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Root-zone soil moisture estimation from assimilation of downscaled Soil Moisture and Ocean Salinity data

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ABSTRACT

The crucial role of root-zone soil moisture is widely recognized in land–atmosphere interaction, with direct practical use in hydrology, agriculture and meteorology. But it is difficult to estimate the root-zone soil moisture accurately because of its space-time variability and its nonlinear relationship with surface soil moisture. Typically, direct satellite observations at the surface are extended to estimate the root-zone soil moisture through data assimilation. But the results suffer from low spatial resolution of the satellite observation. While advances have been made recently to downscale the satellite soil moisture from Soil Moisture and Ocean Salinity (SMOS) mission using methods such as the Disaggregation based on Physical And Theoretical scale Change (DisPATCh), the assimilation of such data into high spatial resolution land surface models has not been examined to estimate the root-zone soil moisture. Consequently, this study assimilates the 1-km DisPATCh surface soil moisture into the Joint UK Land Environment Simulator (JULES) to better estimate the root-zone soil moisture. The assimilation is demonstrated using the advanced Evolutionary Data Assimilation (EDA) procedure for the Yanco area in south eastern Australia. When evaluated using in-situ OzNet soil moisture, the open loop was found to be 95% as accurate as the updated output, with the updated estimate improving the DisPATCh data by 14%, all based on the root mean square error (RMSE). Evaluation of the root-zone soil moisture with in-situ OzNet data found the updated output to improve the open loop estimate by 34% for the 0–30 cm soil depth, 59% for the 30–60 cm soil depth, and 63% for the 60–90 cm soil depth, based on RMSE. The increased performance of the updated output over the open loop estimate is associated with (i) consistent estimation accuracy across the three soil depths for the updated output, and (ii) the deterioration of the open loop output for deeper soil depths. Thus, the findings point to a combined positive impact from the DisPATCh data and the EDA procedure, which together provide an improved soil moisture with consistent accuracy both at the surface and at the root-zone.

1. Introduction

Remotely sensed observations such as those from the Soil Moisture and Ocean Salinity (SMOS) mission provide valuable soil moisture information at the global scale. These soil moisture observations provide large area estimates, about 40 km for SMOS Level 1 observations [26], and are limited to the top few centimeters, ~5 cm of the soil column [22,45]. Typically, analytical procedures such as disaggregation methods [37,41], and data assimilation (DA) procedures [16,18,19,44] along with land surface models can be employed to interpolate the soil moisture observations to unsampled locations, improve its spatial resolution, and extend the surface soil moisture to the root-zone. The Disaggregation based on Physical And Theoretical scale Change (DisPATCh) method developed by Merlin et al. [37], downscales the 40-km SMOS observations using 1-km resolution soil temperature data from Moderate Resolution Imaging Spectroradiometer (MODIS) to generate a high resolution 1-km soil moisture. The DisPATCh approach improves the spatial resolution of the SMOS data through its conversion of soil temperature fields into soil moisture fields. However, the accuracy of these soil moisture estimates is variable, and the method is unable to provide soil moisture at the root-zone.

Root-zone soil moisture is invaluable for initiating land surface models [1,47] and numerical weather forecasting models [7]. In general, soil moisture has several practical uses for terrestrial water and weather monitoring [28,50], but these applications typically require soil moisture at the root-zone to make meaningful impact. In other words, the estimation of root-zone soil moisture from surface estimates [17,31,47] and its integration into hydrologic models is

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crucial to the overall impact on water and weather forecasting systems. Several studies have been undertaken to provide root-zone soil moisture from field measurements [48–50], satellite observations [4,10,17,32,42], physically based analytical approaches and data driven methods [27,31], and data assimilation [15,29,47,51]. Among these methods of estimating root-zone soil moisture, data assimilation remains the most promising approach to combine satellite-based soil moisture with those from land surface models. The data assimilation approach has the capability to provide root-zone soil moisture forward in time, while accounting for uncertainties in the observation data and the simulated output from the model. But current approaches of direct assimilation of SMOS data suffer from low spatial resolution.

Traditionally, soil moisture assimilation studies integrate direct satellite observations [10,32,43] and/or retrieved satellite soil moisture [15,45] at the observed spatial resolution. But very few studies [25,36,39] have actually assimilated disaggregated satellite soil moisture at high spatial resolution into land surface models to improve the root-zone soil moisture estimation. Consequently, this study assimilates the 1-km DisPATCh surface soil moisture into the Joint UK Land and Environment Simulator (JULES) to extend the surface soil moisture to the root-zone. The study employs the advanced evolutionary data assimilation [9,15] to update the JULES model state trajectories after which its root-zone soil moisture are archived and assessed against in-situ OzNet data [48] both at the surface and at the root-zone. The evolutionary data assimilation is appealing in its unification of multi-objective evolutionary strategy and traditional data assimilation, to simultaneously explore the internal dynamics of the prediction model and temporally update its initial states with the potential to improve upon model predictions. The unique capability of the EDA approach has been demonstrated and compared against popular methods including the ensemble Kalman filter and particle filter in [12,13,15]. For example, the EDA has been shown to provide better convergence in model decision space in comparison to the ensemble Kalman filter [15].

2. Materials and methods

2.1. Study area, data sets, and the land surface model

The Yanco area shown in Fig. 1 is located in the western plains of New South Wales, Australia where the topography is flat with very few geological outcroppings. The soil texture is predominantly sandy loams, scattered clays, red brown earths, transitional red brown earth, sands over clay, and deep sands. Information from the Digital Atlas of Australian Soils shows that the soil landscape is predominantly characterized by plains with domes, lunettes, and swampy depressions, and divided by continuous or discontinuous low river ridges associated with prior stream systems [34]. The area is traversed by stream valleys with layered soil or sedimentary materials common at fairly shallow depths: chief soils are hard alkaline red soils, grey and brown cracking clays. The land cover is primarily rainfed cropping/pasture with scattered trees and grassland.

