UCLA
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Geography

New Approaches to IDF and Regional Flood Frequency Estimation

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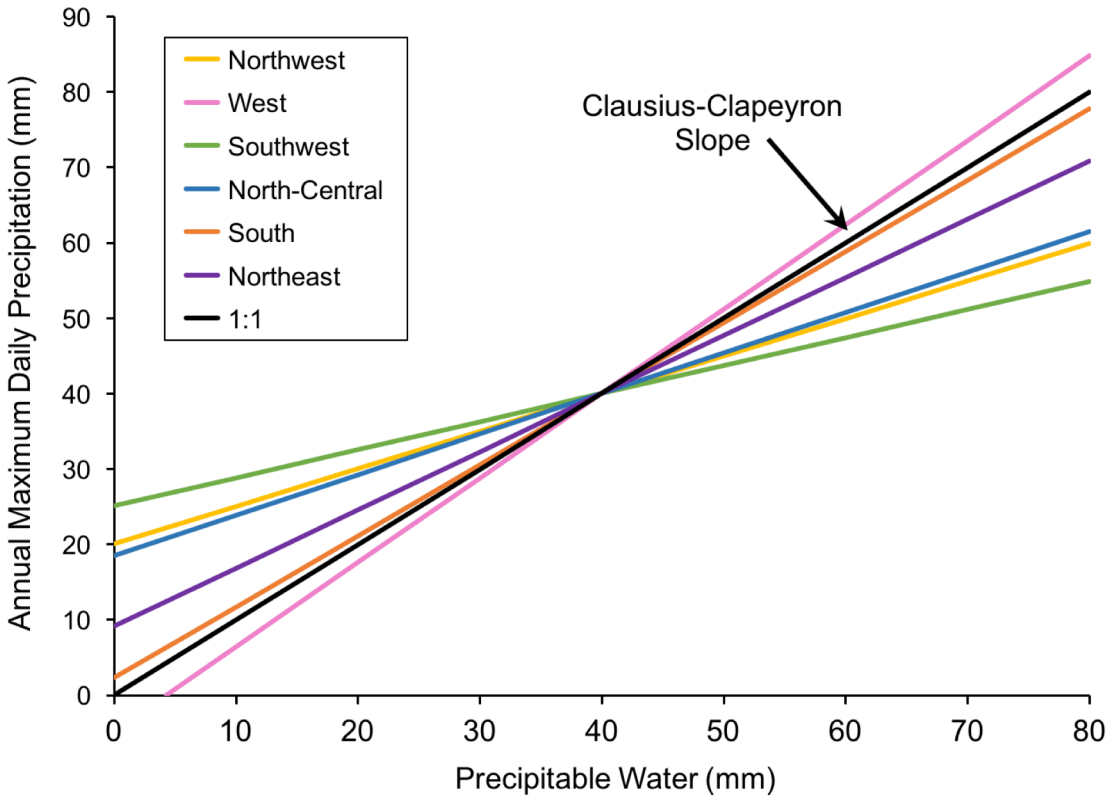
Outline

- Background info
- Historical trends
- IDF curve
- Regional Flood frequency
- Ongoing questions

Background

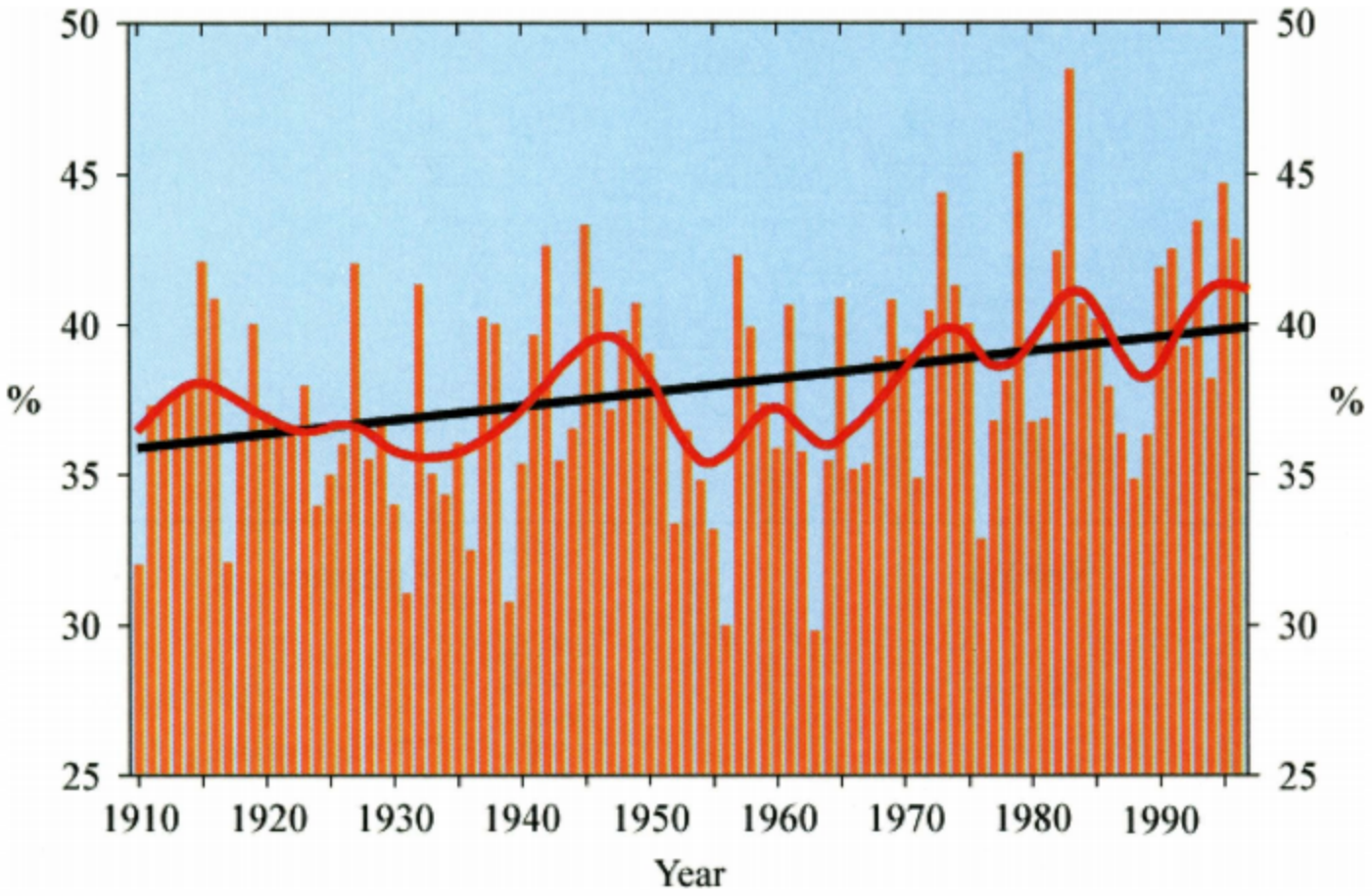
- Extreme precipitation is related to temperature via the Clausius-Clapeyron equation (with some variation)
- (Pall et al., 2006, Lenderink and van Meijgaard, 2008, Kunkel et al., 2012)



