Characterizing regional uncertainty in the initial soil moisture status

Aaron A. Berg and James S. Famiglietti

Department of Earth System Science, University of California, Irvine, USA

Received 6 February 2003; revised 17 March 2003; accepted 2 April 2003; published 6 May 2003.

[1] Using two bias reduced forcing data sets we have simulated the initial soil moisture state for the North American continent (1985–1993). Differences between simulations were shown to persist over regions with the greatest soil memory, and are not strongly associated to patterns of difference in forcing fields. Therefore, processes that contribute to soil memory will also limit our ability to accurately estimate its initial state. Moreover, the regions associated with high soil memory may not be directly observable with present and near future sensors due to high vegetation water contents. Thus, research in these regions should be directed toward minimizing forcing variance and extension of observation networks and technology to increase the ability for monitoring soil moisture. *INDEX TERMS:* 1866 Hydrology: Soil moisture; 1833 Hydrology: Hydroclimatology; 3322 Meteorology and Atmospheric Dynamics: Land/atmosphere interactions; 3337 Meteorology and Atmospheric Dynamics: Numerical modeling and data assimilation. **Citation:** Berg, A. A., and J. Famiglietti, Characterizing regional uncertainty in the initial soil moisture status, *Geophys. Res. Lett.*, *30*(9), 1466, doi:10.1029/2003GL017075, 2003.

1. Introduction

[2] The presence of wet or dry soil moisture anomalies can impose a regional perturbation to the overlying atmospheric state, thus influencing the processes that control precipitation formation. Due to the slow dissipative processes that govern the recovery of a soil moisture anomaly, memory of past atmospheric conditions can feedback to the overlying atmosphere thus enhancing climate prediction in modeling studies over time scales ranging from days to months [e.g., *Fennessy and Shukla*, 1999; *Koster et al.*, 2000a]. Recognizing the importance of the initial soil wetness state, the production of retrospective and near real time soil water estimates are part of the NASA Seasonal to Interannual Prediction Project (NSIPP), the Global Soil Wetness Project (GSWP) [*Dirmeyer et al.*, 1999] and the Global Land Data Assimilation System (GLDAS) [*Rodell et al.*, The global land data assimilation system, submitted to *Bull. Amer. Meteor. Soc.*, 2002]. In the near-term, microwave remote sensors will provide surface soil moisture observations [*Njoku and Li*, 1999]; and real-time assimilation of this data [e.g. *Reichle et al.*, 2001; *Walker and Houser*, 2001] will produce soil moisture estimates through the entire soil profile. Unfortunately however, microwave remote sensing will be limited to regions of low to moderate vegetation cover [*Njoku and Entekhabi*, 1996], and therefore in regions without observations, the initial soil moisture state may have large uncertainties. Inconsistencies in the modeled initial soil moisture state would result from uncertainties between model parameterizations [*Dirmeyer et al.*, 1999; *Koster and Milly*, 1997], inaccuracies in the specification in land surface properties and from variations in the forcing products [*Berg et al.*, 2003]. To date, there has been much emphasis on understanding how differences between land surface parameterization schemes will influence hydrological simulations including soil moisture [*Dirmeyer et al.*, 1999; *Henderson-Sellers et al.*, 1996; *Wood et al.*, 1998]. However much of the uncertainty may also be related to inaccuracies in the forcing used to drive land surface models.

[3] In this study, we concentrate on the impact of uncertainty in the forcing on estimates of the initial soil moisture state. To accurately predict hydrological fluxes and soil moisture within a land surface model (LSM) a comprehensive suite forcing variables (short and long wave radiation, air and dew point temperature, precipitation, wind speed and surface pressure) are necessary over consistent temporal and spatial scales. For many regions of the globe, such data are not available aside from weather reanalysis products. However, the use of reanalysis products for driving LSM simulations is not recommended due to errors in the forcing fields [*Betts et al.*, 1998; *Lenters et al.*, 2000; *Maurer et al.*, 2001; *Roads and Betts*, 2000]. Therefore, in order to utilize reanalysis products for forcing in LSM simulations, previous work has focused on their improvement through bias removal. *Berg* [2001] and *Berg et al.* [2003] has removed bias associated with the European Centre for Medium-Range Weather Forecasts (ECMWF) and National Center for Environmental Prediction and National Center for Atmospheric Research (NCEP/NCAR) reanalyses [*Gibson et al.*, 1997; *Kalnay et al.*, 1996], and used this forcing to produce realistic estimates of the hydrological budget over the Mississippi River basin. The objectives of this study are 1) to use these two bias reduced forcing data sets to produce estimates of the initial soil moisture state over the North American continent and 2) to understand the sensitivity of root zone soil moisture estimates to modest variations (at the sub-monthly timeframe) in the forcing products. The results of this study demonstrate uncertainty in the initial soil moisture state and define regions where LSM simulations are most sensitive to variance in the forcing products.

