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Drought forecasting: Methodological topics from a systems perspective

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Abstract: A systemic framework is presented for organizing knowledge about drought forecasting. It includes these topics: couplings among a descriptive drought model, monitoring system, and forecasting system; propagation of uncertainties; types of forecasts and attributes of performance such as the lead time and skill; sufficient measures of skill and economic value of forecasts; theoretical and operational limits of predictability; and the interface between forecasts and drought management decisions. Reviews of operational forecasts of the seasonal snowmelt runoff volumes and forecasts of the seasonal cyclone frequencies, temperature, and precipitation in the United States illustrate the methodological topics, outline the present limits of drought predictability, and suggest promising research paths. Among them are modeling of forecast uncertainties and their propagation from states of atmospheric circulation to states of a hydrologic regime, and exploring novel forms of the hydro-meteorologic coupling that would extend the lead time and/or increase the skill of long-range drought forecasts.

Key words: Drought forecasts, forecast lead time, forecast skill, forecast value, limits of predictability, propagation of uncertainty, hydrometeorologic coupling, drought management decisions.

1 Introduction

The objective set before us is to chart directions for research in the sciences of drought description, monitoring, and forecasting. The guiding objective of this paper is twofold. Firstly, I have attempted to formulate a *systemic framework* for organizing knowledge about drought forecasting. This framework is somewhat abstract. But it seemed vital to maintain the rigor of definitions and the generality of concepts so that they may, indeed, play the intended role – that of an organizing framework for thoughts of scholars of many disciplines.

Secondly, I have attempted to review two operational forecast systems which produce:

- forecasts of the seasonal snowmelt runoff volumes in the western United States, and
- forecasts of the seasonal cyclone frequencies, temperature, and precipitation in the eastern United States.

The aim of these reviews is to illustrate components of the systemic framework for knowledge organization, to offer a partial assessment of the drought forecasting capabilities in the 1980s, and to provide a springboard for discussing various research topics, particularly at the interface of hydrology and meteorology. I wish to stress that these reviews are more partial than comprehensive, and the few statistics reported are more illustrative than sufficient. The many complexities of drought forecasting will, no doubt, receive brighter illumination as research progresses.

2 A system framework

2.1 Definition of a drought

A drought, unlike a flood, has no universal definition. To arrive at one, let us define four elements:

space areas	– river basin, region, country, hemisphere;
time periods	– month, season, year;
meteorologic variables	– mean temperature and precipitation amount during a time period at a point in space;
hydrologic variables	– runoff volume, mean groundwater level, and mean soil moisture during a time period at a point in space.

Other variables could be included as well. As a function of the space coordinates and time, each variable defines a *stochastic field.* The joint realization over time of the meteorologic fields defines the *climate* for an area.

A spatial average, or some other statistic of the field, summarizes its *state* for a given time period. An example of a state is the average areal precipitation amount accumulated over a river basin during six months from 1 January. Let $s=(t,p,r,g,m)$ denote a vector of states for the fields defined above: t – temperature, p – precipitation, r – runoff, g – groundwater, m – moisture. A *drought* is said to occur in a given area and period when an observation of the state vector s falls within a critical subdomain S_D. Different definitions of a drought are obtained by simply redefining S_D. Some scholars speak of a meteorological drought whenever $(t,p) \in S_M$, a hydrologic drought whenever $(r,g) \in S_H$, and an agricultural drought whenever $(p,m) \in S_A$. Regardless of how one defines the critical subdomain S_D, S_M, S_H, or S_A, to forecast a drought one must forecast the state vector s. We shall assume, therefore, that the two forecasts are synonymous.

2.2 Meteorologic, hydrologic, and impact forecasts

A forecast of meteorologic states provides an input into a forecast of hydrologic states (Figure 1). Both forecasts serve as inputs into forecasting drought impacts; one of them is the quality of the surface and groundwater. Because of the cascade coupling, uncertainties propagate from the meteorologic forecast to the forecast of water quantity and then to the forecast of water quality.

