Application of EVA for climate change adaptation

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Ouranos and McGill University

30 October 2019

Outline

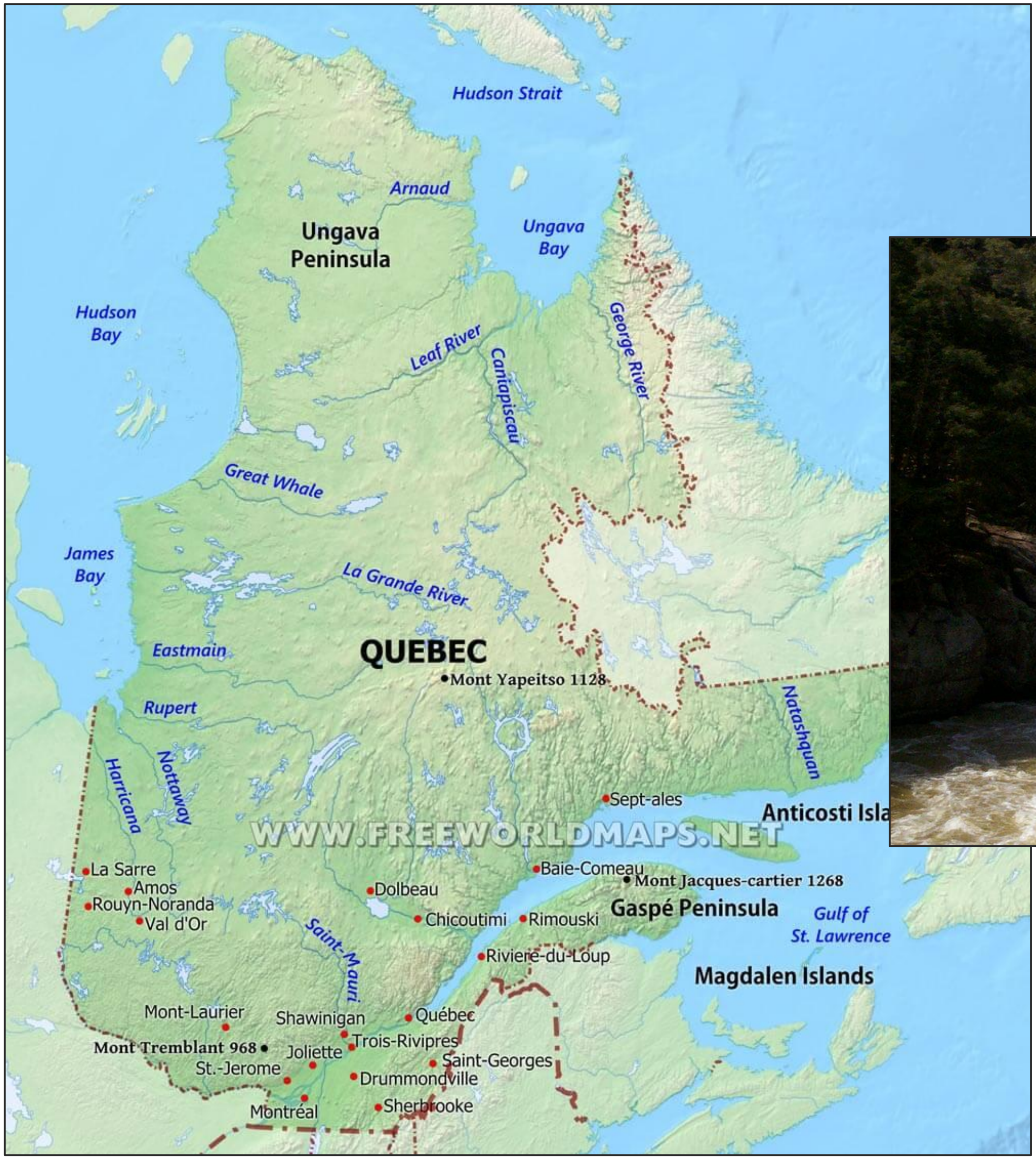
- Context and motivation
- Approach in a stationary climate
- Bringing climate change into the picture
- Conclusion

Québec


Alaska
Canada
United States
Mexico


Hudson Strait
Arnaud
Ungava Peninsula
Ungava Bay
Hudson Bay
Leaf River
Caniapiscau
George River
Great Whale
James Bay
La Grande River
Eastmain
QUEBEC
Mont Yapeitso 1128
Rupert
Natashquan
Harricana
Nottaway
Sept-ales
Anticosti Island
WWW.FREEWORLDMAPS.NET
La Sarre
Amos
Rouyn-Noranda
Val d'Or
Baie-Comeau
Mont Jacques-cartier 1268
Dolbeau
Chicoutimi
Rimouski
Gaspé Peninsula
Gulf of St. Lawrence
Saint-Mauri
Riviere-du-Loup
Magdalen Islands
Mont-Laurier
Shawinigan
Québec
Trois-Rivipres
Mont Tremblant 968
Joliette
St.-Jerome
Saint-Georges
Drummondville
Montréal
Sherbrooke

Québec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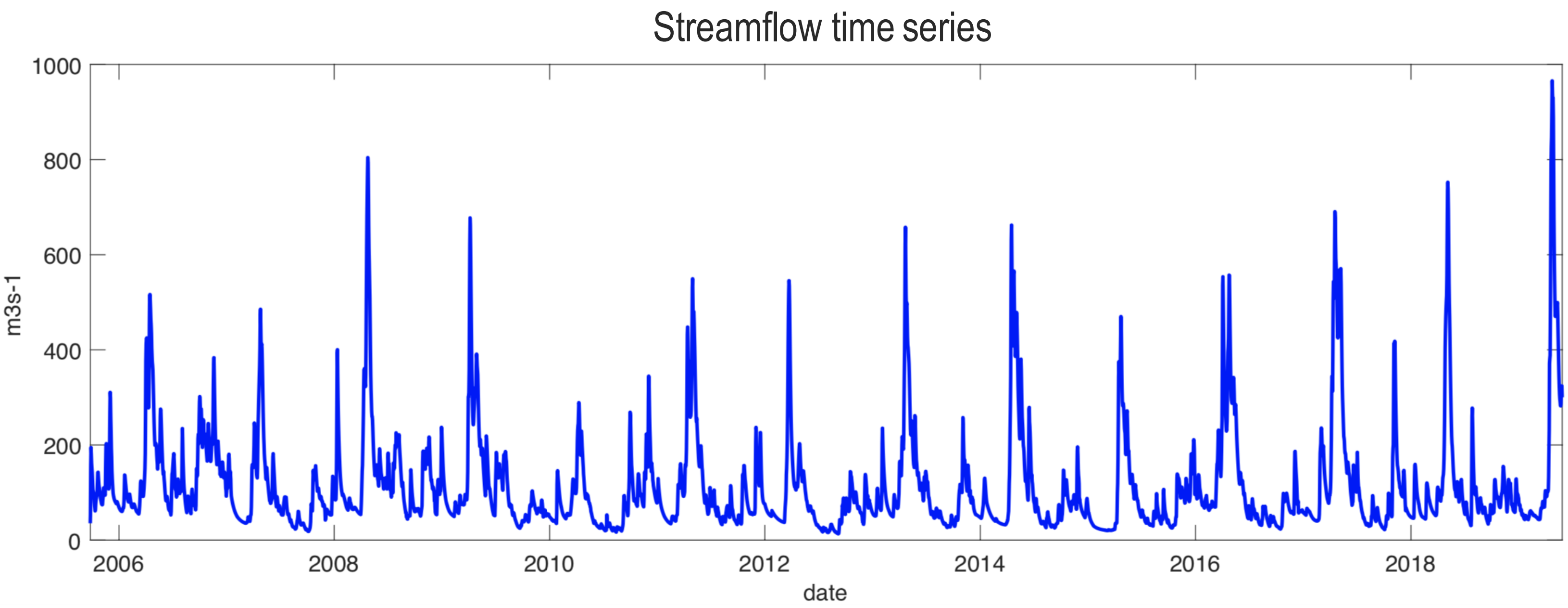
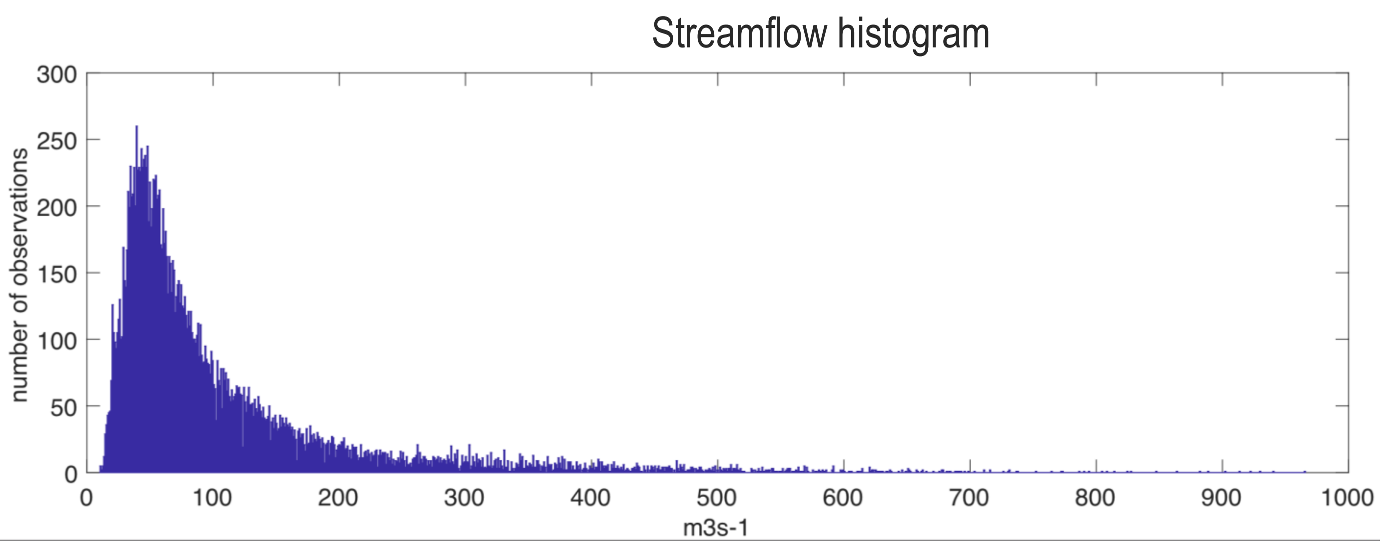
Sherbrooke

Montreal, April 2017

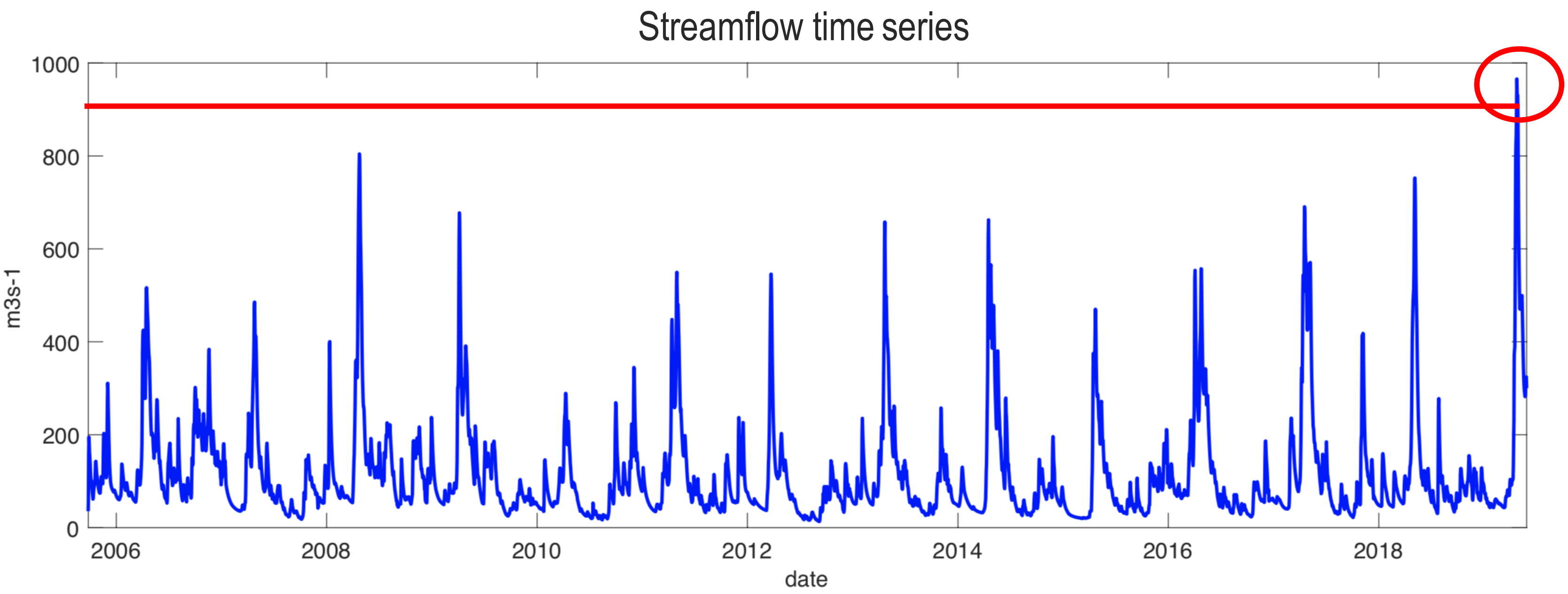
Québec, April 2019

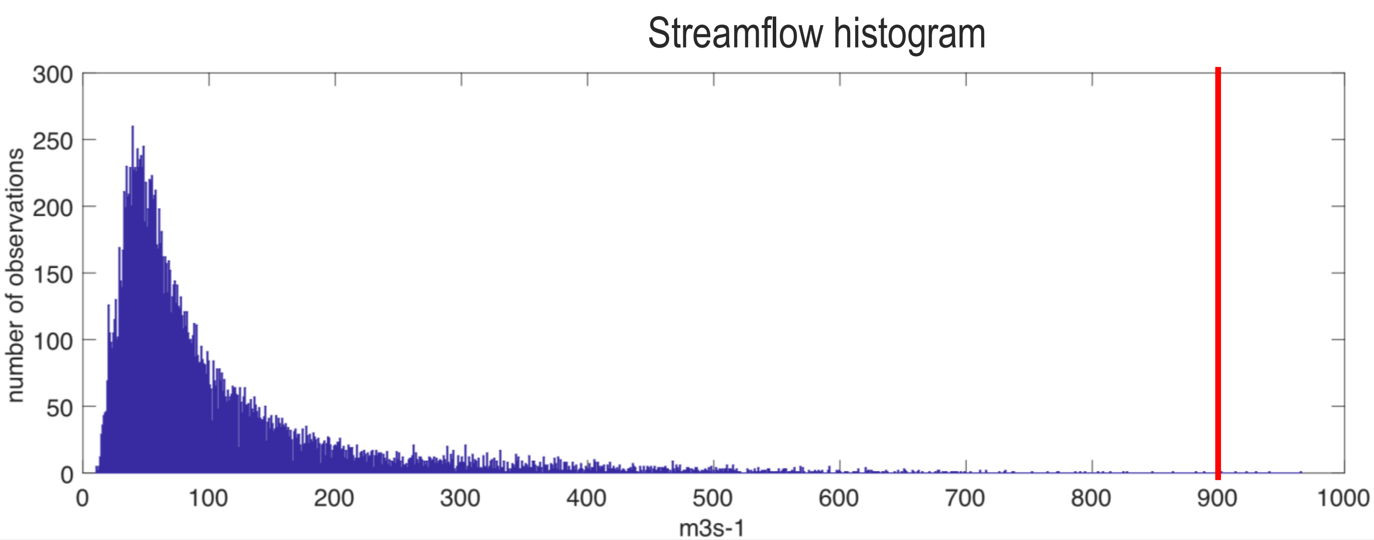
Streamflow, Rouge River





Streamflow, Rouge River





Attributing extreme events to climate change

- Attribution requires to computes the probabilities p_0 and p_1 that a given observed value u (e.g. 2019 record streamflow) is exceeded.

$$p_1 = P(X > u \mid \mathrm{GHG} = \mathrm{on})$$
$$p_0 = P(X > u \mid \mathrm{GHG} = \mathrm{off})$$

Attributing extreme events to climate change

- Attribution requires to computes the probabilities p_0 and p_1 that a given observed value u (e.g. 2019 record streamflow) is exceeded.

$$p_1 = P(X > u \mid \text{GHG} = \text{on})$$
$$p_0 = P(X > u \mid \text{GHG} = \text{off})$$

- From there, several causal metrics can be derived:

$$\text{PN} = \max\left(0, 1 - \frac{p_0}{p_1}\right)$$
$$\text{PS} = \max\left(0, 1 - \frac{1-p_1}{1-p_0}\right)$$
$$\text{PNS} = \max\left(0, p_1 - p_0\right)$$

Question asked for attribution

➡ What is the value of the probability to exceed a given threshold?

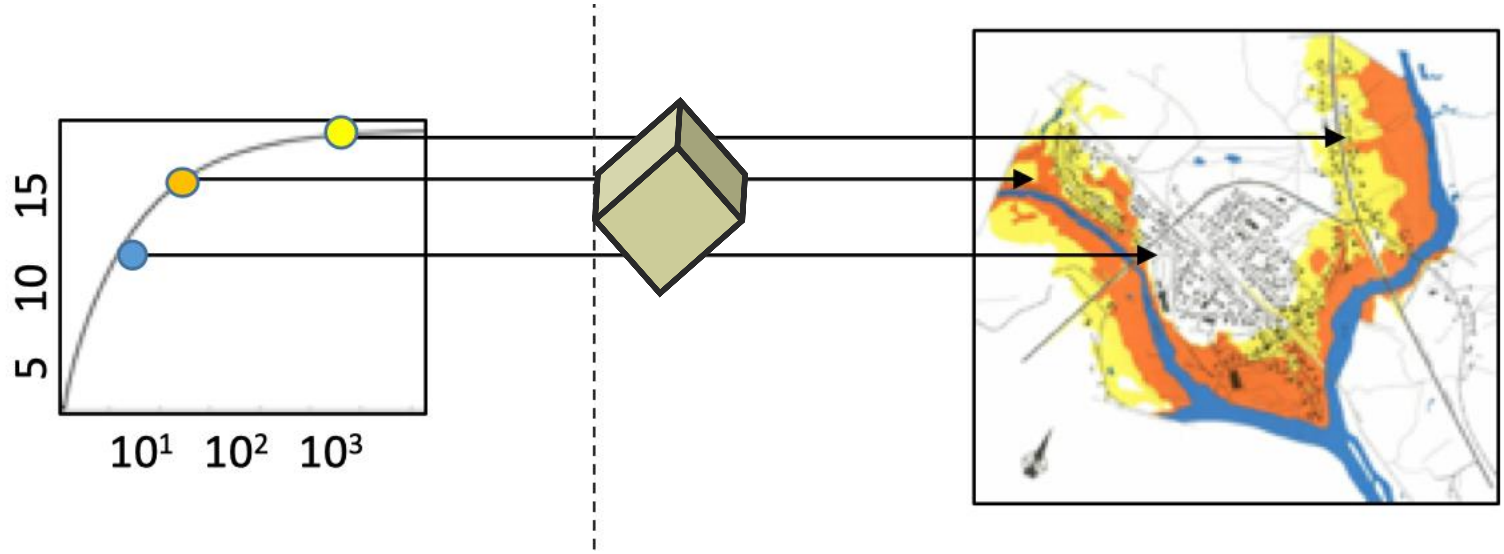
- The threshold is high and may never have been reached in observations (e.g. counterfactual).

Designing maps of flood risk

Return level curve

Digital Elevation Map + Flood model

Map of flood risk



Question asked for flood risk mapping

➡ What are the values of the 20, 50 and 100 years flow ?

- The regulator will enforce only one map in the law. The answer is requested to be a single value.

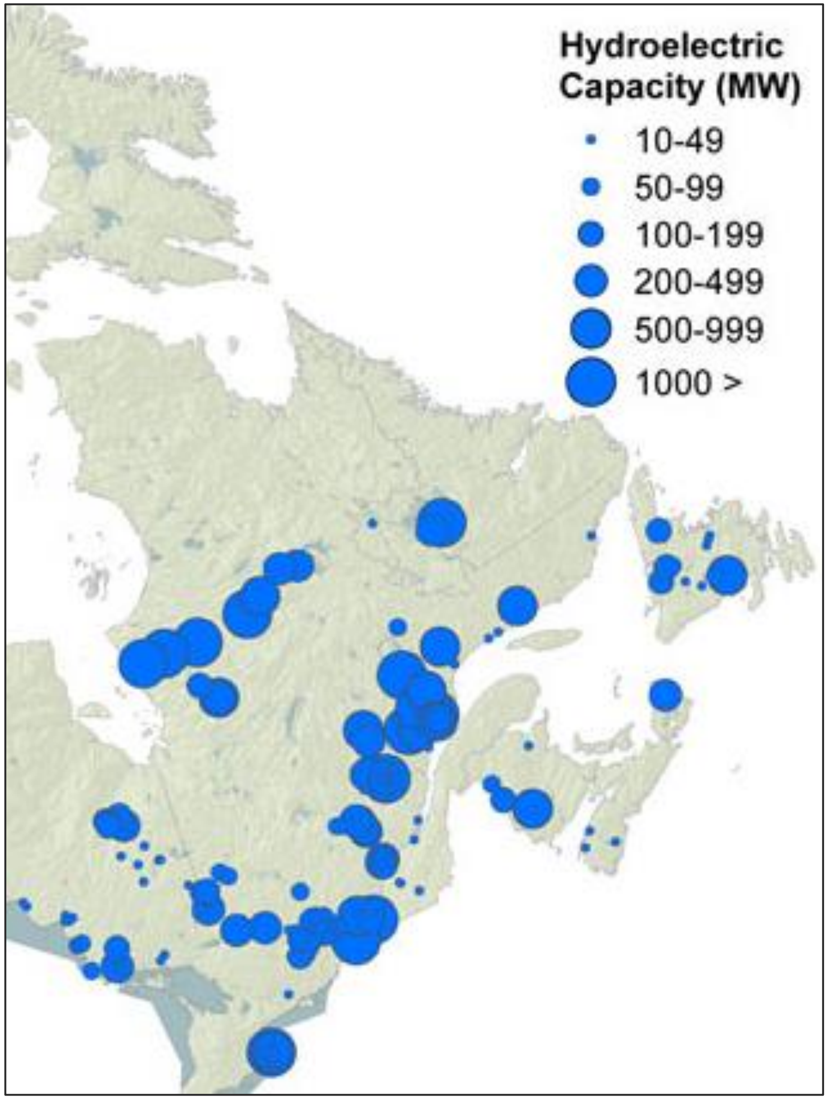
Question asked for flood risk mapping

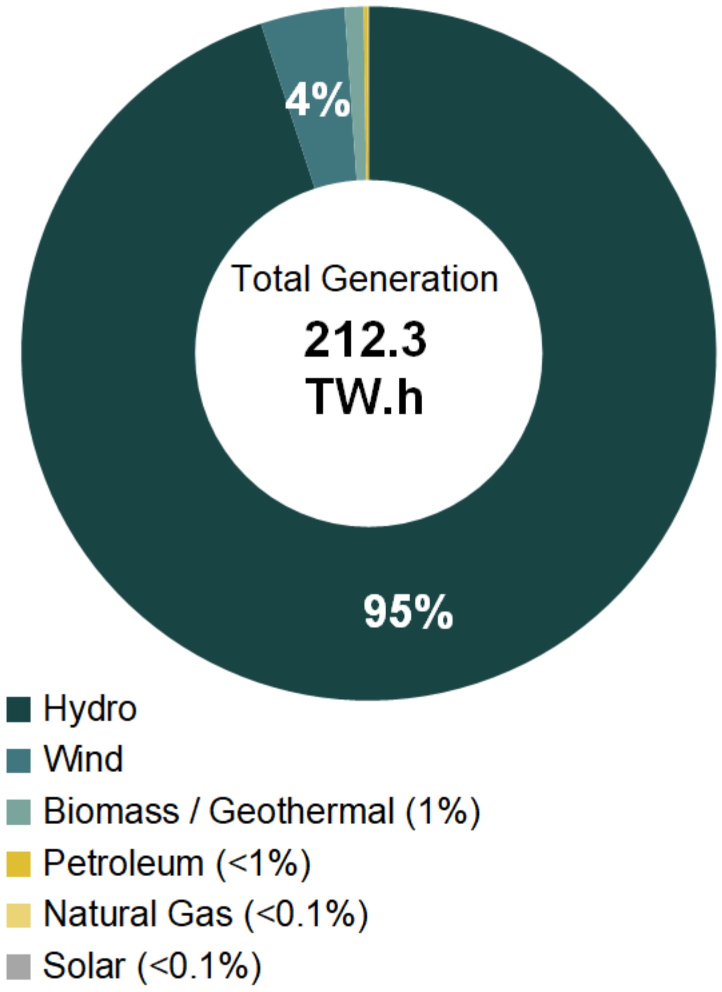
➡ What are the values of the 95%, 98% and 99% quantile ?

