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Soil Moisture Initialization for Climate Prediction: Characterization of Model and Observation Errors

Wenge Ni-Meister (1), Jeffrey Walker(3), and Paul R. Houser (2)
1. Department of Geology and Geography, Hunter College of The City University of New York, New York, NY10021
2.Hydrological Sciences Branch, NASA Goddard Space Flight Center
3 The University of Melbourne Parkville, Victoria 3010, Australia

Abstract

Current models for seasonal climate prediction are limited due to poor initialization of the land surface soil moisture states. Passive microwave remote sensing provides quantitative information on soil moisture in a thin near-surface soil layer at large scale. This information can be integrated with a land surface process model through data assimilation to give better prediction of the near surface and deep soil moisture states than model predictions or remote sensing observations alone. To achieve this, it is necessary to have a good understanding of both the model and observation errors.

We have characterized the model error in the catchment-based land surface model(CLSM) used by the NASA Seasonal-to-Interannual Prediction Project (NSIPP) and the observation error of the near surface soil moisture from Scanning Multifrequency Microwave Radiometer (SMMR) data by comparing them with long term in-situ measurements of soil moisture collected in Russia, Mongolia and China. We found that in dry climate areas, such as Mongolia and central China, central Russia or when the soil is frozen, (e.g. fall and winter in Russia), the CLSM has a dry bias. In wet climate areas, such as the east coast of China and western Russia, the catchment model has a wet bias. The model error in Eurasia is typically less than 0.12(v/v). We also found that SMMR-derived soil moisture data has a wet bias in China, and dry bias in Mongolia and throughout most of Russia. The satellite observation error is large in wet and densely-vegetated regions and small in dry region. This indicates that if correct model error and observation error are used, data assimilation will give better soil moisture in China and Russia.

Our analysis also shows that the SMMR-derived soil moisture data show a over-projected seasonal change than the in-situ measurements, while the modeled soil moisture shows a depressed seasonal change than the in-situ measurements. This indicates that assimilating remote sensed soil moisture with larger seasonal change into the model producing depressed seasonal change will give better soil moisture seasonal change than the soil moisture estimate either pure model output or remote sensing satellite data alone. Lastly, the model predicts the rootzone soil moisture very close to in-situ measurements, indicating the assimilating surface soil moisture into the catchment model will give improved rootzone soil moisture which is important for climate prediction. Our error analysis has many implications for data assimilation and currently we are developing different assimilation algorithm to best take into account the model and satellite observation errors.

I. Introduction

Accurate initialization of land surface moisture and energy stores in fully-coupled climate system models is critical for seasonal-to-interannual climatological and hydrological prediction. Surface moisture exhibits persistence on seasonal-to-interannual time scales, this persistence has important implications for the extended prediction of climatic and hydrologic extremes, and better knowledge of soil moisture initialization plays an important role in seasonal predictions.

The land surfaces influence the atmospheric condition through exchanges of energy and moisture. Improved soil moisture initialization can be obtained through integrating land surface process models with remotely sensed satellite observations.

The NASA Seasonal-to-Interannual Prediction Project (NSIPP) is aimed at improving seasonal to interannual climate predictions using global coupled earth system (ocean-atmosphere-land-sea-ice) models. To enhance climate prediction, innovative data assimilation algorithms are being developed to merge satellite data and model predictions. To this end, Kalman filter-based data assimilation strategy for near surface soil moisture observations has been included in the CLSM model by (Walkeret al. 2001; Reichle et al. 2002) For assimilation effort, one key component is model error and observation error to ensure good performance of data assimilation. Biased model error and observation error used during data assimilation will result in biased assimilation results. As the first step of our data assimilation effort, this study characterizes the model and observation errors using in-situ measurements of soil moisture collected in Eurasia.

