QUANTIFYING HOW POSITIONAL AND TIMING ERRORS IN THE PREDICTION OF SYNOPTIC SCALE SYSTEMS EXTRACT A PENALTY WHEN VERIFYING WEATHER FORECASTS

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1. INTRODUCTION

Recently completed is a piece of work exploring trends in the skill of weather prediction at lead times of 1 to 14 days for Melbourne, Australia – refer to Map 1 (Stern, 2008, Stern, 2017,Stern and Davidson, 2015).

Grams *et al.* (2006), referring to papers by Ebert and McBride (2000) and Baldwin and Wandishin (2002) note that:

"Summertime convective systems are among the most difficult weather events for operational meteorologists and numerical models to predict".

Grams *et al.* (2006) continue:

"Verification of a quantitative precipitation forecast (QPF) made by a fine-grid numerical model for these small-scale features can be just as difficult.

Standard grid-based measures often result in scores that are not consistent with the subjective impression of the forecaster.

Traditional verification statistics severely penalize a precipitation system that may have been forecast with a small positional error or incorrect shape, with resultant low correlation coefficients, high root-mean-square errors (rmse), and poor values of categorical statistics".

The same comment may be applied to the verification of predictions of other weather elements.

2. PURPOSE

An update (Stern, 2017) of the verification statistics documented by Stern and Davidson (2015) is included in the current paper.

In that context, the proposition discussed by Ebert and McBride (2000), Baldwin and Wandishin (2002) and Grams et al. (2006), is explored.

This is done in regard to how positional and timing errors in the prediction of synoptic scale systems extract a penalty, is explored utilising forecast verification data sets for:

- Minimum temperature;
- Maximum temperature;
- Amount of precipitation; and,
- Probability of precipitation.

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The methodology employed to achieve this demonstration is to *separate* the *inter-diurnal component of the percent variance* of the observations explained by forecasts, from the *total percent variance* explained by the forecasts.

By this means, the proposition is demonstrated to have validity in the context of predictions for a range of weather elements.

Map 1 Location of Melbourne
Source: http://www.ga.gov.au/placename

3. DISCUSSION

3.1 Minimum Temperature

Regarding minimum temperature (Figure 1), an overall increase in accuracy is evident.

For Day-1 predictions, 50% of the day-to-day variance in the observations was explained fifty years ago, but this has increased to 85%, now.

For Day 2-4 predictions, 40% of the day-to-day variance in the observations was explained twenty years ago, but this has increased to 75%, now.

For Day 5-7 predictions, 20% of the day-to-day variance was explained fifteen years ago, but this has increased to 50%, now – which is the level displayed by the Day-1 predictions fifty years ago.

It may be shown that in regard to the inter-diurnal (that is, day-to-day) minimum temperature fluctuations (Figure 2), small positional and timing errors in the forecasting of major synoptic systems do, indeed, extract a penalty on account of the resultant errors in the prediction of the day-to-day fluctuations.

To illustrate, for Day-1 predictions, the *inter-diurnal component* of the variance explained is less than 75%, whilst the *total* variance explained is greater than 80%.

For longer lead times, the proportional difference grows.

To illustrate, for Day-5 predictions, the respective components explained were 45% and 60%, whilst by Day-10, almost none of the *inter-diurnal component* of the variance is explained.

3.2 Maximum Temperature

Regarding maximum temperature (Figure 3), an overall increase in accuracy is evident.

For Day-1 predictions, 50% was explained fifty years ago. Now, 85% is explained.

For Day 2-4 predictions, 30% was explained thirty years ago. Now, 80% is explained.

For Day 5-7 predictions, 20% was explained fifteen years ago. Now, 50% is explained. As was the case with minimum temperature, this is the level displayed by the Day-1 predictions fifty years ago.

Some skill, albeit of a modest level (about 15%), is displayed by the Day 8-10 predictions.