The relationship between the annual maximum daily precipitation and the amount of water vapor within various regions of the United States in comparison with the Clausius-Clapeyron relations depicted in black. (Kunkel et al. 2012)

Historical trends

- Precipitation in the CONUS has increased by ~10% since the 1910s
- About half of the increase in overall precipitation is from increases in extreme (top 10% quantile) precipitation events
- Both max intensity and frequency of extreme events has increased (Karl and Knight, 1997)
- Short storms (sub-daily) most sensitive to increases in temperature (Westra et al., 2014)

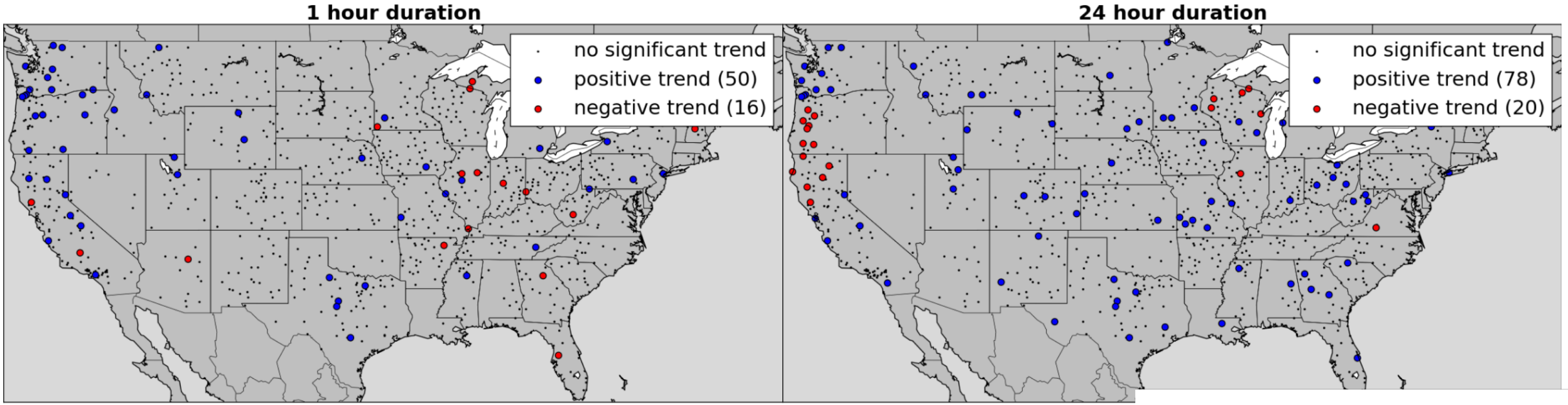


Time series of the percent contribution of the upper 10 percentile of daily precipitation events to the total annual precipitation area-averaged across the United States. Smooth curve is a nine-point binomial filter, and the trend is also depicted. (Karl and Knight, 1997)

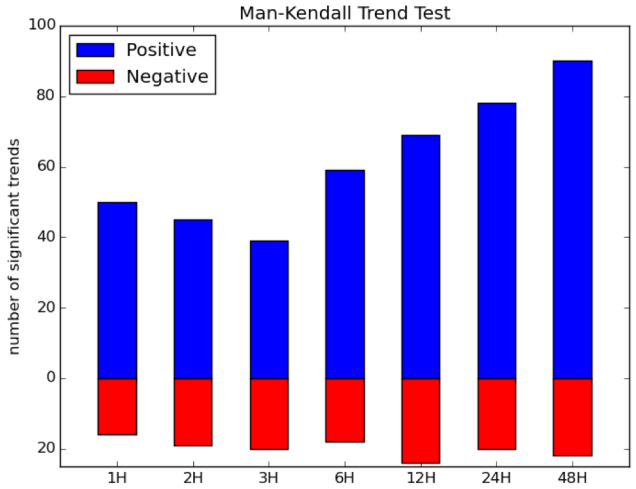
Historical trend detection

- Long records of station data are needed
- Three types of tests commonly employed:
    1. Mann-Kendall test
    2. Student-*t* test
    3. Likelihood ratio test

Mann-Kendall test



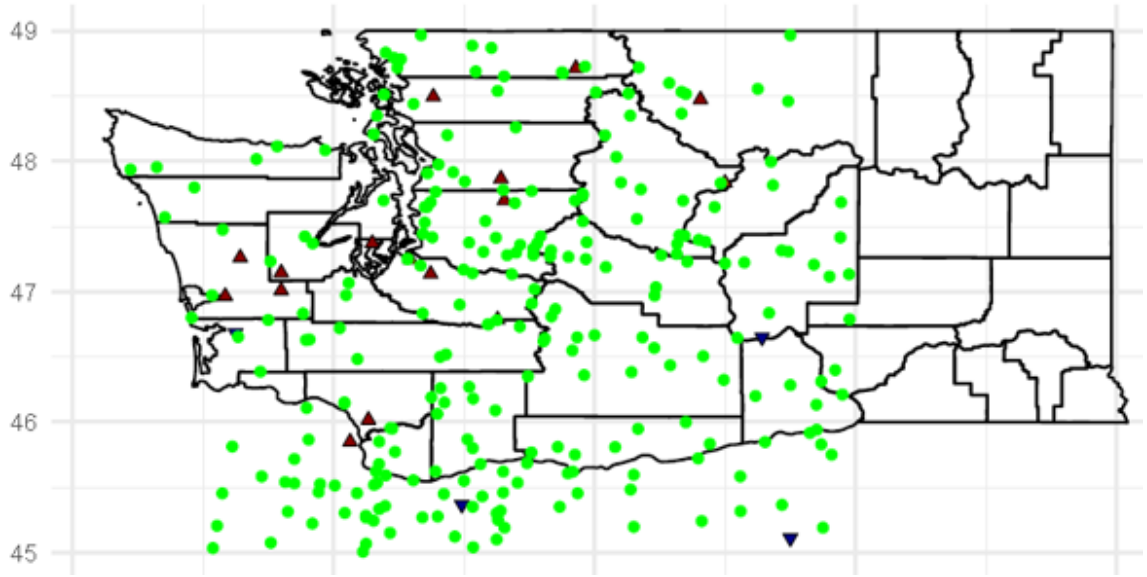
- Results from Mann-Kendall test at 0.05 significance applied to a network of 841 stations across the CONUS shown at the station above.
- To the right is a chart showing the total number of positive or negative trends at each duration over CONUS.



