# Hydrologic Extremes at the Global Scale

## 100-year Analysis and 180-year Reconstruction

B. Renard[1,2,3] D. McInerney[2] S. Westra[2]
M. Leonard[2] D. Kavetski[2] M. Thyer[2] J.-P. Vidal[1]

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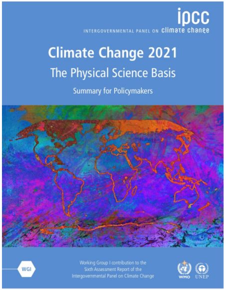
[2]School of Civil, Environmental and Mining Engineering, University of Adelaide, Australia

[3]INRAE, RECOVER Research Unit, Aix-en-Provence, France

EGU General Assembly, 27 May 2022

# Introduction

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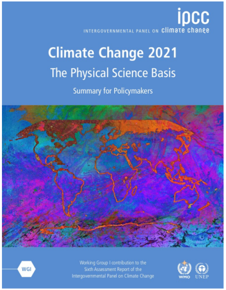


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"*Confidence about peak flow trends over past decades on the global scale is low [. . . ]*"

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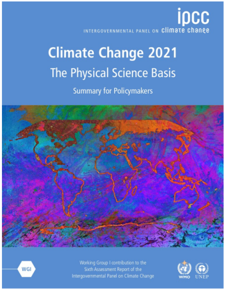


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**Water Resources Research**

**COMMENTARY**
10.1029/2018WR023749

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

**Ashish Sharma[1], Conrad Wasko[2], and Dennis P. Lettenmaier[3]**

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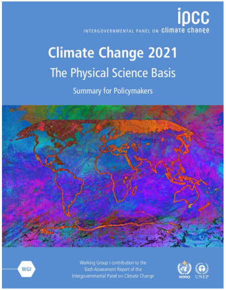


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*" changes may be more complex than simple trends"*

**Water Resources Research**

**RESEARCH ARTICLE**
10.1029/2019WR026575

Key Points:
- A method from Scan statistics is

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

David Lun[1], Svenja Fischer[2], Alberto Viglione[3], and Günter Blöschl[1]

# Objectives

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

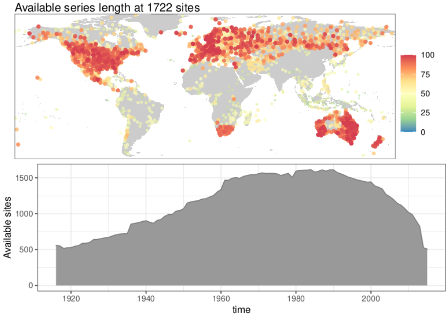
## 100-year analysis

- 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

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




**Q**: a selection from GSIM
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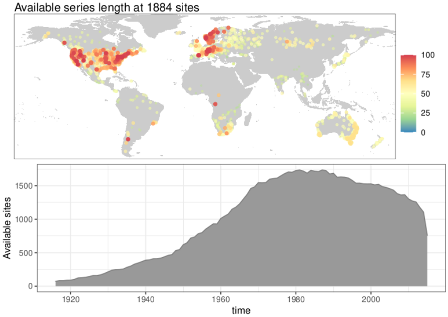

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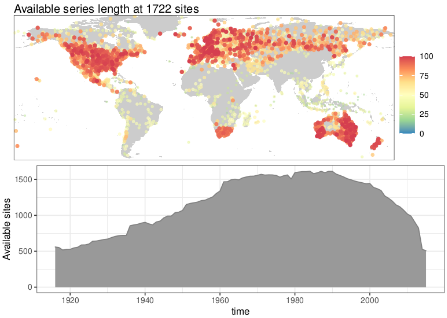


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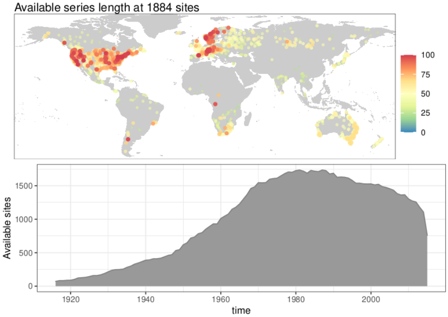


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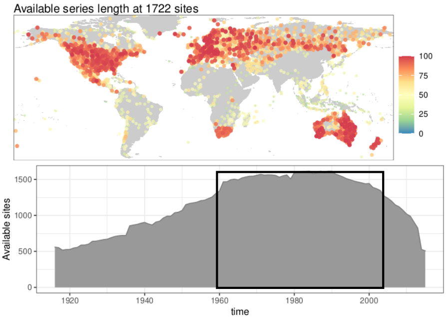


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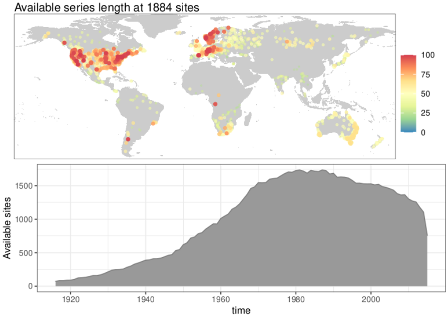


