A Forecast Product that Maximizes Utility for State-of-the-Art Seasonal Climate Prediction

Anthony G. Barnston, Yuxiang He, and David A. Unger
Climate Prediction Center, NCEP/NWS/NOAA, Camp Springs, Maryland

ABSTRACT

The prediction of seasonal climate anomalies at useful lead times often involves an unfavorable signal-to-noise ratio. The forecasts, while consequently tending to have modest skill, nonetheless have significant utility when packaged in ways to which users can relate and respond appropriately. This paper presents a reasonable but unprecedented manner in which to issue seasonal climate forecasts and illustrates how implied “tilts of the odds” of the forecasted climate may be used beneficially by technical as well as nontechnical clients.

1. Introduction

It is well known that the weather averaged over an extended period, such as a three-month season, is ordinarily able to be predicted in advance only with a modest level of accuracy (Gilman 1985; Livezey 1990). During the most recent decade progress has been made in recognizing when opportunities for relatively more confident forecasts of extended period climate conditions present themselves. A recent example appeared in the Northern Hemisphere summer and fall of 1997 when a strong El Niño had developed and was virtually certain to persist through the upcoming winter when it would have predictable climate impacts in portions of North America and elsewhere. The director of the Department of Commerce’s Climate Prediction Center (CPC) appeared on national television, warning that Florida and California would have a rainy winter 1997/98. While this unprecedented “climate alert” provoked controversy, the forecast verified favorably (Changnon 1999; Barnston et al 1999; Mason et al. 1999).

There are other, more subtle, ways in which climate anomalies have some predictability. Gradual trends in temperature and precipitation, which may be due to natural and/or anthropogenic causes, appear for specific regions and seasons. Forecasts of such a trend’s continuation are often correct despite a lack of knowledge of many of the superimposed faster-acting climate-determining factors, or even the cause of the trend itself.

The primary reason for the normally low level of forecast skill is that much of the atmosphere’s natural variations making up a seasonal average are due to individual weather events (e.g., fronts, low pressure systems), as opposed to longer-lived climate tendencies. Weather events are generally only usefully predictable up to about one week into the future. However, statistical and physical modeling approaches can extend a certain amount of predictability out to much longer ranges based on the more consistent influences of boundary conditions such as sea surface temperature (e.g., El Niño or La Niña) that can tilt the odds in a specific direction of climate anomaly. While we cannot say on which day a rainstorm or unseasonable warmth will occur in a given region 3 months from now, we may be able to say that the rainfall or the temperature over the season as a whole is more likely to be above than below normal. Such a forecast inherently carries considerable uncertainty.

Because of their normally modest skill, climate forecasts have not usually been issued in the concrete
been met with mixed reactions from users (e.g., Sonka et al. 1992; Changnon et al. 1995). One such reaction is that the forecasts are not packaged in an obvious, user-friendly format. Another common reaction is that the forecasts have so little skill that they are not worth considering seriously in decision making. While skill is in fact modest in many instances, it is above zero far enough and frequently enough that the forecasts can be exploited to the long-term benefit of certain types of government and private interests. Our philosophy here is that users would be likely to take climate forecasts more seriously if more plentiful and detailed information were offered both in the forecasts themselves and in descriptions of their expected accuracy. More concrete and precise information, even for forecasts whose skill is known to be marginal, would help a user judge their value. Here we describe a product recently produced at the CPC that delivers such extended information.

2. Making the most of the modest skill of seasonal climate forecasts

Together with forecasts of future seasonal climate conditions, expressions of their uncertainty are necessary in order that consumers know what level of confidence to place in them (Gilman 1986). One way to convey uncertainty is evident in the format of the forecasts issued by the CPC since the 1970s. A three-category forecast system has been used, comprising below-, near-, and above-normal ranges for temperature and precipitation across the continental United States, where “normal” is based on observations over a recent 30-yr base period. Before 1995 the three categories were defined as occupying 30%, 40%, and 30% of the climatological distribution, respectively; since 1995 these were redefined to be 33.3% each. In either case, forecasts have been issued that identify only the most favored category, along with its probability. Typically that probability has ranged from its climatological value to about 25% higher. A simple assumption was made that the positive departure of the below- or above-normal category’s probability from the climatological probability was counterbalanced by an equally negative departure of the opposite category’s probability. The near-normal category was not selected as the favored category before 1995, based on an apparent lack of any overall skill in forecasts of that category (Lehman 1987; Van den Dool and Toth 1991). A near-normal forecast only implied climatological probabilities for all three categories; that is, a nonforecast. However, beginning in 1995 the near-normal category occasionally began being forecast to be more likely than its climatological probability, with the assumption that its positive departure was counterbalanced by negative probability departures of one-half the amount from each of the two outer categories. This change was prompted with reasoning that when known climate influences are in their neutral state, or when two influences conflicted, the probability distribution should be somewhat narrowed and be centered near the middle of the climatological distribution.

