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

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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]

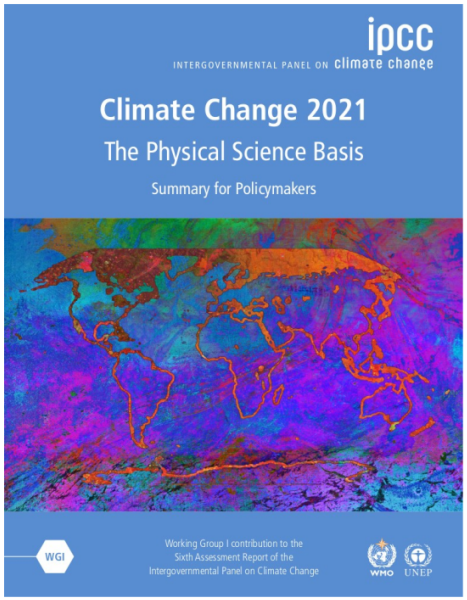
[1]INRAE, RiverLy Research Unit, Lyon, France

[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



" 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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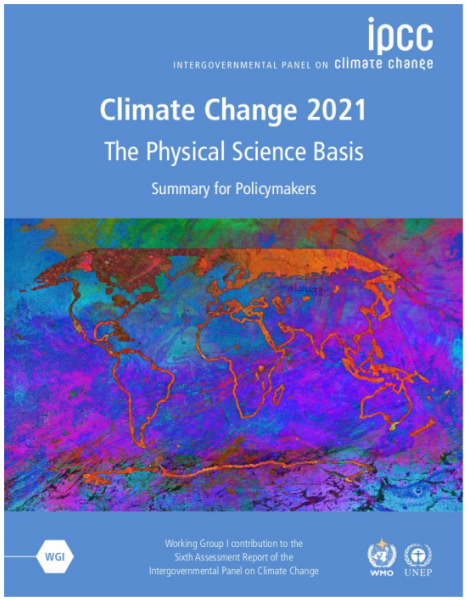

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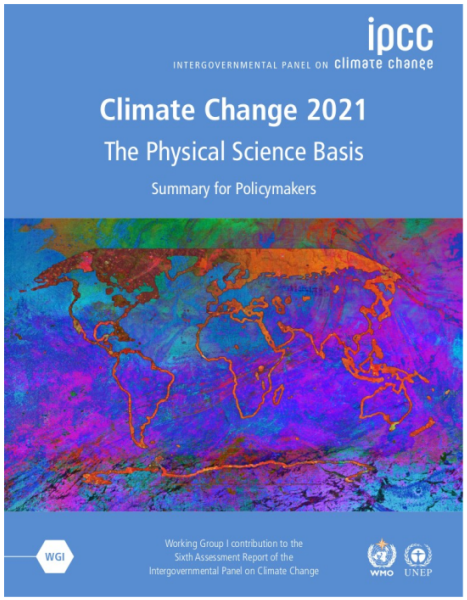

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Water Resources Research

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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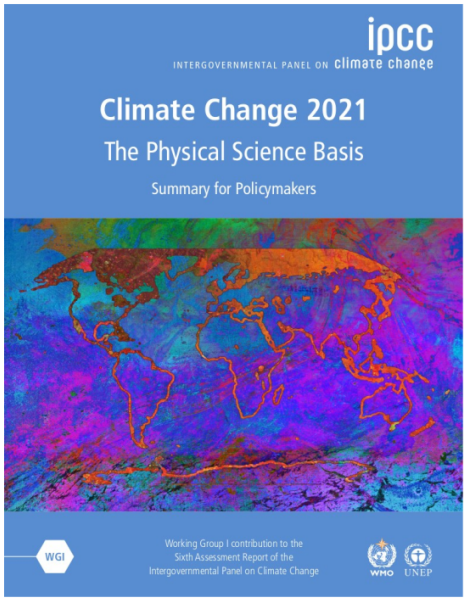

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" changes may be more complex than simple trends"

Water Resources Research

RESEARCH ARTICLE
10.1029/2019WR026575

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

Key Points:
- A method from Scan statistics is

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

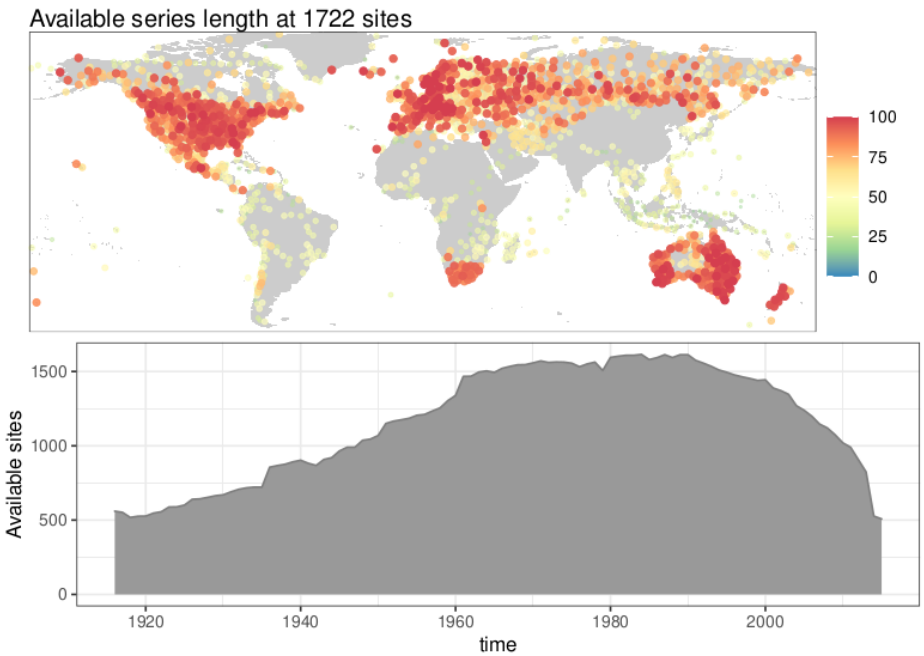
- Identify common (P+Q) vs. specific (P-only or Q-only) signals behind global extremes
- Look for trends and low-frequency variability in those signals

180-year reconstruction

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

Global datasets

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



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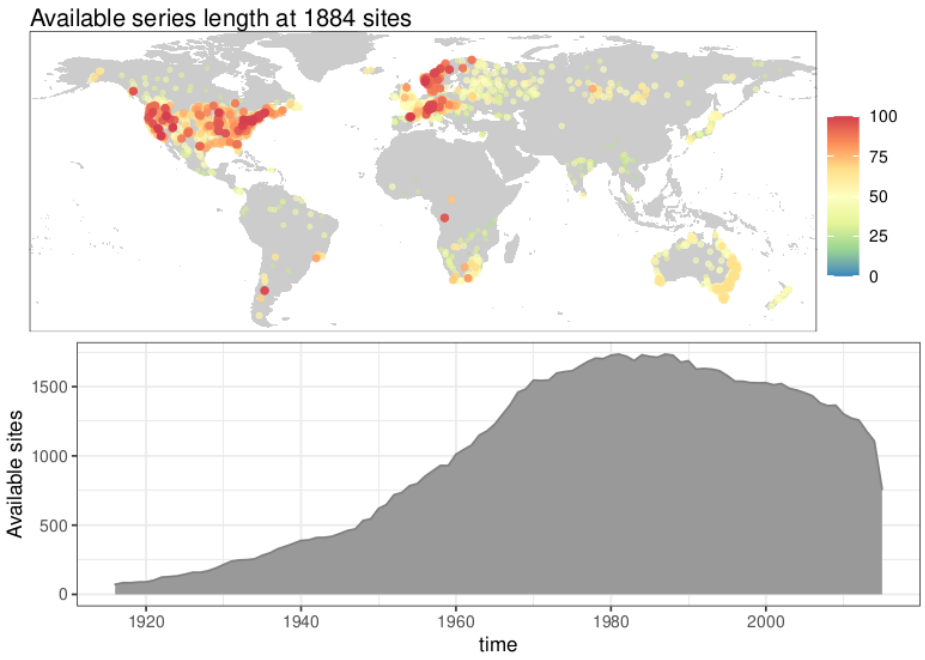

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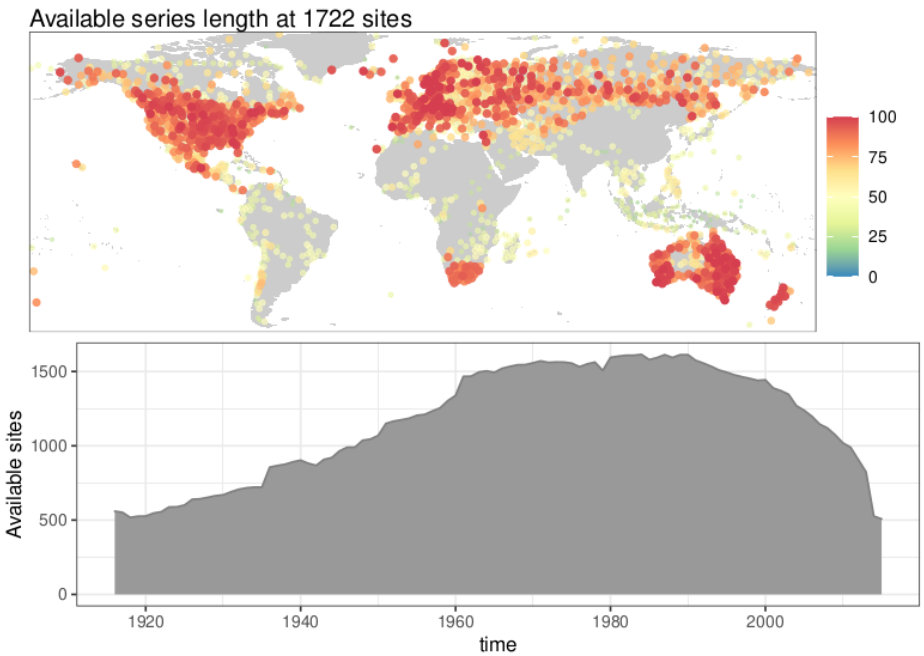

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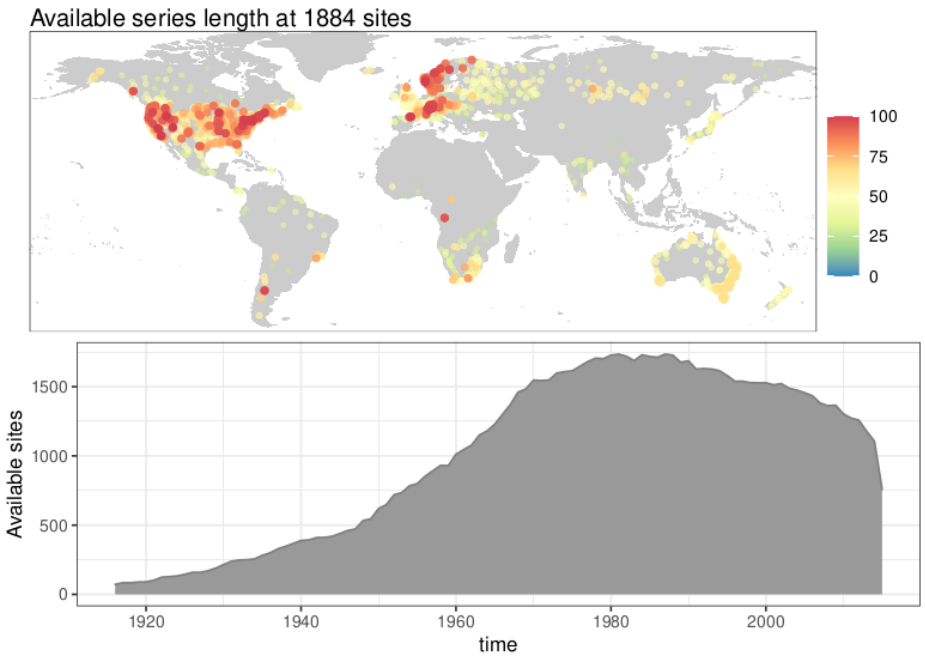

- Extract seasonal maxima at each site (SON, DJF, MAM, JJA)

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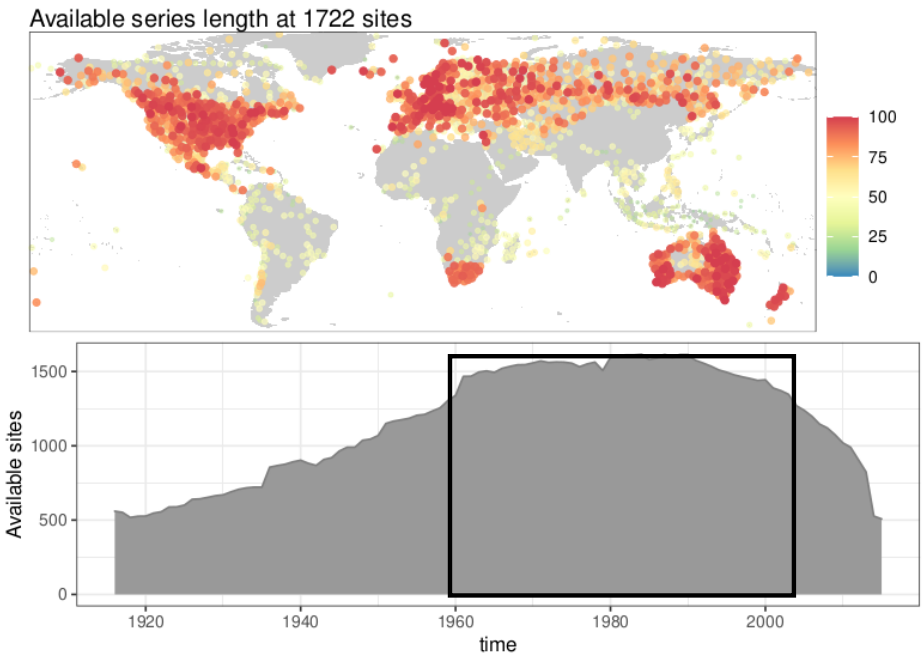

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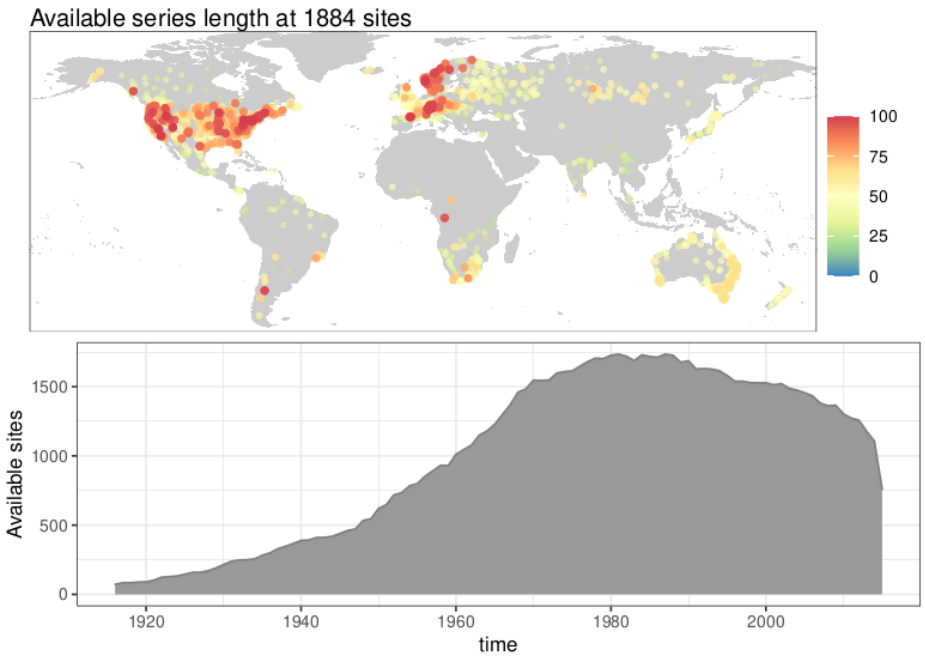

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- The rectangle dilemma...

