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Weighted Parametric Operational Hydrology Forecasting

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Abstract

An existing non-parametric method for using meteorology probability forecasts in operational hydrology builds a sample of possibilities for the future, of climate series from the historical record, which is weighted to agree with selected forecasts of meteorology probabilities. It concentrates on isolated event probabilities rather than on the entire probability distribution of various variables. It sometimes assigns the same weight to all climate series in selected categories, resulting in the same relative frequency for those climate series. This results in a discontinuity in the probability distribution at interval boundaries. By changing to a parametric approach, one determines entire probability distributions that match available forecast meteorology probabilities. This allows a continuous distribution of probability across a variable, allowing more meaningful interpretations for all values of the variable, such as avoiding too much probability in the tails. However, a parametric method is difficult to apply when multiple variables are considered because the assumption of a distribution(s) further constrains the matching of probabilistic meteorology forecasts. The existing non-parametric method provides useful elimination of conflicting probability constraints until a feasible solution exists. The non-parametric method can be extended into a new weighted parametric hydrological forecasting technique to allow the specification of probability distributions for the meteorological variables of interest. Extended forecast comparisons reveal that the old non-parametric method utilizes more meteorological forecast information in a hydrological forecast then the new parametric method, but the new may be doing a more reasonable job in that the derived distributions are more intuitive.

Weighted Non-Parametric Operational Hydrology

Croley (1996, 1997a) describes a non-parametric method for weighting a sample of possible hydrologic scenarios, constructed from pieces of the historical meteorological record with appropriate hydrology models. He extended operational hydrology approaches for generating multiple future hydrology scenarios, similar to ensemble stream flow prediction (ESP) methods (Day 1985, Smith et al. 1992), to allow incorporating forecast meteorology probabilities. The method selects weights for the scenarios so that relative frequencies of selected meteorology events in the resulting sample match forecast meteorology probabilities. To summarize briefly, consider that the probability of any event A, $P[\mathrm{A}]$, is inferred with the estimator, $\hat{P}[\mathrm{A}]$, defined as the number of observations in the sample for which A occurs (i.e., for which the event A is true), n_{A}, divided by the total number of observations in the sample, n:

$$\hat{P}[\mathrm{A}] = \frac{n_{\mathrm{A}}}{n} = \frac{1}{n}\sum_{i|\mathrm{A}} 1 \qquad (1)$$

In (1), the sum is taken over all i (members of the sample) for which A occurs, denoted as $i \mid \mathrm{A}$. The estimate in (1) is seen as the "relative frequency" of A in the sample. Croley (2000a) *altered* samples by multiplying observations by non-negative weights, w_i, to calculate probabilities matching others' *multiple* forecasts of meteorology probabilities (for possibly different locations, time periods, and meteorology variables). Thus (1) becomes, with weights:

$$\hat{P}[\mathrm{A}] = \frac{1}{n}\sum_{i|\mathrm{A}} w_i \tag{2}$$

$$\sum_{i=1}^{n} w_i = n \tag{3}$$

Consider now that others' forecasts of meteorology event probabilities can be interpreted in m probability equations (Croley 1996, 2000a),

$$\hat{P}[\mathrm{A}_k] = a_k, \qquad k = 1, \ldots, m \tag{4}$$

where A_k are various meteorology events and a_k are forecast probabilities. By applying (2) to (4) and adding to (3), we get a system of equations to solve for the weights:

$$\begin{aligned} \sum_{i=1}^{n} w_i &= n \\ \sum_{i \mid \mathrm{A}_k} w_i &= n\, a_k, \qquad k = 1, \ldots, m \end{aligned} \tag{5}$$

Croley (1997b, 2000a) then extended the methodology further to incorporate forecasts of most-probable meteorological events; he interpreted the u probability inequalities in terms of sample weights and added them to the problem formulation of (5):

$$\begin{aligned} \sum_{i=1}^{n} w_i &= n \\ \sum_{i \mid \mathrm{A}_k} w_i &= n\, a_k, \qquad k = 1, \ldots, m \\ \sum_{i \mid \mathrm{A}_k} w_i &\le n\, a_k, \qquad k = m+1, \ldots, m+u \end{aligned} \tag{6}$$

Any weights that satisfy (6) yield weighted-sample relative frequencies of events that match forecasts of meteorology probabilities. These weights also yield other correspondingly weighted sample estimators, which are the derived hydrologic forecasts of interest. The methodology allows inclusion of both types of meteorological forecasts simultaneously for multiple time periods, lag times into the future, meteorological variables, spatial scales, and forecast agencies.