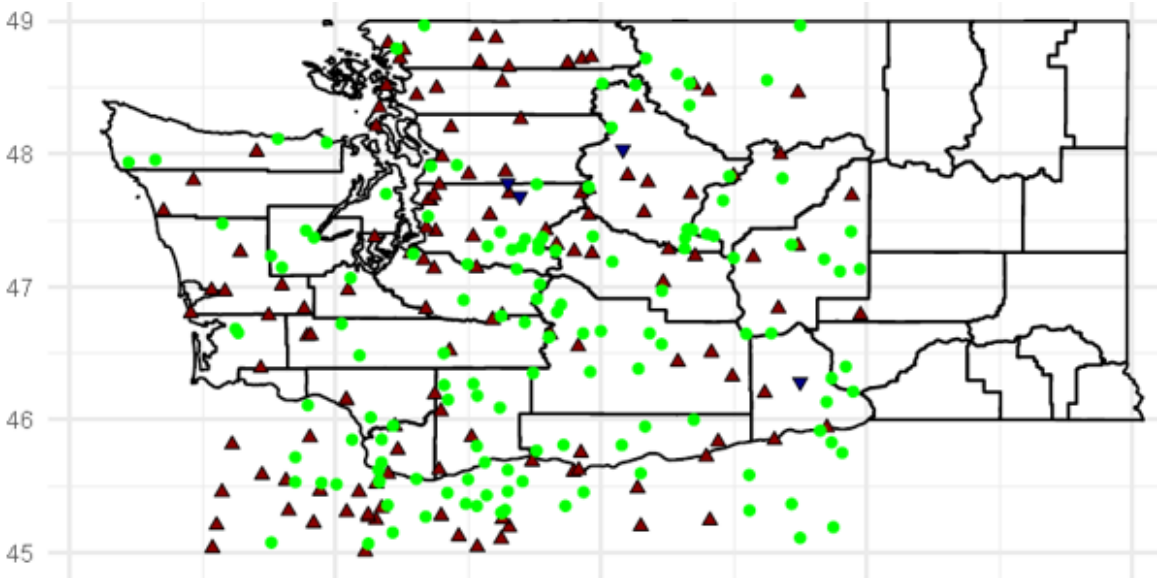
Likelihood Ratio Test

- As applied by Dr. Demissie
- Where CCSM4 with RCP8.5 scenario was used for future (2035-2064) data.

Trend results for past daily precipitation (5% show trend)



Trend results for combined past and future daily precipitation (56% show trend)

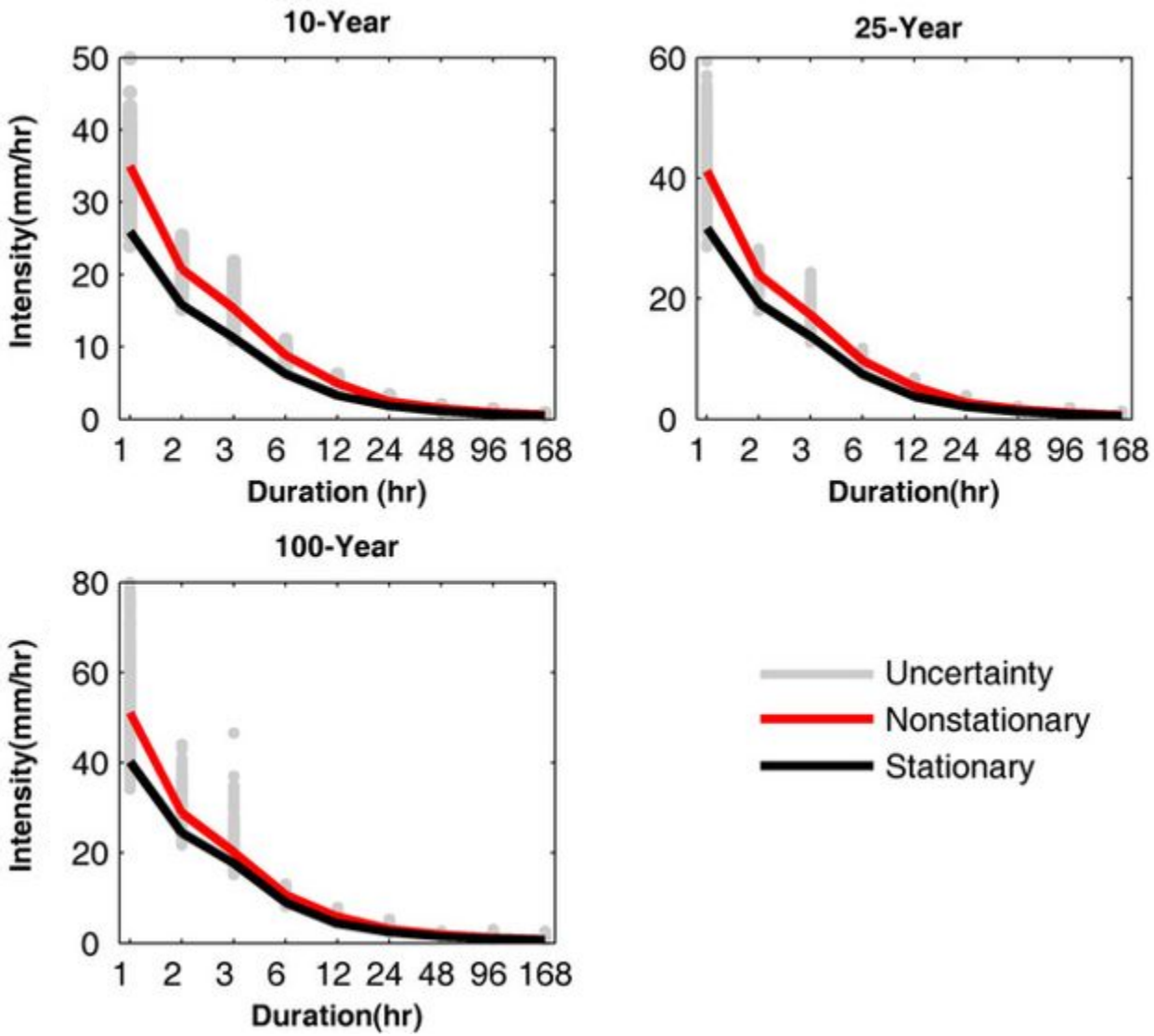


Ongoing challenges in trend detection

- Some argue it is too early to adopt a full nonstationary approach
  - Lins and Cohn (2011), Matalas (2012), Koutsoyiannis and Montanari (2014)
- Others argue it is time to assume the null hypothesis is nonstationary behavior instead of stationary behavior
  - Milly et al. (2008, 2015)
- Climate variability, at-station noise, and short records increase uncertainty in detecting and modeling trend

