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Managing Water in the West

Developing Precipitation Frequency Estimates in Regions of Complex Terrain

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Outline

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2. Precipitation-Frequency Analyses
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3. Case study in Tennessee River Valley
    A. Self-Organizing Map algorithm
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Motivation

Knowledge of extreme precipitation events is vital for engineering planning purposes

Deterministic methods used for design projects, like Probable Maximum Precipitation, provide no information on expected return periods

Precipitation-frequency analyses give the users expected return periods of extreme events

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Question

How do precipitation-frequency estimates developed using the L-moments algorithm compare with estimates developed using Bayesian inference?

L-Statistics

System for 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)

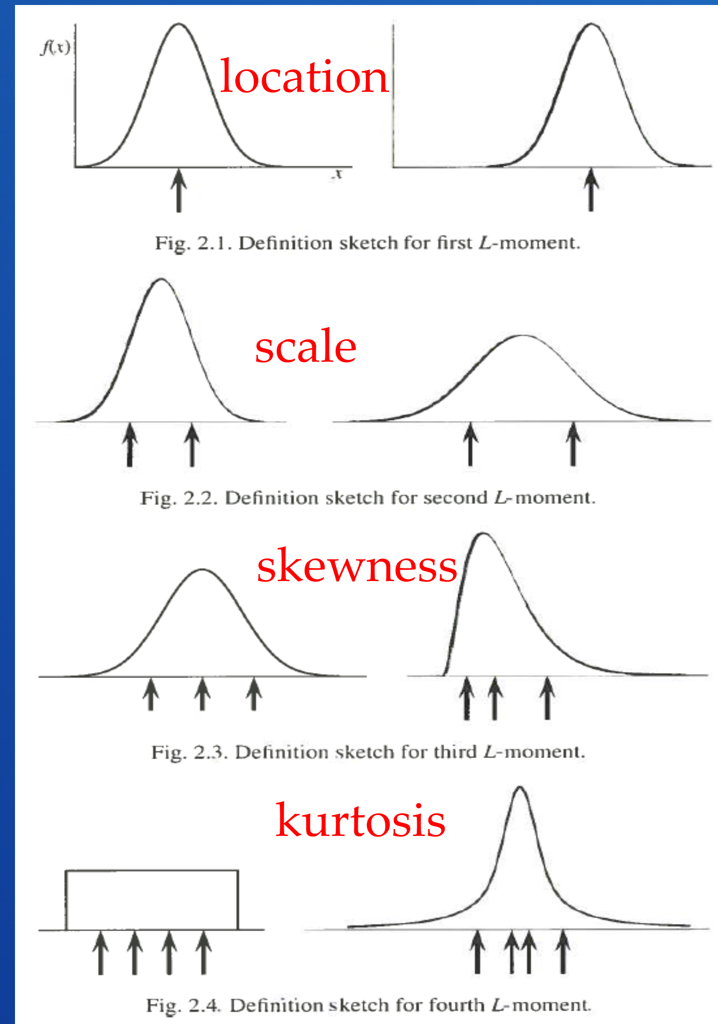

Fig. 2.1. Definition sketch for first *L*-moment.

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

Bayes' Rule in a modeling framework:

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

where $\boldsymbol{Y} = (y_1, y_2, \ldots, y_n)$ and $\theta = (\mu, \sigma, \xi)$

- Define *prior distributions* for model parameters θ (a priori knowledge)
- Consider GEV likelihood function (can consider 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")

