

Summary

- Goal: Build a statistical model for precipitation time series
- Challenges:
 - Precipitation data have a large proportion of zeros
 - They contain extreme values
 - May exhibit autocorrelation
 - Building a statistical model with all the above features can be difficult
- We consider two approaches
 - Generalized Autoregressive Moving Average model (Zheng et al. 2015)
 - Weibull Model with Markov transitions (extending Wilks 1999)

Why Is This of Interest?

- Climate change will affect precipitation
- Some areas will experience more severe drought, others will have more extreme rainfall
- Understanding precipitation patterns and trends may be useful for public policy
- Useful for studying climate models

Data

- Precipitation data obtained from the NOAA Climate Data Online database
- Focus here on Warren, PA and Phoenix, AZ

GARMA Model

- Time series data: Y_1, Y_2, \dots, Y_T
- $Y_t \sim \text{Gamma}(cY_{t-1}^{\phi^d}, cY_{t-1}^{\phi^{(d-1)}})$ where c, ϕ, d are parameters
- It uses a log-link function:
 - $\log(Y_t) = \phi \log(Y_{t-1}) + e_t$
 - e_1, e_2, \dots, e_T are the error terms
- We allow for a seasonal effect via including a monthly term:
 - $\log(Y_t) = \mu_t + \phi \log(Y_{t-1}) + e_t$
- We use Markov Chain Monte Carlo to estimate the parameters

Warren, PA Best Model: Gamma-GARMA(0,0)

- With monthly means regression
- Very little autocorrelation between months
- The monthly means model does a good job of modeling this structure

