3.1 DOES SOCIETY BENEFIT FROM VERY LONG RANGE DAY-TO-DAY WEATHER FORECASTS?

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1. INTRODUCTION

A "real-time" trial of a methodology utilised to generate Day-1 to Day-7 forecasts, by mechanically integrating judgmental (human) and automated predictions, has been ongoing since 20 August 2005 (Stern (2007a).

It has been found that the sets of combined forecasts are not only more accurate (Table 1), but also are more consistent from one day to the next, than either individual set of forecasts.

It has also been shown that that, when undertaking a defensive strategy of purchasing weather derivatives, the cost of protecting against the possibility of weather forecasts being in error reduces as the forecast consistency increases (Stern, 2007b).

Shapiro and Thorpe (2004) note that "THORPEX addresses the influence of sub-seasonal time-scales on high-impact forecasts out to two weeks, and thereby aspires to bridge the 'middle ground' between medium range weather forecasting and climate prediction". Stern (2005) identified a modest level of forecast skill out to ten days.

Since 20 August 2006, forecasts have also been generated for beyond Day-7 (Day-8 to Day-10) by mechanically integrating automated predictions with climate normals, and it is the purpose of this paper to record the accuracy of these very long range forecasts in the context of mechanically integrating predictions (Figure 1), and to consider their value.

2. OVERALL ACCURACY OF THE VERY LONG RANGE FORECASTS

After 365 days, to 19 August 2007, overall, Day-8 forecasts explained 11.22% of the variance, Day-9 forecasts explained 7.23% of the variance, and Day-10 forecasts explained 3.43% of the observed variance.

However, for these very long range day-to-day forecasts, the variance explained was mainly for the temperature components. Specifically:

- For Day-8, Quantitative Precipitation Forecasts (QPFs) explained 4.18% of the observed variance, whilst Minimum Temperature Forecasts (MINFs) explained 17.88% of the observed variance and Maximum Temperature Forecasts (MAXFs) explained 17.46% of the observed variance.

- For Day-9, QPFs explained 3.13% of the observed variance, whilst MINFs explained 10.36% of the observed variance and MAXFs explained 10.00% of the observed variance.

- For Day-10, QPFs explained less than 0.95% of the observed variance, whilst MINFs explained 7.67% of the observed variance and MAXFs explained 4.57% of the observed variance.

3. DOES SOCIETY BENEFIT?

The following question arises from the relatively low level of skill that very long range day-to-day forecasts display:

Does society gain any benefit from very long range day-to-day forecasts, and might it even be suggested that society actually suffers loss from them being issued, on account of false expectations about their accuracy being raised?

A reply to the first part of the question, as to what is the benefit that society gains from very long range forecasts, may be established from the theoretical "fair value" prices of option contracts (weather derivatives) that one is required to purchase in order to protect against adverse conditions.

Sellers of weather derivatives, who utilise low volatility forecasts to price their call and put options, are provided with a competitive advantage over sellers of weather derivatives who utilise high volatility forecasts. This arises because sellers of weather derivatives who utilise low volatility forecasts being able to charge lower, and, therefore, more competitive, prices to purchasers of weather derivatives who wish to use those weather derivatives to protect against the possibility of the weather forecasts being incorrect.

The Root Mean Square Error (RMSE) in the forecasts may be regarded as a measure of

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their volatility, and, therefore, may also be regarded being directly related to the theoretical "fair value" prices of the associated option contracts.

Regarding a climate normal forecast (verified against a *random* observation sourced from the historical data set) as possessing no value, the RMSE of such a forecast $RMSE_r = \surd$*(VARIANCE of the historical observational data set).*

Provided the RMSE of the actual forecast $RMSE_a < RMSE_r$, it may be said that the volatility of the underlying of option contracts derived on the basis of the forecasts, is less than the volatility of the underlying of option contracts derived on the basis of the climate normals.

This means that it may also be said that the price of the option contracts derived on the basis of the forecasts, is less than the price of option contracts derived on the basis of the climate normals.

Furthermore, this means that a benefit is gained in that it becomes cheaper to protect against adverse conditions.

