Abstract: Ensemble Kalman filter is a new sequential data assimilation algorithm which was originally developed for atmospheric data assimilation. It calculates background error covariance matrix using Monte-Carlo method and is able to resolve the nonlinearity and discontinuity existed within model operator and observation operator. When observation data are assimilated at each time step, background error statistics were estimated from the phase-space distribution of an ensemble of model states were used to calculate the Kalman gain matrix and the analysis increments. In this work, we develop a one-dimensional soil moisture data assimilation scheme based on ensemble Kalman filter and simple biosphere model (SiB2) to assimilate soil moisture measurement. We also do some assimilation experiments using GAME-Tibet observation data from July 6 to August 9, 1998, at the MS3608 site on the Tibetan plateau. Once every 12 hours, in situ observations of soil moisture at the depth of 4, 20, 100 cm are assimilated into land surface model (SiB2) and the best estimations of soil moisture at the surface layer, the root zone and the deep layer are calculated. The results indicate that data assimilation can significantly improve the soil moisture estimation in the surface layer, the root zone and the deep layer. And we think that the Ensemble Kalman filter is both practical and effective for assimilating in situ observation into land surface models.

1 Introduction

Soil moisture is a crucial variable required by the study of meteorology, hydrology and agriculture, which affects on the partitioning of energy, runoff, radiance balance, and matter transfer. As a result, the accurate estimation of soil moisture has important effect on studying and understanding biogeochemical processes of land surface. However, the spatiotemporal variation of soil moisture is significant and it is unpractical to build high density soil moisture observation network. Though land process model or hydrology model can simulate the continuous variation of soil moisture, the errors caused by the uncertainties of model and parameters would accumulate gradually and diverged from the true value. Four dimensional data assimilation method, which originates from meteorology and oceanography (Daley, 1991), was eventually introduced into the filed of land surface science and hydrology (McLaughlin, 1995). Data assimilation allows us to address some problems related to uncertainties in model and data, helping us to assess the worth of various data sources and to use this data in an optimal way. We can build land data assimilation system and obtain more accurate descriptions of the system state by assimilating available information such as observation from ground, satellite, and radar. In the fields of land surface and hydrological sciences, some tentative and innovated works were carried out. The methods of assimilating microwave data into hydrological models have been discussed in many literatures (Entekhabi, 1994; Houser, 1998; Schuurmans, 2003; Galantowicz, 1999; Hoeben, 2001). The performance of different data assimilation algorithms coupled with land surface model or hydrological model, is tested and evaluated (McLaughlin, 2002; Reichle, 2001, 2002(a), 2002(b); Walker, 2001; Kumar, 2003; Crow, 2001, Li, 2004; Pathmathevan, 2003(a), 2003(b)). The EnKF is a new sequence data assimilation method (Evensen 1994), and has been proven to efficiently handle strongly nonlinear dynamics and large state spaces and is now used in realistic applications with primitive equation models. In the filed of hydrology, Reichle et al (2002a) applied the EnKF to soil moisture estimation and found it performed well against the variational assimilation method. Reichle et al (2002b) assessed the performance of the EKF and EnKF for soil moisture estimation and concluded that the flexibility and performance of EnKF is better than those of EKF.

In this work, we develop a one-dimensional soil moisture assimilation scheme, which is based on EnKF and simple biosphere model (SiB2) to assimilate soil moisture observation. In order to examine the feasibility of this system, we do some assimilation experiments using GAME-Tibet observation data from July 6 to August 9 in 1998, at the MS3608 site on the Tibetan plateau.

2 Data assimilation methodology

In general, the data assimilation system is composed of the model operator, the observation operator, data assimilation algorithm and data sets. Model operator, in land data assimilation system (LDAS) is usually a land surface model, which simulates energy and mass transfer between the soil, vegetation, and the atmosphere. Observation operator expresses the relationship between state variables and observation data. If observation is brightness temperature from microwave sensor, the observation operator can be expressed by microwave transfer model. Data assimilation algorithm is used to integrate the model operator and observation operator, which utilizes observation data to optimize the state variables that are produced by model operator. Fig. 1 illustrates the flowchart of soil moisture assimilation scheme used in this paper.

In this experiment, model operator is SiB2 model (Sellers et al., 1986). Observation data are soil moisture in surface layer, root zone and deep layer, which are the same as state variables in SiB2, therefore, the observation operator is an
identity matrix. EnKF is the candidate for data assimilation algorithm.

The Simple Biosphere (SiB2) Model, originally developed by Sellers et al. (1986), was substantially modified (Sellers et al., 1996a), and has since been referred to as SiB2. The number of biome-specific parameters was reduced, and most are now derived directly from processed satellite data (Sellers et al., 1996b). SiB2 model includes three soil layers: a surface soil layer of a few centimeters (0-5cm), which acts as a significant source of direct evaporation when moist. A root zone (5-20cm), which is the supplier of soil moisture to the roots and accounts for transpiration; and a deep soil layer, which acts as a source for hydrological base flow and upward recharge of the root zone. The thorough explanations of soil parameterization in SiB2 are given in Li and Koike (2003). In our assimilation scheme, we only assimilate three prognostic state variables (soil moisture in surface layer, root zone, and deep layer).