Overall, the above forecast system indicated, directly or indirectly, the probability forecasts of all three categories. It provided the direction and, in a probabilistic manner, the strength, or confidence, of a seasonal forecast. While such a “sketchy” forecast system may seem consistent with the normally modest expected accuracy, it falls short of providing maximally useful information. It fails to differentiate between the size of an implied shift from climatology of the most likely outcome, and the uncertainty of occurrence of that outcome. Relatively high probability shifts away from climatology, while indicating strong odds in favor of the forecasted direction of departure, are not necessarily accompanied by smaller uncertainties with respect to the best numerical guess of the outcome. In fact, such a best guess has never been indicated. To illustrate, consider two situations. In situation 1, suppose there has been a long-term warming trend for the given location and season, without an identifiable physical cause. While a continuation of the trend is likely, no shorter-term climate information for the current year is available. The same warm forecast could just as easily be made for this same season one year later, or even two years. Factors unrelated to the trend may make this year extremely warm or merely near or even slightly below the climatological average. This situation would imply some confidence that the temperature will be above normal, but with great uncertainty in how much above. In situation 2, suppose that a warm phase of the El Niño–Southern Oscillation (ENSO) is in progress and the forecast is for a season and location for which warm ENSO exerts a mild to
moderate warming influence that is understood physically in terms of teleconnections from the positive sea surface temperature anomaly in the tropical Pacific and consequent extratropical atmospheric Rossby wave dynamics. ENSO’s circulation patterns tend to cut off the supply of cold air from the Arctic and make belownormal temperature very unlikely for the season. In this situation the forecast would be for somewhat above normal in similar fashion to the first situation. However, the certainty of the forecast would be greater than in situation 1, due to the better physical understanding and validation through historical observations. In both situations 1 and 2 the actual temperature forecast (in physical degrees, if one were forced to guess) would be similar. In terms of the probability of the above-normal temperature category, both situations might lead to a 52% probability, considerably greater than the climatological 33.3%. In situation 2, one might wish to indicate a 41% probability for the near-normal category and 7% for the below-normal category. In situation 1 the near- and below-normal categories would more appropriately be set at 30% and 18%. In other words, in situation 1 the probability distribution would be wider than in situation 2, despite their similar central values. The simple procedure used at the CPC could not distinguish between situations 1 and 2, and the forecasts for each would be 52%, 33.3%, and 14.7%. Clearly, the procedure fails to provide as much useful forecast detail as it could.

To maximize utility, probability density functions can be used to characterize both the climatological distribution and the forecast distribution. The climatological, or unconditional, distribution is based only on a representative set of historical observations, representing a no-skill “forecast.” Given the available clues about a present climate situation, this distribution can be modified to some extent into a hopefully narrower conditional forecast probability distribution. The modified distribution is the forecast, together with its uncertainty. The climatological and forecast density functions may make use of fitted distributions (e.g., Gaussian) or may be based more directly on the raw observed and/or dynamical model ensemble forecast data (Krishnamurti et al. 1999). Either way, they express the basic attributes of the forecast in a universal format from which today’s expanding array of forecast users may transform the information in ways that best suit its needs. Forecasts expressed as probability densities could in principle be applied to any set of defined categories and are unaffected by one’s definition of the normal.

