Probabilistic Models for the Uncertain Hydrologist

Benjamin Renard

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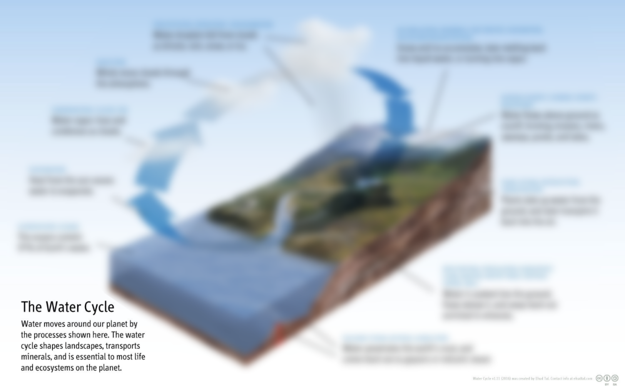

Benjamin Renard
INRAE, UR RECOVER, Aix-Marseille University

Habilitation à Diriger des Recherches
Ecole Doctorale Sciences de l'Environnement / ED 251

Introduction


crédit: Diego Delso

Introduction

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Three Practical Questions

1. What is the discharge flowing in this river right now?

photo: M. Lagouy

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2. Was the great flood of 1910 in Paris a 100-year event?

crédit: héliotypie Ernest Louis Désiré Le Deley

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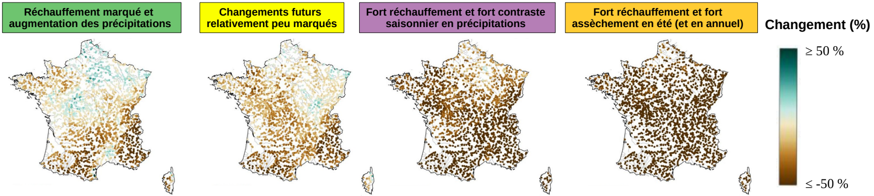
3. How much water will flow in French rivers during the summers of the next 50 years, and how warm will it be?



crédit: EXPLORE 2

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Diversity of situations

- From flood to drought

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- From flood to drought
- Present, past, future

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Diversity of situations

- From flood to drought
- Present, past, future
- From one site to thousands of catchments

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Common Threads

- Water flowing in rivers

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- Estimating unknown quantities affected by uncertainty
- Uncertainty quantification relies on probabilistic models

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Methodological Motto

$\longrightarrow$ Developing **probabilistic models** for the **uncertain hydrologist**

Outline

1. Uncertainty in Streamflow Data

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2. Uncertainty in and around Hydrologic Models

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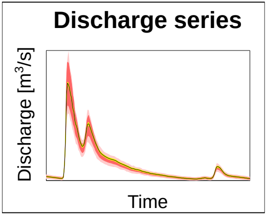
2. Uncertainty in and around Hydrologic Models
3. Hydrologic Variability

Uncertainty in streamflow data

Production of River Discharge Series

- River discharge: a key variable for hydrology... that can't be measured continuously



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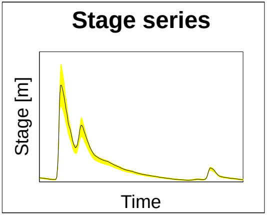
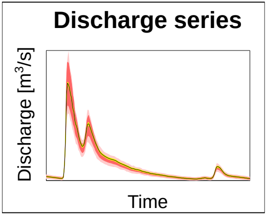
- But river stage can!





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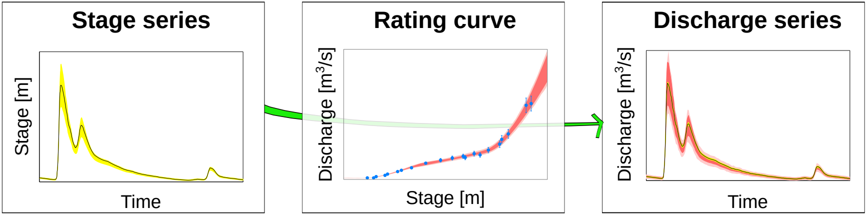
- Rating curve: $Q = f(h)$



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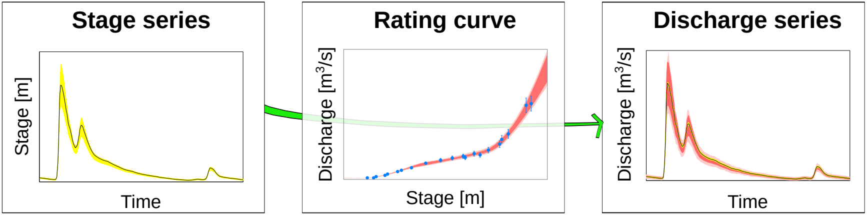
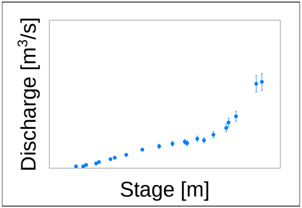


⟶ How to **formulate and estimate rating curves?**

⟶ How to **quantify and propagate uncertainties?**

Rating Curve Formulation

Just fit some flexible curve!



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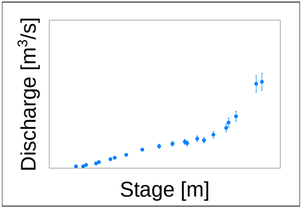

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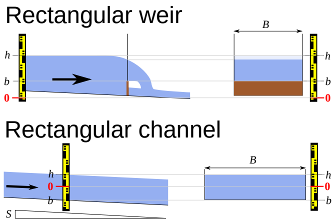
1. Use hydraulics: $Q = a(h - b)^c$

   with a, b, c related to physical quantities that can be measured (albeit uncertainly)



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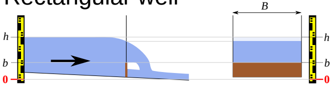
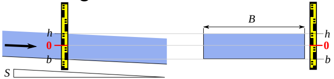
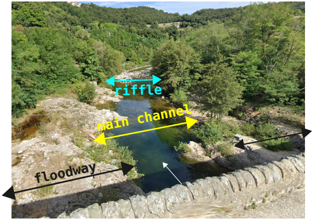


Rectangular channel



2. A ‘control matrix‘ to combine multiple controls



	riffle	channel	floodway	
				κ_1
low stage	1	0	0	$a_1(h-b_1)^{c_1}$
				κ_2
medium stage	0	1	0	$a_2(h-b_2)^{c_2}$
				κ_3
high stage	0	1	1	$a_2(h-b_2)^{c_2} + a_3(h-b_3)^{c_3}$

Rating Curve Estimation

⟶ **Bayesian Rating Curve** estimation (BaRatin)

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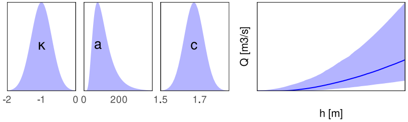
Prior distribution $p(\kappa, a, c) = p(\boldsymbol{\theta})$



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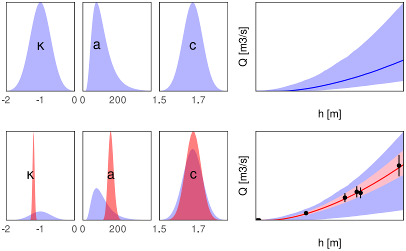

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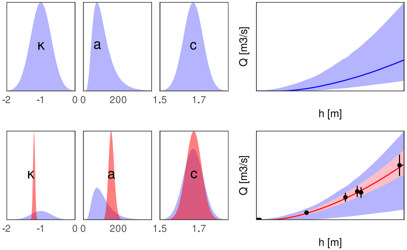

Probabilistic model linking gaugings $(\tilde{h}_i, \tilde{Q}_i)$ and RC $\hat{Q}_i = f_{RC}(h_i | \boldsymbol{\theta})$:

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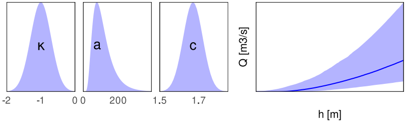

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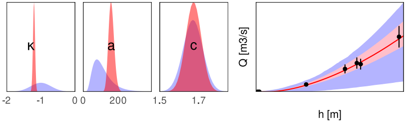

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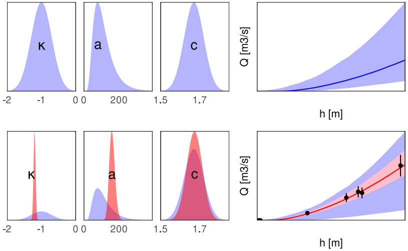

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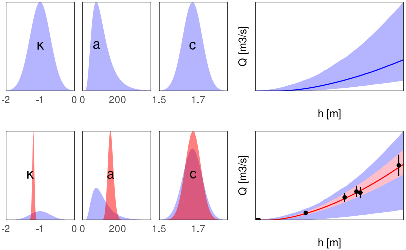

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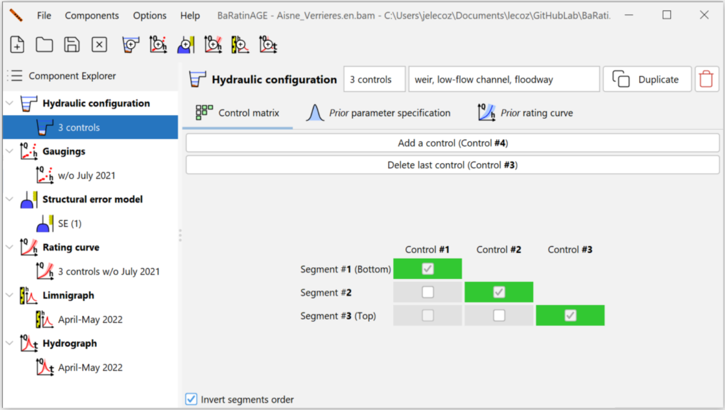
Structural error $\varepsilon_i \sim \mathcal{N}(0, \sigma_i)$; $\sigma_i = \gamma_1 + \gamma_2 \hat{Q}_i$ to be estimated

Operational Tool: BaRatinAGE



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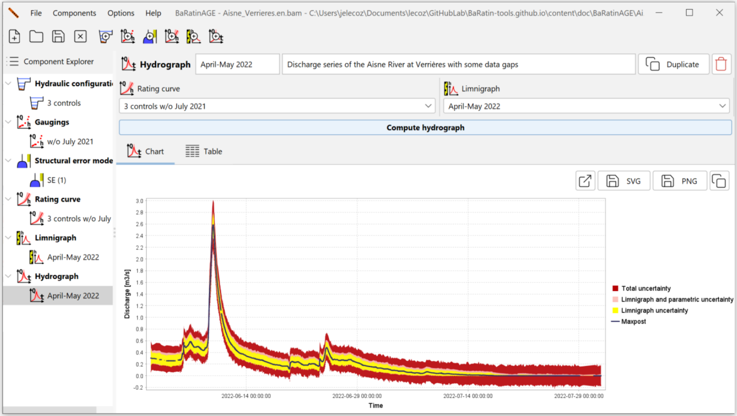

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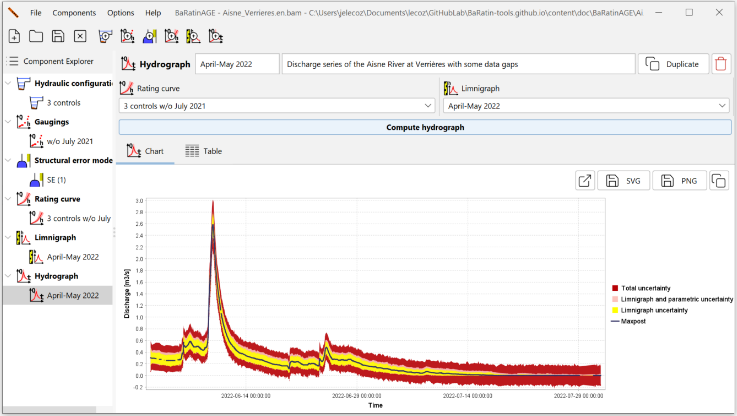

- A viable solution to estimate uncertain $Q = f(h)$ rating curves...