As for minimum temperature, it may be shown that small positional and timing errors in the forecasting of major synoptic systems extract a penalty on account of errors in the prediction of the day-to-day fluctuations (Figure 4).

To illustrate, for Day-1 predictions, the inter-diurnal component of the variance explained is about 80%, whilst the total variance explained is greater than 85%.

For longer lead times, the proportional difference grows, for Day-5 predictions, the respective components being also 50% and 65%.

Also as for minimum temperature, by Day-10, almost none of the inter-diurnal component of the variance is explained.

3.3 Amount of Precipitation

For amount of precipitation forecasts, an overall increase in accuracy is evident (refer to Figure 5), albeit somewhat unsteady, with a peak shown during the very wet summer of 2010-2011 when some extreme events were well predicted.

It may be shown that small positional and timing errors in the forecasting of major synoptic systems extract a far greater proportional penalty (than for the minimum and maximum temperature predictions) on account of errors in the prediction of the day-to-day fluctuations (Figure 6).

To illustrate, for Day-1 predictions, the inter-diurnal component of the variance explained is about 50%, whilst the total variance explained is about 60%.

For longer lead times, the proportional difference grows more rapidly (than for temperature predictions).

By Day-5, less than 10% of the inter-diurnal component of the variance is explained.

3.4 Probability of Precipitation

Regarding probability of precipitation, improvement is evident for Day-1 and Day 2-4 predictions, but not for longer lead times (Figure 7).

As for the amount of precipitation, it may be shown that small positional and timing errors in the forecasting of major synoptic systems extract a far greater proportional penalty (than for temperature predictions) on account of errors in the prediction of the day-to-day fluctuations (Figure 8).

To illustrate, for Day-1 predictions, the inter-diurnal component of the variance explained is about 40%, whilst the total variance explained is about 55%.

For longer lead times, the proportional difference also grows more rapidly (than for temperature predictions), by Day-5, only about 10% of the inter-diurnal component of the variance is explained.

4. CONCLUDING REMARKS

To conclude, it is shown (from a set of graphics representing both the *total* and the *inter-diurnal component* of the variance explained by the forecasts) how one may quantify the extent to which positional and timing errors in the prediction of synoptic scale systems extract a penalty when traditional approaches to the verification of weather forecasts are applied.

The penalty is shown to be proportionally greater for precipitation predictions than for temperature predictions.

This may be due to the fact that whilst most day-to-day changes in temperature are gradual, not-withstanding the impact of the occasional sharp changes associated with the passage of cold fronts, most significant precipitation events are over within a day or two.

The relevance of the two different approaches to forecast verification, total variance and inter-diurnal variance, depends upon the needs of the client.

The inter-diurnal approach is more relevant to those planning for a particular activity on a certain day, for example, a wedding or a sporting event.

The total approach is more relevant to those planning for activities that stretch across a longer period, for example, hay-making or an extended holiday.

5. REFERENCES

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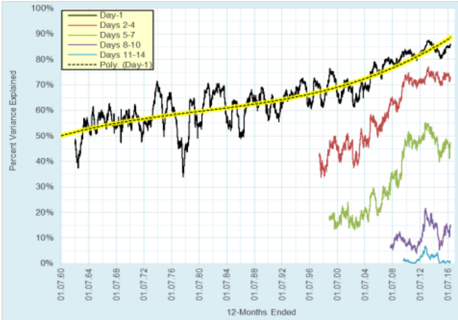

Figure 1 Long-term Trends in Percentage Variance Explained by Melbourne Minimum Temperature Forecasts (from Stern, 2017)

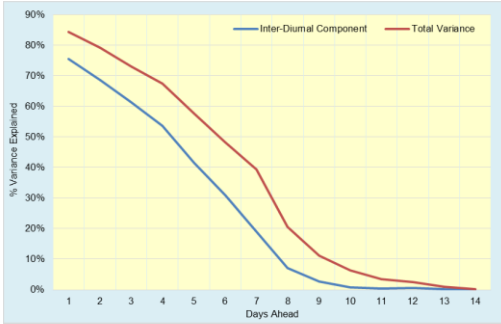

Figure 2 Percentage Variance Explained by Melbourne Minimum Temperature Forecasts (5-Years to Nov-2016)

