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Managing Water in the West

Research to Develop Guidance on Extreme Precipitation Estimates in Orographic Regions

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Outline

1. Motivation
2. Precipitation-Frequency analysis
   A. Frequency Analysis Methods
   B. Datasets
3. Case study in Tennessee River Valley
   A. L-moments
   B. Bayesian
4. Summary & Conclusions

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Motivation

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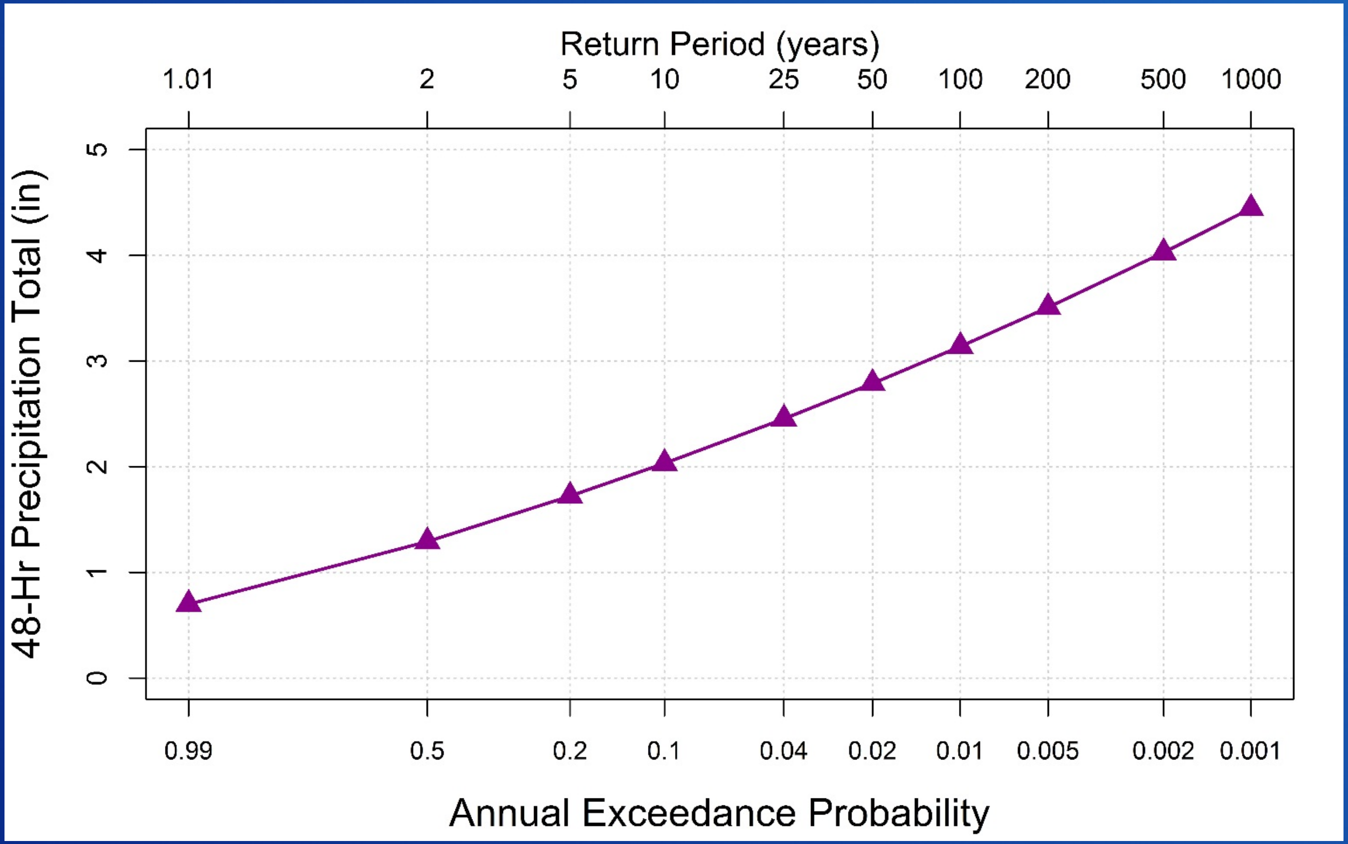
Motivation

Q: What is a precipitation-frequency relationship?



A: Statistical relationship relating precipitation depth to the probability of exceeding that depth.

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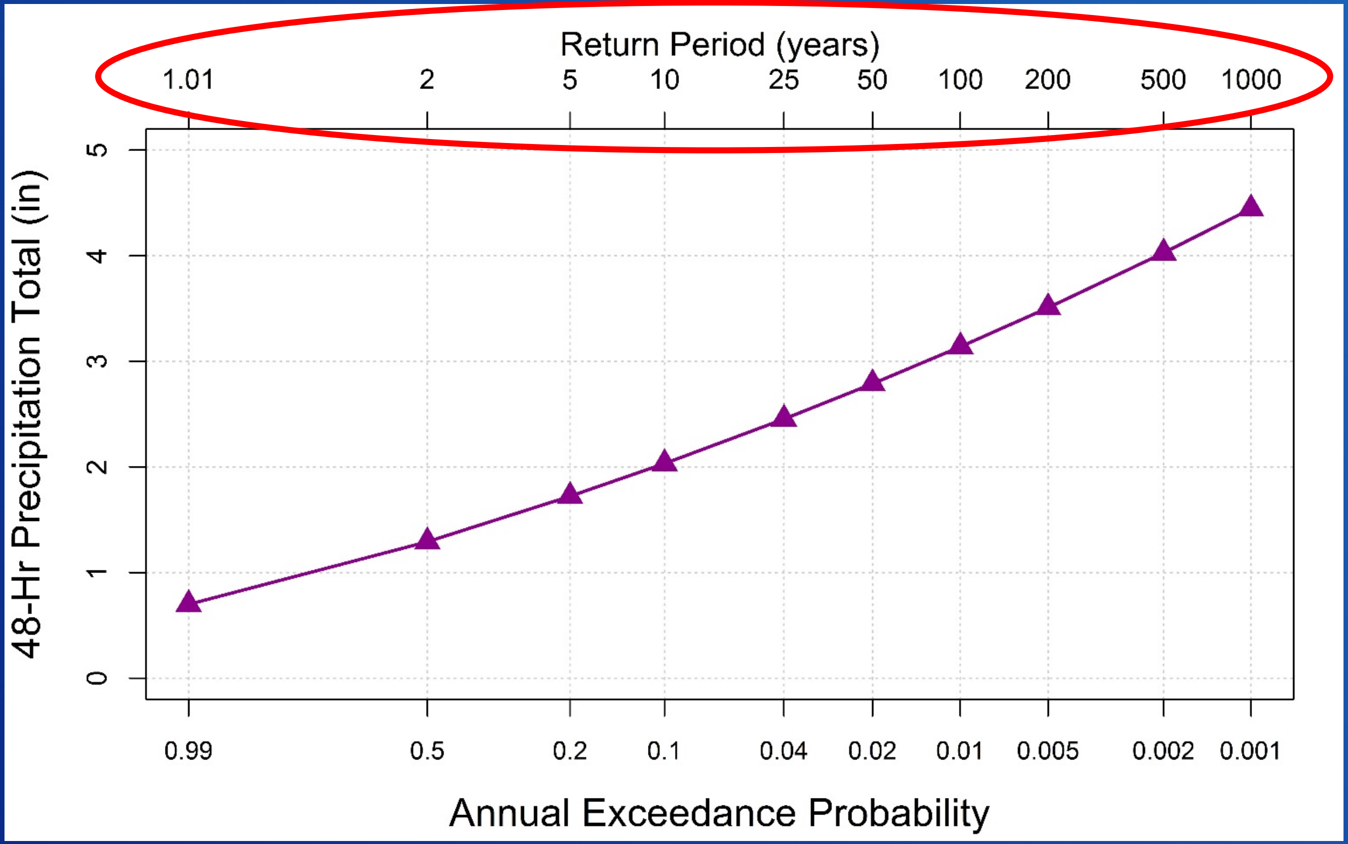
Motivation

Probability reported as "return period" or "average recurrence interval"



Return period of: 100 years means the probability is 1-in-100 (0.01)

500 years means the probability is 1-in-500 (0.002)

1,000 years means the probability is 1-in-1000 (0.001)

Precipitation-Frequency Analysis

Define relevant precipitation duration

→ e.g., 1-day, 2-day, etc.

Extract annual/seasonal maxima from daily time series

QC annual/seasonal maxima for false maxima

Fit extreme value distribution to maxima

→ Estimate $\theta = (\mu, \sigma, \xi)$

Calculate quantiles of distribution

→ Precipitation magnitudes and associated probabilities

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Regional Frequency Analyses

Assume observations within homogeneous region (HR) described by single distribution

→ Pool all annual/seasonal maxima within HR

Scale the annual/seasonal maxima by the at-site mean of the maxima

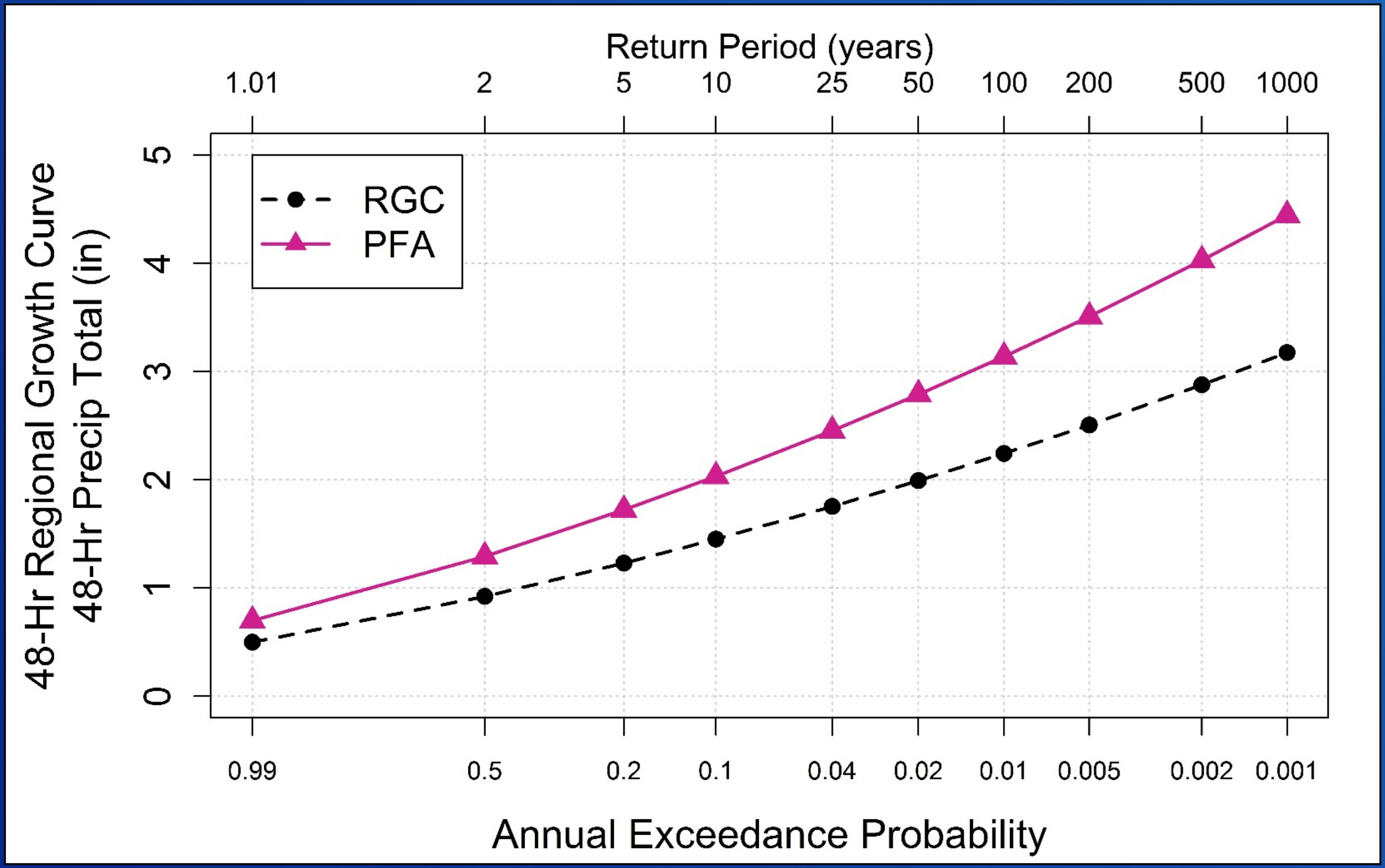
→ Mean at each site -> 1

Compute precipitation-frequency relationship, produce regional growth curve (RGC)

