Performance and analysis of the constructed analogue method applied to U.S. soil moisture over 1981–2001

Huug van den Dool
Climate Prediction Center, National Centers for Environmental Prediction, Camp Springs, Maryland, USA

Jin Huang
Office of Global Programs, National Oceanic and Atmospheric Administration, Silver Spring, Maryland, USA

Yun Fan
Climate Prediction Center, National Centers for Environmental Prediction, Camp Springs, Maryland, USA

Received 31 October 2002; revised 5 March 2003; accepted 31 March 2003; published 23 August 2003.

[1] We have conducted an experiment to assess the real time skill in monthly and seasonal predictions based solely on patterns of antecedent hydrological information over the United States. The hydrological information is contained in a proxy for soil moisture at 102 locations over the lower 48 states. This soil moisture is calculated over the years 1931 to present from a local hydrological equation taking monthly precipitation (P) and temperature (T) as input, and producing soil moisture (w), evaporation (E), runoff (R), and loss to groundwater (G) as output. The initial condition (IC) for the forecast procedure is soil moisture over the United States at the end of the month (w30). We constructed an analogue to the w30 fields, i.e., made linear combinations of soil moisture fields at the same time of year in years past to reproduce the IC to within a small tolerance. The coefficients assigned to the years past are then made to persist, and the subsequent development in the historical years is linearly combined to form a forecast. This method has been running at CPC in real time since 1998, and we added 1981–1997 in "retroactive real time" mode to form a large enough sample. In total, we considered both seasonal and monthly forecasts at leads of −1 to +6 months for 1981–2001, for the elements w30, E, T, and P. From the outset, we wanted to investigate nonlocal forecast methods, considering local effects, on evaporation and temperature mainly, as being established already and well documented [*Huang et al.*, 1996]. In a nonlocal method we entertain the possibility of precipitation (the response) falling downstream of a soil moisture anomaly (forcing). We found that we have about a 0.6 correlation in forecasting monthly soil moisture with a lead of one month (i.e., July at the end of May). This figure is higher in spring and somewhat lower in the early fall. The capability to forecast evaporation anomalies is very seasonal. During the cold half of the year, when E anomalies resemble T anomalies, the correlation is only 0.2–0.3, but in summer, when E anomalies resemble w anomalies, the skill of forecasts goes up to 0.6. We thus have some insight into patterns of anomalous water vapor input from the land surface into the lower atmosphere on a continental scale. Skill of forecasting T is modest, reaching 0.2–0.3 in many months and seasons, but there is no clear seasonal dependence that relates to the presumed physics of land atmosphere interactions. Skill in forecasting P is quite low, barely 0.1 in correlation, but +ve in all months and seasons. We did alternative experiments where the constructed analogue was built on E, T, or P instead of w and verified the forecast of all elements likewise. We found initial w to be the best for forecasting w itself and indeed for forecasting the other fields as well! This is important testimony that soil moisture is indeed the key, as has been suspected by many for ages. *INDEX TERMS:* 1812 Hydrology: Drought; 1860 Hydrology: Runoff and streamflow; 1866 Hydrology: Soil moisture; 3322 Meteorology and Atmospheric Dynamics: Land/atmosphere interactions; 3354 Meteorology and Atmospheric Dynamics: Precipitation (1854); *KEYWORDS:* constructed analog, soil moisture, monthly forecast, surface hydrology

Citation: van den Dool, H., J. Huang, and Y. Fan, 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, 2003.

0148-0227/03/2002JD003114$09.00

1. Introduction

[2] The purpose of this paper is mainly to describe the results of real time monthly and seasonal forecasts for the United States based on antecedent surface hydrological conditions. As is well known the water contained in the soil, down to some depth, can change the partitioning of incoming energy between sensible and latent heat fluxes. Therefore knowledge of soil moisture at the initial time could be a useful predictor for temperature (T) and precipitation (P) at a later time, especially when the incoming solar energy is large (summer). There are several additional or competing physical impacts from wet soil, such as changes in greenness, albedo, emissivity and atmospheric clouds and turbidity which could change either the overall energy coming in and/or its partitioning among sensible and latent heat fluxes. Although the physical arguments apply qualitatively to a wide range of timescales, it should be made clear that, unless stated otherwise, we use monthly mean or seasonal mean data, either observations or model generated data.

[3] The task we have undertaken over a multi-year period, which coincided more or less with the GCIP years, consisted of (1) creating a data set of calculated soil moisture covering the United States over a sufficient number of years, sufficient being many decades at least, (2) designing methods to make T and P forecasts, (3) implementing items 1 and 2 into a reliable real time activity, and (3) the verification of forecasts thereof.

[4] The creation of the first soil moisture data set (1931 to present) followed the method described by *Huang et al.* [1996] (hereinafter referred to as H96) and will be described briefly in section 2. Sometimes it is called the "CPC soil moisture" and it plays an important role in the real time National Drought Monitor [*Svoboda et al.*, 2002]. A much improved and much more comprehensive and higher-resolution data set based on LDAS [*Mitchell et al.*, 2000; *Fan et al.*, 2003] is available for 1948–1998, but for a description of our activities during the now finished GCIP era we use the H96 "leaky bucket," and keep the LDAS results for GCIP's follow-up: GAPP.

[5] Among the methods used to make forecasts we should distinguish local from nonlocal methods. In local methods the direct nearby impact of soil moisture on T and or P matters. Local effects have been gauged for ages [*Reed*, 1925; *Namias*, 1952] generally by local contingency tables of some sort, or time lagged correlation of, for instance, a proxy for soil moisture and temperature at the same position. Our "local" results have already been described by H96 and can be summarized in the following few sentences. As for temperature prediction, antecedent precipitation, or, even better, antecedent soil moisture has a significant negative correlation with temperature in many parts of the United States, thus leading to a well known and easy to understand prediction rules: When it has been dry (wet), chances are it will be warmer (colder) than average at the same spot in the next month and season. These "chances" vary in fact with geographical location, the season, and the lead of the forecast [*Huang and van den Dool*, 1993; H96]. In this paper we seek to go beyond local effects and local forecast methods.

[6] An important negative result of H96 is that local correlations do not show usable local relations that may aid in forecasting precipitation. The physical interpretation is not difficult. While a reduced (enhanced) sensible heat flux over wet (dry) soil leads to an obvious lowering (elevation) of air temperature (the easy forecast), the simultaneously enhanced (decreased) latent heat flux may not cause enhanced (decreased) P anywhere nearby. The physics of precipitation takes time, involves upper level flow, and advection may steer and disperse the consequences downstream. Therefore the impact on P, if detectable, has to be primarily nonlocal. Quite possibly nonlocal impacts of soil moisture on temperature (and other atmospheric variables) exist also.

[7] It is a great challenge to detect the nonlocal impacts of soil moisture anomalies. Without nonlocal effects the role of soil moisture will ultimately be only marginally interesting as a scientific endeavor, because there would be only the local autocorrelation timescale of soil moisture as memory of the system, and, as far as we know, only a local impact on temperature. However, when rain were to fall downstream of the area of forcing, soil moisture anomalies can move around in response and achieve, in principle, far longer predictability times, somewhat in the way a moving cyclone has more predictability than its local (Eulerian) autocorrelation would suggest. (By moving soil moisture we do not mean underground motion, but apparent movement in soil moisture caused by the precipitation.) Demonstration of nonlocal impacts, on precipitation in particular, is thus very important in assessing the ultimate importance of the lower boundary condition over land for seasonal forecasting. A suggestion of nonlocal impacts in parts of the United States was given by *Cayan and Georgakakos* [1995]. While numerical modeling approaches [*Kanamitsu et al.*, 2002, 2003] are certainly helpful, and the H96 soil moisture anomalies have been (and are being) transplanted into GCMs as initial conditions [*Fennessy et al.*, 2000, 2003] we here describe a technique that is rooted in observations from beginning to end. Specifically, we use a forecast method called constructed analogue (CA), which has been used with some success for global SST forecasts [*van den Dool*, 1994; *van den Dool and Barnston*, 1995]. This method, explained briefly in section 4, is applied here to U.S. soil moisture as a predictor. We have made CA forecasts based on soil moisture in real time since early 1998. Retroactively, we made forecasts over 1981–1997. In all we thus have the period 1981–2001 to discuss forecast skill of the CA method. In doing so, we will keep the physical chain of events in mind. That is, in addition to forecast skill for T and P we also keep track of forecast skill in soil moisture itself, and, most notably, evaporation, since this is how the impacts on the atmosphere are supposed to come about in the first place.

[8] We will not go into any detail about the operational implementation, item 3, even though that may have been the most time consuming task by far. For reference and to see the most recent land hydrology diagnostics and forecasts, see the web link http://www.cpc.ncep.noaa.gov/soilmst/index_jh.html.

[9] We should mention up-front three limitations, some by our choice, some unavoidable. First we focus exclusively on soil moisture as the only predictor; that is, we ignore global sea-surface temperature (SST) used in operation at the CPC, where various tools are routinely combined into an official forecast. Second, we accept the arbitrary limitation

from a physical point of view of using soil moisture over the 48 contiguous states only, with abrupt discontinuities in lower boundary forcing near all political and geographical borders. Third, we use a forecast method that works "at the pattern level," and may neglect local effects, some of which are very real (H96).

[10] A final comment: "Soil moisture" is a bit of a catchword. All aspects of surface hydrology in general should be of interest to meteorologists and hydrologists, but in terms of forecasting subsequent T and P only the soil water in the upper 1 to 2 meters that could potentially re-evaporate back into the atmosphere really matters. Hence the fixation on "soil moisture," which, moreover, is not even measured but calculated.

[11] The paper is organized as follows. The model and the observations are described in section 2. The continental hydrological balance as estimated by the *Huang et al.* [1996] hydrological model is presented in section 3. Section 4 features the details about the Constructed Analogue method, while the verification is given in section 5.

2. Data and Soil Hydrology Model

[12] The study of the surface hydrology invariably starts with an equation like

$$dw/dt = P - E - R - G \tag{1}$$

where

- w soil moisture in a single column of depth 1.6 meter, mm;
- P precipitation, mm/month;
- E evaporation, mm/month;
- R runoff, mm/month;
- G loss to groundwater, mm/month.

Equation (1) is applied locally. All quantities are positive, and P is taken to be the input-source, while E, R and G are the loss terms. H96 designed a water balance model; that is, E is calculated (adjusted Thornthwaite) via observed T, and R (surface and base runoff separately) and G are parameterized, such that we have 5 tunable parameters in the expressions for R and G. We take P as observed. The depth of 1.6 meter came about as follows. Tuning the model (see H96) to runoff of several small river basins in eastern Oklahoma resulted in a maximum holding capacity of 760 mm of water. Along with a common porosity of 0.47 this implies a soil column of 1.6 meter. This depth seems reasonable for our goals since evaporation of moisture from deeper levels must be small.