2.3 Drought forecasting system

The scientific knowledge and historical data provide a basis for developing descriptive models of droughts. In a broad sense, a descriptive model outputs a *prior distribution* of the state vector s. Under the assumption that the climate is stationary from year to year, the prior distribution provides a drought forecast for every year in an infinite series. Since this forecast is identical for every year, we shall call it a *naive forecast.* It contrasts with a *perfect forecast* that would specify the actual observation of s for every future year.

The essence of skillful forecasting is the aggregation of the prior distribution with present observations of various hydrometeorologic variables collected by the monitoring system (Figure 2). Through a likelihood function, the observations convey any predictive information they contain about the realization of the state vector s in the immediate future. The output from the forecast system is the *posterior distribution* of the state vector s. The skill of the forecast is demonstrated when the posterior distribution for a given period differs from the prior distribution. More on this later.

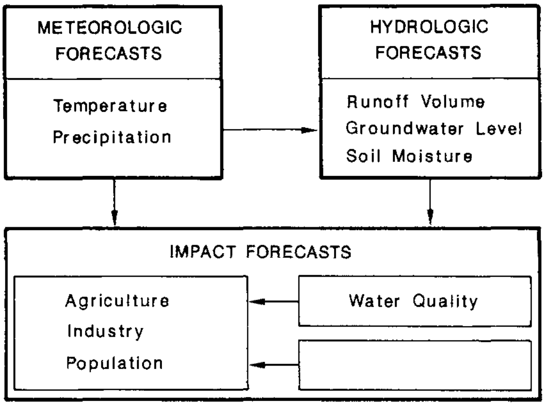


Figure 1. Couplings among meteorologic forecasts, hydrologic forecasts, and impact forecasts

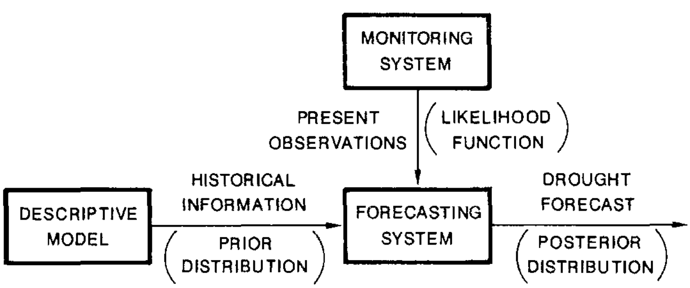
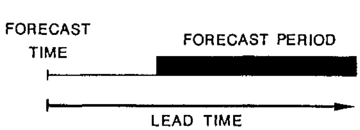


Figure 2. Couplings among the descriptive model, the monitoring system, and the forecasting system



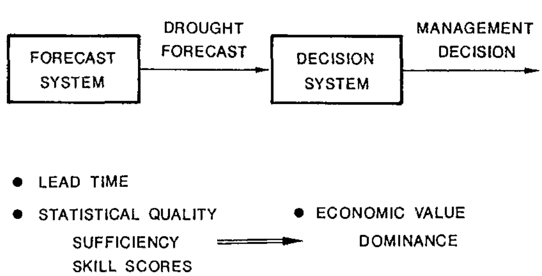


Figure 3

Figure 4

Figure 3. Forecast lead time

Figure 4. Coupling between forecasting and decision making; measures of forecast performance

Behind the scheme in Figure 2, the reader may recognize Bayesian principles. While not every forecasting system is explicitly Bayesian, this scheme offers us a general framework for discussing, evaluating, and comparing various forecast systems.

2.4 Climate change and drought forecasts

The possibility of a climate change is so vigorously studied that we feel compelled to address the topic. Within our Bayesian framework, a change in climate is synonymous with a nonstationarity of the prior distribution. A forecast of the climate change should be expressed in terms of a sequence of distributions of s for some years into the future. A drought forecaster could then use the distribution for the next year as his prior distribution. Practically, this coupling between the climate change forecasting and drought forecasting may be unnecessary; prior distributions estimated from climatological records should suffice. The reason is that within the potential lead time of drought forecasts, which is on the order of a few months or years at most, the nonstationarity of the prior distribution appears insignificant vis-a-vis other sources of the forecast uncertainty.

