Monthly Precipitation–Temperature Relations and Temperature Prediction over the United States

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ABSTRACT

The monthly mean precipitation–air temperature (MMP–MMAT) relation over the United States has been examined by analyzing the observed MMP and MMAT during the period of 1931–87. The authors' main purpose is to examine the possibility of using MMP as a second predictor in addition to the MMAT itself in predicting the next month's MMAT and to shed light on the physical relationship between MMP and MMAT. Both station and climate division data are used.

It was found that the lagged MMP–MMAT correlation with MMP leading by a month is generally negative, with the strongest negative correlation in summer and in the interior United States continent. Over large areas of the interior United States in summer, predictions of MMAT based on either antecedent MMP alone or on a combination of antecedent MMP and MMAT are better than a prediction scheme based on MMAT alone. On the whole, even in the interior United States though, including MMP as a second predictor does not improve the skill of MMAT forecasts on either dependent or independent data dramatically because the first predictor (temperature persistence) has accounted for most of the MMP's predictive variance. For a verification performed separately for antecedent wet and dry months, much larger skill was found following wet than dry Julys for both one- and two-predictor schemes. Upon further analysis, we attribute this to the differences in the climate between the dependent (1931–60) and independent (1961–87) periods (the second being considerably colder in August) rather than to a true wetness dependence in the predictability.

We found some evidence for the role of soil moisture in explaining negative MMP–MMAT and positive MMAT–MMAT lagged correlations both from observed data and from output of multiyear runs with the National Meteorological Center model. This suggests that we should use some direct measure of soil moisture to improve MMAT forecasts instead of using the MMP as a proxy.

1. Introduction

Forecasts of monthly mean air temperature (MMAT or T) near the surface in the midlatitudes are nowadays made using combined dynamical and statistical methods. With increased understanding of physical processes and rapid development in computers, improvements of numerical prediction models have led to a greater emphasis on the dynamical part of the forecast. However, because of the models' internal instability associated with mesoscale and synoptic-scale motions, most of the skill of dynamical models comes from the first ten days (Tracton et al. 1989). At longer lead times, statistical and/or empirical methods become relatively more important (Wagner 1989).

The purpose of this study is to examine the relation between monthly mean precipitation (MMP or P) and MMAT over the United States, both simultaneous and with lag and lead. Such efforts would aid in further developing empirical tools for the monthly or longer-range temperature forecasts over the United States. Also they would document useful background material to understand the physics of the relation between atmospheric circulation (which produces the precipitation), surface hydrology, and surface air temperature. These issues are pertinent to long-range forecasting (Wagner 1989) as well as to climate change (e.g., Schlesinger 1989; Verstraete 1989). As far as forecasting is concerned, in this paper we focus on examining the possibility of using MMP as a predictor in MMAT forecasts.

The physical rationale behind using precipitation to forecast temperature is that precipitation affects soil moisture which in turn affects current and future surface temperature by controlling the partitioning between the sensible and latent heat fluxes. Further feedback may occur through changed cloudiness, heat capacity, relative humidity, surface albedo, and roughness. It is perhaps surprising that the correlation between current precipitation and future temperature has

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until recently not been studied as extensively as, for instance, temperature persistence (Namias 1952; Dickson 1967), which is widely used in empirical forecasting. The reason is, apparently, the almost complete absence of any persistence in precipitation anomalies, which makes it at first sight an unlikely predictor for anything else. However, the soil integrates the incoming precipitation, thus creating a parameter, the soil moisture anomaly, which does have long time scales. A numerical experiment using an idealized geography found that positive soil moisture anomalies persisted for several months owing to significantly enhanced precipitation (Yeh 1989). Just how the soil integrates incoming precipitation we do not know. Ideally we would like to have the most recent (not time-averaged) measured soil moisture data averaged over a suitable spatial domain. Since such measurements are rare we will use in this article the MMP anomaly as a first-order proxy for the soil moisture anomaly. This will be the benchmark for later studies in which we either calculate soil moisture using a physical model, or use streamflow data in which nature has preformed a space–time integration.

The *simultaneous* correlations between MMAT and MMP over the United States in the 12 calendar months, which have been documented in an atlas in Van den Dool (1988, hereafter referred to as D88), will now be briefly summarized. There is generally a negative correlation between MMAT and MMP in all seasons and areas. The only clear exception is the area of Tennessee, Kentucky, and Ohio where advection of warm and moist air in winter leads to a positive correlation. Positive correlations have also been reported for western Europe in winter (Madden and Williams 1978). Clouds explain most of the negative correlation. When it is cloudy it is cooler than normal and also rainier than normal. Soil moisture would also explain some of the negative correlation. There seem to be at least three "regimes" in the 12 monthly mean maps in D88: 1) a negative correlation (down to −0.8) in the northern central states in winter months; 2) a positive correlation (up to +0.5) in the eastern third of the nation in winter; and 3) negative correlations (down to −0.8) in a broad band covering the area over and just east of the Rocky Mountains in summer. In our opinion, only the third regime is of a somewhat local nature and in part related to the role of soil moisture. Numerical experiments [see Mintz (1984) and Yeh (1989) for a review] show that surface air temperature and precipitation are sensitive to prescribed soil moisture. The negative simultaneous correlation between MMP and MMAT in summer is probably further enhanced by a feedback between hydrology and atmospheric circulation. Reduced evaporation from dry soil (in itself a local effect) increases the surface temperatures, which leads to strengthened upper-level anticyclonic flow that will further decrease precipitation and soil moisture. The relation between drought/heat-wave pattern and anticyclonic circulation anomalies aloft has been the subject of many observational studies (e.g., Reed 1933a, 1937; Klein 1952a,b; Namias 1955, 1960, 1982; Chang and Wallace 1987).

Sketchy studies on the *lagged* correlation between MMP and MMAT can be traced back to some old references (e.g., Reed 1933b; Namias 1960) and a set of maps for the United States prepared by Crutcher (1978). The temporal lagged correlation between MMP and MMAT with MMP leading by one month (hereafter referred to as P–T relation) has been calculated and displayed for the United States in D88, which is an update of the work by Crutcher. A strong negative correlation (down to −0.6) is found in the interior continent in the Texas/Oklahoma/Kansas region in summer, which indicates that a dry/wet July in the interior continent tends to be followed by a warm/cold August. This relationship can be identified as the prognostic version of the third regime for simultaneous correlation. The influence of current precipitation on future temperature has also been found in other studies. Walsh et al. (1985) made a series of objective specification experiments (Klein 1983; 1985) with monthly 700-mb height and surface temperature. They found that the errors in the specified temperature have a significant relation to soil moisture. During summer, the errors that can be attributed to soil moisture are 0.3°–0.7°C, that is, the surface air temperature is warmer than that anticipated from the large-scale flow if the soil is dry. Karl (1986) calculated the relationship between temperature and soil moisture indices. His results indicate that the soil moisture may provide some skill in predicting monthly and seasonal temperature during the spring and summer in the interior of the United States continent. Van den Dool et al. (1987) used an intuitive physical model to illustrate how MMAT persistence may be enhanced by random precipitation through accumulated soil moisture anomalies. Chang and Wallace (1987) found that droughts are usually followed by heat waves in summer in the United States Great Plains. Similar effects of soil moisture were also found in a study of the effects of irrigation in the southern Great Plains (Barnston and Schickedanz 1984). The irrigation appears to lower the daily surface maximum temperature by ~1–2°C. The negative P–T correlations (down to −0.4 in summer) are also obtained by Lyons (1990) who studied monthly station data in Texas.

The P–T relationships found in the above studies suggest that precipitation is important for temperature on a local scale and in summer, not only in a diagnostic mode, but also in a prognostic sense. However, the existence of a lagged P–T correlation does not necessarily mean that precipitation can profitably be used as an additional predictor for future temperature. Monthly mean precipitation's predictive variance may already have been accounted for by using temperature persistence, because the simultaneous MMAT–MMP correlation is highly negative (down to −0.8; see maps in D88).

Data analyses suggest that the influence of precipitation on future temperature may be different in dry months than in wet months (i.e., asymmetric relative to the climate mean). For example, Van den Dool (1989) found that the spatial scale of temperature anomalies over the United States following dry months in Oklahoma is much larger than that following wet months. It is interesting to further examine here this asymmetry in terms of the strength of the *P–T* relation. Such asymmetry should be exploited when using precipitation to predict future temperature.

The purpose of this paper is:

1) To describe the seasonality, geographical distribution, and strength of the relations between MMP and MMAT with different leads and lags over the United States. Those relations are shown by calculating the lagged temporal and pattern correlation.

2) To examine whether use of MMP (MMAT) as another predictor increases the forecast skill in MMAT forecasts when previous MMAT (MMP) is used as the initial sole predictor. This examination will be made by comparing the results of a two-predictor (MMAT and MMP) regression model with a one-predictor (either MMAT or MMP) model.

3) To investigate the possible asymmetry of the lagged *P–T* and *T–T* relations with respect to dry versus wet antecedent months.

4) To confirm/reject some of our speculation about soil moisture, we also study the *P–T* relation with data generated by multiyear runs of the National Meteorological Center's (NMC) Medium-Range Forecast (MRF) Model with and without interactive soil moisture feedback.

This study is primarily based on observed monthly temperature and precipitation data for the 1931–87 period at both climate divisions and stations. The reason we use both station and climate division data is that, certainly with a lead time, the *P–T* correlations are weak (0.5–0.6 at best). Hence, the results are sensitive to sampling as well as to data problems. The latter tends to be quite different for division than for station data. The month-to-month temperature correlation described in Van den Dool et al. (1986) is quite different in many areas from that in Dickson (1967). The reason is the spatial averaging used in the temperature data employed by Dickson. Use of both datasets serves as a mutual check on the credibility of the results.

In this paper, we use monthly mean data. It is likely that even if we fix the predictand to be the monthly mean temperature, the optimal averaging (or backward-looking weighted averaging) on precipitation would be quite different from the traditional monthly mean. This depends also on whether the precipitation data are station or division data.

2. Data and methods

a. Data

Three sets of surface air temperature and precipitation data are used. The first two are observed monthly mean data at climate divisions and stations, respectively. Two auxiliary global gridpoint datasets are derived from two multiyear runs with the NMC MRF model, one with and the other without soil moisture feedback.

1) CLIMATE DIVISION MONTHLY MEAN DATA

The monthly mean data for the period 1931–1987 at 344 United States climate divisions were obtained from the National Climatic Data Center (NCDC) of the National Oceanic and Atmospheric Administration. Excluding 17 climate divisions with erroneous or missing data, we actually analyzed the data over 327 climate divisions. The areal distributions of the climate divisions are shown in a location map (Cayan et al. 1986). The number of stations within a division, as well as their spatial distribution, has varied over the 1931–87 period. Such station changes may introduce artificial variability into the data.

2) STATION MONTHLY MEAN DATA

Monthly mean temperature and precipitation at stations are calculated from daily data at 138 cooperative stations that are a subset of the Historical Climatology Network (HCN) stations (Quinlan et al. 1987). The data were obtained from NCDC/National Oceanic and Atmospheric Administration (NOAA) and contain daily maximum and minimum temperature and precipitation total at stations. The beginning time of the data varies from station to station but most starts before 1900. To compare with monthly climate division data, we use the station data for the period of 1931–87.

The daily station data have various problems related to missing data. The criterion for calculating monthly mean data is the following. If the number of missing days is less than 1/3 (of 28, 29, 30, or 31), the monthly mean is calculated from days with data. If more than 1/3 of the days in a month is missing, the monthly mean is "flagged" and is skipped in the analysis for this station and this month. Therefore, the sample size of the time series varies slightly from station to station and from month to month.