Often, it is impossible to satisfy all equations in (6) because they conflict. Different agency forecasts may directly conflict with one another or several forecasts may be at odds, depending on what events have taken place in the historical record. When it is impossible to satisfy all constraints, the solution space is empty and the problem solution is infeasible. When considering incompatible forecasts, or when there are more forecast equations than there are weights to determine (also an infeasible solution), one assigns a priority to each equation in (6), reflecting its importance. Each equation (starting with the lowest priority) is compared to the set of all higher-priority equations and eliminated if redundant or infeasible, repeating until a feasible set is identified. Thus (6) can always be reduced so that the allowed number of equations is less than or equal to the number of historical record pieces (sample size). If less, then there are multiple solutions to (6), and a choice must be made as to which solution to use; identification of the "best" requires a measure or objective function for comparing them. One such measure is the sum of squared differences of the weights with unity, and the objective is its minimization: $\min \sum_{i=1}^{n} (w_i - 1)^2$. Croley (2000a) also formulated the objective of maximizing the probability of a selected event, $\hat{P}[\mathrm{A}_0]$, transforming the probability statement with (2) into a maximization of a sum of some of the weights, $\max \sum_{i|\mathrm{A}_0} w_i$. The problem of (6) can be formulated as an optimization subject to a "constraint set" of equations:

$$
\begin{aligned}
&\min \sum_{i=1}^{n} \left(w_i - 1\right)^2 \quad \text{OR} \quad \max \sum_{i\,|\,\mathrm{A}_0} w_i \\
&\text{subject to} \\
&\qquad \sum_{i=1}^{n} w_i = n \\
&\qquad \sum_{i\,|\,\mathrm{A}_k} w_i = n\,a_k, \qquad k = 1, \ldots, m \\
&\qquad \sum_{i\,|\,\mathrm{A}_k} w_i \le n\,a_k, \qquad k = m+1, \ldots, m+u \\
&\qquad w_i > 0, \qquad k = 1, \ldots, n \\
&\qquad \text{OR} \quad w_i \ge 0, \qquad k = 1, \ldots, n
\end{aligned}
\tag{7}
$$

Equations (7) are amenable to either classical calculus of variations or linear programming optimization techniques; Croley (2000a) describes procedures for both, applied within an iterative elimination of infeasible solution spaces. Multiple optima are possible, depending upon the objective and constraints.

Recently, Croley (2000b, 2001a,b,c) applied the methodology to a different kind of sample of future hydrology possibilities; rather than generate the sample through operational hydrology applied to historical meteorology, he constructed it directly from the historical record of both hydrology and meteorology, as in the classical statistical analysis of annual extremes. This allowed climate weighting of storm-frequency estimates.

A Parametric Approach

Recently, this method was criticized for concentrating on isolated event probabilities rather than on the entire probability distribution for various variables (Stedinger and Kim 2002). The criticism centers on the sometimes assignment of the same weight to all climate series in selected categories (for the univariate case), resulting in the same relative frequency for those climate series. This results in a discontinuity in the probability distribution at interval boundaries. For example, when using the National Oceanic and Atmospheric Administration's (NOAA's) extended climatic forecast prepared by NOAA's Climate Prediction Center, the method selects meteorology events consisting of precipitation or air temperature (defined over 1- and 3-month periods) being in their lower, middle, and upper terciles (as defined from a reference period). The historical relative frequencies of one-third in each of these ranges could be forecast as, say, 40%, 20%, and 40% respectively, but represented as uniform within each interval (resulting in a discontinuity between intervals). Stedinger (personal communication, 2002) suggests the use of a fitted distribution to allow smoother weighting (thereby avoiding discontinuities in the corrected marginal distribution at interval boundaries and giving more meaningful interpretations to all values of the random variable, such as avoiding too much probability in the tails). By hypothesizing a distribution for each key variable, one can calculate distribution parameters so that probabilities over selected intervals match available probabilistic forecasts. This parametric method would generate a consistent and smooth probability adjustment across the entire range of a key variable, reflecting more appropriate changes in the likelihood of each climate series than is done with the non-parametric method.

