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Research papers

Climate-driven prediction of land water storage anomalies: An outlook for water resources monitoring across the conterminous United States

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ABSTRACT

The conterminous United States (CONUS) extends over a region of contrasting climates with an uneven distribution of freshwater resources. Under climate change, most predictions concur on critical disturbances in the terrestrial hydrological cycle with consequences on freshwater resources availability. In the case of the US, an exacerbation of the contrast between dry and wet regions is expected and could drastically affect local ecosystems, agriculture practices, and communities. Hence, efforts to better understand long-term spatial and temporal patterns of freshwater resources are needed to plan and anticipate responses. Since 2002, the Gravity Recovery and Climate Experiment (GRACE) and GRACE Follow-On (GRACE-FO) satellite observations provide estimates of large-scale land water storage changes with an unprecedented accuracy. However, the limited lifetime and observation gaps of the GRACE mission have sparked research interest for GRACE-like data reconstruction. Hence, this study developed a predictive modeling approach to quantify monthly land liquid water equivalence thickness anomaly (LWE) using climate variables including total precipitation (PRE), number of wet day (WET), air temperature (TMP), and potential evapotranspiration (PET). The approach builds on the achievements of the GRACE mission by determining LWE footprints using a multivariate regression on principal components model with lag signals. The performance evaluation of the model with a lag signals consideration shows $0.5 \leq R^2 \leq 0.8$ for 41.2% of the CONUS. However, the model's predictive power is unevenly distributed. The model could be useful for predicting and monitoring freshwater resources anomalies for the locations with high model performances.

1. Introduction

Worldwide, the long-term availability of freshwater resources has become a major concern as many countries have experienced a decline of per capita available water while the demand is continuously increasing (Grafton et al., 2013; Shiklomanov and Rodda, 2004). With the ongoing climate change, many indicators presage significant disturbances in the future hydrological cycle leading to an exacerbation of the freshwater resources decline (du Plessis, 2019; Oki and Kanae, 2006; Held and Soden, 2006). As freshwater resources are unequally distributed in time and space across the globe, a further decline of the existing resources is likely to affect human communities and disturb local ecosystems. In the conterminous United States (CONUS), the unequal distribution of freshwater resources is very pronounced and aligns with the contrasting climate which ranges from arid in the southwest to humid in the southeast and the northeast. Across the country, freshwater resources are used in various sectors including agriculture (i.e. irrigation, livestock), aquaculture, energy production, mining, industries, recreation, and domestic supply. Among these sectors, agriculture sustainability concerns often rise because of a high reliance on irrigation. For instance, irrigation water withdrawal in the US during 2015 has been estimated as 118 billion gallons accounting for 42% of the total freshwater withdrawal (Dieter et al., 2018). Since 1960, the annual irrigation water withdrawal in US has been continuously above 110 billion gallons (Dieter et al., 2018). As consequences of this continuous pressure on water over the last six decades, evidences of freshwater resources depletion (e.g. groundwater decline) are being widely reported across the US (Multsch et al., 2016; Holzer and Galloway, 2005). This situation has raised concerns regarding the sustainability of US agriculture and the need to adapt water resources management plans in response to climate variability.

The components of terrestrial freshwater resources include surface water, glaciers, soil water, and groundwater. Understanding the holistic pattern of these components is critical to envision an effective water management at large-scale. Satellite images such as those from the Gravity Recovery and Climate Experiment (GRACE) and GRACE Follow-On (GRACE-FO) missions enable large-scale understanding of earth surface processes. Indeed, the GRACE satellite mission was

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launched in March 2002 and has continuously collected detailed measurements of Earth's gravity field anomalies for about 15 years (March 2002 to October 2017). GRACE data have been used to estimate the land water storage anomalies at a monthly basis with an accuracy of 1.5 cm equivalent water height (Famiglietti and Rodell, 2013; Scanlon et al., 2012). Even though this capacity of GRACE to provide comprehensive measurement of land water storage anomalies (Landerer and Swenson, 2012) is an undeniably prominent achievement, the data gaps and short-time frame of GRACE observations is a limitation for long-term appreciation of land water storage patterns. The need to reconstruct GRACE-like land water storage changes outside GRACE mission periods has led researchers to investigate data-driven modeling approaches using climate inputs (Li et al., 2020; Yin et al., 2019; Humphrey and Gudmundsson, 2019; Nie et al., 2016). For instance, Humphrey et al. (2017) reported a grid-point land water storage data reconstruction for the period 1985 to 2015 using a statistical model based on precipitation and temperature. Likewise, Yin et al. (2019) attempted to reconstruct long-term GRACE-like data for a period prior to 2002 using precipitation, runoff, and evapotranspiration. Recently, Li et al. (2020) evaluated various analytical approaches for land water storage change retrieval at basin scale using precipitation, land surface temperature, sea surface temperature, and climate indices. While these studies contributed significantly to the understanding of GRACE-like water storage anomalies, more research efforts are needed to reach an unified predictive approach. Indeed, the perspective of forecasting these anomalies is relevant for water resources planning. For instance, an accurate estimate of past and future land water storage anomalies at a given location, could be used to plan or improve water resources management strategies. Hence, the aim of the present study is to propose a potentially predictive framework of land water storage anomalies using climate variables with an inclusion of lag signals.

This study builds on the achievement of the fifteen-year GRACE satellite mission by developing a predictive method for retrieving monthly land water storage signals from climate variables. The use of climate inputs for GRACE-like anomalies estimate assumes that the temporal change of land water storage is governed by land–atmosphere exchange (Sadeghi et al., 2020; Crow et al., 2017). Individually, climate variables exert an influence on the terrestrial water cycle such that for certain regions of the globe, these variables are the main drivers of the water balance (Mueller Schmied et al., 2016; Milly, 1994). Thus, in this study, large-scale monthly land water storage anomalies are assumed to be primarily determined by climate variables. In addition to reporting the method and results, this paper analytically discusses the outcomes and lays the ground for potential considerations in freshwater resources management across the CONUS.

2. Data and method

2.1. Data

In accordance with the study's scope which is to develop a modeling framework to predict land water storage anomalies, 15 years remote sensing and climate datasets were used. The remote sensing dataset consisted of the liquid water equivalence thickness anomalies (LWE) derived from GRACE satellite mission measurement of earth gravity field variation (Swenson, 2012; Landerer and Swenson, 2012). LWE is a measurement of the variation of the vertical extent of land water storage including snow, surface water (i.e. rivers, lakes, reservoirs), soil moisture and groundwater. GRACE's LWE anomalies are estimated in centimeters of equivalent water thickness and released as monthly gridded time-series with a spatial resolution of 1° in both latitude and longitude. At a given grid, the monthly GRACE land water storage deviations were estimated relative to a baseline temporal average of the period 2004–2009 (Cooley and Landerer, 2019). As GRACE satellite's science mission spanned from March 2002 to October 2017, continuous monthly LWE estimates were processed and released separately by three mandated institutions including the Center for Space Research (CSR), the Geo Forschungs Zentrum (GFZ), and the Jet Propulsion Laboratory (JPL). The 15 years monthly gridded time series data released by CRS, GFZ, and JPL were collected from the National Aeronautics and Space Administration (NASA) database (www.nasa.gov). As recommended by Sakumura et al. (2014), the ensemble average of the three LWE datasets (i.e. CRS, GFZ, and JPL) was computed to limit uncertainties.

