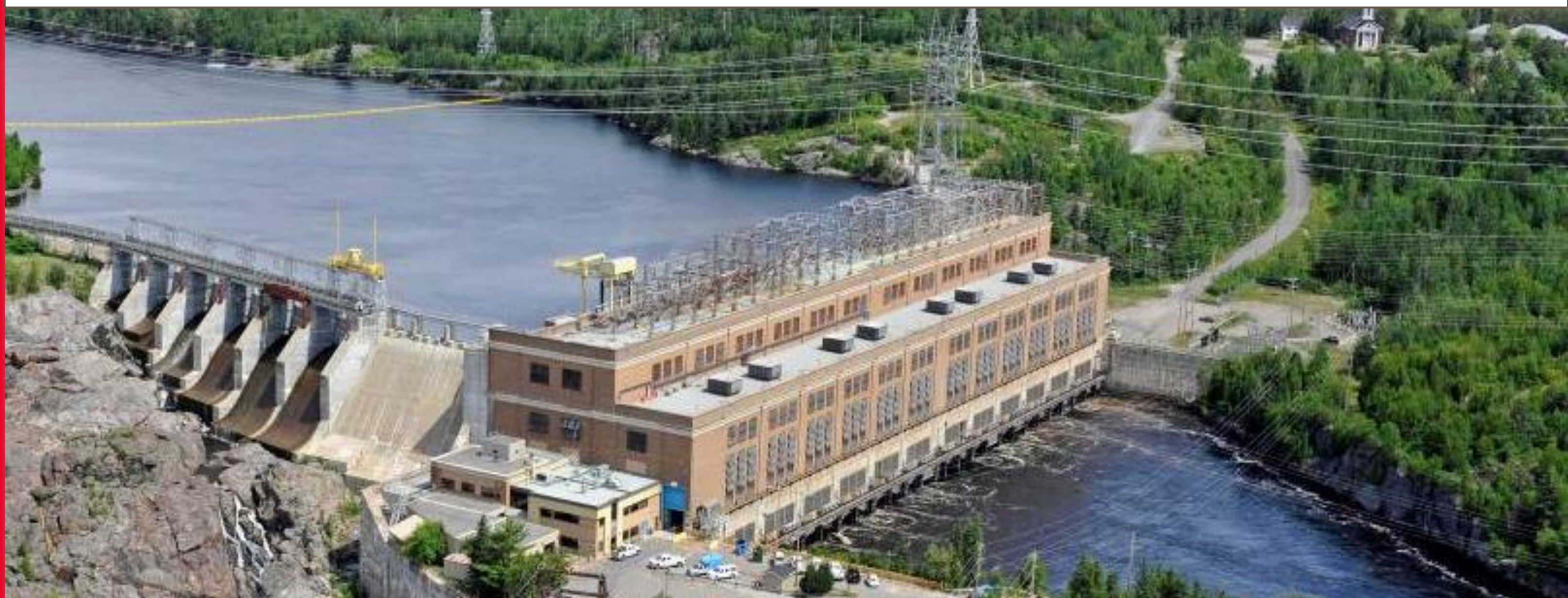
Efficient uncertainty analysis in streamflow prediction for reservoir optimization



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Project summary

Ongoing research project aimed at improving the variability in ensemble streamflow predictions.

- The first part of the project (this presentation!) focuses on the spring *snowmelt runoff volumes* for optimal reservoir management decision-making.
- Hydrologic regime is snowmelt-dominated, therefore snowmelt volume is a crucial part of the management strategy.
- For more details and formal definitions:

Arsenault et al. (2016) “An efficient method to correct under-dispersion in ensemble streamflow prediction of inflow volumes for reservoir optimization”, WRM (accepted, final revision).

