Climate Prediction Center global monthly soil moisture data set at 0.5° resolution for 1948 to present

Yun Fan[1] and Huug van den Dool

Climate Prediction Center, National Centers for Environmental Prediction/National Weather Service/National Oceanic and Atmospheric Administration, Camp Springs, Maryland, USA

Received 10 November 2003; revised 24 February 2004; accepted 24 March 2004; published 20 May 2004.

[1] We have produced a 0.5° × 0.5° monthly global soil moisture data set for the period from 1948 to the present. The land model is a one-layer "bucket" water balance model, while the driving input fields are Climate Prediction Center monthly global precipitation over land, which uses over 17,000 gauges worldwide, and monthly global temperature from global Reanalysis. The output consists of global monthly soil moisture, evaporation, and runoff, starting from January 1948. A distinguishing feature of this data set is that all fields are updated monthly, which greatly enhances utility for near-real-time purposes. Data validation shows that the land model does well; both the simulated annual cycle and interannual variability of soil moisture are reasonably good against the limited observations in different regions. A data analysis reveals that, on average, the land surface water balance components have a stronger annual cycle in the Southern Hemisphere than those in the Northern Hemisphere. From the point of view of soil moisture, climates can be characterized into two types, monsoonal and midlatitude climates, with the monsoonal ones covering most of the low-latitude land areas and showing a more prominent annual variation. A global soil moisture empirical orthogonal function analysis and time series of hemisphere means reveal some interesting patterns (like El Niño-Southern Oscillation) and long-term trends in both regional and global scales. *INDEX TERMS:* 1620 Global Change: Climate dynamics (3309); 1836 Hydrology: Hydrologic budget (1655); 1866 Hydrology: Soil moisture; 3322 Meteorology and Atmospheric Dynamics: Land/atmosphere interactions; *KEYWORDS:* soil moisture data set, land surface hydrology, drought/flood monitoring

Citation: Fan, Y., and H. van den Dool (2004), Climate Prediction Center global monthly soil moisture data set at 0.5° resolution for 1948 to present, *J. Geophys. Res.*, *109*, D10102, doi:10.1029/2003JD004345.

1. Introduction

[2] Data sets of soil moisture have a number of obvious primary applications, such as in real time drought/flood monitoring [*Svoboda et al.*, 2002], climatology studies (of the "how rare is this drought?" variety), river flow forecasts, land surface hydrology process studies, and initial states for coupled land-atmosphere prediction. Less obvious, secondary, applications include geodetic studies, such as the variations in geoid over the course of the annual cycle [*Cazenave et al.*, 1999], the Earth's rotation and temporal variation in gravity [*Velicogna et al.*, 2001]. Gravity, rotation etc change due to any redistribution of mass. A National Research Council study [*Dickey et al.*, 1997] predicted that the interannual variation in continental soil moisture would be among the strongest signals to be detected by a gravity satellite. Conversely, now that we have a dedicated gravity satellite, such as GRACE (launched in 2002), meaningful remote measurements of continental soil moisture may be possible, at least at scales larger than some cutoff [*Rodell and Famiglietti*, 2002].

[3] It is difficult to make representative in situ measurements of soil moisture, and such measurement, even where successful, have been taken only at a few places, and in most cases not for very long. In the United States, the *Hollinger and Isard* [1994] soil moisture data for Illinois stand out as the exception; they cover about 20 years in 1/50th of the country. The situation for other countries is generally not better, see description by *Robock et al.* [2000], but at least there is some data for model validation.

[4] To better serve any application there has been a truly tremendous push in the last 10 years toward calculating soil moisture over certain space-time domains [*Mitchell et al.*, 2000; *Maurer et al.*, 2002]. This is done essentially by integrating a land surface model forward in time over a large area and many years. In essence a land surface model contains an equation of the form

$$dw/dt = P - E - R, \quad (1)$$

where w is soil moisture and P, E, and R are precipitation, evapotranspiration, and runoff, respectively. Assuming that P, E, and R are all known from observation, or at least can

[1] Also at RS Information System, Incorporated, McLean, Virginia, USA.

be calculated from still other observations, it is not difficult to see that w can be integrated in time, and calculated soil moisture can be generated at the space-time resolution we have input data for.

[5] At first sight, equation (1) may not yield much, given that the input to equation (1) consists of three variables, the observation of which has its own serious troubles. So why should this approach work? Of the three variables E is even less observed than w. R can be inferred in principle from river flow, but only by inverting a river routing scheme and inserting the available river flow observation. Fortunately, E and R have been parameterized with some success and thus can be calculated (this may involve still other observations, such as temperature and/or radiation, wind etc, which we assume we have). The main consideration is that the E and R parameterizations are acting usually as negative feedbacks to anomalies in soil moisture, so even if the E and R estimates are somewhat wrong, they will not cause an accumulating bias or runaway effect in w. The main burden in equation (1), certainly in terms of interannual variation, is thus on the quality of P observations. P is the forcing of equation (1) in the sense that large/small P cause, with some delay, large/small w, while E and R mainly react as a restoring negative feedback on w anomalies. Definitely P is far better observed than w, E or R. In the United States alone one can count on thousands of rain gauges daily for a period of at least 50 years [*Higgins et al.*, 2000]. This is why the approach through equation (1) may succeed. Accepting this line of reasoning one must also admit that the w thus obtained is essentially the same as a backward looking integral of P with an integral timescale of 4–5 months [*van den Dool et al.*, 2003]. The integral timescale varies with season and location.

[6] While observing P is not easy, and collecting, QCing the data and analyzing the P observation onto a grid is a daunting problem, especially near orography, we are benefiting from the enormous amount of attention given to this problem over many years by many researchers.

