

Motivation

How do different regions of the United States experience forecast error? (click on images or tabs for details)

Clusters

Cali-Florida



Intermountain West



Southeast



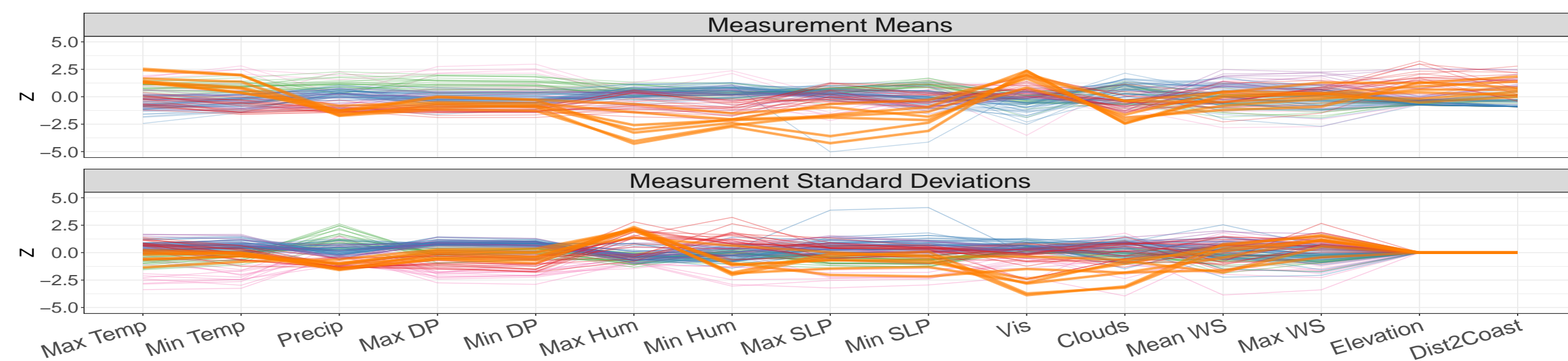
Midwest



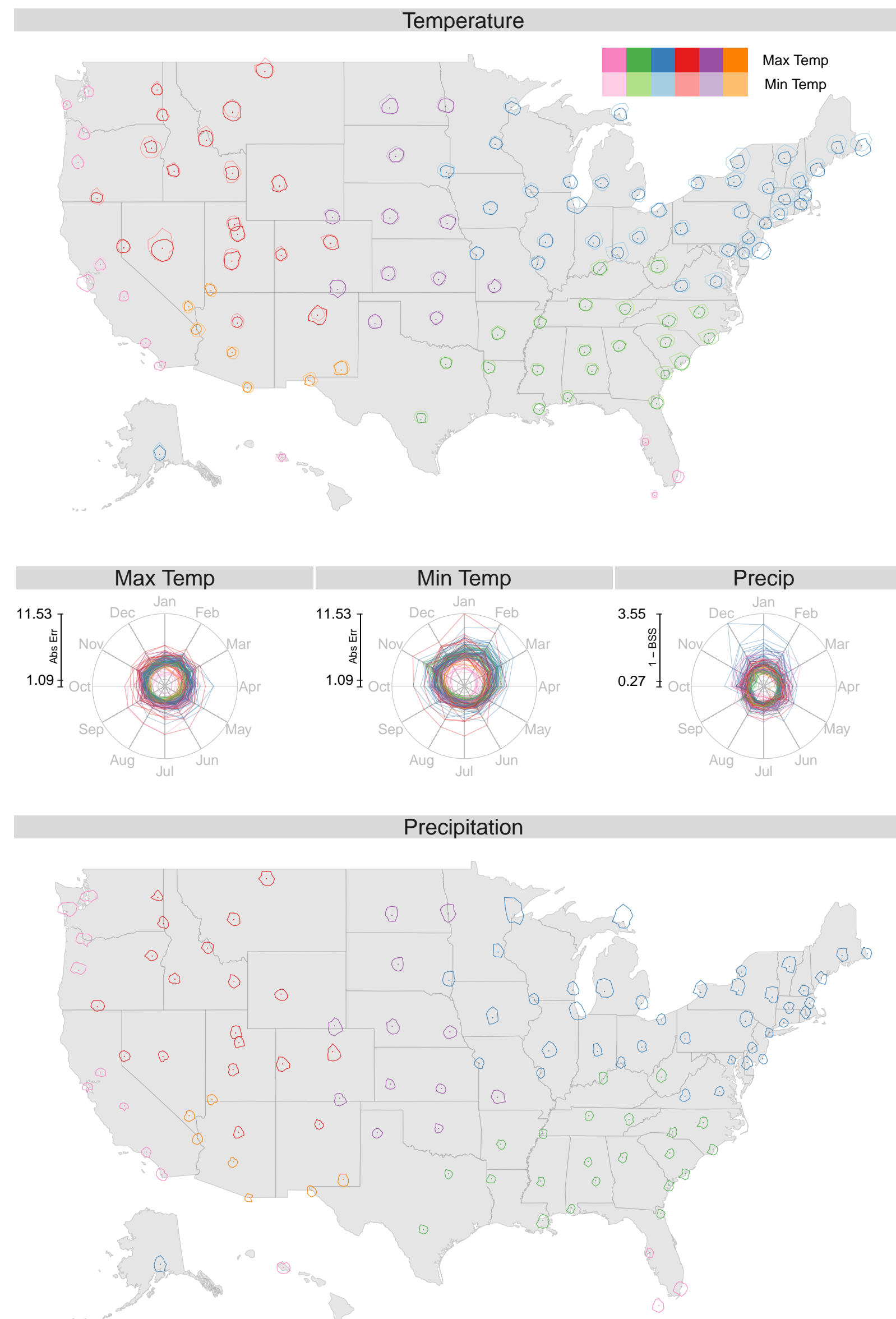
Northeast



Southwest



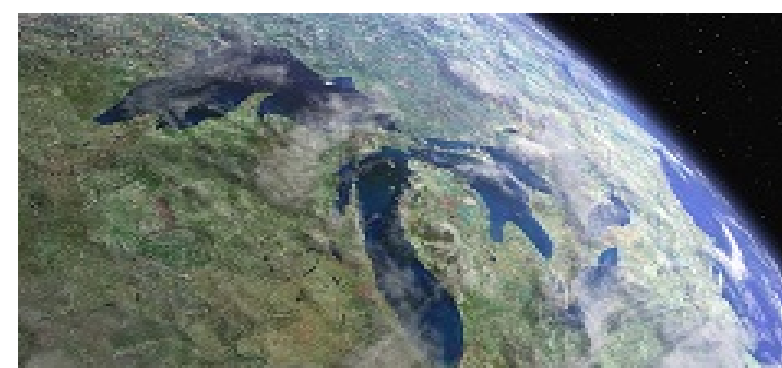
Seasonality