Along with the ensemble averaged LWE dataset, the study used monthly climate data including total precipitation (PRE), number of wet days (WET), average air temperature (TMP), and the potential evapotranspiration (PET). The climate data were collected from the University of East Anglia's Climatic Research Unit (CRU) datasets (Harris et al., 2014). Especially, the CRU's time series version 4.03 datasets were considered and the 0.5° × 0.5° gridded time series of PRE, WET, TMP, and PET were retrieved for the time span 2002–2017, matching the remote sensing data availability period. To generate monthly timeseries of PRE, WET, and TMP, the CRU uses two major sources of historical climate data including the World Meteorological Organization (WMO) and the National Oceanographic and Atmospheric Administration (NOAA) databases (Harris et al., 2014). However, the CRU's PET time-series were estimated using the Food and Agricultural Organization's Penman–Monteith method (Harris et al., 2014; Ekstrom et al., 2007). As the study focused on the CONUS regions, only the grids encompassed by the region were considered for the study. To match the grid resolution of the climate data, the LWE data were rescaled to a 0.5° × 0.5° resolution. Table 1 presents an overview of all the data.

2.2. Method

In general, the terrestrial water balance is influenced by climatic, anthropogenic, geologic, pedologic, topographic, and ecological factors (Mueller Schmied et al., 2016; Oki and Kanae, 2006; Milly, 1994). These factors affect differently the hydrosphere, such that in many regions of the globe, the variations of land water storage are mainly driven by a few dominant factors. This is true with climate factors which are known to play a major role in the terrestrial water cycle (Mueller Schmied et al., 2016; Kunstmann et al., 2008). The present

Table 1
Overview of the data used in the study.

Data	Designation	Time-period	Resolution		Source
			Temporal	Spatial	
Liquid Water Equivalent Thickness Anomaly (cm)	LWE	April 2002-June 2017*	monthly	1.0 × 1.0°	GRACE satellite images
Total precipitation (mm)	PRE	April 2002-June 2017	monthly	0.5 × 0.5°	CRU database
Number of wet days	WET	April 2002-June 2017	monthly	0.5 × 0.5°	CRU database
Average air temperature (°C)	TMP	April 2002-June 2017	monthly	0.5 × 0.5°	CRU database
Average daily potential evapotranspiration (mm/day)	PET	April 2002-June 2017	monthly	0.5 × 0.5°	CRU database

* GRACE data for the following months were not included: June-July 2002, June 2003, January and June 2011, May and October 2012, March and August-September 2013, February 2014, July and December 2014, October-November 2015, April 2016, September-October 2016, February 2017.

study proposes a multivariate model for predicting monthly land water storage variations based on climate variables. The monthly climate variables include PRE, WET, TMP, and PET. A general challenge with multivariate models is the risk of redundancy in the explanatory variables (Todeschini et al., 2004). In the present case, the interplays of climate variables are factual and need to be understood in order to enhance the variables representation in a multivariate model. Hence, the analytical approach used in the study included (i) trend analyses of LWE anomalies, (ii) marginal correlation analysis between LWE and individual climate variable with and without lag time consideration, (iii) multivariate modeling of land water storage changes. All the analyses were conducted for individual 0.5° × 0.5° grid encompassed by the CONUS territory (3452 grids in total).

The trend analyses were conducted on the 15 years monthly gridded time-series of LWE. The objective was to investigate regional patterns of land water storage anomalies across the CONUS. For the analysis, the Mann-Kendall monotonic trend (Hamed, 2008) was tested for individual grid. Indeed, each grid j is associated with a time-series $LWE_j = \{[LWE_{j,i},\ date_i],\ \ldots,[LWE_{j,n},\ date_n]\}$ where $1 \leq i \leq n$, $LWE_{j,i}$ is the measured land water storage anomaly of j at $date_i$ comprised between April 2002 and June 2017. *Kendall's* τ values (Bolboaca and Jäntschi, 2006) were estimated at grids level and the significance at p-value = 0.05 was determined to classify each grid as 'positive trend', 'negative trend', or 'no trend'. Given a random grid j associated with the time-series LWE_j, the corresponding *Kendall's* τ *(j)* is calculated using the equation (1) where n_c and n_d are respectively the numbers of concordant and discordant pairs, t and u the number of ties within LWE and dates.

$$Kendall\ \tau(j) = (n_c - n_d)\left[\left(\frac{n(n-1)}{2} - t\right)\left(\frac{n(n-1)}{2} - u\right)\right]^{-0.5} \tag{1}$$

Marginal correlation analyses were separately conducted by coupling the time series of LWE anomalies with each climate variable (i.e. PRE, WET, TMP, PET). Time lags of 0, 1, 2, 3 months were considered between LWE and each climate variable X. For a random grid j, the coefficient of determination $R^2_{lag}(j)$ was estimated with lag times $lag = \{0,\ 1,\ 2,\ 3\}$ using the equation (2) where $L\bar{W}E_j$ and $\bar{X}_j$ are respectively the average land water storage anomaly and the average climate variable value for the grid j.

$$R^2_{lag}(j) = \frac{\left(\sum_{i=1}^{n}(LWE_{j,i} - L\bar{W}E_j)(X_{j,i+lag} - \bar{X}_j)\right)^2}{\sum_{i=1}^{n}(LWE_{j,i} - L\bar{W}E_j)^2\sum_{i=1}^{n}(X_{j,i+lag} - \bar{X}_j)^2} \tag{2}$$

The objective of the marginal correlation analysis was to evaluate lag signals and for eventual inclusion in the modeling approach. The proposed model was a multivariate regression on principal components (Sousa et al., 2007; Jolliffe, 1982). Indeed, analytical methods developed to investigate the GRACE-like LWE retrieval include multilinear regressions, artificial neural network, autoregressive model, etc. (Yin et al., 2019; Yang et al., 2018; Humphrey et al., 2017; Nie et al., 2016). Recently, Li et al. (2020) compared several of these climate-based analytical methods for GRACE data reconstruction and concluded on the robustness of the multilinear regression on principal components. This study sought to fill an information gap by exploring the joint inclusion of critical land–atmosphere components such a PRE, WET, TMP, PET along with their related marginal lag effects. The modeling framework developed in the study included two stages which were both carried at grid level. The first stage is an application of principal component analysis (PCA) on the four climate variables represented by their time-series. For each grid, the PCA application generated four principal components (PCs) which were orthogonal but captured the essential variance imbedded in the original four climate variables (i.e. PRE, WET, TMP, and PET). Hence, PCA was used here to eliminate redundant effects among the four explanatory climate variables (Abdi and Williams, 2010). The second stage of the model framework was an application of a multivariate regression on PCs' scores for estimating LWE anomalies. For a grid j, Equation (3) presents the model where $PC1_j$, $PC2_j$, $PC3_j$, $PC4_j$ are the principal components; α_j, β_j, χ_j, δ_j and ε_j are the parameters of the model.

$$LWE_{j,i} = \alpha_j PC1_{j,i} + \beta_j PC2_{j,i} + \chi_j PC3_{j,i} + \delta_j PC4_{j,i} + \varepsilon_j \tag{3}$$

At this stage, the inclusion of lag time signals was evaluated to propose a potentially predictive framework for LWE with PCs' scores as inputs. The performances of the model with and without lag signals inclusion were evaluated at grids level by calculating indicators such as R^2, and the root mean squared errors (RMSE). The RMSE is given by equation (4) where $LWE_{j,i}$ and $LWE'_{j,i}$ are respectively the observed and simulated land water storage anomaly for grid j at date i.