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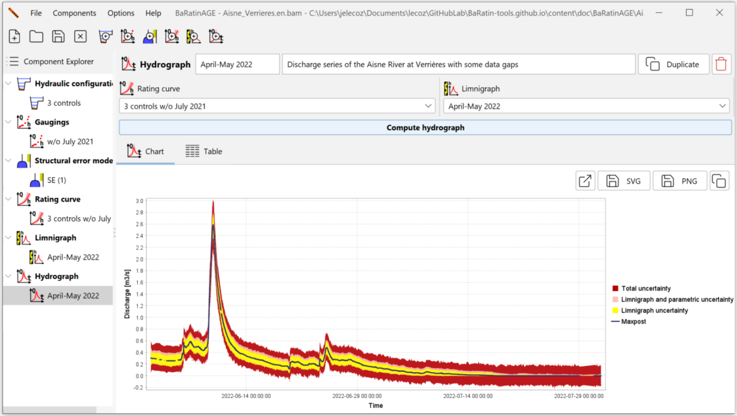

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- ... which are the exception rather than the rule!

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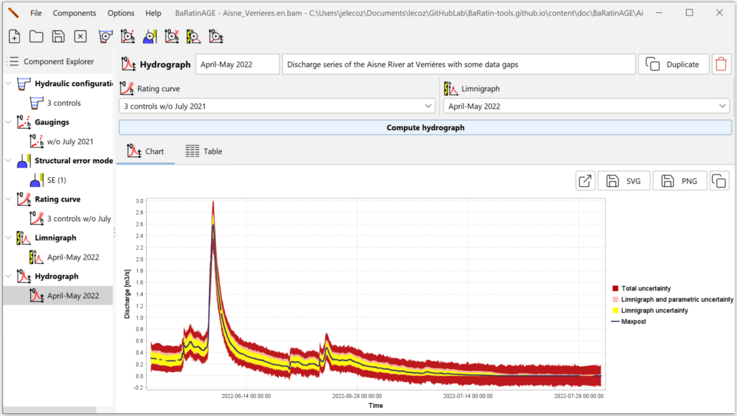

- A viable solution to estimate uncertain $Q = f(h)$ rating curves...
- ... which are the exception rather than the rule!
  1. rating shifts
  2. complex rating curves $Q = f(h, \text{others})$

Rating Shift Happens!

⟶ Detecting rating shifts (M. Darienzo, F. Mendez)

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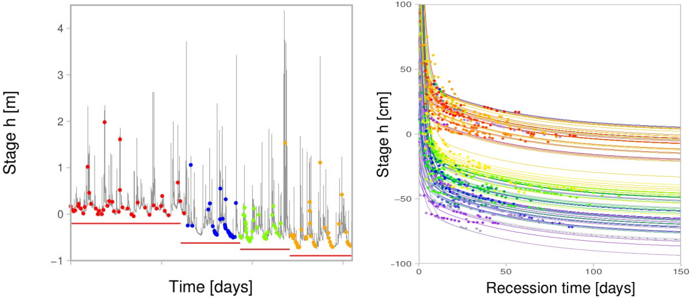
From the stage time series



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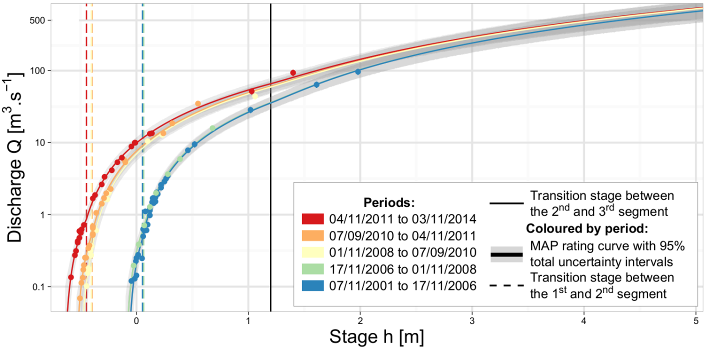
⟶ Detecting rating shifts (M. Darienzo, F. Mendez)

⟶ Estimating shifting curves (V. Mansanarez)



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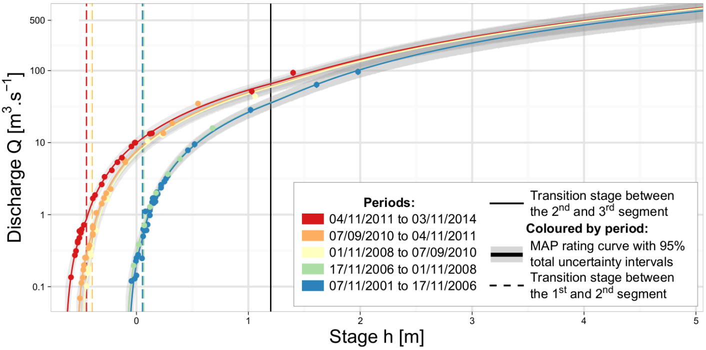
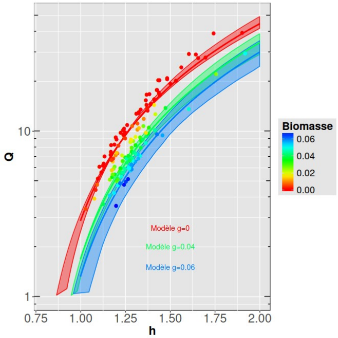


Hydraulic assumptions on what changes $\Longrightarrow$ stable vs. varying RC parameters

Complex Rating Curves $Q = f(h, \ldots)$

⟶ Vegetation model (E. Perret)

$Q = f(h, V)$ due to seasonal aquatic vegetation growth



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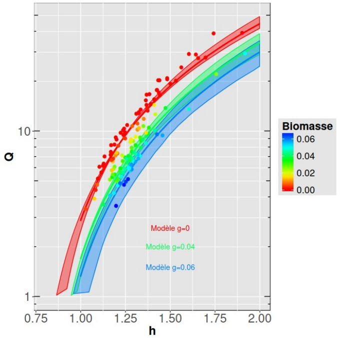
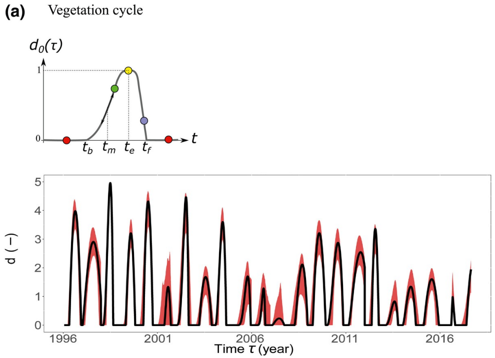
As V is not measured, $Q = f(h, \cancel{V} t)$





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$\longrightarrow$ Vegetation model (E. Perret)

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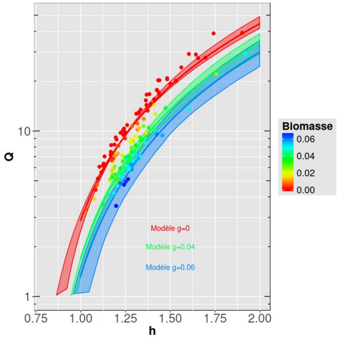
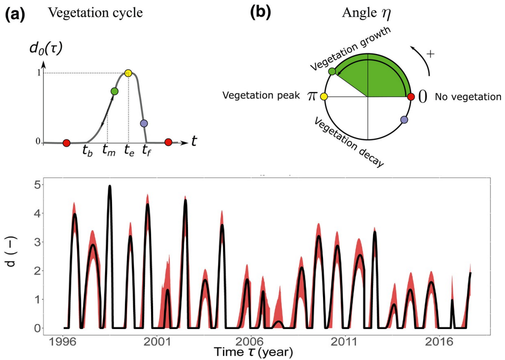
Possible to incorporate qualitative information on the vegetation state.



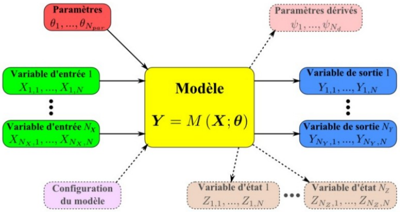


From BaRatin to BaM

Replacing $Q = f(h)$ by another model does not really change the statistical framework used in BaRatin.

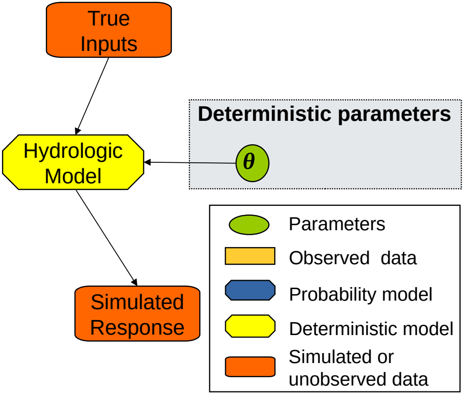
$\longrightarrow$ **Development of BaM** (Bayesian Modeling)

'Any' model can be plugged in. Examples:
sediment transport, optical camera model, chemistry, 1D hydraulics, hydrologic.