San Francisco, CA



Great Lakes



Trends & Outliers

Cali-Florida



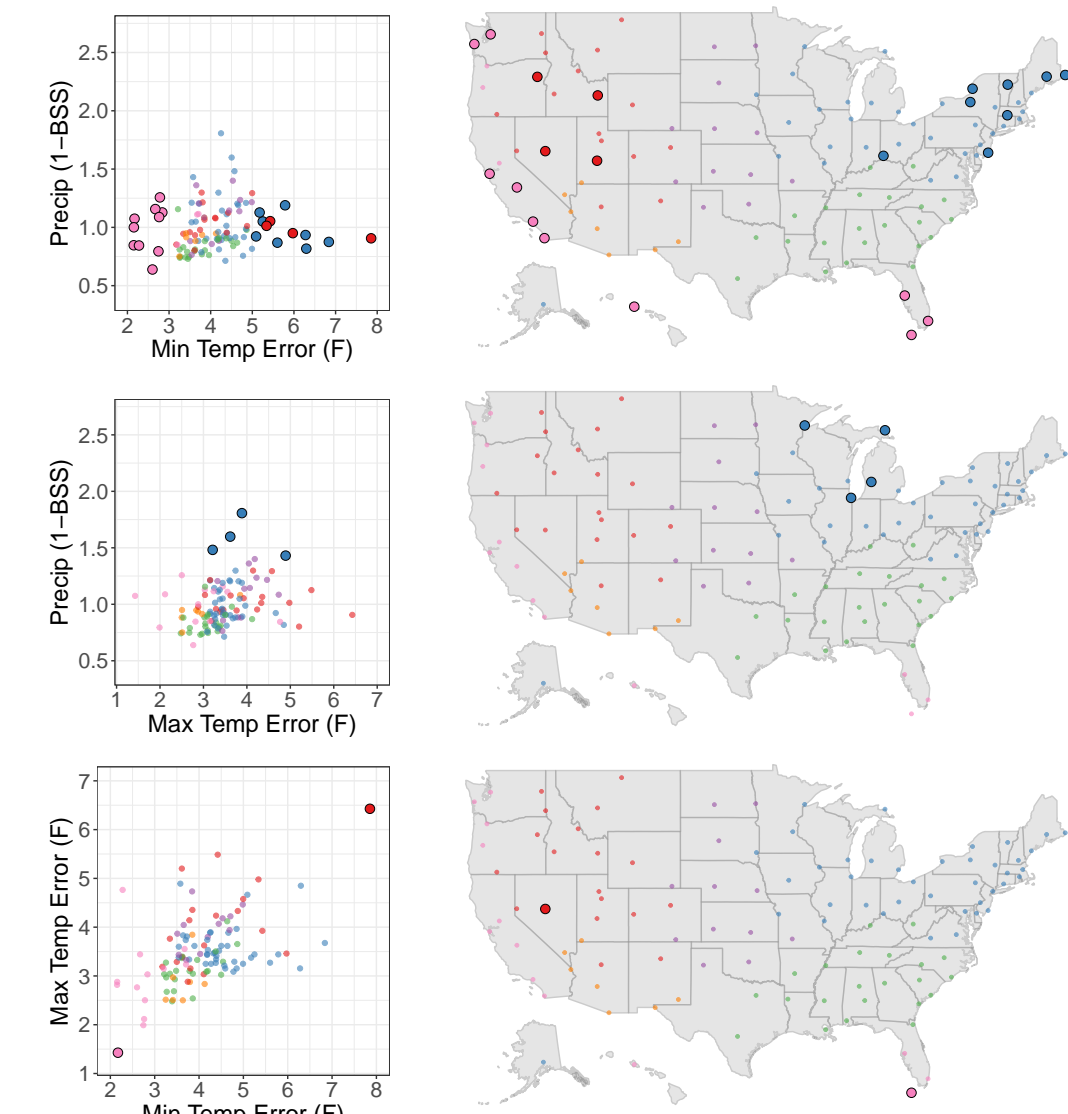
New England



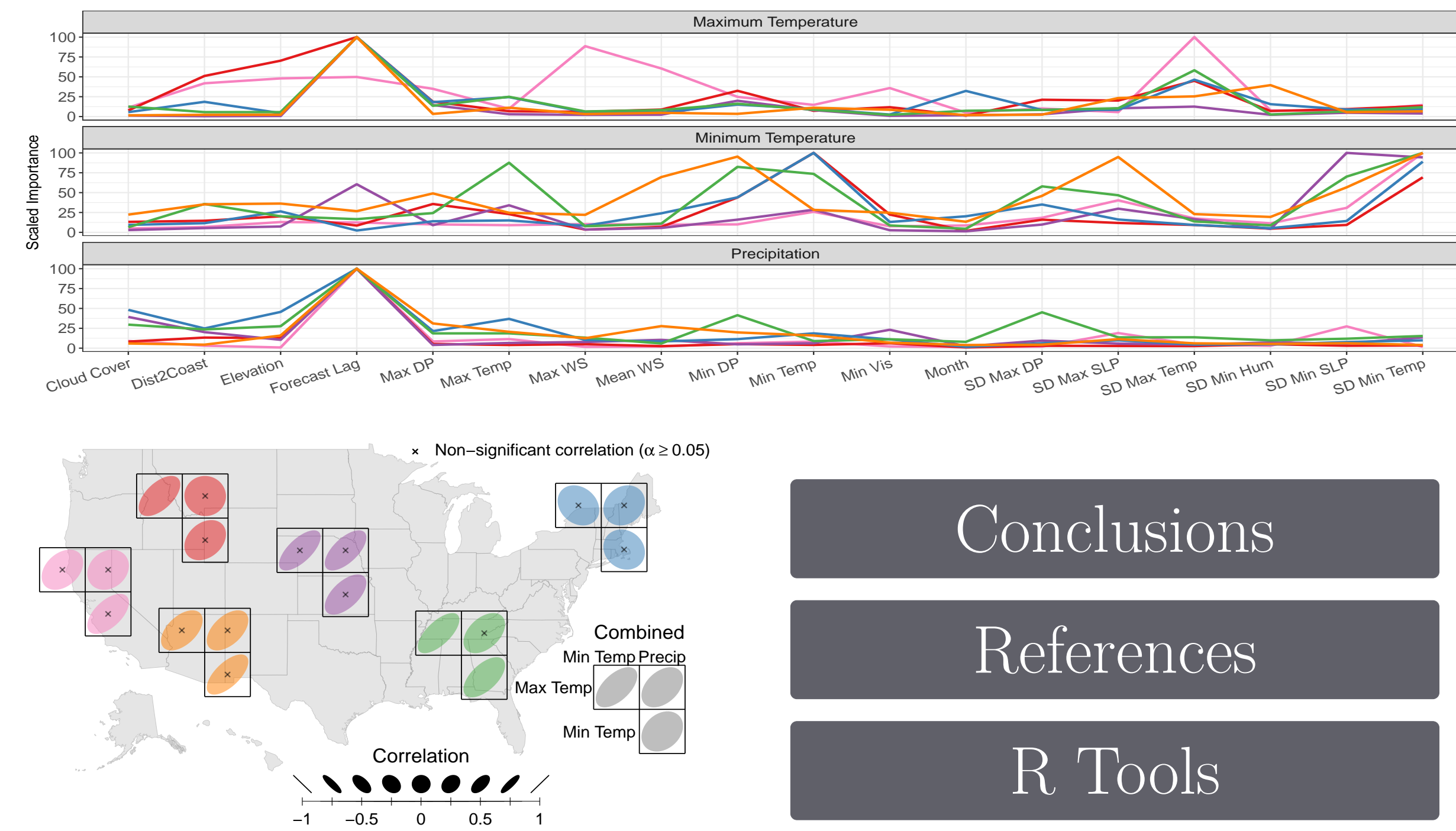
Key West, FL



Austin, NV



Importance & Correlations



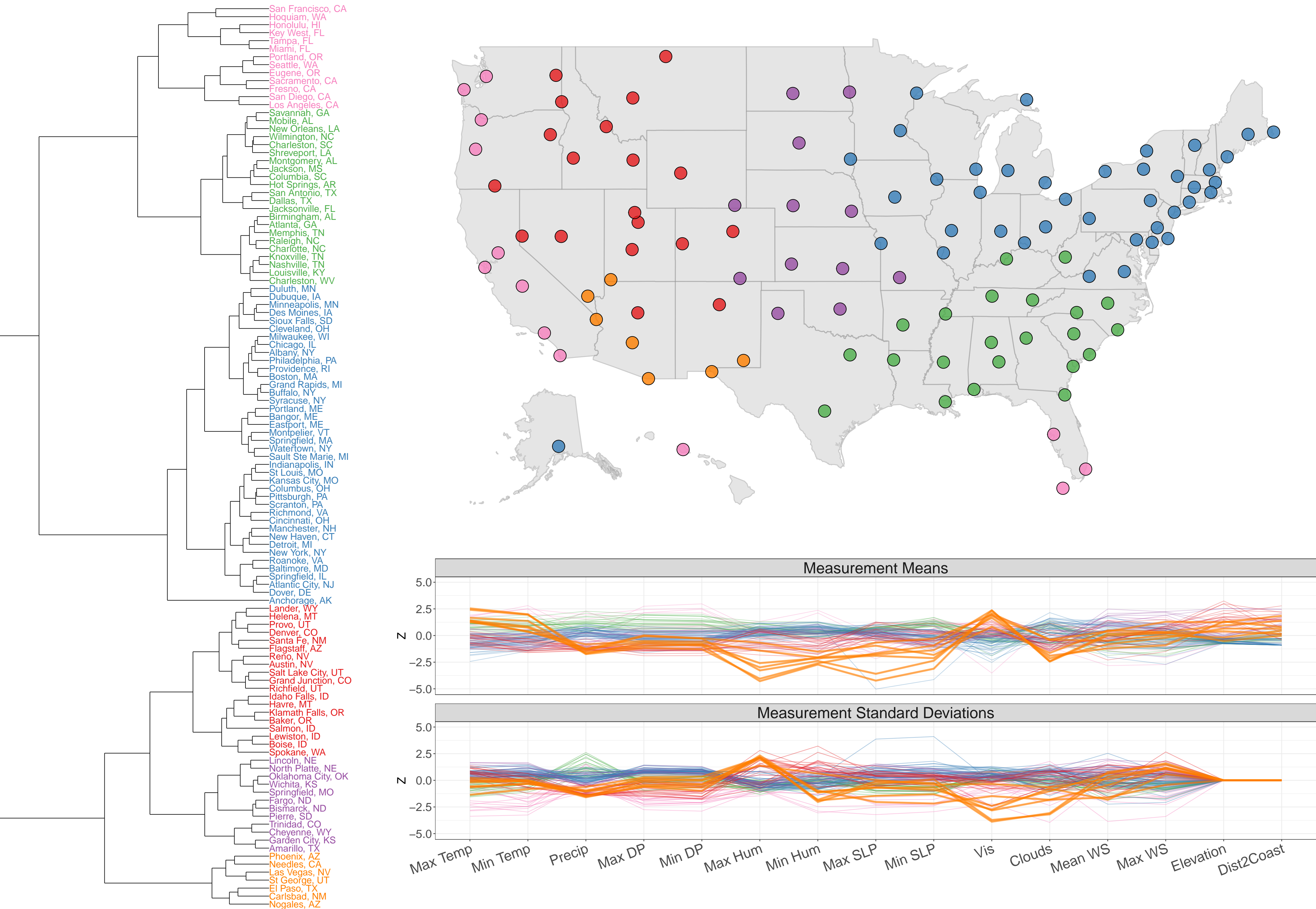
Conclusions

References

R Tools

Cluster Analysis

- Hierarchical clustering using **Ward’s method** and **Euclidean distance**.
- Weather stations cleanly cluster into 6 weather regions:
 - **Cali-Florida**
 - **Southeast**
 - **Northeast**
 - **Intermountain West**
 - **Midwest**
 - **Southwest**
- Parallel coordinate plot of weather variables shows distinct weather patterns within each region (**See the app**).



How does forecast error change by cluster and by season?

