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# A Global-Scale Analysis of Hydrologic Extremes using Hidden Climate Indices

Benjamin Renard, David Mcinerney, Seth Westra, Michael Leonard, Dmitri Kavetski, Mark Thyer, Jean-Philippe Vidal

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# Hydrologic Extremes at the Global Scale

## 100-year Analysis and 180-year Reconstruction

B. Renard<sup>1,2,3</sup> D. McInerney<sup>2</sup> S. Westra<sup>2</sup>  
M. Leonard<sup>2</sup> D. Kavetski<sup>2</sup> M. Thyer<sup>2</sup> J.-P. Vidal<sup>1</sup>

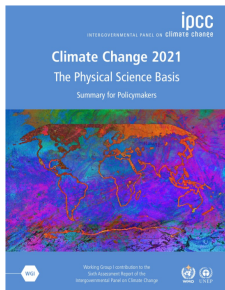
<sup>1</sup>INRAE, RiverLy Research Unit, Lyon, France

<sup>2</sup>School of Civil, Environmental and Mining Engineering, University of Adelaide, Australia

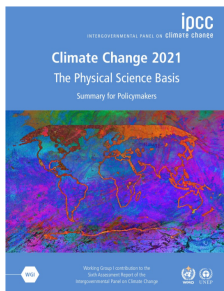
<sup>3</sup>INRAE, RECOVER Research Unit, Aix-en-Provence, France

EGU General Assembly, 27 May 2022





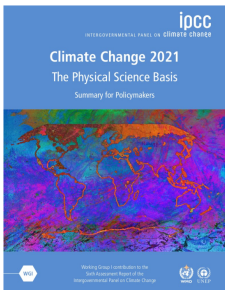
*" The frequency and intensity of heavy precipitation events have increased since the 1950s over most land area for which observational data are sufficient [ . . . ]"*



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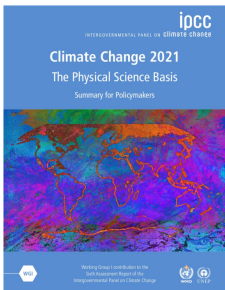
## Water Resources Research

### COMMENTARY

10.1029/2018WR023749

### If Precipitation Extremes Are Increasing, Why Aren't Floods?

Ashish Sharma<sup>1</sup> , Conrad Wasko<sup>2</sup> , and Dennis P. Lettenmaier<sup>3</sup> 



*" The frequency and intensity of heavy precipitation events have increased since the 1950s over most land area for which observational data are sufficient [ . . . ]"*

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### COMMENTARY

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### If Precipitation Extremes Are Increasing, Why Aren't Floods?

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*" changes may be more complex than simple trends"*

## Water Resources Research





### RESEARCH ARTICLE

10.1029/2019WR026575

### Detecting Flood-Rich and Flood-Poor Periods in Annual Peak Discharges Across Europe

#### Key Points:

- A method from Scan statistics is

David Lun<sup>1</sup> , Svenja Fischer<sup>2</sup> , Alberto Viglione<sup>3</sup> , and Günter Blöschl<sup>1</sup> 

# Objectives

Better understand the temporal variability of heavy precipitation (P) and flood (Q) at the global scale by means of an innovative probabilistic model

## 100-year analysis

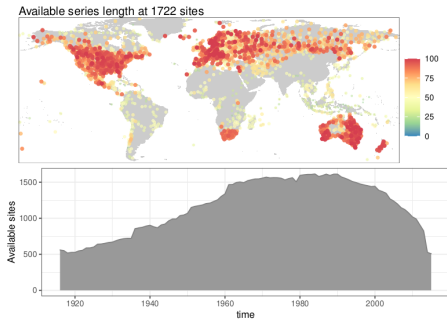
- Identify common (P+Q) vs. specific (P-only or Q-only) signals behind global extremes
- Look for trends and low-frequency variability in those signals

## 180-year reconstruction

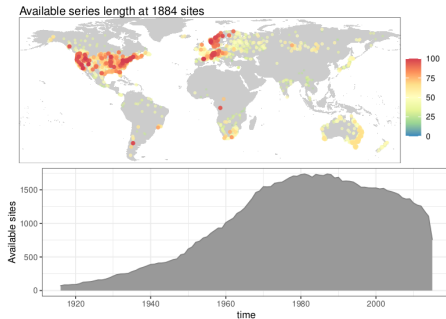
Using 20CRv3, reconstruct probabilities of extreme P/Q since 1836

# Global datasets

**P:** a selection from Hadex 2+3  
Donat et al. (2013); Dunn et al. (2020)

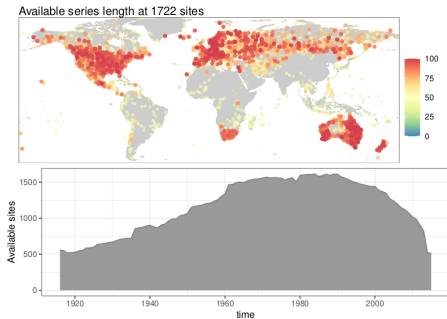


**Q:** a selection from GSIM  
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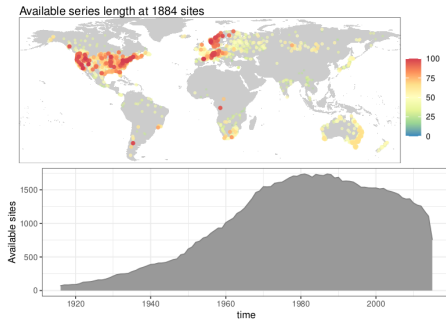