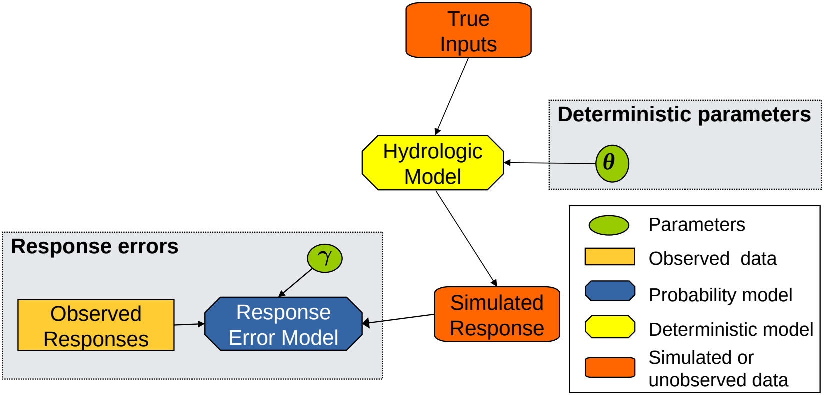
Uncertainty in & around hydrologic models

Bayesian Total Error Analysis



$$\hat{Q}_t = \mathcal{M}(\boldsymbol{r}_{1\to t}|\boldsymbol{\theta})$$

Bayesian Total Error Analysis



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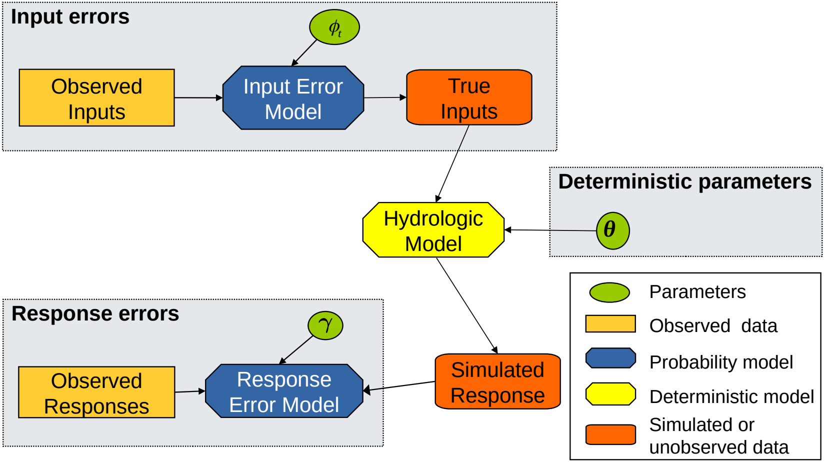
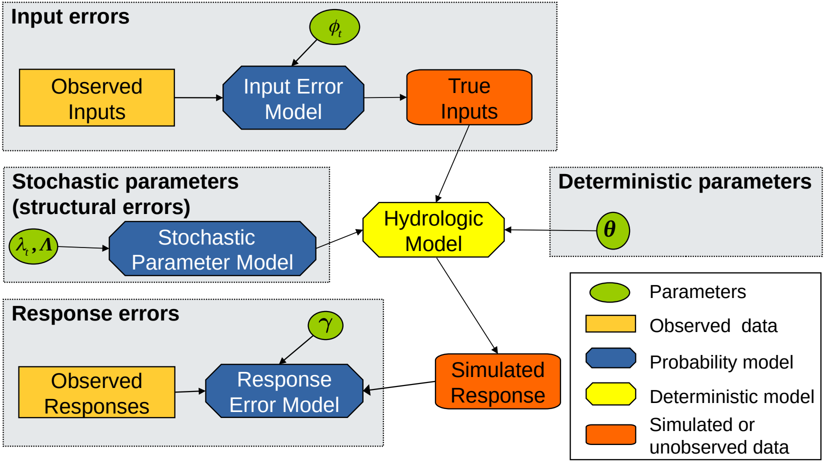


$$\tilde{Q}_t = \mathcal{M}(\tilde{\boldsymbol{r}}_{1\to t} \times \phi_{1\to t} | \boldsymbol{\theta}) + \delta_t + \varepsilon_t$$

$$\phi_k \sim \mathcal{LN}(\mu, \sigma)$$

Bayesian Total Error Analysis

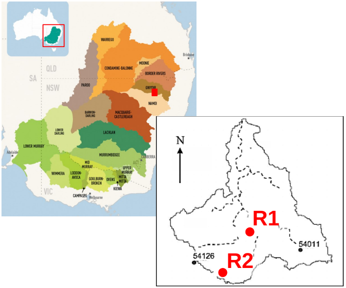


$$\tilde{Q}_t = \mathcal{M}(\tilde{\boldsymbol{r}}_{1\to t} \times \phi_{1\to t} | \boldsymbol{\theta}, \boldsymbol{\lambda}_{1\to t}) + \delta_t + \varepsilon_t$$

$$\lambda_k \sim \mathcal{D}(\Lambda)$$

Recognizing Data Uncertainty

- Horton catchment (1920 km^2), Australia
- Calibrate $\mathcal{M}(\boldsymbol{\theta})$ using rainfall data from either R1 or R2
- Compare inference schemes ignoring or acknowledging streamflow and rainfall data uncertainties (uQ and uR)



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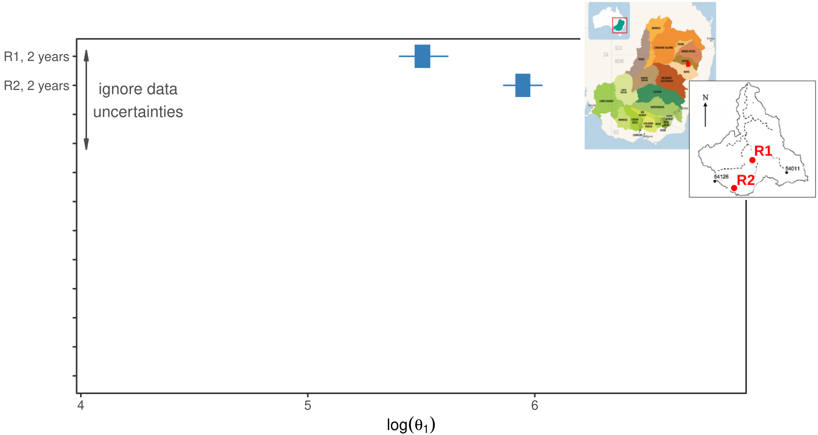

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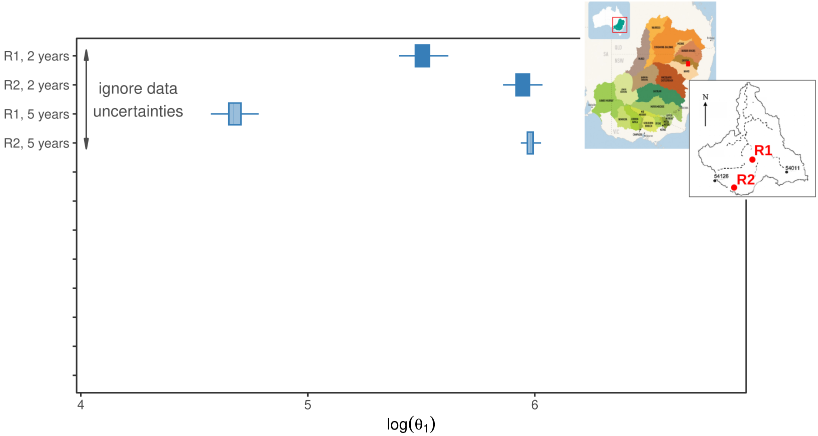

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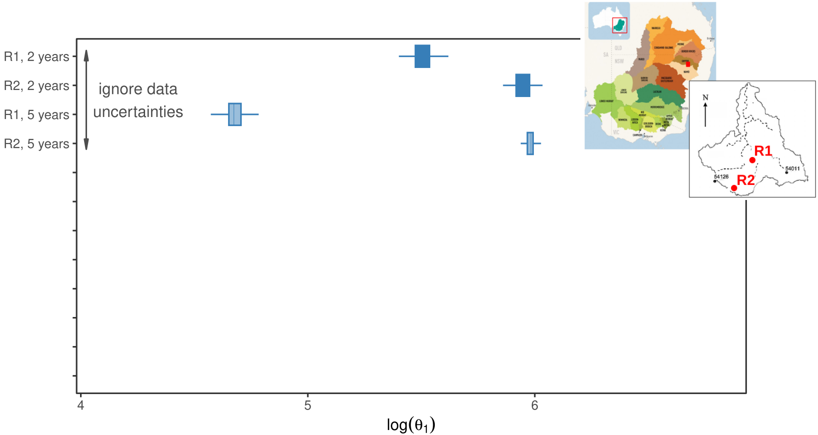

- Ignoring data uncertainties $\Longrightarrow$ parameters fit to data errors

  reliability of streamflow prediction? parameter regionalization?

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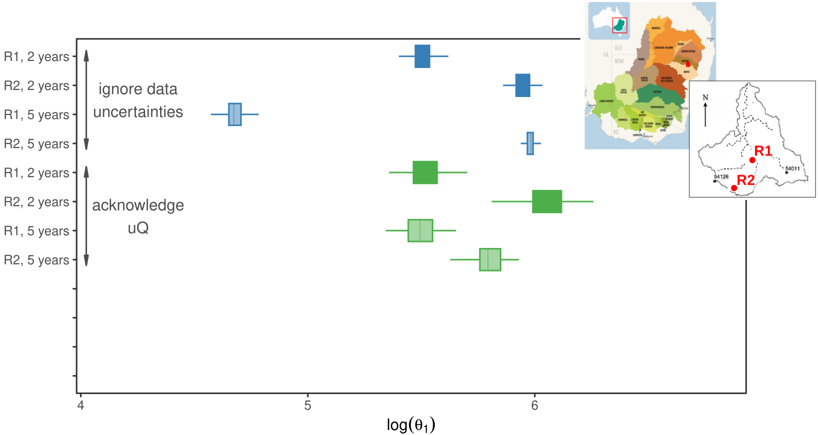

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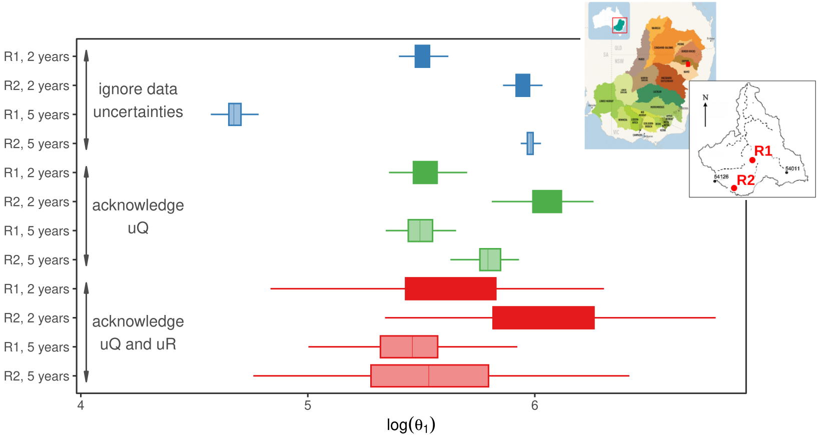

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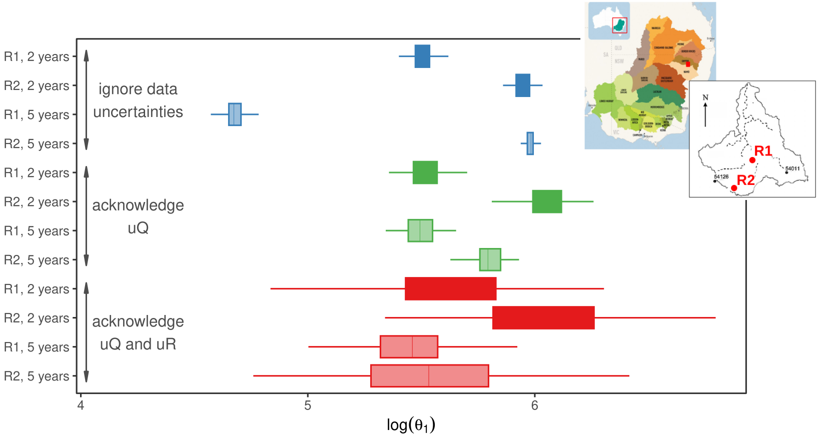

- Ignoring data uncertainties $\Longrightarrow$ parameters fit to data errors
  reliability of streamflow prediction? parameter regionalization?
- Acknowledging data uncertainties $\Longrightarrow$ parameters more stable
  vaguely correct rather than precisely wrong!