IDF Curves

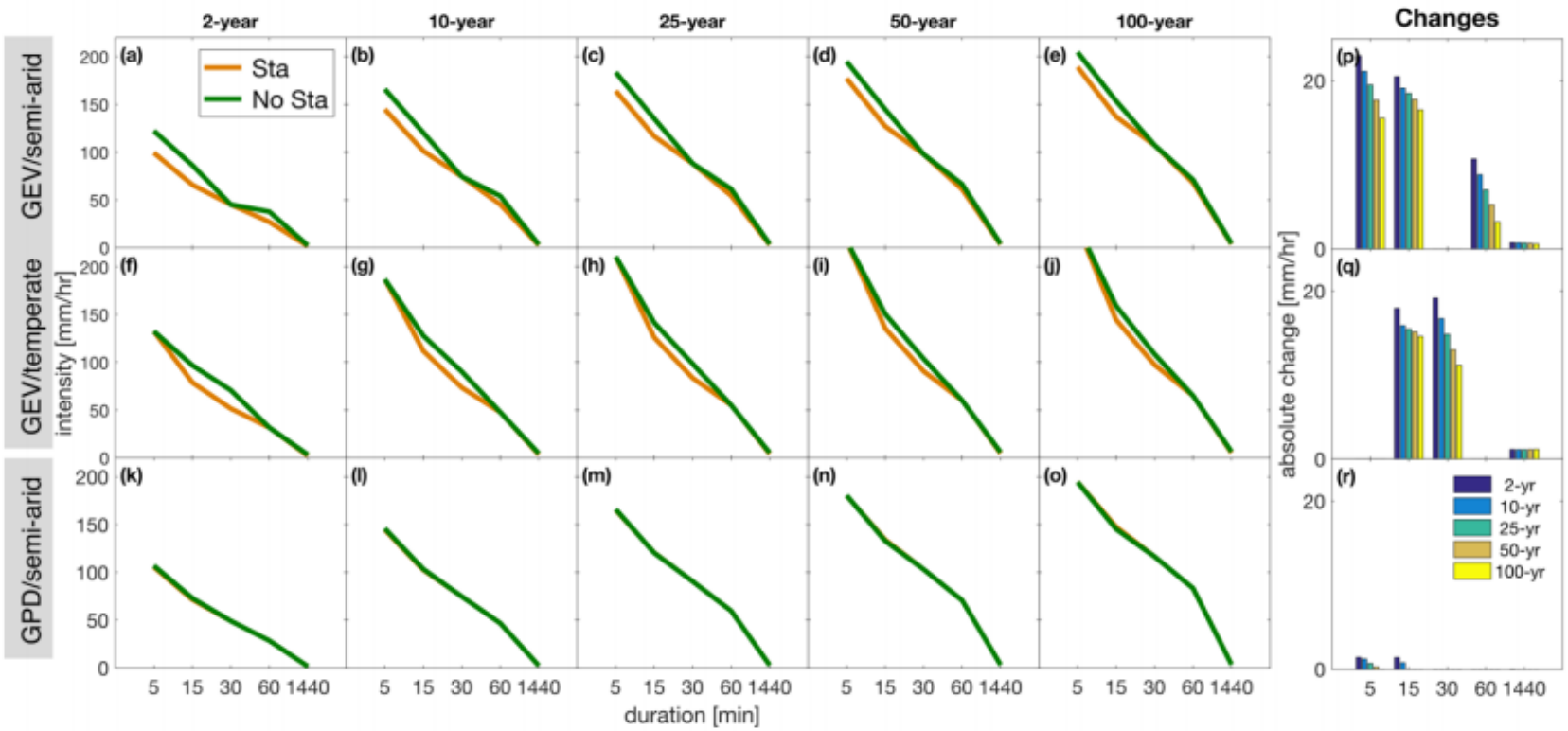
- IDF curves are commonly based on some mathematical formula such as
$$i = \frac{a(T)}{b(d)}$$
- Koutsoyiannis et al. 1998 fit this form to multiple probability distributions (Gumbel, GEV, Gamma, etc)
- Cheng et al. 2014 write a framework that allows a time-varying GEV distribution
- Introducing NS parameters in probability distributions introduce NS into IDF curves using this mathematical framework



Nonstationary vs. stationary IDF Curves for different return periods and durations at the selected station in White Sands National Monument Station, New Mexico. (from Cheng and AghaKouchak (2014))

IDF Curves

- Not incorporating NS into IDF curves can lead to underestimations in precipitation extremes Nie et al. 2009, Rosenberge et al. 2010, Mailhot and Duchesne 2010, Kessler 2011, Cheng and AghaKouchak (2014)



Stationary and non-stationary IDF curves for different return periods and durations at the semi-arid (Arizona) and the temperate (Ohio) watersheds. Plots in the right most panels (p. to r.) show changes between estimated non-stationary and stationary intensities as percentage of the stationary estimates. (from DeMaria et al., 2017)

- Demaria et al. (2017) found that the nonstationary in extreme precipitation may increase the risk of failure of a hydraulic structure by 25% for a 100-year return period and a project life of 100 years.

IDF Curves – current status

- NS-IDF curves based on historical trends are better for short time-horizon projections and not long time-horizon projections
- Ganguli and Coulibaly (2017) find the short-term future projections are useful for about one decade into the future
- Further projections have increasingly high uncertainties

Choosing a covariate

- Time and temperature are common covariates with extreme precipitation
- Other covariates may reflect local, geographic or atmospheric process
  - ENSO, PDO, NAO, IOD
  - Topography,
  - Wind, sea level pressure
- May examine trend on monthly, seasonal, or annual basis
- Each covariate introduces more uncertainty

Consider what type of trend to use

- Most recent work assumes a linear trend to relate the change in extreme precipitation and time

