Statistical and software tools for quantifying uncertainty in event attribution

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Outline

- Statistical methods for event attribution
  - Sources of uncertainty
  - Risk ratio estimation methods
  - Methods for quantifying uncertainty
  - Recommendations
- Illustration with Texas heatwave of 2011
  - Sensitivity analysis with respect to event definition
  - Use of climextremes package for risk ratio estimation
- climextremes package
  - Illustration on station precipitation data
  - Features/capabilities

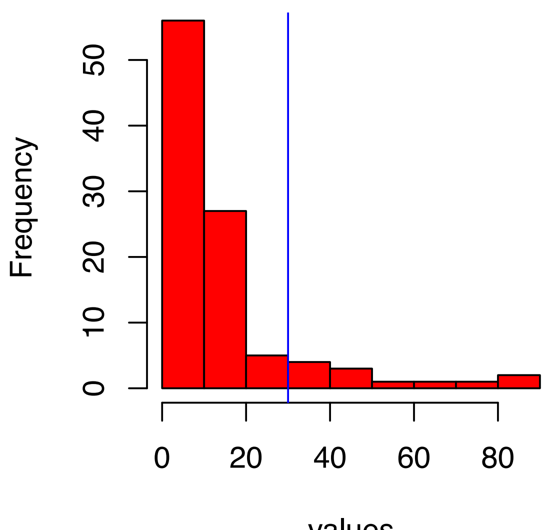
Sources of uncertainty in model-based event attribution

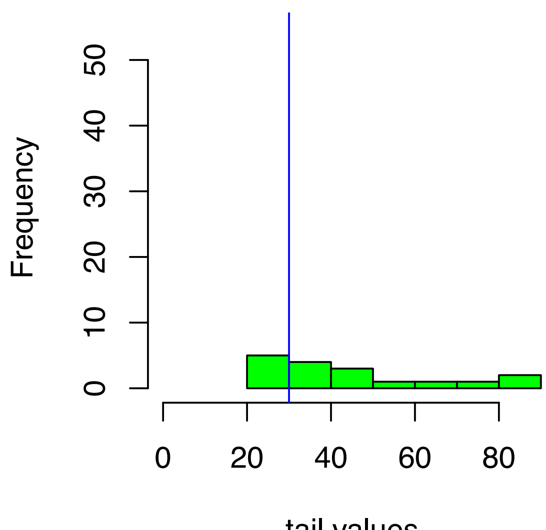
- Sampling uncertainty
  - Due to variability in the earth system
  - Amenable to frequentist or Bayesian statistical treatment
  - Uncertainty decreases with larger ensembles

- Non-sampling uncertainty
  - Sources:
    - Boundary condition uncertainty
    - Model parametric uncertainty
    - Model structural uncertainty
  - Not amenable to frequentist treatment
  - Does not decrease with larger ensembles
  - Possibly characterized based on sensitivity analysis or drawing from prior distribution over boundary conditions, parameter values, models, etc.

Methods to estimate probabilities for risk ratio (RR)

- Fit a parametric statistical model to climate variable values
  - E.g., lognormal or gamma distribution
  - Estimate probability of exceeding the threshold from fitted distribution
  - Strong assumption about appropriateness of model (all data used)
- Count exceedances of threshold (binomial sample) amongst climate variable values
  - "Nonparametric" – no distributional assumption
  - More involved to account for dependence (e.g., daily data)
  - High uncertainty when there are very few events, but can be effective for RR
- Fit extreme value distribution (e.g., GEV or peaks-over-threshold (POT))
  - Theoretically justified when threshold is far in tail
  - Informed only by extreme values
  - Hard to use with seasonal events because of small sample sizes