Structural Uncertainty through Stochastic Parameters

⟶ What do structural errors look like?

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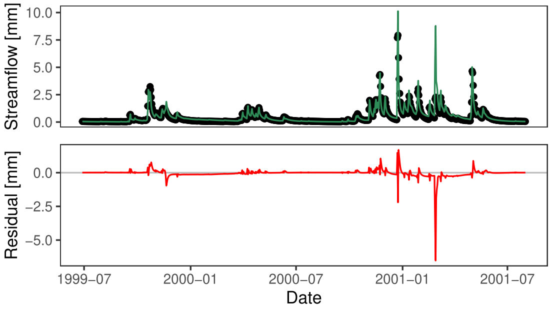

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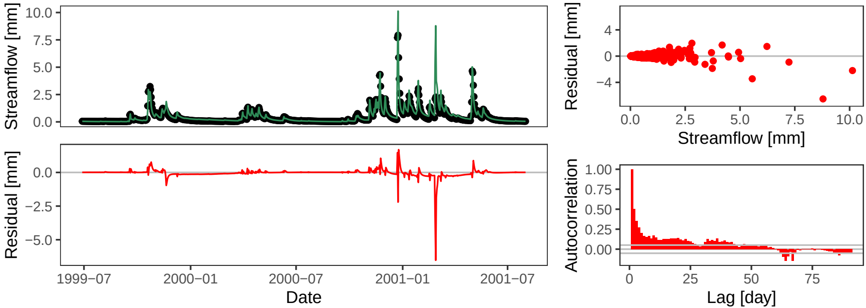

- High heteroscedasticity, complex dependence structure
- Structural error model may be as complex as the model itself...

Structural Uncertainty through Stochastic Parameters

- Allow θ_1 to vary in time according to : $log(\theta_{1,k}) \overset{iid}{\sim} \mathcal{N}(\mu, \sigma)$

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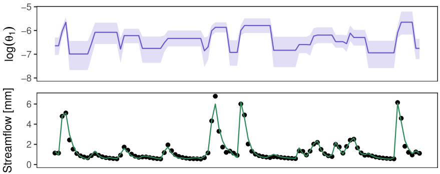

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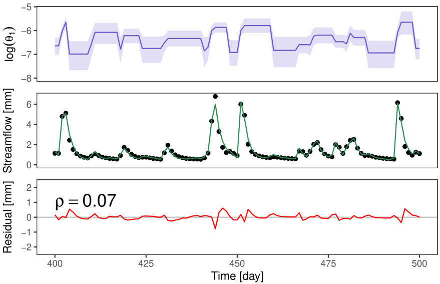

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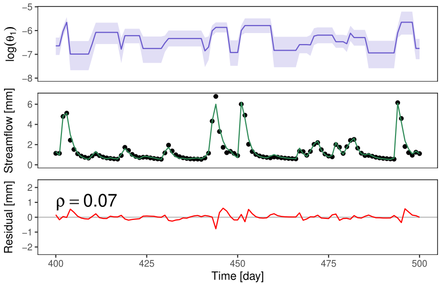

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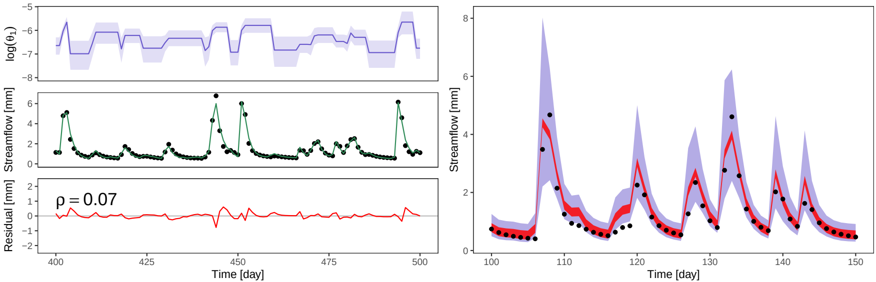
- In prediction, randomly sample $log(\theta_1)$ values from $\mathcal{N}(\hat{\mu}, \hat{\sigma})$



$\longrightarrow$ Stochastic parameters allows using simple statistical models for structural uncertainty, at the cost of a demanding inference

Decomposing Predictive Uncertainty

Putting everything together... $\hat{Q}_t = \mathcal{M}(\tilde{\boldsymbol{r}}_{1\rightarrow t} \times \phi_{1\rightarrow t}|\boldsymbol{\theta}, \boldsymbol{\lambda}_{1\rightarrow t}) + \varepsilon_t$

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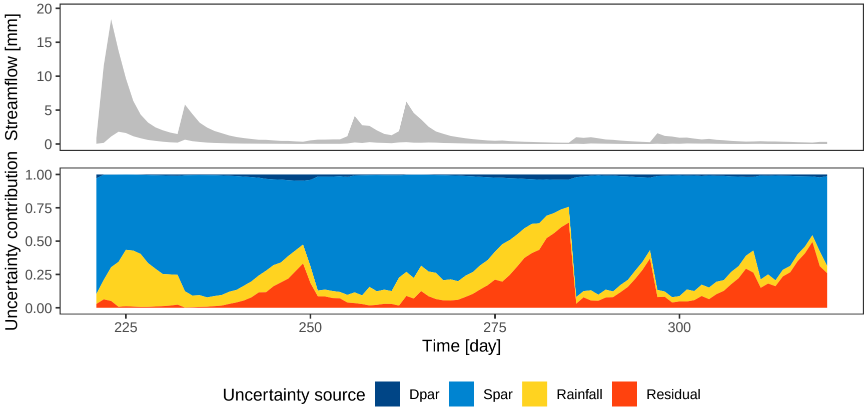

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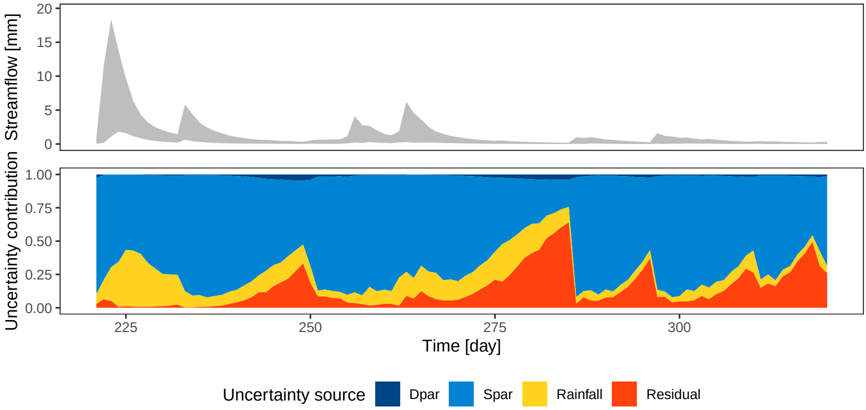

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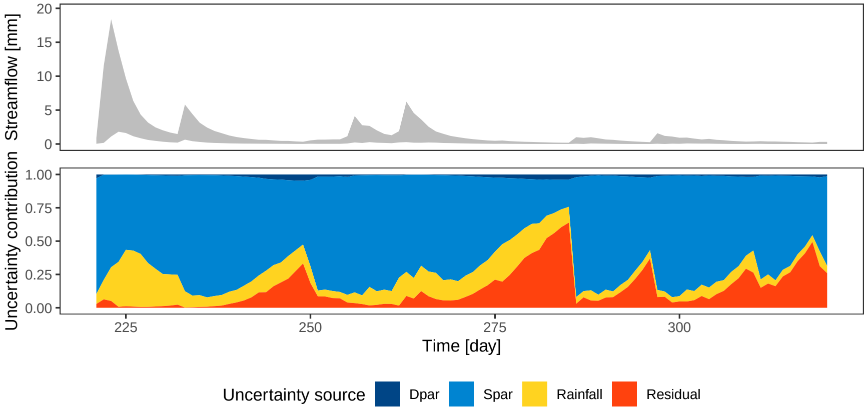

- main sources of predictive uncertainty $\implies$ ways to reduce it
- specific sources may be turned off or replaced

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1. data uncertainties are known beforehand
   If you don't know the quality of data, you won't know the quality of the model

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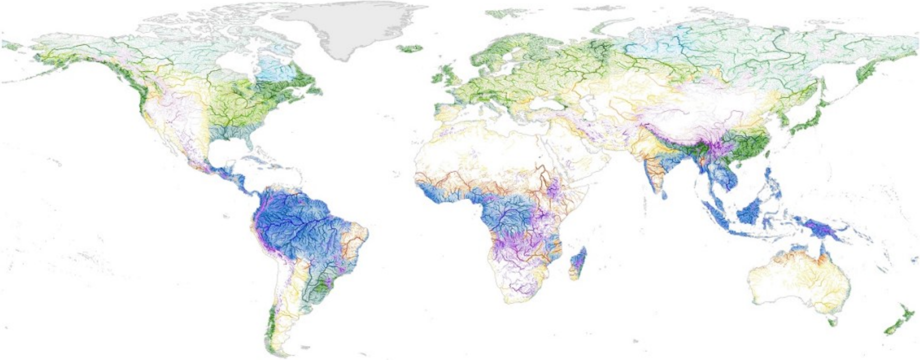
Otherwise, the problem is **ill-posed** due to **non-identifiable parameters**

Hydrologic Variability

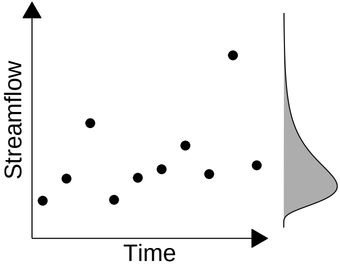


crédit: HydroSHEDS

Estimating Distributions

Managing water resources and risks often requires estimating distributions:

- Dam design: T-year quantile from the **marginal** distribution of streamflow



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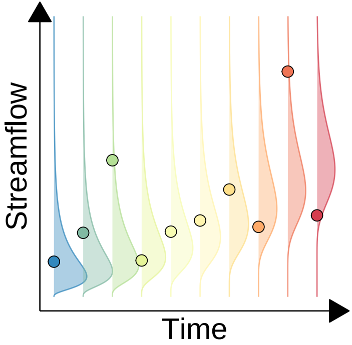

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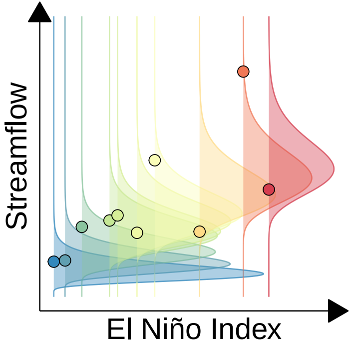

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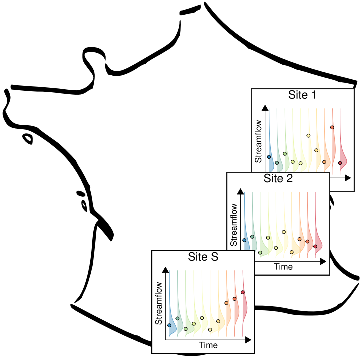

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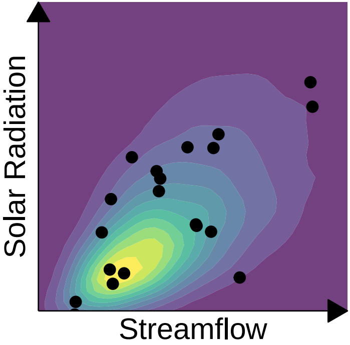
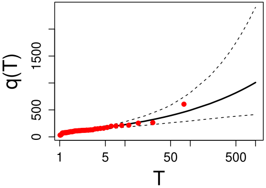
- Renewable energy production depends on the **joint distribution** of wind, solar radiation and streamflow.