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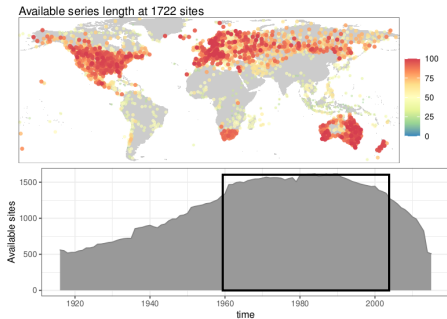
**Q:** a selection from GSIM  
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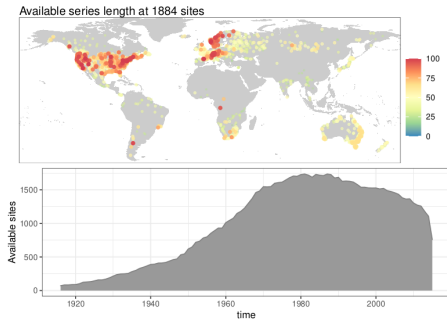
- Extract seasonal maxima at each site (SON, DJF, MAM, JJA)

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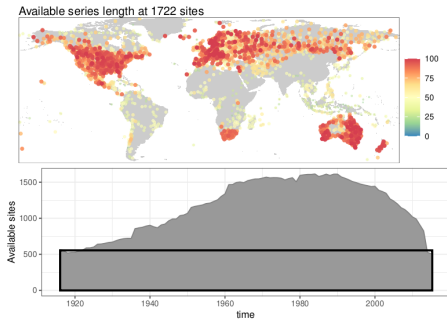
**Q:** a selection from GSIM  
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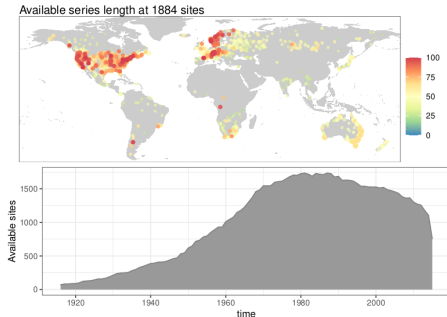
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- The rectangle dilemma...

# Global datasets

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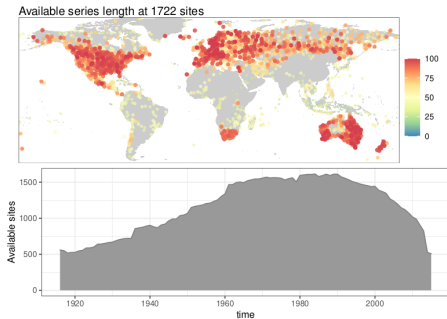
**Q:** a selection from GSIM  
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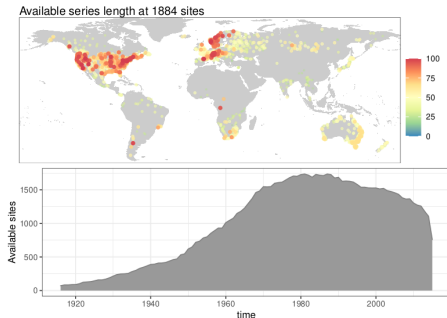
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# Global datasets

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**Q:** a selection from GSIM  
Do et al. (2018); Gudmundsson et al. (2018)



- Extract seasonal maxima at each site (SON, DJF, MAM, JJA)
- The rectangle dilemma...
- In this work, we'll use all data available during 1916-2015



After suitable data transformation...

$$\left\{ \begin{array}{l} \mathbb{E}[P(s, t)] = \\ \mathbb{E}[Q(s, t)] = \end{array} \right.$$

**Legend:** varies in space and time

# Model

After suitable data transformation...

$$\left\{ \begin{array}{l} \mathbb{E}[P(s, t)] = c_P(s) \\ \mathbb{E}[Q(s, t)] = \underbrace{c_Q(s)}_{\text{constant (intercept)}} \end{array} \right.$$

**Legend:** varies in space and time ; varies in space

# Model

After suitable data transformation...

$$\begin{cases} \mathbb{E}[P(s, t)] = c_P(s) + \lambda_P(s)\tau(t) \\ \mathbb{E}[Q(s, t)] = c_Q(s) + \lambda_Q(s)\tau(t) \end{cases}$$

**Legend:** varies in space and time ; varies in space ; varies in time

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**Legend:** varies in space and time ; varies in space ; varies in time

# Model

After suitable data transformation...

$$\begin{cases} \mathbb{E}[P(s, t)] = c_P(s) + \lambda_P(s)\tau(t) + \pi(s)\delta(t) \\ \mathbb{E}[Q(s, t)] = c_Q(s) + \lambda_Q(s)\tau(t) + \theta(s)\omega(t) \end{cases}$$

**Legend:** varies in space and time ; varies in space ; varies in time

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After suitable data transformation...

$$\left\{ \begin{array}{l} \mathbb{E}[P(s, t)] = c_P(s) + \lambda_P(s)\tau(t) + \overbrace{\pi(s)\delta(t)}^{\text{P-specific covariate and its effects}} \\ \mathbb{E}[Q(s, t)] = c_Q(s) + \lambda_Q(s)\tau(t) + \underbrace{\theta(s)\omega(t)}_{\text{Q-specific covariate and its effects}} \end{array} \right.$$

**Legend:** varies in space and time ; varies in space ; varies in time

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**Legend:** varies in space and time ; varies in space ; varies in time

- All covariates are considered unknown and are estimated  
→ *Hidden Climate Indices* (HCI)

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- $\lambda(s) \sim \text{Spatial Gaussian Process}$ . Same for others