2.5 Types of forecasts

Let ω denote the state being forecasted, an element of s. A *categorical forecast* specifies a point estimate x of ω. *Ex post*, one may analyze the forecast error $\varepsilon = x - \omega$. *Ex ante*, the forecast uncertainty is quantified completely in terms of a posterior distribution $H(\omega|x)$ of the state ω, conditional on the estimate x. This distribution is obtained through post-processing of forecasts. The conditional mean $E(\omega|x)$ usually varies with x, but the conditional variance $Var(\omega|x)$ is usually independent of x. In other words, the degree of uncertainty that remains about the state ω does not depend upon present observations that generate the forecast; rather the degree of uncertainty remains the same from year to year.

A *probabilistic forecast* specifies a distribution $P(\omega)$ of the state ω. The forecast itself quantifies the degree of uncertainty that remains about ω, conditional upon all available observations. This degree of uncertainty is likely to vary from year to year, and so is the variance of ω under distribution P. Let $H(\omega|P)$ denote the posterior distribution of ω, conditional on forecast P. The forecast is said to be perfectly calibrated if $H(\omega|P) = P(\omega)$, that is the forecast itself is the posterior distribution.

To encompass both types of forecasts, we shall let ϕ denote either x or P, and $H(\omega|\phi)$ denote the posterior distribution of ω, conditional on ϕ.

2.6 Forecast lead time

The *forecast time* is the instant up to which the hydrometeorologic variables for preparing the forecast have been observed. The *forecast period* coincides with the time period over which the state ω is defined. The *lead time* of the forecast, λ, is the time interval elapsed from the forecast time to the end of the forecast period (Figure 3). For example, a forecast prepared on 1 January of the runoff volume from 1 April through 30 September has a lead time of 9 months.

2.7 Forecast performance and comparison

For a fixed lead time, the performance of a forecast may be gauged on an interval scale bounded by the performance of a naive forecast (specifying the prior distribution of the state) and the performance of a perfect forecast (specifying the actual value of the state). Performance measures characterize two attributes of forecasts:

- statistical quality,
- economic value.

Popular measures of statistical quality are *skill scores*; they are independent of the use of forecasts. On the other hand, the *economic value* depends upon the decision problem in which forecasts are employed and is a function of both the lead time and statistical quality of forecasts (Figure 4).

Suppose two systems produce forecasts x and y of the same state ω, with the same lead time λ. A preference order between x and y may be established either in terms of their economic values (for a given decision problem) or in terms of their skill scores. The two preference orders need not be consistent.

If for every rational decision maker (who maximizes his expected utility of outcomes under the posterior distribution of ω), forecast x has a higher economic value than forecast y does, then x is said to *dominate* y (equivalently, x is said to be more informative than y). There exists one, and only one form of statistical comparison of forecasts which is always consistent with the dominance order, provided such an order exists. This comparison employs a binary relation of sufficiency. Forecast x is said to be *sufficient* for forecast y if, for every fixed value of the state ω, forecast y can be generated from forecast x through an auxiliary randomization. If x is sufficient for y, then x dominates y.

The significance of the sufficiency relation cannot be overemphasized: whenever x is found to be sufficient for y, then one knows, without any further analyses, that x has higher economic value than y for every rational user of forecasts. Ergo, x should be preferred over y from the societal point of view. That is why alternative improvements of drought forecasts which serve many users should always be ranked in terms of the sufficiency relation.

2.8 *Limits of predictability*

It is often, though not always, the case that longer forecast lead times are accompanied by higher uncertainty about the actual state ω. In such a case, the shortest lead time at which every posterior distribution $H(\omega|\phi)$ becomes indistinguishable from the prior distribution $G(\omega)$ defines the *potential lead time* of forecasts, Λ. For every lead time λ shorter than Λ, there is an upper bound on the forecast skill or economic value. The envelope of the highest achievable skill for all lead times λ up to Λ establishes the *limit of drought predictability*. Two kinds of limits may be considered.