- The regulator will enforce only one map in the law. The answer is requested to be a single value.

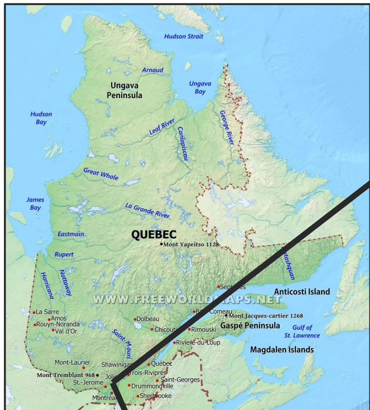
Hydropower generation

Hydropower generation

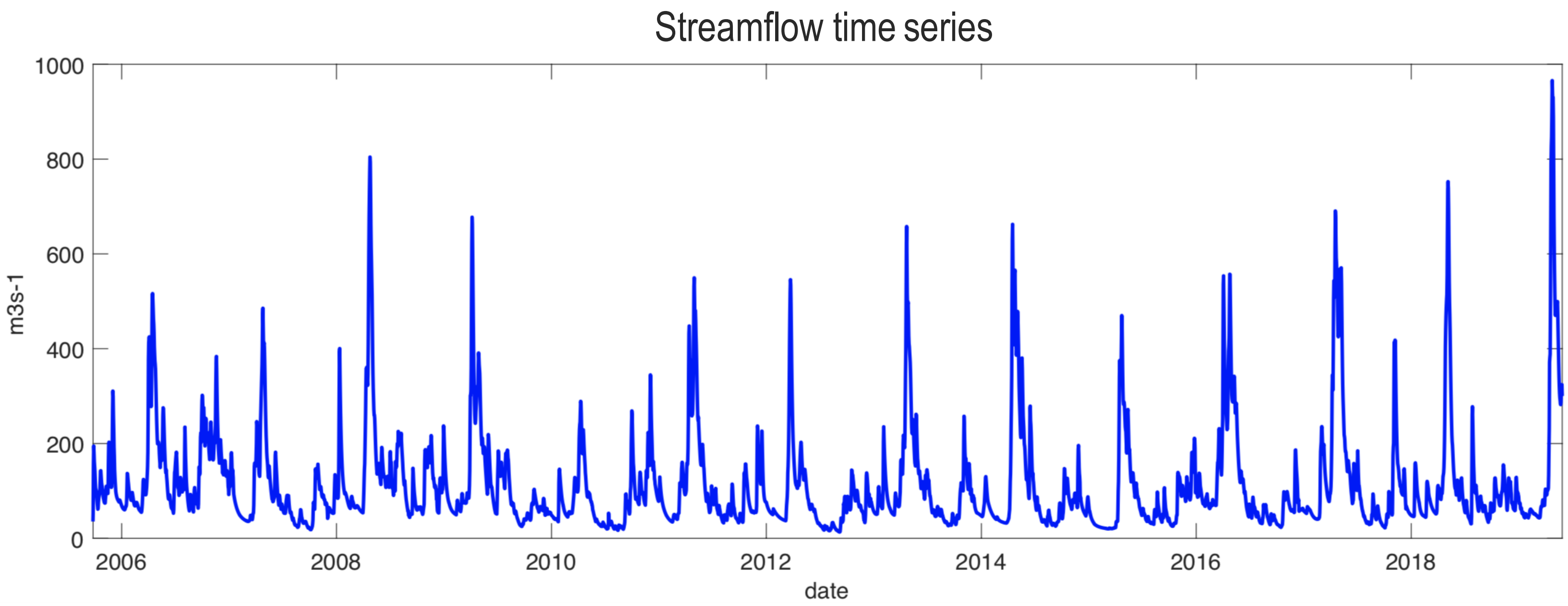


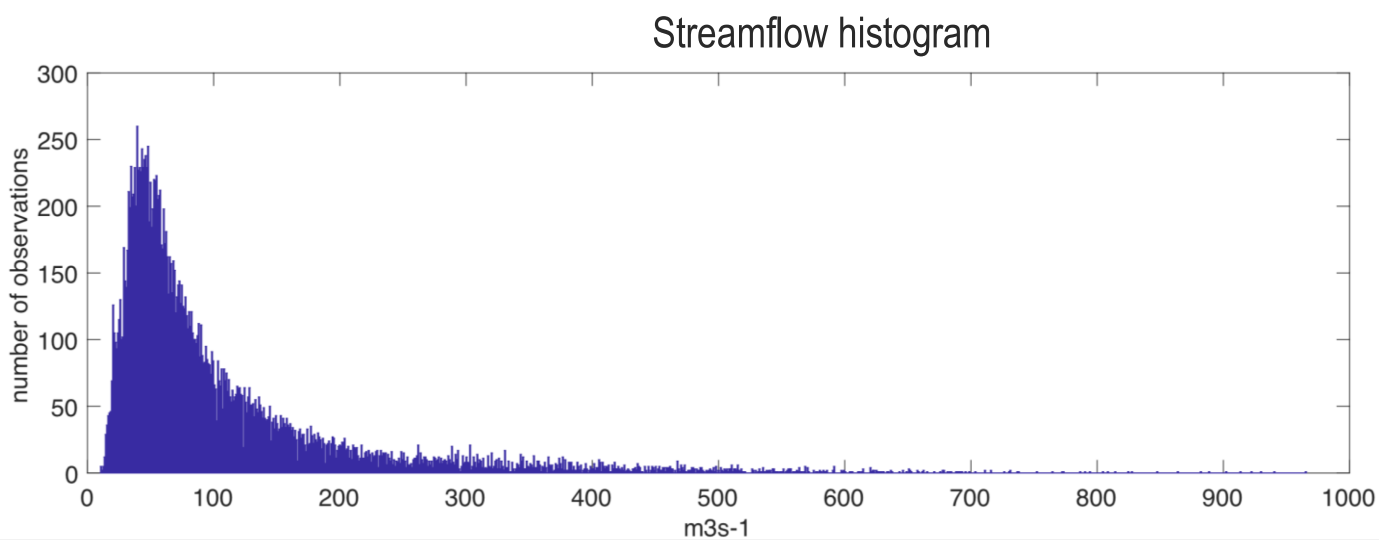


Bell Falls, Rouge River



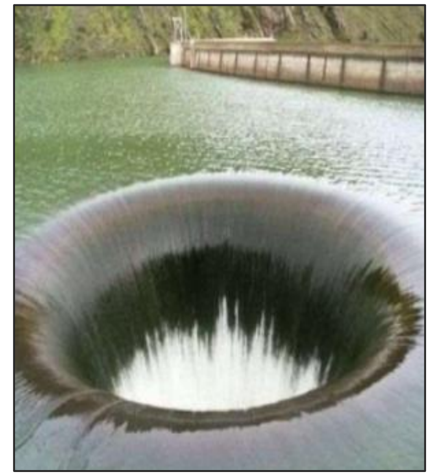
Streamflow, Rouge River

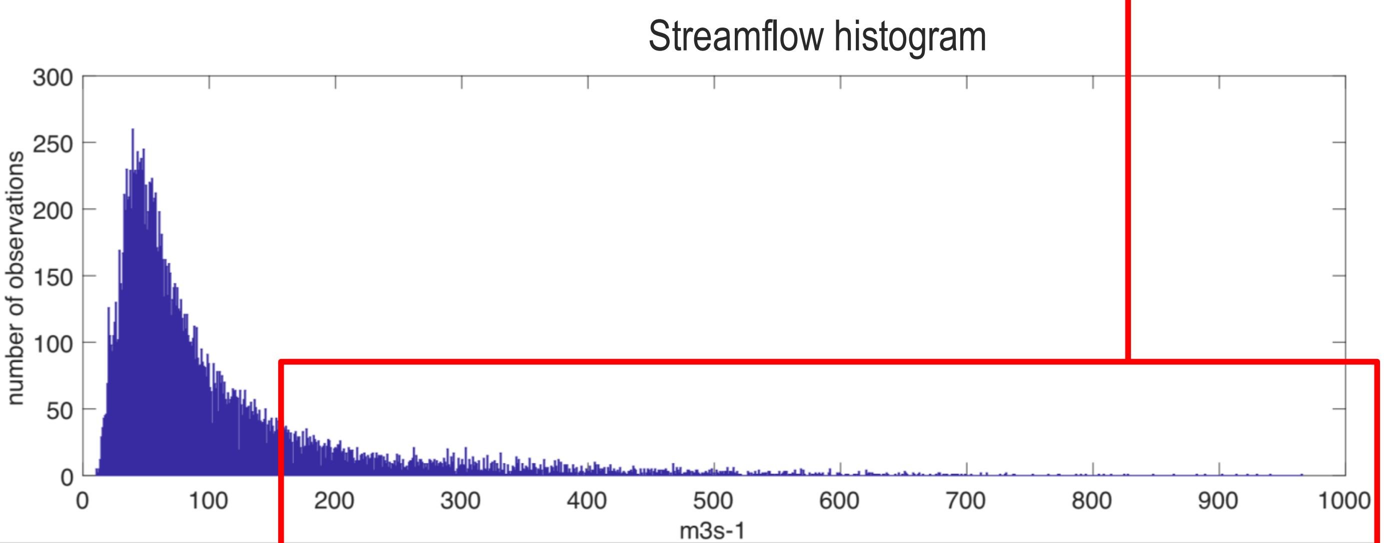




Spillways

A **spillway** is a structure used to release the surplus of flow from a dam into a downstream area.





Bell Falls, April 2019

Bell Falls, April 2019

Fears of failure of Chute-Bell dam prompt evacuations in Quebec

04/26/2019

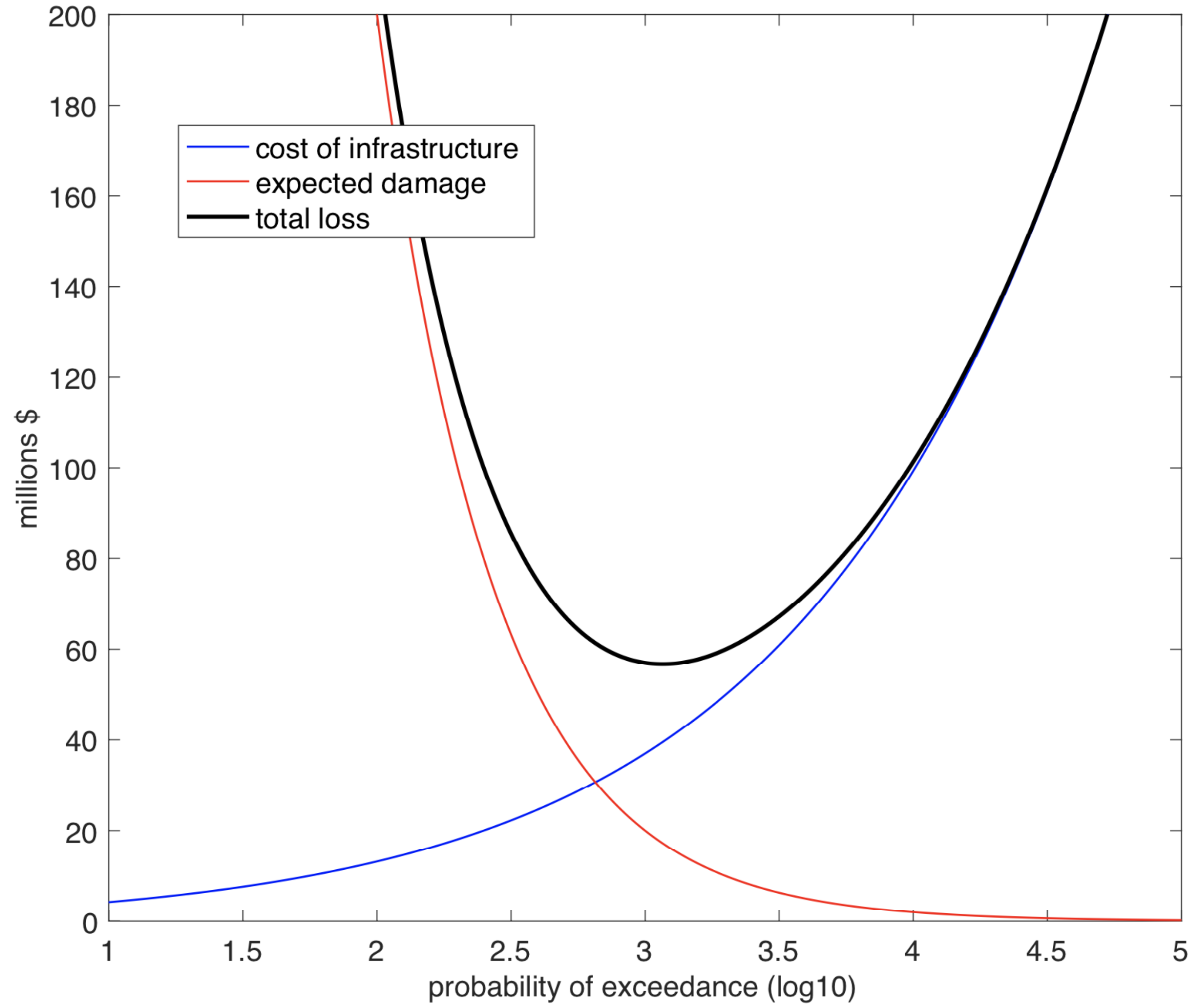
By Elizabeth Ingram
Content Director

The government of Quebec has issued a risk of dam failure alert related to the Rouge River downstream of Chute-Bell dam.

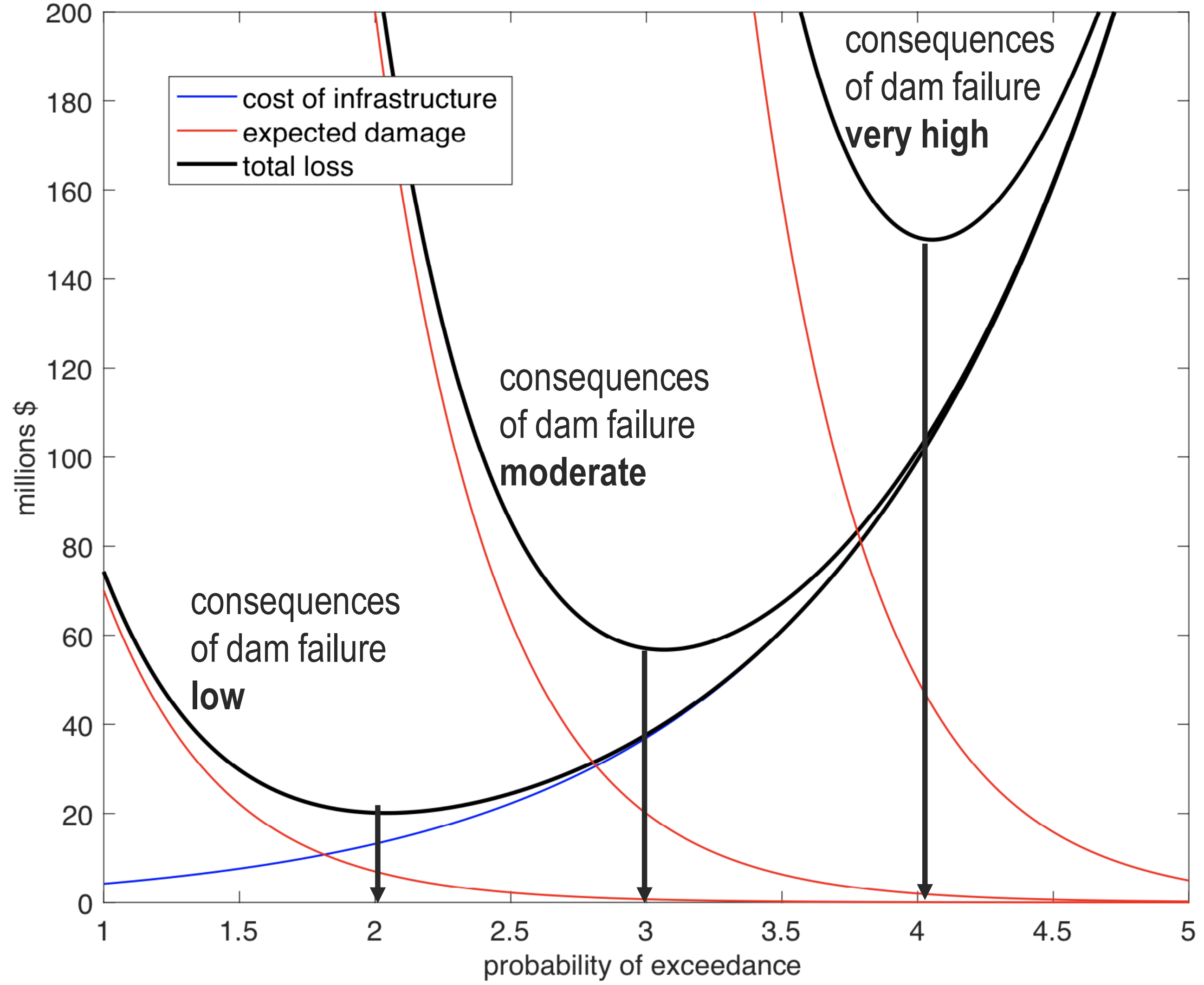
The government has directed people in the affected area to evacuate immediately, effective yesterday afternoon.

The dam impounds water for a 10-MW hydroelectric powerhouse, and water has been overtopping it due to a high flow rate in the river. The run-of-river Chute-Bell facility contains two turbine-generator units and was commissioned in 1915.

Decision making under uncertainty



Decision making under uncertainty



DAM SAFETY

21. Subject to sections 21.1, 22 and 24, every dam must be able to withstand any of the following safety check floods, taking into account the highest dam failure consequence category in flood conditions:

Highest dam failure consequence category in flood conditions	**Safety Check Flood**
Very low or low	Centennial* (1: 100 years)
Moderate or high	Millennial* (1: 1,000 years)
Very high	Decamillennial* (1: 10,000 years)
Severe	Probable maximum flood

* Safety check floods expressed according to their recurrence interval.

O.C. 300-2002, s. 21; O.C. 901-2014, s. 2.

Question asked by hydropower companies and regulating bodies

➡ What is the value of the 10,000 years flow ?

- Civil engineers designing the spillway will build one spillway. The answer is requested to be a single value.

Question asked by hydropower companies and regulating bodies

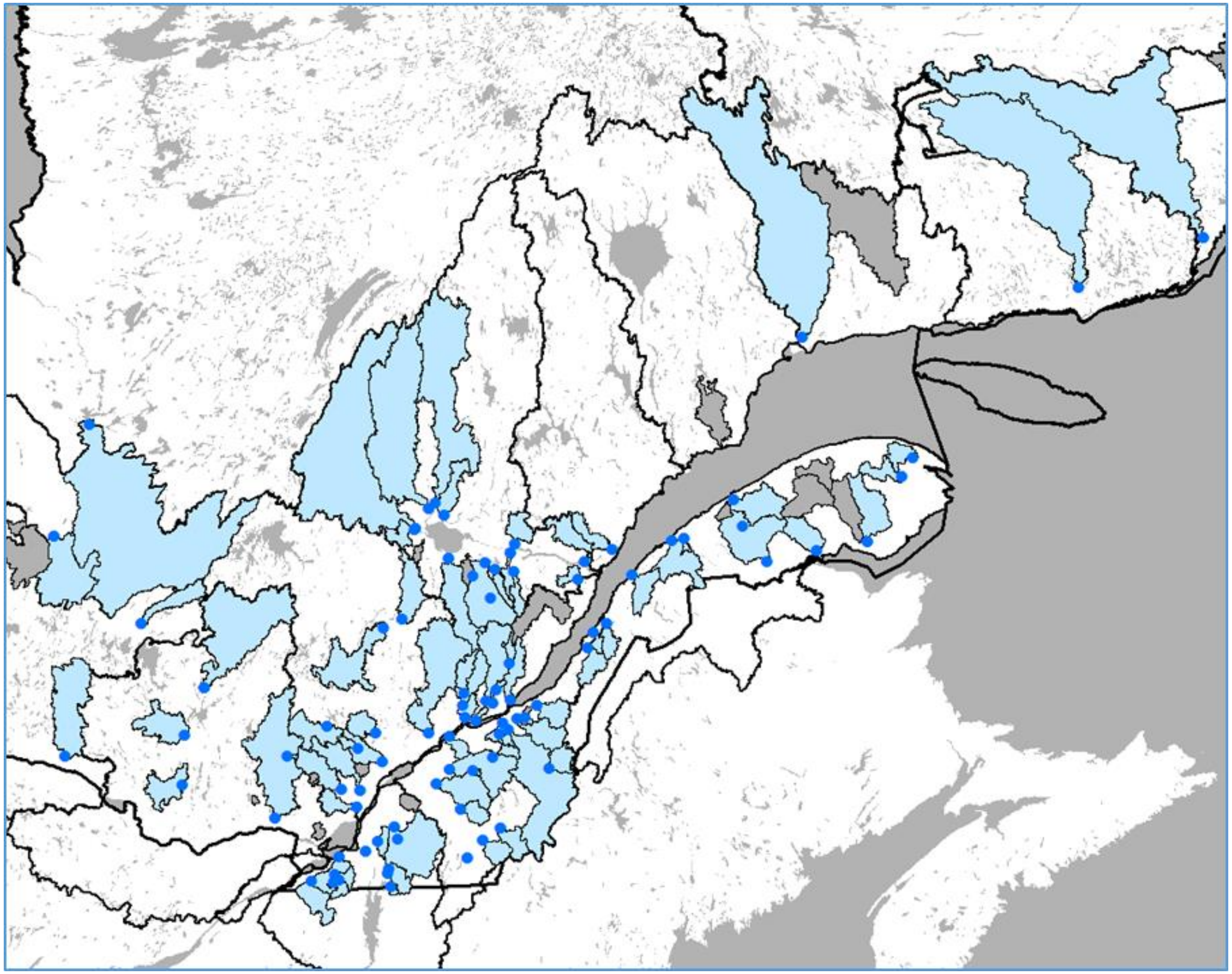
→ What is the value of the 99,99% quantile ?

- Civil engineers designing the spillway will build one spillway. The answer is requested to be a single value.

