Extension of the Climate Prediction Center Long-Lead Temperature and Precipitation Outlooks to General Weather Statistics

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ABSTRACT

The long-lead monthly and seasonal forecasts issued by the Climate Prediction Center literally pertain only to average temperature and total precipitation outcomes, but implicitly contain information regarding other quantities that are correlated with these two variables. This paper presents a method for estimating the conditional probability distribution for any such quantity that is a computable statistic of available daily climatological data, through weighted bootstrap resampling conditional on particular joint (temperature and precipitation) forecast probabilities. Examples illustrating implementation and particular results are provided.

1. Introduction

The format of long-lead monthly and seasonal forecasts issued by the Climate Prediction Center (CPC) has recently been changed to include greater lead times and longer projections, based largely on better understanding of the ENSO phenomenon (O'Lenic 1994). The predictands for these forecasts are monthly or seasonal average temperature and monthly or seasonal precipitation at locations in the United States. Outcomes for these variables pertaining to particular months or seasons in the future are classified as being below, near, or above normal if they fall into the lower, middle, or upper thirds of the respective climatological distribution. The format for each forecast is one of two types. Forecasts of the first type assign a probability, say i, that the outcome will be in the below-normal category, with a probability of 1/3 that the outcome will be in the near-normal category and a probability of $2/3 - i$ that the outcome will be above normal. Forecasts of the second type specify the probability of a near-normal outcome, say j, with the remaining $1 - j$ being allocated equally to the below- and above-normal categories. That is, forecasts of the second type assign probability $(1 - j)/2$ to both the below- and above-normal categories. Specifications of $i = j = 1/3$ imply forecasts of the climatological probabilities.

While these new forecasts offer a wealth of information at lead times sufficient for incorporation into the decision making processes of many climate-sensitive enterprises, initial indications are that they have not been widely adopted for practical planning purposes (Changnon et al. 1995; Pulwarty and Redmond 1996). Likely impediments to more widespread use of this information include 1) the abstract nature of the forecasts themselves (probabilities rather than temperature or precipitation values directly), 2) that the format of the forecasts (two types of forecasts pertaining to three categories of outcomes) may be confusing to many potential users, and 3) that information regarding quantities other than temperature and precipitation may be of interest. Apparently, more effective use of these forecasts will require one or more layers of interpretation, or some "value added" between the CPC and the ultimate user.

One step in this direction is described in Briggs and Wilks (1996a), in which use of the forecasts to compute updated, or forecast-conditional, distributions for monthly or seasonal temperature and precipitation is demonstrated. For example, a forecast for increased probability of above-normal temperature implies an increase in the mean and a decrease in the variance of the distribution of temperature, as compared to the respective climatological distribution. These conditional distributions can then be used to evaluate probabilities associated with user-defined temperature and precipitation outcomes, rather than only the two values defining the three equal portions of the climatological distributions. Some initial efforts to derive information for variables other than monthly or seasonal temperature and precipitation, using the CPC forecasts, are described by Robinson (1996), Croley and Kunkel (1996), Briggs (1996), and Briggs and Wilks (1996b).

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The present paper describes extension of the approach described in Briggs (1996) and Briggs and Wilks (1996b) to projection of statistical attributes of *daily weather,* or any computable function of historical daily weather data, given long-range *climate* forecasts. The underlying idea is the application of a resampling procedure to available historical climatological data, consistent both with the historical relative frequencies of the nine (three temperature times three precipitation) outcomes to which the CPC outlooks pertain and with particular CPC forecast probabilities. Construction of the synthetic conditional climatologies from which conditional daily statistics are computed is described in section 2. Section 3 will present examples of the method applied to both simple linear statistics, such as daily relative frequencies, and to highly nonlinear statistics, such as maximum likelihood estimates of daily precipitation distributions. Also presented in section 3 are examples of operationally usable graphical summaries of the derived forecast quantities, from which a user can simply "pick off" the value of interest as a function of the joint CPC temperature and precipitation forecast. Finally, section 4 concludes with a discussion and suggestions for future work.

2. Methodology

Forecast probabilities deviating from the climatological values of $i = j = 1/3$ imply adjustments to the climatological distributions of temperature and precipitation (Briggs and Wilks 1996a). Considering that monthly or seasonal average temperature and total precipitation are functions of daily values, it is clear that the distributions of daily temperature and precipitation should also change in consistent ways. Similarly, the statistical distributions of quantities that are functions of daily temperature or precipitation (such as growing or heating degree-days), or quantities that are correlated with daily temperature and precipitation (such as snowfall), should also be sensitive to forecasts for monthly or seasonal temperature and precipitation.

We assume here that the CPC forecasts are "reliable" in the sense of being accurately calibrated. That is, it will be assumed that these forecasts "mean what they say" in the sense that, conditional on a particular outcome (say, below-normal temperature) being forecast with probability p, that event occurs in approximately $100 \times p\%$ of the subsequent verifying observations. While formal verification statistics for the new CPC forecasts are as yet unavailable, past long-range forecast products from CPC have exhibited good reliability (Murphy and Huang 1991). Appropriately for forecasts at these long lead times, the range of forecast probabilities actually issued does not deviate greatly from the climatological value of 1/3.