[13] Given all terms on the right hand side of equation (1) can integrate w forward in time for as long a period and at as many locations as one has data for. The calculations are done here using monthly data for 344 U.S. Climate Divisions during 1931 to present. While the hydrological model makes small time steps, the month is the basic unit of time used here in the sense that the input data is monthly averaged; units will be mm/month. The results for 1931 are discarded because of spin-up. For other details, see H96.

[14] There are a number of weaknesses with a model as simple as equation (1). (1) There is no vertical moisture profile; the bucket is just one depth, like a mixed layer. (2) There is no separate equation for snow and ice. P is added to the w budget as a liquid at all times, even in winter. (3) The soil properties and other physiographic properties are assumed to be constant in space and basically tuned to small stream runoff in eastern Oklahoma. A reality check may be in order. We here present a comparison of calculated soil moisture to observations made at 16 sites in Illinois [*Hollinger and Isard*, 1994], over a period of 18 years. We divided the state into three portions (north, central and south), and averaged over the 4–5 stations in each. Figure 1 shows on the right the climatological annual cycle (1984–2001) for the upper 1 meter. Below 1 meter observed variations are minimal. The model is, however, made for 1.6 meters depth without a vertical profile, so we multiplied the calculated values by a rather arbitrary factor, 0.6/0.8 on the left/right of Figure 1. (Hidden in the fudge factor 0.6 is the model's shortcoming of too large interannual soil moisture variation.) In spite of one to two month phase errors, which were noted also in H96's Figure 1 (which was through 1991 only), the annual cycle is passable, least so in the north. The departures from the 1984–2001 monthly climatology for the three regions appear reasonable as well (see the left-hand side of Figure 1); the anomaly correlation is about 0.60–0.75 for all regions. Perhaps we should expect no better. In spite of (compensating) systematic errors in E and (R + G), see section 3, our soil moisture seems very reasonable, at least in Illinois on independent data.

[15] Even though there is legitimate doubt whether w resembles true soil moisture in all seasons in all climates it should be kept in mind that the calculated w contains reality in that it is derived from a history of previous observed P and T.

[16] To recapitulate the data situation, on the input side we have Climate Divisional monthly P and T. On the output side we have monthly w, E, R, G. Of these, only P, T, w and E will be used below. The period is 1932 to present. We frequently use soil moisture at the end of the month, denoted as w30: Note that this is not a monthly average. All data sets are available via ftp from http://www.cpc.ncep.gov/soilmst/index_jh.html.

[17] In the real time setting we also have a daily integration for the period since the end of the last full calendar month up to yesterday 12Z using daily precipitation analyses [*Higgins et al.*, 1996, 2000]. The purpose is to bring w as close as possible to the forecast target. It does happen occasionally that recent heavy rains change materially a soil moisture anomaly pattern that had been in place earlier. However, in this paper we only discuss forecasts that start from the end of the calendar month (using w30) for 1981–2001. Many of the subsequent calculations with P, T, E and w30 are made with 102 "super" CDs. The 102 CDs are a combination of the 344 original CDs, such that the 102 are more or less equal area [*He et al.*, 1998].

[18] For later reference and as an example Figure 2 (lower panel) shows the soil moisture anomaly over the United States at the end of April 2000. (Anomaly means a departure from a thirty-year climatology.) In April 2000, soil was drier than normal over a large area of the SE and mid-west, with wetness straddling to its west from OK to SD.

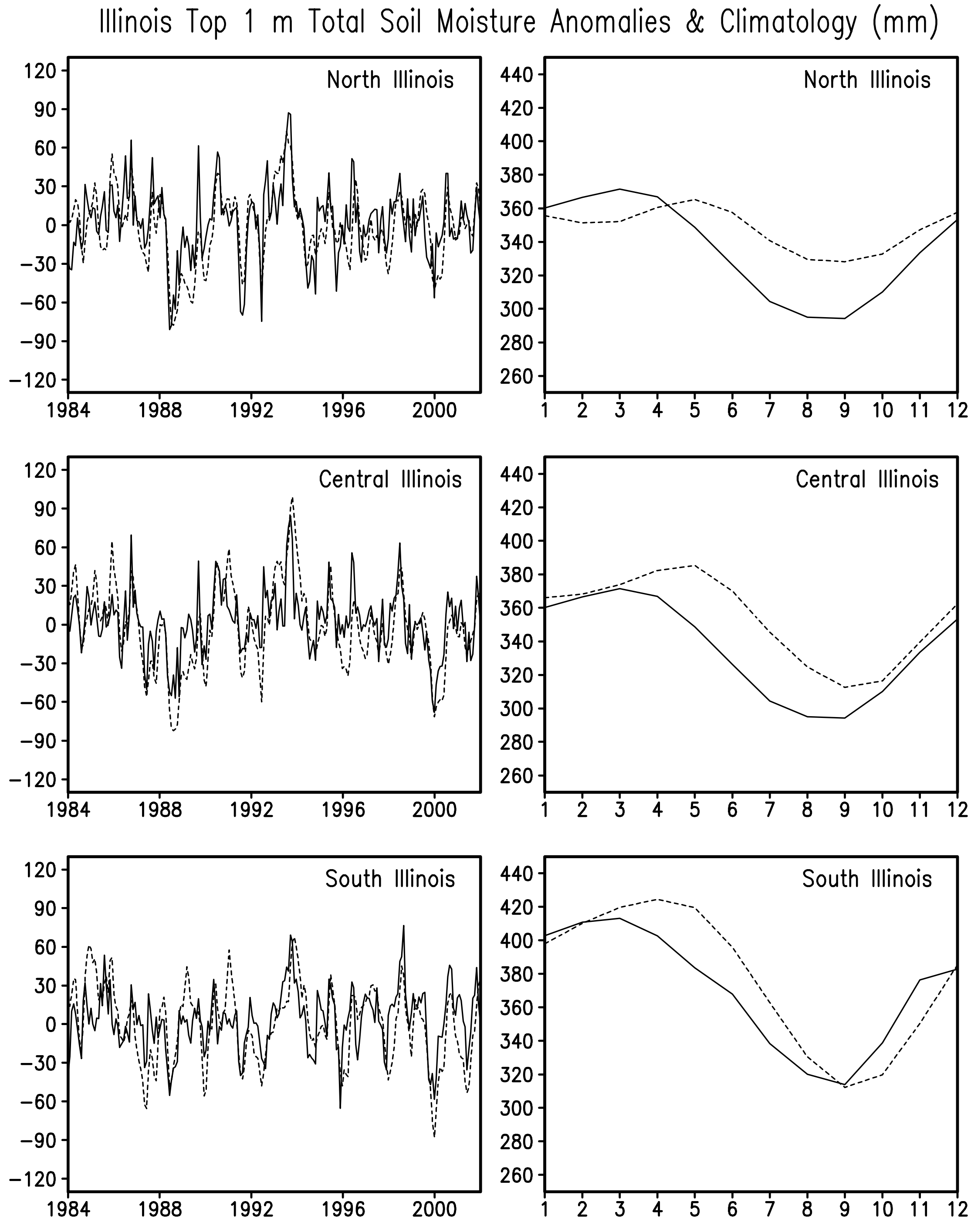

Figure 1. A comparison of the climatological annual cycle (right) and anomalies (left) in soil moisture in the upper one meter over the period 1984–2001, calculated by equation (1), dashed line, and as observed (full line) in Illinois. The three panels are for north, central and south Illinois. The units are mm. To facilitate the comparison, the calculated values are multiplied by 0.8 (right) and 0.6 (left), respectively. See color version of this figure in the HTML.

Typically, this field has large-scale aspects, as well as many local details.

3. Hydrological Balance Over the Continental United States and the Mississippi Basin

[19] It is of interest to discuss the hydrological balance suggested by equation (1) combined with the input data sets such as we used them (readers interested in forecast aspects only may skip section 3). Table 1a shows monthly and annual values for all variables averaged over the United States for 1932–2000. On average we have about 330 mm of soil moisture in the bucket. In the annual mean, when dw/dt is zero, the 65 mm/month that comes down as precipitation on the United States is used, according to this model, as 26 mm/month for evaporation, 13 mm/month for small

