On The Limits Of Predictability Of Day To Day Weather Forecasts For Melbourne, Australia

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Background. The authors have recently completed a piece of work exploring trends in the skill of weather prediction at lead times of 1 to 14 days for Melbourne, Australia.

Reference:

Trends in the skill of weather prediction at lead times of 1–14 days
by Harvey Stern & Noel E Davidson
Quarterly Journal of the Royal Meteorological Society
Volume 141, Issue 692, pages 2726-2736, October 2015 Part A

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http://onlinelibrary.wiley.com/doi/10.1002/qj.2559/abstract

Official Australian Bureau of Meteorology forecasts were used to establish these trends at shorter lead times - out to Day-7. The system that was used to establish these trends at longer lead times - out to Day-14 - was, in part, based upon an algorithm that statistically interpreted the GFS NWP model output to generate local weather forecasts.

More recently, the application of other NWP models towards determining predictability limits has also been explored. To this end, the authors presented preliminary results to the 2015 American Meteorological Society Annual Meeting about what had been achieved using a statistical interpretation of the output (over a six-month period) of the ECMWF monthly control model (which generates predictions out to Day-32).

Reference:

Some aspects of the verification of weather forecasts for Melbourne, Australia
by Harvey Stern & Noel E Davidson
Harry R. Glahn Symposium, Phoenix, AZ, 4-8 Jan. 2015, Amer. Meteor. Soc.
https://ams.confex.com/ams/95Annual/webprogram/Paper267305.html

Since then, further sets of GFS and ECMWF model output data have been collected and it is the purpose of this paper to update the aforementioned results utilising the larger data sets and to reflect on their implication for seasonal climate outlooks.

Results. To this end, Figure 1 depicts the correlation coefficients between forecast and observed inter-diurnal sets of changes in minimum temperature for lead times from Day-1 (the column for Day-1 represents the correlation coefficient between the two sets of changes from Day-2 to Day-1) to Day-31 (the column for Day-31 represents the correlation coefficient between the two sets of changes from Day-32 to Day-31). Figures 2, 3 and 4 respectively depict correlation coefficients between forecast and observed inter-diurnal changes in maximum temperature, precipitation amount and precipitation probability. Positive values of the correlation coefficient suggest that the associated predictions possess skill at forecasting day-to-day changes.

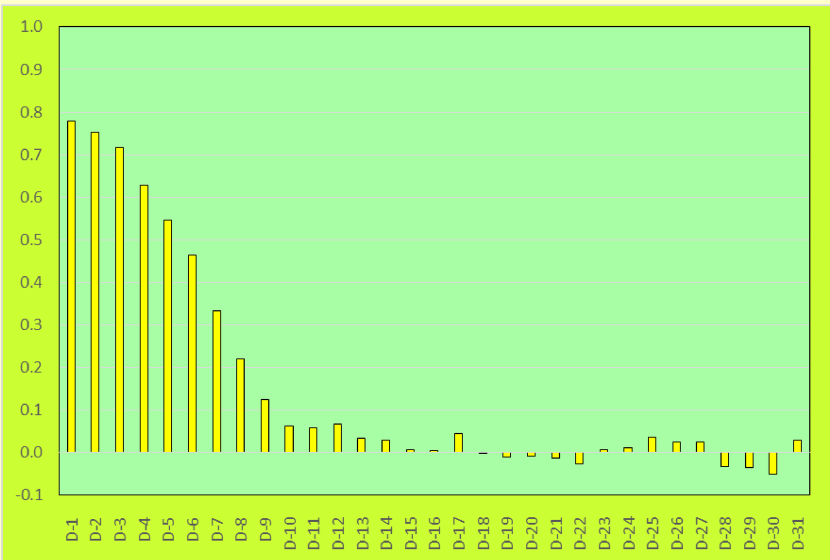

Figure 1 Correlation coefficients between forecast and observed inter-diurnal sets of changes in minimum temperature.