The land cover data used in this study is the Australian National Dynamic Land Cover Dataset (DLCD) [30]. The DLCD was generated from the 16-day Enhanced Vegetation Index composite collected at 250-m resolution from MODIS. The classification scheme used to describe land cover categories in the DLCD conforms to the 2007 International Standards Organization (ISO) Land Cover Standard (19144-2), previously referred to as the Food and Agriculture Organization Land Cover Classification [8]. The DLCD has land cover features clustered into 34 ISO classes with descriptions for the structural character of vegetation, ranging from cultivated and managed land covers (crops and pastures) to natural land covers such as closed forest and sparse open grasslands.

The soils information is derived from the Digital Atlas of Australian Soils [34], which was obtained from the Australian Soil Resource Information System (ASRIS). ASRIS provides a digital map of soil types and their descriptions, typical ranges for soil properties for each soil type, morphology, and physical properties of soil profiles. The soil classification system was based on the widely applied Factual Key of [40] and later revised to the Australian Soil Classification [20,21] into 6 textural groups including sands, sandy loams, loams, clay loams, light clays. Soil properties in the Digital Atlas of Australian Soils include information on texture, clay content, bulk density, saturated hydraulic conductivity, and soil layer thickness for horizons A and B [34,35].

Meteorological forcing data including incoming short and long wave radiations, air temperature, precipitation, wind speed, pressure, and specific humidity are obtained from the Australian Community Climate Earth-System Simulator-Australia (ACCESS-A), at an hourly time step with 12-km spatial resolution [3]. The ACCESS-A precipitation data set has been bias corrected to 1-km using precipitation from the Australian Water Availability Project through the Bureau of Meteorology, herein denoted BAWAP [23,24]. The ACCESS-A precipitation was bias corrected by matching the average precipitation from ACCESS-A to the average precipitation from the overlapping BAWAP grid. The land cover and soils data are mapped to the 1-km model grid through spatial overlap and subsequent determination of the proportions of constituent land cover and soils classes within each grid. The hourly forcing data together with the land cover and soils data are incorporated into JULES to simulate the temporal evolution of soil moisture at hourly time step.

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 [2]. JULES uses meteorological forcing data, surface land cover data, soil data, and values for prognostic variables. The model initialization is conducted for several variables including the temperatures and the liquid and frozen moisture contents of the soil layers; temperature, density, and albedo of the snowpack if present; the temperature and intercepted rain and snow on the vegetation canopy; the temperature and depth of ponded water on the soil surface; and an empirical vegetation growth index. JULES accommodates the specification of several soil layers with variable 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 description for model parameters and forcing variables, and their associated intervals within which they are allowed to be modified or perturbed in the JULES model is presented in Table 1. The parameters are modified using a relative percentage measure where a $\pm 5\%$ uncertainty bound means that the specified parameter is modified to within a maximum of 5% and a minimum of -5% of its original value. It is noteworthy that perturbed values for parameters are also restricted to within intervals acceptable to the JULES model. The original values for model parameters are determined based on the soil, land cover and meteorological forcing data such that they are physically meaningful for the JULES model in the context of the Yanco area.

The driving soil moisture used to correct the state trajectory of the JULES model is the 1-km DisPATCh data set. DisPATCh is a downscaled soil moisture from SMOS level-2 soil moisture product (version-4) using the reprocessed level 1C data, and the version-4 level-2 soil moisture algorithm [37]. An updated version of the DisPATCh data set used in this paper is the one applied to SMOS Level 3 soil moisture product together with daily MODIS Terra/Aqua data. Detailed procedure about how the DisPTACh data set was generated can be found in [37].

The independent OzNet [48] validation data set (see Fig. 1) comprises 13 soil moisture profile stations in the Yanco area. Soil moisture monitoring at all the stations in the Yanco area has been in

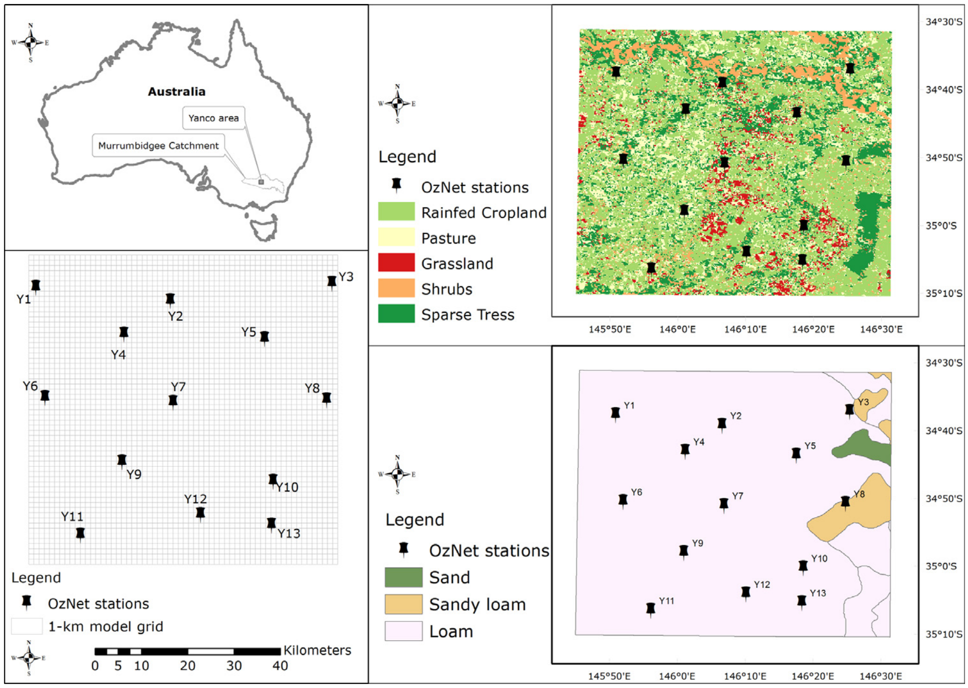


Fig. 1. The experimental area—Yanco, showing the dominant land cover types, soil texture, the 1-km model grid and the ground OzNet soil moisture stations (data source: the Australian Bureau of Meteorology).