Problem

- Estimate a high quantile for a given low probability
- Estimate a low probability for a given high threshold

Hydrological map of the area



Gauge station database = 88 stations

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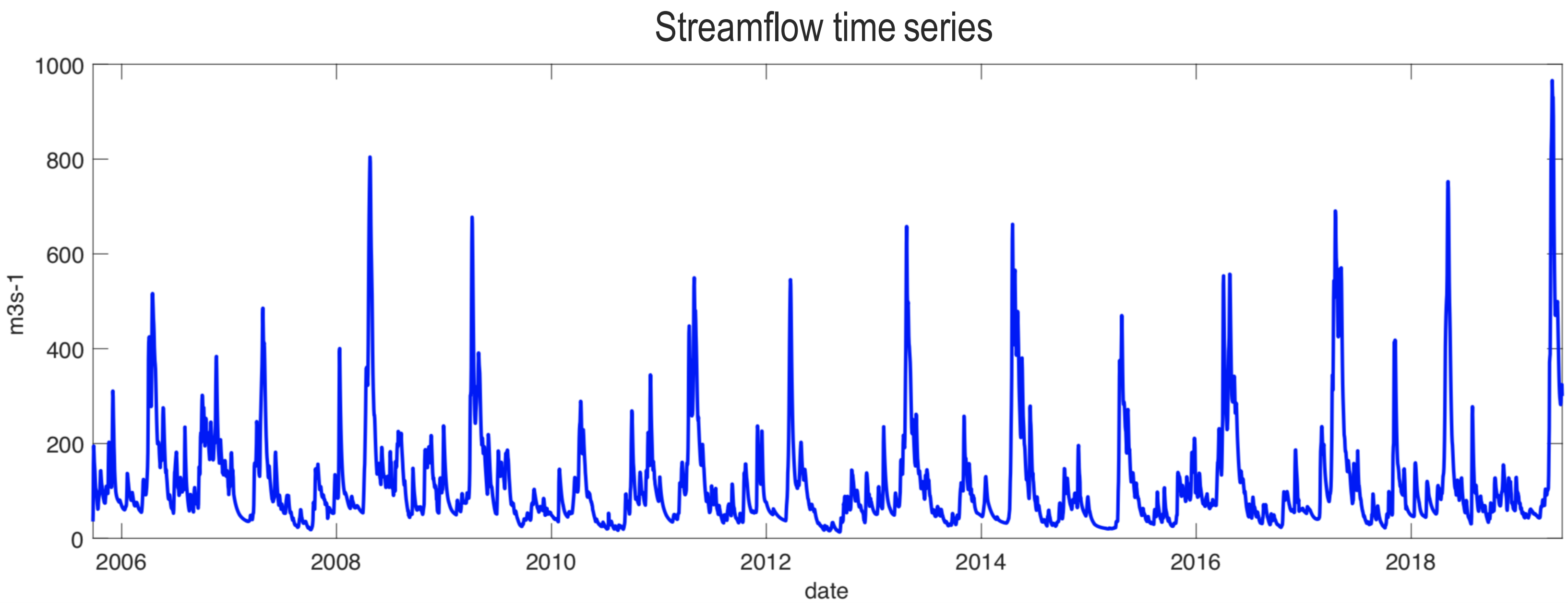
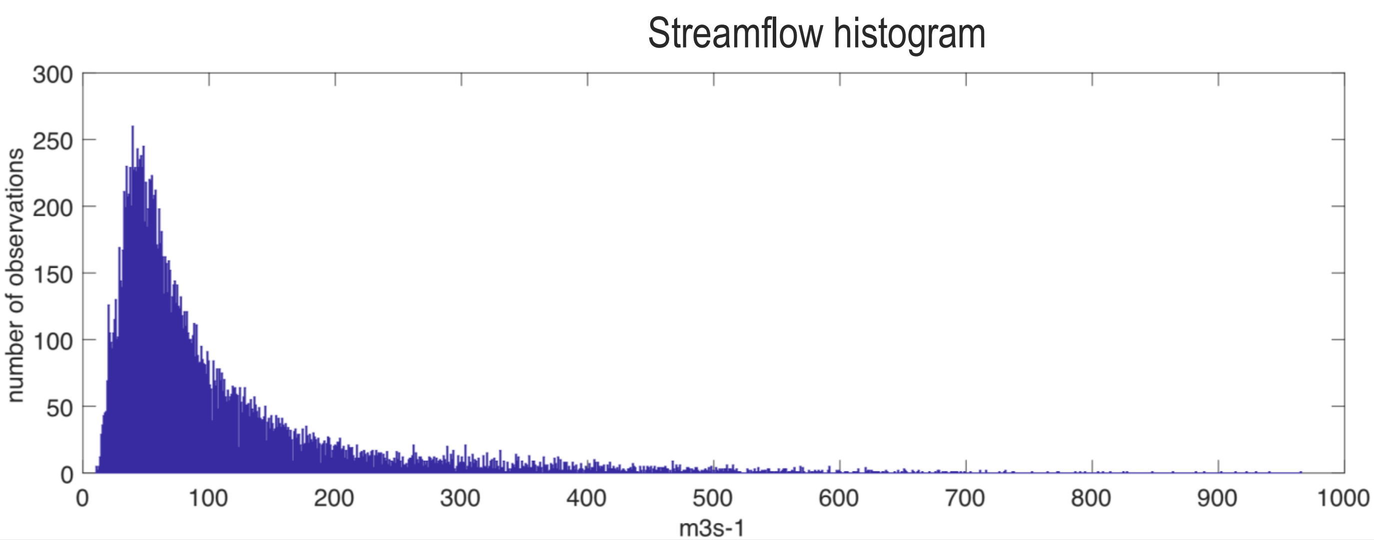
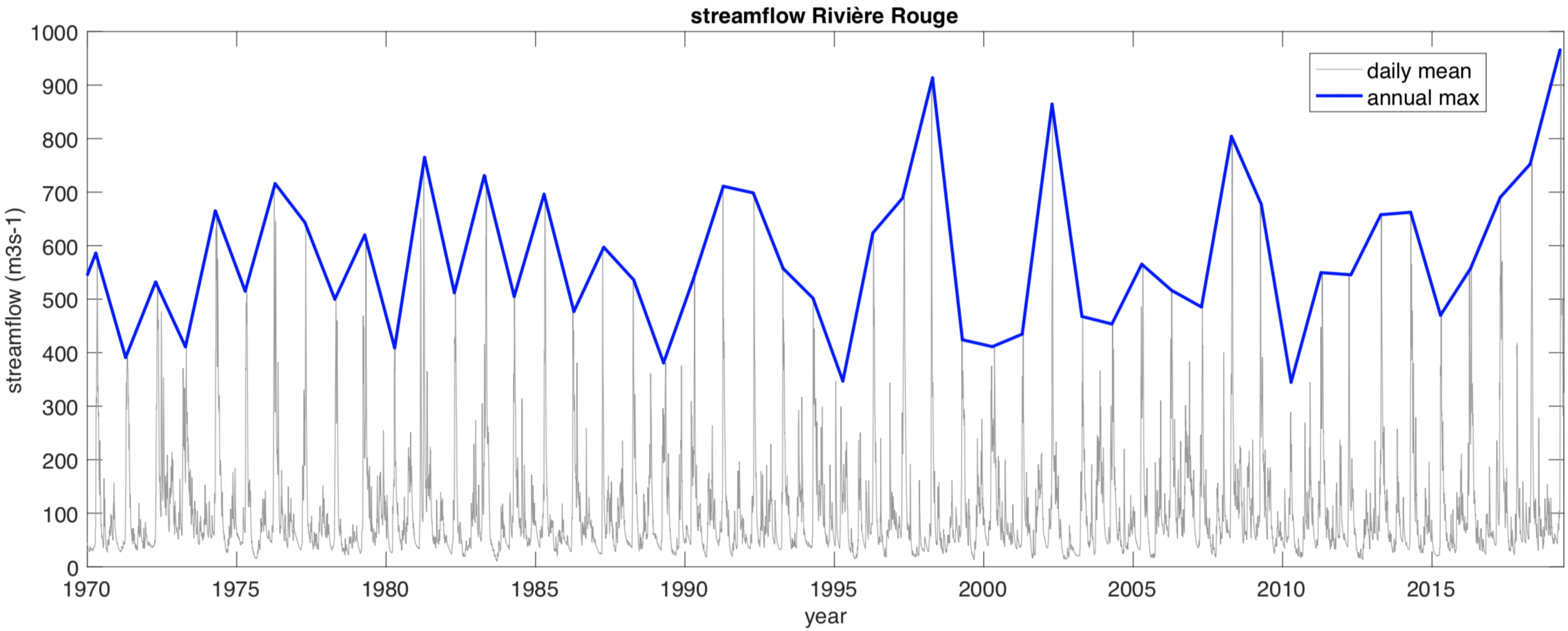
Streamflow, Rouge River





Data: annual maxima



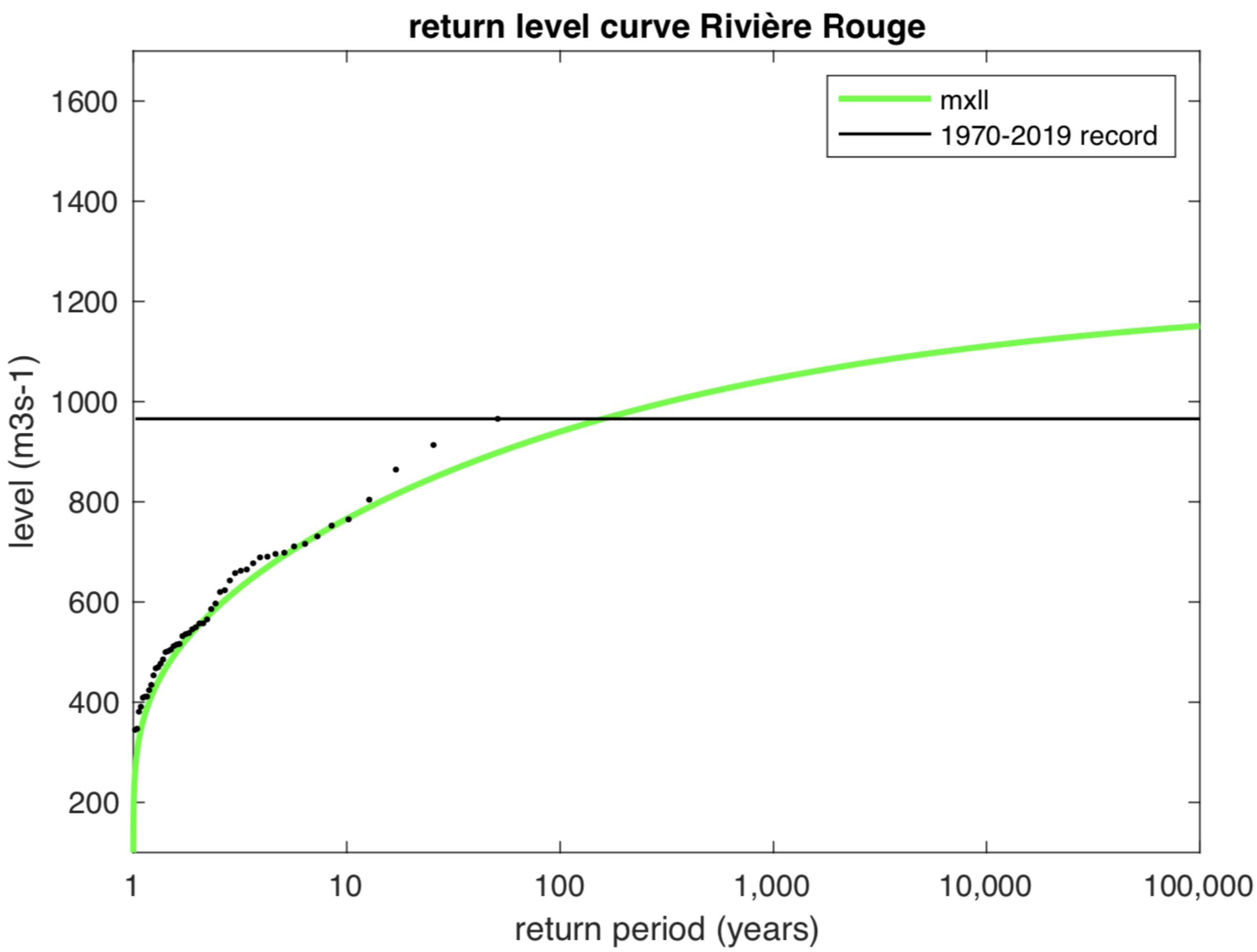
Model: univariate Generalized Extreme Value distribution

$$\boldsymbol{x} = (x_1, x_2, ..., x_n) \text{ i.i.d.}$$

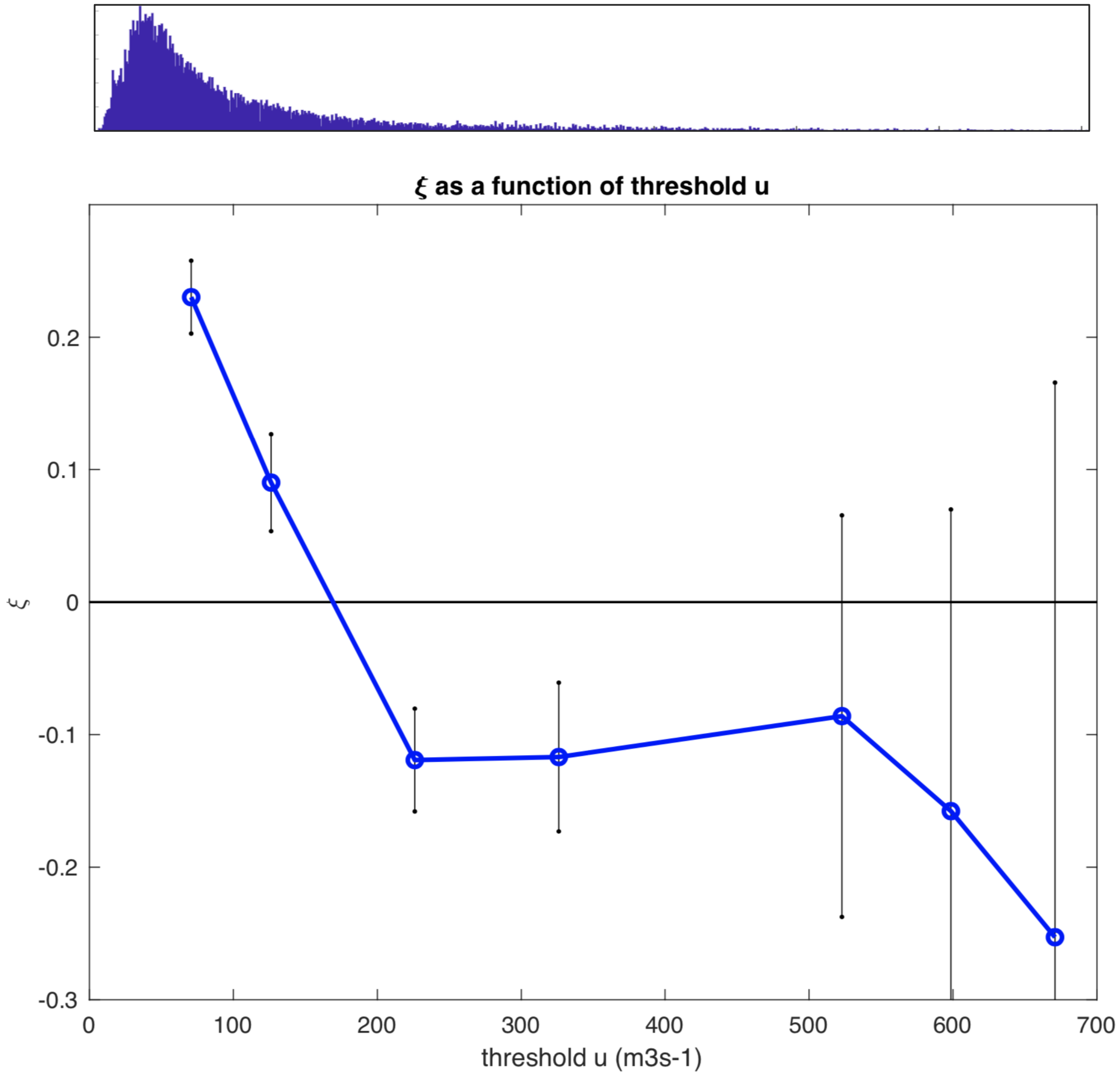
$$p(\boldsymbol{x} \mid \theta) = \Pi_{t=1}^{n} \text{GEV}(x_t \mid \theta)$$

$$\theta = (\mu, \sigma, \xi)$$

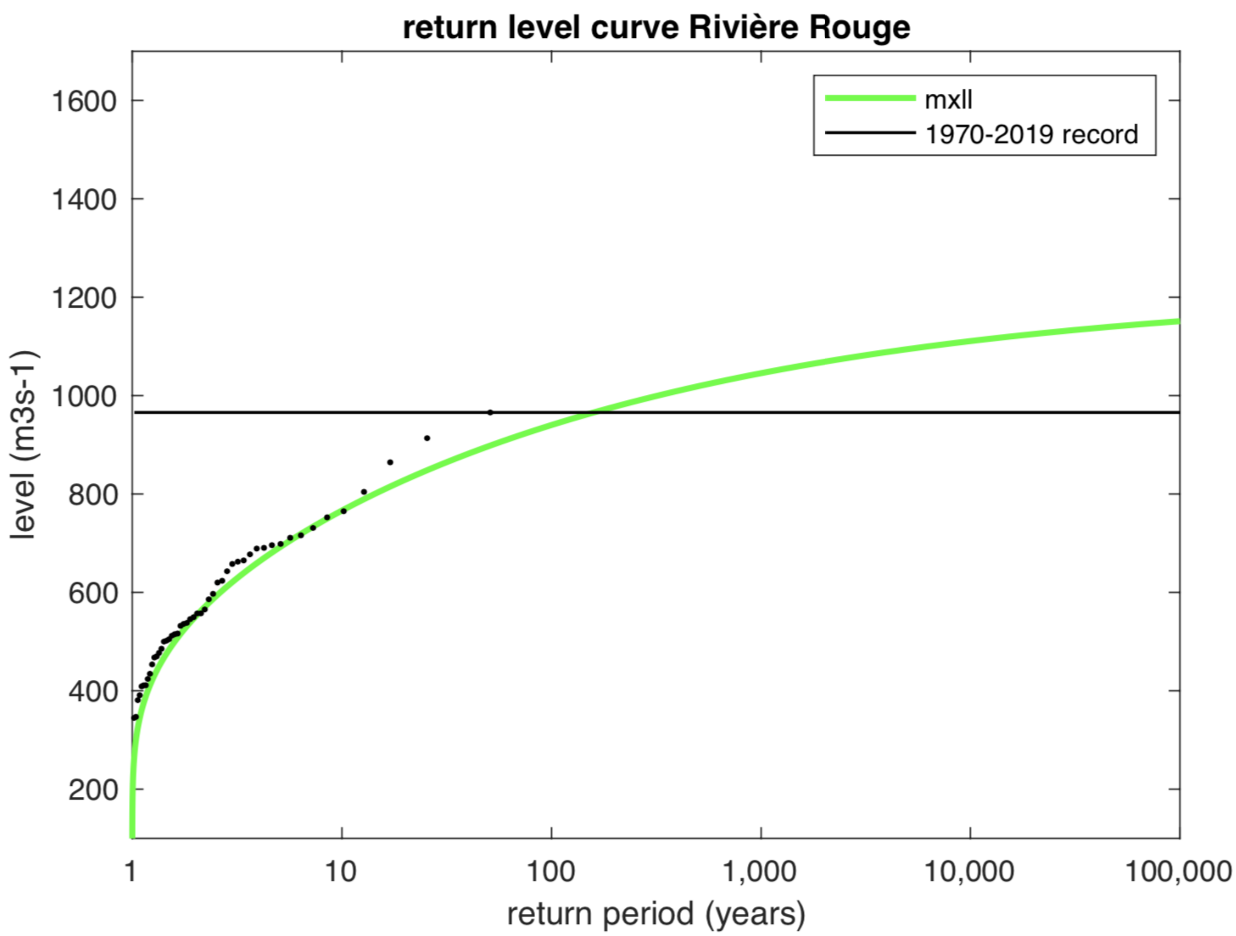
Inference: maximum likelihood



Comparison with the GPD model



Inference: maximum likelihood



Can we come up with a better estimator ?

Bayesian estimation: a brief overview

$$\boldsymbol{x} = (x_1, x_2, \ldots, x_n)$$

$$p(\boldsymbol{x} \mid \theta) = \ldots$$

$$\pi(\theta) = \ldots$$

$$p(\theta \mid \boldsymbol{x}) \propto p(\boldsymbol{x} \mid \theta)\, \pi(\theta)$$

Bayesian estimation: a brief overview

$$\boldsymbol{x} = (x_1, x_2, ..., x_n)$$

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$$(\theta_1, \theta_2, ..., \theta_N)$$ MCMC simulations

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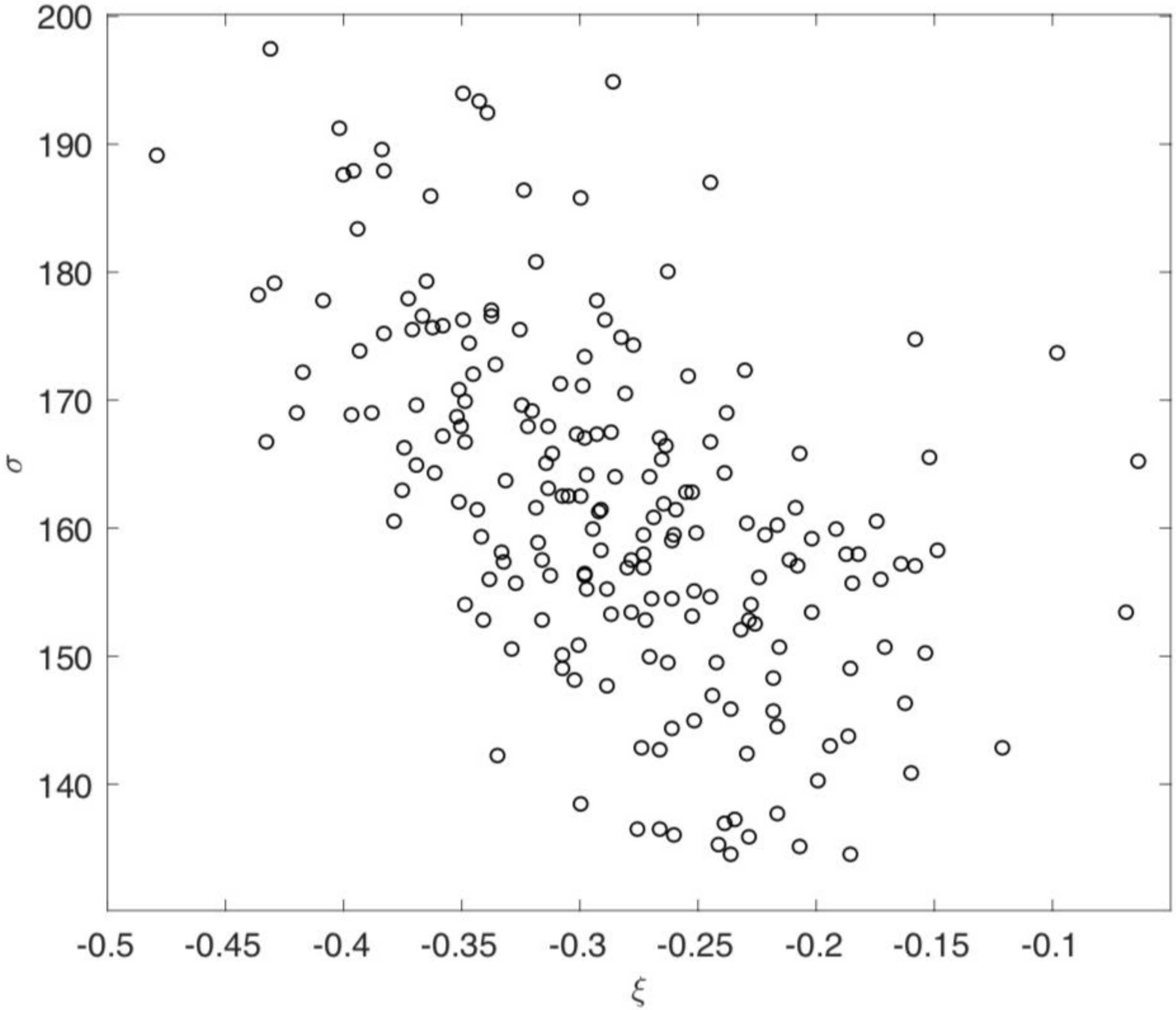
$$\theta = (\mu, \sigma, \xi)$$