Methods to estimate uncertainty in RR

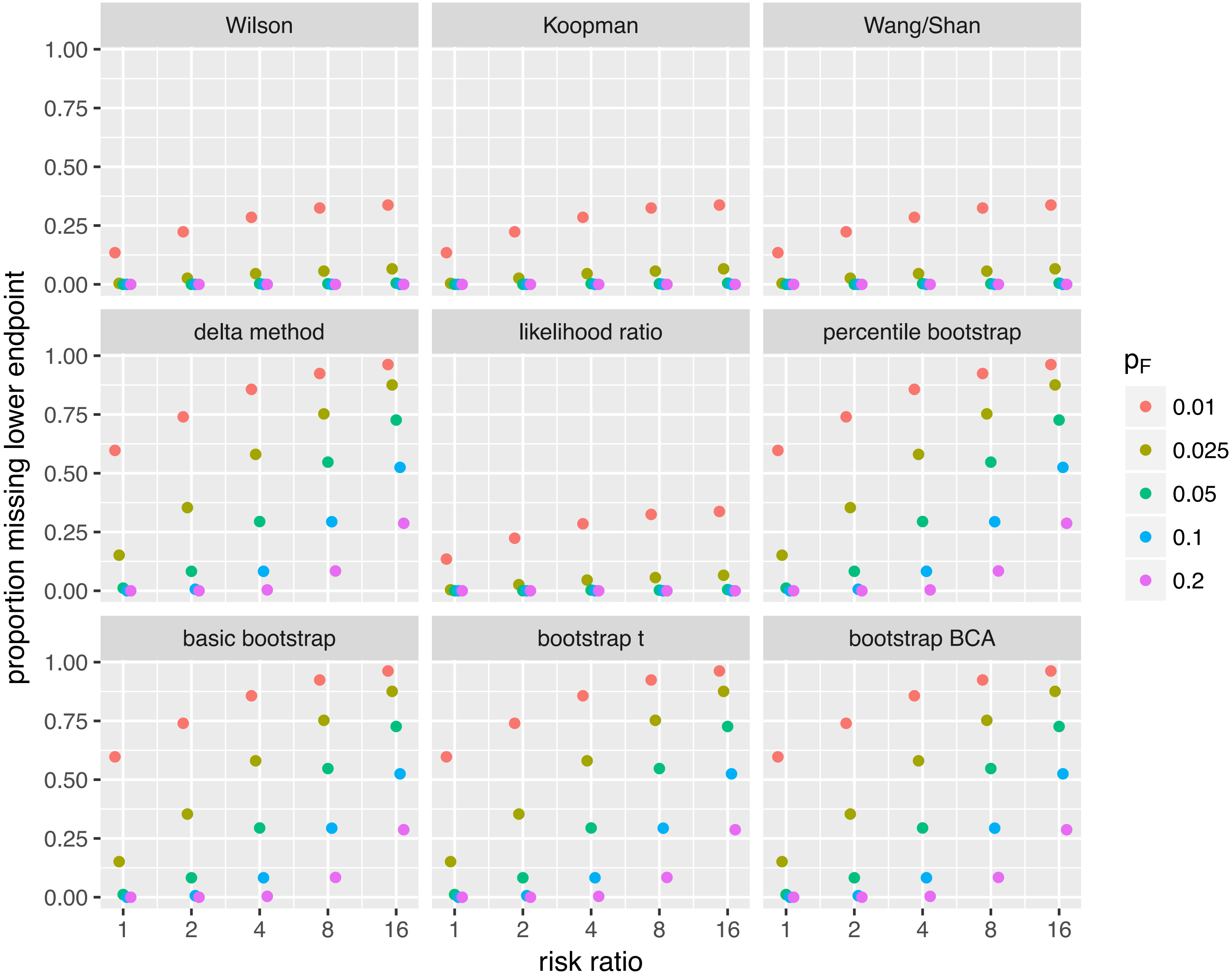
- Methods for **extreme value methods and binomial counting**
  - Asymptotic statistical calculations (delta method / propagation of error)
    - Assumption of normality
  - Bootstrap
    - Standard statistical bootstrap gives a confidence interval, not a Bayesian probability interval
    - Estimation of RR in bootstrap samples often fails (lack of EVA convergence, zeros in binomial counting approach)
  - Likelihood ratio-based interval

- Methods for **binomial counting** (from epidemiology/biostatistics)
  - Wilson's method
  - Koopman's method
  - Wang/Shan method

- All but asymptotic and bootstrap can give interval when RR estimate is 0 or infinity, e.g., (12.8, Infinity)

