Spatial and Temporal Trends in Weather Forecasting and Improving Predictions with ARIMA Modeling

Manasi Sheth[1], Mahalaxmi Gundreddy[1], Vivek B. Shah[2], and Eric A. Suess[3]

[1]College of Business and Economics, California State University, East Bay, CA 94542

[2] Energy, Environment and Chemical Engineering, Washington University in St. Louis, St. Louis, Missouri 63130

[3]Department of Statistics and Biostatistics, School of Engineering, California State University, East Bay, CA 94542

Abstract

The main purpose of the paper is to analyze and improve the accuracy of the weather forecasts made by National Weather Service for the years 2014-2017 for different cities in the United States of America. The accuracy of the forecasts has been evaluated from different perspectives such as spatial, temporal and the time gap between prediction and the actual date. Since the temperatures were found to be autocorrelated, time series based ARIMA models were implemented to improve the maximum and minimum temperature forecasts. Although, there was significant improvement in predictions of minimum temperature, improvement was observed for maximum temperature predictions only for few cities. To improve the maximum temperature predictions for all the cities, another ARIMA model was implemented to predict the residuals from the forecasted temperature. By predicting the residuals, all maximum temperature forecasts as well as minimum temperature forecasts were improved.

Key Words: weather forecasting, time series prediction, ARIMA

1. Introduction

Weather forecasting is critical for agriculture, vegetation, water resources, tourism and prevention of damage from extreme weather hazards such as Hurricanes or snow storms etc. (Ustaoglu, Cigizoglu and Karaca 2008). The weather forecasts have improved over the years due to availability of various numerical, physics based or statistical models. Most of the statistical models, use past data and time series analysis to forecast weather. There are many studies which have investigated weather forecasts using time series globally (Murat, et al. 2018) (Ustaoglu, Cigizoglu and Karaca 2008). However, very few studies have systematically looked at the weather data from United States and analyzed the accuracy of the forecasts of temperatures and improved them with time series (Ropelewski and Halpert 1986).

In this work, we first analyze the accuracy using spatial and temporal trends of the forecasts made by the National Weather Service using the weather data from 2014-2017 for 113 cities in the United States of America. Further, the forecasts for maximum and minimum temperatures are improved with time series based ARIMA models.

The data was generated for Data Expo Session held at 2018 Joint Statistical Meetings, hosted by American Statistical Association in Vancouver. With the help of an R script which ran early each morning, the forecasts were collected from the National Weather Service website and the predictions were documented each morning (usually before the low temperature for the day occurred). The historical weather was downloaded from the "weatherData" package for R (getSummarizedWeather function). The airport closest to the latitude and longitude of the city with data for 2014-2017 was selected and weather data was downloaded. (ASA Data Expo 2018 2018)

2. Analyzing the forecast accuracy

The forecasts for daily minimum temperature and maximum temperature across the 113 cities over the span of 3 years from 2014-2017 are analyzed for their accuracies. First, we look at the mean errors for the forecasts for the whole dataset. Next, we look at the spatial variation in means square error (MSE) for the temperature forecasts of all the cities averaged over the 3 years. The mean square error (MSE) is used as a metric for quantifying the accuracy of forecasts. The mean square error for a forecast (MSE_f) is given by

$$MSE_f = \frac{1}{n-1}\sum_{i=1}^{n}\left(y_{ai} - y_{fi}\right)^2 \quad (1)$$

where y_{ai} is the actual temperature on the i^{th} date, y_{fi} is the forecasted temperature on the i^{th} date and n is the total number of records. Finally, we look at temporal variation in MSE_f of daily forecast combined for all the locations and effect of number of days between the forecast and actual date.

2.1 Overall trends

Table 1 shows the distribution of errors for the maximum temperature and minimum temperature. The mean error in minimum temperature prediction is much higher than the error in maximum temperature. The non-zero mean error shows that the models for maximum temperature and minimum temperature both can be improved.

