Deep Learning-aided Temporal Downscaling of Satellite Gravimetry Terrestrial Water Storage Anomalies Across the Contiguous United States (CONUS) (EGU2023-632)

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Abstract

Gravity Recovery and Climate Experiment (GRACE) and GRACE-FollowOn (GFO) satellites can monitor the global spatio-temporal changes in terrestrial water storage anomalies (TWSA) with monthly temporal and 300 km spatial resolutions. Since these native resolutions may not be adequate for various studies requiring better localization of TWSA signal both in spatial and temporal domains, in recent years, considerable efforts have been devoted to downscaling TWSA to higher resolutions. However, the majority of these studies have focused on spatial downscaling; only a few studies attempted to improve the temporal resolution. Here, we utilized an in-house developed Deep Learning (DL) based model to downscale the monthly GRACE/GFO Mass Concentration (Mascon) TWSA to daily resolution across the Contiguous United States (CONUS). The simulative performance of the DL algorithm is tested by comparing the simulations to independent (non-GRACE) dataset and the land hydrology models. In addition, we assessed the potential of our daily simulations to detect long- and short-term variations in TWSA. The validation results show that our DL-aided simulations do not overestimate or underestimate GRACE/GFO TWSA and can monitor variations in the water cycle at a higher temporal resolution.