→ Scale by specific at-site mean for point estimates

Regional Growth Curve

Unitless curve describing all gauges in HR



Scale by site-specific ASM for site-specific PF curve

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Frequency Analysis Methods

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L-moments

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L-Moments

1. Developed for ***regional*** frequency analysis
2. Identify weather stations (sites) within HR
3. Screen observations
   - annual/seasonal/monthly maxima
   - duration depends on meteorology
4. Quality control data
5. Compute L-statistics* for each site
   - L-mean, L-scale, L-skewness, L-kurtosis
6. Test for heterogeneity
   - Discordancy measures (e.g., $D_i \leq 3$)
7. Identify the "best" distribution
   - GEV, GPD, GNO, GLO, PE3, Wakeby
8. Calculate regional growth curve (weighted by POR)
   - Scale growth curve (point, basin, region)

Available R packages for L-moments:
library("lmom")
library("lmomRFA")

L-statistics

Alternative system of describing probability distribution functions based on linear combinations of moments

<u>L-moments:</u>

λ_1=L-location (mean)

λ_2=L-scale (variability or dispersion)

λ_3=L-skewness (asymmetry)

λ_4=L-kurtosis (thickness of tail)

<u>L-moment ratios (dimensionless):</u>

$T_r=\lambda_r/\lambda_2$

T=L-CV= λ_2/λ_1 (variability)

Hosking and Wallis (1997)

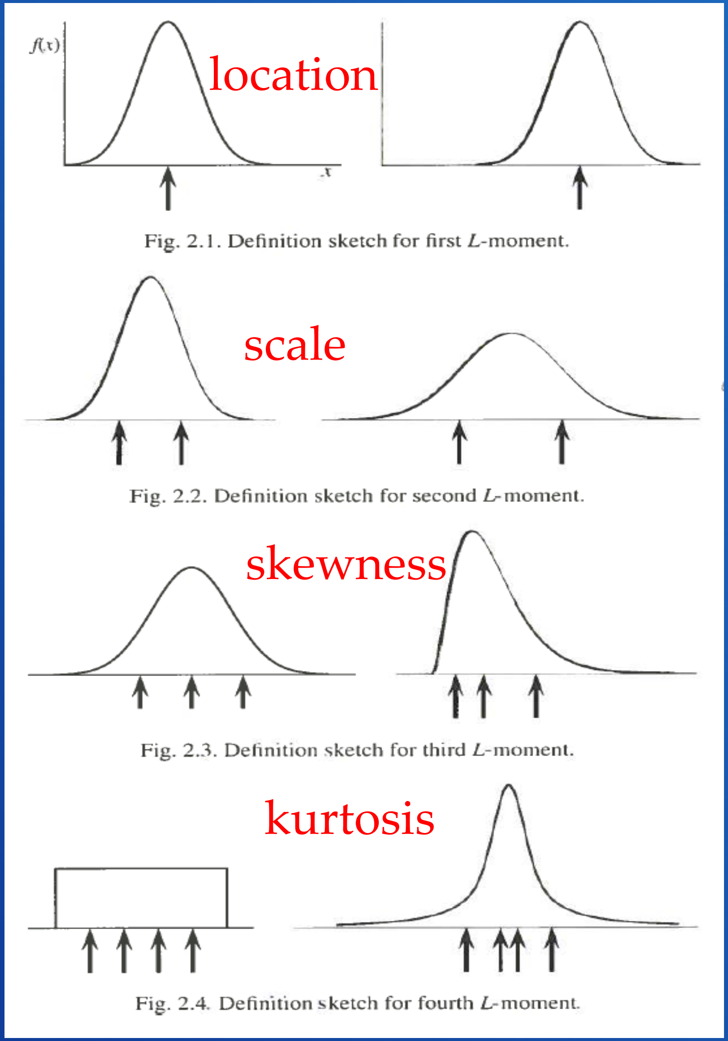

Fig. 2.1. Definition sketch for first *L*-moment.

Fig. 2.2. Definition sketch for second *L*-moment.

Fig. 2.3. Definition sketch for third *L*-moment.

Fig. 2.4. Definition sketch for fourth *L*-moment.

Available R packages for L-moments:
library("lmom")
library("lmomRFA")

Bayesian inference

Bayesian inference

Prior $p(\boldsymbol{\theta})$: the strength of our belief in θ without the data Y

Posterior $p(\boldsymbol{\theta}|\boldsymbol{Y})$: the strength of our belief in θ when the data Y are taken into account

Likelihood $p(\boldsymbol{Y}|\boldsymbol{\theta})$: the probability that the data Y could have been generated by the model with parameter values θ

Evidence p(Y): the probability of the data according to the model, determined by summing across all possible parameter values weighted by the strength of belief in those parameter values

→ typically unknown, can be ignored with proportionality

→ essentially a normalizing constant

→ does not enter into determining relative probabilities (models)

Available R packages for Bayesian inference:
library("rstan")
library("spBayes")

Bayesian inference

Bayes' Rule in a modeling framework:

$$p(\theta|\boldsymbol{Y}) = \frac{p(\boldsymbol{Y}|\theta)p(\theta)}{p(\boldsymbol{Y})} \propto p(\boldsymbol{Y}|\theta)p(\theta)$$

e.g., $\boldsymbol{Y} = (y_1, y_2, \dots, y_n); \theta = (\mu, \sigma, \xi)$

- Define *prior distributions* for model parameters θ (a priori knowledge)
- Can consider numerous likelihood functions (e.g., *GEV*, GNO, GLO, etc.)
- Monte Carlo, acceptance criteria, builds *posterior distributions* of θ

Bayesian inference derives the *posterior probability* as a consequence of a *prior probability* and a *likelihood function*

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Available R packages for Bayesian inference:
library("rstan")
library("spBayes")

Regional Bayesian

Scale annual maxima by at-site mean

Assume scaled maxima within HR described by a single theoretical distribution

Generalized Extreme Value (GEV) distribution

Posterior distributions of $\theta = (\mu, \sigma, \xi)$

→ Quantification of one source of epistemic uncertainty

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Available R packages for Bayesian inference:
library("rstan")
library("spBayes")

Datasets

Historical Observations

Global Historical Climatology Network:

Integrated database of daily climate summaries from land surface stations (100,000+) across the globe

Includes observations from multiple sources that have been subjected to a the same fully-automated quality control process (Durre et al. 2010)

- Duplication of records
- Exceedance of physical, absolute, climatological limits
- Temporal persistence
- Inconsistencies with neighboring observations

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Question:

How do we obtain PF estimates at ungauged locations?

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Newman et al. (2015)

Gridded observation-based ensemble dataset of daily precipitation and temperature from 1980 to 2012

Ensemble generation:

*Locally-weighted regression models are used to produce "best estimate" values of precipitation and temperature at 1/8° lat×lon grid

* Regression residuals are used to perturb the best-estimate values with correlated random samples

Resulting dataset:

*100 plausible precipitation and temperature grids

*Each valid over same period

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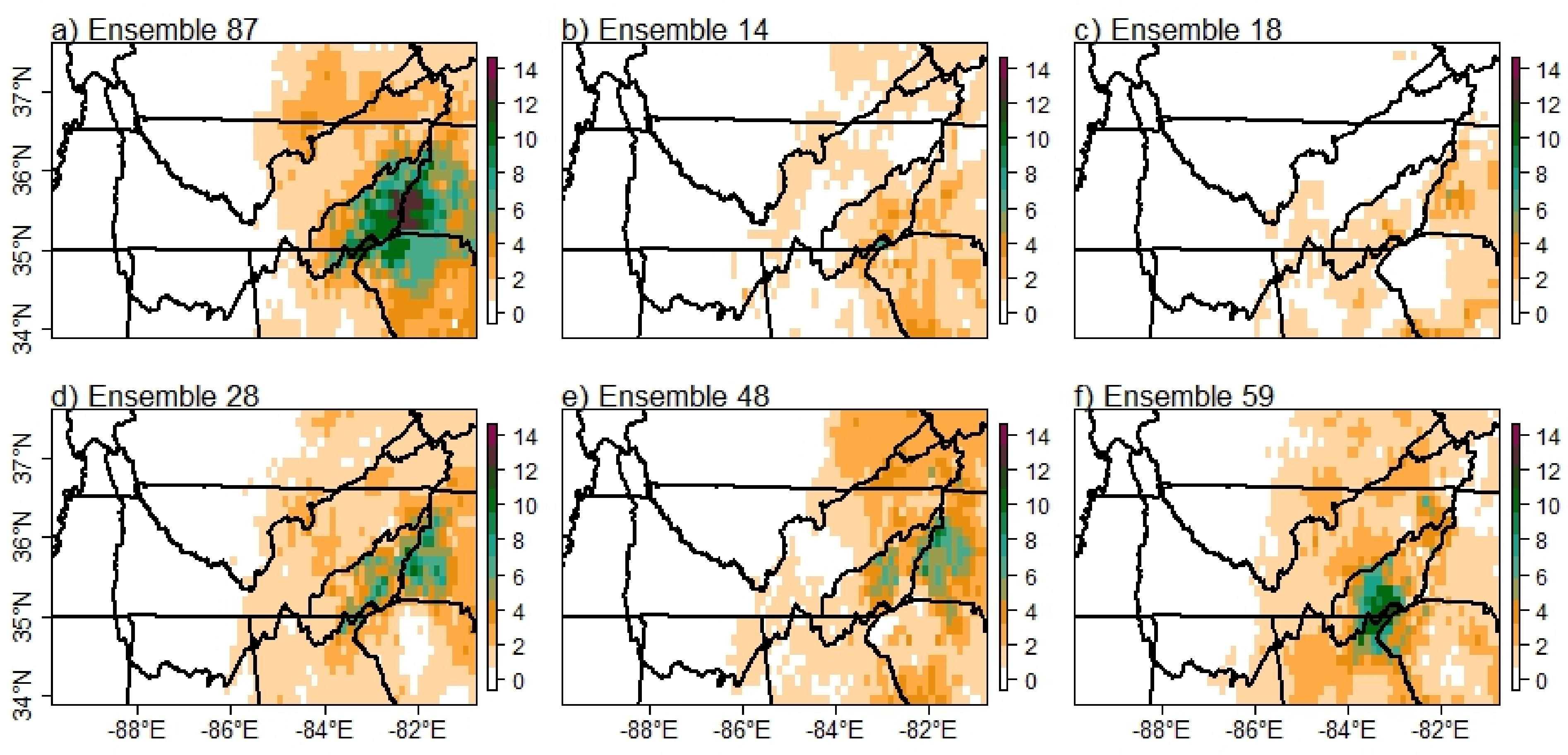
Newman et al. (2015)

Daily precipitation (inches) on September 15, 2004



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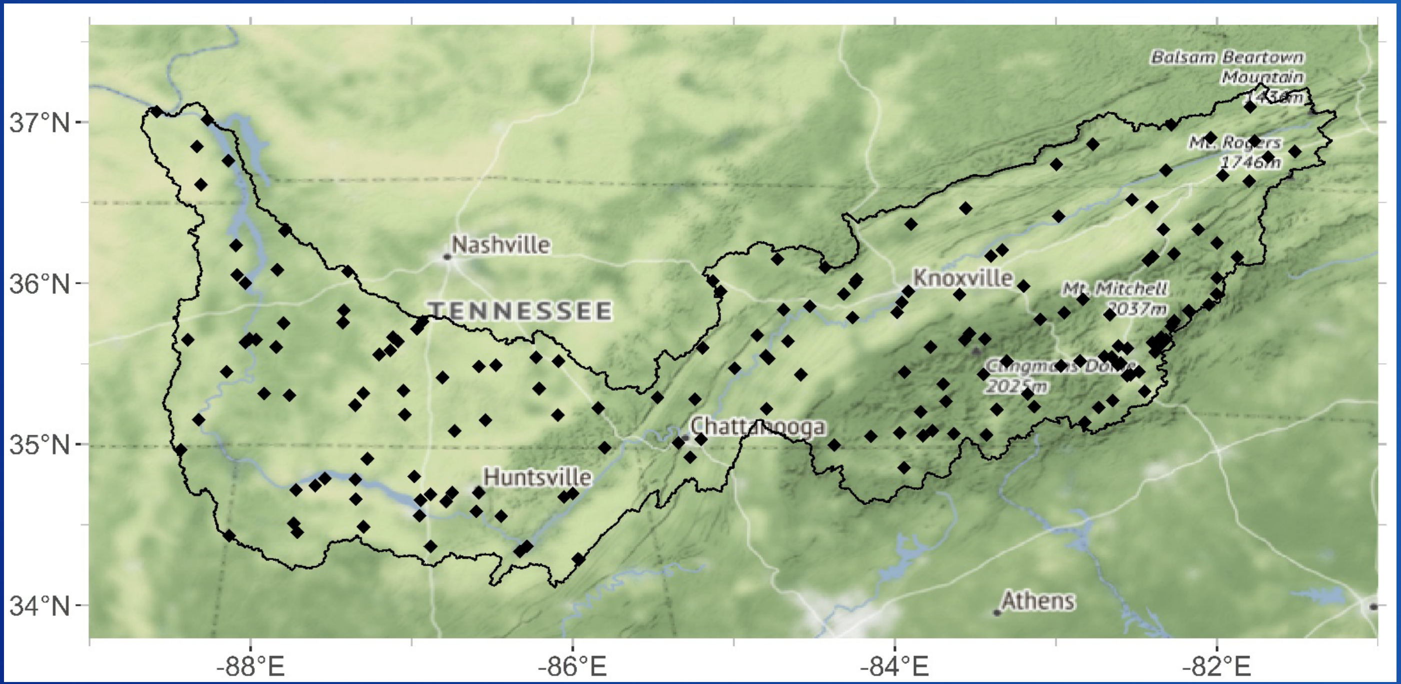
Case Study