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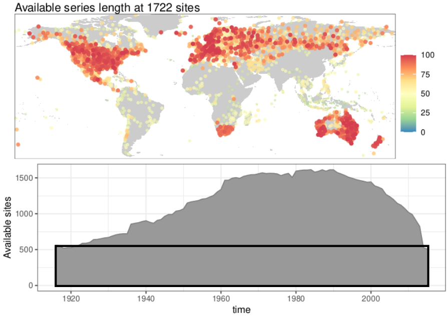


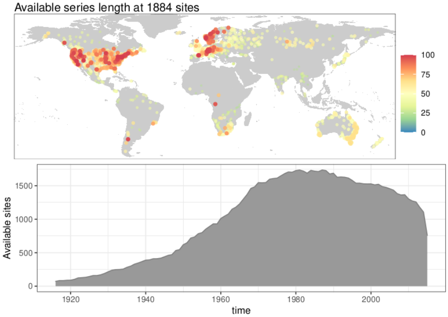


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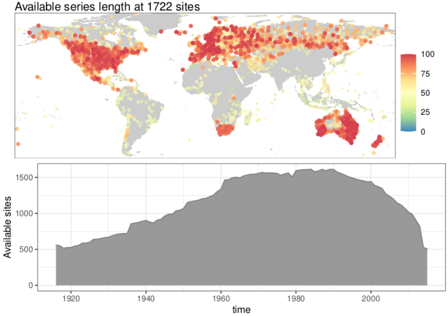


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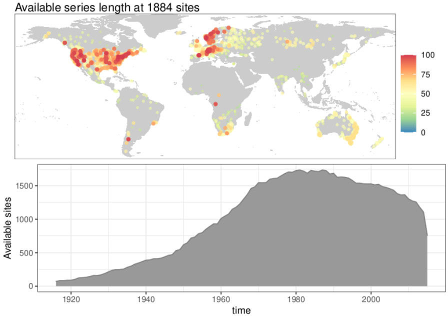


- Extract seasonal maxima at each site (SON, DJF, MAM, JJA)
- The rectangle dilemma...
- In this work, we'll use all data available during 1916-2015

# Model

After suitable data transformation...

$$\begin{cases} \mathbb{E}[P(s,t)] = \\ \\ \mathbb{E}[Q(s,t)] = \end{cases}$$

**Legend**: varies in space and time

# Model

After suitable data transformation...

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

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

# Model

After suitable data transformation...

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

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

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

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

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- $\tau(t) \sim \text{AR}(1) + \text{trend}$.

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- $\tau(t) \sim$ AR(1) + trend. Same for $\delta(t)$ and $\omega(t)$
- $\lambda(s) \sim$ Spatial Gaussian Process. Same for others

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After suitable data transformation...

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

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

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  $\rightarrow$ *Hidden Climate Indices* (HCI)
- $\tau(t) \sim \text{AR}(1) + \text{trend}$. Same for $\delta(t)$ and $\omega(t)$
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- One component not enough at the global scale $\rightarrow$ 5 used here

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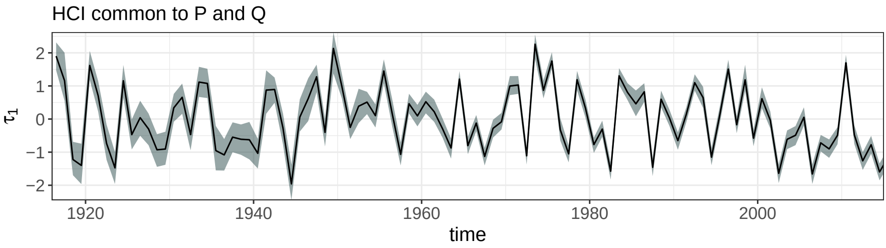
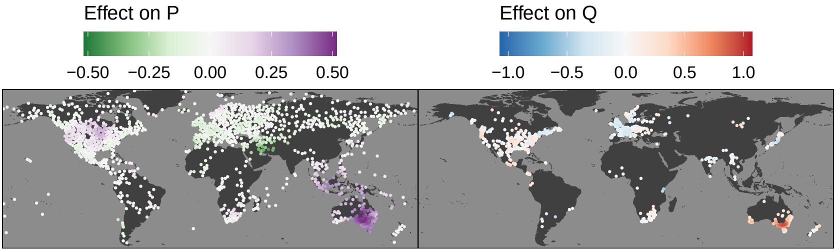
- One component not enough at the global scale $\rightarrow$ 5 used here
- (Bayesian + MCMC) estimation