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1. RTA hydropower systems

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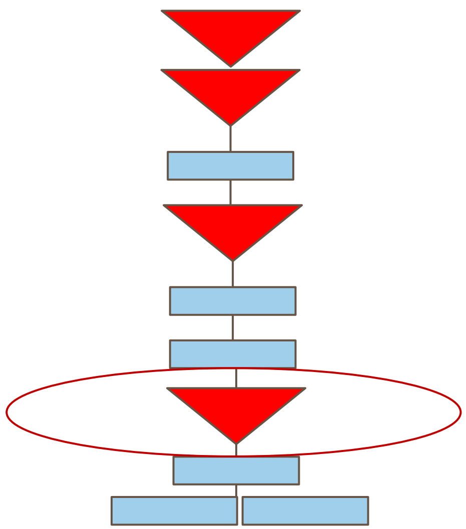
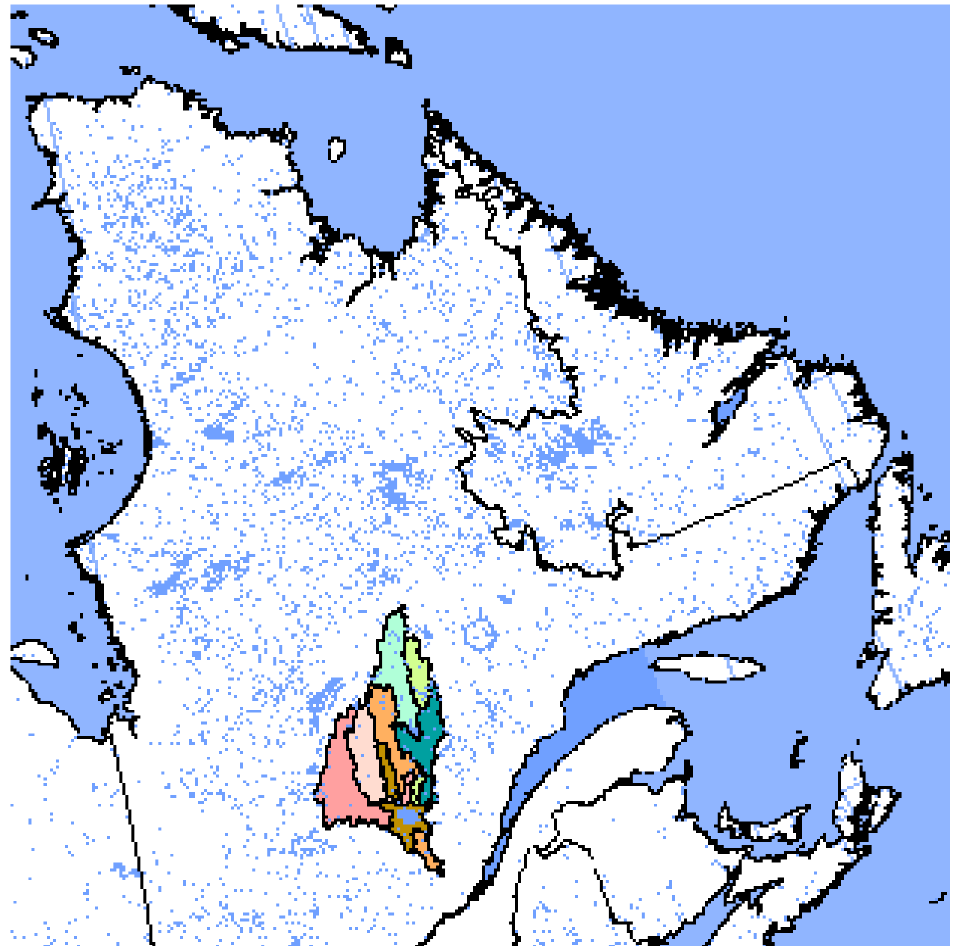
Saguenay-Lac-St-Jean



Item	Value
Installed Capacity	3145 MW
Avg. Generation	2080 MW-yr
Load	2180 MW-yr



~100MW missing! Test bed to compare different approaches to reduce gap (energy costs)