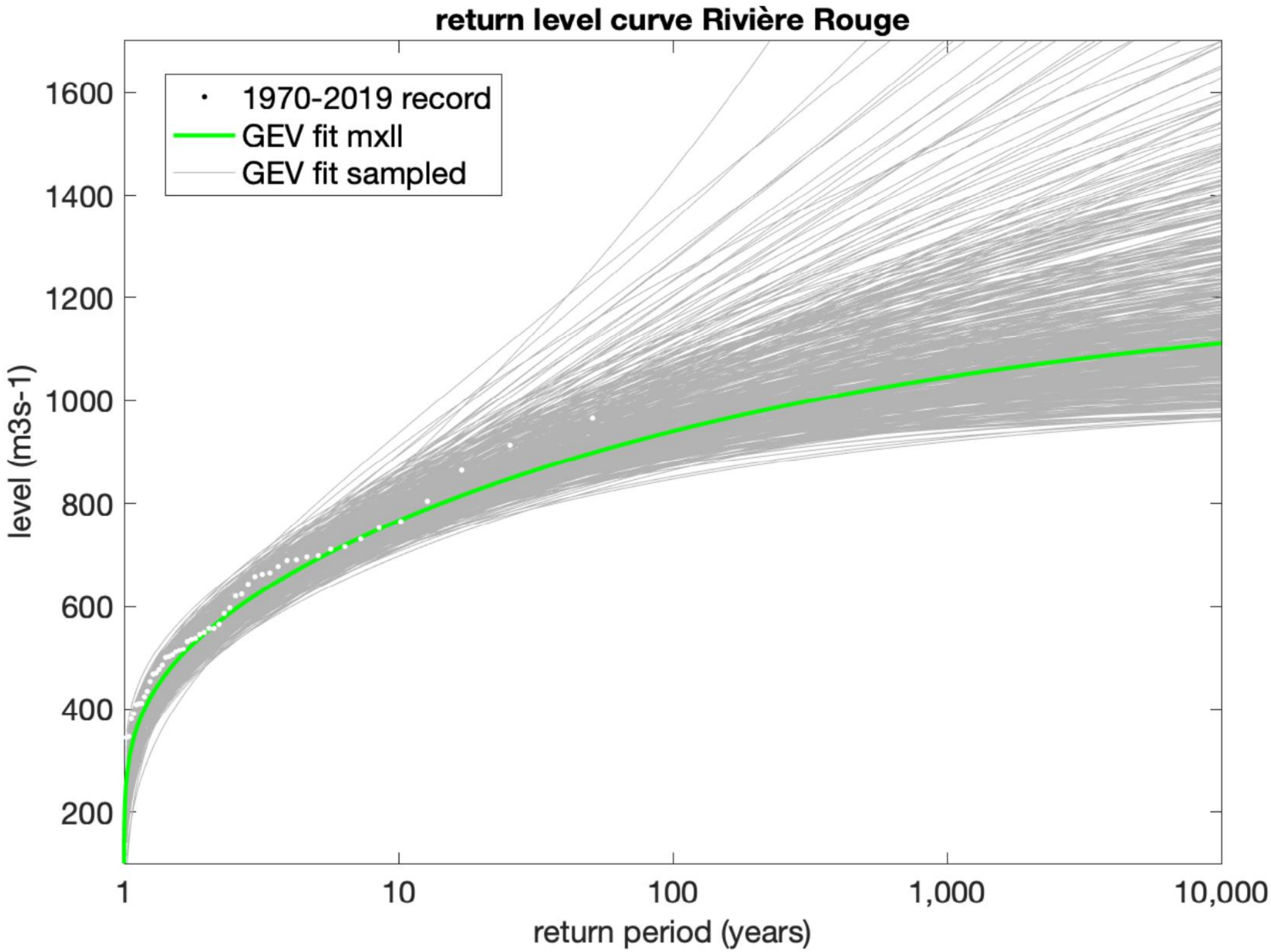
$$\pi(\theta) \propto \sigma^{-1}$$

Northrop and Attalides 2015

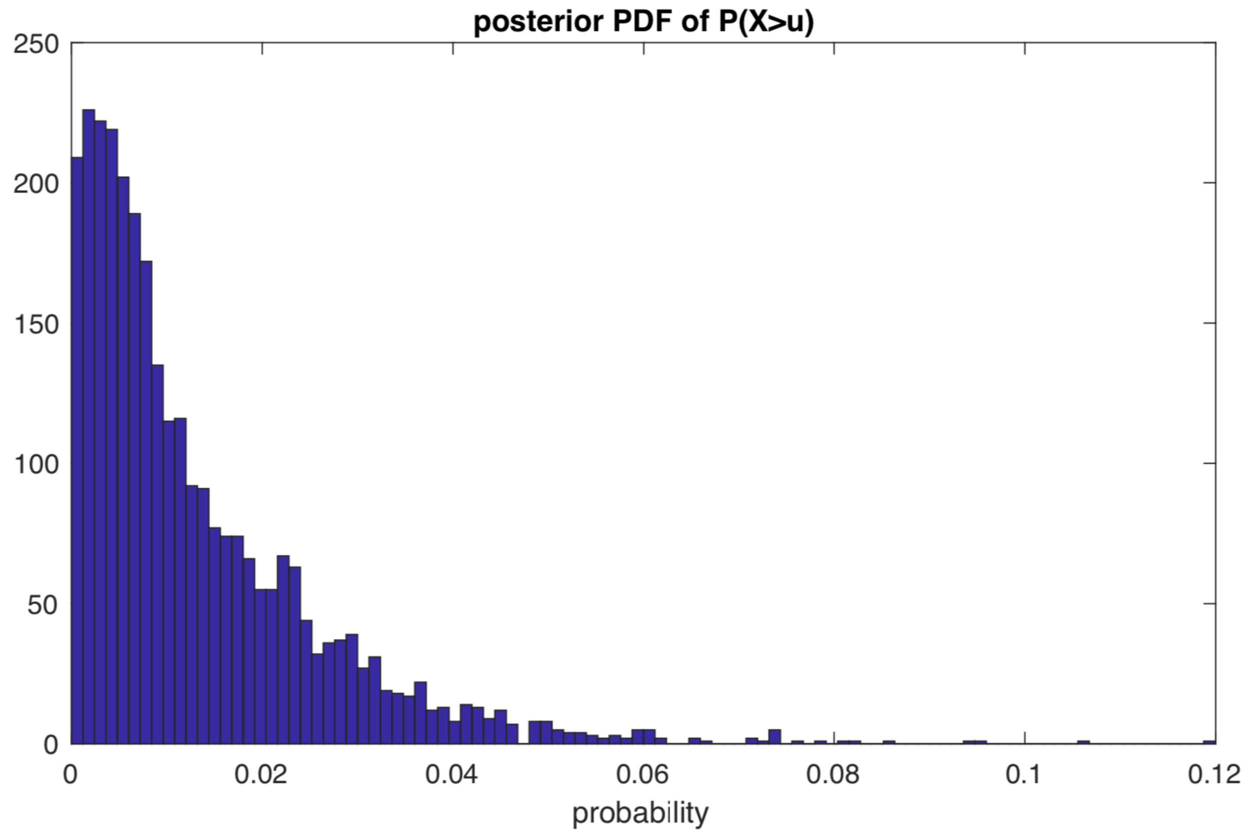
MCMC simulation of the posterior distribution



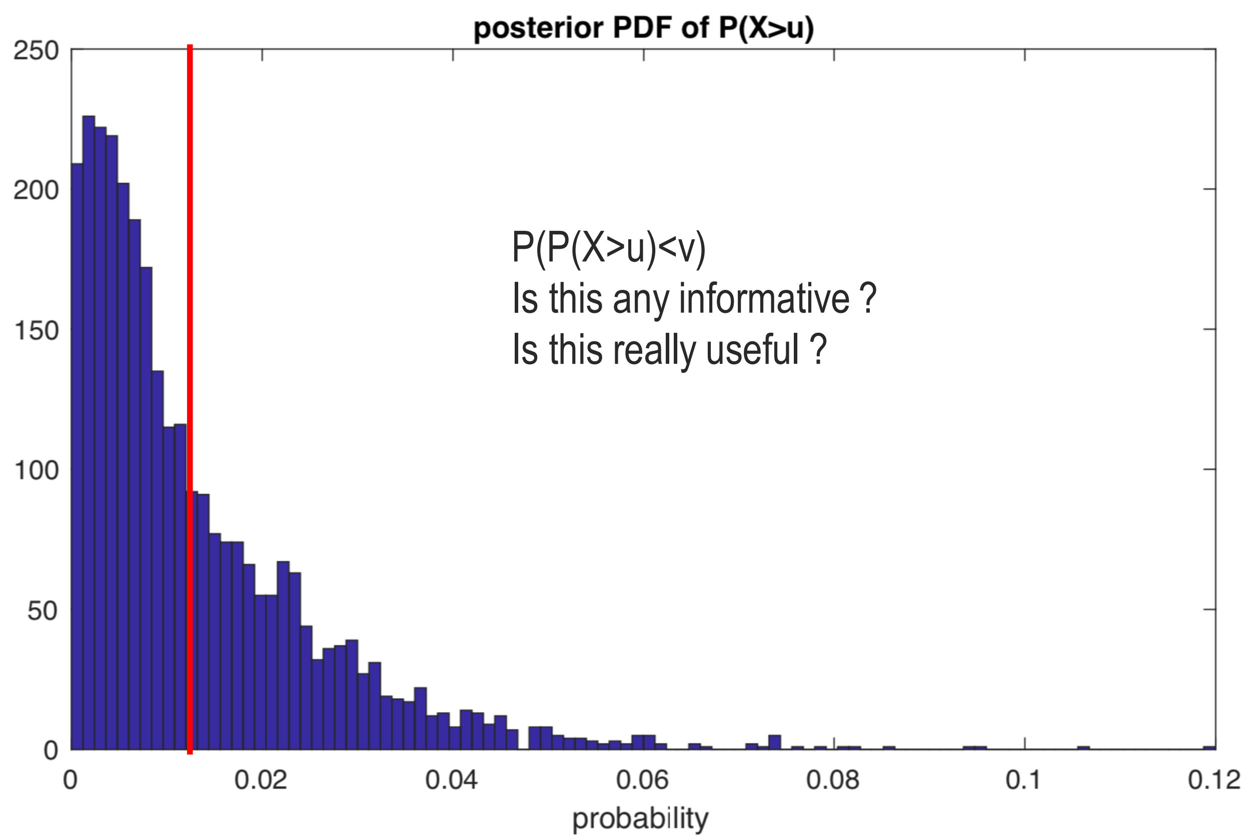
MCMC simulation of the posterior return level curve



MCMC simulation of the posterior PDF of the probability of exceedance

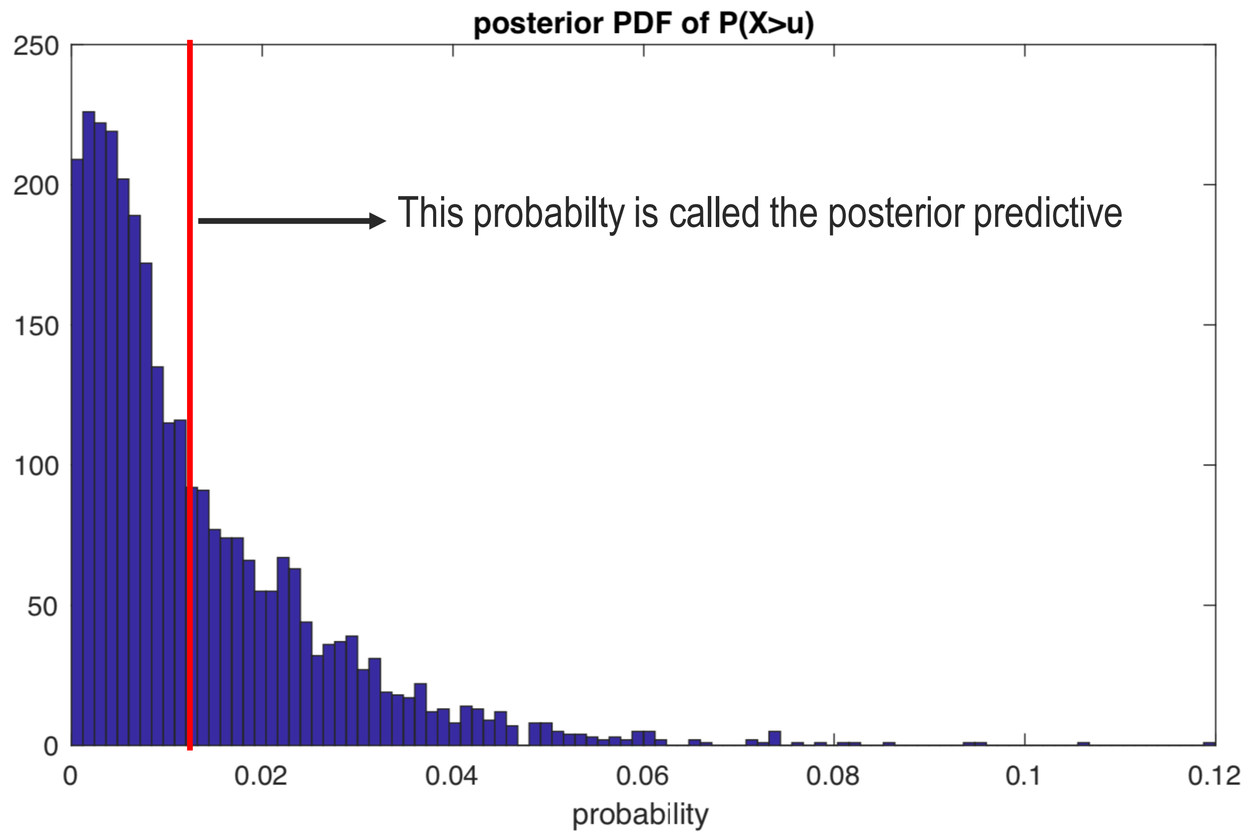


A probability on a probability ?



A probability density on a probability can (arguably should) always be boiled down to a single number.
In this case, P(X>u) = 0.0132, or 75 years return period

A probability on a probability ?



A probability density on a probability can (arguably should) always be boiled down to a single number.
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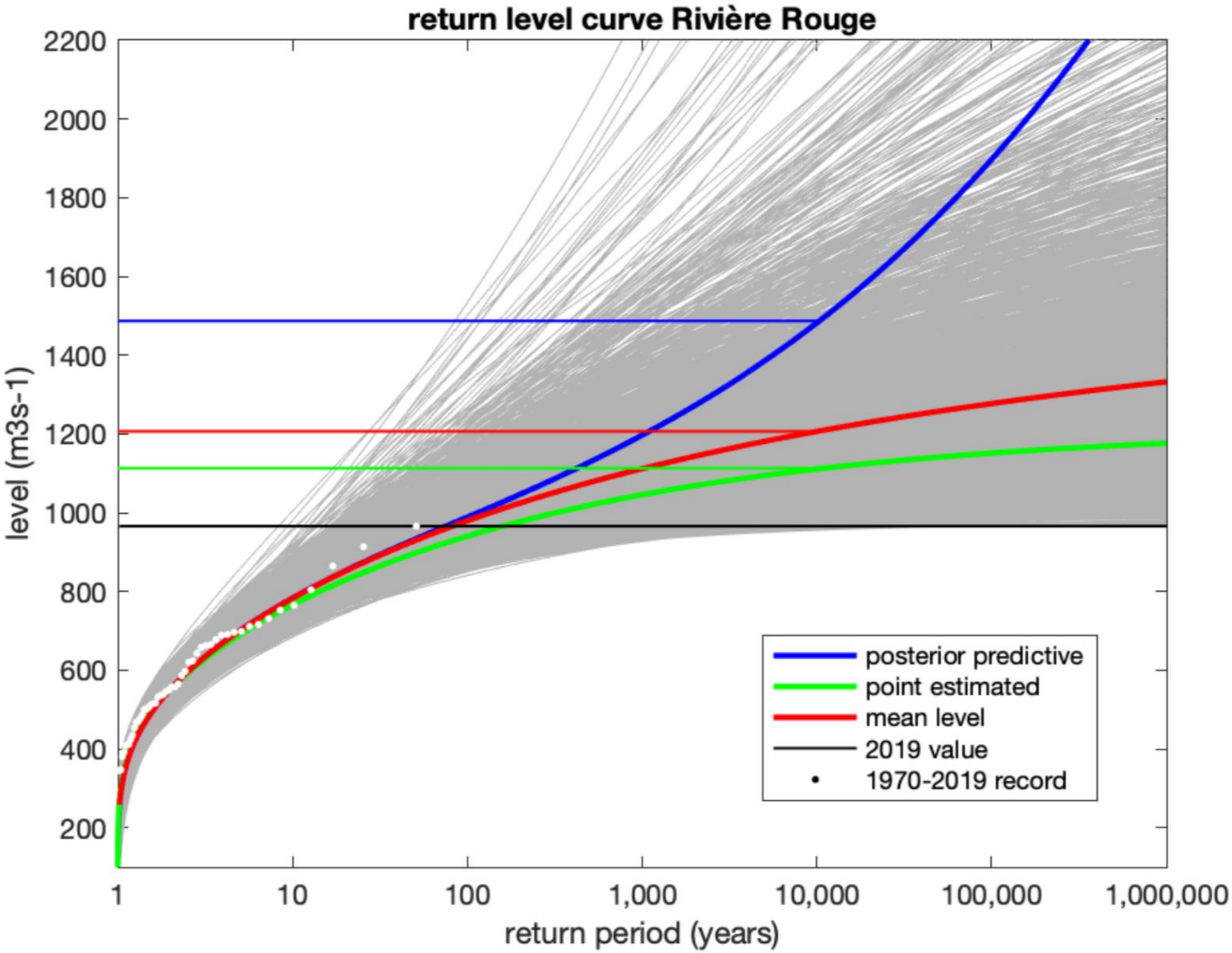
The posterior predictive: a possible estimator of the return level curve



Bayesian estimation: a brief overview

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$$p(\boldsymbol{x} \mid \theta) = ...$$

$$\pi(\theta) = ...$$

$$p(\theta \mid \boldsymbol{x}) \propto p(\boldsymbol{x} \mid \theta)\, \pi(\theta)$$

$$(\theta_1, \theta_2, ..., \theta_N)$$ MCMC simulations

Bayesian estimation: a brief overview

$$\mathcal{C}(\theta, \theta^*) \; = \dots$$

$$\mathcal{C}(\theta^* \mid \boldsymbol{x}) = \mathbb{E}_{\theta \mid \boldsymbol{x}}\left(\mathcal{C}(\theta, \theta^*)\right) = \int_\theta \mathcal{C}(\theta, \theta^*)\, p(\theta \mid \boldsymbol{x})\, \mathrm{d}\theta$$

$$\hat{\theta} = \operatorname{argmin}_{\theta^*} \mathcal{C}(\theta^* \mid \boldsymbol{x})$$

Bayesian estimation: a brief overview

$$\mathcal{C}(\theta, \theta^*) = \{\theta - \theta^*\}^2$$

$$\hat{\theta}_{\text{MMSE}} = \int_\theta \theta\, p(\theta \mid \boldsymbol{x})\, \mathrm{d}\theta \simeq \frac{1}{N} \sum_{i=1}^{N} \theta_i$$

Bayesian estimation: a brief overview

$$\mathcal{C}(\theta, \theta^*) = \mathbf{1}\{\theta \neq \theta^*\}$$

$$\hat{\theta}_{\mathrm{MAP}} = \mathrm{argmax}_{\theta}\ p(\theta \mid \boldsymbol{x}) \ \simeq\ \mathrm{mode}(\theta_1, \ldots, \theta_N)$$

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$$p(\boldsymbol{x} \mid \theta) = \Pi_{t=1}^{n} \text{GEV}(x_t \mid \theta)$$

$$\theta = (\mu, \sigma, \xi)$$

$$\pi(\theta) \propto \sigma^{-1}$$

Attempt 1: conventional cost function and estimator

$$\mathcal{C}(\theta, \theta^*) = \{\theta - \theta^*\}^2$$

$$\hat{\theta}_{\mathrm{MMSE}} = \int_\theta \theta\, p(\theta \mid \boldsymbol{x})\, \mathrm{d}\theta \simeq \frac{1}{N}\sum_{i=1}^{N} \theta_i$$

Attempt 2: conventional cost function and estimator

$$\mathcal{C}(\theta, \theta^*) = \mathbf{1}\{\theta \neq \theta^*\}$$

$$\hat{\theta}_{\text{MAP}} = \text{argmax}_{\theta}\; p(\theta \mid \boldsymbol{x}) \;\simeq\; \text{mode}(\theta_1, \ldots, \theta_N)$$

Attempt 3: new cost function and estimator

$$p = 10^{-4}$$

$$\mathcal{C}(\theta, \theta^*) = \left\{F^{-1}(p \mid \theta) - F^{-1}(p \mid \theta^*)\right\}^2$$

$\hat{\theta}$ verifies :

$$F^{-1}(p \mid \hat{\theta}) = \int_\theta F^{-1}(p \mid \theta)\, p(\theta \mid \boldsymbol{x})\, \mathrm{d}\theta \simeq \frac{1}{N} \sum_{i=1}^N F^{-1}(p \mid \theta_i)$$

e.g :

$$\widehat{F}^{-1}(p \mid \boldsymbol{x}) = \int_\theta F^{-1}(p \mid \theta)\, p(\theta \mid \boldsymbol{x})\, \mathrm{d}\theta \simeq \frac{1}{N} \sum_{i=1}^N F^{-1}(p \mid \theta_i)$$

Attempt 4: new cost function and estimator

$$p = 10^{-4}$$

$$\mathcal{C}(\theta, \theta^*) = \mathbf{1}\left\{F^{-1}(p \mid \theta) \neq F^{-1}(p \mid \theta^*)\right\}$$

$$\hat{\theta} = \text{argmax}_\theta \, p\left(F^{-1}(p \mid \theta) \mid \boldsymbol{x})\right)$$

e.g :

$$\widehat{F}^{-1}(p \mid \boldsymbol{x}) \simeq \text{ mode}\left(F^{-1}(p \mid \theta_1), ..., F^{-1}(p \mid \theta_N)\right)$$

Attempt 5: new cost function and estimator

$$u = \text{fixed threshold (e.g. 2019 record value)}$$

$$\mathcal{C}(\theta, \theta^*) = \{F(u \mid \theta) - F(u \mid \theta^*)\}^2$$

$$\widehat{F}(u \mid \boldsymbol{x}) = \int_\theta F(u \mid \theta)\, p(\theta \mid \boldsymbol{x})\, \mathrm{d}\theta \simeq \frac{1}{N} \sum_{i=1}^{N} F(u \mid \theta_i)$$

Attempt 6: new cost function and estimator

$$u = \text{fixed threshold (e.g. 2019 record value)}$$

$$\mathcal{C}(\theta, \theta^*) = \mathbf{1}\left\{F(u \mid \theta) \neq F(u \mid \theta^*)\right\}$$

$$\widehat{F}(u \mid \boldsymbol{x}) \simeq \text{mode}\left(F(u \mid \theta_1), ..., F(u \mid \theta_N)\right)$$

The posterior predictive: a possible estimator of the return level curve

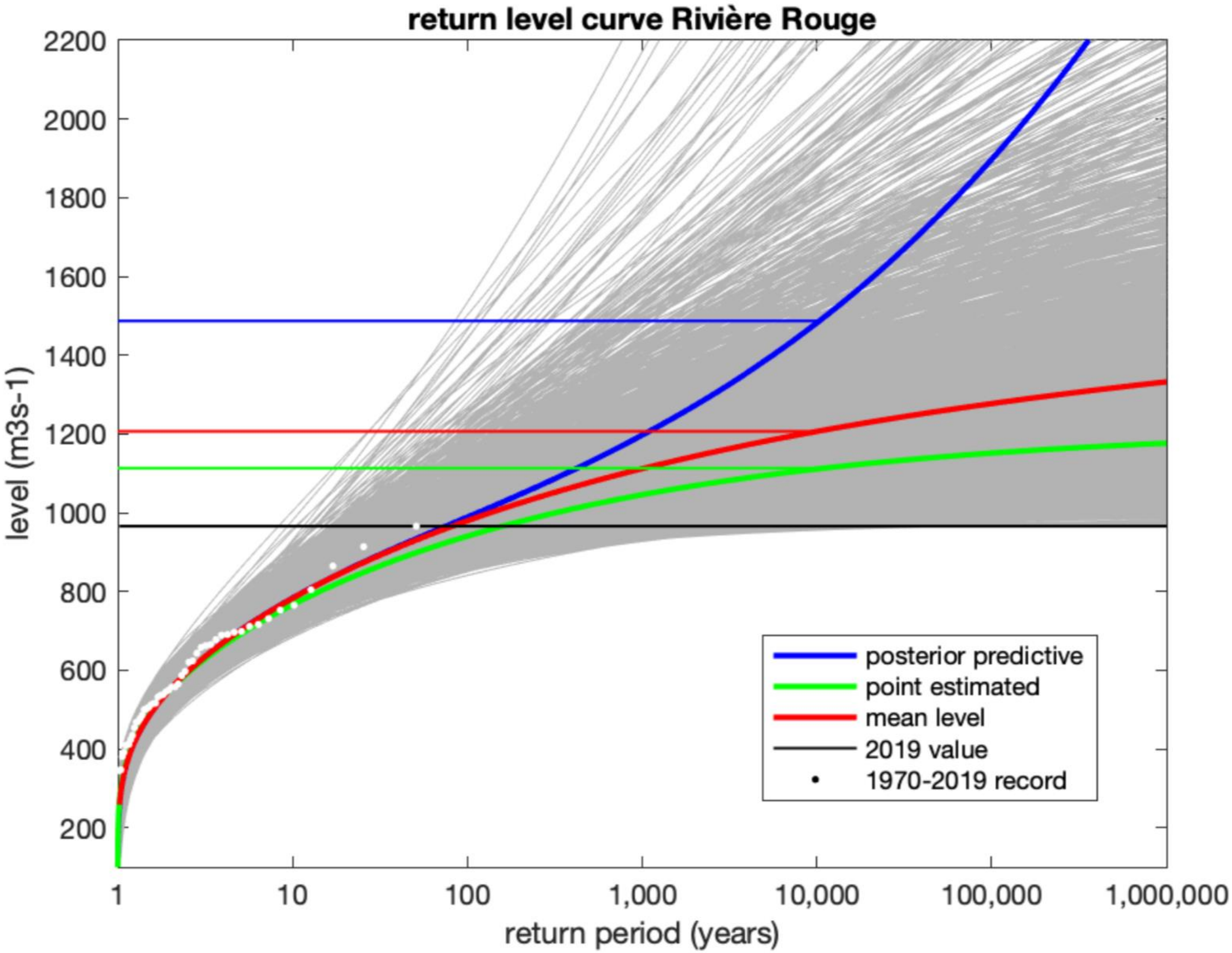
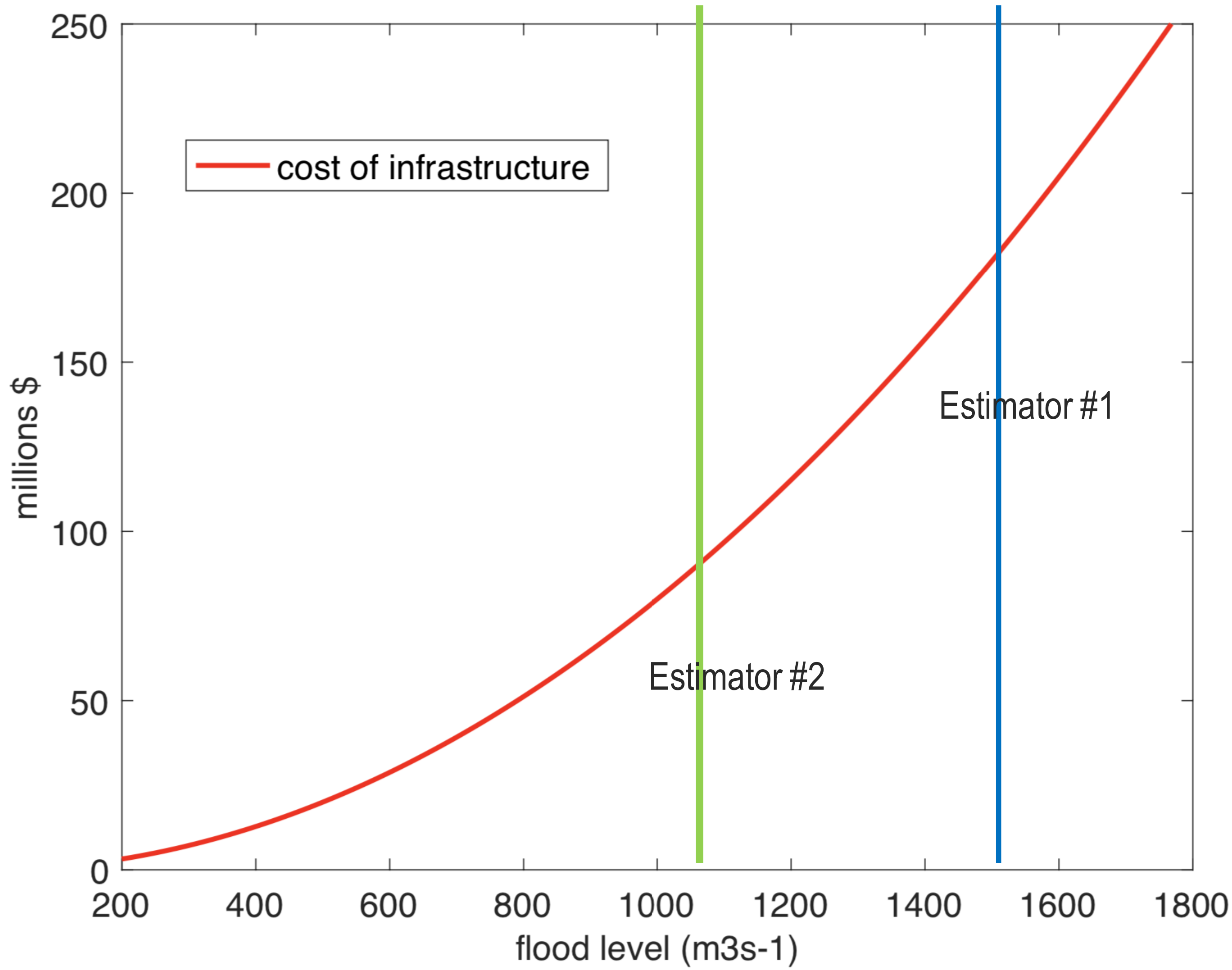