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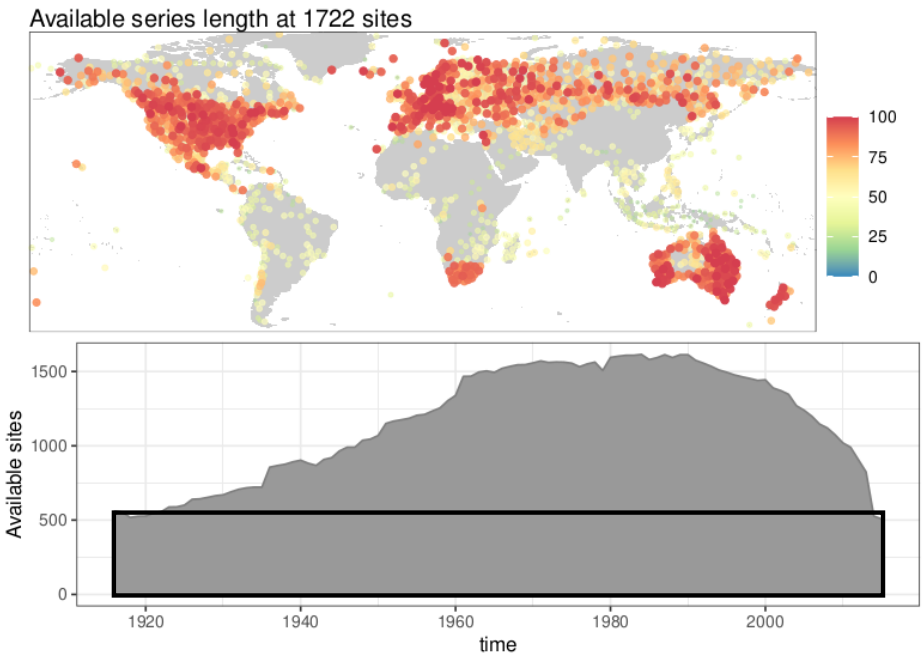

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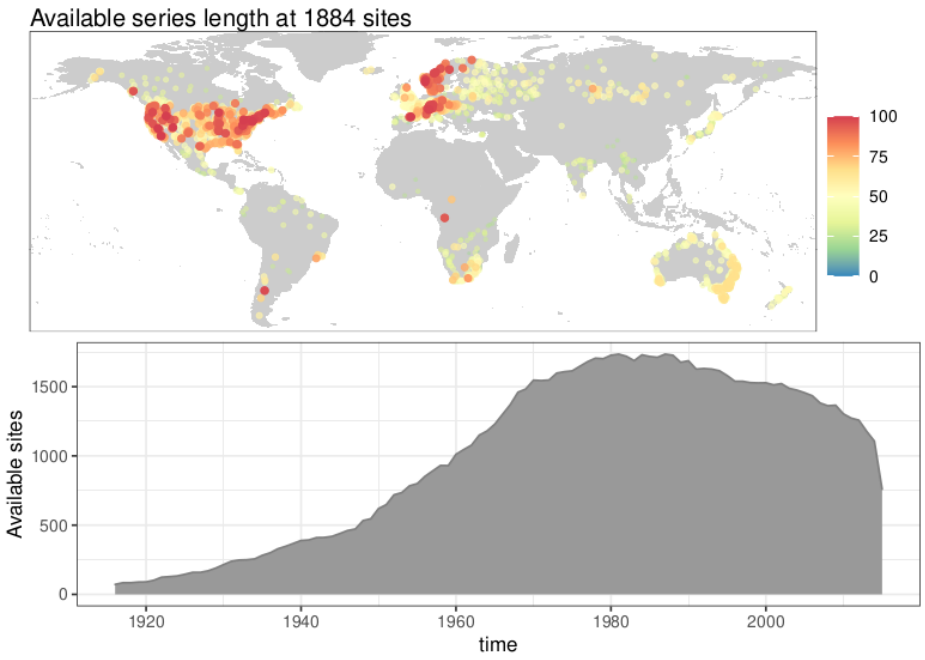

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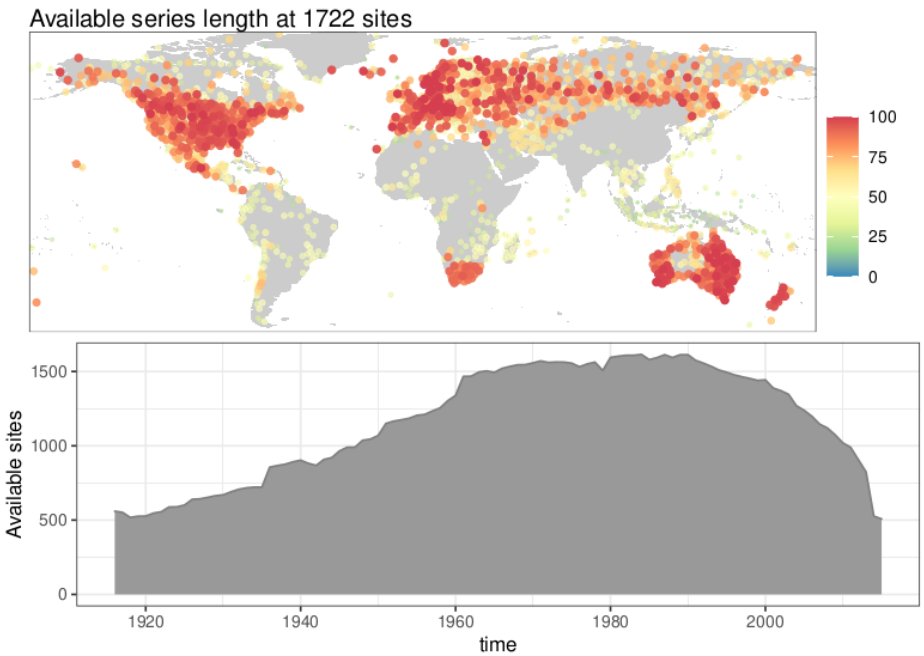

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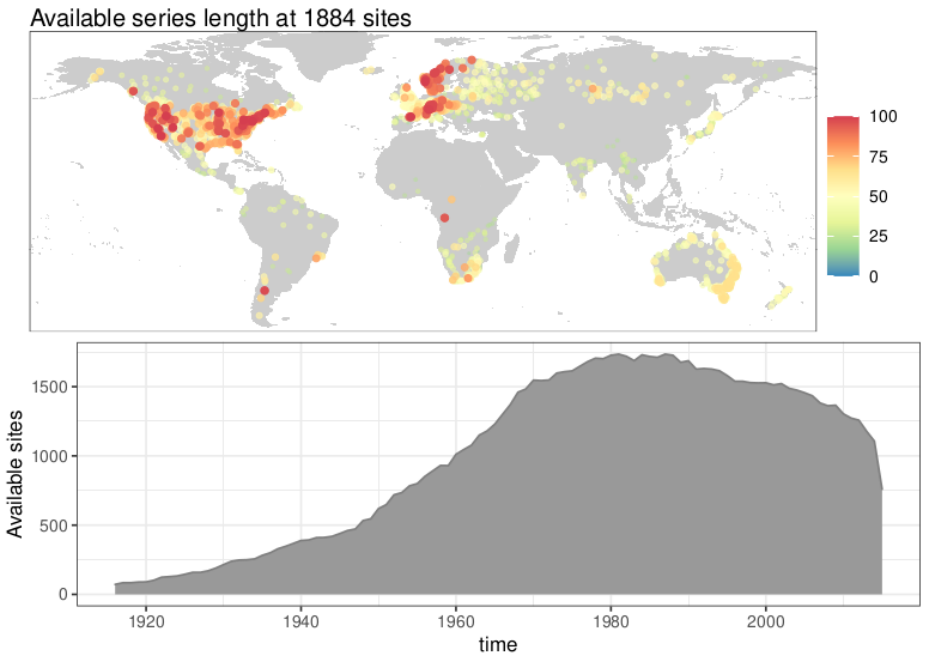

- Extract seasonal maxima at each site (SON, DJF, MAM, JJA)
- The rectangle dilemma...
- In this work, we'll use all data available during 1916-2015

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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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

Model

After suitable data transformation...

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

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
  $\rightarrow$ *Hidden Climate Indices* (HCI)

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

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

Model

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

- All covariates are considered unknown and are estimated
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- $\tau(t) \sim$ AR(1) + trend. Same for $\delta(t)$ and $\omega(t)$

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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

Model

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)
- $\tau(t) \sim$ AR(1) + 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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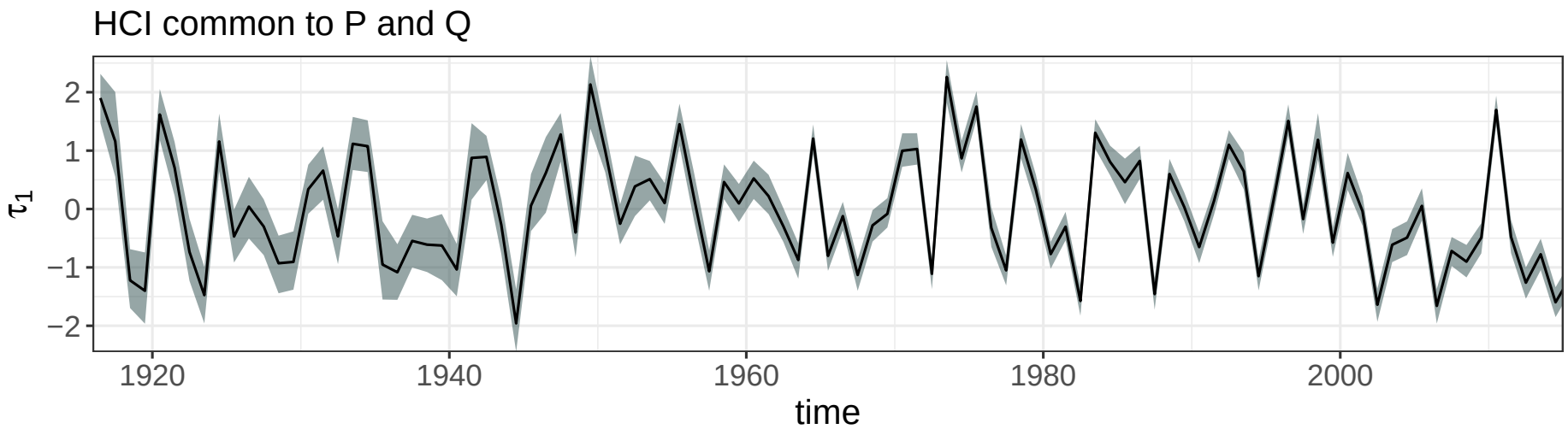
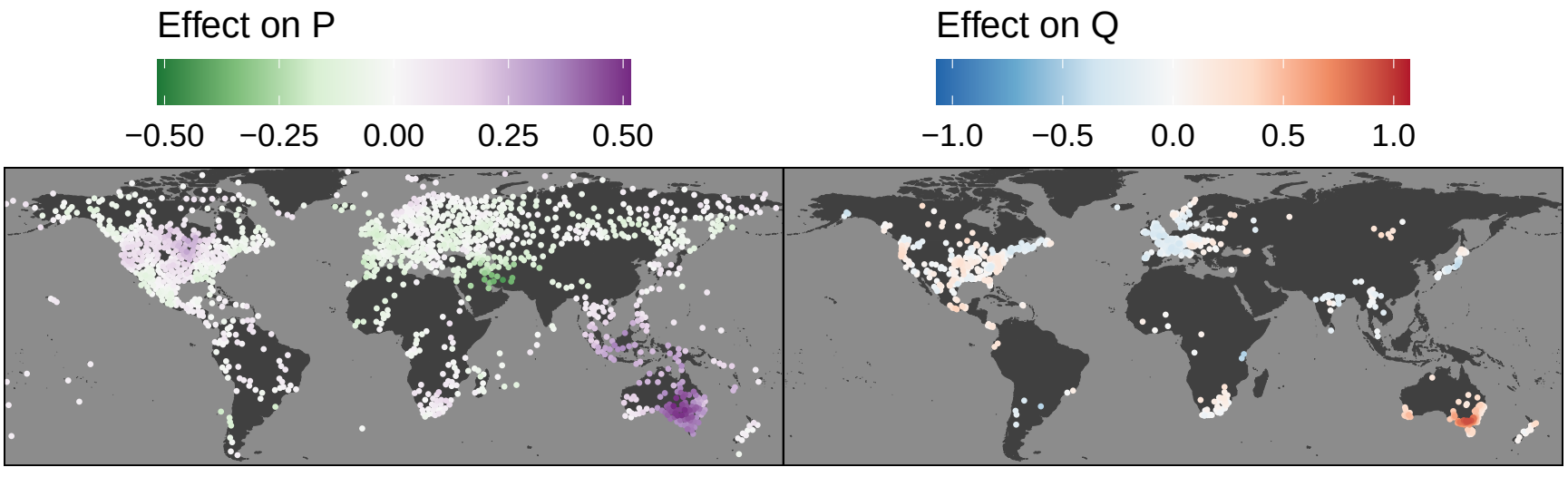
- One component not enough at the global scale $\rightarrow$ 5 used here
- (Bayesian + MCMC) estimation