A. Input and Output Dataset

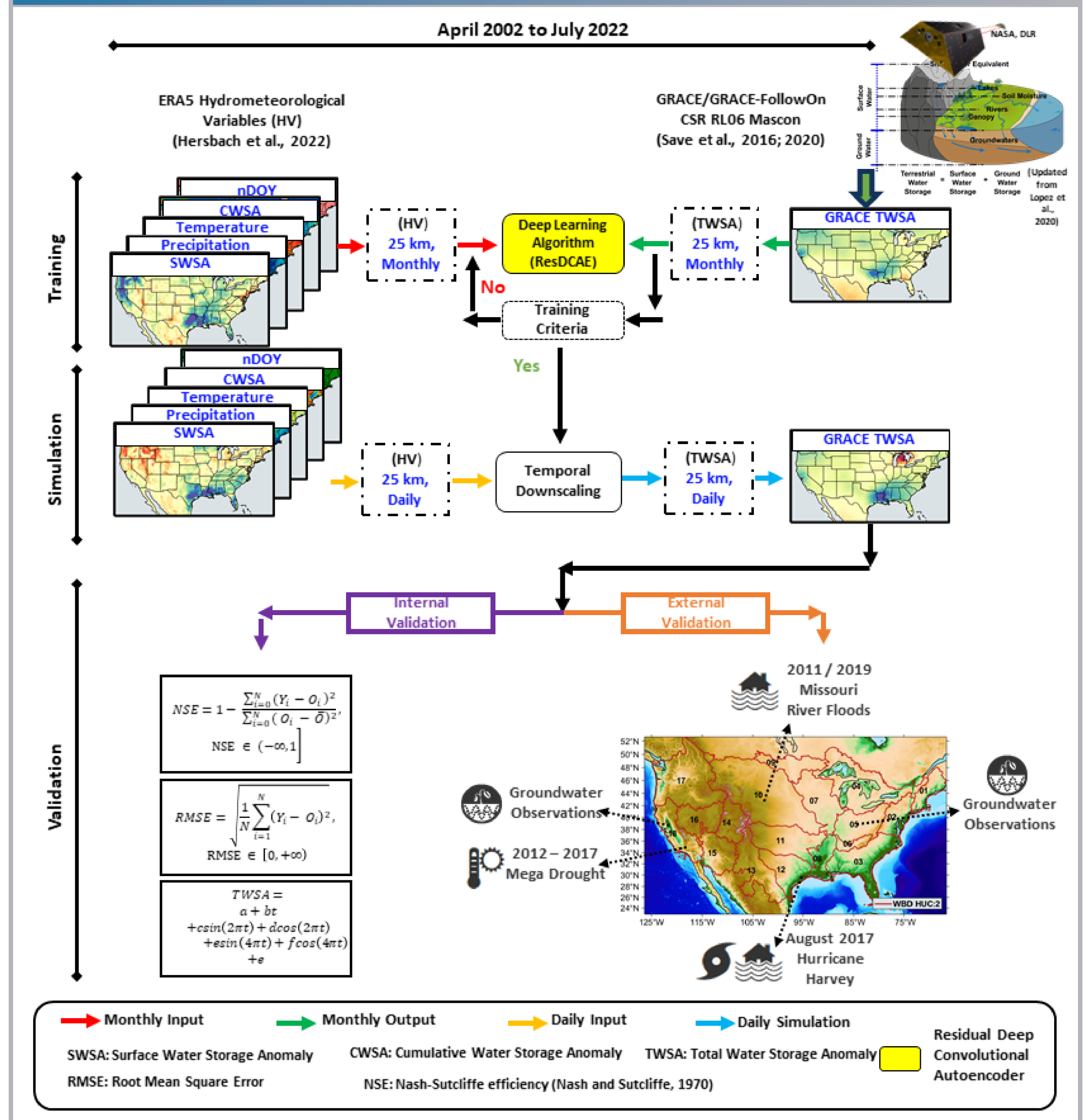

Figure 1: Flowchart of the study

- Study area and temporal partial autocorrelations of input time series

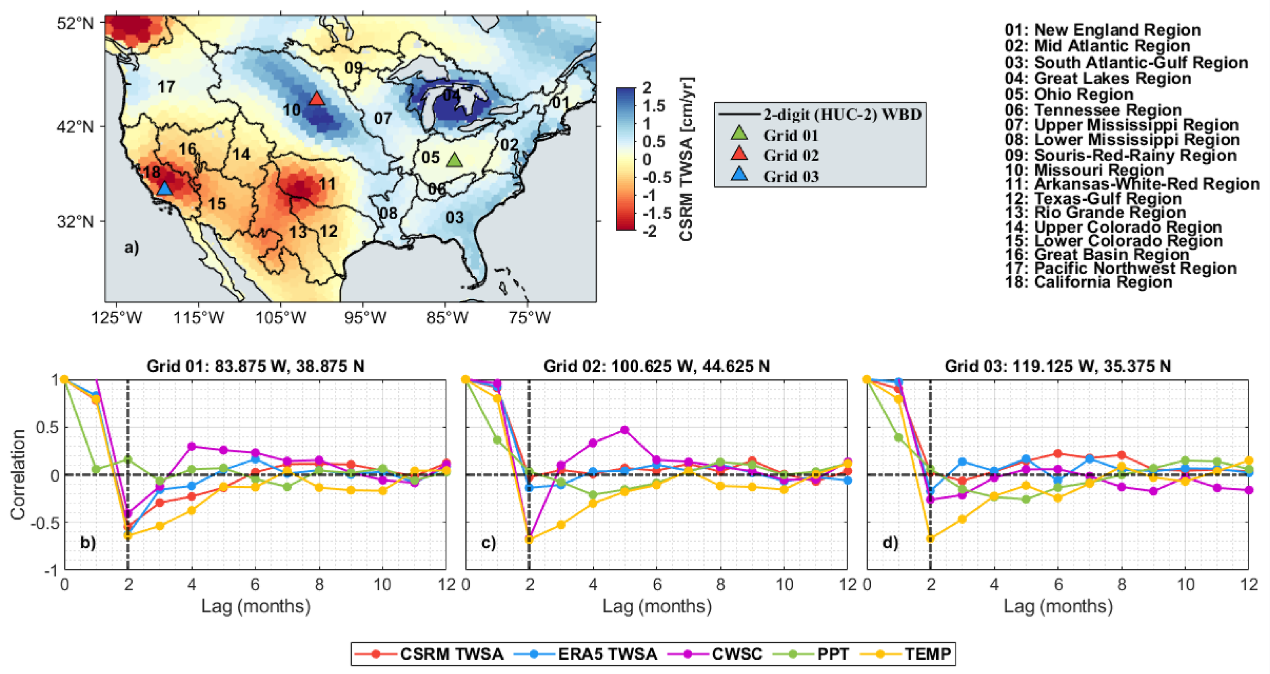

Figure 2: Trend maps derived from CSRM TWSA (a) from April 2002 to July 2022 with 2-digit Hydrologic Unit Watershed Boundry Dataset across CONUS. Temporal correlations of monthly input and output for each chosen grid-points (b-d) as red, blue and green triangle in (a).