Since some derived predictands of interest will depend on both the monthly or seasonal temperature and precipitation outcomes, it is necessary to consider joint, or bivariate, forecasts for these two quantities. We define $q_{t,1/3}$ and $q_{t,2/3}$ as the temperatures delineating the three categories of the climatological distribution of average temperature for a particular month or season and define $q_{p,1/3}$ and $q_{p,2/3}$ as the precipitation totals defining these two points for the precipitation distribution. Then forecasts of the first type i_t and i_p are probabilities that the future average temperature will be below $q_{t,1/3}$ and the future total precipitation will be below $q_{p,1/3}$. Forecasts of the second type, j_t and j_p, specify probabilities that the temperature will fall between $q_{t,1/3}$ and $q_{t,2/3}$, and that the precipitation will fall between $q_{p,1/3}$ and $q_{p,2/3}$, respectively.

Monthly and seasonal temperatures are modeled as following Gaussian distributions, and the two temperatures delineating the three equal partitions of the climatological temperature distribution are found by numerically inverting the Gaussian cumulative distributions function

$$\Phi(x) = P(X \leqslant x) = (2\pi\sigma^2)^{-1/2} \int_{-\infty}^{x} \exp\left[\frac{-(z-\mu)^2}{2\sigma^2}\right] dz \quad (1)$$

to satisfy $1/3 = \Phi(q_{t,1/3})$ and $2/3 = \Phi(q_{t,2/3})$, where μ is the (climatological) monthly or seasonal temperature mean and σ^2 is the monthly or seasonal temperature variance. The resulting boundary values are $-q_{t,1/3} = q_{t,2/3} = 0.43073\,\sigma + \mu$.

Monthly and seasonal precipitation totals are modeled as following gamma distributions, and similar to the procedure for temperature, the quantiles $q_{p,1/3}$ and $q_{p,2/3}$ specifying divisions between precipitation forecast categories are found by numerically inverting the integral of the probability density function of the gamma distribution—that is,

$$\frac{1}{3} = \frac{1}{\Gamma(\alpha)\beta^{\alpha}} \int_0^{q_{p,1/3}} x^{\alpha-1} \exp\left(\frac{-x}{\beta}\right) dx, \quad (2a)$$

and

$$\frac{2}{3} = \frac{1}{\Gamma(\alpha)\beta^{\alpha}} \int_0^{q_{p,2/3}} x^{\alpha-1} \exp\left(\frac{-x}{\beta}\right) dx. \quad (2b)$$

Here α and β are the shape and scale parameters of the climatological precipitation distribution, and $\Gamma(\cdot)$ is the gamma function. For both temperature and precipitation, the CPC forecasts pertain to distributions whose parameters in (1) and (2) are defined with respect to the period 1961–90 (O'Lenic 1994).

The first step in the resampling scheme is to partition the monthly or seasonal climatology into separate bins, which correspond to the nine distinct divisions to which the joint temperature and precipitation forecasts pertain. The joint forecast specifies probabilities that the coming month or season will be statistically similar to past data from each of these bins. The vector of daily weather observations from a given month or season is written as $[w]_m = [w_{1,m}, w_{2,m}, \cdots, w_{N,m}]^T$, where $\mathbf{w}_{n,m} = (w_1, w_2, w_3, \cdots, w_K)_{n,m}$ is a vector of K weather variables for day n in year m in the available climatic record. For monthly data the number of days N in each of these data objects $[w]_m$ will be around 30, and for seasonal data N will be around 90. If w_1 denotes daily maximum temperature, w_2 denotes daily minimum temperature, and w_3 denotes daily precipitation, then the average temperature over month or season m is

$$\overline{T}_m = \frac{1}{N}\sum_{n=1}^{N}\frac{(w_{1,n,m} + w_{2,n,m})}{2}, \qquad (3a)$$

and the corresponding precipitation total will be

$$\Sigma P_m = \sum_{n=1}^{N} w_{3,n,m}. \qquad (3b)$$

Each data object $[w]_m$ is classified as below, near, or above normal in temperature according to the relationship of (3a) to the two temperature quantiles $q_{t,1/3}$ and $q_{t,2/3}$. Similarly, the data $[w]_m$ are classified as below, near, or above normal in precipitation according to the relationship of (3b) to $q_{p,1/3}$ and $q_{p,2/3}$. The data for the month or season in question for each year m thus belongs to one of nine possible groups according to its temperature and precipitation classification. These classifications can be visualized as the matrix

$$[\mathbf{C}] = \begin{bmatrix} c_{B,B} & c_{B,N} & c_{B,A} \\ c_{N,B} & c_{N,N} & c_{A,N} \\ c_{A,B} & c_{A,N} & c_{A,A} \end{bmatrix}, \qquad (4)$$

in which the first of the pair of subscripts indicates temperature and the second indicates precipitation. For example, the bin $c_{B,A}$ contains all $[w]_m$ for which (3a) is smaller than $q_{t,1/3}$ and (3b) is larger than $q_{p,2/3}$. Each $[w]_m$ is placed whole into its respective bin, including all variables w_k, $k = 1, \cdots, K$, and with the time ordering intact.

