autocorrelation at 4- and 6-month lags. The area with >0.37 autocorrelation in GRACE/FO data remains high, above 75% even at the 6-month lag.~~

To further investigate~~explore~~ contributors of~~contributing factors to~~ TWS persistence, we examine domain averaged autocorrelation of soil moisture of the unsaturated soil and groundwater storage from the reanalysis (Fig.8~~7~~). Noah-MP simulates weak groundwater persistence which, ~~It is clear that the weak persistence in Noah-MP reanalysis TWS is closely linked to the weak persistence in its simulated groundwater.~~ a~~A~~t the 1- and 2-month lags, ~~persistence in Noah-MP groundwater~~ is even lower than that of ~~its~~ soil moisture and remains low at longer lags. In contrast, CLSM simulates stronger groundwater~~r~~ ~~shows much stronger~~ persistence than ~~its simulated~~ soil moisture, with groundwater persistence contributing ~~with average persistence in groundwater~~ nearly all ~~identical to that~~ of TWS persistence. Compared to ~~reanalysis,~~ GRACE/FO observations, reanalysis TWS from both models exhibits a slower~~more rapid~~ decline in persistence at 0–2-month lags, but a faster~~slower~~ decline afterwards.

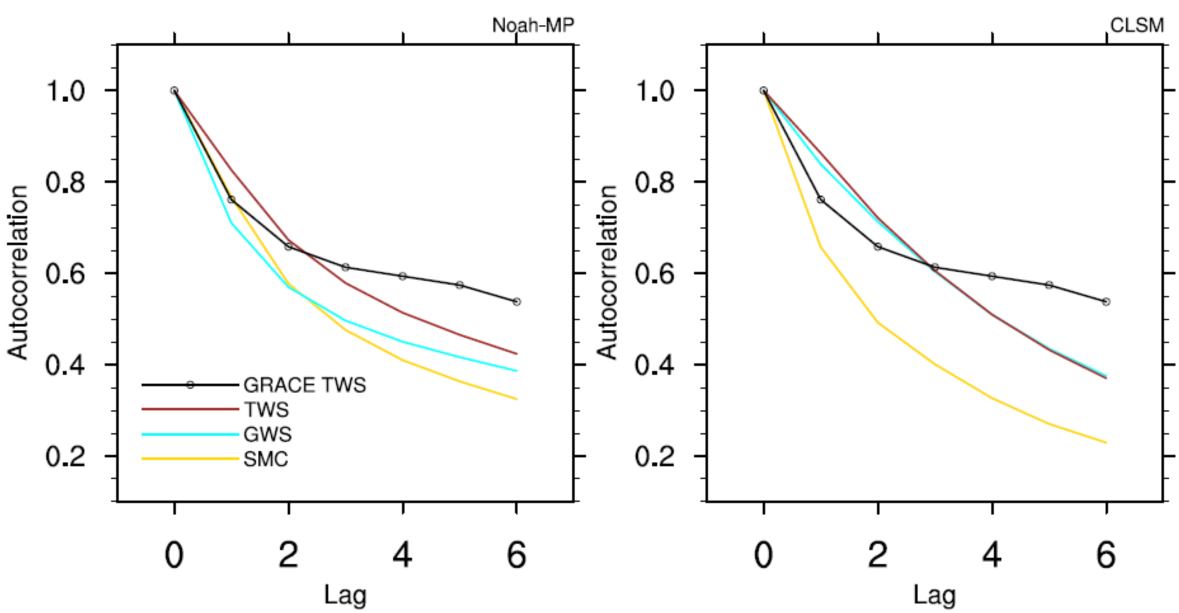
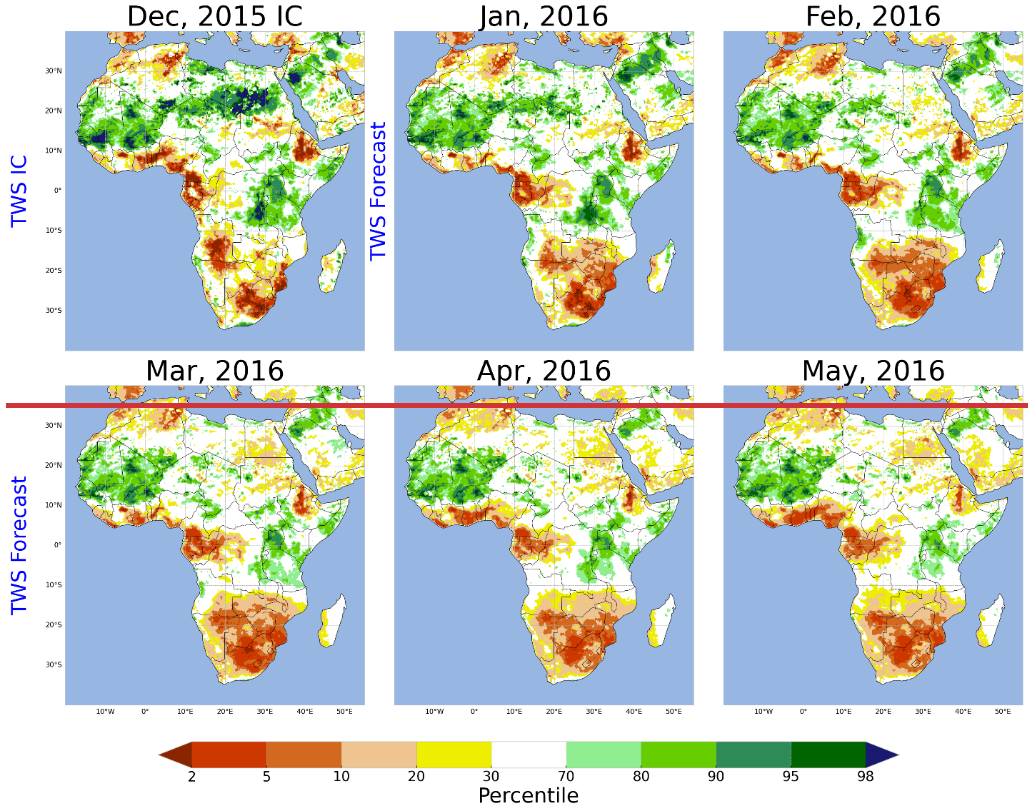