Overview

Clusters

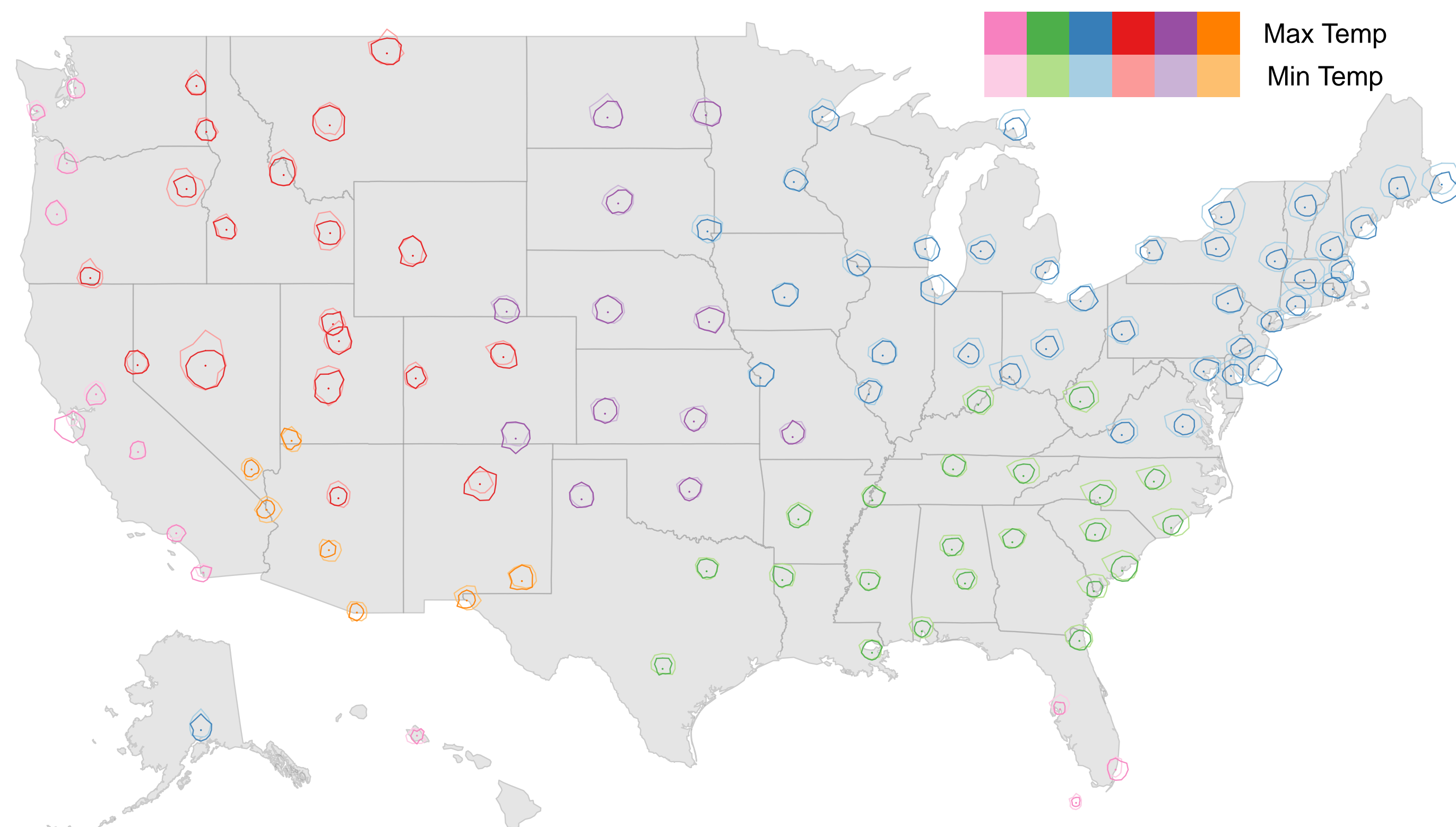
Seasonality

Trends & Outliers

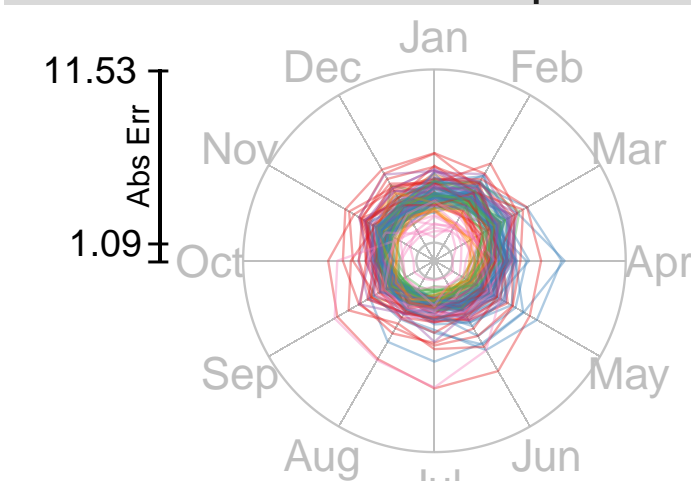
Importance & Correlations

Conclusions

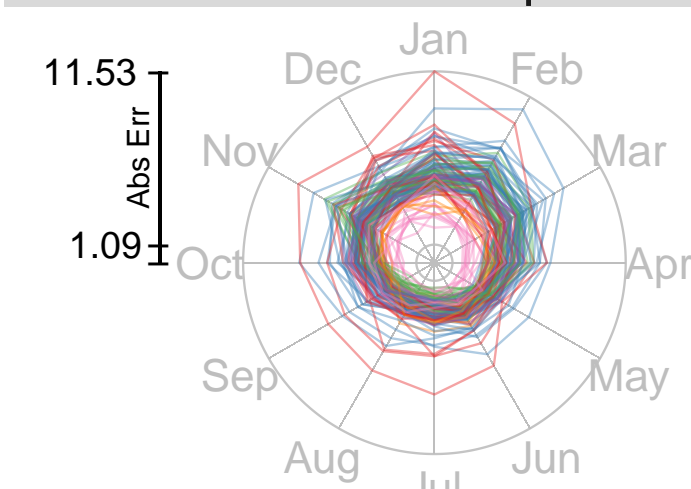
Temperature



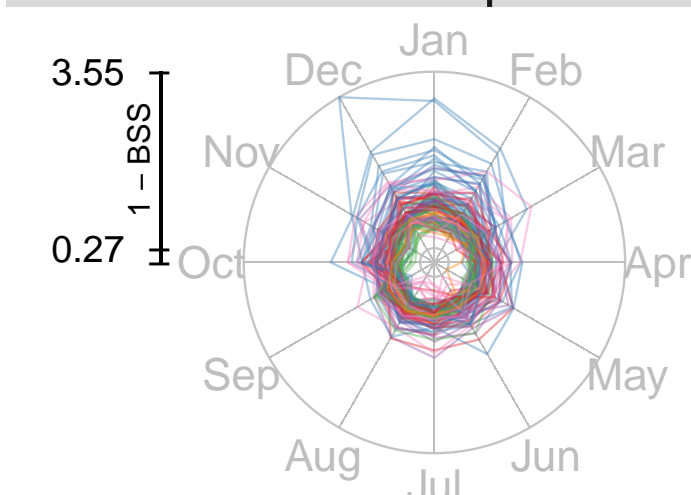