After suitable data transformation...

$$\begin{cases} \mathbb{E}[P(s, t)] = c_P(s) + \lambda_P(s)\tau(t) + \pi(s)\delta(t) + \text{more components...} \\ \mathbb{E}[Q(s, t)] = c_Q(s) + \underbrace{\lambda_Q(s)\tau(t)}_{\text{one component}} + \theta(s)\omega(t) + \text{more components...} \end{cases}$$

**Legend:** varies in space and time ; varies in space ; varies in time

- All covariates are considered unknown and are estimated  
→ *Hidden Climate Indices* (HCI)
- $\tau(t) \sim \text{AR}(1) + \text{trend}$ . Same for  $\delta(t)$  and  $\omega(t)$
- $\lambda(s) \sim \text{Spatial Gaussian Process}$ . Same for others
- One component not enough at the global scale → 5 used here

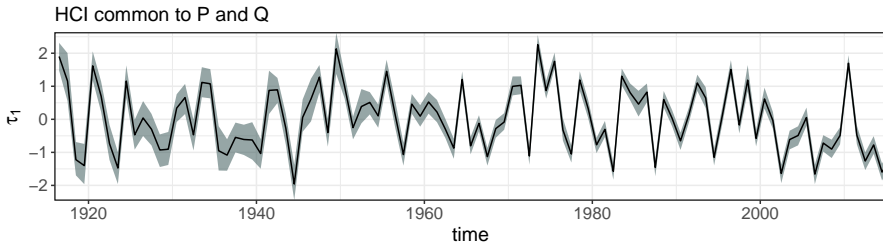
After suitable data transformation...

$$\left\{ \begin{array}{l} \mathbb{E}[P(s, t)] = c_P(s) + \lambda_P(s)\tau(t) + \pi(s)\delta(t) + \text{more components...} \\ \mathbb{E}[Q(s, t)] = c_Q(s) + \lambda_Q(s)\tau(t) + \theta(s)\omega(t) + \text{more components...} \end{array} \right.$$

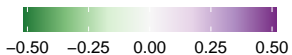
**Legend:** varies in space and time ; varies in space ; varies in time

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- One component not enough at the global scale → 5 used here
- (Bayesian + MCMC) estimation

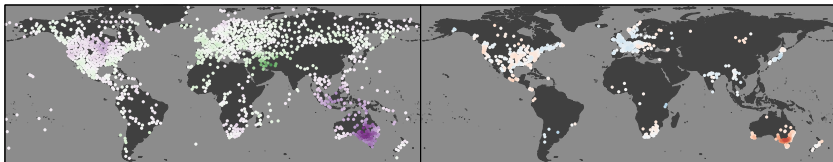
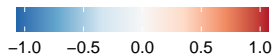
# Ex.: SON season, 1st common HCI



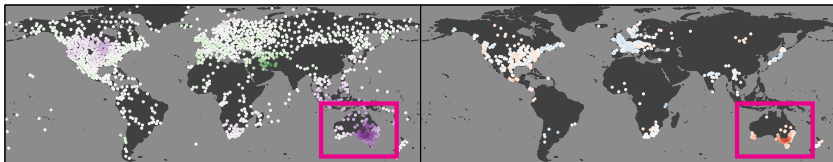
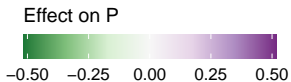
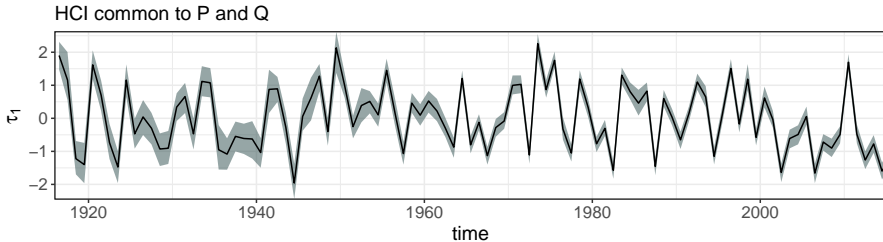
Effect on P



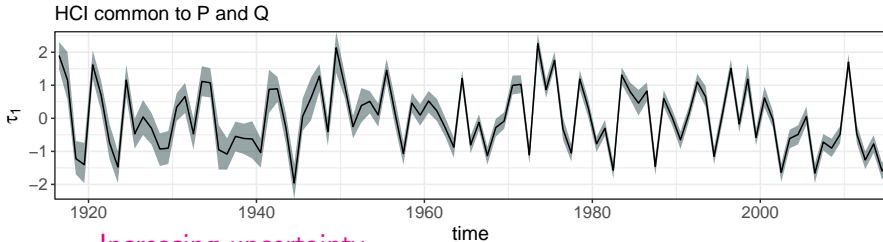
Effect on Q



# Ex.: SON season, 1st common HCI



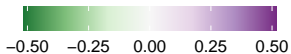
# Ex.: SON season, 1st common HCI



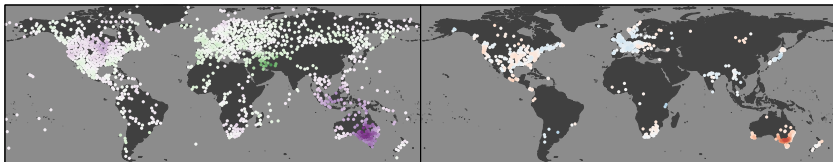
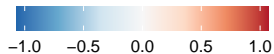
Increasing uncertainty



Effect on P



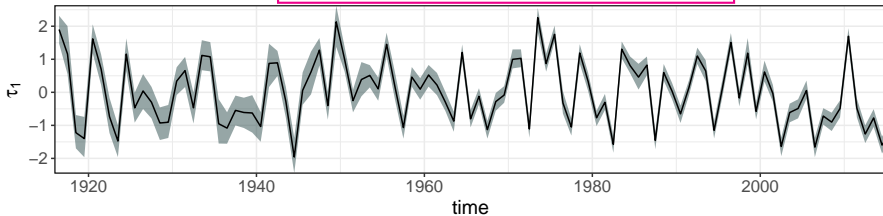
Effect on Q



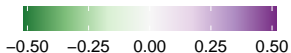
# Ex.: SON season, 1st common HCI

HCI common to P and Q.

