Space-Time Variability of Hydrologic Extremes: an Approach Based on Hidden Climate Indices

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AGU Fall Meeting, Washington D.C, USA, 10-14 Dec 2018

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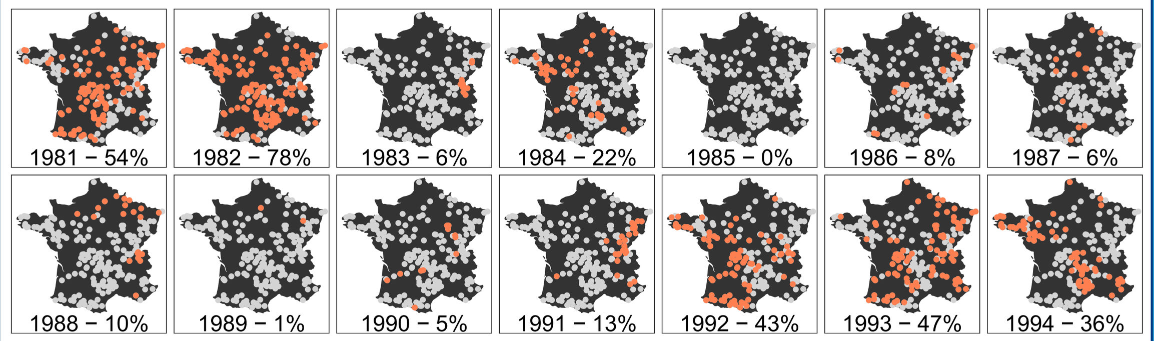
1. Introduction

Context

Space-time variability of flood occurrences

Consider the occurrence of 5-year autumn floods in France

(% denote the proportion of stations where a flood occurs each year)



1. Strong evidence of spatial clustering
2. Maybe some temporal clustering? (flood rich/poor periods)
3. Managing floods at this national scale is not a smooth sail through average years, but rather an alternation of problem-free and catastrophic years! (slightly exaggeratedly)

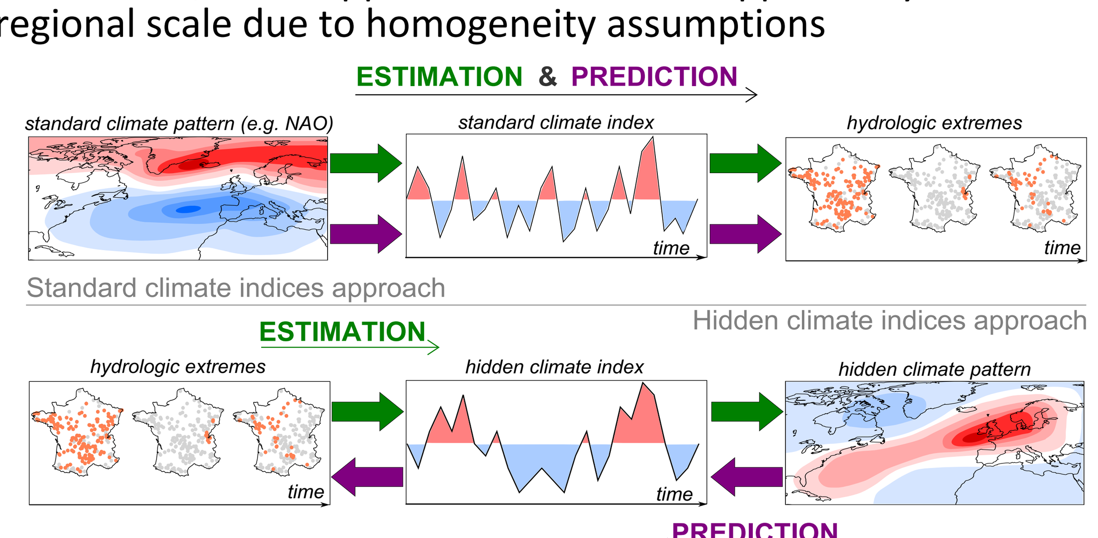
What drives this space-time variability?