Study Region

Tennessee River Valley watershed



GHCN-Daily gauges with 85% data availability for 10+ years period of record (POR)

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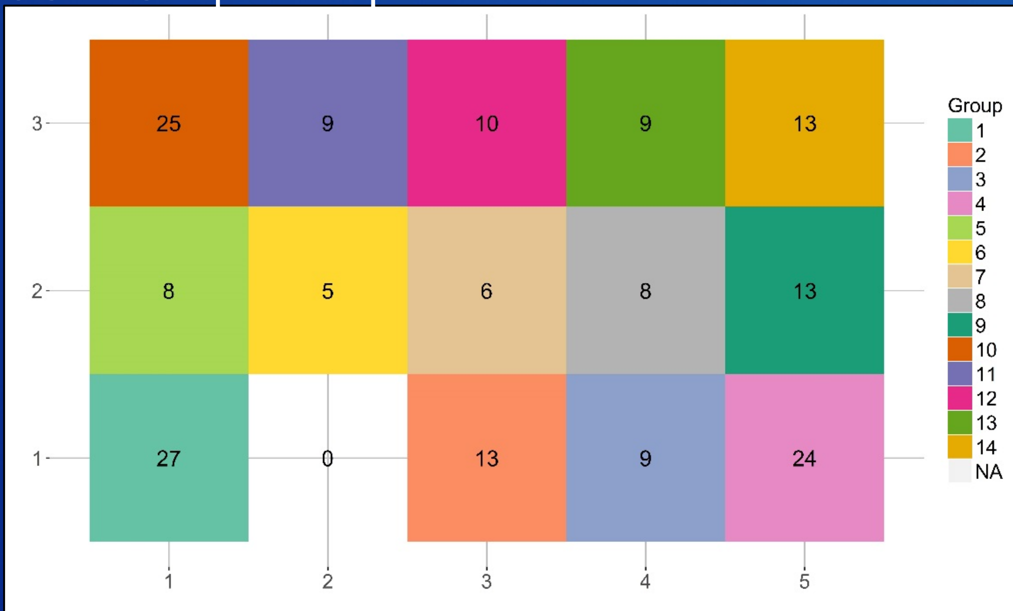
Homogeneous Regions

- Methods to define HR (Hosking and Wallis 1997)
  - Subjective methods
    - Geographical location
    - Seasonal timing of peak events
    - Mean annual precipitation (MAP)
    - Similar forcing mechanisms (synoptics)
  - Objective methods
    - Self-Organizing Maps (SOM)
    - Hierarchical clustering analysis (HCA)
    - Principle component analysis (PCA)
    - Heterogeneity measure

Self-Organizing Map

SOM Output Map



Clustering algorithm used to "group" stations with similar attributes

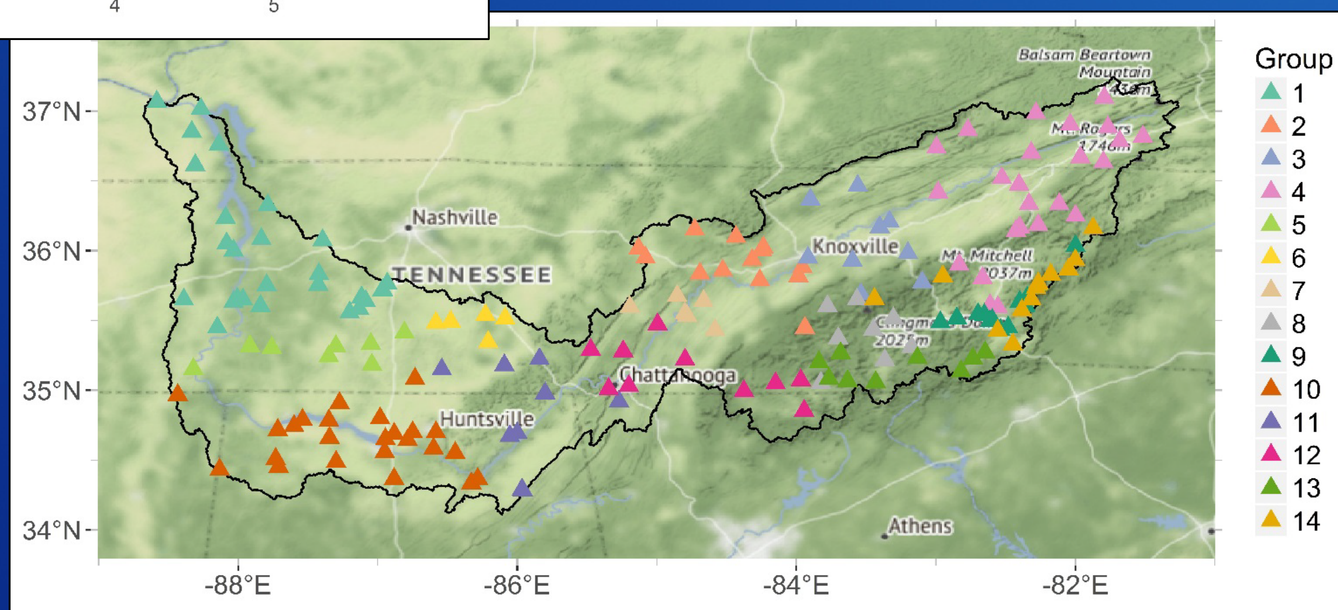
Apply SOM algorithm to :

- Latitude
- Longitude
- Elevation
- *Avg annual precipitation*
- *Avg annual max one-day precipitation*

Each station maps to a single SOM node

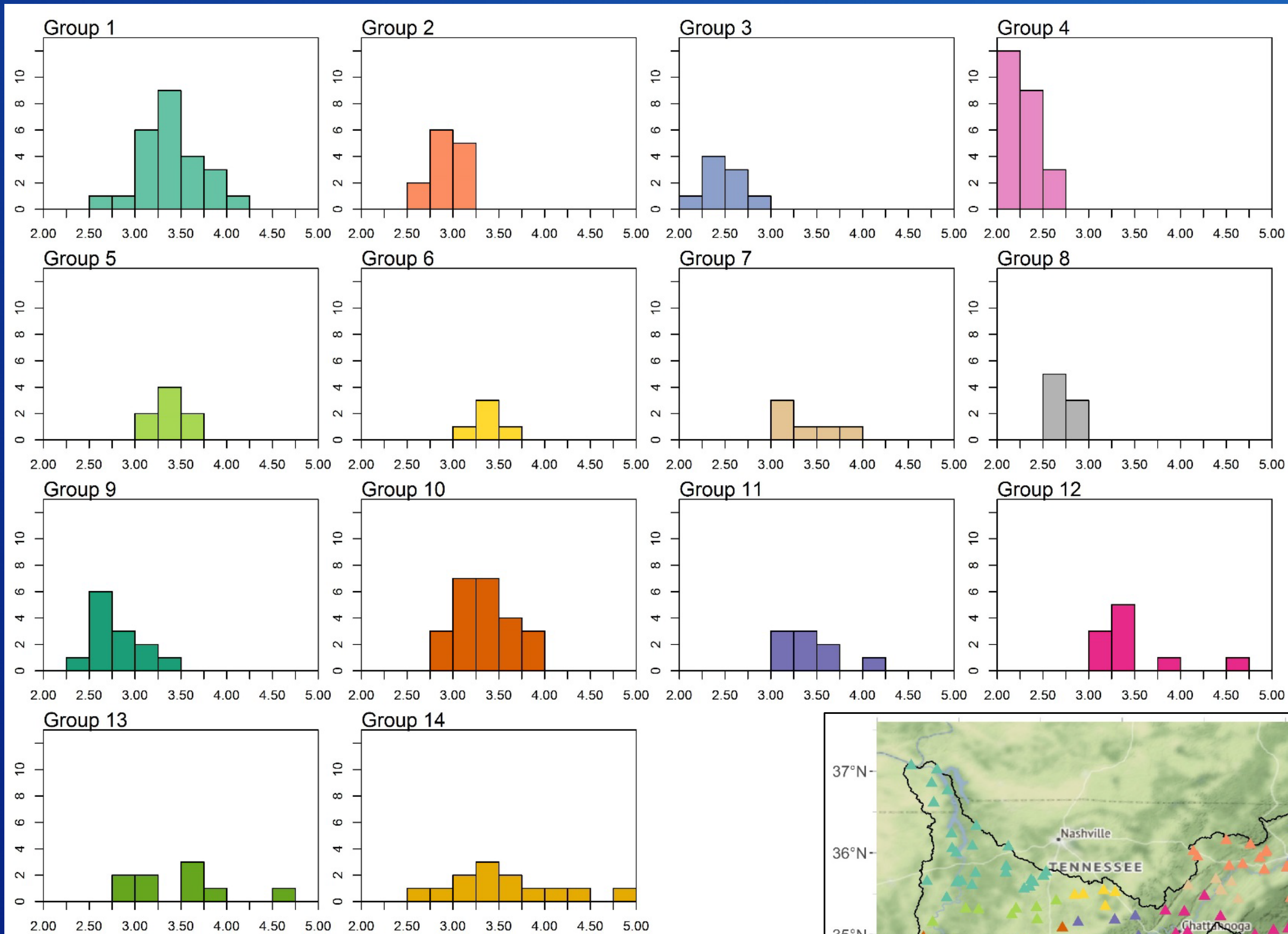
Gauges mapped to same node define homogeneous regions

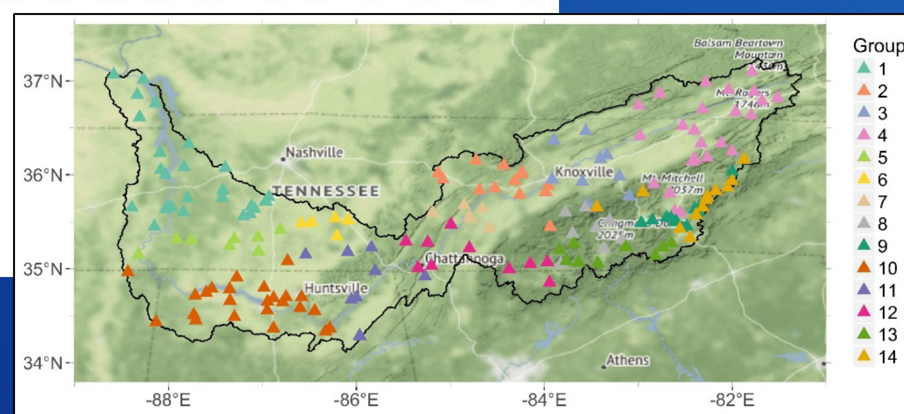
Homogeneous regions need not be contiguous



Available R packages for SOM analysis:
library("som")
library("kohonen")