Moments of the marginal distribution for a variable X can be estimated from a weighted sample with sample moments (only an example here; "hats" denote estimators):

$$
\begin{aligned}
\hat{m}_X &= \frac{1}{n}\sum_{i=1}^{n} w_i x_i \\
\hat{s}_X^2 &= \frac{1}{n-1}\sum_{i=1}^{n} w_i \left(x_i - \hat{m}\right)^2 \\
\hat{y}_X &= \ldots, \qquad \text{etc.}
\end{aligned}
\tag{8}
$$

where $\hat{m}_X$, $\hat{s}_X^2$, and $\hat{y}_X$ are sample mean, variance, and skew, respectively. By transforming the sample through weighting, we can construct a marginal distribution for each variable, which matches boundary constraints given by probabilistic meteorology forecasts, as in (4). Given the cumulative distribution families $F_X\left(x; m_X, s_X^2, \ldots\right)$, …, $F_Z\left(z; m_Z, s_Z^2, \ldots\right)$, for each variable X, …, Z, respectively ("$m_\bullet, s_\bullet^2, \ldots$" represent the distribution parameters), the probability forecasts of (4) are rewritten by expressing the events, A_k ($k = 1, \ldots, m$), in terms of their constituent variables: X, …, Z. For example:

$$
\begin{array}{lcl}
F_X\left(x_{g_1}; m_X, s_X^2, \ldots\right) = a_1 & & F_Z\left(z_{g_{m-j+1}}; m_Z, s_Z^2, \ldots\right) = a_{m-j+1} \\
\vdots & \cdots & \vdots \\
F_X\left(x_{g_i}; m_X, s_X^2, \ldots\right) = a_i & & F_Z\left(z_{g_m}; m_Z, s_Z^2, \ldots\right) = a_m \\
\vdots & & \vdots
\end{array}
\tag{9}
$$

where there are i probability constraint forecasts for variable X, …, and j for Z. The distributions must be compatible (i population moments to estimate for X, …, and j for Z).

By solving (9) for the corresponding values of the population moments for each distribution and remembering that the sample moments from (8) are estimators of the population moments, we can write equations for the sample weights:

$$
\begin{array}{rclcrcl}
\frac{1}{n}\sum_{i=1}^{n} w_i x_i & = & m_X & & \frac{1}{n}\sum_{i=1}^{n} w_i z_i & = & m_Z \\
\frac{1}{n-1}\sum_{i=1}^{n} w_i \left(x_i - m_X\right)^2 & = & s_X^2 & \cdots & \frac{1}{n-1}\sum_{i=1}^{n} w_i \left(z_i - m_Z\right)^2 & = & s_Z^2 \\
 & \vdots & & & & \vdots &
\end{array}
\tag{10}
$$

These equations are linear in the weights. Any number of equations on each variable and even two-boundary intervals in the probability statements could be used, as required by the probability forecasts of (4). The number of probability forecast equations for each variable limits the distribution types that may be considered. The number of distribution parameters must be less than or equal to the number of available forecast equations. With alternate numbers of equations for each variable, the details of (10) will differ in the number of sample moment equations required, but the method would be essentially the same. Likewise, if distributions such as the lognormal were used (where the normal distribution was fit to the logarithms of the data), then (10) would be written in terms of the logarithms of the sample values. In all cases, it should be possible to derive a set of equations.