Fig.8~~7~~ Domain average autocorrelation for soil moisture of the unsaturated soil, groundwater storage and TWS as a function of lags (in months).

3.5~~4~~ TWS forecast percentiles: a case study

To demonstrate~~explore~~ the value of TWS forecasts, we examine TWS percentile maps derived using equation (1) ~~from CLSM~~ for hind~~fore~~casts initialized in December 2015 and GRACE/FO data (Fig.9~~8~~). Both Noah-MP and CLSM forecasts identified~~Severe~~ pronounced droughts ~~(<10th percentile)~~ ~~affected much of~~ in southern Africa and parts of the southwestern coastal region including Ghana and Gabon, and wet conditions in eastern Africa and the northwestern Africa including Mauritania, Mali and Senegal. ~~throughout the 6-month forecast period (Fig.8),~~ The southern Africa drought~~-~~ was attributed ~~in association with~~ to the 2015-2016 El Niño event which is known to ~~typically~~ bring~~s~~ dry conditions to southern Africa~~southern Africa~~ (Mason & Goddard, 2001). ~~Drought conditions were further intensified by record-setting global temperature in 2016. TWS percentiles indicate most severe droughts (<5th percentile) between December 2015 and March 2016. In particular, t~~The spatial extent and severity of drought ~~conditions~~ forecasted for March 2016 are broadly~~generally~~ consistent with the FEWS NET ~~drought~~ assessment released in March 2016, ~~which is~~ based on cumulative precipitation analysis (FEWS NET, 2016). ~~Additionally, t~~Th~~e~~is drought caused up to 66% ~~decline in~~ crop production declines in some areas and affected at least 18 million people (Ainembabazi et al., 2018), ~~. This highlights~~underscoring the potential ~~and benefit~~ value of TWS forecasts for providing early warnings for agricultural failures and food insecurity~~severe and persistent droughts~~. The El Niño also brought ~~Drought conditions are also evident in the southwestern coastal countries including Ghana and Gabon.~~ wet conditions in eastern Africa, with relentless rainfalls ~~trigging~~triggering landslides and causing considerable human fatality and property damage (Bishumba, 2016). Sustained wet conditions in the northwestern Africa may have contributed to severe floods in Mali and Burkina Faso in July 2016 (FloodList, 2016). Noah-MP and CLSM generally agree on regional placement of extreme events, but they may differ on the extent and severity estimate. For instance, CLSM identified more severe drought areas in southern Africa~~n~~ than Noah-MP.