The (3×3) matrix $[\mathbf{P}]$ is also defined as containing the climatological probabilities for membership in the nine categories in (4). A first approximation to these probabilities would be the relative frequencies with which the $[w]_m$, $m = 1, \cdots M$, were placed in each bin, or $P_{\cdot,\cdot} = \#\{[w]_m \in c_{\cdot,\cdot}\}/M$. Unless the climatic record is very long (i.e., M is large), these nine estimates will be highly variable, and as a practical matter some smoothing of the raw relative frequencies may be desirable (Wilks and Murphy 1986). Over parts of the United States, particularly in the northeast, correlations between temperature and precipitation in particular months or seasons are weak (Van den Dool 1988). For these cases, one could reasonably assign all elements of $[\mathbf{P}]$ equal to $1/9$. Depending on the month or season, correlations between temperature and precipitation are often negative in other parts of the United States. (Van den Dool 1988). In these instances one might expect $P_{B,B} \approx P_{A,A} < P_{A,B} \approx P_{B,A}$.

We desire to build a conditional climatology of size L months or seasons, which is consistent both with the climatological probabilities $[\mathbf{P}]$ and with the forecasts. This is done in the following by bootstrapping, or resampling, the bins of $[\mathbf{C}]$ with replacements. It is convenient for this purpose to express the forecasts in the form of the diagonal matrices

$$[\mathbf{F}]_{1,t} = \begin{bmatrix} i_t & 0 & 0 \\ 0 & 1/3 & 0 \\ 0 & 0 & 2/3 - i_t \end{bmatrix};$$

$$[\mathbf{F}]_{1,p} = \begin{bmatrix} i_p & 0 & 0 \\ 0 & 1/3 & 0 \\ 0 & 0 & 2/3 - i_p \end{bmatrix} \qquad (5a)$$

for forecasts of the first type and

$$[\mathbf{F}]_{2,t} = \begin{bmatrix} (1 - j_t)/2 & 0 & 0 \\ 0 & j_t & 0 \\ 0 & 0 & (1 - j_t)/2 \end{bmatrix};$$

$$[\mathbf{F}]_{2,p} = \begin{bmatrix} (1 - j_p)/2 & 0 & 0 \\ 0 & j_p & 0 \\ 0 & 0 & (1 - j_p)/2 \end{bmatrix} \qquad (5b)$$

for forecasts of the second type. Then the number of samples to be taken from each element of $[\mathbf{C}]$ can be computed as

$$[\mathbf{L}_C] = 9L[\mathbf{F}]_t[\mathbf{P}][\mathbf{F}]_p, \qquad (6)$$

where, as appropriate, the forecasts of the first (5a) or second (5b) types are used. That is, in many cases both $[\mathbf{F}]_t$ and $[\mathbf{F}]_p$ will be taken from (5a), but some forecasts will indicate, say, that $[\mathbf{F}]_t$ is to be taken from (5b) while $[\mathbf{F}]_p$ is taken from (5a). For the climatological ("no information") forecast $i_t = i_p = j_t = j_p = 1/3$, (6) reduces to $L[\mathbf{P}]$, indicating resampling in proportion to the observed climatology. If monthly or seasonal temperature and precipitation are uncorrelated, and both the temperature and precipitation forecasts are of the first type, (6) becomes

$$[\mathbf{L}_C] = L\begin{bmatrix} i_t i_p & i_t\frac{1}{3} & i_t(\frac{2}{3} - i_p) \\ \frac{1}{3}i_p & \frac{1}{3}\frac{1}{3} & \frac{1}{3}(\frac{2}{3} - i_p) \\ (\frac{2}{3} - i_t)i_p & (\frac{2}{3} - i_t)\frac{1}{3} & (\frac{2}{3} - i_t)(\frac{2}{3} - i_p) \end{bmatrix}. \qquad (7)$$

For example, according to (7), the bin $c_{B,B}$ is resampled $i_t i_p L$ times. If $L = 15\,000$ (the value used in section 3), $i_t = 1/3 + 1/5$ and $i_p = 1/3 + 1/10$, then (7) becomes

$$[\mathbf{L}_C] = 15\,000\begin{bmatrix} 0.231 & 0.178 & 0.125 \\ 0.144 & 0.111 & 0.078 \\ 0.058 & 0.044 & 0.031 \end{bmatrix} = \begin{bmatrix} 3465 & 2670 & 1875 \\ 2160 & 1665 & 1170 \\ 870 & 660 & 465 \end{bmatrix} \quad (8)$$

for this cold and dry forecast. That is, 3465 samples would be drawn with replacement from the data objects in the cold and dry bin $c_{B,B}$, etc. Note that summing the probabilities across the rows of the matrix in the middle equality of (8) yields the temperature probabilities, and summing the columns yields the precipitation probabilities.