Ex.: SON season, 1st common HCI





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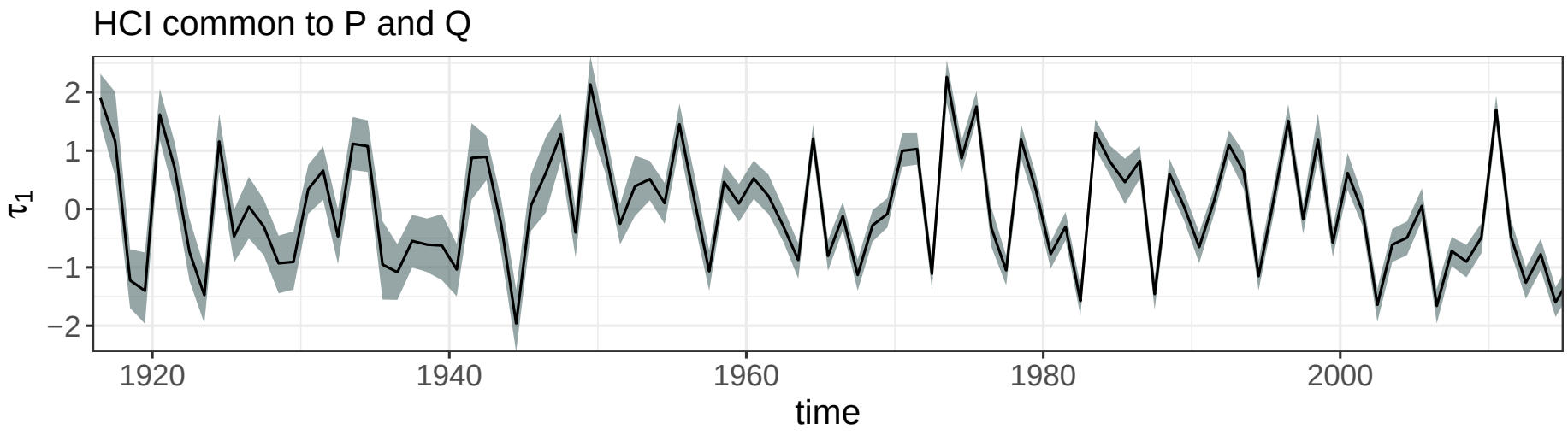

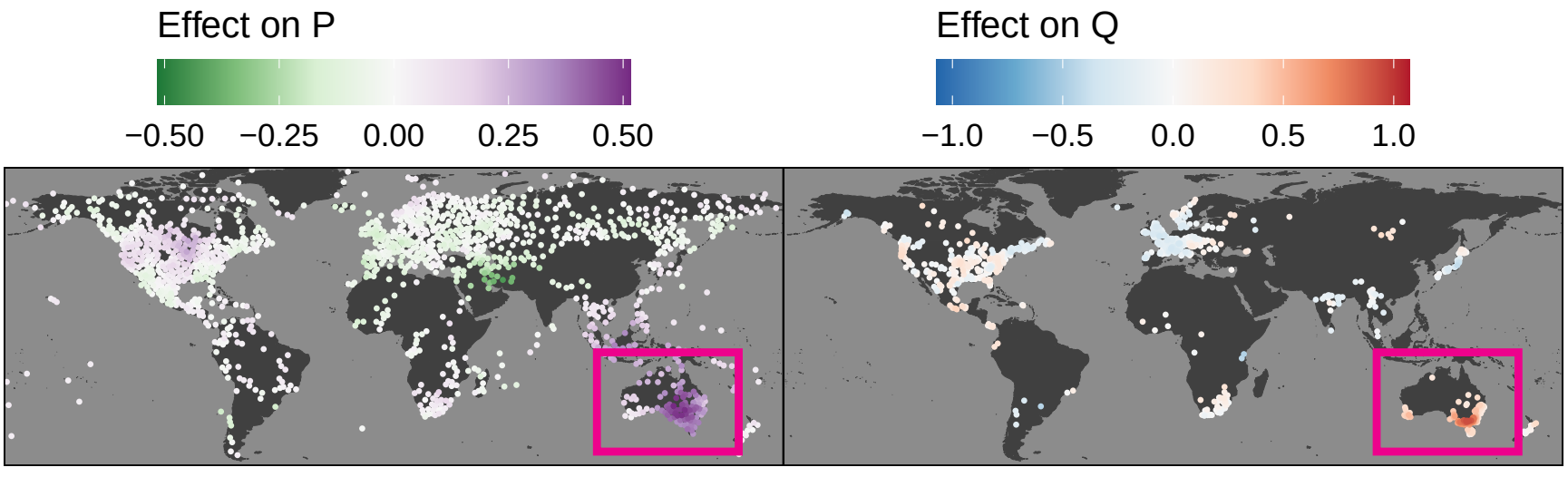

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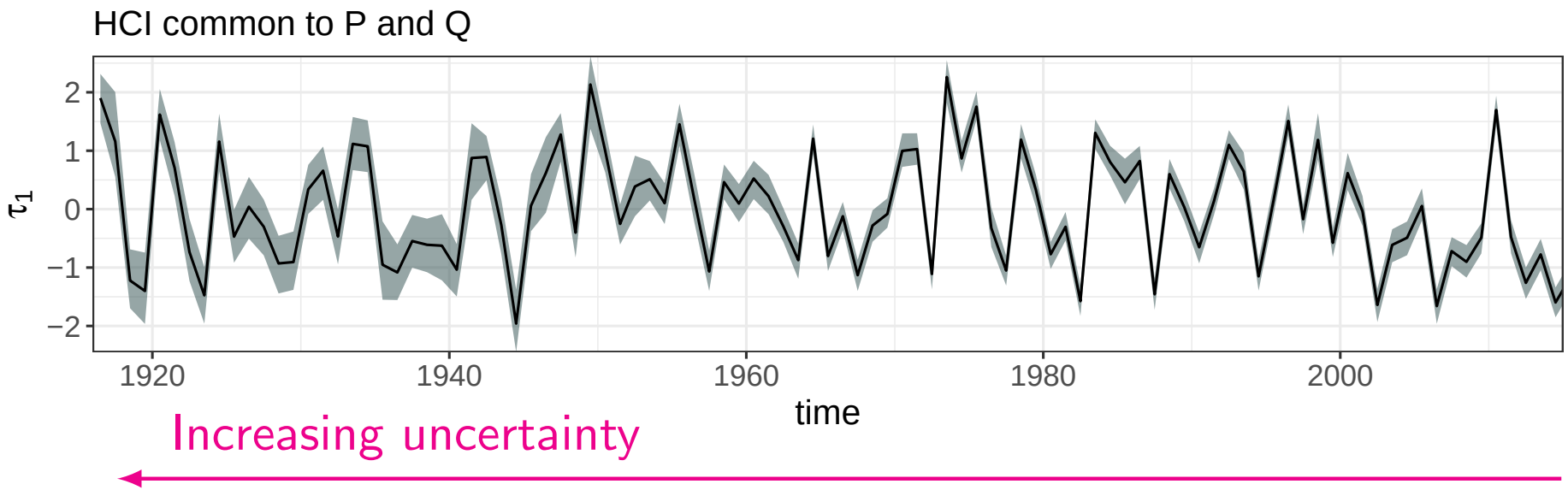
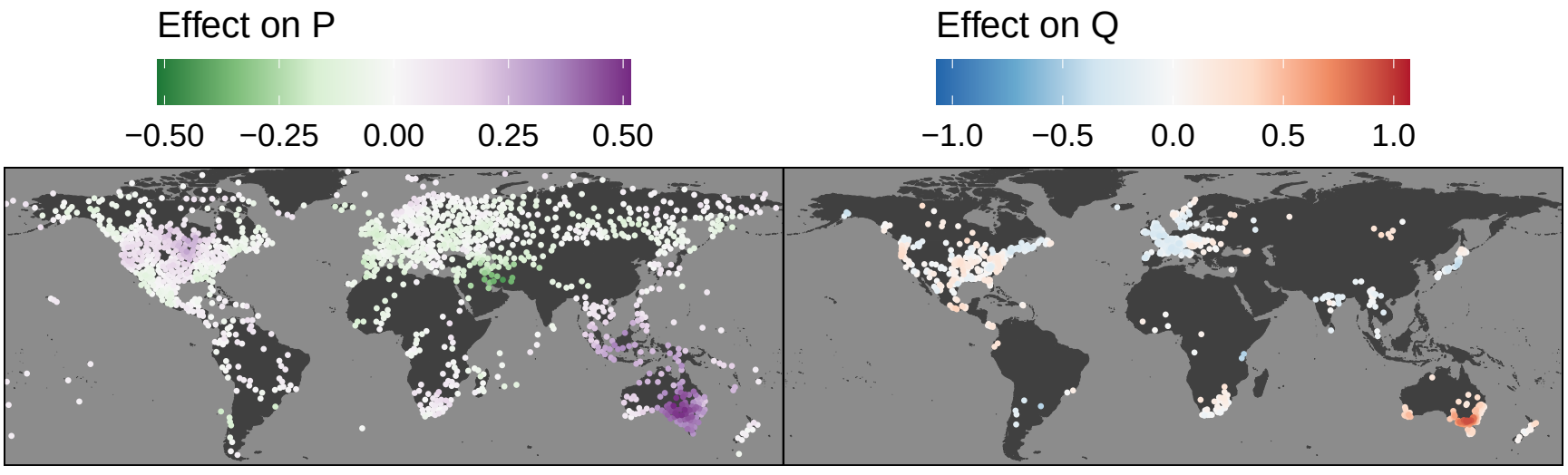


Increasing uncertainty



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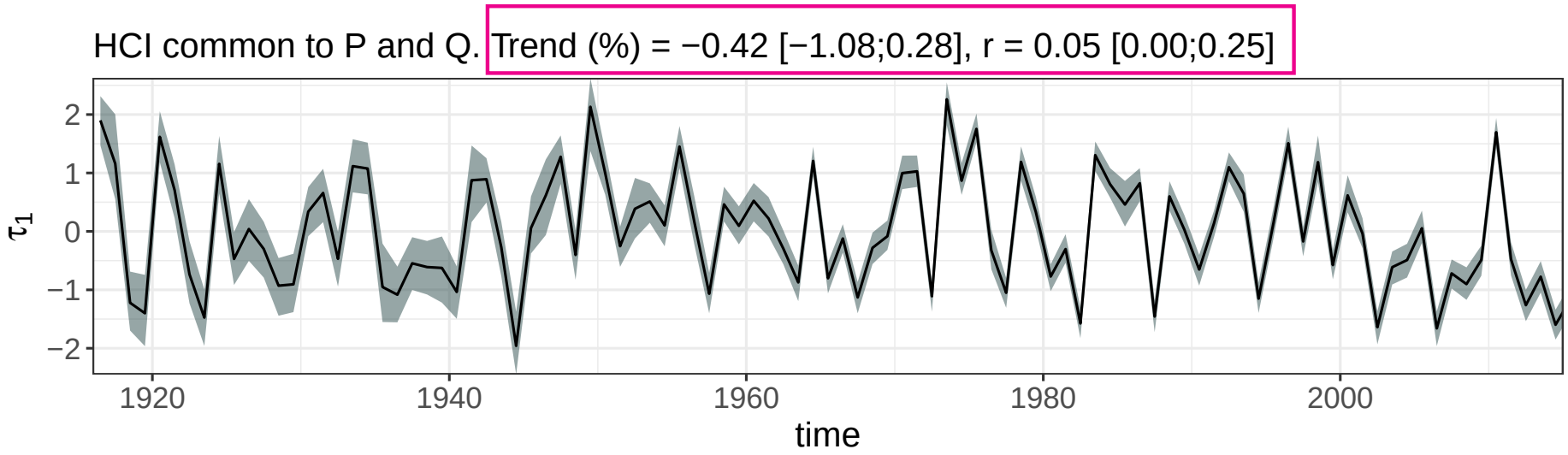
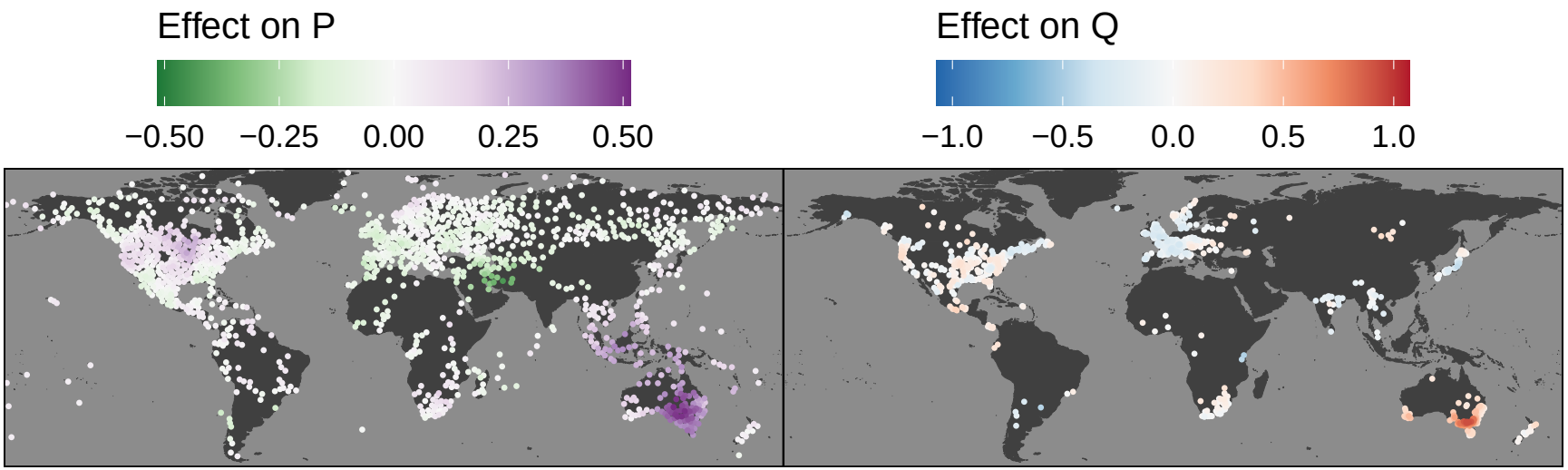
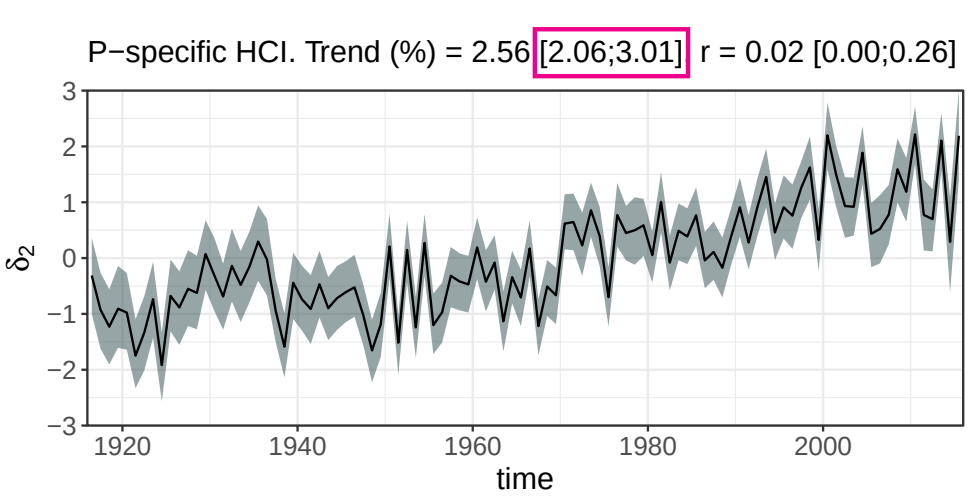
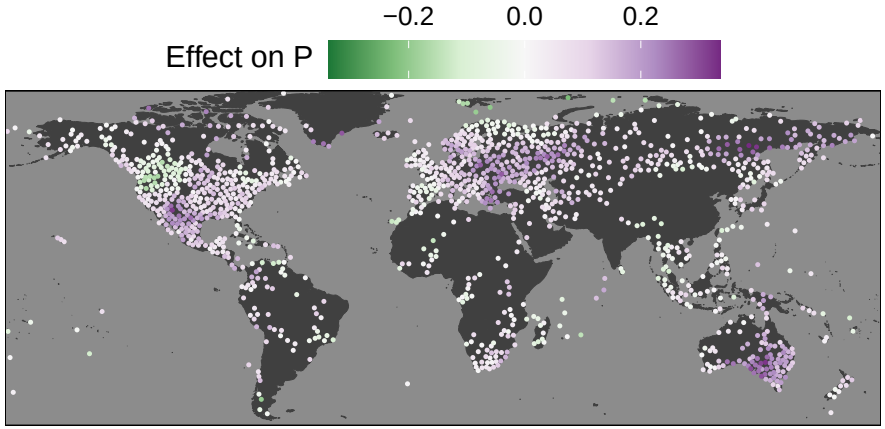