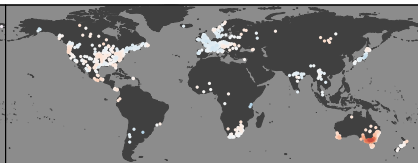
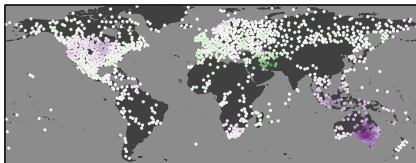
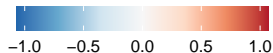
Trend (%) =  $-0.42$   $[-1.08; 0.28]$ ,  $r = 0.05$   $[0.00; 0.25]$



Effect on P

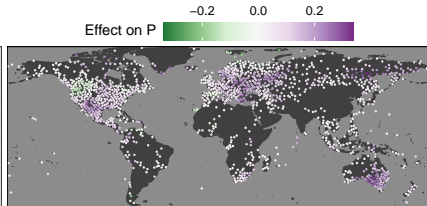
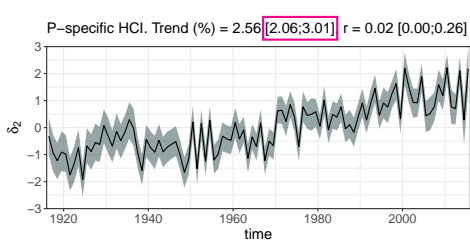