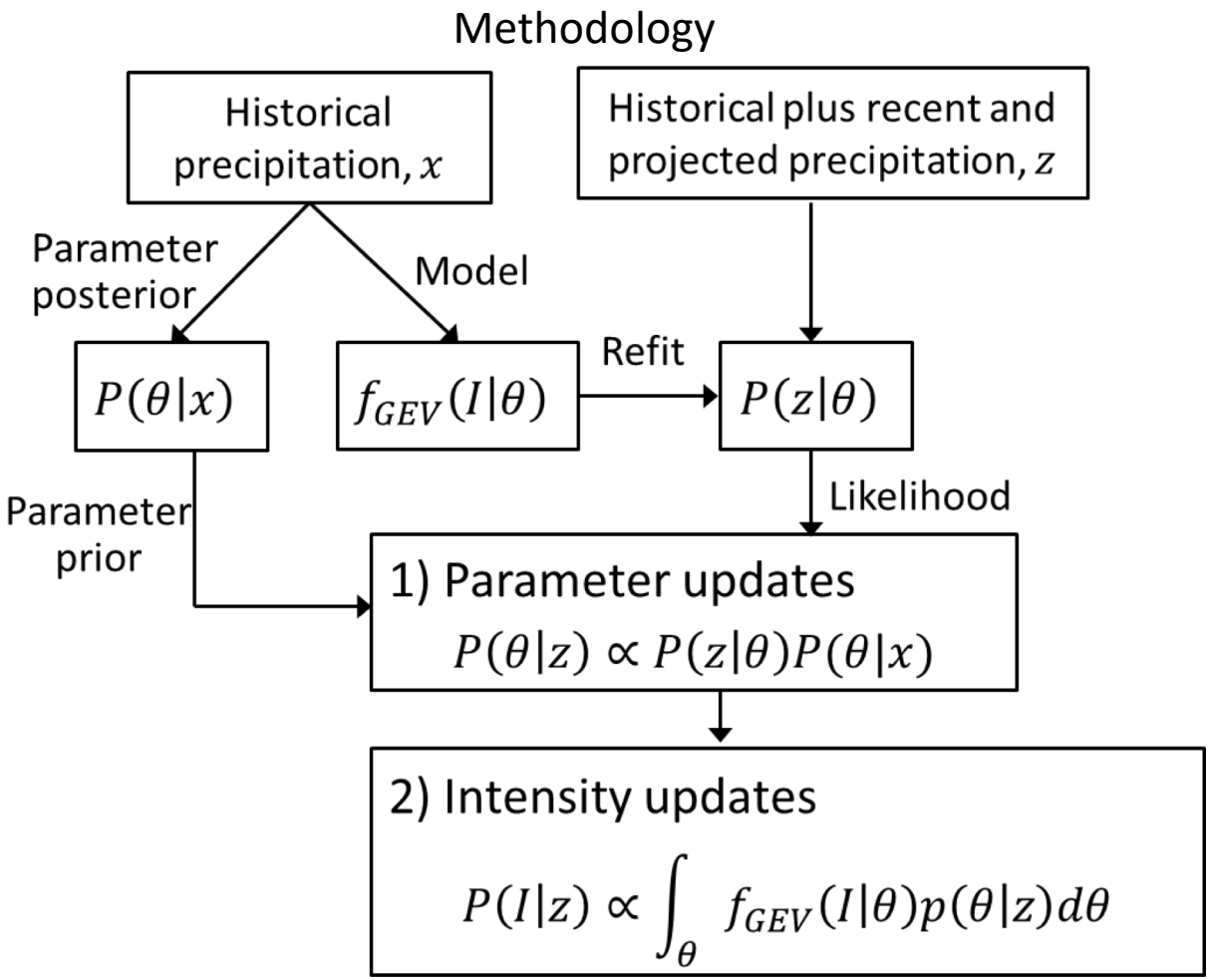
$$\mu(t) = \mu_0 * t + \mu_1$$

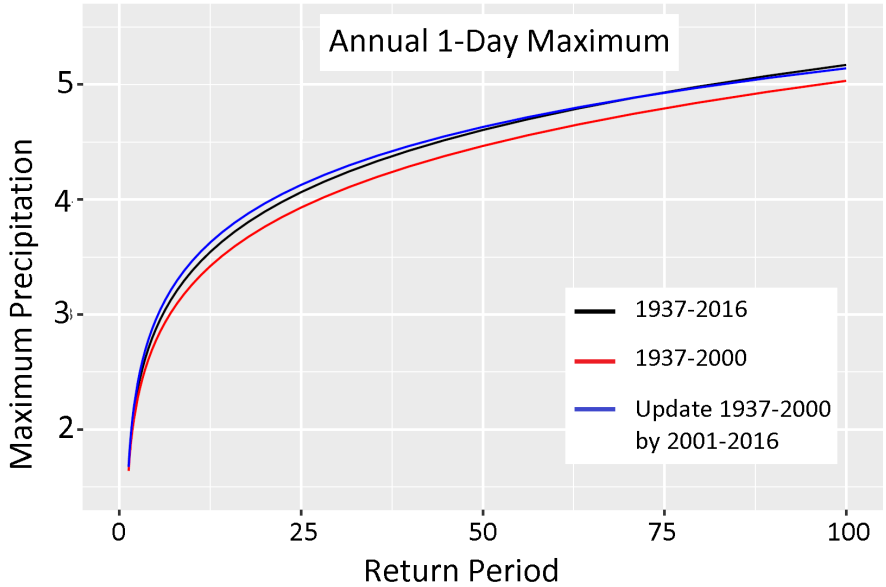
- Not much work has been done to justify this choice
- Other types of functions may be nonlinear, exponential, or periodic

Estimating distribution parameters

- Maximum likelihood method
- Generalized maximum likelihood method
- Bayesian approach
- Generalized model for location, scale and shape (GAMLSS) framework
- Probabilistic neural network
- Multi-objective genetic algorithm

