THE ACCURACY OF WEATHER PREDICTIONS, FROM THE NEXT DAY TO THE NEXT SEASON – AN ILLUSTRATION FROM AUSTRALIA

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1. INTRODUCTION

In a paper by the same author also being presented to a conference at the 2017 AMS Annual Meeting (Stern, 2017), it is demonstrated how positional and timing errors in the prediction of synoptic scale systems extract a penalty when verifying weather forecasts. In the course of analysing verification data, that paper briefly touches upon trends on the accuracy of day-to-day weather forecasts for **Melbourne, Australia** (Map 1), out to the end of Week-2.

This is the primary focus of the current paper, which updates previously published work in this area (Stern and Davidson, 2015a, 2015b, 2016) and also in the area of seasonal outlook verification (Stern and Pollock, 2011, 2013).

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

2. PURPOSE

The purpose of this paper is to consider, in detail, the accuracy of predictions for Melbourne of four weather elements, out to the end of Week 4. The four elements considered are minimum temperature, maximum temperature, probability of precipitation and amount of precipitation. The accuracy of official seasonal climate outlooks for Australia is also considered.

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3. ANALYSIS

The accuracy of the predictions of the four weather elements, especially for lead times out to Day-7, has increased substantially over the years.

To illustrate, the frequency of major Day-1 minimum temperature forecast errors (5 deg C or greater) is shown to have fallen from between 2% and 4% per year during the 1960s to the current situation, where there has not been a single such error since February 2014, 33 consecutive months having been error free (Figure 1).

The percent variance in the observations explained by these Day-1 forecasts has increased from between 50% and 60% during the 1960s to between 80% and 90% more recently (Figure 2).

Day 2-4 minimum temperature forecasts explained just 40% of the variance when they were first introduced in the mid-1990s, but now explain just over 70%.

There is a similar story for Day 5-7 minimum temperature forecasts, which explained just 15% of the variance in the late 1990s, but more recently have explained between 40% and 50%.

Over the decade since experimental Day 8-10 minimum temperature forecasts have been generated, the percent variance explained has increased slightly from just under 10% to just over 10%.

However, the percent variance explained by the experimental Day 11-14 forecasts has remained below 5%.

The frequency of major Day-1 maximum temperature forecast errors is shown to have fallen from about 10% per year during the 1960s and 1970s to fewer than 2% more recently (Figure 3).

The percent variance in the observations explained by these Day-1 forecasts has increased from between 50% and 60% during the 1960s to between 80% and 90% more recently (Figure 4).

Day 2-4 maximum temperature forecasts explained 30% of the variance when they were first introduced in the mid-1980s, but now explain between 70% and 80%.

There is a similar story for Day 5-7 minimum temperature forecasts, which explained just 20% of the variance in the late-1990s, but more recently have explained about 50%.

Over the decade since experimental Day 8-10 maximum temperature forecasts have been generated, the percent variance explained has increased slightly from just under 10% to just over 10%.

However, the percent variance explained by the experimental Day 11-14 forecasts has remained about 5%.

The percent variance in the observations explained by *rainfall amount* Day-1 forecasts fluctuates markedly, but has increased from between 25% and 35% 15 years ago to between 50% and 65% more recently (Figure 5), having peaked at about 70% during the very wet 2010-2011 La Niña event.

Figure 5 shows improvement in the Day 2-4 *rainfall amount* forecasts. They explained between 20% and 35% of the variance 15 years ago, but now explain between 40% and 50%, having peaked at about 55% during the very wet 2010-2011 La Niña event.

However, there is little overall improvement shown in regard to the Day 5-7 *rainfall amount* forecasts, which has explained between 5% and 20% of the variance for most of the last 15 years, aside from peaking at around 30% during the very wet 2010-2011 La Niña event.

The skill displayed by the experimental Day 8-10 *rainfall amount* forecasts has also shown little improvement, having fluctuated around 5%, whilst the skill displayed by the corresponding Day 11-14 forecasts has remained at or below 2%.

The percent variance in the observations explained by *rainfall probability* Day-1 forecasts also fluctuates markedly, but has increased from between 30% and 45% 10 to 15 years ago to over 50% more recently (Figure 6).

Day 2-4 *rainfall probability* forecasts have only improved slightly, from between 30% and 35% to about 40%, whilst forecasts for longer lead times have shown little improvement.