Estimating a Marginal Distribution

A simple statistical problem, plagued with sampling uncertainty.
Ex: estimate $GEV(\mu, \sigma, \xi)$ with 40 years of data.



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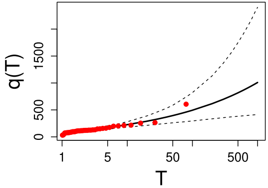

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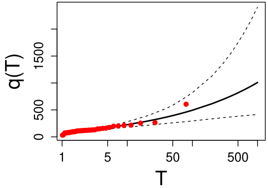

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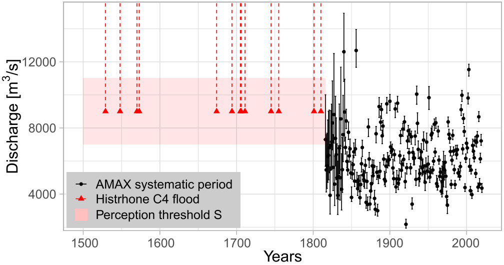

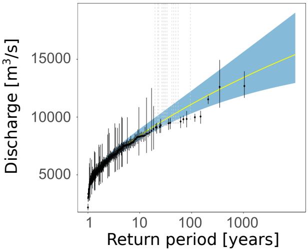

(M. Lucas PhD)

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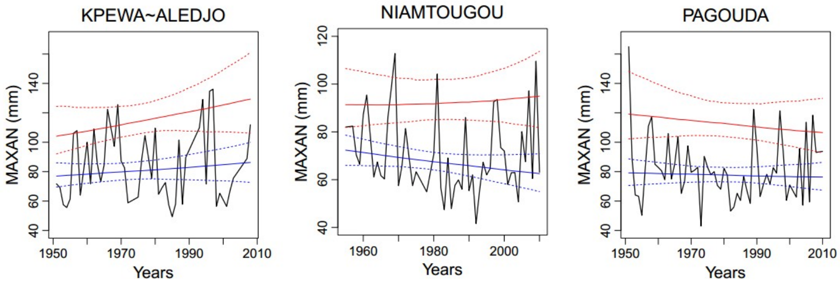

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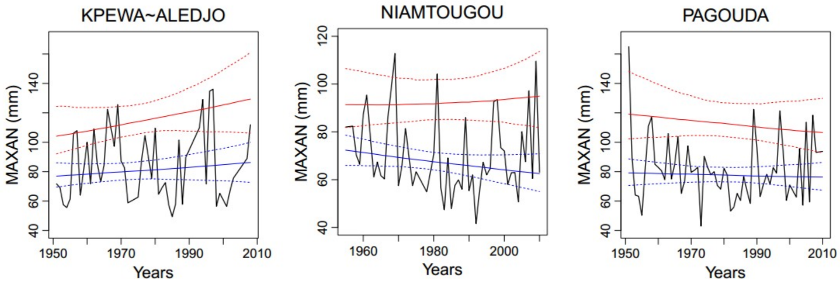

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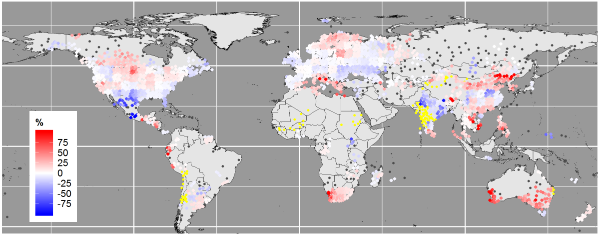

Hidden Climate Indices Models

⟶ Standard vs. Hidden Climate Index model

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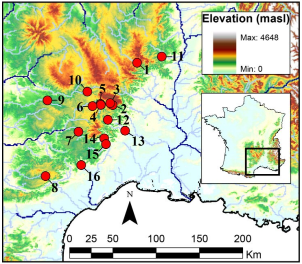

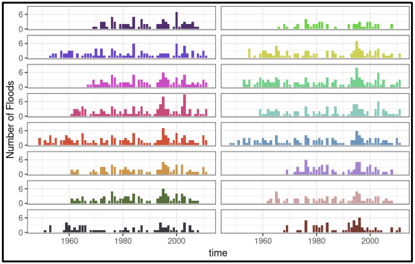

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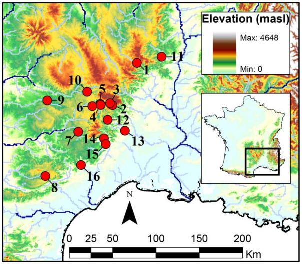

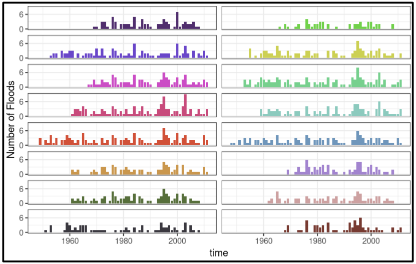

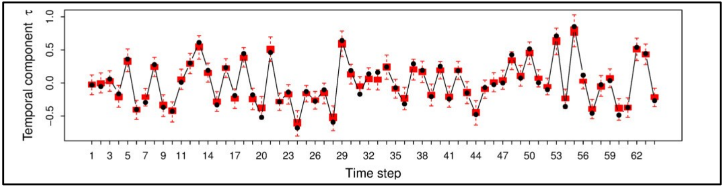

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$\longrightarrow$ Multi-variate extension + large-scale scalability

Hidden Climate Indices Models

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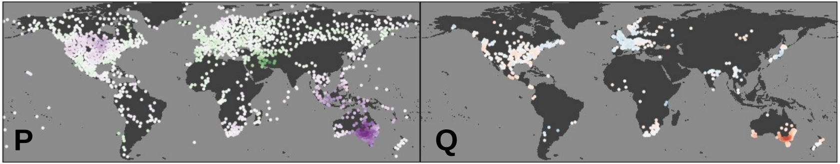

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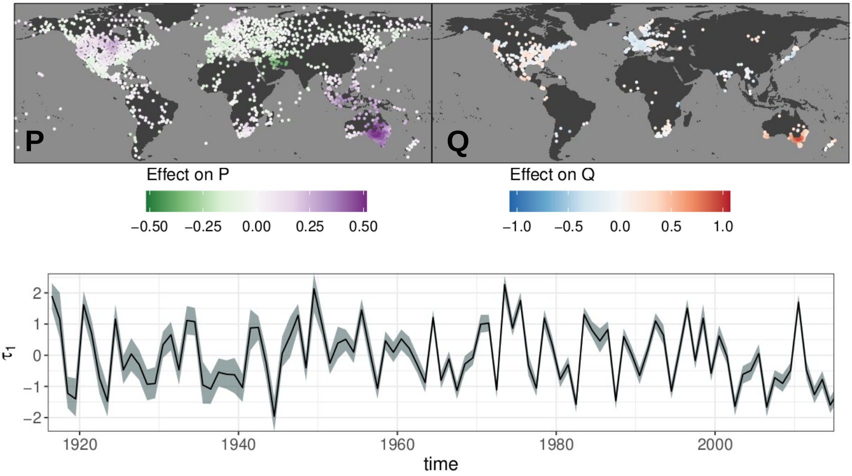

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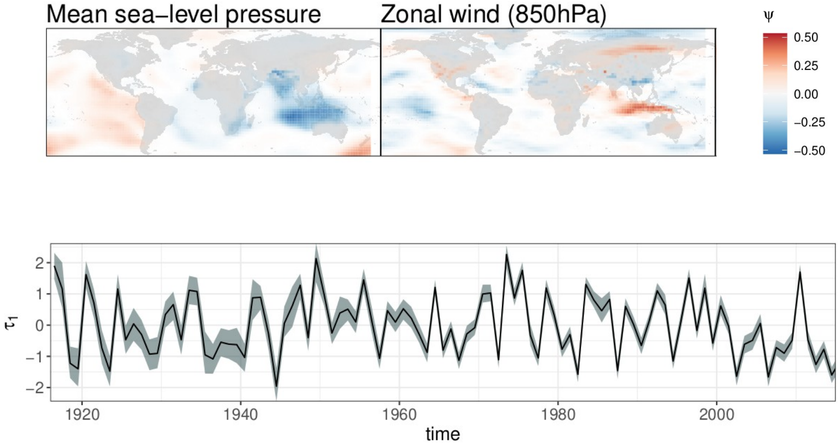

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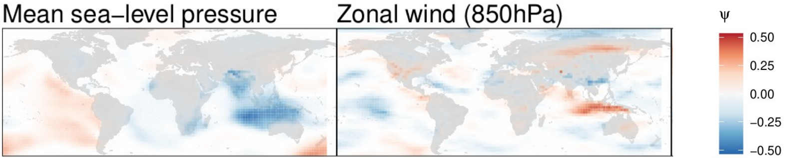