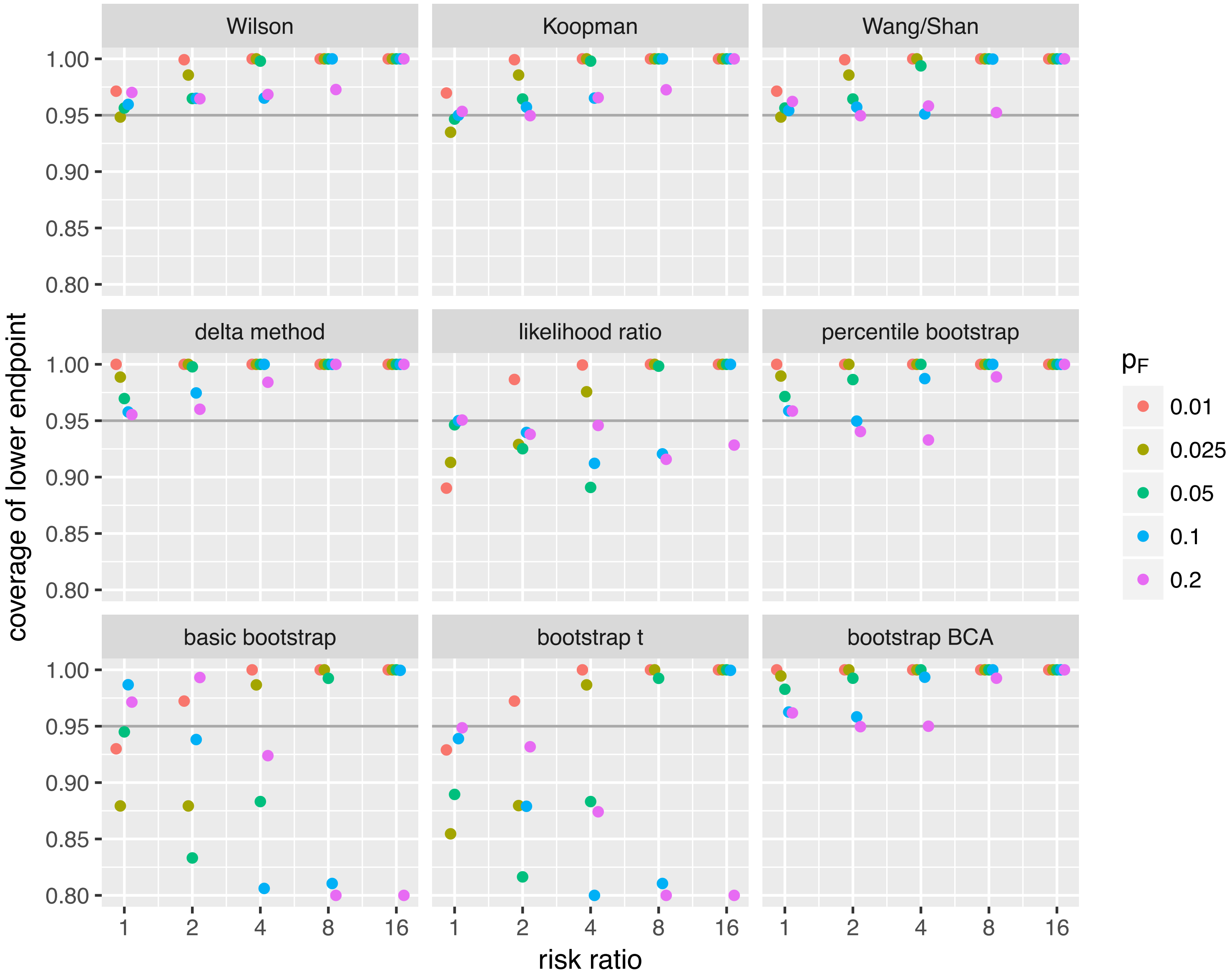
RR confidence intervals (binomial counting) simulation results

Proportion of times interval cannot be calculated (e.g., 0 events / 0 events)