The two most fundamental components of a forecast expressed as density functions are 1) the expected value (i.e., the best guess or “point forecast,” or the numerical center of the forecast distribution), and 2) the uncertainty, or spread and shape of the probability distribution, about the expected value. When the forecast is made in a linear framework with a Gaussian model, the distributions for the climatology and the forecast are unimodal and symmetric. Three-month mean temperature is often satisfactorily modeled this way. For a climate variable that does not fit this description, such as precipitation with its typically positive skew, the data can be transformed so as to possess approximate Gaussian symmetry prior to the modeling process and then transformed back to its natural state at the end of the forecast formulation process. Or one can use a model that itself accommodates skewed distributions, such as a gamma or chi-square distribution. The precipitation forecast product illustrated below is based on a Gaussian model following a power transformation (Graedel and Kleiner 1985).

3. A “probability of exceedance” curve

Figures 1 and 2 illustrate the forecast information that is possible under typical conditions of low expected skill. It shows a forecast for 3-month total precipitation for the January–March 2000 period, made in mid-September 1999, for a 36 738 mi² region in northeastern Florida and southeastern Georgia, centered at 31.04°N, 83.18°W. The “probability of exceedance” curve gives the forecast probability that the precipitation quantity, shown on the abscissa, will be exceeded. The graph is a backward cumulative probability density function. It displays the probability distribution on a continuum such that the probability of any category can be calculated by differencing the values of the curve between two limiting precipitation values. Figure 2 shows the geographical distribution across the continental United States of the climatologically expected precipitation for January–March 2000 (dark lines), with the best-guess prediction of the departure from that normal superimposed upon it. It is noted that the location detailed in Fig. 1 is near the center of a larger region in the southeastern United States that is predicted to be on the dry side of normal in winter 1999/2000, owing to the expected continuation of La Niña conditions that had been occurring since June of 1998. Thus, although this example falls within the normal range of typically low
expected climate forecast skill, the ENSO circumstances make possible a relatively more confident forecast for this particular location. On the other hand, precipitation has generally lower forecast skill than temperature in North America, whether using statistical (Barnston and Smith 1996) or dynamical methods (Peng et al. 2000).

The curves in the graph include, first, the normal, or climatological probability distribution, fitted by a Gaussian model following linearization using a power function appropriate for the degree of skewness in the original precipitation data. Thus, the probability distribution shown in the figure incorporates the skewness, although it is difficult to notice by eye. The central positioning of the climatological curve, as defined by the precipitation amount corresponding to the 50% probability of exceedance, is based on the 1961–90 base period defined as normal during the 1990s, in accordance with World Meteorological Organization protocol. The variability, or breadth, of the climatological distribution is based on the longer 1941–90 period to obtain a more accurate estimate, given that estimation of the variability requires more cases than estimation of the central tendency. Gradual trends are not allowed to contribute to the breadth, however; this is accomplished by using a sliding 30-yr period, within the 40-yr period, to calculate the means about which the variations are defined. A second curve, labeled observed data, is a probability of exceedance curve derived from the observed data without any model fitting. It steps down by 3.33% every time an observed datum in the 1961–90 period no longer exceeds the value on the x axis. This curve allows the user to judge how good a fit the smoothed climatological curve is to the actual data and whether the discrepancies appear random or, alternatively, suggest systematic irregularities.

1This is true because in computing the standard deviation, the deviations of the data elements from the mean are squared, allowing the several most extreme values to become even more influential than they otherwise would be. This effectively reduces the number of values that contribute a given proportion to the total result; that is, it reduces the effective sample size, requiring a large actual sample to obtain a given effective sample.

Fig. 1. Graph showing the probability of exceedance of precipitation amounts (in.) for Jan–Mar 2000, made in mid-September 1999, in a region covering northeastern Florida and southeastern Georgia. The curve representing the 1961–90 climatology is shown in black, and that showing the long-range forecast is in red. See the text for details.
A third curve, labeled final forecast, is the probability distribution of the forecast. This is the distribution that results from the estimation of the shift in the central location of the distribution, combined with a possible change (decrease) in the dispersion of the distribution. The forecast shift is determined by the indications of the various tools used as input to the forecast, including both statistical and dynamical tools. The size of the shift is related to the shifts indicated by the tools, combined with estimates of their skills based on past performances. Past performances are estimated using hindcast simulations with cross-validation designs. The influence of a strong forecast by a tool with relatively poor past performance would be smaller than that of a similar forecast by a tool with a better skill history. Because tools may overlap in their sources of forecast skill, care is taken to ensure that specific climate signals (e.g., ENSO or a particular decadal trend) are not allowed to contribute to the final forecast more than once. The algorithm used to consolidate the forecasts of several tools is similar to multiple linear regression but is somewhat less formal to accommodate differing periods of the historical record among the tools. The amount of narrowing of the distribution, if any, is related to an estimate of the total variance in the climate being explained by the predictors exploited by the forecast tools. In a location that is affected by the ENSO state, for example, the forecast probability distribution is narrowed to the extent that the ENSO state can be anticipated for the forecast target period and the probability of the given climate response to ENSO. When a narrowing of the forecast distribution occurs, the downward slope of the final forecast curve in a probability of exceedance graph becomes steeper than the slope of the climatological curve, by an amount proportional to the