[7] Here we report on the details of making a global data set of monthly soil moisture at 0.5° resolution for the period 1948 to present. The land model used is exactly as described in *Huang et al.* [1996] and the input P and temperature (T) are due to *Chen et al.* [2002] and *Kistler et al.* [2001] respectively. In section 2 we present a few details of the land model, the P and T input and a validation discussion. In section 3 we present a few salient features of calculated soil moisture and its variation during 1948 to present. In a short section 4 we explain how the data can be obtained by interested readers. Section 5 has concluding remarks, discusses caveats and looks ahead at better data sets that may become available fairly soon.

2. Model and Observations

2.1. Land Model

[8] A full explanation of the soil model can be found in the work of *Huang et al.* [1996] (hereinafter referred to as H96), their section 2. H96 is a one-layer "bucket" model in a modeling tradition started by *Manabe* [1969]. The tradition of forcing bucket models off-line by observed inputs was started by *Mintz and Serafini* [1981], and continued by *Schemm et al.* [1992] and *Mintz and Walker* [1993]. Briefly, we integrate equation (1) pointwise, using observed monthly P as input. E is estimated using an adjusted Thornthwaite expression, depending on monthly temperature (T), T thus being another required observed input variable. The runoff consists of surface runoff ($R1$), base runoff ($R2$) and loss to groundwater (G), which, as in operational hydrological practice, are all parameterized in terms soil moisture and rainfall. H96 differs most from the Mintz and Serafini models in the treatment of runoff. The tuning of $R1$, $R2$ and G was done on a few small streams in Oklahoma for 1961–1990 following *Georgakakos* [1986a, 1986b]. This procedure requires five empirical coefficients to be fitted, one of which is the effective holding capacity of 76 cm of water, which at a porosity of 0.47 corresponds to a 1.6-m-deep "leaky" bucket. Importantly, we keep these five coefficient constant in space. H96 is integrated with a time step that depends on the amount of precipitation; with high P the calculation of nonlinear R requires a small time step. Note that the time step is very much smaller than monthly data input would suggest. In their original work, H96 was applied to 344 climate divisions of varying size covering the United States for which monthly P and T are available back to 1931. In this new study the P and T inputs are global and gridded at 0.5° resolution, but over the United States the results should be close to H96. In order to avoid a long-lasting spin-up of soil moisture, the model was run through 1948 about 15 times. Also in some of the colder climates the evaporation parameterization had to be slightly adjusted in order to avoid unreasonable results; that is, in those colder areas we set potential evaporation to be zero when the air temperature (T) $\leq$ (°C) or the heat index (I) ≤ 0.1 (see equation (3a) in H96).

2.2. Precipitation Input

[9] The monthly precipitation data set chosen here is described by *Chen et al.* [2002]. This product was selected not only because of its quality, but because it is kept up to date, and any future improvements in the analysis method can be readily implemented retroactively to 1948. *Chen et al.* [2002] use over 17,000 gauges worldwide for each monthly analysis. The main effort by *Chen et al.* [2002] was the choice of analysis scheme, so as to produce gridded products. They considered several analysis schemes (Barnes, Shepard and Cressman) but decided that Optimum Interpolation [*Gandin*, 1965] was the most accurate and stable for representation on a grid. The analysis for anomalies is done separately from analysis of climatology (long-term means), then added up to obtain total P for each month. For more recent years the analysis could have been based on satellite and radar measurements as well as gauge data. In the interest of homogeneity we here opt for a data set that uses rain gauges only throughout the 56 years.

2.3. Temperature Input

[10] As of 2003 it is harder to find a reliable up-to-date monthly surface global temperature analysis than precipitation. This may be in part because T analysis would seem easier than P, because the scales are much larger, so less innovative work has been done. In fact T analysis is very difficult also, especially for orographic adjustments, considering a daily cycle in lapse rate etc. Keeping in mind that T is used in a fairly minor role (in terms of high-frequency

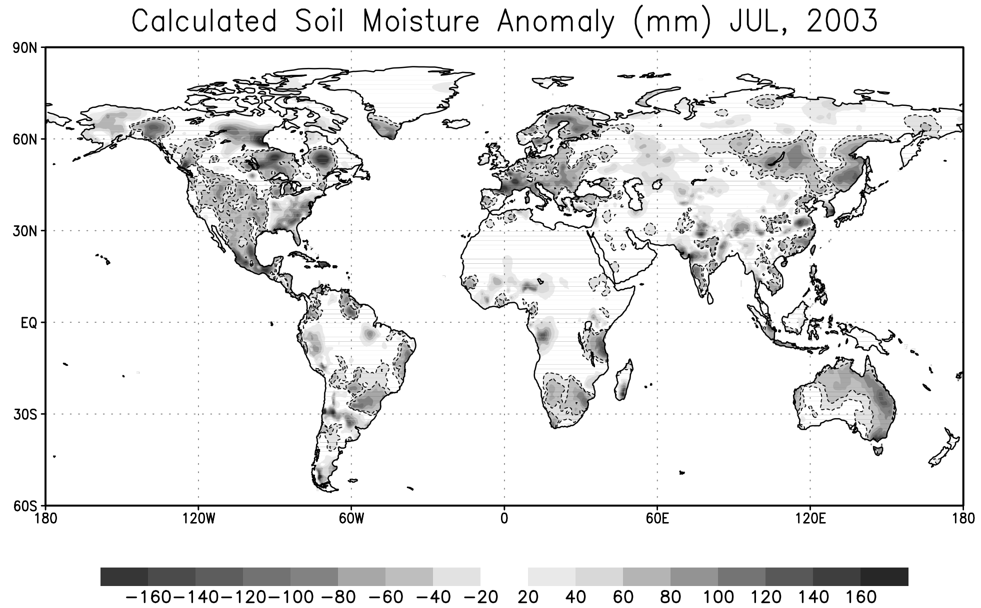

Figure 1. Global soil moisture anomaly in July 2003, defined as the departure relative to the 1971–2003 climatology. Units are in millimeters, and negative values are inside the dashed contour. See color version of this figure in the HTML.

