Compound and Cascading Hazards: Modeling and Risk Assessment

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Coastal Flooding

Compound Coastal Flooding

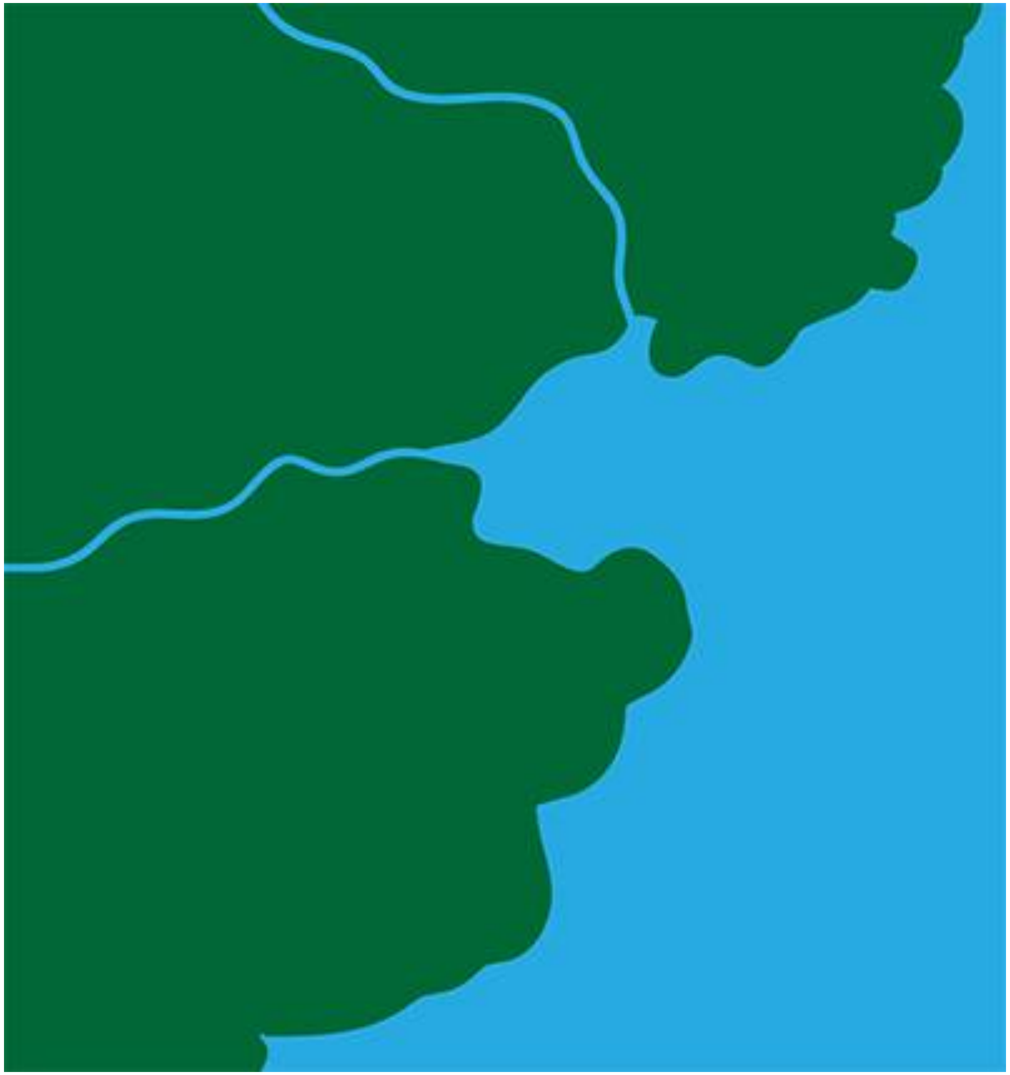


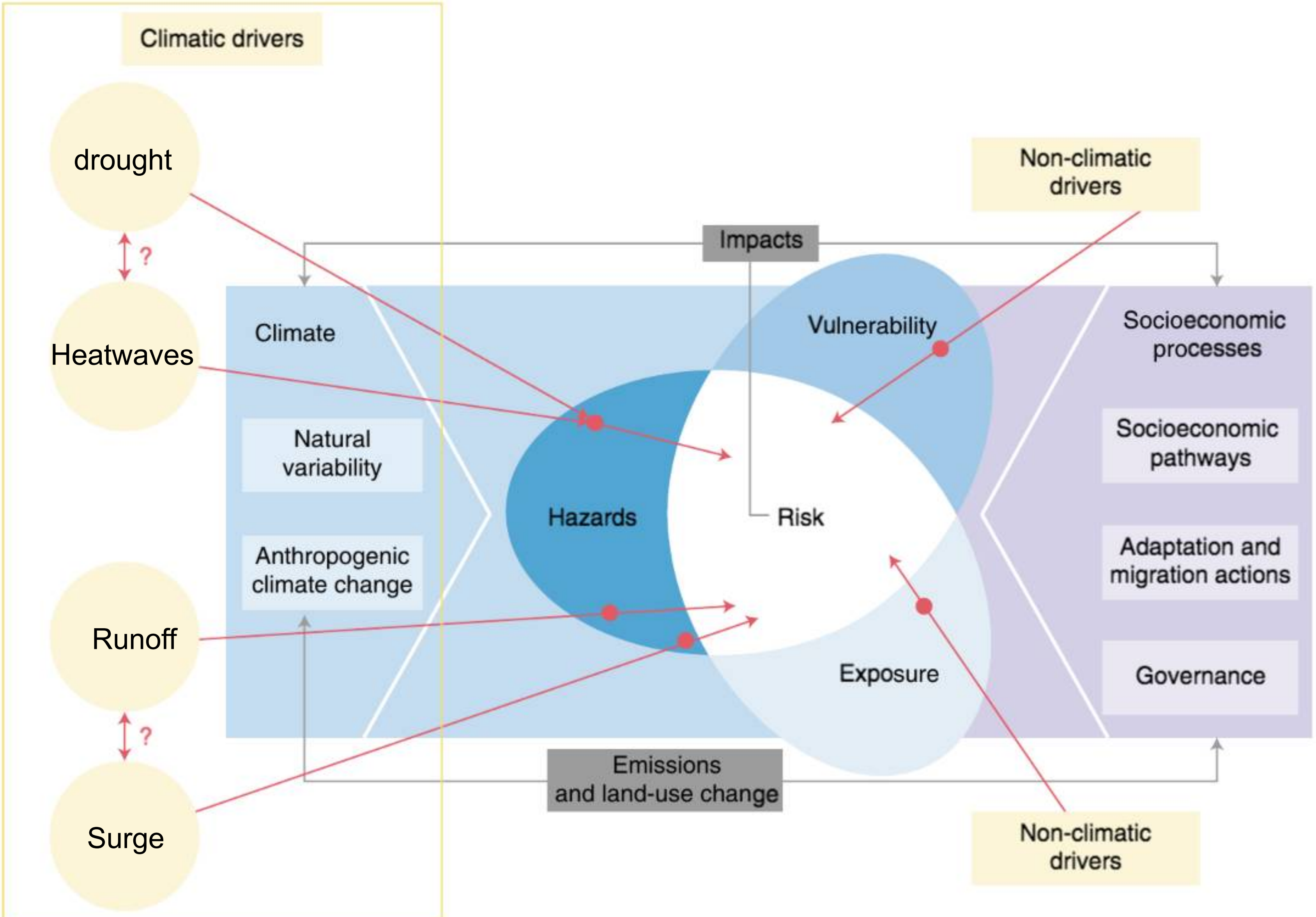
Image Credit: NASA/JPL

Compound Ocean-Fluvial Flooding

Compound Ocean-Fluvial (terrestrial)-Pluvial (local rain) Flooding

Compound Events

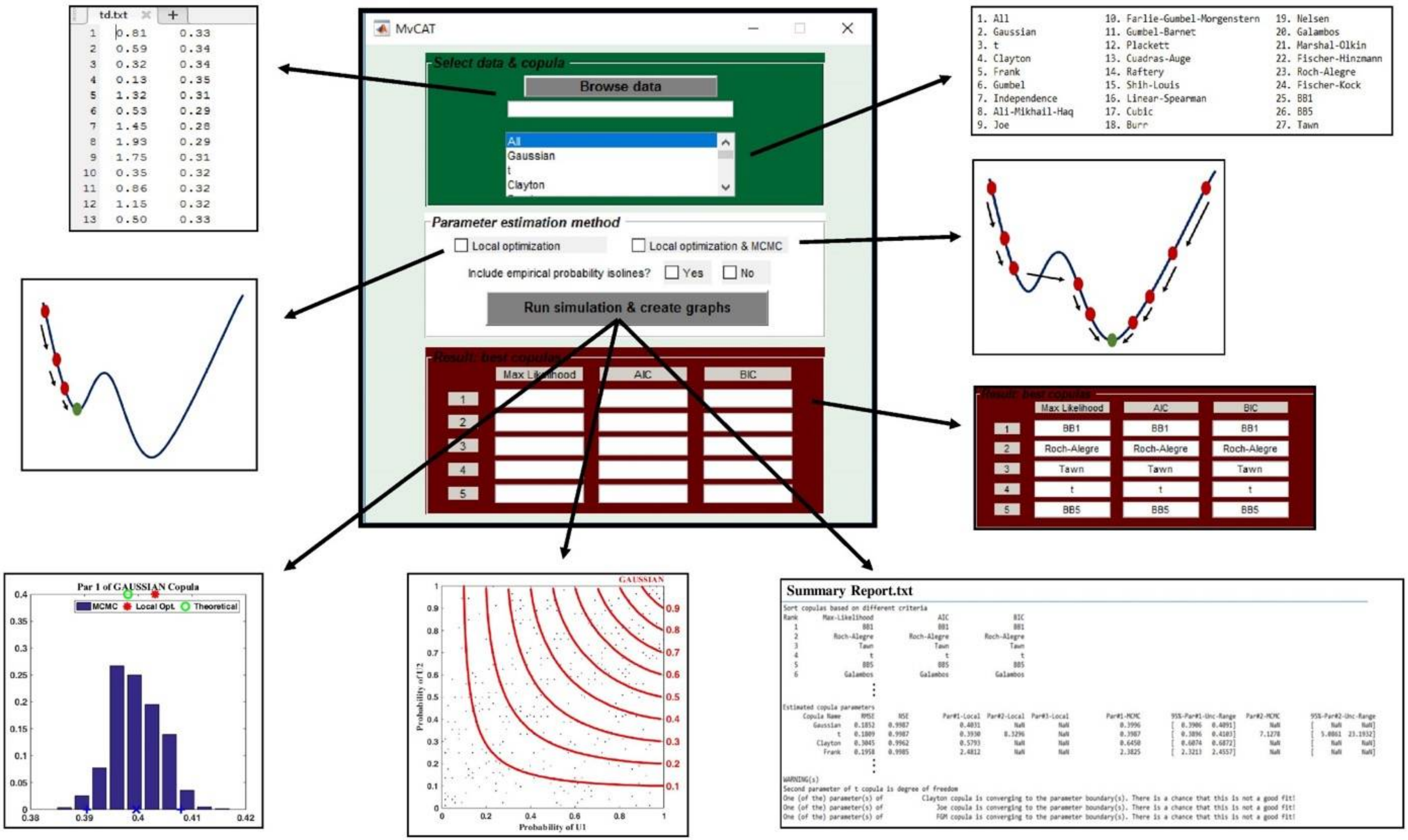
- *Two or more extreme events occurring simultaneously or successively*
- *Combinations of extreme events with underlying conditions that amplify the impact of the events*
- *Combinations of events that are not themselves extremes but lead to an extreme event or impact when combined.*
- *Consecutive inter-dependent events that do not occur at the same time, but they have compounding impacts.*



Zscheischler J., et al., *Nature Climate Change*, 8 (6), 469-477, doi: 10.1038/s41558-018-0156-3.

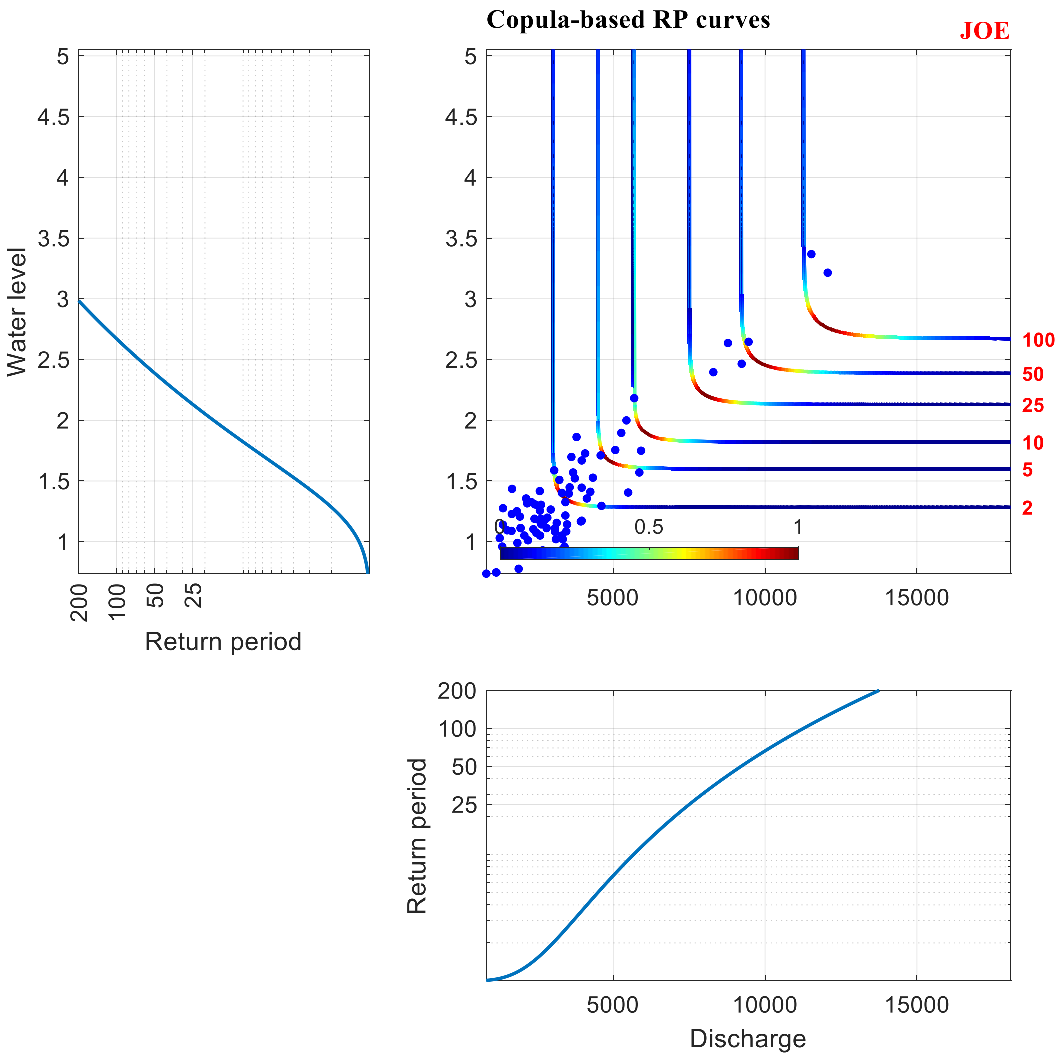
https://www.nature.com/articles/s41558-018-0156-3