Dec, 2015 IC
Jan, 2016
Feb, 2016
Mar, 2016
Apr, 2016
May, 2016
TWS IC
TWS Forecast
TWS Forecast
2
5
10
20
30
70
80
90
95
98
Percentile

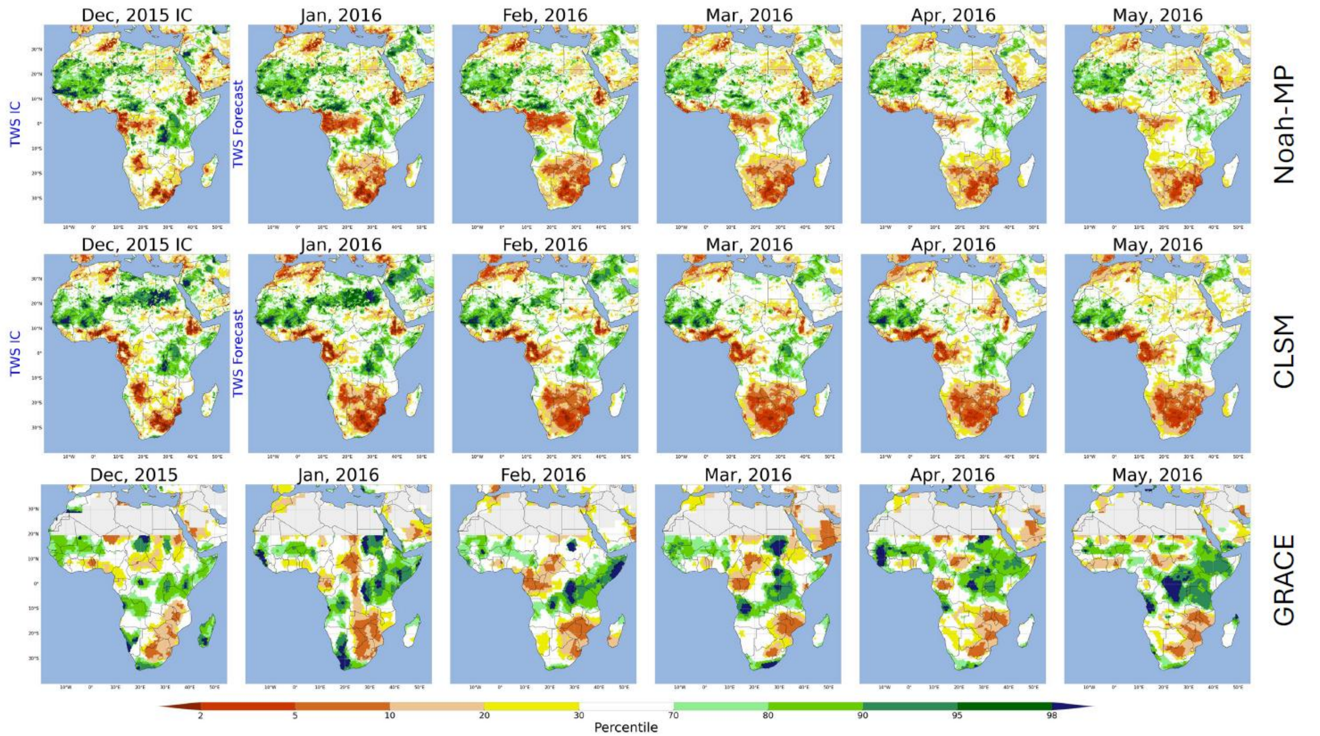


Fig.9~~8~~ TWS percentile maps derived from Noah-MP and CLSM ensemble mean TWS forecasts (top two rows) of all NMME ~~ensemble~~ models, initialized in December 2015, and corresponding maps for GRACE/FO data (bottom row).