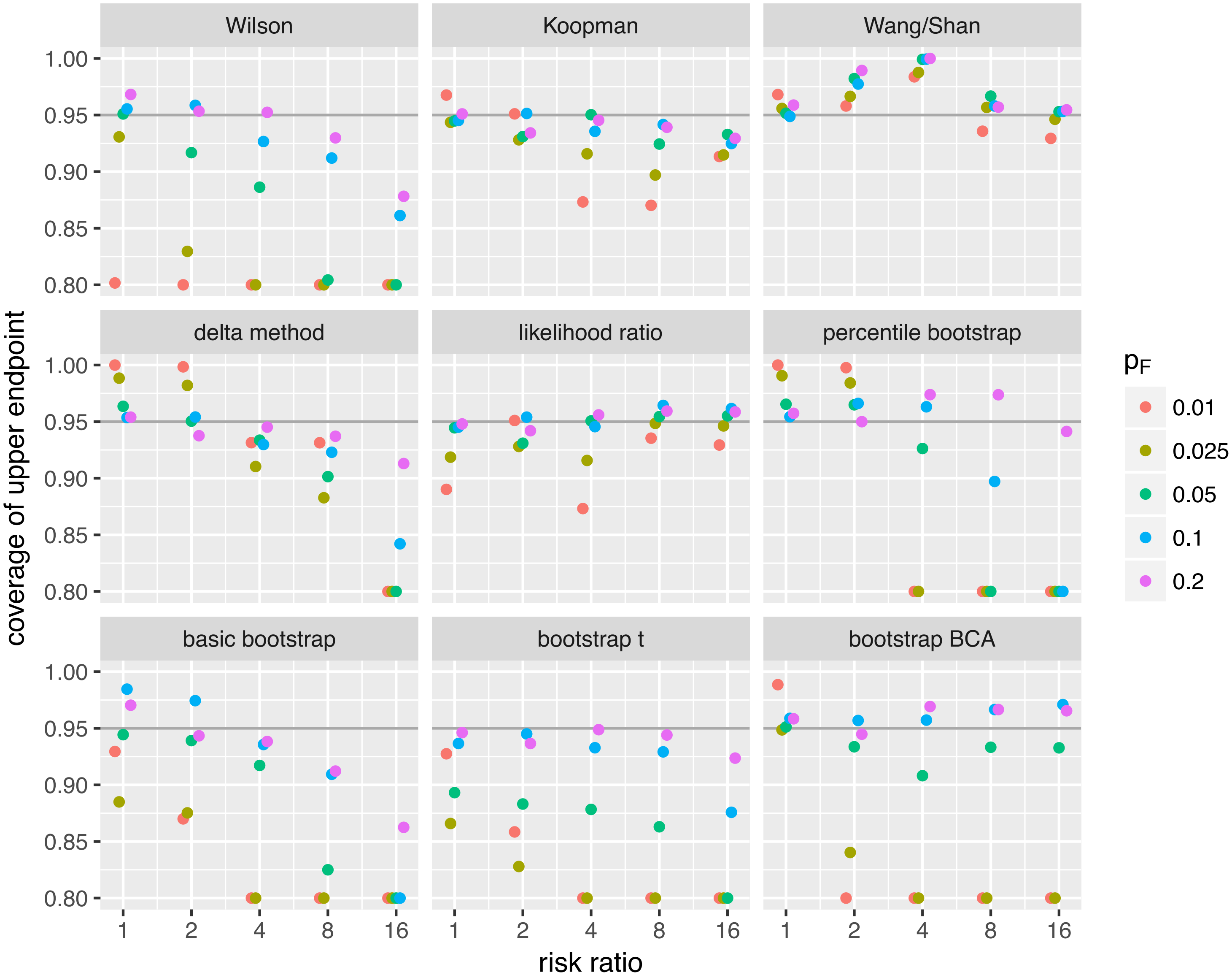
RR confidence intervals (binomial counting) simulation results

Proportion of times lower interval