A schematic view of the resampling process is shown in Fig. 1. In the climatology partition [**C**] in (4) the bin $c_{B,B}$ contains $M_{B,B}$ separate data objects $[w]_m$, the bin $c_{N,B}$ contains $M_{N,B}$ objects, and so on until the bin $c_{A,A}$, which contains $M_{A,A}$ separate data blocks. Below the bins in Fig. 1, the number of months to be resampled is indicated. Assuming (7), this number for the bin $c_{B,B}$, for example, is $i_t i_p L$. This many resamples

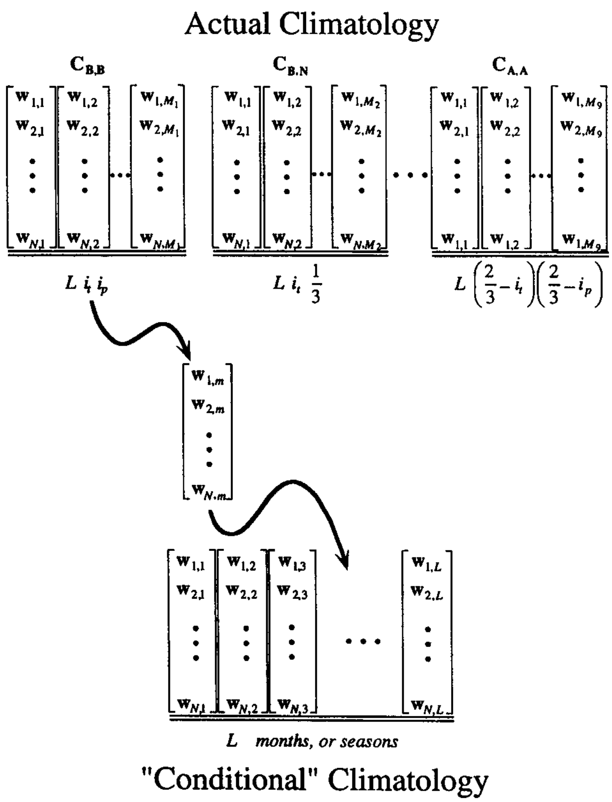

FIG. 1. Schematic illustration of the conditional resampling. The data objects $w_{i,j}$ indicate the observed weather to be resampled. Here, and in all figures, i_t and i_p are the temperature and precipitation probability forecast values for below-normal occurences.

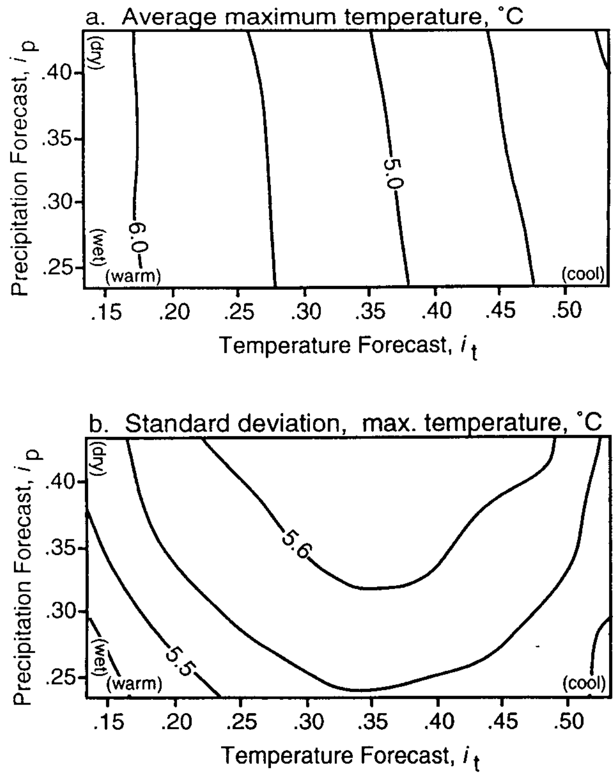

FIG. 2. (a) Average and (b) standard deviation of daily January maximum temperatures, conditional on occurrence of precipitation, at Central Park. Here, and in all subsequent figures, the labels (warm), (cool), (wet), and (dry) have been included for easier forecast interpretation.

from this bin are drawn with replacement, by generating $i_t i_p L$ discrete uniform random numbers on the interval $[1, M_{B,B}]$, with each selected $[w]_m$ being copied whole into the conditional climatology (lower part of the figure). The selected $[w]_m$ remains in place in $c_{B,B}$ so that it may be sampled again. This process is then repeated for the other bins $c_{N,B}$, $c_{A,B}$, etc. At the end, the conditional climatology will contain L months drawn from the observed record, with probabilities consistent with both the forecasts and the underlying climatology.

As a practical matter, it is not difficult to imagine that the available climatic records for some stations may be short enough that some $c_{\cdot,\cdot}$ in (4) would contain very few or zero $[w]_m$. In the latter case, the procedure described above will be unworkable. However, in many specific forecasting situations, one or the other of the temperature or precipitation forecasts may be for climatological probabilities. In these situations the (3 × 3) classification of the $[w]_m$ in (4) can be collapsed into a (3 × 1) classification according to the element for which the nonclimatological probability is forecast, with the resampling conducted on that reduced set. If both the temperature and precipitation forecasts deviate

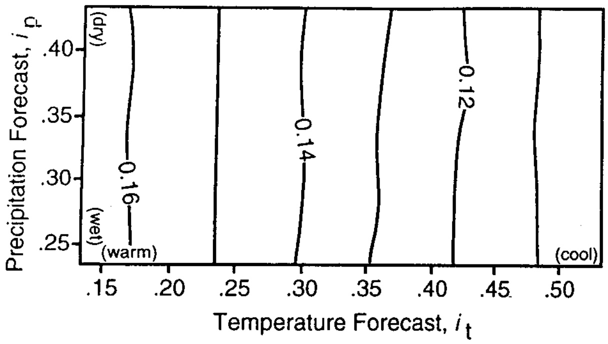

FIG. 3. Probabilities of daily August maximum temperature greater than 32.2°C at Central Park.

from climatological probabilities, the single dimension into which (4) should be collapsed may be chosen according to which element is being forecast more confidently, or which element has the greater influence over the statistic of interest.