- The processing steps and background force models considered in our approach using the EBA software of the study [?].

	Month/Day	Definition
GRACE/GFO	211	total number of existing GRACE/GFO Mascon solutions
Training	166 (80%)	number of randomly selected training months
Test	45 (20%)	number of randomly selected test months
Gap	33	Number of data gaps along the GRACE/GFO time series
Monthly Simulations	244	total number of monthly simulations
Daily Simulations	7427	total number of daily simulations

Table 1: Numbers in Deep Learning paradigm

B. Training, Simulation and Validation

- INTERNAL VALIDATION.

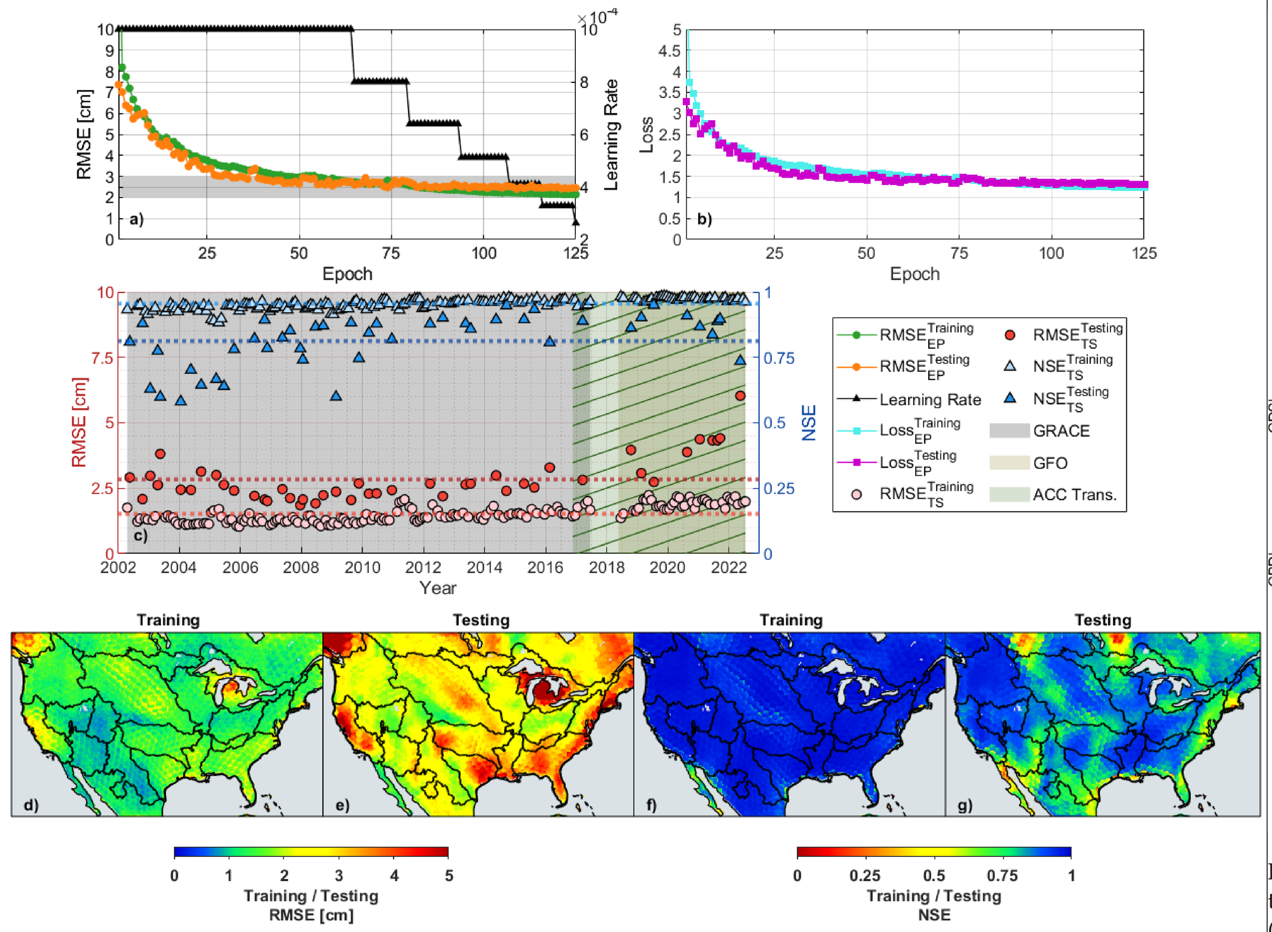

