RE-THINKING SENSITIVITY OF MODEL PARAMETER VALUES IN SOIL MOISTURE ASSIMILATION USING THE EVOLUTIONARY DATA ASSIMILATION

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1. INTRODUCTION

The sensitivity of land surface model parameters is usually examined for one parameter at a time in response to changes in observation data and/or the model estimated output. This parameter independence approach assumes that there are limited interactions between model parameters - a precondition which is highly unlikely for land surface models. Additionally, the model parameter values are widely assumed as time-invariant, particularly, in most data assimilation (DA) studies where model states are updated in response to changes in observation data. However, a demonstration of time-variant nature of physically representative model parameters values has not been thoroughly investigated in the DA literature. The sensitivity of model parameter values is important because their variability constitute an integral component of the overall accuracy of land surface model outputs for quantities such as soil moisture.

This study assimilates the Soil Moisture and Ocean Salinity (SMOS) Level 2 soil moisture data into the Joint UK Land Environment Simulator (JULES) to investigate the sensitivity of its model parameter values. The study demonstrates the sensitivity of JULES model parameter values in the estimation of soil moisture through the Evolutionary Data Assimilation (EDA) procedure. The EDA employs stochastic and adaptive properties of multi-objective evolutionary strategies to evaluate the continuous interaction between several model parameters. Analysis of these parameter sets across all assimilation time steps allows the sensitivity of model parameter values in response to changes in observation data to be determined. This approach is evaluated through comparison to conventional soil moisture assimilation for dual state-parameter estimation using the Ensemble Kalman Filter (EnKF).

2. STUDY AREA, DATA SETS, AND THE LAND SURFACE MODEL

The Yanco area is located in the western plains of New South Wales, Australia where the topography is flat with very few geological outcroppings. According to information in the Digital Atlas of Australian Soils, the soil texture is predominantly sandy loams, scattered clays, red brown earths, transitional red brown earth, sands over clay, and deep sands [1, 2]. The land cover is predominantly rainfed cropping/pasture with scattered trees and grassland.

The chosen land surface model is the Joint UK Land Environment Simulator (JULES) - a widely used tiled model of sub-grid heterogeneity which simulates water and energy fluxes between a vertical profile of variable soil layers, land surface, vegetation, and the atmosphere [3]. The JULES model uses meteorological forcing data, surface land cover data, soil data, and initial values for prognostic state variables. The model accommodates the specification of soil layers and their thicknesses, and can simulate several land surface categories including broadleaf, needleleaf, grass (temperate and tropical), shrub, urban, inland water, bare soil, and ice-covered surfaces. The soils data are obtained from the Australian Soil Resource Information

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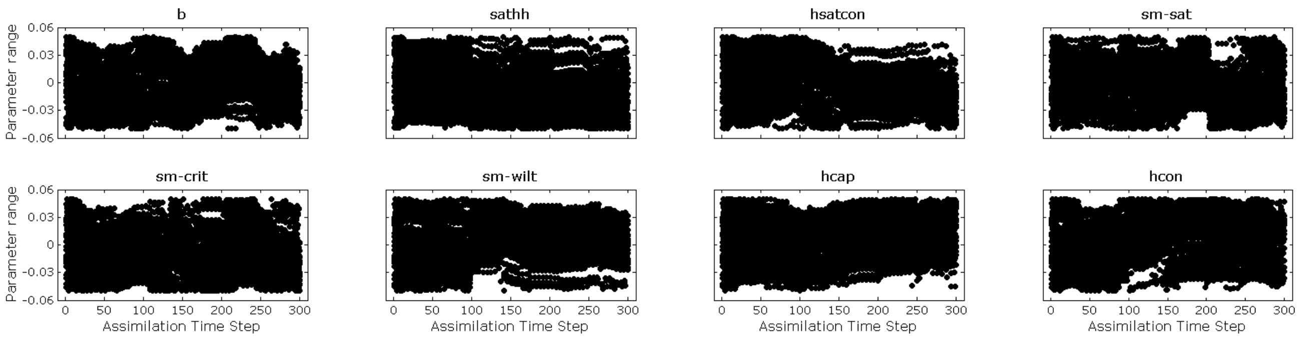
System [2, 1], and the land cover data from the Australian National Dynamic Land Cover Dataset [4]. The meteorological forcing variables used in JULES include short and long wave incoming radiation, air temperature, precipitation, wind speed, pressure, and specific humidity. The forcing data are obtained from the Australian Community Climate Earth-System Simulator (ACCESS-A) at hourly time step with a $12km$ spatial resolution [5]. The ACCESS-A precipitation dataset was bias corrected using daily observations from the Australian Water Availability Project through the Bureau of Meteorology [6, 7].