Having drawn the conditional climatology of L elements, any statistic of interest may be computed for each of these L objects $[w]_m$. These can range in complexity from simple totals of one of the w_k over its N observations, to statistics reflecting the serial correlation of one or more w_k (which will have been preserved because the time ordering within each $[w]_m$ is preserved), to highly nonlinear functions of some of the w_k, such as maximum likelihood gamma distribution parameter estimates based on the nonzero values of w_3. Depending on the application, the entire synthetic set of L members can be pooled to produce a single estimate, or L separate statistics can be computed and ranked to form an approximation to the conditional cumulative distribution function for the statistic of interest. The next section presents a few examples of the kinds of statistics that can be computed.

3. Examples

This section presents a variety of conditional statistics computed from synthetic climatologies, constructed as described in the previous section. All of the examples pertain to forecasts of the first type at locations in the northeastern United States, so (7) will be assumed, with $L = 15\,000$. The results are shown as surfaces that are functions of i_t and i_p. The results are restricted to operationally meaningful probability ranges, which are $^1/_3 \pm {}^1/_5$ for i_t and $^1/_3 \pm {}^1/_{10}$ for i_p (O'Lenic 1994). Similar plots could easily be constructed with one or both of the temperature and precipitation forecasts being of the second type as well. Operationally, it would be possible to compute *in advance* plots of the kind shown below, from which a user merely has to read off the statistic(s) of interest given the current joint forecast.

In Fig. 2, average daily maximum temperature (Fig. 2a) and standard deviation of daily maximum temperature (Fig. 2b) are depicted, both conditional on the occurrence of days with at least 0.25 mm (0.01 in., i.e., the standard minimum measurable amount) of precipitation for January at Central Park, New York. As would be expected, the predominant effect in Fig. 2a is for warmer temperatures associated with smaller probabilities of cold Januarys, i_t. Surprisingly, however, there appears to be a slight dependence of these conditional average temperatures on the monthly precipitation outcome as well. The corresponding plots for unconditional temperatures (not shown) also exhibit a slight tendency for wetter Januaries (lower part of the figure) to have warmer daily temperatures. While Fig. 2a is nearly planar, Fig. 2b shows a more nonlinear response for wet-day temperature variability, with more variable Januarys being associated with dry but near-normal temperature months, and less variable situations associated with higher monthly precipitation and either cool or warm temperatures.

Figure 3 illustrates that information on extreme daily events can also be inferred from the long-lead outlooks. In this case, the dependence of the unconditional probability of daily maximum temperature warmer than 32.2°C (90°F) during August at Central Park is shown.

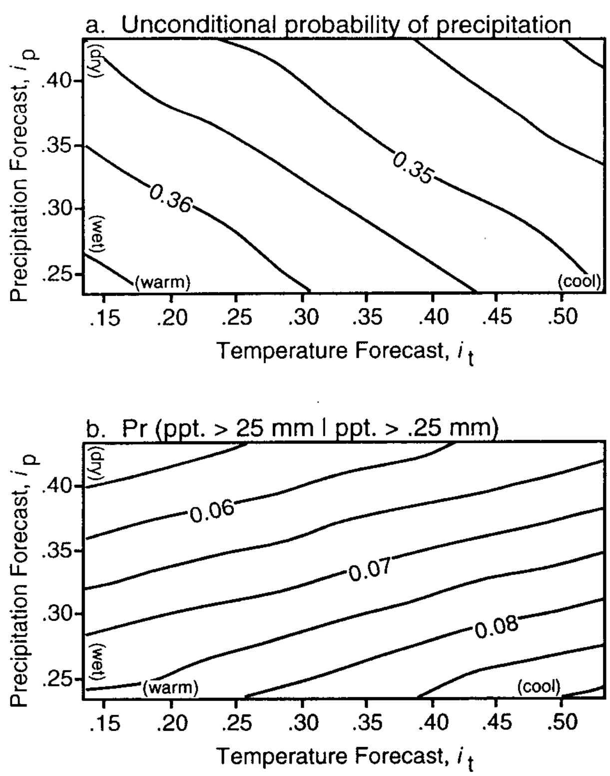

FIG. 4. (a) Unconditional daily probability of precipitation and (b) conditional probability of greater than 25 mm given at least 0.25 mm of precipitation for January at Central Park.