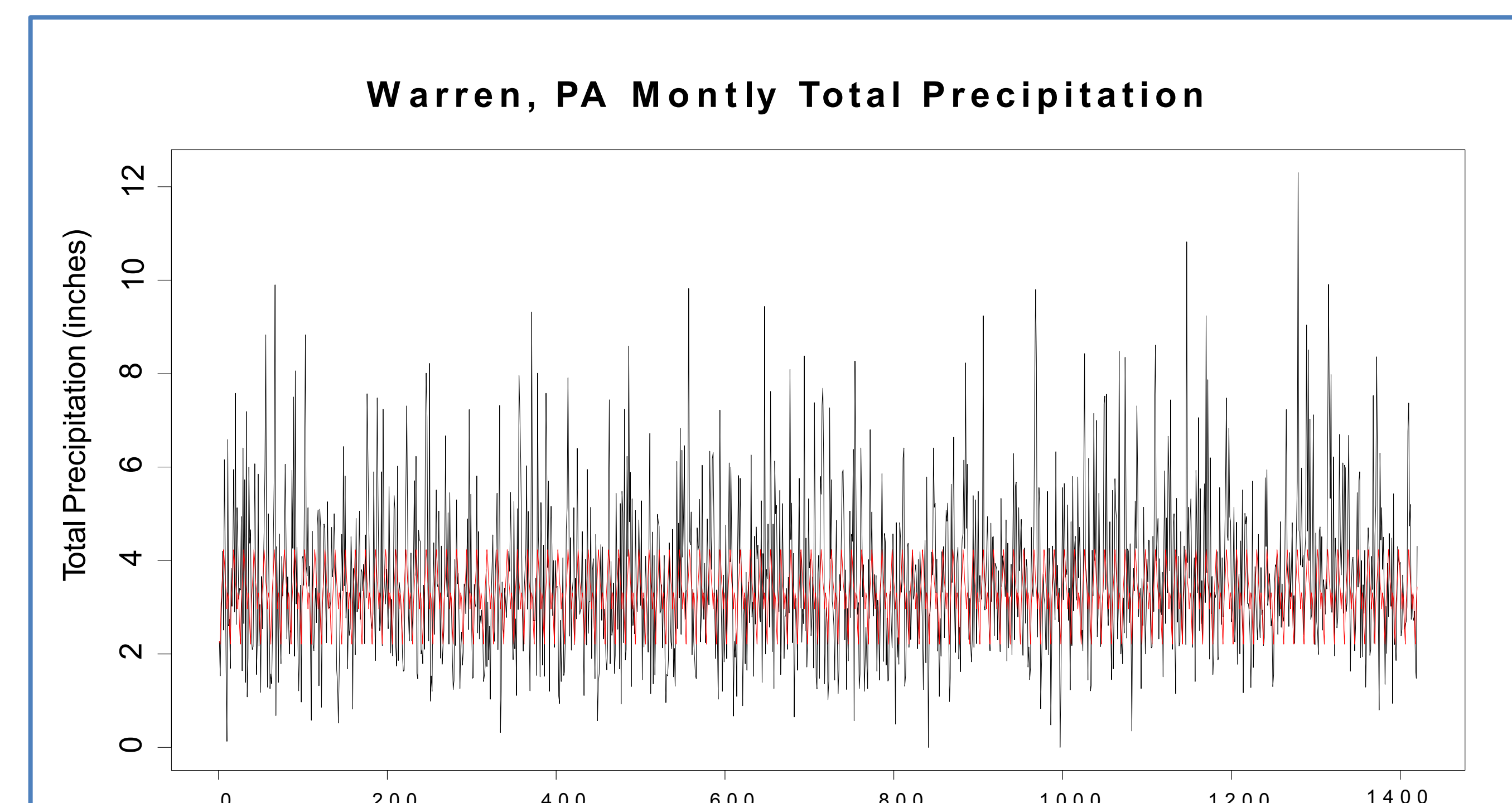


Figure 2 – Warren, PA (1897-2015)
The precipitation data is in black, with GARMA forecasts in red.

Phoenix, AZ Best Model: Gamma-GARMA(1,0)

- A monthly means regression model still has correlated residuals
- This model accounts for the autocorrelation that was seen in the data

