A NEW OBSERVATION ERROR ESTIMATION METHOD IN REGIONAL SOIL MOISTURE DATA ASSIMILATION

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ABSTRACT: Recently, it has been suggested that soil moisture could be better estimated through assimilating various observations into ecosystem models in order to effectively use all sources of information. While, accurate estimation of the spatial distribution of observation error is always difficult due to its spatial heterogeneity. In previous studies, observation error derived from remote sensing data was assumed only correlated with time and isotropic in space. This assuming alleviates the computing pressure, but ignores the inversion error of special heterogeneity and increases error to the assimilation process. In this study, a drought index of remote sensing data is used to get the observation soil moisture. In consideration of that the spectrum of land surface is mixed spectrum of soil and vegetation, a classified inversion method which based on vegetation coverage has been put forward. In the method, different functions are selected to invert soil moisture which is based on the LAI level of each pixel, and also the error of each inversion result is based on the selected function. A case study is conducted in several areas in Ningxia province of China. The soil moisture inverted by SPSI is used as observation data to be assimilated into BEPS (Boreal Ecosystem Productivity Simulator), and an Ensemble Kalman Filter is used to perform the data assimilation. The result demonstrates that the method considering the spatial distribution of error variance in soil moisture from remote sensing can not only improve the model prediction of daily soil moisture, but also help to understand the spatial variations of soil moisture better.

1. INTRODUCTION

Soil water content is a key variable for estimating plant growth and energy exchange between the surface and the atmosphere, and it is improtant in agricultural production, weather forecast, climate change and global change research(Zhan, Z. etc. 2006). Nevertheless, under the impact of spatial heterogeneity, such as soil properties, land cover conditions, climatic conditions, Soil moisture vary very much in both space and time, which make it difficult to conduct large-scale continuous monitoring of soil moisture. In recent years, data assimilation technology involved with remote sensing has increasingly become the hot spots and cutting-edge in eco-hydrological process model and remote sensing inversion researches (Han X., Li X., 2008). Some studies have indicated that soil moisture could be better estimated through assimilating various remote sensing observations into ecosystem models(Zhu L., 2009a). However, when the data assimilation process extended to a regional scale from a single point, how to accurately estimate the spatial distribution of observation data error is a very critical step. Because of the lack of prior knowledge for the error level of observation, the error variance of observation data is considered as static and spatially isotropic(Buehner, M., etc. 2005). The disadvantage of this approach is, using a sole value to represent the error level of the entire image will ignore the spatial variability of error, and it may lead to erroneous results for heterogeneous soil surface. Thus, more accurate estimation of observation errors according to the spatial variability of the regional parameters, thereby improving accuracy of soil moisture after data assimilation, is of great significance.

This article has put forward a method to improve the defect that the error variance of observation data is considered as static and spatially isotropic. LAI(leaf area index) has been introduced to estimate the error variance of inverted soil moisture from drought index. As a result, we propose some improve strategies for the data assimilation of soil moisture.

2. RESEARCH METHOD

A typical data assimilation model should include three aspects: continuous dynamic model, discontinuous observations and assimilation algorithm. This study selected BEPS (Boreal Ecosystem Productivity Simulator), a Process-base terrestrial ecosystem model, as a continuous simulation model of soil moisture; made use of SPSI(Shortwave Infrared Perpendicular Water Stress Index) derive from remote sensing data to invert soil moisture as observation and utilized Ensemble Kalman Filter as assimilation method. This article combined these three aspects and proposed improvement program.

2.1 The BEPS Model

The ecosystem model, BEPS(Liu, J., etc. 1997; Chen, J.M., etc. 1999) was developed by Canada Centre for Remote Sensing, and it is a computer simulation system of soil moisture which based on remote sensing data. It was a integrative model developed to simulated ecosystem carbon budget and water consumption. It includes energy partitioning, photosynthesis, autotrophic respiration, soil organic matter (SOM) decomposition, hydrological processes and soil thermal transfer modules. BEPS model can be well combined with remote sensing data: it takes land cover types from remote sensing as input parameter, on the other hand, it use the Leaf Area Index derived from remote sensing to update model parameters.