2. Ensemble forecast under-dispersion

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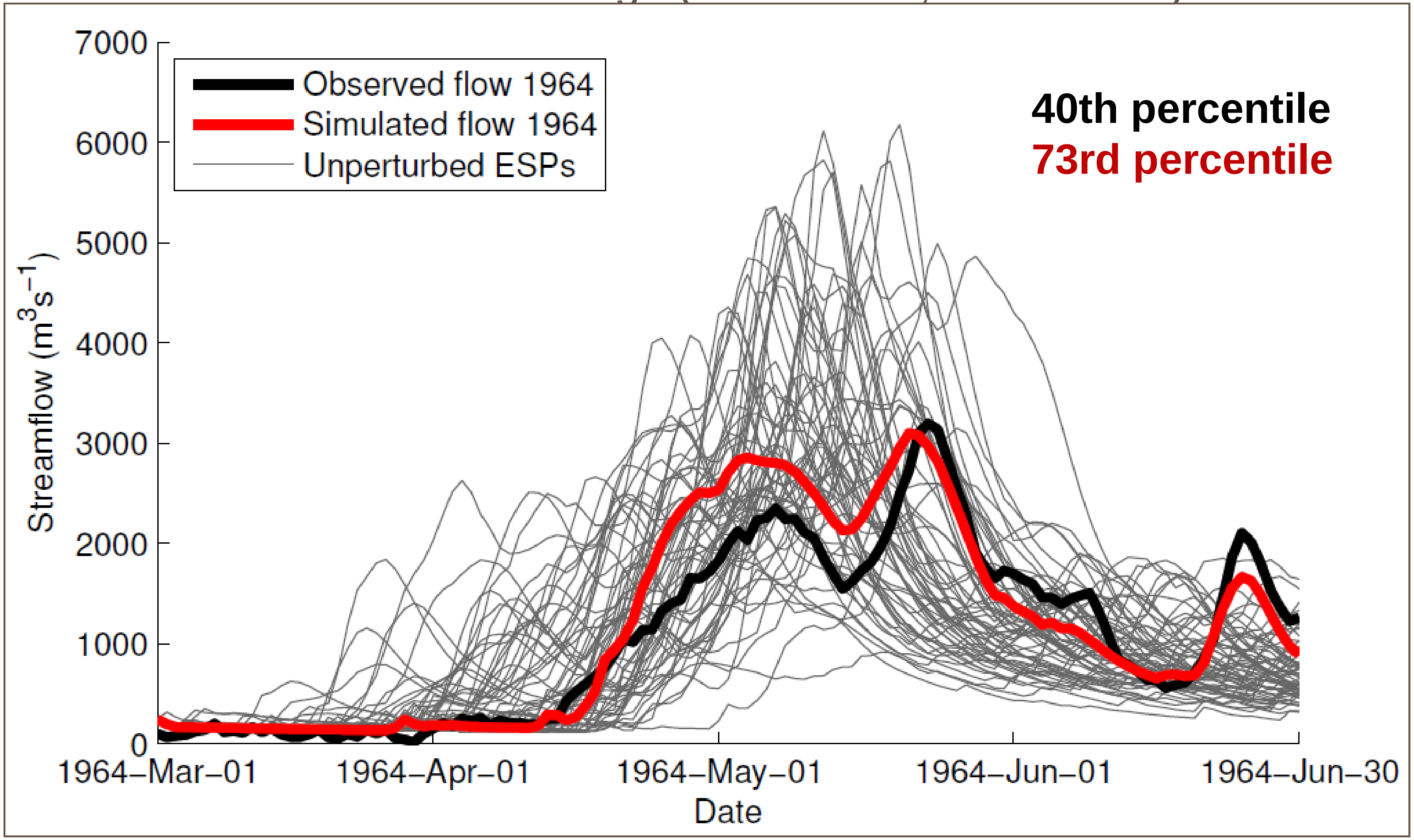
Ensemble streamflow prediction (ESP)

- Hindcasting mode for year 1964
- Historic climate forcings (1954-1963; 1965-2014)



2. Ensemble forecast under-dispersion

Lets play a (forecast) game!
(Werner & Ramos, yesterday!)

SDP optimization algorithm requires equiprobable ensembles
SDP optimization algorithm is based on the CL ratio (max. expectation)
We want each member to have equal probability of occurence
If we don't, some members will make us take suboptimal decisions…

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2. Ensemble forecast under-dispersion

Lets play a (forecast) game!
(Werner & Ramos, yesterday!)