Note that (10) is similar to (6) except the coefficients on the weights are not strictly zero or one. At this point an optimization, such as minimizing $\sum_{i=1}^{n}\left(w_i - 1\right)^2$ or maximizing the probability of a selected event, could be used to find a solution to (10) supposing that a feasible solution exists.

$$
\min \sum_{i=1}^{n}\left(w_i - 1\right)^2 \quad \text{OR} \quad \max \sum_{i \mid A_0} w_i
$$

subject to

$$
\begin{array}{rclcrcl}
\frac{1}{n}\sum_{i=1}^{n} w_i x_i & = & m_X & & \frac{1}{n}\sum_{i=1}^{n} w_i z_i & = & m_Z \\
\frac{1}{n-1}\sum_{i=1}^{n} w_i \left(x_i - m_X\right)^2 & = & s_X^2 & \cdots & \frac{1}{n-1}\sum_{i=1}^{n} w_i \left(z_i - m_Z\right)^2 & = & s_Z^2 \\
 & \vdots & & & & \vdots & \\
w_i & \geq & 0, & i = 1, \ldots, n & & &
\end{array}
\tag{11}
$$

The existing non-parametric method provides a very useful and carefully engineered mechanism for eliminating conflicting probability constraints until a feasible solution exists. This is a real-world approach to the problem, recognizing that multiple probabilistic meteorology forecasts from several agencies (perhaps) are not always sensible. Its iterative elimination of infeasible solution spaces can be used with (11) in a new weighted parametric hydrological forecasting technique. However, if an equation is indicated as infeasible, both it and its mate(s) [as in the grouping in (10) or (11)] should be removed. Previously, only the infeasible equation was removed when each dealt with an individual probability statement and not distribution parameters. Note that both non-parametric and parametric weighting solutions often yield some zero-valued weights. The corresponding weighted historical observations would not be in the "sample" from which derivative forecasts are made. One can reformulate a sample of size n to use only d non-zero weights by scaling them to sum to d by multiplying each by the ratio d/n.

Example

Given the 56 forecast meteorology probabilities from NOAA's Climate Prediction Center, issued 1 October 1996 over Lake Superior, we derived sets of weights in the following manner. We ordered forecast probability equations as follows: month one 1-month air temperature lower- and upper-tercile probabilities and 1-month precipitation lower- and upper-tercile probabilities, month one 3-month temperature lower- and upper-tercile probabilities and 3-month precipitation lower- and upper-tercile probabilities, month two 3-month probabilities (in similar order), and so forth up to month twelve probabilities (in similar order). We transformed these equations as in (4)—(5) and minimized $\sum_{i=1}^{n}(w_i - 1)^2$ by converting the constrained optimization of (7) into an unconstrained optimization of the Lagrangian and solving with classical calculus techniques (Croley 2000a). By using non-negative constraints on the weights, in an attempt to use as many of the probability equations as possible, the optimization satisfied the first 29 of the 56 equations but yielded a *maximum* of $\sum_{i=1}^{n}(w_i - 1)^2$ rather than a minimum and the weights are unusable. By constraining the weights to be strictly positive, thereby disallowing zero weights (all historical time series are used in the sample), the optimization yielded a minimum but satisfied only the first 9 of the 56 equations. By maximizing the probability of 6-month air temperature, $T_{Oct'96-Mar'97}$, and precipitation, $Q_{Oct'96-Mar'97}$, being in the middle terciles ("normal" weather)

$$\max \hat{P}\left[\left\{\hat{t}_{Oct-Mar,0.333} < T_{Oct'96-Mar'97} \le \hat{t}_{Oct-Mar,0.667}\right\} \cap \left\{\hat{q}_{Oct-Mar,0.333} < Q_{Oct'96-Mar'97} \le \hat{q}_{Oct-Mar,0.667}\right\}\right] \quad (12)$$

subject to the same set of constraints, a linear programming optimization (Croley 2000a) satisfied the first 30 of the 56 equations.