Multivariate Copula Analysis Toolbox (MvCAT)
Multi-hazard Scenario Analysis Toolbox (MhAST)



http://amir.eng.uci.edu/software.php Sadegh et al., 2017, *Water Resources Research*

Multi-hazard Scenario Analysis Toolbox (MhAST)



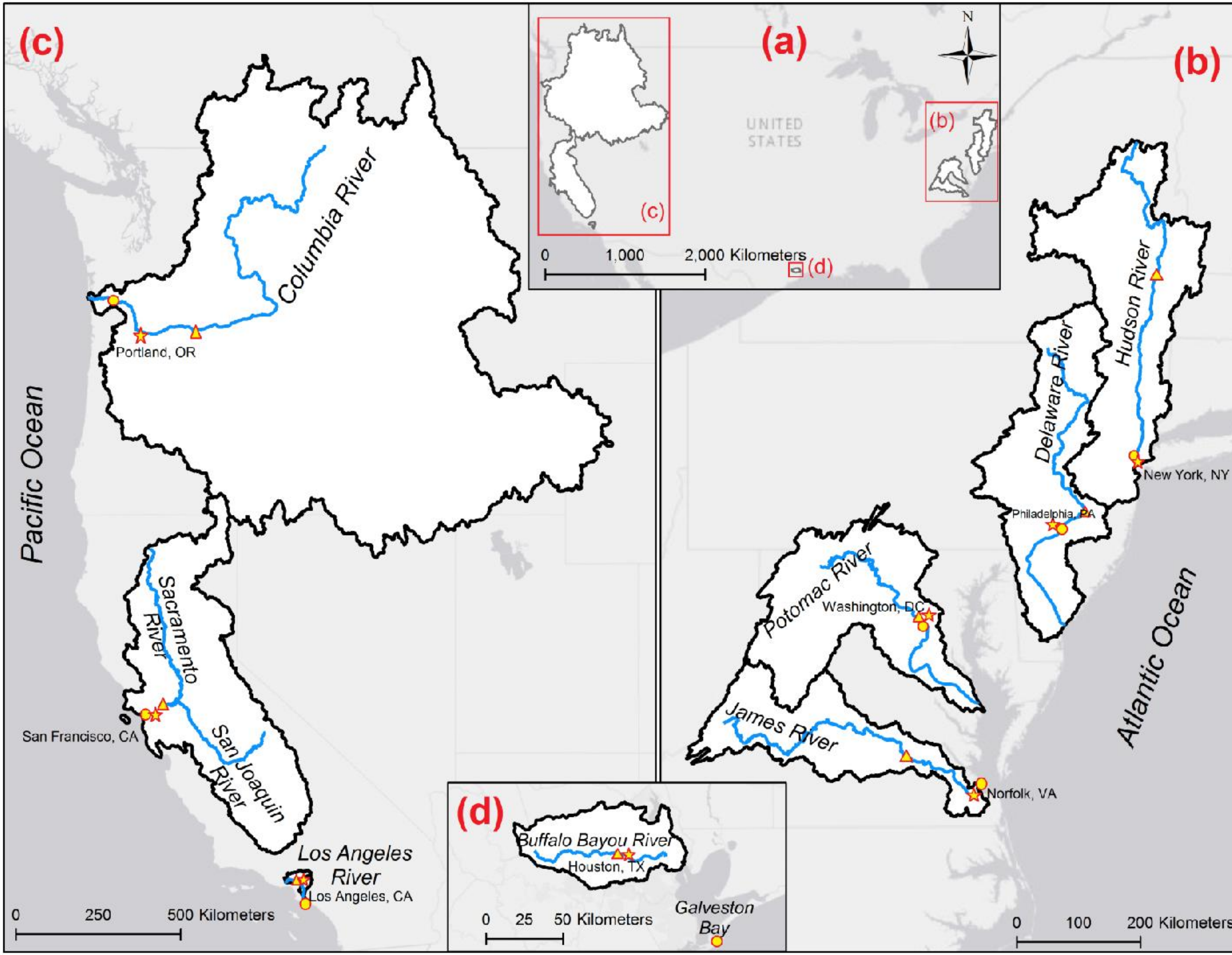
1. Estimates the most likely scenario on any critical layer (isoline): highest density on any critical layer

2. Includes different Hazard Scenarios (e.g., AND, OR, Kendall).

3. Uncertainty analysis and posterior distribution of the parameter using a Bayesian MCMC approach

http://amir.eng.uci.edu/software.php Sadegh et al., 2018, *Geophysical Research Letters*

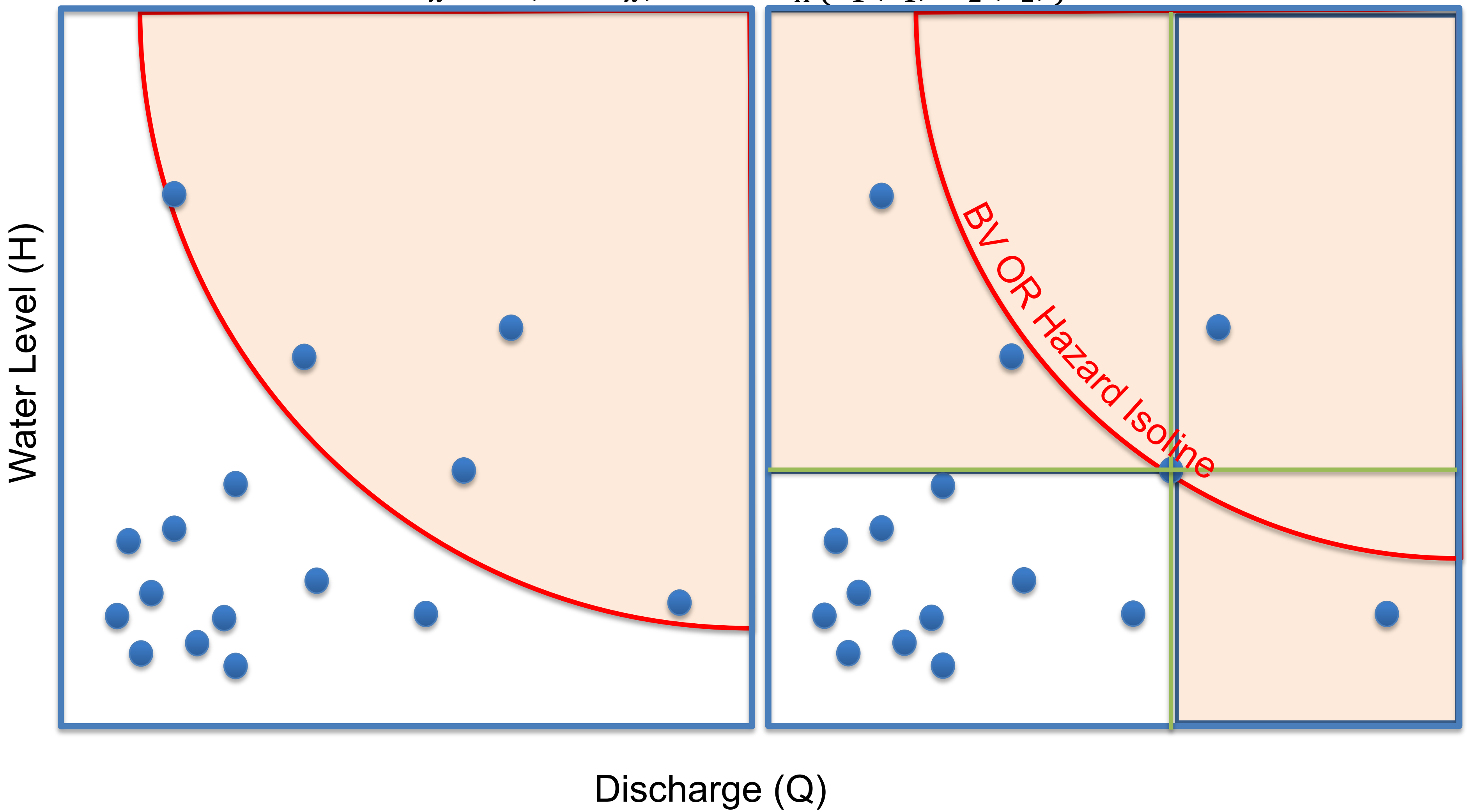
Compound Coastal Flooding



(a)
(b)
(c)
(d)
N
UNITED STATES
0
1,000
2,000 Kilometers
Columbia River
Portland, OR
Pacific Ocean
Sacramento River
San Francisco, CA
San Joaquin River
Los Angeles River
Los Angeles, CA
0
250
500 Kilometers
Buffalo Bayou River
Houston, TX
Galveston Bay
0
25
50 Kilometers
Hudson River
Delaware River
New York, NY
Philadelphia, PA
Potomac River
Washington, DC
James River
Norfolk, VA
Atlantic Ocean
0
100
200 Kilometers

Hazard Scenarios for Compound Coastal Flooding

$$\alpha_x^{\vee} = P(X \in S_x^{\vee}) = 1 - C_X\big(F_1(x_1), F_2(x_2)\big)$$



Moftakhari H.M., Salvadori G., AghaKouchak A., Sanders, B.F., Matthew, R.A., 2017, Compounding Effects of Sea Level Rise and Fluvial Flooding, *Proceedings of the National Academy of Sciences*, doi: 10.1073/pnas.1620325114.

Failure Probability: Compound Coastal Flooding

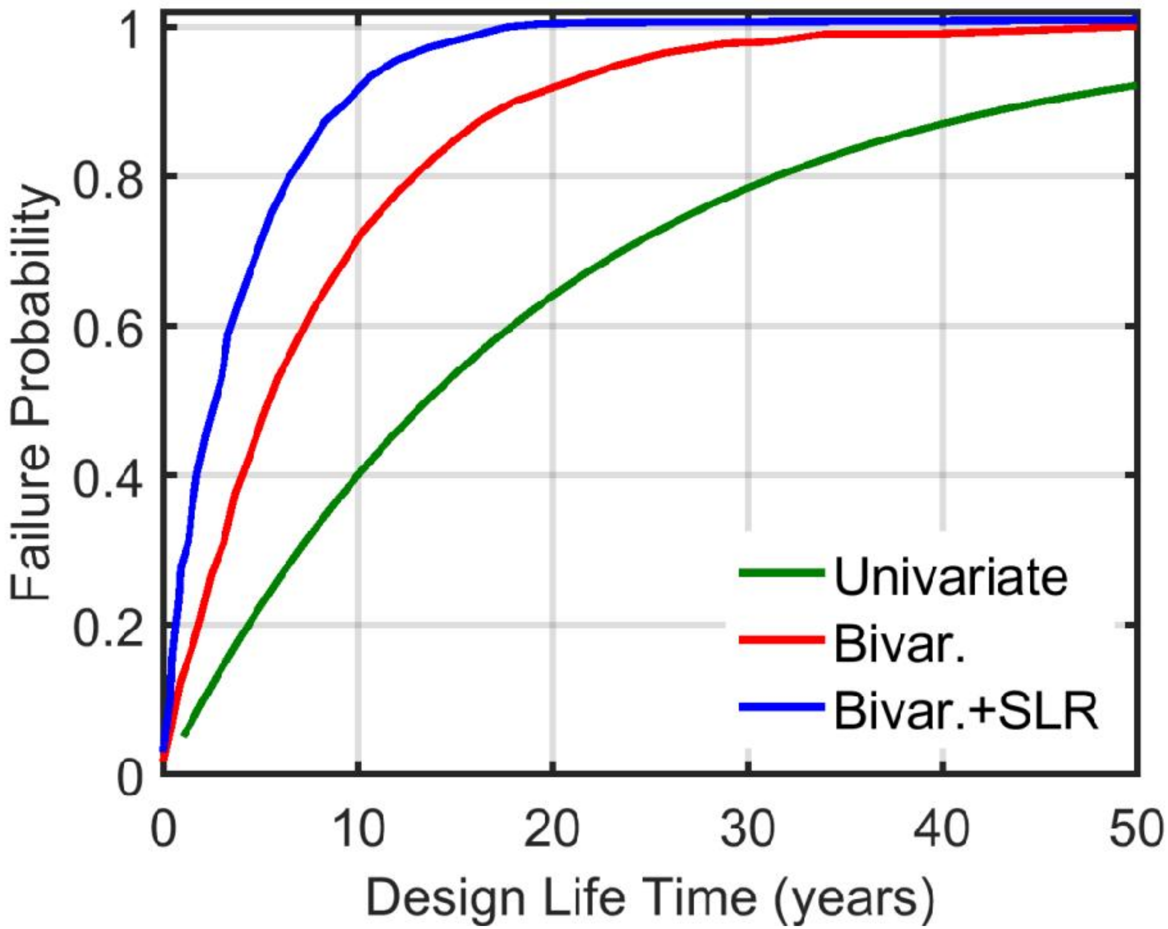
For a given design life time of T the failure probability ($\check{P}_T$) is calculated as

Univariate

$$\check{P}_T = 1 - (1-p)^T$$

Multivariate

$$\check{P}_T = 1 - P\left(X_1 \in S_1^C, \ldots, X_T \in S_T^C\right)$$
$$= 1 - \left(C_X\left(F_1(\tilde{x}_1), F_2(\tilde{x}_2)\right)\right)^T$$