2. Data Sets

2.1 In-situ Measurements

The soil moisture measurements collected in China, Mongolia and Russia archived in the Soil Moisture Data Bank (Robock et al.,2000). The Soil Moisture Data Bank has soil moisture measurements collected at 43 meteorological stations in China, 42 meteorological stations in Mongolia and 130 meteorological stations in Russia over more than 8 years. The Russian dataset covers the period of 1978-1985, while the Chinese dataset covers the period of 1981-1991 and the Mongolian dataset with varied length records at different stations, starting in 1973 and ending in 1997. Soil moisture profiles were measured from 0 to 1m deep at 10cm increment. The majority of moisture monitoring sites were located either in grass or crop fields. This dataset is not pointed measurements. Each measurement is the averaged value of several measurements from several sample points. Particularly the soil moisture measurements for each station in Russia were obtained by averaging soil moisture over a small region so that the soil moisture measurement represents at a regional scale (K. Vinnikov, personal conversation). More details on the dataset and its collection can be found in Robock et al. (2000). For Russian and Mongolia datasets, only plant available soil moisture measurements are available. Since both SMMR-derived and modeled values are total soil moisture, The plant available soil moisture were converted into total soil moisture by adding the wilting point to plant available soil moisture.

2.2Model

The land surface model used in NSIPP is the Catchment-based Land Surface Model (CLSM) developed by et al. Koster (000c)nd Ducharne et al (2000) It uses a non-traditional land surface model framework that includes an explicit treatment of sub-grid soil moisture variability and its effect on runoff and evaporation. The fundamental hydrologic unit is the watershed defined by the topography rather than an arbitrary grid. Soil moisture heterogeneity induced by topography within the watershed is treated statistically. An analytical form of the TOPMODEL equation is used to produce consistent predictions of baseflow out of the watershed and out of the saturated fraction within it, which has a direct effect on evaportranspiration and surface runoff.

Atmospheric forcings used are the bias corrected reanalysis data of ECMWF forcings at half-degree from 1979 to 1993 developed by Berg et al. (2000) by adjustment of the re-analysis fields to match monthly mean observations. The gridded forcings were converted into catchment-based forcings and the model was run for the period of 1979 to 1993 over Eurasia. The model was first spinned up for ten years using the forcings of 1979 to initialize the model.

2.3 Satellite Observations

Passive microwave remote sensing techniques have been used to retrieve soil moisture content of a shallow surface soil layer (1cm) at globally 1/4 degree spatial resolution from the C-band Scanning Multifrequency Microwave Radiometer (SMMR) on the Nimbus-7 satellite for the period of 1979-1987 \citep{Owe2001}. The SMMR instrument was in a sun-synchronous orbit, resulting in one daytime measurement at local solar noon and one nighttime measurement at local midnight. The algorithm used by Owe et al. (2001) is different from other traditional approaches in that it uses both the horizontal (H) and vertical (V) polarization at 6.6 GHz (C-band)bands together with temperature derived from 37Ghz to solve simultaneously for surface soil moisture and vegetation optical depth. The algorithm was validated using in-situ soil moisture measurements from Illinois, US. The validation results indicate that the reliability of the soil moisture estimates becomes somewhat poor at large vegetation optical depths.

3. Results and Discussion

3.1 Bias of Model Prediction

Figure 1 shows the seasonal change of the difference of the modeled and in-situ measured surface and rootzone soil moisture. In Mongolia, central China and southern Russia, whose climate is relative dry, the model gives drier both surface and rootzone soil moisture. In the east coast of China and the boundary of Mongolia and Russia, whose climate is relative wet, both the modeled surface and rootzone soil moisture has a wet bias. In the northwestern Russia, the modeled surface soil moisture has a very dry bias in winter and fall and a wet bias in spring and summer. The dry bias in the winter and fall maybe related to the fact that the model is not be able to handle the frozen soil moisture well yet. For all seasonal, the modeled rootzone soil moisture tends to have a wet bias in China and Russia (except for the drier bias during winter and fall) and a dry bias in Mongolia. In summary, the model has a dry bias in dry climate or when the soil is frozen and wet bias in wet climate. Overall the dry bias is less than 0.12 for both surface and rootzone soil moisture. In some extreme wet areas, such as southeastern China, in the boundary of Russia and Mongolia next to Lake Baikal, and western Russia, the model error is over 0.12. The wet bias for the surface soil moisture is less than 0.16. The above analysis implies that the model error shows large spatial and temporal variations and using one constant model error will results in biased assimilation results. The spatial and temporal distribution of the model error has to be taken into account in order to obtain realistic assimilation results.

