Model Lead-Time Accuracy for Pricing Weather Derivatives

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Abstract

Hindcast models were used to determine the accuracy of model prediction and lead-time. We examined the models accuracy for predicting average temperatures for February and August between 1979 and 1999 and compared this with actual average temperatures.

I. Introduction

The weather derivative market was unofficially introduced in the winter of 1996 when two companies, Enron and Koch Energy, swapped heating degree-days (HDD) to hedge their weather risk for the approaching winter. The weather derivative market has now grown into a multi-billion dollar market as many private companies are trying to cut their losses based on climate forecasting.

The weather derivative is similar to insurance with some notable differences. Weather derivatives are bought and sold between private investors without insurance licenses and companies. Weather derivatives protect against high probability, low risk weather events, such as lower or higher than average temperatures, while insurance protects against low probability high-risk weather events such as tornados.

The weather derivative market is governed by the outcome of the weather. The need to predict future weather has taken a new urgency in the twenty-first century. Forecast models are now being used by investors on Wall Street for pricing weather derivatives, and by private companies such Koch Energy that may consider using them to protect assets.

This paper will examine the accuracy of model prediction as lead-time is reduced from six months to one month before the desired time of interest. If investors and consumers of weather derivatives know when the forecast models will output an accurate forecast they can make the appropriate accommodations to protect their investments.

II. Method

The forecast model that we used is an ensemble of twenty models, which are varied in how certain aspects of a forecast are determined. The ensemble output gives monthly averages of temperature, forecasted for each month, up to six months into the future, as well as the total standard deviation between the models. Monthly average temperatures were found for our location of interest by taken the recorded high and low temperature values, as reported in the archive data of the National Climatic Data Center (NCDC).

Our study began by examining forecasted temperatures from our model ensemble and comparing them to the observed temperatures in Des Moines, IA. Early results showed consistent differences in some of our forecasted values and the observed values. We believed this was because the temperature forecast at each grid point is an average over the entire domain represented by that grid point, and that our errors could be attributed to local effects. We then increased the number of cities we used to compare, adding Ames, IA and Marshalltown, IA.

Our study examined the years from 1979 to 1999. The time period of our data was limited by the availability of input data to the model, but should still allow enough time for anomalous years to be averaged out. Two months were chosen in each year, due to time constraints. February and August were chosen to be representative of the coldest and warmest times of the year, respectively.

III. DATA & RESULTS

First, we examined differences within the forecast itself based on changes in lead time. Figure 1 compares the forecasted temperature values for both February and August with a one month lead time and a six month lead time. From the graphs shown, it is evident that little change exists between the forecasts despite the five month difference in lead time of the forecast. There is also little difference in each of the years in the forecast run.

The lack of difference between years is not particularly surprising, since the model produces a forecast for the average temperature during the month, and is generally going to be consistent. However, the lack of variation is somewhat surprising, since a one month lead time should have substantially less possible variation than a six month lead time forecast would. This may be due to the lack of small scale variance that the model includes, instead looking at large scale motions. Large scale motion may have more structure associated with it, which would reduce the amount of variation, even at a six month lead time.

Figure 2 shows the observed temperatures for each of the three cities we examined within our selected grid point. Some variation is evident between the cities, with Des Moines consistently reporting an average temperature slightly higher than the other cities, and Marshalltown reporting a lower average temperature. Overall, though, a consistent trend of rising and dropping temperatures over the years is reflected, and reported temperatures for each year are approximately equal. An average of the three temperatures is used as the observed value for comparison to forecasted values, since forecast values are an average over the grid point.

Comparing the forecasted temperatures to the observed temperatures over our twenty-one year period also produced consistent results for each month. Figure 3 shows the difference between the forecasted value and the average observed value for February and August. For February, model forecasted values are very accurate, and observed values are typically within five degrees of the forecasted value. In contrast, the model ensemble consistently predicted forecasts six to twelve degrees above the observed values for August.

IV. CONCLUSION

After comparing the differences between the forecast values produced by a model ensemble and the actual average monthly temperature for two specific months over a twenty-one year period, certain trends become apparent that may help for weather derivative trading based on climate predictions.

Most notable is the lack of variation in forecasted temperatures with lead time. Since it is apparent that average monthly forecasts do not change drastically from a six month to a one month lead time, derivative traders can begin forecasting demand for weather related products at least half a year in advance. Though there may be differences in need on small spatial or time scales, it would appear that this is balanced out in larger spatial and time scales.

Trends in forecast accuracy also become important for derivative traders. In this study, February produced generally accurate forecasts over the twenty-one year period, while August forecasts consistently trended around nine degrees higher than the actual observed temperature. Although only one grid point and two months were selected for study, it is reasonable to assume that a similar trend can be expected for the months around the two studied, and for grid points in the same general region as the one selected for this study.