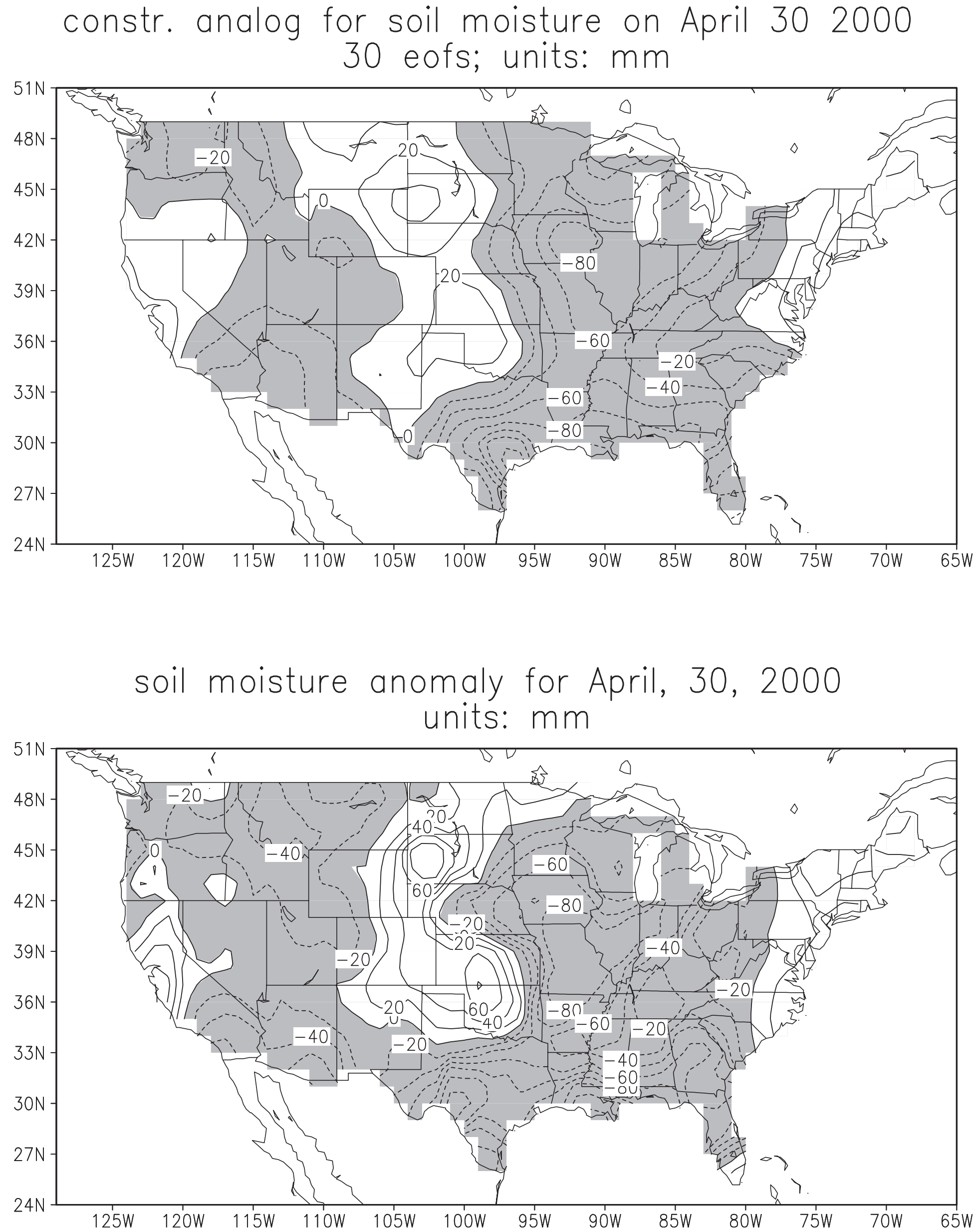

Figure 2. The calculated soil moisture anomaly for 30 April 2000 in mm over the continental United States. Anomaly is relative to a thirty-year climatology. A smooth version truncated to 30 EOFs is shown at the top, while the raw field is in the bottom panel. The contour interval is 20, and negative contours are dashed. A color scheme is applied for values in excess of 25, 100 (absolute value). See color version of this figure in the HTML.

stream runoff and 26 mm/month for loss to groundwater. Over the Mississippi drainage basin (the main GCIP objective) these numbers are not very different, i.e., 66(P), 27(E), 12(R) and 28(G) mm/mo, see Table 1b. Compared to Table 2 of *Roads et al.* [2003] our simple model has reasonable P (of course, this is input), w is somewhat lower, R seems reasonable, but E appears much lower than most other models, while G (not explicitly present in other models) makes up the difference. While the unobservable G as a loss to ground water makes some sense for small-scale hydrology, it may be best to look upon R + G as runoff on continental scales. After all one cannot recharge groundwater forever, so this water has to go somewhere. Our results indicate we thus have a model that is strikingly low on E and high on runoff (R + G). The soil moisture is lower by 25% than that in most models described by *Roads et al.* [2003], but since equation (1) does well against observation in Illinois (see Figure 1), the other models may be too wet.

[20] The comparison to the VIC hydrological model [*Liang et al.*, 1994] is the most pertinent since it too was forced with observed P, but even that model has about 50mm/month as annual mean E as per Table 2 of *Roads et al.* [2003]. Our low E may be caused by the absence of an explicit vegetation factor in Thornthwaite's expression. However, this cannot be the full reason since even if we evaporated at full potential all the time we would have no

Table 1a. U.S. Mean Monthly Values of Temperature and All Components of Surface Hydrology[a]

Month	T, °C	P, mm/month	w30, mm	E, mm/month	R, mm/month	G, mm/month	P-E-R-G, mm/month
1	−0.3	62.5	351.4	2.8	17.8	27.3	14.6
2	1.9	56.4	357.7	4.6	17.3	28.1	6.4
3	5.9	65.7	365.6	10.0	19.0	28.7	8.0
4	11.0	63.6	361.7	22.7	15.9	28.8	−3.8
5	16.0	73.3	352.8	40.0	13.7	28.3	−8.7
6	20.5	74.6	334.1	54.6	11.4	27.2	−18.6
7	23.2	69.4	311.0	57.4	9.5	25.5	−23.0
8	22.4	65.5	294.7	49.7	8.0	24.0	−16.1
9	18.4	63.9	292.4	35.0	7.8	23.2	−2.2
10	12.7	56.5	298.7	19.2	7.6	23.4	6.4
11	6.0	60.9	317.7	7.0	10.3	24.4	19.1
12	1.3	62.8	336.7	3.0	14.7	26.0	19.1
Year	11.6	64.6	331.2	25.5	12.8	26.2	0.1

[a]Period mean is taken over 1932–2000.

more than 56mm/month which is still less than the actual evaporation in some of the other models quoted by *Roads et al.* [2003]. In all likelihood our model is too low at E and high at R + G, but the sum of E, R and G is reasonable. In a comparison involving many more land models the partitioning of (annual) P into E and (R + G) had an enormous range [*Chen et al.*, 1997], and the H96 model is not out of range. Unfortunately, the absence of ground truth measurements of E for any length of time over a large area is a very serious impediment in judging surface hydrology models.

[21] Table 1a also shows the annual cycle of the variables involved in the U.S. averaged hydrological balance according to this model. For the continent as a whole P does not vary all that much over the course of the annual cycle. E obviously has a very pronounced annual cycle with a maximum (minimum) when the temperature is highest (lowest). Soil moisture itself has a range of 70 mm nation averaged. The sum of P-E-R-G equals dw30/dt by definition, so as long as (E + R + G) > P soil moisture decreases during that month. The minimum in w is reached in September. Soil water is recharged from October through March when P exceeds the loss terms E, R and G, hence a maximum in w in March. For the Mississippi basin (Table 1b) much the same can be said except that P has a clearer annual cycle with a maximum in June (90 mm/mo) and a minimum in February (46 mm/mo).

[22] For later reference we also mention the aggregate inter-annual standard deviation of monthly means, see Table 2. First we calculated locally the variance of any variable X as var(s,m) = Σ {X(s, j, m) − X^{climo}(s, m)}^{2}, where m is month (1..12) and s is a space index (1..102) and summation is over j = 1932–2000. We then summed var(s,m) over s and m, and divided by total number of years, locations (102) and months (12). A final square root yields the inter-annual standard deviation. For T, P, w30, E, R, G, in this order we found a standard deviation of 1.8°C, 37.2 mm/month, 51.3 mm, 5.4 mm/month, 13.4 mm/month, and 3.9 mm/month, respectively. The anomalies in soil moisture, of typical magnitude 51.3 mm, will drive the forecasts discussed below. Note that the standard deviation of P is typically 7 times larger than those of E in our calculations. That is, with a view toward recycling, the interannual variation of E falls completely short of explaining quantitatively the interannual of variation of P. This statement is still true, even if E (and its standard deviation) were twice as large. Table 2 shows the standard deviation by month (in that case var(s,m) is summed only over s). Note that both w and P have the lowest standard deviation in September when w itself is lowest also, while E has the highest standard deviation in June and July when E itself is high, but w (from which it draws) is on the way down.

[23] One may wonder what is the relationship between the variance in P (37.2 mm/mo forcing) and w (51.3 mm response). Because E, R and G have all a strong element of negative feedback on w, one could simplify equation (1), in anomaly form, to first order as

$$dw/dt = P - \lambda w \tag{2}$$

Table 1b. Same as Table 1a, but Now for the Mississippi Drainage Area

Month	T, °C	P, mm/month	w30, mm	E, mm/month	R, mm/month	G, mm/month	P-E-R-G, mm/month
1	−3.0	49.6	357.1	1.5	12.4	28.0	7.7
2	−0.7	46.7	359.5	2.8	13.1	28.4	2.5
3	4.0	64.5	370.2	8.2	16.7	28.9	10.8
4	10.1	72.0	374.0	22.5	16.0	29.5	4.0
5	15.7	88.5	375.2	42.3	15.2	29.7	1.3
6	20.5	90.6	363.1	60.6	12.7	29.2	−12.0
7	23.3	82.6	342.6	64.5	10.6	27.9	−20.3
8	22.4	74.4	326.4	55.5	8.5	26.5	−16.1
9	17.8	69.1	324.0	37.4	8.0	25.8	−2.1
10	11.7	55.3	326.0	19.4	7.4	25.7	2.7
11	4.3	53.7	338.6	5.8	8.4	26.3	13.1
12	−1.0	50.3	349.6	1.8	10.2	27.3	11.0
Year	10.4	66.4	350.5	26.9	11.6	27.8	0.2

Table 2. Standard Deviation of Monthly Mean Variables Around Their Local Climatological Mean, Averaged Over the United States

Month	T, °C	P, mm/month	w30, mm	E, mm/month	R, mm/month	G, mm/month	P-E-R-G, mm/month
1	2.8	42.4	56.8	2.5	21.6	4.4	29.5
2	2.6	36.6	53.8	3.0	18.5	4.3	26.4
3	2.1	36.4	52.4	4.5	17.4	4.1	26.2
4	1.6	34.2	51.1	5.1	13.3	4.0	26.4
5	1.5	36.7	50.0	7.0	10.7	3.8	30.7
6	1.4	35.9	49.1	7.8	8.2	3.7	30.1
7	1.1	31.9	45.5	7.9	6.4	3.6	28.0
8	1.2	30.5	42.4	6.9	5.0	3.3	27.8
9	1.3	38.4	47.0	5.4	6.5	3.3	32.5
10	1.5	39.4	52.3	4.5	6.8	3.7	33.4
11	1.8	41.2	55.4	3.1	12.8	4.1	33.1
12	2.2	40.4	57.2	2.1	19.0	4.3	30.4
Year	1.8	37.2	51.3	5.4	13.4	3.9	29.6

where all variables are anomalies, and λ is a coefficient that relaxes w toward 0 (=climatology). Simplifying land surface hydrology to a Markov process has been done before by *Delworth and Manabe* [1988], H96, and *Koster and Suarez* [2001]. Equation (2) is also identical to a mixed ocean layer's temperature subject to random heat forcing [*van den Dool and Horel*, 1984]. We proceed from here assuming P is white noise forcing for $\Delta t = 1$ month. Under equation (2), the soil moisture is a reddened version of precipitation. The variance in w is given by the usual $\sigma_w^2 = \sigma_{P'}^2/(1 - \rho_w^2)$, where $P' = P/(1 + \lambda/2)$ is rescaled monthly P (we discretized equation (2) with an implicit scheme); one can alternatively write $\sigma_w^2 = \sigma_{P'}^2/(2\lambda)$. The soil moisture autocorrelation ρ_w is given by $(1 - \lambda/2)/(1 + \lambda/2)$. The larger ρ_w the more σ_w^2 gets amplified relative to $\sigma_{P'}^2$. Given that the month-to-month autocorrelation in w is close to 0.82 (annually averaged) the damping λ is about 0.22 month^{-1} and the effective timescale of soil moisture anomalies is order 4 months. In some areas and some portions of the annual cycle these figures may be very different, but in general an order 4-month memory seems reasonable.

