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研究課題名（和文）Improving flood and drought prediction using downscaled GRACE terrestrial water storage

研究課題名（英文）Improving flood and drought prediction using downscaled GRACE terrestrial water storage

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研究成果の概要（和文）：The downscaled TWS provides a great opportunity to monitor drought and predict flood with high spatial resolution on a sub-regional to local scales. The outcomes of the study make it possible to extent the application of remote sensing-based TWS to regions such as Japan and South Korea.

研究成果の学術的意義や社会的意義
1. Improve the understanding of the spatiotemporal variation of terrestrial water storage, which is important for water management and related policy making.
2. Monitor and forecast flood and drought on a sub-regional to local scale, which benefits more accurate and targeted hazards mitigation.

研究成果の概要（英文）：Flood and drought are global issue causing devastating damage to the ecosystem, human lives, and economics. Monitoring the sptaio-temporal variation of terrestrial water storage (TWS) is important for water management and hazard mitigation. However, current remote sensing-based TWS data has coarse spatial resolution (300 km), which limits its application to sub-regional scale. The study used a deep learning approach to downscale remote sensing-based TWS in space, providing more details of water mass variation at sub-regional to local scale. The downscaled TWS provides a great opportunity to monitor drought and predict flood with high spatial resolution on a sub-regional to local scales. The outcomes of the study make it possible to extent the application of remote sensing-based TWS to regions such as Japan and South Korea.

研究分野：Hydrology

キーワード：GRACE　TWS　Downscaling　Deep Learning　Flood　Drought

１．研究開始当初の背景

Hydrological extremes, in the form of floods and droughts, have great influence on water availability, food security, and economic growth. The frequency of extreme flood and drought events is increasing due to climate change and human activities. It is extremely important to characterize and quantify the timing, duration, and severity of flood and drought, but also challenging, especially over data-sparse regions. Many drought studies heavily rely on precipitation, soil moisture, and evapotranspiration without considering deep soil moisture and groundwater due to the lack of continuous reliable observations (Houborg et al., 2012). In flood prediction, most studies focused on storm-driven floods but the contribution of baseflow from groundwater are often ignored, limiting the lead time for flood forecast.

The Gravity Recovery and Climate Experiment (GRACE) satellite mission monitors changes in Earth's gravitational field and retrieves variation of terrestrial water storage (TWS) at a global scale. During the past twenty years, GRACE and its successor mission GRACE Follow-On (GRACE-FO) have achieved tremendous success in quantifying changes in freshwater availability for water resources management, climate extremes prediction, and human and ecosystem health. However, the coarse spatial resolution of GRACE TWSA data (~300 km) limited its application to sub-regional scale study. In recent years, machine learning (ML) is has been increasingly used for GRACE downscaling due to its advantage in dealing with complex nonlinear problems. For example, Seyoum and Milewski (2017) spatially downscaled GRACE TWSA for better understanding of sub-watershed terrestrial water dynamics using an artificial neural network (ANN) model. Sahour et al. (2020) compared the performance of different ML techniques to downscale GRACE TWSA using hydro-climate input variables from land surface models and observations. Foroumandi et al. (2023) further demonstrated the advantage of deep learning Convolutional Long Short-Term Memory on the downscaling of GRACE data.

２．研究の目的

The purpose of this study is to build a systematic framework to downscale GRACE TWS retrievals using an ML technique to enhance flood and drought prediction. It is noted that ML-based downscaling methods are established on the assumption of data stationary between coarse and fine resolutions. However, such assumption has not been well investigated in previous studies. Therefore, prior to the GRACE TWSA downscaling, a synthetic experiment was designed to examine the assumption. Thus, the objectives of this study are to (1) examined the data stationary assumption in ML-based downscaling methods using a synthetic experiment; (2) downscale GRACE data and predict high-resolution TWSA for flood and drought monitoring and forecasting.

３．研究の方法

3.1 The Long Short-Term Memory

The Long Short-Term Memory (LSTM) is a type of recurrent neural network and has been increasingly used for sequential problems. LSTM is explicitly designed to overcome the long-term dependency issue by introducing cell states and gates to control the information to be stored, conveyed, and neglected, thus it can better process long-term temporal dynamics. A basic LSTM model consists an input layer, a hidden layer, and an output layer, and the hidden block is composed of a cell state and three logic gates, namely the forget gate, the input gate, and the output gate. The forget gate and input gate controls the information to be forgotten and added at current time step t. The cell state is then updated and used to stores the accumulation of previous information. Finally, the output gate is used to determine the information of the cell state flows into the new hidden state.