Illustration on Rouge River



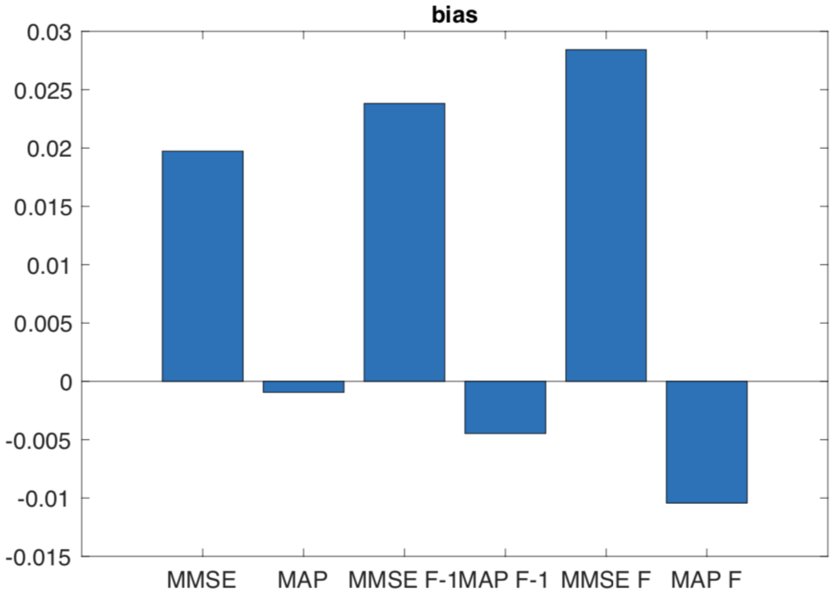
Properties and performance of estimators

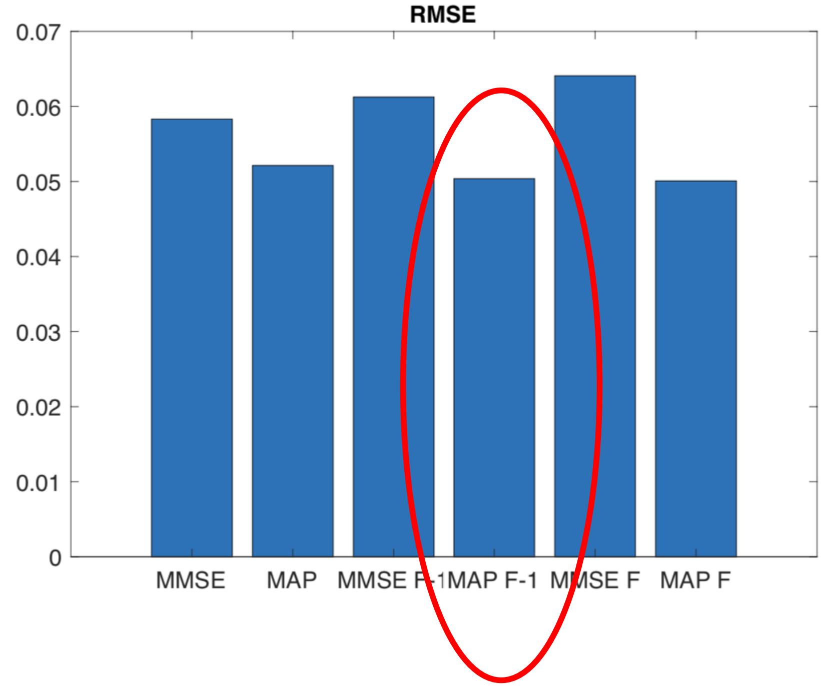
$$\mathbb{E}_{\boldsymbol{x}}\left(\widehat{F}^{-1}(p \mid \boldsymbol{x})\right) = \int_{\boldsymbol{x}} \widehat{F}^{-1}(p \mid \boldsymbol{x})\, p(\boldsymbol{x} \mid \theta)\,\mathrm{d}\boldsymbol{x} = F^{-1}(p \mid \theta) \quad ?$$

$$\mathbf{V}_{\boldsymbol{x}}\left(\widehat{F}^{-1}(p \mid \boldsymbol{x})\right) \to 0 \;\text{ as } n \to \infty \quad ?$$

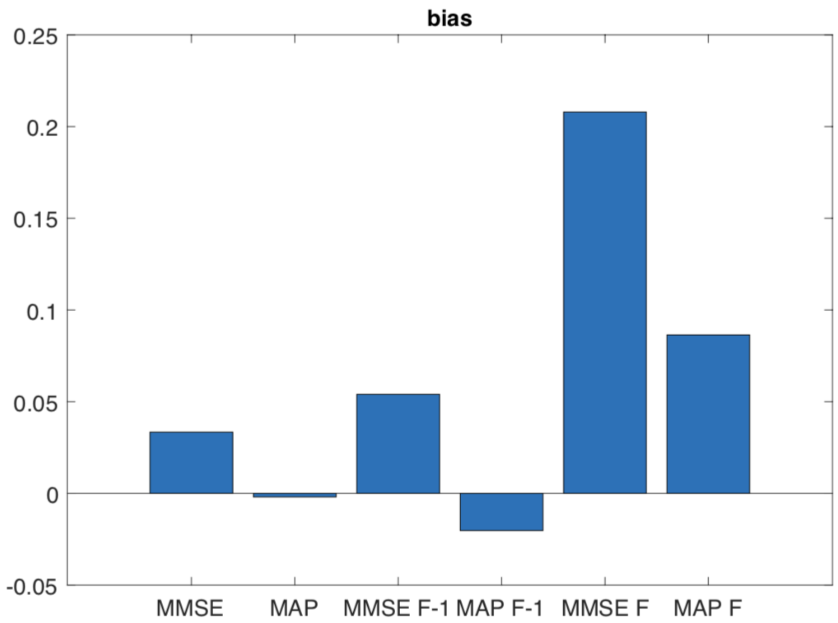
$$\text{MSE} = \mathbb{E}_{\boldsymbol{x}}\left(\left\{\widehat{F}^{-1}(p \mid \boldsymbol{x}) - F^{-1}(p \mid \theta)\right\}^2\right) \;\text{ minimal ?}$$

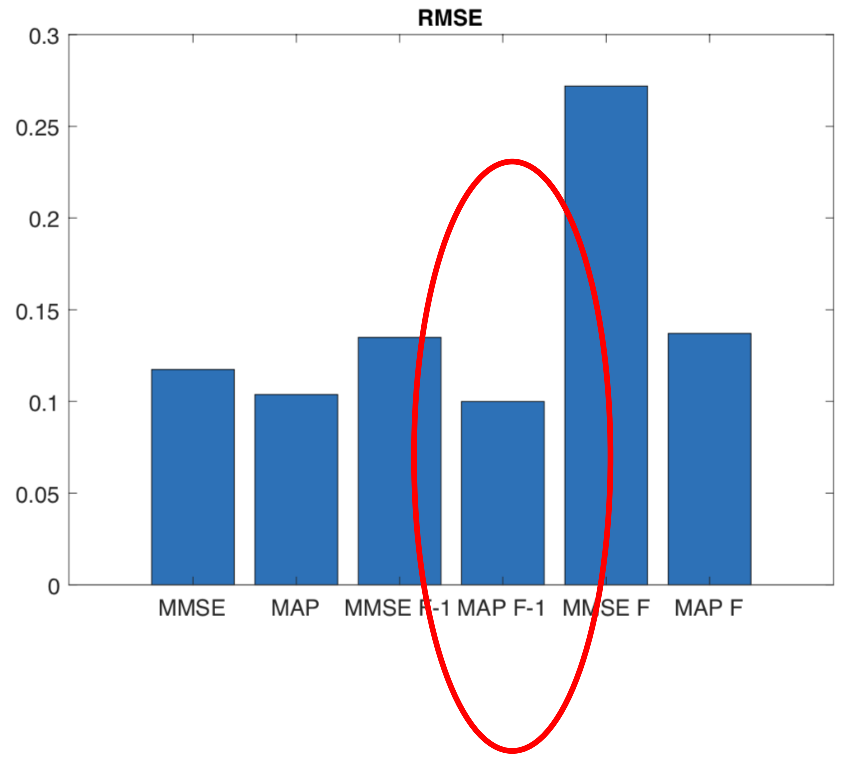
Simulation testbed results for $p = 10^{-2}$ and xi < 0



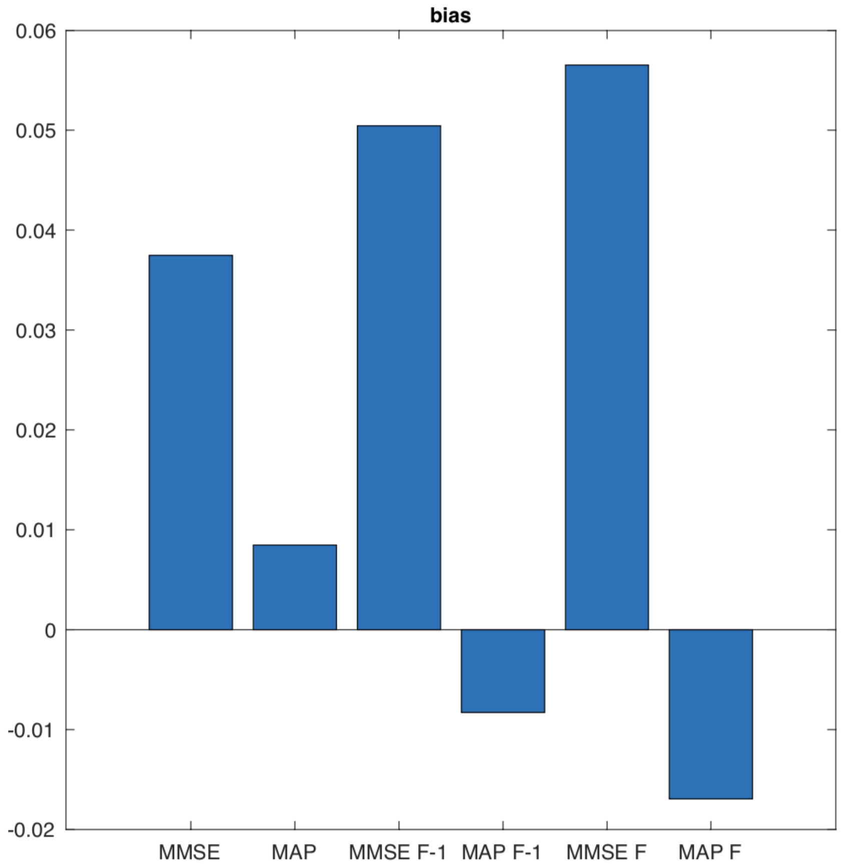


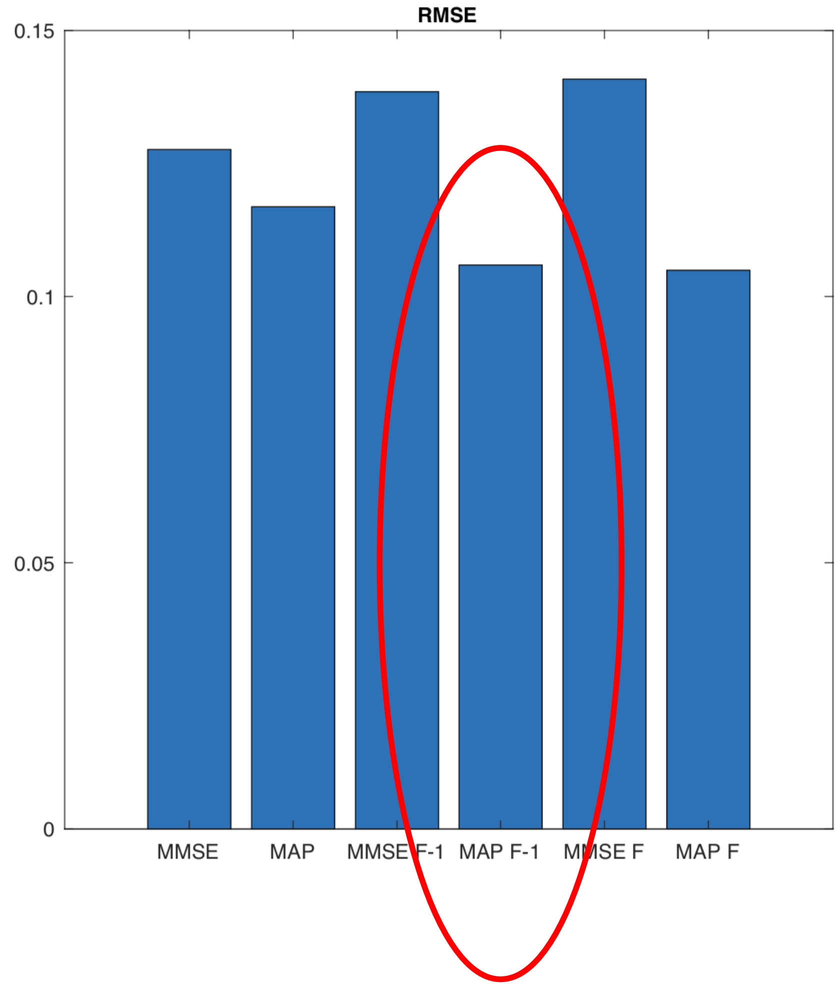
Simulation testbed results for $p = 10^{-4}$ and $xi < 0$



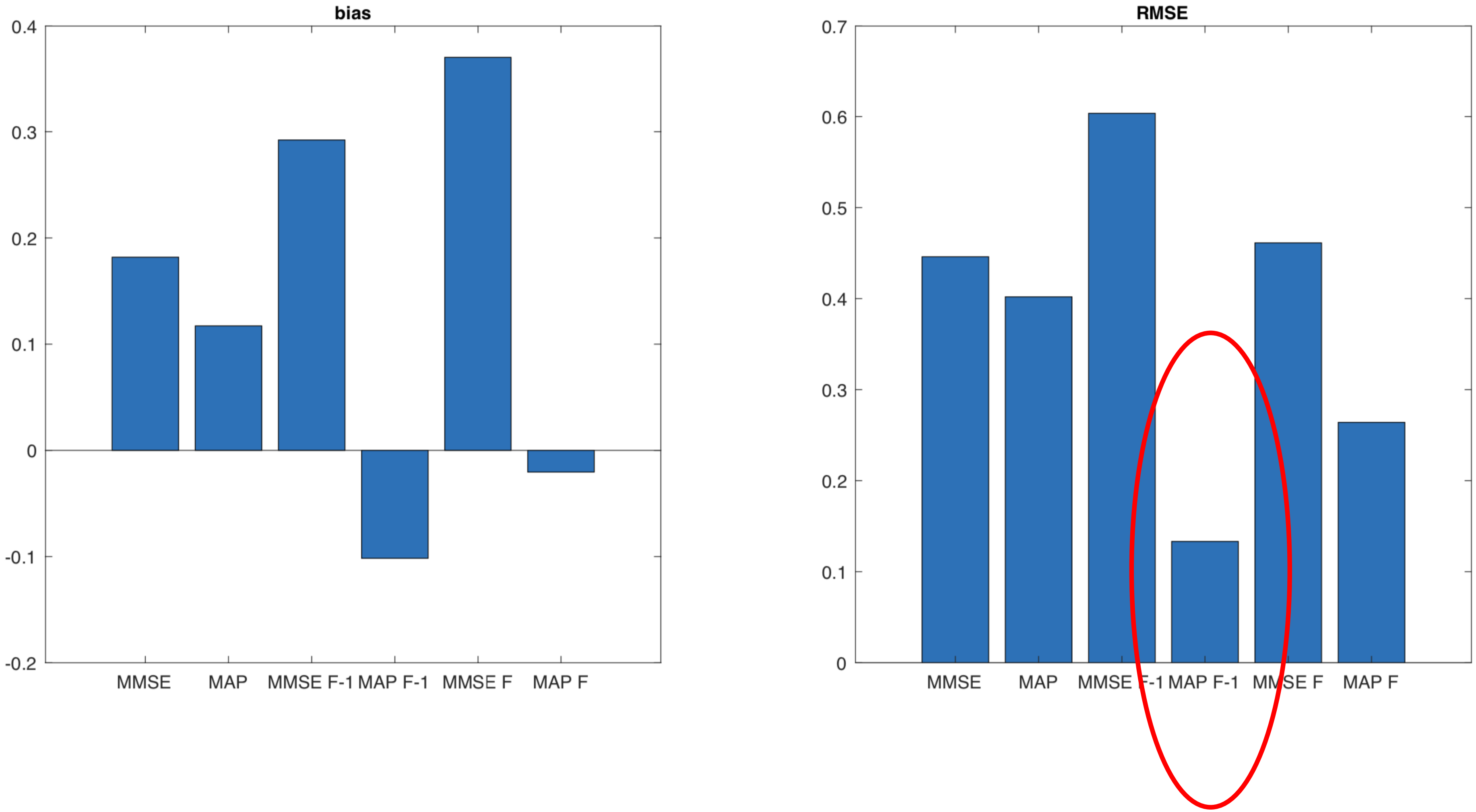


Simulation testbed results for $p = 10^{-2}$ and xi > 0





Simulation testbed results for $p = 10^{-4}$ and xi > 0



Preliminary conclusion

- Even for a single parametric model, several different point estimators of high quantiles and low probabilities can be proposed.
- Within a Bayesian approach, such estimators can be obtained by choosing alternative cost functions that are ad-hoc to the problem.
- The conventional estimator of a high quantile (inverse CDF evaluated at p with MLE of theta) is not necessarily the best solution. Neither is the intuitive solution of the « posterior predictive ».
- Instead, the « MAP quantile » estimator appears to consistently perform best, based on simulation results.
- More simulation and theoretical grounding for these estimators is needed.
- Significant implications for high quantiles.

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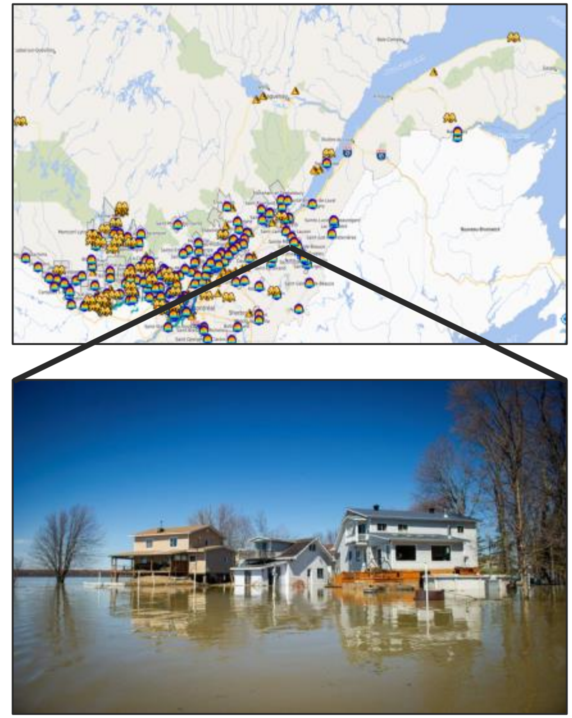
Spring floods 2017 and 2019

Avril 2017

Avril 2019



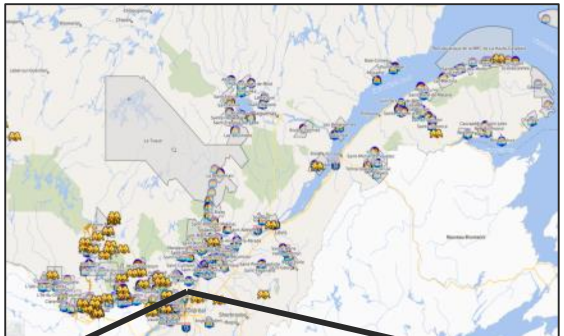
Read in the media:

- *« These events are more and more frequent, and they will become even more frequent in the future. »*

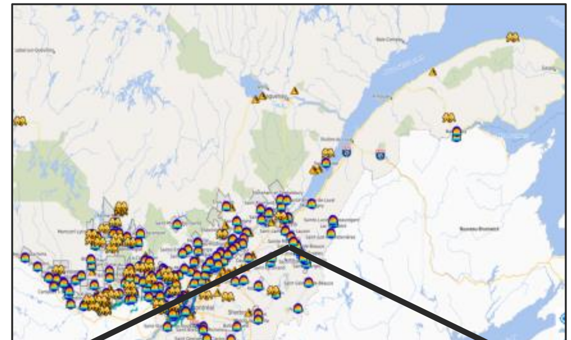
Source: GéoMSP, Québec

Spring floods 2017 and 2019

Avril 2017



Avril 2019



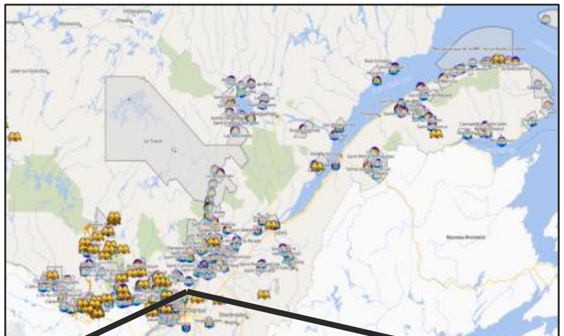
Return period: 50 years

Return period: 50 years

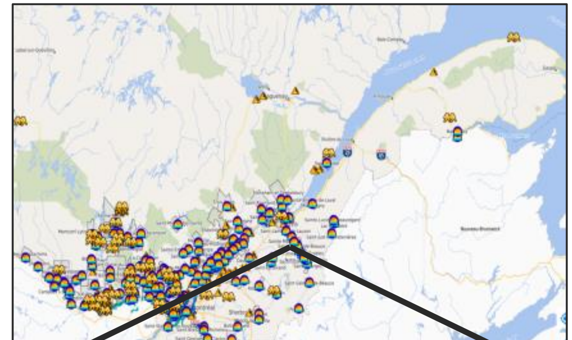
Two in three years:
Return period 850 years
under independance assumption

Questions

Avril 2017



Avril 2019



- What is the influence of CC on flood risk in Québec ?
- How can it be taken into account in the new flood risk maps ?