~~Wetter conditions are observed in eastern Africa, especially in Rwanda where relentless rainfalls in May 2016 trigged landslides that killed dozens of people and destroyed hundreds of homes (Bishumba, 2016). Above normal conditions also occurred in the northern part of western Africa such as Mauritania, Mali and Senegal from December to May. These wet conditions may have contributed to the devasting floods in Mali and Burkina Faso in July 2016 (FloodList, 2016)~~

GRACE/FO TWS observations show broad agreement with TWS hindcasts, identifying dry anomalies in southeastern and southwestern Africa and wet anomalies in eastern Africa and the western Sahel, but may differ in severity, extent and temporal evolvement of these extreme conditions. For instance, while both models suggest wet conditions in eastern Africa weakened from January to May of 2016, GRACE/FO indicates they intensified and spread to larger areas. As discussed earlier, interannual variability of NMME precipitation decreases with lead time and thus may result in less severe TWS anomalies forecasted for long lead times. Compared to GRACE/FO, Noah-MP more accurately captured the extent of droughts in southeastern Africa, while CLSM performed better in forecasting wet conditions in eastern Africa at longer lead times. Note the north-south dry pattern in GRACE/FO for January 2016 is the well-known de-aliasing error associated with limited observations, which can occur even after the regularization procedures applied to CSR GRACE/FO data (Save et al., 2016).

~~Probability maps indicate strong agreement among NMME forecasts for these wet and dry anomalies (Supplementary Fig.S7). In addition, probabilities generally decrease with increases in lead time, reflecting increased uncertainty in both meteorological and TWS forecasts.~~

Surface and root zone soil moisture ~~forecasts~~ exhibit ~~show similar dry and wet patterns~~ dry and wet anomalies ~~as~~ comparable to those of TWS ~~forecasts~~in the first two months but diverge in later months, reflecting their more rapid responses to changes in meteorological conditions (Supplementary Fig~~s~~.S7~~8,9~~). This divergence is especially evident for Noah-MP surface moisture, ~~However, the severity and extent of wet and dry anomalies may differ depending on the indicator. For instance, surface soil moisture identified <5th percentile drought conditions in Gabon in December 2015 which improved to 10-20th percentiles by May 2016, while TWS anomalies remained in <10th percentiles throughout the 6-month period. Similarly, the wet anomalies in eastern Africa returned to normal more quickly in surface soil moisture than in TWS.~~ which indicates only moderately dry conditions (10-20th percentiles) in southern Africa by May 2016, compared to large areas of more severe droughts (5-10th percentiles) suggested by Noah-MP TWS. CLSM surface soil moisture and root zone soil moisture indicate more persistent anomalies conditions like CLSM TWS, consistent with the tighter coupling among CLSM water storage components. These results further underscore the strong impact of model physics and the added value of TWS forecasts for predicting hydrological extremes. ~~Root zone soil moisture percentiles also show faster changes in anomalies with lead time than TWS percentiles, but less so than surface soil moisture (Supplementary Fig.S9). These results reflect lagged responses to changes in precipitation as the soil depth increases.~~

4 Summary and discussions

We evaluated terrestrial water storage (TWS) forecasts produced by the FLDAS Hydrological Forecasting System (FLDAS-Forecast) over~~in~~ Africa using GRACE/FO TWS observations as an independent benchmark. Statistical analyses showed ~~indicate~~ that the Catchment land surface model (CLSM) exhibit~~demonstrate~~s considerable S2S predictive skill~~s in forecasting terciles at S2S scales~~, with ~~>0.6~~ ROC scores for tercile forecasts exceeding 0.6 (the threshold for~~indicating~~ predictive skill) over more than half~~50%~~ of the study domain~~area~~ across 1- to 6-month lead times. CLSM forecasts also ~~show stronger~~ correlat~~e~~~~ions~~ more strongly with GRACE/FO data than those of Noah-MP, especially at longer lead times. ~~A key contributing factor is that CLSM reanalysis, used as initial conditions, better captured the interannual variability in GRACE/FO observations, with >0.7 correlation for domain averaged TWS anomalies. Furthermore, the skill in initial conditions is retained at longer lead times through persistence associated with strong interannual variability in its simulated TWS. As interannual variability determines climatology, the combination of more accurate initial conditions and persistence led to more accurate~~

~~anomaly forecasts.~~ In contrast, Noah-MP forecasts generally show lower skill than CLSM, especially in central Africa where the skill declines quickly with increases in lead times.