Max Temp



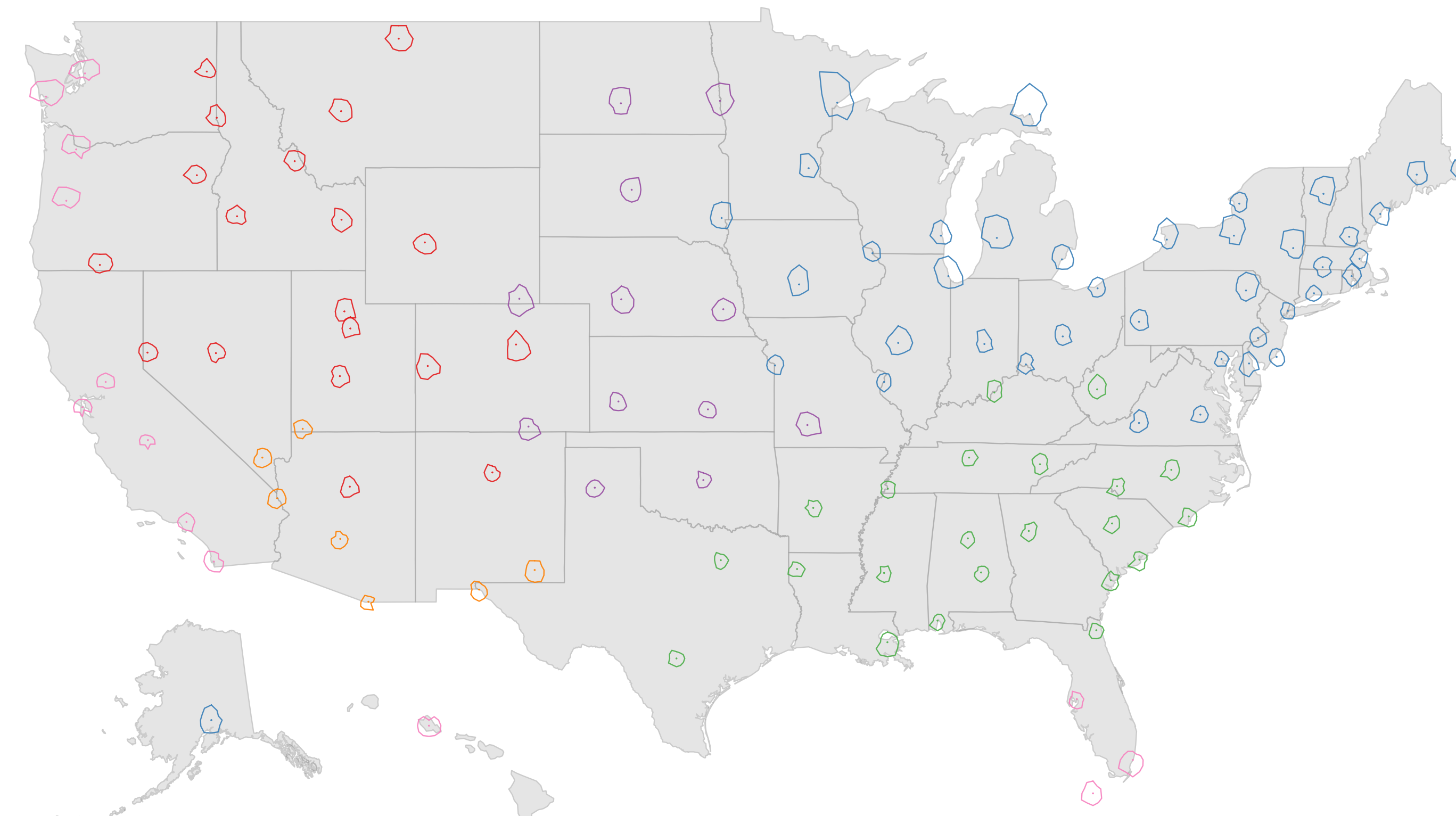
Min Temp



Precip



Precipitation



Error Variables

- Absolute Maximum Temperature Error
- Absolute Minimum Temperature Error
- 1 - Brier Skill Score (BSS) for Precipitation