- The theoretical limit of predictability is imposed by the status of the hydrometeorological sciences. To extend this limit, new knowledge about drought-causing processes must be gained and present theories must be expanded.
- The operational limit of predictability, naturally shorter than the theoretical one, stems from the level of technology and resources employed by a forecast service. Too sparse measurements of the atmosphere, too slow computers, or too little manpower are just a few examples of the limiting factors.

Matching the operational and theoretical limits of predictability may seem an ideal goal. But the economic rationality demands a tradeoff: we must decide when to push the operational limits of predictability within the confinements of the present theories, and when to invest in research that may move the theoretical limits of predictability to a higher level, thereby creating a potential for more cost-effective operational improvements.

2.9 *Interface with decision making*

While gaining the capabilities of a clairvoyant is the ideal goal of research on drought forecasting, selecting feasible goals is by no means a clear cut task. Should we pursue research towards increasing the lead time of forecasts having a specified level of skill, or should we research ways of increasing the skill of forecasts for some fixed lead time? The climatic and hydrometeorologic considerations may point out promising research paths. But to ascribe to them a rational preference order, it is necessary to examine the ultimate purpose of drought forecasts – which is to provide information for decision making. The normative needs of decision processes should thus be identified. A few exemplary questions:

- How should forecast uncertainty be expressed in order to provide a basis for rational decisions?
- What should be the lead time of forecasts for strategic planning and operational decisions?
- What is the optimal frequency of updating forecasts for adaptive (sequential) decision strategies?

Naturally, the answers to these and other questions will vary across decision problems. Problems most sensitive, economically and otherwise, to the characteristics of drought forecasts should guide the research.

3 Seasonal runoff forecasts

3.1 System description

Each year the Soil Conservation Service (SCS) of the U.S. Department of Agriculture, in cooperation with other agencies, prepares a series of five forecasts of runoff volumes during the snowmelt season. The snowmelt process extends over several months, depending on the geographic location: from January to May in Arizona, from April to September in Montana. Forecasts are issued at the beginning of each month from January through May for 533 river gauging stations in 11 western states. The first forecast is thus prepared five to nine months before the actual runoff can be observed. The SCS disseminates the forecasts through a computerized system, known as the "Centralized Forecast System," and through a monthly bulletin, entitled "Water Supply Outlook for the Western United States," which is published jointly with the National Weather Service. In summary:

- forecasted states: runoff volumes at 533 stations,
- forecast period: 1-6 months,
- lead time: 1-9 months.

3.2 Forecasting methodology

The forecasts are categorical, objective/subjective. For each station and forecast period, a multivariate regression model outputs an estimate of the runoff volume which may next be adjusted judgmentally by the hydrologist in charge of a given river basin. The predictors in the regression models include soil moisture and temperatures antecedent to snowpack formation, and precipitation, snow water equivalent, temperatures, and runoff observed up to the forecast time. Future precipitation and states affecting the snowmelt process, such as temperatures and winds, are not known, of course, and they are the main source of uncertainty. The long lead times and skills of these forecasts derive mainly from the fact that 50-80% of the mean annual runoff in the West comes from snowmelt.

3.3 Posterior uncertainty

The extent to which forecasts reduce the prior uncertainty is illustrated in Figure 5 for the Boise River near Twin Springs, Idaho. The prior density of the runoff volume ω during the April-July period is contrasted with two posterior densities of ω, conditional on forecasts x_1 and x_5 issued on 1 January, with the lead time of 7 months, and 1 May, with the lead time of 3 months, respectively. The forecasts happened to indicate the same runoff, $x_1 = x_5 = 100$. Inasmuch as the forecasts are categorical, the posterior variances remain constant from year to year, and only the posterior means vary with x_1 and x_5.