Problem: in some regions of the world, standard climate indices such as above are poor predictors of hydrologic extremes (e.g. Grantz et al. 2005, Giuntoli et al. 2013, Westra and Sharma 2009)

Objectives

The concept of Hidden Climate Indices (HCI)

1. Rather than relying on predefined climate indices, is it possible to extract the relevant indices directly from the hydrologic data?
2. In other words, the relevant climate indices are **HIDDEN**, and we want to uncover them using the hydrologic data
3. Examples of HCI-like approaches include Thyer & Kuczera (2000), Renard & Lall (2014) and Ahn et al. (2017)
4. However, these approaches cannot be applied beyond a small regional scale due to homogeneity assumptions



Specific objectives

1. Develop a probabilistic model to describe the space-time variability of hydrologic extremes, using Hidden Climate Indices
2. Should avoid strong homogeneity assumptions and hence be applicable at a large (national/continental) spatial scale
3. Assess the HCI approach using both synthetic and real data

Grantz, Rajagopalan, Clark and Zagona. **2005**. A technique for incorporating large-scale climate information in basin-scale ensemble streamflow forecasts. *Water Resour. Res.*

Giuntoli, Renard, Vidal and Bard. **2013**. Low flows in France and their relationship to large scale climate indices. *J. Hydrol.*

Westra and Sharma. **2009**. Probabilistic Estimation of Multivariate Streamflow Using Independent Component Analysis and Climate Information. *J. Hydrometeorol.*

Thyer and Kuczera. **2000**. Modeling long-term persistence in hydroclimatic time series using a hidden state Markov model. *Water Resour. Res.*

Renard and Lall. **2014**. Regional frequency analysis conditioned on large-scale atmospheric or oceanic fields. *Water Resour. Res.*

Ahn, Palmer and Steinschneider. **2017**. A hierarchical Bayesian model for regionalized seasonal forecasts: Application to low flows in the northeastern United States. *Water Resour. Res.*

2. HCI model

Hierarchical model

Legend: Varies in time; Varies in space; Varies in space and time; Inferred quantities

Occurrence data: Bernoulli distribution

Flood occurrence (0/1) at year t and site x; Probability of occurrence

$$Y(t,x) \sim B(\theta(t,x))$$

Probabilities of occurrence

Ensures probability is in (0;1); intercept term ('normal' probability of occurrence)

$$logit(\theta(t,x)) = \lambda_0(x) + \tau_1(t) \times \lambda_1(x)$$

Hidden Climate Index (HCI); HCI effect

Note: the model can be extended to K hidden climate indices

$$logit\,(\theta(t,x)) = \lambda_0(x) + \sum_{k=1}^{K} \tau_k(t) \times \lambda_k(x) \qquad (1)$$

Spatial models

$$(\lambda_k(x_1), \ldots, \lambda_k(x_n)) \sim \mathcal{N}(\boldsymbol{\mu}, \boldsymbol{\Sigma})$$

Spatial mean: constant or with effect of covariates $\boldsymbol{Z}$ (e.g. elevation)

$$\boldsymbol{\mu} = \boldsymbol{Z\beta}$$

Spatial covariance: function of intersite distance ('variogram')

$$(\boldsymbol{\Sigma})_{i,j} = \gamma_1^2 exp\left(-\frac{\|x_i - x_j\|}{\gamma_2}\right)$$

Final hypotheses

1. **CONDITIONAL** space-time independence of occurrences, given the probabilities $\theta(t,x)$

Note: this does **NOT** imply that occurrences are independent!