3) OUTPUT FROM MULTIYEAR RUNS WITH MRF MODEL

This model is a T40 version of the global spectral MRF model at NMC in Washington D.C. The model has 18 vertical levels. The model was integrated from the initial conditions on 31 July 1990. The solar radiation was updated every day according to the astronomical calendar. All boundary conditions (sea ice, sea surface temperature, snow depth, and cover) were updated every day according to their climatology, except soil moisture. There are two runs of the MRF model. The first is a ten-year integration with no interactive changes in the boundary conditions. Therefore, soil moisture anomalies did not exist and could not be the cause of any P–T relations. The second is a five-year integration with interactive soil moisture feedback in the model. The output used for this study is surface temperature and total rainfall, which are on a regular 2.5° latitude × 2.5° longitude grid (Van den Dool et al. 1991).

b. *Analysis*

1) Mean, standard deviation, and standardization

In this paper, $T(s, m, j)$ stands for monthly mean temperature at station or climate division s, month m, and year j; $P(s, m, j)$ stands for monthly total precipitation, where the station s ranges from 1 to 327 for climate division data and 1 to 138 for station data, the year j ranges from 1 to 57, and the month m from 1 to 12. The mean temperature over 57 years is

$$\bar{T}(s, m) = \frac{1}{57} \sum_{j=1}^{57} T(s, m, j). \tag{2.1}$$

The standard deviation of the temperature at station s and month m is

$$\mathrm{SDT}(s, m) = \left[\frac{1}{57} \sum_{j=1}^{57} T^2(s, m, j) - \bar{T}^2(s, m)\right]^{1/2}. \tag{2.2}$$

Then the standardized temperature anomaly is

$$\hat{T}(s, m, j) = \frac{T(s, m, j) - \bar{T}(s, m)}{\mathrm{SDT}(s, m)}. \tag{2.3}$$

Similar notations are used for precipitation, that is, $\bar{P}(s, m)$, $\mathrm{SDP}(s, m)$, and $\hat{P}(s, m, j)$.

2) Temporal correlation

The temporal correlation (TC) between the two standardized variables $\hat{T}$ and $\hat{P}$ can be defined as

$$\mathrm{TC}(s, m, \tau) = \frac{1}{57} \sum_{j=1}^{57} \hat{P}(s, m, j)\hat{T}(s, m + \tau, j), \tag{2.4}$$

where positive τ means that precipitation leads temperature by τ months and negative τ means temperature leads precipitation by τ months. When $\hat{P}$ is replacing $\hat{T}$, (2.4) represents the temporal correlation between current temperature and future temperature.

3) Pattern correlation

A pattern correlation (PC) averaged over a range of years between $\hat{P}$ and $\hat{T}$ is defined here as

$$\mathrm{PC}(m, \tau) = \frac{1}{327} \frac{1}{57 - 2} \sum_{s=1}^{357} \sum_{j=1}^{57-2} \hat{P}(s, m, j) \times \hat{T}(s, m + \tau, j). \tag{2.5}$$

Because τ varies from 0 to 2 years in this analysis, the averaged PC is based on (57 − 2) or 55 years of data. The standardization is also based on 55 years, using terms that are slightly different from (2.1) and (2.2).

c. *Multiple linear regression*

The linear regression used is an ordinary regression which can be found in any standard statistics book. Only a short description is given here. Because we are interested in predicting the temperature of the next month based on temperature and/or precipitation of the current month, a two-predictor regression is described here. Regressions with more predictors are similar. In this study, the two predictors are the current temperature T_0 and precipitation P_0, and the predictand is next month's temperature T. All the quantities are standardized and the symbol '^' is omitted below for simplicity. The multiple linear regression relation is the following:

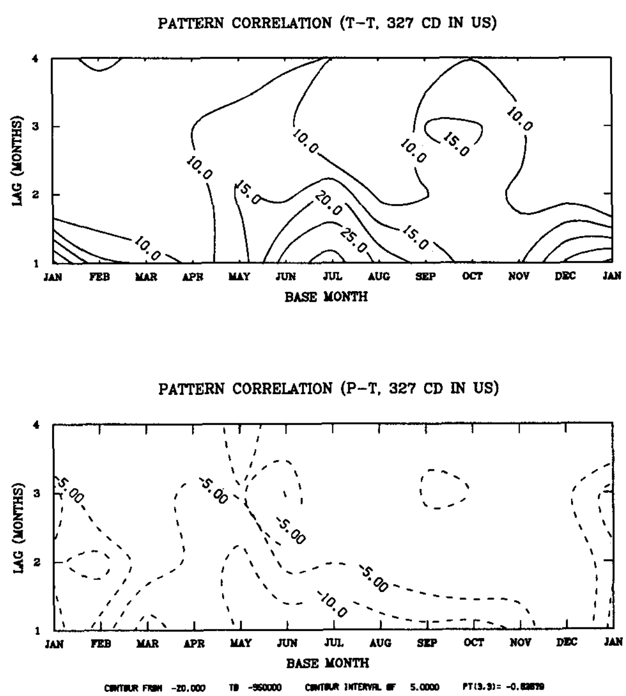

FIG. 1. Pattern correlation (%) over the United States at lags from one to four months as a function of season. The data are for 1931–87 at 327 climate divisions. The upper panel: MMAT autocorrelation, that is, T–T correlation. Values less than 10% are not analyzed; the interval is 5%; Lower panel: MMP–MMAT cross correlation, that is, P–T correlation. Values greater than −5% are not analyzed. The interval is 5%.

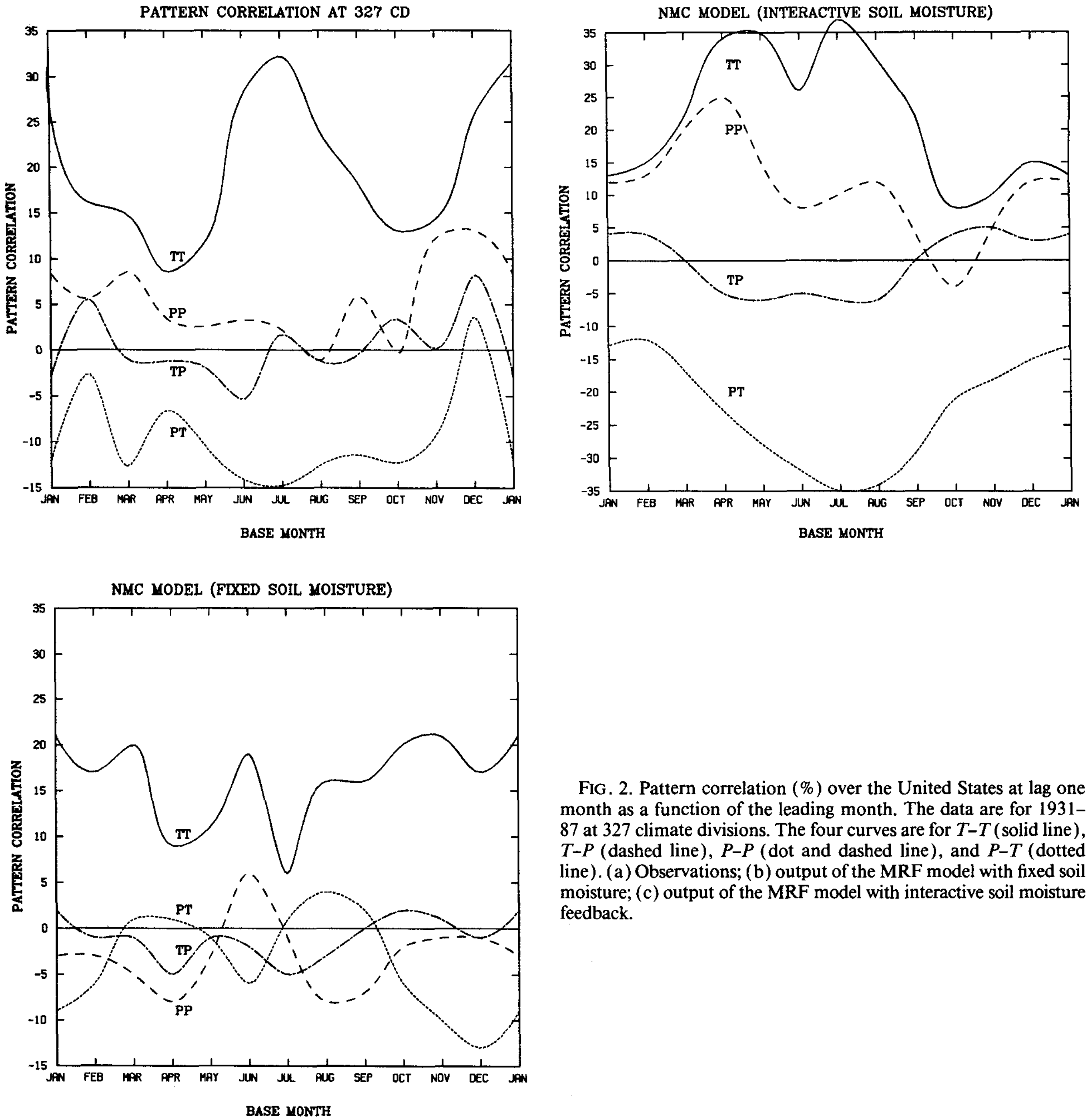

FIG. 2. Pattern correlation (%) over the United States at lag one month as a function of the leading month. The data are for 1931–87 at 327 climate divisions. The four curves are for *T–T* (solid line), *T–P* (dashed line), *P–P* (dot and dashed line), and *P–T* (dotted line). (a) Observations; (b) output of the MRF model with fixed soil moisture; (c) output of the MRF model with interactive soil moisture feedback.

$$T^f(s, m+1) = a(s, m)T_0(s, m) + b(s, m)P_0(s, m), \quad (2.6)$$

where $T^f(s, m+1)$ is the forecast temperature in month $(m+1)$ by linear regression at station s and month m, while $a(s, m)$ and $b(s, m)$, determined from least-squared methods, are regression coefficients, which are functions of location s and month m. Note that the predictors describe conditions only at the station (or division) being forecast. Since the quantities are anomalies, there is no constant term in (2.6).

d. Verification of regression forecasts

We use a so-called independent verification method. In this method, we divide the time series of the data into two parts. The first part is used to calculate the regression coefficients and develop the prediction model. The second part is used to verify the results of the prediction. The data in the second part are standardized based on the mean and standard deviation of the first part, just as would be possible in verifying a real forecast in an operational setting. The verification skill measure is either the temporal or the regional pat-