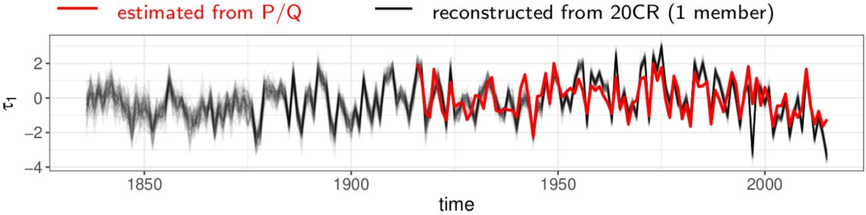

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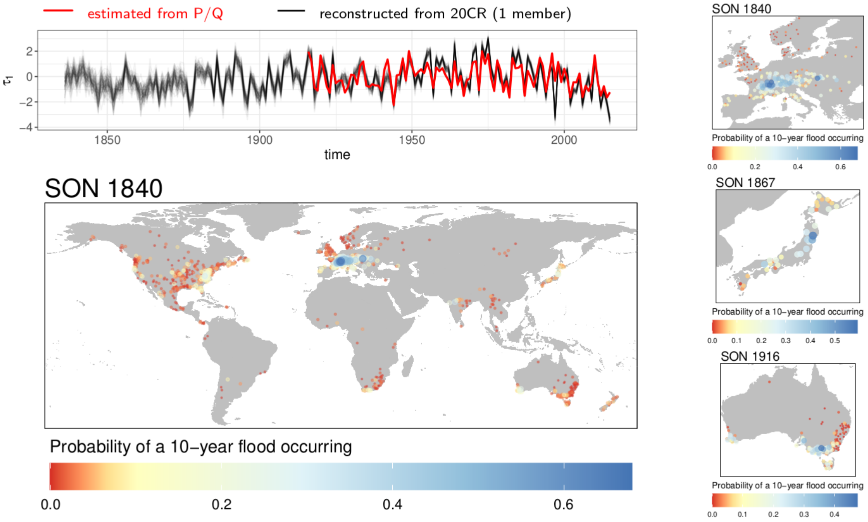
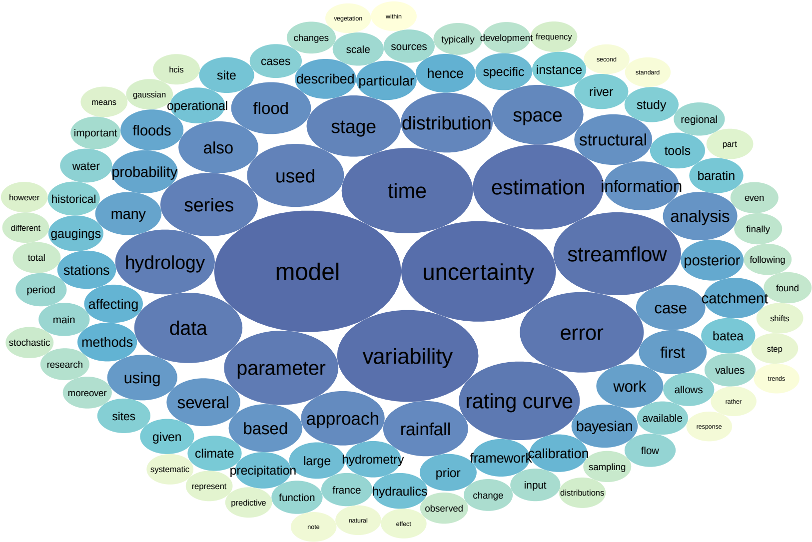


Conclusion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- Key contributions:
  1. Uncertainties affecting streamflow time series
  2. Uncertainties affecting hydrologic models
  3. Modeling hydrologic variability in space, time and between variables

Perspectives

⟶ **Uncertainties in Hydrologic Data and Models**

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   - Evaluate non-zero-mean residual models (conditional biases)

2. **Distributed models**
   - Hydrologic (SMASH) or Hydraulics
   - Define spatialized error models

Perspectives

⟶ **Uncertainties in Hydrologic Data and Models**

1. **Treatment of structural errors**
   - Further assess the interest of stochastic parameters
   - Evaluate non-zero-mean residual models (conditional biases)

2. **Distributed models**
   - Hydrologic (SMASH) or Hydraulics
   - Define spatialized error models

3. **Beyond streamflow series**
   - What other data types are valuable to constrain model calibration?
   - Sporadic gaugings, flood videos, flood marks, satellite (SWOT), etc.

Perspectives

⟶ **Hydrologic Variability**

Perspectives

⟶ **Hydrologic Variability**

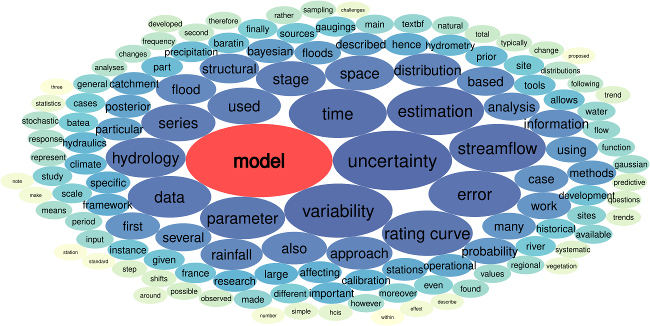
1. **Methodological questions**
   - Using Hidden Climate Indices to derive spatial extremes models?
   - Clarify the link between HCI models and Machine Learning approaches such as probabilistic PCA

Perspectives

⟶ **Hydrologic Variability**

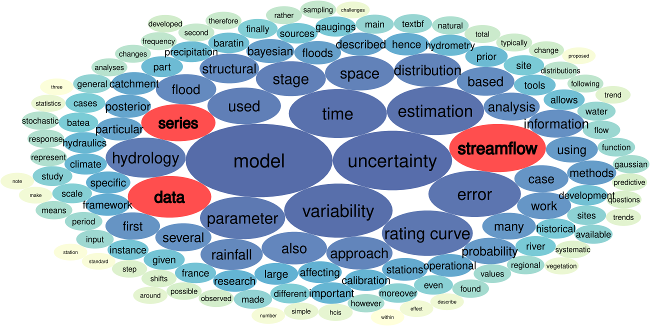
1. **Methodological questions**
   - Using Hidden Climate Indices to derive spatial extremes models?
   - Clarify the link between HCI models and Machine Learning approaches such as probabilistic PCA
2. **Applications**
   - Global droughts (low flows and precipitation deficit)
   - Relation with the wildfire hazard: a testbed for multi-risk assessment?

Key aspects



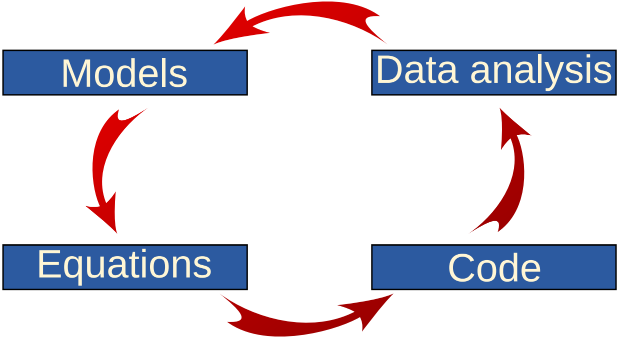
- Probabilistic modeling is central

Key aspects



- Probabilistic modeling is central
- Data are invaluable, and models should adapt to data

Key aspects



- Probabilistic modeling is central
- Data are invaluable, and models should adapt to data
- Coding is an important component

Key aspects

- Probabilistic modeling is central
- Data are invaluable, and models should adapt to data
- Coding is an important component
- Operational transfer as both an output and an input of research work

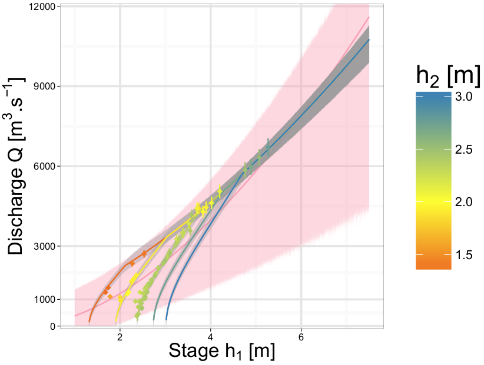
And most importantly... Thank You!

Xtra

Complex Rating Curves $Q = f(h, \ldots)$

$\longrightarrow$ Stage-Fall-Discharge model (V. Mansanarez)

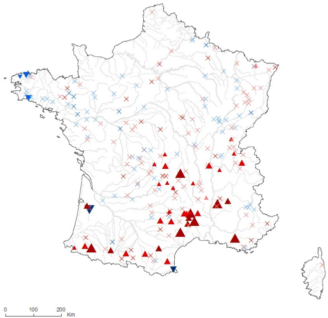
$Q = f(h_1, h_2)$ due to variable backwater (dam, tide)
Used operationally for dam-influenced stations
Work still in progress for tide-influenced stations



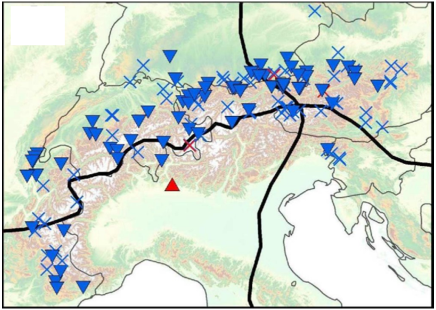
Estimating a Time-Varying Distribution

⟶ Trend detection studies

Drought duration, 1968-2008

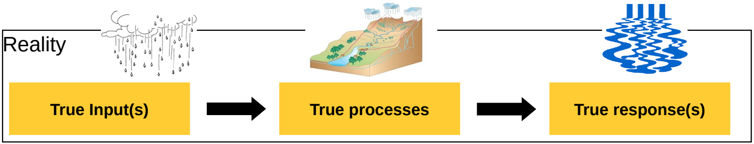


Snowmelt flows start, 1961-2006



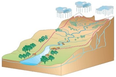
(I. Giuntoli, A. Bard)

Error Sources in Hydrologic Modeling



Error Sources in Hydrologic Modeling

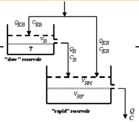
Reality



True Input(s) → **True processes** → **True response(s)**

Model

Conceptualized processes



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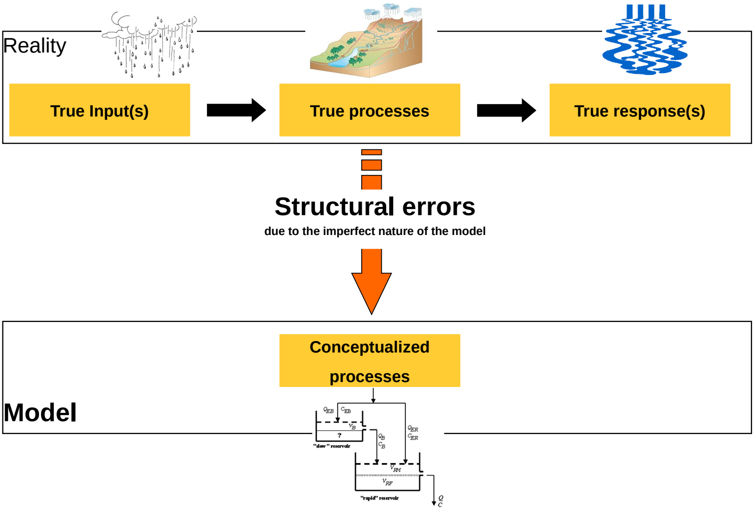