SDP optimization algorithm requires equiprobable ensembles
SD … n)
We …
If w …

3. Uncertainty in long-term freshet inflow volume forecasting

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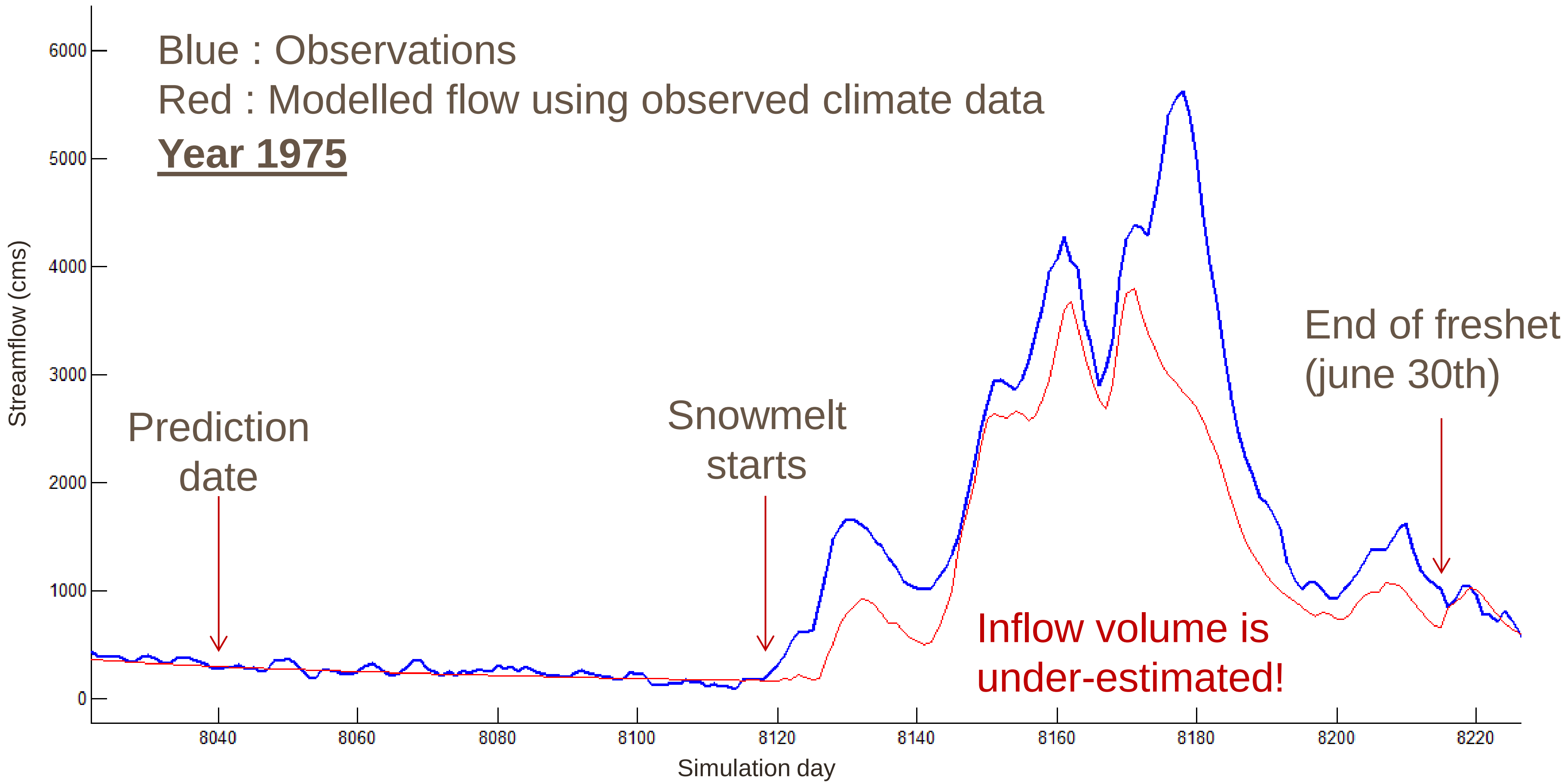
Addressing the uncertainties issue

- Many sources of uncertainty:
  - Model input measurment (T, P, Snow on ground…)
  - Weather forecasts (or historical climate records)
  - Hydrological model and catchment initial conditions
  - Model structure and parameterization uncertainty

- Very difficult to address individually!

3. Uncertainty in long-term freshet inflow volume forecasting

Proposed solution: encompass overall uncertainty in a single variable (hydrological model's snow water equivalent) by evaluating historical simulation errors.