Table 1
Description of model parameters and forcing data variables for the JULES model.

Parameter	Description	Interval (%)
Model parameters		
b	Exponent in soil hydraulic characteristics curve	±5
sathh	Absolute value of the soil matric suction at saturation (m)	±5
hsatcon	Hydraulic conductivity at saturation (kg m^{-2}s^{-1})	±5
sm-sat	Volumetric soil moisture content at saturation (m^3 water per m^3 soil)	±5
sm-crit	Volumetric soil moisture content at critical point (m^3 water per m^3 soil)	±5
sm-wilt	Volumetric soil moisture content at wilting point (m^3 water per m^3 soil)	±5
hcap	Dry heat capacity (J m^{-3}K^{-1})	±5
hcon	Dry thermal conductivity (W m^{-1}K^{-1})	±5
albsoil	Soil albedo	±5
Meteorological forcing variables		
SWR	Downward component of shortwave radiation at the surface (Wm^{-2})	±5
LWR	Downward component of longwave radiation at the surface (Wm^{-2})	±5
rain	Rainfall (kgm^{-2}s^{-1})	±5
tempr	Atmospheric temperature (K)	±5
wind	Wind speed (ms^{-1})	±5
press	Surface pressure (Pa)	±5
spHum	Atmospheric specific humidity (kg kg^{-1})	±5
Initial state variables		
canopy	Amount of intercepted water that is held on each tile (kg m^{-2})	Updated
tstar-t	Surface or skin temperature of each tile (K)	Updated
t-soil	Temperature of each soil layer (K)	Updated
sthuf	Soil wetness for each soil layer; mass of soil water expressed as a fraction of water content at saturation	Updated

operation since 2004 using Campbell Scientific water content reflectometers (CS615, CS616) and the Stevens Hydraprobe for four soil layers: 0–5 cm, 0–30 cm, 30–60 cm and 60–90 cm [48]. The CS615 and CS616 sensors are sensitive to soil temperature fluctuations [46], so temperature sensors were installed to provide a continuous record of soil temperature at the midpoint along the reflectometers. Calibration of the sensor observations showed that the average root mean square error is 0.03 m^3/m^3 for both the Campbell Scientific [52] and Hydraprobe [38] sensors. Additional information about the OzNet data set can be found in [48].

2.2. Data assimilation method

The evolutionary data assimilation (EDA) procedure, presented in Fig. 2, is a unified formulation combining computational evolutionary strategy with temporal updating from data assimilation [9,15]. The EDA approach to data assimilation is unique in a way that its updated estimates are inherently linked to values in model decision space, ensuring that water and energy balance are preserved in the updated output. The EDA has been employed in assimilating soil moisture [10,11], brightness temperature [10], streamflow [12,14], and has been

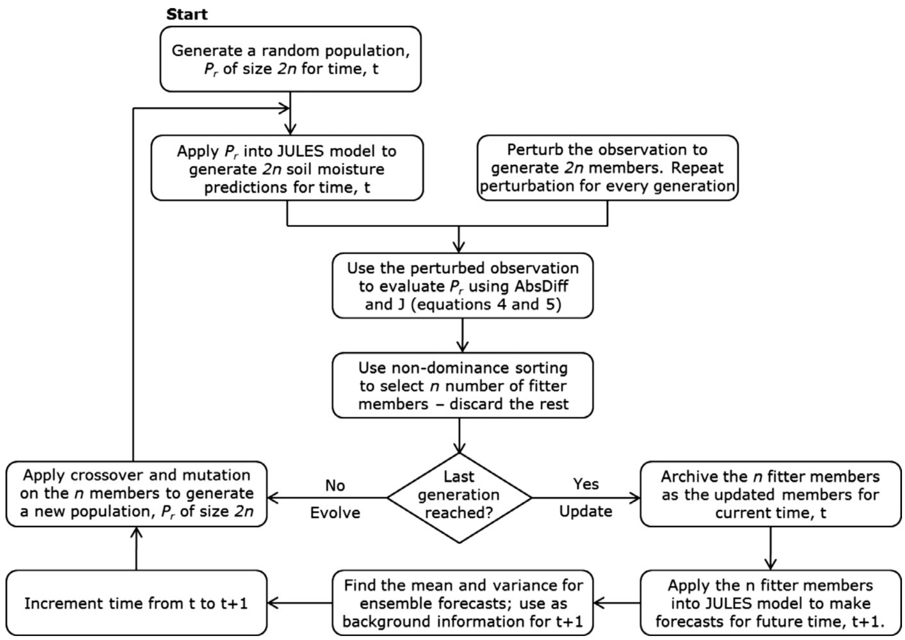


Fig. 2. Computational procedure for a sequential assimilation using the EDA method—combining evolutionary strategy with temporal model updates (updated from [9]).

compared against popular data assimilation methods such as particle filter and ensemble Kalman filter [13]. Though the EDA is not limited to a specific evolutionary algorithm, the one employed in this study is the Non-Dominated Sorting Genetic Algorithm-II (NSGA-II) which was developed by Deb et al. [5,6].