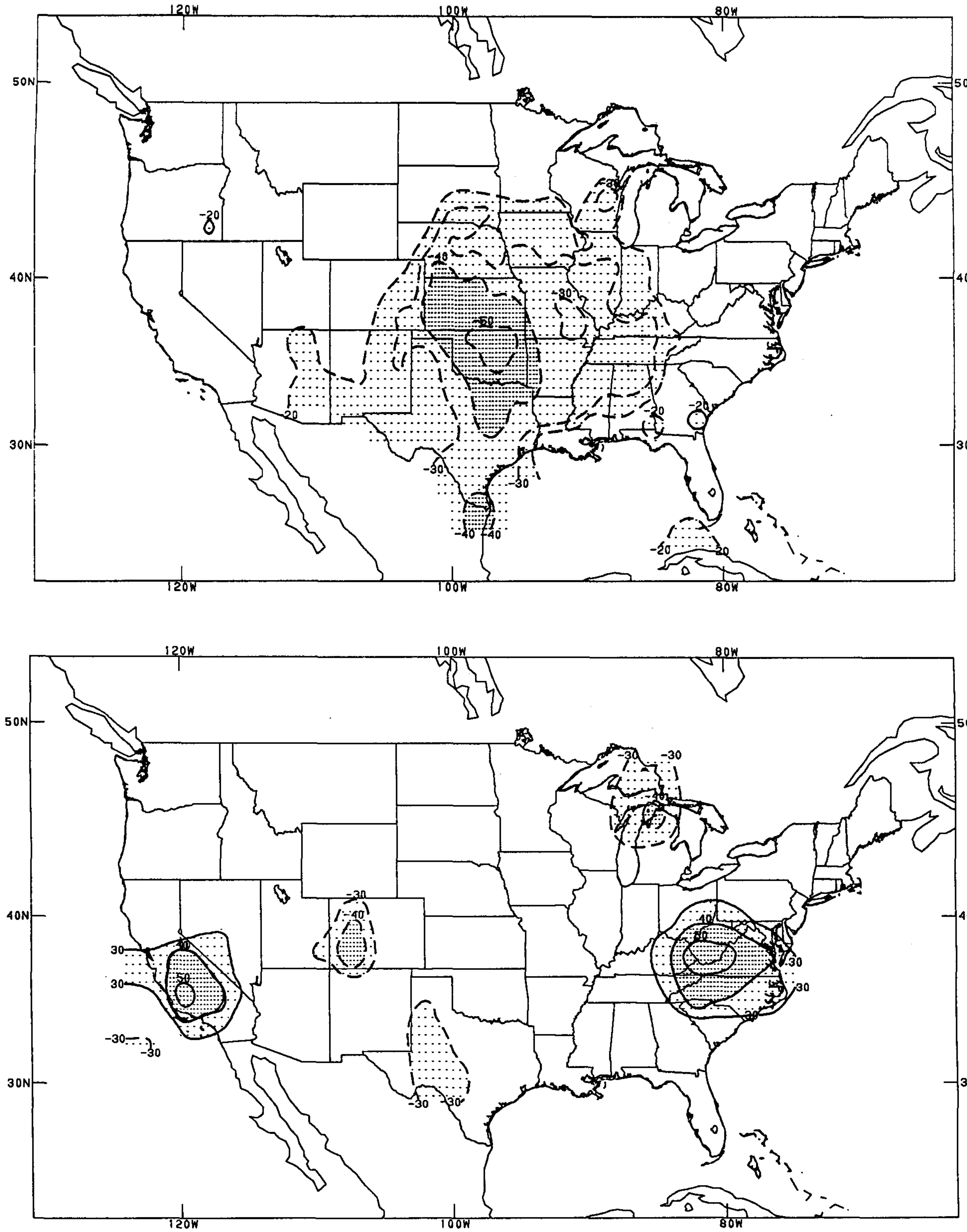

FIG. 3. (a) Temporal correlation between July MMP with August MMAT over the United States at 327 climate divisions; the data are for 1931–87. Correlations of 20% to 40% or −20% to −40% are lightly stippled and correlations larger than 40% or smaller than −40% are heavily stippled. Solid lines are for positive correlation and dashed lines for negative correlation. (b) The data is the output of a ten-year run of MRF model without soil moisture feedback. (c) The data is the output of a five-year run of MRF model with soil moisture feedback.

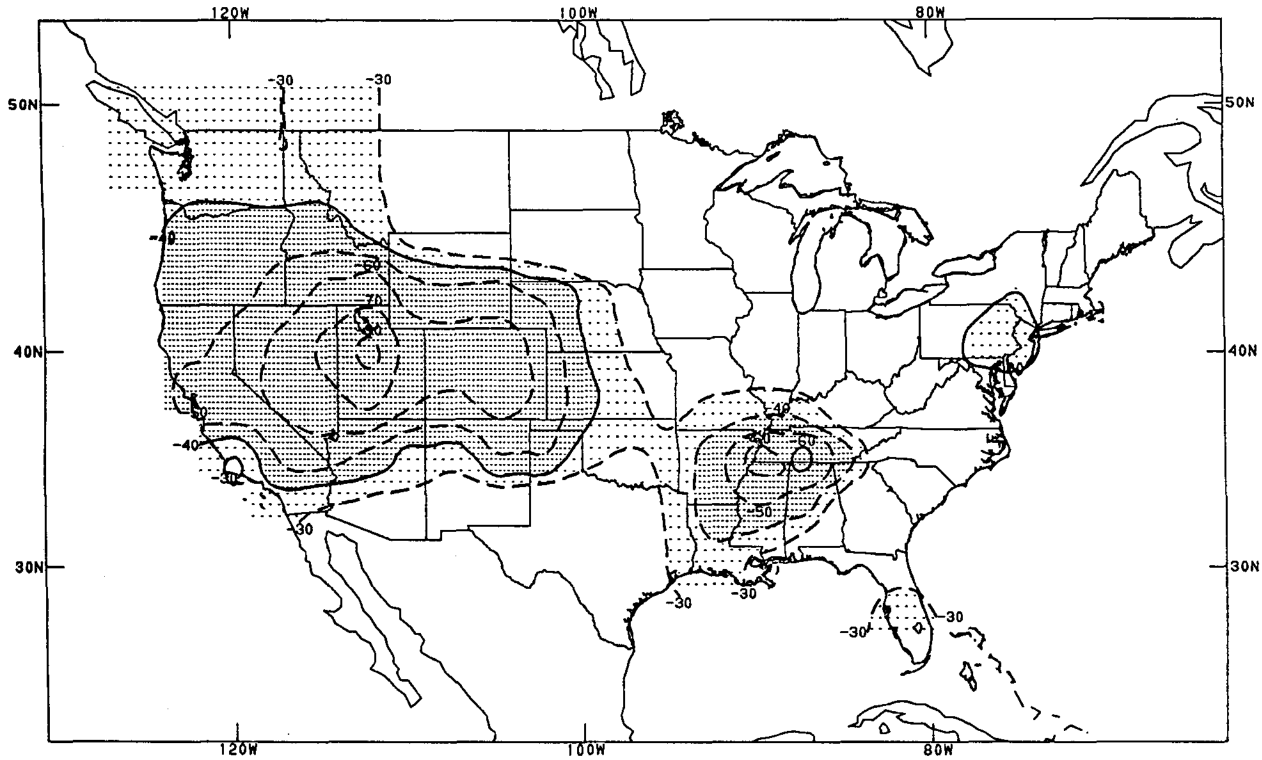

FIG. 3. (*Continued*)

tern correlation between the predicted value and the observed value. The temporal correlation is defined as

$$\mathrm{TC}(s, m) = \frac{\sum_{j=j_1}^{j_2} \hat{T}^f(s, m, j)\hat{T}(s, m, j)}{[\sum_{j=j_1}^{j_2} (\hat{T}^f(s, m, j))^2]^{1/2}[\sum_{j=j_1}^{j_2} (\hat{T}(s, m, j))^2]^{1/2}}, \tag{2.7}$$

and the regional pattern correlation averaged over a range of years is defined as

$$\mathrm{PC}(m) = \frac{\sum_{s=s_1}^{s_2} \sum_{j=j_1}^{j_2} \hat{T}^f(s, m, j)\hat{T}(s, m, j)}{[\sum_{s=s_1}^{s_2} \sum_{j=j_1}^{j_2} (\hat{T}^f(s, m, j))^2]^{1/2} \times [\sum_{s=s_1}^{s_2} \sum_{j=j_1}^{j_2} (\hat{T}(s, m, j))^2]^{1/2}}. \tag{2.7a}$$

Summing stations or climate divisions from s_1 to s_2 is done to form regional pattern correlations; $s = 1{,}327$ is the whole country for climate divisions.

The dataset is divided as follows. The sample size of the data for this study is 57 years, from 1931 to 1987. The last 27 years are used for verification, that is, $j_1 = 1961$, $j_2 = 1987$. However, most of the last 27 years may also be used as part of the first (developmental) dataset. The size of the developmental dataset depends on the year being verified, ending one year earlier than the verification year. For example, to verify the results at the 31st year, the first dataset spans from year 1 to year 30. In verifying year 57, the data from year 1 to year 56 are used to develop the regression model. Notice that the observed and forecast anomalies refer to departure from the mean over the developmental dataset, that is, the forecast for 1961 is expressed and verified relative to 1931–60, 1962 relative to 1931–61, etc. That is the reason we used zero (that is, the mean for the developmental period) as the means of the two variables in Eqs. (2.7) and (2.7a) for the verification. In this way, we faithfully mimic a possible operational setting, thereby neither inflating nor degenerating the estimates of skill (to the best of our knowledge). We have to deal, however, with more sampling fluctuation simply because the regression and the verification are based on smaller samples. Also, the "climate change factor" (1961–87 is different from 1931–60 in many ways) becomes enormously important in understanding the verification results.

The forecasts will also be verified separately for antecedent wet and dry months using (2.7) or (2.7a) except summing over years only with antecedent wet or dry months.

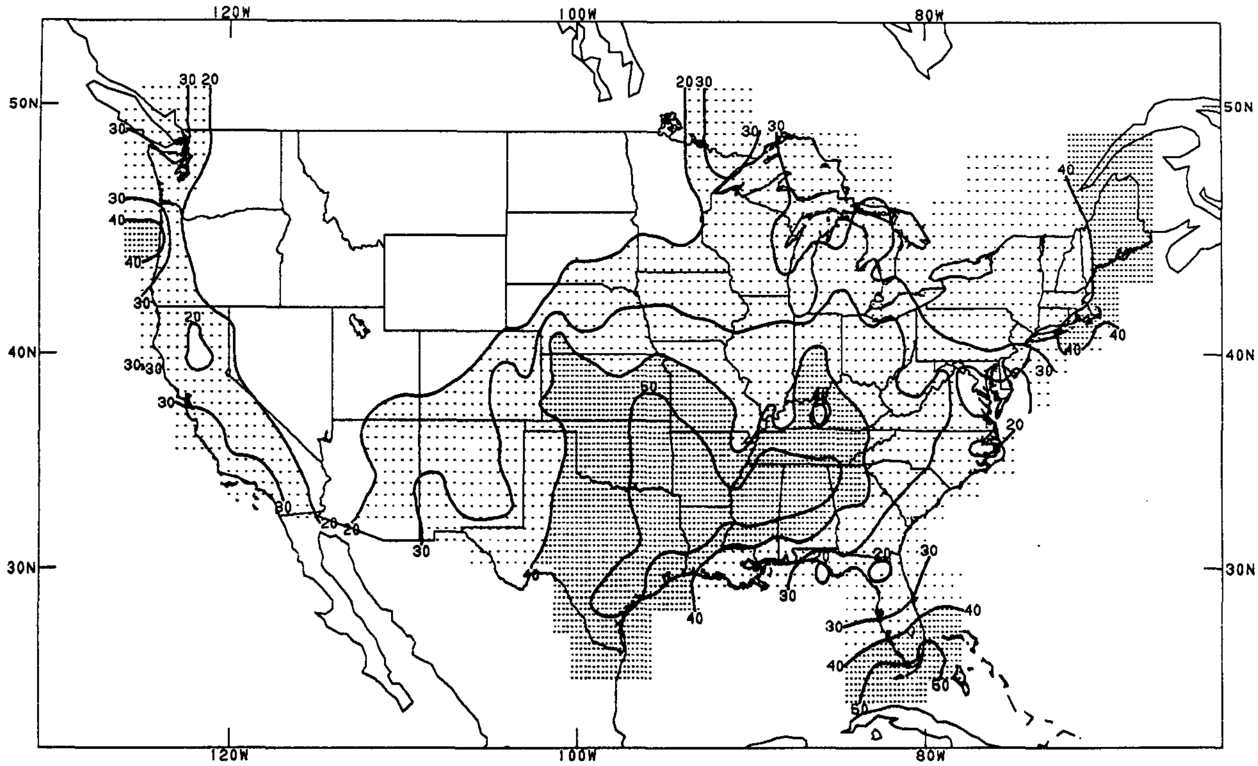

FIG. 4. As in Fig. 3a for July MMAT–August MMAT correlations.