Figure 3: Training and testing RMSE (a) and Loss (b) values of ResDCAE algorithm in each iteration in training with learning rate values. The time series of RMSE and NSE scores that are calculated separately from differences between each monthly simulated and CSRM TWSA for training and testing months (c). The spatial distributions of the overall RMSE and NSE metrics over study area, i.e., CONUS, throughout study time period for training (d, f) and testing months (e, g).

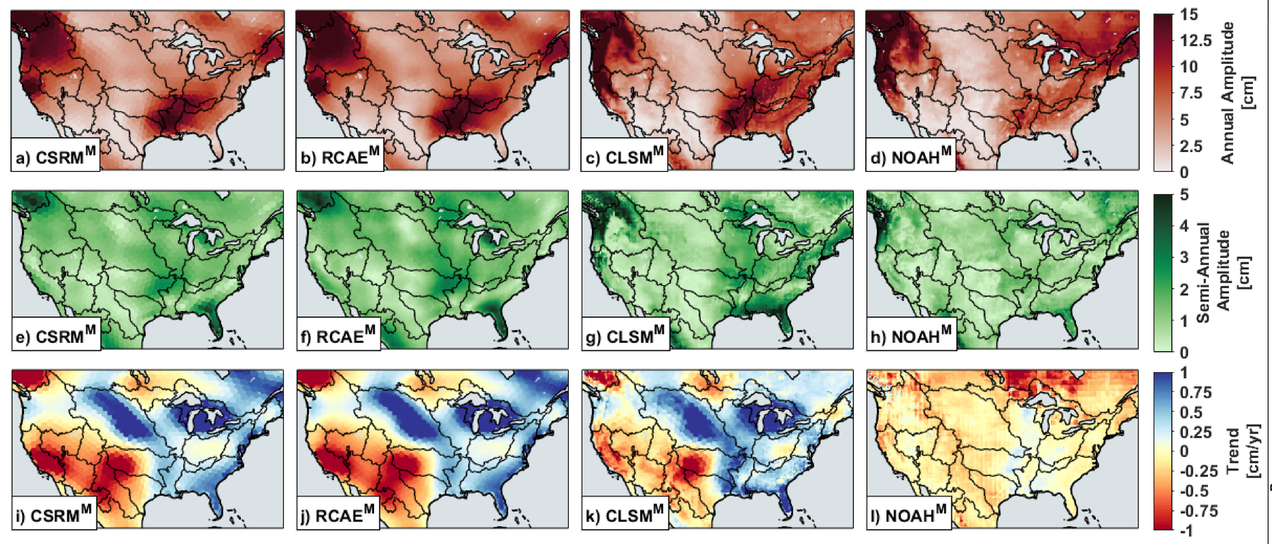

Figure 4: The spatial distributions of annual, semi-annual and trend components that are derived from the monthly TWSA signals of RCAE, CSRM, CLSM and NOAH throughout study time period.

- EXTERNAL VALIDATION.