Next, taking air temperatures as normally distributed and precipitation as log-normally distributed, we used the sample mean and variance (from the operational hydrology sample) to estimate the population mean and variance for the normal distribution and the sample mean and variance of logarithms of the sample to estimate the population mean and variance for the log-normal distribution, thus setting up constraint equations as in (11). We then minimized $\sum_{i=1}^{n}(w_i - 1)^2$ subject to these constraints and non-negative weights and found the optimization satisfied the first 14 of the 56 equations but again yielded a maximum instead of a minimum. For strictly positive weights, the optimization yielded a minimum but satisfied only the first 3 of the 56 equations. By again maximizing the probability of (12) subject to these constraints, an optimization satisfied the first 16 of the 56 equations.

All six of these optimizations were repeated for every month of the 1996—2000 period with the appropriate NOAA 56-equation forecast of meteorological probabilities. They were made also with appropriate expression of the probability of "normal" weather as in (12) but defined in terms of air temperature and precipitation over the six-month period beginning on the first month of forecast. The number of forecast equations used in each is summarized in Table 1.

Table 1. Number of Forecast Meteorological Probabilities Used in Lake Superior NBS Forecast.

Forecast Date	Non-Parametric			Parametric			Forecast Date	Non-Parametric			Parametric		
	Most Out-looks	All Time Series	Linear Pro-grams	Most Out-looks	All Time Series	Linear Pro-grams		Most Out-looks	All Time Series	Linear Pro-grams	Most Out-looks	All Time Series	Linear Pro-grams
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
Jan. '96	28	8	31	9	3	9	Jul. '98	31	14	31	11[a]	4	11
Feb. '96	29[a]	23	29	7[a]	3[a]	7	Aug. '98	29[a]	16	29	12[a]	4	12
Mar. '96	32	26	32	6[a]	1	6	Sep. '98	24	13	25	13[a]	3	13
Apr. '96	34	19	34	9[a]	3	9	Oct. '98	30	9	30	14[a]	3	14
May '96	24	17	35	5[a]	1	5	Nov. '98	25[a]	13	25	17[a]	1	17
Jun. '96	36	10	36	5[a]	3	5	Dec. '98	24[a]	8	24	12[a]	1	12
Jul. '96	31	16	31	11[a]	3	11	Jan. '99	16	9	29	9	3	9
Aug. '96	31	19	32	14[a]	4	14	Feb. '99	30	14	30	7[a]	0	7
Sep. '96	34	18	34	13[a]	3	13	Mar. '99	32	26	32	6[a]	1	8
Oct. '96	29[a]	9	30	14[a]	3	16	Apr. '99	35	25	35	10[a]	3	10
Nov. '96	31	11	31	17[a]	1	17	May '99	23	17	34	5[a]	1	5
Dec. '96	27	13	27	13[a]	1	13	Jun. '99	30	4	30	4[a]	3	4
Jan. '97	26	15	34	9	3	9	Jul. '99	32	16	33	11[a]	3	11
Feb. '97	30	25	30	7[a]	1	7	Aug. '99	32	17	33	14[a]	4	14
Mar. '97	32	26	32	6[a]	1	6	Sep. '99	25	13	27	12[a]	3	12
Apr. '97	37	20	37	7[a]	3	9	Oct. '99	24	9	24	13[a]	3	13
May '97	23	14	28	5[a]	1	5	Nov. '99	20	11	20	17[a]	1	17
Jun. '97	32	14	33	5[a]	3	5	Dec. '99	28	10	28	11[a]	1	12
Jul. '97	28	16	28	11[a]	3	11	Jan. '00	28	15	28	9	3	9
Aug. '97	24	15	24	0[a]	4	12	Feb. '00	27	19	29	7[a]	0	7
Sep. '97	31	13	31	13[a]	3	13	Mar. '00	32	18	33	7[a]	1	8
Oct. '97	20[a]	9	20[b]	11[a]	3	11	Apr. '00	26[a]	12	26	7[a]	3	8
Nov. '97	26[a]	7	26	16[a]	5	16	May '00	24	13	34	5[a]	1	5
Dec. '97	17[a]	4	19	8[a]	1	9	Jun. '00	35	10	35	5[a]	3	5
Jan. '98	15	4	21	9[a]	3	9	Jul. '00	35	16	35	11[a]	3	11
Feb. '98	18	10	24	7[a]	3	7	Aug. '00	34	21	34	14[a]	5	14
Mar. '98	25[a]	5	25	6[a]	0	6	Sep. '00	28	17	30	13[a]	3	13
Apr. '98	23[a]	11	23[b]	7[a]	3	9	Oct. '00	28	12	29	15[a]	3	17
May '98	22	14	28	5[a]	1	5	Nov. '00	36	11	36	17	1	17
Jun. '98	32	9	32	5[a]	3	5	Dec. '00	32	21	33	13[a]	1	13

[a]Langrangian optimization maximized $\sum(w_i - 1)^2$ instead of minimizing.