The original BEPS model is "barrel type model", calculated the balance of soil moisture daily, according to rainfall, infiltration and evaporation process(Liu, J., etc. 2003). In order to use The ecosystem model and soil moisture of surface layer converted by remote sensing data into data assimilation, Zhu etc. modified the "barrel type model" into "two layers model" which set the 0-10cm as the surface layer and 10cm below as another layer. Soil moisture of each layer is calculated base on the theory of water balance, and infiltration of water between two layers is also considered(Zhu, L., etc. 2009b). Figure 1 has shown the water fluxes included in BEPS.

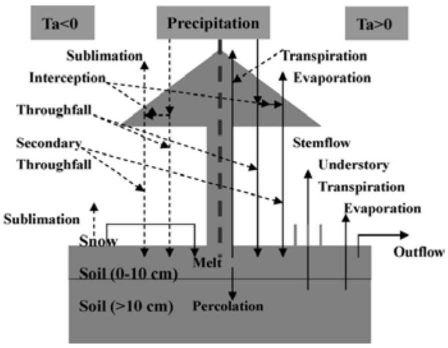


Figure.1. Water fluxes included in BEPS

2.2 Observation Data

In the process of continuous simulation of soil moisture with BEPS, the error of simulation results will gradually accumulate over time, which makes it necessary that observation values be imported to correct simulation results and enhance the accuracy of model simulation.

Remote sensing has the characteristic that wide coverage, fast data acquisition, bulk information and so on. Since some bands are extremely sensitive to surface moisture conditions, remote sensing data can be taken advantage of to get surface soil moisture as the observation of data assimilation. Ghulam has found that shortwave Infrared Perpendicular Water Stress Index(SPSI), constructed with the spectral feature space,has a strong correlation with soil moisture and canopy water content(Ghulam, A., etc. 2007).

In this study, the SPSI was derived from MODIS images (intial 500 m resolution was aggregated to 1 km resolution), the 0-10 cm soil moisture data was measured in weather stations of Ningxia province. We conducted linear fit of the two,and verify the strong correlation between them with a correlation coefficient of 0.78. The fitting formula is as follows:

$$\theta_{layer1} = -0.74*SPSI + 0.39 \quad (1)$$

Where θlayer1 represents 0-10 cm soil water content. Therefore, this study derives 0-10cm soil water from SPSI as the observation data of assimilation.

2.3 Data Assimilation Methods

Evensen (1994) proposed Ensemble Kalman Filter(EnKF),which is based on Monte Carlo sampling method. Over the last decade, ENKF has been widely used in the studies of surface data assimilation, because it limberly process uncertain data and its algorithm is easy to implement.

Kalman filtering analysis equation update the predicting result x_n^f by observed value y_n^{obs} and Kalman gain matrix K_n:

$$x_n^{ana} = x_n^f + K_n(y_n^{obs} - H_n x_n^f) \quad (2)$$

K_n is calculated by the equation below:

$$K_n = P_n^f H_n^T (H_n P_n^f H_n^T + R_n)^{-1} \quad (3)$$

where H_n is observation operator, P_n^f is error variance matrix of predicted value x_n^f, R_n is covariance matrix of observation error and the sum of error of H_n.

Zhu has developed "two stage data assimilation model for soil moisture (TSDA)" based on smoothing assimilation(Zhu L., 2009a). Driving parameters of ecological model will be updated in first stage, while soil moisture will be updated after the program run again with the updated parameter in second stage. This method don't only increase the precision of soil moisture, also improves the driving parameters of ecological model, which corrects the running state of model. Thus, in this study, we select TSDA as assimilation algorithm, to correct the model predicted value of the BEPS.

2.3.1 Assimilation Program

In the study, the assimilation model based on TSDA has a flow chart as Figure 2.