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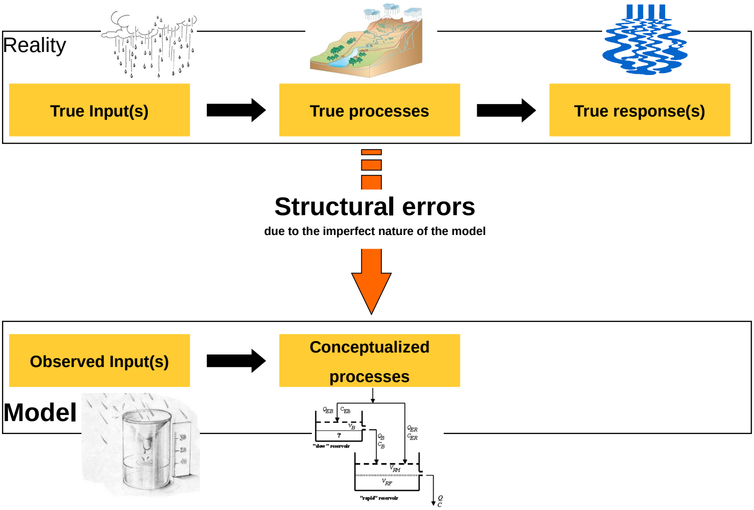

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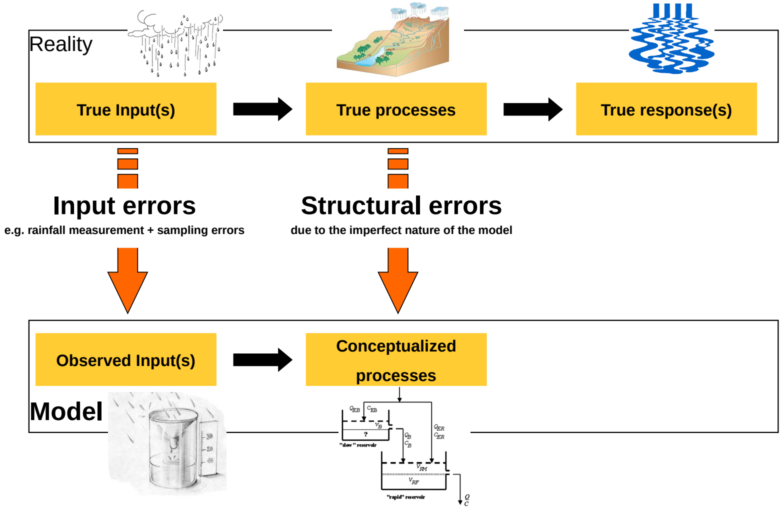

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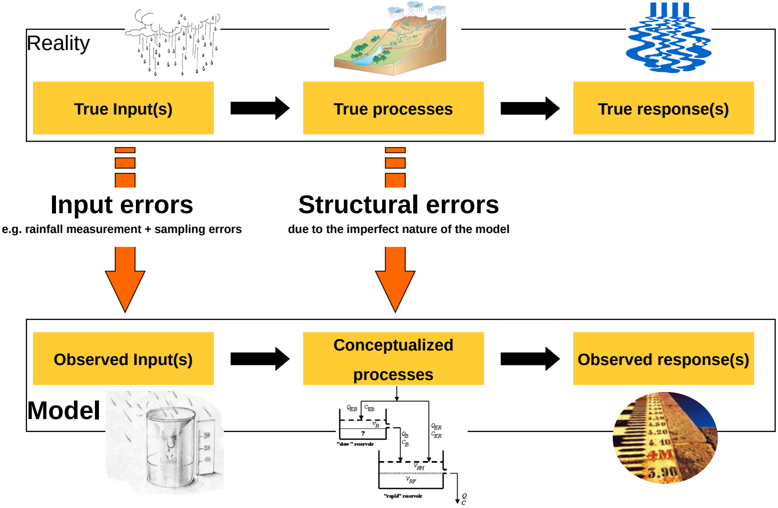

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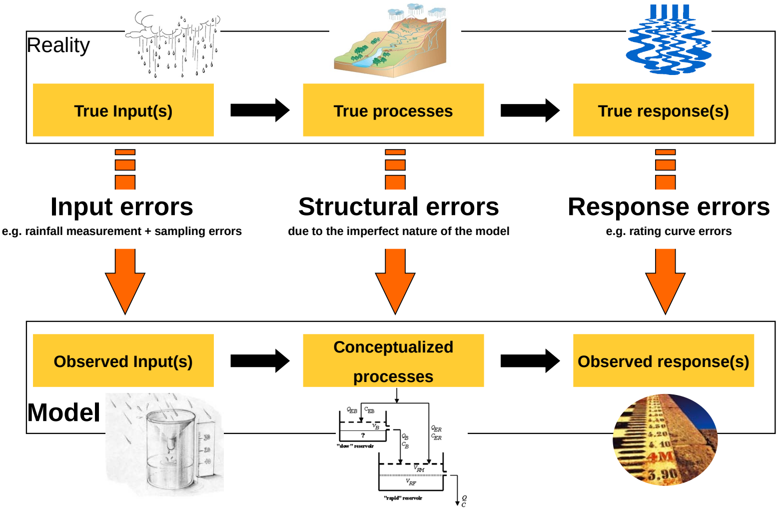

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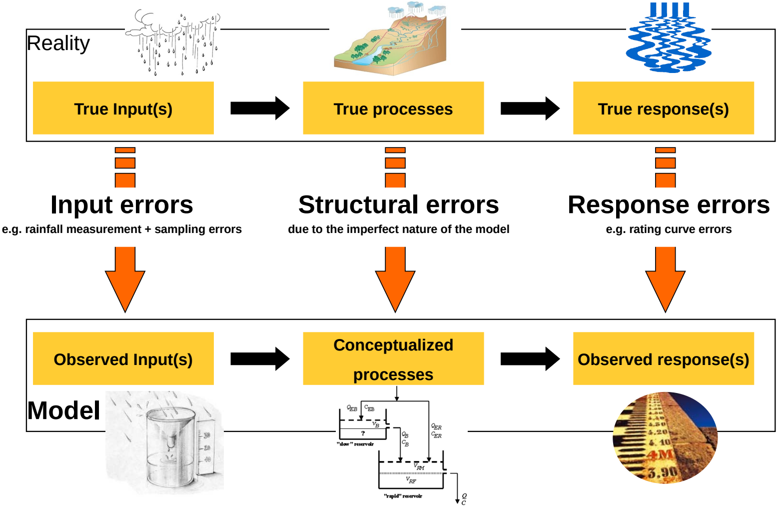
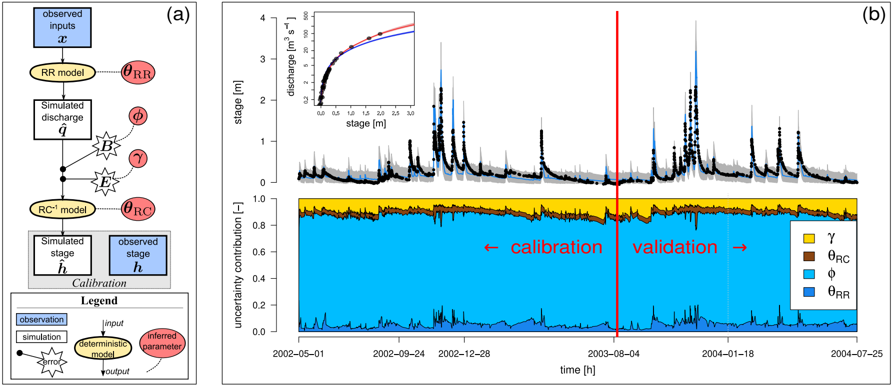
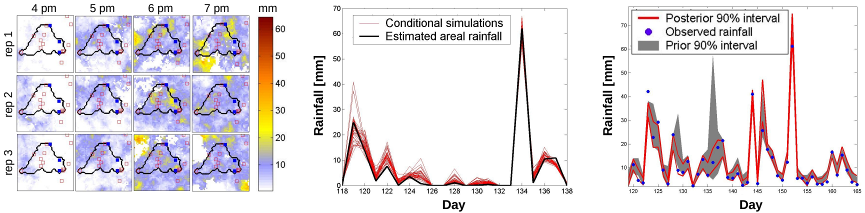


+ Parametric uncertainty

Systematic Rating Curve Errors



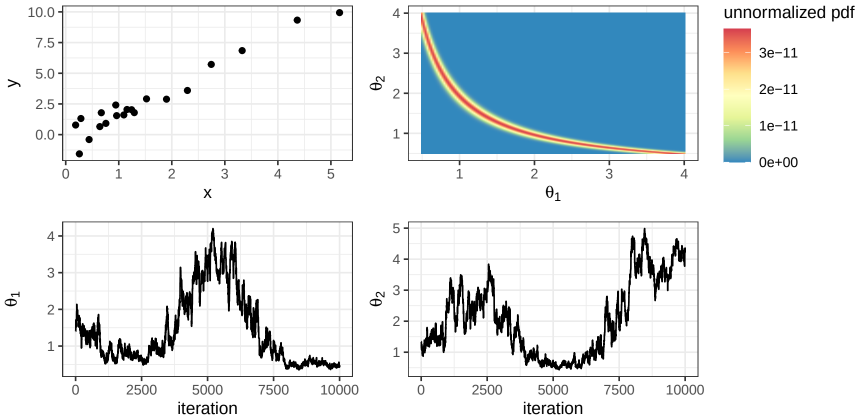
Rainfall Uncertainty



(a) (b) (c)

Non-identifiability

Model: $\hat{y} = \theta_1 \theta_2 x$



Identifying θ_1 and θ_2 based on this information is an ill-posed problem.