~~In contrast, Noah-MP forecasts showed low skills, especially in central Africa where ROC scores generally fall below 0.6 at the 4- and 6-mth lead times. This reduced performance is partly attributed to the reanalysis-based initial conditions that exhibit smaller interannual variability compared to GRACE/FO data, degrading accuracy of climatology and anomalies. Weak interannual variability also led to a more rapid decline in forecast skill with lead time in Noah-MP.~~

The superior performance of CLSM is attributed to its ability to simulate strong groundwater dynamics across seasonal to interannual scales. This capability enables CLSM to better capture the interannual variability in TWS observed by GRACE/FO, thereby producing more accurate initial conditions. Enhanced interannual variability also increases persistence in CLSM TWS estimates, allowing the benefit of more accurate initial conditions to propagate to longer forecast lead times. Interannual variability is important for S2S forecasts because TWS, has a long memory process, retains information about past wet and dry conditions over months. Moreover, long-term variability directly affects the climatology used for determining TWS anomalies, thus affecting forecast skill.

Consistent with this long memory behavior, TWS forecasts exhibit strong sensitivity to inter-annual variability of precipitation forecasts, which varies substantially across NMME models. TWS forecasts driven by precipitation forecasts with larger interannual variability (e.g., GEOSv2) show lower correlation and higher RMSEs with respect to GRACE/FO observations, whereas those forced by precipitation forecasts with lower interannual variability (e.g., GFDL and CSM5) yield more accurate TWS predictions. TWS forecasts also respond differently to changs in precipitation forecasts across lead times. NMME precipitation forecasts generally show decreasing interannual variability with increasing lead time, likely reflecting reduced forecast skill at long leads when prediction reverts toward climatology (Zhang et al., 2021). This decrease leads to contrasting model behaviors, with CLSM TWS forecasts showing reduced RMSEs with increases in lead time, whereas Noah-MP forecasts exhibit increasing RMSEs. These results underscore not only the importance of improving S2S precipitation forecasts but also the need to better understand how land surface models filter and propagate precipitation variability.

Autocorrelation analysis further reveals differences in how the two models represent TWS processes. CLSM simulates much stronger persistence in groundwater than in soil moisture, owing to its two-way interactions between the unsaturated zone and the aquifer. This coupling enhances groundwater sensitivity to climate variability and persistence that supports extended forecast skill. In contrast, Noah-MP produces similar persistence in groundwater and soil moisture, reflecting its weak representation of groundwater upward movement, which limits groundwater responses to droughts and results in reduced temporal variability. Additional factors such as overestimation of surface runoff may further limit groundwater dynamics by reducing infiltration and groundwater recharge. Importantly, while persistence can contribute to predictability, our analyses show that simulated persistence does not always agree with GRACE/FO data, especially in regions with strong trends, and therefore may overstate forecast skill. In addition, persistence quantified using short-lag (1-6 months) autocorrelations may be a poor indicator of predictability when TWS exhibits substantial interannual variability. These findings underscore the inherent challenges of accurately simulating persistence in long-memory processes, where uncertainties in input data and model physics accumulate over time.

Together, these findings emphasize the critical role of realistically representing groundwater variability in improving S2S TWS forecasts. For models such as Noah-MP, where groundwater dynamics are primarily driven by recharge from the overlying soil layers, improved simulation of capillary rise, the upward groundwater flux, is particularly critical for simulating realistic groundwater responses to climate variability. More broadly, because TWS is a long-memory process that integrates the cumulative impacts of precipitation, evapotranspiration and human interventions, forecast skill can be further enhanced by improving simulation of both climate-driven long-term variability and anthropogenic trends.

~~Accuracy of TWS forecasts showed strong dependency on interannual variability of precipitation forecasts. TWS forecasts based on GEOSv2 precipitation, which exhibits the largest interannual variability, showed the lowest correlation and highest RMSEs with respect to GRACE/FO observations. On the other hand, TWS forecasts based on GFDL and CSM5 precipitation, which have the lowest interannual variability, yielded the highest correlations and lowest RMSEs. Predicting precipitation interannual variability is challenging due to limited temporal samples (McKinnon and Deser, 2021) and can therefore entail greater uncertainty. On the other hand, model physics can exert stronger influences on accuracy of TWS forecasts than precipitation forecasts. This effect is more evident with CLSM which may overestimate TWS responses to precipitation interannual variability and thus, can produce more accurate TWS forecasts with precipitation forecasts of reduced interannual variability such as for some NMME models at long lead times.~~ Evaluation relative to the reanalysis yielded much smaller RMSEs and higher correlation than evaluation relative to GRACE/FO, underscoring substantial uncertainties in model physics and the importance of using independent observations as the benchmark. GRACE/FO data are sensitive to climate variability, climate change and anthropogenic effects, which are often poorly represented or inconsistently treated in reanalysis systems. While this study provides insight into the impact of groundwater representation on TWS predictability, future work should focus on improving groundwater simulation by leveraging more than two decades of GRACE/FO observations to advance S2S hydrological predictability.