# Ex.: SON season, 1st common HCI



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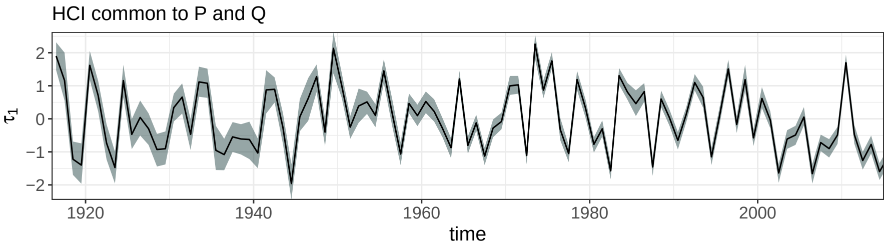


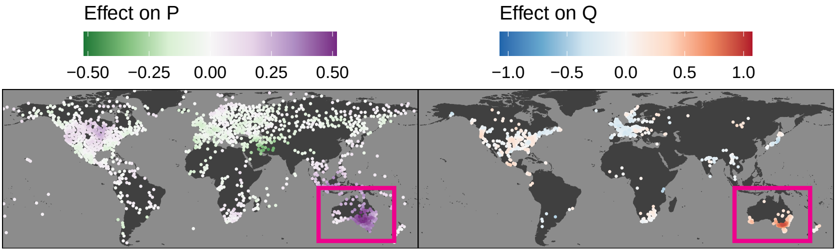

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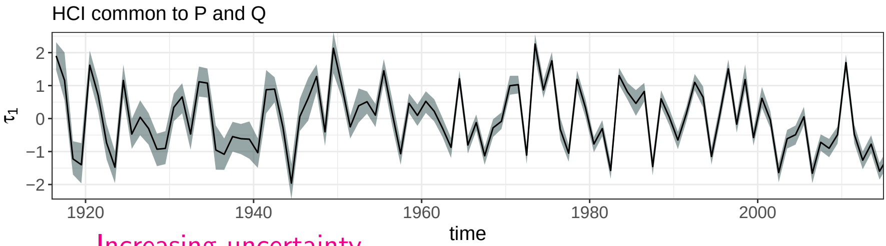
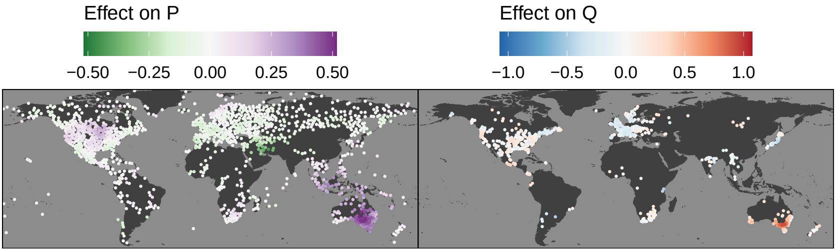



Increasing uncertainty



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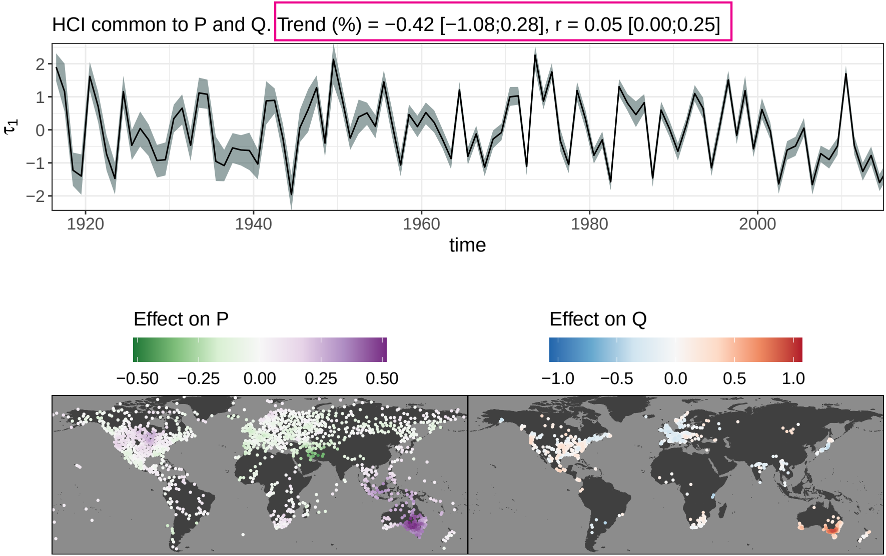
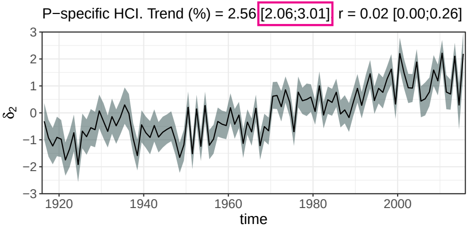
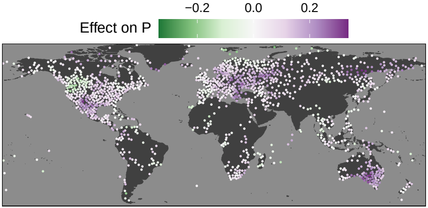