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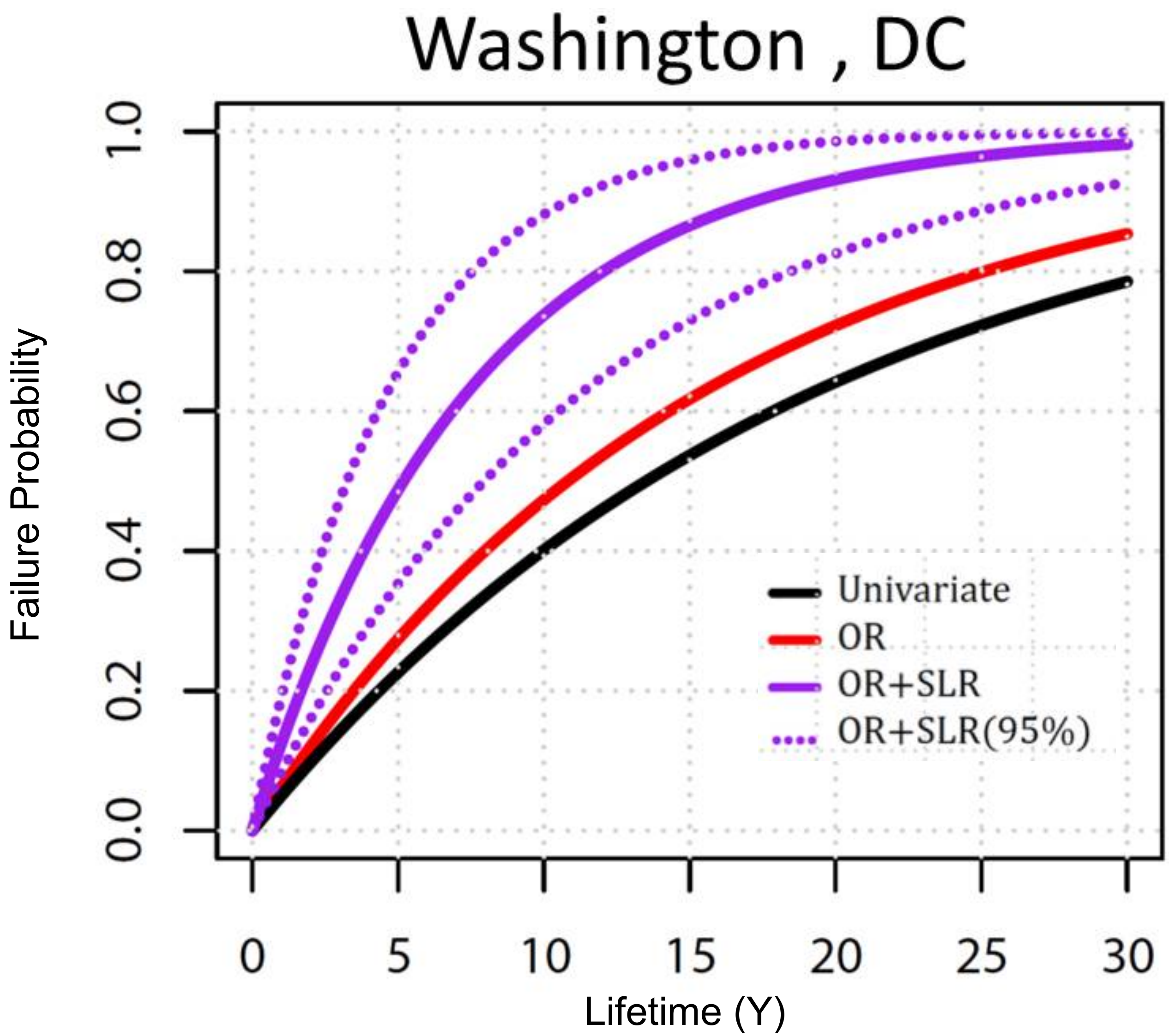
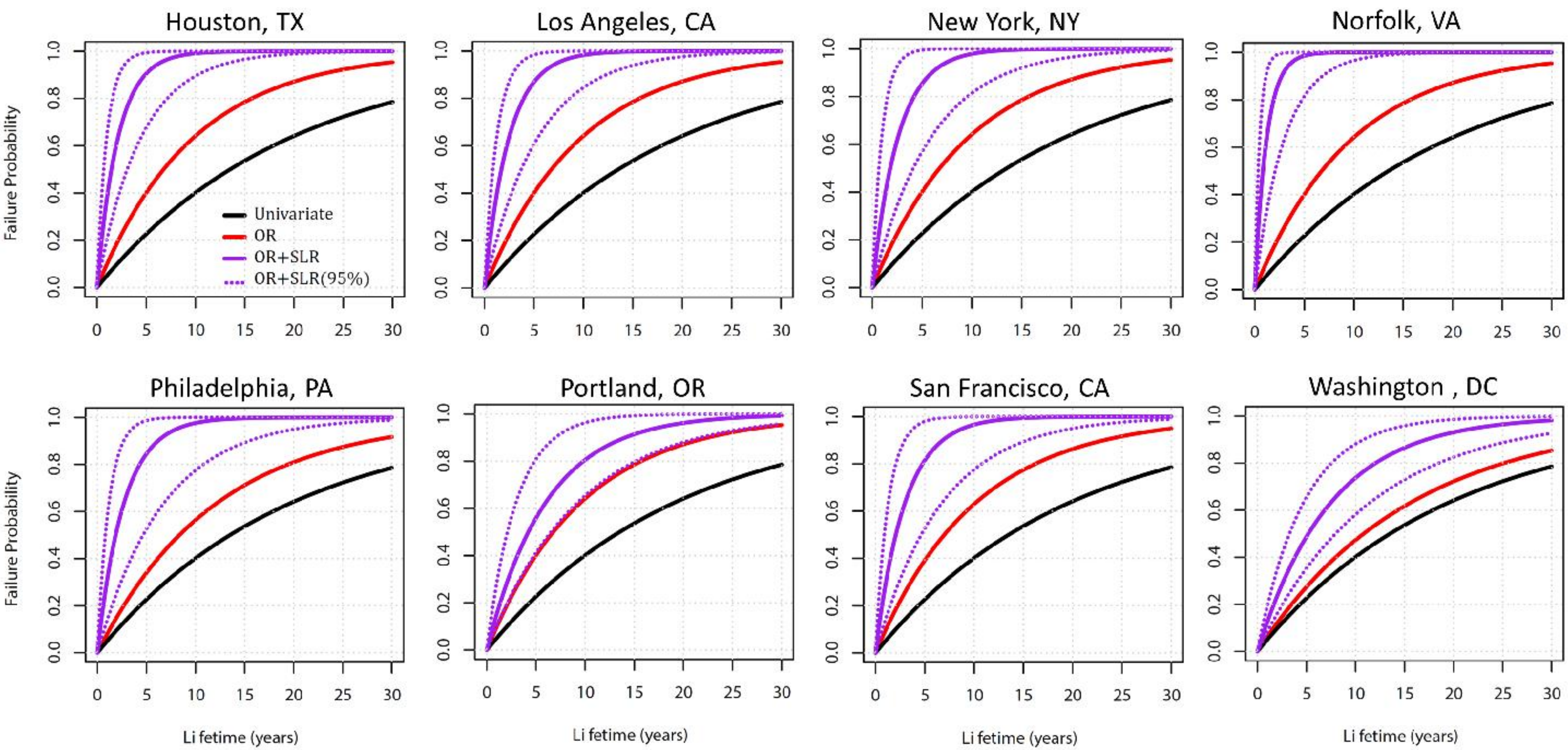
Failure Probability: Compound Coastal Flooding



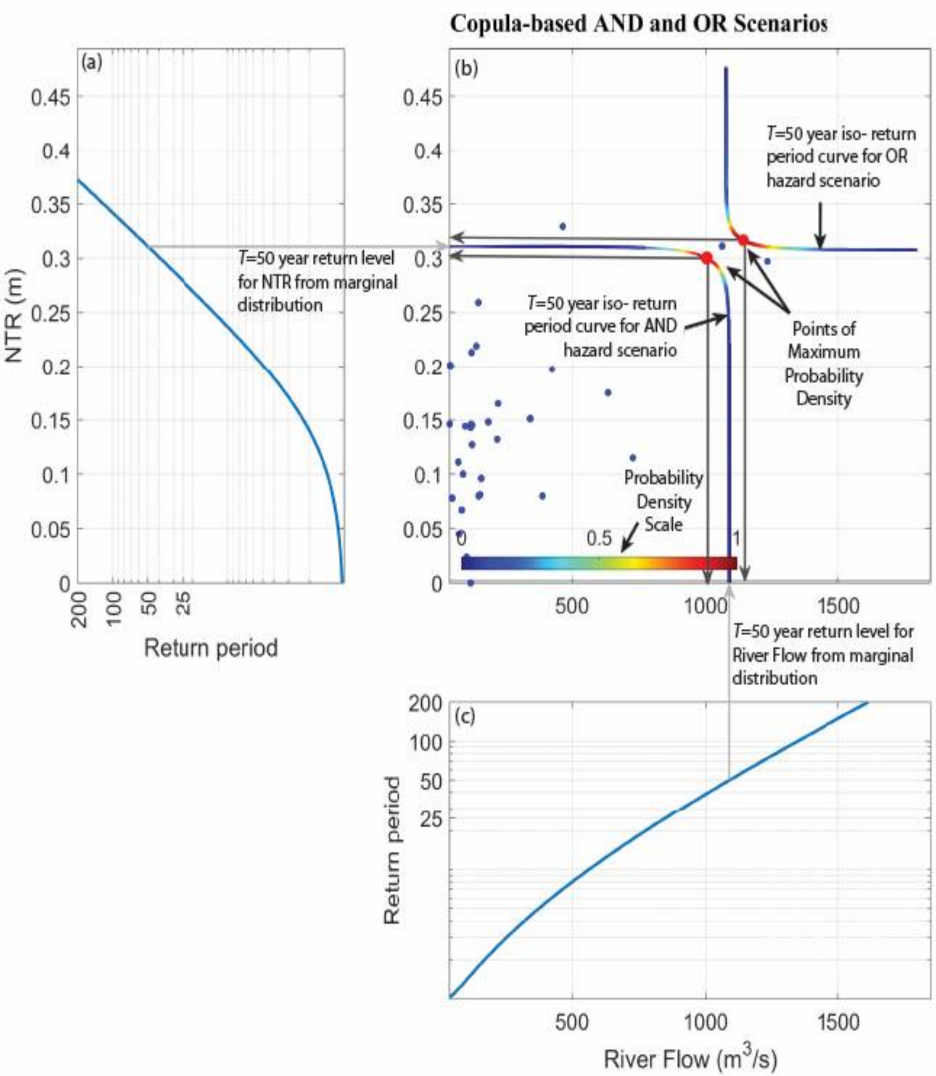
Link: http://www.pnas.org/content/early/2017/08/22/1620325114

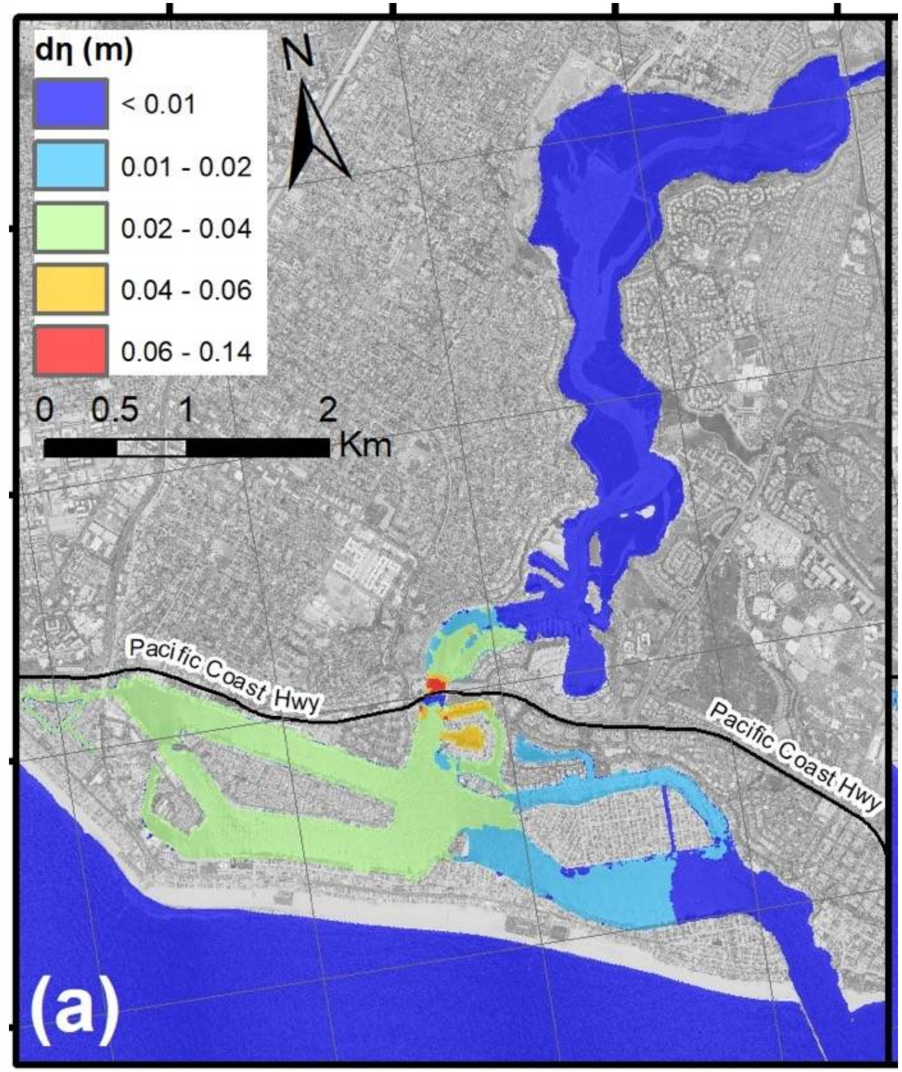
Failure Probability: Compound Coastal Flooding



Estimated failure probability for a temporal horizon of 30 years. The solid black and red curves show, respectively, the estimated failure probability computed based on the univariate and bivariate OR hazard scenarios, according to the presently observed climate conditions. The solid and dashed purple curves show the estimated probability of failure using a bivariate OR approach and an associated 95% confidence band considering the projected SLR for 2030 under RCP 4.5.