2. Methods and Modeling Framework

[4] This study utilizes the catchment-based LSM (CLSM) [*Koster et al.*, 2000b; *Ducharne et al.*, 2000]. The CLSM uses atmospheric forcing (short and longwave downwelling radiation, convective and total precipitation, two-meter air and dew point temperatures, ten-meter wind speed, and surface pressure) and surface parameter descriptions (vegetation type, height, greenness, and leaf area index, rough-

0094-8276/03/2003GL017075

ness length at the surface, albedo, and the soil hydrologic properties) to perform calculations of land surface energy and mass exchange.

[5] The atmospheric forcing supplied to the CLSM was corrected using the methodology of *Berg* [2001] and *Berg et al.* [2003]. Bias to ECMWF and NCEP/NCAR reanalysis was removed for 2-meter air and dew point temperature, short and longwave downwelling radiation, and precipitation through difference and ratio-based corrections to monthly observational datasets. Because both reanalyses were bias corrected to the same monthly observations, differences between the datasets are related to sub-monthly differences in the forcing products (including the diurnal range of the 2-meter air and dew point temperatures, short and longwave downwelling radiation, and the frequency of reanalysis precipitation). Differences also exist between the uncorrected forcing fields, which include wind speed and surface pressure.

[6] To evaluate the differences between the root zone soil moisture simulated with each of the bias corrected forcing products, the CLSM was driven with the corrected version of the ECMWF re-analysis (CERA) and NCEP/NCAR re-analysis (CNRA) for the time period 01/1985–12/1993. We performed both simulations with identical versions of the CLSM, employing identical initialization (spin-up) schemes. During model spin up, the initial model state is determined by driving the model to equilibrium for January 1, 1985. Therefore, each run (CERA and CNRA) have starting positions in equilibrium with the forcing data. Here our analysis focuses on the initial soil water conditions forecasted for the snow free season (May–July) as previous work by other researchers [e.g., *Koster et al.*, 2000a] have shown that greater coupling between the land surface and the atmosphere occurs over summer.

3. Results and Discussion

[7] We created estimates of the initial soil moisture state using the CLSM driven by the two bias reduced forcing data sets described above for the period 1985–1993. Images of average (1985–1993) July root zone soil moisture (top meter) as forecast by the CLSM are presented in Figures 1a and 1b. Soil moisture patterns obtained from the CERA forcing (Figure 1a) are slightly drier than those derived from the CNRA (Figure 1b), although the patterns observed in both simulations are well replicated over the entire spatial domain. In Figure 1c we present average differences between the two simulations of root zone soil moisture (July, 1985–1993). The differences observed in Figure 1c, are due to modest variations (sub-monthly time scale) to the atmospheric forcing and are most significant over the US southeast extending northwards along 95th meridian towards Hudson's Bay and north of 55 degrees latitude, extending from Hudson's Bay to Alaska. Over the illustrated region (area in yellow and orange in Figure 1c), the average volumetric soil moisture difference (cm^3/cm^3) between the simulations was 4.2%, and the maximum difference observed was 13%. This corresponds to relative differences of approximately 10 to 30%, which are significant and likely to result in important feedbacks to the atmosphere.