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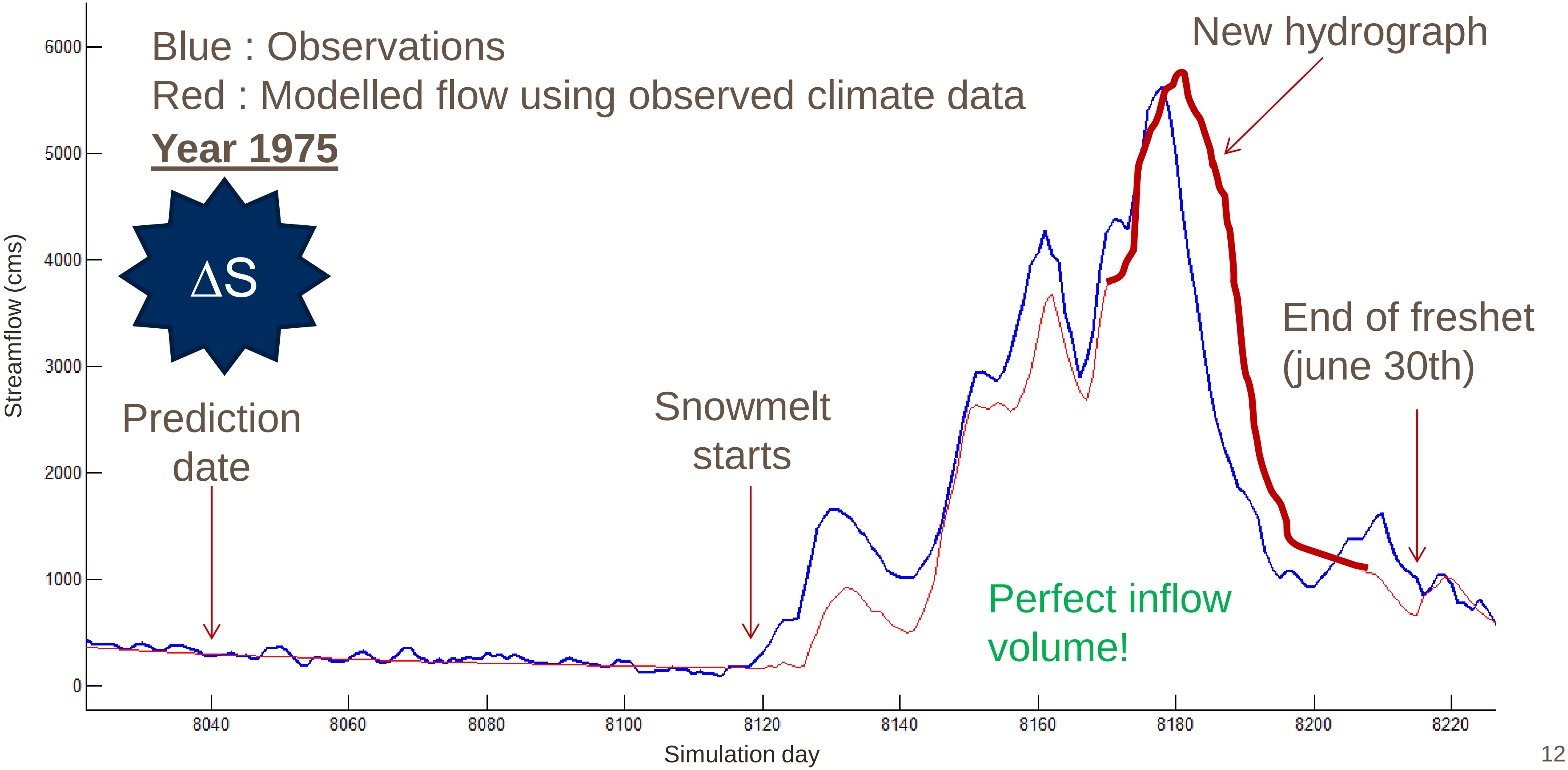

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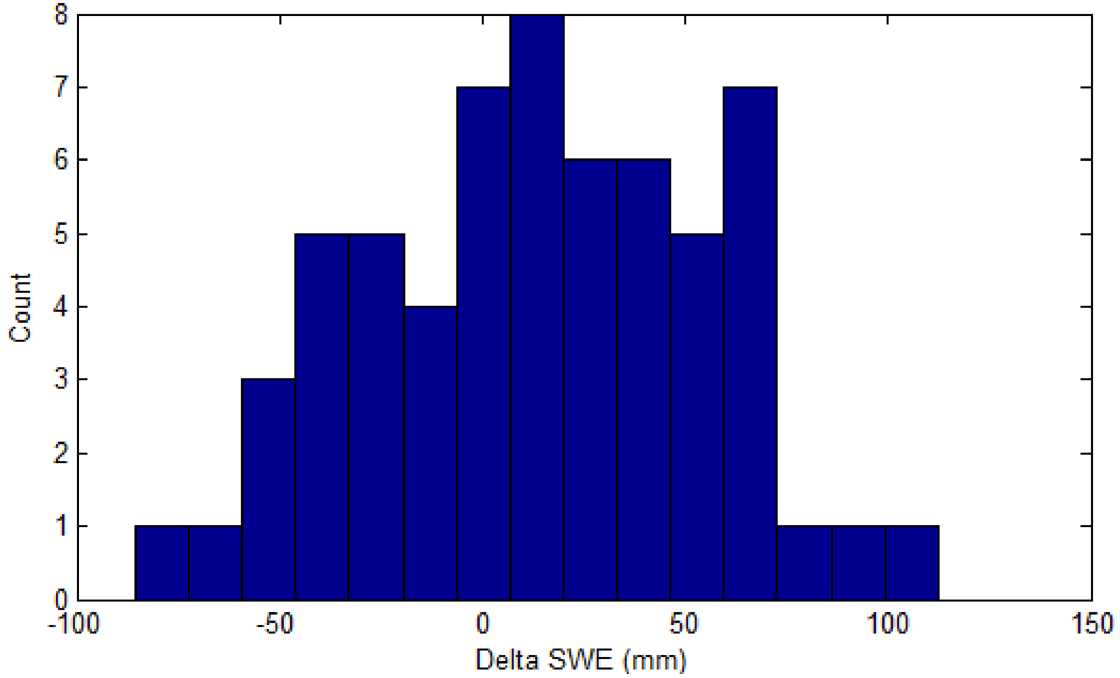
3. Uncertainty in long-term freshet inflow volume forecasting