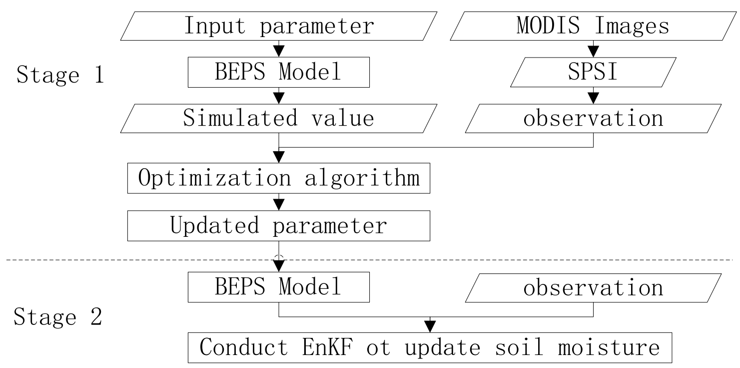


Figure 2.Flow chart of EnKF assimilation model

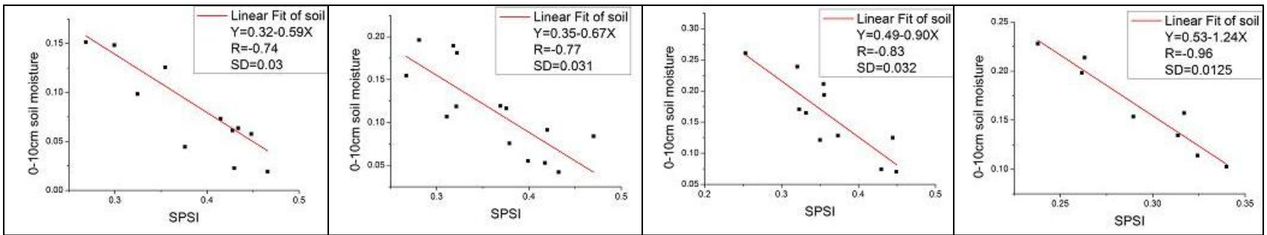
2.3.2 Analysis of Spatial Variability of Soil Moisture

When apply ENKF for each pixel of remote sensing image, the correction of state variables is determined by the Kalman gain coefficient. The error variances of observations and simulation are factors for calculating the Kalman gain, so more accurately estimating the error variance of observations will improve the accuracy of the results of assimilation. As surface conditions (Such as vegetation cover, topography, etc) differ a lot, the errors of soil moisture derived from SPSI are not quite the same. SPSI is computed through short-wave infrared and near infrared bands; the short-wave infrared is very sensitive to water content in leaves while near-infrared is not, so some certain combination of near infrared and shortwave infrared bands can be used to represent vegetation crop growth.

Meanwhile SPSI also reflect soil moisture condition, considering there is a strong correlation between vegetation water content and soil water content(Zhu L., 2009a). However, SPSI only consider the distance from the pixel to the soil line dry point in the two-dimensional scatter plot, made up according short-wave infrared and near-infrared bands, without taking into account the effects of vegetation. Theoretically speaking, the water retentivity of surface soil decreased with the reduction of vegetation coverage; as a result, soil moisture will also decrease. The error of soil moisture computed by SPSI should theoretically decrease with the increase in vegetation biomass and vegetation coverage. That is to say, the higher the level of vegetation coverage is, the more reliable the results of inversion are, and vice versa.

In view of the above-mentioned problem, this study takes LAI representing the level of vegetation coverage, classifies SPSI and measured soil moisture according to different LAI, and fit different inversion formulas under corresponding LAI condition.

The observation soil moisture data is offered by observation stations in Ningxia Province, including Guyuan, Haiyuan, Longde, Weizhou and Jingyuan. The fitting result and correlation between the measured soil moisture and SPSI in different LAI range is shown in Figure 3:



LAI = 0	LAI ∈(0.1, 0.5)	LAI ∈(0.6, 1.0)	LAI > 1.0

Figure 3. Inversion of soil moisture classified according to LAI

From the above fitting results, it can be clearly verified that, the relationship between SPSI and real soil moisture is very different under different levels of surface vegetation coverage. The correlation coefficient (R) increases clearly with LAI.