Global Trends

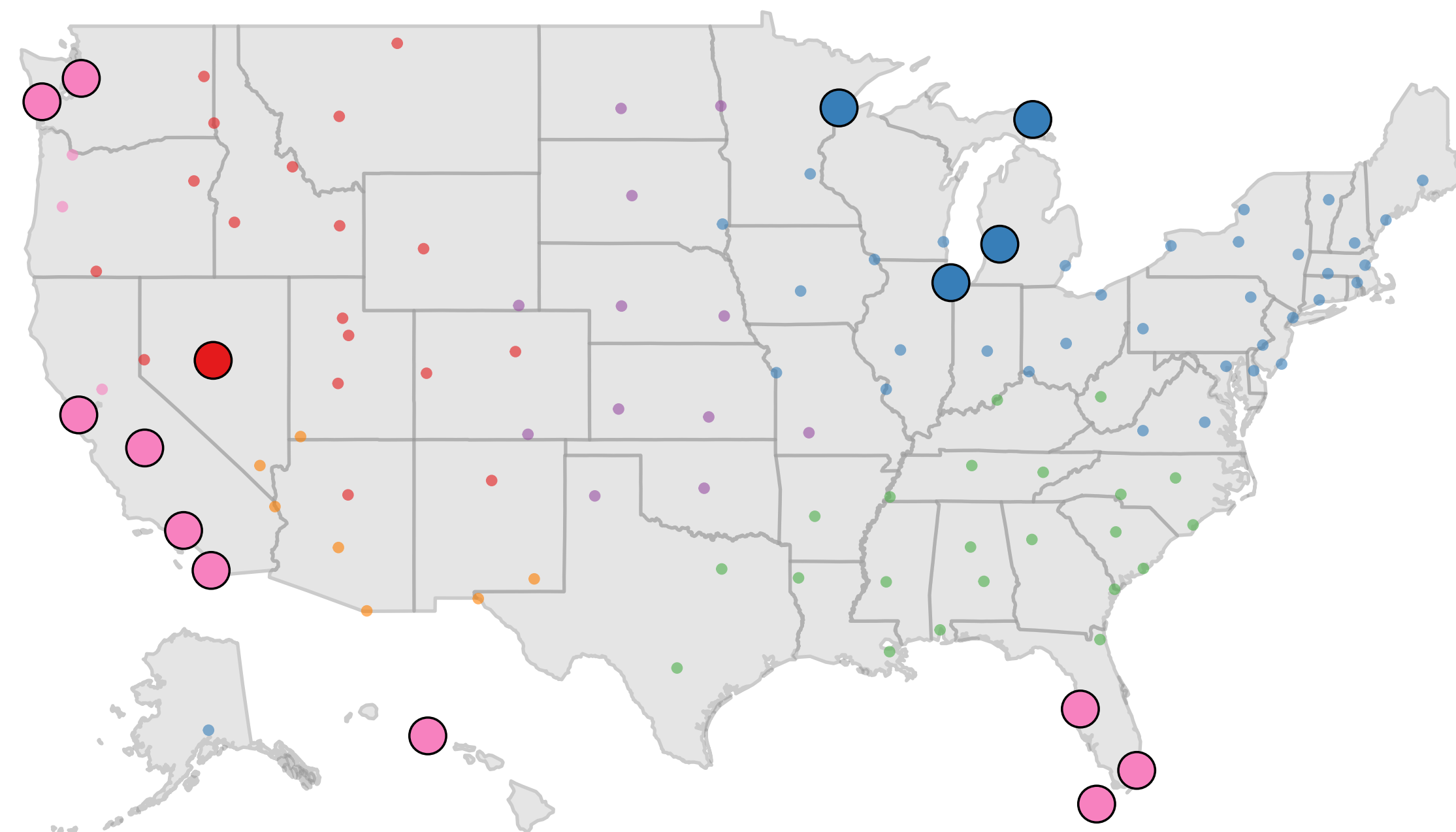
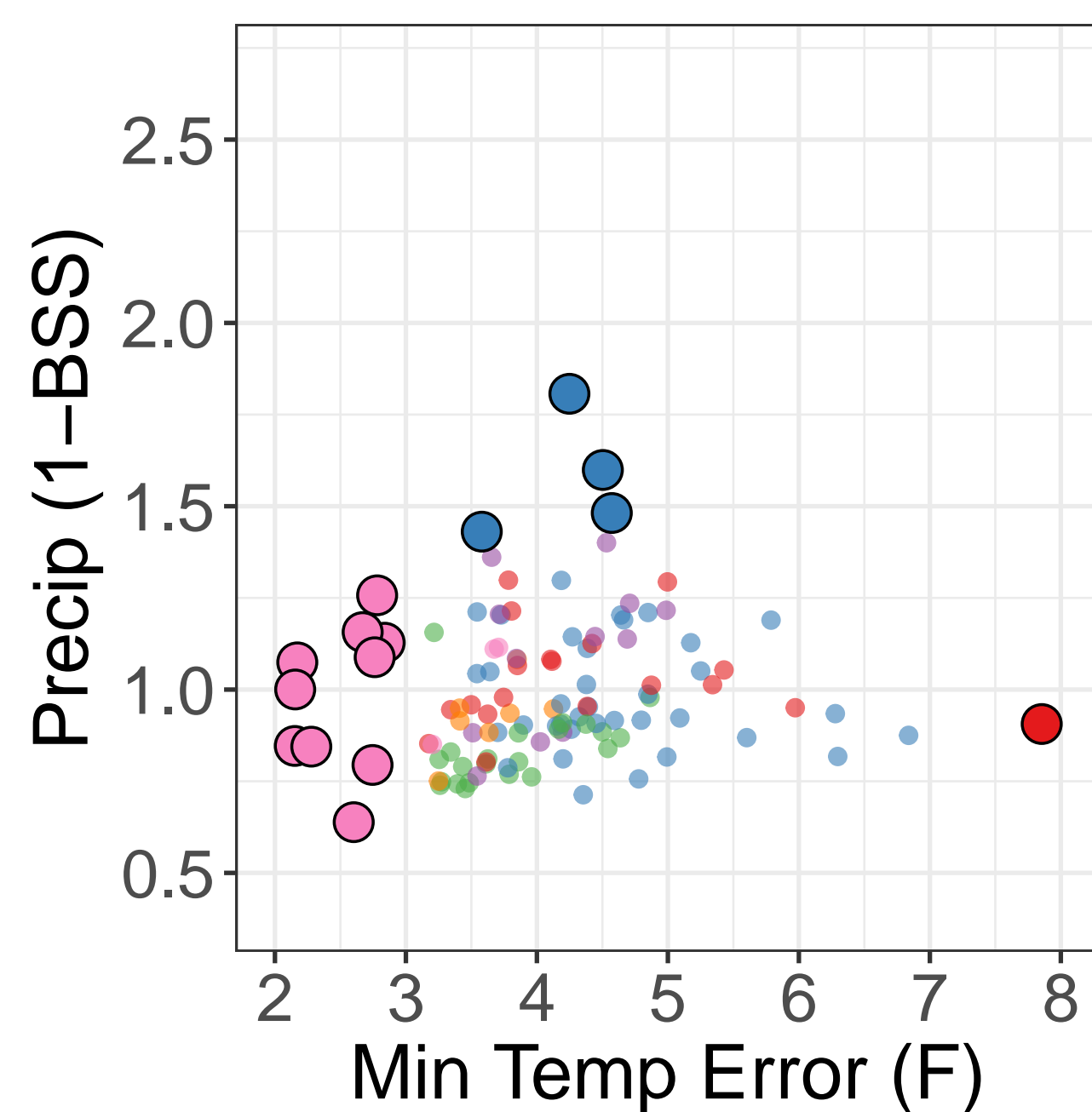
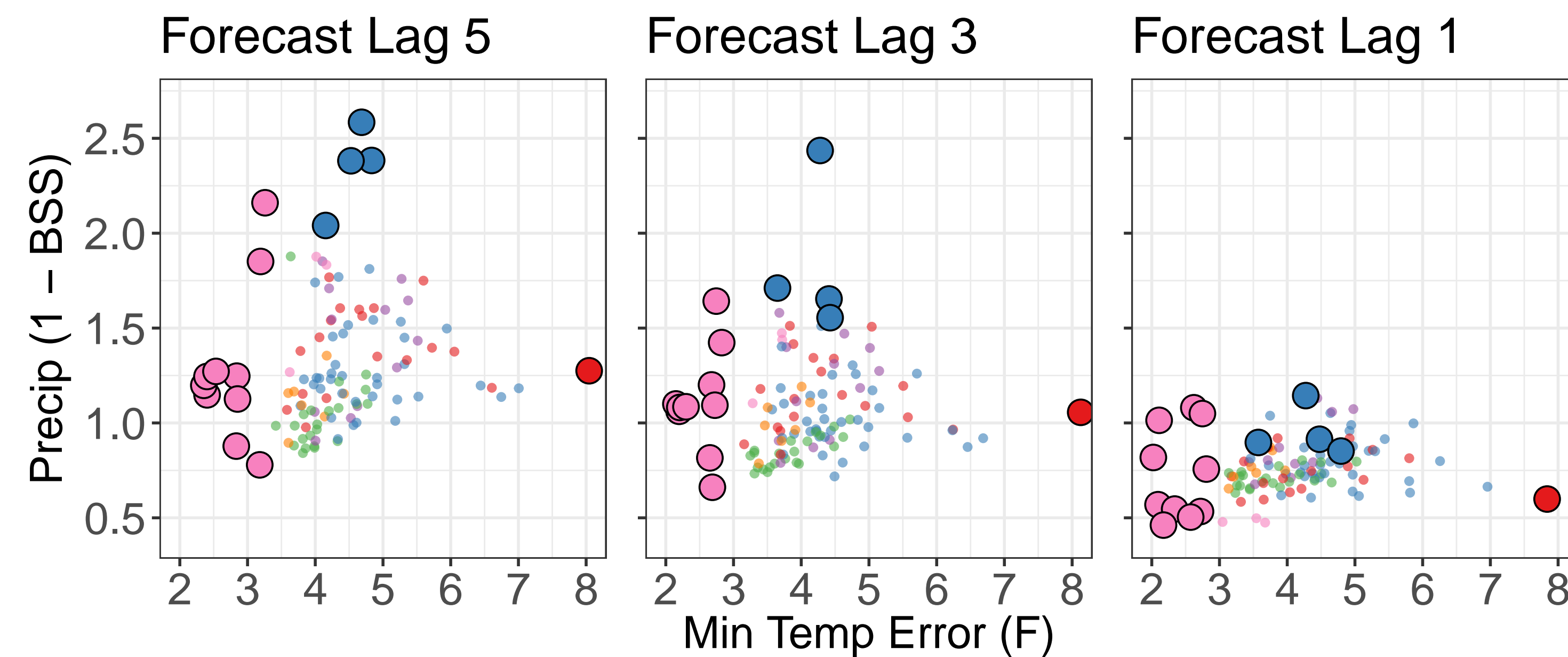
- Distinct seasonality in forecast accuracy.
- Max temp usually more accurate than min temp.
- Forecast accuracy improves north to south.