endpoint includes true RR (95% is best)



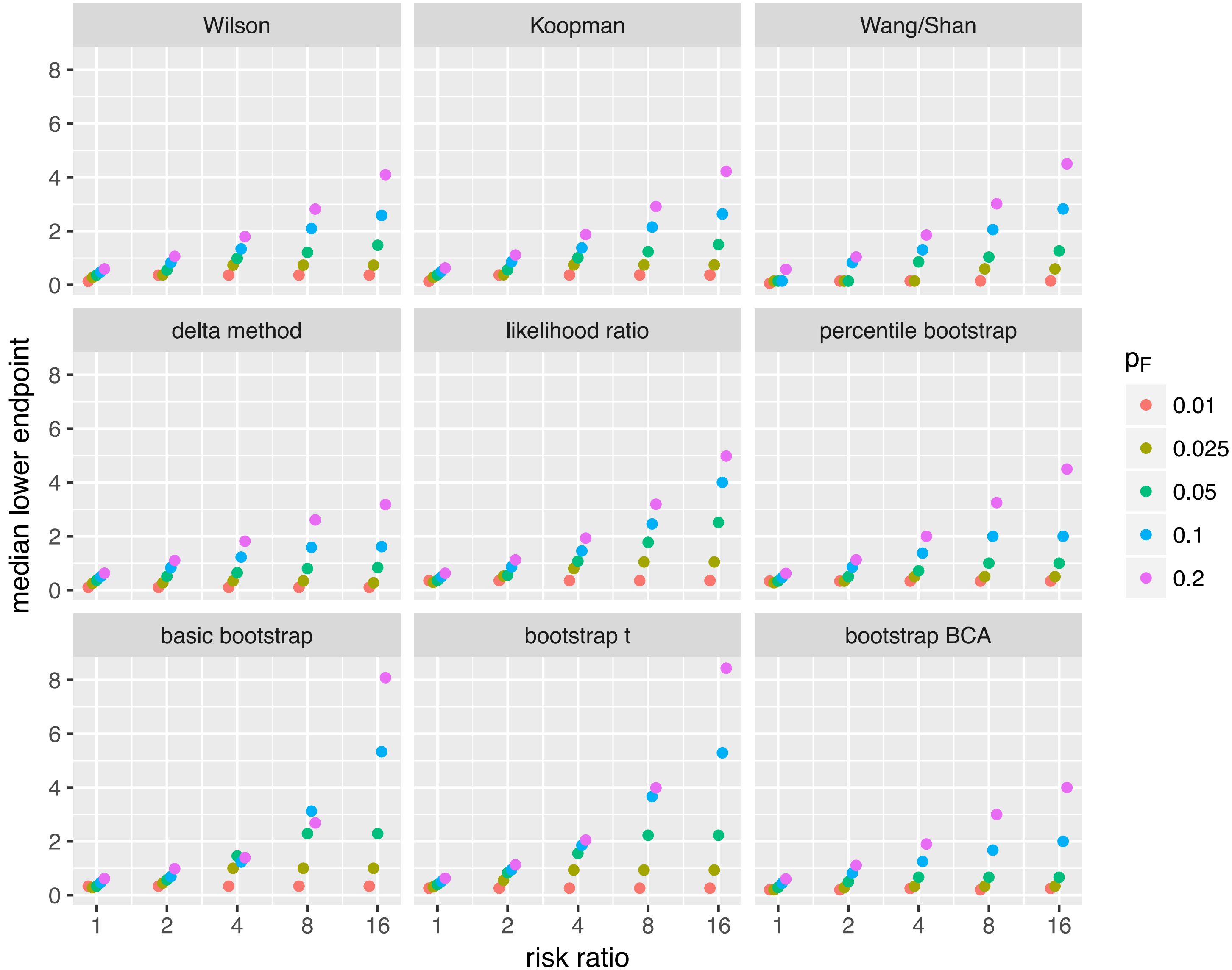
RR confidence intervals (binomial counting) simulation results