$$RMSE\ (j) = \left[\frac{1}{n}\sum_{i=1}^{n}(LWE_{j,i} - LWE'_{j,i})^2\right]^{0.5} \tag{4}$$

3. Results

3.1. Trends of land water storage anomalies

Average LWE anomalies have been calculated for the 15 years monthly land water storage changes estimated by GRACE satellite mission. Fig. 1a presents the spatial distribution of these average values across the CONUS. Overall the average land water storage anomalies in the CONUS, gradually change from North to South and East to West. Specifically, Fig. 1a shows northward positive average land water storage anomalies while negative anomalies are observed in the southwestern part of the US. These tendencies may be linked with the results of the Mann-Kendall trend analysis reported in Fig. 1b which shows a demarcation of three zones of LWE anomalies trends. These include a zone of positive trend in the north, a zone of negative trend in the southwest and both zones separated by a transitional zone with no significant trend. The patterns observed in both Fig. 1a and b are consistent and they confirm the uneven distribution of freshwater resources across the CONUS. A persistence of the decreasing trend in the southwest and an increasing trend in the north and the east coast is likely to accentuate the regional water resources contrast. On the long run, such contrast could have a profound impact on human activities and the environment.

3.2. Lag signals analysis

The marginal inter-relations between LWE anomalies and each of the explanatory variables (i.e. PRE, WET, TMP, and PET) were evaluated using correlation analyses. The outcomes are presented as boxplots of R^2 values (Figs. 2b, d, 3b, d) along with maps showing the spatial distribution of the highest lag signals (Figs. 2a, c, 3a, c). Especially, Fig. 2 reports the analyses related to the couples (LWE, PRE) and (LWE, WET), while Fig. 3 reports the analyses of (LWE, TMP) and (LWE, PET). The lag time signals analyses show some similitudes between the couples (LWE, PRE) and (LWE, WET) in Fig. 2, and the couples (LWE, TMP) and (LWE, PET) in Fig. 3. Specially for the couples (LWE, TMP) and (LWE, PET), the two-month lag time signals are the strongest (Fig. 3b and d). For instance, the inclusion of a two-months lag time, raises the median of R^2 values from 0.07 to 0.37 for (LWE, TMP), and from 0.02 to 0.38 for (LWE, PET). Similitudes are also noticeable in Fig. 3a and c which display the spatial distribution of the R^2 with the two-month lag time. In the case of the couples (LWE, PRE) and (LWE, WET) the disparity among the lag signals (Fig. 2b and d) are not as remarkable as it is in Fig. 3b and b. However, a closer appraisal shows a higher median and interquartile range for the one-month lag signals, particularly in Fig. 2d. Fig. 2a and c present the spatial distribution of the R^2 with one-month lag for the couples (LWE, PRE) and (LWE, WET)

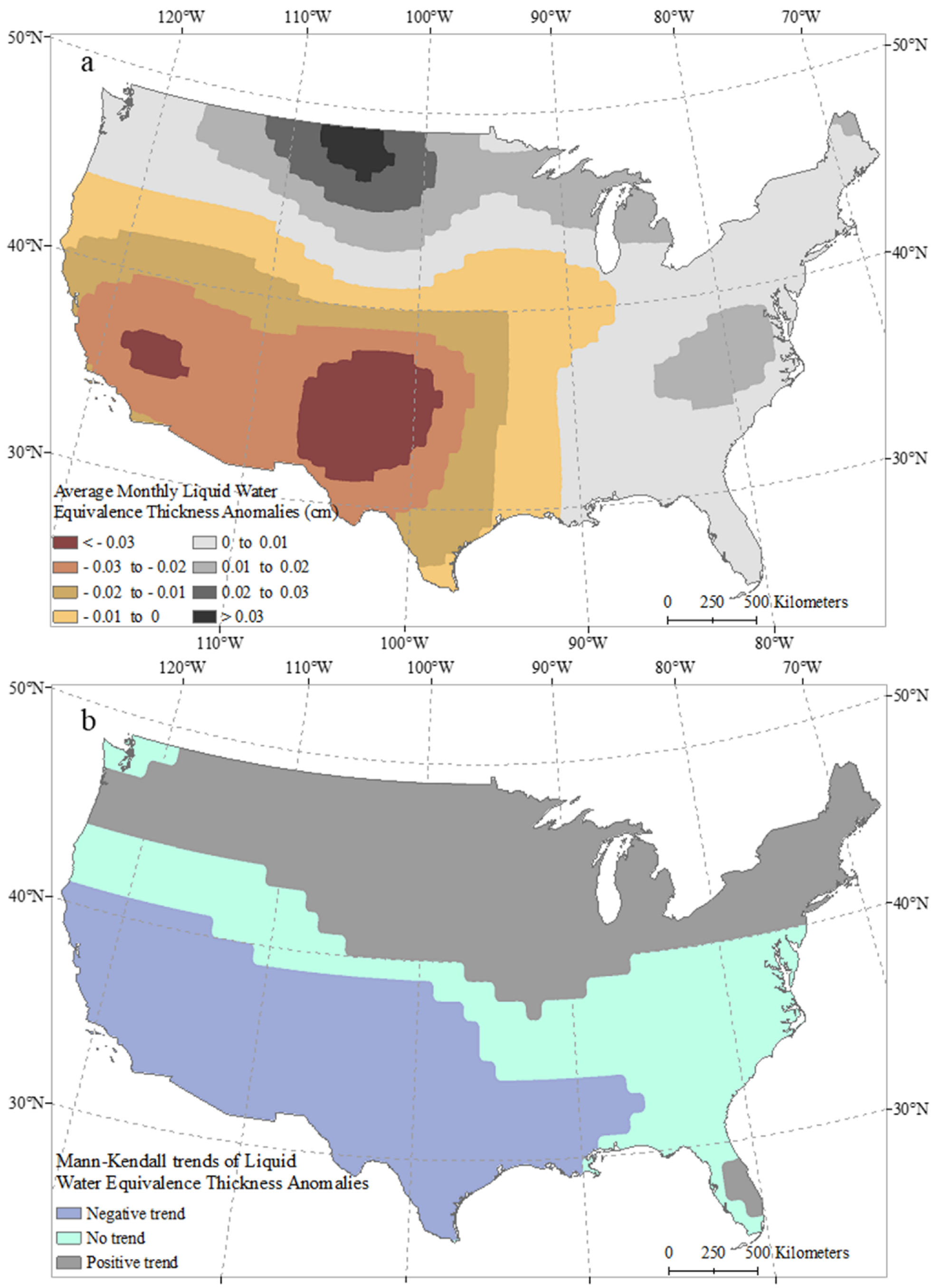

Fig. 1. Overview of the average (a) and trend (b) of the monthly liquid water equivalence thickness anomalies (LWE) across the conterminous United States. The monotonic Mann-Kendall trends were tested at p-value = 5%.

respectively. Overall, the lag time analyses suggest predictive relationships between LWE anomalies and the climate events during the previous months. These signals can henceforth be considered when developing a predictive framework for land water storage anomaly estimates.