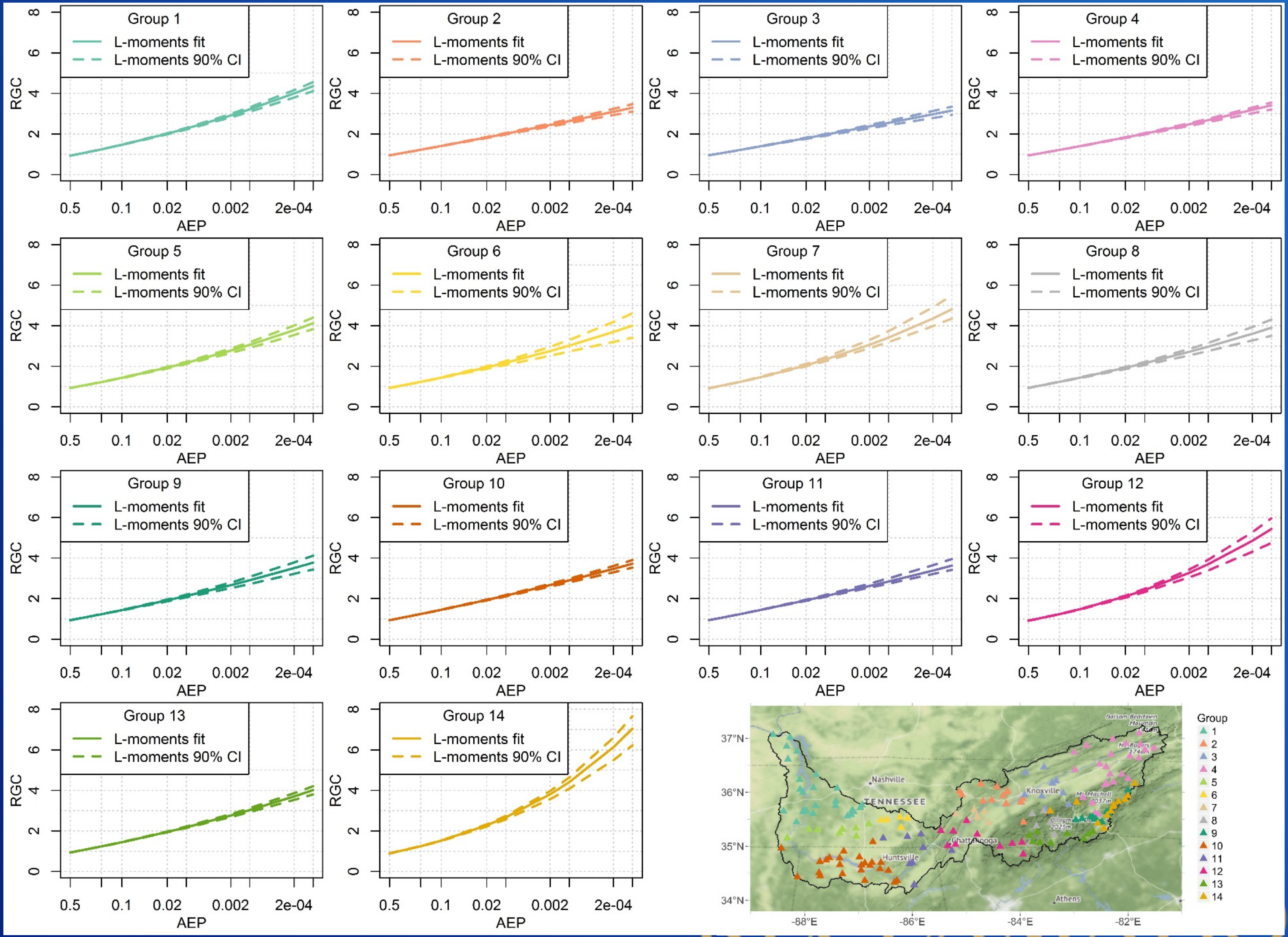
SOM Results – At-Site Means



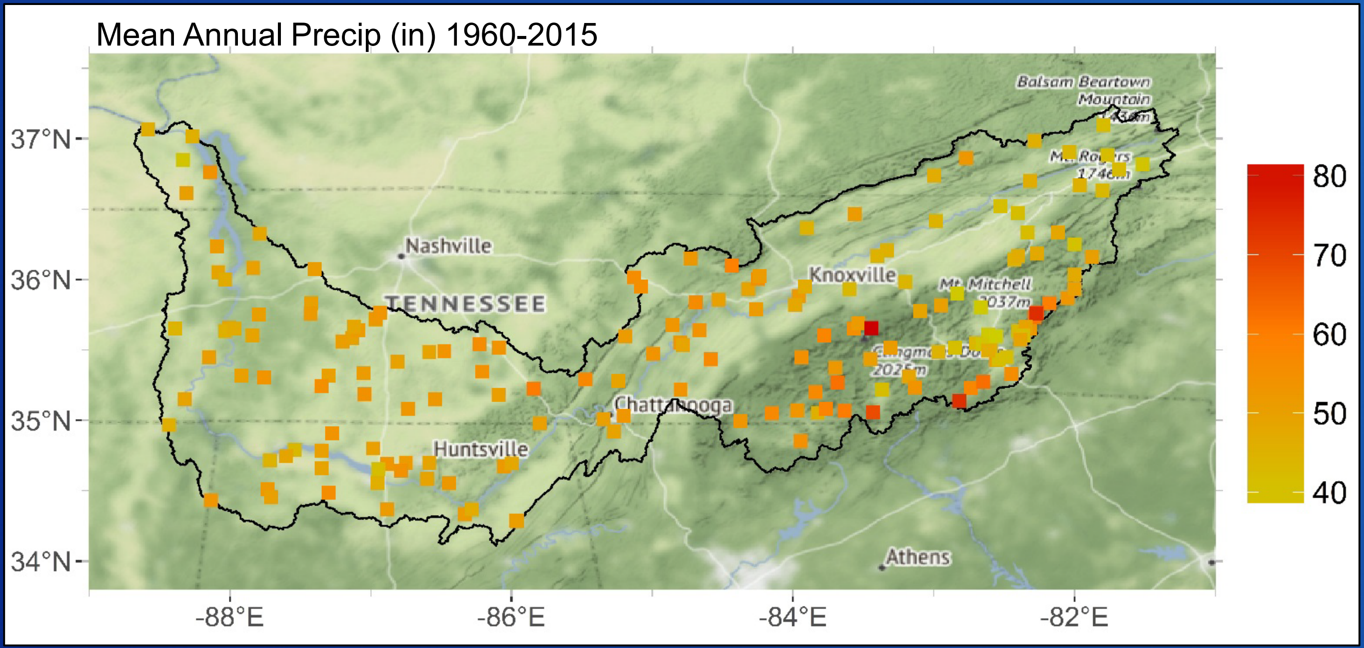


L-Moments

L-Moments RGCs

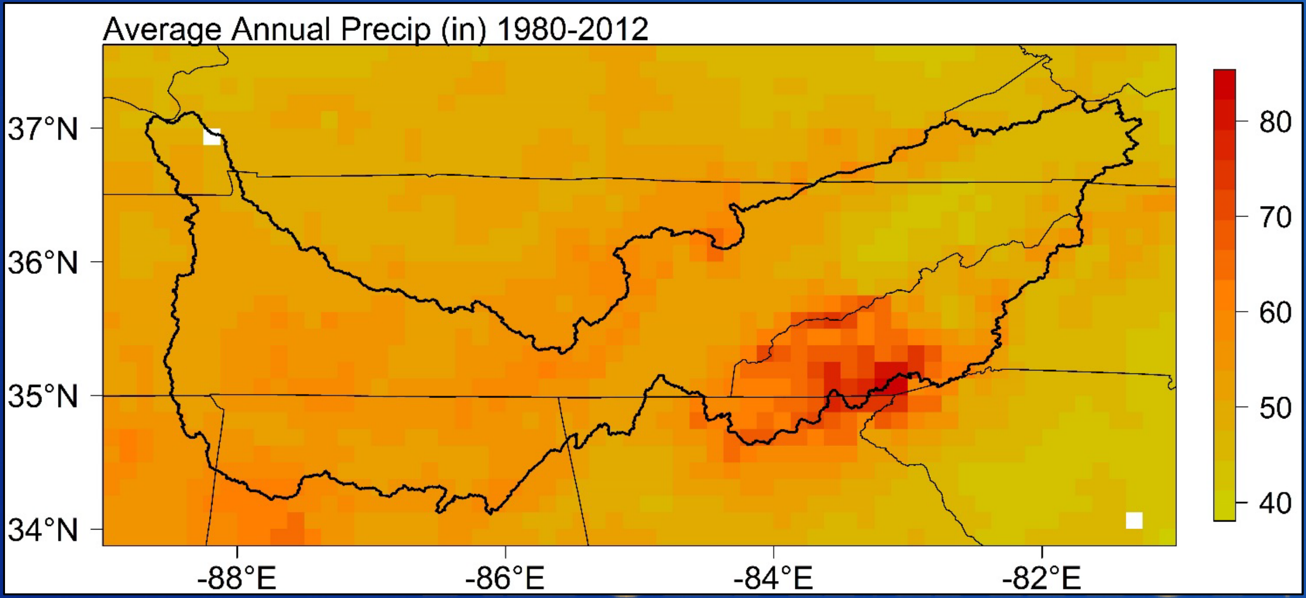


Data Availability

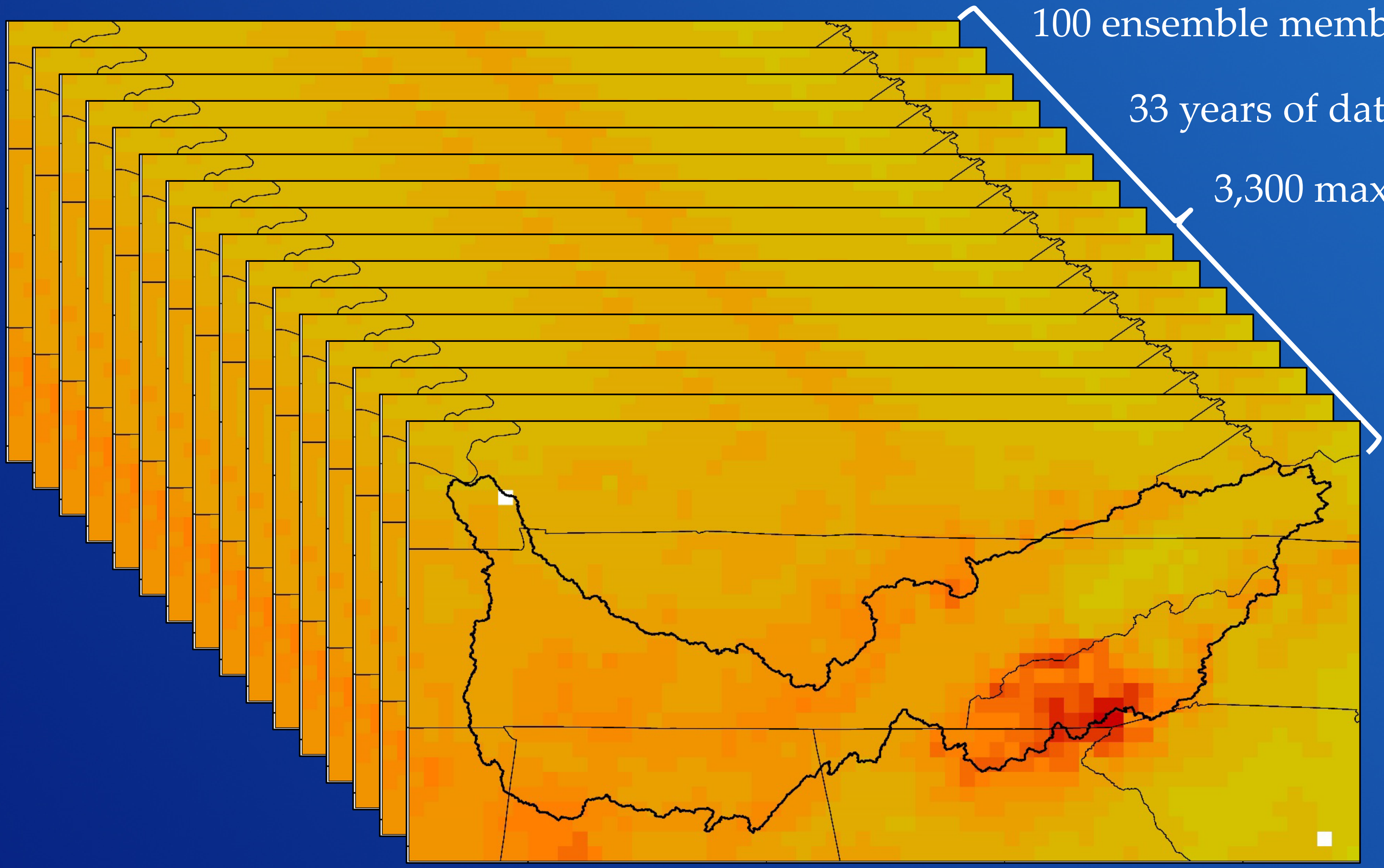


GHCN-Daily dataset

Newman et al. (2015) gridded ensemble



Combined Ensemble



100 ensemble members

33 years of data

3,300 maxima/cell

Newman et al. (2015)