~~Statistical analysis showed that forecast skill is substantially lower when evaluated against GRACE/FO data than when assessed relative to reanalysis for both models, further underscoring substantial uncertainty in model physics. These effects are most pronounced in central Africa where forecast skill varies considerably between the two models. As discussed above, the ability to simulate multi-year responses to precipitation variability is critical for skillful TWS forecast in regions with strong precipitation interannual variability. CLSM performs better in this regard because it realistically represents upward~~

~~groundwater movement during extended dry periods, sustaining ET and creating storage capacity for groundwater recharge when precipitation returns, thereby resulting in pronounced interannual variability in TWS. In contrast, Noah-MP's weak representation of capillary rise limits groundwater storage capacity and its ability to capture long-term precipitation variability, especially during prolonged droughts.~~

~~Auto-correlation analysis showed that TWS persistence is strongly impacted by persistence in simulated groundwater, underscoring the need to improve groundwater representation, especially in capturing long-term precipitation variability. In addition, this study shows that while persistence contributes to predictability, inaccurate persistence can lead to erroneous forecasts. This is especially true in regions experiencing secular trends in precipitation and anthropogenic effects such as groundwater withdrawals and deforestation that are often poorly simulated by land surface models (Döll et al., 2014).~~

~~As discussed above, interannual variability is critical for accurately forecasting TWS anomalies.~~ GRACE/FO data assimilation has been shown to be an effective means to constrain the temporal variability of groundwater and TWS, leading to more accurate estimates of TWS anomalies ~~and its components~~ (Li et al., 2019b). However, higher ~~Due to the~~ computational costs and a 2-4 month~~s of~~ data latency limit~~,~~ its application ~~GRACE/FO data assimilation is~~ to ~~only feasible for~~ reanalysis ~~based simulation,~~ rather than~~not suited for~~ near-real time forecasting ~~runs~~. Consequently~~As a result~~, ~~while~~even when GRACE/FO data assimilation ~~may~~ improves ~~reanalysis-based~~ initial conditions, deficiencies in model physics, such as weak groundwater persistence as seen in Noah-MP,~~such as inability to properly simulate responses to precipitation variability~~ can prevent these improvements ~~in initial conditions~~ from translating into skill at ~~translating into enhanced forecast skill at~~ long~~er~~ ~~-~~lead times~~times~~. However, quantifying the influence of improved initial conditions on TWS forecast skill remains an important area for future research. In addition, studies assessing the potential benefits of reduced GRACE/FO data latency could help motivate efforts to deliver more timely GRACE/FO observations for operational forecasting. ~~Therefore, improving physical representation of TWS processes, especially their responses to anthropogenic effects and long-term precipitation variability, should be a key priority for future research aimed at improving TWS forecasts.~~

Finally, separating surface water signals from GRACE/FO data can improve diagnosis of modeled TWS processes in regions dominated by large surface water bodies. However, due to the spatial smoothing inherent in GRACE/FO measurements, surface water signals are distributed over broad surrounding areas, rendering the simple grid-scale mass balance calculations inadequate. Specialized modeling approaches are required to properly isolate surface water contributions (Deggim et al., 2021; Sharifi et al., 2025). Because such techniques are not yet widely available, there is a need for surface water datasets that are harmonized with GRACE/FO observations and accompanied by uncertainty estimates. Beyond temporally consistent local observations of surface water elevation and extent, this effort requires improved modeling of surface water and groundwater interactions, processes currently absent in most hydrological models but can substantially influence TWS variability, particularly in wet climates (Bierkens and Wada 2019).

Data availability: FLDAS forecast data are available at https://ldas.gsfc.nasa.gov/fldas/models/forecast.

Author contribution: BL: conceptualization, formal analysis, methodology, investigation, visualization, writing (original draft preparation). AH: Data curation, software, writing (review and editing). AM: project administration, supervision, writing (review and editing). KS: project administration, writing (review and editing). SS: Funding acquisition, supervision, writing (review and editing) WA: writing (review and editing).

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