To get a better idea of forecasting trends for weather derivative investors, a more extensive study is required. More grid points need to be selected, both in the same region and differing regions, to get an idea of how accurately the observed trends are, and what other trends may occur in differing climate regions.

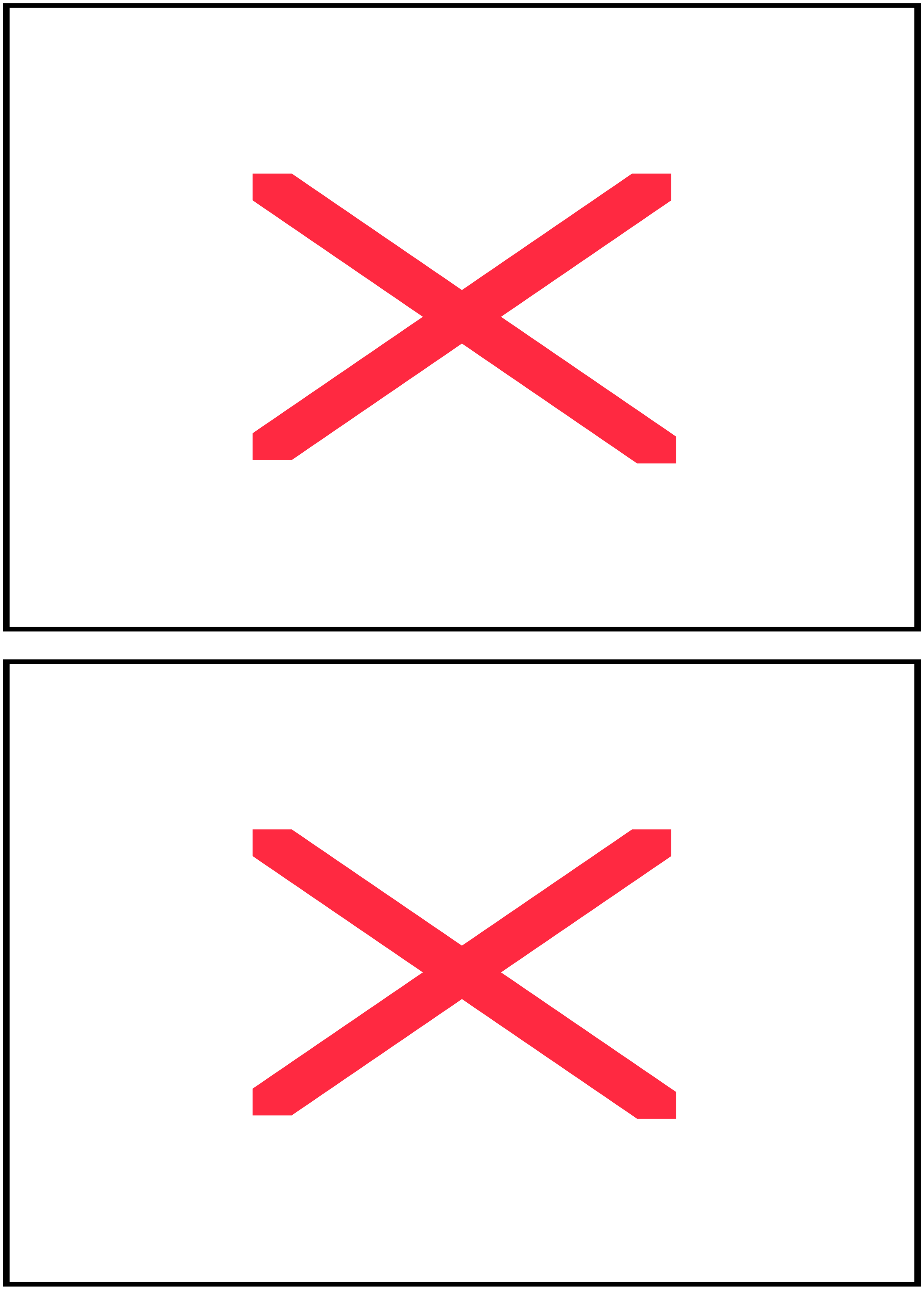

Figure 1: Forecasted temperatures with lead times of one month and six months, respectively. Average ensemble forecast is graphed, with one standard error of the ensemble represented by the error bars.