Overall workplan

thématique	axe de recherche		projet		expertise	%	2019	2020	2021	2022	2023
documentation des crues											
modélisation hydraulique											
évolution du climat	Axe 1	Incidence du changement climatique sur les crues	Projet 1.1	analyse, détection et attribution	hydro, climat, stat, obs	17%					
			Projet 1.2	production des simulations contrefactuelles	hydro, climat	3%					
	Axe 2	Modélisation hydroclimatique et incertitudes	Projet 2.1	modèles, simulations et observations climatiques	climat, stat, obs	12%					
			Projet 2.2	modèles, simulations et observations hydrologiques	hydro, climat, stat, obs	12%					
			Projet 2.3	nouvelles simulations hydrologiques	hydro	6%					
			Projet 2.4	analyse fréquentielle	stat, hydro	15%					
			Projet 2.5	intégration et transition vers l'hydraulique fluviale	hydro, crues, obs	15%					
	Axe 3	Questions pointues et divulgation	Projet 3.1	veille et analyses ad-hoc	com, ad-hoc	10%					
			Projet 3.2	communication de la qualité des résultats	com, hydro, climat, stat, obs	10%					

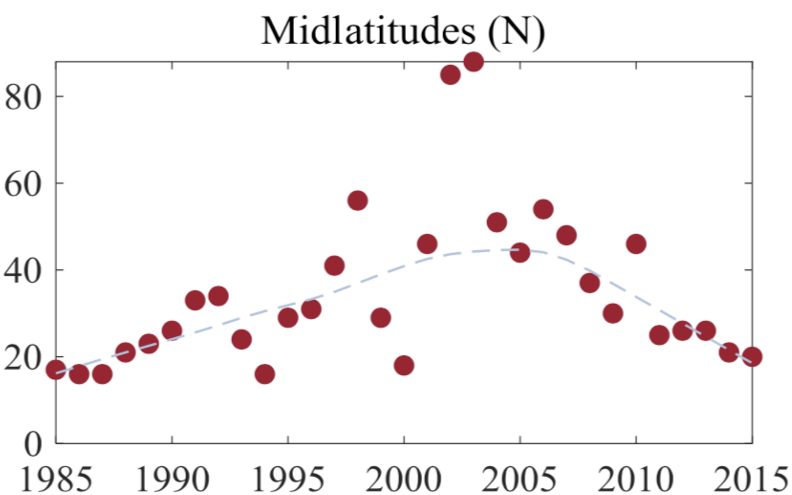
- 3 years,
- ~7m CAD,
- ~30 people.

Outline

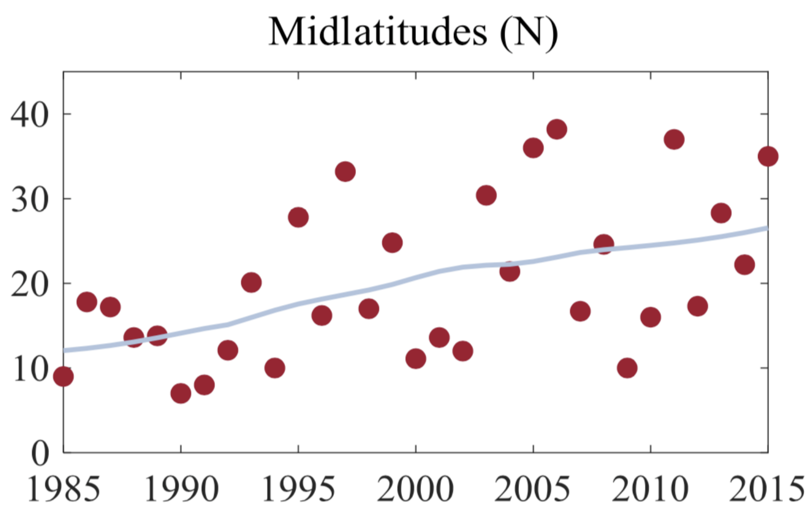
- Context and motivation
- Approach in a stationary climate
- Bringing climate change into the picture: detection
- Conclusion

Detection: is there a change ?

frequency



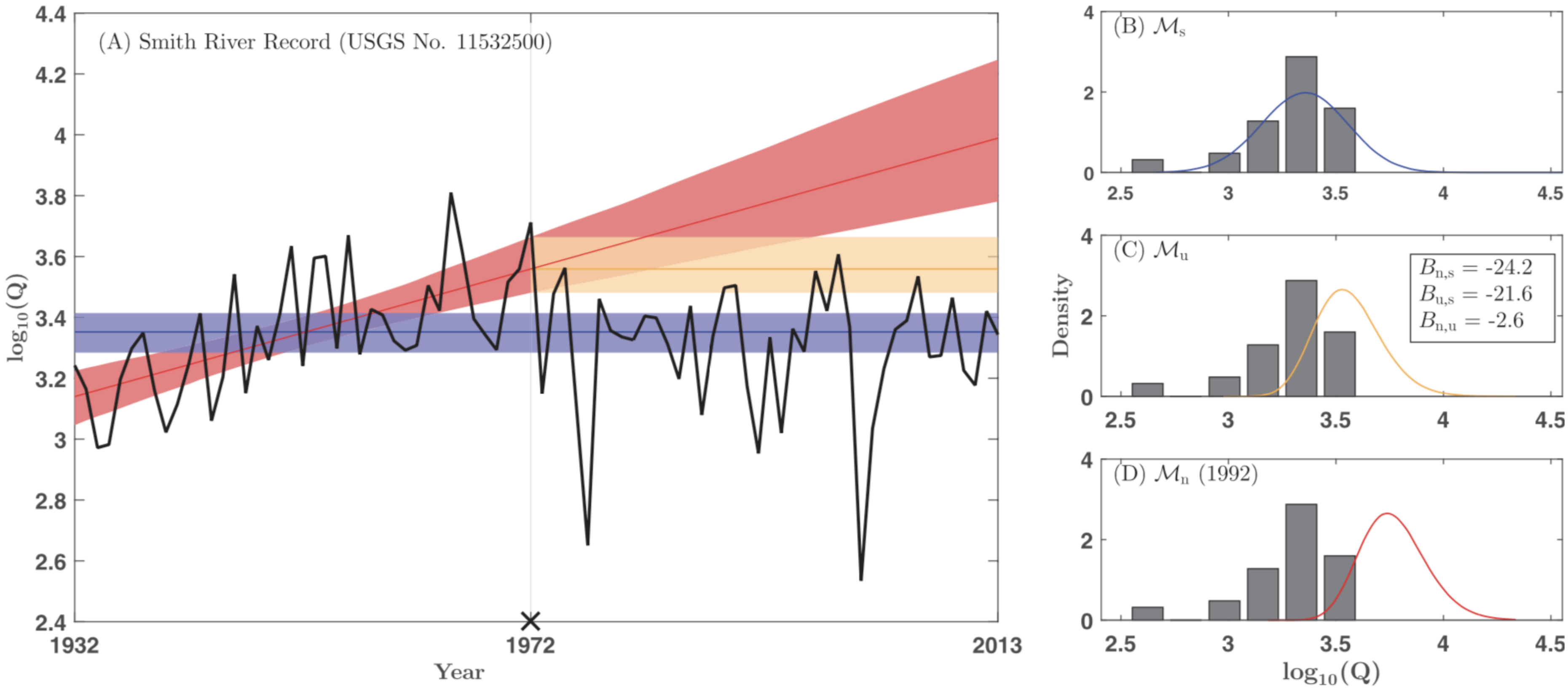
duration



Dartmouth Flood Observatory database

Najibi et al. 2018

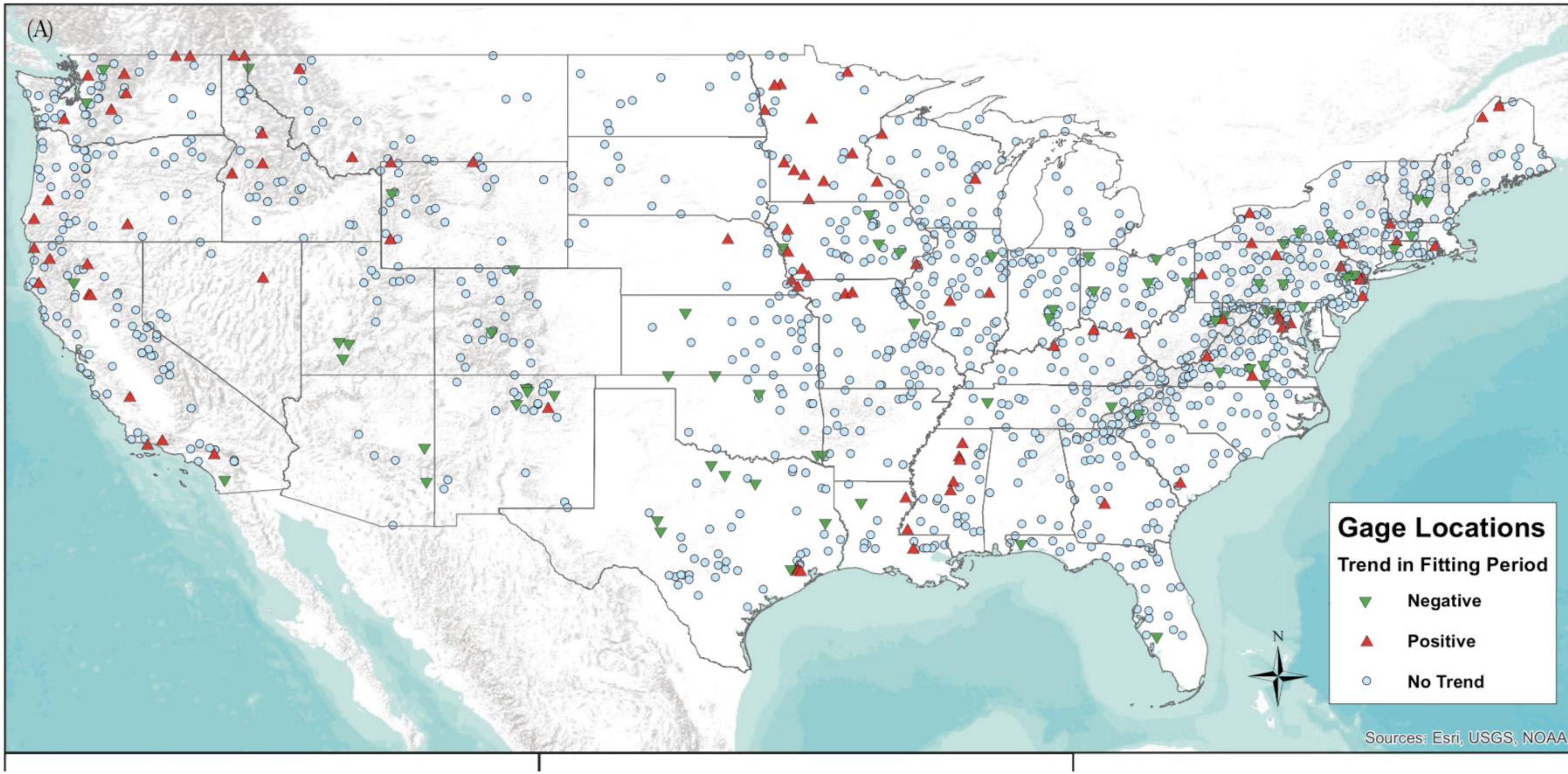
Detection: is there a change ?



USGS database

Luke et al. 2017

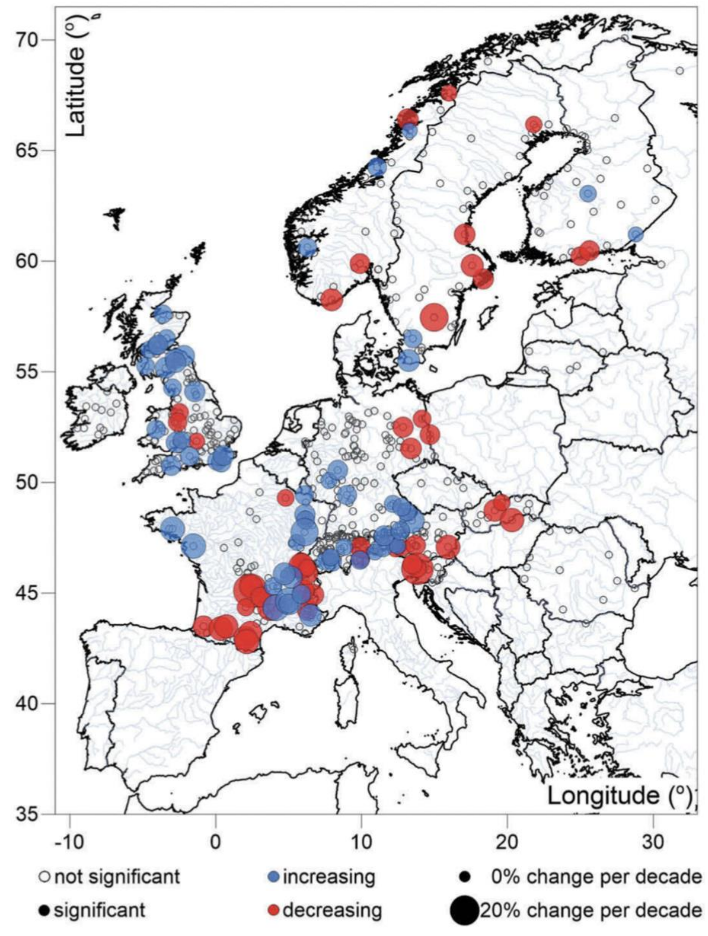
Detection: is there a change ?



USGS database

Luke et al. 2017

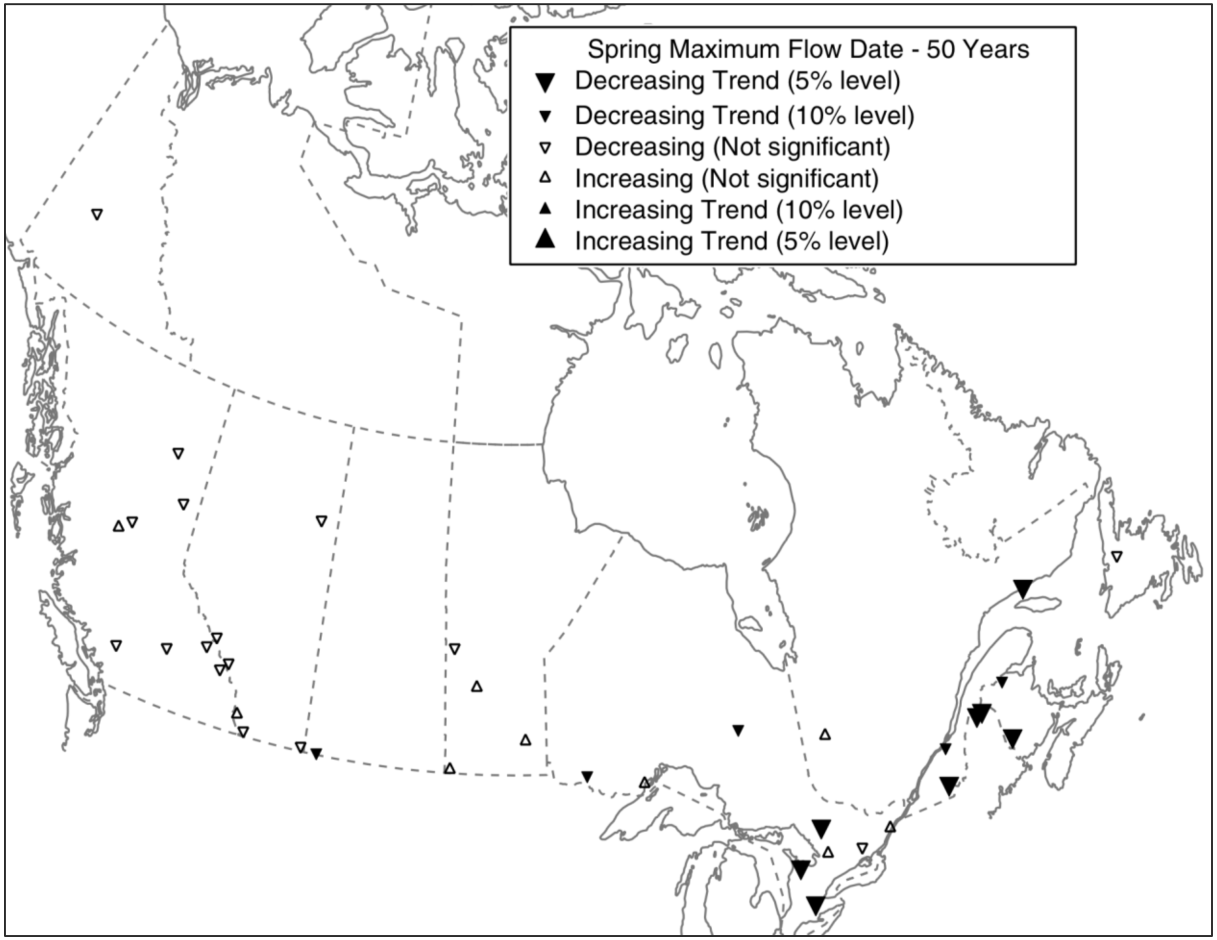
Detection: is there a change ?



GRDC database

Mangini et al. 2018

Detection: is there a change ?

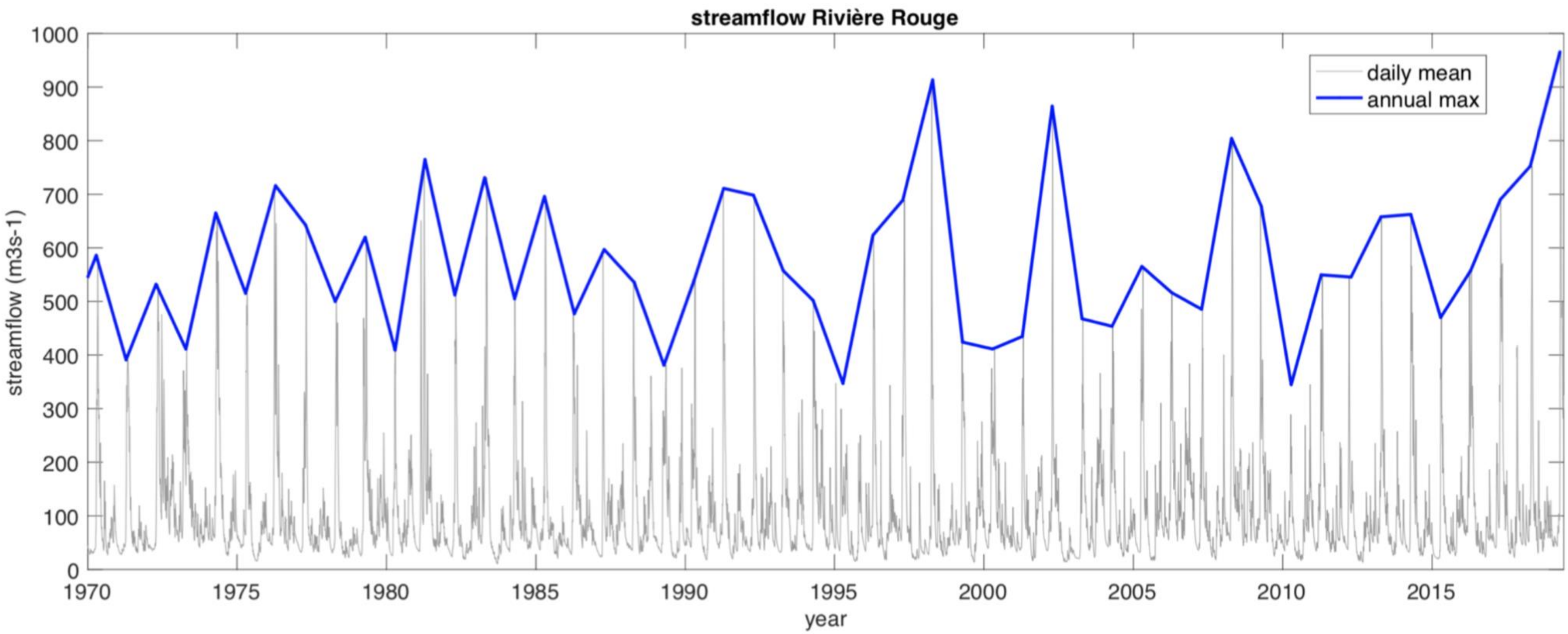


Gauge station database

Burn et al. 2010

Burn and Withfield 2018

Detection: is there a change ?



Gauge station database

Hannart et al. EVA 2019

Outline

- Context and motivation
- Approach in a stationary climate
- Bringing climate change into the picture: attribution
- Conclusion