[24] Since we intend to use only soil moisture anomalies as predictor one may well question whether we really need the "full" hydrological equation (1). We might not have been that much worse off for the P and T prediction to be discussed below by using equation (2) instead of equation (1), and using a reasonable λ. However, in that case we could not have commented on verification of E forecasts of course. Moreover, equation (2) is an approximation for anomalies only, so we need the full equation (1) to study the climatological annual cycle of the hydrological components.

[25] Plenty of exceptions to the validity of equation (2) may also be noted, even for anomalies [see also *Koster and Suarez*, 2001]. In the cold season the anomaly in E is determined by temperature, so the $-\lambda w$ breaks down as a parameterization for E. During periods of significant P, the parameterized R is too nonlinear to fit a $-\lambda w$ approximation.

[26] The approximate validity of equation (2) suggests that the T input into equation (1), via E, is not all that important for the evolution of soil moisture anomalies. This can also be surmised from Table 2, where we noted that the standard deviation of E is very much smaller than that of P. This suggests that P is, by and large, the process that forces w anomalies. The only role for E is that of a mild feedback on w, so as to limit the excursions of w away from its climatology; modeling this feedback, to first order, does not require knowledge of T.

4. Constructed Analogue Method

4.1. Diagnostic Aspects

[27] Given is a data set X(s,j,m) of monthly data. X is a function of space s (102 positions), year j (1, N; N = 66 (1932–1997)) and month m (1–12). Given is an initial condition (IC) $X^{IC}(s, j_0, m)$, for example the most recent realization of X, where, in real time, j_0 is outside the range j = 1..N. A monthly climatology is removed from the data; henceforth X shall be the anomaly. A constructed analogue is defined as

$$X^{CA}(s, j_0, m) = \sum_{j=1}^{N} \alpha_j \, X(s, j, m) \tag{3}$$

where the coefficients α are determined so as to minimize the ms difference between $X^{CA}(s, j_0, m)$ and $X^{IC}(s, j_0, m)$. Since the X(s, j, m) are not orthogonal states the weights α_j cannot be found trivially; in fact, no unique solution exists. An approximate solution to this problem is given by *van den Dool* [1994]. The resulting equation is the classical:

$$\mathbf{A}\,\alpha = \mathbf{b} \tag{3'}$$

where the N by N symmetric covariance matrix **A** has the elements a(i, j) formed from the inner products Σ X(s, i, m). X(s, j, m) for all combinations of i and j, summation is over s, and i and j are years in the range 1..N. Similarly, the vector **b** has elements $\Sigma X(s, j, m).X^{IC}(s, j_0, m)$, while the vector α is what we solve for.

[28] Part of the approximations underlying equation (3′) is that all fields X need to be truncated in EOF space, keeping a number of modes that is at most order N/2; here we keep 30 modes. With 30 modes we explain 90% (summer) to 93% (winter) of the historical (1932–1997) soil moisture variance, but on the initial condition, which is not part of the EOF calculation, this figure is closer to 85% and moreover varies considerably from situation to situation; situations of weak anomalies are hard to "explain" by EOFs. Figure 2 (top) shows what happens when a field

Table 3. Weights α Assigned to Each Year's End of April Soil Moisture Anomaly so as to Reproduce the U.S. Soil Moisture Anomaly on 30 April 2000[a]

	α_j										
	2	3	4	5	6	7	8	9	0	1	10-year $\Sigma\ \alpha$
1930s–1940s	−0.01	−0.09	0.01	−0.01	0.00	−0.04	−0.04	0.08	0.02	0.03	−0.06
1940s–1950s	0.10	−0.01	−0.05	0.02	−0.09	−0.03	−0.01	−0.08	−0.13	−0.05	−0.33
1950s–1960s	−0.03	−0.04	0.17	0.07	0.13	−0.10	0.07	−0.13	−0.01	0.00	0.13
1960s–1970s	−0.02	0.11	−0.12	−0.19	−0.11	0.06	0.04	−0.06	0.07	0.04	−0.18
1950s–1980s	−0.02	0.03	0.13	−0.08	0.00	0.05	−0.01	−0.11	0.11	−0.01	−0.09
1980s–1990s	−0.05	−0.06	0.00	−0.05	0.04	0.08	0.01	0.06	0.11	−0.11	0.03
1990s	−0.10	−0.01	0.12	−0.01	0.03	0.04	NA				0.07
$\Sigma\ \alpha$											−0.25
$\Sigma\ \alpha^2$											0.37
$\Sigma\|\alpha\|$											3.90

[a]Years (j) run from 1932 to 1997. Column headings refer to years; for example, "2" indicates 1932, 1942, 1952, etc. The weights are dimensionless numbers. There are 66 weights. If the initial condition is in the 1981–1997 (example 1993) period, then a weight is assigned to 1998 and no weight to 1993 (cross-validation).

(such as Figure 2 (bottom)) is truncated to 30 EOFs (calculated from 1932–1997). The large-scale features are well maintained, but local features, as big as half a state, can be seriously compromised.

[29] A detailed example may be helpful. For the soil moisture anomaly in April 2000 in Figure 2, the coefficients α_j are given in Table 3. With this set of weights, the field shown in Figure 2 can be reproduced to within a few mm, i.e., very accurate. Note the following: (1) the weights are all small (≤ 0.20); that is, there are no good natural analogues (in that case there would be one $\alpha = 1$ and all the other $\alpha = 0$) in a system with that many degrees of freedom and less than a century of data [*van den Dool*, 1994]. (2) The weights can be negative; that is, we follow a linear approach once the climatology is subtracted. (3) The sum of the α is not constrained to be zero (it actually would be if the anomaly was relative to 1932–1997), nor (4) is the sum of absolute α constrained to unity (here a large 3.90). (5) In order to keep the amplitude of forecasts in check we want the sum of α^2 to be less than unity. (A large α^2 points to an unstable solution.) This is achieved by sufficiently "ridging" the covariance matrix **A**, i.e., adding small positive constants to the main diagonal of **A** [*van den Dool*, 1994]. In the last column of Table 3 we have 10-year sums of the weights so as to gauge any inter-decadal dependency. On this occasion, the 1940s are slightly favored.

4.2. Forecast Aspects

[30] Equation (3) is only diagnostic, just stating that within truncation to 30 EOFs the current (or any) condition can be expressed as a linear combination of conditions observed in other years at the same date. We now seek a forecast at lead τ of variable Y (which could be X itself) as follows:

$$Y^F(s, j_0, m + \tau + 1) = \sum_{j=1}^{N} \alpha_j\ Y(s, j, m + \tau + 1) \qquad (4)$$

That is, we have the initial weights persist and make linear combinations of the anomalies in Y that followed in the 66 historical years. (If $m + \tau + 1 > 12$, the Y fields would be in the next year ($j + 1$), and $m + \tau + 1 - 12$ would be the forecast month.) The "lead" τ, in units of months, is defined, as per CPC nomenclature, as the amount of time between the end of the month (of construction) and the first moment of validity. Thus the +1 in expressions like $m + \tau + 1$ in equation (4). For example, a monthly forecast for July 2000 made at the end of April has lead 2. A seasonal forecast for JJA 2000 has lead 1 (in units of months). At lead −1 we deal with "specification," i.e., calculate the field of variable Y given a constructed analogue to a simultaneously observed field X. Backcasts (not discussed) occur when the lead is larger negative.) Admittedly, there is an ambiguity as to whether the fields Y on the rhs of equation (4) should be truncated to within the "same" EOF space (if the latter notion is even defined). In this paper we made forecasts with the raw data for Y, accepting a nonzero noise component, which is considerable because soil moisture has many degrees of freedom (H96).

[31] How well does equation (4) work? In case X = Y = w, one can verify the soil moisture forecast; that is, the left-hand side of equation (4), against the observed $w(s, j_0, m + \tau + 1)$. In case X = w, and Y = T or P or E, one can verify temperature, precipitation or evaporation forecasts against observations. (Keep in mind that w and E "observations" are calculated from T and P observation; they are not directly observed.) The verifying observations are not truncated in EOF space, but always the "true raw" data.

[32] Note that equation (4) is not formulated so as to minimize the mean square error in the predictand Y. The weights α_j are unaware of the forecast target. This may explain rather large forecast anomaly amplitudes, even in low skill situations. In this sense CA differs from any traditional statistical method. One advantage of the procedure is that we cannot possibly be over-fitting the relationship between predictor X and predictand Y. A different advantage is that consistency among variables is maintained. For instance a linear combination of pressure and wind fields maintains the quasi-geostrophic nature of the wind-pressure relationship.

4.3. Example and Nonlocalness of CA Forecast

[33] Using the weights in Table 3 the JJA T and P 2000 forecast is given in Figure 3 (left column), along with the verifying observations for JJA2000 (right column). By the standards of seasonal forecasting the JJA2000 case was very successful, particularly on P. We will discuss the skill of this particular forecast later. Here we want to highlight the nonlocalness of the forecast, both in T and in P. Relative