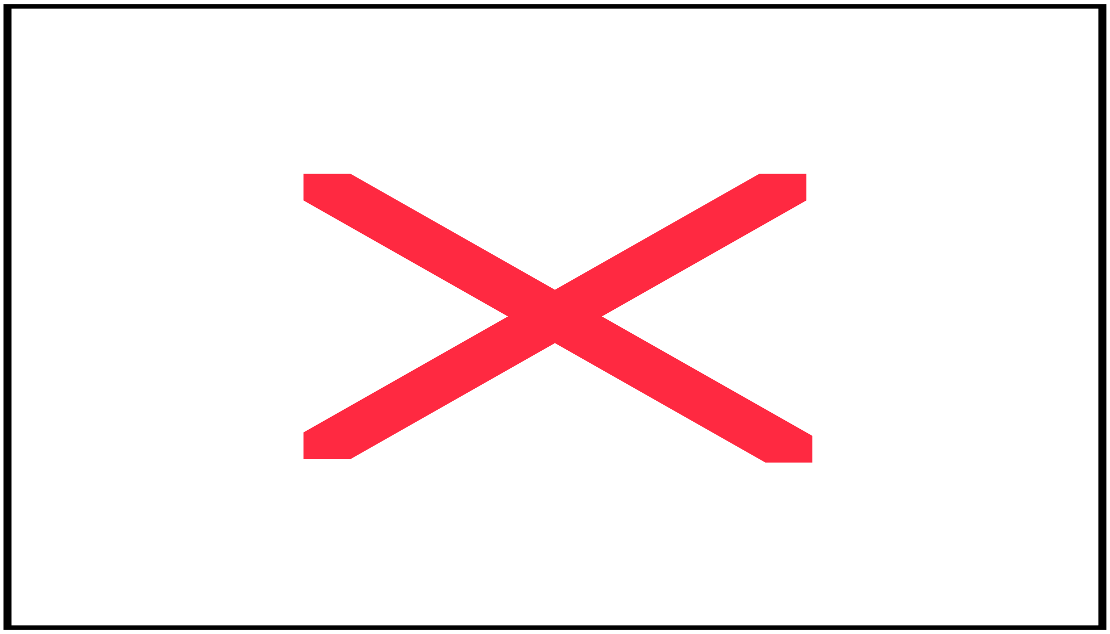

Figure 2: Monthly average of observed temperatures for the three cities studied within the central Iowa grid point.

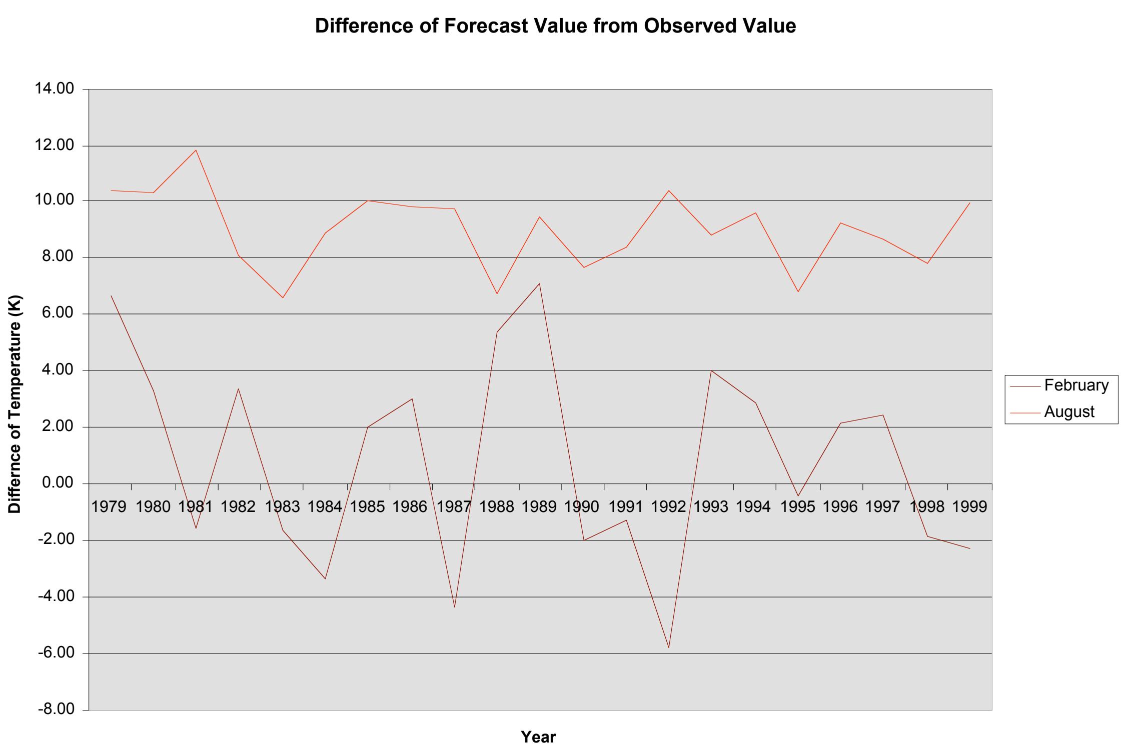

Figure 3: Differences between the observed monthly average and the average ensemble forecast. (Forecasted Temp. – Observed Temp.)