Proportion of times upper interval endpoint includes true RR (95% is best)



RR confidence intervals (binomial counting) simulation results

Average value of lower endpoint (higher is better)

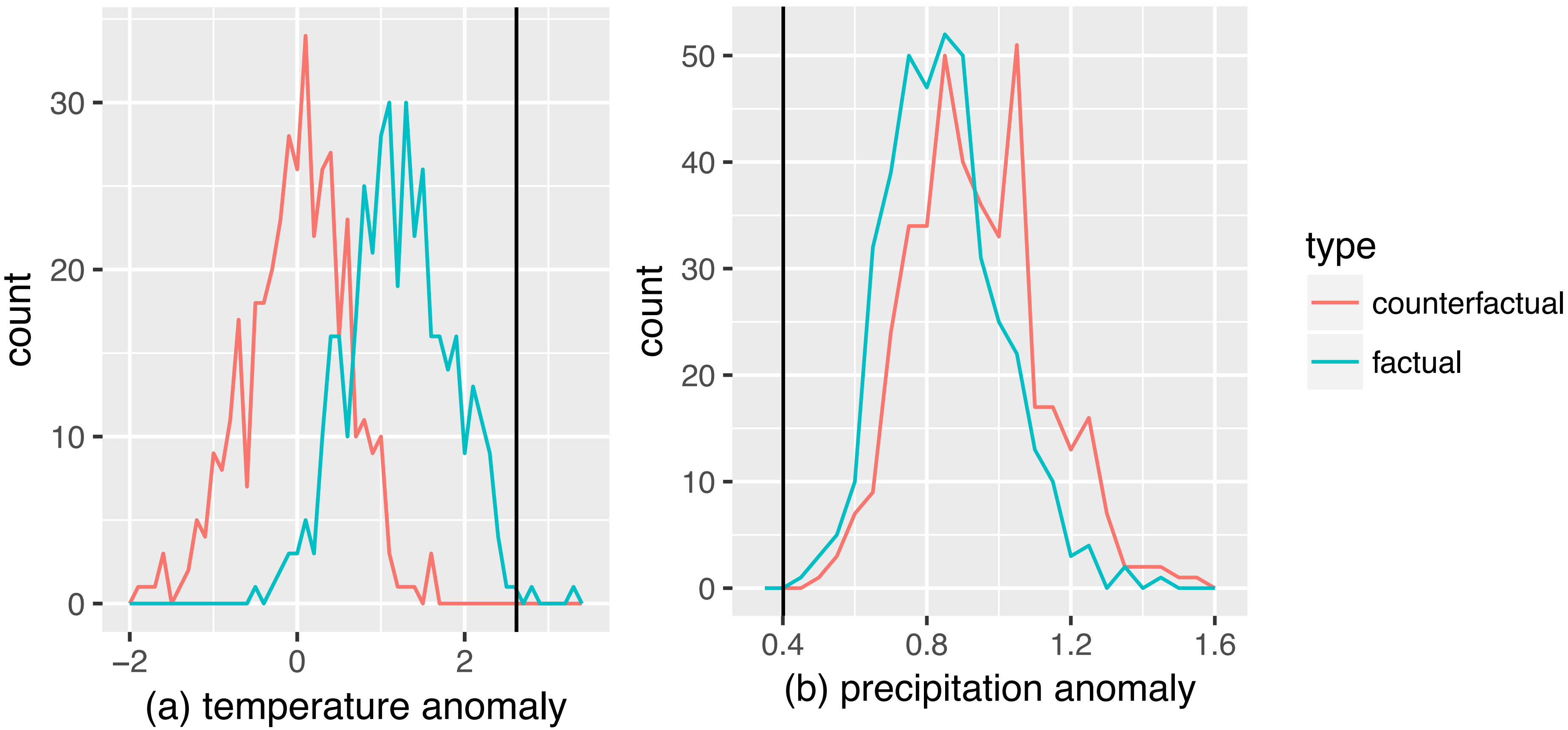


Methods to estimate uncertainty in RR: conclusions

- Bootstrap methods
  - Often fail to provide an interval
  - Poor statistical performance
- Likelihood ratio method
  - Reasonably good statistical performance, but coverage sometimes too low
  - Will work with both extreme value analysis and binomial counting
- Epidemiology/biostatistical methods
  - Work only for binomial counting
  - Koopman and Wang-Shan methods generally perform well
- All methods except Wang-Shan available in climextremes software package

RR analysis example: Texas 2011 heatwave / drought

- CAM5.1 400-member ensembles for factual and counterfactual
- March-August temperature and rainfall over Texas
- Estimation done using climextremes software
- Temperature: 2/0 is RR count-based estimate
- Precipitation: 0/0 is RR count-based estimate