Effect on Q

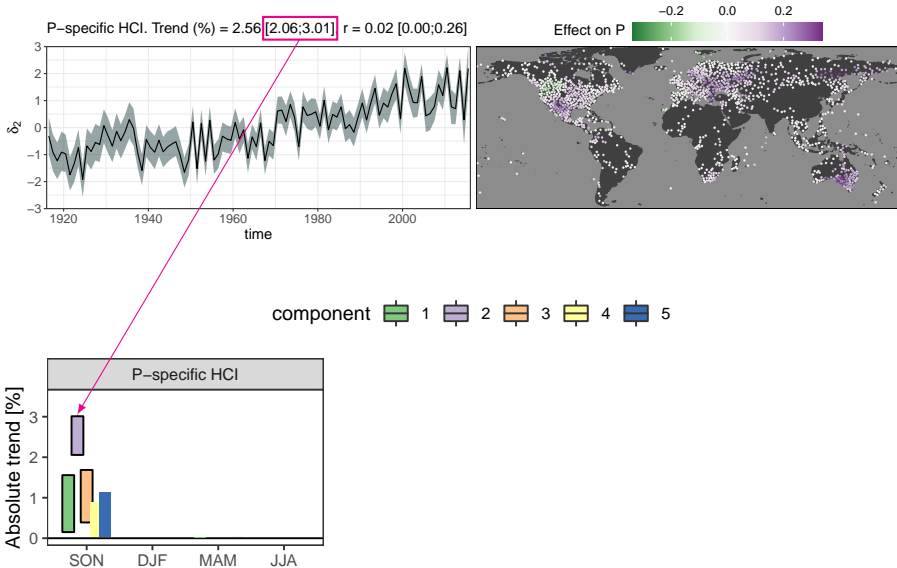




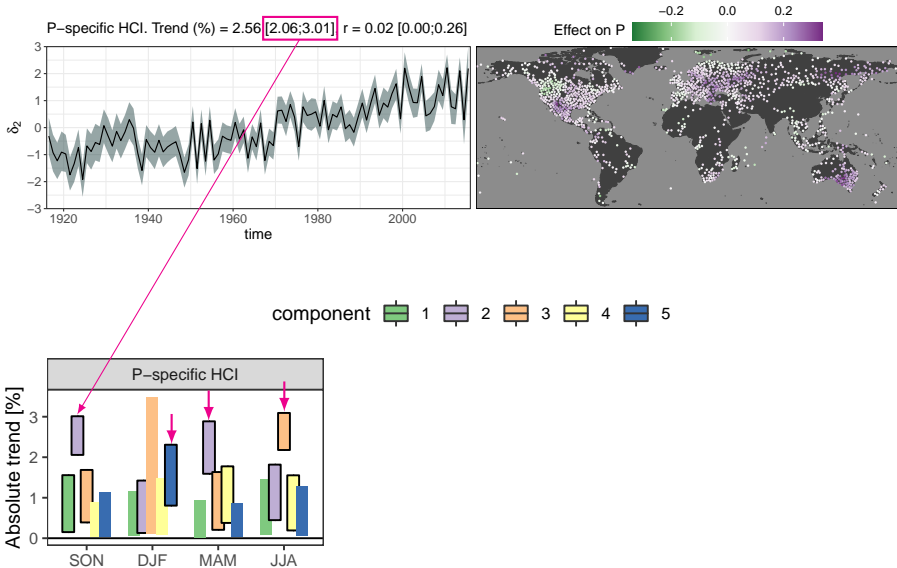
# Trends and autocorrelations



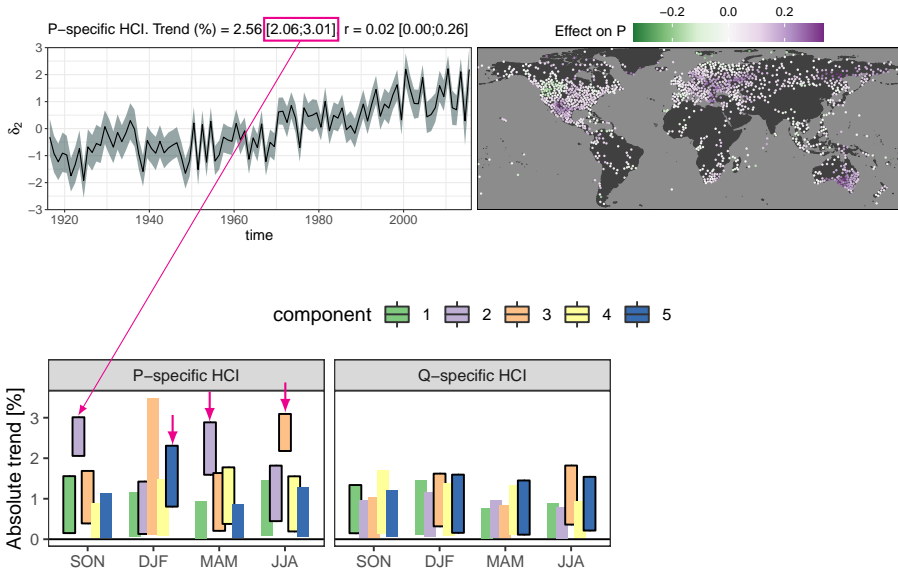
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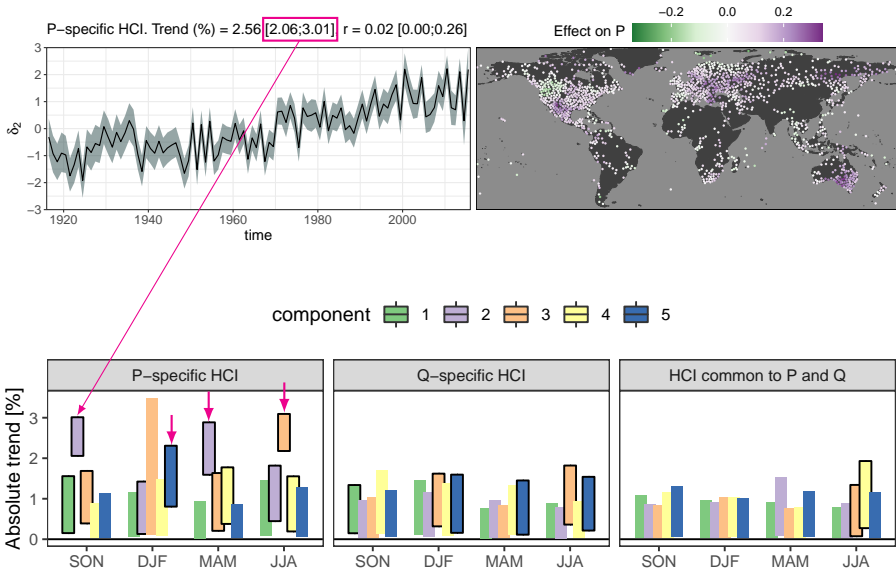
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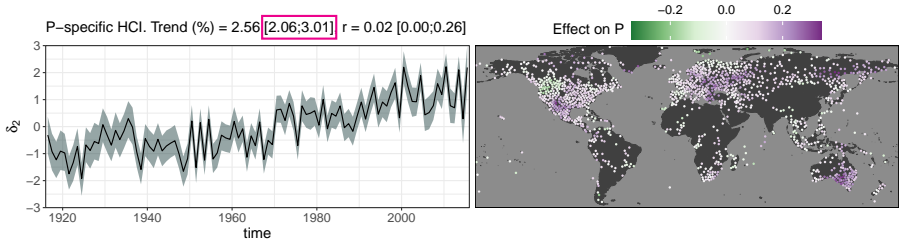
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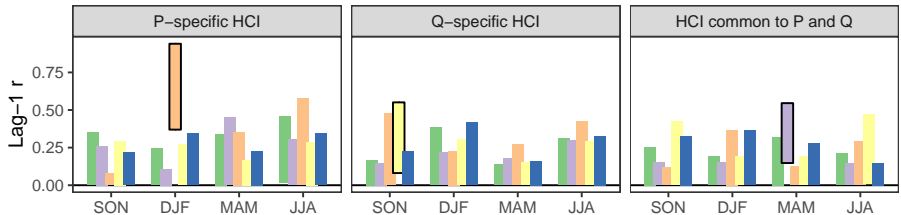
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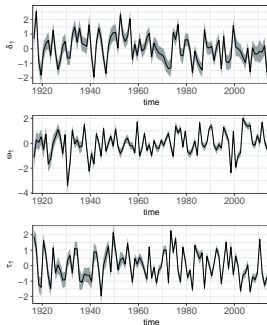
# Trends and autocorrelations