Trends and autocorrelations





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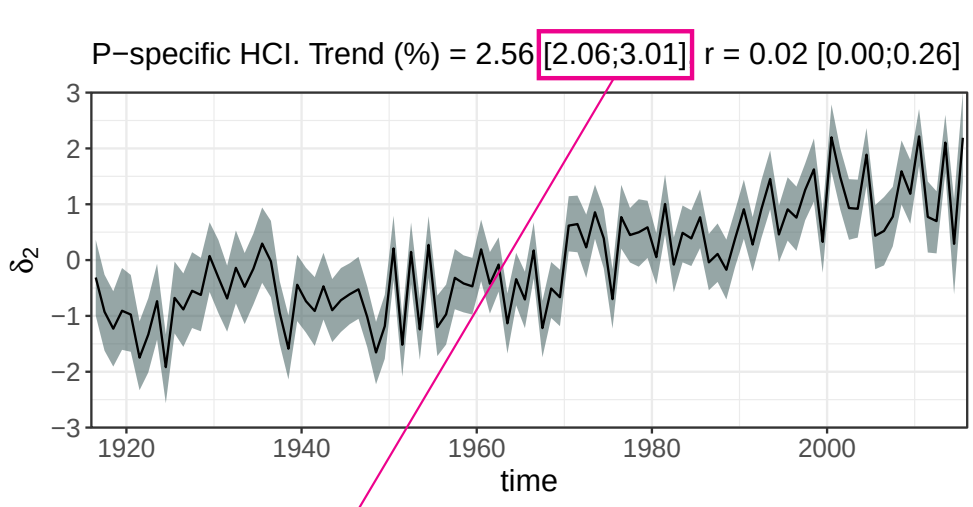
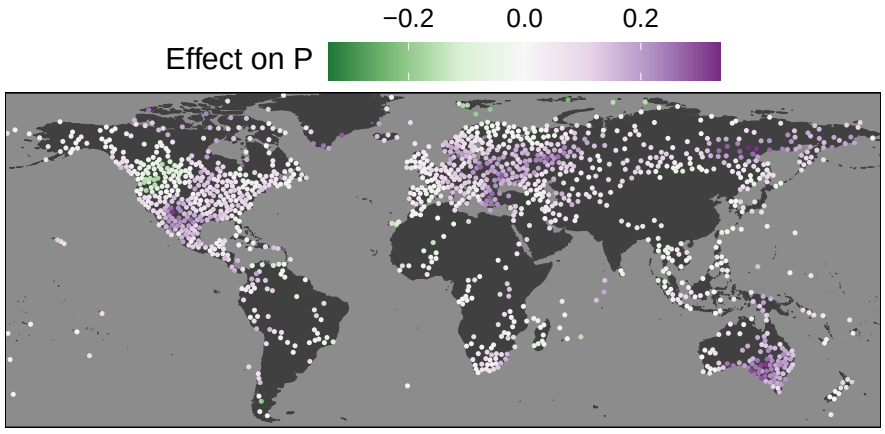
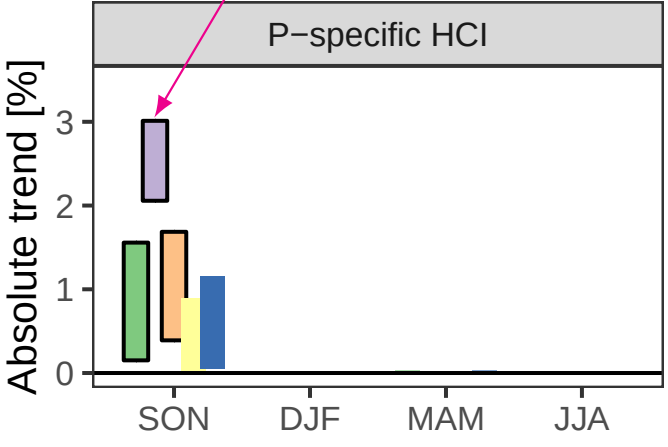




component 1 2 3 4 5



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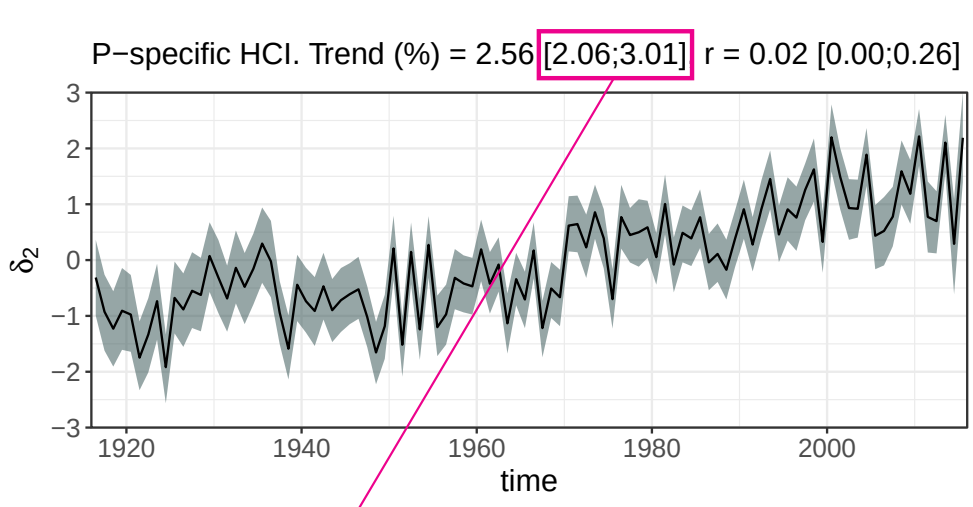

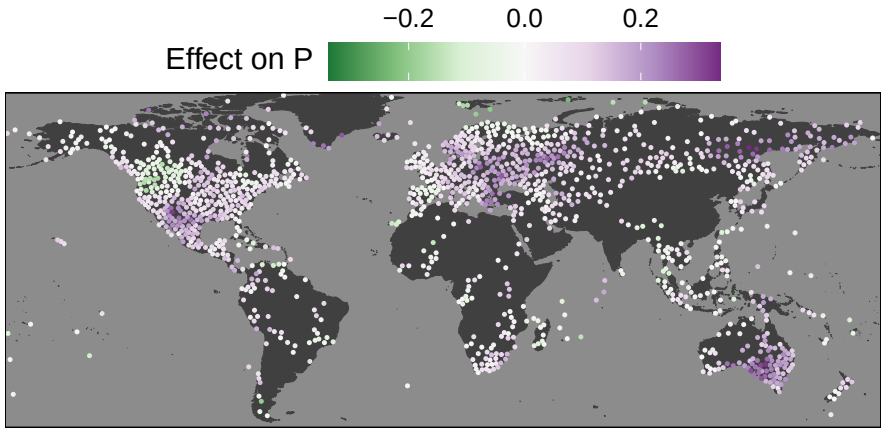

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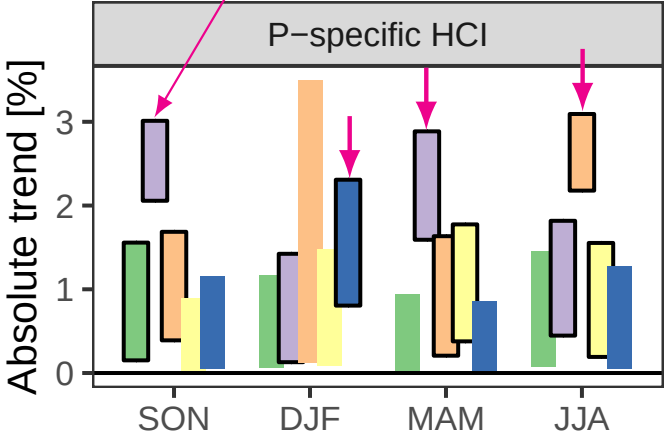

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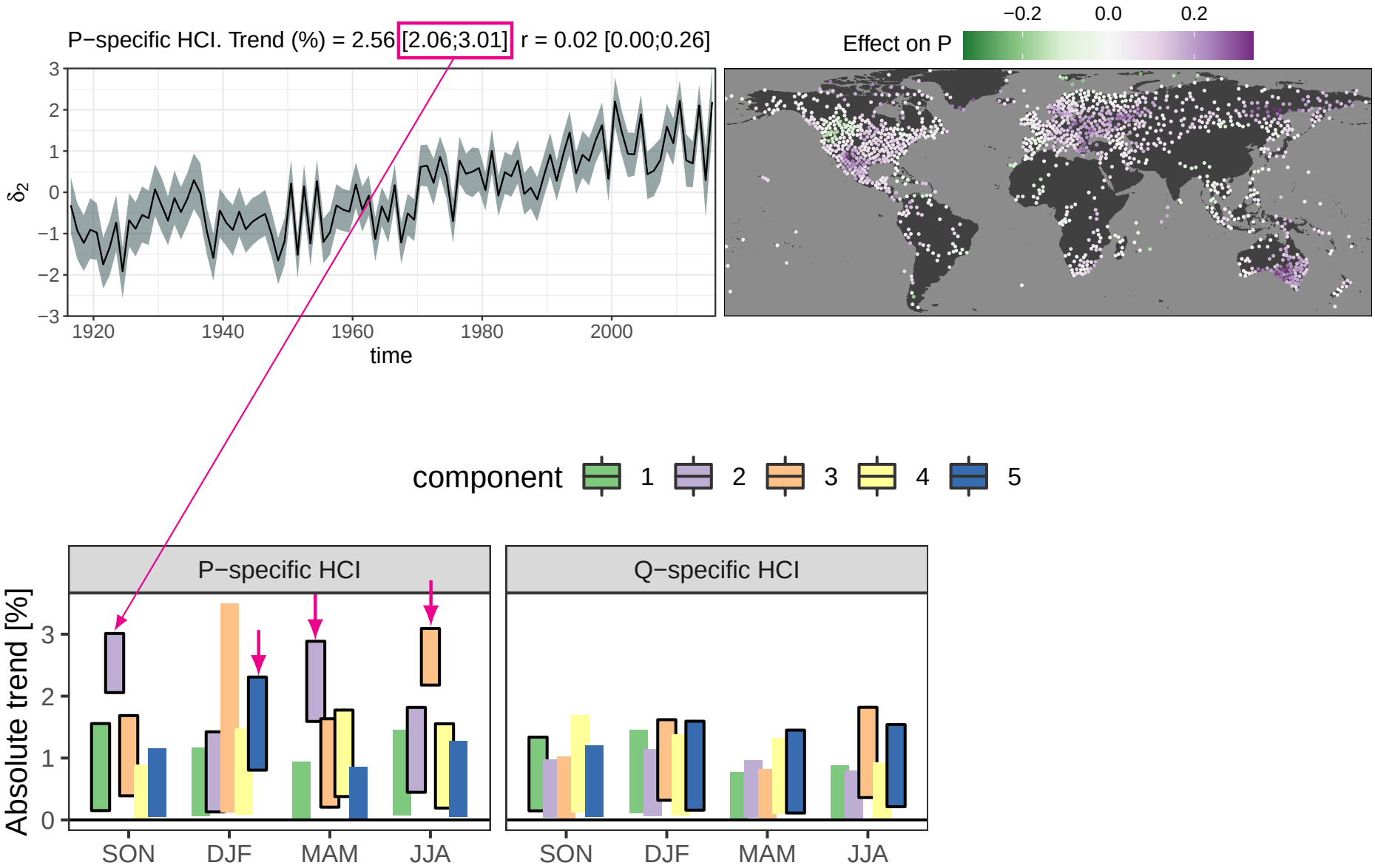