# Trends and autocorrelations



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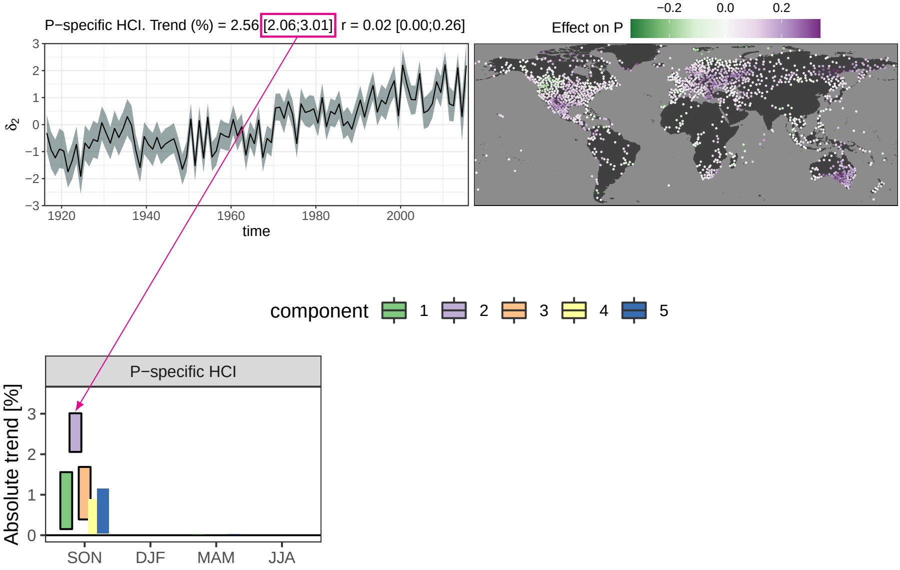

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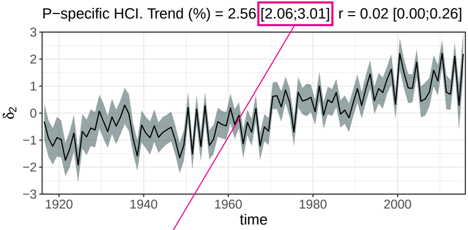


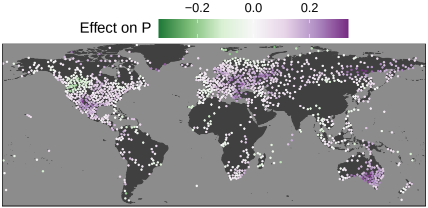


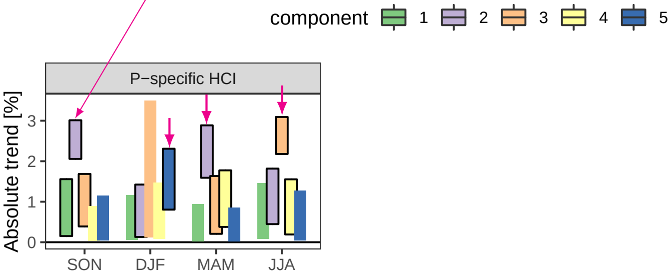

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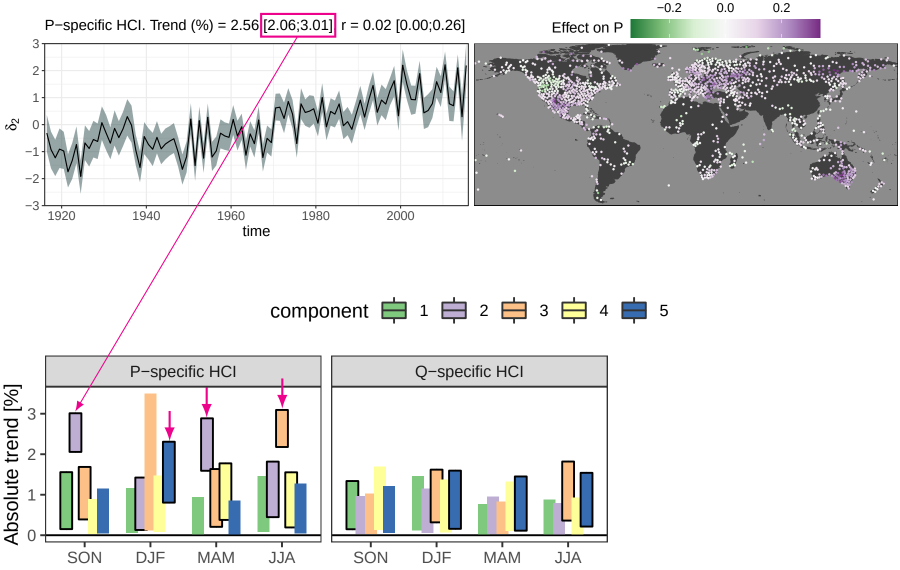