Figure 7 and Figure 8 illustrate how variations in *rainfall amount* forecast skill might be related to the different types of synoptic patterns associated with La Niña and El Niño events. Significant peaks and troughs in the skill are shown to coincide with the occurrence of significant peaks and troughs in the Southern Oscillation Index (SOI).

One intriguing aspect of this feature, for which the author is uncertain as to its explanation, is that the peaks and troughs in skill appear to slightly <u>*lead*</u> the peaks and troughs in the SOI. The left hand image of Figure 9 suggests a lead of 5 months. One colleague has proposed a plausible cause. This is that it is possible that it is the weather phenomena that drives the El Niño Southern Oscillation (ENSO) phenomenon, rather than *vice versa* (Davidson, 2016). This raises the following question:

Is the application of our understanding of the ENSO phenomenon responsible for the skill displayed by seasonal rainfall predictions?

The right hand image suggests that perhaps it may not, and that persistence of the prevailing synoptic evolution may be a larger factor.

This brings us now to an analysis of the accuracy of official seasonal climate outlooks for Australia that are issued by the Bureau of Meteorology.

Regarding the accuracy of these seasonal climate outlooks, three elements are considered - precipitation, and overnight and daytime temperature. In each case, some skill is evident, although that level of skill varies from State to State and with time of the year.

To illustrate, the skill displayed by the minimum temperature outlook peaks in the middle of the year and is at its nadir at the end of the year (Figure 10), the skill displayed by the maximum temperature outlook also peaks in the middle of the year but is at its nadir in spring (Figure 11), whilst the rainfall outlook's skill peaks in spring and is at its minimum during autumn. (Figure 12).

Regarding the geographic distribution of skill, the performance is better in the tropical or sub-tropical States than in those further south (not unexpected given that the key driving forces are the Indian Ocean Dipole and ENSO phenomenon, both features of the tropical oceans).

To summarise, the skill displayed by the minimum temperature outlook peaks in the Northern Territory and is at its weakest in Tasmania (Figure 13), that displayed by the maximum temperature outlook peaks in Queensland and is also at its weakest in Tasmania (Figure 14), whilst the rainfall outlook is at its best in Western Australia and at its worst in South Australia (Figure 15).

Examination of trends in the accuracy of the outlooks yields an unexpected result. Whilst the skill displayed by both minimum temperature and maximum temperature outlooks appear to be declining (Figures 16 and 17), the skill displayed by the rainfall outlooks is increasing (Figure 18).

The day-to-day weather forecasts for Melbourne beyond Week-2 are weather forecasts that have been generated by an algorithm that interprets the output of the ECMWF Ensemble Control Model. It is found that little skill is evident for day-to-day predictions of weather with lead times beyond Day-14. Specifically, little skill is displayed by any of these long range forecasts, as depicted for *minimum temperature* by Figure 19, for *maximum temperature* by Figure 20, for *rainfall amount* by Figure 21, and for *rainfall probability* by Figure 22.

4. KEY CONCLUSIONS

The frequency of major Day-1 *maximum temperature* forecast errors (greater than 5 deg C) is shown to have fallen from about 30 per year during the 1960s and 1970s to fewer than 5 per year now. The percent variance in the observations explained by these Day-1 forecasts has increased from around 50% during the 1960s and 1970s to between 80% and 90% more recently. The accuracy of *maximum temperature* forecasts for days 5-7, is now comparable to that displayed by the Day-1 predictions of several decades ago.

Rainfall amount forecasts have also increased in accuracy, with Day-1 rainfall amount forecasts, having explained just 30% of the variance some 15 years ago, now explaining about 60% of the variance. However, fluctuations in the level of skill appear to be strongly related to the synoptic regimes associated with various phases of the ENSO phenomenon.

Regarding the accuracy of seasonal climate outlooks, three elements are considered - precipitation, and overnight and daytime temperature. In each case, some skill is evident, although that level of skill varies from State to State and with time of the year. For example, the precipitation outlook, which has been issued officially since the late 1980s, displays greater skill in the second half of the calendar year than in the first half and also displays greater skill in areas covering the tropics than in more southern regions.

Before closing, it needs to be recorded that day-to-day weather forecasts for Melbourne beyond Week-2, which have been generated by an algorithm that interprets the output of the ECMWF Ensemble Control Model, display little skill.