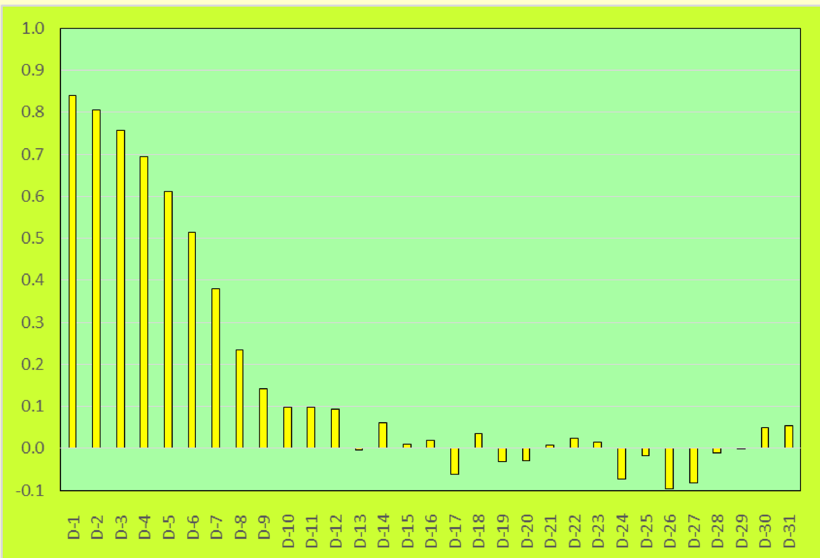

Figure 2 Correlation coefficients between forecast and observed inter-diurnal sets of changes in maximum temperature.

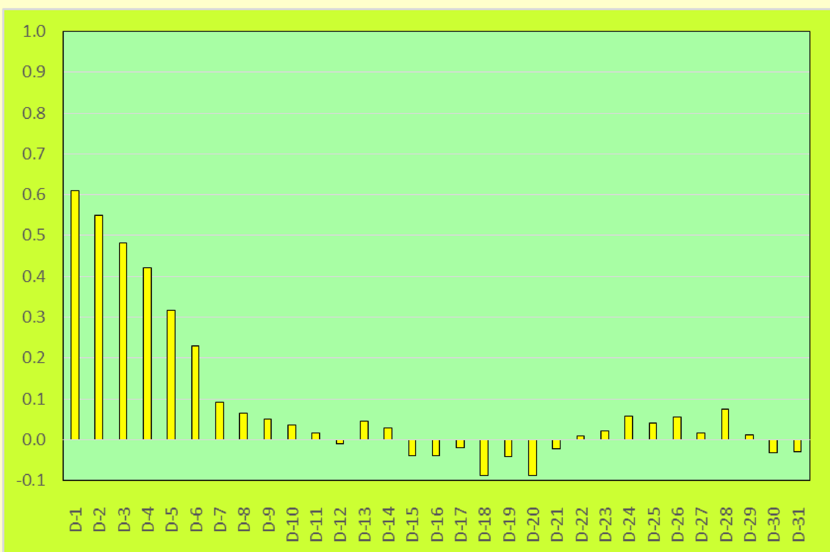

Figure 3 Correlation coefficients between forecast and observed inter-diurnal sets of changes in precipitation amount.

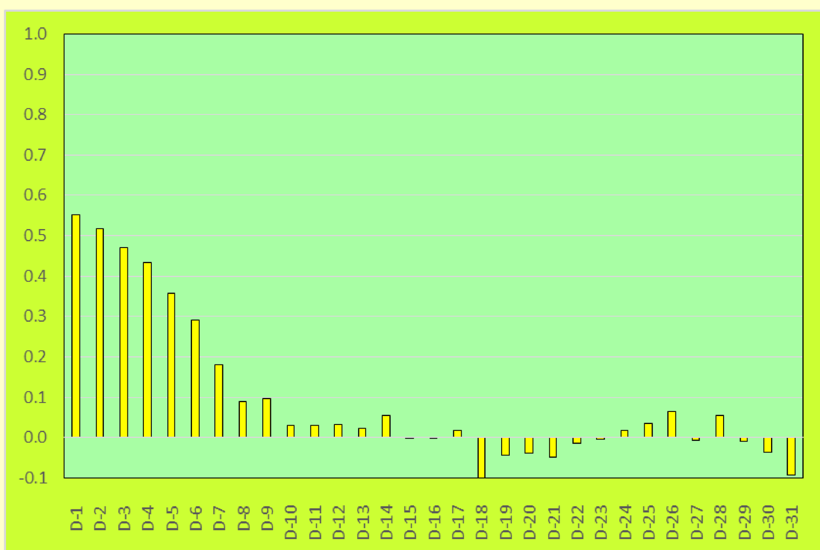

Figure 4 Correlation coefficients between forecast and observed inter-diurnal sets of changes in precipitation probability.