3.3. Predictive model for land water storage anomalies

Two scenarios of multivariate regression on PCs were applied to the climate variables for estimating land water storage anomalies. The first scenario assumed no lag time between the explanatory variables and the response (i.e. LWE), while the second scenario emphasized the inclusion of lag time between the explanatory variables and the response. In accordance with the lag signals analysis, the second scenario considered one-month lag time for PRE and WET, two-month lag time for TMP and PET. For each of the scenarios, the model performances were evaluated by calculating the RMSE and the R^2 values of individual grid. The results of this evaluation are reported in Table 2 and Fig. 4. Table 2 presents the percentage areas of the CONUS associated with different ranges of R^2 and RMSE values for each scenario. With no lag in the model, 7.7% of the total area has $R^2 \geq 0.5$ while the inclusion of lag signals increases this percentage to 41.2%. This remarkable increase, as portrayed by Fig. 4a and b, indicates a significant improvement of the ability of the model to estimate land water storage anomalies. This tendency corroborates with the RMSE analysis which showed a remarkable increase of accuracy (Fig. 4c and d) as the percentage of areas with RMSE < 0.05 shifts from 43.4% to 66.4%. Hence, the multivariate regression on PCs performed better with the inclusion of lag

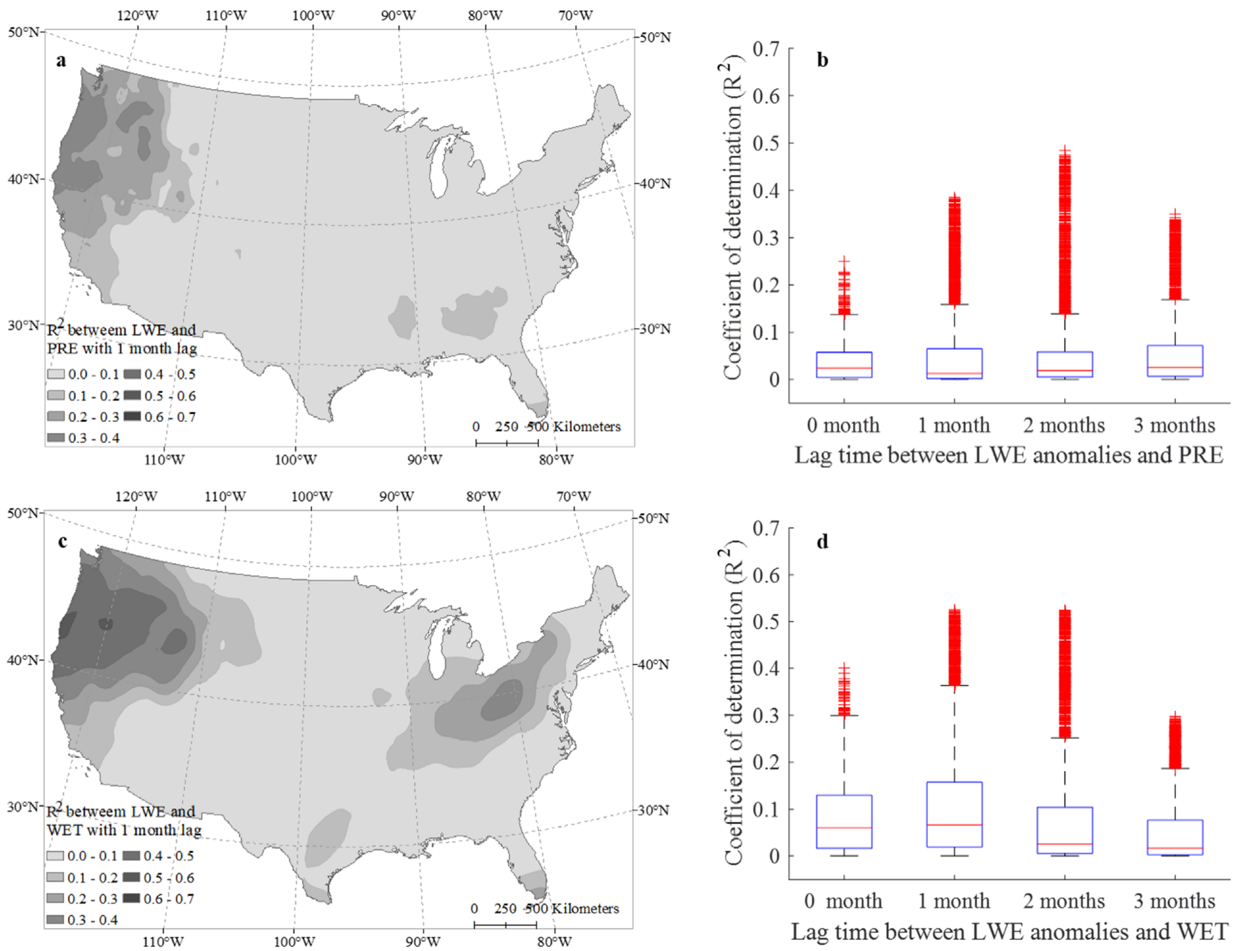

Fig. 2. Analysis of the lag time effect on the coefficient of determination (R^2) between GRACE satellite derived monthly liquid water equivalence thickness anomalies LWE and the monthly total precipitation (PRE) and the monthly number of wet days (WET). (a) Presents the spatial distribution of R^2 between LWE and PRE with one-month lag; (b) presents the boxplots or R^2 between LWE and PRE with different lag times. (c) Presents the spatial distribution of R^2 between LWE and WET with one-month lag; (d) presents the boxplots or R^2 between LWE and WET with different lag times.

signals. Interestingly, the lag signal inclusion also shows the opportunity of predicting closely the land water storage anomalies at a given month based on the knowledge of PRE and WET from the previous month, and TMP and PET from two months prior. The model performance of the model varies across the CONUS. This aspect is presented in Fig. 5 which shows the spatial distribution of the performance indicator values (R^2 and RMSE) for both modeled scenarios (i.e. no lag, with lag).

A juxtaposition of Fig. 5a and b shows an improvement of the lag signals inclusion on the model performance. Likewise, a comparison between Fig. 5c and d shows an expansion of areas with lower RMSE which indicates an enhancement of the model estimates. In addition, relevant spatial patterns are noticeable in the scenario with lag signals inclusion. For instance, in Fig. 5b, grids with high model performances (e.g. $0.5 \le R^2 \le 0.8$) are collocated. This collocation offers the possibility to delineate regions where this model could be used for predicting and monitoring water resources anomalies.

3.4. Testing the model's predictive capacity

The model's predictive capacity was tested for all the CONUS grids using the period 2002–2014 for calibration and the period 2015–2017 for validation. The calibration procedure consists in estimating the parameters α_j, β_j, χ_j, δ_j and ε_j in Equation (3). The estimated parameters are thereafter used in the model to predict GRACE-like LWE anomalies for the validation period. The model performance during the calibration and the validation stage were analyzed and reported in Fig. 6a and b which present boxplots of performance indicators at the validation stage based on ranges of R^2 and RMSE at the calibration stage. Hence, in Fig. 6a, the boxplots corresponding to the grids with $R^2 \ge 0.50$ at calibration, show medians close or above 0.50. This result sustains the predictive capacity of the model for the grids with high model performance values. In Fig. 6c and d, the performance indicators of the model when calibrated based on the period 2002–2014 (subset of the data availability period), were compared to those based on the period 2002–2017 (entire data availability period). The results show that the calibration period 2002–2014 is representative to the period 2002–2017. However, such a configuration may not be the case when a shorter subset the satellite records time period is used to calibrate the model for GRACE-like LWE anomalies predictions. Owing to the statistical uncertainties related to the lack of data, the use of large time periods data for calibration is desirable for a robust computational model setting (Lee et al., 2019).