3. Results

We mainly show the results calculated at climate divisions. However, the results at stations are also mentioned for comparison when necessary.

a. Pattern and temporal correlations

Figure 1 shows the United States pattern correlation as functions of lag (in months) and base month (defined as the predictor's month). The lag τ between the two variables ranges from one to four months. The upper panel of Fig. 1 illustrates the *T–T* pattern correlation at climate divisions. Contour lines for correlations less than 0.1 are not plotted, because they are not statistically significant at the 95% confidence level (see Appendix). Results shown in Fig. 1 indicate that temperature persistence is largest in summer and winter, and smaller in spring and fall. The 0.15 or greater levels of temperature persistence extend to at least two months only in summer. We calculated the pattern correlations with lags up to 24 months (not shown). At longer lags ($\tau \geqslant 3$ months), we see an occasional 0.15 appear but without clear structure. Those results are broadly similar to those obtained by Van den Dool et al. (1986) (using station data) and our updated analysis for station data (not shown). The only difference between station data and climate division data is that there is a clearer summer-to-summer persistence based on station data (also see Madden and Shea 1978), while this interannual temperature persistence is smaller in the analysis based on climate division data.

The lower panel of Fig. 1 shows the *P–T* relation. Absolute values of less than 0.05 are not analyzed (see Appendix). It is found that the *P–T* correlation is generally negative and highest in summer (May–Oct.), but the effects of MMP on MMAT exist for a shorter time than temperature persistence on an all United States basis. The *P–T* correlations with lags of more than one month are very small.

Figure 2a shows the annual variation of one-month lag pattern correlation based on climate division data. The four curves are for *T–T*, *P–P*, *P–T*, and *T–P*, respectively. The results of the analyses based on station data (not shown) are similar. The most significant feature is that a negative *P–T* correlation exists in each month of the year except December, with the maximum in summer. Both one-month lagged *T–P* and *P–P* correlations are generally very small, staying within the limits (± 0.04) set for statistical significance in most months (see Appendix). This suggests that, in line with experience, the MMP prediction for next month cannot be helped very much by either the MMAT or the MMP of the current month. The one exception is the November–December period when MMP anomalies have a slight tendency to persist. It is important to note that the *P–T* correlation is so much

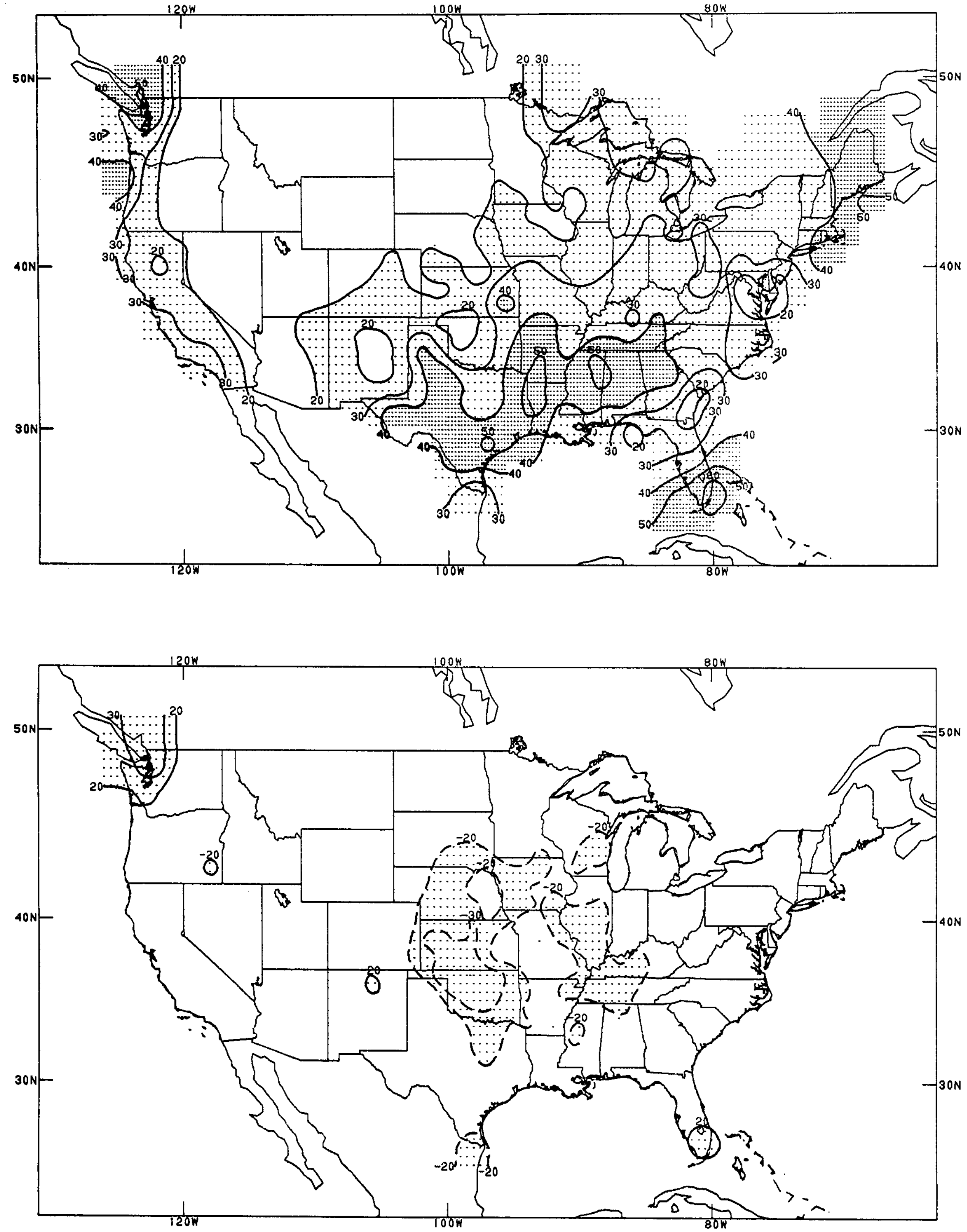

FIG. 5. Regression coefficients (a) a_0 and (b) b_0 in regression model $T_{Aug} = a_0 T_{Jul} + b_0 P_{Jul}$. The data are MMP and MMAT at 327 climate divisions during the period 1931–87. The regression coefficients have been multiplied by a factor of 100.

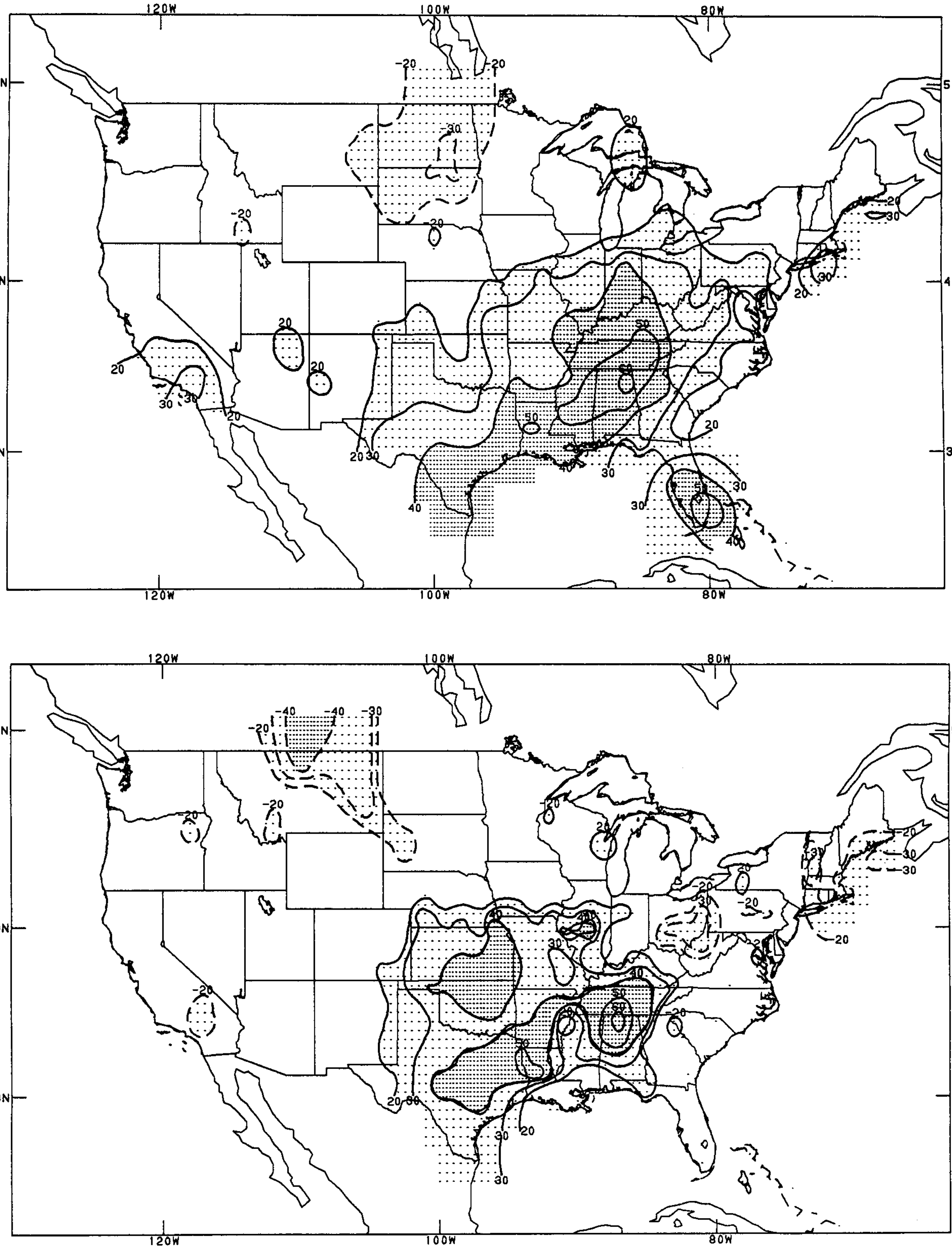

FIG. 6. Temporal correlation between actual August MMAT and the MMAT predicted by regular regression models with (a) July MMAT as the predictor; (b) July MMP as the predictor; (c) both July MMAT and MMP as the predictors. Correlations of 20% to 40% or −20% to −40% are lightly stippled and correlations larger than 40% or smaller than −40% are heavily stippled. Solid lines are for positive correlation and dashed lines for negative correlation.