Historical Data

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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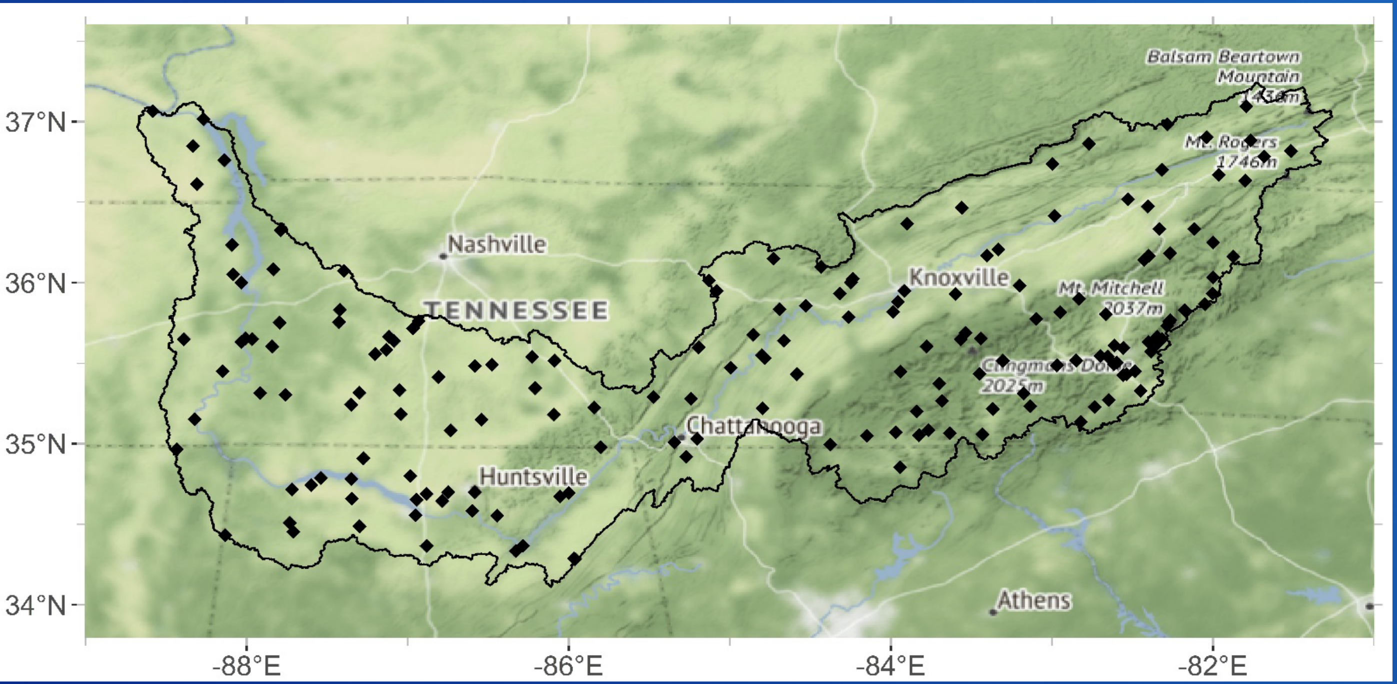
Tennessee River Valley Watershed



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

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Regional Frequency Approach

1. Identify homogeneous region(s)
2. Screen observations for false/erroneous records
3. Compute annual (or seasonal) maxima
4. Compute frequency distribution
   - L-moments
   - Bayesian inference
5. Estimate point precipitation frequency results

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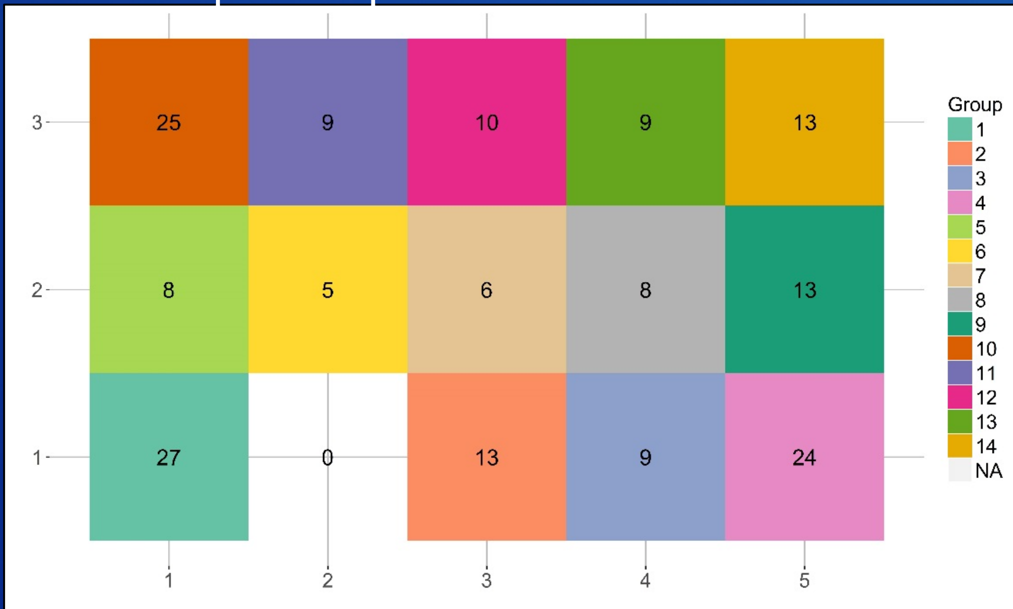
Self-Organizing Map