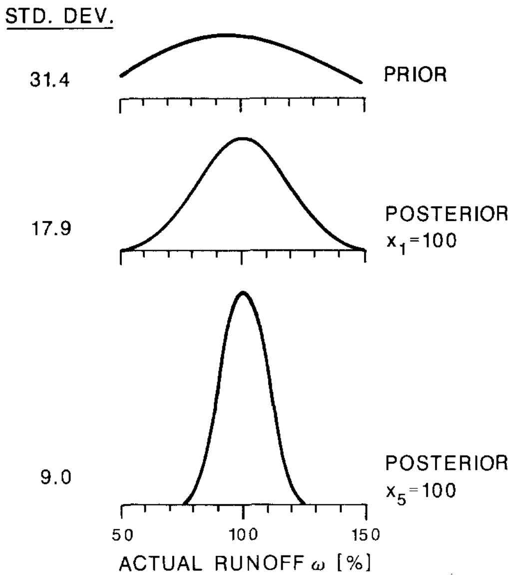


Figure 5. Prior and posterior densities of seasonal runoff volume. Station: Boise River near Twin Springs, Idaho. Runoff season: April-July. January forecast x_1; May forecast x_5. Units: percentages of the 25-year (1961-1985) mean runoff volume

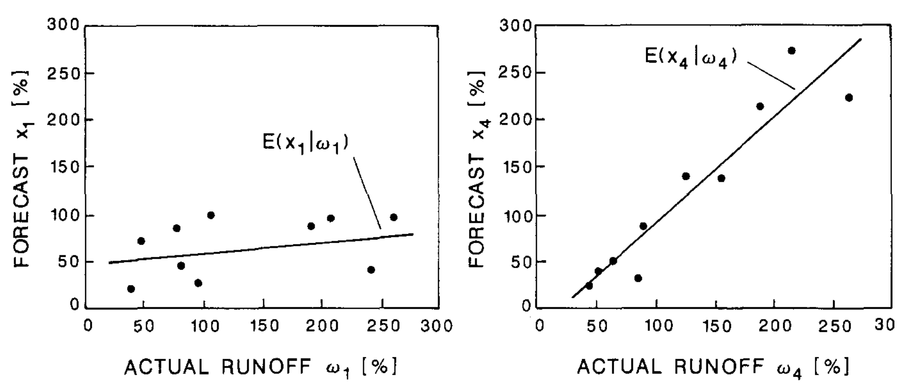


Figure 6. Forecast versus actual seasonal runoff volume. Station: Salt River near Roosevelt, Arizona. Period of record: 1979-1988. January forecast x_1 of the January-May runoff. April forecast x_4 of the April-May runoff. Units: percentages of the 25-year (1961-1985) mean runoff volume

3.4 Forecast performance

3.4.1 Model of forecast errors

Several studies have analyzed the seasonal runoff forecasts with respect to their statistical quality (Shafer and Huddleston, 1985; Krzysztofowicz and Watada, 1986; Krzysztofowicz and Reese, 1991) and economic value (SCS, 1977; Krzysztofowicz, 1986). We found that the relationship between the actual runoff ω_n and the forecast x_n issued on the first of the nth month (n=1,2,3,4,5) could be modeled in terms of a linear equation

Table 1. Two seasonal runoff forecasts for the Salt River near Roosevelt, Arizona

Forecast	x_1	x_4
Forecast Time	1 January	1 April
Forecast Period	Jan.-May	April-May
Lead Time (Months)	5	2

Table 2. Parameter estimates for forecasts listed in Table 1

n	a_n	b_n	σ_n	S_n	SSC_n
1	0.11	50.66	25.74	80.23	2.92
4	1.13	-24.23	29.53	70.95	0.37

Table 3. Lead times of forecasts having about the same quality

River	Forecast Time	Lead Time (months)
Boise	1 January	7
Yellowstone	1 April	6
Salt	15 February	3.5

$$x_n = a_n\omega_n + b_n + \theta_n, \tag{1}$$

where a_n and b_n are fixed parameters, and θ_n is a random variable, stochastically independent of ω_n, and having a normal density with moments $E(\theta_n) = 0$ and $Var(\theta_n) = \sigma_n^2$. The conditional mean

$$E(x_n | \omega_n) = a_n\omega_n + b_n \tag{2}$$

then gives the regression line.