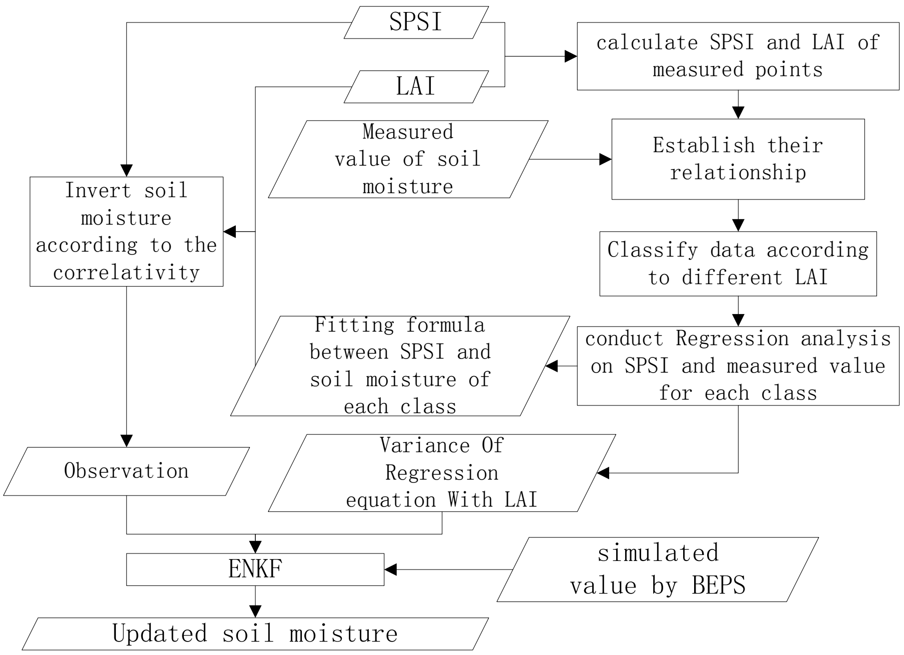


Figure 4. Flow chart of modified soil moisture assimilation under different LAI

In the process of ENKF, we take a modified method on the basis of above fitting relationship. The specific modifications are: 1) when adding noises to observation to generate ensemble of observations in the beginning, it select corresponding residual standard deviation (SD) under specific LAI as the mean square deviation of soil moisture;2) when update assimilation parameters and results with Kalman equation, it as well take specific SD as error variance of observations. The flow chart of these steps is as Figure 4.

3. RESULT AND VERIFICATION

3.1 Result of Different Cycles

In the verification, the measured surface soil moisture is observed in weather stations of Ningxia Province. Study area is Guyuan (106°16'E, 36°00'N). BEPS model runs from 8th March 2004 to 8th June 2004. And the days executing assimilation are 8th, 18th, 28th of April, May and June. Figure 5 has shown the difference between soil moisture of simulation and that after assimilation.

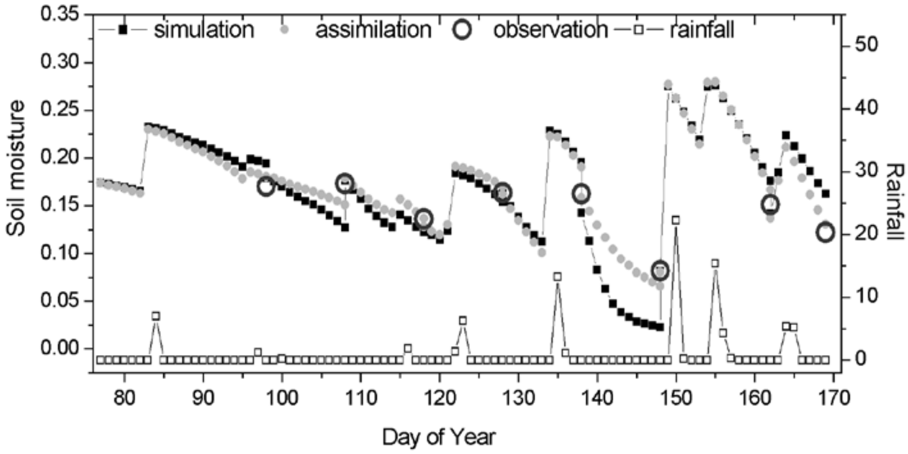


Figure 5 Result of soil moisture assimilation in Guyuan

The values of simulation, assimilation and observation show that (1) as the model running, simulation values have gradual deviation from observation, while values are closer to observation after assimilation; (2) the updated parameter in the cycle before will be used to improve the model in next cycle; (3) when the difference between simulation and observation, assimilating has great effect.