Figures 1, 2, 3 and 4 show that some skill is evident at predicting day-to-day fluctuations in each of the four weather elements out to at least Day-10. However, little skill is evident in regard to predictions of any of the weather elements beyond Day-14. Figure 5, which depicts a set of averages of the correlation coefficients shown in Figures 1, 2, 3 and 4, and represents, therefore, an attempt to illustrate 'overall' skill, underlines the aforementioned conclusion.

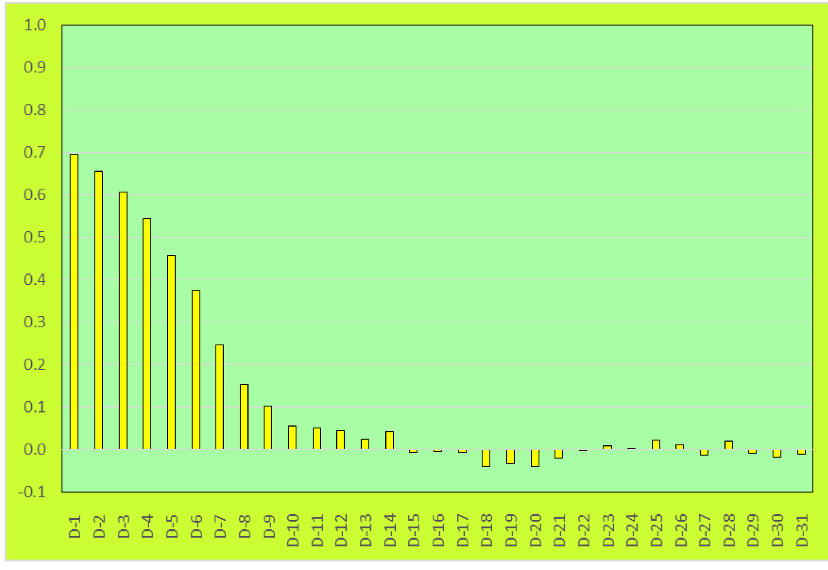

Figure 5 Averages of the sets of correlation coefficients between forecast and observed inter-diurnal changes in minimum temperature, maximum temperature, rainfall amount and rainfall probability and, therefore, an illustration of 'overall' skill.

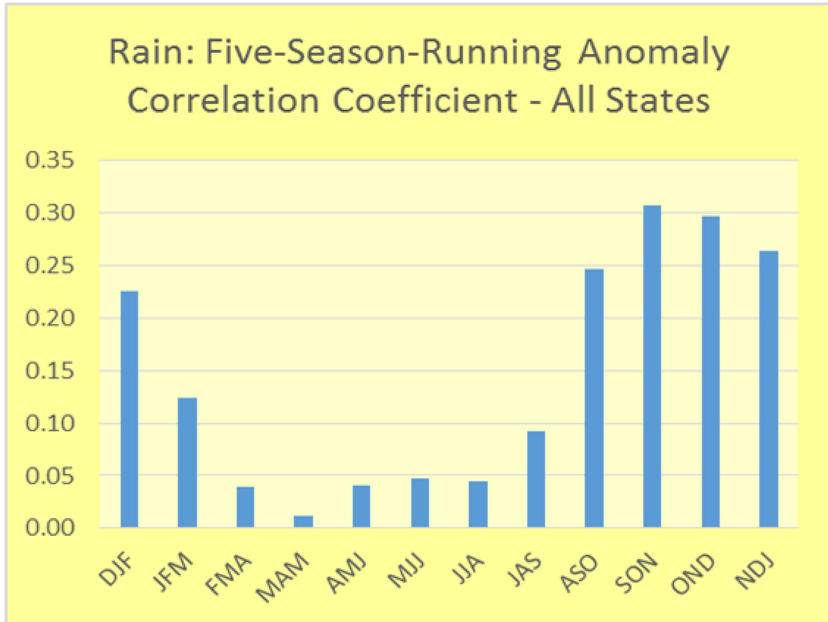

Figure 6 Five season running anomaly correlation coefficient, averaged across all Australian states, between forecast and observed seasonal rainfall (2000-2015).