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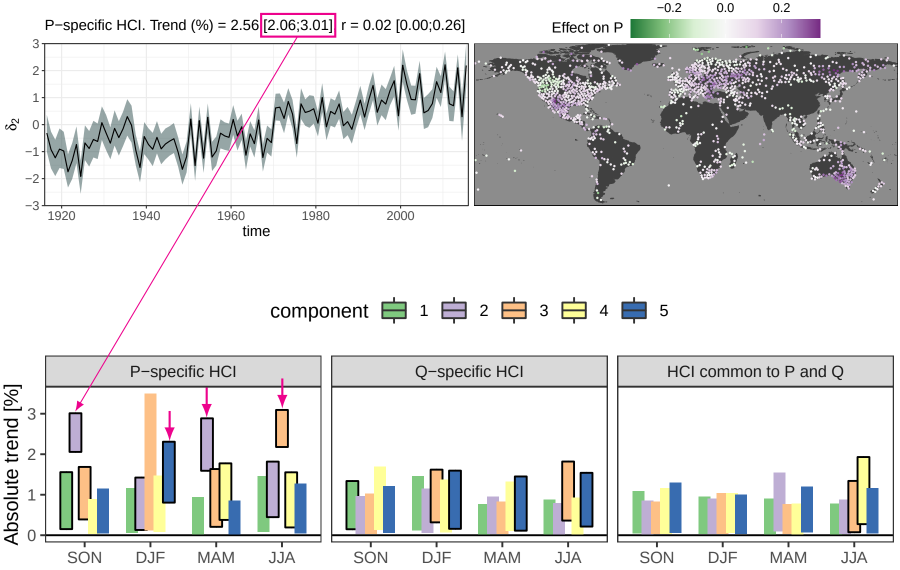

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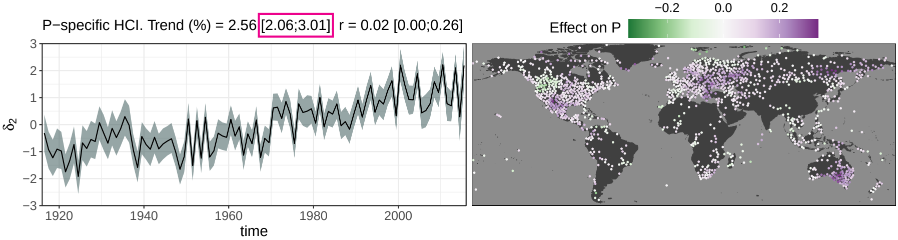
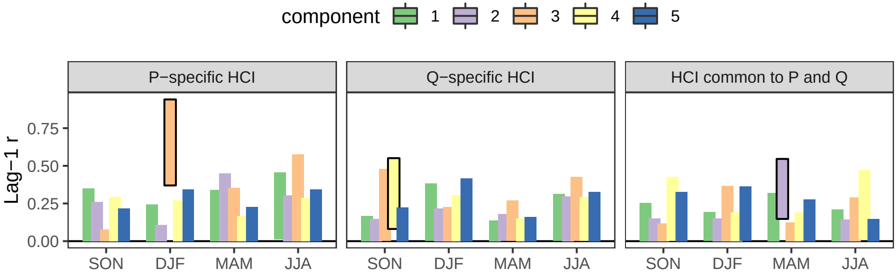
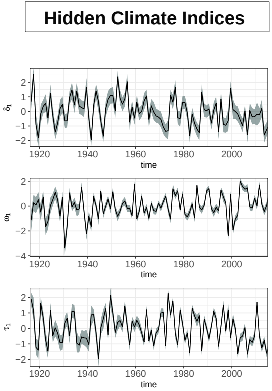


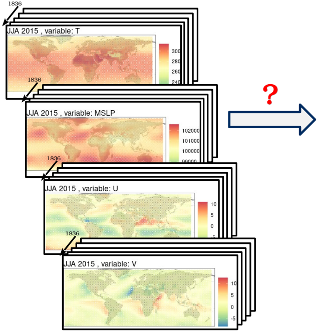



# 180-year reconstruction

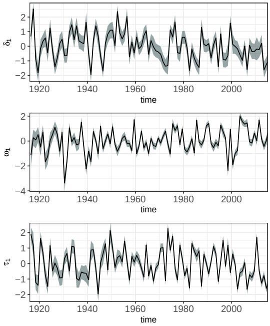


# 180-year reconstruction

**Climate predictors**




**Hidden Climate Indices**



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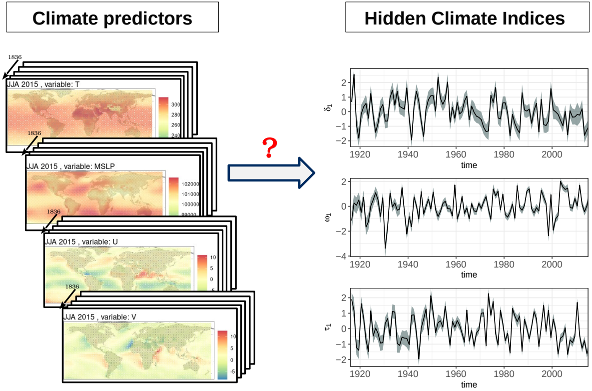