Bayesian Framework example as set up by Dr. Demissie

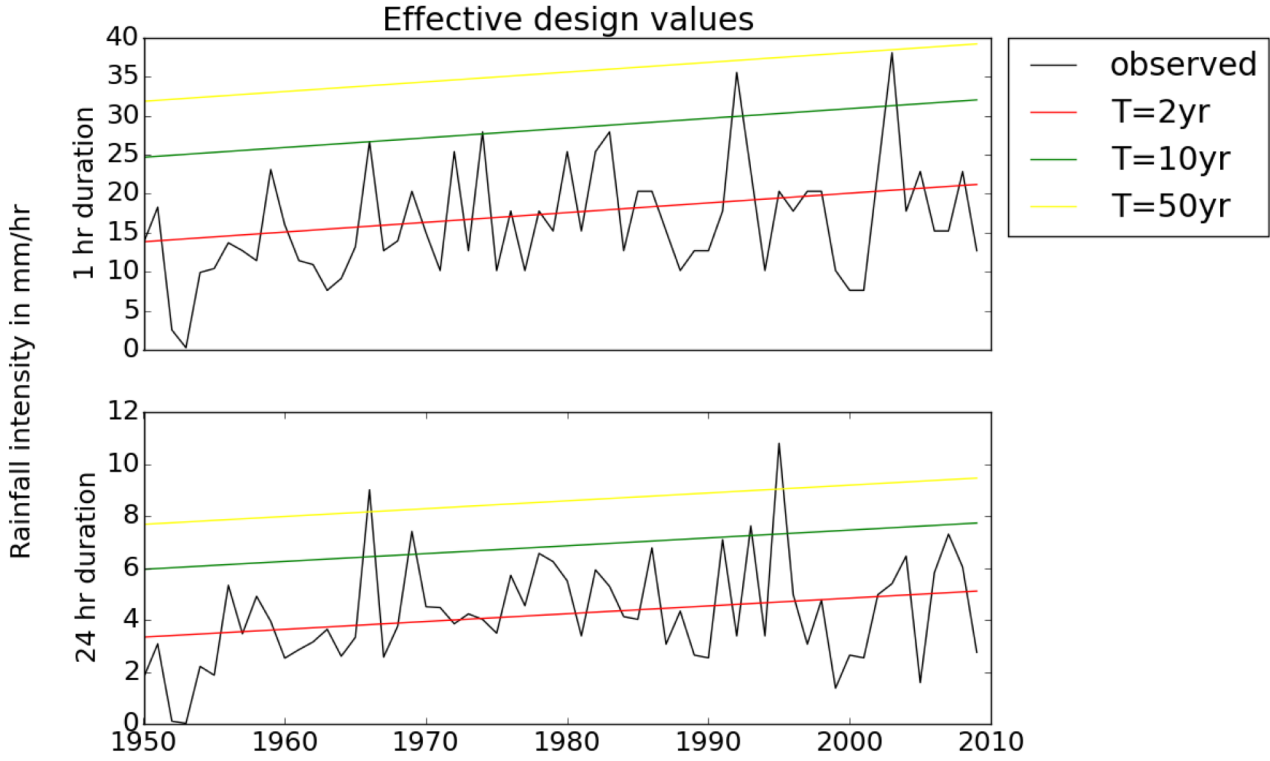




Comparison of the updated IDF curves with the IDF curves constructed using the entire data (1937-2016) for an example station in Washington state

Redefine terms

- There is now an added dimension to characteristics
- Ex: the design storm depends on storm duration and reoccurrence interval
- New design storm now depends on time as well



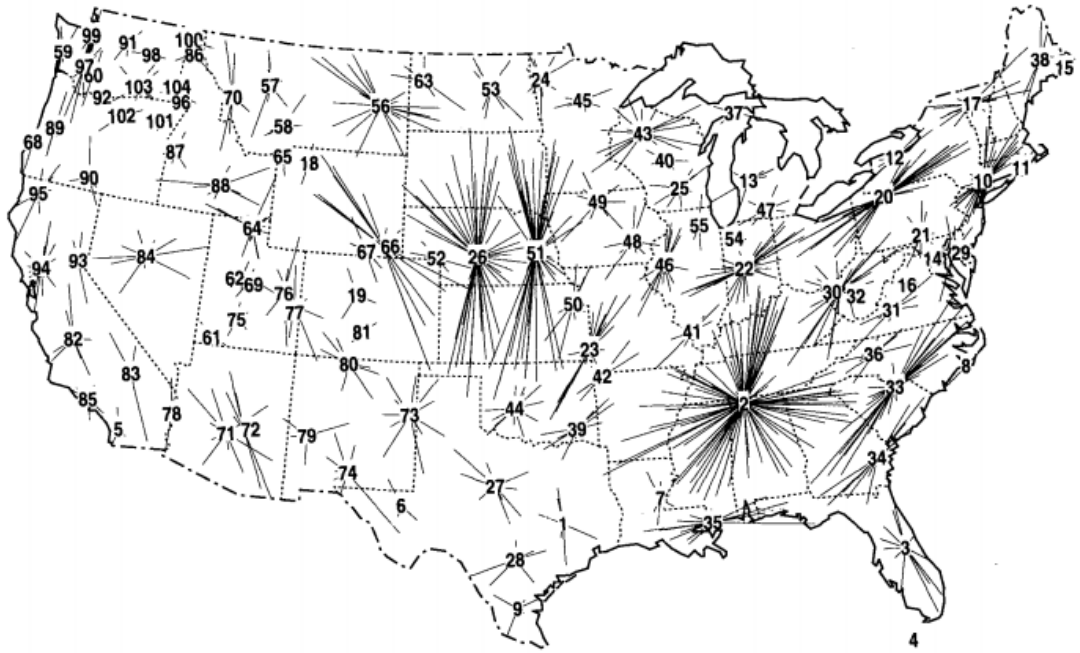
Effective design values for Palomar Mountain, CA, station (COOP ID:046657) showing how the extreme precipitation intensity changes for a fixed return period. The observed data, plotted in grey, is the AMS of the station.

Challenges in NS-IDF

- Inconsistent trends across storm durations leads to mathematical complications
- High uncertainty, especially with short record length
- No well-established agreement on how to approach problem

Regional Flood Frequency

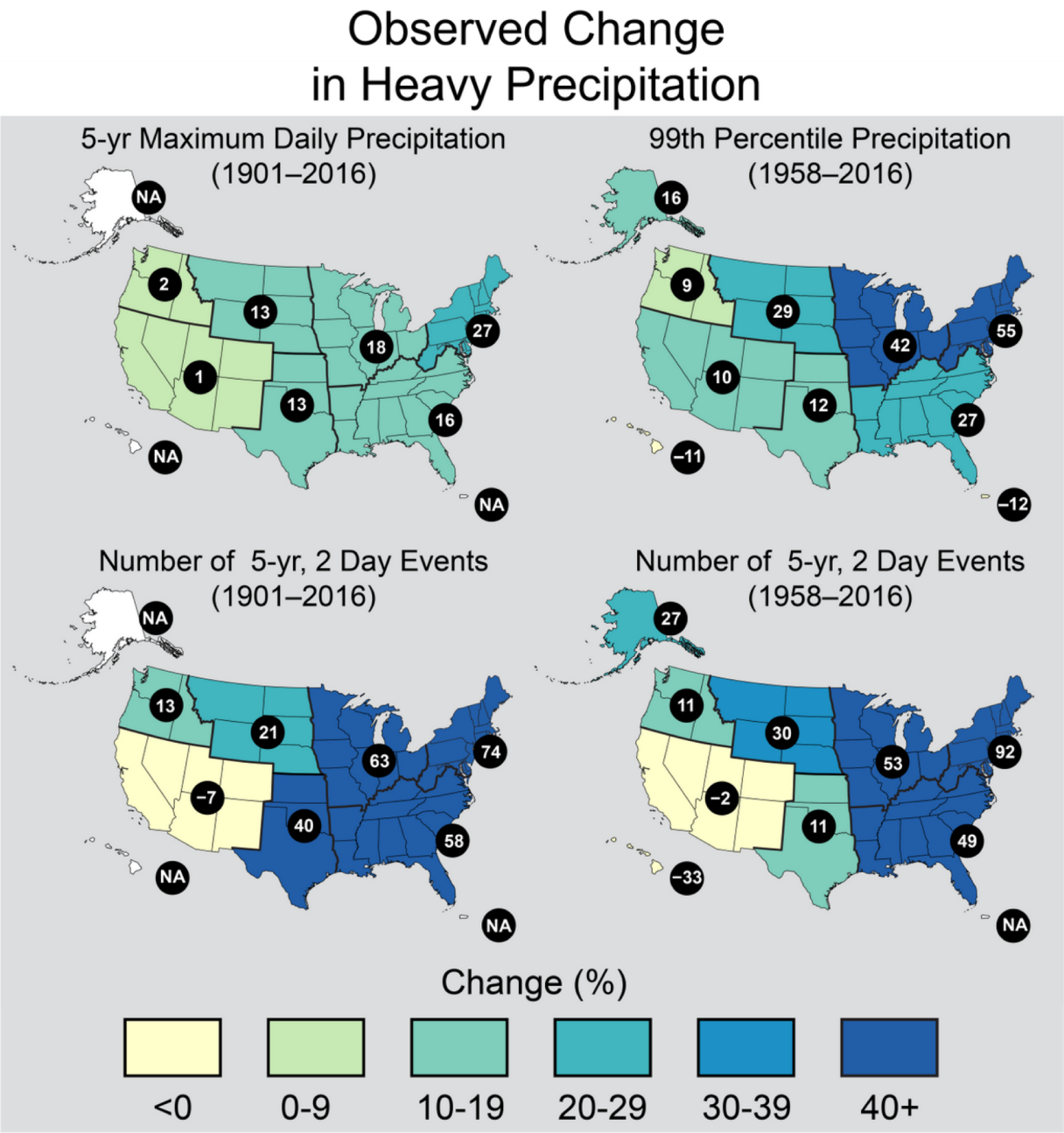
- Regional flood frequency can exploit information across stations (Lettenmaier et al., (1987), Hosking and Wallis (1997))
- Typically depends on creation and use of homogeneous regions
- Where homogeneous regions implies that all sites within the region are presumed to have the same underlying distribution
- Homogeneous regions do not have to be physically contiguous
- Many studies still use physically contiguous areas instead of homogeneous areas