3.2 Bias of Satellite Observation

Figure 2 shows the climatological seasonal changes of the differences of the SMMR-derived and in-situ measured surface soil moisture and between the SMMR-derived and the modeled surface soil moisture. Compared to the in-situ measurements, SMMR gives drier surface soil moisture in Mongolia and Russia (except for the northeastern Russia where the climate is wet), and a wetter surface soil moisture in China for all seasons. However, compared to model results, the SMMR data gave a wetter surface soil moisture in Mongolia and China and a dry bias in Russia (strongest in western Russia).

4 Conclusions

We have estimated the model error and the satellite observation errors by comparing the modeled and SMMR-derived soil moisture with the in-situ measurements in three different climate environment regions in Eurasia. The three climate environments include China -- a strong monsoon climate and Mongolia -- a dry climate and Russia -- a strong seasonal climate including heavy snow during winter. Our study shows that 1) both the model and satellite observation errors/bias have large spatial and temporal variations. In general, the model tends to give a dry bias during winter and fall season when the ground is frozen and the model tends to give a dry bias under a dry climate and a wet bias under a wet climate. SMMR tends to overestimate soil moisture values in China and underestimate soil moisture in Russia during summer and fall. This implies that single constant values of model error and satellite observation error for data assimilation will result in biased assimilation results. RMSE of SMMR-derived soil moisture shows larger values than the one derived based on vegetation optical depth; 2). SMMR-derived soil moisture shows over-projected seasonal change than the observation, however the modeled soil moisture show depressed seasonal change. If the seasonal change of satellite observation is corrected assimilated into the model, we expect that the assimilated soil moisture will show a similar seasonal change to the in-situ measurements; 3) Spatially, some areas, SMMR data and the model estimate give opposite bias, for example, in Russia during the summer season, SMMR gives a dry bias and the model gives a wet bias; and in China, the model gives a dry bias and SMMR data give a wet bias. If the bias is correctly assimilated, then the assimilated soil mois ture will close to the ground truth. The current version of EnKF does not include bias correction; Also even in Mongolia, over the area where the absolute bias from SMMR is less than the absolute bias from model, we still expect improved soil moisture estimation through data assimilation. 4) Vertically, although the model does give too much vertical variations, the modeled rootzone soil moisture is very close to the in-situ measurements, which is extremely valuable for assimilation. In indicates that we can assimilate satellite-observed surface soil moisture into the catchment to be able to obtained improved rootzone soil moisture. The rootzone soil moisture is more important for climate prediction than the surface moisture.

Currently we are developing different assimilation algorithms to 1) take into account for the spatial and temporal variation of model and satellite observation errors in our data assimilation algorithm; 2) to assimilate the seasonal change by scaling the soil moisture, assimilating the soil moisture difference and implementing a bias correction in our assimilation algorithm.

Acknowledgments

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Reference:

Koster, R. and M. J. Suarez, 2000
Soil moisture memory in climate models, JMH, 2:558-570.

Koster, R. and M. J. Suarez and A. Ducharne and M. Stieglitz and P Kumar,2000, A catchment-based approach to modeling land surface processes in a general ciculation model, 1: Model structure",JGR,105(20):24,809-24,822".

Owe M. and R. de Jeu and J. P. Walker,
2001,A metholody for surface soil moisture and vegetation optical depth retrieval using microwave polarization difference index,TGRS,39:1643-1654.