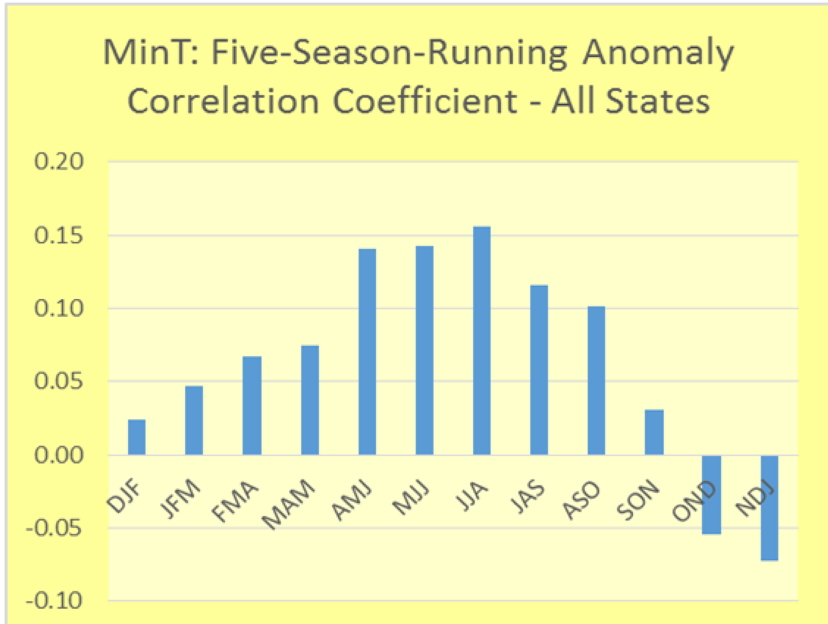

Figure 7 Five season running anomaly correlation coefficient, averaged across all Australian states, between forecast and observed seasonal minimum temperature (2000-2015).

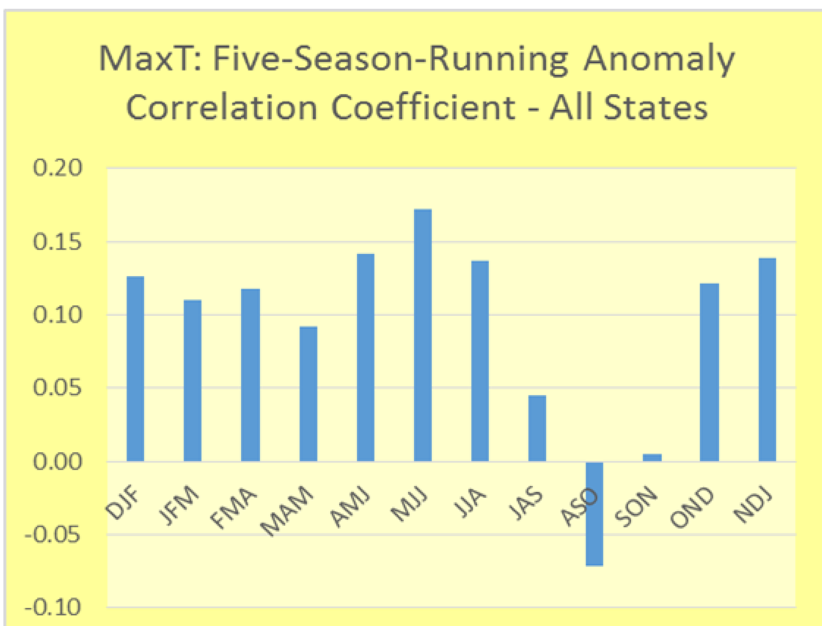

Figure 8 Five season running anomaly correlation coefficient, averaged across all Australian states, between forecast and observed seasonal maximum temperature (2000-2015).

Implications for day-to-day forecasting. The average of the seventeen (Day-15 to Day-31) correlation coefficients associated with:

- minimum temperature is +0.0005,
- maximum temperature is -0.0111,
- rainfall amount is -0.0068,
- rainfall probability is -0.0123,
- 'overall' is -0.0074.