5. REFERENCES

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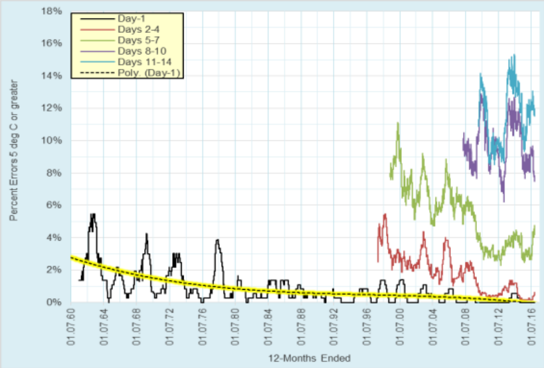

FIGURE 1 Trends in the accuracy of *minimum temperature* forecasts: % errors 5 deg C or greater.

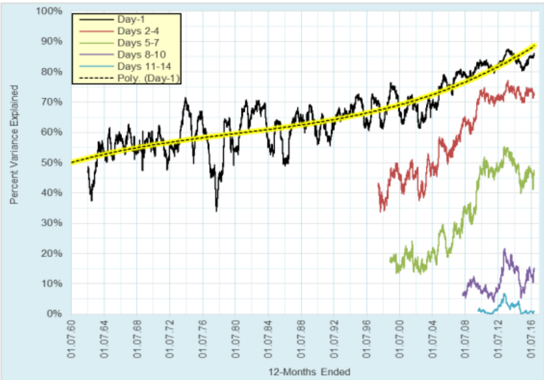

FIGURE 2 Trends in the accuracy of *minimum temperature* forecasts: % variance in the observations explained.

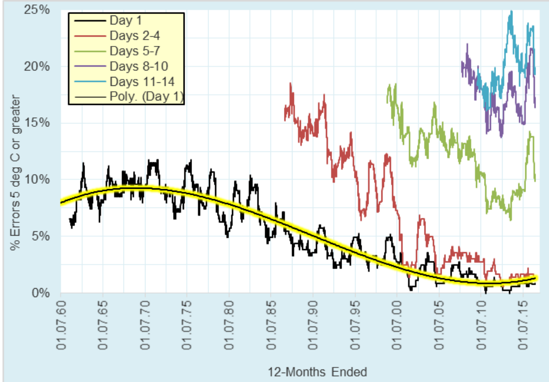

FIGURE 3 Trends in the accuracy of *maximum temperature* forecasts: % errors 5 deg C or greater.

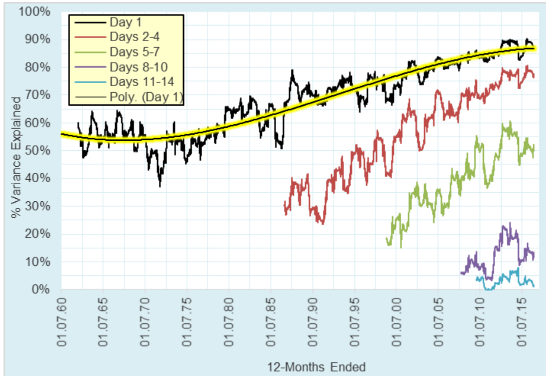

FIGURE 4 Trends in the accuracy of *maximum temperature* forecasts: % variance in the observations explained.

FIGURE 5 Trends in the accuracy of *rainfall amount* forecasts: % variance in the observations explained.

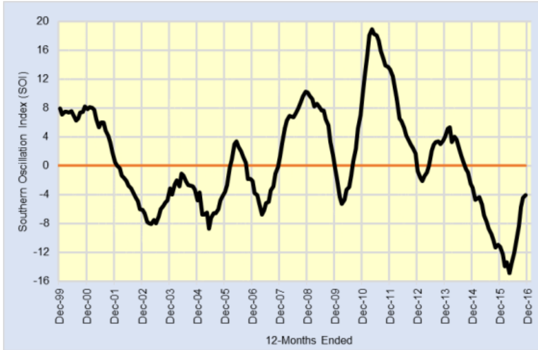

FIGURE 7 Fluctuations in the value of the *Southern Oscillation Index (SOI).*

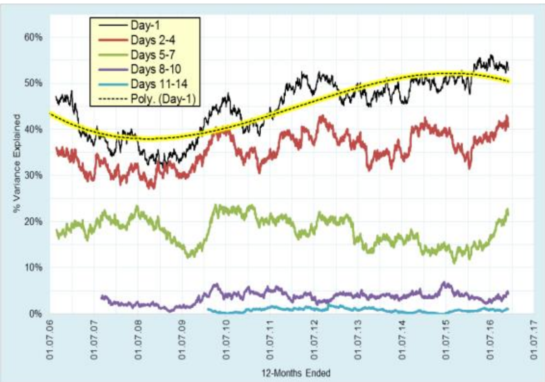

FIGURE 6 Trends in the accuracy of *rainfall probability* forecasts: % variance in the observations explained.