4. Synthesis and discussion

The study unveiled salient patterns of freshwater resources across the CONUS. The Mann-Kendall trend analysis of the 15 years GRACE's LWE anomalies revealed three major zones in the CONUS including a zone with an increasing trend in the north, a zone with a decreasing trend in the southwest, and a transitional zone with no significant trend (Fig. 1b). The decreasing trend of LWE anomalies observed in the

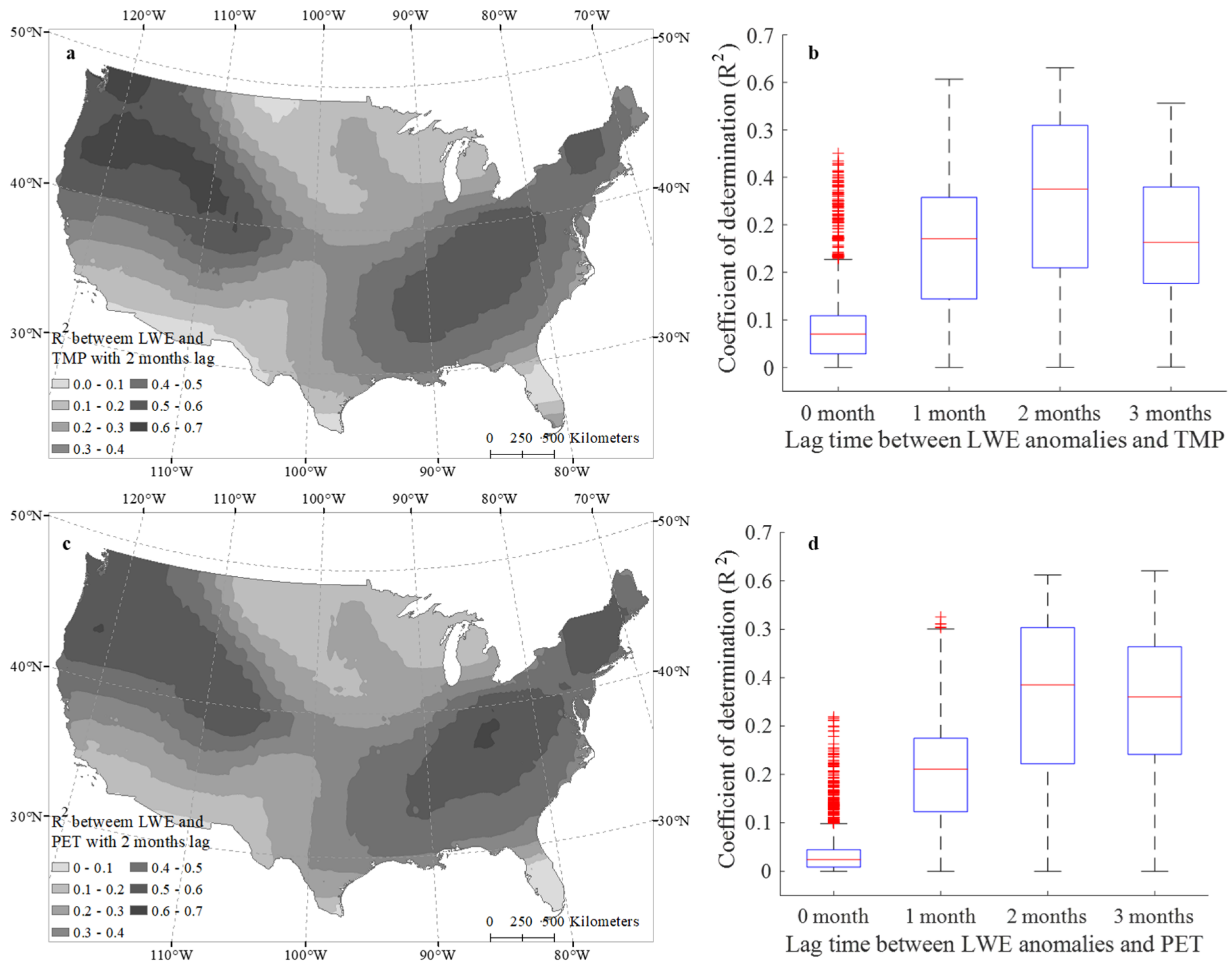

Fig. 3. Analysis of the lag time effect on the coefficient of determination (R^2) between GRACE satellite derived monthly liquid water equivalence thickness anomalies (LWE) and the monthly average air temperature (TMP) and the monthly average potential evapotranspiration (PET). (a) Presents the spatial distribution of R^2 between LWE and TMP with two-months lag; (b) presents the boxplots or R^2 between LWE and TMP with different lag times. (c) Presents the spatial distribution of R^2 between LWE and PET with two-months lag; (d) presents the boxplots or R^2 between LWE and PET with different lag times.

Table 2
Comparing the performance of the multiple regression on principal component model with and without lag time between the climate variables (predictors) and the LWE anomalies (predictand).

Percentage Area by R^2 ranges (%)				Percentage Area by RMSE ranges (%)			
R^2	No lag in model	Lag in model	Δ*	RMSE	No lag in model	Lag in model	Δ*
0.0–0.1	5.9%	0.0%	−5.9%	0.00–0.01	0.0%	0.0%	0.0%
0.1–0.2	30.5%	6.0%	−24.6%	0.01–0.02	0.8%	0.9%	0.1%
0.2–0.3	19.7%	20.3%	0.6%	0.02–0.03	2.8%	4.2%	1.4%
0.3–0.4	22.8%	15.3%	−7.4%	0.03–0.04	15.5%	29.0%	13.5%
0.4–0.5	13.4%	17.2%	3.8%	0.04–0.05	24.3%	32.3%	8.0%
0.5–0.6	7.1%	22.6%	15.5%	0.05–0.06	33.3%	29.2%	−4.2%
0.6–0.7	0.6%	18.6%	18.0%	0.06–0.07	19.0%	4.5%	−14.6%
0.7–0.8	0.0%	0.0%	0.0%	0.07–0.08	4.2%	0.0%	−4.2%

* Δ is the difference computed as Percentage Area (Lag in model) – Percentage Area (No lag in model).

southwest is consistent with previous studies which reported evidences of freshwater resources decline in the southwest US (Sohoulande, 2017; Scanlon et al., 2012; Holzer and Galloway, 2005). In the long term, a persistence of the declining trend could affect human society and disturb local ecosystems as all organisms require water for their survival (Oki and Kanae, 2006). This could be perceived as an alert to envision plans for freshwater resources sustainability. For instance, with the high dependency of US agricultural sector on groundwater withdrawal (Dieter et al., 2018), food security could be compromised as the population grows while water resources decline. Hence, the sustainability of human society depends on freshwater availability in time and space. At a given location, the land water storage includes snow, surface water, soil moisture, and groundwater. The fluctuation of land water storage is often a result of multiple interplays between biophysical factors (Bosilovich et al., 2017; Wang et al., 2012). Understanding these interplays is important for modeling the land water storage. At large scales, GRACE's LWE anomalies are good estimates of the monthly variation of the vertical extent of land water storage (Cooley and Landerer, 2019; Famiglietti and Rodell, 2013). As intended, 15 years monthly GRACE's LWE and climate data have been used to develop a potentially predictive framework for land water storage anomalies.