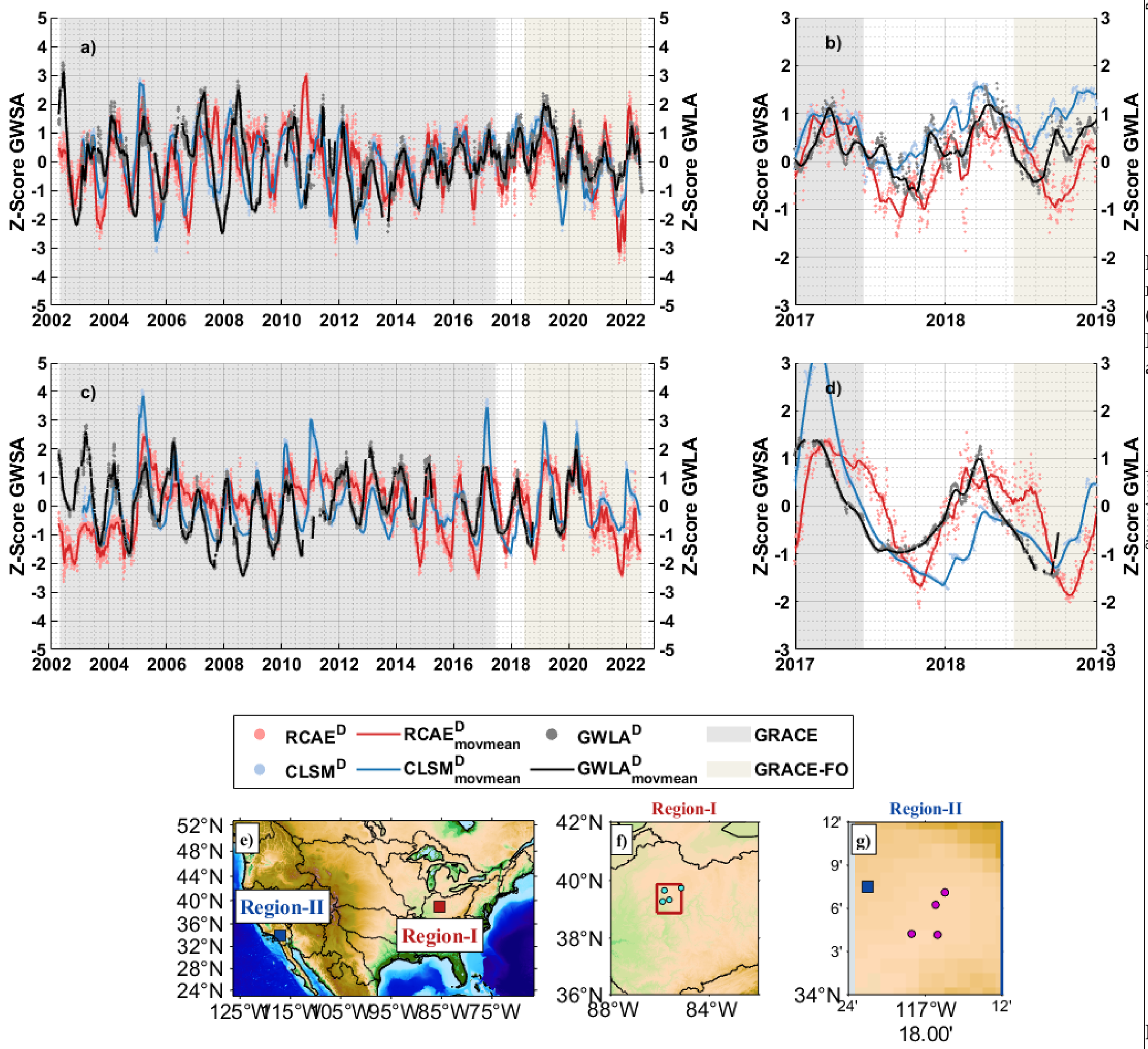

Figure 5: Comparison of detrended and normalized daily GWL measurements with the detrended and normalized daily GWSA simulations and CLSM models within 31 days moving averaged time series at region-I (a) covering 100 km spatial scale and at region – II (b) that is grid point covering 25 km spatial scale. Zoom view of time series (b, d) from 2017 – 2019 including gaps between GRACE/GFO.