spatial-temporal variations) to drive the E calculation, we here opted for a data set, CDAS-Reanalysis, which was selected mainly for its availability and timely monthly updates. *Van den Dool et al.* [2003] argued that the H96 model is reasonable even when the same climatological T is used every year. The global Reanalysis [*Kistler et al.*, 2001] used here is first and foremost a three-dimensional atmospheric four-times-daily analysis 1948 to present with the best results for tropospheric fields away from the surface. We averaged 28/29/30/31 days multiplied by four analyses per day into a monthly mean. The surface T analysis is not very good in an absolute sense as indicated by the status "B variable" [*Kistler et al.*, 2001], but is used here until better analyses become available. Presumably, the interannual variation in T (driven by data assimilated aloft) is acceptable.

[11] The Reanalysis also comes with P and soil moisture. As is shown in http://www.cpc.ncep.noaa.gov/soilmst/sm_ill.html as well as *Kanamitsu et al.* [2002, Figure 7], the soil moisture of Reanalysis/CDAS is not very good in

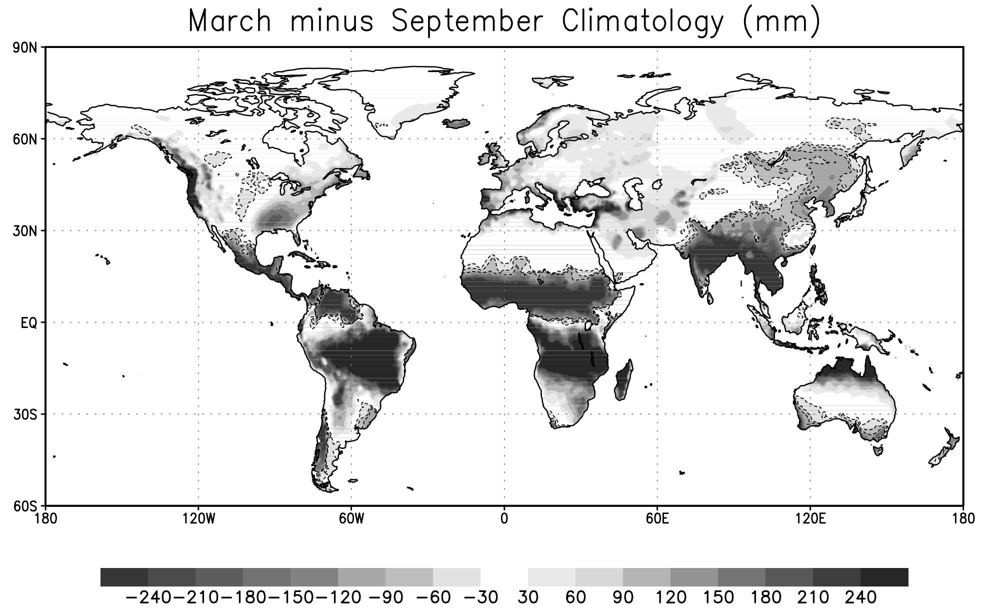

Figure 2. The difference of soil moisture in March and September based on 1971–2000 climatology. Units are in millimeters, and negative values are inside the dashed contour. See color version of this figure in the HTML.

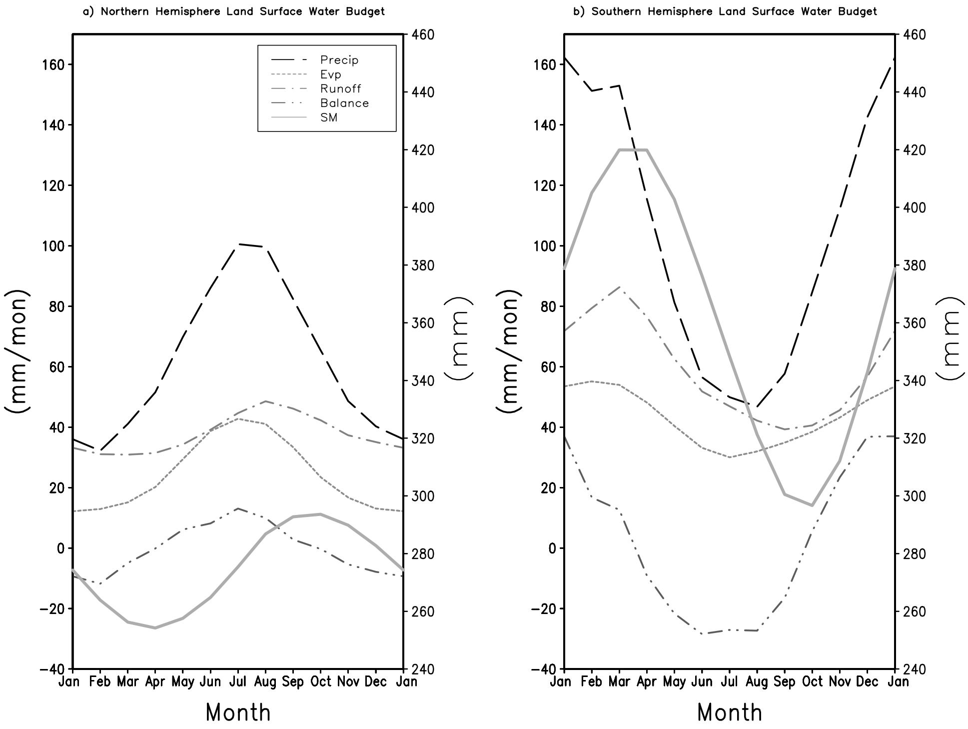

Figure 3. Annual cycle of the land surface water budgets over the (a) Northern and (b) Southern Hemispheres. Units are in millimeters for w (right scale) and millimeters/month for P, E, R, and balance (left scale). See color version of this figure in the HTML.