→ Using 20CRv3, reconstruction of HCIs from 1836

→ Hydro-extreme probability maps from 1836

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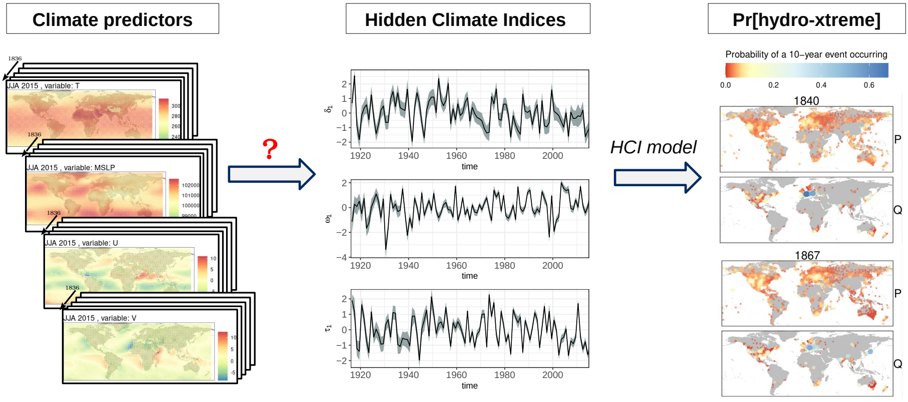


→ Using 20CRv3, reconstruction of HCIs from 1836

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# 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/

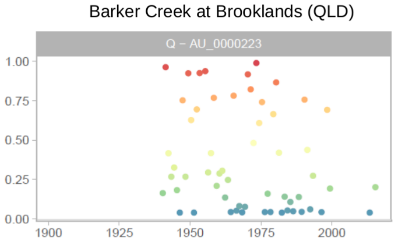
https://github.com/STooDs-tools

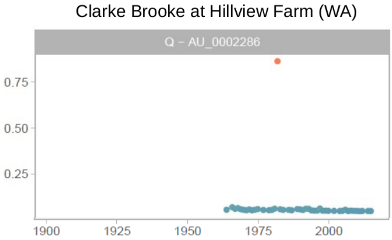
This project has received funding from the European Union's Horizon 2020 research and innovation programme under the Marie Sklodowska-Curie grant agreement No 835496

# Analyzed variables

Non-exceedance probability (⇔ return period) of the largest event of the season

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

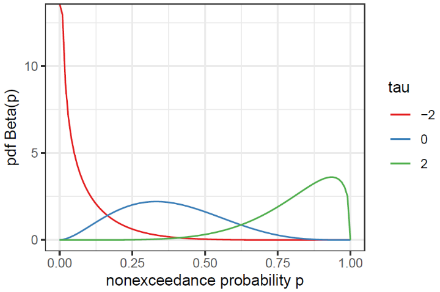


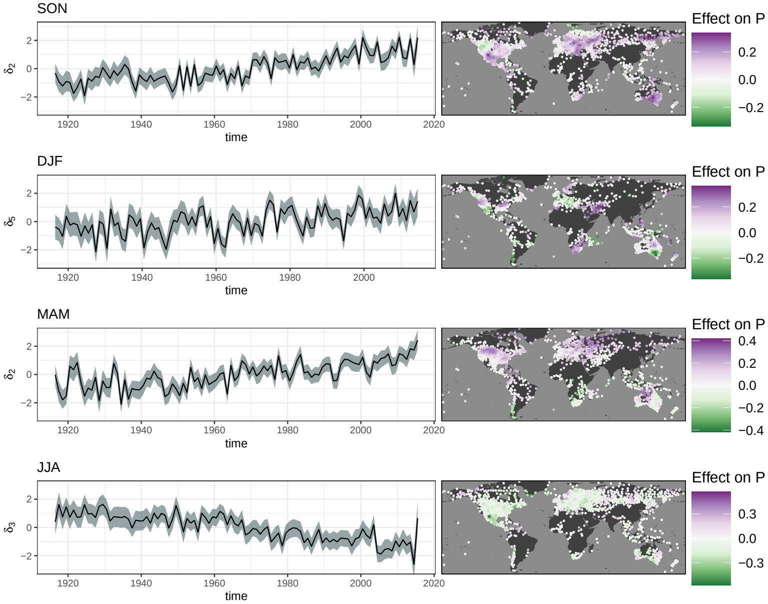
# Model

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

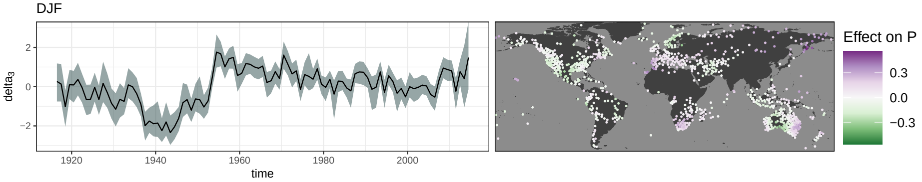
$$\begin{cases} P(s,t) \sim Beta\left(\mu_P(s,t), \gamma_P(s)\right); Q(s,t) \sim Beta\left(\mu_Q(s,t), \gamma_Q(s)\right) \\ logit\left(\mu_P(s,t)\right) = \lambda_{P,0}(s) + \sum_{k=1}^{K} \lambda_{P,k}(s)\tau_k(t) + \sum_{k=1}^{K} \pi_k(s)\delta_k(t) \\ logit\left(\mu_Q(s,t)\right) = \lambda_{Q,0}(s)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