[8] To understand the relationship between the differences in the forcing and resulting differences in patterns observed in the soil moisture fields, we evaluate average daily differences between the CERA and CNRA forcing fields for the months of May, June, and July. Average monthly differences in the daily maximum, minimum, range, average, and standard deviation were calculated for air and dew point temperature, short and longwave radiation, and ten-meter wind speed. For precipitation, we calculated average daily differences, and differences between the frequencies of precipitation for each of the months listed above. Next, we calculated the pattern correlations between the forcing fields (CERA and CNRA forcing differences), and the differences in soil moisture simulation presented in Figure 1c. In Table 1, we present the variables with the highest levels of correlation (all correlation statistics presented in this study are significant at the 1% level). Of the forcing fields, it appears that differences to daily maximum temperatures, the frequency of precipitation, average daily vapor pressure, maximum shortwave radiation, and daily minimum longwave radiation account for greatest effect on soil moisture differences. However, the

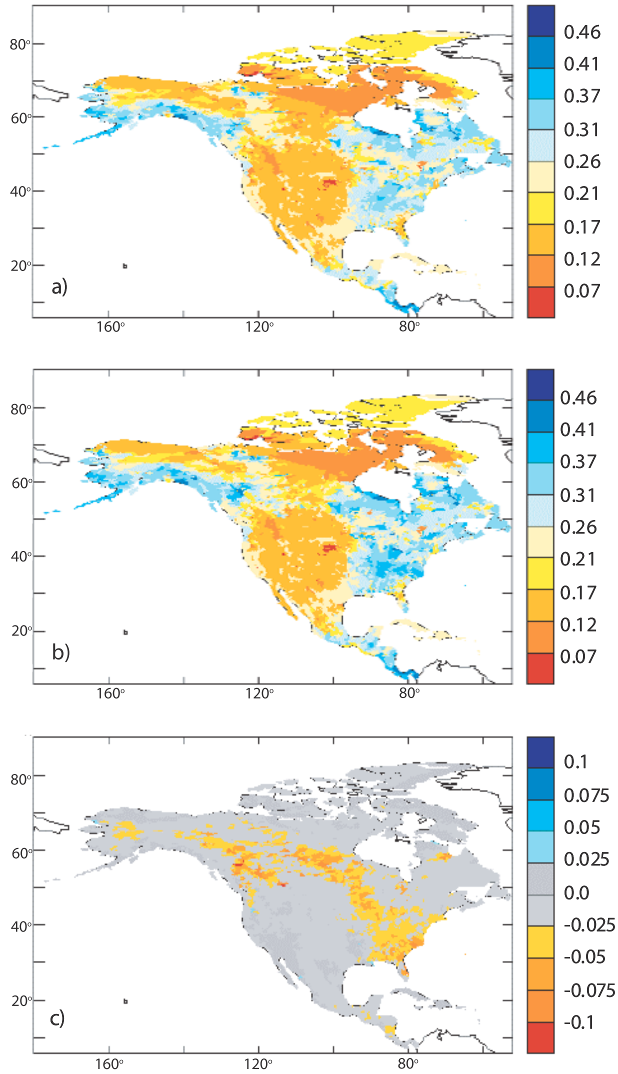

Figure 1. Average July (1985–1993) volumetric (cm^3/cm^3) root zone soil moisture conditions for simulations completed with a) CERA, and b) CNRA forcing. Differences between a) and b) are shown in c).

Table 1. Correlations Between Forcing Differences and Figure 1c

Forcing Field	Correlation		
	May	June	July
2-meter air temperature (daily maximum)	.35	.30	.23
2 meter vapor pressure (daily average)	.22	.26	.26
Precipitation Frequency (monthly)	0.17	.21	.20
Longwave Radiation (daily minimum)	.20	.24	.25
Shortwave Radiation (daily maximum)	.17	.11	.07
Wind speed (daily average)	.24	.25	.23

correlations between the spatial patterns in the forcing products and differences in soil moisture (Figure 1c) are weak overall. This suggests that while differences in forcing fields are responsible for the results presented in Figure 1c, no one forcing field stands out as the main cause of the observed pattern of differences.

[9] To ensure that the differences observed (Figure 1c) are not due to an identifiable pattern contained within a combination of many of the variables presented above, we calculated the principle components (PC) of the differences to forcing fields (for all fields presented in Table 1). Next, correlations between the PC fields and the results of Figure 1c were calculated. The highest correlations are between Figure 1c and PC1, PC2, and PC5 (−0.27, −0.25, and 0.29 respectively). Based on the results of this analysis, observed differences in soil moisture are not highly correlated to observable patterns in the forcing fields (as defined by their PC fields). Thus, we cannot explain the results of Figure 1c through observable patterns in the forcing.