The study evaluated the marginal relationships between the monthly GRACE's LWE anomalies and each of the climate variables PRE, WET, TMP, and PET. The overall results show low R^2 values, but lag signal analyses unveil a substantial increase of R^2 values particularly for the couples (LWE, TMP) and (LWE, PET). For instance, with a two-month lag time, the median of R^2 reached 0.37 for (LWE, TMP), and 0.38 for (LWE, PET). In view of the spatial scale, the lag signals are probably the result of complex biophysical interplays which can be portrayed as the delayed effect of rain on surface flow (Muthanna et al., 2008) or vegetation (Sohoulande et al., 2015). The lag signals have been integrated in a multivariate regression on PCs model (Sousa et al., 2007; Jolliffe, 1982) for estimating land water storage anomalies. The

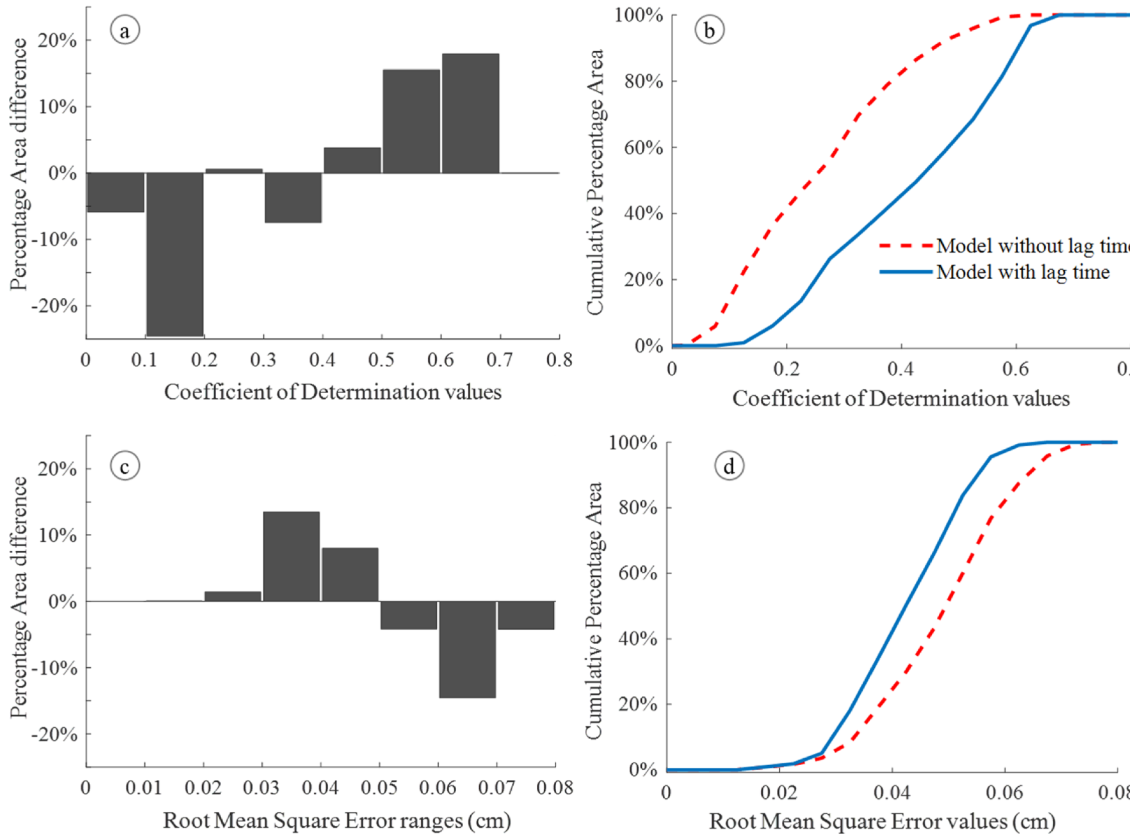

Fig. 4. Analysis of the area coverage changes within ranges of R^2 and RMSE as affected by the inclusion of lag time into the multivariate regression on PCs model.

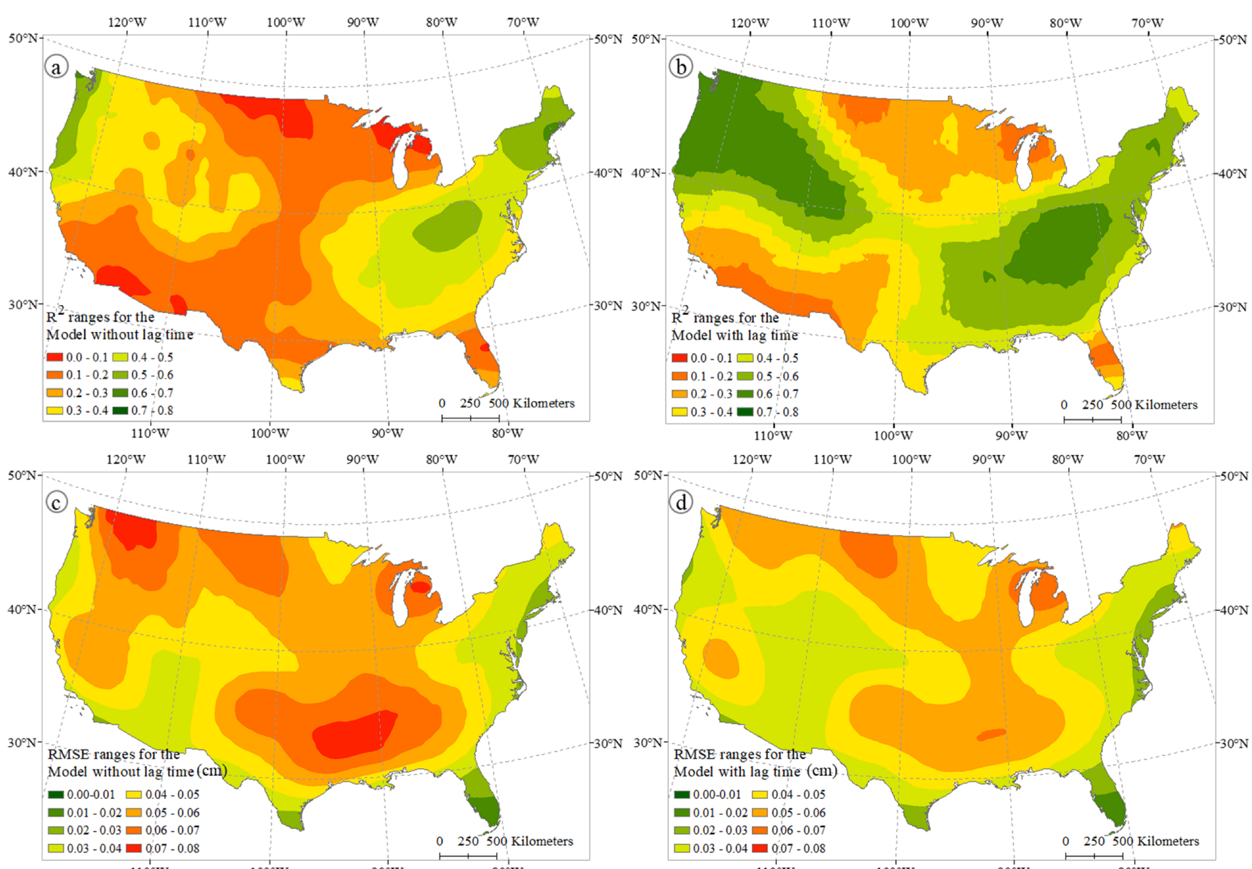

Fig. 5. Spatial patterns of the multivariate regression on PCs model across the conterminous United States. a and c present the model performance (i.e. R^2 and RMSE distribution) without lag time consideration, b and d present the performance with lag time consideration in the model.