Hybrid Statistical-Dynamic Compound Coastal Flooding

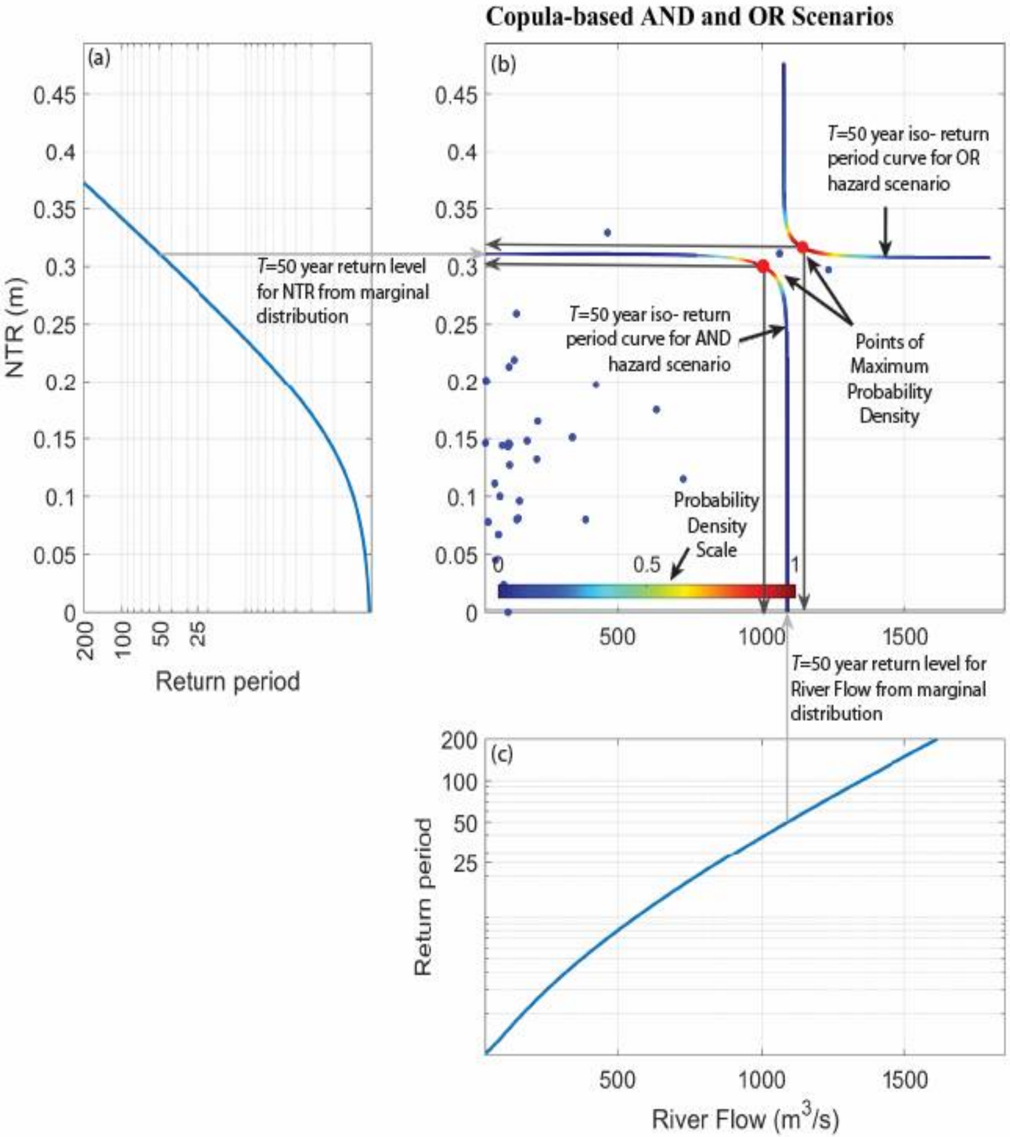




Difference in water surface elevations a) given by the proposed composite profile method compared to the FEMA method

Moftakhari, et al., 2019, *AWR*

Compound Extreme Events




```
g=9.81; %gravitational constant
mn=0.02; %manning n
L=10000; %length of estuary
N=100; %number of points to plot/save

Qavg=10; %average flow into estuary
QT=1090; %marginal Q for return period T
QAND=1005; %bivariate AND Q
QOR=1167; %bivariate OR Q

etaMHHW=1.673; %mean higher high water
NTRT=0.311; %marginal NTR for return period T
NTRAND=0.3001; %bivariate AND NTR
NTROR=0.3189; %bivariate OR NTR


%Note: the model assumes that estuary is a channel with a
%       rectangular cross section of width W and bottom
%       elevation Z. Estuary geometry data is saved in
%       "geometry.m"


% Compute water levels = MHHW + NTR
%   Assumption: TWL = MHWW + NTR
%   This assumption makes sense if NTR >> Tide heights
%   When NTR << Tide Heights, better to analyse TWL directly.

etaavg=etaMHHW;
etaT=etaavg+NTRT;
etaAND=etaavg+NTRAND;
etaOR=etaavg+NTROR;

options=odeset('RelTol',1e-6);
x=linspace(0,L,N)';

%Integrate water surface profile from mouth (x=0) to head (x=L)
```

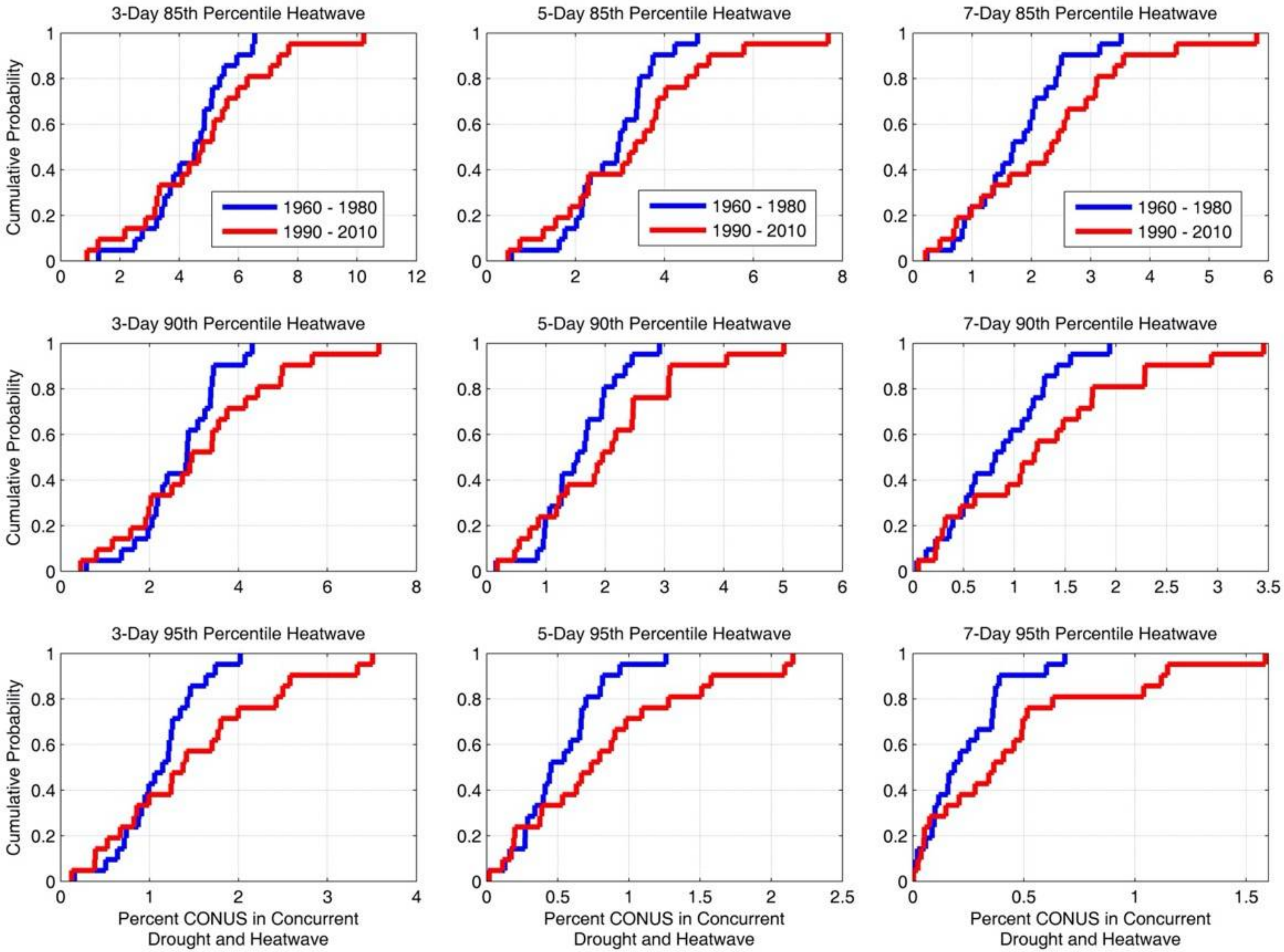
Moftakhari, et al., 2019, *AWR*

Alaska, USA

California, USA

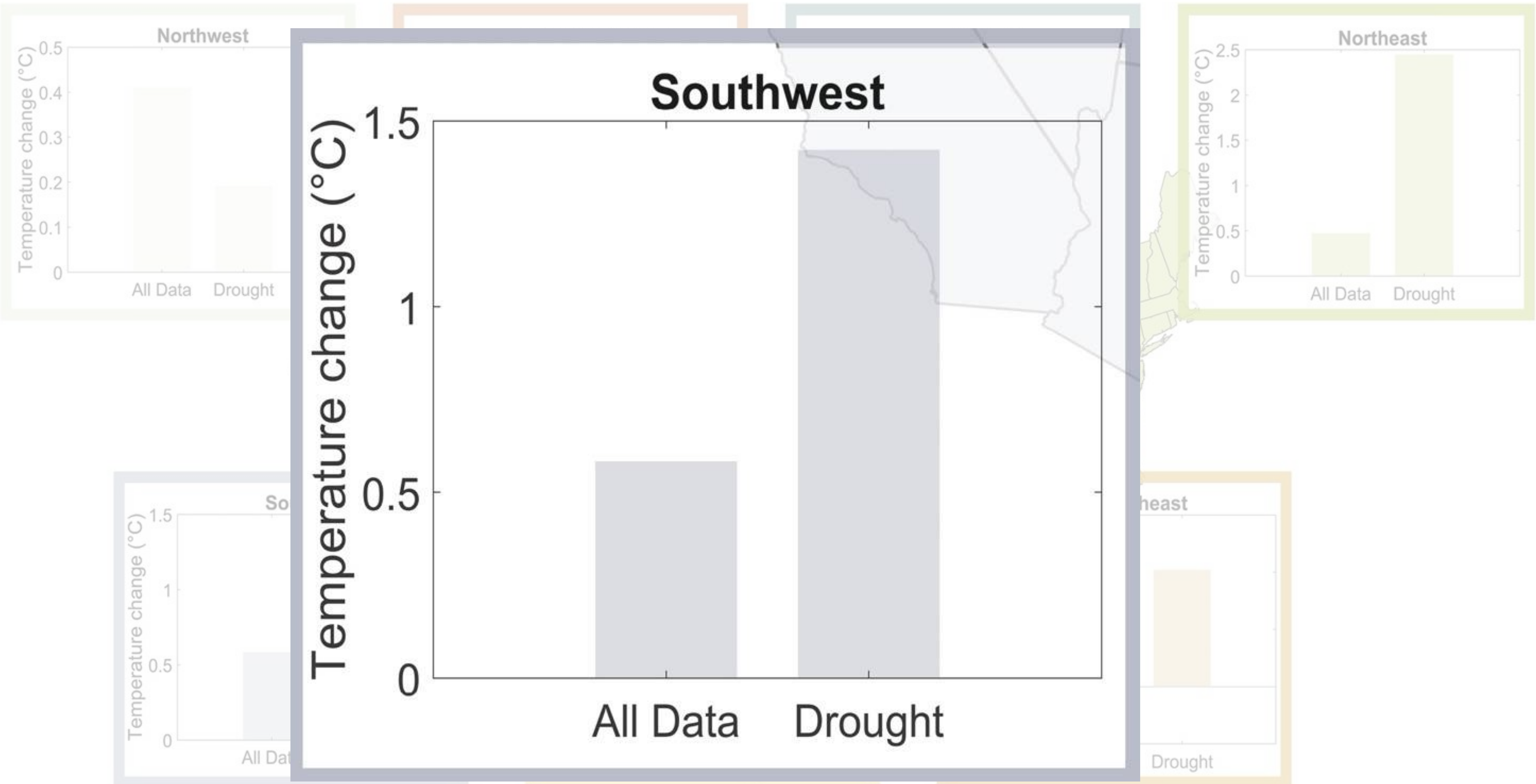
Drought and Heatwaves

Compound Drought and Heatwaves



Mazdiyasni O., AghaKouchak A., 2015, Substantial Increase in Concurrent Droughts and Heatwaves in the United States, *Proceedings of the National Academy of Sciences*, doi: 10.1073/pnas.1422945112.

Amplified Warming of Droughts in Southern United States in Observations and Model Simulations