[10] Lagged autocorrelations are used in several climate-modeling studies to understand how wet or dry anomalies in soil moisture persist [*Delworth and Manabe*, 1989; *Huang et al.*, 1996; *Maurer et al.*, 2001]. *Koster and Suarez* [2001] present a framework for predicting regions with high soil moisture memory based on a number of model and climatic factors. In this study, we calculate one-month lagged autocorrelation of soil moisture in the CLSM driven by the bias reduced forcing data. Here the one-month autocorrelation considers root zone soil moisture on July 1 with that on July 31 for both the CERA and CNRA simulation (1985–1993). The results, plotted in Figure 2, are an average of the CERA and CNRA autocorrelation maps (because both maps showed excellent agreement averaging the fields was appropriate). In Figure 2, an arc of high autocorrelation is visible surrounding the Great Plains region of the United States and Canada. This region of high autocorrelation is similar to that illustrated in the *Koster and Suarez* [2001] study although different LSMs were used.

[11] It is important to note that the areas of high autocorrelation (Figure 2) correspond closely to the regions identified in Figure 1c, which identified regions where differences between the two simulations of soil moisture were most pronounced. Correlations between patterns of July soil moisture autocorrelation and differences between the CERA-CNRA simulations are much higher (r = 0.44) than to any of the correlations calculated between the forcing fields or the principle component fields. High correlation between Figure 1c and Figure 2 demonstrates that uncertainty in forcing is manifest most directly in soil moisture estimates over regions with high soil memory (as identified by high July 1 to July 31 autocorrelations). Therefore, an estimate of the initial soil moisture state will have the lowest certainty over these regions unless steps are taken to reduce inconsistencies in forcing data or incorporate data assimilation techniques.

[12] To understand the significance of regions illustrated in Figure 1c we consider the results of *Koster et al.* [2000a] and *Owe et al.* [2001]. *Koster et al.* [2000a] examine precipitation predictably over the continents given sea surface temperatures (SST), and SSTs together with information of the land surface moisture state. Their results demonstrate that knowledge of soil moisture enhances precipitation predictability particularly over the south central and southeast regions of the United States, extending north and westward towards the Pacific Northwest, an area that shows important overlap with region identified in Figure 1c. Therefore, the results of Figure 1c have implications to the *Koster et al.* [2000a] study because for certain regions over North America, the areas where knowledge of the land surface wetness state is important for precipitation prediction may have higher uncertainty in the initial soil moisture content.

[13] Furthermore, soil moisture may not be observable by satellite over this same region. The study of *Owe et al.* [2001] describes the production of a surface soil moisture data set from Scanning Multichannel Microwave Radiometer (SMMR) satellite observations (1978–1987). Their methodology solves for soil wetness using a radiative transfer equation and observed brightness temperatures at 6.6GHz. Areas where soil moisture estimates were obtained by SMMR are comparable to those where the Advanced Microwave Scanning Radiometer (AMSR) will retrieve soil wetness observations as both instruments operate over similar frequencies [*Njoku and Li*, 1999]. In Figure 3, we plot the average number of SMMR based observations 1979–1987 derived from the *Owe et al.* [2001] study for the month of July.

[14] As discussed in *Njoku and Entekhabi* [1996] and illustrated in Figure 3, observations of soil moisture over the North American continent are limited to areas of low vegetational water contents. Comparison of Figure 1c to Figure 3 shows that the regions where there is the most uncertainty in the estimate (Figure 1c) exist over regions where AMSR satellite soil moisture observations may not be possible (Figure 3), moreover, some of these regions may

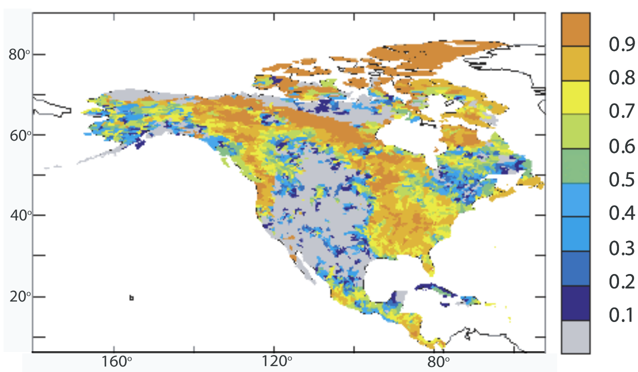

Figure 2. Simulated lagged autocorrelations of root zone soil moisture for July 1 to July 31 (1985–1993).