Illinois (where we have data to compare). The main reason is bias in P, which in the absence of negative feedbacks can drive soil moisture far away from realistic values. This likely happens at many places. Because of widespread bias in P, neither P nor w produced by Reanalysis are of much use. This is the main reason off-line studies, like the present one, or Land Data Assimilation Studies in general are taking place.

2.4. Soil Moisture Validation

[12] As shown in H96 and *van den Dool et al.* [2003], their Figures 1, the H96 model does well on independent soil moisture data observed in Illinois. Both the annual cycle and interannual soil moisture anomalies are fairly well simulated. The anomaly correlation is about 0.60–0.75 over the state during the 1984–2001 period. Recently P. Dirmeyer et al. (Validation and forecast applicability of multiyear global soil wetness products, submitted to *Journal of Hydrometeorology*, 2004) examined the characteristics of eight global soil wetness products and validated their abilities to simulate the phasing of the annual cycle and to accurately represent interannual variability by comparing to in situ measurements in China, Illinois, India, Mongolia, and Russia. The results show that the Climate Prediction Center (CPC) global soil moisture data, in spite of its simplicity, simulates the seasonal to interannual variability of observed soil moisture reasonably well in many places. We refer the reader interested in validation to these publications. A totally new validation may be imminent. Early results of GRACE for 2002 and 2003 [*Wahr et al.*, 2004] show remarkable similarity in the soil moisture annual cycle and the mass anomaly seen by this gravity satellite.

[13] Data analysis also shows a long-term trend in the CPC soil moisture data set, due to the trends in the input precipitation and temperature forcing. We will discuss this in next section.

3. Results

[14] The main purpose of this article is to describe the makings of the global soil moisture data set, so users know what they have. However, in this section we show a few results about the annual cycle of the water balance components and interannual variability of the soil moisture.

[15] Figure 1 shows the global distribution of the soil moisture anomaly, defined as the departure relative to the 1971–2000 climatology, in July 2003. This type of product is useful in flood and drought monitoring. One can see major wetness in portions of Alaska, northern Canada, eastern United States, Argentina, Peru, northeast Brazil, central Asia into northern India and west central Africa, while major shortages of water are noted for much of Europe (contributing to their record heat), Australia, East Asia, South Africa, western United States, and southeast Brazil. Over the United States the field should be similar to what is shown in http://www.cpc.ncep.noaa.gov/soilmst/index_jh.html, the H96 version with the U.S. climate division data as input forcing, but with more frequent (daily) updates through yesterday 12Z. On average, both Northern Hemispheric and Southern Hemispheric means show that the year 2003 is dry, relative to its climatology.

[16] Figure 2 displays the difference in soil moisture in March and September, based on 1971–2000 climatology. Figure 2 characterizes the annual cycle in a nutshell. One might think schematically of two type of climates. Those in