In the EDA procedure, the initial step begins by generating a random population P_r of size $2n$ for ensemble members which comprise model parameters, initial states, and forcing data uncertainties shown in Table 1. Each member of P_r is applied into JULES to determine the soil moisture prediction according to Eq. (1), where the forcing data are perturbed by using Eq. (2). The soil moisture observation is perturbed using Eq. (3) to generate a corresponding $2n$ members.

$$y_{s,i} = h[x_i, z_i, u_i] \tag{1}$$

where $y_{s,\,i}$ is the soil moisture prediction for population member i; $h[.]$ is the system transition function (or the measurement model, i.e. the JULES model); x_i is initial state for population member i; z_i is the model parameters for population member i; and u_i is the forcing data for population member i.

$$u_i = u_t + \gamma_t, \quad \gamma_t \sim N(0, \beta_t^u) \tag{2}$$

where u_i is the forcing data for population member i; u_t is the forcing data at time t; and γ_t is the forcing data error with variance β_t^u at each time step.

$$y_{o,i} = y_t + \varepsilon_t, \quad \varepsilon_t \sim N(0, \beta_t^y) \tag{3}$$

where $y_{o,\,i}$ is the perturbed observation for population member i; y_t is the observed data at time t; ε_t is the observation error with covariance β_t^y at time t.

Each of the $2n$ predictions is evaluated against the perturbed observation using the absolute difference in Eq. (4) and the cost function in Eq. (5). The AbsDiff and J are minimized such that the fitter members have smaller values in at least one or both objectives. The AbsDiff ranks members high when their absolute residual between the prediction and the perturbed observation is smallest, whereas J finds fitter members as the ones which best represent the compromise between the background value and the perturbed observation. The background value is the average estimate for ensemble predictions, which are determined by applying updated members of the population from the previous assimilation time step into JULES to make a prediction for the current time step. The background value for the initial assimilation time step is estimated from a randomly generated population of members.

$$\text{AbsDiff} = |y_{s,i} - y_{o,i}| \tag{4}$$

$$J = \sum_{i=1}^{k} J(y_i) = \sum_{i=1}^{k} \left\{ \frac{(y_{s,i} - y_{b,i})^2}{{\sigma_b}^2} + \frac{(y_{s,i} - y_{o,i})^2}{{\sigma_o}^2} \right\} \tag{5}$$

where $y_{s,\,i}$ is the analysis (i.e., the searched) value for ith data point which minimizes $J(y_i)$. $y_{b,\,i}$ is the background value for ith data point. $y_{o,\,i}$ is the perturbed observed value for ith data point. σ_b^2 is the variance for background soil moisture error. σ_o^2 is the variance for observed soil moisture error. k is the number of data points (k is set to 1 for sequential data assimilation).

The population P_r is sorted using Pareto dominance to select n fitter members which in turn are varied and recombined to determine new members for the population P_r of size $2n$. The evaluation and evolution procedures are repeated through several generations where each generation attempts to increase the overall quality (or fitness) of members in P_r. The final n fitter members obtained at the referenced generation are archived into the population P_e where they represent the updated members for the current assimilation time step. The updated members represent a subset chosen from several members which are evaluated for the current assimilation time step.

The archived population P_e is applied into JULES to estimate n number of soil moisture predictions forward in time to $t+1$, where the average and its associated variance from the n members are used as background information. The assimilation time step is then incremented from t to $t+1$ with P_e from t serving as a seed population for $t+1$, where it is varied and recombined to generate a new population P_r of size $2n$. The increment in assimilation time step and the seed population represent the update step in the EDA procedure. The seed population provides the new state for the prediction model and the background information to penalize model outputs. The new P_r, with new members, again undergoes continuous evaluation and evolution through several generations to determine the final n members where they are archived into P_e. The P_e members are stored as updated members for the current assimilation time step $t+1$. For each assimilation time step, the above procedures are repeated to assess

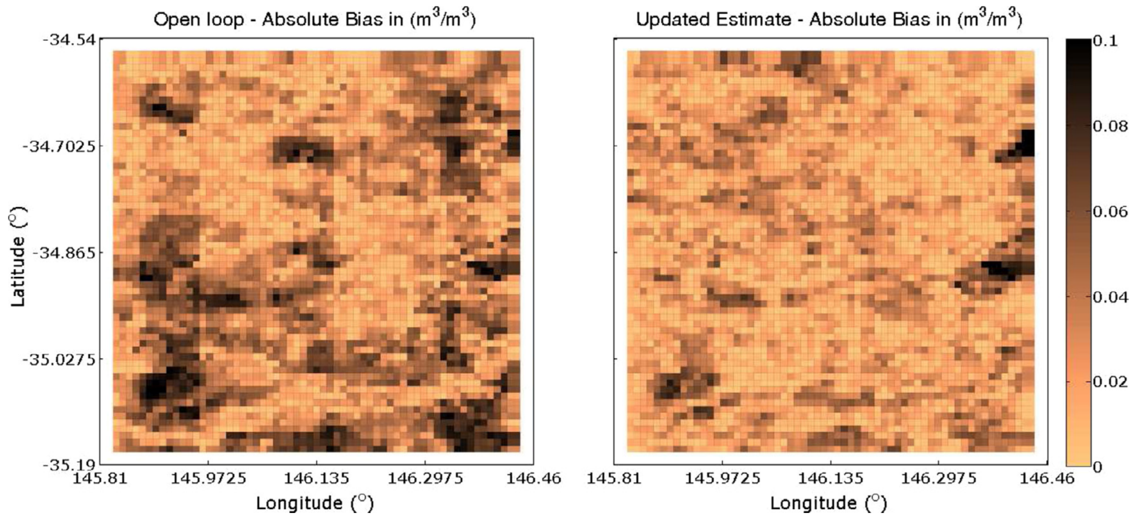


Fig. 3. Evaluation of the open loop and updated soil moisture against the observation DisPATCh data based on spatial plot of the overall absolute bias across all assimilation time steps for the 1-km model grids.

and evolve members through several generations, and to determine the final n members as updated members.