SOM Output Map



Clustering algorithm used to "group" stations with similar attributes

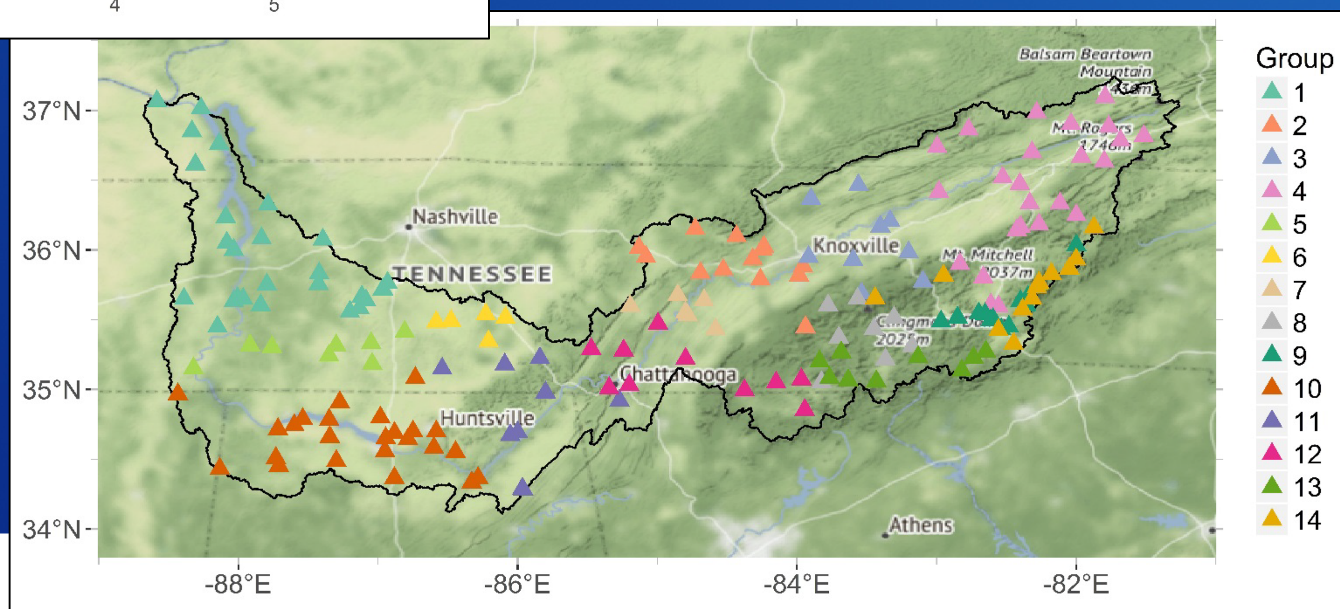
Apply SOM algorithm to :