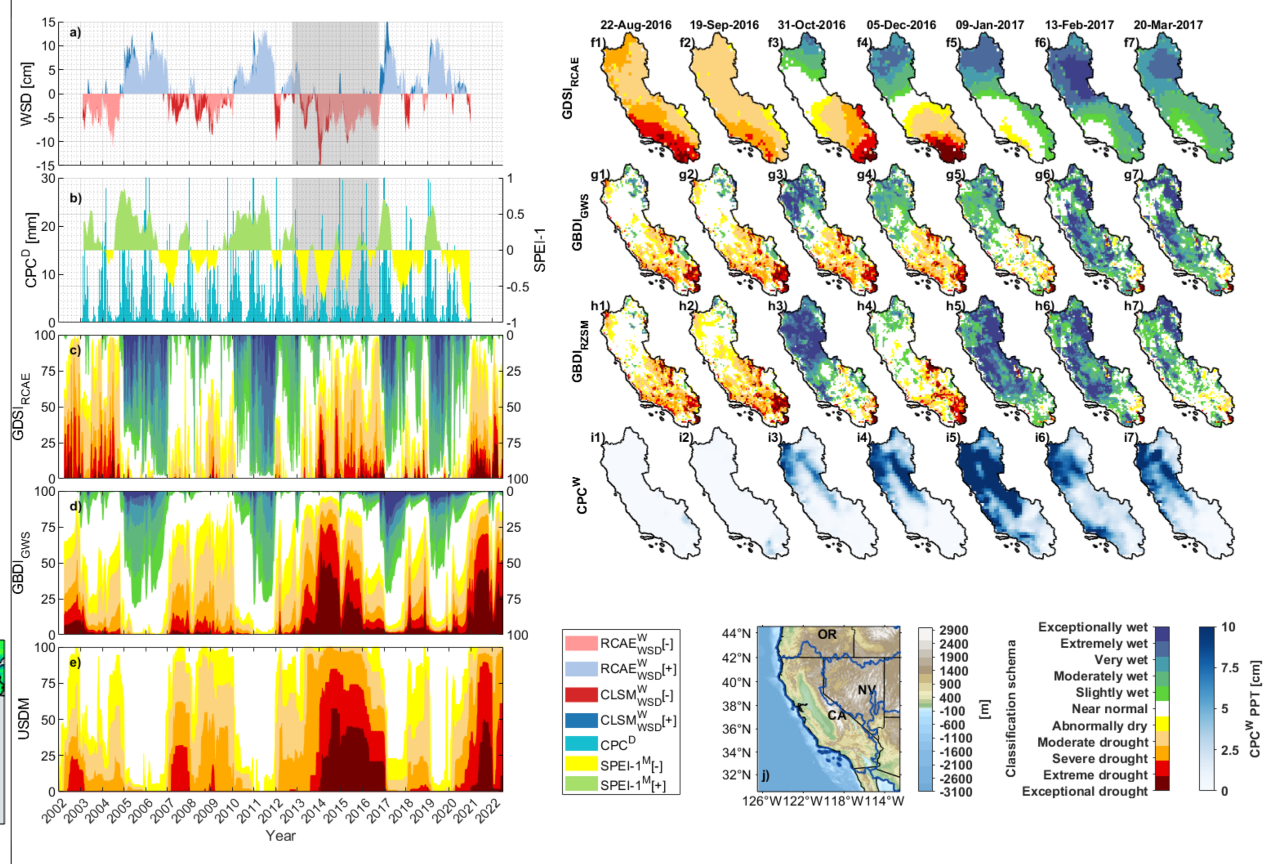

Figure 6: Water storage deficit time series for weekly RCAE and CLSM (a) as well as the monthly Standardized Precipitation Evapotranspiration Index and daily CPC Unified Gauge-Based precipitation time series (b) for California Region (HUC-2: 18). Weekly GRACE-Drought Severity Index percentiles that are calculated from weekly water storage deficit time series of RCAE (c) and groundwater percentiles of GRACE-Based Drought Indicator (d) as well as U.S. Drought Monitor percentiles (e) for California Region. Weekly GDSI maps of RCAE simulation, groundwater and root zone soil moisture indicator maps of GBDI and weekly cumulative precipitation maps that are derived from daily CPC dataset from end of August 2016 to Mar 2017 (from f1 to i7).