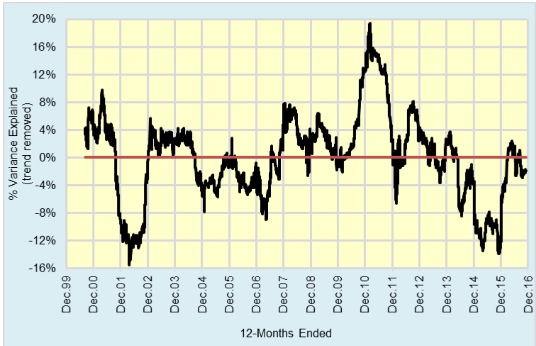

FIGURE 8 Fluctuations in the % variance in the *rainfall amount* observations explained by the forecasts (trend removed).

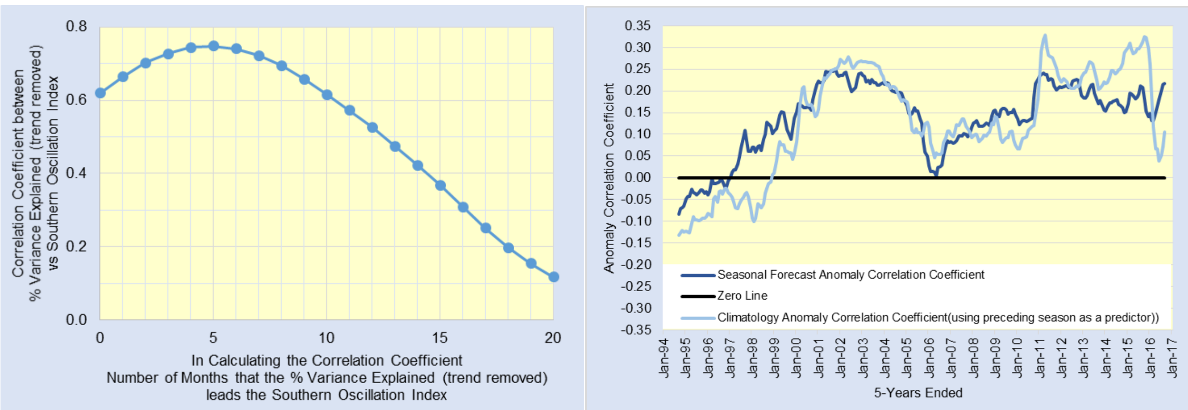

FIGURE 9 Dependence of the correlation coefficient

- between the % variance in the *day-to-day* observed rainfall that is explained by the *day-to-day* predictions **and** the average SOI over the past 12 months
  on the number of months that the % variance explained leads the SOI (left hand image):

Comparison of the 5-year 'running' Anomaly Correlation Coefficient

- between the observed seasonal rainfall, **and** the observed seasonal rainfall three months prior with that between observed seasonal rainfall, and forecast seasonal rainfall (right hand image).

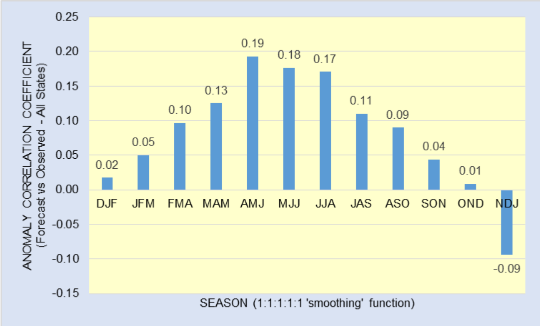

FIGURE 10 The accuracy of seasonal predictions of *minimum temperature* [2000-2016], by season.

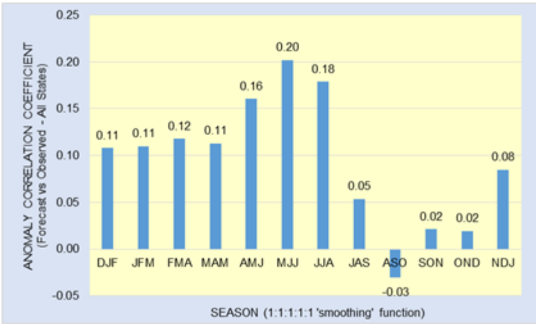

FIGURE 11 The accuracy of seasonal predictions of *maximum temperature* [2000-2016], by season.