Local Trends

- The worst precip predictions are in the **Great Lakes** in winter.
- **San Francisco, CA**, predicts max temp well only in winter.
- **Austin, NV**, has the worst forecasts for both max and min temp.

“The coldest winter I ever spent was a summer in San Francisco.”
- attr. Mark Twain

Who are the winners and losers in terms of overall forecast accuracy?

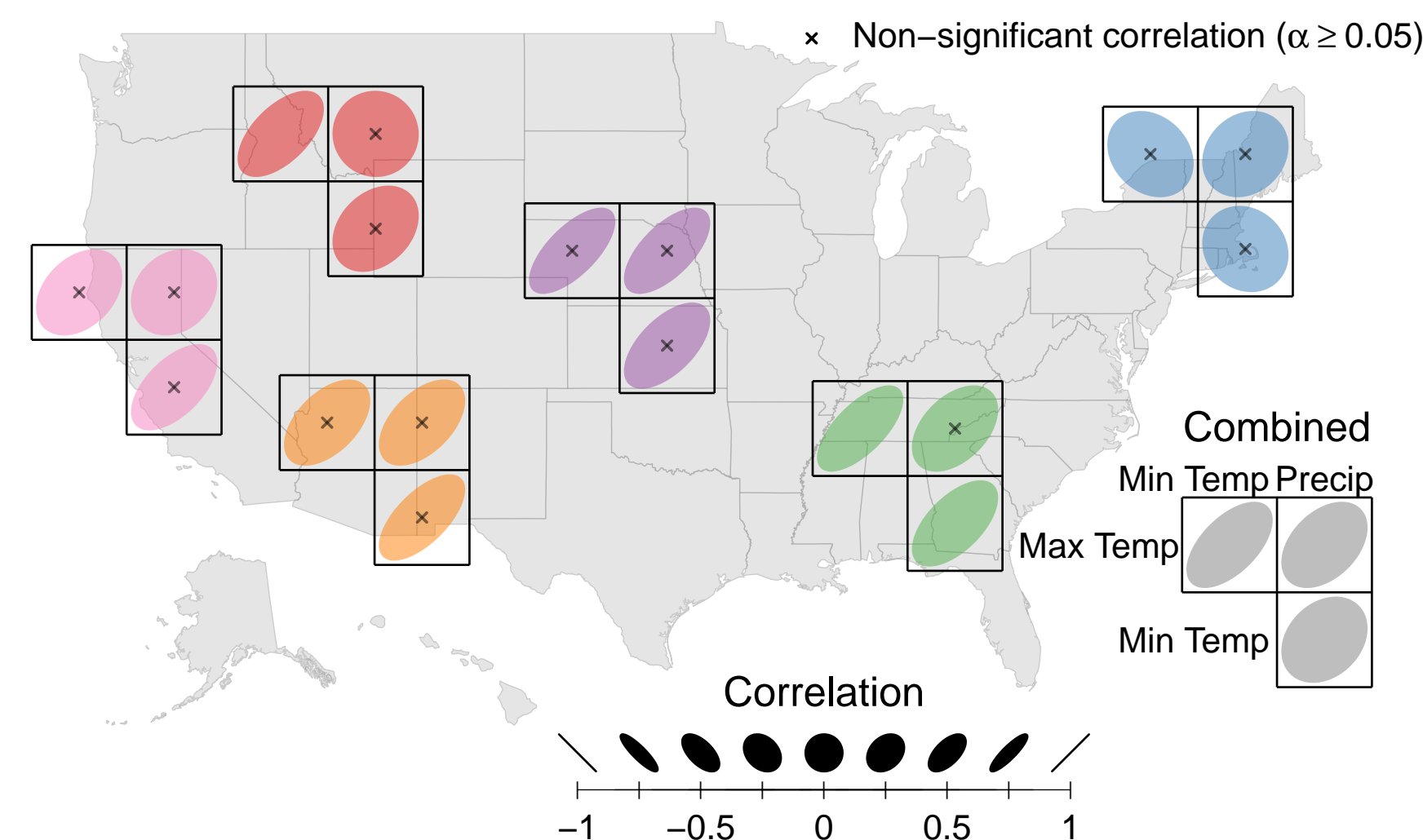
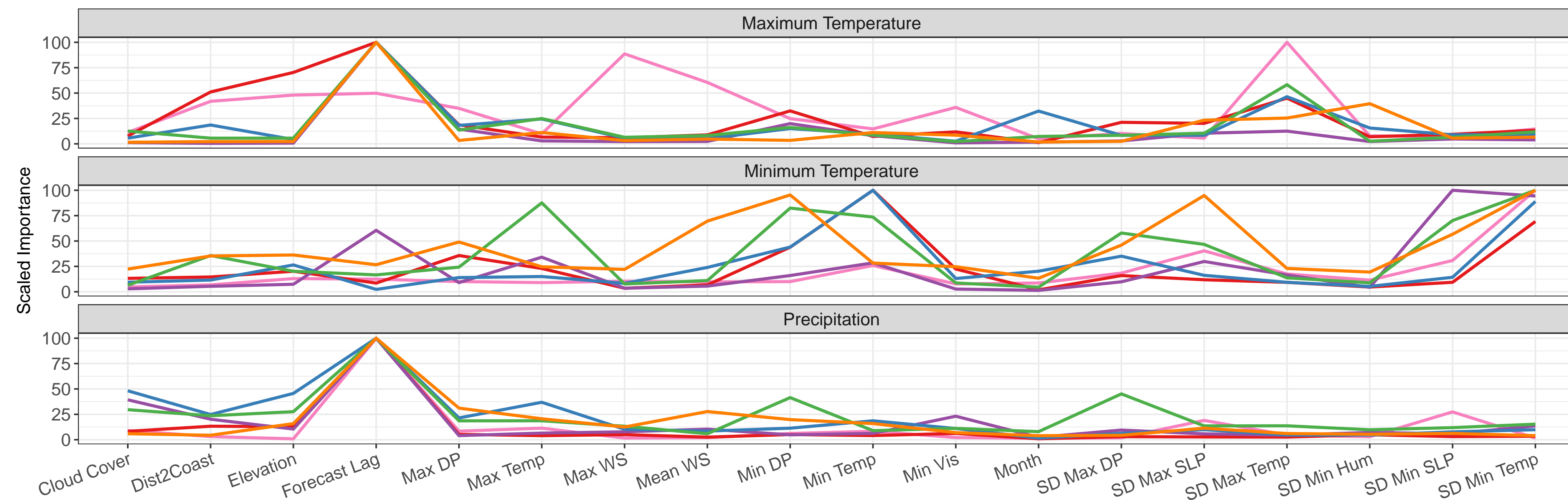
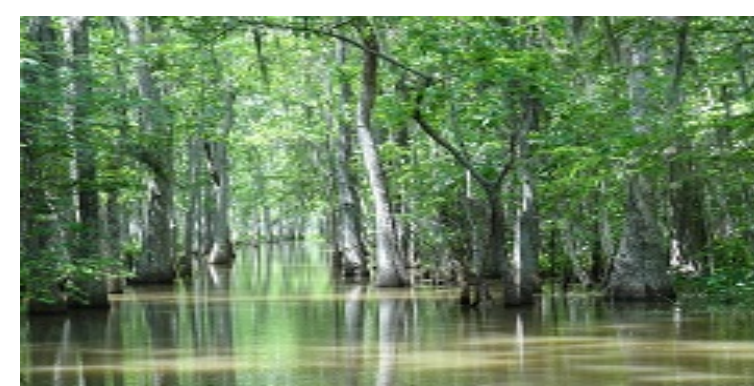
[Overview](#)[Clusters](#)[Seasonality](#)[Trends & Outliers](#)[Importance & Correlations](#)[Conclusions](#)