[b]Used average of multiple linear programming solutions.

As can be seen in Table 1, in general, many more constraints are satisfied in the non-parametric approach than in the parametric approach. Linear programming allows the most constraints to be considered since the non-negativity constraints are part of the linear programming formulation (Croley 2000a). In minimizing $\sum_{i=1}^{n}\left(w_i-1\right)^2$, non-negativity or strictly positive constraints are considered peripherally in successive solution attempts, thus not guaranteeing all solution points are considered in every successive optimization. Furthermore, use of non-negativity constraints in the minimization of $\sum_{i=1}^{n}\left(w_i-1\right)^2$ allows use of the most outlooks compared to use of strictly positive constraints (which allows all non-zero weights and the entire sample is used). The weights yielded by both the non-parametric and the parametric maximization of the probability of "normal" weather contain some zero values, although the non-parametric optimization has fewer zero weights in general.

Evaluation

Weights obtained in all of the manners described in the last section were evaluated by using them in a hydrologic forecast of net basin supply (NBS) to Lake Superior and comparing the forecast with derived NBS, based on observed data. The Great Lakes Environmental Research Laboratory (GLERL) simulated probabilistic hydrological forecasts for 1996—2000 with their Advanced Hydrologic Prediction System (AHPS), which uses estimates of antecedent moisture and heat storage conditions with six-month pieces of the 1948—1995 historical meteorological record. They did this for each month of 1996—2000 and assembled the six-month NBS scenarios into a sample for that month from which to estimate a six-month forecast beginning that month. Only provisional data were used to estimate antecedent conditions, as they would have been available in near real time. GLERL then took NOAA's 1- and 3-month meteorological outlooks, for each month of the period and used the six methods of the preceding section to consider the forecast 56 meteorology probabilities in their hydrological outlooks: non-parametric and parametric versions of minimizing $\sum_{i=1}^{n}\left(w_i-1\right)^2$ (both using the most outlooks and using all time series) and linear programming with the normal weather objective.

The six-month probabilistic NBS outlooks were simplified to deterministic outlooks for comparison to actual conditions by taking the mean, median, mid-range between the 5% and 95% quantiles, mid-range between the 15% and 85% quantiles, and mode (assuming a normal distribution). There were little differences between uses of the various combinations, but the mean consistently gave the better results and was used in the following comparisons. GLERL then compared each deterministic forecast with what actually occurred to compare the non-parametric and parametric methods. Figure 1 shows a comparison between the non-parametric and parametric linear programming methods using the normal weather objective. In all cases, the statistics are much superior for the non-parametric approach, presumably because more of the probabilistic meteorology forecasts can be used in the non-parametric approach. Root mean square error (RMSE) drops, correlation increases, bias drops, maximum error drops, and skill improves. [Skill measures the difference between forecast and actual NBS, weighted more for the extremes, normalized by reference to a climatic outlooks (average from the historical record). Lower skill scores indicate better performance and a climatic outlook has a skill of 1.0]. The choice of distributions used in the parametric approach might have some effect, but was not explored here.

