

Assimilation of microwave brightness temperatures for soil moisture estimation using particle filter

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Abstract. Soil moisture plays a significant role in global water cycles. Both model simulations and remote sensing observations have their limitations when estimating soil moisture on a large spatial scale. Data assimilation (DA) is a promising tool which can combine model dynamics and remote sensing observations to obtain more precise ground soil moisture distribution. Among various DA methods, the particle filter (PF) can be applied to non-linear and non-Gaussian systems, thus holding great potential for DA. In this study, a data assimilation scheme based on the residual resampling particle filter (RR-PF) was developed to assimilate microwave brightness temperatures into the macro-scale semi-distributed Variance Infiltration Capacity (VIC) Model to estimate surface soil moisture. A radiative transfer model (RTM) was used to link brightness temperatures with surface soil moisture. Finally, the data assimilation scheme was validated by experimental data obtained at Arizona during the Soil Moisture Experiment 2004 (SMEX04). The results show that the estimation accuracy of soil moisture can be improved significantly by RR-PF through assimilating microwave brightness temperatures into VIC model. Both the overall trends and specific values of the assimilation results are more consistent with ground observations compared with model simulation results.

1. Introduction

Soil moisture is a key state variable in land surface processes. It controls the partitioning of water and energy fluxes at the land surface and also influences the terrestrial water cycles [1]. There are commonly three ways to obtain soil moisture information. The first way is to simulate it by running a land surface model (LSM). However, the model simulation results often deviate far from the true values due to uncertainties in meteorological forcing data, model parameters, and model structure [2]. The second way is to derive the soil moisture from in-situ measurements. However, in situ soil moisture measurements are generally expensive and no large soil moisture networks exist to measure soil moisture at high temporal frequency. Microwave remote sensing data provide another means to estimate soil moisture at large scales, but only surface soil moisture can be retrieved due to the limitation of microwave penetration depth [3]. Integrating the benefits of these three methods can improve the soil moisture accuracy. Data assimilation (DA) provides a way to effectively combine model simulations and various observations and thus yield superior soil moisture estimations [4-5].

Among various DA methods, the most popular data assimilation method is the Kalman filter (KF)

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which was developed for linear systems. Later it was extended to nonlinear systems, resulting in the extend Kalman filter (EKF). But the EKF will lead to inaccurate and unstable results when the nonlinearities of the system are strong [6]. To address this problem, the ensemble Kalman filter (EnKF) was introduced. It uses ensembles to represent state and parameter distributions and thus can be applied to nonlinear systems. However, there are common limitations in the above three KFs. They all hold the assumption that the probability density function (pdf) of state variables is Gaussian, and the evolution of the filter is governed only by its second-order characteristics [7]. These limitations can be relaxed by the particle filter (PF) which is based on Monte Carlo simulation [8]. Compared with three KFs, PF relaxes the assumption of Gaussian distribution of state variables. Hence, it can be applied to non-linear and non-Gaussian state-space models. In addition, PF only updates weights of particles instead of updating the state variables directly, so it can better maintain the balance and stability within the LSM [9]. Since PF has so many great advantages, it has received considerable attention in land data assimilation in recent years [10-13]. However, there is a common problem with PF that is the degeneracy phenomenon which means after some time steps most particles have negligible weights. This problem can be addressed by a resampling method [14]. Douc et al. [15] compared different resampling methods in his study, and found that the residual resampling method could effectively reduce the variances of particle weights with higher computational efficiency than other methods.

In this study, a data assimilation scheme was developed based on the residual resampling particle filter (RR-PF) to estimate surface soil moisture. The Variance Infiltration Capacity (VIC) model [16] was used as the LSM, with a radiative transfer model (RTM) [17] as the observation operator to link brightness temperatures with surface soil moisture. Then two comparative experiments were performed to verify the data assimilation scheme with experimental data obtained during Soil Moisture Experiment 2004 (SMEX04) in Arizona.

2. Residual resampling particle filter

The principle of PF is to represent the required posterior pdf of state variable by a set of random particles with associated weights [8]. Suppose N particles $\{x_k^i\}_{i=1}^N$ with associated weights $\{w_k^i\}_{i=1}^N$ are sampled from the posterior pdf $p(x_k | z_{1:k})$. Then the posterior pdf can be approximated as:

$$p(x_k | z_{1:k}) \approx w_k^i \sum_{i=1}^N \delta(x_k - x_k^i) \quad (1)$$

Where δ is the Dirac function. Since it is difficult to directly sample from the posterior pdf, the particles are often generated from a known important density, denoted by $q(x_k | z_{1:k})$. In practical application, the sequential importance sampling (SIS) method is often used. It updates the particle weights in a recursive form, as equation (2):

$$w_k^i = w_{k-1}^i \frac{p(z_k | x_k^i) p(x_k^i | x_{k-1}^i)}{q(x_k^i | x_{k-1}^i, z_k)} \quad (2)$$