Fig. 2. Map showing the geographical distribution of the best-guess forecast of precipitation anomaly (in.) for Jan–Mar 2000, made in mid-September 1999. The climatologically normal precipitation amount for the period is shown by the black contours, while the shift of the median of the forecast distribution from normal is indicated by shading.
amount of narrowing; that is, the confidence associated with the best guess of the numerical forecast. (Note that with perfect confidence, the curve would be a vertical line downward, i.e., a step function from 100% to 0% associated with one abscissa value.) In the current probability of exceedance product the amount of distributional narrowing, or steepening of the slope, is the same regardless of the locational shift of the curve. It is based only on the estimate of the overall skill of the forecast based on the location, the season, and the lead time.\(^2\) In some cases there could be a locational shift of the forecast curve relative to the climatological curve but without a steepening of the slope. This would indicate some confidence in the shift away from the normal, but without a decrease in the range of possibilities in the shifted climate. This might occur when a trend, or recent apparent climate change, is believed to be occurring, but no information specific to the current forecast year is known (as in situation 1 in section 2). While such a shifted climate may be viewed as a modern normal, the shift becomes a component of the forecast when viewed with respect to the mean observed over the 1961–90 period defined as the “official” normal at the time of this writing.

A fourth pair of curves, shown by thin red lines, represents an “error envelope” paralleling the final forecast curve on each side. These lines demarcate an error estimate with respect to the forecast curve as a whole. While the forecast curve itself already conveys uncertainty about the forecast by virtue of the lack of steepness of its downward slope, the error envelope is related to uncertainty in aspects of the forecasting process such as errors in the most recent observed data, errors in the forecasters’ perception and judgement of the current climate state, or errors in the data fitting process (as revealed by nonrandom differences between the yellow and black curves). Because part of this error is related to human behavior, direct quantification is impossible. Here it is estimated subjectively, and in our opinion conservatively, based on the sampling variability of a binomial distribution with 45 yr of data. That is, the interval is set to be \(\pm (pg/45)^{1/2}\) where \(p\) is the probability of exceedance and \(g = 1 - p\). The sample size of 45 was chosen arbitrarily to yield an envelope of width deemed approximately representative of the size of climate shift required to be regarded as a “noticeable” (though not necessarily statistically significant) departure of the forecast curve from the climatological curve. Less arbitrary was the need for the envelope’s width to vary in binomial fashion as a function of the probability of exceedance value. Using the above definition, the envelope extends 7.5% upward and downward from the probability of exceedance value near the center (~40% to ~60%) of the distribution, slowly contracting toward each end. This envelope size requires that the probability anomaly for the favored tercile of the climatological distribution be at least 6%–8% in order for the forecast’s error envelope to exclude the fitted climatological probability of exceedance curve over a major portion of the range of the forecast curve. This requirement may be somewhat too strict, considering the clearly significant (but numerically modest) skills of CPC’s seasonal probability forecasts in the 1970s and 1980s as reported by Lehman (1987) in which roughly one-quarter of all forecast probability anomalies for the below- and above-normal terciles were assigned values of less than 7% and the maximum anomalies were 20%–25%. Although the error envelope may not be the correct width due to its arbitrary construction, it serves to remind users that in addition to the basic uncertainty of the future climate expressed by the forecast curve, the curve itself may be misplaced. We believe it is best to display the envelope for its conceptual value, even if its size is not correct, rather than to omit it. It is clear that uncertainty in the position of the curve is considerably smaller than the uncertainty related to the probability distribution of the climate forecast itself (i.e., the lack of a steep slope in the forecast curve, due to unpredictable internal atmospheric variability).