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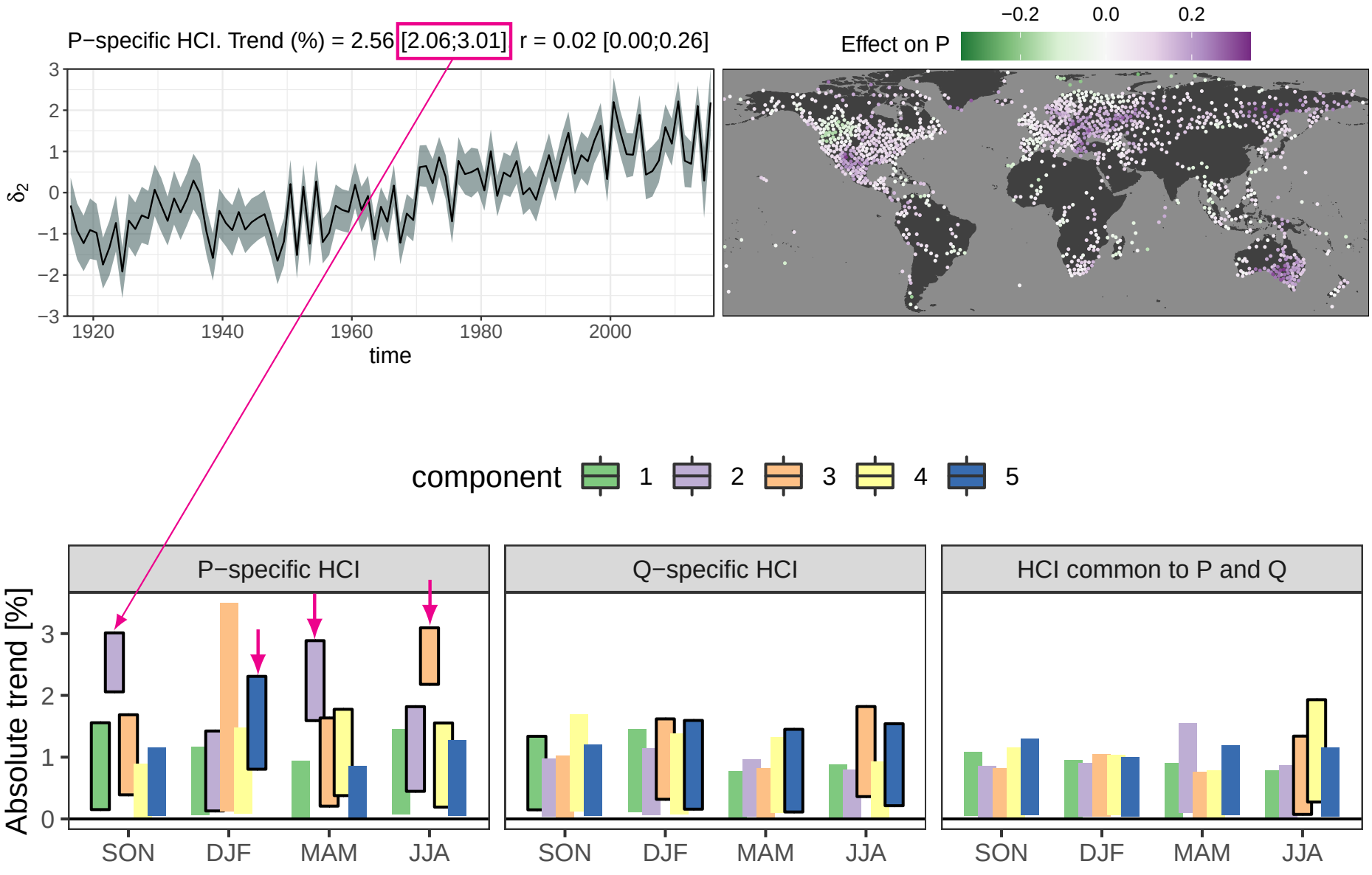

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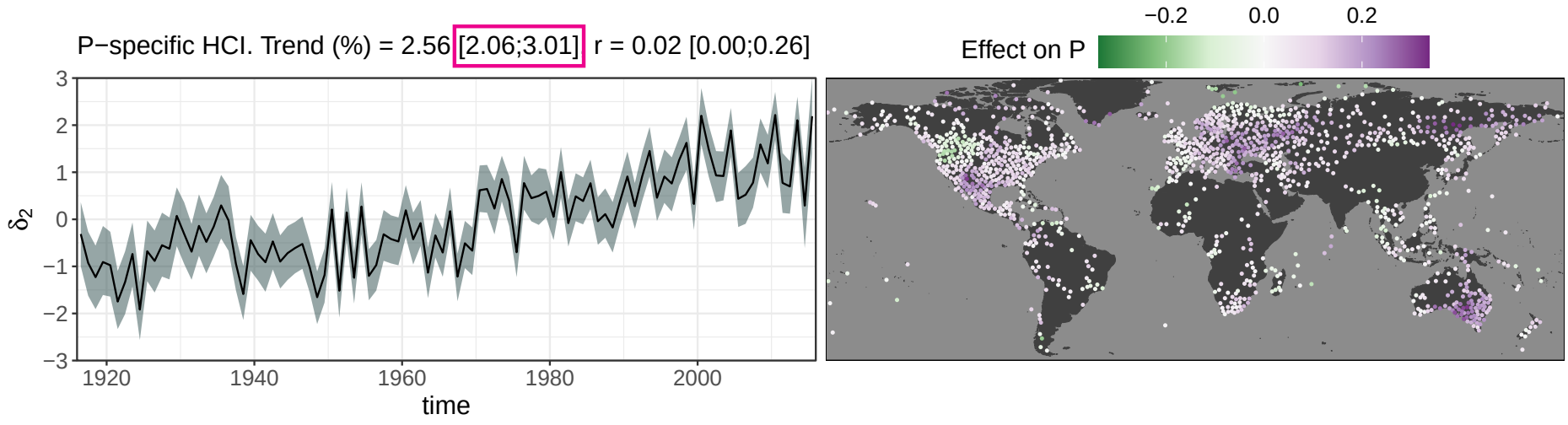
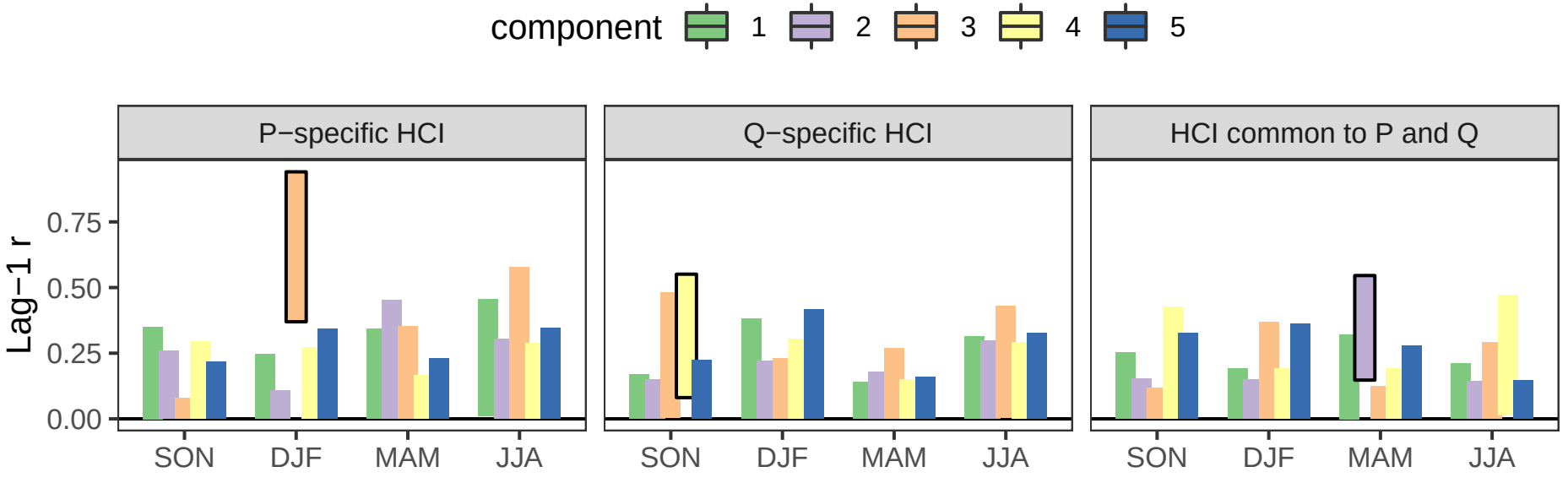
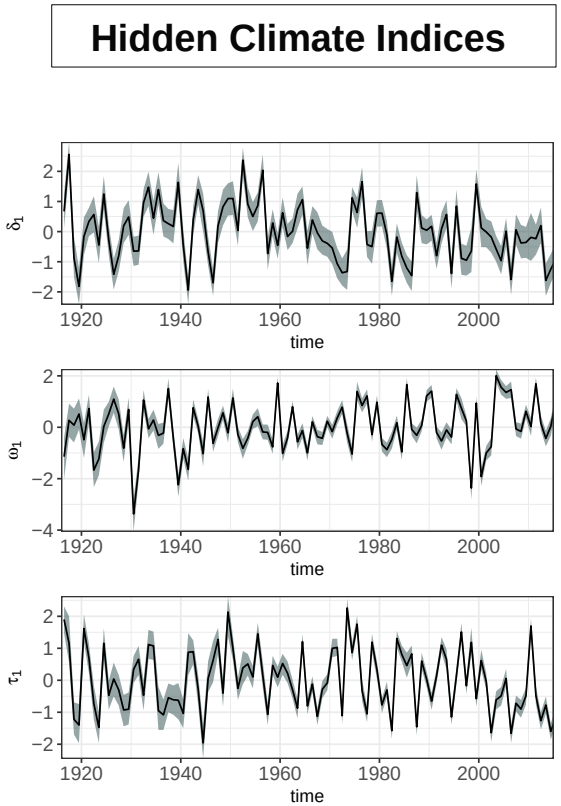




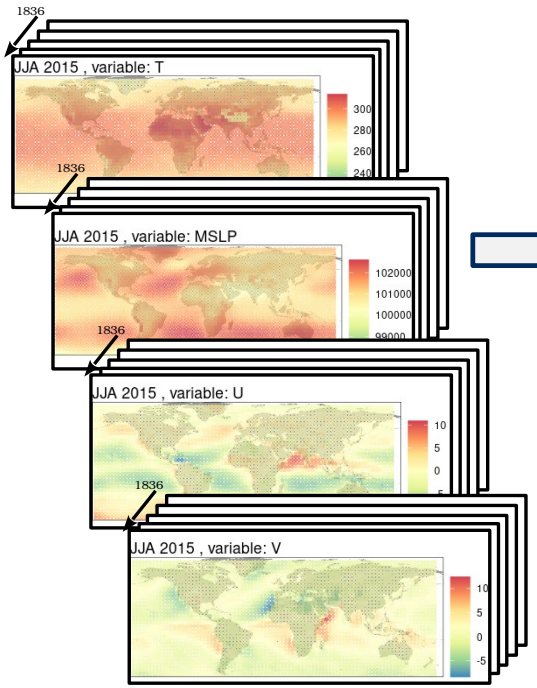
180-year reconstruction



180-year reconstruction

Climate predictors

Hidden Climate Indices



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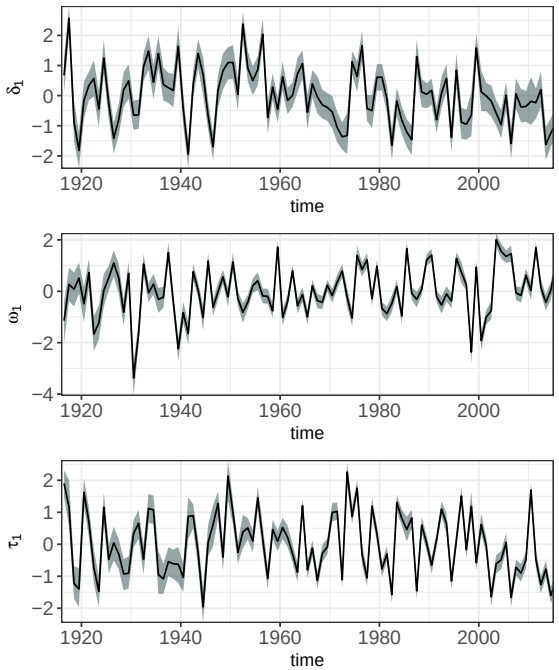
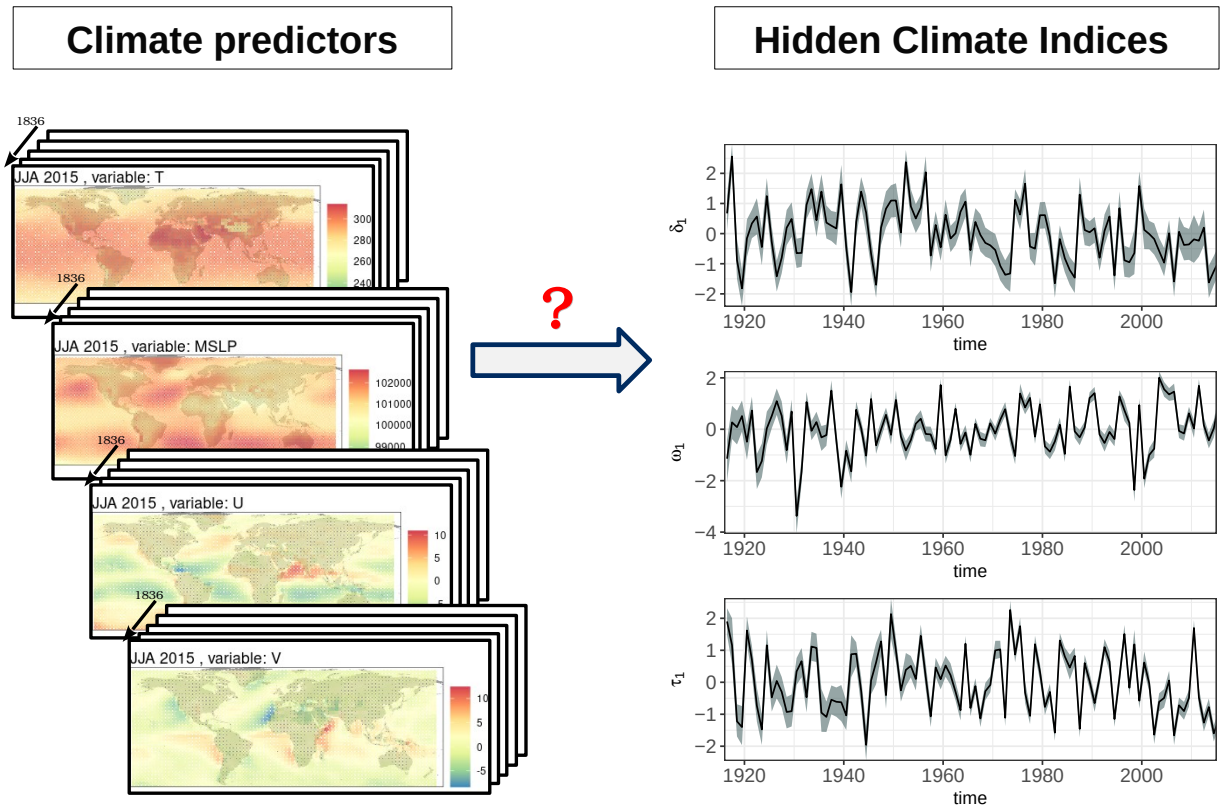