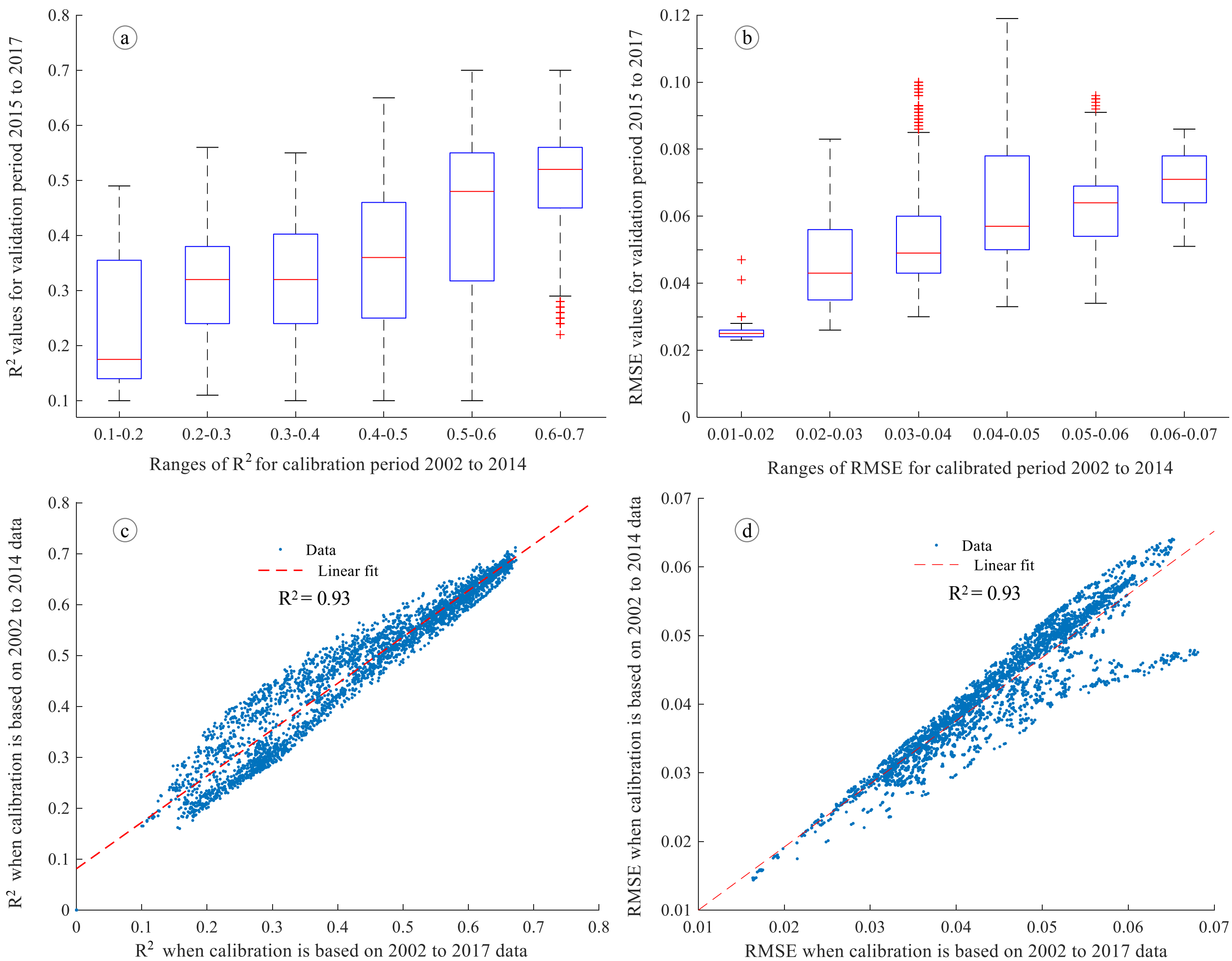

Fig. 6. Testing the predictive capacity of the multivariate regression on PCs model with lag time consideration using the period 2002–2014 for calibration and 2015–2017 for validation. All the CONUS grids are addressed. a and b report boxplots of R^2 and RMSE at validation stage based on ranges of performances at calibration. c and d compares the performance indicators of the model when calibrated based two different periods (i.e. 2002–2014, 2002–2017).

modeling framework has two steps: the first step is a principal component analysis on climate variables (i.e. PRE, WET, TMP, and PET); the second step is a multivariate regression carried on the principal components. Li et al. (2020) asserted the robustness of the multivariate regression on PCs for GRACE-like water storage change retrieval at basin levels. The PCA eliminates redundant signals among the targeted climate variables. The resulting PCs are orthogonal variables (Abdi and Williams, 2010) and are henceforth used as inputs in lieu of the original explanatory climate variables. For individual 0.5° × 0.5° grid encompassing the CONUS, the parameters of the model have been estimated for two distinct scenarios, one with no lag and another with lag signals. The grid-wise evaluation of the model across the CONUS shows different performance levels (Fig. 5). However, the inclusion of lag signals has clearly enhanced the model performance. In addition, the spatial patterns of the performance indicators (i.e. R^2 and RMSE) suggest potential usage of the model for land water storage monitoring. Indeed, acceptable performances (i.e. $R^2 \geq 0.5$) were noted for approximatively 41.2% of the CONUS. For the corresponding grids, one can assume that the temporal change of land water storage is explained by climate variables' fluctuations. The predictive capacity of the model was tested for all the CONUS grids using the time slices 2002–2014 and 2015–2017 for calibration and validation respectively. The model performance at validation sustained its potential use as a predictive tool. However, the use of long data period for model calibration is desirable as it reduces statistical uncertainties in the simulations (Lee et al., 2019). Hence, the model could be recommended for parts of the CONUS shown in Fig. 5b by the green areas with $R^2 \geq 0.50$. As an example, Fig. 7 illustrate a comparison of the model simulations to GRACE's LWE at a random location (i.e. Latitude 36.25°, Longitude −82.25°) with high model performance $R^2 = 0.65$). For such a location, the multivariate regression on PCs with an inclusion of lag signals can valuably complement GRACE's LWE measurements. Thus, the model could be used to provide estimates of land water storage anomalies for months with no satellite records of earth gravity field change (e.g. periods preceding GRACE satellite mission). Likewise, the model could serve to fill gaps within the satellite records time periods.