The choice of importance density is one of the most critical issues in the design of PF. The most widely used choice is the transitional prior pdf, where: $q(x_k^i | x_{k-1}^i, z_k) = p(x_k^i | x_{k-1}^i)$. Then the weight updating formula in equation (2) becomes:

$$w_k^i = w_{k-1}^i p(z_k | x_k^i) \quad (3)$$

The final estimated state $\hat{x}_k$ is the weighted mean of these particles, as follows:

$$\hat{x}_k = \sum_{i=1}^N x_k^i w_k^i \quad (4)$$

A common problem with PF is the particle degeneracy, where after a few iterations most particles have negligible weights. In order to solve this problem, Gordon et al. [14] put forward the method of resampling. Douc et al. [15] made a comparative analysis of different resampling algorithms, and

found that the residual resampling method could effectively reduce the variances of particle weights and was computationally more efficient than other methods. Hence, the residual resampling algorithm was used to solve the problem of particle degeneracy in this study. Details about this algorithm can be found in Douc et al. [15].

3. Experiment site and data

The experiment site is located in the southeast of Arizona in the United States with an area of 32km×32km. Three soil moisture field observation networks are deployed in the experiment site with a total of 31 soil moisture observation sites, shown in figure 1. Moreover, the Polarimetric Scanning Radiometer (PSR) with polarimetric channels of C-band (7.32GHz) and X-band (10.7GHz) obtained brightness temperatures of the experiment site for nine days which were 5 August, 8-10 August, 12-13 August and 24-26 August, respectively. The PSR/CX has a footprint size of 800m×800m, with both horizontal and vertical polarizations. Microwave signal is more sensitive to soil moisture when the frequency is lower. Additionally, the horizontal polarization brightness temperatures are more sensitive to soil moisture than the vertical polarization. Therefore, the C-band brightness temperatures with horizontal polarization were selected as the observation data in this study.

In order to eliminate the spin-up period, VIC model began to run on 20 June. The assimilation period was chosen from 5 August to 26 August with a total of 22 days. Three soil depths of VIC model were defined as 5cm, 30cm and 100cm and only surface soil moisture was updated by brightness temperatures. In addition, VIC model was run with a time resolution of 24 hours. The spatial resolution was defined as 800m×800m to be consistent with that of brightness temperatures. Besides, meteorological forcing file, soil file and vegetation file are required for the operation of VIC model. The meteorological forcing file was extracted by joint interpolation of the meteorological data provided by both the meteorological stations in the experiment site and the North American Land Data Assimilation System (NLDAS). The vegetation file was obtained from the global land cover type data and the vegetation parameters library file provided by the University of Maryland and the NLDAS, respectively. The soil file was determined by the CONUS-SOIL database. All data were projected to the same coordinate system, and resampled to the resolution of 800m×800m.

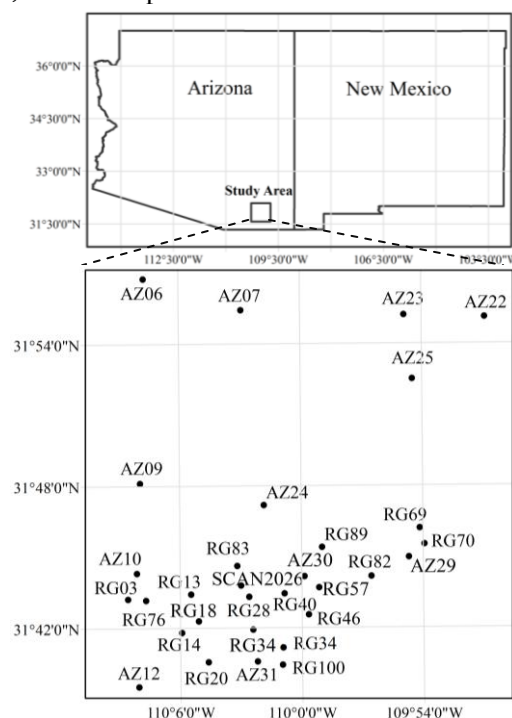


Figure 1. The location of the experiment site and the distribution of all soil moisture observation sites.