3.2 Experiment Design

3.2.1 Synthetic Experiment

Due to the lack of high-resolution TWSA observations for real-world experiment evaluation, a synthetic experiment was first conducted to examine the assumption for the LSTM model that the relationship established between the predictor and target variables on a coarse resolution is valid for fine-resolution data. GLDAS Noah-based TWSA estimates were used to generate synthetic "truth" to mimic the GRACE TWSA mass concentration (mascon) solution. Model-based estimates from the Today's Earth (TE) System and the NASA Catchment Land Surface Model (CLSM) were used as predictors (Figure 1). The synthetic "true" TWSA from Noah was used the predictand for LSTM model training. A cross-validation was conducted from April 2002 to August 2018 (time period T1) to select the optimal LSTM model. The LSTM model trained on the mascon scale (i.e., coarse scale) was subsequently applied to fine resolution predictors (i.e., 0.5°) for the TWSA downscaling. Moreover, the trained LSTM model was used with fine-resolution predictor data from January 2019 to August 2021 (time period T2) to evaluate its ability to forecast high-resolution TWSA. Finally, the downscaled TWSA during time periods T1 and T2 were evaluated against the "truth" from Noah on the 0.5° scale.

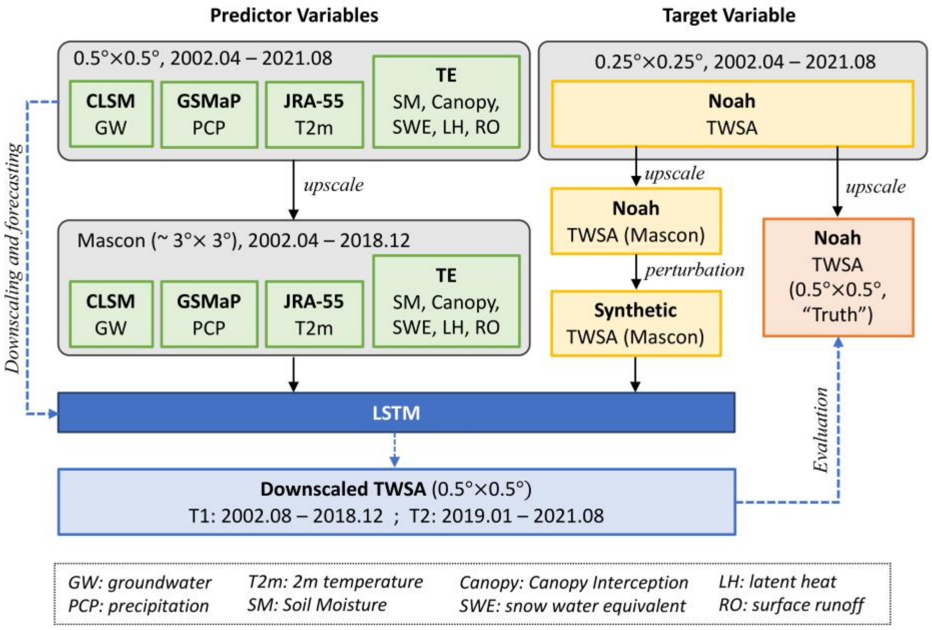

Figure 1. Flowchart of the downscaling approach in the synthetic experiment.

3.2.2 Real-world Experiment

In the real-world experiment, GRACE mascon solution from the Jet Propulsion Laboratory (JPL) was used for downscaling. Similarly, data from the TE system and the CLSM simulation were used as the predictor data. The same cross-validation, downscaling, and prediction procedure was conducted as the synthetic experiment. However, due to the lake of observed TWSA on the fine-resolution scale, the downscaled TWSA were directly compared with GRACE TWSA at basin scale, and indirectly assessed with subregional drought from the U.S. Drought Monitor (USDM) and local flood events from the National Oceanic and Atmospheric Administration (NOAA) National Centers for Environmental Information (NCEI) storm event database. Additionally, the performance of fine-resolution TWSA from the direct resampling and interpolation of GRACE data, as well as Noah estimates were also examined as the baseline.