Figure 6 shows exemplary relationships estimated from a 10-year record (1979-1988) for the Salt River near Roosevelt, Arizona. The two forecasts being compared are described in Table 1, and the parameter estimates are shown in Table 2. They support the visual impression from Figure 6 of the distinct statistical qualities of forecasts. On the average, forecast x_1 with a 5-month lead time overestimates low runoffs and substantially underestimates high runoffs. On the other hand, forecast x_4 with 2-month lead time shows only a small opposite tendency. Still, the errors of individual forecasts may occur as large as 50% of the mean runoff volume.

3.4.2 Standardized sufficiency characteristic

Under model (1), the statistical quality of forecasts is completely summarized in a *Standardized Sufficiency Characteristic* (SSC), defined as the ratio of the standard deviation σ_n of the residual θ_n to the product of the absolute value of the slope coefficient a_n and the prior standard deviation S_n of the runoff volume ω_n:

$$SSC_n = \frac{\sigma_n}{|a_n| S_n}. \tag{3}$$

For the perfect forecast, $SSC_n = 0$. For the forecast produced by guessing, or a random number generator, $SSC_n = \infty$. In a comparison of any two forecasts: forecast x_m is sufficient for forecast x_n if, and only if,

$$SSC_m < SSC_n. \tag{4}$$

The *SSC* values reported in Table 2 vividly differentiate between the statistical qualities of forecasts having different lead times.

3.4.3 Limits of predictability

To obtain some indication of the limits of predictability, we have plotted the SSC as a function of the forecast time for three stations:

Yellowstone River at Billings, Montana,

Boise River near Twin Springs, Idaho,

Salt River near Roosevelt, Arizona.

Figure 7 shows these SSC plots, as well as the forecast periods. Several observations can be made.

1. For every station, the forecast quality generally improves as the lead time becomes shorter. Most of these improvements take place between the January and March forecast times.

2. Tradeoffs between the quality and lead time of forecasts are distinct for each river. Forecasts for the Boise River exhibit the highest quality, even though they do not have the shortest lead times. Forecasts for the Yellowstone River have the longest lead times, yet their quality is not uniformly the lowest. These facts pinpoint that the limit of runoff predictability is, not unexpectedly, a function of the geographic location and climate.

3. Another way of characterizing the limits of predictability is to fix a level of forecast quality and compare the longest achievable lead times. Figure 7 indicates that three forecasts, listed in Table 3, have about the same quality. These forecasts can be prepared with the lead times of 7 and 6 months for the Boise and Yellowstone Rivers, respectively, but only 3.5 months for the Salt River.

3.5 Extending the limits of predictability

Since by the end of May, almost all snowpack has already accumulated, the quality of the May forecasts indicates the limit of runoff predictability by hydrologic models employed presently. Figure 7 suggests that there is still room for some improvement. One possible research avenue is to better harness the capabilities of conceptual hydrologic and hydraulic models, as exemplified by the Extended Streamflow Prediction program of the National Weather Service (Day, 1985).

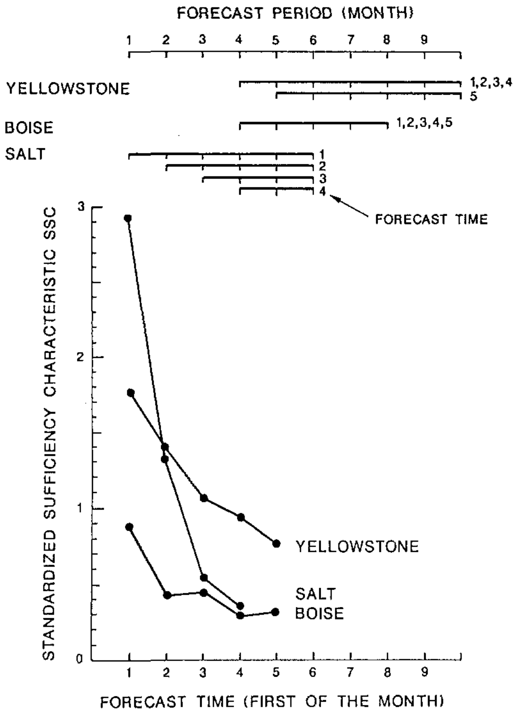
But to improve the quality of the early forecasts, it will be necessary to couple hydrologic models with long-range meteorologic forecasts of states such as precipitation, temperature, and winds during the snowmelt season. Likewise, in order to extend the lead times of the runoff forecasts, forecasts of meteorologic states such as snowfall during the winter season would have to be inputted into hydrologic models.