2. Identifiability constraint: all HCIs have mean 0 and variance 1

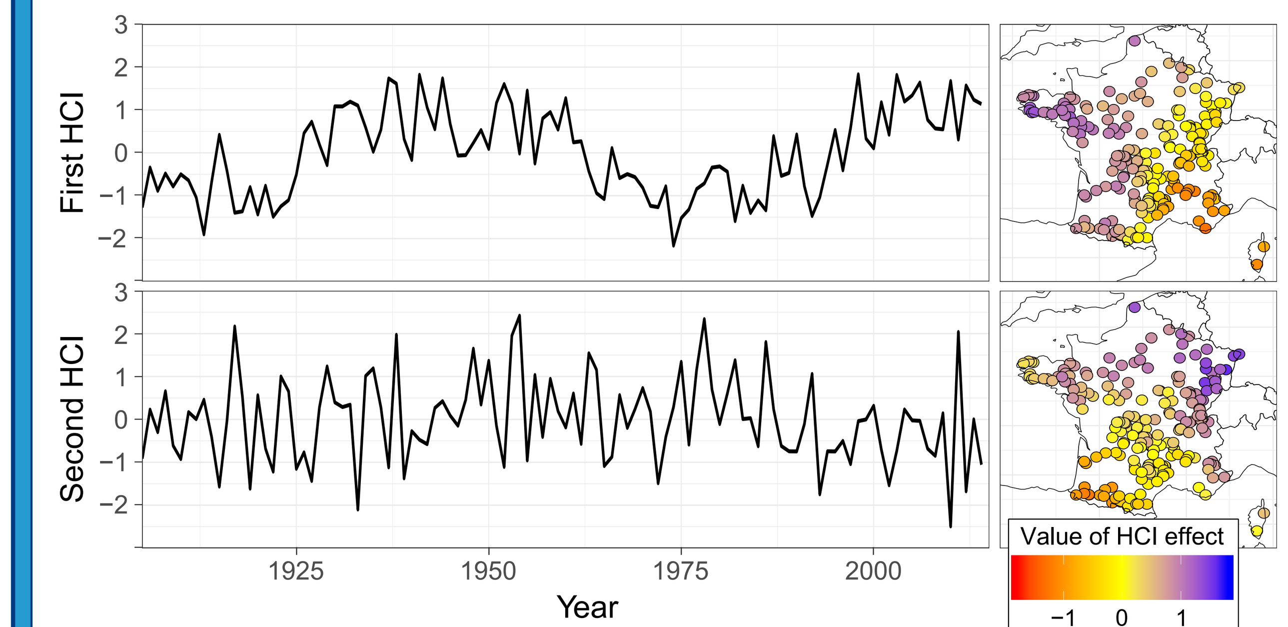
Parameter estimation

1. Hundreds of unknown parameters to be inferred (typical of such hierarchical models)
2. Classical Bayesian/MCMC approach for hierarchical models
3. Stepwise inference: one HCI at a time
4. MCMC sampling: customized block Metropolis sampler taking advantage of the conditional independence assumptions