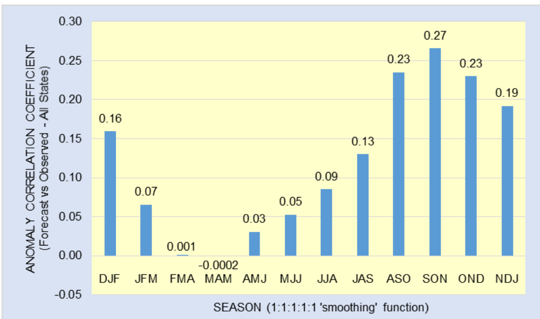

FIGURE 12 The accuracy of seasonal predictions of *rainfall* [1989-2016], by season.

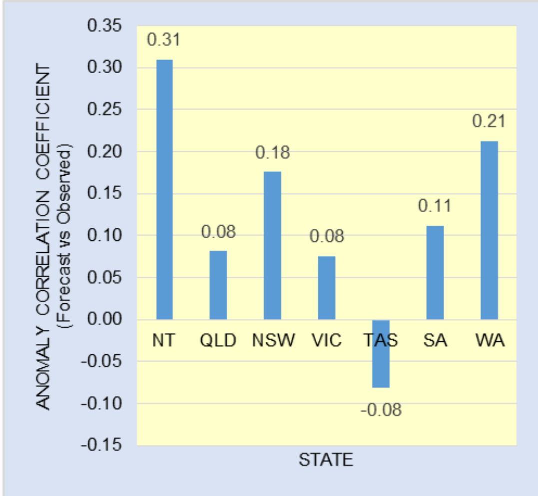

FIGURE 13 The accuracy of seasonal predictions of *minimum temperature* [2000-2016] by State.

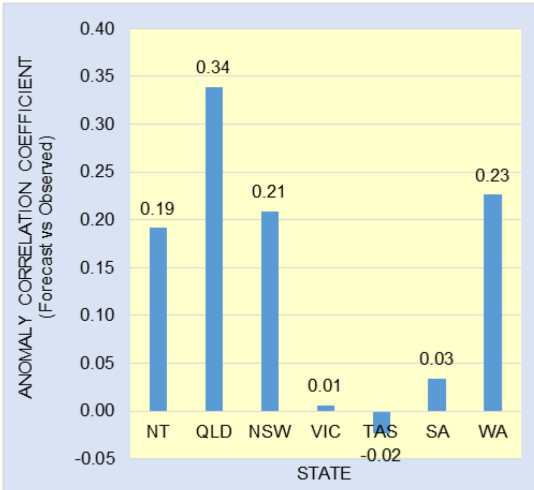

FIGURE 14 The accuracy of seasonal predictions of *maximum temperature* [2000-2016] by State.

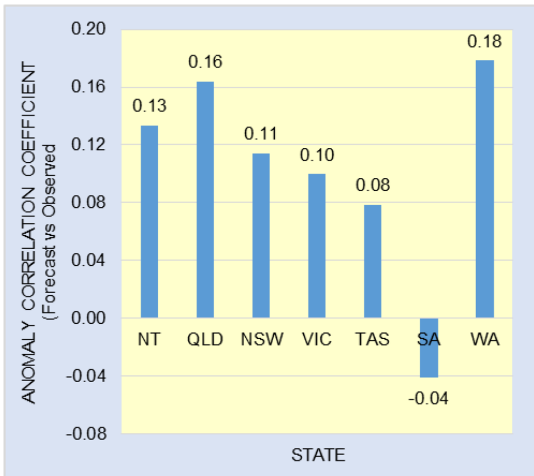

FIGURE 15 The accuracy of seasonal predictions of *rainfall* [2000-2016] by State.

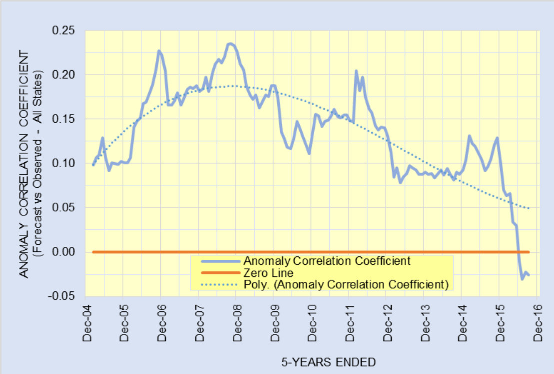

FIGURE 16 Trends in the accuracy of seasonal predictions of *minimum temperature*.