Chiang et al., 2018, Science Advances

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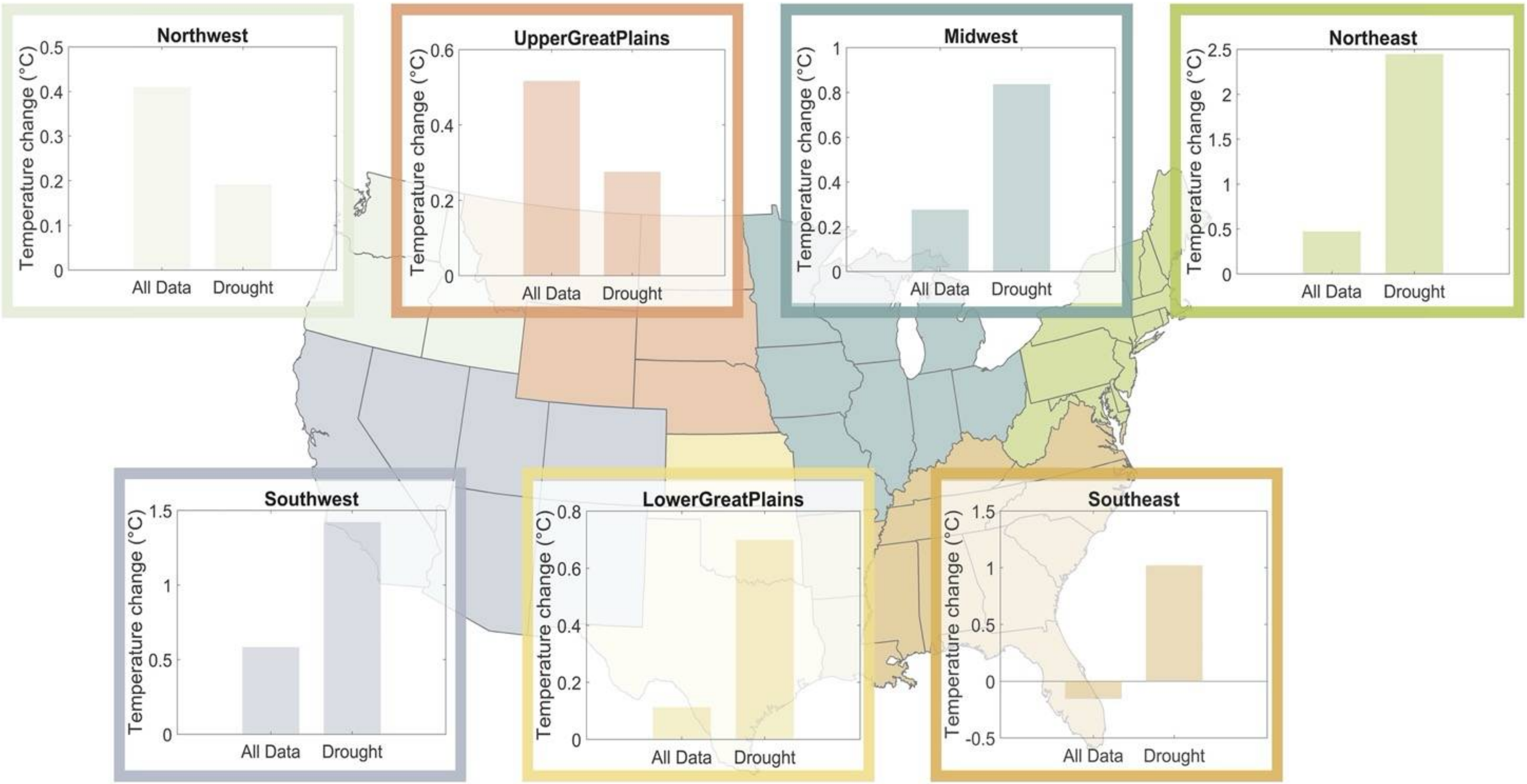
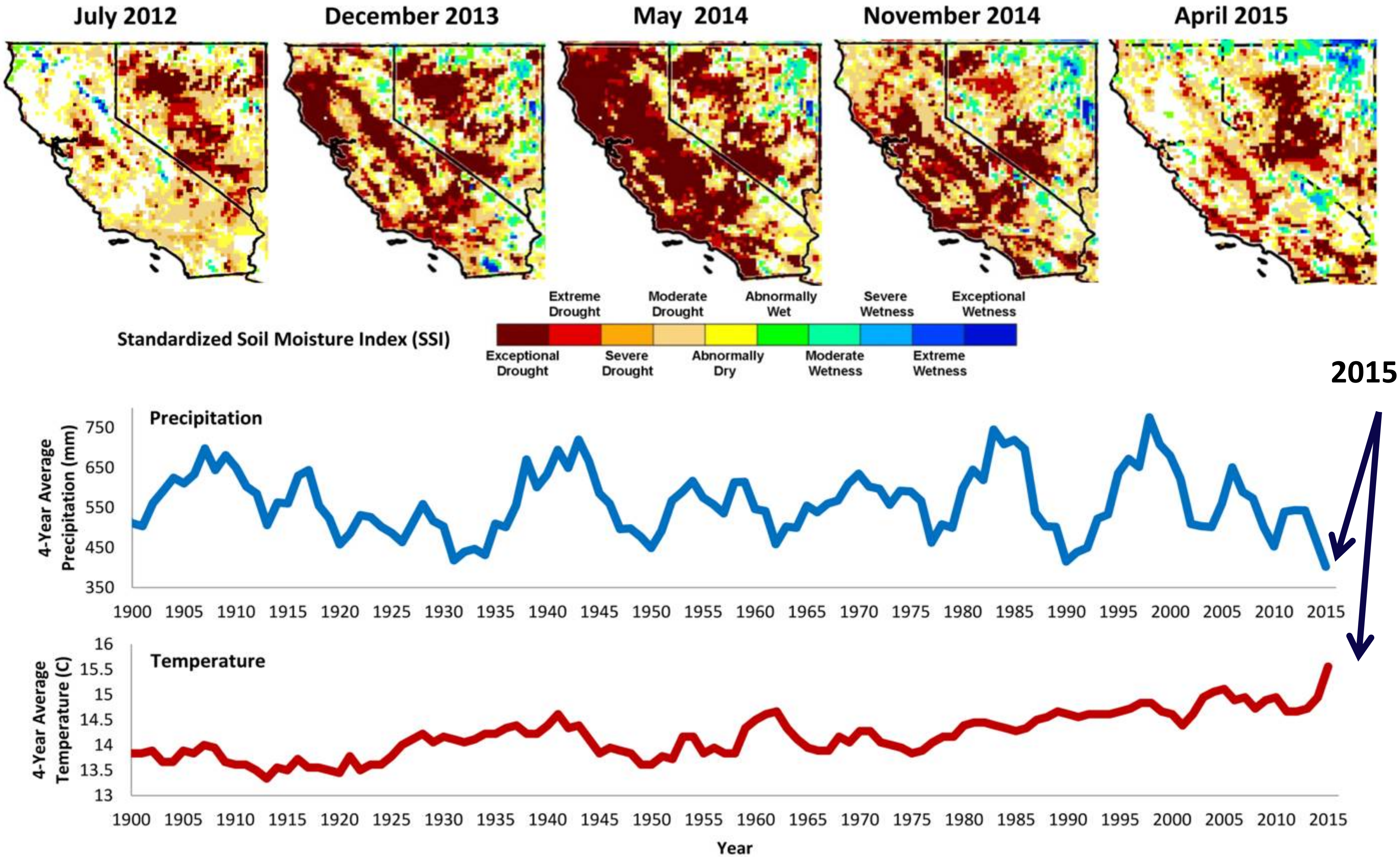


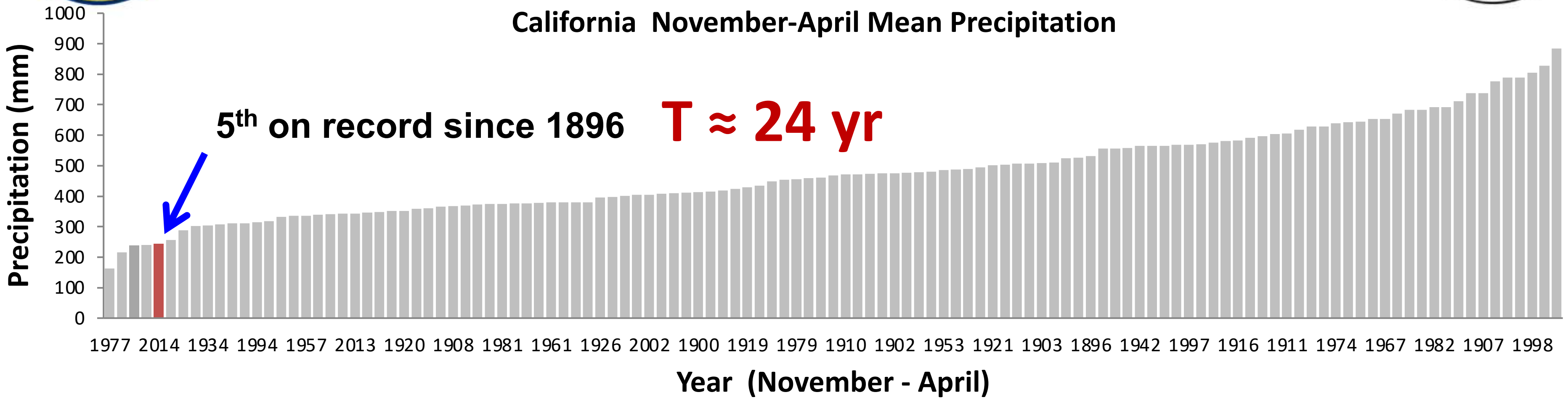
Chiang et al., 2018, Science Advances

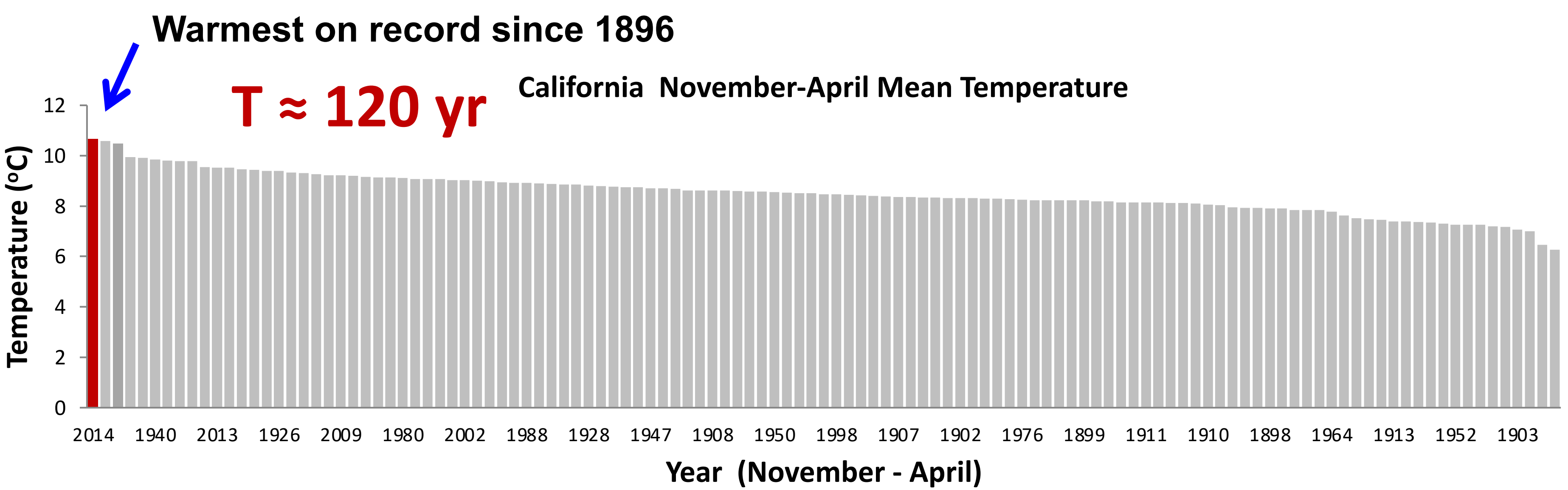
Compound Extreme Events



AghaKouchak A., Cheng L., Mazdiyasni O., Farahmand A., 2014, Global Warming and Changes in Risk of Concurrent Climate Extremes: Insights from the 2014 California Drought, *Geophysical Research Letters*, doi: 10.1002/2014GL062308.

2014 California Drought: How Bad is It?





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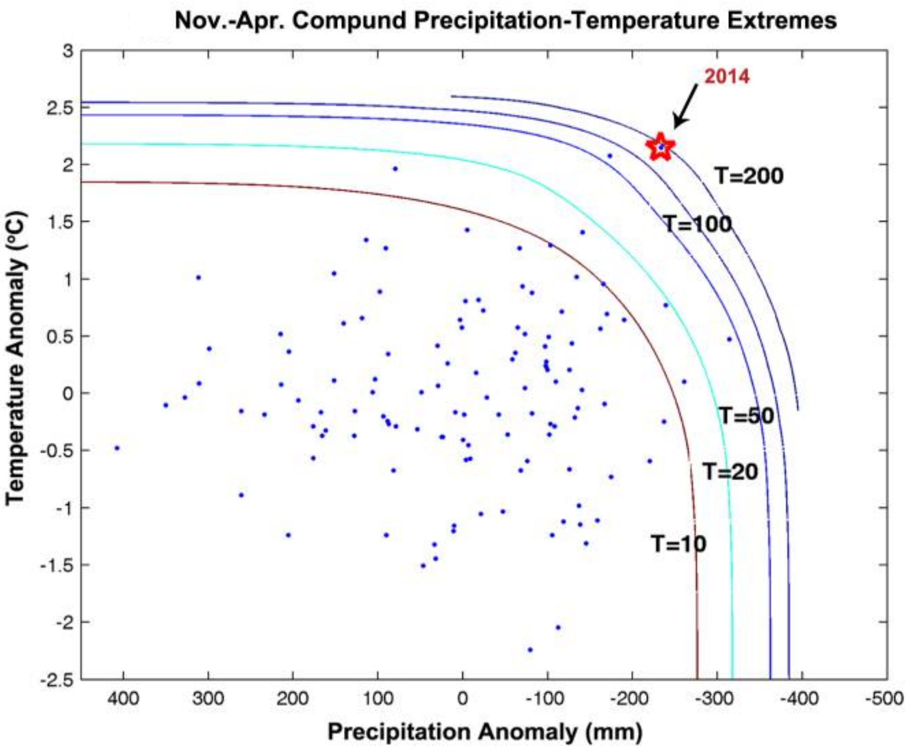
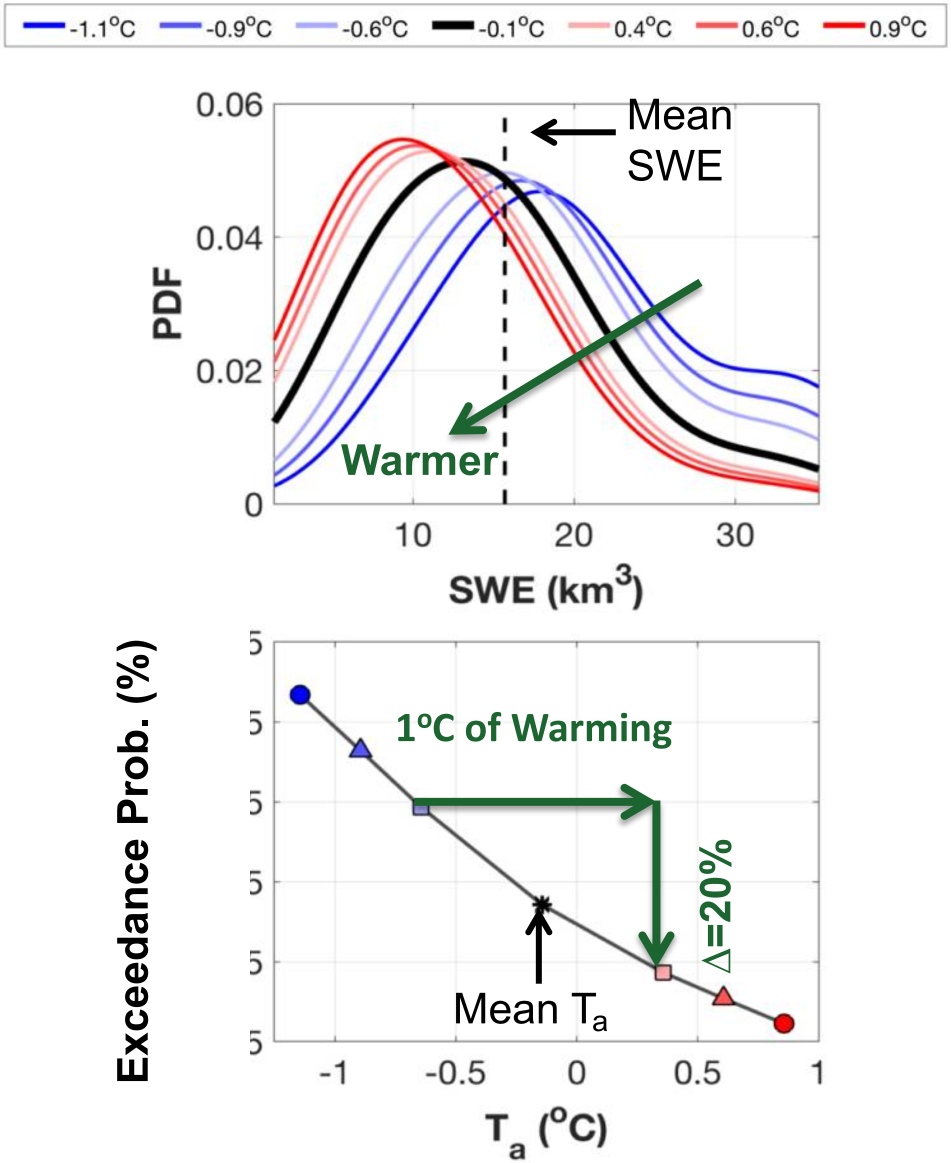


Assuming two variables X (precipitation) and Y (temperature) with cumulative distribution functions $F_X(x) = \Pr(X \leq x)$ and $F_Y(y) = \Pr(Y \leq y)$, the copula (C) can be used to obtain their joint distribution function:
$F(x,y) = C\big(F_X(x), F_Y(y)\big)$, where $F(x,y)$ is the joint distribution function of X and Y:
$F(x,y) = \Pr(X \leq x, Y \leq y)$
The joint survival distribution $\bar{F}(x,y) = \Pr(X > x, Y > y)$ can be obtained using the concept of survival copula:
$\bar{F}(x,y) = \hat{C}(\bar{F}_X(x), \bar{F}_Y(y))$
$\bar{F}_X$ and $\bar{F}_Y$ (i.e., $\bar{F}_X = 1 - F_X$, $\bar{F}_Y = 1 - F_Y$) are the marginal survival functions of X and Y, and $\hat{C}$ is the survival copula.
Survival critical layer (or isoline) is then defined as:
$\mathcal{L}_t^{\bar{F}} = \{x, y \in R^d\colon\ \bar{F}(x,y) = t\}$ where $\mathcal{L}_t^{\bar{F}}$ is the survival critical layer associated with the probability t.