Homogeneous precipitation regions as set up by Guttman (1993) using station network across the CONUS.

Historical trends – Regional level

- When aggregated from station to regional level, trends show more consistent increases in regions, with the exception being the southwest
- This figure uses physically contiguous regions instead of homogeneous regions



Observed changes (%) in heavy defined different ways for two different time periods (Easterling et al. 2017).

Detecting regional nonstationary behavior

- Regional Bootstrap Resampling (Cunderlik and Burn, 2003)
- Extreme Precipitation Index (Kunkel, 2003)
- Monte Carlo simulations (Livezey and Chen, 1983)
- Need to establish the understanding that if a region tests for significant nonstationarity, then all points/stations within the region should be modeled as nonstationary as well

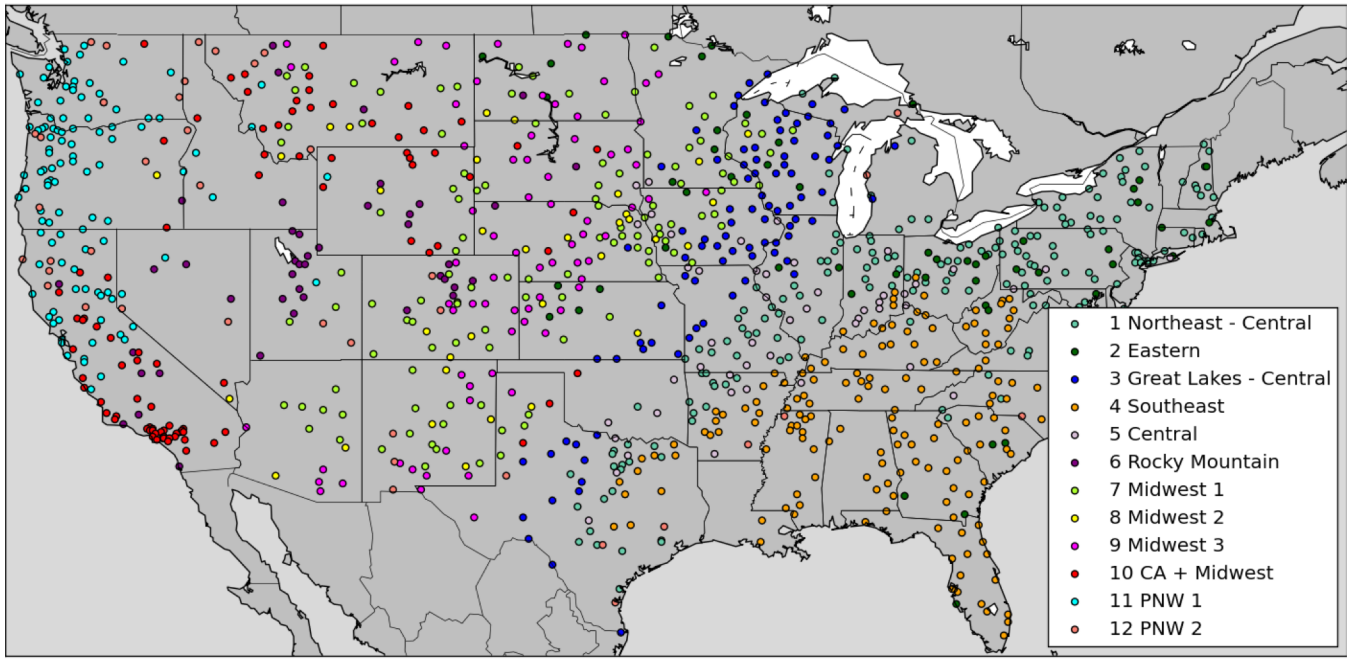
Growth Curve

- Growth curve represents underlying distribution within a homogeneous region
- Regional parameters are estimated by an average of the at-site parameters, weighted by the station's record length