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

Each station maps to a single SOM node

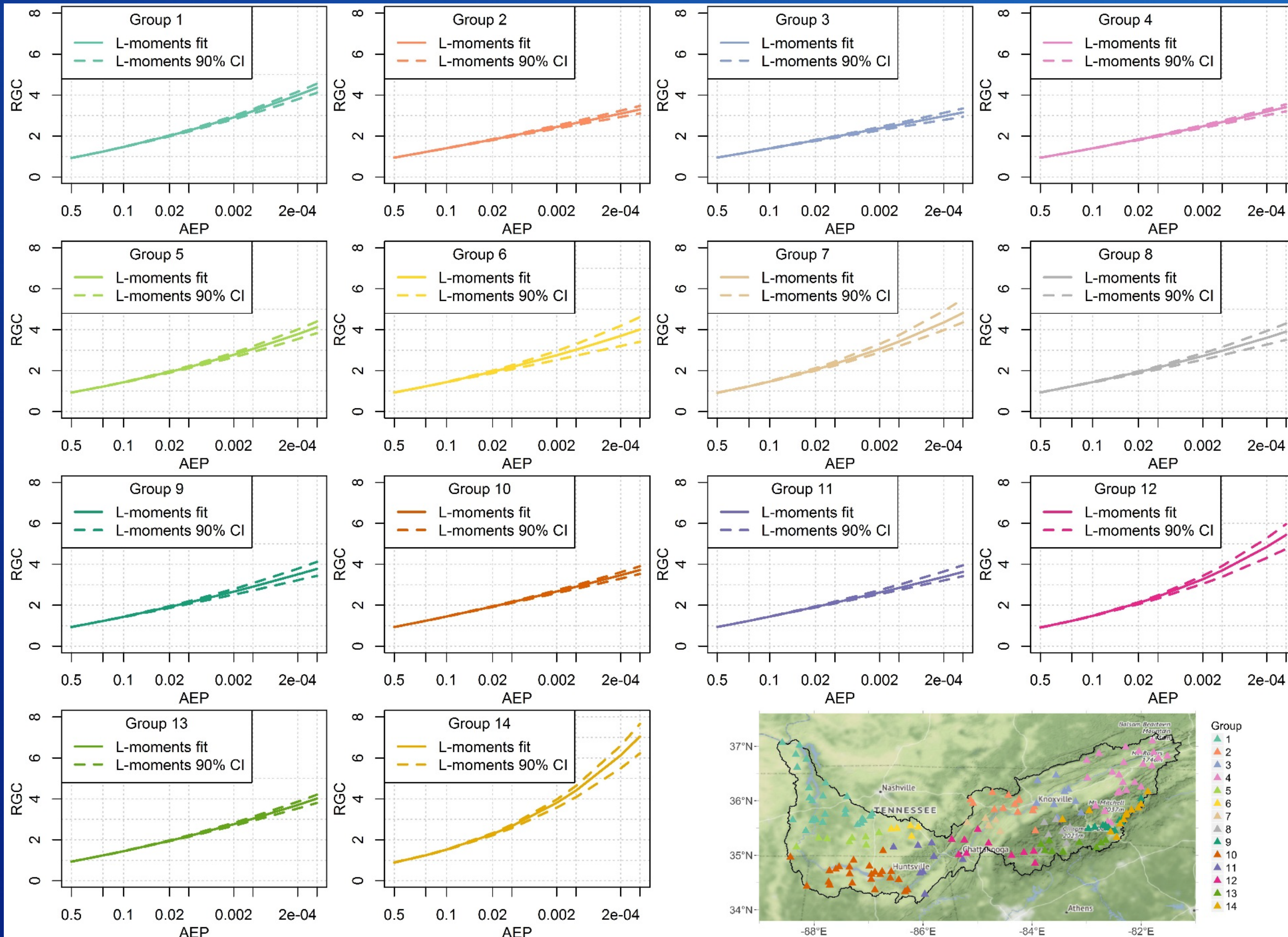
Gauges mapped to same node define homogeneous regions