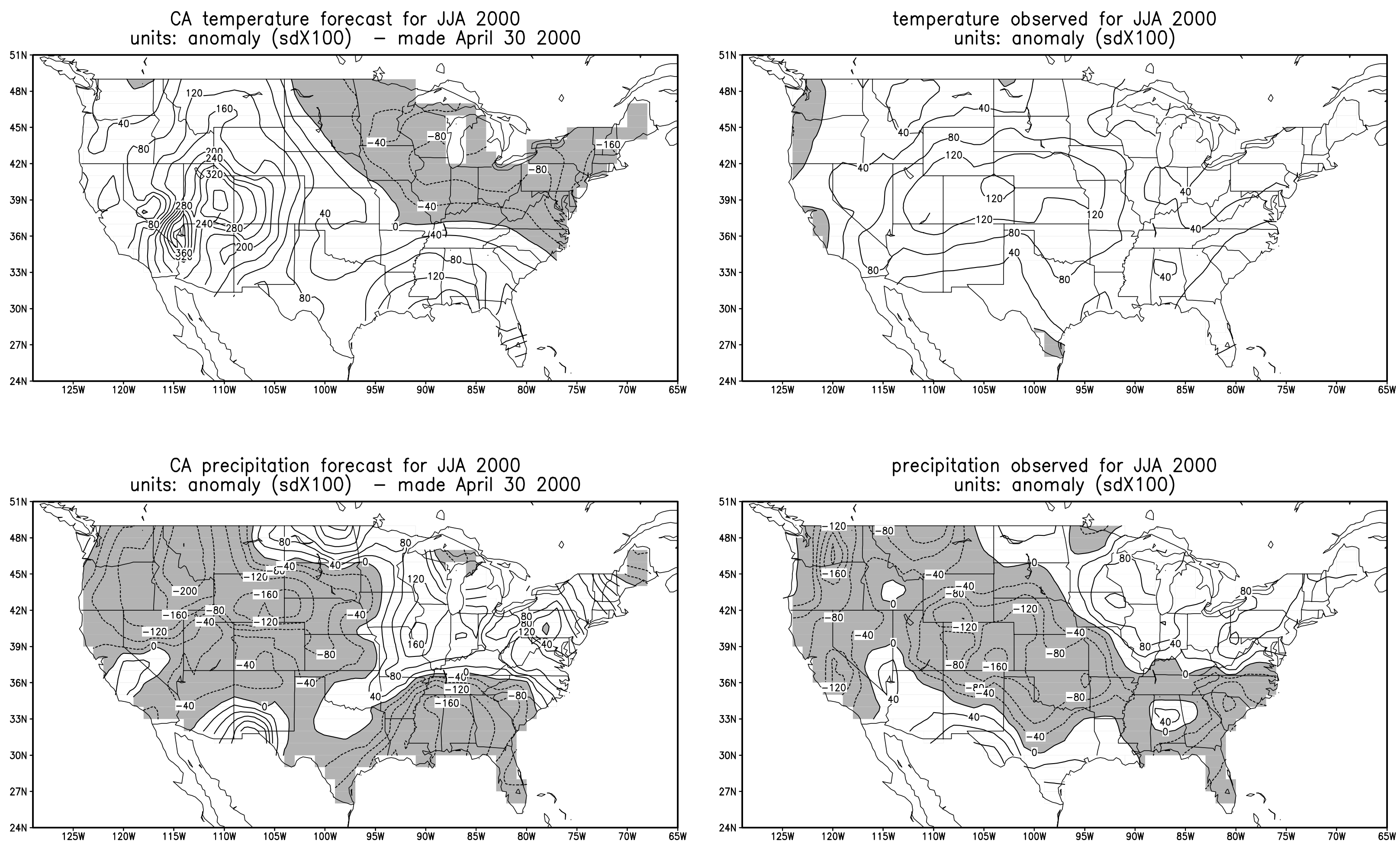

Figure 3. The JJA 2000 forecast for temperature (top left) and precipitation (bottom left). Units are local standard deviation times 100. The forecast method is constructed analogue and the situation to which an analogue is constructed is the soil moisture situation shown in Figure 1, with weights as shown in Table 3. The verifying observations are on the right in the same units. Contour interval is 40, and negative contours are dashed. A color scheme is applied for values in excess of 25, 100 (absolute value). See color version of this figure in the HTML.

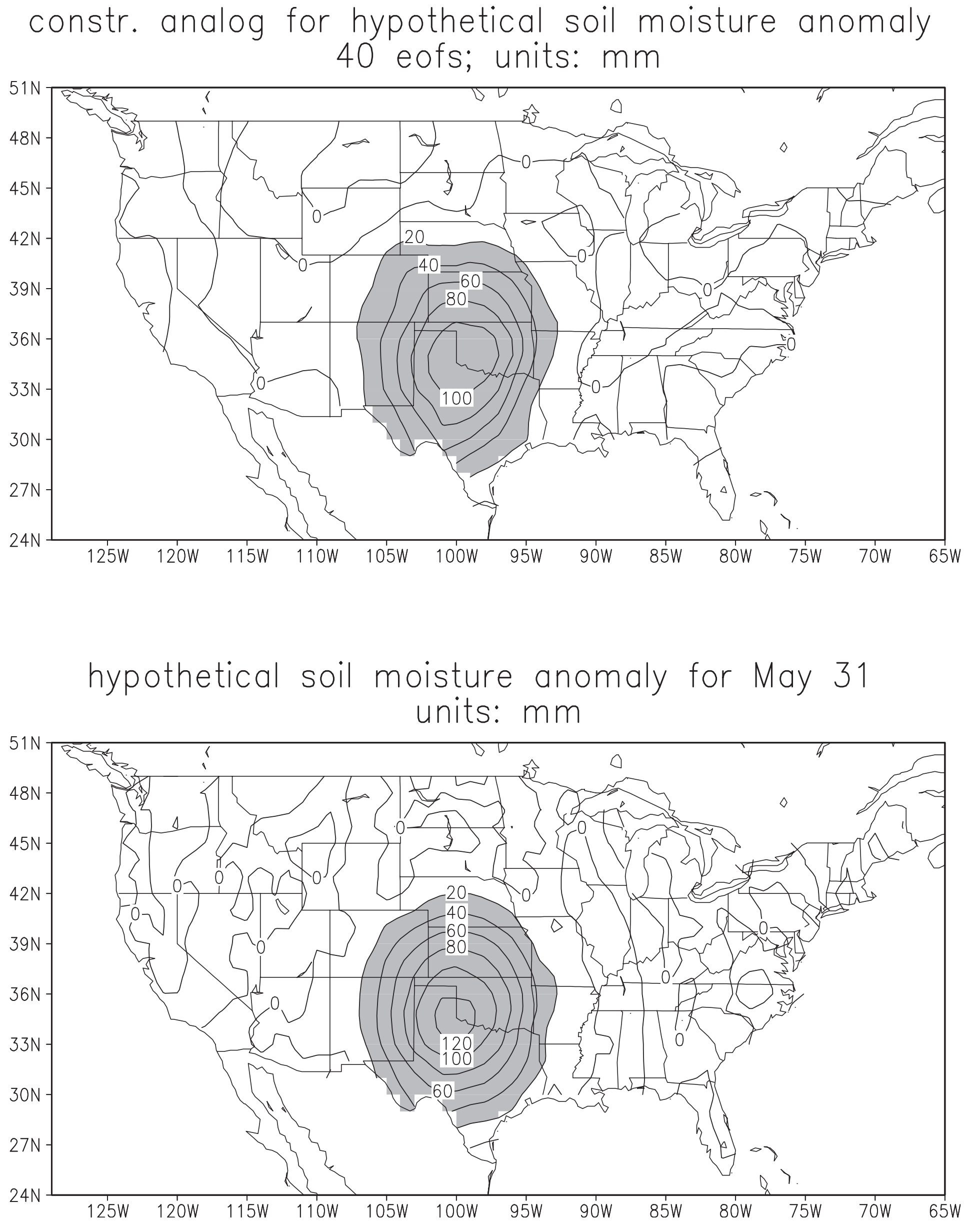

Figure 4. A hypothetical soil moisture anomaly for 31 May in mm. A version truncated to 40 EOFs is shown at the top, while the intended wet patch is at the bottom. Contour interval is 20, only positive contours. A color scheme is applied for values in excess of 25. See color version of this figure in the HTML.

to the soil moisture configuration in Figure 2 large anomalies in T and P appear outside areas where soil moisture anomalies are large. Even the sign may conflict with a pure local interpretation - for instance a warm JJA on top of wet soil in Southwestern SD. A local regression (not shown) would show weak anomalies, such that +ve (−ve) T forecast anomalies, where significant, coincide with −ve(+ve) soil moisture anomalies in the IC. The P forecast by local regression would be zero anomalies everywhere because of a lack of skill (H96).

[34] There is no question that the forecast is nonlocal, but to drive the point home explicitly for precipitation Figure 4 (bottom) shows a hypothetical localized soil moisture anomaly distribution in May. We placed a wet (or dry, since the calculation is linear) patch at 100 W, 35 N with a radius of 8 degrees (counting latitude and longitude degrees equal). The central value is twice the local standard deviation and the w30 anomaly decreases linearly to the rim. Equally important: outside the patch w30 = 0. Figure 4 (top) shows that there are weights that allow us to reproduce a situation that never occurred (and never will). Figure 5 (bottom) shows the P forecast for June following a May ending with the w30 field shown in Figure 4. P anomalies $\geq$ 30 mm (order 1 standard deviation) are shown (almost entirely) downstream from the wet patch. (Winds at 700 mb are normally from WSW). Nonlocalness of the forecast is obvious. As a result of this configuration the soil moisture anomaly will actually move to the Northeast, a little more with each passing summer month (not shown). Indeed, CA makes an attempt to integrate dw/dt = P-E-R-G empirically.