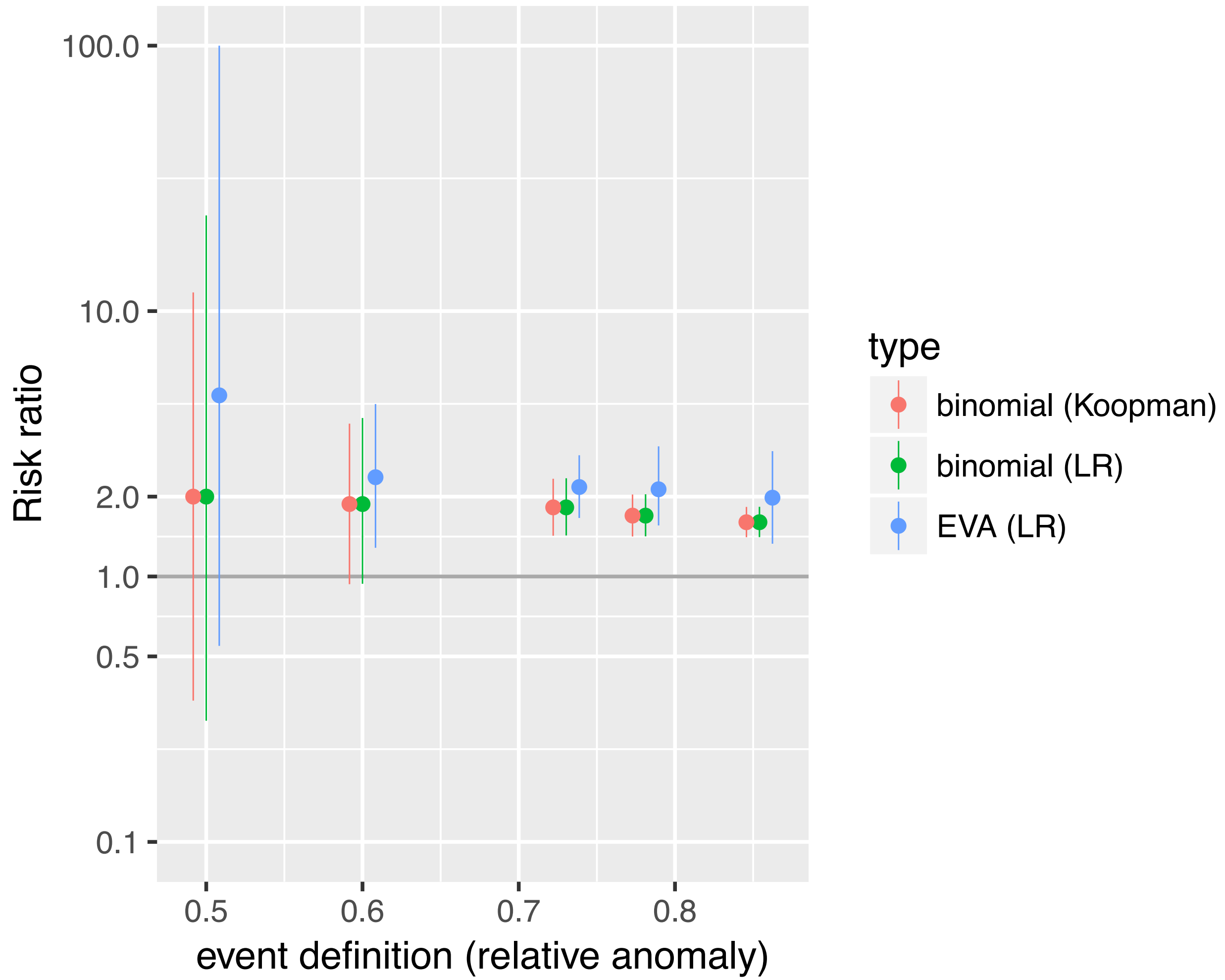
Texas 2011 temperature analysis

Actual event is 2.62 degree anomaly

Event	Number exceedances	RR esti-mate	EVA lik ratio CI	Binomial lik ratio CI	Binomial Koopman CI
2.62 (actual)	2/0	Inf	(12.8, Inf)	(1.0, Inf)	(0.7, Inf)
2.0	43/0	Inf	NA	(31, Inf)	(16, Inf)
1.5	129/3	43	NA	(19, 133)	(17, 108)
1.03 (20-year event)	245/11	22	NA	(14, 38)	(14, 36)
0.73 (10-year event)	314/40	7.9	NA	(6.2, 10.2)	(6.1, 10.1)
0.43 (5-year event)	357/90	4.0	NA	(3.4, 4.7)	(3.4, 4.6)

Texas 2011 precipitation analysis

- Recall that actual event (40% of historical average precipitation) has no events in factual or counterfactual ensembles
- Extreme value analysis (EVA) gives (0.01, Inf) as interval
- EVA not really appropriate for less extreme events but shown anyway



