Western Region Technical Attachment
No. 89-10
April 4, 1989

THE FORECASTER CONTRIBUTION TO THE FORECAST PRODUCT

The debate rages on. Are we yet at the point where we can allow the machine to take over the complete production of the NWS forecast products? Is the "man" really an important part of the so-called "man-machine mix"? Do the subjective forecasts produced by the forecaster really contain any useful information regarding a particular atmospheric variable when compared to the objective (numerical/statistical) forecasts?

A recent paper by Murphy, Chen and Clemen (1988; hereafter, MC&C) attempts to answer these questions. In this paper, they examine relationships between objective and subjective temperature forecasts, utilizing NWS forecast products and LFM MOS output. Previous work by Clemen and Murphy (1986) had indicated that subjective probability of precipitation (PoP) forecasts contained information beyond that included in the objective PoP forecasts at all locations and lead times examined. Overall, that study indicated that "the subjective forecasts contained significant information vis-a-vis precipitation occurrence that was not included in the objective forecasts".

The MC&C paper is similar to Clemen and Murphy. The main difference is that it concentrates on verification of and relationships between objective and subjective *temperature* forecasts. In the MC&C study, objective and subjective maximum and minimum temperature forecasts were used between April 1980 through March 1986 for six NWS forecast offices representing differing climatic regimes. These offices were Portland (OR), Minneapolis (MN), Boston (MA), Atlanta (GA), Oklahoma City (OK), and Phoenix (AZ). LFM MOS data were used for the objective forecasts. Subjective forecasts were produced by NWS forecasters. It is important to note that the NWS forecasts were made after assimilating the numerical guidance, including the MOS temperature forecasts. This study looked at forecasts for lead times of 24, 36, 48, and 60 hours from both the 00Z and 12Z cycles. The data were also divided into warm and cool seasons. Thus, given 4 projection times, 2 forecast cycles, 6 offices, and 2 seasons for which data were gathered, there were 96 cases for which the data could be examined. Regression and "independent expert" analyses were performed to determine the relative contribution of the objective and subjective portions of the forecasts to an optimum combined forecast product for each of these cases, as well as for various case stratifications; i.e., cool season only, maximum temperatures only, and so on. It is very important that the terminology being used here is clear. If it isn't, you may have trouble following the remainder of this discussion. The objective forecasts (f_o) are the LFM MOS forecasts. The subjective forecasts (f_s) are those output by the NWS forecaster, normally after having seen MOS. The combined forecast (f_c) is an optimum forecast which is produced using the following simple regression form:

$$f_c = b_c + b_o f_o + b_s f_s$$

where b_c, b_o and b_s are the regression coefficients and f_c, as it is produced through the regression analysis, can be considered the expected value of the observation based on the objective and subjective forecasts. Given the above relationship, the study evaluates the contribution of the subjective (forecaster) and objective (MOS) forecasts to the combined forecast.

Results of the regression analyses of the objective and subjective forecasts on the observations can be summarized using Table 1 as an example. Specifically of interest here are the estimated regression coefficients (b_o and b_s) and the t-test values. We can consider the magnitude of the regression coefficients in terms of the contribution of the respective forecasts toward producing an optimum combined forecast, i.e., the observations. The t-test values indicate the significance of the regression coefficients, where values greater than 2.6 are significant at the 0.01 probability level (see Panofsky and Brier, 1958). In other words, we can be more than 99% certain that by virtue of the size of the regression coefficients, the corresponding forecast numbers play at least some role of importance in producing the optimum combined forecast product. By determining that a coefficient is statistically significant, we recognize that the forecast product represented by that coefficient has value that is not simply a statistical quirk which would go away if more cases were considered.

For the 24 and 48-hour forecast time periods, MC&C found that b_s is significant at the 0.01 probability level for all cases, and that b_o was significant at the same probability level in 94% of the cases. Similar results were noted for the 36 and 60-hour forecasts. Therefore, the subjective coefficient to the combined forecasts was statistically significant in all cases, and the objective portion was significant in most cases. It is also interesting to note that the magnitude of b_s is greater than that of b_o in all cases in Table 1. In fact, this was true in 88% of all cases studied. This indicates that the contribution of the subjective forecasts to the combined (optimum) forecast is normally greater than that of the objective forecasts.

Table 2 stratifies the results of the regression analyses. With no stratification, the subjective forecast is weighted twice that of the objective forecast. The forecaster input is weighted more heavily in the maximum temperature forecasts than it is for the minimum forecasts, thus suggesting that the forecaster is able to add more to the maximum forecast than the minimum forecast. Following similar reasoning, it is also clear that the forecaster input is much more important during the cool season than it is in the warm season. There are marked differences between the relationship of the subjective and objective forecasts at the individual offices studied, though each one showed the subjective forecasts carrying more weight than the objective forecasts. Interestingly enough, the Phoenix office is the only one studied where the subjective forecast had more weight than the objective forecast in all seasons, projection times and variables. Not too unexpectedly, as the lead time of the forecast increases, the weight of the subjective forecast normally decreases. However, on average, the 60-hour subjective forecast still carries 1-1/2 times as much weight as the 60-hour objective forecasts.