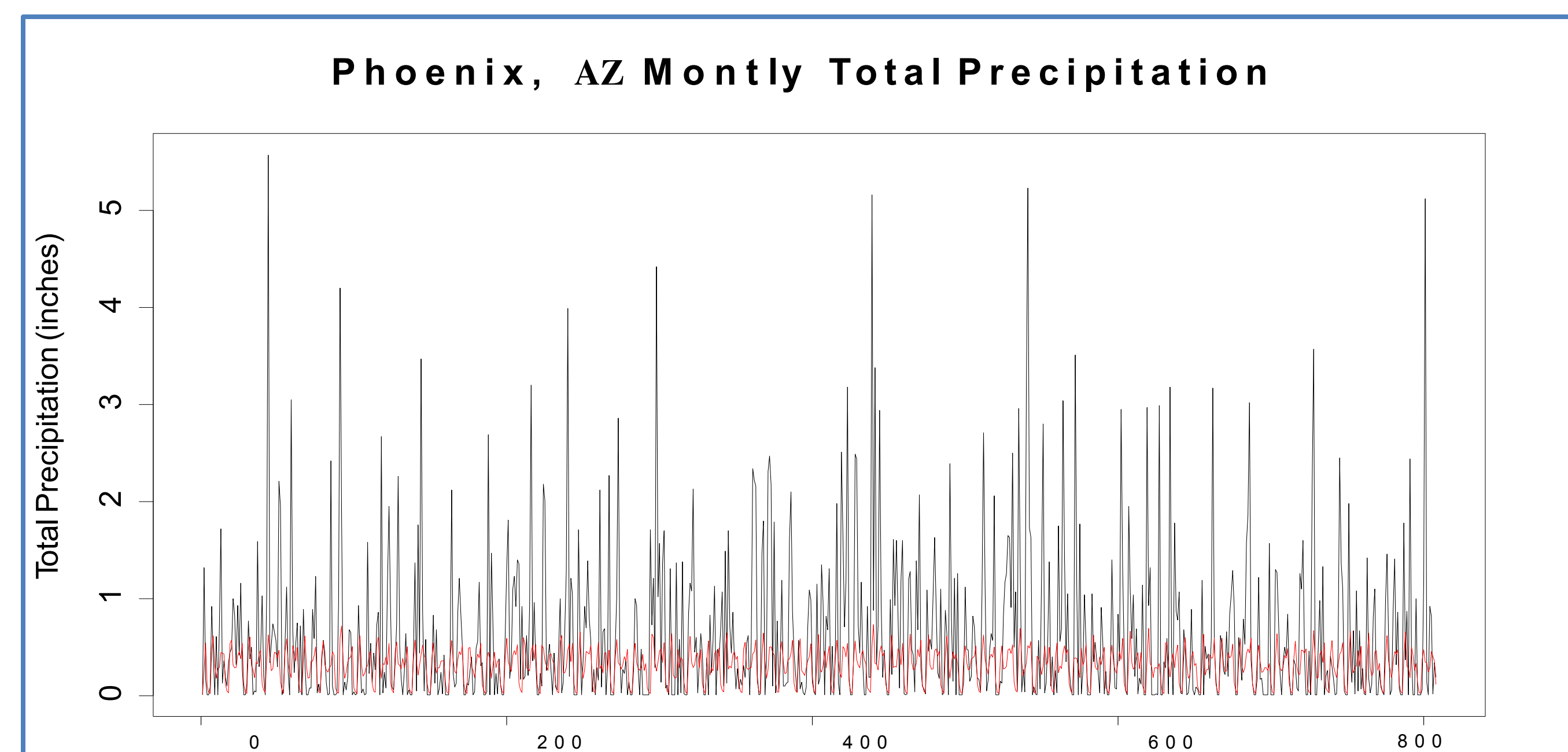


Figure 3 – Phoenix, AZ (1948-2015)
The precipitation data is in black, with GARMA forecasts in red.

GARMA Discussion

- The GARMA models do a good job at accounting for autocorrelation
- Fail to account for zeros in data and extreme values

References

- Zheng, T., et al., Generalized ARMA models with martingale difference errors. Journal of Econometrics (2015). <http://dx.doi.org/10.1016/j.jeconom.2015.03.040>
- Wilks, D.S. "Interannual Variability and Extreme-value Characteristics of Several Stochastic Daily Precipitation Models." Interannual Variability and Extreme-value Characteristics of Several Stochastic Daily Precipitation Models. Agricultural and Forest Meteorology, 12 Mar. 1999. Web. 21 Mar. 2016.

Weibull Model

- $Y_t \sim \text{Weibull}(\lambda, k)$ with probability $P^{k_{ij}}$
- Where $P^{k_{ij}}$ is the transition probability of a Markov chain, with $i, j = \{\text{Dry, Wet}\}$, and $k = \{1, 2, 3, \dots, 12\}$, corresponding to the months of the year
- Time dependence between presence-absence (rain/ no rain) via Markov model
- Amount of rain is conditionally independent given rain/ no rain:
 - If it rains, amount is drawn independently

Warren, PA

- Weibull model accounts for monthly variability of the amount of rain on wet days