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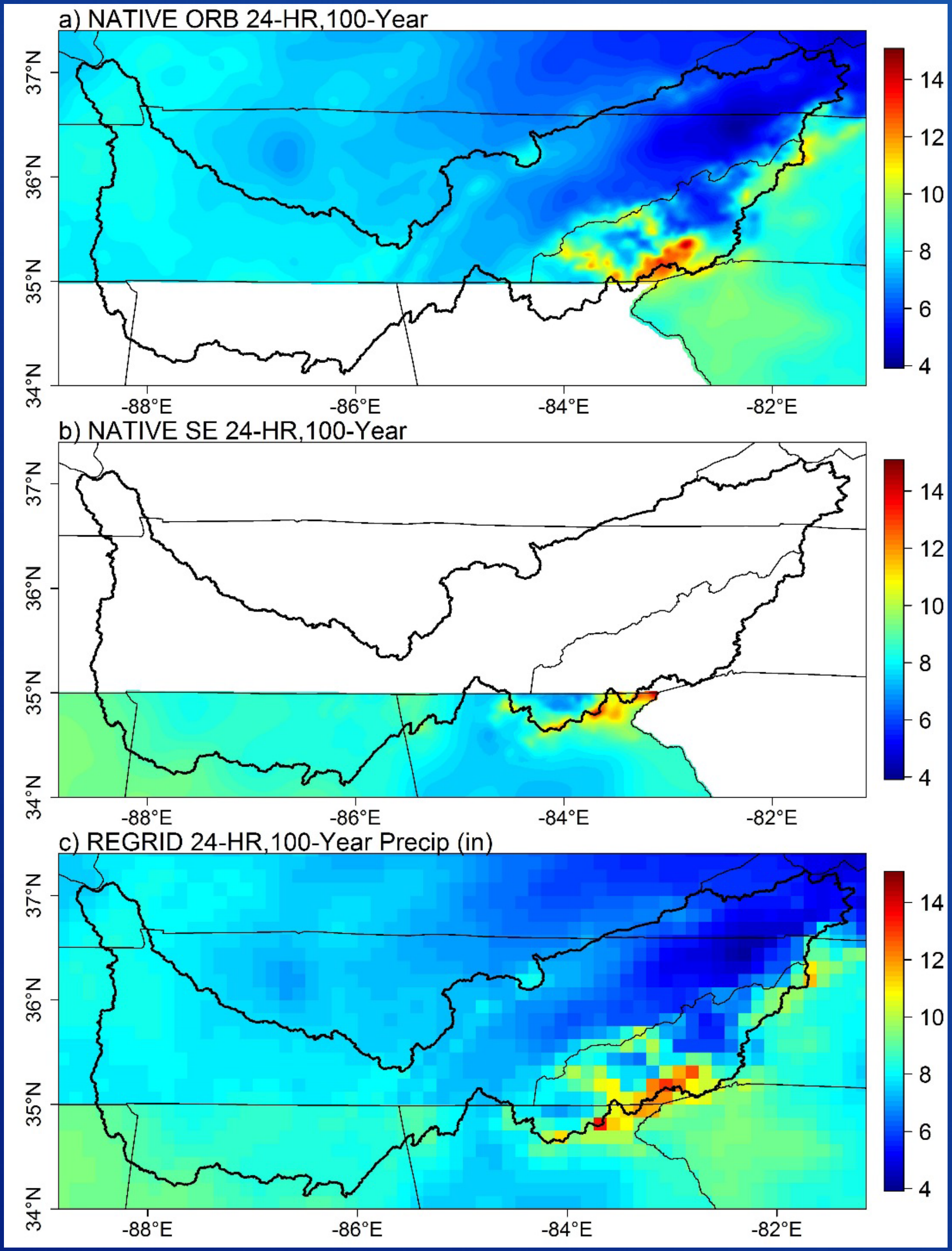
NOAA Atlas 14



Data from Ohio River Basin and Southeast domains use different lat/long grids

Regrid each field to the Newman resolution and then combine fields to produce a single field

In order to compare with Newman estimates, applied two <u>scale factors</u>

1) Duration correction
2) Areal-reduction factor

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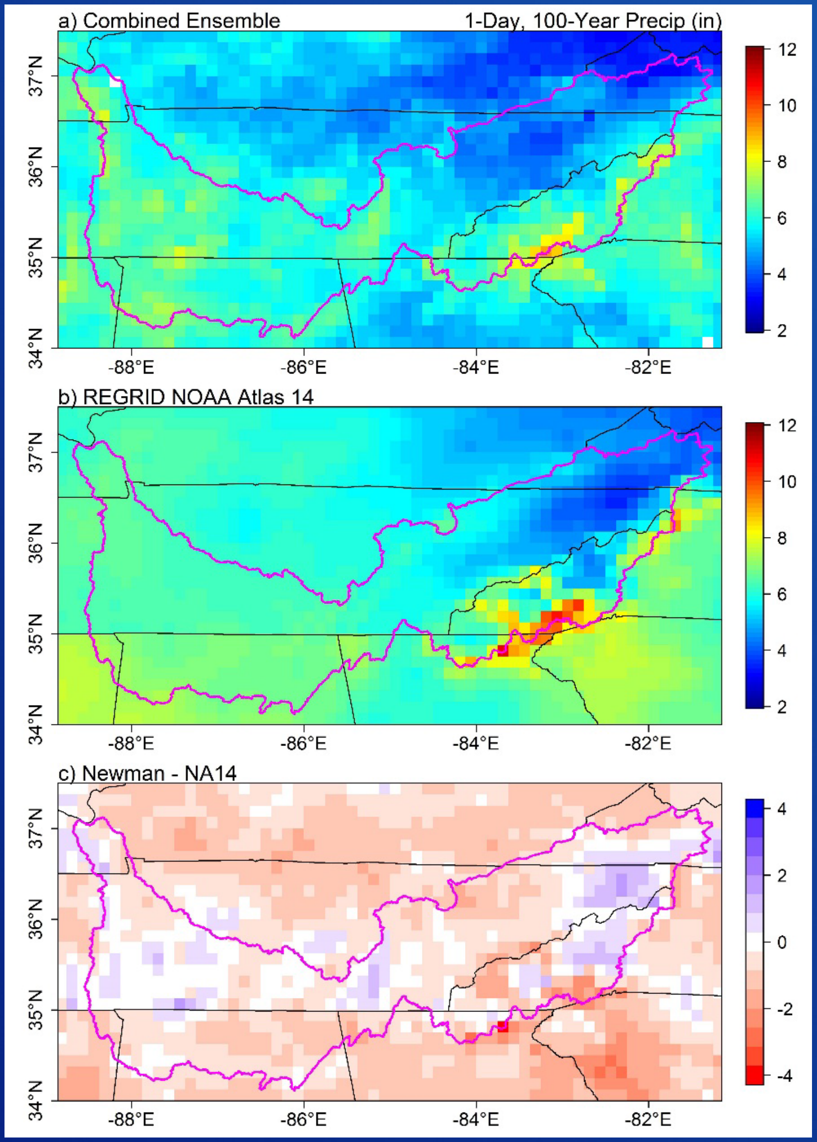
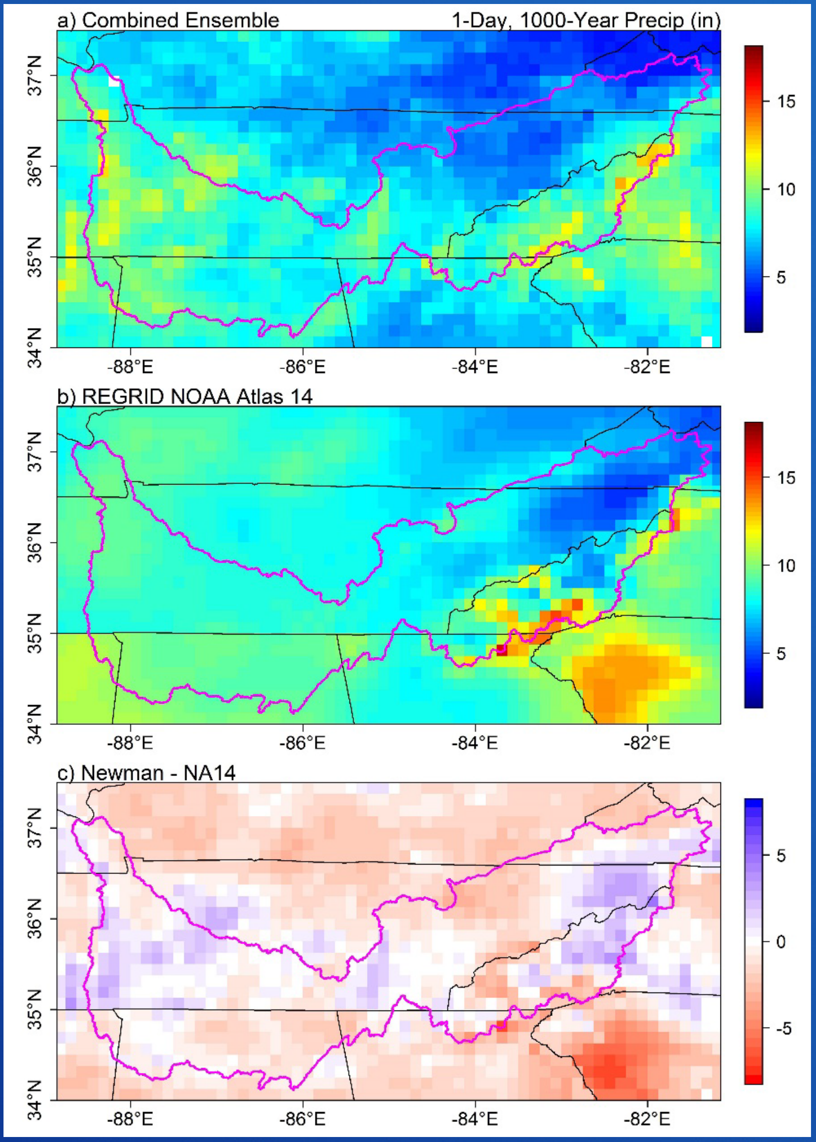
Gridded L-moments