The "independent experts" (hereafter, IE) analysis is another statistical method which determines how much independent information is contained in both the objective and subjective forecasts. This is done by comparing the combined temperature forecasts with the subjective and objective forecasts by themselves. The IE values essentially show the amount of information contained in each of the individual (subjective or objective) forecasts that the other individual forecast does not contain. These values are obtained by comparing the error variance of the individual forecasts with the error variance of the combined forecasts, as produced in the regression analysis. Results of the IE analyses are summarized using Table 3 as an example. The error variances for the objective and subjective forecasts are shown by s_o^2 and s_s^2, respectively, and the correlation coefficient of these errors is r_{os}. The number of "independent experts" are shown by $d_{s|o}$ and $d_{o|s}$, where $d_{s|o}$ indicates the amount of independent information provided by the subjective forecasts, given the objective forecasts and $d_{o|s}$ indicates the amount of independent information provided by the objective forecasts, given the subjective forecasts. The larger $d_{s|o}$ is, the more information the subjective forecast contains which is not in MOS. Similarly, the larger $d_{o|s}$ is, the more information MOS contains which is not incorporated into the subjective forecast.

It is interesting to note that the error variance is generally less for the subjective forecasts than for the objective forecasts. MC&C note that the variances tend to increase as the forecast projection time increases, as would be expected. It is also not surprising to note the strong positive correlation between the subjective and objective forecast errors, given that the subjective forecasts are produced using the objective forecasts as guidance. The independent experts values near zero in Table 3 suggests that the objective forecasts in those cases added little or no additional information to the combined forecast relative to the subjective forecast. The asterisks in Table 3 indicate values which are not significantly different from zero (statistically) at the 0.05 probability level. MC&C note that the independent information contained in the subjective forecasts is significantly greater than zero at the 0.01 probability level in all cases. The independent information contained in the objective forecasts is significantly greater than zero at the same level in 92% of the cases. The subjective incremental information was greater than that of the objective incremental information in 88% of the cases, the exceptions normally occurring at longer lead times.

Table 4 further stratifies the IE results. Similar to the results suggested in the regression analysis, this analysis shows that the subjective forecasts contain much more information than the objective forecasts, especially in the cool season. Again, there were differences between the offices studied, and again, Phoenix was the only office where the independent subjective information always exceeded the independent objective information. This table clearly shows that the independent information contained in the subjective forecasts decreases as the projection time increases. Still, even at 60 hours, the subjective forecasts contain about three times as much independent information as do the objective forecasts (0.129 vs. 0.044).

MC&C take the viewpoint that simply looking at the accuracy and skill of the objective and subjective temperature forecasts is not necessarily a proper approach to take in order to determine the relative contributions of each to a state-of-the-art forecast. They adopted an information-content approach which determines whether each forecast separately contains information with respect to the observations that the other forecast does not.

There are important conclusions that should be pointed out from this study, conclusions which yield answers to the questions posed at the beginning of this paper. The two methods of analysis used by MC&C yielded similar results, showing that both the objective and subjective forecasts contain useful information that the other does not. This appears to be especially true in the case of the subjective forecasts, which appear to contribute considerably more incremental information to the combined, optimum forecasts than do the objective forecasts. It is, therefore, clear that **the forecasters do make a significant contribution** to the official temperature forecasts.

It is also apparent, however, that there is information in the objective forecasts which is not currently contained in the subjective forecasts. MC&C recommend that procedures be developed whereby incremental information contained in the objective forecasts be extracted and incorporated into the subjective forecasts. The obvious way to implement such a procedure is to utilize a multiple regression technique similar to that used by

MC&C in performing this study. This, in fact, may be the easiest way for NWS forecasters to improve their numerical forecasting abilities over the next few years. We concur with MC&C that such a project should be undertaken. This would be a nice, neat way of utilizing statistics to improve the operational temperature forecast products.

References:

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Forecast office	Maximum temperature (TMAX) Regression coefficients (standard errors)	t-value	R^2	n	Minimum temperature (TMIN) Regression coefficients (standard errors)	t-value	R^2	n
PDX	b_o: 0.349 (0.056) b_s: 0.624 (0.059)	6.3 10.5	0.831	798	b_o: 0.363 (0.060) b_s: 0.687 (0.055)	6.1 12.4	0.778	806
MSP	b_o: 0.315 (0.044) b_s: 0.689 (0.043)	7.1 15.9	0.945	846	b_o: 0.281 (0.044) b_s: 0.742 (0.042)	6.4 17.7	0.929	839
BOS	b_o: 0.268 (0.053) b_s: 0.749 (0.052)	5.1 14.5	0.905	821	b_o: 0.290 (0.047) b_s: 0.734 (0.044)	6.2 16.5	0.910	750
ATL	b_o: 0.094 (0.058) b_s: 0.908 (0.055)	1.6* 16.6	0.887	846	b_o: 0.156 (0.042) b_s: 0.850 (0.040)	3.7 21.1	0.924	839
OKC	b_o: 0.185 (0.042) b_s: 0.797 (0.039)	4.4 20.6	0.923	880	b_o: 0.092 (0.035) b_s: 0.890 (0.032)	2.6 27.5	0.924	871
PHX	b_o: 0.132 (0.077) b_s: 0.875 (0.076)	1.7* 11.5	0.917	808	b_o: 0.330 (0.060) b_s: 0.668 (0.058)	5.5 11.6	0.891	818

* Corresponding regression coefficient estimate *not* significantly different from zero at 0.05 probability level.