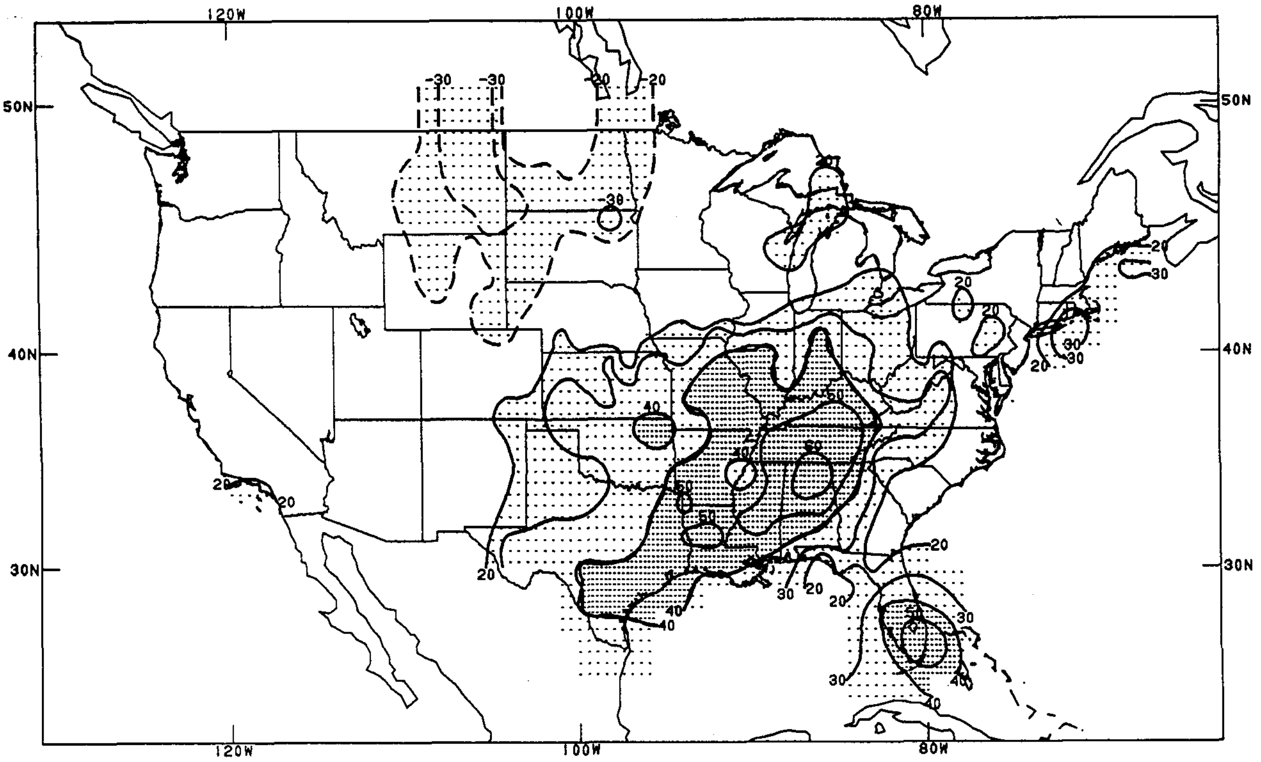

FIG. 6. (*Continued*)

higher than the T–P correlation, which is an important feature of the physics explaining the P–T relationship through soil moisture anomalies.

Recently, multiyear integrations of the NMC's MRF model with and without soil moisture feedback made by Van den Dool et al. (1991) lend further support for this argument. In the model with fixed soil moisture (later on referred to as model 1), there is no effect of soil moisture anomalies on temperature. Nor can antecedent precipitation have an impact on future temperature through soil moisture anomalies. Figure 2b is the same as Fig. 2a except for using the output of model 1. We use all summer months to increase the sample size to 30. For example, the P–T correlation in July here is calculated using June–July–August MMP and July–August–September MMAT data. Here, T–T correlation less than 0.1 and P–T correlation less than 0.06 are not statistically significant (see Appendix). It is found that the negative P–T correlation present in the observation (Fig. 2a) does not exist in the output of model 1. Moreover, the T–T correlation in summer is smaller than in the observation.

In contrast, the model with interactive soil moisture feedback (model 2) shows much more similarity to observation than to model 1. Figure 2c is the same as Figs. 2a and 2b, except for the output of model 2. As it is a five-year integration, we use six months to keep the same sample size as for model 1. It is found that P–T correlation is negative everywhere and T–T correlation is highly positive in summer. The T–P correlation is negligible. The contrast between model 1 and model 2 and the qualitative similarity between model 2 and the observations support the presumed role of the soil moisture in the observed P–T correlation and the role of the soil moisture in enhancing the temperature persistence in summer.

We now examine the geographical distribution of the P–T temporal correlation. The P–T temporal correlation for July/August at climate divisions is shown in Fig. 3. Heavier stippling is used for correlations less than −0.4 or greater than 0.4; lighter stippling is for correlation of absolute value of 0.2 to 0.4. Lines for correlations between 0.2 and −0.2 are not analyzed, because with the $sd = 1/\sqrt{55}$, the correlations less than 0.22 are not statistically significant. Figure 3 is similar to maps shown by D88, except no temporal smoothing with nearby months is made for the maps shown here. It is found that any positive correlation is absent in the map; thus in general, a wet (dry) July is followed by a cool (warm) August. The maximum center is in the eastern portions of Oklahoma, Texas, and Kansas. The geographical patterns of P–T correlation at stations (not shown) are similar to those at climate divisions. However, the magnitudes of the P–T correlation at stations

TABLE 1. Averaged regional pattern correlation (×100) for the independent verification period of 1961–87 over the United States interior continent (latitude ≤ 45°, 85° ≤ longitude ≤ 104°) between the predictions and observations for *July/August* [see Eq. (2.7a) for definition]. Each column is for different predictor(s). Each row is for a different type of regression model or verification method.

	MMP	MMAT	MMP and MMAT
Regular	24.9	37.2	38.2
Dry	−5.9	23.0	17.1
Wet	51.1	52.2	58.0

are slightly smaller (by about 0.1) than those at climate divisions. We attribute this to the beneficial impact of spatially averaging the noisy precipitation data.

Local temporally lagged P–T correlations using the output from model 1 and model 2 are shown in Figs. 3b and 3c, respectively. Only lines 0.3 and larger are drawn, because for the sample size $M = 30$, correlations less than 0.3 are not statistically significant. The prominent negative correlation in the interior of the continent present in the observations is missing in model 1 (Fig. 3b). However, a clear bias toward negative P–T correlation can be seen from the output of model 2 (Fig. 3c). The model's largest negative P–T correlation does not collocate with the observation (i.e., centered in Utah vs Oklahoma), also model 2 has stronger correlation. While precision in the simulation is missing, the comparison of model 2 versus model 1 does show strong influence of soil moisture on the P–T correlation.

The T–T correlation at climate divisions is also shown in Fig. 4 for comparison. The general patterns for station data are about the same (not shown), that is, the temperature persistence in summer is large along coastlines and in the interior continent. The analyses with the MRF output (not shown) indicate that the positive T–T correlations are much less widespread and weaker in model 1 than in model 2.

b. *Possible contribution of precipitation to temperature forecasts*

Figure 5 shows the spatial distributions of two-predictor regression coefficients a and b calculated for the period of 1931–87. In most places, the MMAT forecast for August through linear regression is carried by the temperature term. However, in a large inland area of

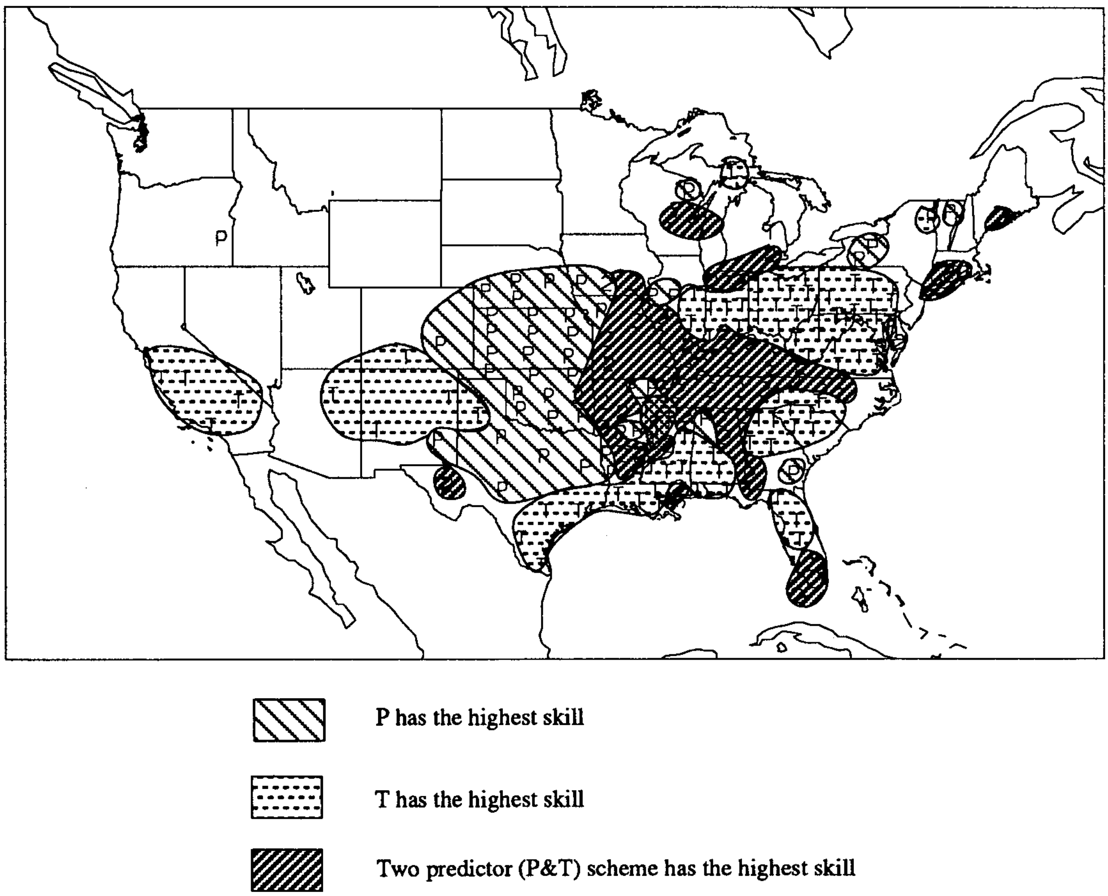

FIG. 7. Geographical map of the winner of the three regression schemes on the 1961–87 independent dataset.

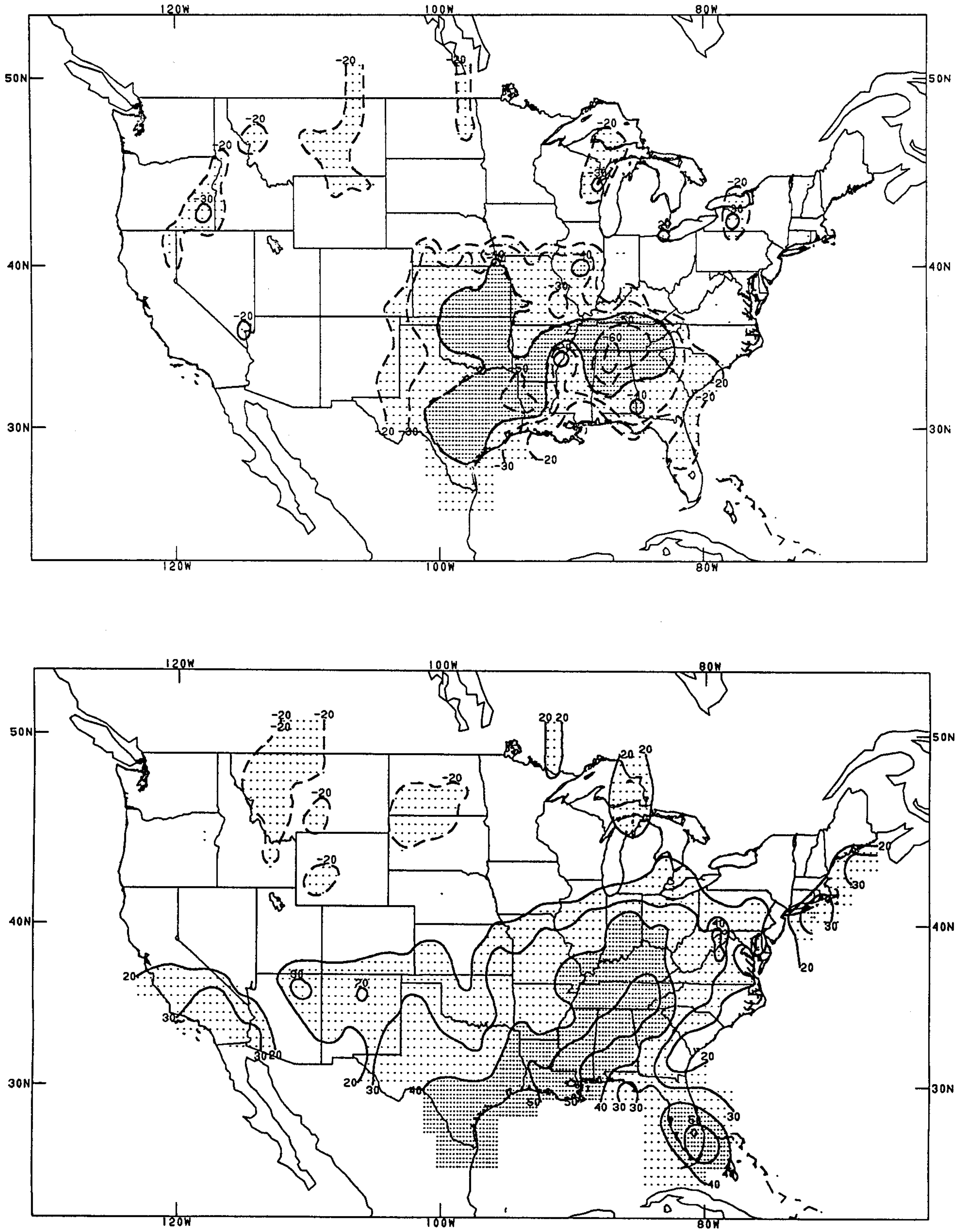

FIG. 8. (a) As in Fig. 4 except for the time period of 1961–87; (b) as in Fig. 3a except for the time period 1961–87. The anomalies are obtained based on the mean over the period of 1961–87.