Trends & Outliers

- Previously seen poor forecasts for precip in the **Great Lakes** area and in min and max temp in **Austin, NV**, are apparent in these plots.
- Precip forecasts improve considerably as forecast lag decreases.
- **Cali-Florida** predicts min temp exceptionally well regardless of forecast lag.
- **See the app** for further interaction with forecast lag and trends.

Which variables are important in determining forecast error?

How do error variables correlate?

[Overview](#)[Clusters](#)[Seasonality](#)[Trends & Outliers](#)[Importance & Correlations](#)[Conclusions](#)**Cali-Florida****Northeast****Midwest****Southeast****Intermountain West****Southwest**

Importance and Correlation

- **Random Forests** used to determine **importance** of each weather variable to forecast errors.
- Forecast lag most important in precip and important for max temp error with the exception of **Cali-Florida**, but not very important for min temp error.
- Important variables vary largely for each region with min temp error, but also differ with max temp error.
- **Correlations** between error variables differ for each region.

What did we learn?

[🏠 Overview](#)[Clusters](#)[Seasonality](#)[Trends & Outliers](#)[Importance & Correlations](#)[Conclusions](#)

Conclusions

- United States cleanly clusters into weather regions.
- Forecast error patterns differ by region, by season, and are related to regional climate characteristics.
- Forecasting anomalies exist within each region (**Great Lakes**; **San Francisco, CA**; **Austin, NV**).
- Forecast lag is the most important variable for precip across all regions, but important variables for max and min temp vary across regions.
- Correlations between error variables differ for each region.

Cali-Florida



Southeast



Northeast



Intermountain West



Midwest



Southwest



References and Tools

 Overview

Clusters

Seasonality

Trends & Outliers

Importance & Correlations

Conclusions

References

- [1] A. Unwin, “Requirements for interactive graphics software for exploratory data analysis,” *Computational Statistics*, vol. 14, no. 1, pp. 7–22, 1999.

[2] H. Wickham, H. Hofmann, C. Wickham, and D. Cook, “Glyph-maps for visually exploring temporal patterns in climate data and models,” *Environmetrics*, vol. 23, no. 5, pp. 382–393, 2012.

[3] C. Nolte, “The story of the San Francisco summer is a bit foggy.” <https://www.sfchronicle.com>, August 2016.

[4] R. W. Scott and F. A. Huff, “Impacts of the Great Lakes on regional climate conditions,” *Journal of Great Lakes Research*, vol. 22, no. 4, pp. 845–863, 1996.
- [5] N. Silver and R. Fischer-Baum, “Which city has the most unpredictable weather?.” <https://fivethirtyeight.com>, December 2014.

[6] J. Cohen, K. Pfeiffer, and J. A. Francis, “Warm Arctic episodes linked with increased frequency of extreme winter weather in the United States,” *Nature Communications*, vol. 9, no. 1, p. 869, 2018.

[7] “Austin, Nevada: So much to do.” <http://austinnevada.com>.

[8] A. P. Weigel, M. A. Liniger, and C. Appenzeller, “The discrete Brier and ranked probability skill scores,” *Monthly Weather Review*, vol. 135, no. 1, pp. 118–124, 2007.

[9] D. Murdoch and E. Chow, “A graphical display of large correlation matrices,” *The American Statistician*, vol. 50, no. 2, pp. 178–180, 1996.

R Tools

- fields (D. Nychka et al. 2015)
 - fiftystater (W. Murphy 2016)
 - geosphere (R. Hijmans, 2016)
 - ggforce (T. Pedersen 2018)
 - gridExtra (A. Baptiste, 2017)
 - latex2exp (S. Meschiari, 2015)
- reshape2 (H. Wickham, 2007)
 - mapproj (D. McIlroy et al. 2017)
 - randomForest (A. Liaw and M. Wiener, 2002)
 - RColorBrewer (W. Neuwirth, 2014)
 - reshape2 (H. Wickham, 2007)
- rgbif (S. Chamberlain, 2017)
 - rgdal (R. Bivand et al. 2018)
 - sp (E. Pebesma and R. Bivand, 2013)
 - tidyverse (H. Wickham, 2017)
 - weatherData (R. Narasimhan, 2017)