Homogeneous regions need not be contiguous

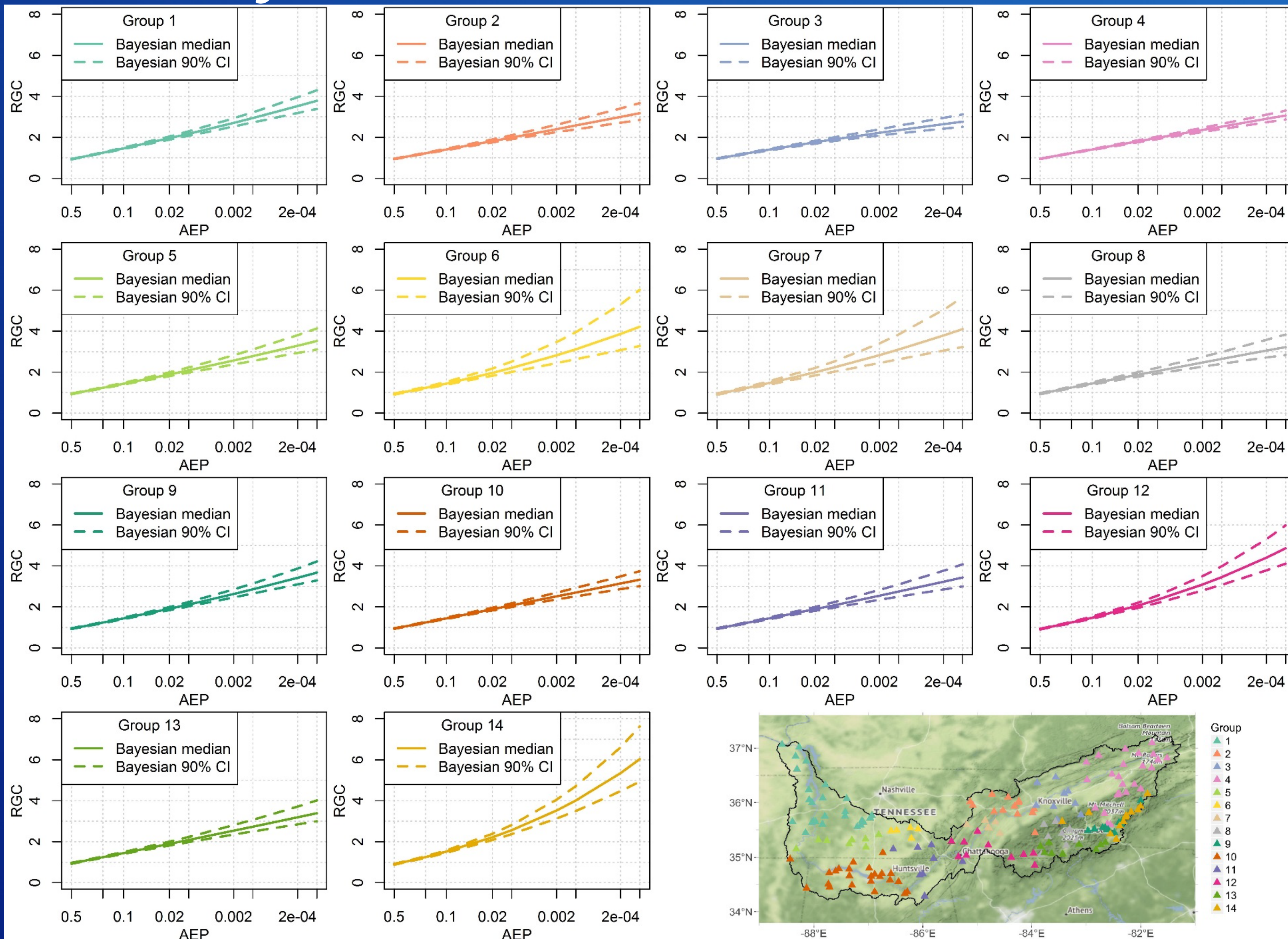


Available R packages for SOM analysis:
library("som")
library("kohonen")