which the states Oklahoma/Kansas are the clearest examples, the MMP term appears to play some role. Comparing the coefficients in the two-predictor model with those in one-predictor models, that is, Fig. 5b to 3a and Fig. 5a to Fig. 4, one can see that in some areas the two predictors describe the same variance. Figure 5b is similar to Fig. 3a except that the temperature term has already accounted for the variance in Arkansas and Missouri. Figure 5a is similar to Fig. 4 except that low coefficient values appear over Oklahoma where the precipitation also makes contributions. It looks as though in many areas the *P–T* and *T–T* correlations indicate the same underlying physics. We believe that soil moisture is the common element here. Remember that in the observations the *T–P* correlation is negligible (see Fig. 2a), which suggests that the *P–T* correlation is not due to another common slowly varying process.

Figure 6 shows the local temporal correlation (TC) between actual August MMAT and the predicted value over 1961–87, where the predictor is July MMAT in Fig. 6a, July MMP in Fig. 6b, and both July MMAT and MMP in Fig. 6c. The comparison between Fig. 6a and Fig. 6c indicates that including MMP as a second predictor in the regression model increases the skill of MMAT forecasts only a little. The largest independent contribution due to MMP is in the Oklahoma/Kansas/Texas/Louisiana area, which agrees with Fig. 5. The largest temperature persistence contribution not supported by the *P–T* correlation occurs in the northeast region and along some coastlines (see Fig. 6). Table 1 (first row) lists the regionally averaged pattern correlation [see Eq. (2.7a) for the definition] over the verified years (1961–87) between the predictions and the observations. The averaged correlation increases from 0.37 to 0.38 due to inclusion of MMP as the second predictor, and increases from 0.25 to 0.38 due to inclusion of MMAT when using MMP as the first predictor.

The comparison of Fig. 6b to 6a and 6c shows that MMP on its own is quite sufficient for MMAT forecasts in some areas in the interior continent. In Fig. 7 we summarize which of the three schemes (i.e., MMP as the only predictor, MMAT as the only predictor, both MMP and MMAT as the predictors) has the highest skill. In the blank area, none of them has skill (by some standard: TC < 0.2) to forecast August MMAT. In the northern Texas/Oklahoma/Kansas area, the scheme using MMP as the single predictor is the best. In the east central area, Arkansas, Alabama, Tennessee, and Kentucky, the two-predictor scheme is the best.

These results extend Karl's (1986) finding that precipitation is a better predictor than temperature persistence in spring and summer in the interior continent in two aspects. First of all, our results are more location specific. Second, our results are more quantitative. We found that the differences between the above three schemes are small, that is, inclusion of precipitation as a predictor does not improve the MMAT forecasts dramatically.

It is interesting to notice that compared with the temporal correlations (TC) for 1931–87 (Fig. 3a for *P–T* and Fig. 4 for *T–T*), the regions with large TC in verification (see Fig. 6) are not completely congruent. The primary reason is that the *T–T* relation in the most recent 27 years (1961–87) is different from that in the full sample of 57 years. Figure 8a shows the temporal *P–T* correlation for July/August over the most recent 27 years (using 1961–87 means). The TC in Oklahoma and Mississippi decreased from the full sample to just 1961–87, while the TC in Texas, Arkansas, Tennessee, Louisiana, and Alabama increased relative to Fig. 3a. This conclusion is confirmed by the same analysis based on station data. For the *T–T* correlation [see Fig. 8b], the temperature persistence has decreased in the Oklahoma-Texas-Arkansas region during the most recent 27 years. The region with large *T–T* correlation (the heavier shading area) has shifted eastward in the last 27 years. In spite of these shifts the skill on independent data is positive in the areas discussed. This is because the sign of the correlation has not been changed. Over North Dakota, where the *T–T* correlation is low, the sign of the regression based on 1931–60 led to forecasts that have a sign often opposite the verifying anomalies.

We also analyzed the other months in summer season. The skill for June/July and August/September is slightly lower, which is consistent with lower *P–T* and *T–T* correlations shown in Fig. 2a. The skill performances of three schemes for those months (not shown) also indicate the role of precipitation, but the role is weaker and the spatial patterns are less organized, especially for the August/September case. This is probably due to the weaker effects of evaporation and soil moisture on temperature in late summer and fall.

c. *Possible difference between wet and dry months?*

In this section, we will determine the skill for the wet and dry antecedent months separately. The purpose is to anticipate the degree of success of a forecast (so-called forecast of forecast skill). This work is further motivated by the finding by Van den Dool (1989) of the different future temperature anomalies after dry and wet months.

Rows 2 and 3 in Table 1 show the averaged regional pattern correlations between the regression forecast and actual values for dry and wet antecedent months, respectively. It is found that for any predictor(s), the correlations in wet antecedent months are much larger than those in dry months. For example, with July MMP as a predictor, the correlation for the wet cases is 0.51 while the correlation for the dry cases is -0.06. The temporal correlations between forecasts with MMP as the predictor and actual values [see Eq. (2.7) for definition] are shown in Fig. 9a (wet cases) and 9b (dry

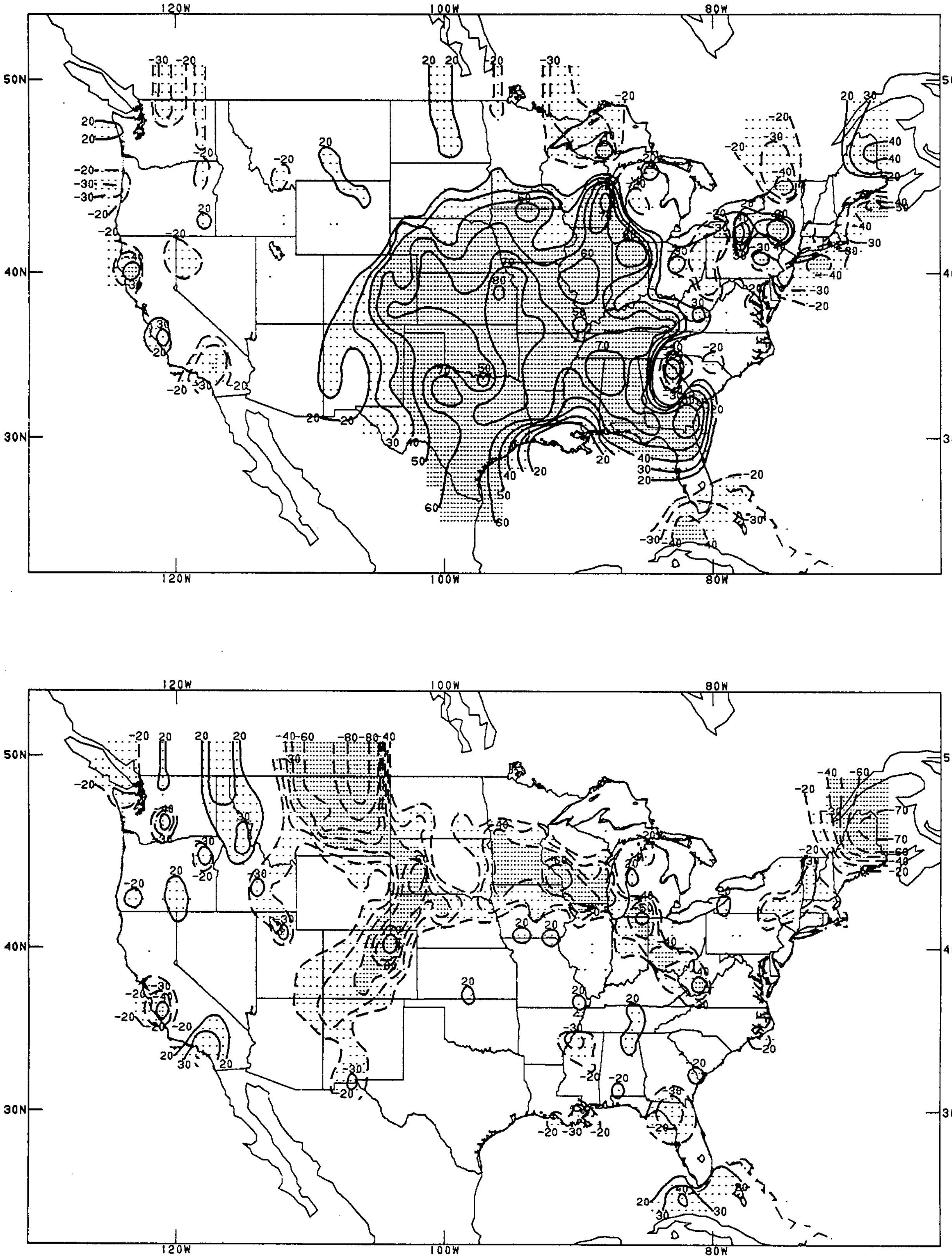

FIG. 9. Temporal correlation between actual August MMAT and predicted values with July MMP as the predictor (a) in wet months, (b) in dry months.