Figure 2 shows that, for the QPFs, $RMSE_a$ is only marginally less than $RMSE_r$ for Day-8 and Day-9 forecasts, and the same as $RMSE_r$ for Day-10 forecasts. This means that the QPFs will not be very effective in reducing the cost of protecting against adverse conditions for Day-8, Day-9 and Day-10.

Figures 3 and 4 show that, for the minimum and maximum temperature forecasts, $RMSE_a$ is significantly less than $RMSE_r$ for Day-8, Day-9 and Day-10 forecasts. This means that the temperature forecasts will be effective in reducing the cost of protecting against adverse conditions for Day-8, Day-9 and Day-10.

A reply to the second part of the question, as to whether society actually might even suffer loss from very long range forecasts, may be responded to in the negative, provided users of these forecasts are provided with suitable verification statistics about their accuracy.

4. SUMMARY

The accuracy of a set of very long range precipitation and temperature forecasts has been documented, and it is suggested that only the temperature forecasts display significant value.

5. REFERENCES

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Stern, H. 2007b: Employing weather derivatives to assess the economic value of high-impact weather forecasts out to ten days - indicating a commercial application. 22nd Conference on Weather Analysis and Forecasting/18th Conference on Numerical Weather Prediction, Park City, Utah, USA 25-29 Jun., 2007.

Table 1 Enhanced Day-1 to Day-7 forecast accuracy for various weather elements
(20 August 2005 to 19 August 2007)

Element	Verification parameter	Human (official)	Combined
All elements	% variance explained	36.72	41.94
Rain or no rain	% correct	71.37	77.32
Rain amount	RMS error ($mm^{0.5}$)	0.94	0.88
Min temp	RMS error (°C)	2.37	2.30
Max temp	RMS error (°C)	2.88	2.67
Thunder	Critical Success Index (%)	13.3	17.9
Fog	Critical Success Index (%)	14.8	16.5

Figure 1 Summarising the overall performance of the combined forecasts

(Day-1 to Day-7: Combining automated predictions with human predictions 20 August 2005 to 19 August 2007;

Day-8 to Day-10: Combining automated predictions with climate normals 20 August 2006 to 19 August 2007)