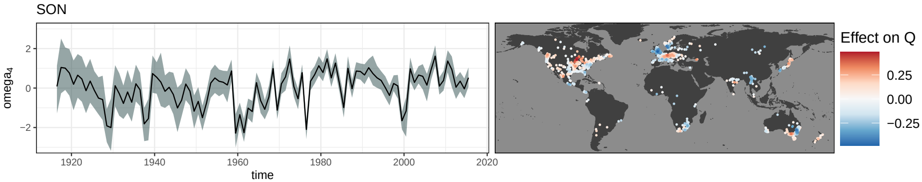


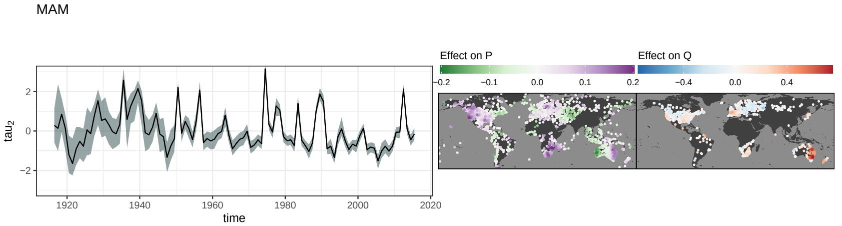
# P-specific HCIs with large trends



# HCIs with notable autocorrelation



# Downscaling approach

## Method: inverted regression

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

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

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

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

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

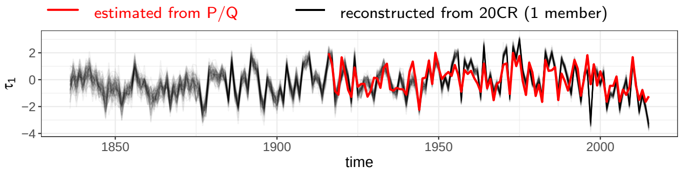
$\widehat{\psi}_k(s)$: estimated from previous step

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

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

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

# Reconstructions from 20CRv3 (1836-2015)



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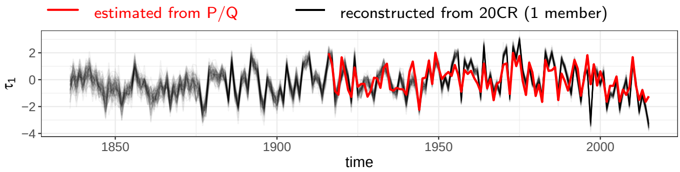


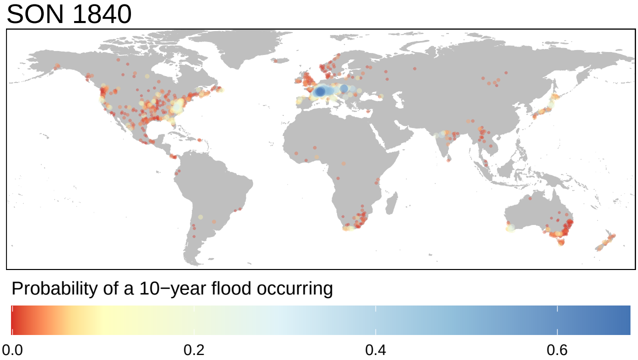

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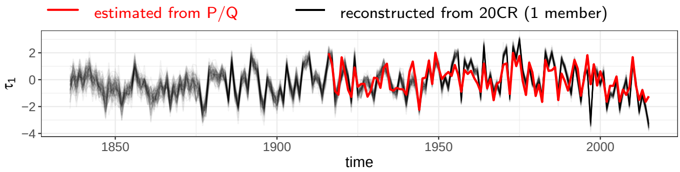