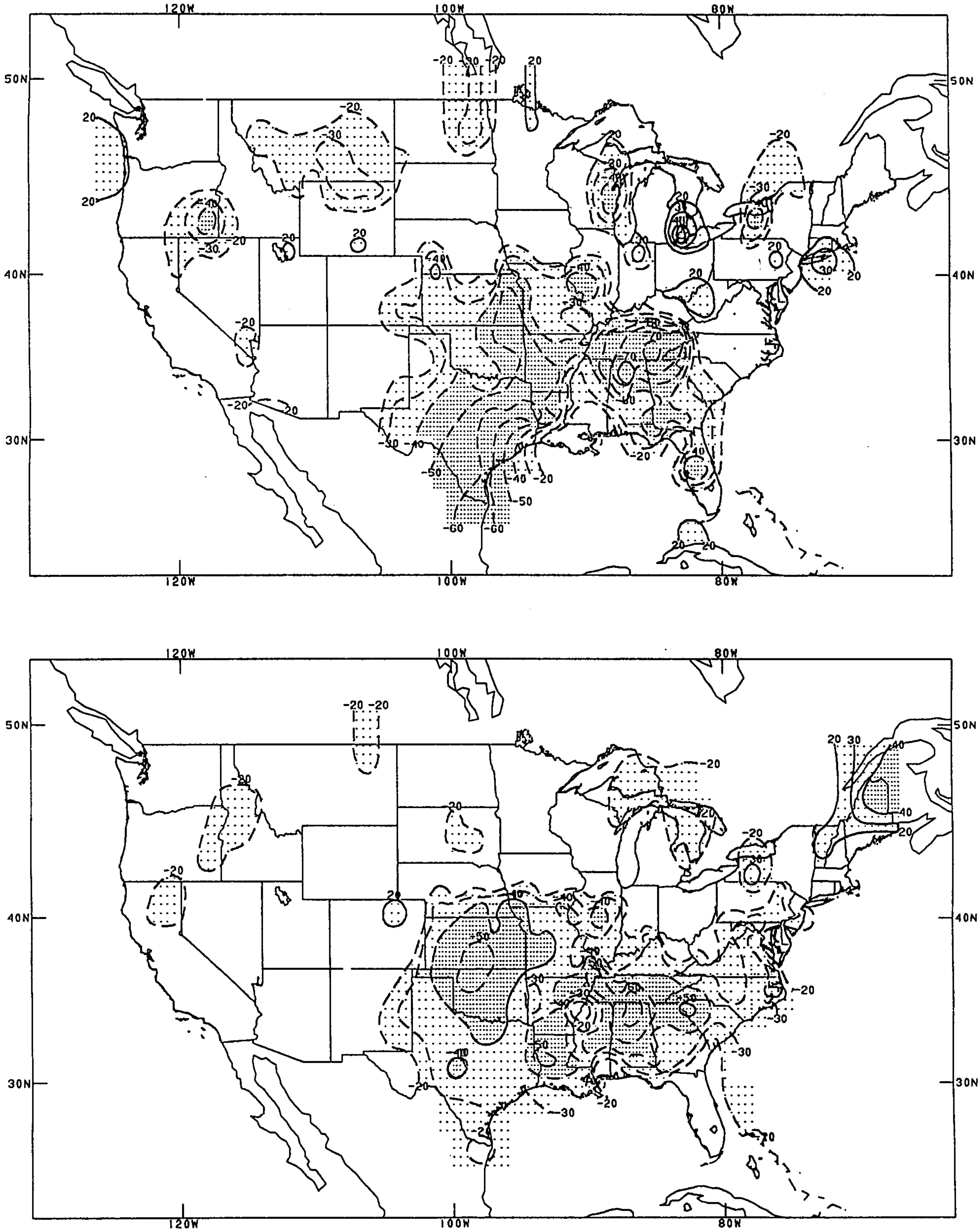

FIG. 10. Temporal correlation between July MMP and August MMAT (a) in wet months; (b) in dry months. The anomalies are obtained based on the mean over the period 1961–87. (c) and (d) the same as (a) and (b) except that the anomalies are obtained based on the mean over the previous period of the verified year.

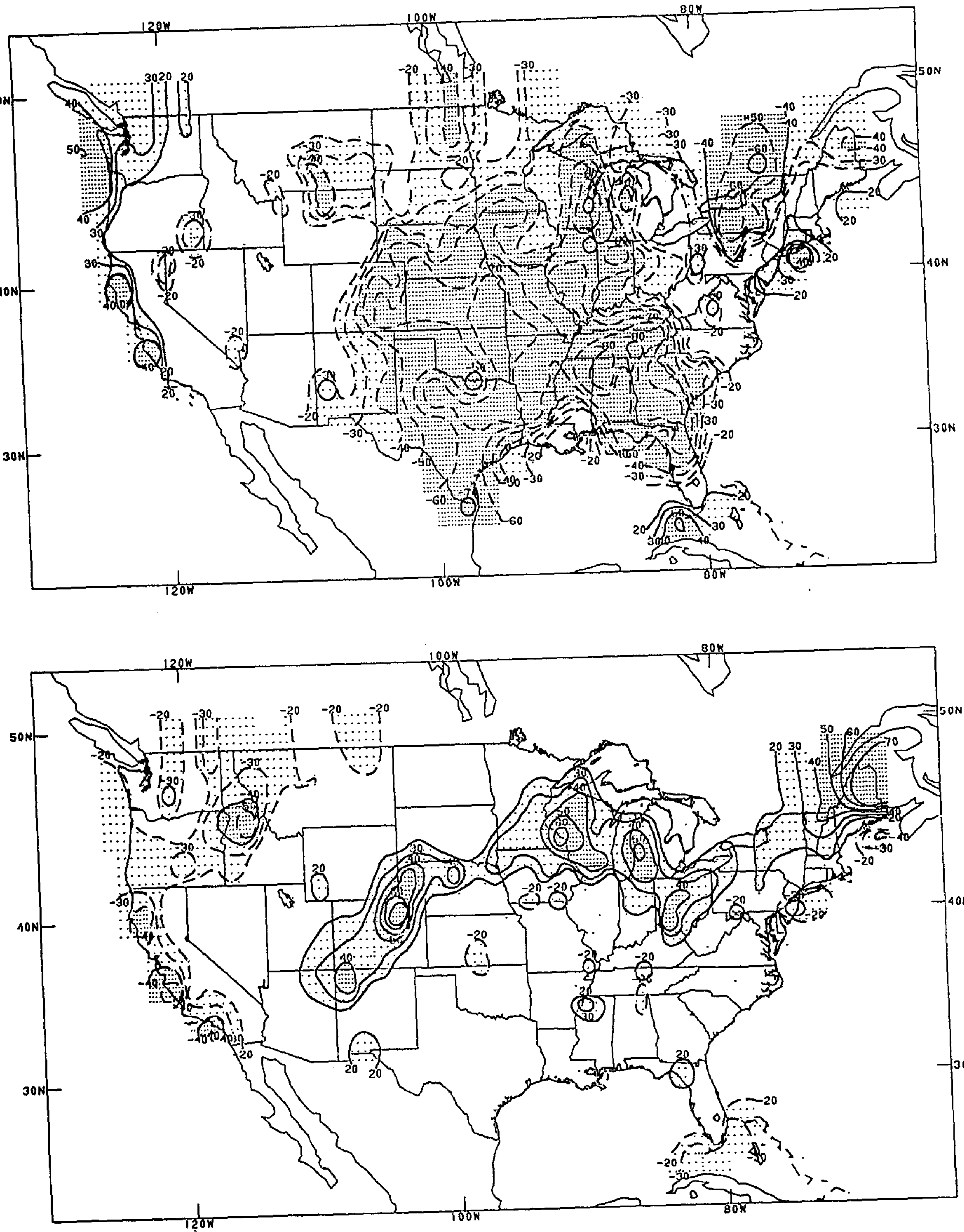

Fig. 10. (*Continued*)

cases). For the wet case, the maximum TC in the central United States reaches 0.8, while TC for the dry case is basically zero or highly negative.

Before jumping to the conclusion that the skill of forecasts based on MMP, MMAT, or both is higher in wet months than that in dry months, we should examine and understand where the enormous discrimination in the skill for wet and dry cases comes from. We only show the results for MMP as the predictor, although the case for MMAT as a single predictor has also been examined with similar outcome. Since the skill is verified using the data during the period of 1961–87, we first determine if the P–T correlation during this period is asymmetric for wet and dry antecedent months. The correlation is calculated using an equation similar to (2.7) except that the two variables (July MMP and August MMAT) are normalized over 1961–87 instead of 1931–87. The P–T correlation for the wet case (Fig. 10a) is slightly larger than that for the dry case (Fig. 10b) in the Alabama, Tennessee, and Texas region and smaller in Oklahoma/Kansas. Overall, however, the difference is too small to explain the large difference in skill observed from Fig. 9. Thus, although the distribution of MMP is nonnormal, this does not cause a big difference in P–T correlation between dry and wet cases.

If the data during the period of 1961–87 are normalized based on the statistics of the previous period, that is, 1931–60 for 1961 and 1931–86 for 1987, as in the independent verification, the difference in the P–T correlation between wet and dry cases becomes much larger (see Figs. 10c and 10d). The P–T correlation in wet antecedent months reaches −0.8, while the P–T correlation for dry cases is close to zero in the interior continent and is positive in the Great Lakes area and Colorado region. Since we use the same regression coefficients in the prediction for wet and dry cases, the asymmetry between wet and dry cases in the P–T correlation during the period of 1961–87 and thus in the verification skill must be caused by the climate difference between 1961–87 and 1931–60.

Figure 11a shows the difference in July MMP between 1961–87 and 1931–60 and Fig. 11b represents the August MMAT. It is found that the climate difference between these two periods in MMP occurred in the east and central areas. The magnitude of the difference is up to 40 mm. The southern and eastern areas such as Texas/Oklahoma/Louisiana/Arkansas/Mississippi and East Coast were drier during 1961–87, while the northern region was wetter. Tennessee and northern Alabama were also wetter during 1961–87. For the MMAT, the period of 1961–87 was colder than the period of 1931–87 over almost the entire United States continent except in the west. The maximum difference was about 1°C.

In Fig. 12, we use schematic diagrams to show how the cooling from 1931–60 to 1961–87 in August causes the more negative P–T correlation in wet months and thus higher skill in forecasts in wet months. The x axis is the July MMP anomaly and the y axis is the August MMAT anomaly. The dots represent the data in different years. The solid dots in dry/warm and cold/wet quadrants indicate hits in the sense that the regression will always forecast in the dry/warm and wet/cold quadrants. The open circles in the wet/cold and dry/warm quadrants indicate misses. We have one fewer dot in the wet/warm and dry/cold quadrants to keep the total P–T correlation mildly negative. Figure 12a shows the control case and Fig. 12b is the case with temperature change only. If MMP and MMAT are normalized based on the data in 1961–87 as in Fig. 12a, P–T correlations are the same for wet and dry cases and the hit–miss ratio is 4:3, while the overall hit–miss ratio is 8:6. When using the previous years' temperatures to standardize, however, more cold years appear because the previous period is warmer, which is equivalent to moving the origin of T_{August} up toward the warm direction (see Fig. 12b). It is found that the hit–miss ratio is 6:1 for the wet cases and 2:5 for the dry cases. Thus the P–T correlation is highly negative in wet cases and positive in dry cases. When using a negative regression coefficient that is obtained from the data in the previous period to make the forecasts, it is expected that higher skill will be obtained in wet cases and low or negative skill for the dry cases.

Figure 12c shows the case in which 1961–87 is colder and drier than before and Fig. 12d is for the colder and wetter case. These figures correspond to the situations in the southern and northern United States, respectively. In both cases we find that the wet cases benefit more than the dry cases, in terms of proportions of hits, from the climate change. Therefore, it is primarily the cooling from 1931–60 to 1961–87 that causes the more negative P–T correlation in wet antecedent months and thus higher skill in verification.

4. Summary and discussions

The lagged monthly precipitation–temperature relation (P–T relation) has been examined by analyzing the observed MMP and MMAT during the period of 1931–87 at 327 climate divisions and 130 stations, as well as the gridded output of multiyear model runs with and without interactive soil moisture. The main purpose of this study is to examine the possibility of using MMP as another predictor in addition to MMAT in MMAT forecasts for the following month and to better understand the physics of the relation between soil hydrology and surface temperature.

Correlation and regression are used in the analysis. The predictions of the regression model are verified by a so-called independent verification in which we use the dataset of the first period to make the prediction and use the independent dataset in the second period (1961–87) to verify the results.