Table 1: The statistical description of errors for forecast of maximum temperature and minimum temperature in Fahrenheit.

	Errors in Maximum temperature forecast	*Errors in Minimum temperature forecast*
Mean, F	1.01	2.94
Standard deviation, F	4.83	15.5
Median, F	1	2
99.5 %, F	16	51
0.5 %, F	-15	-31
Counts	651000	651000

2.2 Spatial trends in forecasting errors

MSE_f of maximum and minimum temperatures for all the cities in the dataset is plotted using the proportional symbol maps, where the increasing size of circle and darkness represents larger MSE. Figure 1(a) shows the distribution of MSE_f for maximum temperature for various cities. For maximum temperature, the cities in the mountain zone or in the north have high MSE_f. However, lower MSE_f for maximum temperature is observed in the southern most cities.

Figure 1(b) shows the distribution of MSE_f for minimum temperature for various cities. There are more accurate forecasts of minimum temperature in the northern cities but the MSE_f increases towards south. There is very high MSE_f for minimum temperature for southern cities close to ocean.

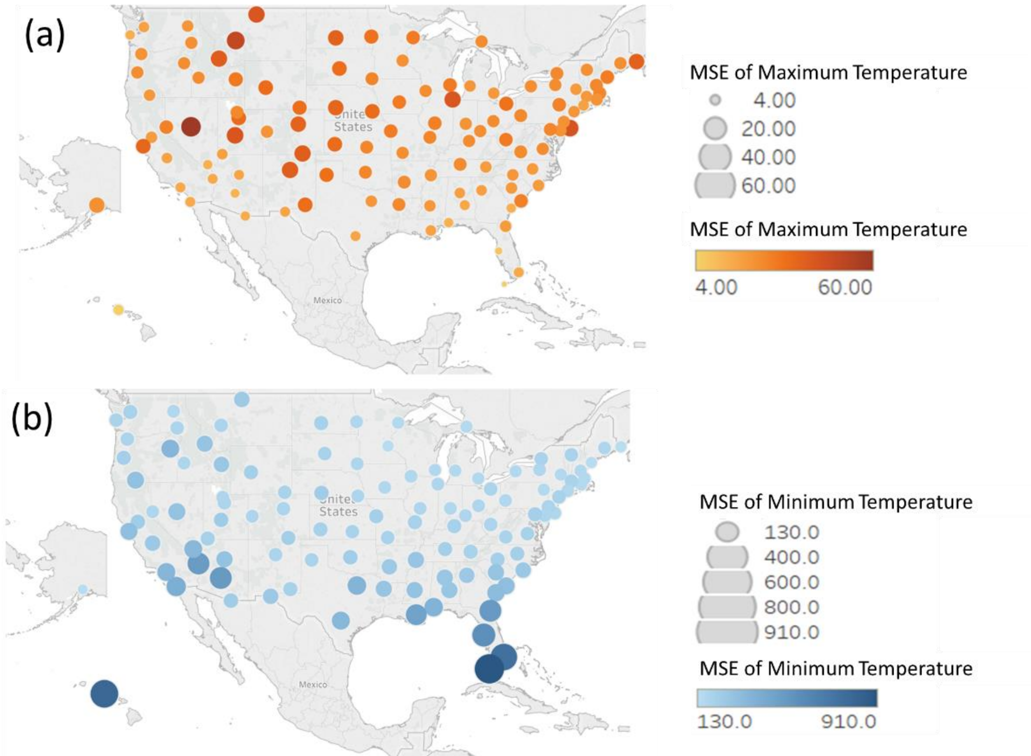

Figure 1: The distribution of mean square of error across different cities in United States for (a) maximum temperature (b) minimum temperature. The five cities with highest errors have been labelled.