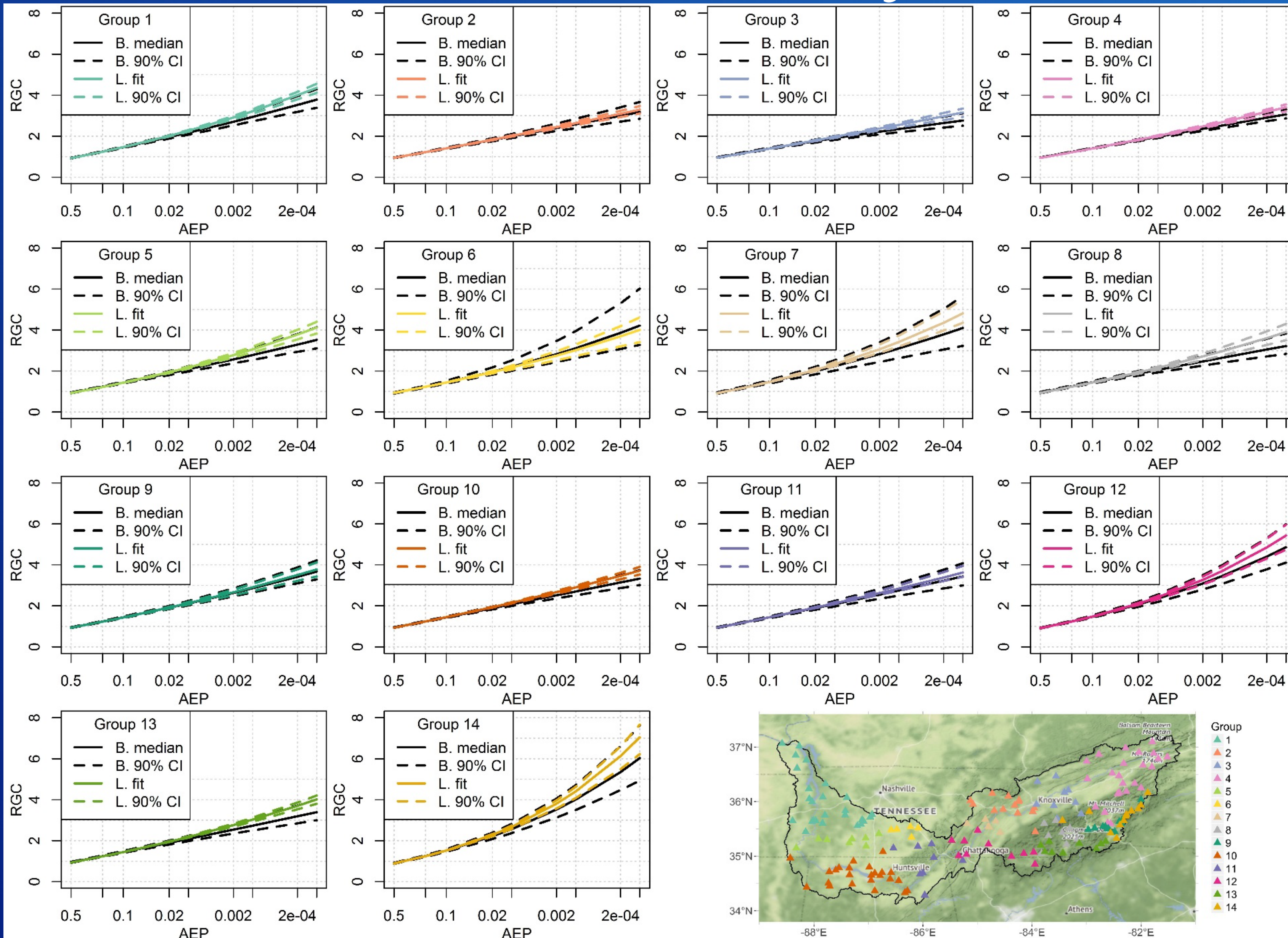
L-Moments RGCs



Bayesian Inference RGCs



L-Moments vs. Bayesian



Summary

Precipitation-frequency analyses provide users with expected return periods of heavy events

Frequency estimates vary based on methodology

- In all but one region, L-moments best-estimates exceed Bayesian best-estimates
- Uncertainty bounds from Bayesian inference exceed L-moments

Additional testing is needed to understand benefits of Bayesian over L-moments

Questions?

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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")

SOM Results – At-Site Means