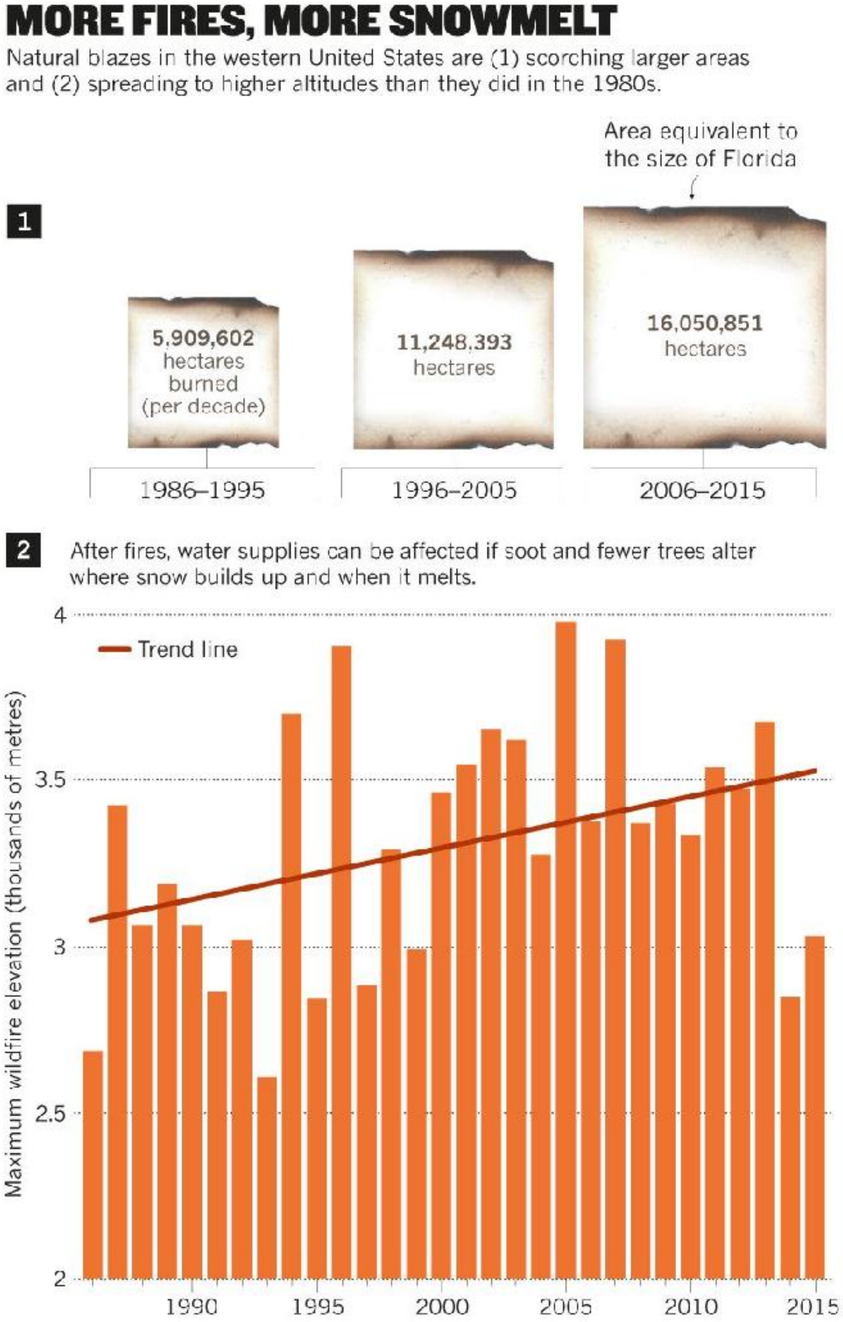
The survival return period of X and Y is defined as: $\bar{\kappa}_{XY} = \frac{\mu}{1-\bar{K}(t)}$ where $\bar{\kappa}_{XY}$ is called the survival Kendall's return period; $\mu > 0$ is the average interarrival time of X and Y ($\mu = 1$ indicates the average interarrival time between subsequent values in the time series is one year); and $\bar{K}$ is the Kendall's survival function associated with $\bar{F}$ defined as:
$\bar{K}(t) = \Pr(\bar{F}(X,Y) \geq t) \ = \Pr(\hat{C}(\bar{F}_X(x), \bar{F}_Y(y)) \geq t)$
For any return period T, the corresponding survival critical layer $\mathcal{L}_t^{\bar{F}}$ can be estimated by inverting the Kendall's survival function $\bar{K}(t)$ at the probability level $p = 1 - \frac{\mu}{T}$: $\quad \bar{q} = \bar{q}(p) = \bar{K}^{-1}(p)$,

Temperature-Wildfires-Snow

Mountain Snowpack Response to Different Levels of Warming



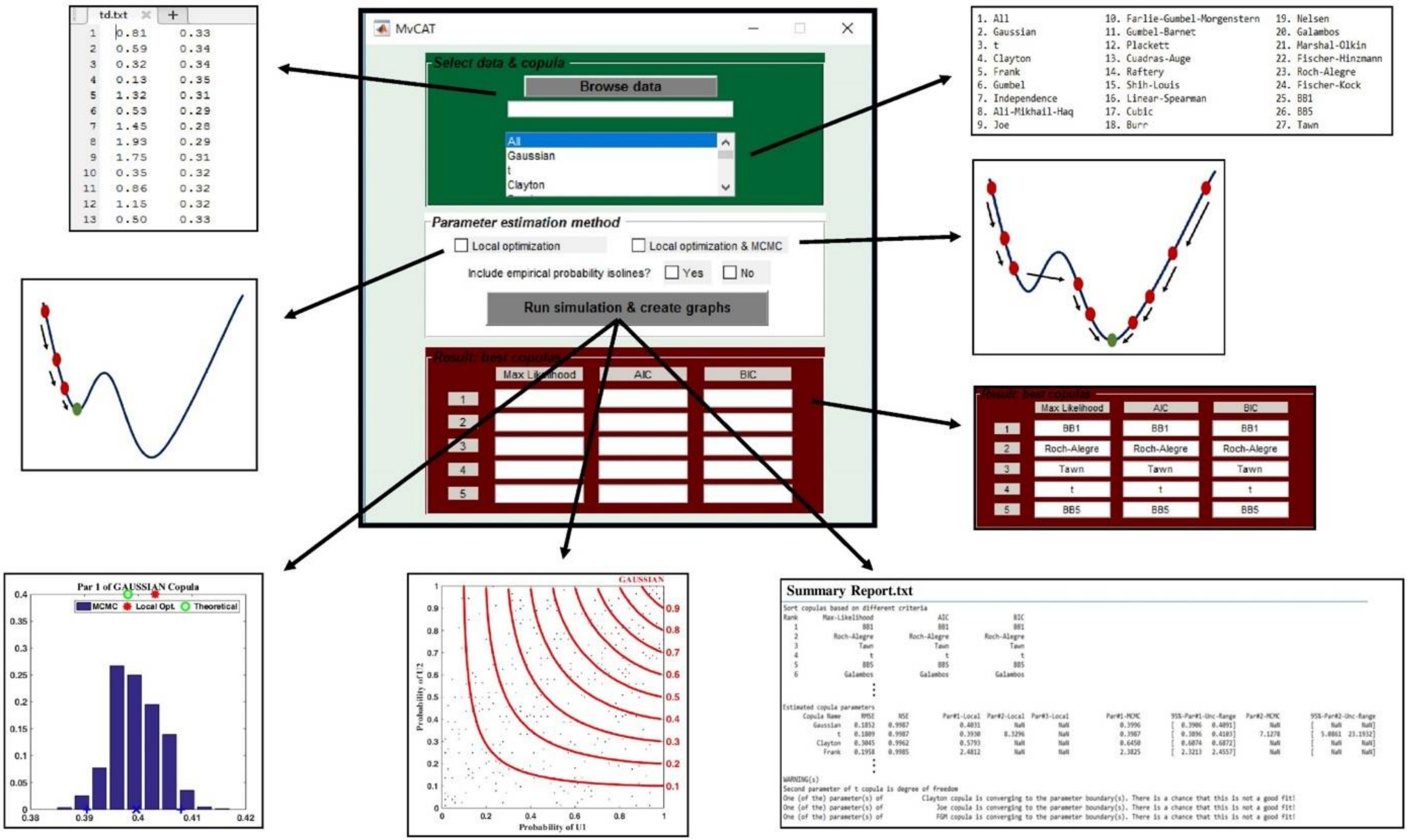
Huning & AghaKouchak, 2018 PNAS



AghaKouchak, 2018 Nature

Rain over Burned Areas: Cascading Hazards

Multivariate Copula Analysis Toolbox (MvCAT)
Multi-hazard Scenario Analysis Toolbox (MhAST)



http://amir.eng.uci.edu/software.php Sadegh et al., 2017, *Water Resources Research*

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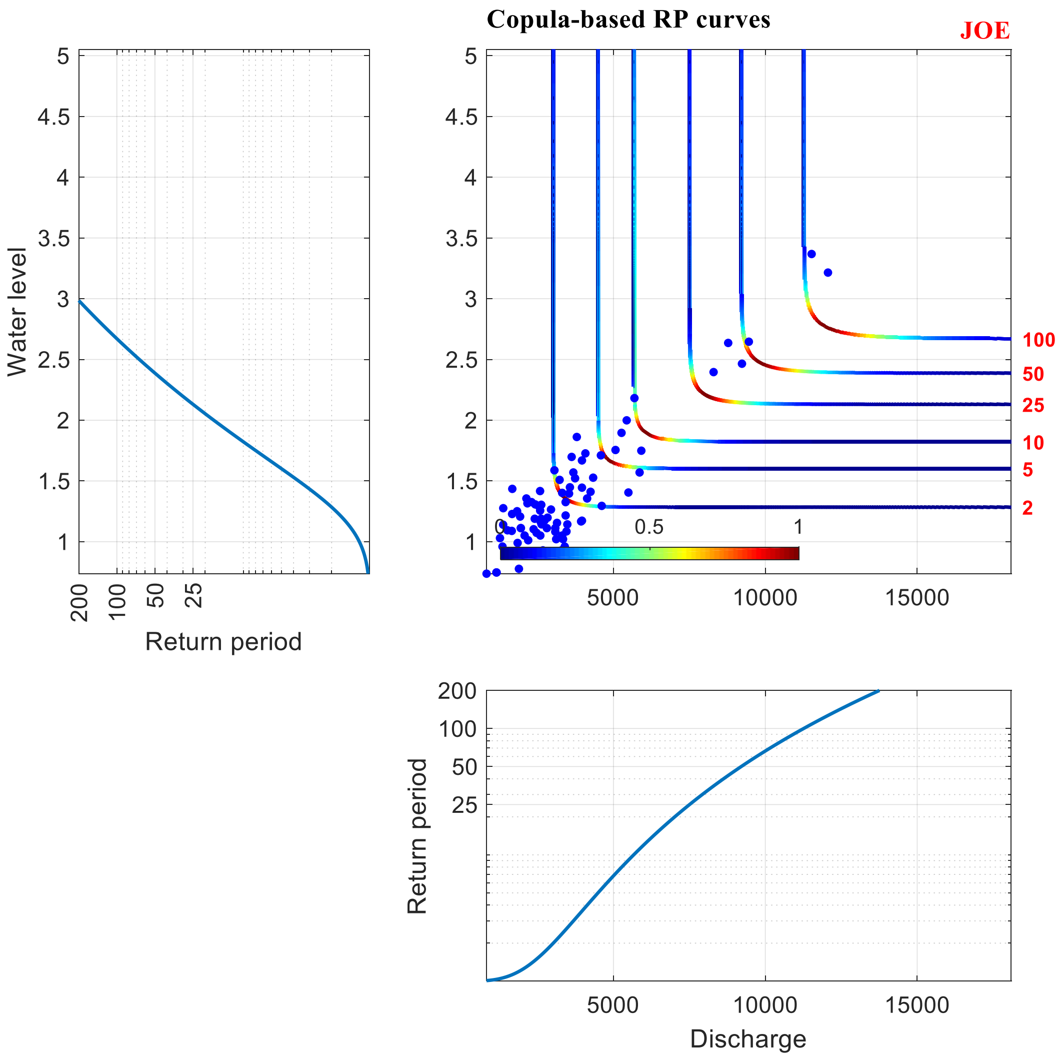

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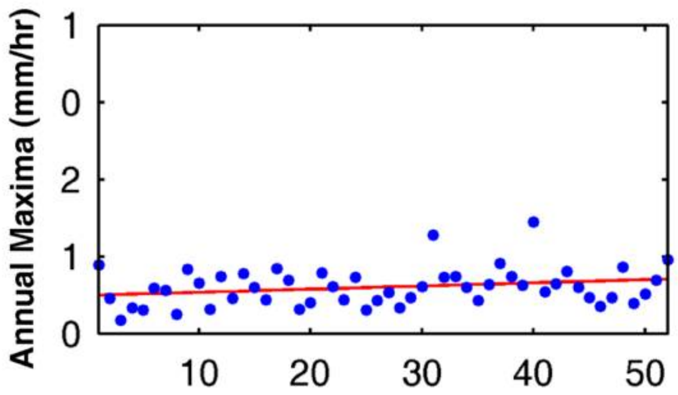
Rain over Burned Areas: Cascading Hazards

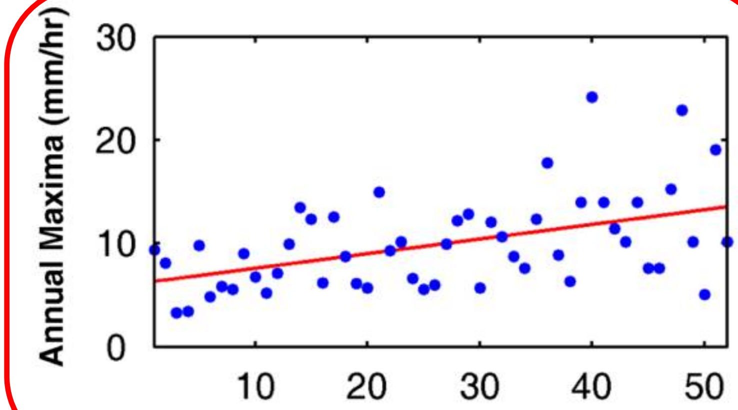
ProNEVA Toolbox

STATIONARITY

$$G(x) = \exp\left\{-\left[1+\xi\left(\frac{x-\mu}{\sigma}\right)\right]^{-1/\xi}\right\}$$