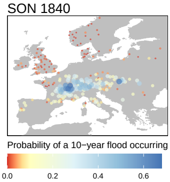


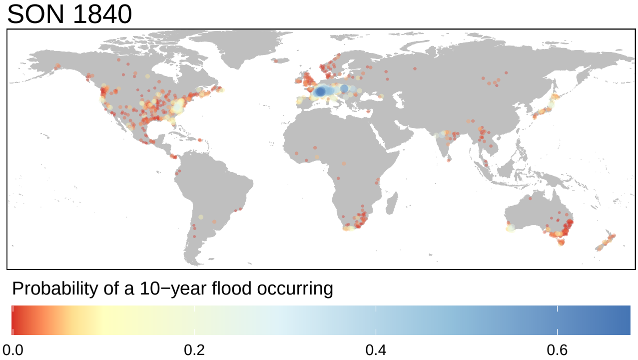

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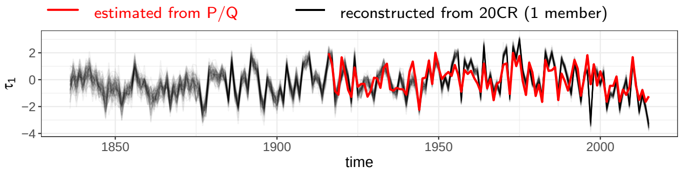


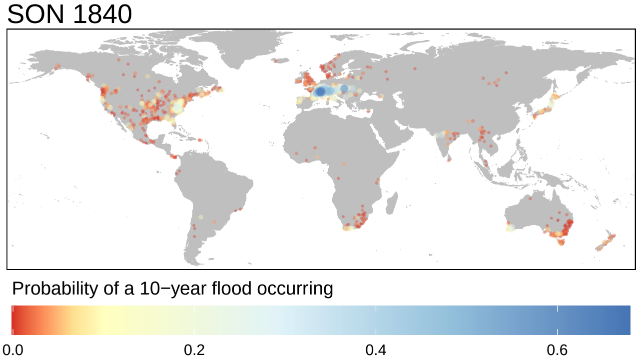


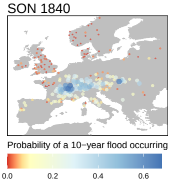


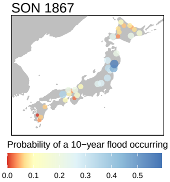

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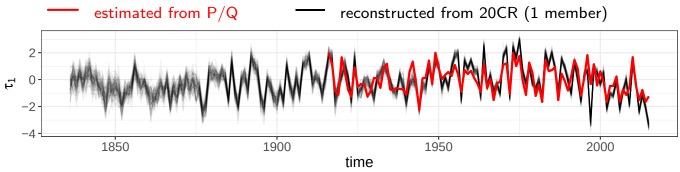


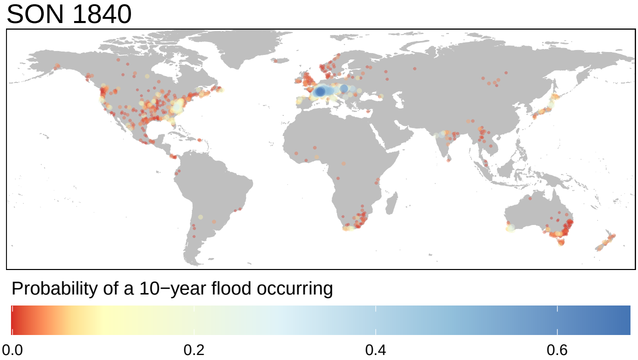


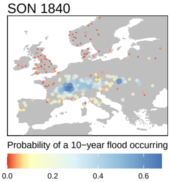


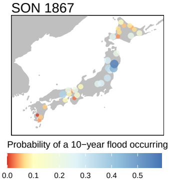


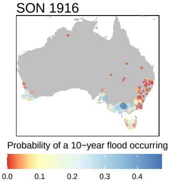

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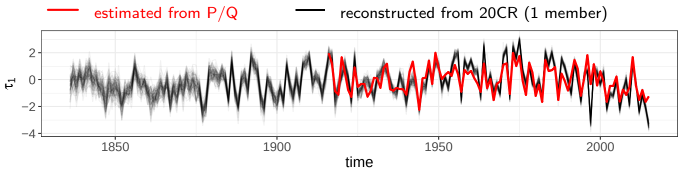


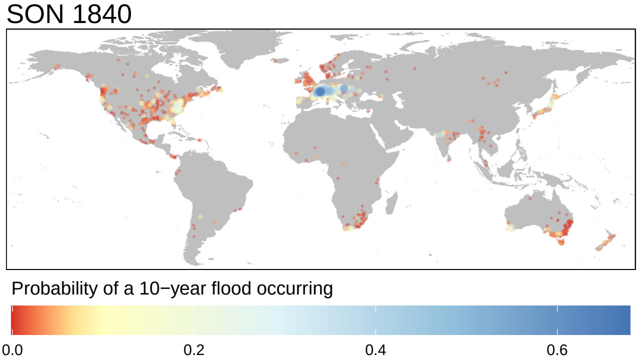


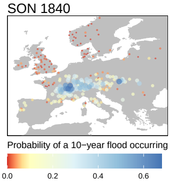


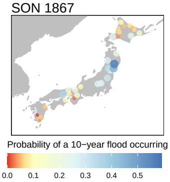


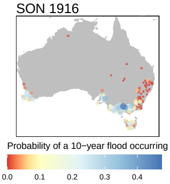


→ **Reliability**: good (cross-validation); **Sharpness**: poor (P) to good (Q)