The five averages being very close to zero strongly suggest the absence of any skill in day-to-day weather forecasting beyond Day-14.

Implications for seasonal forecasting.

Whilst we have documented the absence of skill in Melbourne's day-to-day weather forecasts beyond Day-14, this does not necessarily have any implications for seasonal forecasting on account of the latter's goal of providing an overall picture of the next few months' weather. Indeed, verification statistics demonstrate that some capability exists in regard to predicting the characteristics of the forthcoming season, particularly in regard to rainfall.

Figure 6 shows that the rainfall seasonal outlooks issued by the Australian Bureau of Meteorology display some skill throughout the year, performing best during the spring half. The spring rainfall outlooks are especially good in the case of Queensland, New South Wales, Victoria and the Northern Territory, whose rainfall at that time of the year is sensitive to Pacific Ocean sea surface temperature anomalies and the El Niño phenomenon.

Figure 7 shows that the minimum temperature seasonal outlooks, whilst somewhat less skilful than the rainfall outlooks, perform well during the winter half of the year. The winter minimum temperature outlooks for the Northern Territory and Queensland are better than those for the other states.

Figure 8 shows that the maximum temperature seasonal outlooks display some skill in all seasons except autumn, and are best for Queensland, Northern Territory and Western Australia.

Finally, Figure 9 depicts an unsteady, but nevertheless positive, trend in the skill displayed by the rainfall outlooks, since they were first issued in the late 1980s.

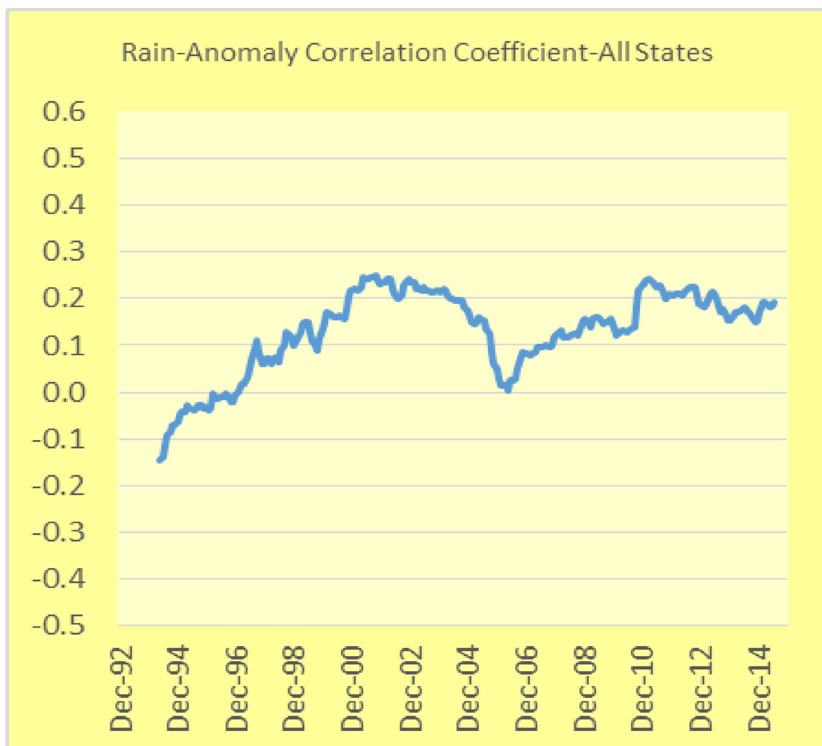

Figure 9 Five-year running mean anomaly correlation coefficient, averaged across all Australian states, between forecast and observed seasonal rainfall.

Summary. **Some skill is evident at predicting day-to-day fluctuations in each of the four weather elements out to at least Day-10. However, little skill is evident in regard to predictions of any of the weather elements beyond Day-14. This absence of day-to-day skill beyond Day-14 does not have any implications for seasonal forecasting on account of the latter's goal of providing an overall picture of the next few months' weather. Indeed, verification statistics demonstrate that some capability exists in regard to predicting the characteristics of the forthcoming season.**