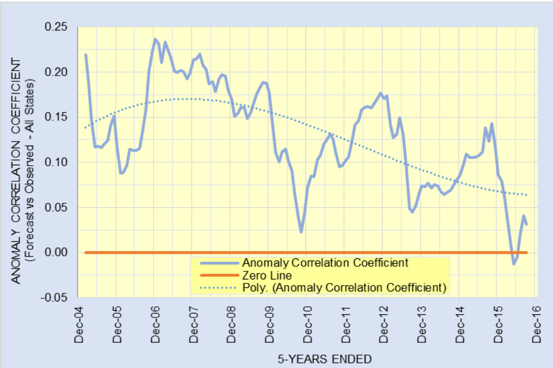

FIGURE 17 Trends in the accuracy of seasonal predictions of *maximum temperature*.

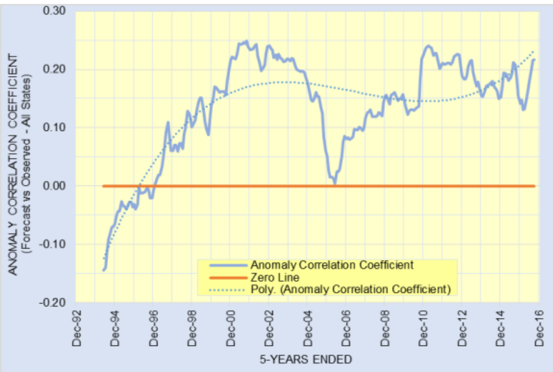

FIGURE 18 Trends in the accuracy of seasonal predictions of *rainfall*.

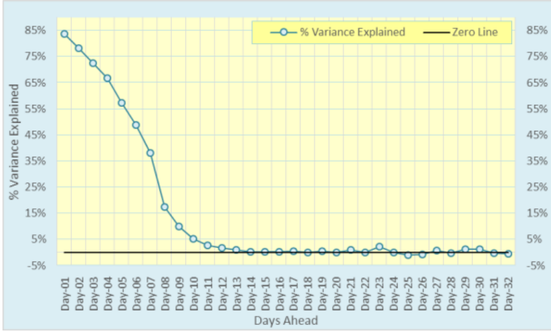

FIGURE 19 The accuracy of Day 1-32 predictions of *minimum temperature*.

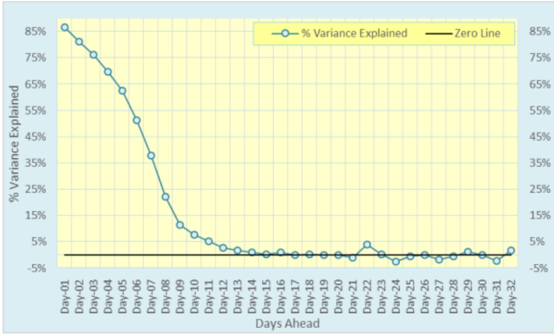

FIGURE 20 The accuracy of Day 1-32 predictions of *maximum temperature*.

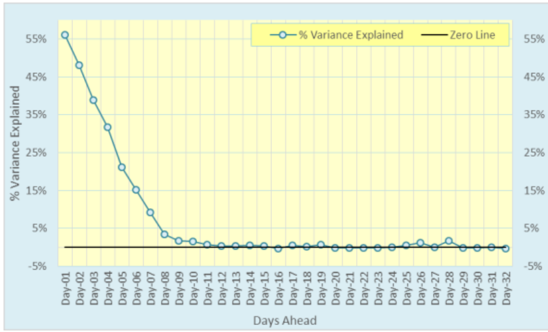

FIGURE 21 The accuracy of Day 1-32 predictions of *rainfall amount*.

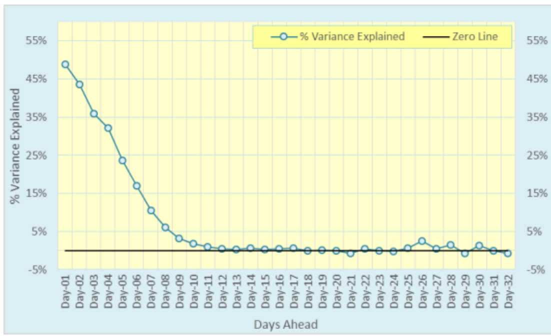

FIGURE 22 The accuracy of Day 1-32 predictions of *rainfall probability*.