2.3 Temporal trends in forecasting errors

Figure 2 shows the daily mean square error in the forecasts (MSE_f) of minimum and maximum temperature for all the cities. The MSE_f shows a cyclical pattern. The minimum temperature forecasts have high MSE_f in winters. In contrast, the maximum temperature forecast shows slightly higher variations in the spring time. Overall the MSE_f for the minimum temperature is significantly higher than maximum temperature.

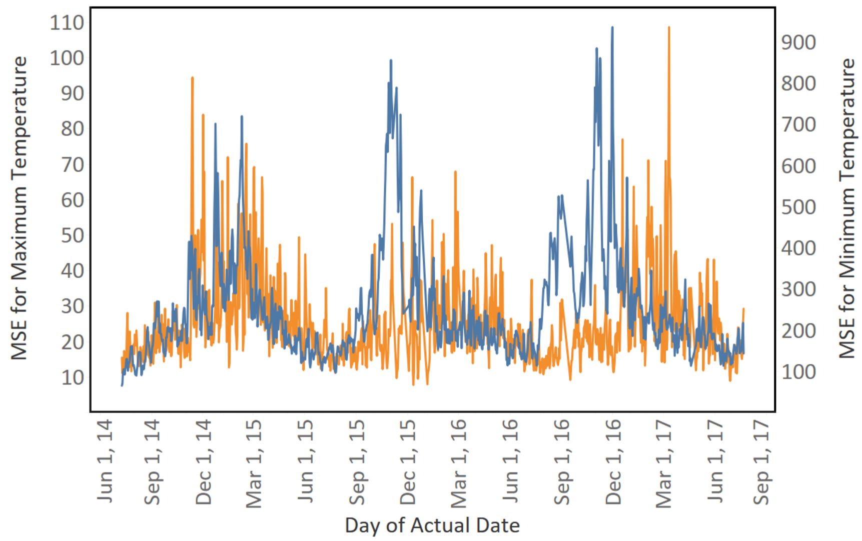

Figure 2: Daily distribution of MSE in maximum (left axis, orange color) and minimum temperature (right axis, blue color) forecasts spanned over three years, 2014 – 2017

2.4 Effect of days between forecast and actual date

Figure 3 shows the change in mean square of error (MSE) in forecasts as the number of days between forecast and actual changes from zero to six. For maximum temperature, the MSE for the forecast decreases as the days between prediction and actual dates decrease. However, no such trend is observed for the minimum temperature.

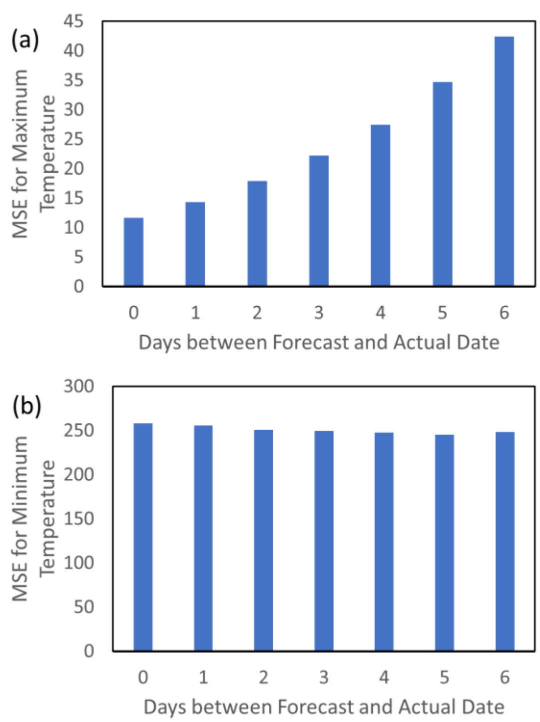

Figure 3: Mean square of error (MSE) with number of days between forecast and actual for forecasts of (a) maximum temperature (left) and (b) minimum temperature on right.