2.3. Setup of model and data assimilation runs

The EDA procedure is applied to assimilate daily DisPATCh soil moisture into the JULES model for dates when data are available. Soil moisture was simulated in JULES for four different soil layers including: 0–5 cm, 5–30 cm, 30–60 cm, and 60–90 cm, to approximately correspond to the OzNet validation data set. The top 0–5 cm soil moisture from JULES was compared to the DisPATCh data set during the assimilation. The soil moisture observation error is based on the standard deviation of the daily DisPATCh soil moisture error [37]—this error accounts for only the downscaling and retrieval errors and not the sensor error. The errors for model parameters and forcing data uncertainties are presented in Table 1 as uncertainty interval values. The soil moisture prediction error is time-variant and adaptive, and is made up of the model error and the background error. The model error is derived from the ensemble members which evolve between and at each assimilation time step, whereas the background error is determined from the seed population as outlined in Section 2.2. The adaptive property of the model error is based on the evolution of the forcing error applied to the original forcing data sets—the forcing error is distinct for each assimilation time step and variable across generations (i.e. during evolution).

The initial population is generated by using the model parameter/variable bounds and the forcing data uncertainties as shown in Table 1. According to the standard NSGA-II procedure, a crossover probability of 0.8 and a mutation probability of $1/n$ (where n is the number of variables) are used. The assimilation was run at a daily interval from January to December 2010 with 200 ensemble members. To evaluate 200 members, the EDA divides the ensemble size of 200 into smaller population of 40 members where it is evolved through 5 generations. A subset of 20 updated members is determined from the final population for each assimilation time step, where it is archived for evaluation.

3. Results and discussion

3.1. Evaluation of the updated soil moisture

An initial evaluation of the updated soil moisture from the assimilation procedure is conducted by comparing it against the observation DisPATCh data. An open loop estimate of soil moisture determined from the JULES model was also compared to the observation DisPATCh data. Using absolute bias as the evaluation criterion, the open loop and the updated estimates are compared against the DisPATCh data in Fig. 3, showing a spatial plot of the estimated absolute bias values for each 1-km model grid across all assimilation time steps (135). The results show that model grids with high absolute bias values from the open loop output also have corresponding high absolute bias in the updated output. But the model grids in the updated output are mostly associated with lower absolute bias compared to the open loop estimate, which has several model grids with higher absolute bias values. Overall, the updated soil moisture improved upon the accuracy of the open loop estimate across all the model grids. Specifically, the updated output has improved the open loop estimate by 34% based on the absolute bias criterion for all the model grids combined. This initial absolute bias evaluation is consistent with findings in several studies [15,32,33,45] which showed that the updated output improved upon the open loop estimate.

Additional evaluation of the updated and open loop outputs is undertaken using the root mean square error (RMSE) criterion. The comparison of the open loop and the updated estimates against the DisPATCh data is presented in Fig. 4, showing a spatial plot of the estimated RMSE values for each 1-km model grid across all assimilation time steps (135). Again, the results show that the model grids with higher RMSE values from the open loop estimate have corresponding higher RMSE values in the updated output. In contrast with the absolute bias evaluation, the number of model grids associated with higher RMSE values is similar in both open loop and updated outputs, but with much lower RMSE values represented in the updated output. Overall, the open loop estimate is slightly inferior to the updated estimate based on the RMSE values across all the model grids. The accuracy improvement of the updated output over the open loop estimate is 2% based on the RMSE criteria for all the model grids combined.

It is noted that the finding from the RMSE evaluation is not overwhelmingly consistent with the absolute bias evaluation and those from several studies including [15,32,33,45]. Ideally, it is expected that the updated output show a stronger agreement with the observation, and to improve upon the open loop estimate, because the observation DisPATCh was used to drive the assimilation procedure. However, the temporal updating in the simulation model (JULES, in this case) usually modifies the model trajectory from those found in the open loop. The modified model trajectory in the updated output, in this case, does not provide an overwhelming improvement over the

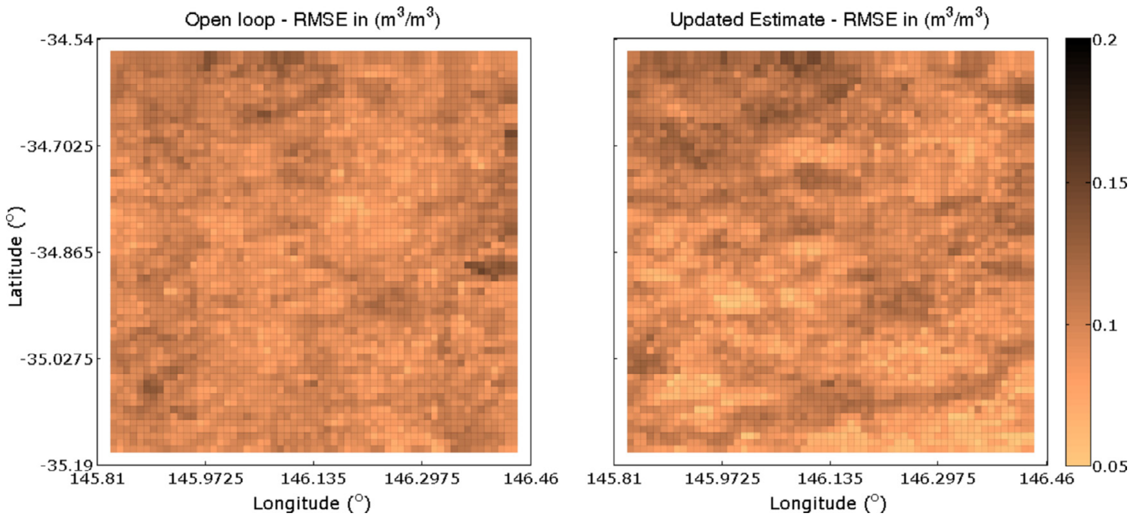


Fig. 4. Evaluation of the open loop and updated soil moisture against the observation DisPATCh data based on spatial plot of root mean square error (RMSE) across all assimilation time steps for the 1-km model grids.