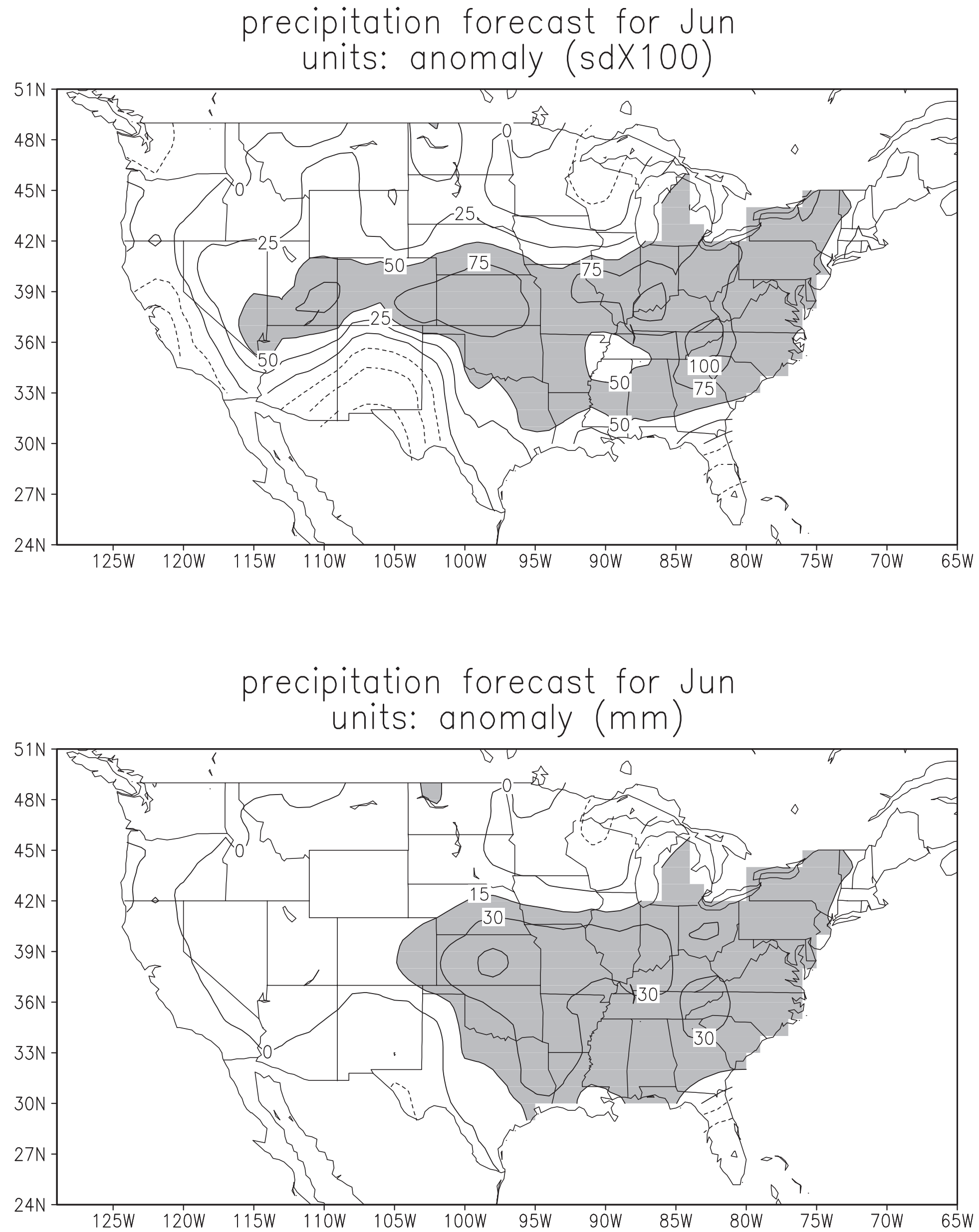

Figure 5. CA precipitation forecast for June following the hypothetical situation shown in Figure 3. (top) Units in local standard deviation × 100. (bottom) Units in mm. The contour interval is 25 (top panel) and 15 (bottom panel), and negative contours are dashed. A color scheme is applied for values in excess of 25 (top panel) and 15 (bottom panel). See color version of this figure in the HTML.

It should be noted that the downstream P anomaly (in terms of overall water mass) is much larger than the E anomaly (which lies right on top of the patch; not shown). The implication is that the atmosphere brings in large amount of water from the sides, the Gulf of Mexico in particular. In terms of standardized units, see Figure 5 (top), the "response" of P to an isolated wet patch is not just "downstream" Figure 5 (top) shows some effects in terms of enhanced/suppressed P (order 0.5 sd) upstream in Utah and NM as well.

[35] The advantage of the hypothetical case is that forcing and response are clearly separated, and attribution is unambiguous, while in a "real" case like April 2000 the patchwork of +ve and −ve forcing covering the whole domain makes it difficult to say what exactly forces the rainfall anomalies in the JJA forecast in say Iowa. The disadvantage of the hypothetical case is that we cannot verify the subsequent forecast; it may be instructive, but only the forecasts based on as realistic as possible w30 can be verified against observations.

5. Results of Forecasts: 1981–2001

5.1. Details of Forecast and Verification

[36] Following the method given in section 4.1, equation (3), we constructed an analogue to all 252 soil moisture anomaly fields at the end of all months during 1981–2001. The soil moisture fields are at the end of the month (rather

than a monthly mean) in order to be as close as possible to the forecast target. For example consider May 1993. Construction for May 1993 means that we have 66 weights, one for each end-of-May in the period 1932 to 1998, excepting the year 1993 itself of course. Leaving out the year in question is called cross validation (CV). We use 66 years; the year 1998 would only get a weight when the IC is in the range 1981–1997. In order to avoid common "compensation" problems with CV [*Barnston and van den Dool*, 1993] we expressed anomalies relative to 1951–1980; that is, the climatology has no knowledge about 1993 (or any other year in 1981–2001). Forecasts for T, P, w30 and E were then made by linearly combining (keeping the weights constant, see equation (4)), fields observed in the months and seasons following the 66 historical Mays. We consider leads from −1 to +6 months. The longer lead forecasts have not been verified for the early part of 1981, so for a few leads/target there are only 20 years.

[37] For June (say) at fixed lead τ we have, in all, 21 forecasts, one for each year's June. That is not much if one wants to decide whether a correlation between forecast and observed anomalies at a single location is significant. In order to enlarge the sample we "pool" like forecasts for neighboring months (seasons). For example, the τ month lead forecasts for June are combined with those for May and July when calculating the correlation for June. Similarly, JJA is combined with MJJ and JAS, in case of seasonal forecasts. The pooling increases stability. The forecasts for 1998 and beyond are not influenced by CV considerations because we used only past years, i.e., keep the covariance matrix at 66 × 66 (we could have enlarged by one with each passing year, but did not).

[38] We further use the following definitions:

$$\text{Covariance} \qquad \mathrm{cov}(f, o) = \Sigma\, f(z)o(z), \tag{5}$$

where f is the forecast, o is observed, z is either time or space, and summation is over all z, i.e., over 102 when z is space, over 3 × 21 = 63 when z is time, or over 102 × 63 cases when we sum over both time and space. There is no explicit weighting necessary, because the 102 positions are considered equal area. There is implicit weighting in that the large anomalies count for more in these calculations.

[39] The anomaly correlation is given by

$$\rho = \frac{\mathrm{Cov}(f, o)}{\{\mathrm{Cov}(f, f) \times \mathrm{Cov}(o, o)\}^{1/2}} \times 100 \tag{6}$$

5.2. Forecast Skill

[40] Figure 6 shows line graphs of the U.S. aggregate correlation between forecast and observed for the variables w30 and E. Soil moisture at a lead of one month; for example, June at the end of April) can be forecast with a correlation that varies from close to 0.7 in spring to less than 0.5 in fall. Verification scores of 0.6 sound rather high, certainly compared to T and P, which are typically more like 0.1–0.3. There is undoubtedly a demonstrated capability to know about future soil moisture anomalies (of the calculated variety), given current conditions and a decent forecast method. Coincidentally or not, the trace of skill follows rather precisely the climatological mean soil moisture itself as well as the annual cycle of the interannual standard deviation (Table 2). That is, forecasting soil moisture anomalies is most difficult when (1) the bucket is emptiest and (2) when anomalies are smallest (least "signal").

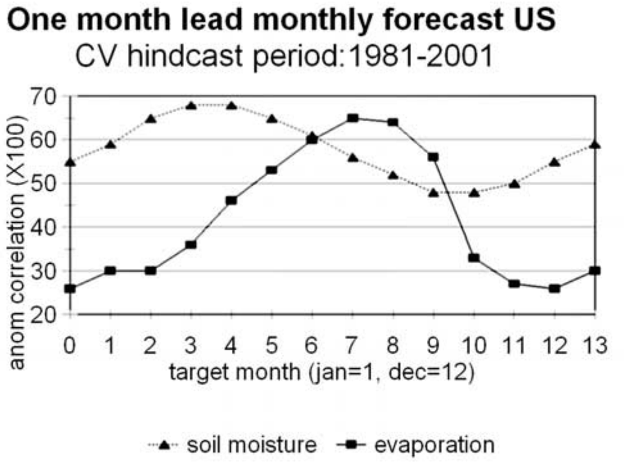

Figure 6. The skill of the one-month lead monthly forecast of w30 (triangles, dashed line) and E (squares, full line), as a function of the target month (1 = January, 12 = December). For a better representation the December value (at 0) and January value (at 13) are repeated. Skill is expressed as correlation (times 100), which ranges from 0 to 100 (dimensionless). The period is 1981–2001. See color version of this figure in the HTML.

[41] Converting the skill of soil moisture prediction into something more useful depends on E as an intermediary. Forecast skill for monthly evaporation (Figure 6) has a rather dramatic maximum (0.65) in July and August. In winter, when E anomalies are minimal, the skill is just below 0.3. Elevation of skill above this background 0.3 level lasts from March through October. This seasonality is entirely reasonable from a physical point of view. As is the case with w30, E is best predictable when a large signal may occur, i.e., the time of year when both E and its inter-annual variability (see Table 2) are large.

[42] Figure 7 shows the skill of forecasting monthly mean evaporation during summer (target months May to September) at leads from −1 to +6. One can see the skill increase from 0.2 at long lead (i.e., from previous winter w30) to close to 0.6 as one gets closer to the target. The shortest lead of practical importance would be about 0.5. The −1 lead is interesting to understand the CA method. Given a very good constructed analogue to just w30 one knows implicitly the evaporation during that same initial month (at lead = −1) at a skill level of 0.6 to 0.7, i.e., not perfectly. For comparison, persistence of E anomalies, as a forecast method starts as "perfection" for lead −1, but drops off much more rapidly, at least in the summer months, than the CA forecast. That is, we are doing better than persistence in forecasting E for any of the leads > −1.

[43] In conclusion, Figures 6 and 7 demonstrate a capability to forecast evaporation anomalies during summer. This is the necessary physical link to explain any success in forecasting T and P during these months.

[44] Figure 8 shows the skill of forecasts of seasonal mean T and P at a lead of one month. Scores (correlation)

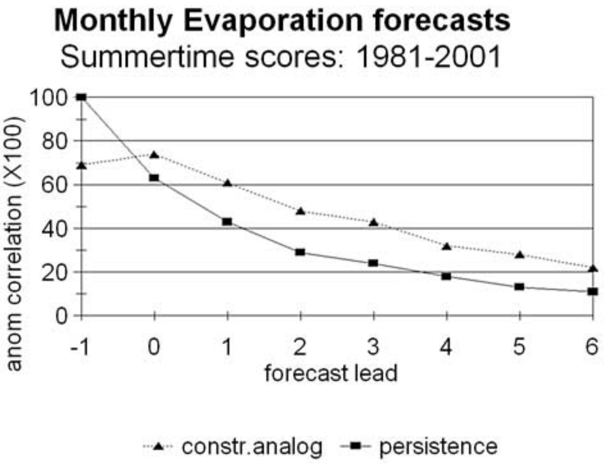

Figure 7. The skill of monthly E forecasts verifying from May to September, as a function of lead. Line for persistence has squares and for constructed analogue triangles. Skill is expressed as correlation (times 100), which ranges from 0 to 100 (dimensionless). The period is 1981–2001. See color version of this figure in the HTML.

for temperature hover around 0.25 for much of the year, with the exception of September and October when there is a sharp minimum of only 0.10. Scores for seasonal mean P are near 0.10 or slightly below. Because all 12 seasons are positive there is no question that the correlations are nonzero, even for P. Nonetheless, scores for P remain next to useless. The seasonality of the scores, neither in P nor T, gives much of a clue about the exact source of this skill. The simple physical arguments in the first paragraph of the introduction make us expect skill in summer, which we found. However, the CA method on w30 somehow has as much skill in winter as in summer. The source of skill in winter is unlikely to be related to evaporation anomalies. Rather the calculated w30 may reflect (1) snow cover or lack thereof or (2) the circulation anomalies that caused the P and T anomalies over the last 4–5 months.