3. Improving weather forecasts

As seen from Table 1, the mean errors for maximum and minimum temperature forecasts are non-zero, thus the forecasts can be improved. Since, the maximum and minimum temperature data have a very high autocorrelation, time series based ARIMA models are evaluated to predict minimum and maximum temperatures. We have picked Austin, NV and Richfield, UT, the 2 cities with worst maximum temperature forecast, and Honolulu, HI and Phoenix, AZ, the 2 cities with worst minimum temperature forecast, for testing the model predictions. The time series based ARIMA models are implemented in two ways – first to predict the daily maximum and minimum temperatures and second to predict the residuals for the daily maximum and minimum forecasts.

The data for each city is split into 60% training and 40% for testing the model. Since the temperature and its variation are strongly related to location of the cities, the models for each city are built independently. The R function auto.arima (Hyndman and Athanasopoulos 2018) (Hyndman and Khandakar 2008), available from the forecast R package, which uses AIC, AICc or BIC, is used for determining optimal model based on test dataset.

3.1 ARIMA model for temperature forecasts

The ARIMA model uses the historical data to make predictions for the daily maximum and minimum temperature. The predictions from the ARIMA model are compared with the weather forecasts obtained from the National Weather Service.

Mean square error for prediction (MSE_p) is given by

$$MSE_p = \frac{1}{n-1}\sum_{i=1}^{n}\left(y_{ai} - y_{pi}\right)^2 \qquad (2)$$

where y_{ai} is the actual temperature on the *i* date, y_{pi} is the predicted temperature by ARIMA model on the *i* date and *n* is the total number of records.

Table 2 summarizes the parameters for the ARIMA model used for each city, the MSE_p from predictions, MSE_f from forecast and the percentage reduction in MSE due to model. The percentage reduction in MSE is given by

$$\%\, reduction\ in\ MSE = \left(1 - \frac{MSE_p}{MSE_f}\right) \times 100 \qquad (3)$$

The ARIMA model predictions maximum temperature for Austin and Honolulu have lower MSE than the forecasts. However, for Richfield and Phoenix the weather forecasts from National Weather Service data are better than the ARIMA model predictions. Table 3 shows the improvement in forecasts of the minimum temperature by ARIMA model. A 79%-97% reduction in MSE is observed for the model predictions of minimum temperature, and the MSE_p for minimum temperature are comparable to those of maximum temperature. From Table 1, it is observed the overall errors for minimum temperature forecasts is larger than the maximum temperature, hence it is imperative that large improvements can be observed in temperature prediction for minimum temperature with an appropriate model.

Table 2: Comparison of MSE for maximum temperature with ARIMA model and MSE for forecasts

City	*ARIMA model parameters (p, d, q)*	*MSE_p for maximum temperature with ARIMA model*	*MSE_f for forecasted maximum temperature*	*% Reduction in MSE*	*Number of test records*
Austin	(2,0,2)	46.8	49.2	5	304
Honolulu	(1,1,1)	3.7	4.6	21	391
Richfield	(1,1,2)	56.4	33.0	-71	327
Phoenix	(1,1,2)	21.2	5.0	-328	392

Table 3: Comparison of MSE for minimum temperature with ARIMA model and MSE for forecasts

City	*ARIMA model parameters (p, d, q)*	*MSE_p for minimum temperature with ARIMA model*	*MSE_f for forecasted minimum temperature*	*% Reduction in MSE*	*Number of test records*
Austin	(1,1,1)	35.4	311.8	89	304
Honolulu	(2,1,2)	21.4	729.0	97	391
Richfield	(1,1,1)	54.8	265.3	79	327
Phoenix	(2,1,2)	15.2	480.3	97	392

3.2 ARIMA model for prediction of residuals

In the weather forecasts data, obtained from Nation Weather Service, we observed high autocorrelation for the residuals of the forecasts. Thus, another way to improve the model would be to predict the autocorrelated residuals from the forecast, ε_{ri}. The actual temperatures can be expressed as a sum of weather forecast and residuals,

$$y_{ai} = y_{fi} + \varepsilon_{ri} \quad (4)$$

MSE_f can be split into MSE_e from the ARIMA predictions of residuals and the MSE_u, which is the unexplained part.

$$MSE_f = MSE_e + MSE_u \quad (5)$$

Table 4 shows the ARIMA models used for prediction of the residuals for maximum temperature. The prediction of the residuals for maximum temperature have significantly reduced the MSE for all the cities, even the cities with low MSE_f.