component  1  2  3  4  5

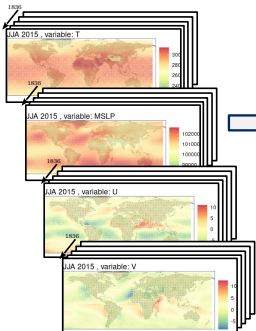


## Hidden Climate Indices

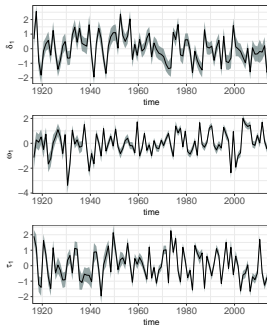


# 180-year reconstruction

## Climate predictors

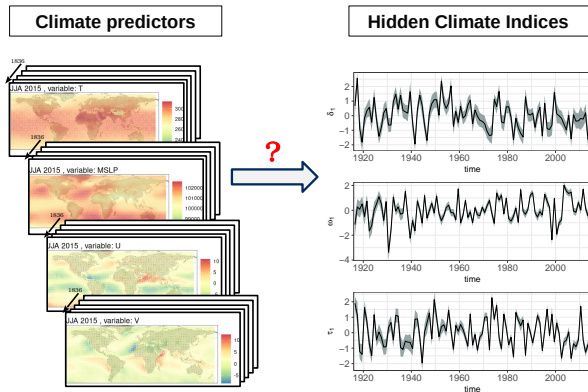


## Hidden Climate Indices



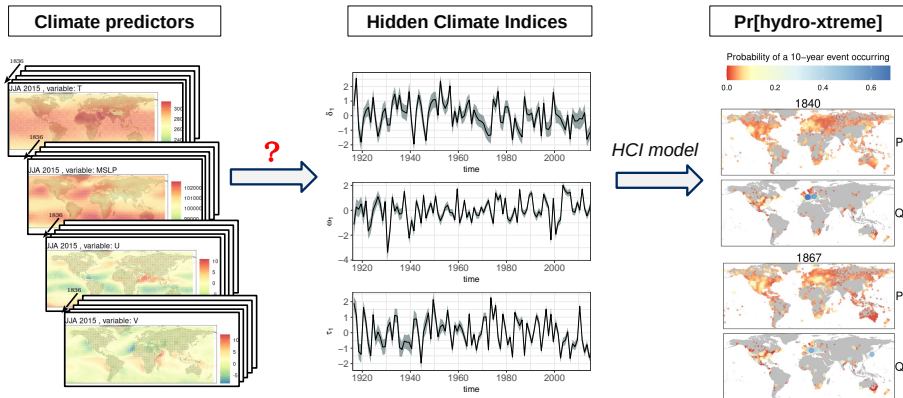


# 180-year reconstruction



- Using 20CRv3, reconstruction of HCIs from 1836
- Hydro-extreme probability maps from 1836

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- Hydro-extreme probability maps from 1836

# Thank you!

Renard & Thyer (2019). Revealing Hidden Climate Indices from the Occurrence of Hydrologic Extremes. *Water Resources Research*.

Renard et al. (2021). A Hidden Climate Indices Modeling Framework for Multi-Variable Space-Time Data. *Water Resources Research*.



<https://globxblog.inrae.fr/>



<https://github.com/STooDs-tools>



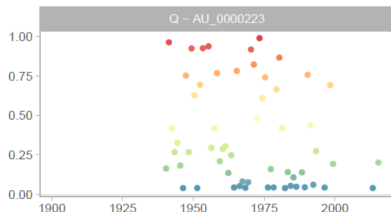
This project has received funding from the European Union's Horizon 2020 research and innovation programme under the Marie Skłodowska-Curie grant agreement No 835496

# Analyzed variables

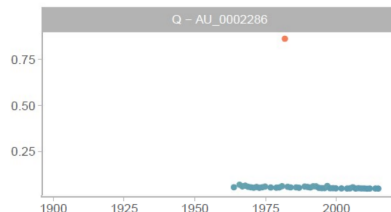
Non-exceedance probability ( $\Leftrightarrow$  return period) of the largest event of the season

**Example:** Maximum streamflow in December-January-February for 2 Australian stations

Barker Creek at Brooklands (QLD)



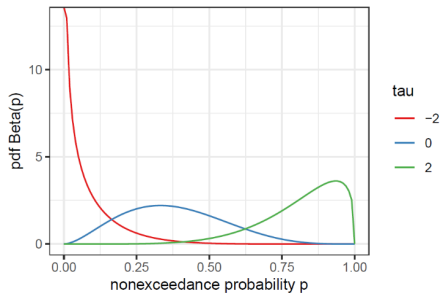
Clarke Brooke at Hillview Farm (WA)



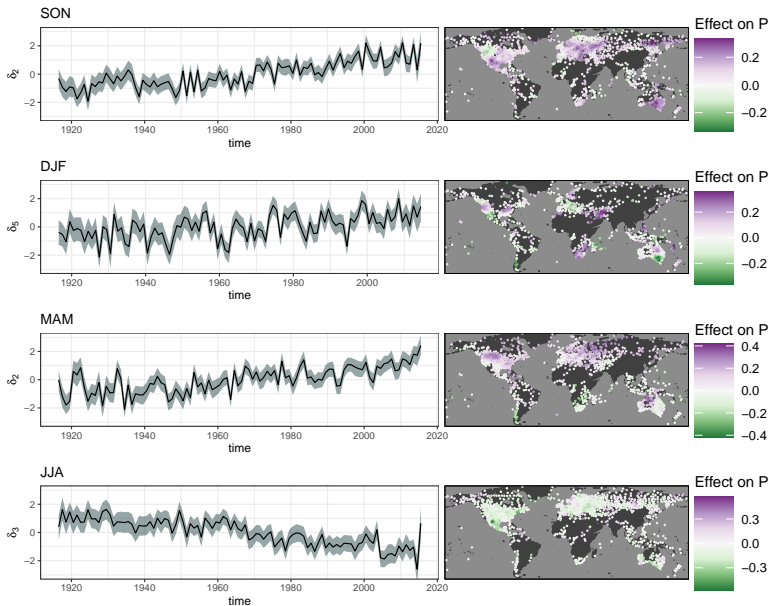
# Model

Beta distribution reparameterized in terms of mean  $\mu$  and precision  $\gamma$