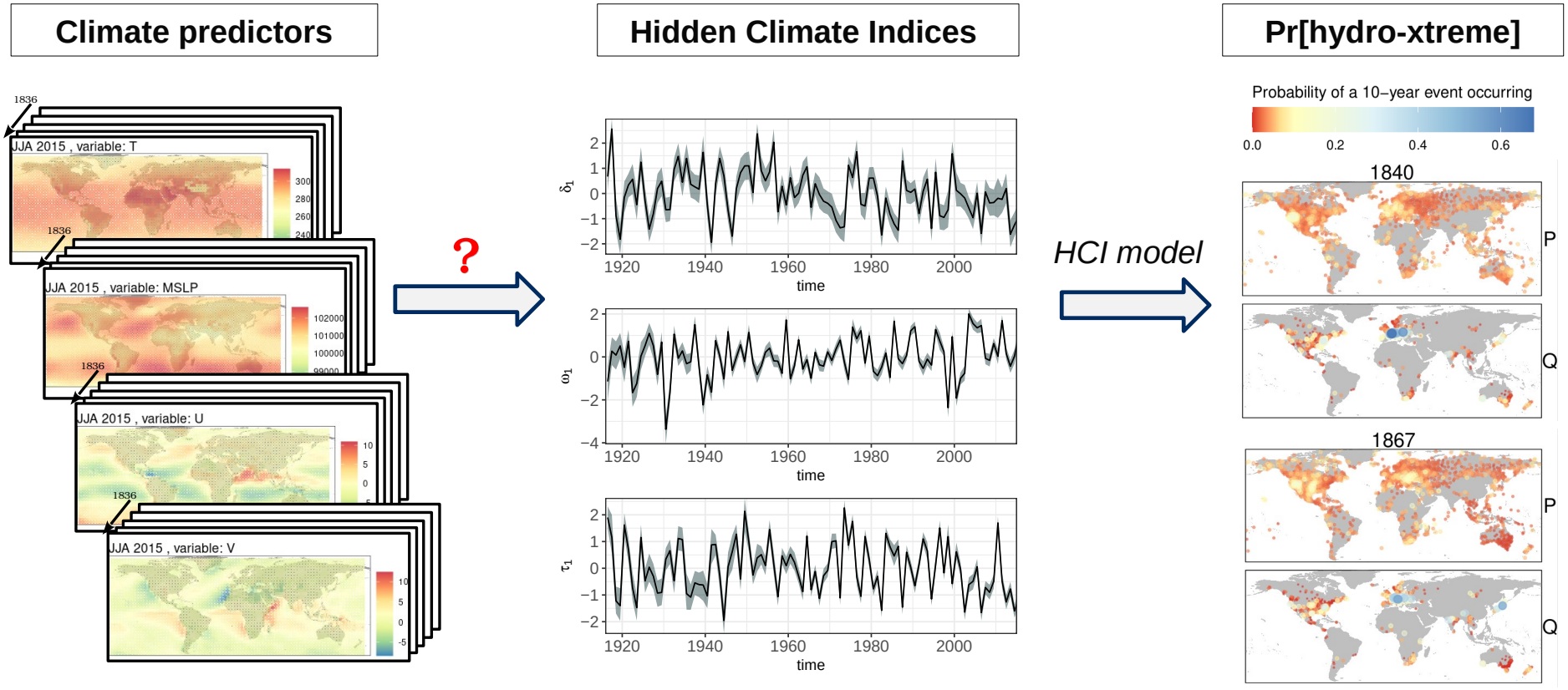
180-year reconstruction



→ Using 20CRv3, reconstruction of HCIs from 1836

→ Hydro-extreme probability maps from 1836

180-year reconstruction



→ Using 20CRv3, reconstruction of HCIs from 1836

→ 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/

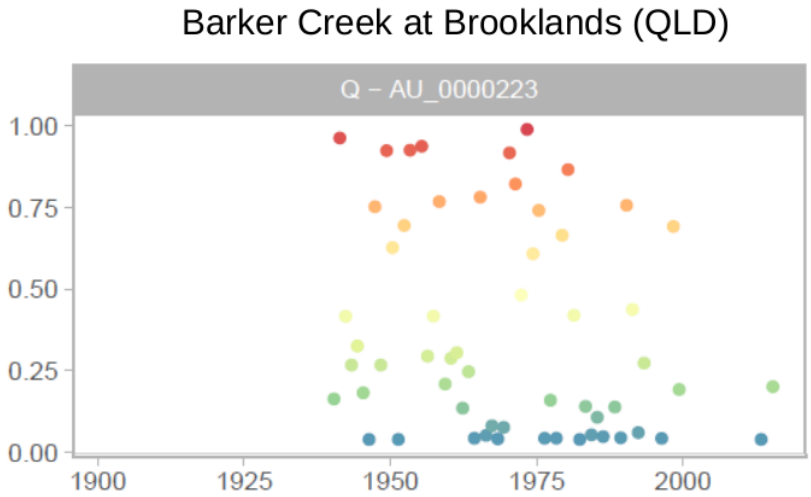
https://github.com/STooDs-tools

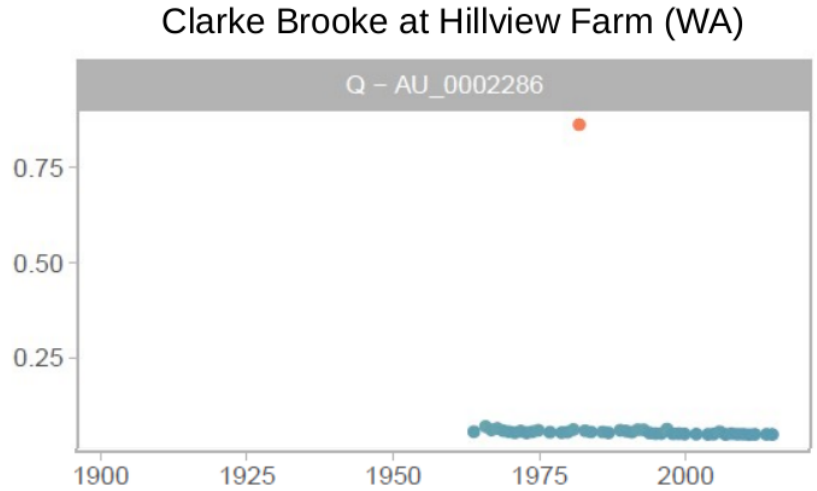
This project has received funding from the European Union's Horizon 2020 research and innovation programme under the Marie Sklodowska-Curie grant agreement No 835496