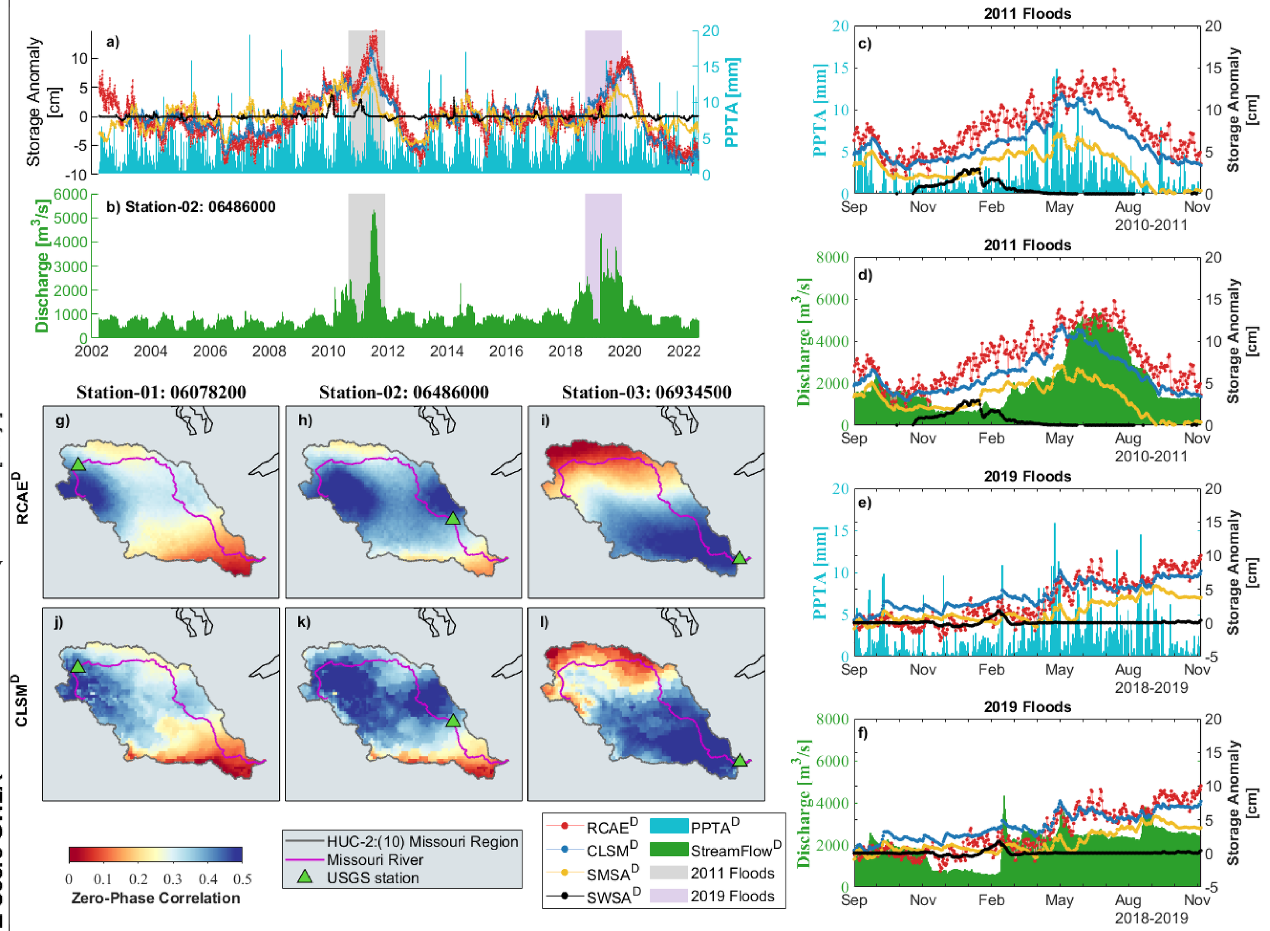

Figure 7: Detrended and deseasoned TWSA time series of daily RCAE and CLSM within daily NOAH root zone soil moisture and snow water equivalent as well as daily CPC precipitation dataset for (HUC-2: 10) Missouri River Region (a). Time series of USGS streamflow discharge gauge station of 06486000 (b). Zoom view of 2011 and 2019 Missouri River Flooding episodes (c, d and e, f). Zero-phase correlation maps between gauge stations (06078200, 06486000 and 06934500) and daily RCAE as well as CLSM TWSA time series (g, h, i and j, k, l).