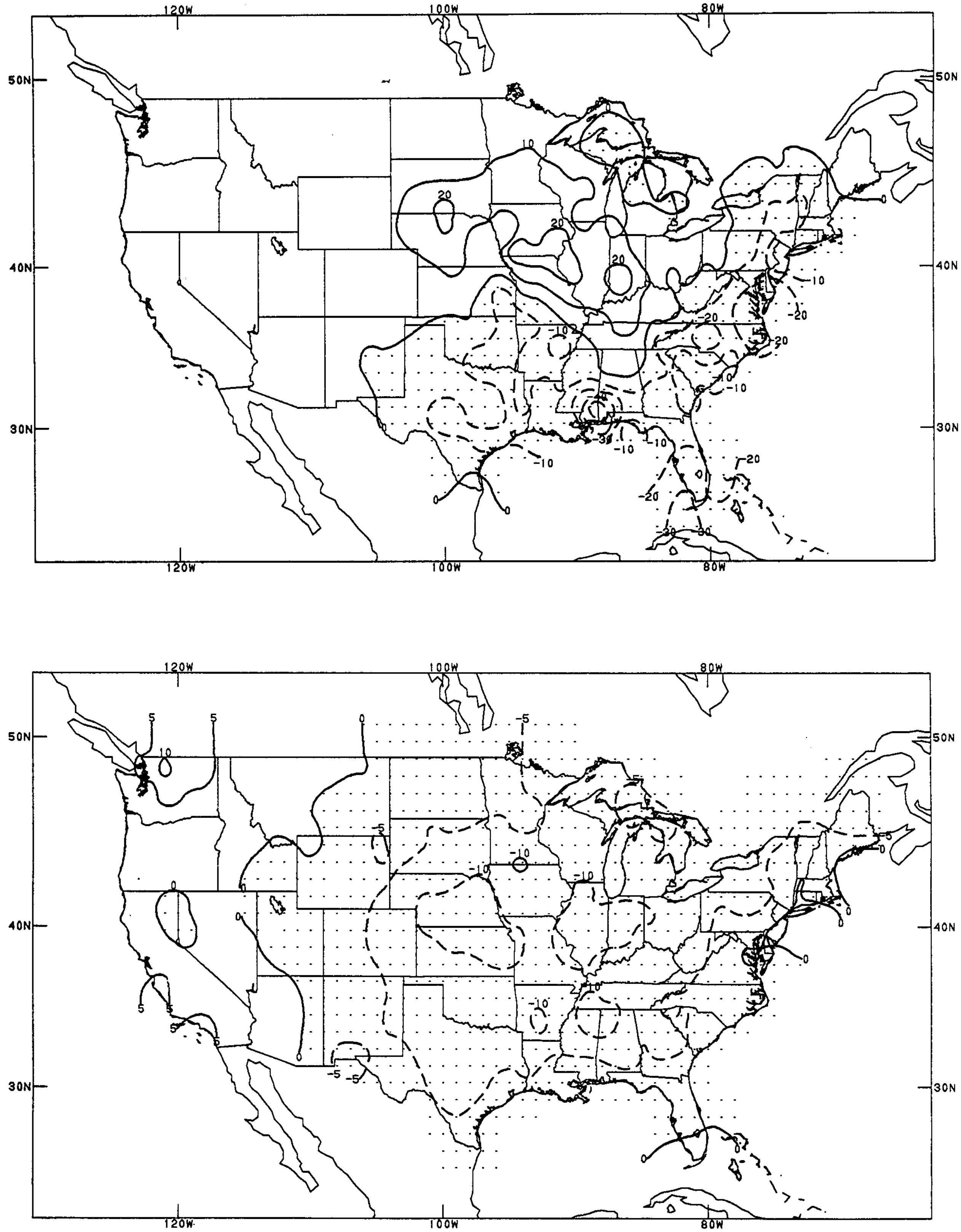

FIG. 11. Difference between the period of 1961–87 and the period of 1931–60 (a) in July MMP (unit: mm); (b) in August MMAT (×10°C).

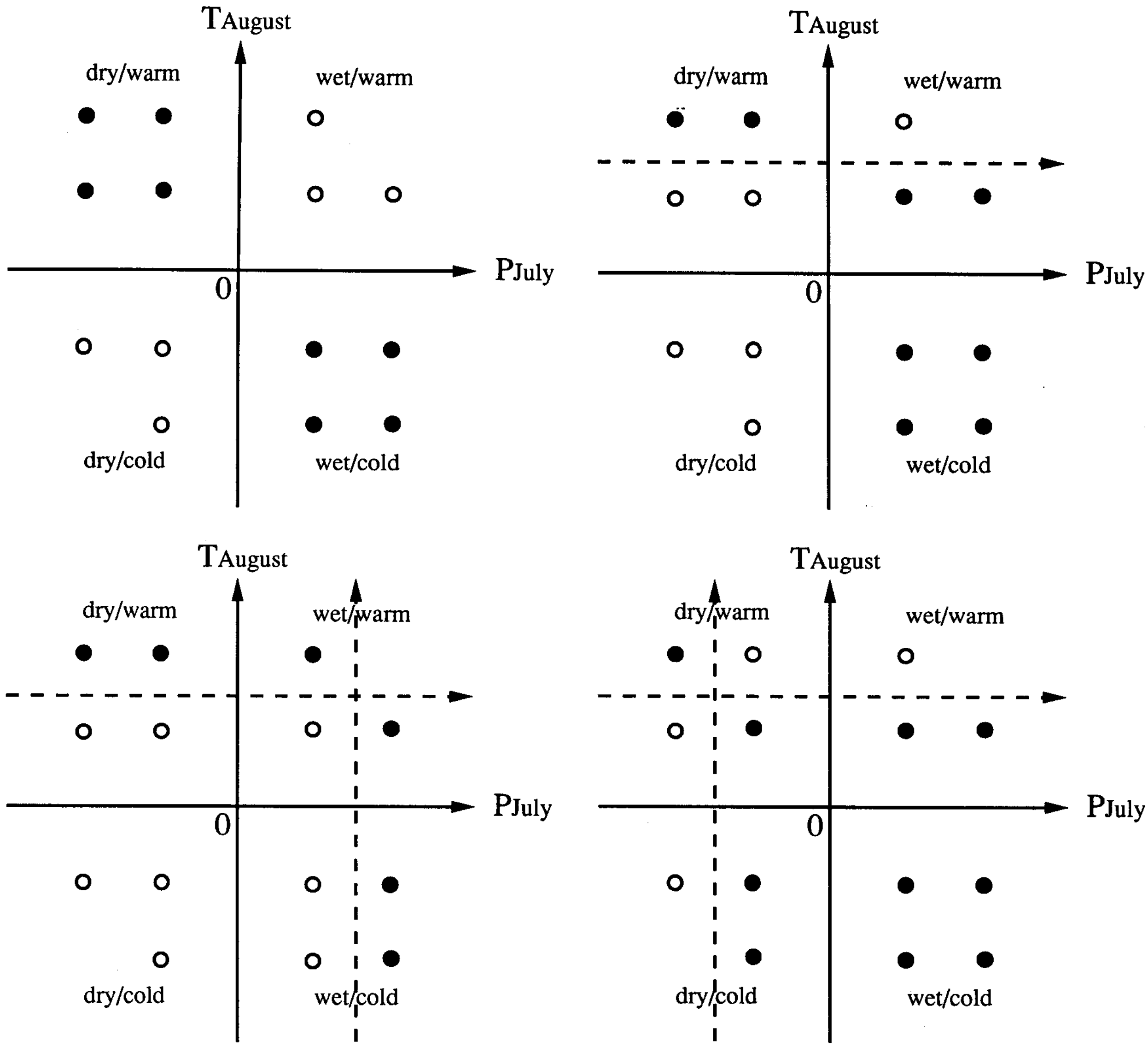

FIG. 12. Schematic diagrams to show how the climate difference between 1931–60 and 1961–87 causes the more negative P–T correlation and thus higher skill in forecasts in wet antecedent months. The x axis is July MMP anomaly and y axis is August MMAT anomaly. The dots represent the data in different years. (a) Normalized based on its own mean; (b), (c), and (d) data is normalized based on previous period and (b) 1961–87 is colder; (c) 1961–87 is colder and wetter, and (d) 1961–87 is colder and drier.

The lagged P–T correlation has been found to be generally negative with a maximum in summer and in the interior of the United States continent. The effects of the current month MMP on future MMAT can last almost 2–3 months. The magnitude of the P–T correlations is smaller than that of T–T correlations.

In order to determine whether including MMP can improve MMAT forecasts, we have compared a two-predictor regression model using both MMAT and MMP as the predictors to one-predictor models with MMAT or MMP as the only predictor. It has been found that over large areas of the interior United States in summer, predictions of MMAT based on either antecedent MMP alone, or on a combination of antecedent MMP and MMAT are better than a prediction scheme based on MMAT alone. Nevertheless, the verification indicates that including MMP as a second predictor does not improve the MMAT forecasts dramatically. This may be because the MMP's information has been accounted for by using temperature persistence, as the simultaneous MMAT–MMP correlation is already strongly negative. Considering the difficulty of measuring a meaningful soil moisture anomaly, it may also mean that MMAT is as good a proxy for soil moisture as MMP.

When verifying the regression results for wet and dry months separately, we found that the MMAT forecast skill is higher in wet months than in dry months.

This is true for MMAT forecasts based on MMP and/or MMAT. Further analysis indicated that the higher skill for the wet months is due to the systematic cooling from the period of 1931–60 to the period of 1961–87 over the entire United States continent. This result suggests that the skill in independent verification has been affected strongly by the climate difference between the developmental dataset and verification dataset.

The negative P–T correlation is caused primarily by short-term climate anomalies. When applying the P–T regression on the independent data, the verification correlation can be smaller/larger than expected. For instance, if the climate became colder/wetter or dryer/warmer, the MMP-based forecasts will score better than expected. Therefore, we cannot be too confident of forecasts of MMAT unless we also correctly forecast (by other means) the interdecadal MMAT and MMP changes.

The occurrence of a substantial climate change between two consecutive approximately 30-year periods underscores the danger in an assumption of climatic stationarity in a wide variety of studies. When this assumption is unrealistically made, broad climate changes can become disguised as other relationships, potentially resulting in misleading conclusions.

In the introduction, we alluded to the role of soil moisture in the lagged P–T and T–T relationships. We here summarize the evidence consistent with this idea.

1) The observed P–T correlation, with MMP leading MMAT by a month, is much larger than the T–P correlation. This rules out the possibility that MMP and MMAT are correlated only because each of them is correlated to some common slowly varying cause. The precipitation appears to be leading the temperature, and the correlations are negative.

2) When using data generated by a model with fixed soil moisture, the lagged P–T correlation over the center of the United States is entirely absent. Also the T–T correlation is generally lower, leaving a role for soil moisture to enhance temperature persistence. In the model with interactive soil moisture, the P–T correlation is significantly negative and the T–T correlation is highly positive in summer.

3) The negative P–T relation is present mostly in the warmer months, when the potentially large latent heat flux is subject to large change as a result of soil moisture variation.

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APPENDIX

The Statistical Significance of a Pattern Correlation

Suppose the sample size is $n = MN$, where $M = 55$ is the number of years and N is the spatial degrees of freedom. If the parent distribution of PC is (0, sd), where $sd = 1/\sqrt{n-2}$, the sampled PC could be in a range of 0 to $t\ 1/\sqrt{n-2}$, where the t value for a one-sided t test is 1.65 for the 95% confidence level. For MMAT, N ranges from 8 (winter) to 15 (summer) and for MMP, N is 25 to 60 (see Van den Dool et al. 1986). Thus using $N = 8$, a PC greater than 0.08 is significant for the T–T relation and a PC greater than 0.04 is statistically significant for the P–T relation (using $N = 30$).

If $M = 30$ (as for the model output), the T–T correlation smaller than 0.1 and P–T correlation smaller than 0.06 are not statistically significant.

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