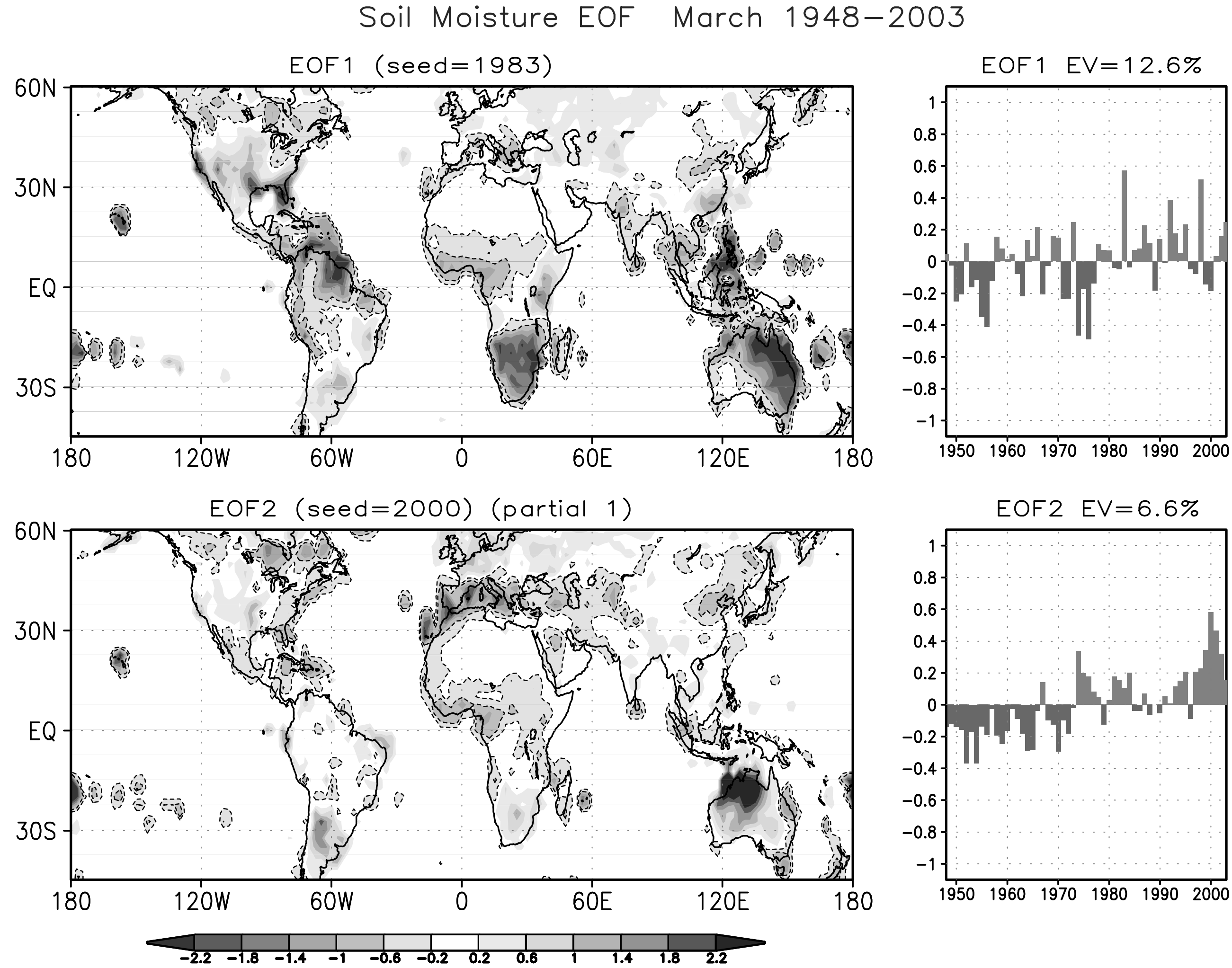

Figure 4. Soil moisture empirical orthogonal function (EOF) (top) 1 and (bottom) 2 for March 1948–2003. (left) Spatial patterns (units are in millimeters, and negative values are inside the dashed contour. (right) Time series (dimensionless). See color version of this figure in the HTML.

midlatitudes where soil moisture is the lowest at the end of the summer (midlatitude, high evaporation during summer, annual cycle in precipitation not dominant, recharge in winter), and the monsoonal climates where soil moisture is the highest at the end of the wet monsoon season (in spite of high *E*). Figure 2 delineates these two types of climates, with the monsoonal ones covering a larger area and more potent annual variation. Climates over interior North America and East Asia show weaker monsoonal signature reaching into the midlatitudes. It may be that March and September are not the optimal months everywhere.

[17] Figure 3 shows the annual cycle of the components of the water balance for the two hemispheres (averaged over all land), month by month. The monsoonal climates dominate in these graphs, so the recharge (positive dw/dt or "balance" or positive $P - E - R$) is mainly in summer, and the discharge is mainly in the respective winter. Therefore the soil moisture reaches its maximum in the fall and minimum in the spring. Overall, the water budget components in Southern Hemisphere show a more prominent annual cycle than those in the Northern Hemisphere. On the basis of the annual means, we established that the water budgets are very well closed; that is, the water balances ($P - E - R$) are very close to zero in both hemispheric and global domains.

[18] Figures 4 and 5 show the interannual variability in March and September, as per the two first empirical orthogonal functions (EOFs) of global soil moisture 1948–2003. The spatial maps on the left multiply by the time series (zero mean) on the right. Although the explained variance is not all that high (compared to, say, sea surface temperature) one can clearly see the dominance of El Niño-Southern Oscillation in the first EOF in March (United States wet in 1983, 1998 for instance). In both March and September trend modes are among the leading EOFs, featuring strong projection on the Sahel, especially in September. *Dai et al.* [1998] did a similar EOF analysis with the Palmer Drought Severity Index (PDSI).

[19] To elaborate further on the issue of long-term trends, Figure 6 shows global and hemispheric (land only!) averages of soil moisture and the model input *T* and *P*. A 5 year running mean is applied to focus on the low frequencies. Clearly soil moisture has decreased since 1980 in both hemispheres, by a few millimeters. This is caused primarily

