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

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M. Leonard$^2$  D. Kavetski$^2$  M. Thyer$^2$  J.-P. Vidal$^1$

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$^3$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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"Confidence about peak flow trends over past decades on the global scale is low […]"
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If Precipitation Extremes Are Increasing, Why Aren’t Floods?
Ashish Sharma, Conrad Wasko, and Dennis P. Lettenmaier
"The frequency and intensity of heavy precipitation events have increased since the 1950s over most land area for which observational data are sufficient [...]"

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

"changes may be more complex than simple trends"
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
Do et al. (2018); Gudmundsson et al. (2018)
Global datasets

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- Extract seasonal maxima at each site (SON, DJF, MAM, JJA)
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- Extract seasonal maxima at each site (SON, DJF, MAM, JJA)
- The rectangle dilemma...
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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...

\[
\begin{align*}
\mathbb{E}[P(s, t)] &= c P(s) + \lambda P(s) \tau(t) + \pi(s) \delta(t) + \text{more components...} \\
\mathbb{E}[Q(s, t)] &= c Q(s) + \lambda Q(s) \tau(t) + \theta(s) \omega(t) + \text{more components...}
\end{align*}
\]

Legend: varies in space and time
Model

After suitable data transformation...

\[
\begin{align*}
\mathbb{E}[P(s, t)] &= c_P(s) \\
\mathbb{E}[Q(s, t)] &= c_Q(s) \\
&\text{constant (intercept)}
\end{align*}
\]

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

After suitable data transformation...

\[
\begin{align*}
E[P(s, t)] &= c_P(s) + \lambda_P(s)\tau(t) \\
E[Q(s, t)] &= c_Q(s) + \lambda_Q(s)\tau(t)
\end{align*}
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Legend: varies in space and time; varies in space; varies in time
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\]

the SAME covariate \(\tau\) affects both P and Q

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 (HCl)
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 → Hidden Climate Indices (HCl)
- \(\tau(t) \sim AR(1) + \text{trend.}\)
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Legend: varies in space and time; varies in space; varies in time

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- \(\tau(t) \sim \text{AR}(1) + \text{trend. Same for } \delta(t) \text{ and } \omega(t)\)
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- All covariates are considered unknown and are estimated
  \(\rightarrow\) *Hidden Climate Indices* (HCI)
- \(\tau(t) \sim AR(1) + \text{trend. Same for } \delta(t) \text{ and } \omega(t)\)
- \(\lambda(s) \sim \text{Spatial Gaussian Process. Same for others}\)
Model

After suitable data transformation...

\[
\begin{align*}
\mathbb{E}[P(s, t)] &= c_P(s) + \lambda_P(s)\tau(t) + \pi(s)\delta(t) + \text{more components}
\end{align*}
\]

\[
\begin{align*}
\mathbb{E}[Q(s, t)] &= c_Q(s) + \lambda_Q(s)\tau(t) + \theta(s)\omega(t) + \text{more components}
\end{align*}
\]

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
Model

After suitable data transformation...

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\mathbb{E}[P(s, t)] &= c_P(s) + \lambda_P(s)\tau(t) + \pi(s)\delta(t) + \text{more components} \\
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- \(\lambda(s) \sim \text{Spatial Gaussian Process. Same for others}\)
- One component not enough at the global scale → 5 used here
- (Bayesian + MCMC) estimation
Ex.: SON season, 1st common HCI

HCI common to P and Q

Effect on P

Effect on Q

Increasing uncertainty

Trend (%) = −0.42 [−1.08; 0.28], r = 0.05 [0.00; 0.25]
Ex.: SON season, 1st common HCI

HCI common to P and Q

\[ \tau \]

Effect on P

Effect on Q

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Ex.: SON season, 1st common HCI
Ex.: SON season, 1st common HCI

HCl common to P and Q. Trend (%) = −0.42 [−1.08;0.28], r = 0.05 [0.00;0.25]
Trends and autocorrelations

P-specific HCI. Trend (%) = 2.56 [2.06;3.01], r = 0.02 [0.00;0.26]