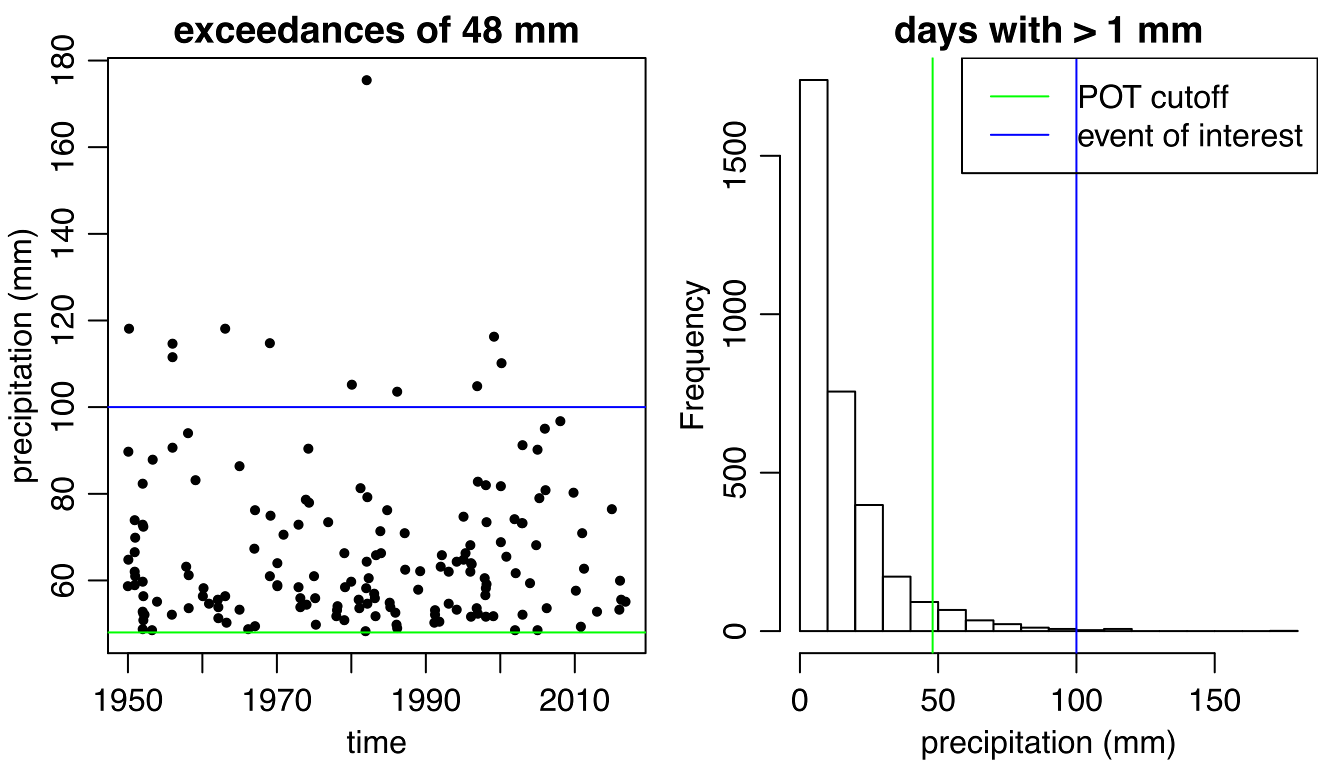
climextremes software

- High-level goals
  - Operate from Python or R
  - Provide risk ratio calculations and extreme value analysis fitting (GEV and POT)
  - Handle common situations with climate data
  - Designed for both observations and model output

- Technical features
  - Use of covariates for any extreme value distribution parameter (nonstationary fitting)
  - Estimation with uncertainty for risk ratios, return values, return periods, differences in return values
  - Various techniques for estimating uncertainty
  - Statistically rigorous estimation with model ensembles
  - Statistically rigorous treatment of missing values (for POT)
  - Allows weighting (e.g., weighting nearby stations)

climextremes example

- US GHCN Santa Cruz precipitation
  - 1950-2016
  - November-May rainy season
  - 270 missing days



climextremes example

Stationary peaks-over-threshold fit

result = climextremes.fit_pot(numpy.array(exc.y), nBlocks = nyears, threshold = threshold, firstBlock = missing.seasonyear[0], blockIndex = numpy.array(exc.seasonyear), index = numpy.array(exc.day), proportionMissing = numpy.array(missing.propMiss), declustering = 'noruns', returnPeriod = 20, returnValue = 100, bootSE = False)

Nonstationary peaks-over-threshold fit

linear location trend in time -
contrast 2015 returnValue and return probability with that for 1950

resultNS = climextremes.fit_pot(numpy.array(exc.y), x = numpy.array(missing.seasonyear), locationFun = 1, nBlocks = nyears, threshold = threshold, firstBlock = missing.seasonyear[0], blockIndex = numpy.array(exc.seasonyear), index = numpy.array(exc.day), proportionMissing = numpy.array(missing.propMiss), declustering = 'noruns', xNew = 2015, xContrast = 1950, returnPeriod = 20, returnValue = 100, bootSE = False)

climextremes example

Stationary peaks-over-threshold fit

```
# 20-year return value and standard error
result['returnValue']
# 120.3 mm
result['se_returnValue']      # return value standard error (asymptotic)
#   7.9 mm
result['logReturnProb']       # log of probability of exceeding 'returnValue=100'
# -1.98
# confidence interval on return probability for 100 mm event
np.exp(result['logReturnProb'] + np.array((-2, 2))*result['se_logReturnProb'])
# (0.0872262, 0.2200104)
```

Nonstationary fit with location linear in year

```
# change in return value (2015 - 1950) and standard error of the change
resultNS['returnValueDiff']
# -2.68  mm
resultNS['se_returnValueDiff']
#  5.37 mm
# risk ratio 2015 / 1950 for 100 mm event with confidence interval
np.exp(resultNS['logReturnProbDiff'])
#  0.88
np.exp(resultNS['logReturnProbDiff'] + np.array((-2, 2))*resultNS['se_logReturnProbDiff'])
# (0.51, 1.49)
```

References / Links

- Statistical methods:
  - Paciorek C.J., D.A. Stone, and M.F. Wehner. 2018. Quantifying statistical uncertainty in the attribution of human influence on severe weather. Weather and Climate Extremes, accepted.
  - https://arxiv.org/abs/1706.03388

- climextremes software (version 0.2.0):
  - Available via conda for python
  - Available via CRAN for R
  - Repository: https://bitbucket.org/lbl-cascade/climextremes-dev