3. Synthetic case study

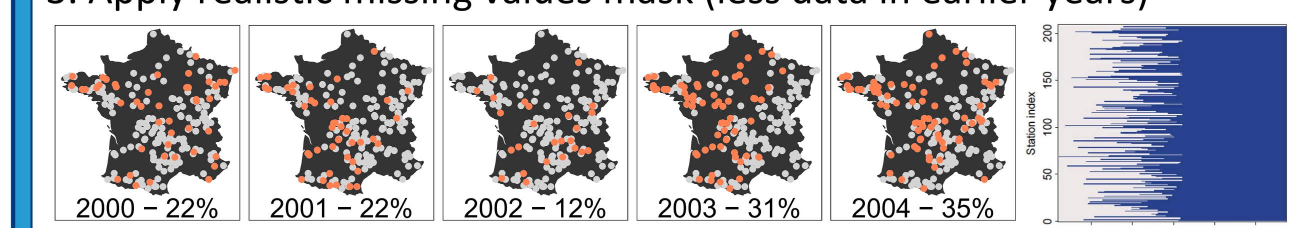
Data generation

True Hidden Climate Indices and their effects



Generate occurrence data

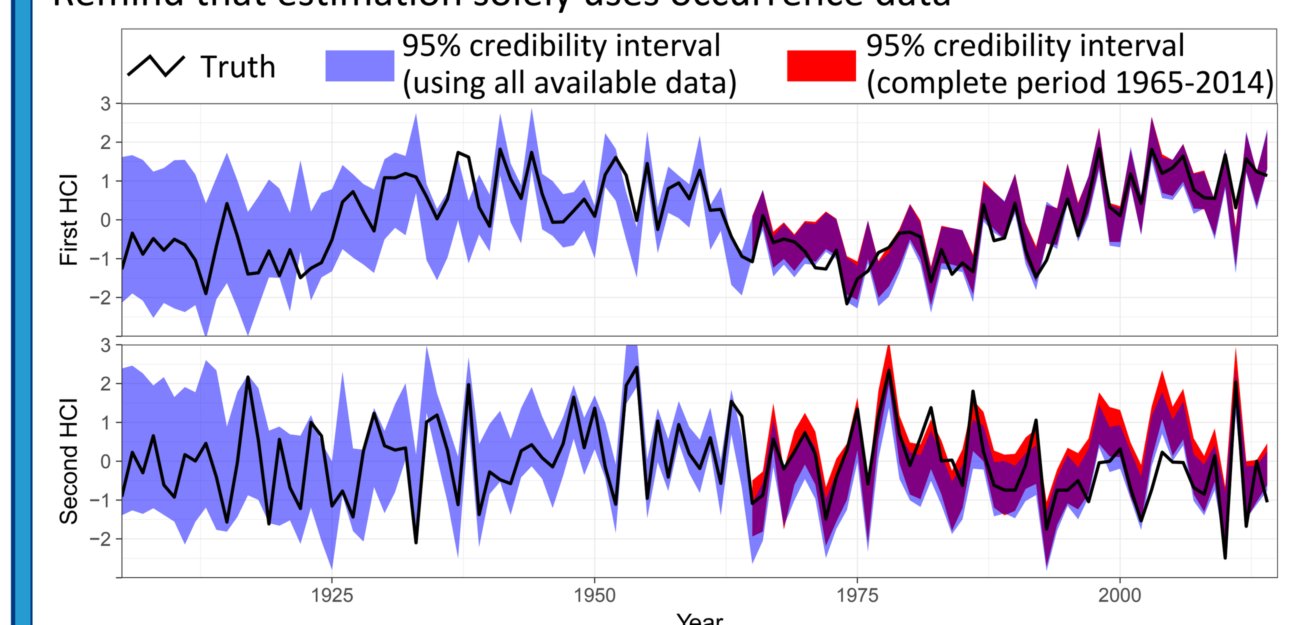
1. Compute probabilities of occurrence with eq. (1) ($\lambda_0 \equiv logit(0.2)$)
2. Generate occurrences (5-year extract below)
3. Apply realistic missing values mask (less data in earlier years)



Results

Estimated HCIs

Remind that estimation solely uses occurrence data



Comments

1. Feasability: HCIs can be retrieved from occurrence data alone
2. Allow using all available data, while recognizing that uncertainty increases as data availability decreases (see earlier years)
3. Other (not shown): HCI effects and probabilities of occurrence are also reliably retrieved

4. Autumn floods in France

Data

Hydrologic data

1. 207 stations in France, 1904-2016, but very sparse before 1960
2. At each station, derive the series of autumn (OND) maxima
3. Set threshold = empirical 80% quantile of this series
4. Occurrence = autumn max. exceeds this threshold (=> proba ~20%)
5. See figure in introduction for a 14-year extract