Near the bottom of the graph the observations of the last 15 yr are shown by the last two digits of the year (e.g., 98 indicates the observation for 1998). These digits provide information about the climate at the given location and season during recent years, with the median shown by an asterisk on the overriding line. The most recent 15 yr are chosen to represent the recent climate for precipitation, while 10 yr are chosen for temperature, based on the “optimum climate normal” work of Huang et al. (1996). More years are used for precipitation than for temperature because of its

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\(^2\)While this is a reasonable first approximation to the slope change, it can be shown in linear regression theory that higher-amplitude forecasts should be accompanied by a somewhat larger spread; that is, less steepness (Draper and Smith 1981). In other words, while a high-amplitude forecast guarantees relatively high confidence in the shift direction, the uncertainty in the exact outcome (e.g., expected mean square error with respect to best guess) increases.
noisy character, requiring a larger sample to evaluate recent tendencies. When this display of the recent-year observations indicates that the climate in the recent years is not representative of the overall normal in location or in variability, the user is faced with the question of whether the climate to occur for the forecast period may follow the tendency of the recent years. At CPC this issue is examined thoroughly and is considered as a potentially major component of the forecast. In some cases a strong trend is believed to exist and is clearly reflected in the forecast, while in others a difference in the recent climate is considered only a random occurrence. When a trend is believed to exist, the mean anomaly over the last 15 (or 10) yr is still not used at its full amplitude in the forecast; rather, it is damped toward climatology in proportion to the estimated uncertainty of its continuation, an uncertainty that is never zero given that the trend is never completely explainable physically.

Selected summarizing numerical information is provided by text inside the graph. The block of text at the upper left shows the point forecast, the numerical forecast expected to minimize squared forecast errors over an extended period using the same forecast procedure. Additional information includes the anomaly forecast and the normal (or center). For precipitation, the normal is a fitted median. The raw (nonfitted) median is also shown farther to the right. A forecast percentile is shown relative to the fitted climatological distribution. Due to the normally large uncertainty in the forecasts, the point forecasts rarely rank in the top or bottom 15% of the climatological distribution. On the upper-right side of the graph, 50% and 90% confidence intervals are given for the forecast. For precipitation, a positive skew is normally revealed in these intervals.

Three types of confidence measures are shown for the forecast. The confidence tests use cross validation, in which forecast skill is evaluated iteratively where the data being forecast are not used for forecast model development. The confidence in shift direction is confidence that the climate will deviate from the normal in the direction indicated, regardless of the size of the deviation. It is the ratio of the estimated probability that the climate will deviate in the forecast direction to the probability that it will not. Ranging from 1 to infinity, scores of 1.2 or higher are considered useful. The second confidence measure, the confidence in the point forecast, is the standard error of estimate in a linear regression context; this represents a contraction of the forecast distribution relative to the width of the climatological distribution. Its range is from 1 to 0, with 0.9 or lower considered useful. While a broadening of the forecast distribution relative to climatology (> 1.0) would also represent useful information, to date such a forecast has not been deemed issuable. As discussed briefly below, further advances with dynamical ensemble climate forecasts may lead to more complex changes to the forecast probability distribution able to be reflected in the forecast curves. The third measure, the integrated confidence, is confidence that the probability distribution as a whole will be different from the climatological probability distribution. It accounts for contributions from each of the first two confidence measures and is maximized when either of them is maximized. Its range is 0 to 1, with 0.2 or above considered useful. Verbal descriptions of the confidence levels (e.g., none, low, fair, moderate, high) accompany the ratings. It is hoped that this set of skill measures includes at least one that is suitable to most users.

The middle block of text on the right side of the graph provides forecast probabilities of selected categorical outcomes (highest and lowest 10%, and each of the three terciles, each of whose defining limits are shown) with respect to the climatological distribution. The lower block of text pertains to the observations of the most recent 15 yr, to help interpret the recent climate trend. The “center” refers to the fitted median, or representative center of the distribution, if there is skew (as often found in precipitation, as in Fig. 1). It is the 15-yr median computed in the power-transformed data, then converted back to the skewed natural state using the reciprocal of the same power. The mean is the simple average rainfall over the recent years, and the unfitted sample median shown to the right, is simply the center-ranked value of the 15 raw precipitation values. These latter two measures do not use the power transformation.