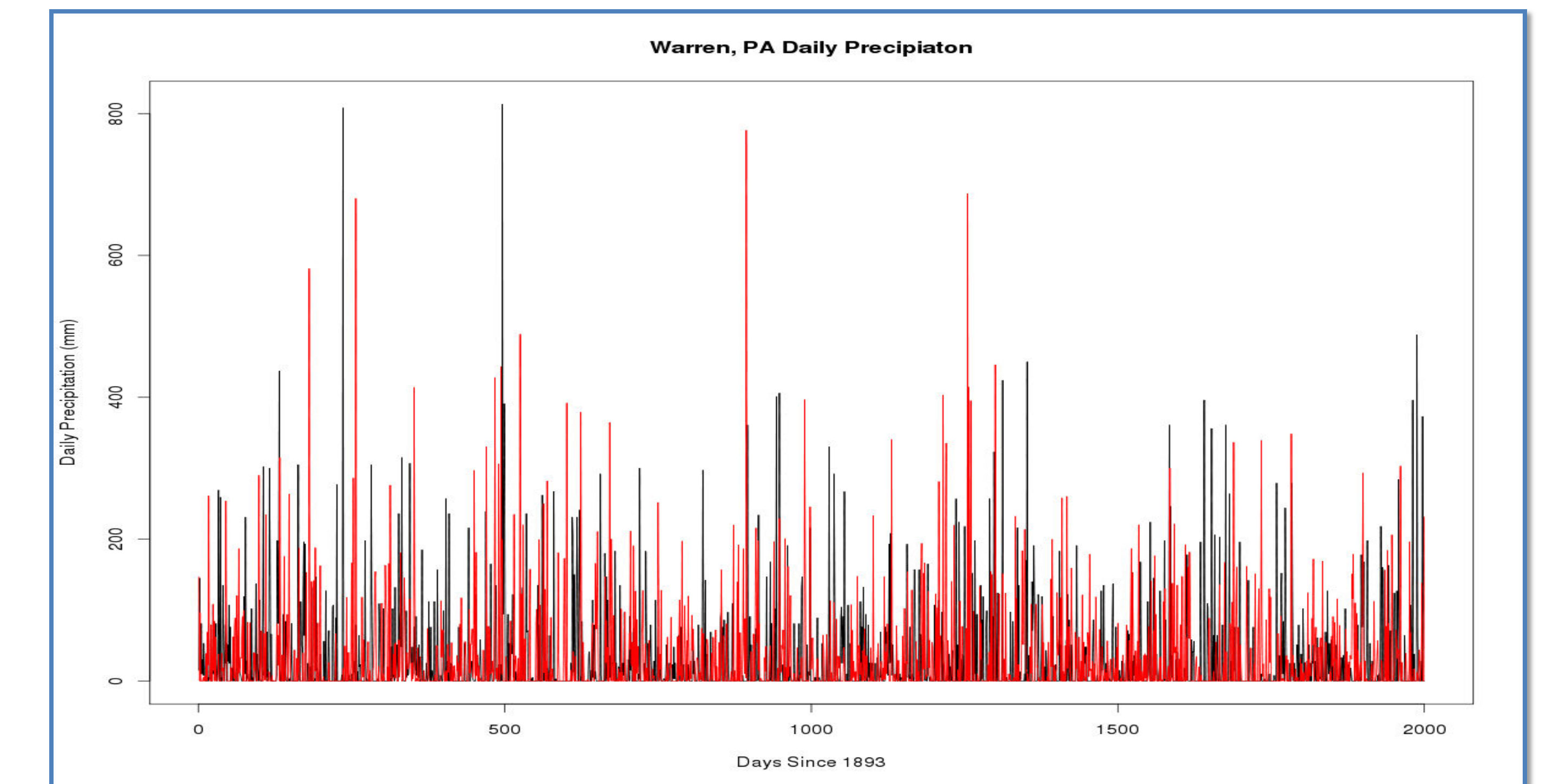


Figure 3 – Warren, PA since 1893
The precipitation data is in black, and a Weibull simulation in red.

Phoenix, AZ

- Markov model accounts for variability throughout the year of transitions between rain/ no rain

