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A High-Resolution Land Data Assimilation System Optimized for Drought Monitoring in the Western United States

Jessica M. Erlingis[1,2], Matthew Rodell[2], Christa Peters-Lidard[2], Bailing Li[1,2], Sujay Kumar[2]
[1]Earth System Science Interdisciplinary Center, University of Maryland, College Park, MD
[2] NASA Goddard Space Flight Center, Greenbelt, MD
Author E-mail: jessica.erlingislamers@nasa.gov

Motivation

Numerical modeling of the land surface is a way to provide physically consistent, spatially and temporally continuous information about the water and energy budgets of the surface, subsurface, vegetation canopy, and snowpack. As much of the western United States exists in a near-constant state of freshwater scarcity, information about the amount of water available is critical for decision makers. The Western Land Data Assimilation System (WLDAS; Erlingis et al. 2021) is a custom instance of the National Aeronautics and Space Administration (NASA) Land Information System (LIS) that combines land surface parameters, meteorological forcing data, and satellite products within a land surface model to produce publicly-available 1-km daily estimates of the water and energy budget variables for the western United States using the Noah-Multiparameterization (Noah-MP) Land Surface Model (LSM).

The goal of WLDAS is to provide estimates of variables such as groundwater recharge, soil moisture, snow water equivalent (SWE), and evapotranspiration (ET) in support of groundwater sustainability and agricultural decision making in the western United States using a combination of land surface models and remote sensing data.

WLDAS Configuration

The LIS Software (Kumar et al. 2006; Peters-Lidard et al. 2007) developed at NASA Goddard Space Flight Center (GSFC) enables land surface parameter processing and simulation and multivariate data assimilation using multiple land surface models in a single open-source framework (https://github.com/NASA-LIS/LISF). WLDAS uses the Noah-MP land surface model and is run uncoupled from the atmosphere.