4. Present and future applications of the probability of exceedance graph

Nontechnical users can grasp the sense of the forecast both from the locational displacement of the forecast curve relative to the climatological curve and from the printed information on the graphs. For more technical users, in addition to the basic advantage of cumulative probability density functions—the opportunity to assess the likelihood of an infinite number of categorical outcomes—there are also more de-
Fig. 3. Correspondence between observed 3-month mean temperature (°F) and heating degree days (with 65°F base) in southern Florida for the Jan–Mar period. The crosses show observed data points for the 1931–98 period, and the dots illustrate a smoothed fit to the data points using a running weighted mean filter.

The number of days in a 3-month period expected to exceed or to fall below a given temperature or precipitation threshold, for example, might be related to selected aspects of the density curve for a 3-month period. Forecasts of heating and cooling degree days would be a similar type of derived forecast extension. In locations and seasons in which the daily mean temperature, that is, \((\text{max} + \text{min})/2\), may fall on either side of the commonly used 65°F degree-day threshold for heating and cooling demands, and only deviations on one side of the threshold contribute to the accumulated degree-day total, the relationship between seasonal mean temperature and degree days is nonlinear. (This is in contrast to the linear relationship that results when the temperature never crosses 65°F, e.g., Stockholm in winter for heating or Miami in summer for cooling.) Figure 3 represents the correspondence of 3-month mean temperature and heating degree days (for daily temperatures below 65°F) in southern Florida in the January–March period. The crosses represent the actual data points for the 1931–98 period, and the dots describe an empirical fit used to find the degree-day implication of a temperature forecast. This correspondence could be applied to a degree-day forecast based on the temperature point forecast (the best guess) or to a probability-weighted set of forecast temperatures where the probabilities could be those for each of several categories in an \(n\)-category system (e.g., “below normal,” etc.) Taking the latter notion to its limit, an entire probability of exceedance curve for temperature could be mapped onto Fig. 3 and a degree-day probability of exceedance forecast curve developed.

The strength of relationship between measures of daily weather, such as degree-day totals, and the 3-month density curve may increase as progress continues in research with ensemble forecasts made using dynamical models. Such model research, currently under way at several climate diagnostics and/or forecasting organizations [e.g., the National Oceanic and Atmospheric Administration’s (NOAA) Climate Diagnostics Center and NCAR in Colorado; the European Centre for Medium-Range Weather Forecasts in the United Kingdom; the Center for Ocean–Land–Atmosphere Studies in Calverton, Maryland; NOAA’s National Centers for Environmental Prediction near Washington, D.C.; NOAA’s Geophysical Fluid Dynamics Laboratory in Princeton, New Jersey; and the International Research Institute/Lamont-Doherty Earth Observatory group of Columbia University in New York], is seeking to determine the meaningfulness of the probability density functions created by the individual members of ensembles of dynamical climate model integrations using identical SST boundary conditions but differing initial atmospheric conditions. If case-specific irregularities (e.g., skewness, clustering, large gaps, etc.) in these model distributions are found to reflect more than haphazard sampling variations, more detailed probability of exceedance graphs would be possible, leading to stronger relationships with derived forecasts such as daily degree-day accumulations or frequencies of significant weather events.

Using either today’s relatively first-order (e.g., Gaussian and symmetric, but skew fitted for precipitation) probability of exceedance graphs or those that may be forthcoming with improved uses of dynamical model ensemble integrations, the sophisticated user might wish to use a long history of such graphs as input for their own integrated result, as, for example, the...
price of a financial weather derivative instrument. Deriving relationships empirically rather than logically amounts to a “correction” to the probability of exceedance curves, accounting for systematical biases of the central value and/or the spread and shape of the forecast distribution.

5. Real-time access

The CPC issues a new set of experimental forecasts for 3-month mean temperature and total precipitation for 102 mainland U.S. climate divisions every month, usually near the middle of the month. The probability of exceedance curves representing these forecasts, which go out to approximately one year in advance, can be found on the CPC Web site at http://www.cpc.ncep.noaa.gov/under “forecasts.”

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References


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