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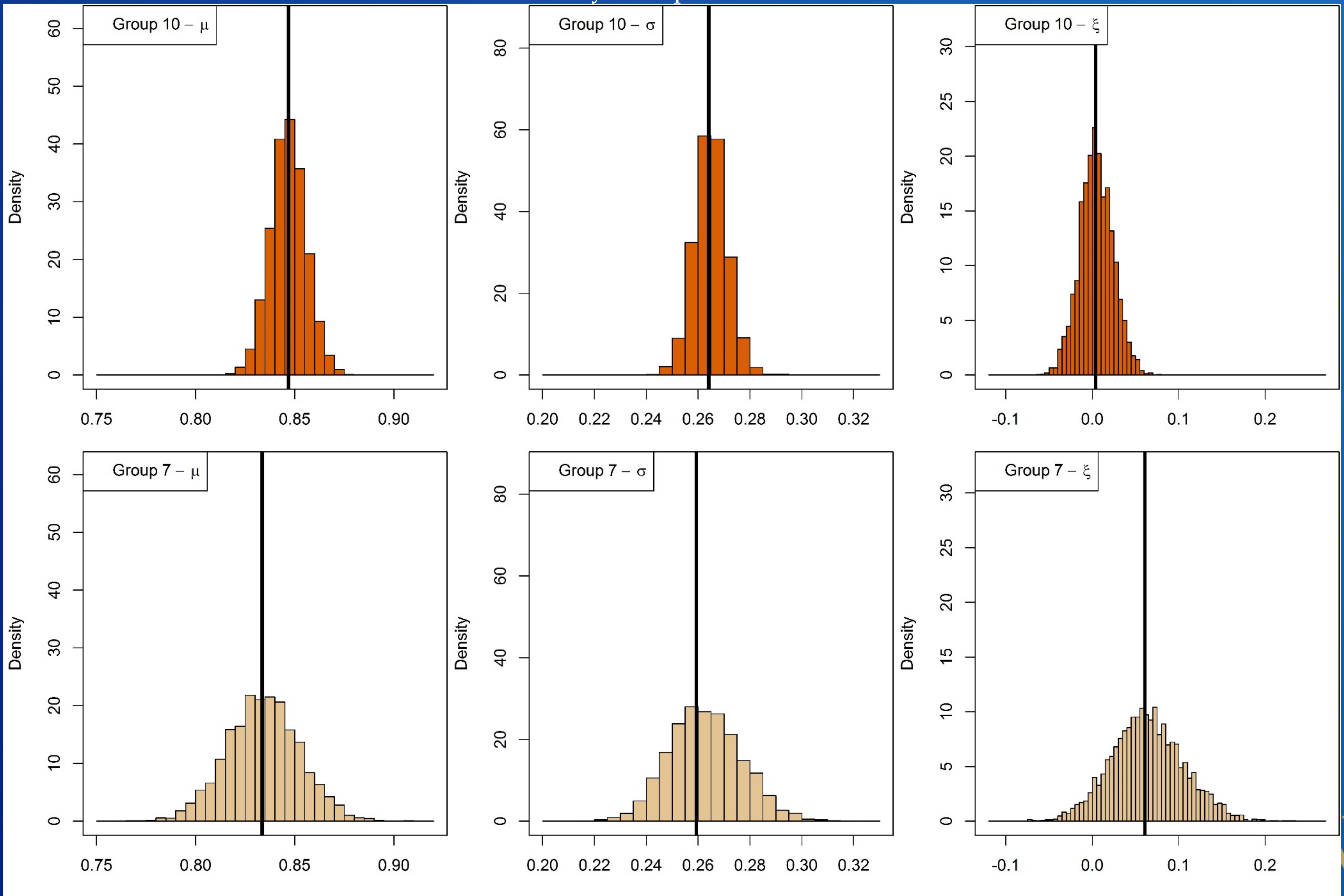
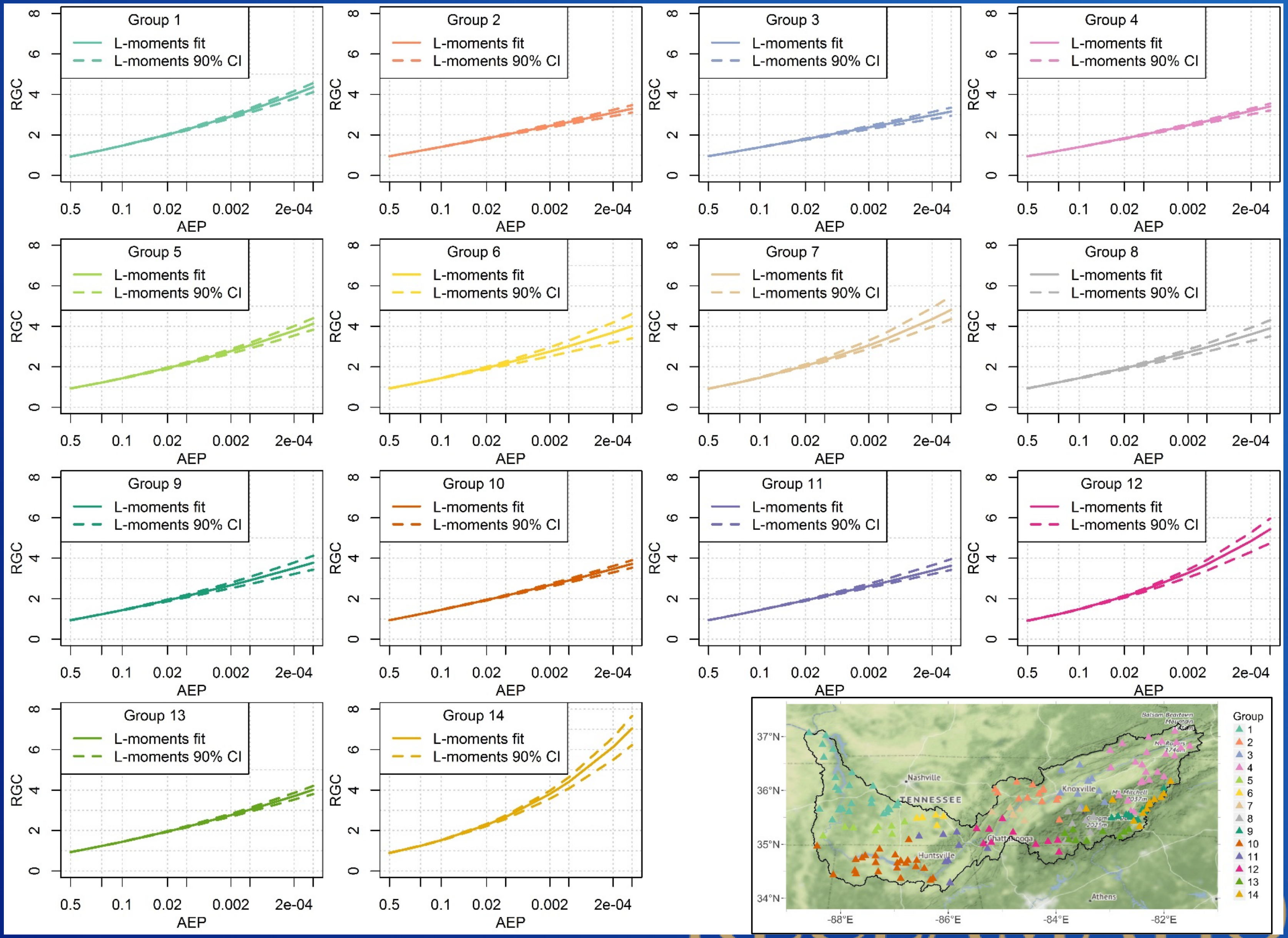
Bayesian