Table 4: Comparison of MSE for residuals in maximum temperature forecast with ARIMA model and MSE for forecasts

City	*ARIMA model parameters (p, d, q)*	*MSE_u for residuals in maximum temperature forecasts with ARIMA model*	*MSE_f for forecasted maximum temperature*	*% Reduction in MSE*	*Number of test records*
Austin	(1,1,2)	14.5	49.2	70	304
Honolulu	(1,0,2)	3.2	4.6	32	391
Richfield	(1,0,2)	21.3	33.0	36	327
Phoenix	(1,0,0)	4.4	5.0	12	392

Table 5 shows the comparison of ARIMA model based MSE_u for residuals of minimum temperature predictions with MSE_f in forecasted minimum temperature. Though the percentage reduction in MSE is less compared to previous model, there is still significant reduction in MSE for all the cities.

Table 5: Comparison of MSE for residuals in predictions of minimum temperature with ARIMA model and MSE for forecasts

City	*ARIMA model parameters (p, d, q)*	*MSE_r for residuals in minimum temperature predictions with ARIMA model*	*MSE_f for forecasted minimum temperature*	*% Reduction in MSE*	*Number of test records*
Austin	(1,0,3)	127.3	311.8	59	304
Honolulu	(1,1,2)	154.3	729.0	79	391
Richfield	(1,0,2)	135.0	265.3	49	327
Phoenix	(1,1,1)	151.3	480.3	68	392

4. Conclusions

The National Weather Service forecasts for maximum temperature are better than the forecasts for minimum temperature. The MSE for maximum temperature improves as the days between the forecast and actual date decrease, however MSE for minimum temperature remain the same. The ARIMA model used to estimate the maximum temperature has lower MSE than the National Weather Service forecasts for two cities, however for other cases the forecasts by National Weather Service are better. However, the minimum temperature predictions can be improved by a large margin by using ARIMA model. The maximum temperature forecasts from National Weather Service can be further improved by predicting the residuals with ARIMA model. The predictions of the residuals for minimum temperature does not show much improvement in MSE since the forecasts by the National Weather Service are not accurate. In the future, the predictions can be further improved by using multivariate time series analysis.

Acknowledgements

The data was generated for Data Expo Session held at 2018 Joint Statistical Meetings, hosted by American Statistical Association in Vancouver. More details on the data collection methods can be found on the website - http://community.amstat.org/stat-computing/data-expo/data-expo-2018.

References

2018. *ASA Data Expo 2018.* http://community.amstat.org/stat-computing/data-expo/data-expo-2018.

Hyndman, Rob J, and George Athanasopoulos. 2018. *Forecasting: Principles and Practice.* April.

Hyndman, Rob, and Yeasmin Khandakar. 2008. "Automatic time series forecasting: The forecast package for R." *Journal of Statistical Software* 27 (3).

Murat, Małgorzata, Iwona Malinowska, Magdalena Gos, and Jaromir Krzyszczak. 2018. "Forecasting daily meteorological time series using ARIMA and regression models." *Int. Agrophys.* 32: 253-264.

Ropelewski, C F, and M S Halpert. 1986. "North American Precipitation and Temperature Patterns Associated with the El Niño/Southern Oscillation (ENSO)." *Monthly Weather Review* .

Ustaoglu, B., H. K. Cigizoglu, and M. Karaca. 2008. "Forecast of daily mean, maximum and minimumtemperature time series by three artificial neural networkmethods." *Meteorological Applications* 15: 431–445.