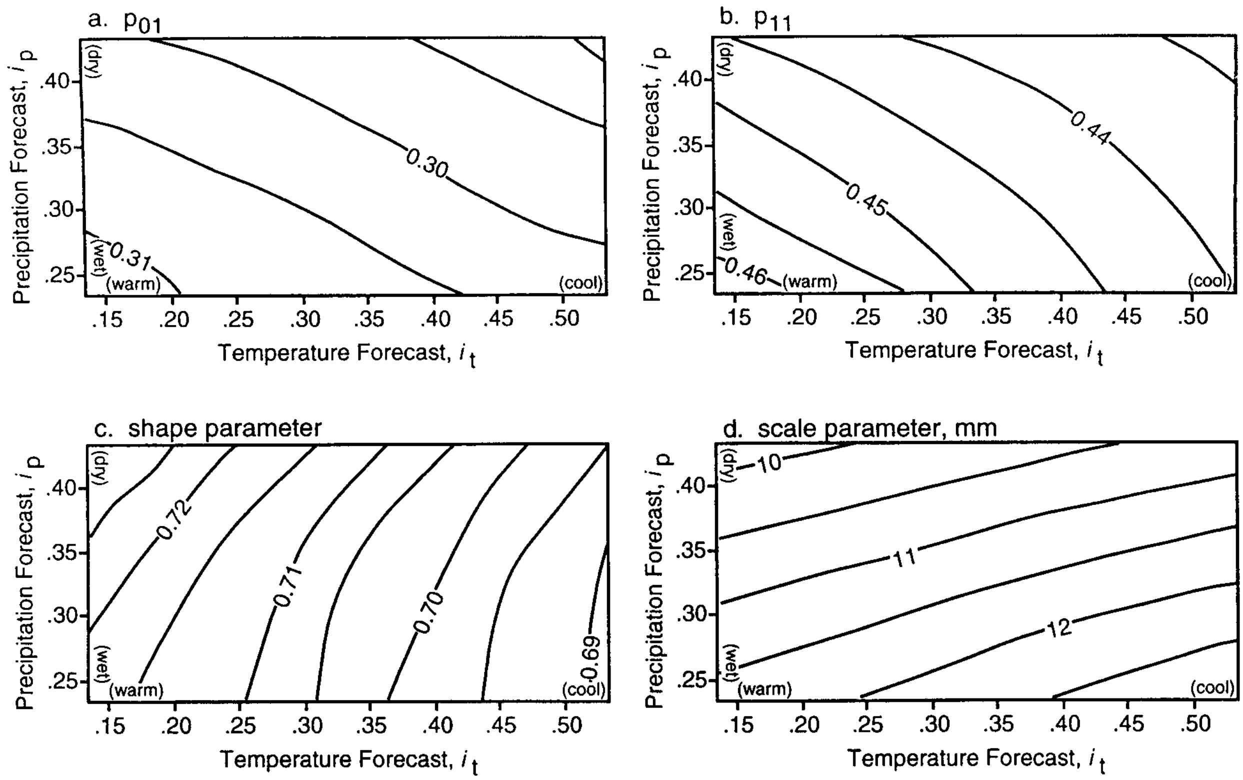

FIG. 5. Parameters for chain-dependent process model of daily precipitation. (a) Probability of a wet day following a dry day, (b) probability of a wet day following a wet day, (c) shape parameter for gamma distributions of wet-day precipitation amounts, and (d) scale parameters for those gamma distributions for January at Central Park.

This quantity shows little or no relationship with the precipitation forecast, but varies roughly ±25% from the climatological value of 0.135 over the plausible range of the temperature forecasts. The expected number of days in August that the daily maximum temperature exceeds 32.2°C can be computed by simply multiplying each probability by 31 (the number of days in August). Similar figures showing, for example, probabilities for runs of warm days of particular lengths could be easily constructed as well.

Two contrasting aspects of daily precipitation are shown in Fig. 4, again for January at Central Park. Figure 4a, for the daily unconditional probability of precipitation, exhibits dependence on the precipitation forecasts as would be expected, but also on the temperature forecasts. Highest probabilities of daily precipitation occur for the warm and wet probabilities in the lower left portion of the figure, and the smallest probabilities occur for the cool and dry probabilities in the upper right. Figure 4b shows the results for the conditional probability of greater than 25 mm (1 in.) of daily precipitation (liquid equivalent), conditional on the occurrence of at least 0.25 mm (0.01 in.). This statistic also depends on both the temperature and precipitation forecasts, but with smallest conditional probabilities of large precipitation amounts occurring for the warm and dry probabilities in the upper left portion of the figure, and the largest conditional probabilities occurring in the cold and wet lower right. While the variation of unconditional precipitation probabilities over the range of plausible long-lead forecast probabilities in Fig. 4a is modest, the conditional probabilities for large precipitation events again yield variations of roughly ±25% around the climatological expectation of 0.07. While the directions of the slopes of the two surfaces in Figs. 4a and 4b are quite different in this case, the same relationship does not necessarily occur for other locations or other months.