Effect on P

Effect on P

P-specific HCI
Q-specific HCI
HCI common to P and Q

SON DJF MAM JJA SON DJF MAM JJA SON DJF MAM JJA

0.00 0.25 0.50 0.75

Lag−1 r

component 1 2 3 4 5

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Trends and autocorrelations

P-specific HCI. Trend (%) = 2.56 [2.06;3.01], r = 0.02 [0.00;0.26]

Effect on P
Trends and autocorrelations

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Effect on P

P-specific HCI
Q-specific HCI
HCI common to P and Q

SON DJF MAM JJA SON DJF MAM JJA SON DJF MAM JJA

Absolute trend [%]

Lag−1 r

component 1 2 3 4 5

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Trends and autocorrelations

P-specific HCl. Trend (%) = 2.56 [2.06;3.01] \( r = 0.02 [0.00;0.26] \)

Effect on P

Effect on P−specific HCI. Trend (%) = 2.56 [2.06;3.01] \( r = 0.02 [0.00;0.26] \)

P−specific HCI
Q−specific HCI
HCI common to P and Q

SON
DJF
MAM
JJA
SON
DJF
MAM
JJA
SON
DJF
MAM
JJA

Absolute trend [%]

Component 1 2 3 4 5
Trends and autocorrelations

P-specific HCI. Trend (%) = 2.56 [2.06;3.01], r = 0.02 [0.00;0.26]

Effect on P

<table>
<thead>
<tr>
<th>Component</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
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</thead>
<tbody>
<tr>
<td>Absolute trend [%]</td>
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<tr>
<td>P-specific HCI</td>
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<td>Q-specific HCI</td>
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<tr>
<td>HCI common to P and Q</td>
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</table>

Lag-1 r

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Trends and autocorrelations

P–specific HCI. Trend (%) = 2.56 [2.06;3.01], r = 0.02 [0.00;0.26]

Effect on P

Effect on Q

Effect on HCI common to P and Q

component 1 2 3 4 5

P–specific HCI Q–specific HCI HCI common to P and Q

SON DJF MAM JJA SON DJF MAM JJA SON DJF MAM JJA

Absolute trend [%]

Lag–1 r

SON DJF MAM JJA SON DJF MAM JJA SON DJF MAM JJA

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180-year reconstruction

Hidden Climate Indices

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

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180-year reconstruction

Climate predictors

Hidden Climate Indices

Using 20CRv3, reconstruction of HCIs from 1836
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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!


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

![Barker Creek at Brooklands (QLD)](image1)

![Clarke Brooke at Hillview Farm (WA)](image2)
Model

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

\[
\begin{align*}
P(s, t) & \sim \text{Beta} \left( \mu_P(s, t), \gamma_P(s) \right) ; Q(s, t) \sim \text{Beta} \left( \mu_Q(s, t), \gamma_Q(s) \right) \\
\logit \left( \mu_P(s, t) \right) & = \lambda_{P,0}(s) + \sum_{k=1}^{K} \lambda_{P,k}(s) \tau_k(t) + \sum_{k=1}^{K} \pi_k(s) \delta_k(t) \\
\logit \left( \mu_Q(s, t) \right) & = \lambda_{Q,0}(s) + \sum_{k=1}^{K} \lambda_{Q,k}(s) \tau_k(t) + \sum_{k=1}^{K} \theta_k(s) \omega_k(t)
\end{align*}
\]
P-specific HCIs with large trends

- SON
- DJF
- MAM
- JJA
HCIs with notable autocorrelation

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

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

**Alternatives:** LASSO, RIDGE and other form of penalised regression, but first attempts inconclusive
Reconstructions from 20CRv3 (1836-2015)

- Estimated from P/Q
- Reconstructed from 20CR (1 member)

Probability of a 10-year flood occurring

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

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SON 1840

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SON 1840

Probability of a 10-year flood occurring
Reconstructions from 20CRv3 (1836-2015)

- Estimated from P/Q
- Reconstructed from 20CR (1 member)

Time series showing probability of a 10-year flood occurring over time from 1850 to 2000.

SON 1840

Probability of a 10-year flood occurring

SON 1867

Probability of a 10-year flood occurring

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