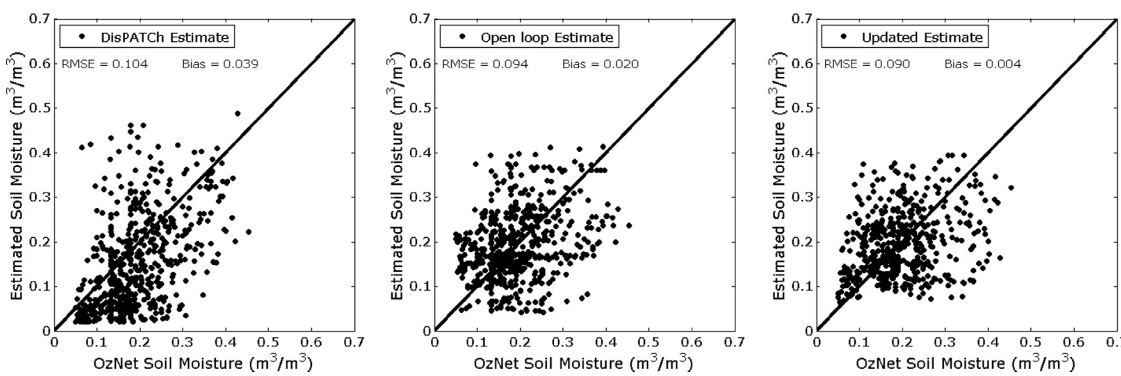


Fig. 5. Evaluation (based on RMSE and bias both in m^3/m^3) of the DisPATCh data, the open loop estimate, and the updated estimate against in-situ OzNet soil moisture at 0–5 cm soil depth, for all 13 stations with available data which overlap the assimilation time periods.

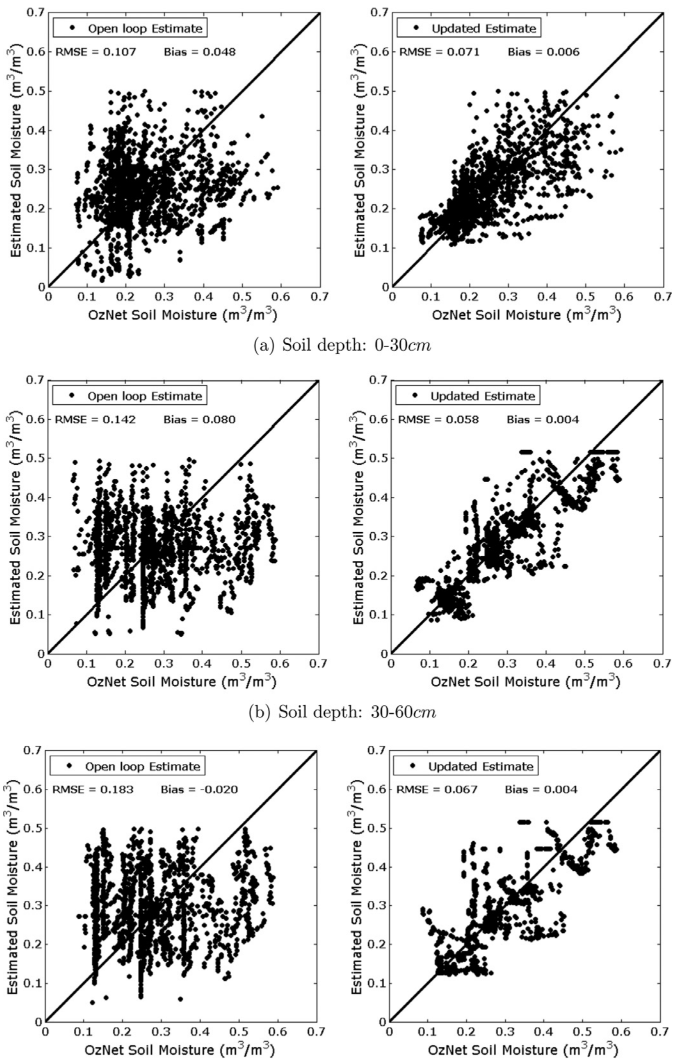
open loop estimate for all the model grids. It is noted that for some model grids, the agreement with the observation DisPATCh data and the estimated soil moisture is similar for both open loop and updated outputs, but the updated estimate has better RMSE values with all the model grids combined.

Further assessment of the estimated soil moisture is undertaken using in-situ OzNet [48] soil moisture. The updated and the open loop estimates together with the DisPATCh data are evaluated by comparing them against the in-situ OzNet surface (0-5 cm) soil moisture in Fig. 5. This comparison uses all the 13 OzNet stations for all time periods which overlap the assimilation time periods. The rationale to include the comparison of DisPATCh data against the in-situ soil moisture is to examine its impact, whether positive or negative, on the assimilation procedure. The DisPATCh comparison is also aimed to recognize the differences that currently exist between the observation DisPATCh data and the in-situ OzNet soil moisture. The comparisons show that the soil moisture errors (based on RMSE and bias) in the updated estimate are not worse than those that exist in the DisPATCh data. Also, the updated soil moisture is slightly better than the open loop estimate based on both RMSE and bias estimates. That is, the increasing order of accuracy for the estimated soil moisture is DisPATCh data, open loop output and updated estimate. Combining the outputs presented in Figs. 3–5, it is found that the simulated soil moisture from the JULES model is moderately in agreement with the in-situ soil moisture, and that the assimilation of the DisPATCh data into the JULES model has a positive impact on the soil moisture estimation accuracy.