μ = cte
σ = cte
ξ = cte





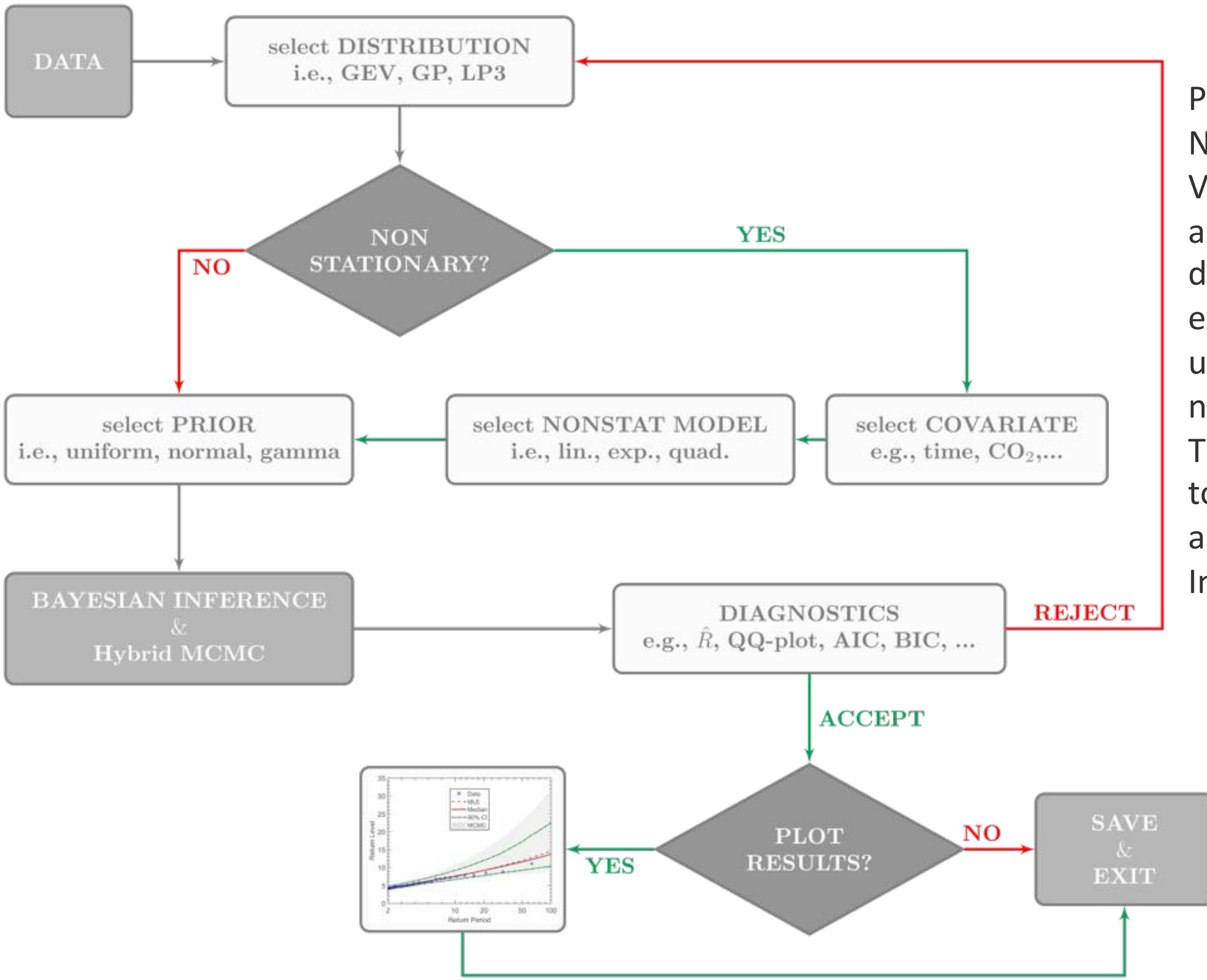
NONSTATIONARY

$$G(x) = \exp\left\{-\left[1+\xi\left(\frac{x-\mu}{\sigma}\right)\right]^{-1/\xi}\right\}$$

μ (function of time t)
σ (function of time t)
ξ (function of time t)

Process-informed Nonstationaty Extreme Value Analysis (ProNEVA)

ProNEVA Matlab Toolbox

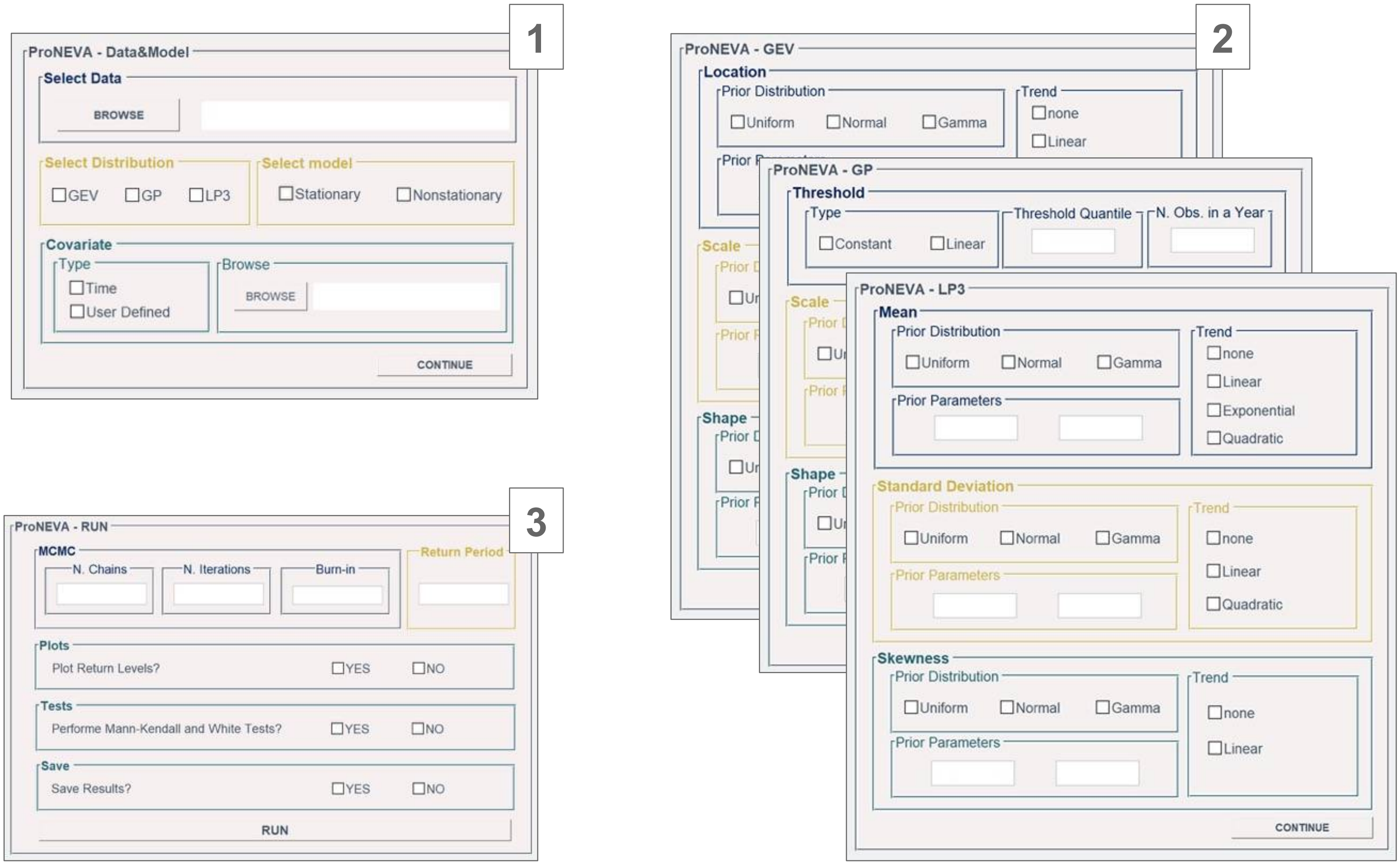


Process-informed Nonstationary Extreme Value Analysis (ProNEVA) is a software package designed to facilitate extreme value analysis under both stationary and nonstationary assumptions. The source code of the toolbox is freely available along with a Graphical User Interface (GUI).

http://amir.eng.uci.edu/downloads/ProNEVA.zip

Process-informed **N**onstationaty **E**xtreme **V**alue **A**nalysis (ProNEVA)

ProNEVA Matlab Toolbox **GUI**



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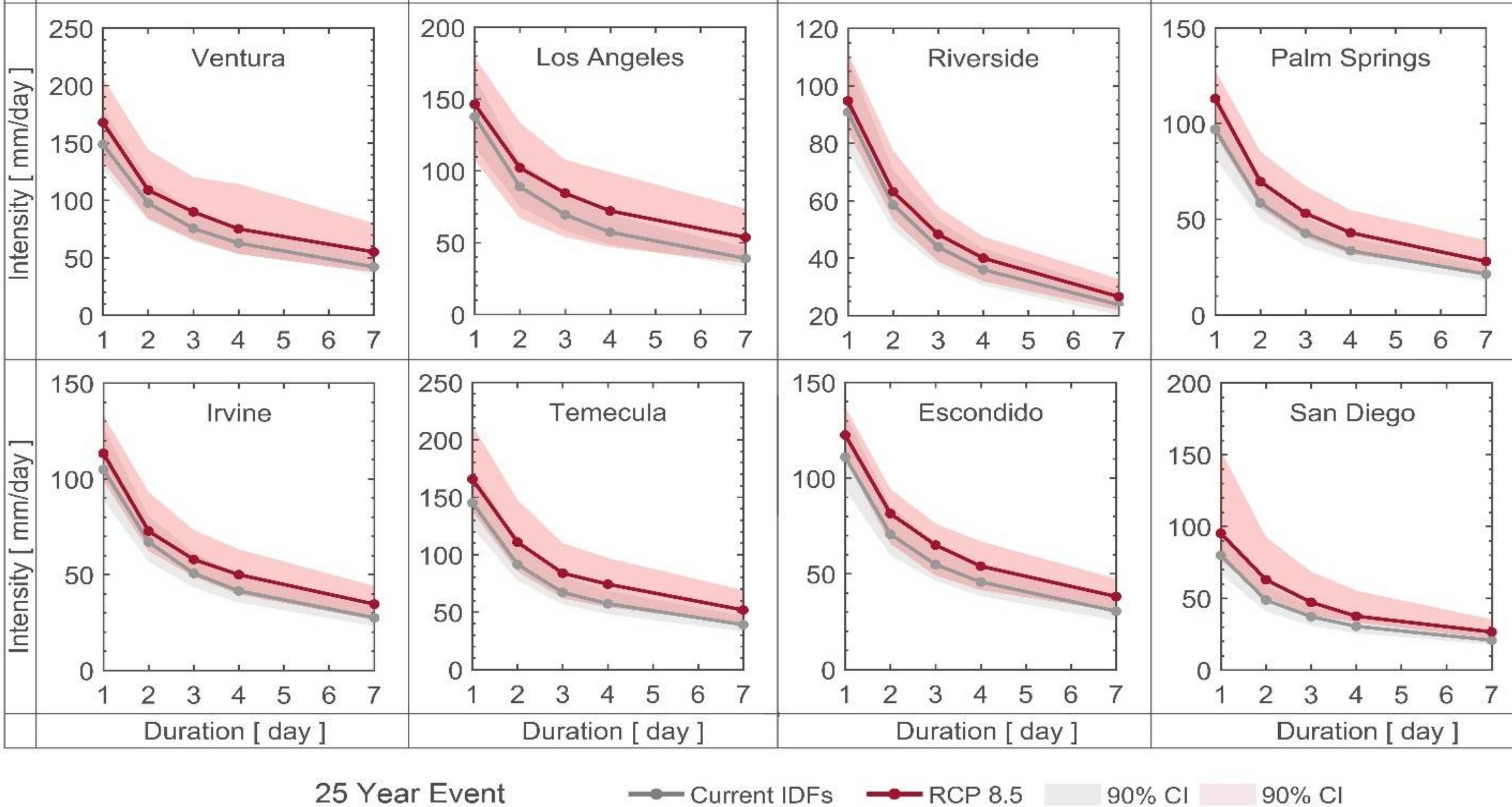


AGU PUBLICATIONS

Water Resources Research

RESEARCH ARTICLE

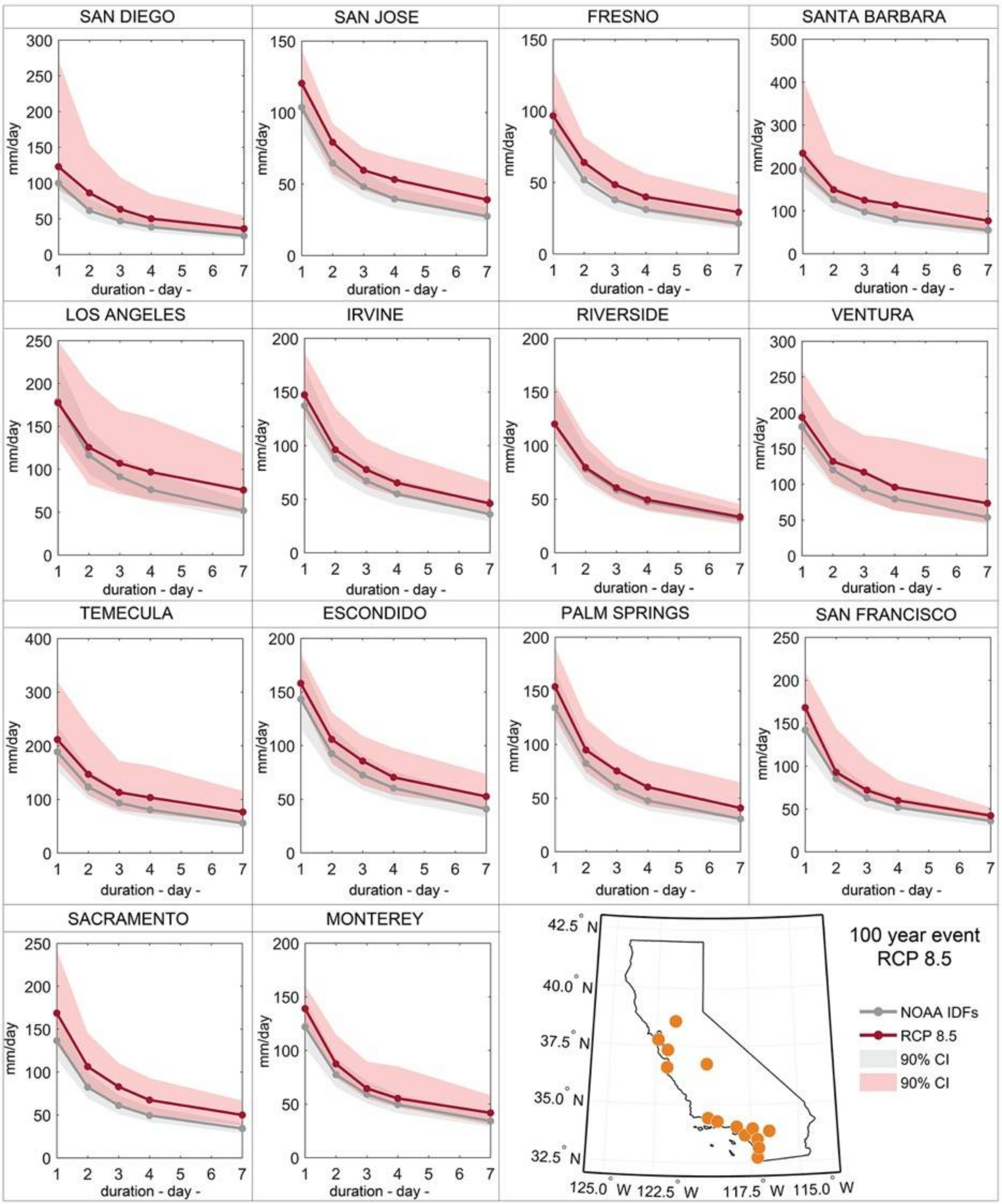
10.1002/2017WR021975

Quantifying Changes in Future Intensity-Duration-Frequency Curves Using Multimodel Ensemble Simulations