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

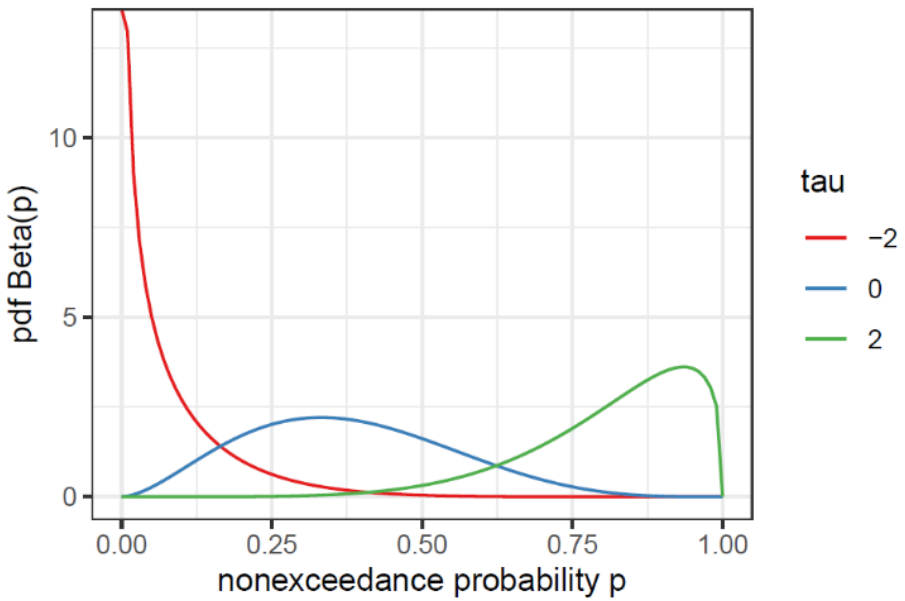




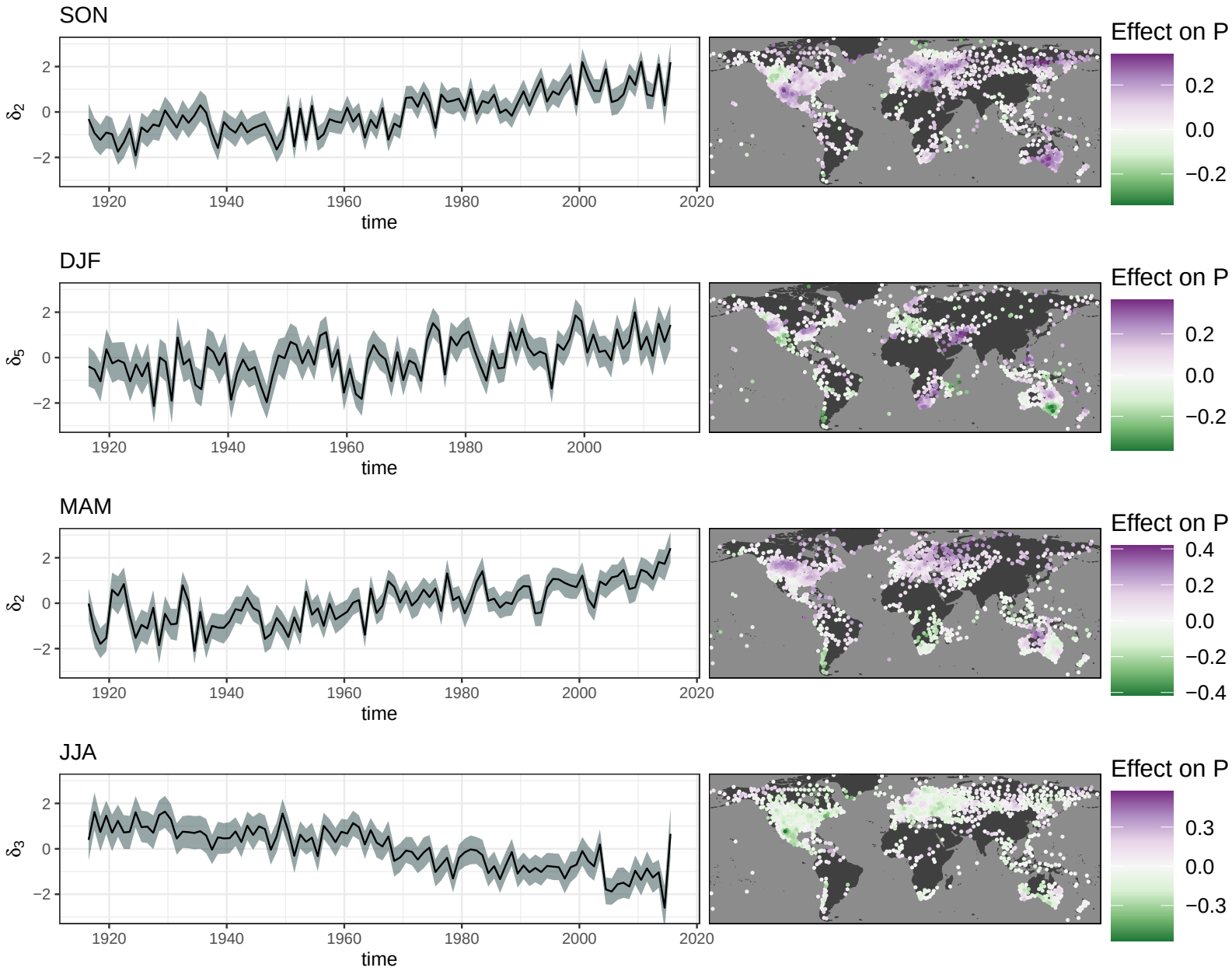
Model

Beta distribution reparameterized in terms of mean μ and precision γ

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

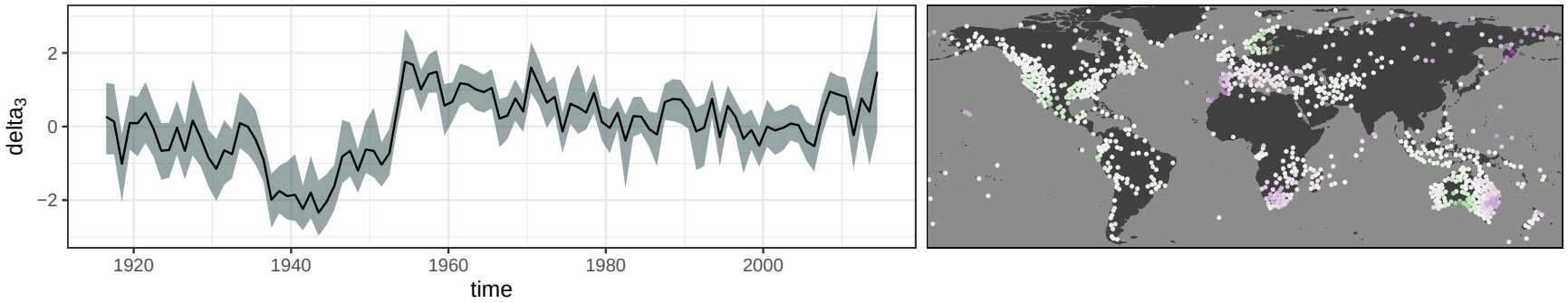


P-specific HCIs with large trends



HCIs with notable autocorrelation

DJF



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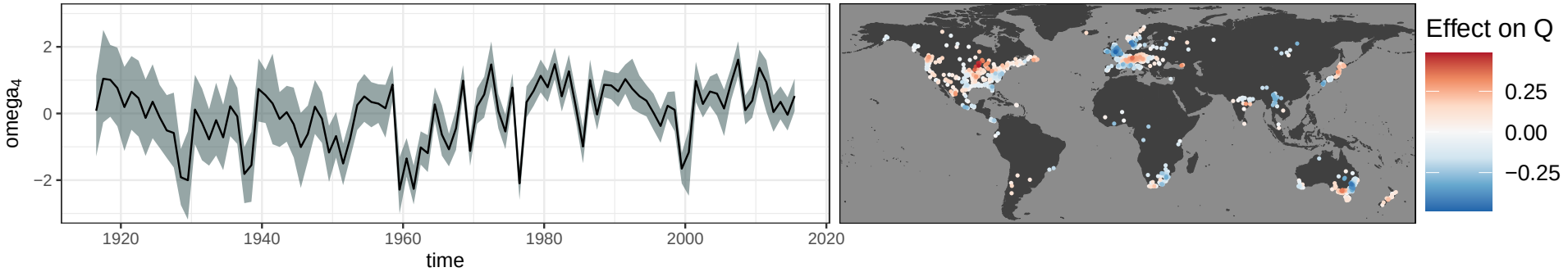
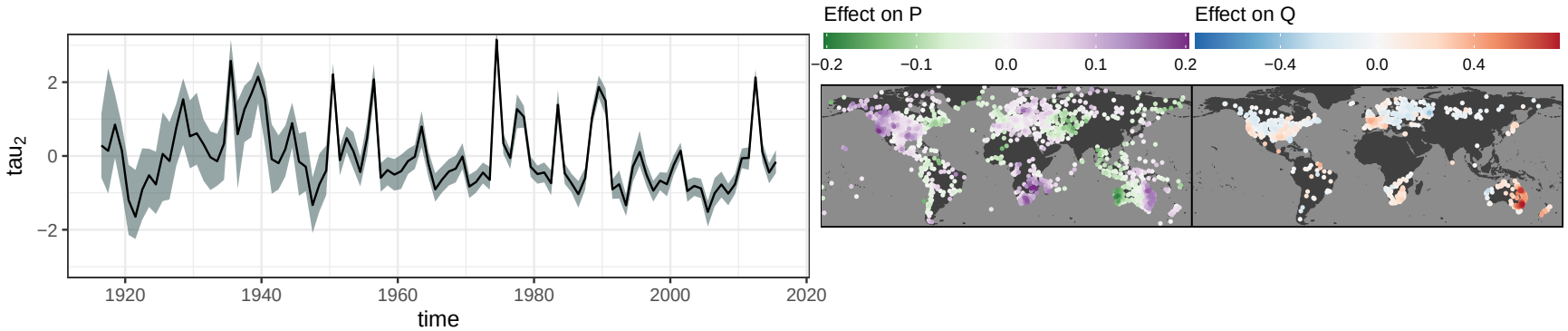


MAM



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

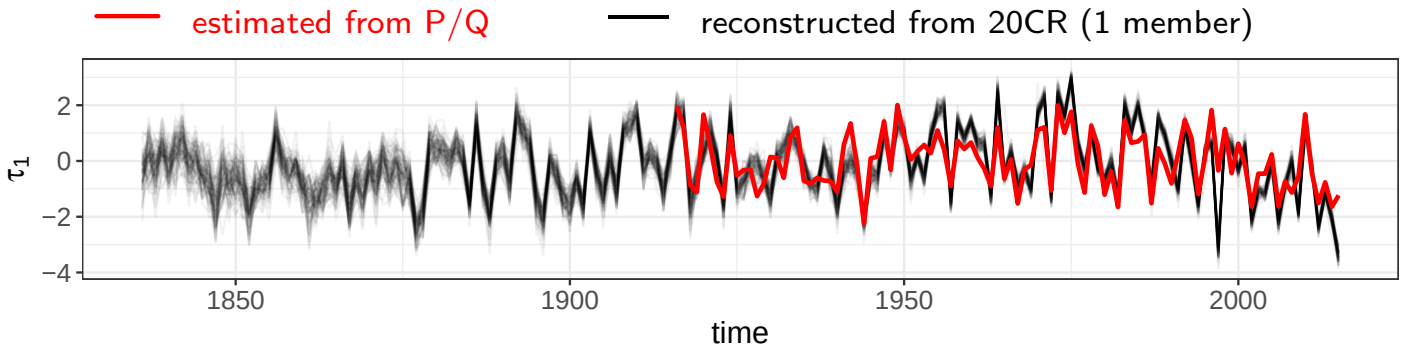
$\widehat{\psi}_k(s)$: estimated from previous step

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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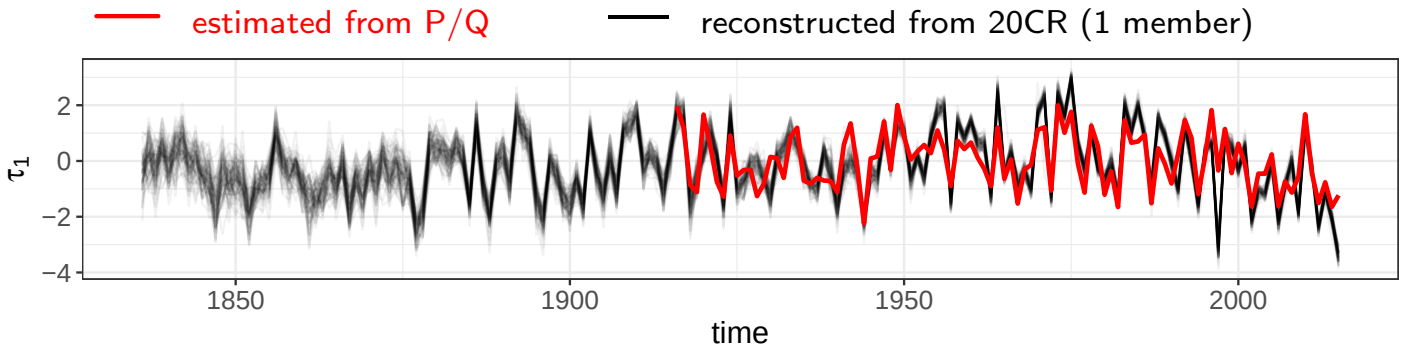
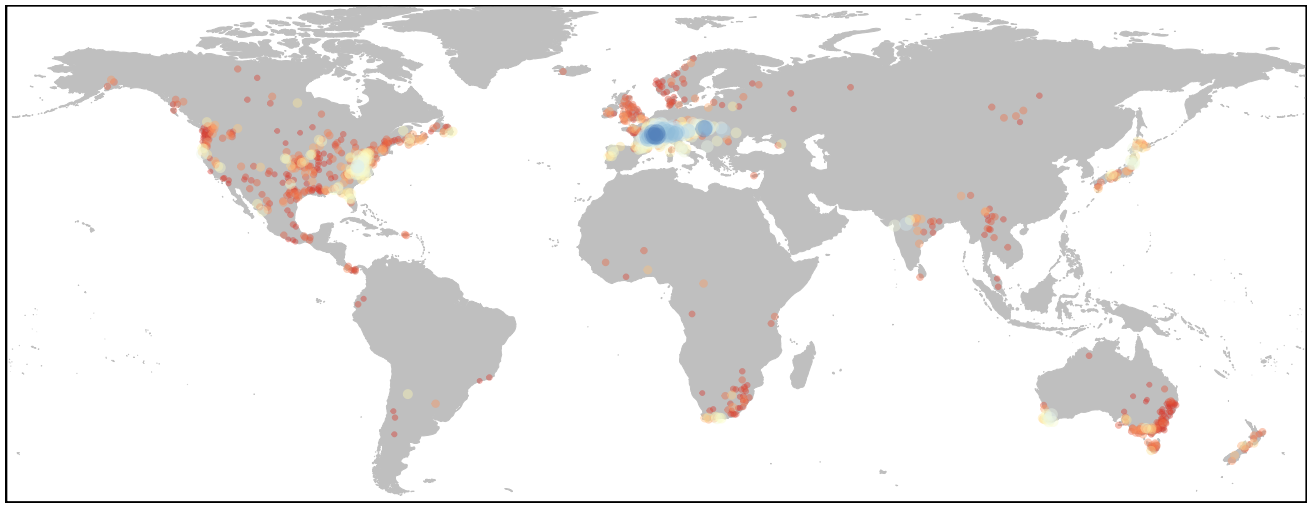
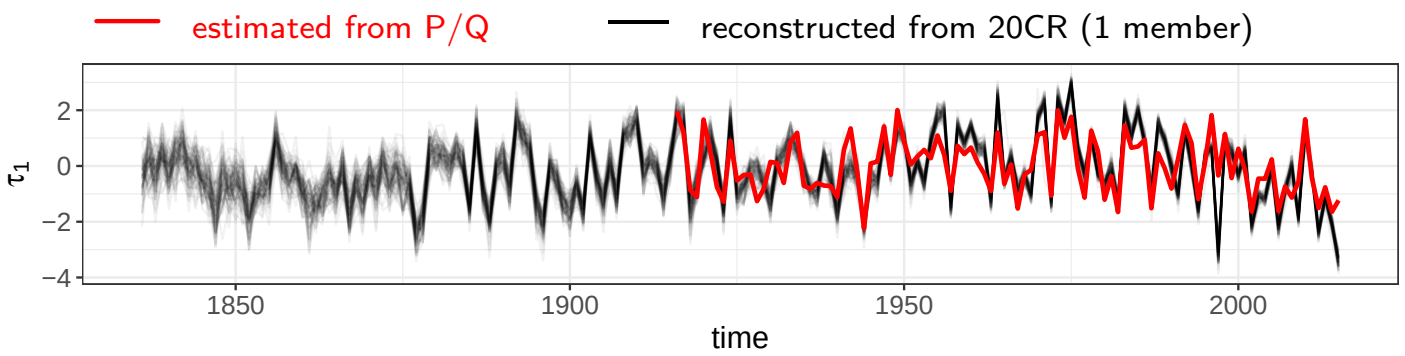


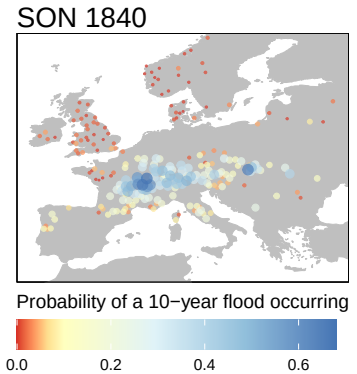
SON 1840



Probability of a 10−year flood occurring

Reconstructions from 20CRv3 (1836-2015)





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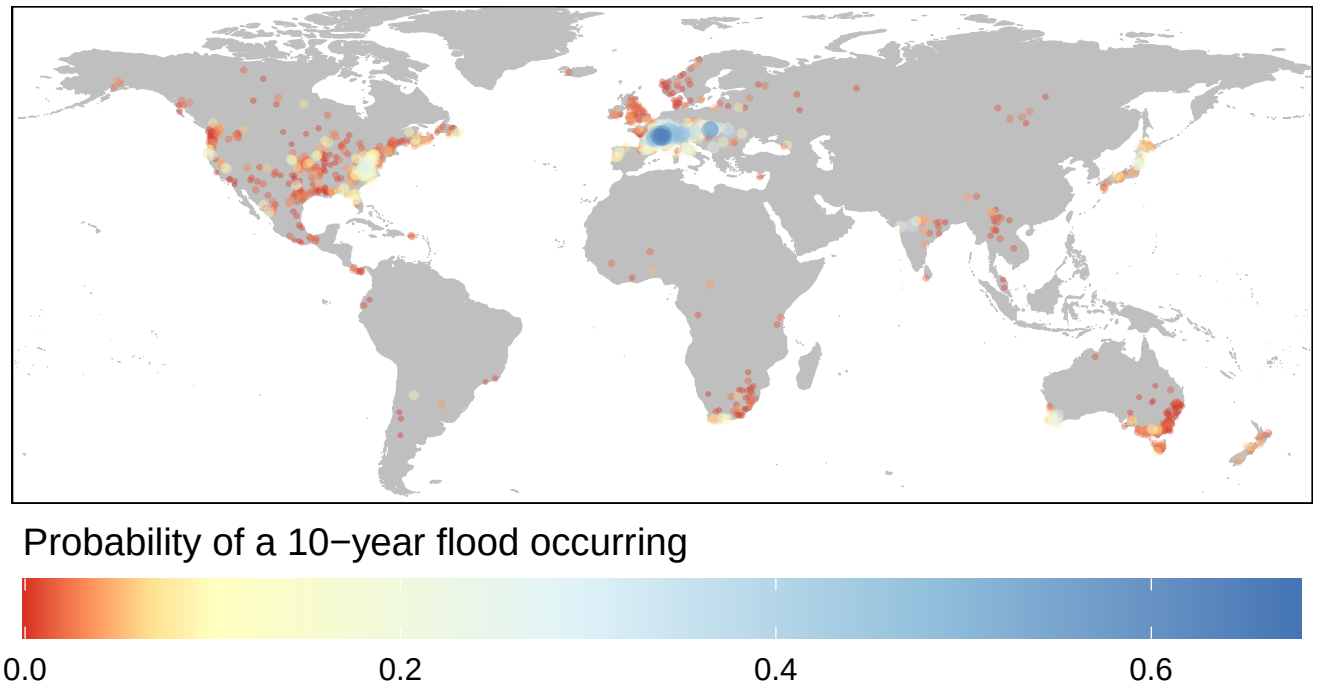
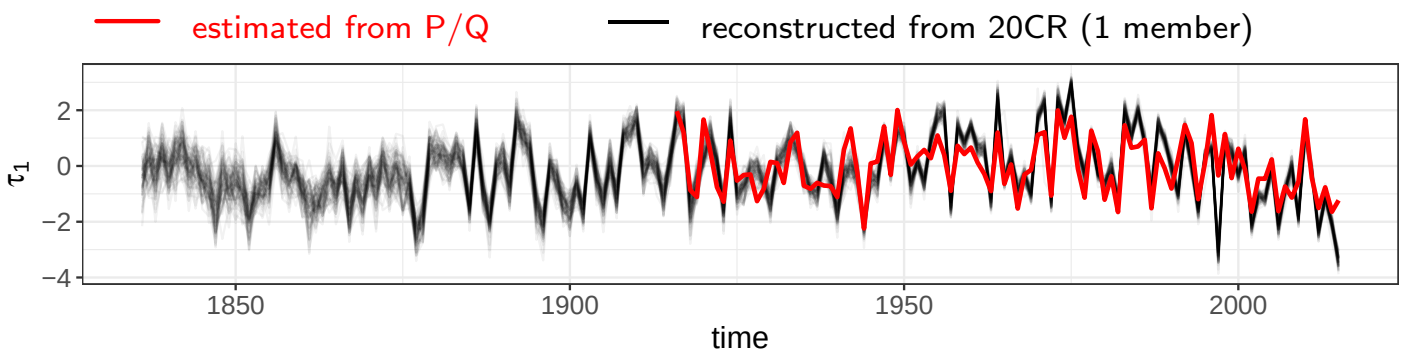