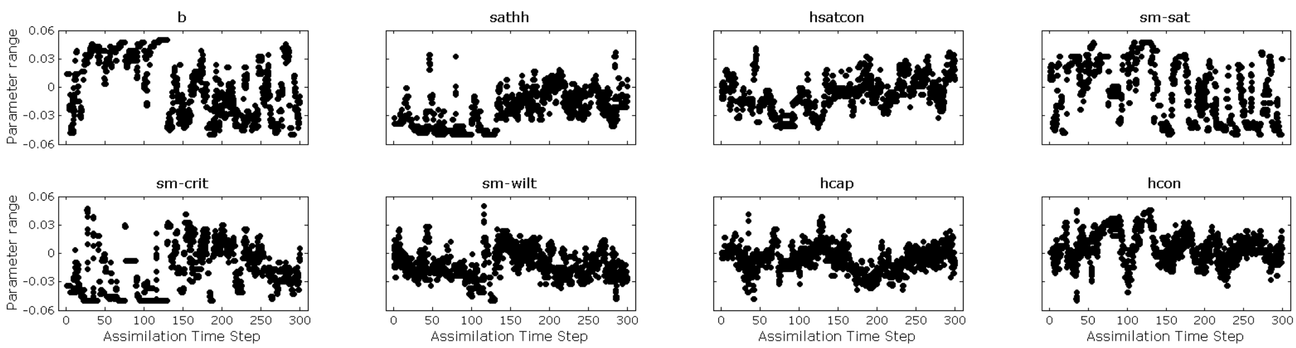
3. METHODS AND RESULTS

To investigate the sensitivity of JULES model parameter values, this study assimilates the Soil Moisture and Ocean Salinity (SMOS) Level 2 soil moisture data into the JULES model using the EDA and the EnKF. The SMOS Level 2 soil moisture used is the value reported on the $15km$ Discrete Global Grid (DGG) [8]. The EDA is a new formulation based on a multi-objective evolutionary strategy which has been applied in assimilation of streamflow [9, 10] and soil moisture [11, 12]. In this study, both the EDA and the EnKF are applied in a dual state-parameter estimation through assimilation of SMOS Level 2 soil moisture into the JULES model. Through continuous evolution the EDA evaluates the dynamics between values for each model parameter, and the interaction between model parameters across assimilation time steps in response to changes in observation data.

The resulting distribution of model parameter values are shown in Figure 1 for the EnKF and EDA methods. The distribution of model parameter values obtained using the EnKF method is uniform with values spread within the entire range of parameter values. In contrast, the EDA result shows a clustering pattern for the model parameter values. The distribution of model parameter values across all assimilation time steps are examined through clustering analysis to quantify the overall level of sensitivity for each model parameter. The estimated level of sensitivity represents the overall response of each model parameter to changes in observation data. This integrated assessment of model parameter values provide a framework for a thorough assessment of sensitivity for model parameter values.