Non-identifiability

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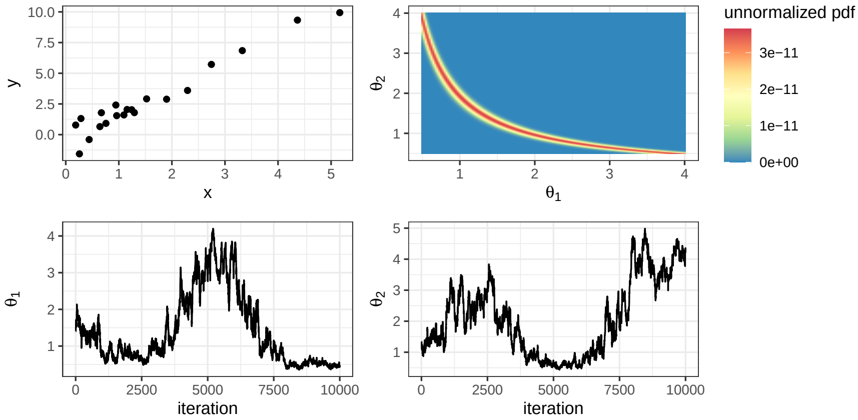
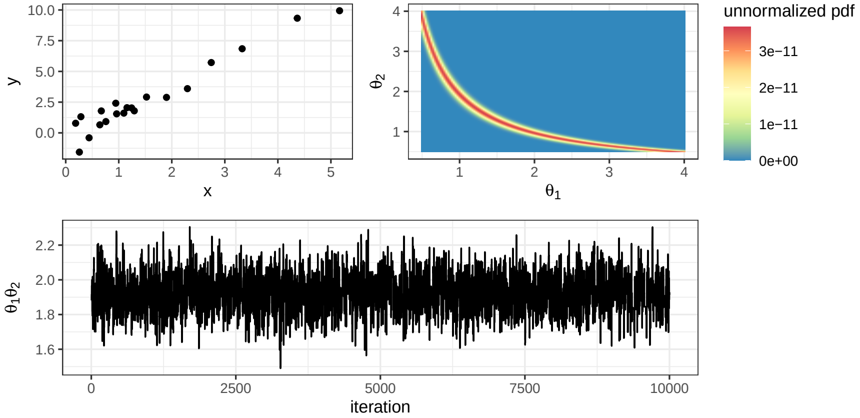


Identifying θ_1 and θ_2 based on this information is an ill-posed problem.
Non-identifiability and ill-posedness are frequently encountered in the calibration of hydrologic models

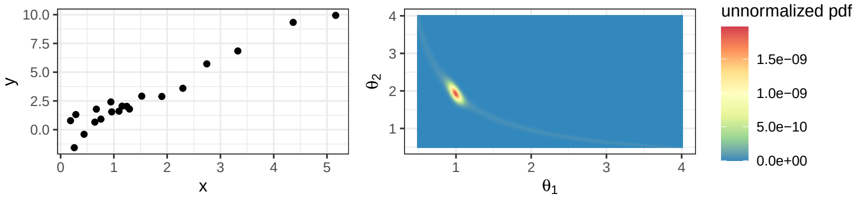
Non-identifiability

Solution 1: 'under-parameterize', $\hat{y} = \gamma x$ with $\gamma = \theta_1\theta_2$



Non-identifiability

Solution 2: use prior, $\theta_1 \sim \mathcal{N}(1, 0.1^2)$



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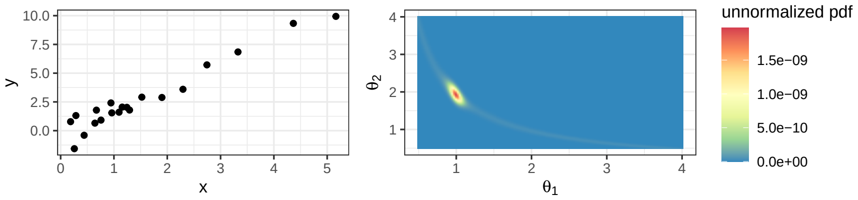
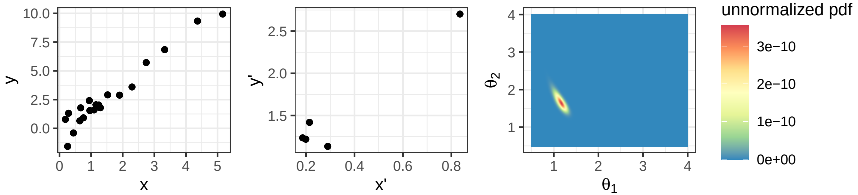
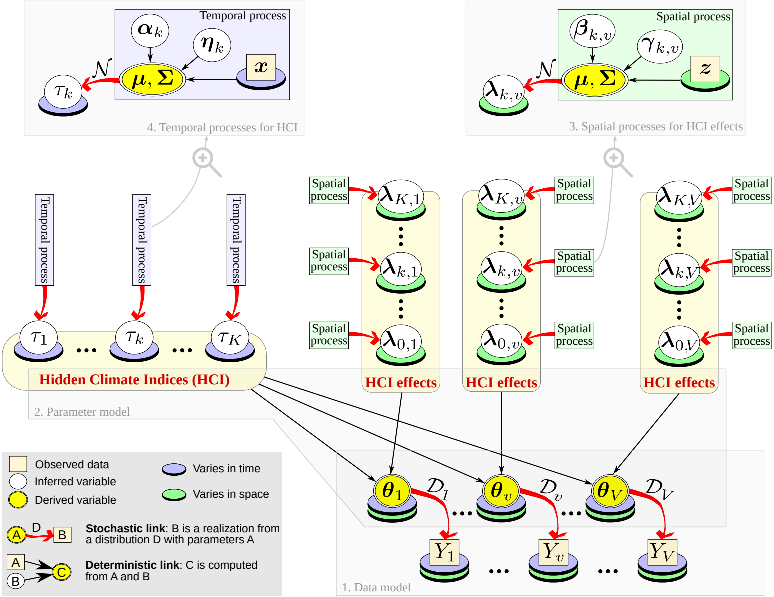


Solution 3: use other data (not more of the same!)
$\hat{y} = \theta_1\theta_2 x$ and $\hat{y}' = \exp(\theta_1 x')$



HCI framework



Hidden Climate Indices Models

⟶ Generalization to non-homogeneous regions

$$\mathcal{M}_0 : Y(s, t) \sim \mathcal{D}\left(\theta(s) \times (1 + \lambda\tau(t))\right)$$

Hidden Climate Indices Models

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Hidden Climate Indices Models

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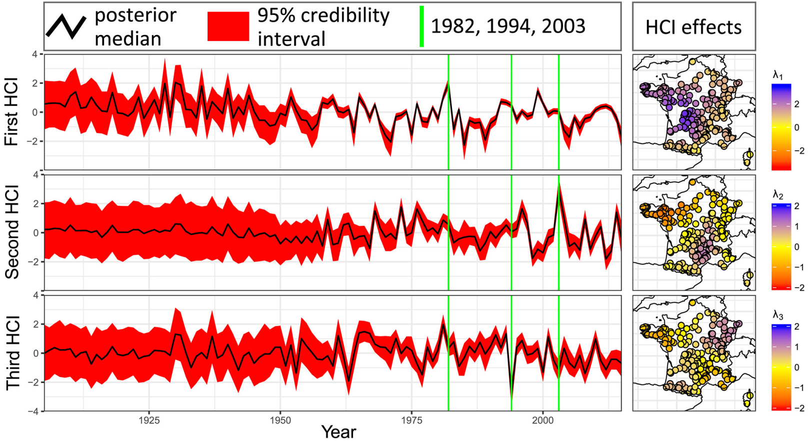
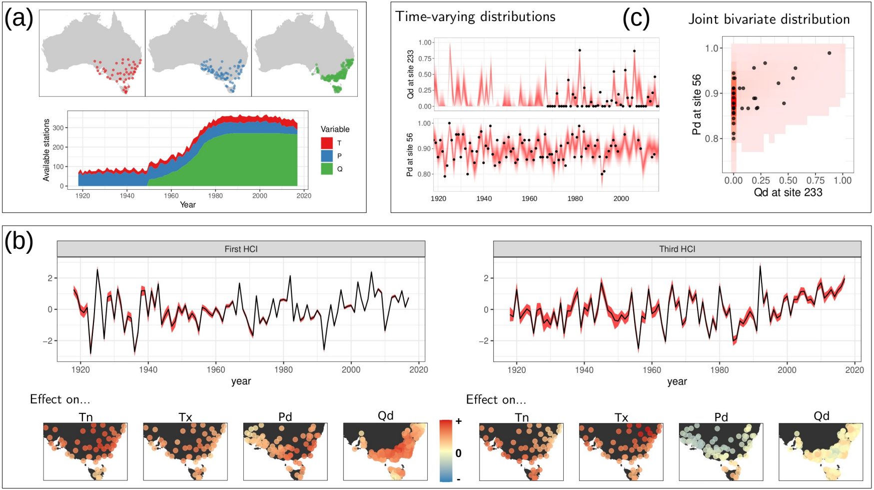
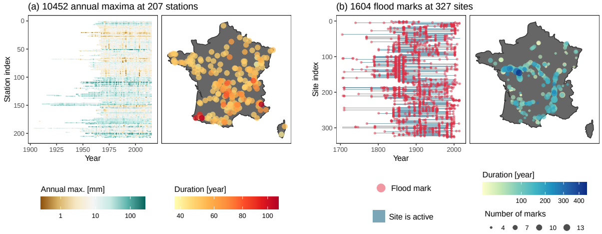


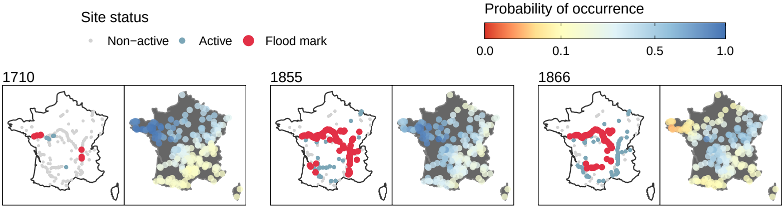
Hot-and-Dry Australian Summers



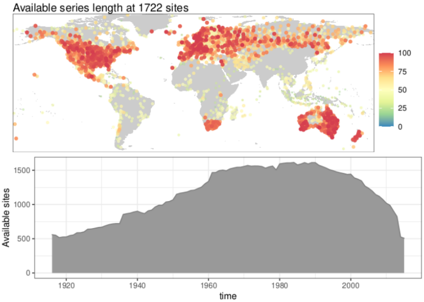
Flood Marks Case Study

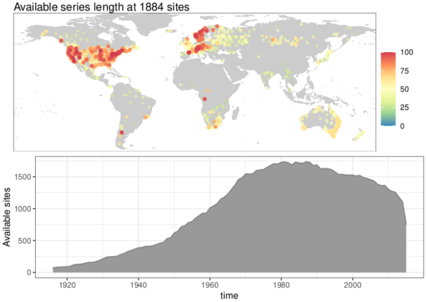


$$\begin{cases} Q(s,t) \sim GEV\left(e^{\mu_0(s)} \times \left(1+\sum_{k=1}^{K} \mu_k(s)\tau_k(t)\right), e^{\mu_0(s)} \times e^{\gamma(s)}, \xi(s)\right) \\ O(r,t) \sim \mathcal{B}\left(logit^{-1}\left(\lambda_0(r)+\sum_{k=1}^{K} \lambda_k(r)\tau_k(t)\right)\right) \end{cases}$$



Floods and Heavy Precipitation at the Global Scale





$$
\begin{cases}
P(s,t) \sim Beta\left(\mu_P(s,t), \nu_P(s,t)\right); Q(s,t) \sim Beta\left(\mu_Q(s,t), \nu_Q(s,t)\right) \\
logit\left(\mu_P(s,t)\right) = \zeta_{\mu_P}(s) + \sum_{k=1}^{K} \lambda_{k,P}(s)\tau_k(t) + \sum_{k=1}^{K} \theta_{k,P}(s)\delta_k(t) \\
logit\left(\mu_Q(s,t)\right) = \zeta_{\mu_Q}(s) + \sum_{k=1}^{K} \lambda_{k,Q}(s)\tau_k(t) + \sum_{k=1}^{K} \theta_{k,Q}(s)\omega_k(t)
\end{cases}
$$