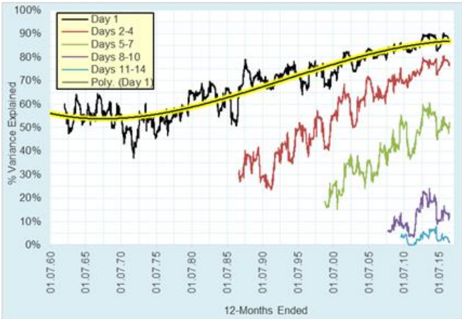

Figure 3 Long-term Trends in Percentage Variance Explained by Melbourne Maximum Temperature Forecasts (from Stern, 2017)

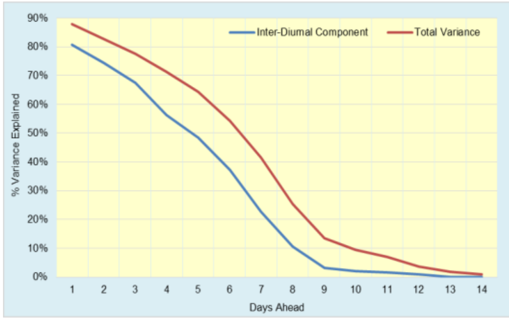

Figure 4 Percentage Variance Explained by Melbourne Maximum Temperature Forecasts (5-Years to Nov-2016)

Figure 5 Long-term Trends in Percentage Variance Explained by Melbourne Precipitation Amount Forecasts (from Stern, 2017)

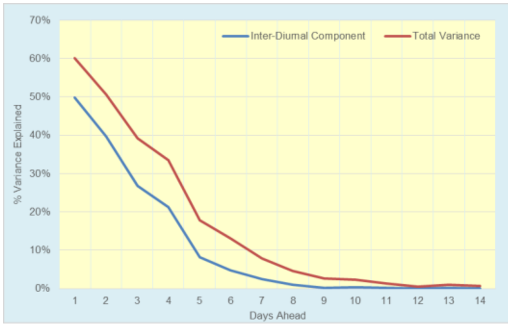

Figure 6 Percentage Variance Explained by Melbourne Precipitation Amount Forecasts (5-Years to Nov-2016)

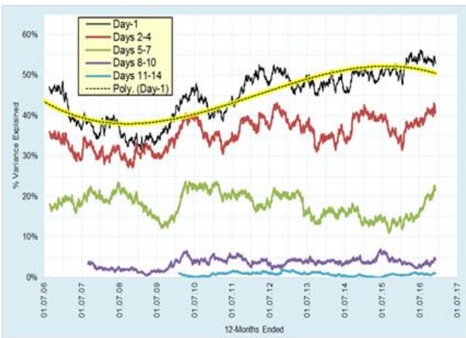

Figure 7 Long-term Trends in Percentage Variance Explained by Melbourne Precipitation Probability Forecasts (from Stern, 2017)

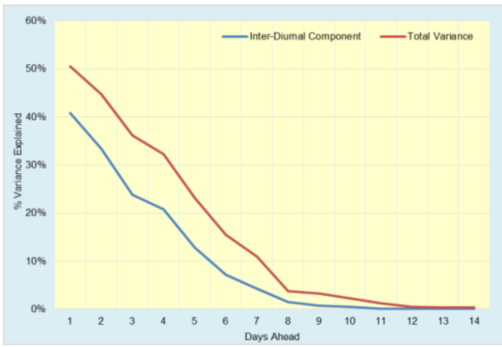

Figure 8 Percentage Variance Explained by Melbourne Precipitation Probability Forecasts (5-Years to Nov-2016)