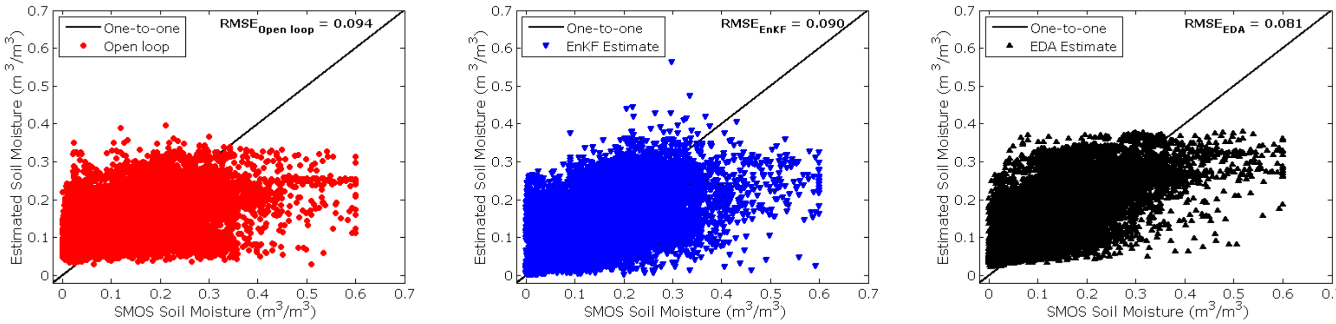
(a) EnKF method - the labels above each plot denote JULES model parameters



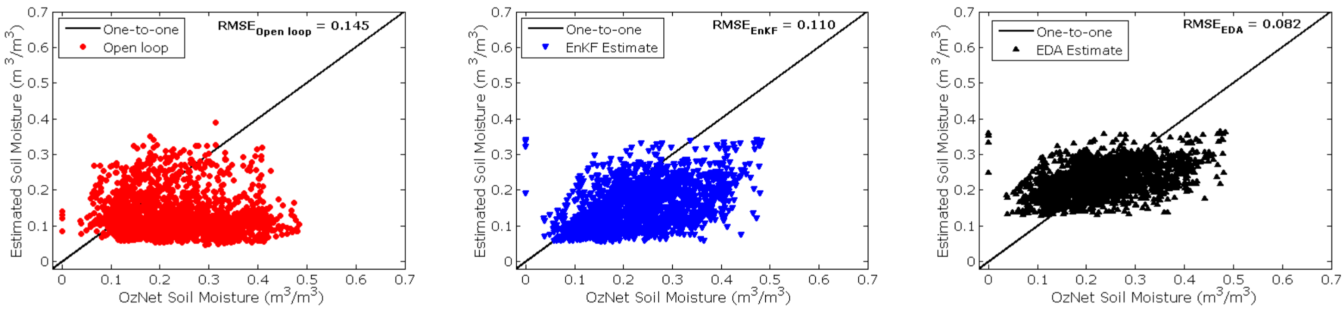
(b) EDA method - the labels above each plot denote JULES model parameters

Fig. 1. Distribution of estimated model parameter values across assimilation time steps for the EnKF and the EDA.

The ensemble estimates of soil moisture for the EnKF and the EDA are also compared to the SMOS soil moisture and validated against in-situ OzNet (www.oznet.org.au) soil moisture [13] in Figure 2. It is noteworthy that the open-loop in this case is ensemble estimate before update. Both methods have improved the soil moisture estimation as they have higher root mean square error (RMSE) values than the open-loop estimate. The significant bias shown in the open-loop estimate is mostly repeated in the EnKF estimate. The EDA has the highest estimation accuracy with a RMSE of $0.082m^3/m^3$ whereas the EnKF has a RMSE value of $0.110m^3/m^3$ at the validation stage. The improved estimation in the EDA is attributable to the estimated model parameter values.



(a) Evaluation using SMOS soil moisture



(b) Validation using in-situ OzNet data

Fig. 2. Evaluation of ensemble estimates of soil moisture from open-loop, EnKF and EDA methods against SMOS and in-situ OzNet estimates of near-surface soil moisture.

4. CONCLUSIONS

This study examined the sensitivity of model parameter values through assimilation of SMOS Level 2 soil moisture into JULES using the EDA and the EnKF procedures. The ensemble parameter values across all assimilation time steps were evaluated to determine the level of sensitivity for individual model parameters, and the persistence of model parameter values. The integrated assessment of ensemble parameter values across assimilation time steps in response to changes in observation data provides a thorough framework to quantify sensitivity of model parameters. The results demonstrate the utility of the EDA approach when compared to ensemble estimates of soil moisture from EnKF method.

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