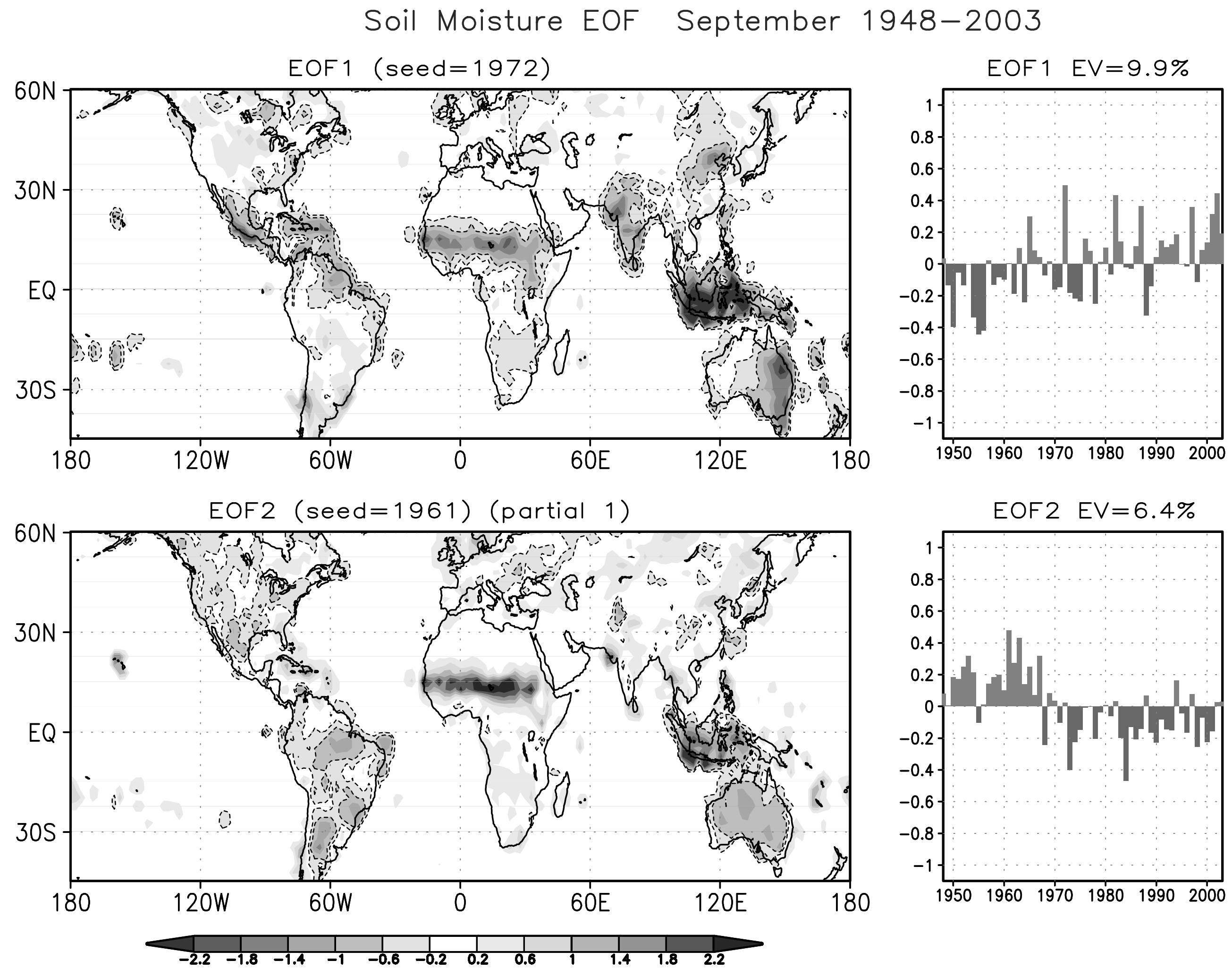

Figure 5. Same as Figure 4, but for September 1948–2003. See color version of this figure in the HTML.

by decreasing *P* and secondly by increasing *T*. According to the above EOF analysis, the downward trend of soil moisture in the Northern Hemisphere is prominent in the Sahel area. Whether the global trend is realistic or an artifact is hard to establish. According to P. Xie (personal communication, 2004), the decreasing *P* after 1980 may in part be caused by changes in the gauge net work. The upward trends in *T* have been widely reported. The Reanalysis/CDAS trends in *T* were found to be realistic [*Chelliah and Ropelewski*, 2000] and elaborated on further by *Chelliah and Bell* [2004].

[20] One should notice that without a 5 year running mean the long-term trends in *w*, *P* and *T* are dwarfed by higher-frequency variation. So while interest in trends is high because of "global change" concerns it should be kept in mind that spatially uniform trends in this data set do not explain very much of the variance, a lot less than leading EOFs.

4. Getting the Data Set

[21] Interested readers can download the data set from http://www.cpc.ncep.noaa.gov/soilmst/leaky_glb.htm through a facility on the front page of the Web site. Alternatively, one can contact Yun Fan. Many graphical products are available for inspection at this same site, both of input and output, also both climatologies and anomalies. The emphasis in the Web graphics is on the last 12 months, for the purpose of monitoring recent climate anomalies. The update through the latest calendar month takes place around the 10th of the month. We also split the map into six regions: North America, South America, Asia, Africa, Australia and Europe. By clicking on the image map of the region of interest, one can see more details from the amplified figures. The completion of the data set described in this paper also implies that an earlier version (at lower spatial resolution, and for 1979–1998 only, and with much sparser precipitation) produced at CPC several years ago for research purposes should now be considered obsolete.

5. Conclusion and Discussion

[22] We have produced a $0.5^\circ \times 0.5^\circ$ monthly global soil moisture data set for the period 1948 to the present. The land model is identically the same as described by *Huang et al.* [1996], while the driving input fields are the gauge based monthly CPC global land precipitation due to *Chen et al.* [2002] and monthly global Reanalysis/CDAS 2 m air