Hypothetical drivers

Climate Change

Snowpack

Snowmelt

Rainfall

ETP

River

Catchment

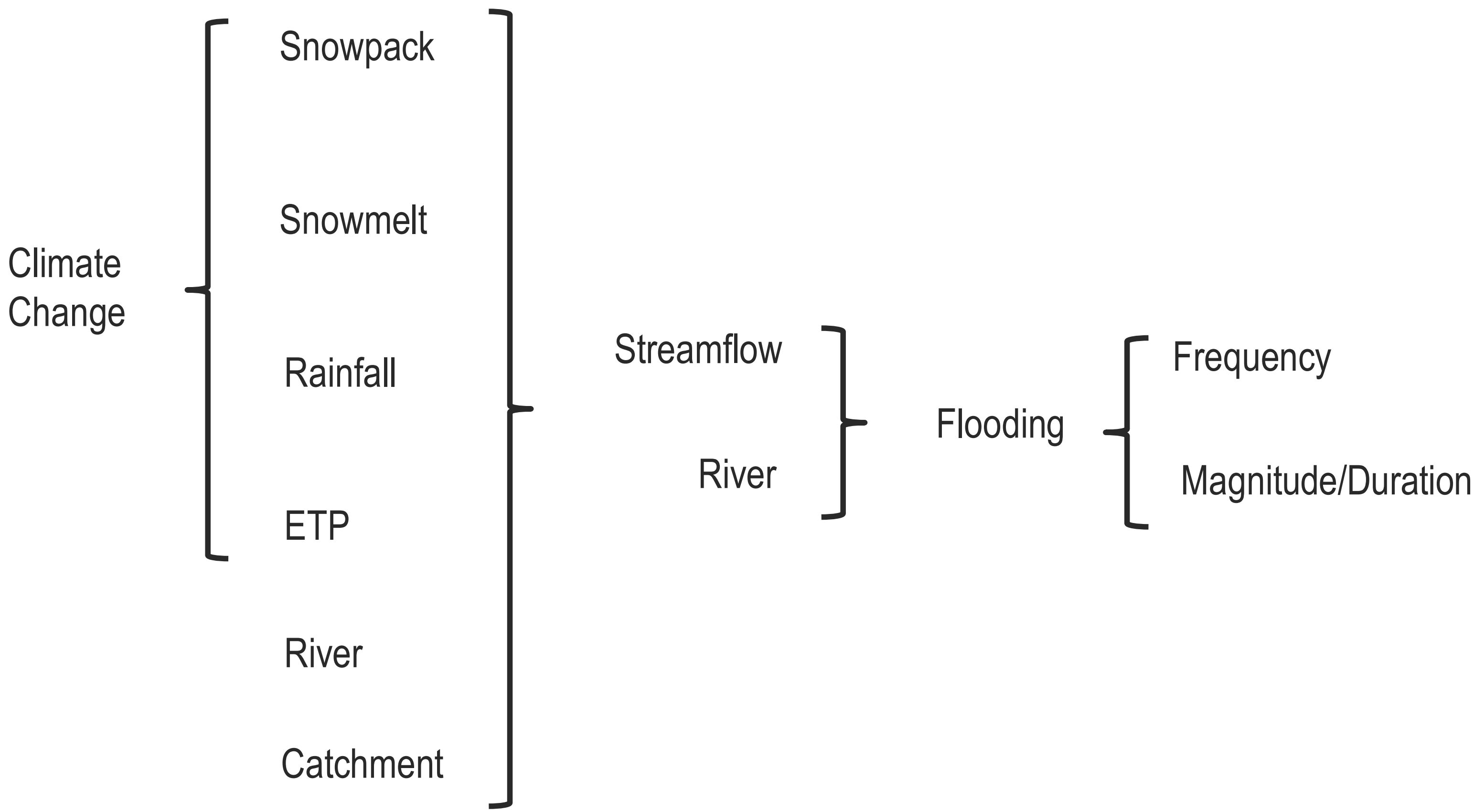
Streamflow

River

Flooding

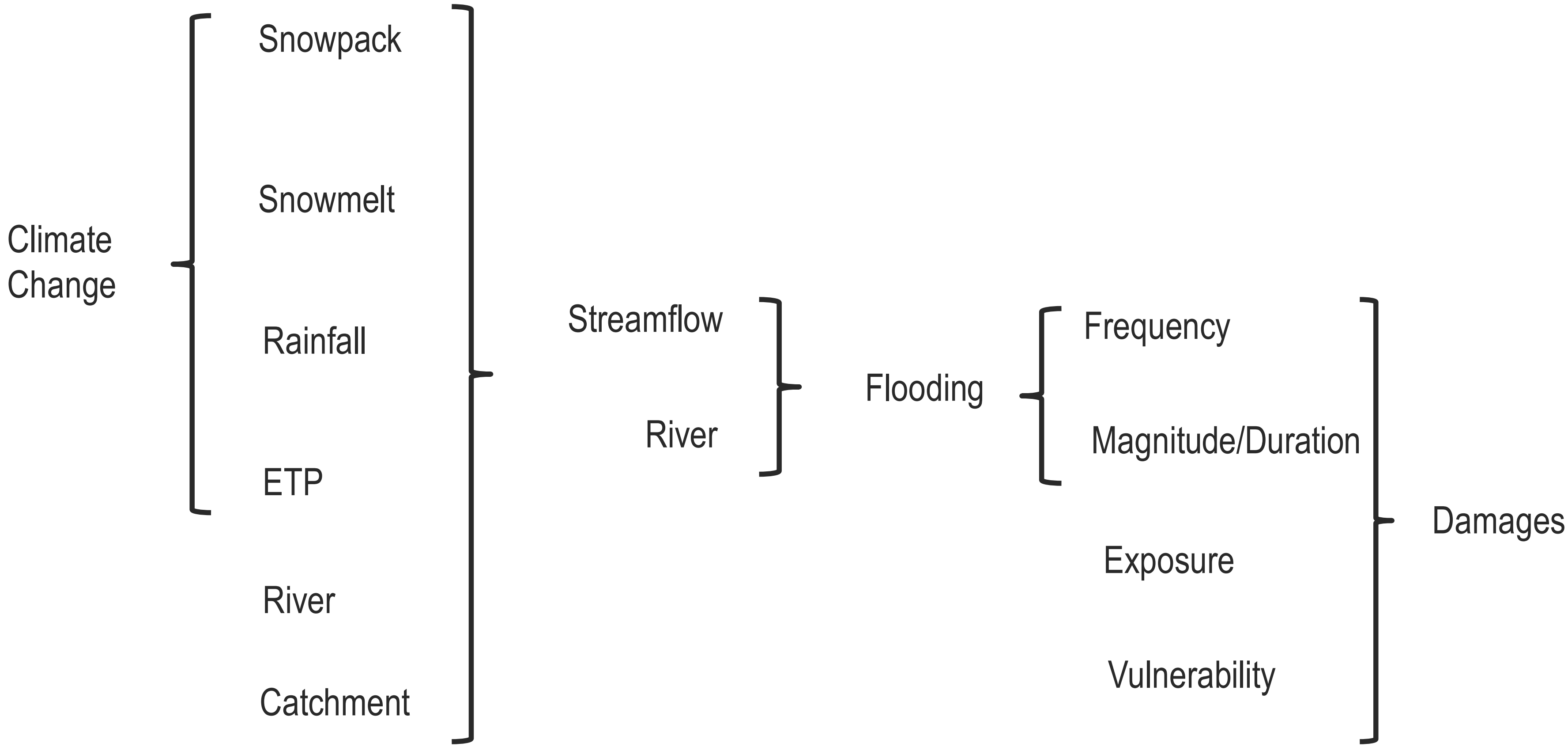
after Kreibich et al. 2019

Hypothetical drivers



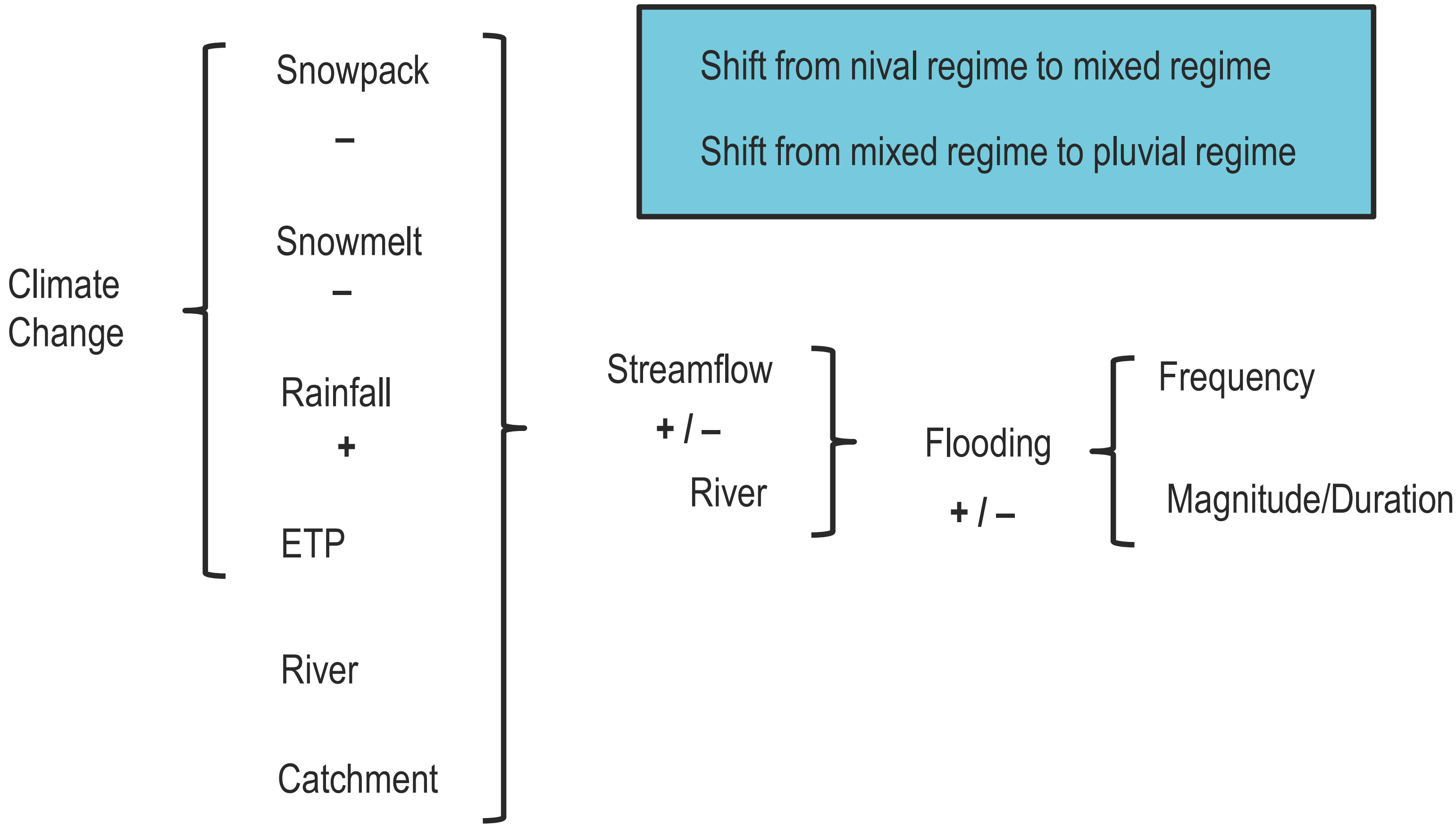
after Kreibich et al. 2019

Hypothetical drivers



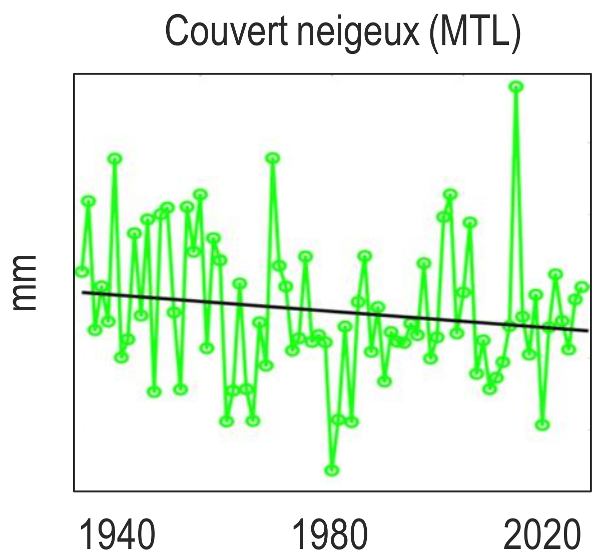
after Kreibich et al. 2019

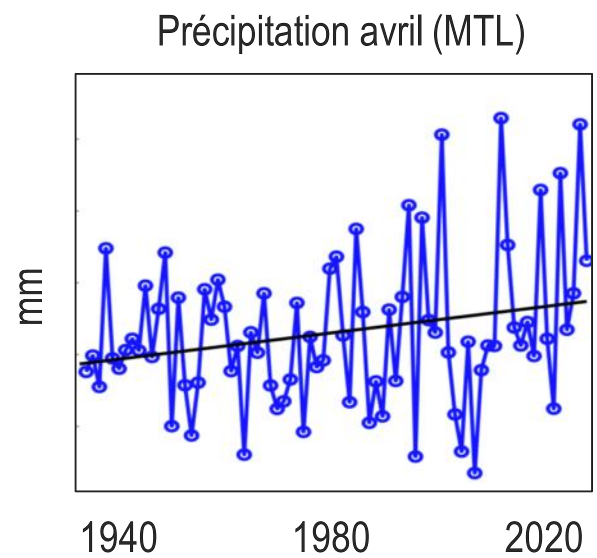
Hypothetical drivers



after Kreibich et al. 2019

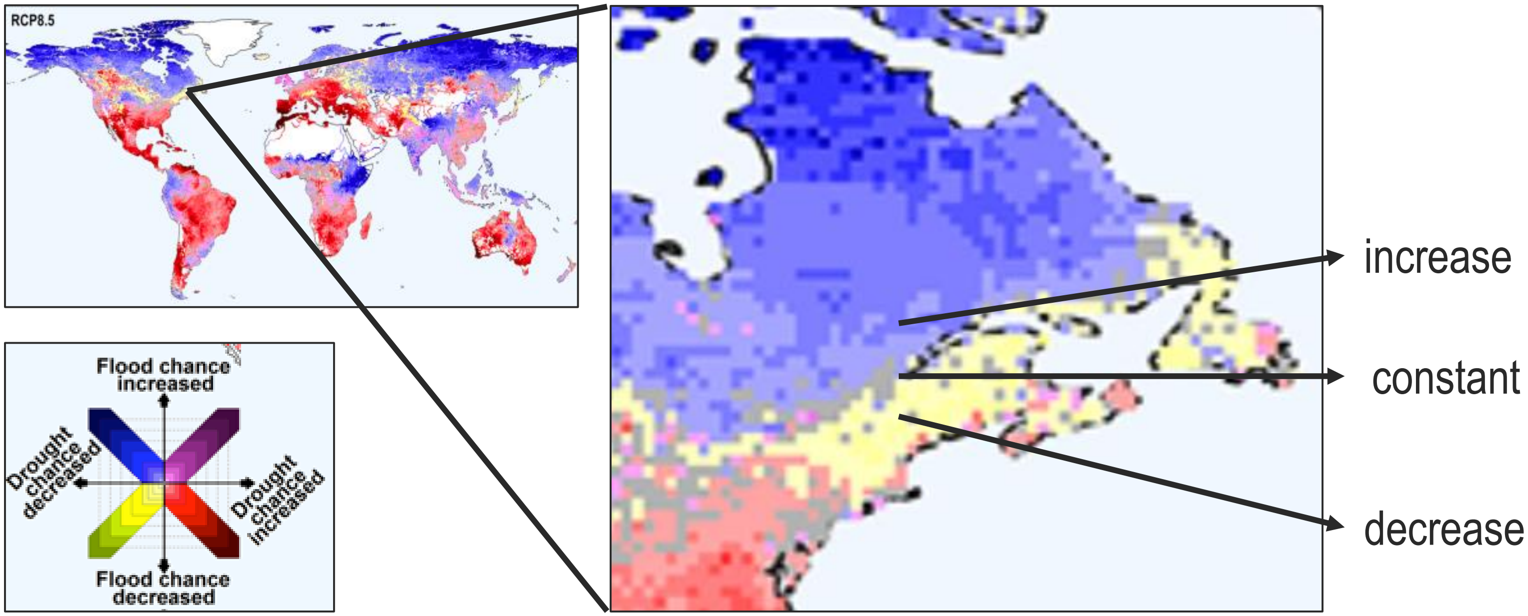
Two main antagonic effects





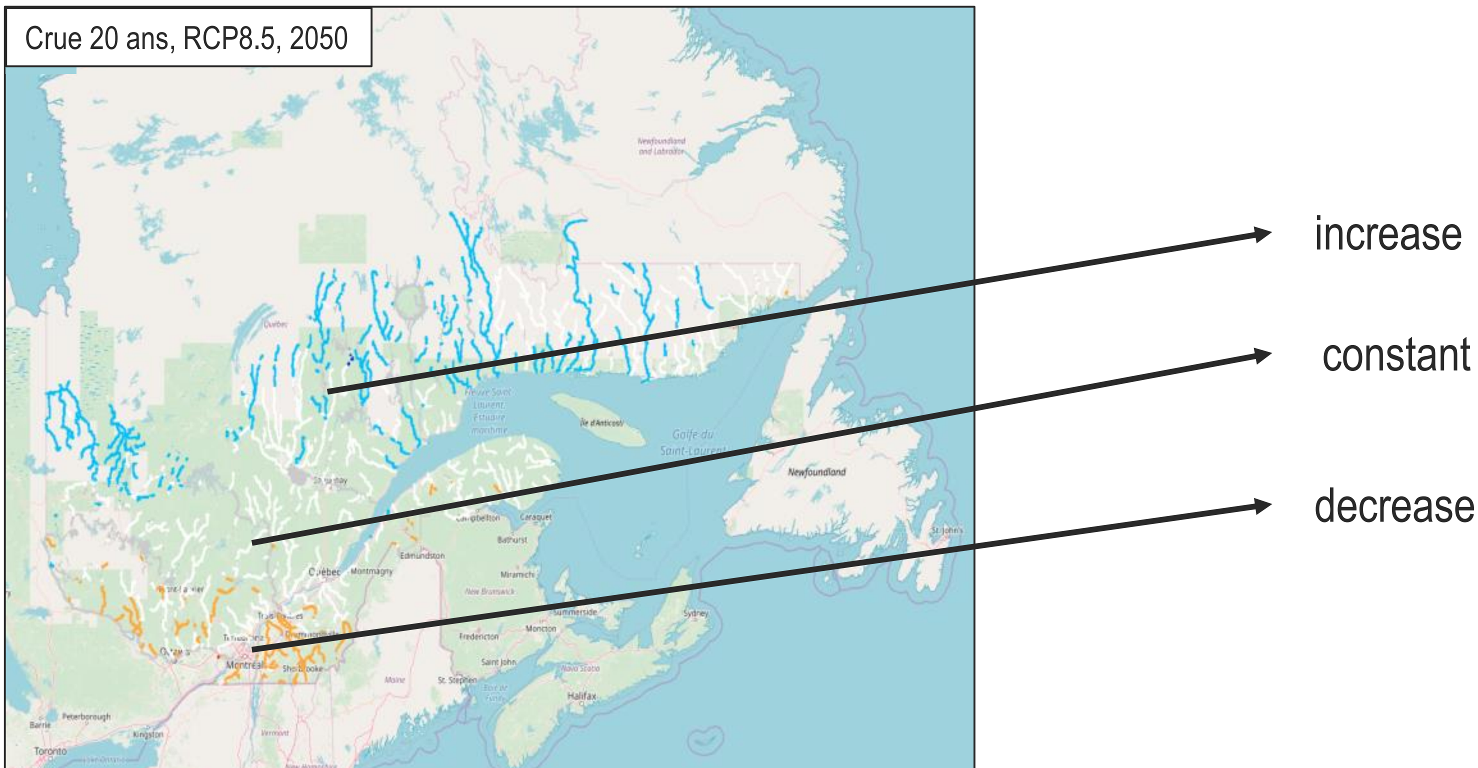
Source: ECCC

Projected changes (ISI-MIP)



Source: Asadieh and Krakauer 2017

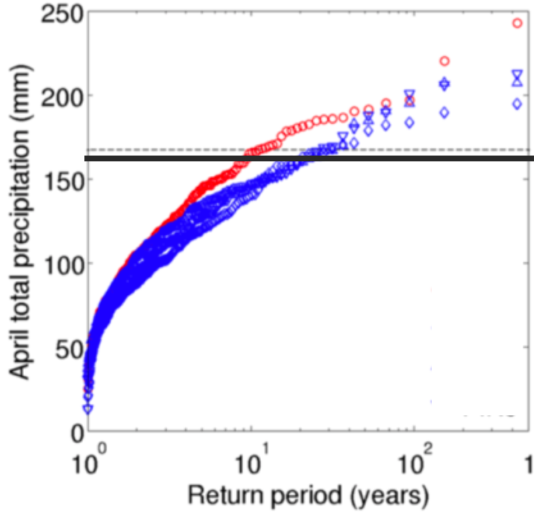
Projected changes (CQ2)



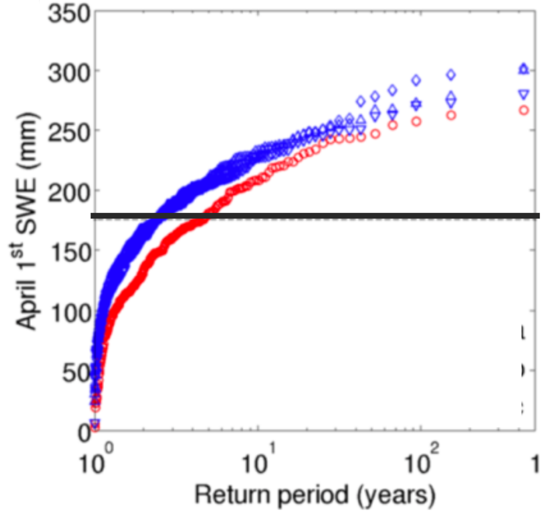
Source: Atlas 2018, DEH/Ouranos

Numerical experiments

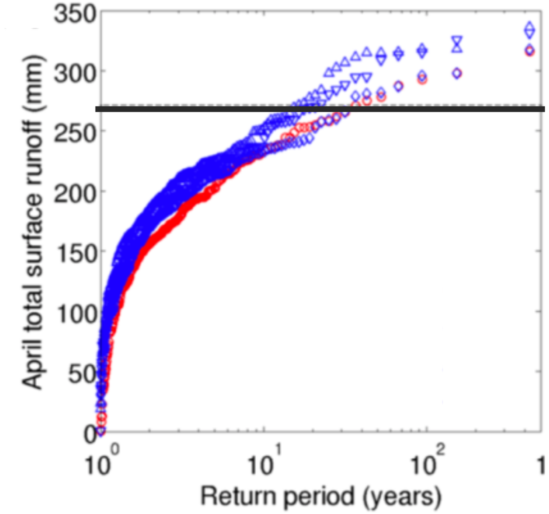
Précipitation avril (MTL)



Couvert neigeux (MTL)



Débit avril (MTL)



— niveau observé en 2017 ● simulation climat présent ● simulation climat passé

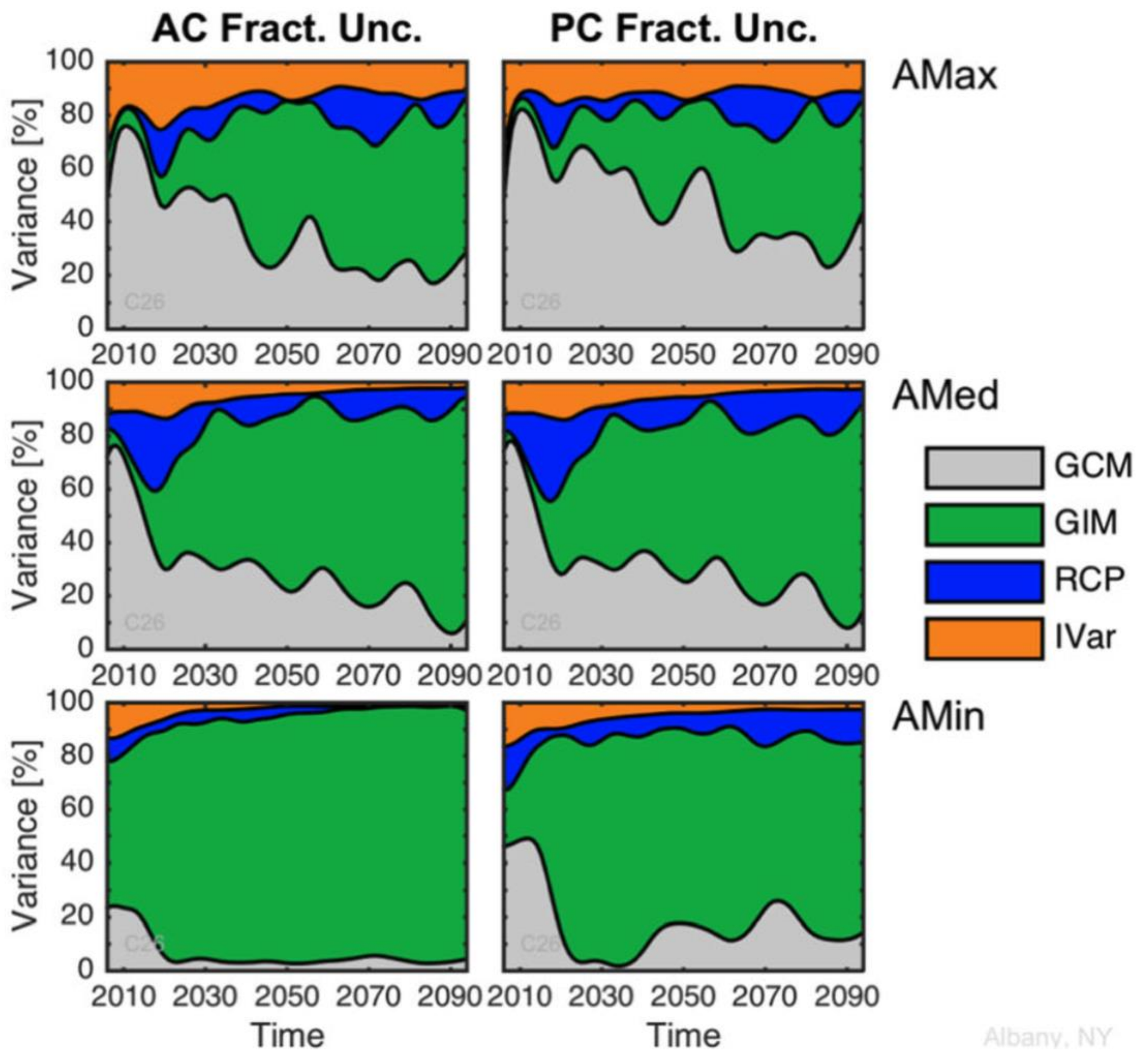
Pluie:
augmentation
de la fréquence
~ facteur 2

Couvert neigeux:
baisse
de la fréquence
~ facteur 2

Débit:
pas de modification
de la fréquence.