Table 1. Results of multiple regression analysis of 24-hour forecasts on corresponding observations in cool season (R^2 is the square of the multiple correlation coefficient and n is the sample size).

Stratification	Average regression coefficients $\langle b_o \rangle$	$\langle b_s \rangle$	Range of regression coefficients b_o	b_s
None	0.338	0.662	(0.092, 0.655)	(0.344, 0.908)
Variable				
TMAX	0.324	0.682	(0.094, 0.644)	(0.370, 0.908)
TMIN	0.353	0.642	(0.092, 0.655)	(0.344, 0.890)
Season				
Cool	0.275	0.727	(0.092, 0.506)	(0.484, 0.908)
Warm	0.401	0.597	(0.132, 0.655)	(0.344, 0.869)
Forecast office				
PDX	0.348	0.641	(0.159, 0.513)	(0.456, 0.815)
MSP	0.382	0.616	(0.211, 0.644)	(0.370, 0.811)
BOS	0.421	0.602	(0.265, 0.630)	(0.424, 0.754)
ATL	0.281	0.735	(0.094, 0.556)	(0.519, 0.908)
OKC	0.319	0.668	(0.092, 0.655)	(0.344, 0.890)
PHX	0.279	0.711	(0.132, 0.409)	(0.564, 0.875)
Lead time				
24 h	0.300	0.701	(0.092, 0.584)	(0.450, 0.908)
36 h	0.316	0.685	(0.117, 0.501)	(0.493, 0.886)
48 h	0.362	0.642	(0.132, 0.644)	(0.370, 0.869)
60 h	0.375	0.621	(0.128, 0.655)	(0.344, 0.815)

Table 2. Summary of results of multiple regression analyses.

Forecast office	Variances s_o^2	s_s^2	Correlation coefficient r_{os}	Number of independent experts $d_{s\|o}$	$d_{o\|s}$	Sample size n
(a) TMAX						
PDX	16.5	14.7	0.816	0.178	0.049	798
MSP	20.9	17.0	0.737	0.302	0.059	846
BOS	21.5	17.7	0.805	0.251	0.030	821
ATL	25.6	19.3	0.837	0.331	0.003*	846
OKC	28.1	19.6	0.699	0.486	0.036	880
PHX	9.9	8.5	0.905	0.168	0.003*	808
(b) TMIN						
PDX	17.4	15.1	0.820	0.196	0.037	806
MSP	28.4	21.4	0.726	0.384	0.043	839
BOS	18.6	14.1	0.729	0.376	0.043	750
ATL	19.2	12.7	0.723	0.537	0.017	839
OKC	25.1	13.6	0.644	0.872	0.014	871
PHX	8.8	7.9	0.827	0.165	0.046	818

* $d_{o|s}$ *not* significantly different from zero at 0.05 probability level.

Table 3. Results of independent experts analysis for 24-hour forecasts in cool season.

Stratification	Average number of independent experts $\langle d_{s\|o}\rangle$	$\langle d_{o\|s}\rangle$	Range of number of independent experts $d_{s\|o}$	$d_{o\|s}$
None	0.178	0.044	(0.031, 0.872)	(0.003, 0.147)
Variable				
TMAX	0.169	0.036	(0.031, 0.486)	(0.003, 0.082)
TMIN	0.187	0.051	(0.033, 0.872)	(0.008, 0.147)
Season				
Cool	0.229	0.030	(0.061, 0.872)	(0.003, 0.069)
Warm	0.126	0.058	(0.031, 0.248)	(0.004, 0.147)
Forecast office				
PDX	0.169	0.052	(0.091, 0.287)	(0.011, 0.147)
MSP	0.162	0.051	(0.031, 0.384)	(0.012, 0.082)
BOS	0.119	0.046	(0.042, 0.376)	(0.018, 0.146)
ATL	0.225	0.033	(0.098, 0.537)	(0.003, 0.143)
OKC	0.254	0.052	(0.038, 0.872)	(0.014, 0.137)
PHX	0.138	0.028	(0.091, 0.178)	(0.003, 0.068)
Lead time				
24 h	0.262	0.052	(0.096, 0.872)	(0.003, 0.147)
36 h	0.180	0.036	(0.077, 0.418)	(0.004, 0.081)
48 h	0.140	0.043	(0.031, 0.305)	(0.004, 0.102)
60 h	0.129	0.044	(0.033, 0.287)	(0.011, 0.137)

Table 4. Summary of results of independent experts analyses.