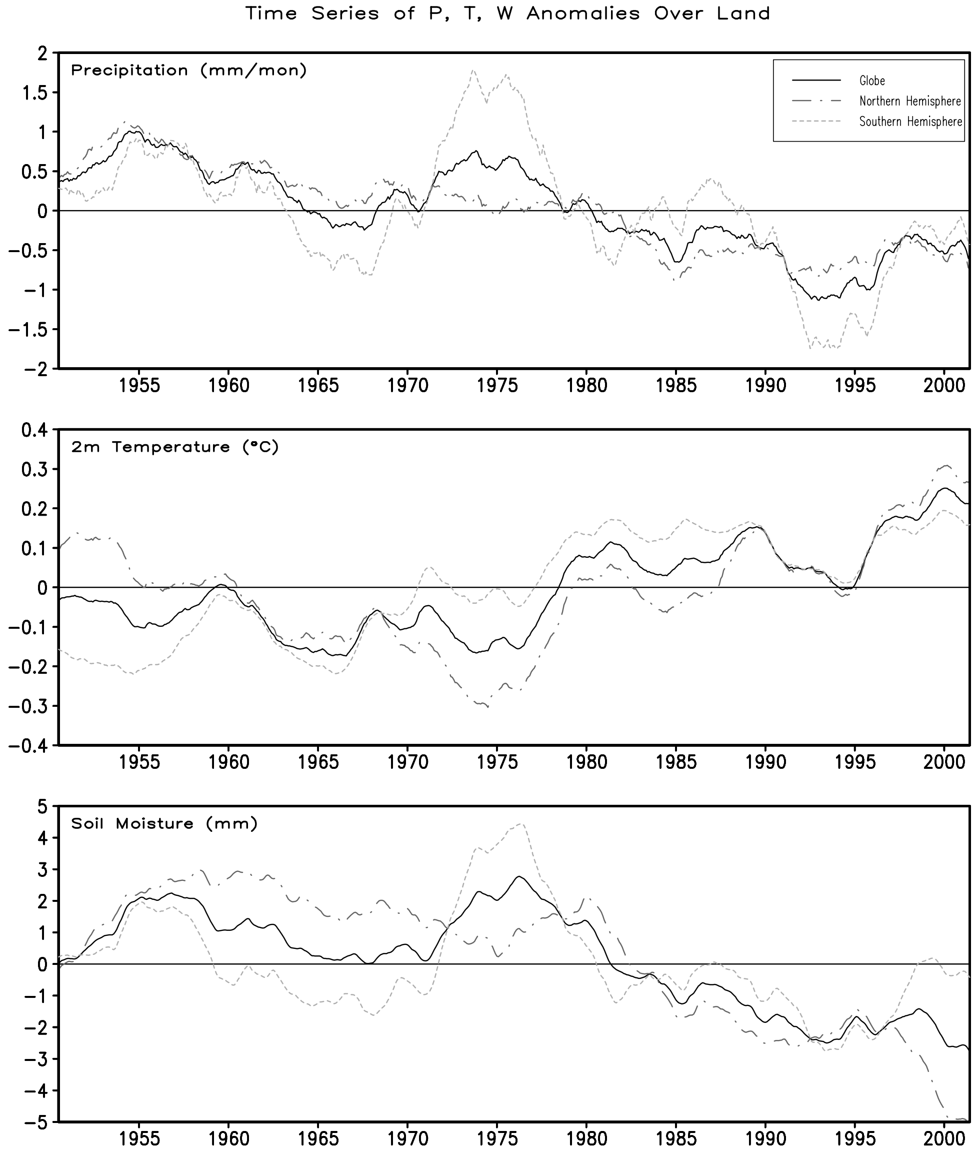

Figure 6. Time series of hemispheric and global means (land only) of precipitation, 2 m air temperature, and soil moisture (units are in millimeters/month, °C, and millimeters, respectively). A 5 year running mean is applied. The period is 1948–2003. First (last) point shown is centered at 1950 (2001). See color version of this figure in the HTML.

temperature due to *Kistler et al.* [2001]. The output consists of soil moisture, evaporation and surface runoff and groundwater loss. All fields are updated monthly for near-real-time applications. The coverage is global, allowing various applications in fields like hydrology and geodesy. The real time aspect allows application in real time Drought Monitoring and Hazards assessment on any continent. A representative set of real-time products can be viewed via http://www.cpc.ncep.noaa.gov/soilmst/leaky_glb.htm.

[23] Among the caveats of using this data and frequently asked questions we note the following.

[24] 1. Should we look upon calculated w as the liquid soil water or liquid plus solid (snow and ice) mass. The answer actually lies in between these two possibilities. We administer total observed P (including snow, sleet etc) to equation (1) as a liquid; we do not explicitly carry frozen soil water. Since evaporation is small in cold climates the mass thus added lies around for a while. However, not long enough because R acts on the liquid, prematurely when it is still cold.

[25] 2. How about mass anomalies due to runoff? The R generated by equation (1) disappears in a "black hole" and is not tracked by a river routing system. It actually could take months before runoff reaches the oceans, and river routing calculations [*Lohmann et al.*, 2004] in association with soil moisture data sets may become standard in the future.

[26] 3. The five empirical parameters are estimated for Oklahoma. Using them at other locations may produce suboptimal results, although results for Illinois seemed reasonable good. Rather than tuning each area separately, we look forward to better models (see last paragraph) in the near future.

[27] 4. The temperature fields used for the calculation are not very good, so-called *B* variables from CDAS Reanalysis. If a better data set, with real time updates, becomes available we will change over and recalculate the soil moisture.

[28] 5. The precipitation (CPC PRECipitation RECon-struction over Land) will undergo the following improvements in the near future by *Chen et al.* [2002]: (1) orographic adjustment/enhancement, (2) dealing with inhomogeneity resulting from changes in number of gauges over time. Soil moisture calculations will be repeated when such improvements are implemented.

[29] In the (near) future we expect quantum leaps forward from better soil models. The type of bucket models used here may continue as a sanity check for more comprehensive models, but ultimately we will change over to those more advanced models. We have completed an hourly analysis over the United States at 1/8th of a degree for 1948–1998 with a very detailed four-layer land surface model, named Noah [*Mitchell et al.*, 2000]. Some details of this 50 year data set are given by *Fan et al.* [2003a, 2003b]. The output variables number order 25 and include all the energy components, separation of frozen and liquid water, explicit evaporation by bare soil, open water, plants etc. Especially impressive are high-spatial-resolution fixed fields, such as orography, soil type, vegetation type, greenness (function of calendar month). All such details were subsumed crudely in bulk expressions in H96. Soon NCEP will undertake a global analysis with the Noah model. At other institutions global analyses with advanced models have been made for restricted periods, but usually not in real time, a good example being the VIC model [*Nijssen et al.*, 2001], for 1980–1993.

[30] **Acknowledgments.** The authors thank Jin Huang and Jae Schemm for their assistance in the early part of this project. We also acknowledge support by GCIP grant GC00-095 and GAPP grant GC04-039. Thanks are also due to Doug Lecomte and Jae Schemm for internal reviews and to the three anonymous reviewers for their constructive comments.