4. Experiment results and analysis

To validate the data assimilation scheme, two comparative experiments were performed: (1) In experiment 1, a forward reference run of VIC model was performed to simulate surface soil moisture; (2) In experiment 2, brightness temperatures were assimilated by RR-PF to estimate surface soil moisture. The results of two comparative experiments are compared with ground soil moisture observations at AZ06 and RG100 soil moisture observation sites, shown in figure 2. The following conclusions can be drawn from figure 2: (1) from the results of experiment 1, we can see that the simulation results of the reference run deviate far from the ground observations. This is mainly due to the uncertainty resources in VIC model, including the meteorological forcing data, model structure and model parameters. (2) Comparing the results of experiment 1 and experiment 2, it can be seen that RR-PF can effectively reduce the uncertainties in VIC model by assimilating brightness temperatures, thus improving the accuracy of soil moisture estimations significantly. Both the specific values and overall trends of the assimilation results are more consistent with the ground observations in contrast to the model simulation results.

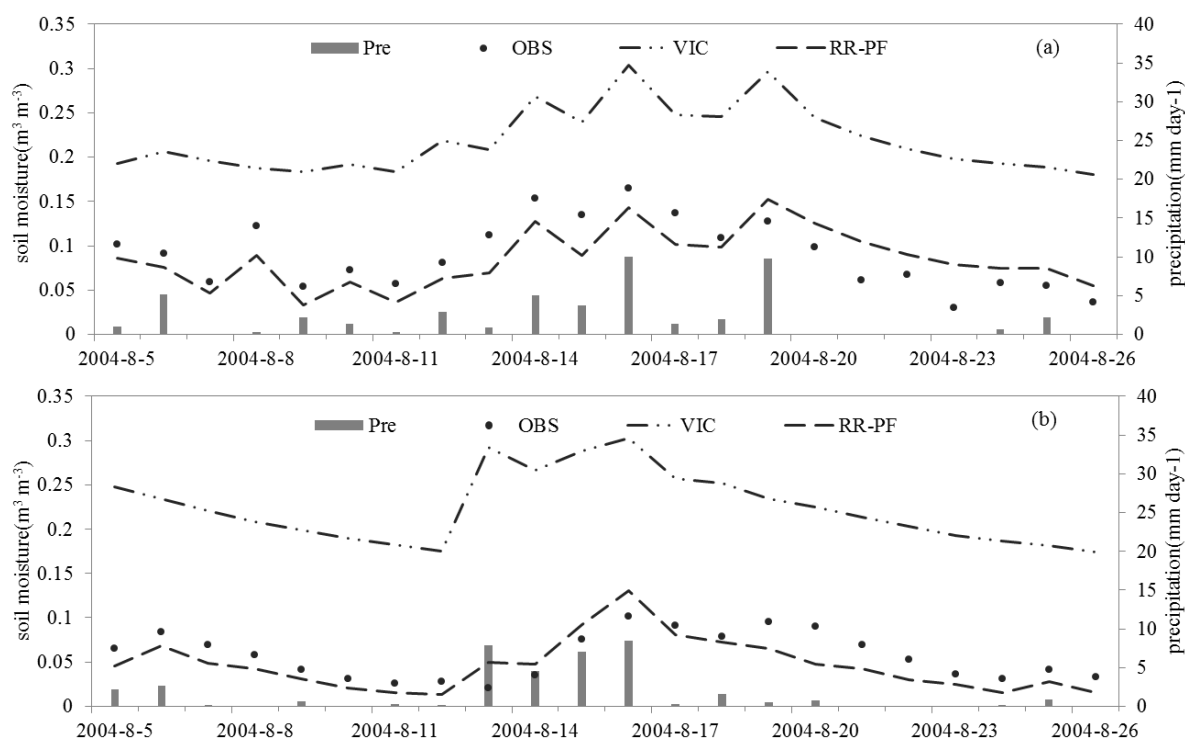


Figure 2. Comparison of the results of two comparative experiments with soil moisture observations. (a) Comparison results at AZ06 site. (b) Comparison results at RG100 site. Pre denotes the precipitation, OBS denotes the ground observations, VIC denotes the model simulation results and RR-PF denotes the assimilation results.

At the same time, the root mean square error (RMSE) and the mean bias error (MBE) are used to compare the results of two experiments quantitatively. The RMSE and MBE values of two comparative experiments are listed in table 1. As shown in table 1, the RMSE and MBE values of the assimilation results are much smaller than those of the model simulation results. This further indicates that the accuracy of soil moisture estimations can be greatly improved by RR-PF through assimilating brightness temperatures into VIC model.