Source: Teufel et al. 2018

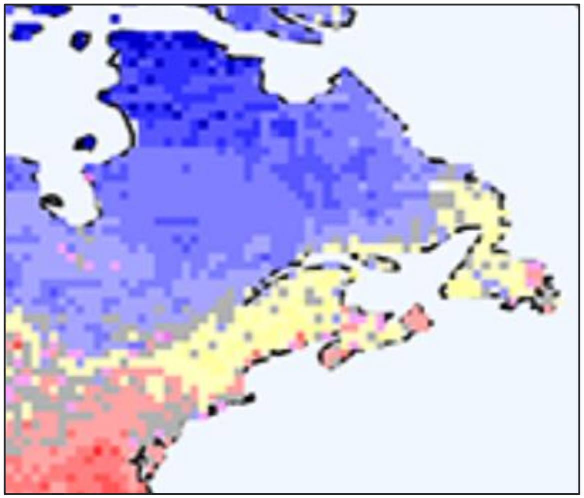
Large uncertainty in hydroclimatic model response



Giuntoli et al. 2018

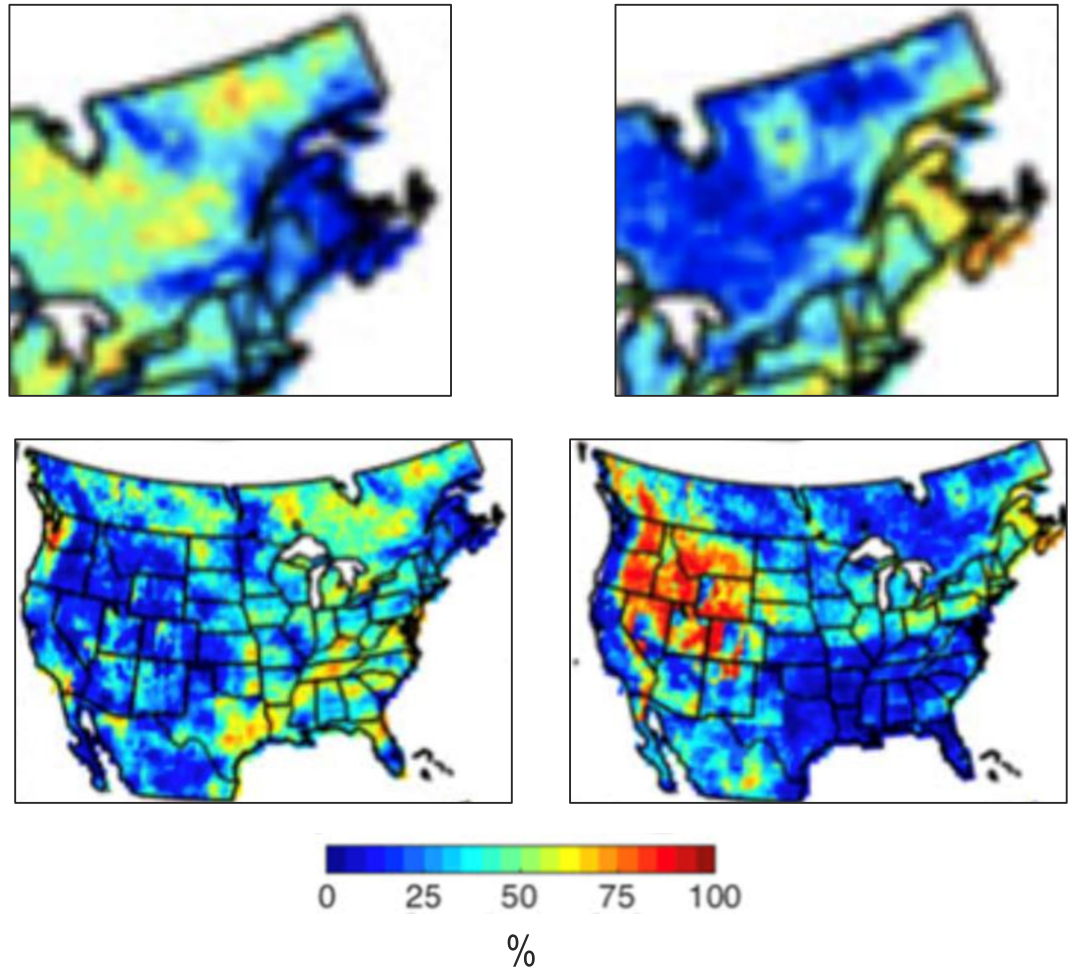
Large uncertainty in hydroclimatic model response

Réponse moyenne
de tous les modèles



Dispersion générée
par les modèles climat

Dispersion générée
par les modèles hydro



Giuntoli et al. 2018

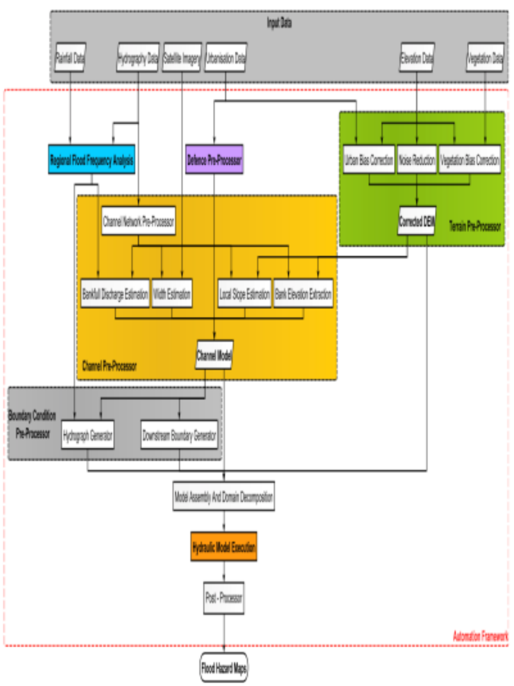
Outline

- Context and motivation
- Approach in a stationary climate
- Bringing climate change into the picture: mapping
- Conclusion

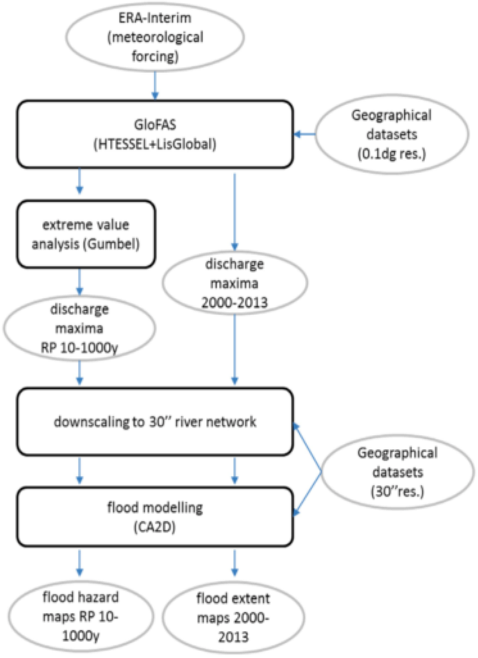
Mapping: models and observations in cascade

- Schéma conceptuel d'un modèle de calcul de cartographie du risque de crue.

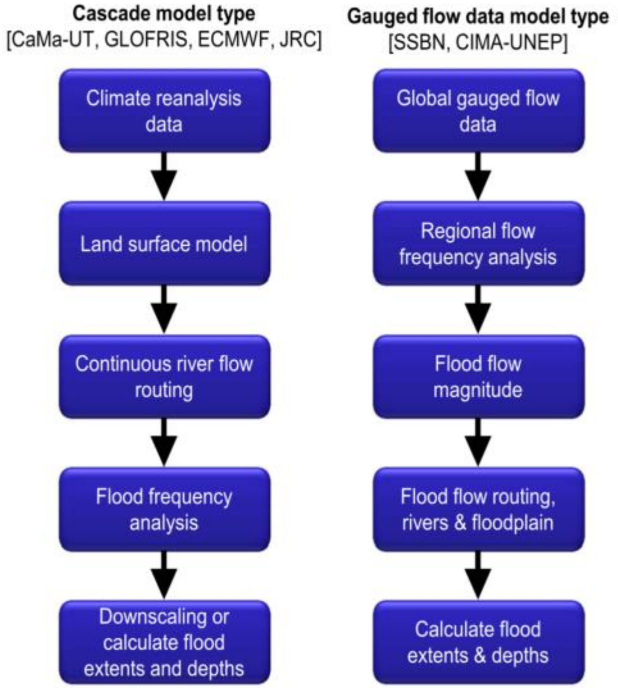
Sampson et al. 2015



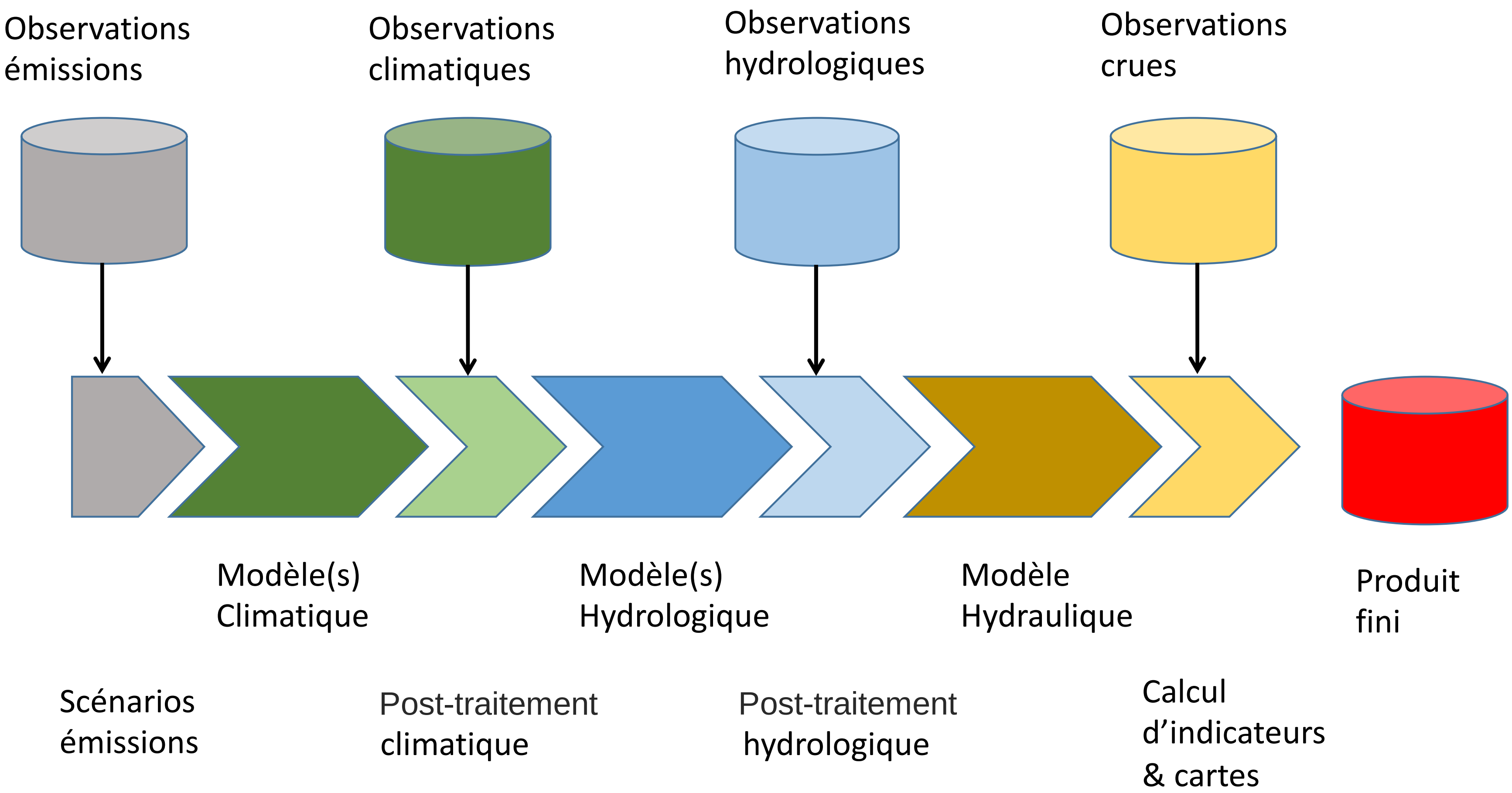
Dottori et al. 2016



Trigg et al. 2016

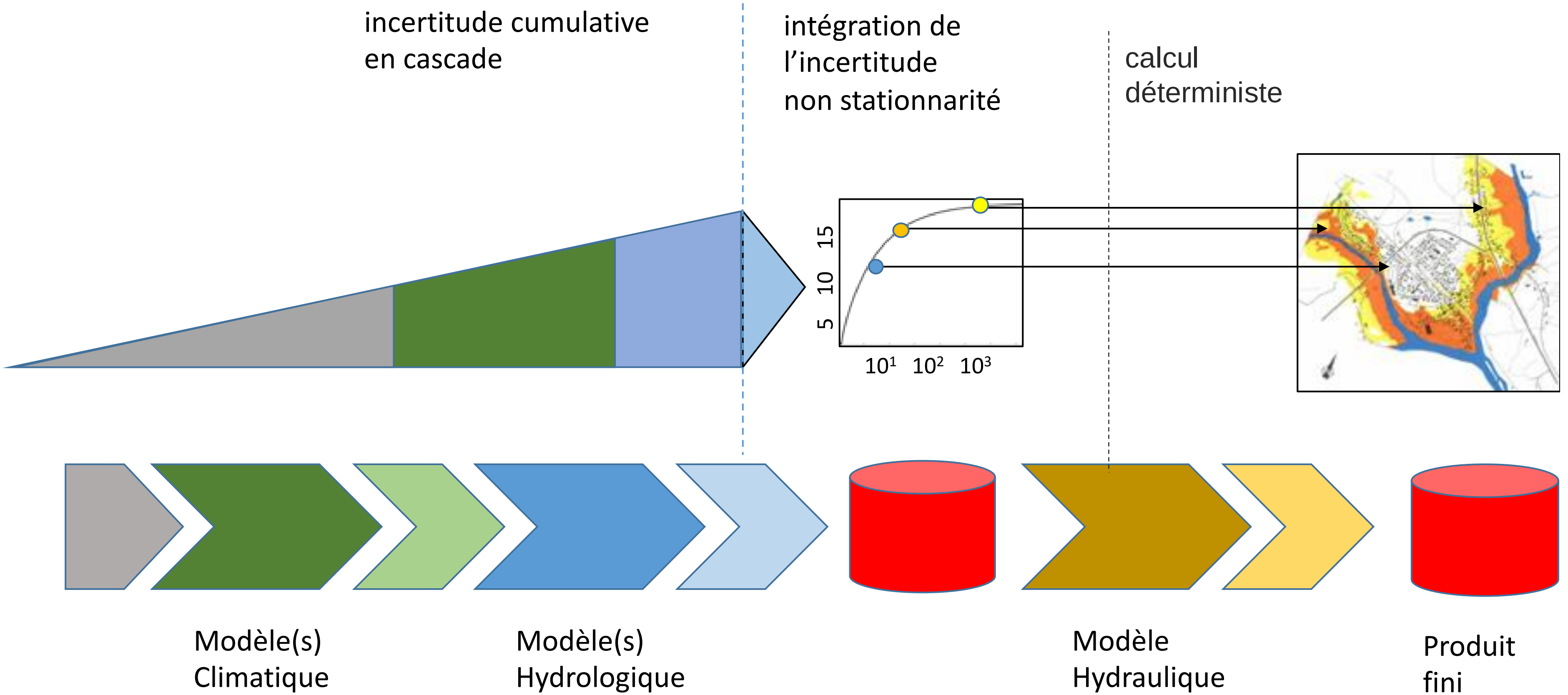


Computation: models and observations in cascade

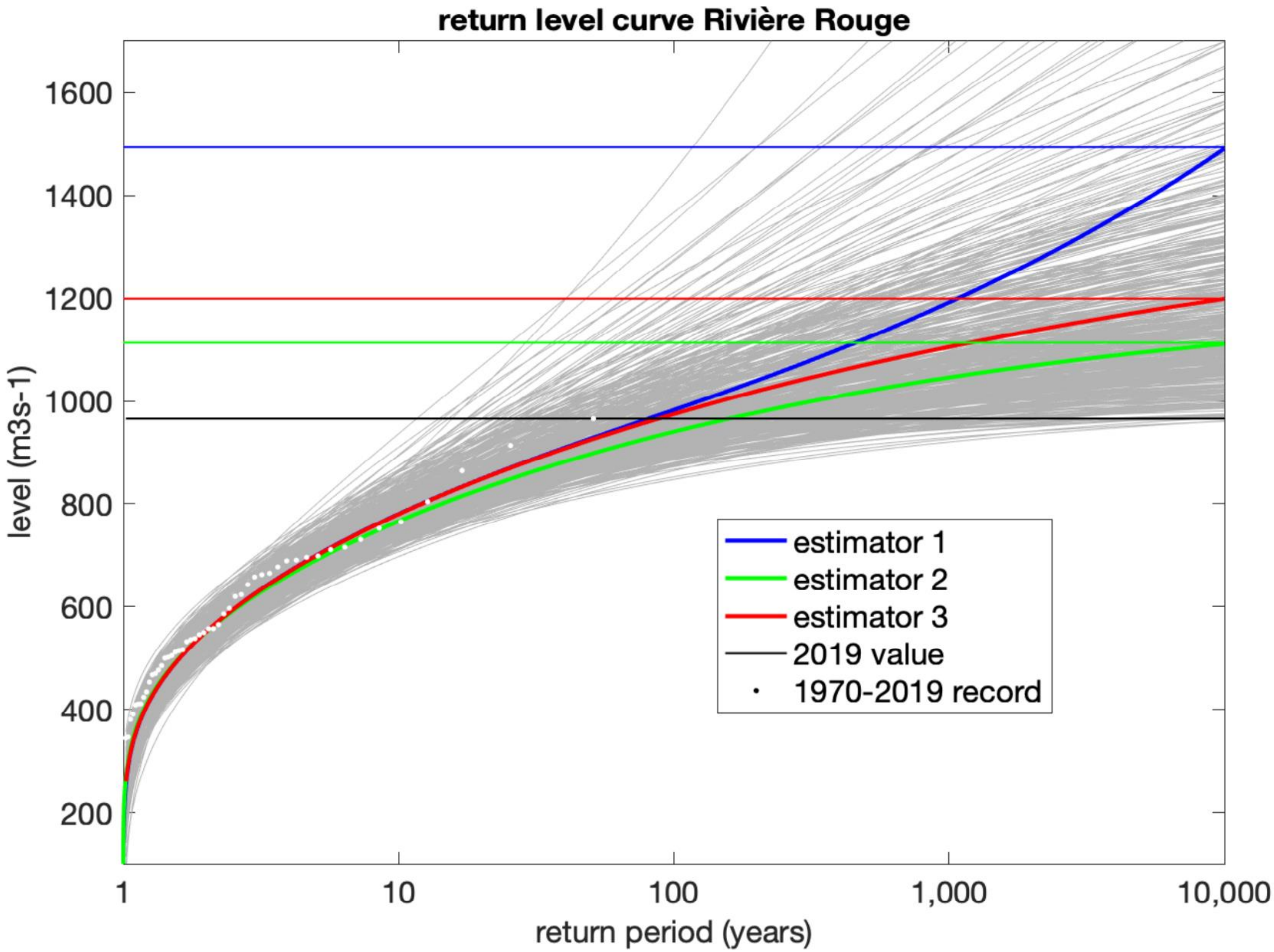


Solution retenue: schéma en cascade complet.

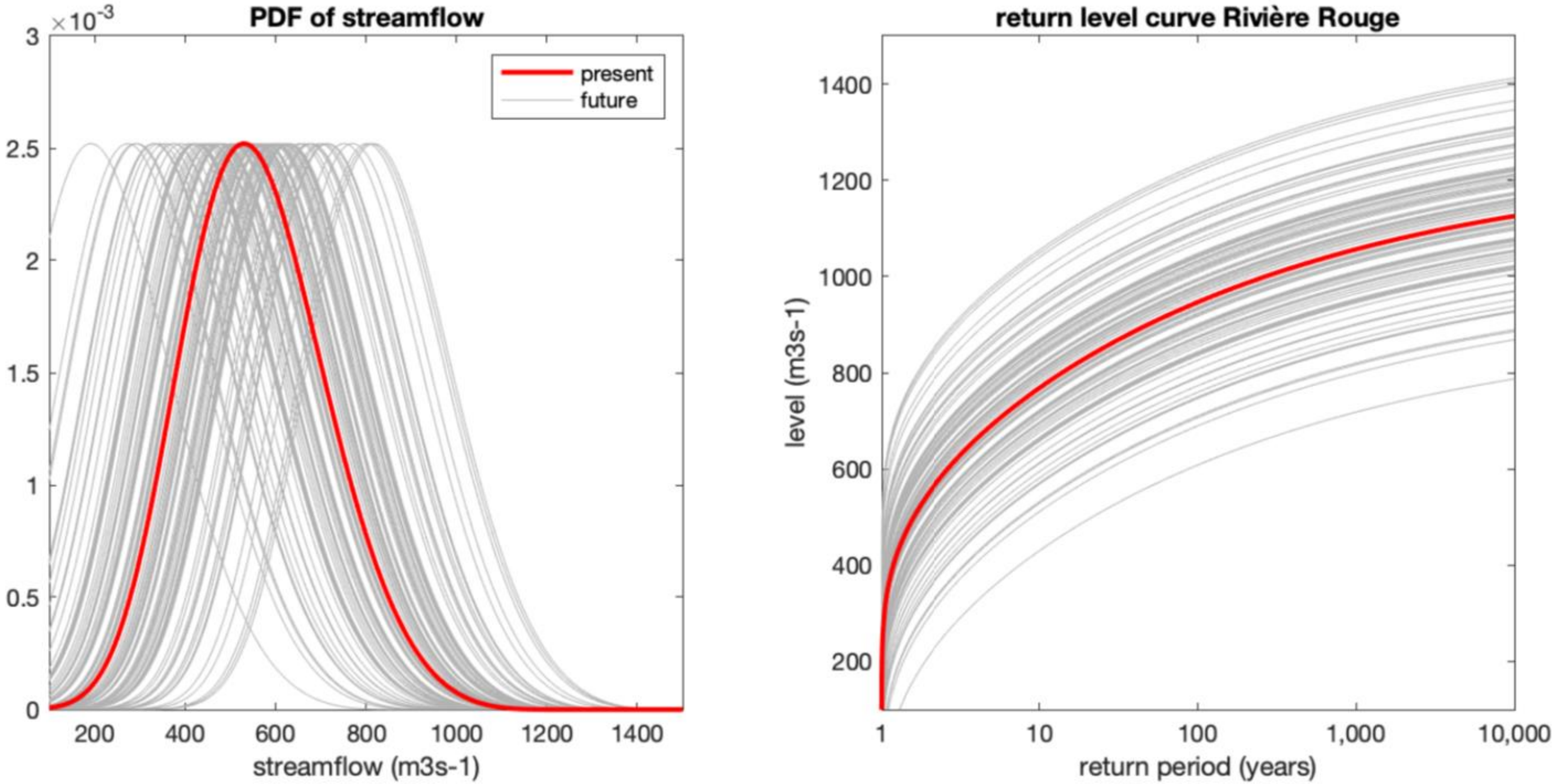
Computation: models and observations in cascade



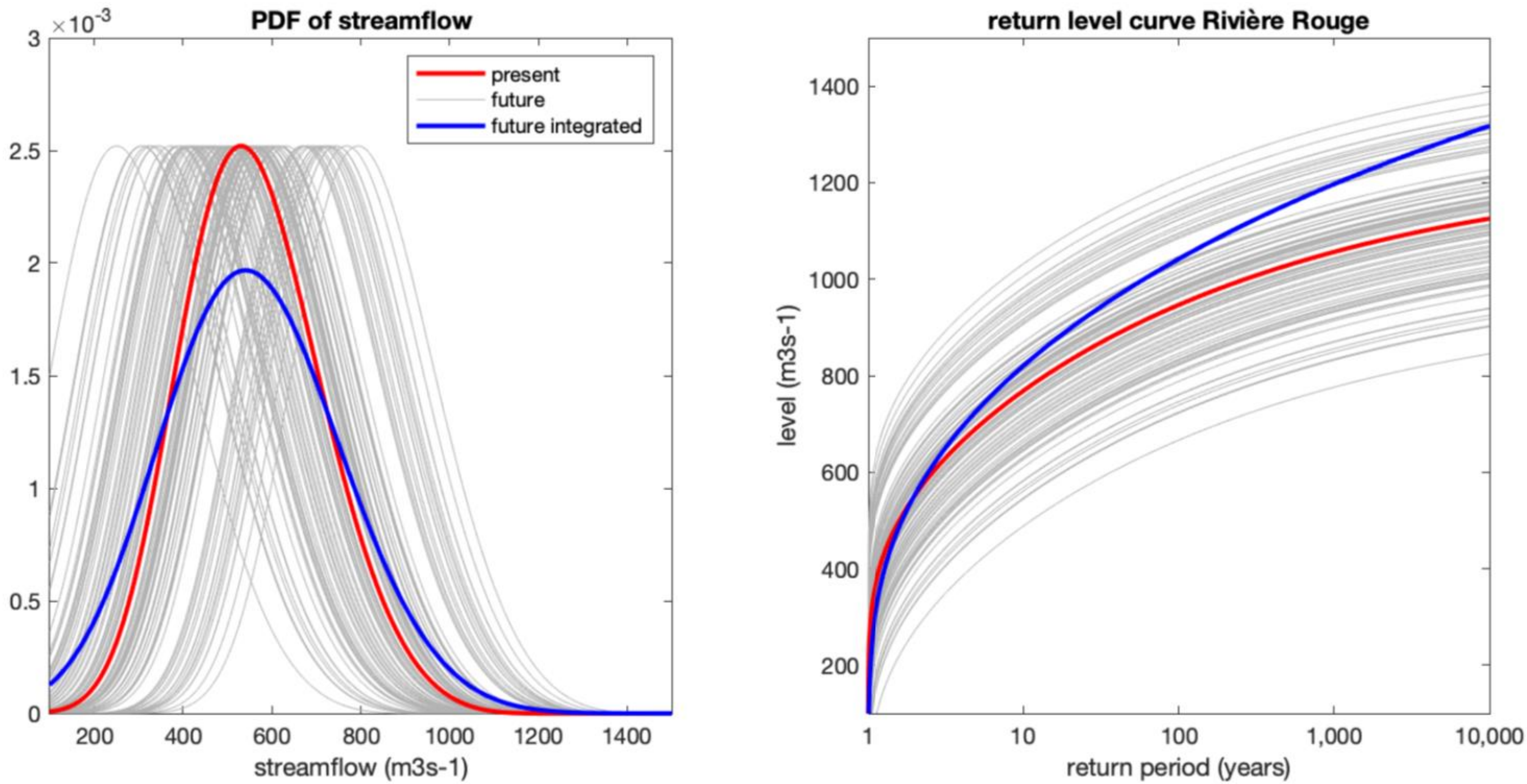
Rouge River sampling uncertainty



Climate change uncertainty effect on return levels



Climate change uncertainty effect on return levels



Agenda

- Context and motivation
- Model and inference
- Results
- Conclusion

Conclusion

- Estimating high quantiles is difficult.
- The GEV extrapolation has many well-known (and less well-known) problems, but still the ‘least worst’ option by default thus far.
- Physics may come to the rescue of statistics.
  - careful attribution of extremes to identify drivers,
  - careful modelign of the dependence between drivers.
- Building climate change into the picture complexifies what is already a difficult problem.
- How to do this in practice is an active and interesting area of research.

Thank you