The variation of the four parameters of the "chain-dependent process" stochastic model for daily precipitation of Katz (1977), again for January at Central Park, is shown in Fig. 5. The four parameters are the probability of a wet day following a dry day (Fig. 5a), the probability of a wet day following a wet day (Fig. 5b), the shape parameters for gamma distributions describing the variation of wet-day precipitation amounts (Fig. 5c), and the scale parameters for those distributions (Fig. 5d). These results could be used to generate synthetic precipitation sequences, conditional on the long-lead forecasts, to drive a precipitation-sensitive model of interest. Katz's chain-dependent model constitutes the precipitation portion of certain stochastic weather models, which also include daily temperature and radiation values (e.g., Richardson 1981). The other portions of these stochastic weather models include forecast-sensitive parameters, such as those shown in Fig. 2. These larger "weather generator" models can be used as input to crop simulation models (e.g., Jones and Kiniry 1986) in order to project probability distributions over crop yield and other responses, such as soil moisture.

Briggs (1996) and Briggs and Wilks (1996b) discuss in more detail the modification of the parameters of stochastic weather generators conditional on particular long-lead forecasts, through results such as those shown in Figs. 2 and 5 and their use with crop simulation models. A simplified example of such a simulation is given to demonstrate the concept. Table 1 summarizes some hypothetical distributions for crop yield at Ithaca, New York, computed using the CERES Maize model (Jones and Kiniry 1986), which uses Richardson model synthetic weather conditional on different long-lead temperature and precipitation forecasts. For the sake of easy exposition, each month of the growing season has been assumed to have the same joint forecast. (This, of course, is unrealistic, but it does allow us to present results that can be considered the most extreme possible.) In order to assess the distribution of crop yield produced for each of the five different forecasts, 1000 separate crop model simulations were made for each of the forecasts. Shown in Table 1 are the means and standard deviations of crop yields, relative to yield at the climatological forecasts. For the "warm and wet" forecast ($i_t = 0.133$ and $i_p = 0.233$) the mean yield is 24% greater than for the climatological forecast ($i_t = 0.333$ and $i_p = 0.333$), but with standard deviation that is 9% larger. For the "cool and dry" forecast ($i_t = 0.533$ and $i_p = 0.533$) the mean yield is reduced by 28%, and the yield variability also is reduced. Yield distributions for the "warm and dry" and "cool and wet" are similar to those obtained from climatological forecasts. Of course, more rigorous and realistic forecast simulations could be developed (see Briggs 1996), but this small example serves to show the promise of the technique. Other physical models that require daily weather as input could also be used in this manner, such as the hydrologic models described in Kunkel et al. (1995).

Examples presented thus far have been based on pooling all L members of the conditional climatology to yield, for each joint forecast, a single estimated conditional expected value for the quantity or parameter of interest. Figure 6 shows that the resampling procedure can also be used to estimate full conditional probability distributions, in this case for total January snowfall at Ithaca. Here, using the L resamples separately for each combination of i_t and i_p, a conditional cumulative distribution of total snowfall has been formed. Figures 6a–e show, respectively, the 10th, 25th, 50th, 75th, and 90th percentiles of these conditional distributions. Figure 6f shows the interquartile ranges. It is clear that these snowfall statistics depend on both the temperature and precipitation forecasts, with distributions indicating deeper snows occurring at Ithaca for cold and wet forecasts, and shallower snows occurring for warm and dry forecasts. These surfaces are clearly more complicated than simple planes, with a strong gradient for the 10th percentile toward the warm and dry forecasts, and strong gradients for the 75th and 90th percentiles toward the cold and wet forecasts. In many instances the estimated quantiles are large modifications to the climatological values in the centers of the figures. The variability of these snowfall distributions also increases for colder and wetter forecasts (Fig. 6f), due largely to the extension of the right tails of the snowfall distributions.

4. Conclusions

This paper has presented a conceptually simple approach to extending the CPC long-lead temperature and precipitation forecasts to yield consistent information regarding any computable function of daily, monthly, or seasonal weather data. The broad applicability of the procedure was illustrated through a variety of examples, but these are by no means exhaustive. Operationally, for example, one might want to produce geographic maps for a predictand or set of predictands of interest, consistent with the current (spatially varying) joint temperature and precipitation forecast. Discontinuities in the spatially varying forecasts should not be

TABLE 1. Percentage of changes in means and standard deviations of crop yield as simulated by CERES Maize for Ithaca, as a function of four joint temperature and precipitation forecasts, which are assumed to apply to all months in the growing season.

	Climatology	Warm/wet	Warm/dry	Cool/wet	Cool/dry
i_t	0.333	0.133	0.133	0.533	0.533
i_p	0.333	0.233	0.433	0.233	0.433
Percentage of change, mean	0	+24	−5	0	−28
Percentage of change, standard deviation	0	+9	+3	−1	−18