Overall, the study shows that the joint inclusion of PRE, WET, TMP, PET along with their related marginal lag effects could help achieve acceptable estimates of GRACE-like land water storage anomalies. The multivariate regression on PCs with lag signals show an uneven predictive power across the CONUS. This result corroborates with previous studies focus on GRACE-like data retrieval which also highlighted the variability of data-driven analytical models' performance across study regions (Li et al., 2020; Yin et al., 2019; Yang et al., 2018). In general, computational models imbed three categories of uncertainties including physical, modeling, and statistical (Lee et al., 2019; Harmel et al., 2010). The physical uncertainties are associated to measurements, while the modeling uncertainties are intrinsic to the model itself and the statistical ones are inherent to the lack of data (Lee et al., 2019). These uncertainties are undeniably represented in this study and could

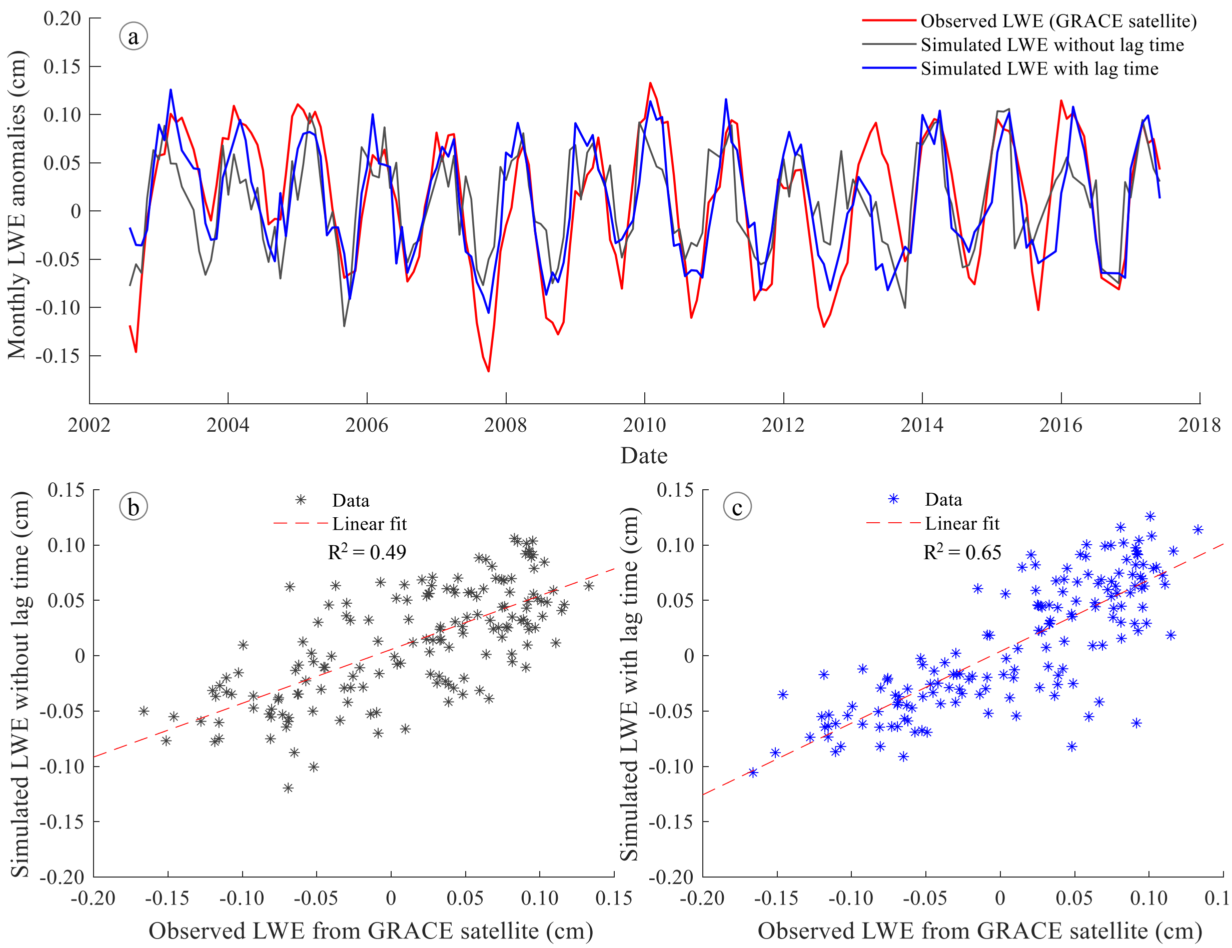

Fig. 7. Comparing the multivariate regression on PCs model performance for the 0.5° × 0.5° grid at Latitude = 36.25, Longitude = −82.25.

somewhat explain the spatial variability of the model performance across the CONUS. For instance, Landerer and Swenson (2012) assessed the accuracy of gridded GRACE estimates of terrestrial water storage and reported spatial variations in the accuracy of GRACE measurements. Likewise, the spatial accuracy of the climate inputs is arguable since the gridded CRU datasets are generated using NOAA stations which are unevenly distributed across the CONUS (Sohoulande et al., 2019; Harris et al., 2014). In this context, the model performance is likely to vary from grid to grid confirming the tendency in Fig. 5. Besides the bias associated to the input data and the modeling procedure, the noted spatial variability of the model performance could also be explained by the geophysical, ecological, or anthropological configurations of the study region. For instance, Sadeghi et al. (2020) reported that GRACE-based retrieval of surface soil wetness is more effective in the wet region of the CONUS compared to arid regions. This contrast seems to be true in the present case study (Fig. 5b) as the retrieval of GRACE-like LWE appeared less effective in the arid region (Southwest CONUS) compared to the wet region (East coastal and Northwest CONUS). Regardless this uneven spatial distribution of the model's predictive power, a value of the model could be its potential use for predicting with a month in advance the land water storage anomalies. Such predictions of land water storage variations can be useful to plan the enhancement of water resources allocation and management.

5. Conclusion

The study provides insight into the spatial patterns of land water storage anomalies across the CONUS. Using 15 years GRACE satellite mission data, a multivariate regression on PCs model has been employed to evaluate the predictability of monthly land water storage anomalies based on climate variables. Inclusion of lag signals in the model has enhanced its performance and offers an option for predicting land water storage variations based on climate information. Even though, the model performed unequally across the CONUS, the outcomes are consistent and lead to the following conclusions:

(i) Lag signals of climate variables such as monthly precipitation, number of wet days, air temperature, and evapotranspiration explain more than 50% of the variance (i.e. $R^2 \geq 0.5$) of land water storage changes for at least 41% of the CONUS territory.
(ii) When climate data are available, the multivariate regression on PCs with lag signals inclusion can complement satellite measurements of earth gravity field variations by providing estimates of land water storage anomalies for months outside the satellite mission periods.

Overall, the outcomes corroborate previous studies which related temporal changes in local water balance with the fluctuation of climate variables such as precipitation, temperature, and evapotranspiration (Crow et al., 2017; Wang et al., 2012; Milly, 1994). For certain locations, the low model performance illustrates the limitation of relying only on climate variables and a single model to predict land water storage change. In view of this drawback and the limitations noted in previous studies focused on GRACE-like LWE anomalies reconstruction (Li et al., 2020; Yin et al., 2019; Humphrey et al., 2017) additional research is needed to achieve a spatially uniform model performance. Perhaps, future studies could capitalize all the scientific contributions by investigating a multi-model approach including anthropogenic, geologic, pedologic, topographic, and ecological variables in addition to the climate ones.

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CRediT authorship contribution statement

Clement D.D. Sohoulande: Conceptualization, Methodology, Data curation, Formal analysis, Writing - original draft, Writing - review & editing. **Jerry Martin:** Data curation, Writing - review & editing. **Ariel Szogi:** Supervision, Writing - review & editing. **Kenneth Stone:** Supervision, Writing - review & editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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