Table 1. The RMSE and MBE values of two comparative experiments

Station	VIC		RR-PF	
	RMSE	MBE	RMSE	MBE

AZ06	0.13	0.13	0.03	-0.01
RG100	0.17	0.17	0.02	-0.01

Only the experimental results at AZ06 and RG100 observation sites are shown above. In order to demonstrate the effectiveness of the data assimilation scheme in the entire study area, the two comparative experiments mentioned above were performed at all 31 soil moisture observation sites. The RMSE and MBE values of two comparative experiments at all 31 sites are shown in figure 3. As can be seen from figure 3, the RMSE and MBE values of the assimilation results are significantly lower than those of the VIC model simulation results. The RMSE and MBE values of the assimilation results are mainly concentrated in the range of 0 to 0.05 and -0.05 to 0, respectively, while the RMSE and MBE values of the model simulation results are mainly concentrated in the range of 0.1 to 0.15 and 0.05 to 0.15, respectively. This further indicates that the data assimilation scheme proposed in this study can greatly improve the estimation accuracy of soil moisture.

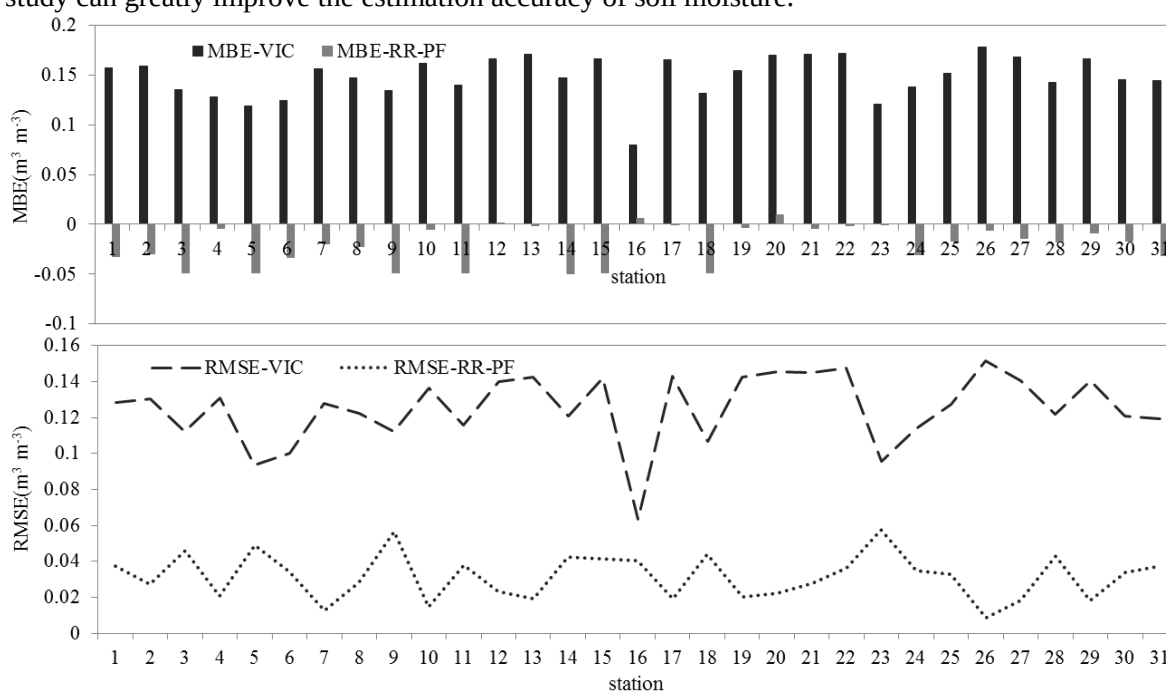


Figure 3. Comparison of the MBE and RMSE values of two comparative experiments at all 31 sites.

5. Conclusions

Accurate soil moisture estimation is of significant importance due to its strong influence on many water resources applications, such as agriculture and meteorology. DA can effectively combine model dynamics with observations and thus yield superior soil moisture estimations. Among various DA methods, RR-PF is free from the constraints of system linearity and Gaussian distribution of state variables, thus showing great promise for DA. In this study, a data assimilation scheme based on RR-PF was developed to estimate surface soil moisture. Microwave brightness temperatures were assimilated into the macro-scale semi-distributed VIC model, with a RTM to link brightness temperatures with surface soil moisture. Then the data assimilation scheme was validated by the experimental data obtained in Arizona during SMEX04. The results show that RR-PF can improve the accuracy of soil moisture estimations significantly through assimilating microwave brightness temperatures into VIC model. Compared with the VIC model simulation results, the assimilation results show much better conformity with ground soil moisture observations, thus demonstrating the validity of the data assimilation scheme.

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