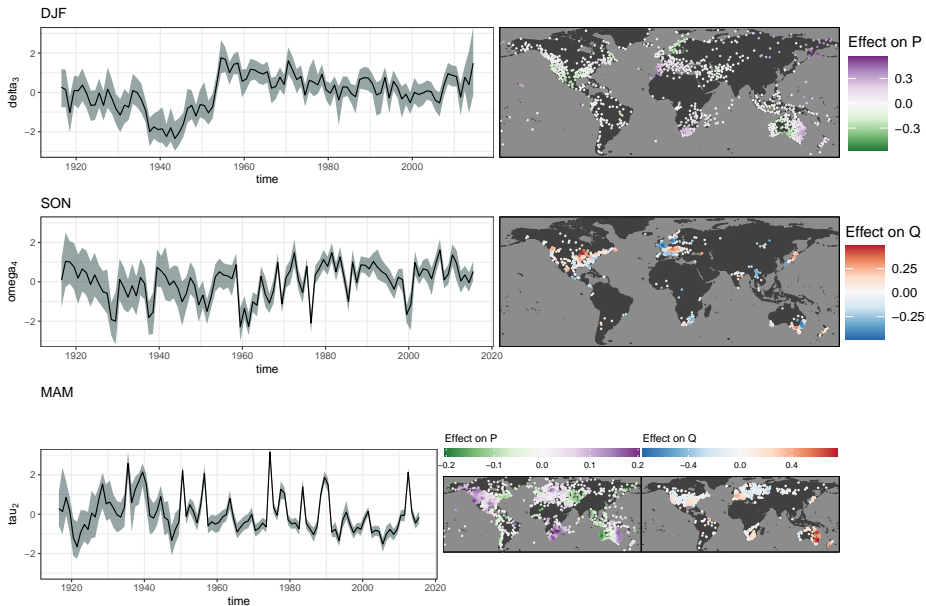
$$\left\{ \begin{array}{l} P(s, t) \sim \text{Beta}(\mu_P(s, t), \gamma_P(s)); Q(s, t) \sim \text{Beta}(\mu_Q(s, t), \gamma_Q(s)) \\ \text{logit}(\mu_P(s, t)) = \lambda_{P,0}(s) + \sum_{k=1}^K \lambda_{P,k}(s)\tau_k(t) + \sum_{k=1}^K \pi_k(s)\delta_k(t) \\ \text{logit}(\mu_Q(s, t)) = \lambda_{Q,0}(s) + \sum_{k=1}^K \lambda_{Q,k}(s)\tau_k(t) + \sum_{k=1}^K \theta_k(s)\omega_k(t) \end{array} \right.$$



# P-specific HCIs with large trends



# HCI with notable autocorrelation



## Method: inverted regression

**Step 1:**  $w(s, t)$ : climate field at time  $t$  and location  $s$

$\hat{\tau}_k(t)$ : estimated HCI's (from previous analysis)

Goal: estimate  $\psi_k(s)$ 's in:

$$w(s, t) = \psi_0(s) + \psi_1(s)\hat{\tau}_1(t) + \dots + \psi_K(s)\hat{\tau}_K(t) + \varepsilon(s, t)$$

**Step 2:**  $w(s, t^*)$ : climate field at time  $t^*$  and location  $s$

$\hat{\psi}_k(s)$ : estimated from previous step

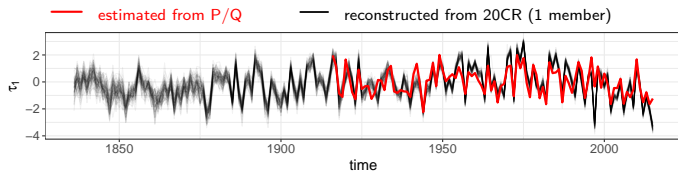
Goal: estimate  $\tau_k(t^*)$ 's in:

$$w(s, t^*) = \psi_0(s) + \hat{\psi}_1(s)\tau_1(t^*) + \dots + \hat{\psi}_K(s)\tau_K(t^*) + \varepsilon(s, t^*)$$

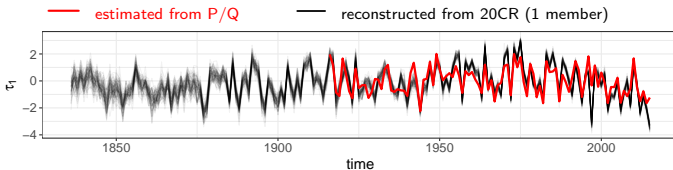
**Alternatives:** LASSO, RIDGE and other form of penalised regression, but first attempts inconclusive



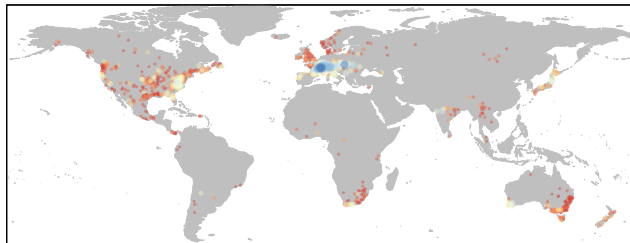
# Reconstructions from 20CRv3 (1836-2015)