3.2. Evaluation of the updated root-zone soil moisture

The improved estimate of surface soil moisture is important, but for practical applications in agriculture, water resource management, and weather forecasting, the root-zone soil moisture is critically important. Again using the in-situ OzNet soil moisture but at the root-zone for the three soil depths of 0–30 cm, 30–60 cm, and 60–90 cm, the open loop and updated outputs are evaluated using both RMSE and bias. It is noted that since the DisPATCh data is limited to only the surface soil moisture, it is not included here for the root-zone evaluation. The open loop and updated estimates of the root-zone soil moisture are compared to the in-situ OzNet root-zone soil moisture in Fig. 6 for the three soil depths at 0–30 cm, 30–60 cm, and 60–90 cm. Again, these evaluations used all the 13 OzNet stations for all time periods which overlap the assimilation time periods.

The results show that the updated output has increased the soil moisture estimation accuracy at the root-zone in comparison to the open loop output. For all the three soil depths, the updated root-zone soil moisture is consistently superior to the open loop root-zone estimate based on both RMSE and bias values. The comparisons show that the updated output has increased the open loop accuracy, based on RMSE, by 34% for the 0–30 cm data, 59% for the 30–60 cm data, and 63% for the 60–90 cm data. Statistical tests using significance levels of 0.05 and 0.1 for open loop and updated outputs found that both estimates for all three soil layers come from populations with unequal means. Additionally, the correlation coefficient (r) for the updated output was found to be 0.70, 0.89, and 0.84 respectively for



(a) Soil depth: 0-30cm

(b) Soil depth: 30-60cm

(c) Soil depth: 60-90cm

Fig. 6. Evaluation (based on RMSE and bias both in m^3/m^3) of the open loop and updated estimates against in-situ OzNet soil moisture at deeper soil depths of 0–30 cm, 30–60 cm, and 60–90 cm, for all 13 stations with available data which overlap the assimilation time periods.

0–30 cm, 30–60 cm, and 60–90 cm soil layers with p-value of zero in all three cases. In the case of the open loop output the r (and p) values were found to be 0.2(0.0), 0.1(0.08), and 0.1(0.01) respectively for 0–30 cm, 30–60 cm, and 60–90 cm soil layers.

The increasing accuracy of the updated output over the open loop estimate for deeper soil depths is not due to increased improvement in the updated estimate for deeper soil layers, but that the open loop estimation deteriorates for deeper soil depths. That is, the agreement between the in-situ OzNet soil moisture and the estimate from the updated output is similar across the three soil depths, in a way that there is no significant increase or decline in soil moisture estimation accuracy. Whereas in the open loop output, the agreement between the in-situ OzNet data and the estimated root-zone soil moisture is weak at the shallower soil depth of 0–30 cm, weaker at 30–60 cm soil depth, and weakest at the deeper soil depth of 60–90 cm. This is mainly because in the open loop output, the temporal consistency for dry and wet soil moisture conditions have poor matchings (or agreement) in comparison with those from the in-situ OzNet data. This is supported by a time series evaluation of the open loop and updated outputs against the in-situ OzNet data at station Y4 for the three soil depths presented in Fig. 7. The consistent performance of the updated output demonstrates the positive impact of the observation DisPATCh data and the assimilation procedure on root-zone soil moisture estimation.

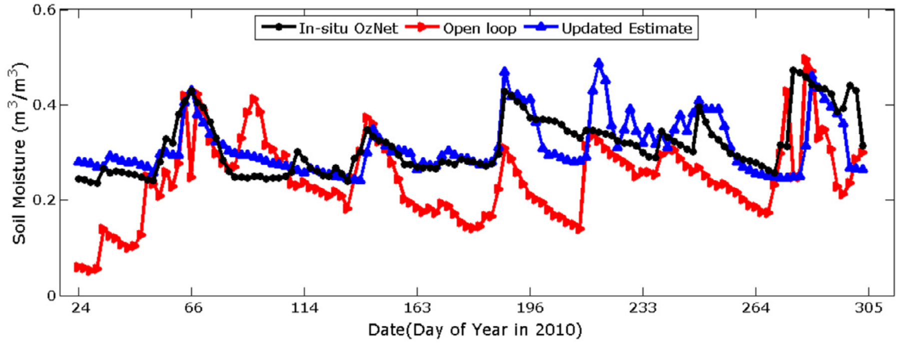
The improved estimation accuracy at the root-zone for the updated output points to an important implication for soil moisture data assimilation. It is notable that the accuracy difference between the open loop and the updated estimate is almost negligible for the surface soil moisture in terms of RMSE. As shown, the surface is not much different in terms of RMSE but the temporal evolution is improved leading to an improved correlation. Thus, the improvement at the root-zone for the updated output is primarily due to: (i) the observation DisPATCh data, and (ii) the EDA approach. The major role of the DisPATCh data is its soil moisture signature which was suitably adapted by the EDA method into the JULES model trajectory. In other words, the soil moisture signature from the DisPATCh data at the surface corresponds well with the deeper soil moisture. This is an important feature of the DisPATCh data which has not been previously noted, and for that matter a unique property which needs to be assessed for all surface soil moisture products. The EDA approach is also credited for its characterization of the JULES model in response to the DisPATCh soil moisture signature. A unique feature of the EDA approach is its identification of stable parameter values in model decision space through several assimilation time steps. The evolutionary feature of the EDA also means that soil moisture memory is properly maintained between assimilation time steps.