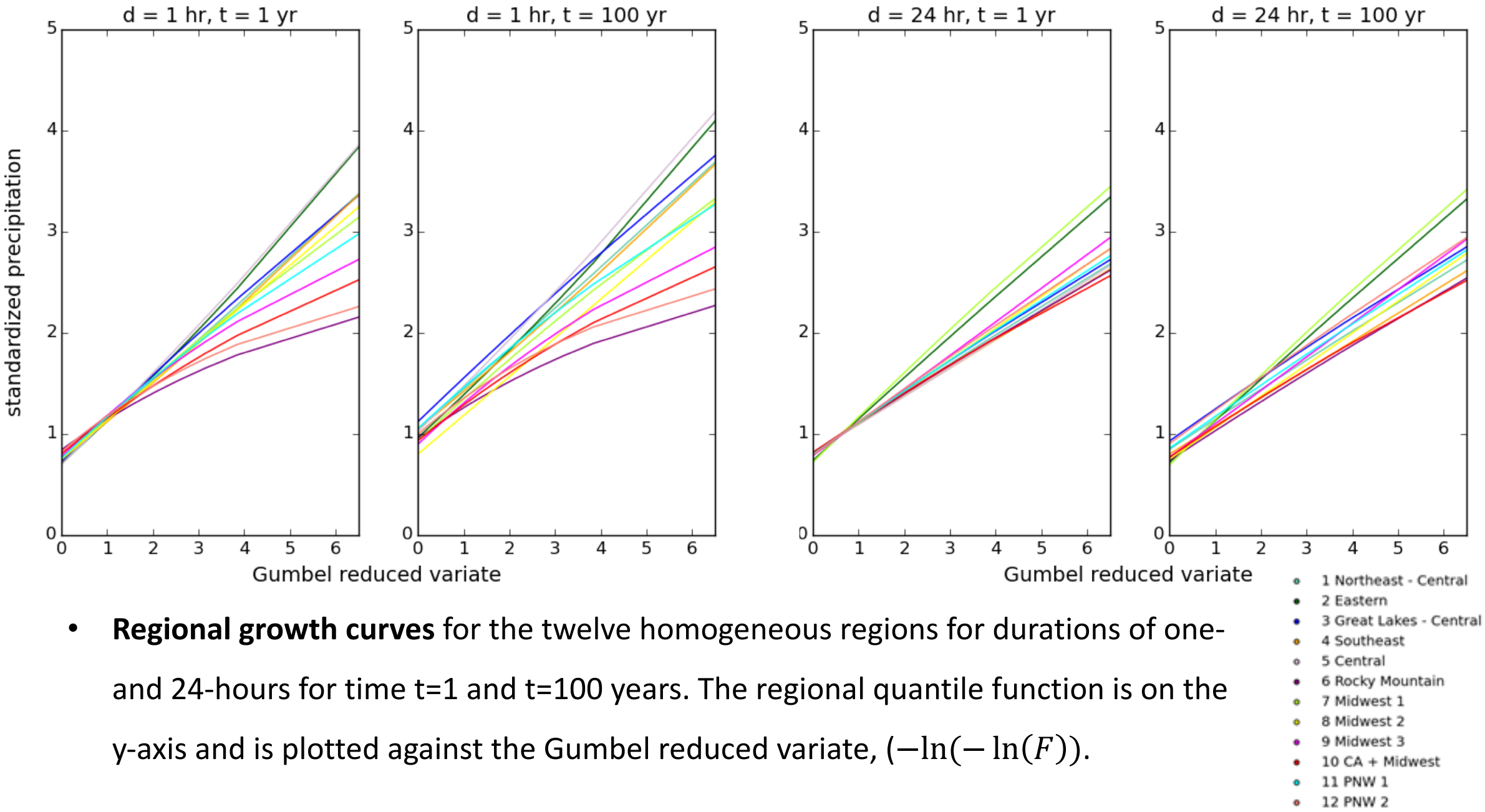
$$q(F) = \frac{Q_i(F)}{\mu_i}$$

NS-growth curve

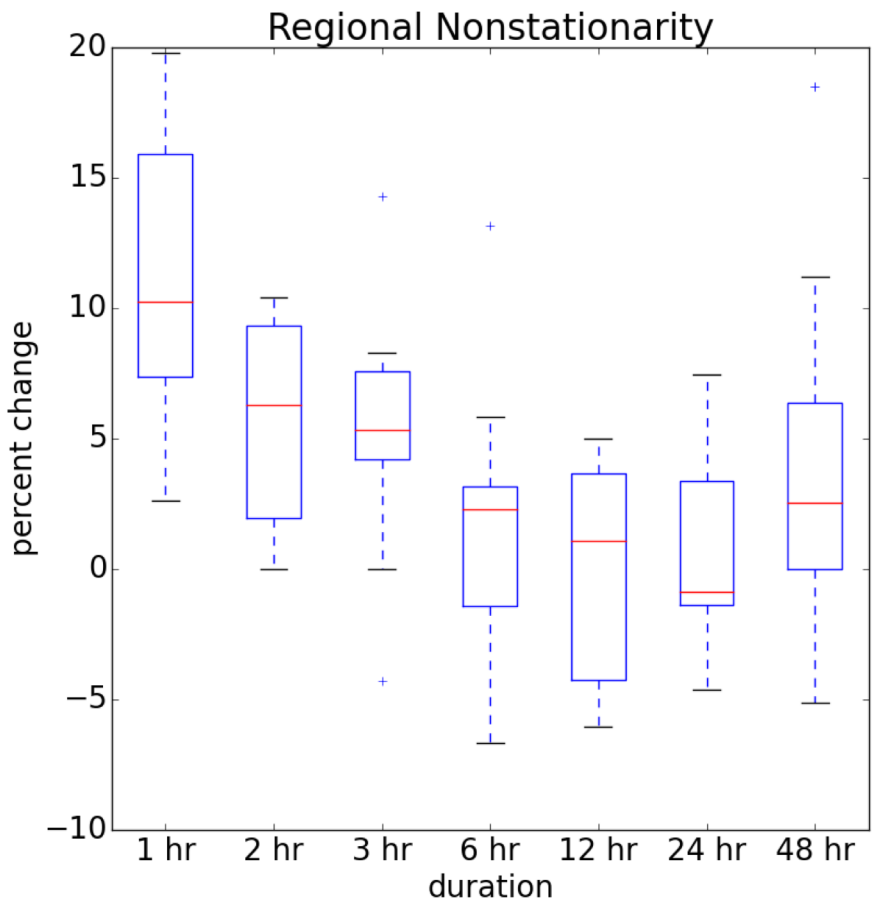
- Incorporate time trend into growth curve distribution by way of introducing a time-varying term (or other covariate) to the distribution parameters



Homogeneous regions across a station network in the CONUS



- **Regional growth curves** for the twelve homogeneous regions for durations of one- and 24-hours for time t=1 and t=100 years. The regional quantile function is on the y-axis and is plotted against the Gumbel reduced variate, $(-\ln(-\ln(F))$.



- Percent changes in 50-year return period intensities across all regions for time index = 0 (1960) to 100 years (2060).
- Percent changes range over -5.14% to +19.8%.
- Stations are assumed to have a nonstationary location parameter in the estimation of regional growth curves.

Challenges in Regional Flood Frequency

- Disagreements at-site in behavior for different durations only further complicated
- Will be more difficult to establish statistically significant NS behavior in regions

Ongoing questions

- Much of the work is still ongoing
- Is it safer to assume stationary or nonstationary behavior as the null hypothesis?
- How to resolve against storm durations?
- How to reduce uncertainty in estimating the trend?

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