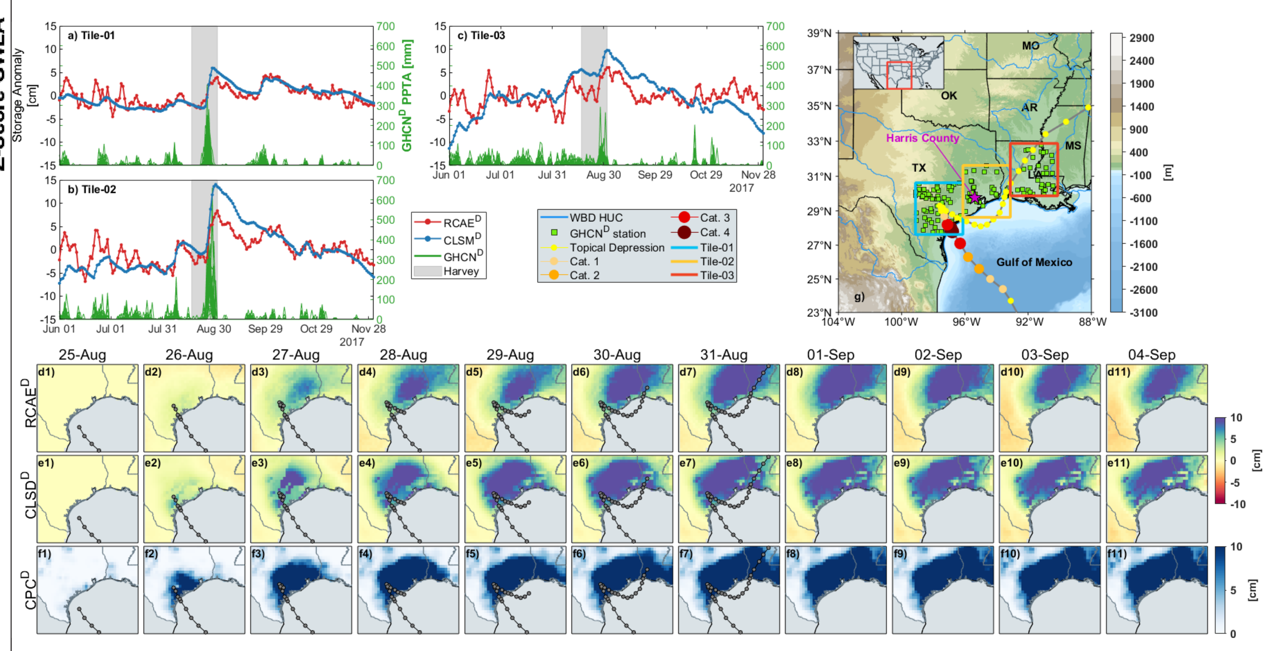

Figure 8: Daily detrended and deseasoned time series of RCAE and CLSM TWSA for Tile-01, -02 and -03 with daily precipitation time series of Global Historical Climatology Network stations that are (a, b and c) from Jun. to Dec. 2017. Maps of TWSA differences of RCAE and CLSM from reference day 25'th August to 4'th Sep. 2017 (from d1 to e11). Cumulative precipitation maps of daily CPC time series from 25'th Aug. 2017 to 4'th Sep. 2017.

C. Discussion and Conclusion

- Since ResDCAE is able to directly implement input and output data in training or downscaling, TWSA simulations can be predicted without applying de-trending, de-seasoning, or signal decomposition to the input or output.
- We simulate monthly and daily TWSAs similar to GRACE by avoiding bias or aliasing resulting from interannual or longer-term climate signals and extreme weather events.
- The simulative performance of our monthly and daily TWSAs is evaluated in internal and external validations utilizing performance metrics, i.e. RMSE and NSE, and GRACE-independent datasets in comparison to the monthly and daily Land Hydrology Model TWSAs.
- The result of internal testing confirmed that the aggregate RMSE of TWSA is approximately 2 to 3 centimeters, which is consistent with GRACE TWSA uncertainties over land areas. When monthly and daily simulated TWSA are compared to GLDAS NOAH and CLSM models using performance metrics, one of the most significant findings of this study is that our simulation is more consistent with CSR RL06 Mascon's.
- Daily simulations are able to capture both long-term and short-term variations in the TWSA signal caused by natural hazards such as floods and droughts.
- It is discovered that daily simulations are capable of accurately simulating both spatial and temporal variations from the onset to the termination of a drought.
- Using external streamflow and precipitation data, the incidence of changes resulting from extreme rainfall and flooding is demonstrated.
- This study provides a thorough evaluation of the temporal downscaling of GRACE/GFO TWSA maps. This enables us to conclude that our DL algorithm is capable of simulating TWSA variations at native monthly and daily resolutions. Thus, TWSAs that have been temporally downscaled could be used to monitor natural hazards related to the water cycle, such as floods and droughts.

D. References

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