Reconstructions from 20CRv3 (1836-2015)



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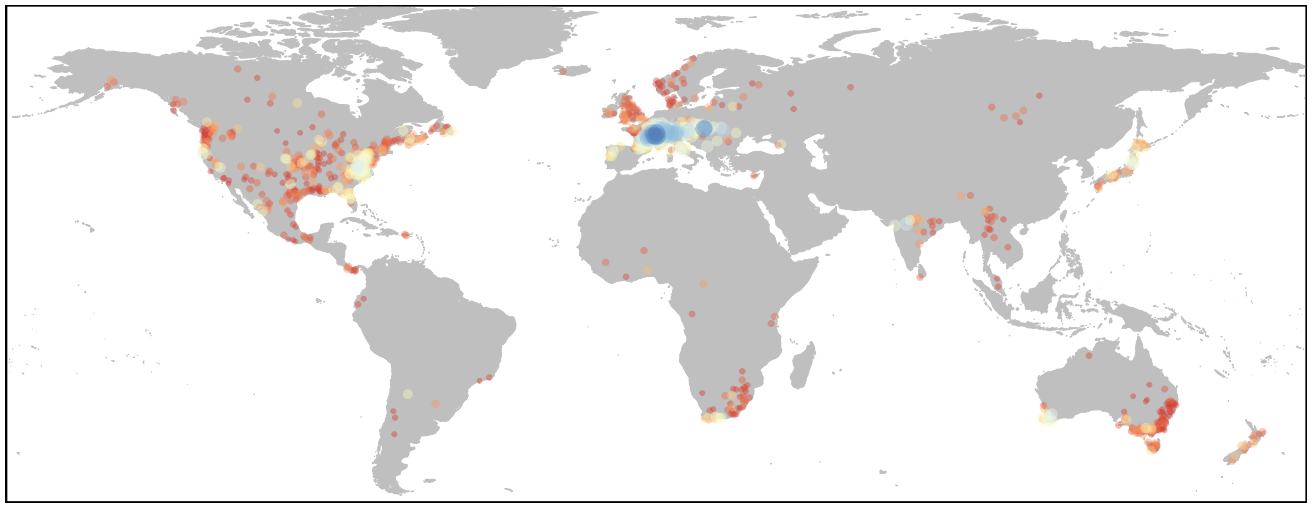
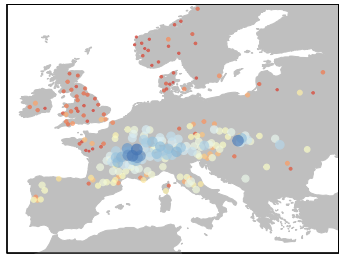
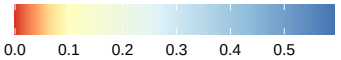


Probability of a 10−year flood occurring

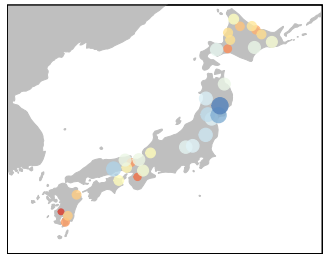
SON 1840



Probability of a 10−year flood occurring



SON 1867



Probability of a 10−year flood occurring

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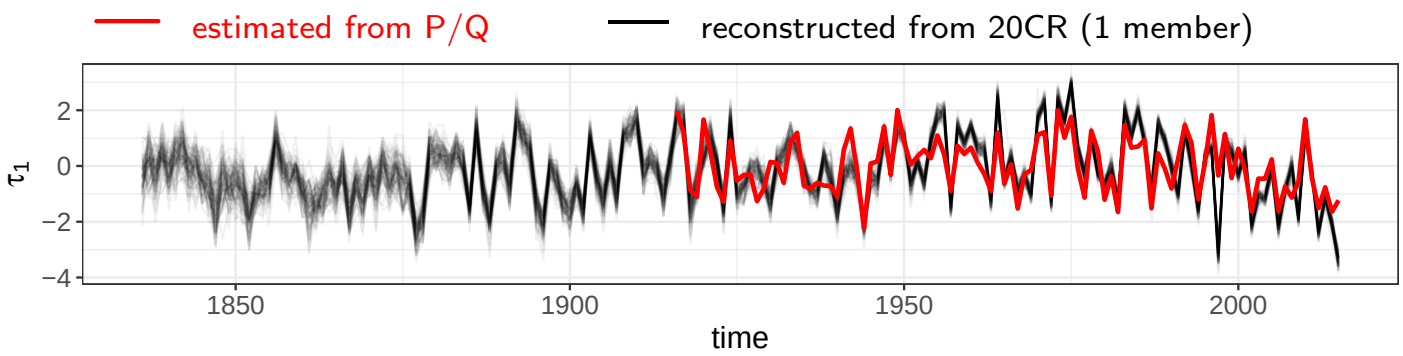
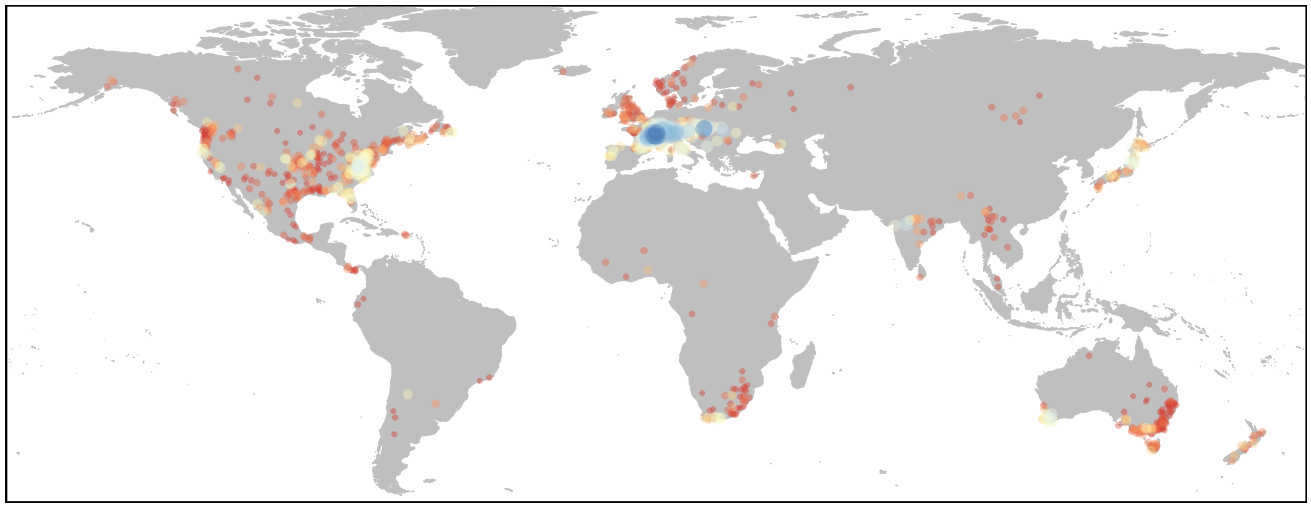
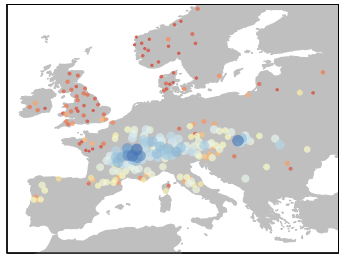


SON 1840

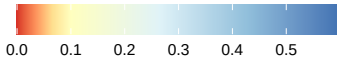


Probability of a 10−year flood occurring

SON 1840



Probability of a 10−year flood occurring



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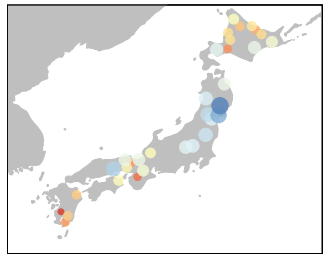
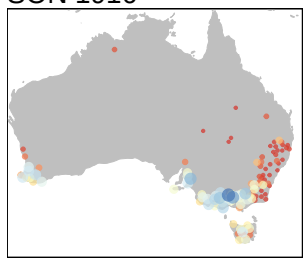
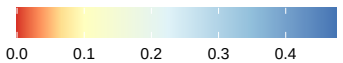


Probability of a 10−year flood occurring

SON 1916



Probability of a 10−year flood occurring



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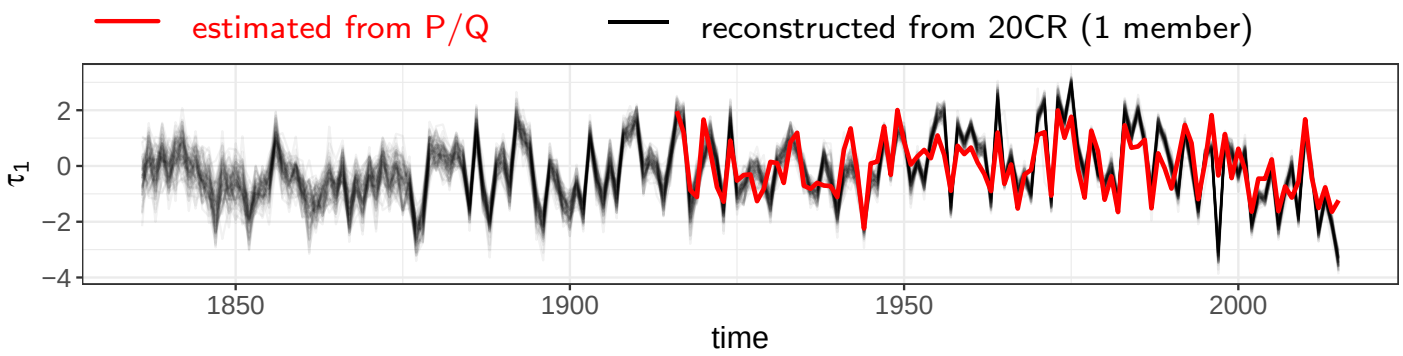

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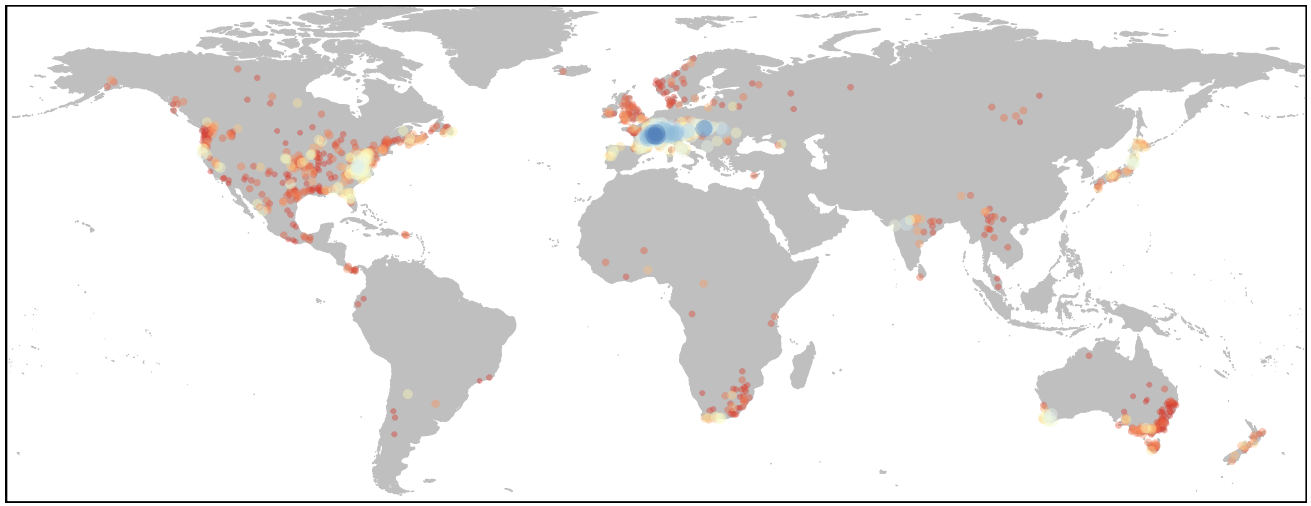
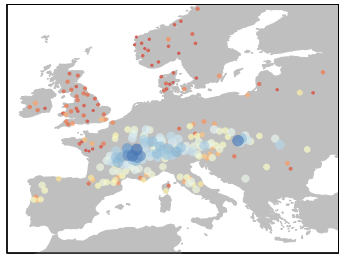


Probability of a 10−year flood occurring

0.0 0.2 0.4 0.6

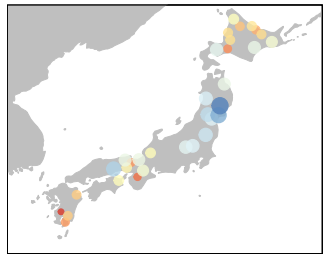
SON 1840



Probability of a 10−year flood occurring

0.0 0.2 0.4 0.6

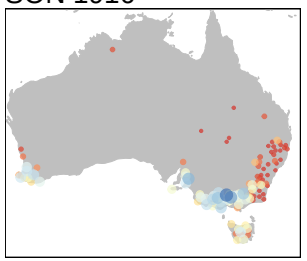
SON 1867



Probability of a 10−year flood occurring

0.0 0.1 0.2 0.3 0.4 0.5

SON 1916



Probability of a 10−year flood occurring

0.0 0.1 0.2 0.3 0.4

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