There are strong economic reasons for extending the limits of runoff predictability. Most of the major planning decisions associated with agricultural production and water allocation in the West are, or should be, made prior to March, sometimes even as early as in November of the previous year (Krzysztofowicz and Reese, 1988). Figure 7 assures us that there still remain great challenges en route to improving the first forecasts or to preparing them a few months earlier.

4 Long-range meteorologic forecasts

4.1 Emerging predictability

The field of long-range weather forecasting has made a few strides in the last two decades (Nicholls, 1980, 1988; Madden, 1983; Hastenrath, 1987; Lehman, 1987). Sys-



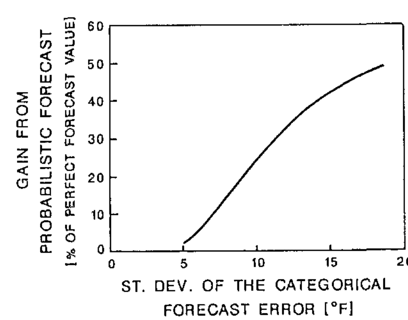


Figure 7

Figure 8

Figure 7. Performance of seasonal runoff forecasts for three gauging stations

Figure 8. Economic gain from a probabilistic forecast of daily temperature (relative to the economic value of a categorical forecast), as a function of the standard deviation of the categorical forecast error, for a single-period quadratic decision problem

tems have been developed that produce long-range forecasts of various meteorologic states with some positive measure of skill. Some of these systems have been tested on historical records as well as used operationally, and verification data have been accumulating. All these developments suggest that it may be worthwhile to initiate research toward coupling the long-range weather forecasts with hydrologic runoff models. The goal of such research would be to increase the lead time of hydrologic drought forecasts. Before examining the methodological issues involved in modeling of this interface, let us briefly review one particular system for seasonal weather forecasting.

4.2 Seasonal forecasts of cyclone frequencies

The UVA Climate Forecast System was developed by Hayden and his associates (Hayden and Smith, 1982; Hayden, 1984). It consists of multivariate statistical models that forecast cyclone frequencies during the next 6 months, based on the cyclone frequencies observed during the 6 months preceding the forecast time. Thus, when the forecasts are prepared every month, there are 12 forecast periods in a year. A forecast specifies the expected frequency of cyclones in each of 87 cells of a rectangular grid, 2.5° latitude by 5.0° longitude, covering the eastern United States and western Atlantic. The field of the expected cyclone frequencies enables the forecaster to trace the expected most frequent storm tracks during the forecast period.

The skill of these forecasts derives from the season-to-season persistence discovered in stochastic fields of cyclone frequencies (Hayden and Smith, 1982). The system was verified by making hindsight forecasts for the years 1960-1980 (not used in the estimation of model parameters), and by making operational forecasts for the years 1981-83. Hayden (1984) reports several measures of skill, one of them being the hit rate: the proportion of grid cells in which the forecasted and actual cyclone frequencies are both either below the prior (climatological) mean for a given forecast period, or above the mean. The average (over the years) hit rate varied slightly among the 12 forecast periods. The overall average hit rate was about 75%. By comparison, the simple persistence forecast scored only 69%.

4.3 Seasonal forecasts of temperature and precipitation

The seasonal forecast of the cyclone frequencies is used next to produce forecasts of the mean seasonal temperature and precipitation at designated ground stations. Such forecasts have been prepared operationally for the state of Virginia since 1981 in the Office of the State Climatologist headed by Dr. Patrick J. Michaels. The operational forecasts are prepared for several stations at the beginning of each quarter, for two consecutive forecast periods, each 3-months long. The model outputs a continuous point estimate of the forecasted state which may next be adjusted judgmentally by a forecaster to account for local geographical effects. The final forecasts are thus categorical, objective/subjective, and have lead times of 3 and 6 months. They are disseminated through a quarterly publication "Virginia Climate Advisory."