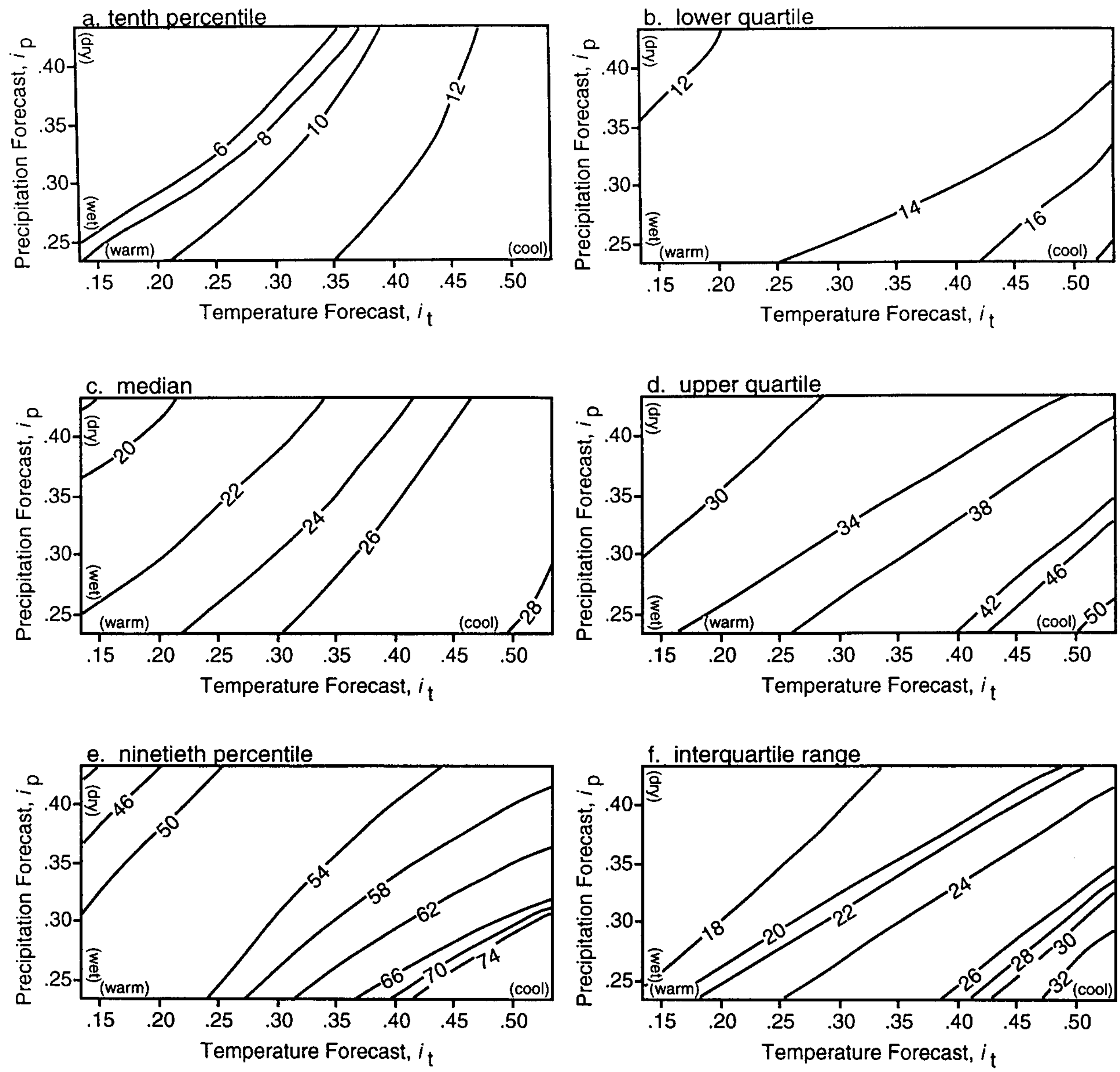

FIG. 6. Aspects of the conditional distributions of total January snowfall (cm) at Ithaca: (a) 10th percentile, (b) 25th percentile, (c) median, (d) 75th percentile, (e) 90th percentile, and (f) interquartile range.

problematic as this resampling method operates on single stations, so that each site is only dependent on the point location value of the forecast—that is, neighboring forecast values do not influence the resampling scheme.

We have advocated the use of a resampling approach, as this is easy to implement regardless of the complexity of the statistic of interest and, with the availability of inexpensive computing, can be made to yield results of any desired precision. Particularly for simple statistics such as monthly or seasonal means, however, these results can be obtained more elegantly without resampling. While the empirical climatological distribution places a weight of $1/N$ on each observation in the available record, particular joint temperature and precipitation forecasts will effectively modify these weights in computable ways. Thus, different conditional distributions for statistics of interest can be constructed using weightings other than the climatological $1/N$, although this process might become quite involved for statistics that are complicated functions of the underlying climatological data.

Only the problem of constructing conditional statistics consistent with a joint temperature and precipitation forecast for a single month or season has been addressed here. However, the format of the CPC outlooks includes simultaneous forecasts for 13 overlapping 3-month seasons, plus a forecast for the first month of the first season. Fuller use could be made of the CPC outlooks if a robust and consistent method for disaggregating the seasonal forecasts could be found. Croley (1996) and Croley and Kunkel (1996) present an initial approach to this problem.

Long-range forecasts have potentially substantial value for decisions regarding a wide variety of climate-sensitive problems (although it is still an open question as to whether or not the current generation of forecasts are statistically reliable). Their use is resisted by many decision makers, however, both because information on quantities other than average temperature or total precipitation is needed and because additional forecast interpretation is required. The methods presented here should allow amelioration of both of these problems.

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