4．研究成果

4.1 Synthetic Experiment Analysis

Experiment was conducted over the Texas-Gulf Basin in the southern United States. The spatial distribution of correlation coefficient for the fine-resolution TWSA derived from LSTM, direct interpolation, and TE were shown in Figures 2. LSTM-based TWSA provides the highest consistency with synthetic "true" TWSA from Noah, yielding an area-averaged correlation coefficient R of 0.91 and 0.87 for the study period T1 and

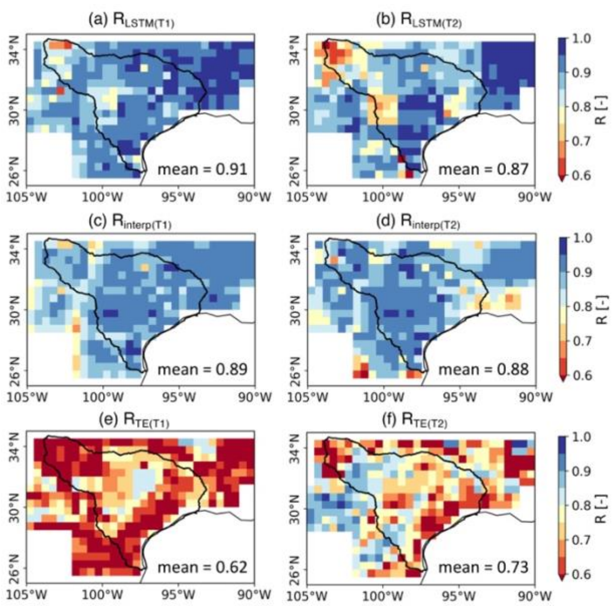

Figure 2. R map between (a)-(b) LSTM and Noah; (c)-(d) GRACE interpolation and Noah, and (e)-(f) TE and Noah during T1 and T2 period.

T2, respectively. The highest R values were witnessed in the eastern area, whereas R values smaller than 0.7 were mainly found in the northwestern region of the Texas-Gulf Basin (Figure 2a-b) and along the western boundary of the basin (Figure 2b). The better performance during the T1 period is anticipated as the LSTM model was trained with coarse resolution data during the same period. While coarse resolution TWSA data during T2 was not used in the training process, providing an independent experiment to evaluate the capability of the trained LSTM model to forecast fine-resolution TWSA. Comparing the LSTM accuracy with the baseline cases (i.e., the Interp and TE cases), it is found that the spatial distribution of R in the interpolation case is less variable than the LSTM case, with area-averaged R values of 0.89 and 0.88 for T1 and T2, respectively. As for the TE case, it yielded the smallest R values across the study domain, suggesting the capability of LSTM model to capture complex relationship between predictor and target variables.

4.2 Real-world Experiment Analysis

4.2.1 Downscaled TWSA Assessment

The average TWSA of Texas-Gulf Basin from August 2002 to August 2021 provided by GRACE, LSTM, and Noah are shown in Figure 3a. The fine-resolution TWSA from both LSTM and Noah show high consistency with GRACE TWSA in terms of inter-annual and seasonal variations. The agreement of TWSA between LSTM and GRACE is more prominent than the Noah versus GRACE case, with a higher correlation coefficient R ($R_{LSTM} = 0.91$ and $R_{Noah} = 0.84$) and smaller errors (MAE_{LSTM} = 2.48 cm and MAE_{Noah} = 2.70 cm). Substantial discrepancy between GRACE-based and Noah-based TWSA was witnessed during the period from 2011 to 2015, when the Texas-Gulf basin suffered an extended drought (Figure 3b). In the LSM simulation, due to the lack of deep groundwater component, Noah may fail to capture the extremely dry condition, yielding a less negative TWSA. LSTM-based TWSA lies between the GRACE and Noah cases during the drought period, and represents the extreme drought in 2011 and the subsequent slow recovery process in a better manner than Noah estimates.