4. Implication of findings and conclusions

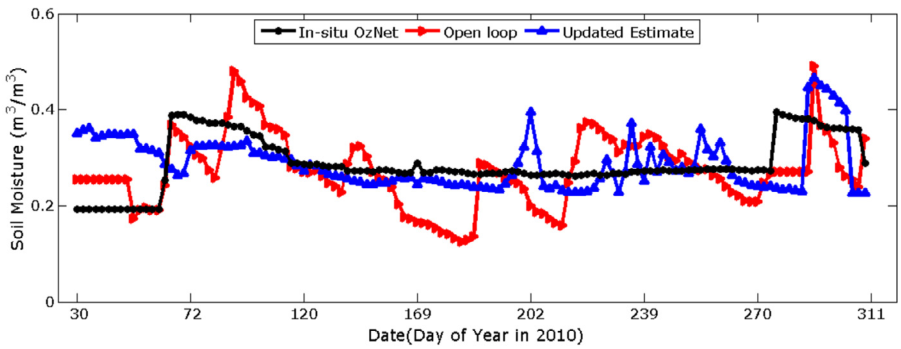
This study has demonstrated improved estimation of root-zone soil moisture through the assimilation of the 1-km DisPATCh surface soil moisture into the JULES land surface model. The assimilation was undertaken using the advanced evolutionary data assimilation, a promising framework combining computational evolutionary strategy with temporal updating from traditional data assimilation. The DisPATCh assimilation using the EDA procedure was conducted for the Yanco area in south eastern Australia, where the open loop and updated outputs were evaluated using in-situ OzNet soil moisture data both at the surface and at the root-zone.

Evaluation of the outputs for the surface soil moisture showed that the updated estimate is superior to the open loop output based on both RMSE and bias. Although the updated output has better estimation accuracy measures (RMSE and bias) than the open loop, its estimated soil moisture is not significantly different in comparison to the open loop estimate. That is, when evaluated using the in-situ OzNet surface soil moisture for RMSE criterion, the open loop output was found to be 95% as accurate as the updated output, with the updated estimate improving the DisPATCh soil moisture by about 14%. It was found that the DisPATCh data has a positive impact on the assimilation, because the soil moisture estimation error obtained from the updated output is not worse than those that exist in both the DisPATCh data and the open loop output.

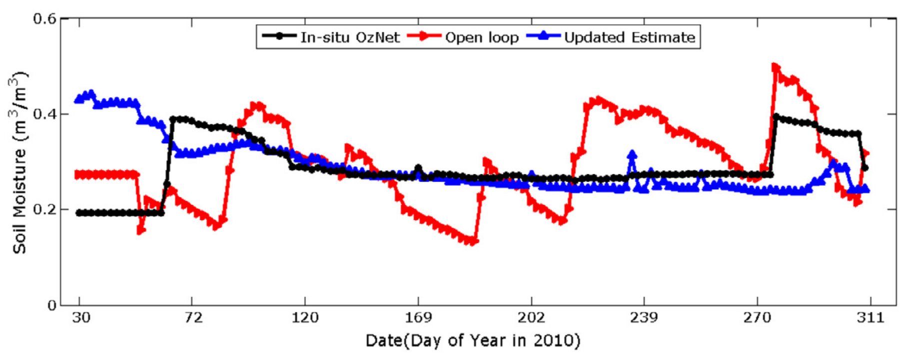
Furthermore, the open loop and the updated outputs were evaluated using the in-situ OzNet root-zone soil moisture at soil depths of 0–30 cm, 30–60 cm and 60–90 cm. The evaluations showed that the root-zone soil moisture estimation accuracy in the updated output remained stable across the three soil layers, and that the estimation accuracy was found to be independent of the depth of soil. In contrast, the open loop estimate was found to deteriorate with increasing soil depth, in a way that the shallower soil depth has a relatively moderate accuracy, with the deeper soil depth having the worst estimation accuracy. Based on evaluation with in-situ OzNet data, the updated root-zone soil moisture was found to be consistently better than the open loop output across all the three soil depths. Also, the evaluation based on the RMSE criterion showed that the updated output



(a) Soil depth: 0-30cm



(b) Soil depth: 30-60cm



(c) Soil depth: 60-90cm

Fig. 7. A time series evaluation of the open loop and updated estimates against in-situ OzNet soil moisture for station Y4 at deeper soil depths of 0–30 cm, 30–60 cm, and 60–90 cm.

increased the open loop estimate by 34% for the 0–30 cm data, 59% for the 30–60 cm data, and 63% for the 60–90 cm data, resulting in an overall accuracy increment of 52%.

These findings point to a combined positive impact from the DisPATCh data and the EDA procedure, which together have provided an improved soil moisture with consistent accuracy both at the surface and at the root-zone. The soil moisture estimations and their subsequent evaluations showed a limited positive impact from the assimilation on the surface soil moisture in comparison to the open loop output, yet having significant impact at the root-zone level. In other words, the updated soil moisture estimation accuracy was found to remain similar both at the surface and root-zone, but the deterioration of the open loop estimate at deeper soil layers partly contribute to the demonstrated greater impact of the assimilation at the root-zone. These findings are subject to the limited modeling time period, mainly due to the scarcity of consistent forcing and observation data sets. But the key finding is the provision of root-zone soil moisture based on capability from the EDA approach and the DisPATCh data set.

The implications of these findings on soil moisture estimation are important. The findings highlight the need to assess the signature of surface soil moisture products and their impact on root-zone soil moisture. The study has shown results which validate the soil moisture signature of the downscaled DisPATCh data to support root-zone soil moisture estimation. Given the strong impact of the DisPATCh data on root-zone soil moisture, there is potential to provide high resolution root-zone soil moisture at the global scale from downscaled SMOS data.

The findings demonstrated in this study also point to additional questions for future investigation. Soil moisture assimilation studies have been conducted in the past to integrate direct satellite observations and retrieved satellite soil moisture. This study has added disaggregated satellite soil moisture with particular focus on root-zone soil moisture estimation. It is important for future studies to compare and contrast these independent soil moisture assimilation procedures to determine which data set provides the most improvement to root-zone soil moisture estimation, and under what conditions the different data sets perform favorably.

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