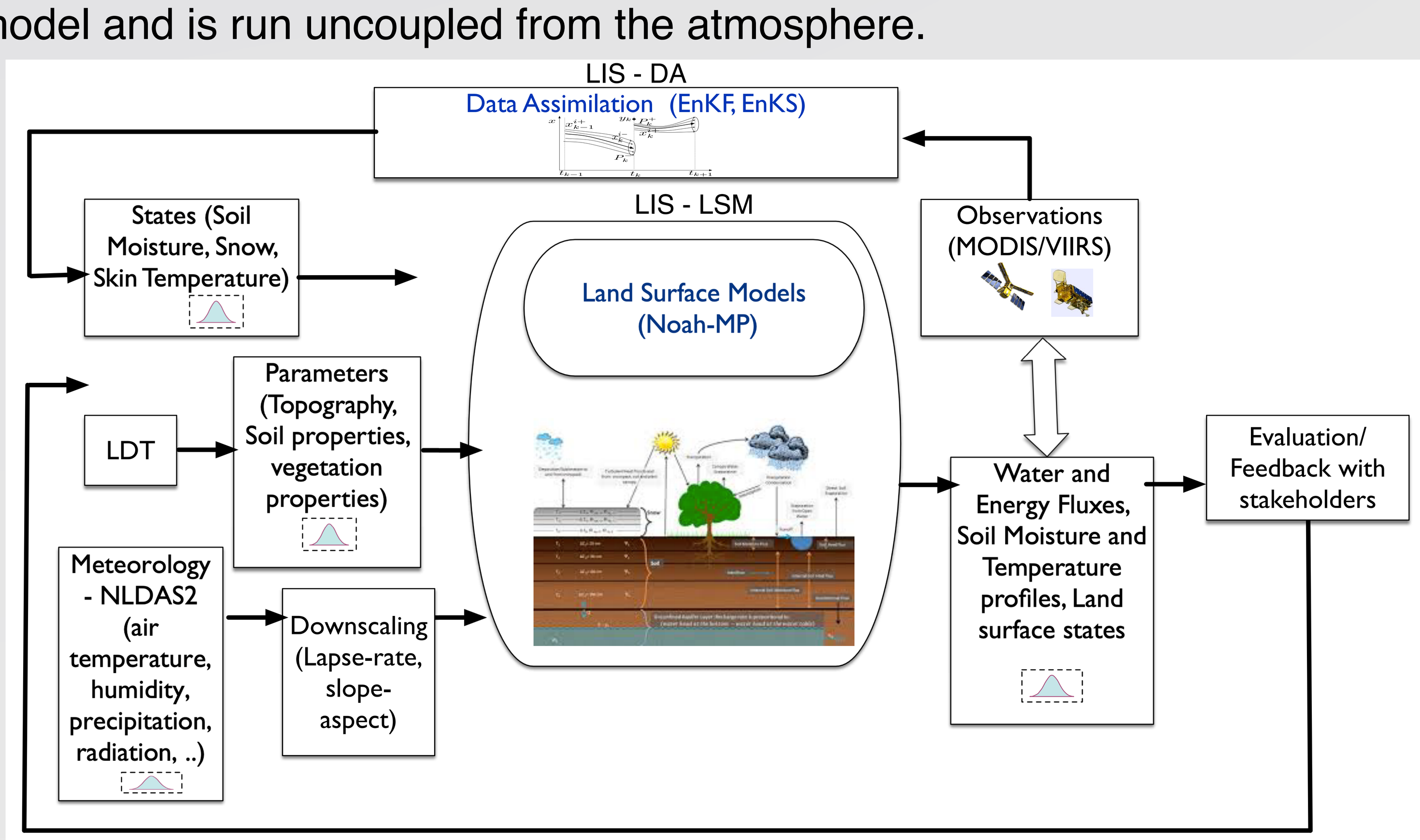

Figure 1 Schematic of WLDAS product generation process.

Data Availability

- Project website: https://ldas.gsfc.nasa.gov/wldas/wldas-project-goals
- Data download: https://portal.nccs.nasa.gov/datashare/WLDAS/

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Methods

In order to constrain the behavior of the dynamic vegetation model within Noah-MP, Leaf Area Index (LAI) assimilation was enabled over California. The one-dimensional ensemble Kalman filter (EnKF; Reichle et al., 2002) within LIS was applied to the state vector of simulated LAI; the updated LAI was also used to update the prognostic leaf biomass variable of the vegetation physics using the LSM's physics formulations. The ensemble contained 20 members. The Global LAnd Surface Satellite (GLASS) LAI product (Xiao et al., 2016), which is available at 8-day intervals on a 0.05˚ x 0.05 ˚ grid. The 8-day observations were linearly interpolated to a daily frequency.

Results

The impact of including LAI assimilation in the model was compared against four satellite-based ET products: Atmosphere-Land Exchange Inverse (ALEXI; Anderson et al., 2007), Global Land surface Evaporation: the Amsterdam Methodology (GLEAM; Miralles et al., 2011), University of Washington (UW; Tang et al. 2009), and FLUXNET Multi-Tree Ensemble (MTE; Jung et al. 2009). The performance of the data assimilation (DA) and open loop (OL) runs are shown below. The Kling-Gupta efficiency (KGE; Gupta et al., 2009) is calculated as

$$KGE = 1 - \sqrt{(r-1)^2 + \left(\frac{\sigma_{sim}}{\sigma_{obs}} - 1\right)^2 + \left(\frac{\mu_{sim}}{\mu_{obs}} - 1\right)^2}$$

where r is correlation, σ_{sim} is the standard deviation of the model, σ_{obs} is the standard deviation of the observations, μ_{sim} is the mean of the model, and μ_{obs} is the mean of observed values.