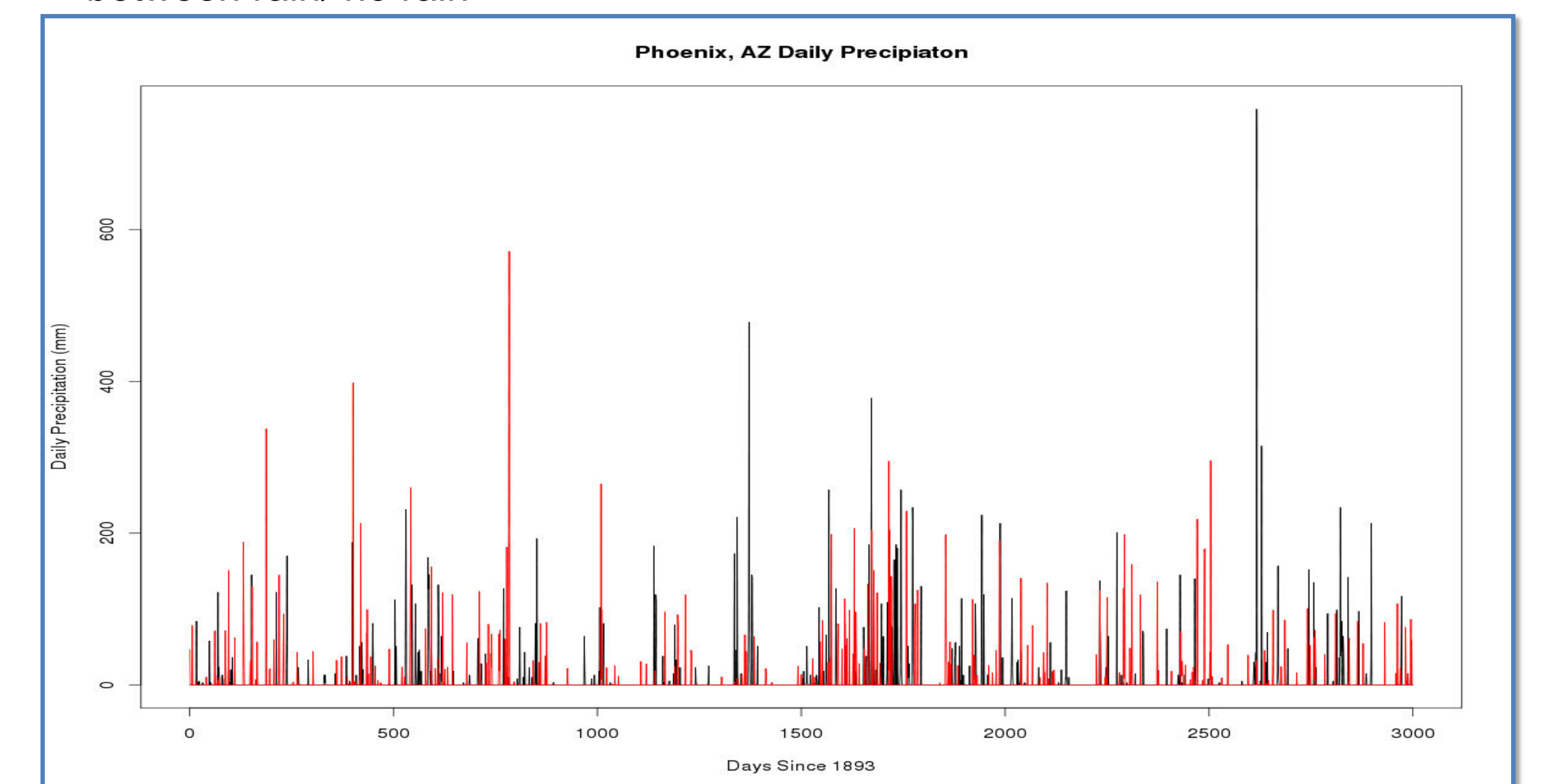


Figure 4 – Phoenix, AZ since 1893
The precipitation data is in black, and a Weibull simulation in red.

Weibull Discussion

- Weibull model with Markov transitions accounts for zeros and extremes
- Seasonal models account for variability in distribution of positive data
- Future: 1) Flexible model dependence in amount of rain
2) Interpret model fit

Acknowledgements

This work was supported by the National Science Foundation through the Network for Sustainable Climate Risk Management (SCRiM) under NSF cooperative agreement GEO-1240507.