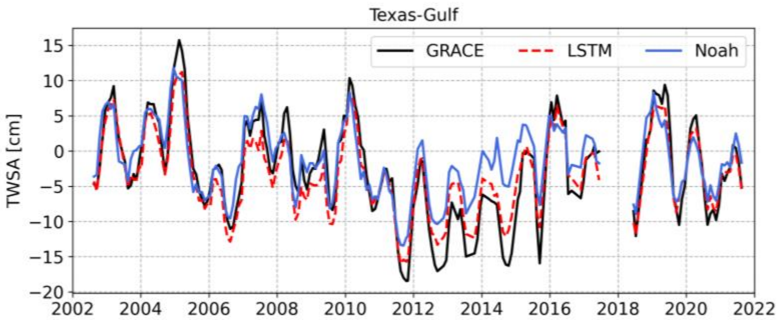

Figure 3. Averaged TWSA in the Texas-Gulf Basin provided by GRACE (black line), LSTM (red dashed line), and Noah estimates (blue line) from August 2002 to August 202.

4.2.2 Downscaled TWSA-based Drought Monitoring

In the study, TWSA derived from GRACE, LSTM, and Noah were compared with USDM drought area percentage at different severity levels at sub-basin scale. Results for two example sub-basins, the Galveston Bay-San Jacinto (#4) and the Middle Brazos (#6), were shown in Figure 4. In the sub-basin #6, LSTM provides a more negative correlation between TWSA and USDM index ($R_{LSTM} = -0.74$) than the other two cases ($R_{GRACE} = -0.66$ and $R_{Noah} = -0.70$) during the T1 period, indicating a higher consistency between water mass variation and drought intensity. It is also noticed that Noah failed to capture the record drought from 2011 to 2015 over the sub-basin #6, while GRACE underestimated the slightly less extreme drought events in 2006 and 2009. LSTM successfully reflected both the record drought and the less extreme events in 2006 and 2009, yielding a better consistency with USDM. The relatively small sub-basin along the coast, Galveston Bay-San Jacinto (# 4), also experienced the record drought in 2011 but recovered from drought more quickly than the inland area based on the USDM. Both Noah and LSTM represent the extreme dry and slowly recovery process, while GRACE TWSA failed to reflect the quicker recovery process and remained low from 2011 to 2015 due to its coarse resolution. The separation of signals from land and ocean may also add additional noise to the GRACE data.

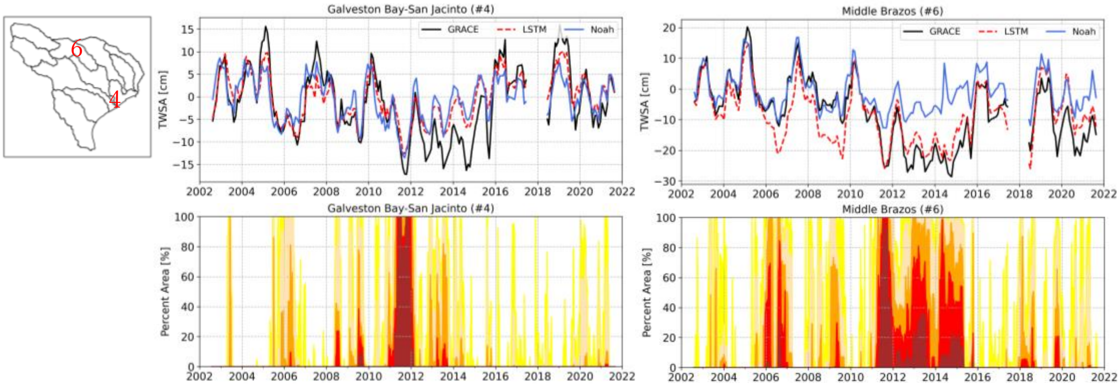

Figure 4. TWSA time series derived from GRACE (black line), LSTM (red dashed line), and Noah (blue line) from August 2002 to August 2021 for the two example sub-basins (#4 and #6) in the Texas-Gulf Basin. The drought area percentage from USDM for each sub-basins are displayed below corresponding TWSA time series figures.

4.2.3 Downscaled TWSA-based Flood Prediction

The flood potential index (FPI) calculated by using TWSA were compared with flood events from NOAA NCEI dataset. FPI value close to 1 indicates a higher chance of flood occurrence and it cannot be larger than 1. Results for an example month in June 2010 were shown in Figure 5 to assess the capability of the downscaled TWSA to capture local water mass variation. NCEI record shows that flood happened mainly over the northwestern, central, and southern Texas-Gulf Basin. GRACE data can predict the high flood potential in the southern region with FPI values larger than zero and close to 0.8 in the most southern part of the basin. However, it failed to forecast the flood potential over other regions. In terms of Noah, it provides a relatively accurate forecast for the location where flood may happen, whereas it largely underestimated the flooded area. LSTM-based FPI generally shows the highest agreement with NCEI flood record. LSTM predicted the flood potential over the northwestern, southern and some part of central regions, however, it still misses the local flood over the most eastern county of the study domain. Similar findings were also witnessed in many other months, especially during the summer months.