Posterior Distributions

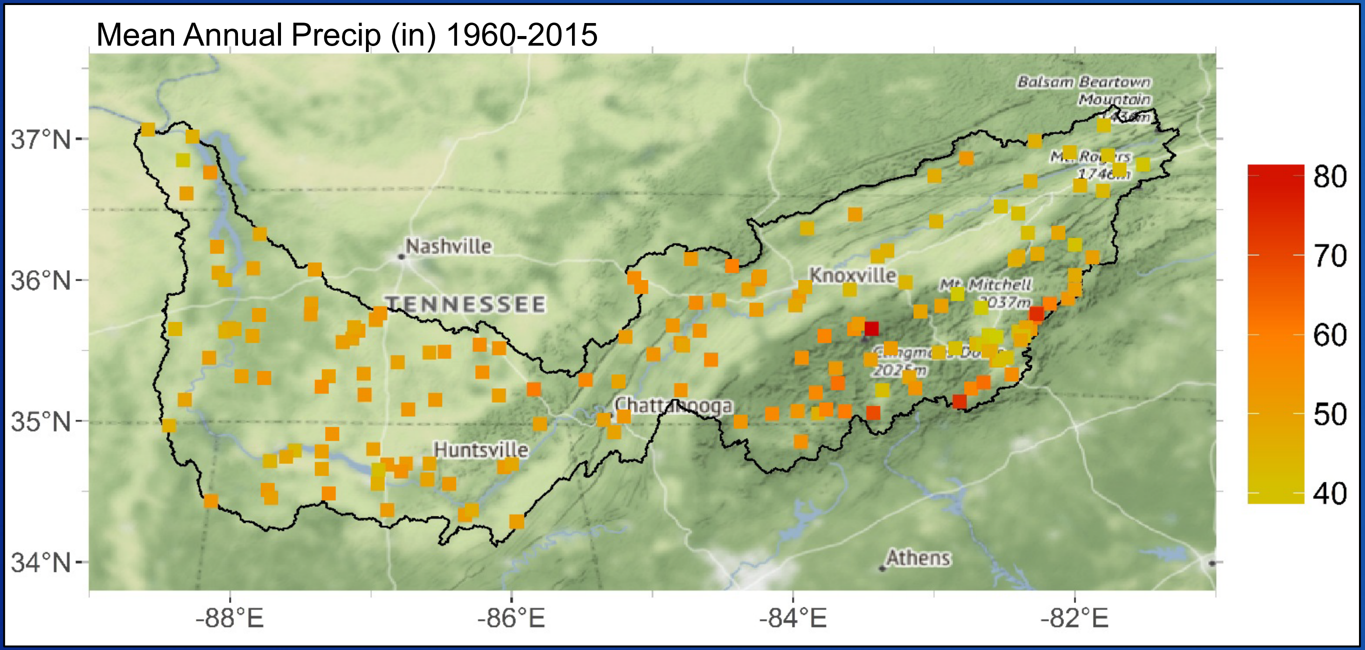
One-Day Precipitation Totals



Regional Growth Curves

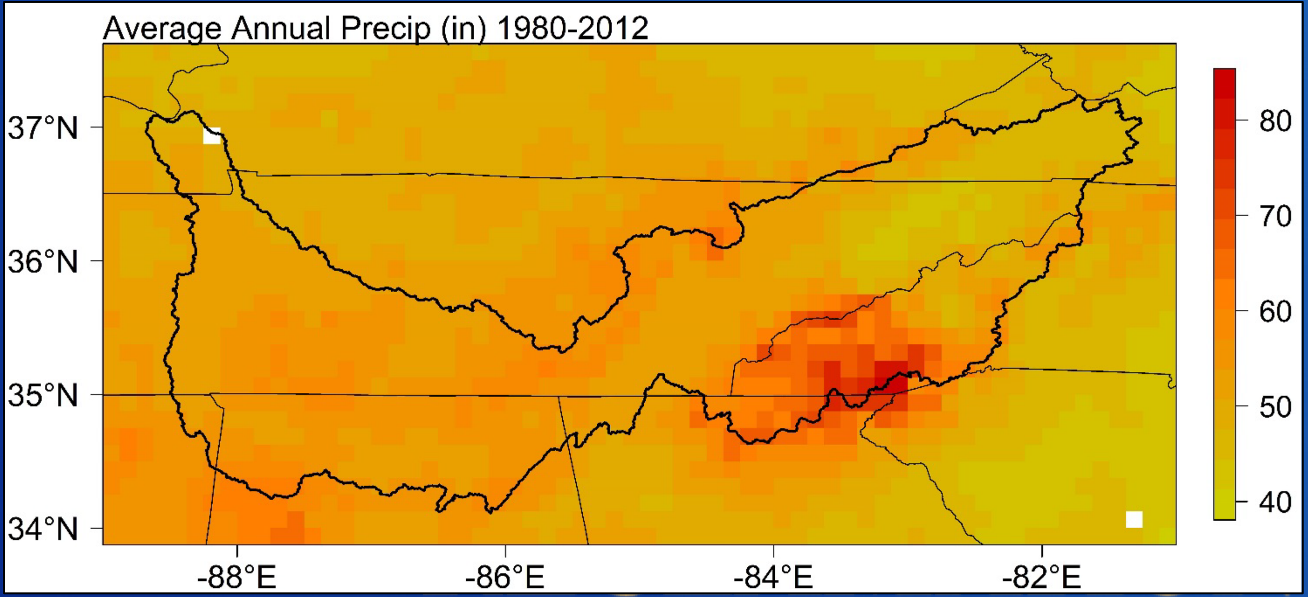


Data Availability

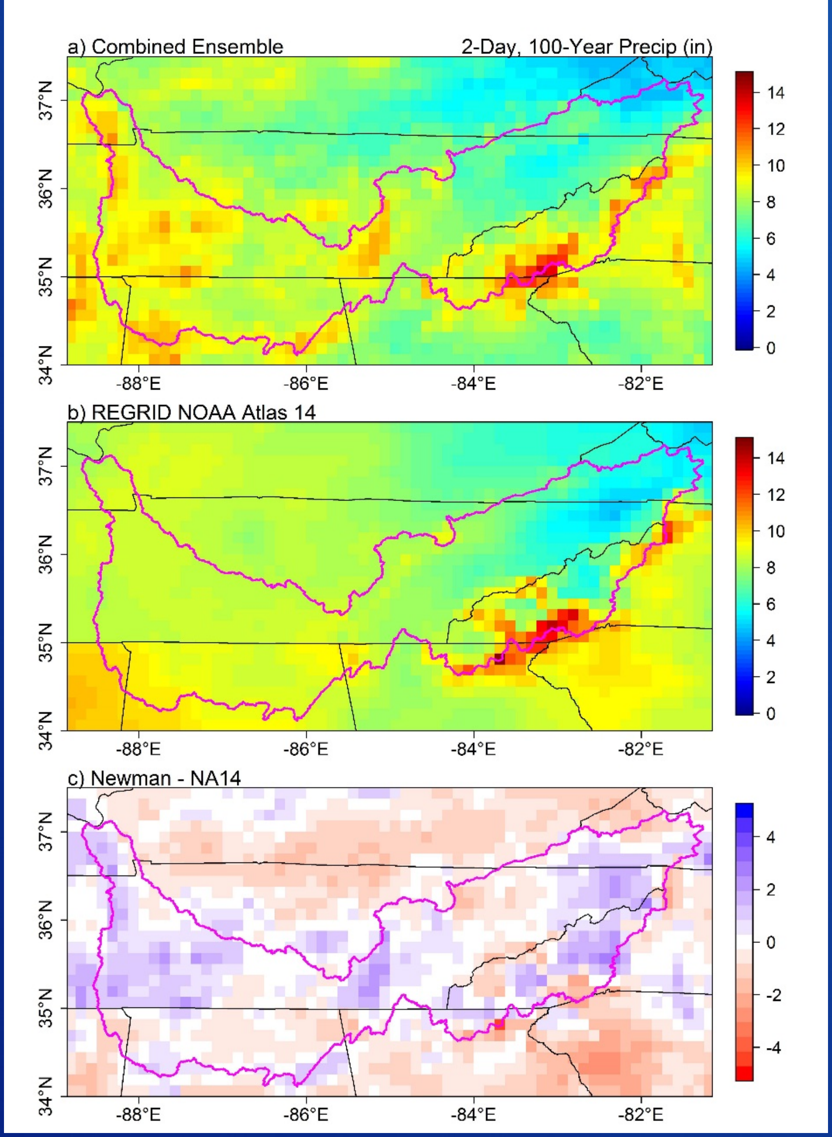


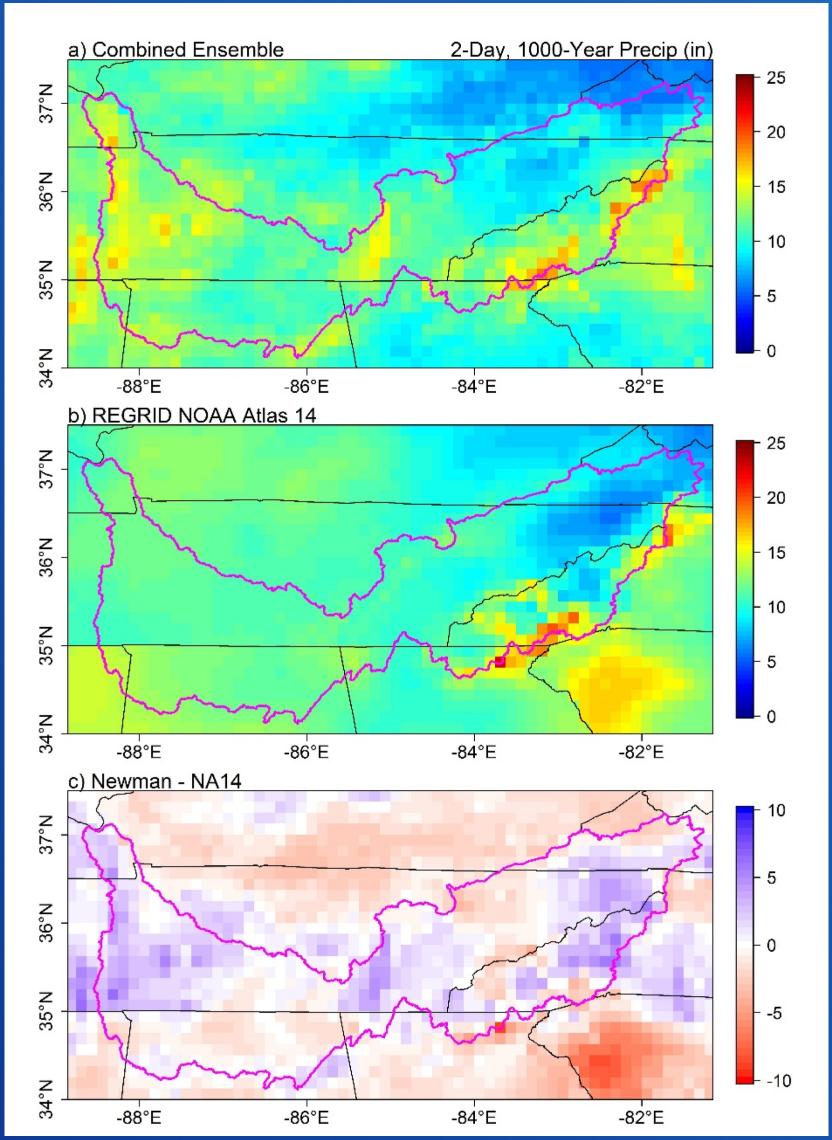
GHCN-Daily dataset

Newman et al. (2015) gridded ensemble



Gridded Bayesian - Medians





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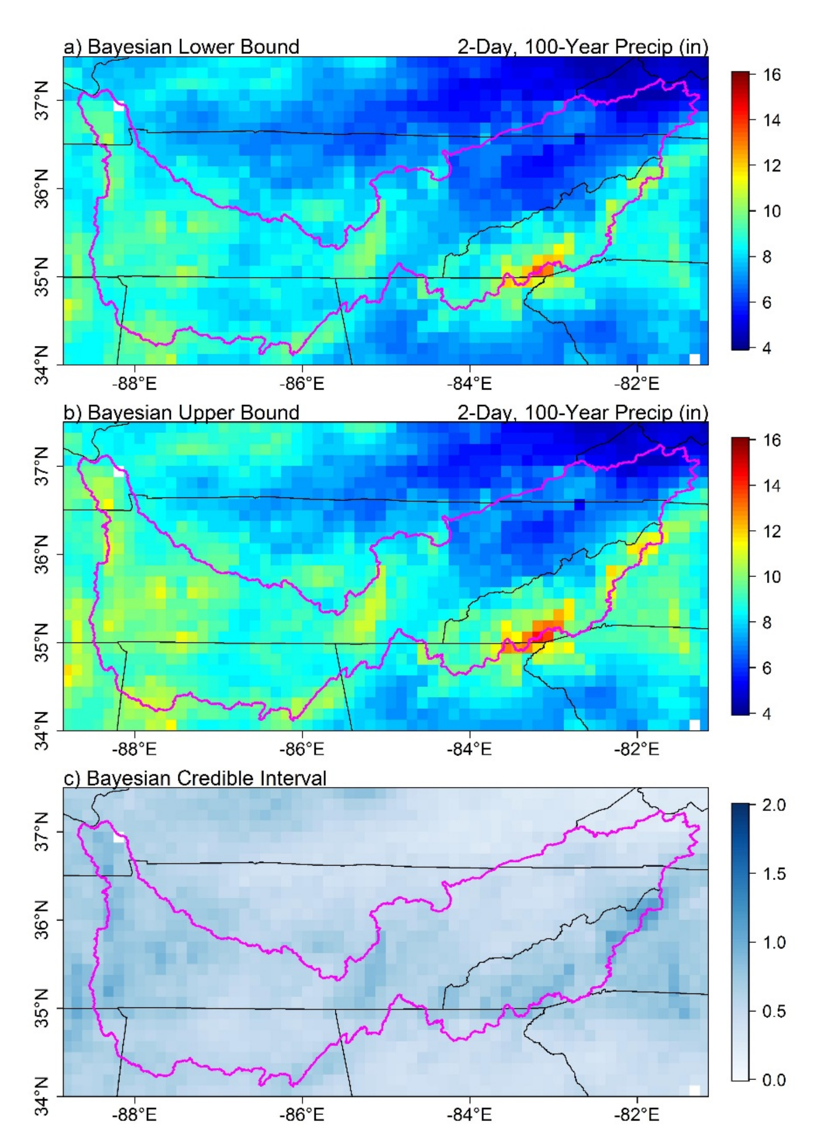
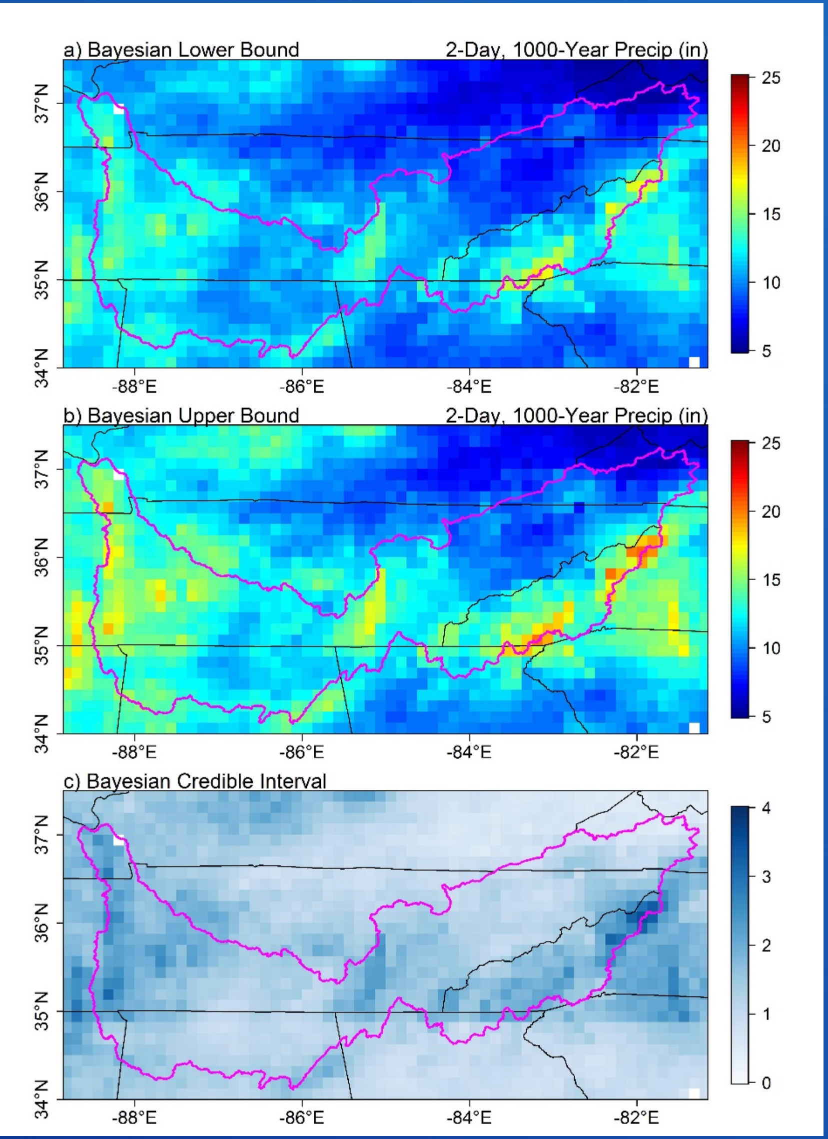
Gridded Bayesian - Uncertainty





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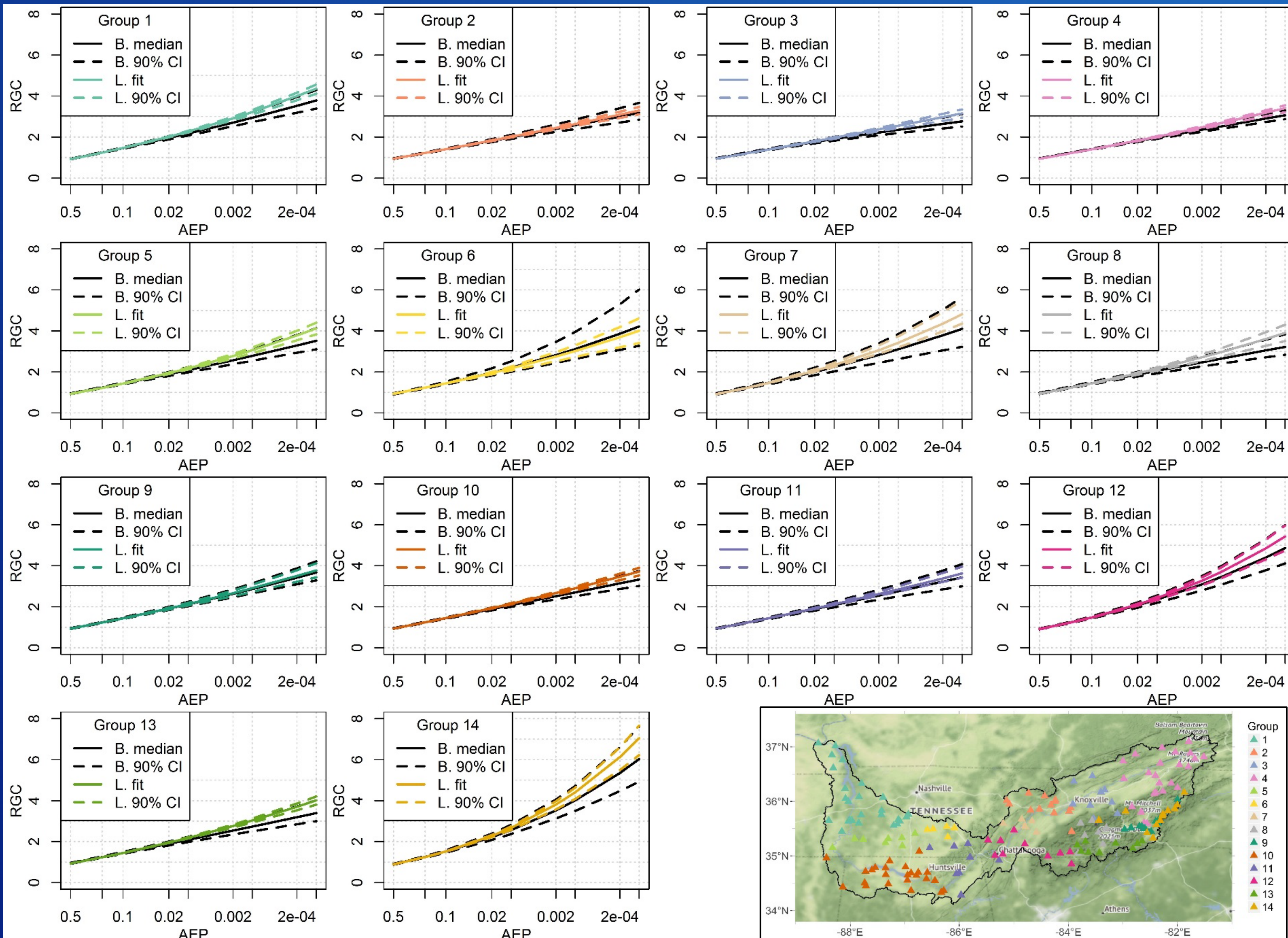
L-Moments vs. Bayesian