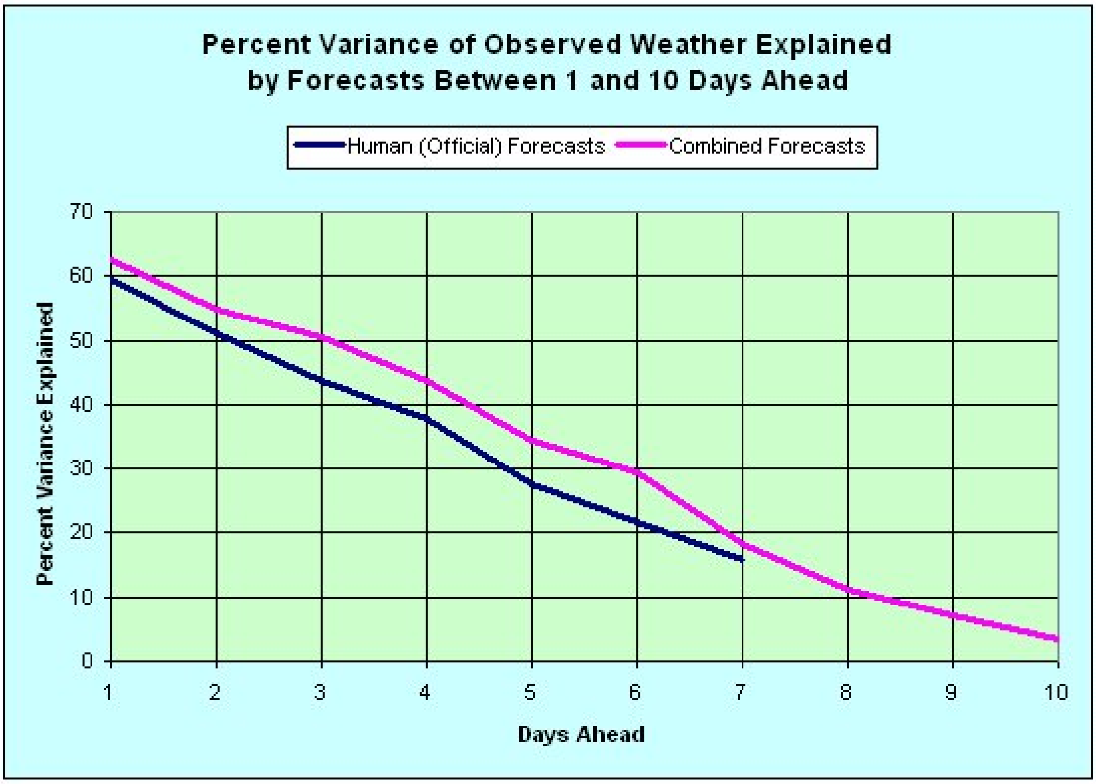

Figure 2 Comparing the accuracy of *actual* very long range QPFs (as measured by the Root Mean Square Error - $RMSE_a$) with the accuracy of a climate normal forecast (verified against a *random* observation sourced from the historical data set) - $RMSE_r$

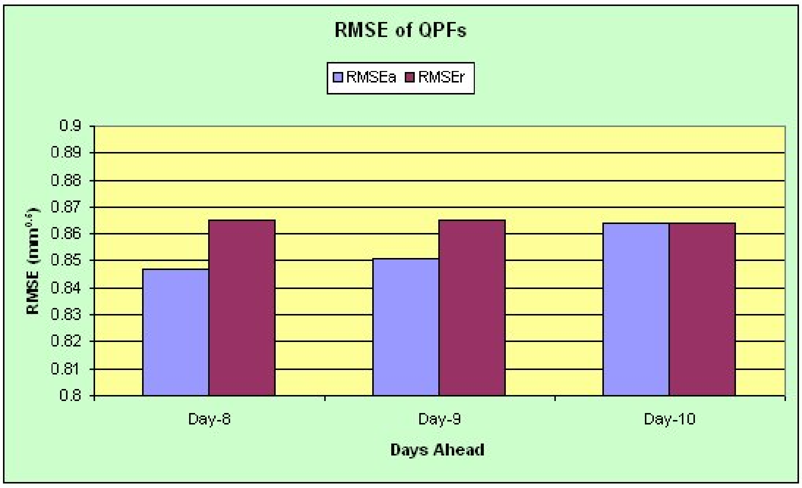

Figure 3 Comparing the accuracy of *actual* very long range Minimum Temperature forecasts (as measured by the Root Mean Square Error - $RMSE_a$) with the accuracy of a climate normal forecast (verified against a *random* observation sourced from the historical data set) - $RMSE_r$

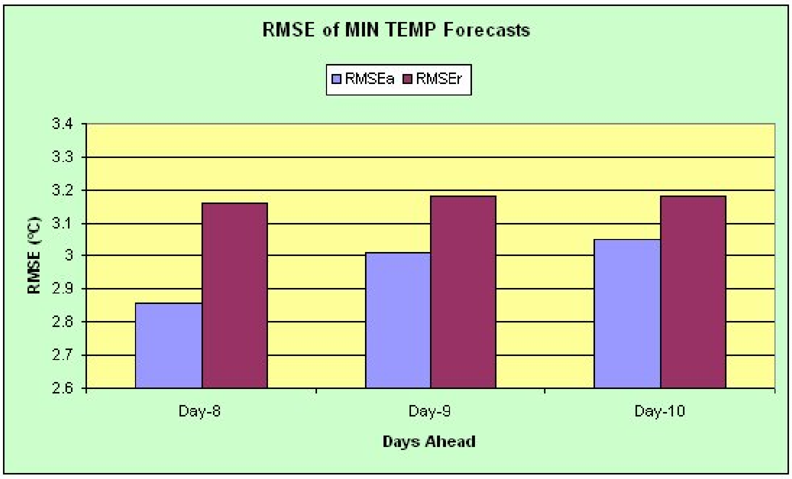

Figure 4 Comparing the accuracy of *actual* very long range Maximum Temperature forecasts (as measured by the Root Mean Square Error - $RMSE_a$) with the accuracy of a climate normal forecast (verified against a *random* observation sourced from the historical data set) - $RMSE_r$