3.2 Result of Different Areas

We have also used our model in other palces of Ningxia, including Guyuan(106°16'E, 36°00'N), Haiyuan(105°34'E, 36°34'N), Longde(106°06'E, 35°37'N), Weizhou (106°31'E, 37°19'N) and Jingyuan(106°21'E, 35°31'N). BEPS model runs from 8 March 2004 to 28 March 2004. The figures below show the fitting results of soil moisture between simulated and measured.

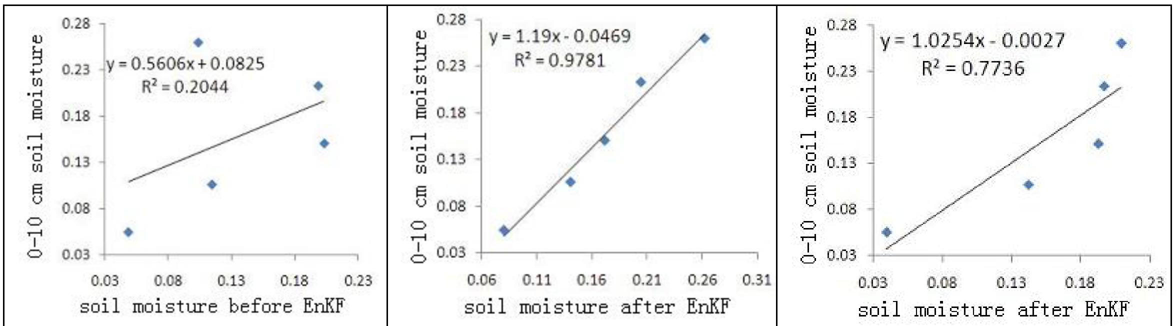


figure 6a	figure 6b	figure 6c

Figure 6. the fitting results of soil moisture between simulated and measured.

It's shown apparently that the correlation coefficient after data assimilation(R) is higher than the one before. The sum of error (the difference between calculated and measured values) squares could show the error level. We can see the sum of error squares before EnKF (S1) is 0.02751 and the one after that (S2) is 0.00227, which is more than ten times smaller than S1.

If we use the same formula to inverse soil moisture from SPSI without considering the different vegetation coverage in different areas, and use the same error variance to noise the observation, the result will be obtained as figure 6c. Compared with figure 6b, it has a smaller correlation coefficient and its sum of error squares (S3) is 0.00609 which is bigger than S2. So our solution can make the result of data assimilation more precise.

4. CONCLUSION AND DISCUSSION

In our study, we find the correlation between the surface soil moisture and SPSI is responsive to vegetation coverage of land surface. Through the experiment, it is proved that with the increase of LAI, the correlation will be increase and the error of inversion soil moisture by SPSI will be decrease.

With the result of this research, we propose an improved program. According to different LAI, we classify SPSI and measured values, fit different inverting formulas and calculate observation value, and set specific parameters of ENKF equation. Through this method, we have simulated the moisture of surface soil by combining BEPS model with data assimilation techniques. The results verify that this program can avoid error getting larger when we use SPSI to inverse soil moisture in areas of low vegetation coverage. It provides a method for real-time monitoring of soil moisture in large-scale and different vegetation coverage areas.

For the number of observation stations is small, and the spatial distribution of stations is discrete, the type of surface soil and vegetation is obvious differences. In our study, the impact on inversion model isn't considered while the land cover is different. In addition, the time of remote sensing data we used last more than three months. Climate and the solar altitude angles of remote sensing image is also different. These reasons led to increasing of uncertainty of observation soil moisture to a certain extent. Thus, more observation data which is continuous in space and time will be helpful to our future research.

5. ACKNOWLEDGEMENT

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