Reichle R. and J. P. Walker and R. D. Koster and P. R. Houser",2002, "Extended vs ensemble kalman filtering for land data assimilation", JHM,3(6):728-740.

Robock A. and K. Y. Vinnikov et al.,2000, The Global Soil Moisture Data Bank, BAMS,81:81,1281-81,1299.

Walker, J. and P. R. Houser, 2001, A methology for initializing soil moisture in a global climate model: assimilation of near-surface soil moisture observations", 2001,JGR,106 (D11):11,761-11,774.

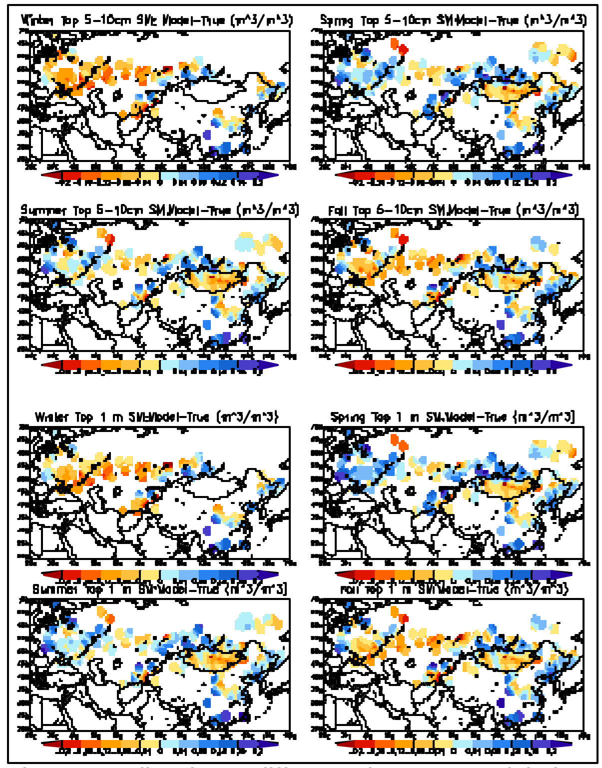

Figure 1. Soil moisture difference between modeled at 2cm depth and in-situ measurements at 5cm (China) and 10cm (Mongolia and Russia) depth in Eurasia during the period of 1979-1987.

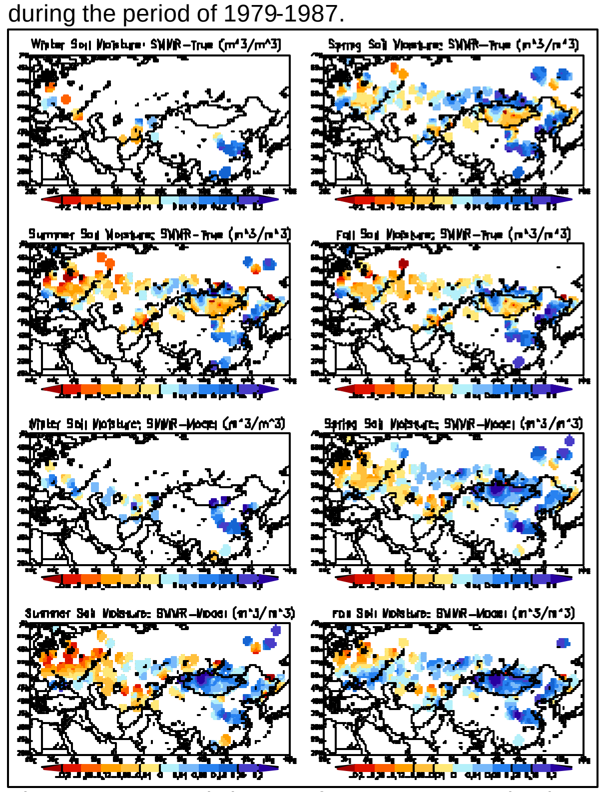

Figure 2. Seasonal change of SM_SMMR-SM_in-situ and SM_SMMR-SM_model over Eurasia during the period of 1979-1987