EnKF was proposed firstly by Evensen (1994) and has been used widely by scientists in atmosphere, ocean and hydrology. In our experiment, we adopt EnKF with perturbed observations as assimilation algorithm, which was proposed by Burgers (1998). It adds random perturbations with the correct statistics to the observations and generates an ensemble of observations which then is used in updating the ensemble of model states. Experiment has showed that this method can result in an updated ensemble with a low variance. The complete procedure of EnKF is described by Burgers (1998).

3 data

The Tibetan Plateau, which is considered as a heat source of atmosphere in summer and to have an important impact on the Asian monsoon system (Ye and Gao, 1979), is one of studying regions of the GEWEX (Global Energy and Water Cycle Experiment), Asian Monsoon Experiment (GAME). To understand the interactions between the land surface and the atmosphere over the plateau in the context of the Asian monsoon system, a plateau-scale experiment and a meso-scale experiment were carried out by the prophase observation period (POP) field work in August-September 1997 and the intensive observation period (IOP) field work in May-September 1998 as well. A much dense automatic observation network of meteorology and land surface hydrology has been established for long-period observation (Fig. 2). Numerous high quality data is being obtained and a database of GAME-IOP and POP has been developed.

MS3608 is located at 31°13.6' N latitude, 91°47.0' E longitude with an elevation of 4610 m. The landscape at the site is short-grazed grassland, which usually lasts 3-4 months in summer. Automated weather system (AWSs) and soil moisture and temperature system (SMMTS) were installed at MS3608.

In order to run SiB2 at MS3608, we need many parameters, including land cover, soil types, spatio-temporal varied vegetation parameters and aerodynamic parameters. Most of the static parameters are derived from Sellers et al. (1996b) directly, while other parameters are obtained by field measurements in GAME-Tibet experiment and optimization. A thorough description of the parameters has been presented in other papers (Li and Koike, 2003, Pathmathevan, Koike and Li, 2003).

4 Result

In this test, parameters used in ensemble Kalman filter algorithm are: the ensemble size is 30, assimilation cycle is 12
hours. The model error covariance matrix and observation error covariance matrix that we used are:

\[ Q = \begin{bmatrix}
2.5 \times 10^4 & 0 & 0 \\
0 & 1.44 \times 10^4 & 0 \\
0 & 0 & 2.5 \times 10^4
\end{bmatrix} \quad R = \begin{bmatrix}
1 \times 10^4 & 0 \\
0 & 1 \times 10^4 \\
0 & 0 & 1 \times 10^4
\end{bmatrix} \]

The time series of assimilation and control run results of soil moisture in surface layer, root zone and deep layer are given in fig. 3(a)-(c) at MS3608 site. As for surface layer, when it rains, the results of control run will overestimate and assimilation results are closer to observation in 4cm than the results of simulation. However, assimilation results are worse than simulation results without rain. In a whole, the RMSE of control run and assimilation are the same (about 0.021). Soil moisture estimation in surface layer can not be improved much by assimilating observation in 4cm because of the representative error of observation and drastic fluctuation of soil moisture in the surface layer.

The soil moisture variation in root zone is given in fig. 3(b). In comparison with soil moisture observation in 20cm, results show the improvement of soil estimation from assimilation obviously. The results of assimilation are closer to observation in 20cm than those of control run. When it rains, the results of assimilation and control run will rise increasingly. During the whole process of experiment, the RMSE of control run and assimilation in root zone are 0.063 and 0.026, respectively. The soil moisture estimation in root zone can be improved greatly by assimilating observation.

The fig. 3(c) is the results of soil moisture estimation in deep layer. Compared with observation in 100cm, the results of assimilation are much closer to observation. The RMSE of control run and assimilation are 0.018 and 0.004, respectively.

Fig. 4 is the variance propagation of soil moisture after assimilation. In surface layer, when observation exists, the variance of soil moisture goes up significantly. This indicates that assimilation does not take effect at the surface layer. We consider that it is caused by the model error and the representative error of observation. In root zone and deep layer, the variance goes down when observation exists. So, assimilating observation can avoid the variance increase and improve the estimation of soil moisture in root zone and deep layer in certain degree.

5 Summary

In this work, we develop a one-dimensional soil moisture assimilation system based on ensemble Kalman filter algorithm and SiB2. We tested the feasibility of this scheme using GAME-Tibet observation data from July 6 to August 9 in 1998, at the MS3608 site on the Tibetan plateau. We can draw the following conclusions: (1) the soil moisture estimation can be improved by using Data Assimilation. (2) In surface layer, assimilation effect is not prominent. On the whole, assimilation value is lower than observation value. (3) In root zone, simulation error is large and assimilation can decrease error drastically. (4) In deep layer, soil moisture is stable and assimilation result is close to observation value. In a word, Ensemble Kalman filter is both practical and effective for assimilating in situ observation into land surface models.

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