[45] For both T and P the scores in Figure 8, although very modest, are better than persistence from T and P observations available at lead 1 (not shown). Moreover, persistence has a different annual cycle than seen in Figure 8. For instance, persistence in P is entirely absent in summer, and around only around 0.05 in winter.

[46] In Figure 9 we show the scores for 1-month lead JJA T and P forecasts for each year during 1981–2001. In this case the covariance in equations (5) and (6) is summed only over space. As is common with all forecast methods, the skill fluctuates wildly (understanding this would be desirable, but beyond the scope of this paper) from case to case, especially for temperature. A good aspect of CA is that real terrible forecasts (highly negative correlations) are rare. JJA in 2000, a forecast that was available in real time, shown in Figure 3, worked out very well, both for P and T. Famous years from a hydrological standpoint include 1993 and 1988. In neither year did we do well on P, but T in 1988 was one of the best. The forecast for summer 1998, the first we made in real time, was interesting because it followed the El Nino winter 1997/98. During 1998 the 66 weights continued to be positive, on average, for historical El Nino years all the way through August, thus suggesting a degree of determinism in the forecast and reasonable skill as well. The physics appear to be that the soil moisture condition in spring, left behind by a prominent winter El Nino winter precipitation anomaly pattern, gets carried over into summer by land surface feedbacks.

[47] One can display the correlation in many different ways. So far we showed line graphs for the United States as a whole for a fixed lead as a function of month/season

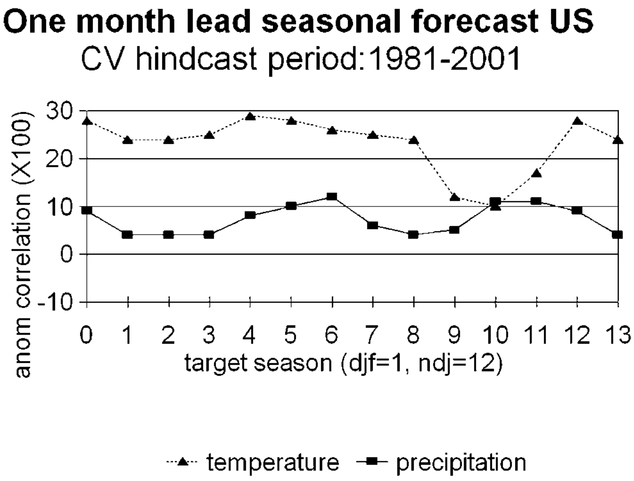

Figure 8. The skill of one-month lead seasonal forecasts of temperature (triangle) and precipitation (squares), as a function of target season (1 = DJF, 12 = NDJ). For a better representation the NDJ value (at 0) and DJF value (at 13) are repeated. Skill is expressed as correlation (times 100), which ranges from 0 to 100 (dimensionless). The period is 1981–2001. See color version of this figure in the HTML.

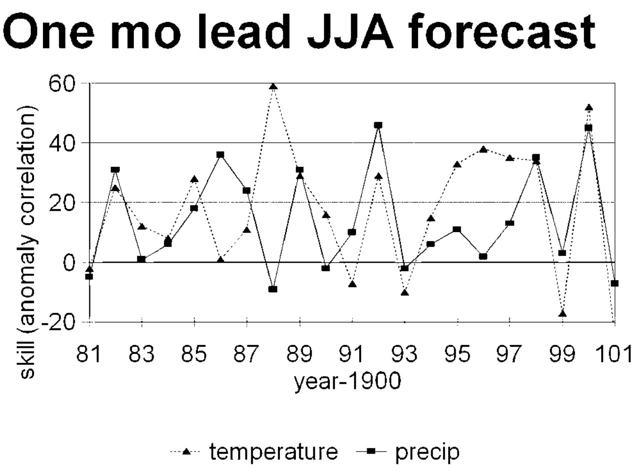

Figure 9. The skill of one-month lead seasonal forecasts of temperature (triangle) and precipitation (squares) for JJA, year-by-year for 1981–2001. Skill is expressed as correlation (times 100), which ranges from 0 to 100 (dimensionless). The year is indicated as year-1900; that is, 81 means 1981. See color version of this figure in the HTML.

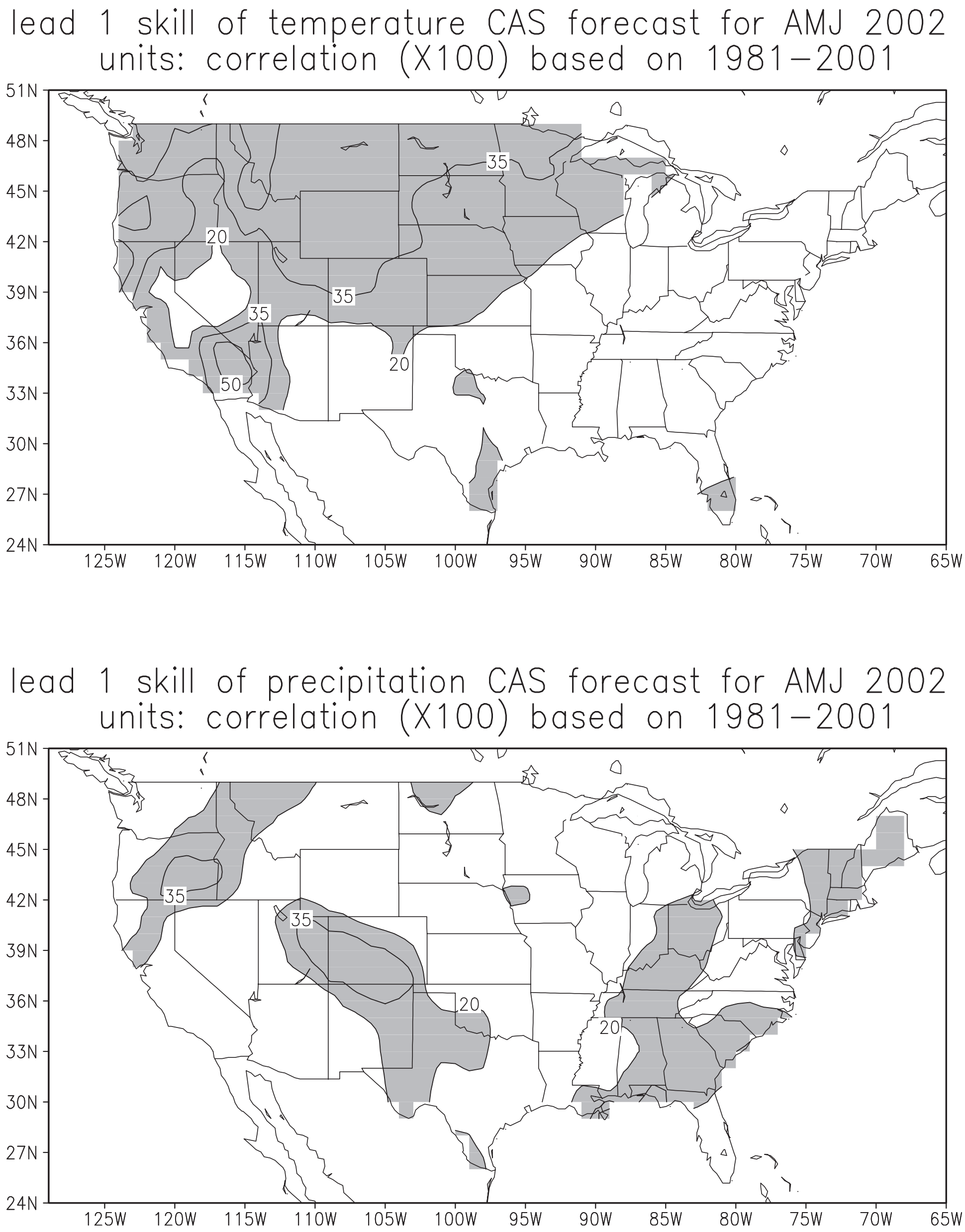

Figure 10. Example of the spatial distribution of skill (correlation times 100) of seasonal forecasts for T (top) and P (bottom). Contours are 20, 35, 50, etc., with color scheme coinciding. The target season is AMJ, and the lead is 1 month. Maps like this have been prepared for all target seasons and months and leads from −1 to +6. See color version of this figure in the HTML.

(Figures 6 and 8), as a function of lead for a fixed target (Figure 7), and as a function of year for a fixed target and lead (Figure 9). For the forecasters, another useful way is skill in map-form. That is, we now sum the covariance in (5) only over time. We have made maps of skill for T and P, for all leads from −1 to +6 months, for all verifying months and seasons. The full display can be seen at ftp://ftpprd.ncep.noaa.gov/pub/cpc/wd51hd/soil/skill.html. An example is given in Figure 10, where we show skill (correlation) for AMJ at a lead of one month. The real time forecaster would use these skill maps as a mask, i.e., mask out from the latest forecast for AMJ those areas that by this verification have no skill at all. In this way, the verification over 1981–2001 (soon 2002) functions as an a-priori skill estimate for, say, future AMJs. For this season the North central states and the Northwest enjoy some skill for temperature, while P correlation reaches 0.35 only in 3 or 4 states.

6. Conclusions

[48] We have conducted an experiment to assess the real time skill in monthly and seasonal predictions based solely on patterns of antecedent hydrological information over the

limited domain of the United States. The hydrological information is contained in a proxy for soil moisture at 102 locations over the lower 48 states. This soil moisture is calculated for 1931 to the present from a local hydrological equation taking monthly precipitation (P) and temperature (T) as input, and producing soil moisture (w), evaporation (E), runoff and loss to groundwater as output. The initial condition (IC) for the forecast procedure is soil moisture at the end of the month (w30). We constructed an analogue to the w30 fields, i.e., made linear combinations of soil moisture fields in the same months in years past so as to reproduce the IC to within a small tolerance. The coefficients assigned to the years past are then made to persist, and the subsequent developments in the historical years are linearly combined to form a forecast. This method has been running at CPC in real time since 1998, and we added 1981–1997 in "retroactive real time" mode to form a large enough sample. In total, we considered both seasonal and monthly forecasts at leads −1 to +6 months for 1981–2001, for the elements w30, E, T and P. From the outset, we wanted to investigate nonlocal forecast methods, considering local effects, on evaporation and temperature mainly, as being established already and well documented [*Huang et al.*, 1996]. In a nonlocal method we entertain the possibility of precipitation (the response) falling downstream of a soil moisture anomaly (forcing).