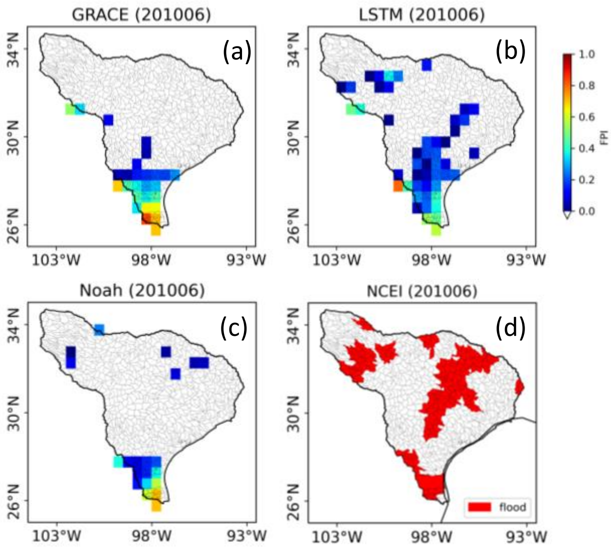

Figure 5. The flood potential index (FPI) using TWSA from (a) GRACE, (b) LSTM, and (c) Noah for June 2010. (d) shows the county experienced flood event in June 2010.

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５．主な発表論文等

〔雑誌論文〕　計2件（うち査読付論文　2件／うち国際共著　2件／うちオープンアクセス　2件）

１．著者名 Yin Gaohong、Baik Jongjin、Park Jongmin	４．巻 59
２．論文標題 Comprehensive analysis of GEO-KOMPSAT-2A and FengYun satellite-based precipitation estimates across Northeast Asia	５．発行年 2022年
３．雑誌名 GIScience & Remote Sensing	６．最初と最後の頁 782～800
掲載論文のDOI（デジタルオブジェクト識別子） 10.1080/15481603.2022.2067970	査読の有無 有
オープンアクセス オープンアクセスとしている（また、その予定である）	国際共著 該当する

１．著者名 Yin Gaohong、Yoshikane Takao、Yamamoto Kosuke、Kubota Takuji、Yoshimura Kei	４．巻 612
２．論文標題 A support vector machine-based method for improving real-time hourly precipitation forecast in Japan	５．発行年 2022年
３．雑誌名 Journal of Hydrology	６．最初と最後の頁 128125～128125
掲載論文のDOI（デジタルオブジェクト識別子） 10.1016/j.jhydrol.2022.128125	査読の有無 有
オープンアクセス オープンアクセスとしている（また、その予定である）	国際共著 該当する

〔学会発表〕　計3件（うち招待講演　2件／うち国際学会　1件）

１．発表者名 Gaohong Yin
２．発表標題 A support vector machine-based method for improving real-time hourly precipitation forecast in Japan
３．学会等名 The Joint PI Meeting of JAXA Earth Observation Mission（招待講演）
４．発表年 2022年

１．発表者名 Gaohong Yin
２．発表標題 Application of GRACE in Hydrology Study
３．学会等名 Lecture at Lahore University of Management Sciences（招待講演）
４．発表年 2022年

1．発表者名 Gaohong Yin, Kei Yoshimura
2．発表標題 Towards Assimilation of GRACE Terrestrial Water Storage into a Land Surface Model for Flood and Drought Prediction
3．学会等名 Land Surface Modeling Summit（国際学会）
4．発表年 2022年

〔図書〕　計0件

〔産業財産権〕

〔その他〕

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6．研究組織

	氏名 （ローマ字氏名） （研究者番号）	所属研究機関・部局・職 （機関番号）	備考

7．科研費を使用して開催した国際研究集会

〔国際研究集会〕　計0件

8．本研究に関連して実施した国際共同研究の実施状況

共同研究相手国	相手方研究機関