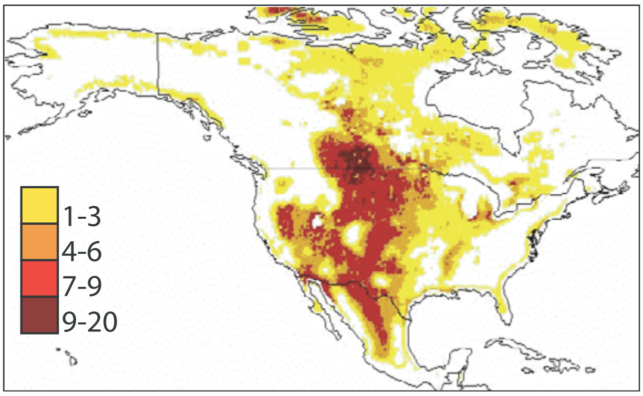

Figure 3. Average number of SMMR based soil moisture observations over North America for July (1979–1987).

be important for precipitation predictability [*Koster et al.*, 2000a]. Therefore, these uncertainties are unlikely to be constrained with current observations and assimilation approaches [e.g., *Walker and Houser*, 2001]. However, future (L-band) passive microwave sensors [e.g., *Jackson et al.*, 1999] that are less affected by high vegetation water contents may expand the observable region and thus minimize the differences observed.

4. Conclusions

[15] The results of this work suggest that the processes that contribute to soil memory will also limit our ability to accurately estimate its initial state for climate model simulations. Differences in simulated soil moisture resulting from inconsistencies in the CERA and CNRA forcing are manifest most clearly over regions associated with higher soil memory. Moreover, these same areas may be important for weather and climate predictions but are not directly observable with present sensors. Therefore, the results of this study suggest that further research towards minimizing forcing uncertainty and extending observational networks (both satellite and ground-based) are necessary for increasing the capability to accurately resolve the initial soil moisture state.

[16] **Acknowledgments.** This work was supported by NASA grants NAG5-11645, 12344, and the NASA Earth Science Fellowship Program. We would also like to acknowledge the comments and insights of two anonymous reviewers.