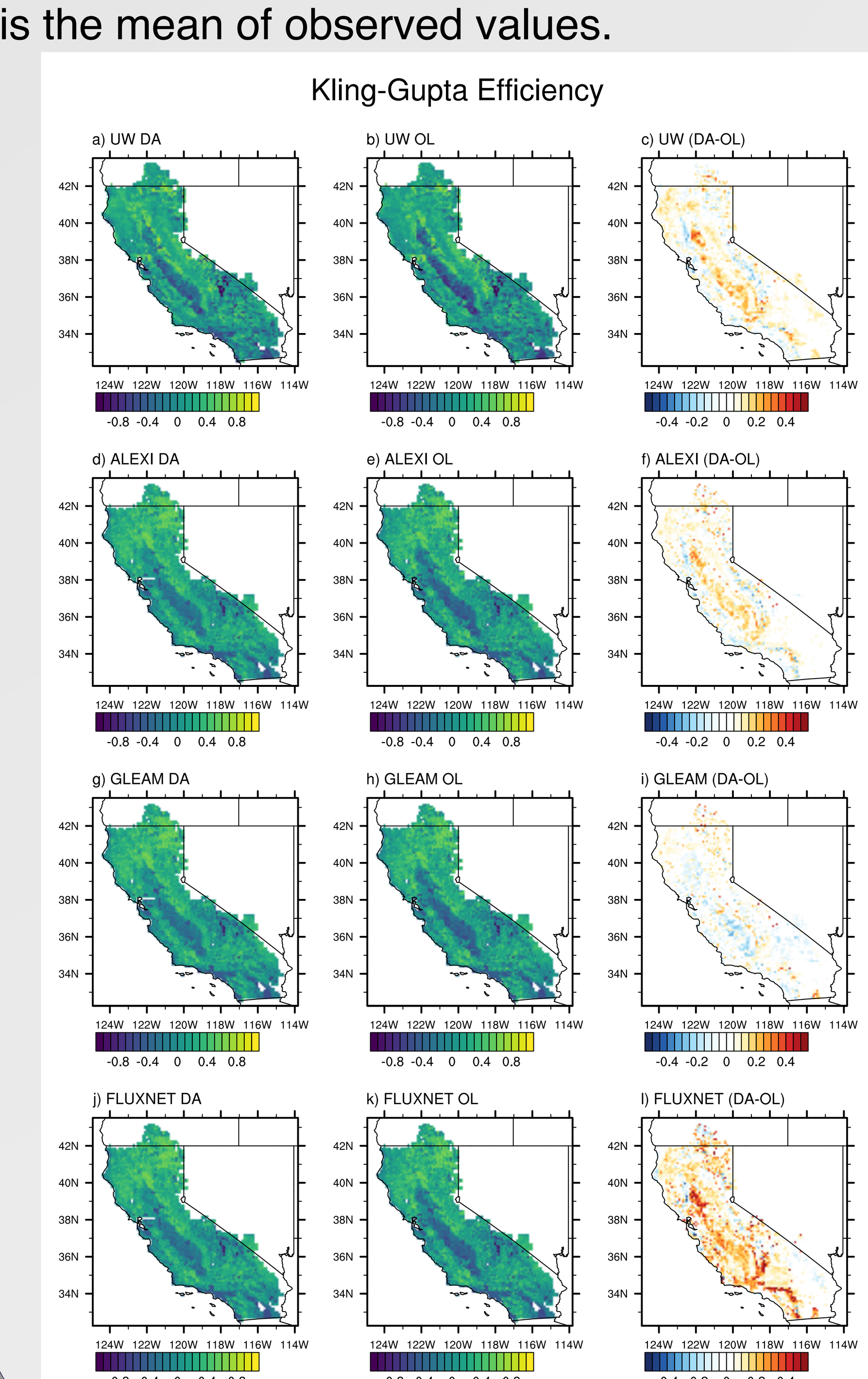

Figure 2 KGE and difference in KGE (DA-OL) for UW (a-c), ALEXI (d-f), GLEAM (g-i), and FLUXNET (j-l) ET. Warm colors represent improvements using data assimilation.

A perfect score of KGE is 1, and a value less than -0.41 signifies that the mean of the observations performs better than the model timeseries.

The DA runs over California showed an improvement in ET over agricultural areas in California when compared with ALEXI, UW, and FLUXNET MTE data. The improvements show strong seasonality and are largest over the Central Valley during June-September (Figure 2), coinciding with the growing season. Though these simulations did not contain crop or irrigation modules, the assimilation of LAI offers the potential for improving estimates of ET over agricultural regions.

Results

A strength of WLDAS is its relatively long record, which allows users to place present hydrological events in historical context. Tools for these applications include percentile and anomaly information. Terrestrial Water Storage (TWS) and root zone (0-1 m below ground) soil moisture (RZSM) percentiles were calculated for each day, using a 5-day moving average of the calendar day +/- 2 days. WLDAS captures the severity of a recent California drought as well as the recovery (Figure 3).