Regional Growth Curves

One-Day Precipitation Totals



Regional Growth Curves

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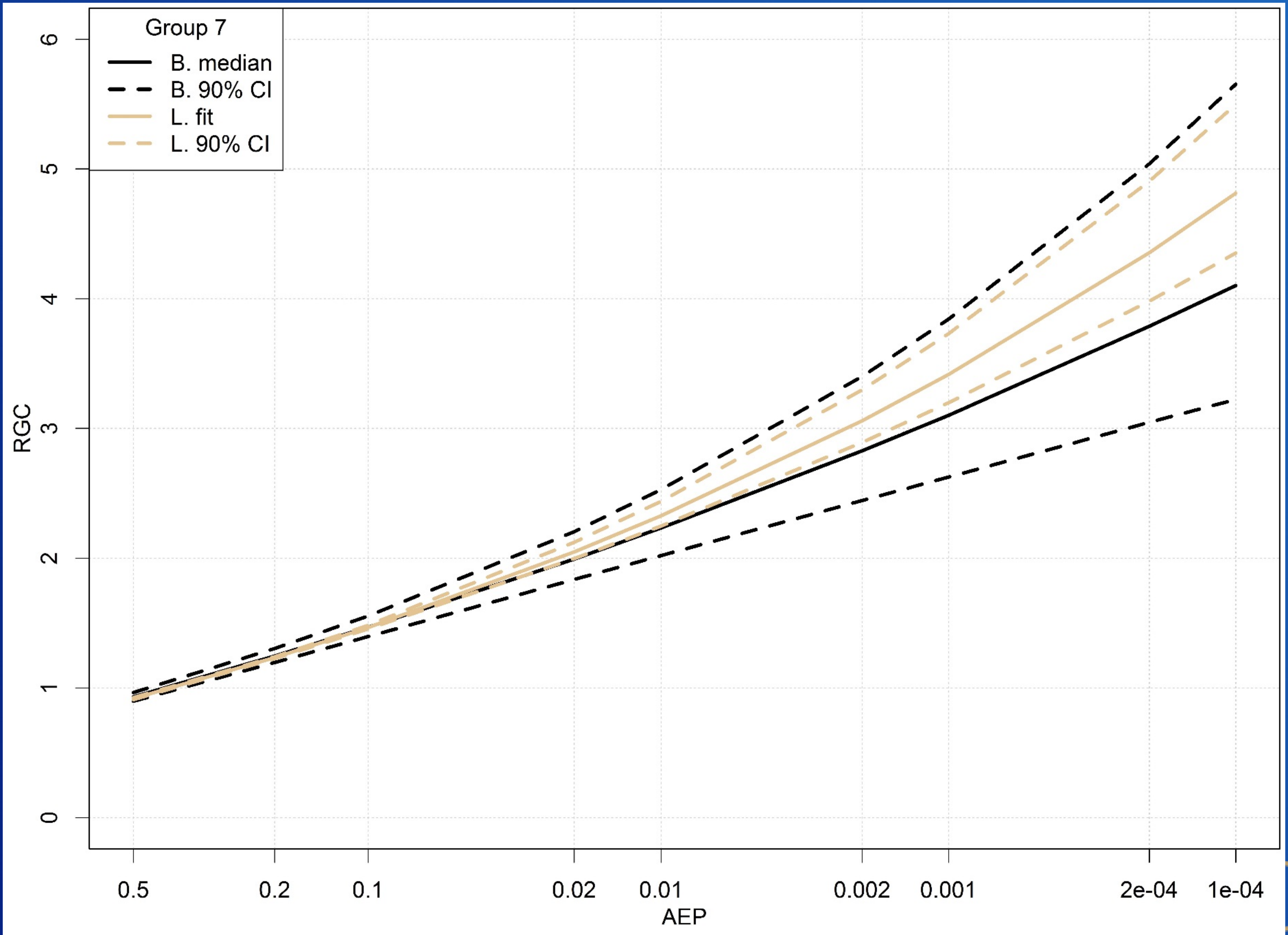
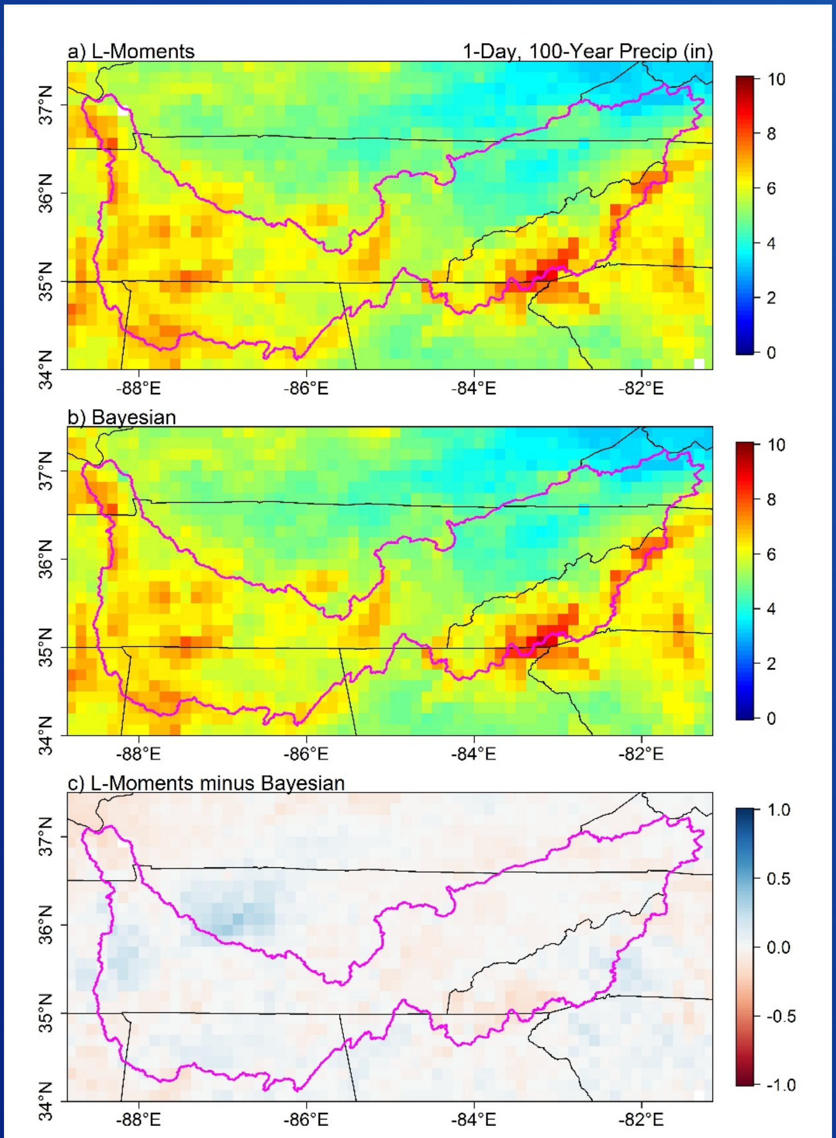
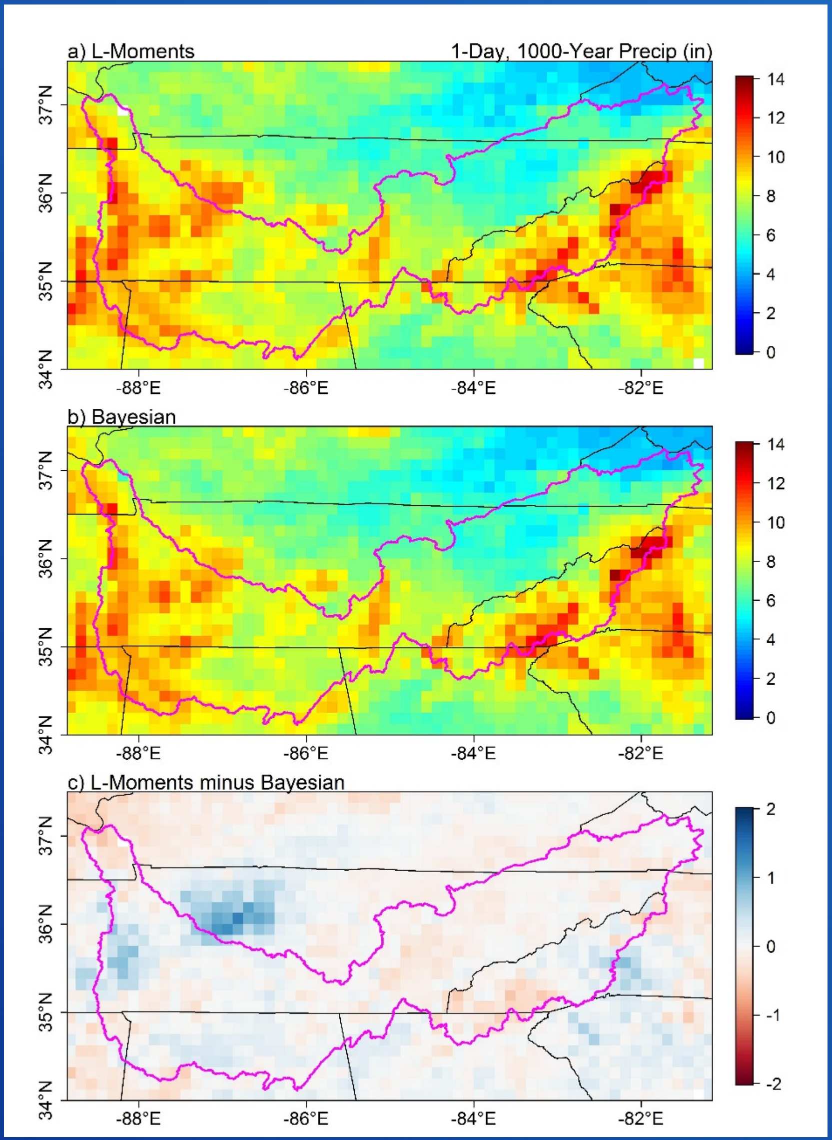


Gridded Frequency Analysis





Summary

Regional frequency analysis using two methods

- L-moments and Bayesian inference

Homogeneous regions defined using semi-objective clustering algorithm, SOM (Self-Organizing Maps)

- Lon, lat, elev, mean annual precip, mean 1-day maxima
- Effectively accounts for orographics by clustering similar stations

Precipitation-frequency results and uncertainty bounds vary by method

- L-moments uses drop-10% bootstrap resampling
- Bayesian uses Monte Carlo, prior knowledge, likelihood function, acceptance criteria to build *posterior distributions*

Summary

Regional frequency estimation methods possible on any gridded dataset

- Newman used to address aleatory variability

L-moments and Bayesian produce similar estimates

- Bayesian median and L-moments fit show good agreement (< +/- 2" at 1,000-year return period)
- L-moments uncertainty estimation method lacking for large datasets (3,300 data points, drop-10% bootstrapping)
- Bayesian uncertainty also likely underestimated due to correlated data

Future work could entail multi-model combination

- Better quantify epistemic uncertainty via numerous gridded datasets, station-based datasets

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Questions?

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