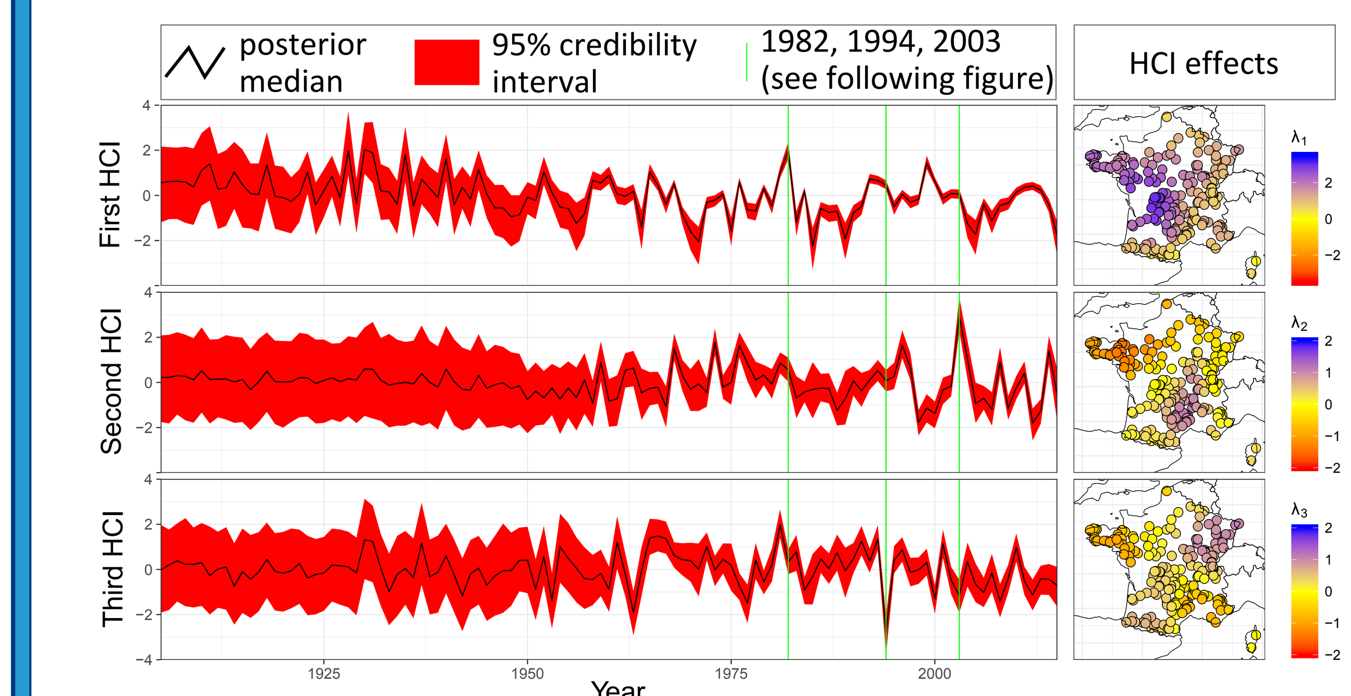
Climate data

1. Atmospheric variables over the North-Atlantic (NCEP/NCAR and 20CR)
2. SST: global (NOAA ESRL) and Mediterraneean (CMEMS)
3. A selection of standard climate indices (NOAA)

Results

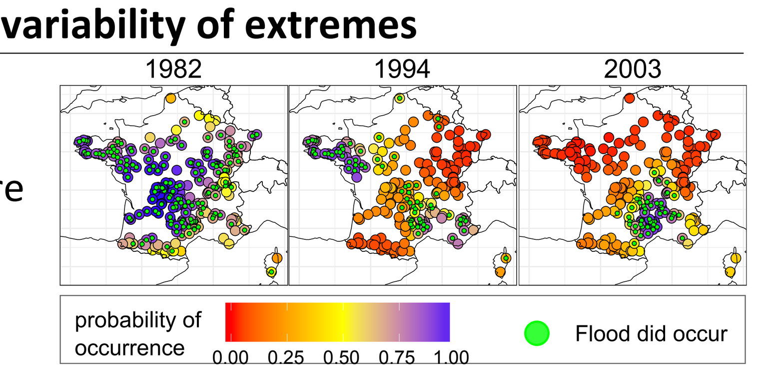
Estimated Hidden Climate Indices

1. HCI1: controls flood occurrence in the oceanic region (West, large effects)
2. HCI2: opposition Britany-Mediterranean
3. HCI3: highlights northeastern France, but effects become small (=> stop)
4. All HCIs are *iid*: no trend, autocorrelation or low-frequency variability
5. Estimated HCIs are weakly correlated with standard climate indices