[49] We found that we have about a 0.6 correlation in forecasting monthly soil moisture with a lead of one month (i.e., July at the end of May). This figure is higher in spring and somewhat lower in the early fall. The capability to forecast evaporation anomalies is very seasonal. During the cold half of the year, when E anomalies resemble T anomalies, the correlation is only 0.2–0.3, but in summer, when E anomalies resemble w anomalies, the skill of forecasts goes up to 0.6. We thus have some insight in patterns of anomalous water vapor input from the land surface into the atmosphere on a continental scale. Skill of forecasting T is modest, reaching 0.2–0.3 in many months and seasons, but there is no clear seasonal dependence that relates unambiguously to the presumed physics of land atmosphere interactions. Skill in forecasting P is quite low, barely 0.1 in correlation, but +ve in all months and seasons.

[50] We did alternative experiments where the constructed analogue was built on E, T or P instead of w, and verified the forecast of all elements likewise. We found initial w to be the best for forecasting w itself and indeed for forecasting the other fields as well! This is important testimony that soil moisture is indeed the key, as has been suspected by many for ages.

[51] While CA is a powerful exploratory method, a potential drawback is that one needs to truncate data in EOF space in order to find solutions. With about 70 years of data we feel comfortable retaining about 30 EOFs, which generally explain from 90% (summer) to 93% of the soil moisture variance. EOF truncation deleted many mainly local features. So, in pursuing a remote response method we shaved off a lot of the local information, which, as we know (H96), contributes to forecast skill also. In view of *Guetter and Georgakakos* [1996] the linearity of CA in combination with EOF truncation may pose a particular problem if large-amplitude wet anomalies occur on tiny spatial scales. Some merging of local and nonlocal forecast methods may have to be considered in practice.

[52] It is not clear as to why the low skill in T and P especially is due to a low predictability ceiling in general or a particular weakness in any of the building blocks used here. Among the potentially weak points of our approach we should include that soil moisture over the United States only is an unrealistic limitation from a physical point of view. Certainly land conditions over Canada and Mexico should be included, and it may even be that a proper evaluation of the role of soil moisture can only be made when the lower boundary condition over the (nearby or global) oceans are also included. On the other hand GCM work along the same lines [*Kanamitsu et al.*, 2003] reports skill in T similar to what we found, but only in summer, and absolutely no skill at all for P.

[53] Progress can be made along many lines. The most obvious one is to improve the estimate of soil moisture. Various land reanalyses are underway, yielding much more detailed and physically realistic soil moisture over many decades [*Maurer et al.*, 2002; *Fan et al.*, 2003]. The LDAS experiments are geared toward making model consistent soil moisture, so using full blown GCMs for a real time forecast is an obvious alternative to CA. Ultimately, global land surface conditions will be prepared for the whole world, including a true assimilation of soil data [*Walker and Houser*, 2001], but this may be a few years away. Merging lower boundary condition over the ocean and land, in the context of the CA method, is another point to consider. Anomalies in evaporation over land near the ocean need to be merged with E anomalies over the ocean itself, for the system to make physical sense. Of course, if predictability is fundamentally limited to start with, none of these improvements may yield much new forecast skill. *Kanamitsu et al.* [2003] report zero skill in P. A recent study [*Koster et al.*, 2003] found empirical evidence of feedback of soil moisture onto precipitation over the United States to be only in July, and only in the center of the country.

[54] There is no question that the CA forecast is nonlocal, and this aspect may well be realistically modeled by CA; however, this does not prove that the forecast is, or should be, skillful. If the forecast is too sensitive to the details of the initial soil moisture distribution we may not have any skill at all, no matter how well we model the physics. This could be a problem of just the CA method (i.e., maybe CA is too sensitive), or for all methods, we do not know. One has to realize that the notion of predictability of the first kind, i.e., sensitivity to uncertainty in the IC, has to be extended here to uncertainties in the initial lower boundary condition as well. Indeed, when moving around the hypothetical anomaly in Figure 4 over a few degrees in all directions leads to a marked variation in P response one month later (not shown), suggesting tremendous sensitivity. The question as to how accurately we will ever know soil moisture is well beyond current insights.

[55] **Acknowledgments.** We gratefully acknowledge GCIP funding under GC99-367 and helpful discussions with John Schaake, Song Yang, and Cheng-Hsuan Lu. The anonymous reviews were very helpful as well. Jae Schemm and Suranjana Saha provided technical assistance. The input by CPC forecasters during 1998–2002 has also helped in shaping this project.

References

Barnston, A. G., and H. M. van den Dool, A degeneracy in cross-validated skill in regression based forecasts, *J. Clim.*, *6*, 963–977, 1993.

Cayan, D. R., and K. P. Georgakakos, Hydroclimatology of continental watersheds: 2. Spatial analyses, *Water Resour. Res.*, *31*, 677–697, 1995.

Chen, T. H., et al., Cabauw experimental results from the Project for Intercomparison of Land-surface Parameterization Schemes (PILPS), *J. Clim.*, *10*, 1194–1215, 1997.

Delworth, T. L., and S. Manabe, The influence of potential evaporation on the variabilities of simulated soil wetness and climate, *J. Clim.*, *1*, 523–547, 1988.

Fan, Y., H. van den Dool, K. Mitchell, and D. Lohmann, 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. Pred. Cent., Natl. Cent. for Clim. Pred., Camp Springs, Md., 2003.

Fennessy, M. J., P. A. Dirmeyer, J. L. Kinter III, A. Schlosser, J. Shukla, J. Huang, and L. Sun, Impact of initial soil wetness anomalies on seasonal atmospheric predictions over the U.S. during March–April–May 2000, in *Proceedings of the Climate Diagnostics Workshop, 23–27 October, 2000*, pp. 239–241, Clim. Pred. Cent., Natl. Cent. for Clim. Pred., Camp Springs, Md., 2000.

Fennessy, M., P. Dirmeyer, J. Kinter, L. Marx, and C. Schlosser, Origins of the summer 2002 continental US drought, in *Proceedings of the Climate Diagnostics Workshop, 21–25 October, 2002* [CD-ROM], Clim. Pred. Cent., Natl. Cent. for Clim. Pred., Camp Springs, Md., 2003.

Guetter, A. K., and K. P. Georgakakos, Large-scale properties of simulated soil water variability, *J. Geophys. Res.*, *101*(D3), 7175–7183, 1996.

He, Y., A. G. Barnston, and D. Unger, An improved seasonal forecast product from CPC, in *Proceedings of the XXIIIrd Climate Diagnostics and Prediction Workshop*, pp. 112–114, Natl. Oceanic and Atmos. Admin., Boulder, Colo., 1998.

Higgins, R. W., J. E. Janowiak, and Y.-P. Yao, A gridded hourly precipitation data base for the United States, *NCEP/CPC Atlas 1,*Clim. Pred. Cent., Natl. Cent. for Clim. Pred., Camp Springs, Md., 1996.

Higgins, R. W., W. Shi, E. Yarosh, and R. Joyce, Improved United States precipitation quality control system and analysis, *NCEP/CPC Atlas 7*, Clim. Pred. Cent., Natl. Cent. for Clim. Pred., Camp Springs, Md., 2000.

Hollinger, S. E., and S. A. Isard, A soil moisture climatology of Illinois, *J. Clim.*, *7*, 822–833, 1994.

Huang, J., and H. M. van den Dool, Monthly precipitation-temperature relation and temperature prediction over the U.S., *J. Clim.*, *6*, 1111–1132, 1993.

Huang, J., H. M. van den Dool, and K. G. Georgakakos, Analysis of model-calculated soil moisture over the US (1931–1993) and applications to long range temperature forecasts, *J Clim.*, *9*, 1350–1362, 1996.

Kanamitsu, M., et al., NCEP Dynamical Seasonal Forecast System 2000, *Bull. Am. Meteorol. Soc.*, *83*, 1019–1037, 2002.

Kanamitsu, M., C.-H. Lu, J. Schemm, and W. Ebisuzaki, The predictability of soil moisture and near-surface temperature in hindcasts of the NCEP seasonal forecast model, *J. Clim.*, *16*, 510–521, 2003.

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, W. Higgins, and H. M. van den Dool, Observational evidence that soil moisture variations affect precipitation, *Geophys. Res. Lett.*, *30*(5), 1241, doi:10.1029/2002GL016571, 2003.

Liang, X., D. P. Lettenmaier, E. Wood, and S. J. Burges, A simple hydrologically based model of land surface water and energy fluxes for general circulation models, *J. Geophys. Res.*, *99*(D7), 14,415–14,428, 1994.

Maurer, E. P., A. W. Wood, J. C. Adam, D. P. Lettenmaier, and B. Nijssen, A long-term hydrologically-based data set of land surface fluxes and states for the conterminous United States, *J. Clim.*, *15*(22), 3237–3251, 2002.

Mitchell, K., et al., Recent GCIP-sponsored advancements in coupled land-surface modeling and data assimilation in the NCEP Eta mesoscale model, paper presented at 15th Conference on Hydrology, Am. Meteorol. Soc., Long Beach, Calif., 2000.

Namias, J., The annual course of month-to-month persistence in climatic anomalies, *Bull. Am. Meteorol. Soc.*, *33*, 279–285, 1952.

Reed, C. D., Monthly forecasts by correlation, *Mon. Weather Rev.*, *53*, 249–251, 1925.

Roads, J., et al., GCIP Water and Energy Budget Synthesis (WEBS), *J. Geophys. Res.*, *108*(D16), 8609, doi:10.1029/2002JD002583, in press, 2003.

Svoboda, M., et al., The drought monitor, *Bull. Am. Meteorol. Soc.*, *83*, 1181–1190, 2002.

van den Dool, H. M., Searching for analogues, how long must one wait?, *Tellus, Ser. A*, *46*, 314–324, 1994.

van den Dool, H. M., and A. G. Barnston, Forecasts of global sea surface temperature out to a year using the constructed analogue method, in *Proceedings of the 1*9th *Annual Climate Diagnostics Workshop, Nov. 14–18, 1994*, pp. 416–419, Natl. Oceanic and Atmos. Admin., Boulder, Colo., 1995.

van den Dool, H. M., and J. D. Horel, An attempt to estimate the thermal resistance of the upper ocean to climatic change, *J. Atmos. Sci.*, *41*, 1601–1612, 1984.

Walker, J. P., and P. R. Houser, A methodology for initialzing soil moisture in a global climate model: Assimilation of near-surface soil moisture observations, *J. Geophys. Res.*, *106*(D10), 11,761–11,774, 2001.

Y. Fan and H. van den Dool, Climate Prediction Center, NCEP, WWB, W/NP51 Room 604, 5200 Auth Road, Camp Springs, MD 20746, USA. (huug.vandendool@noaa.gov)

J. Huang, Office of Global Programs, NOAA, 1100 Wayne Avenue, Suite 1210, Silver Spring, MD 20910, USA.