References

Cazenave, A., F. Mercier, F. Bouille, and J. M. Lemoine (1999), Global-scale interactions between the solid Earth and its fluid envelopes at the seasonal time scale, *Earth Planet. Sci. Lett.*, *171*(4), 549–559.
Chelliah, M., and G. Bell (2004), Tropical multi-decadal and interannual climate variability in the NCEP/NCAR Reanalysis, *J. Clim.*, *17*, 1777–1803.
Chelliah, M., and C. F. Ropelewski (2000), Reanalysis-based tropospheric temperature estimates: Uncertainties in the context of global climate change detection, *J. Clim.*, *13*, 3187–3205.
Chen, M., P. Xie, J. E. Janowiak, and P. A. Arkin (2002), Global land precipitation: A 50-yr monthly analysis based on gauge observations, *J. Hydrometeorol.*, *3*, 249–266.
Dai, A., K. E. Trenberth, and T. R. Karl (1998), Global variations in droughts and wet spells: 1900–1995, *Geophys. Res. Lett.*, *25*, 3367–3370.
Dickey, J. C., et al. (1997), Satellite gravity and the geopshere: Contributions to the study of the solid Earth and its fluid envelope, *Rep. LoC CCN 97-67450*, Natl. Res. Counc., Washington, D. C.
Fan, Y., H. van den Dool, K. Mitchell, and D. Lohmann (2003a), NWS-CPC'S monitoring and prediction of US soil moisture and associated land surface variables: Land Data Renalysis, in *Proceedings of the Climate Diagnostics Workshop, 21–25 October, 2002* [CD-ROM], Clim. Predict. Cent. Natl. Cent. for Environ. Predict., Camp Springs, Md.
Fan, Y., H. van den Dool, K. Mitchell, and D. Lohmann (2003b), A 51 year reanalysis of the US land-surface hydrology, *GEWEX News*, *13*(May), 6–10.
Gandin, L. S. (1965), *Objective Analysis of Meteorological Fields*, translated by Isr. Prog. Sci. Transl., 242 pp., Gidrometeoizdat, Leningrad, Russia.
Georgakakos, K. P. (1986a), A generalized stochastic hydrometeorological model for flood and flash-flood forecasting: 1. Formulation, *Water Resour. Res.*, *22*(13), 2083–2095.
Georgakakos, K. P. (1986b), A generalized stochastic hydrometeorological model for flood and flash-flood forecasting: 2. Case studies, *Water Resour. Res.*, *22*(13), 2096–2106.
Higgins, R. W., W. Shi, E. Yarosh, and R. Joyce (2000), Improved United States precipitation quality control system and analysis, *NCEP/Clim. Predict. Cent. Atlas, 7*, NOAA, U.S. Dept. of Commer., Washington, D. C.
Hollinger, S. E., and S. A. Isard (1994), A soil moisture climatology of Illinois, *J. Clim.*, *7*, 822–833.
Huang, J., H. M. van den Dool, and K. G. Georgakakos (1996), Analysis of model-calculated soil moisture over the US (1931–1993) and applications to long range temperature forecasts, *J. Clim.*, *9*, 1350–1362.
Kanamitsu, M., W. Ebisuzaki, J. Woollen, S.-K. Yang, J. J. Hnilo, M. Fiorino, and G. L. Potter (2002), NCEP-DOE AMIP-II Reanalysis (R-2), *Bull. Am. Meteorol. Soc.*, *83*, 1631–1643.
Kistler, R., et al. (2001), The NCEP-NCAR 50-Year Reanalysis: Monthly means CD-ROM and documentation, *Bull. Am. Meteorol. Soc.*, *82*, 247–268.
Lohmann, D., et al. (2004), Streamflow and water balance intercomparisons of four land surface models in the in the North American Land Data Assimilation System project, *J. Geophys. Res.*, *109*, D07S91, doi:10.1029/2003JD003517.
Manabe, S. (1969), Climate and the ocean circulation, *Mon. Weather Rev.*, *97*, 739–774.
Maurer, E. P., A. W. Wood, J. C. Adam, D. P. Lettenmaier, and B. Nijssen (2002), A long-term hydrologically-based data set of land surface fluxes and states for the conterminous United States, *J. Clim.*, *15*, 3237–3251.
Mintz, Y., and Y. Serafini (1981), Global fields of soil moisture and land-surface evapotranspiration, *NASA Tech. Memo., 83907*, 178–180.
Mintz, Y., and G. K. Walker (1993), Global fields of soil moisture and land surface evapotranspiration derived from observed precipitation and surface air temperature, *J. Appl. Meteorol.*, *32*(8), 1305–1334.
Mitchell, K., et al. (2000), Recent GCIP-sponsored advancements in coupled land-surface modeling and data assimilation in the NCEP Eta mesoscale model, paper presented at the 15th Conference on Hydrology, Am. Meteorol. Soc., Long Beach, Calif.
Nijssen, B. N., R. Schnur, and D. P. Lettenmaier (2001), Global retrospective estimation of soil moisture using the VIC land surface model, 1980–1993, *J. Clim.*, *14*, 1790–1808.
Robock, A., K. Y. Vinnikov, G. Srinivasan, J. K. Entin, S. E. Hollinger, N. A. Speranskaya, S. Liu, and A. Namkhai (2000), The Global Soil Moisture Data Bank, *Bull. Am. Meteorol. Soc.*, *81*, 1281–1299.
Rodell, M., and J. S. Famiglietti (2002), The potential for satellite-based monitoring of groundwater storage changes using GRACE: The High Plains aquifer, central U.S., *J. Hydrol.*, *263*(1–4), 245–256.
Schemm, J., S. Schubert, J. Terry, and S. Bloom (1992), Estimates of monthly mean soil moisture for 1979–1989, *NASA Tech. Memo., 104571*, 260 pp.
Svoboda, M., et al. (2002), The drought monitor, *Bull. Am. Meteorol. Soc.*, *83*, 1181–1190.
van den Dool, H., J. Huang, and Y. Fan (2003), Performance and analysis of the constructed analogue method applied to U.S. soil moisture over 1981–2001, *J. Geophys. Res.*, *108*(D16), 8617, doi:10.1029/2002JD003114.
Velicogna, I., J. Wahr, and H. van den Dool (2001), Can surface pressure be used to remove atmospheric contributions from GRACE data with sufficient accuracy to recover hydrological signals?, *J. Geophys. Res.*, *106*(B8), 16,415–16,434.
Wahr, J., S. Swenson, V. Zlotnicki, and I. Velincogna (2004), Time-variable gravity from GRACE: First results, *Geophys. Res. Lett.*, *31*, doi:10.1029/2004GL019779, in press.

Y. Fan and H. van den Dool, Climate Prediction Center, 5200 Auth Road, Room 806, Camp Springs, MD 20746, USA. (yun.fan@noaa.gov)