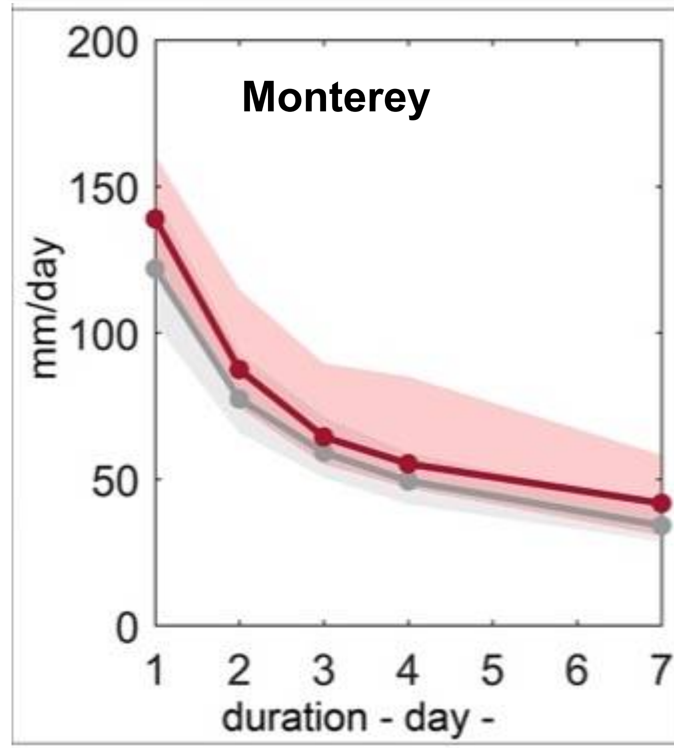
Elisa Ragno[1], Amir AghaKouchak[1], Charlotte A. Love[1], Linyin Cheng[2], Farshid Vahedifard[3], and Carlos H. R. Lima[4]

Key Points:

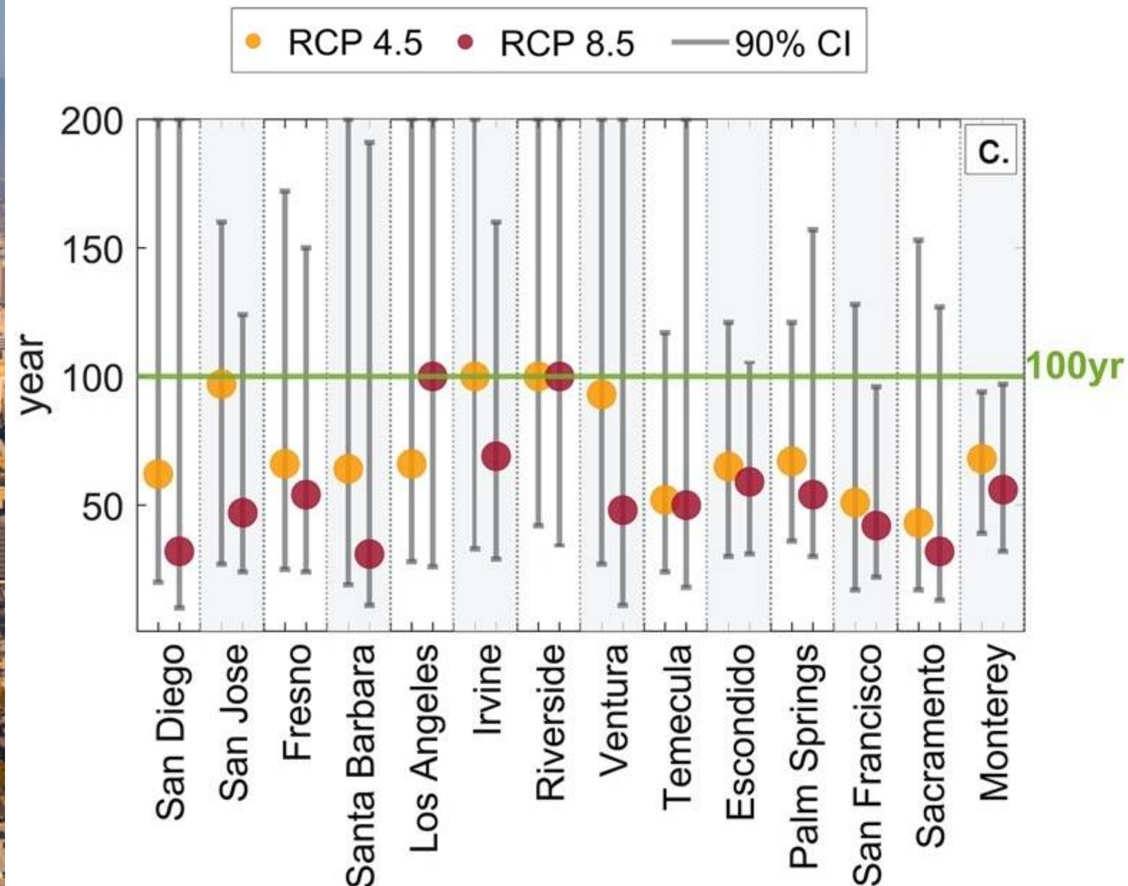
- A methodology for deriving nonstationarity precipitation



Key Point: Climate change is expected to increase the intensity and frequency of future rainfall events and hence, using current IDF curves may lead to underestimation of the future flood risk.

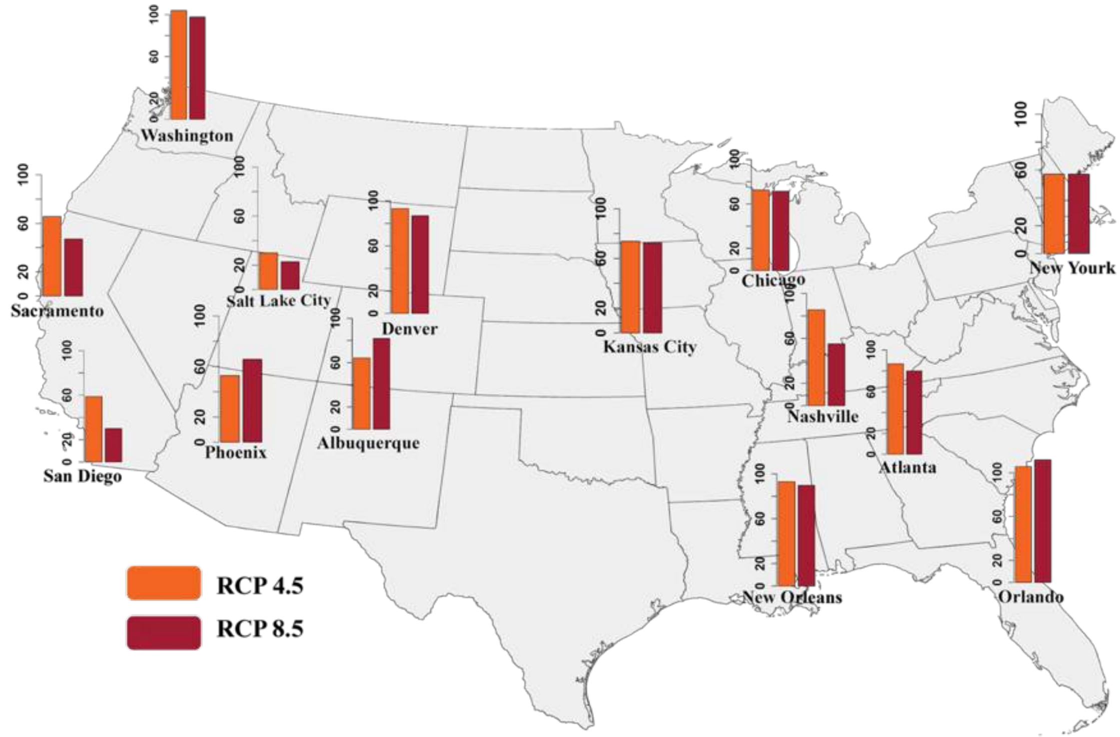


Comparison between the current (grey lines) and future climate (orange lines) 100-yr IDF curves (RCP8.5), along with 90% confidence intervals (Ragno et al., 2018, Water Resources Research).



Key Point: Today's 25-yr, 50-yr and 100-yr events are expected to occur more frequently in a warming climate.

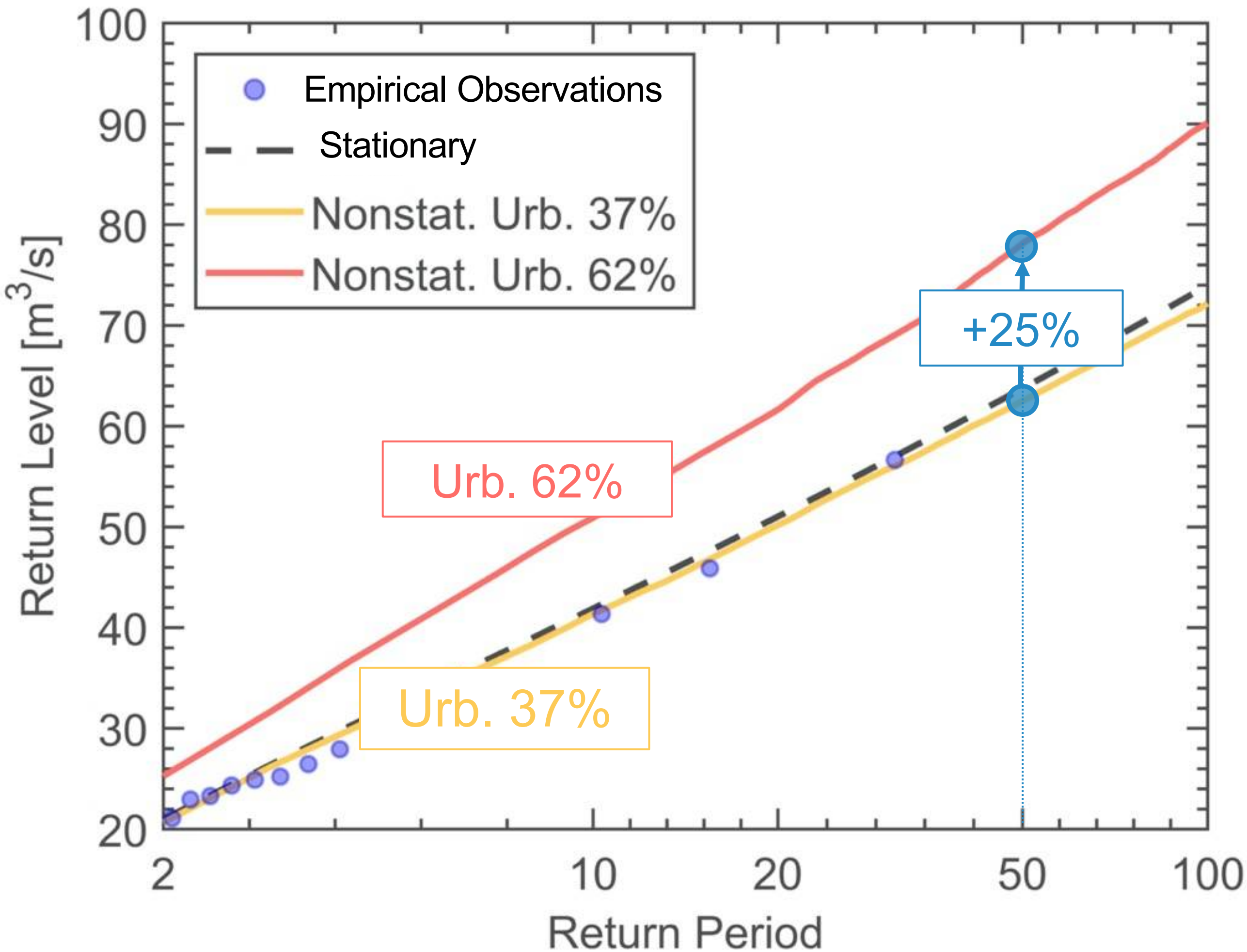
Return periods of future events (orange and red dots), historically associated with return periods of 25-, 50-, and 100-year in California (green lines). Panels a, b, and c show the projected return periods considering two future scenarios: RCP 4.5 (orange dots) and RCP 8.5 (red dots) along with their 90% confidence interval (gray lines).



Key Point: Today's 25-yr, 50-yr and 100-yr events are expected to occur more frequently in a warming climate.

Return periods of extreme precipitation under future climate of events currently associated with return periods of 100 years in urban locations across the United States. For instance, in San Diego, a flood currently associated with a 100 year return period is projected to have a return period of 59 and 30 years under RCP 4.5 and 8.5, respectively (data from Ragno et al., 2018).

ProNEVA – Example Application, Ferson Creek



ProNEVA also allows investigating change in statistics of extremes relative to another variable (e.g., driver of change). This figure shows an example on changes in statistics of floods in response to urbanization.

- Ignoring compounding effects of hazard drivers can lead to underestimation of the risk.
- Droughts have warmed faster than the average climate in the southern and northeastern U.S.
- MvCAT and MhAST can be used for modeling the relationship between different hazards (analysis of compound hazards).
- ProNEVA allows process-informed stationary and nonstationary extreme value analysis including rainfall intensity-duration-frequency curves. The model allows evaluating change in today's extreme return period return levels given multi-model future projections.

Questions?

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