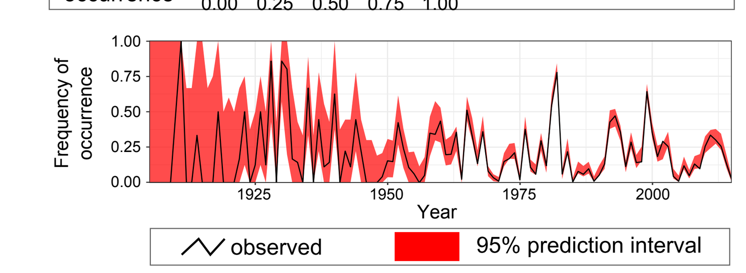


Ability to describe the space-time variability of extremes

1. Spatial variability: for 3 example years, estimated probabilities are consistent with the spatial structure of actual flood occurrences

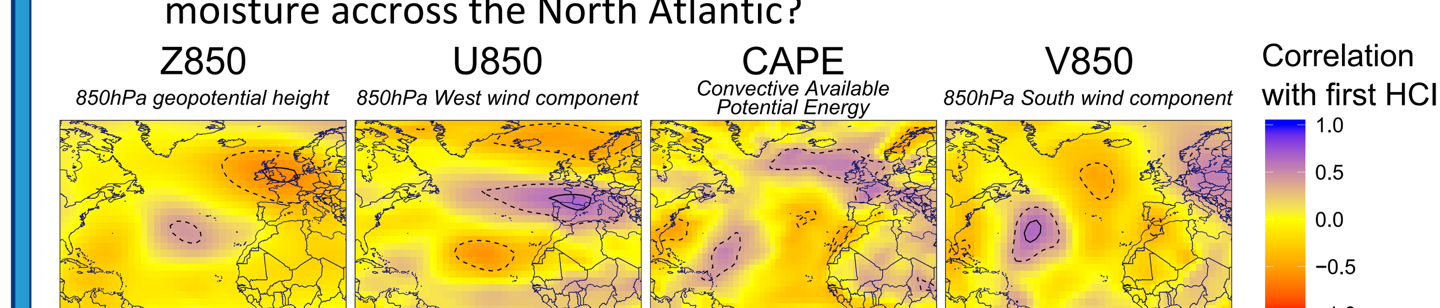


2. Temporal variability: predicted frequency of occurrence accross available stations consistent with observed one (flood rich / flood poor years)



Interpretation of the Hidden Climate Indices

1. First HCI shows coherent correlation patterns with several atmospheric variables, giving hope for predictability from large-scale climate information
2. Large values of HCI1 (high flood proba. in Western France) associated with:
    a. negative pressure anomaly and stronger westerlies over France
    b. increased convection potential and stronger southerlies over the northern Caribbean area => conditions favoring the transport of tropical moisture accross the North Atlantic?



3. No association between first HCI and SST
4. For second and third HCI, no association found, neither with atmospheric variables nor with SST => poor predictability from large-scale climate

5. Conclusion and perspectives

Conclusion

The Hidden Climate Indices approach

1. A hierarchical model describing the space-time variability of data
2. Extract hidden climate indices directly from hydrologic data, rather than relying on standard climate indices
3. Particularly useful in regions where the latter are poor predictors

Insights from the case studies

1. Feasability to uncover hidden climate indices from hydrologic data
2. Use all available data (more uncertainty during data-poor periods)
3. Climate interpretation of the first HCI: suggests that it is related to a genuine climate mechanism, with potential predictability?

Perspectives

Development of the Hidden Climate Indices approach

1. Generalize the (flood occurrence / Bernoulli) setup, e.g. (flood intensity / GEV), or even more generally, (variable / distribution)?
2. Move beyond simple correlation maps, and develop a genuine predictive framework to estimate HCIs (and hence flood probabilities) directly from large-scale climate fields

Potential applications

1. Past reconstructions: e.g. using long reanalyses (20CR/ERA20C) to estimate flood probabilities in the late 19th / early 20th century.
2. Future flood hazard projections (GCM projections as predictors)
3. Seasonal forecasting of flood hazard / early warning systems