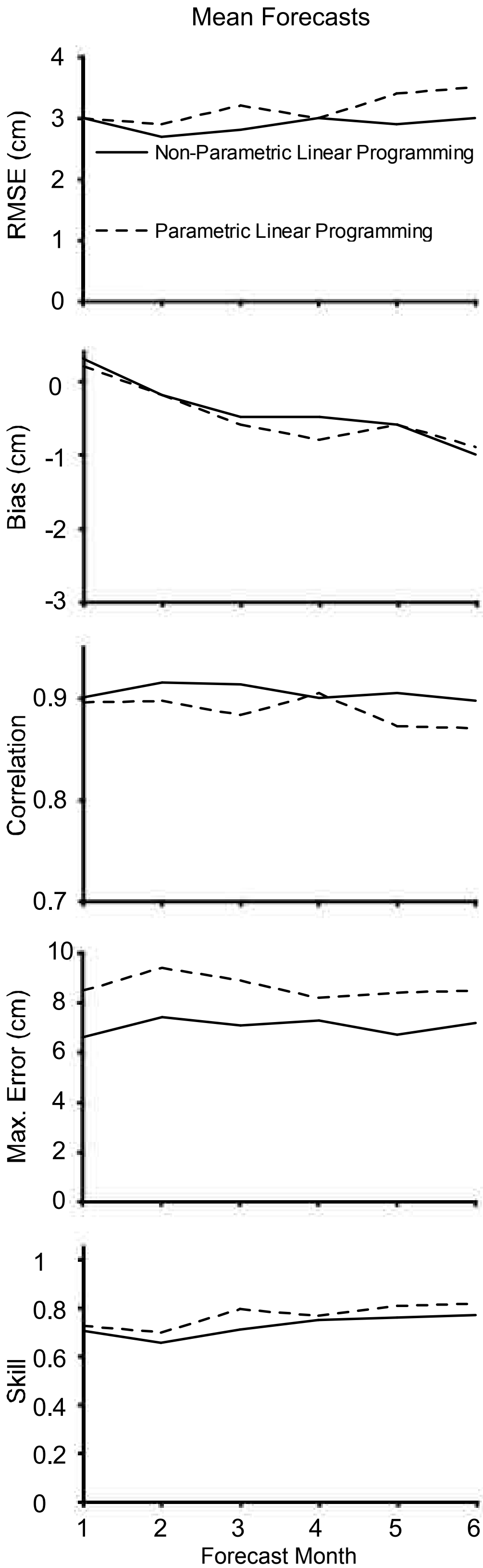

Figure 1. Non-Parametric and Parametric NBS Forecast Statistics.

Inspection revealed the best forecasting method used non-parametric linear programming with the normal weather objective (Croley 2001c, 2002).

Summary

An existing non-parametric method is summarized for weighting an operational hydrology sample to reflect available meteorology probability forecasts in making derivative hydrologic forecasts. A parametric modification is introduced to allow probability distributions for the meteorological variables of interest. Both methods are applied in simulated forecasting of Lake Superior net basin supplies for 1996—2000. It is found that, while the non-parametric method sometimes assigns the same weight to several sample observations, resulting in discontinuities in relative frequency over the range of a variable, it performs better than the parametric method in terms of utilizing more meteorological forecast information in a hydrological forecast. On the other hand, the loss of matched forecast meteorology probabilities with the parametric method arises from imposing additional conditions in terms of assumed distributions but we may be doing a more reasonable job in weighting the sample so that derived distributions are more intuitive.

This paper only evaluated long-term NBS forecasts over a large area with limited objectives in determining the weights and only one distribution was considered for each variable in the parametric approach. Comparison results between non-parametric and parametric approaches might be different for other areas, hydrology, short-term forecasts, and objectives. For example, short-term forecasts depend more on near-future meteorology then do extended forecasts, requiring possibly fewer outlooks to match; then the more-limited constraint-matching ability of the parametric method might not be a problem.

Complete software, in the form of an easy-to-use interactive *Windows*Ô graphical user interface, worked examples, and tutorial materials are available free of charge over the World Wide Web at http://www.glerl.noaa.gov/wr/outlookweights.html.

The software enables all minimization of $\sum_{i=1}^{n}\left(w_i - 1\right)^2$ or maximization of user-defined probabilities for both non-parametric and parametric approaches. The latter includes eight distributions: normal, lognormal, two-parameter gamma and log gamma, three-parameter gamma and log gamma (log Pearson Type III), chi-square, and exponential.

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