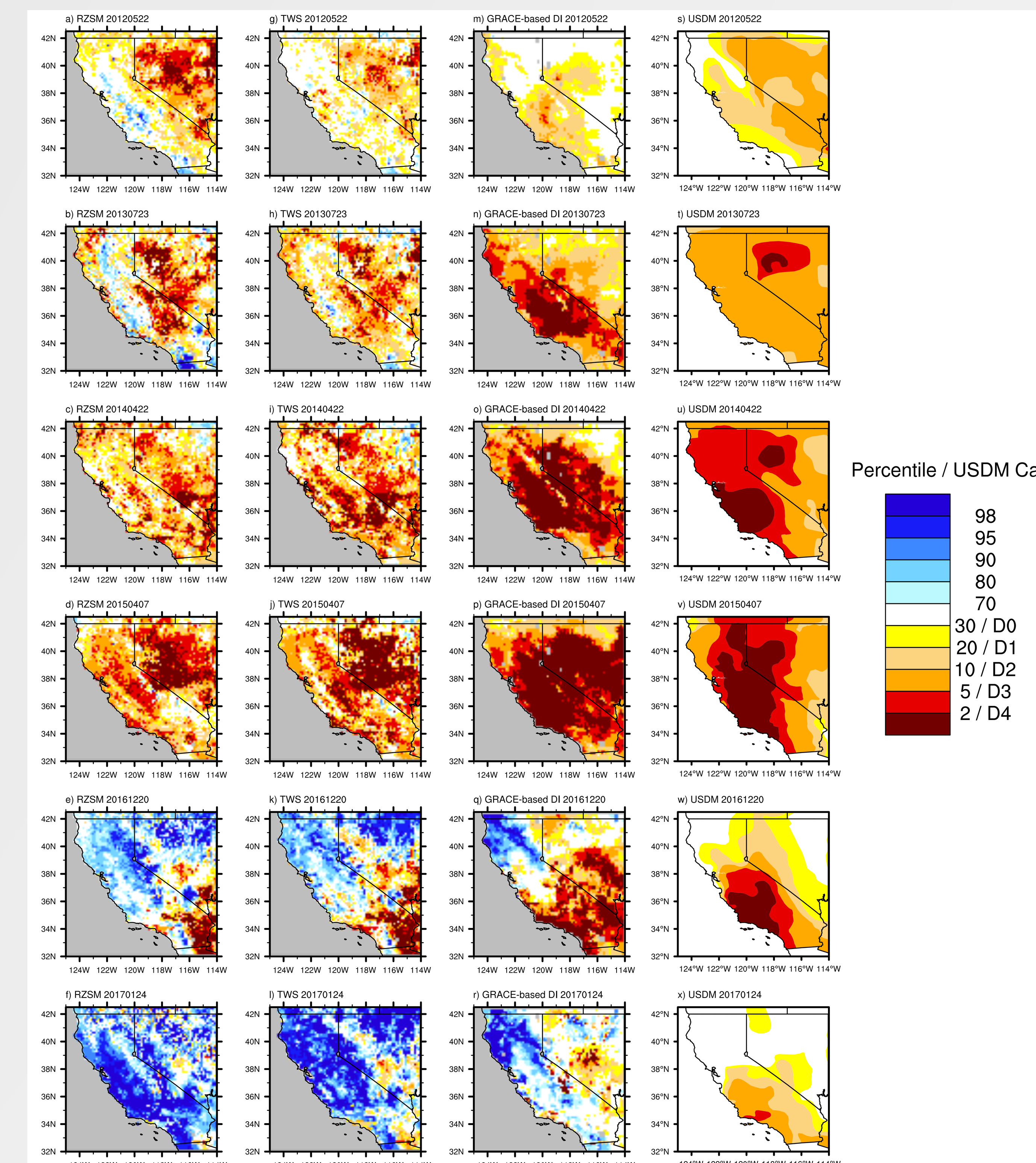

Figure 3 Root zone soil moisture percentiles (first column; a-f), terrestrial storage percentiles (second column; g-l), GRACE-based shallow groundwater indicators (third column; m-r), and United States Drought Monitor (fourth column; s-x) for 22 May 2012, 23 July 2013, 22 April 2014, 7 April 2015, 20 December 2015, and 24 January 2017.

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