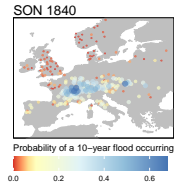
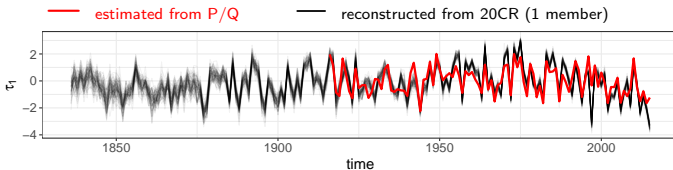
# Reconstructions from 20CRv3 (1836-2015)



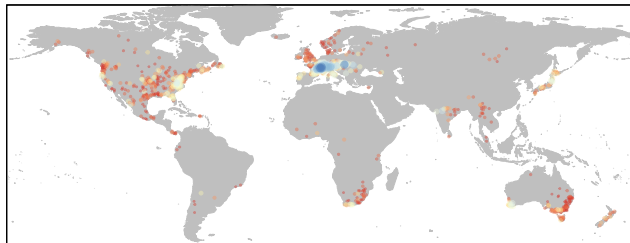
## SON 1840



# Reconstructions from 20CRv3 (1836-2015)



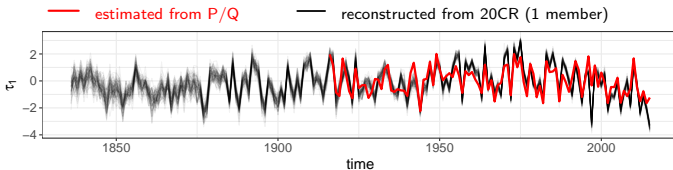
SON 1840



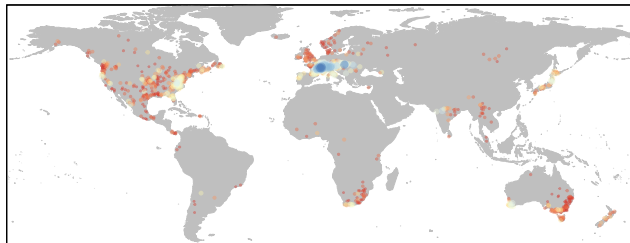
Probability of a 10-year flood occurring



# Reconstructions from 20CRv3 (1836-2015)



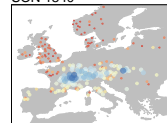
## SON 1840



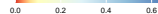
Probability of a 10-year flood occurring



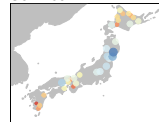
## SON 1840



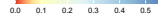
Probability of a 10-year flood occurring



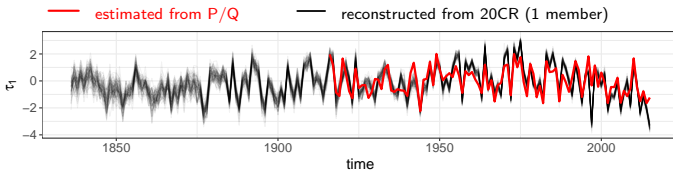
## SON 1867



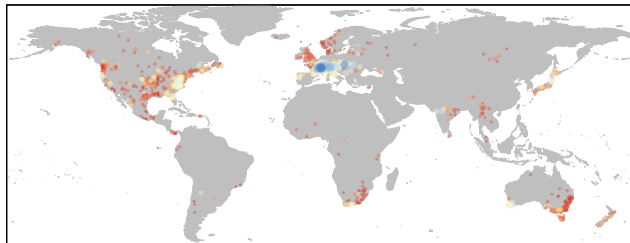
Probability of a 10-year flood occurring



# Reconstructions from 20CRv3 (1836-2015)



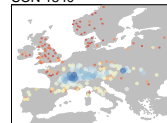
## SON 1840



Probability of a 10-year flood occurring



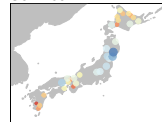
## SON 1840



Probability of a 10-year flood occurring



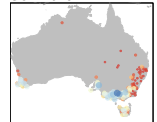
## SON 1867



Probability of a 10-year flood occurring



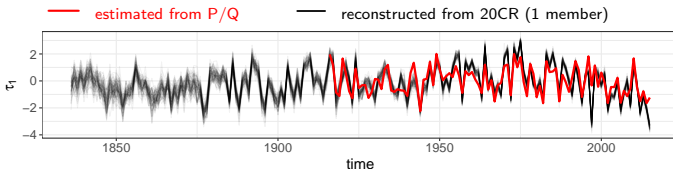
## SON 1916



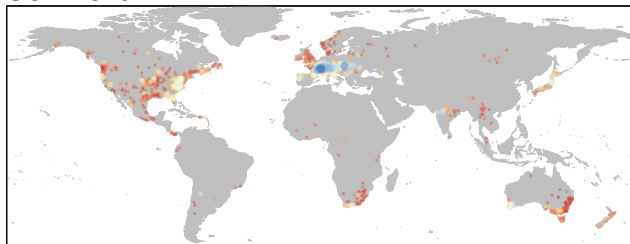
Probability of a 10-year flood occurring



# Reconstructions from 20CRv3 (1836-2015)



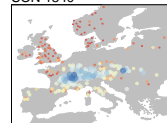
## SON 1840



Probability of a 10-year flood occurring



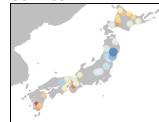
## SON 1840



Probability of a 10-year flood occurring



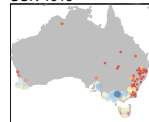
## SON 1867



Probability of a 10-year flood occurring



## SON 1916



Probability of a 10-year flood occurring



→ **Reliability**: good (cross-validation); **Sharpness**: poor (P) to good (Q)