References

Berg, A. A., The sensitivity of land surface model simulations to bias correction of the European Centre for Medium Range Weather Forecasts reanalysis, Unpublished M.S. Thesis, The University of Texas at Austin, 2001.
Berg, A. A., J. S. Famiglietti, J. P. Walker, and P. R. Houser, The impact of bias correction to reanalysis products on simulations of North American soil moisture and hydrological fluxes, *J. Geophys. Res.*, in press, 2003.
Betts, A. K., P. Viterbo, A. C. M. Beljaars, H.-L. Pan, S.-L. Hong, M. Goulden, and S. Wofsy, Evaluation of land-surface interaction in ECMWF and NCEP/NCAR reanalysis models over grassland (FIFE) and boreal forest (BOREAS), *J. Geophys. Res.*, *103*, 23,079–23,085, 1998.
Delworth, T. L., and S. Manabe, The influence of soil wetness on near-surface atmospheric variability, *J. Clim.*, *2*, 1447–1462, 1989.
Dirmeyer, P. A., A. J. Dolman, and N. Sato, The pilot phase of the global soil wetness project, *Bull.Amer. Meteorol. Soc.*, *80*, 851–878, 1999.
Ducharne, A., R. D. Koster, M. J. Suarez, M. Stieglitz, and P. Kumar, A catchment-based approach to modeling land surface processes in a general circulation model, 2, Parameter estimation and model demonstration, *J. Geophys. Res.*, *105*, 24,823–24,838, 2000.
Fennessy, M. J., and J. Shukla, Impact of initial soil wetness on seasonal atmospheric prediction, *J. Clim.*, *12*, 3167–3180, 1999.
Gibson, J. K., P. Kållberg, S. Uppala, A. Nomura, A. Hernandez, and E. Serrano, ERA Description, *ECMWF Reanal. Proj. Rep. Ser.*, vol. 1, 72 pp., Eur. Cent. For Medium-Range Weather Forecasts, Reading, England, 1997.
Henderson-Sellers, A., K. McGuffie, and A. J. Pitman, The project for the intercomparison of land surface parameterization schemes:1992-1995, *J. Clim. Dyn.*, *12*, 847–859, 1996.
Huang, J., H. M. van den Dool, and K. P. Georgakokos, Analysis of model-calculated soil moisture over the United States (1931–1993) and applications to long-range temperature forecasts, *J Clim.*, *9*, 1350–1362, 1996.
Jackson, T. J., D. M. LeVine, A. Y. Hsu, A. Oldak, P. J. Starks, C. T. Swift, J. D. Isham, and M. Haken, Soil Moisture Mapping at Regional Scales Using Microwave Radiometry: The Southern Great Plains Hydrology Experiment, *IEEE Trans. Geosci. and Remote Sens.*, *37*, 2136–2151, 1999.
Kalnay, E., et al., The NCEP/NCAR 40-year reanalysis project, *Bull. Amer. Meteorol. Soc.*, *77*, 437–471, 1996.
Koster, R. D., and P. C. D. Milly, The Interplay between Transpiration and Runoff Formulations in Land Schemes used with Atmospheric Models, *J. Clim.*, *10*, 1578–1591, 1997.
Koster, R. D., and M. J. Suarez, Soil moisture memory in climate models, *J. Hydrometeorol.*, *2*, 558–570, 2001.
Koster, R. D., M. J. Suarez, and M. Heiser, Variance and predictability of precipitation at seasonal to interannual timescales, *J. Hydrometeorol.*, *1*, 26–46, 2000a.
Koster, R. D., M. J. Suarez, A. Ducharne, M. Stieglitz, and P. Kumar, A catchment-based approach to modeling land surface processes in a general circulation model, 1: Model structure, *J. Geophys. Res.*, *105*, 24,809–24,822, 2000b.
Lenters, J. D., M. T. Coe, and J. A. Foley, Surface water balance of the continental United States, 1963–1995: Regional evaluation of a terrestrial biosphere model and the NCEP/NCAR reanalysis, *J. Geophys. Res.*, *105*, 22,393–22,425, 2000.
Maurer, E. P., G. M. O'Donnell, D. P. Lettenmaier, and J. O. Roads, Evaluation of NCEP/NCAR Reanalysis water and energy budgets using macroscale hydrologic model simulations, *Land Surface Hydrology, Meteorology and Climate: Observations and Modeling: Water Science and Applications*, *3*, edited by L. Venkataraman, J. Albertson, and J. Schaake, AGU, Washington D.C., 2001.
Njoku, E. G., and D. Entekhabi, Passive microwave remote sensing of soil moisture, *J. Hydrol.*, *184*, 101–129, 1996.
Njoku, E. G., and L. Li, Retrieval of land surface parameters using passive microwave measurements at 6–18 GHz, *IEEE Trans. Geosci. and Remote Sens.*, *37*, 79–93, 1999.
Owe, M., R. DeJeu, and J. P. Walker, A Methodology for Surface Soil Moisture and Vegetation Optical Depth Retrieval Using the Microwave Polarization Difference Index, *IEEE Trans. Geosci. and Remote Sens.*, *39*, 1643–1654, 2001.
Reichle, R. H., D. B. McLaughlin, and D. Entekhabi, Variational Data Assimilation of Microwave Radiobrightness Observations for Land Surface Hydrology Applications, *IEEE Trans. Geosci. and Remote Sens*, *39*, 1708–1718, 2001.
Roads, J. O., and A. K. Betts, NCEPP-NCAR and ECMWF reanalysis surface water and energy budgets for the Mississippi basin, *J. Hydrometeorol.*, *1*, 88–94, 2000.
Walker, J. P., and P. R. Houser, A methodology for initializing soil moisture in a global climate model: Assimilation of near-surface soil moisture observations, *J. Geophys. Res.*, *106*, 11,761–11,774, 2001.
Wood, E. F., et al., The project for intercomparison of land surface parameterization schemes (PILPS) Phase 2(c) Red-Arkansas River basin experiment: 1 Experiment description and summary intercomparisons, *Glob. Planet. Change*, *19*, 115–135, 1998.

A. A. Berg and J. S. Famiglietti, Department of Earth System Science, University of California, Irvine, USA. (jfamigli@uci.edu)