The cumulative verification analysis of over 370 forecasts issued through June 1989 indicated the average expected hit rate of about 60% for both temperature and precipitation. A hit is recorded for a station whenever the forecasted and actual values are both either below the prior (climatological) mean for a given forecast period, or above the mean.

4.4 Discussion

4.4.1 On the value of long-range forecasts

If we take the forecasts produced by the UVA Climate Forecast System as illustrative of the present limits of seasonal weather predictability, then the question often posed is whether such forecasts have the skill high enough to merit their use as inputs into hydrologic models and management decisions. The question cannot be answered based on skill scores alone. What is necessary first, is a complete quantification of uncertainties about the forecasted states in terms of prior and posterior distributions, such as those shown earlier in Figure 5. Next, the original question should be rephrased: By how much does the seasonal weather forecast reduce the prior uncertainty? The answer may be sought either in terms of statistical measures of informativeness or, preferably, in terms of economic benefits accrued from the resultant *drought management decisions* – rational decisions that optimally account for the posterior uncertainty.

There is a dearth of scientific studies on the subject. One of the few, by Brown et al. (1986), investigated the economic value of the 30-day and 90-day precipitation outlooks disseminated monthly and bimonthly, respectively, by the National Weather Service. The decision problem concerned crop production planning by farmers in the northern Great Plains in the states of Montana and North Dakota. The study concluded that for this particular problem, current forecasts are of minimal value, but a relatively modest increase in forecast quality would have large economic benefits. Since forecast value is problem-dependent, many more studies are needed to allow us any generalizations.

4.4.2 On modeling of uncertainties

There is a general theoretical result (Krzysztofowicz, 1983) to the effect that the less skillful a categorical forecast, the more valuable a probabilistic forecast (which explicitly quantifies the uncertainty). Figure 8 shows an example of such a relationship. Inasmuch as the long-range weather forecasts have generally low skill, proper extraction of information is particularly important. A Bayesian decision procedure is recommended for drought management decisions because it is the only procedure that automatically guards against realizing a negative value of information from notoriously poor forecasts. We should, therefore, research ways of modeling uncertainties associated with long-range forecasts within a Bayesian framework of information-processing.

4.4.3 On the hydro-meteorologic coupling

If the state of interest is runoff, then it becomes necessary to couple a meteorologic forecast system with a hydrologic forecast system and to model the *propagation of uncertainties*. The posterior distributions of runoff with and without a long-range weather forecast would then provide a basis for determining the value of the coupling.

My final thought is a conjecture on the possible forms of couplings. It appears that Professor Hayden's forecast system lends itself to two alternative coupling schemes. The first scheme could follow the phenomenological chain:

$$\begin{array}{c}\text{forecast of cyclone frequencies}\\ \downarrow \\ \text{forecast of precipitation}\\ \downarrow \\ \text{forecast of runoff}\end{array}$$

The second scheme could be direct:

$$\begin{array}{c}\text{forecast of cyclone frequencies}\\ \downarrow \\ \text{forecast of runoff}\end{array}$$

The conjecture is that, with both coupling schemes being of equal complexity, the second scheme will produce runoff forecast x that is sufficient for runoff forecast y produced by the first scheme. The support comes from statistical theory of sufficiency: if we begin with a multivariate distribution over the field of cyclone frequencies, then en route to deriving a distribution of the runoff, scheme one involves an auxiliary stochastic transformation since the precipitation forecast is unlikely to constitute a sufficient statistic of the cyclone frequency field. If x is sufficient for y, then the economic payoff from the second scheme will exceed that from the first scheme.

The conjecture offers, therefore, a rationale for invigorating research on *stochastic hydrometeorology of droughts*. In a broad sense, the aim would be to search for direct stochastic transformations between states of atmospheric circulation and states of a hydrologic regime – transformations that minimize the propagation of uncertainty and thereby attain the theoretical limit of drought predictability.

Acknowledgments

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