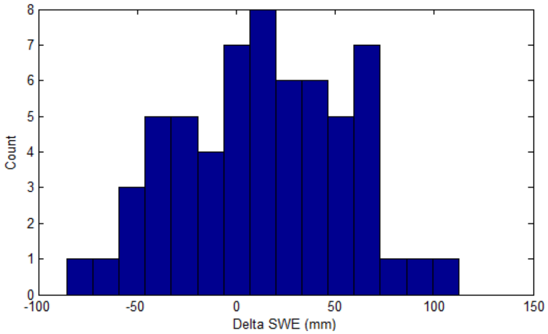
- We compute a ΔS for each year on record (61 years), which yields a distribution:



- The distribution can be modelled with a non-parametric kernel method or estimated with a parametric distribution.

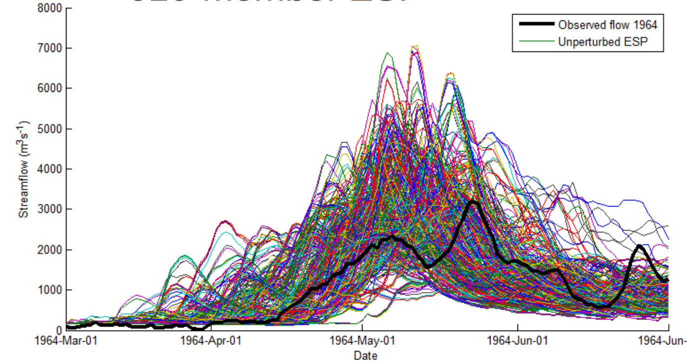
3. Uncertainty in long-term freshet inflow volume forecasting

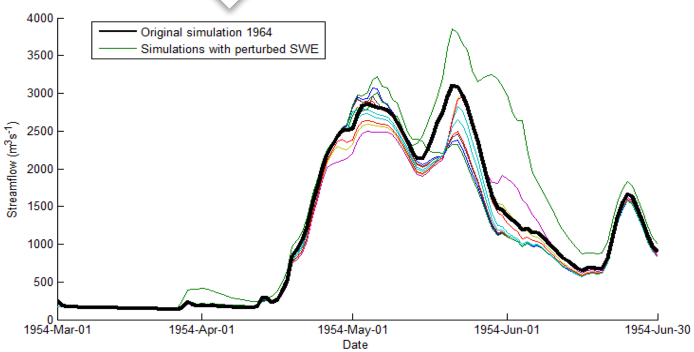
- We can now sample from the distribution to add variability to the ESP during its generation.



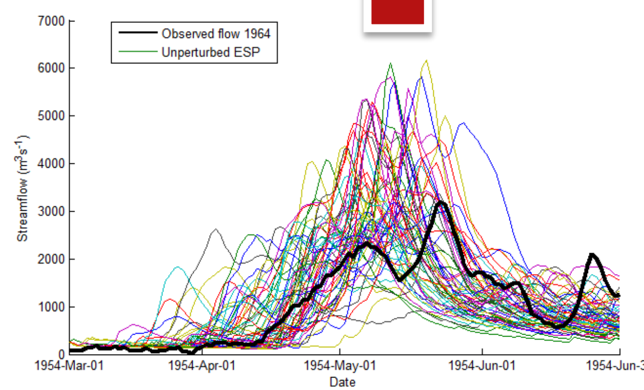
We can compute the actual inflow volume's percentile in the ESP forecasts.

610-member ESP





Year 1964 with 10 modified initial conditions

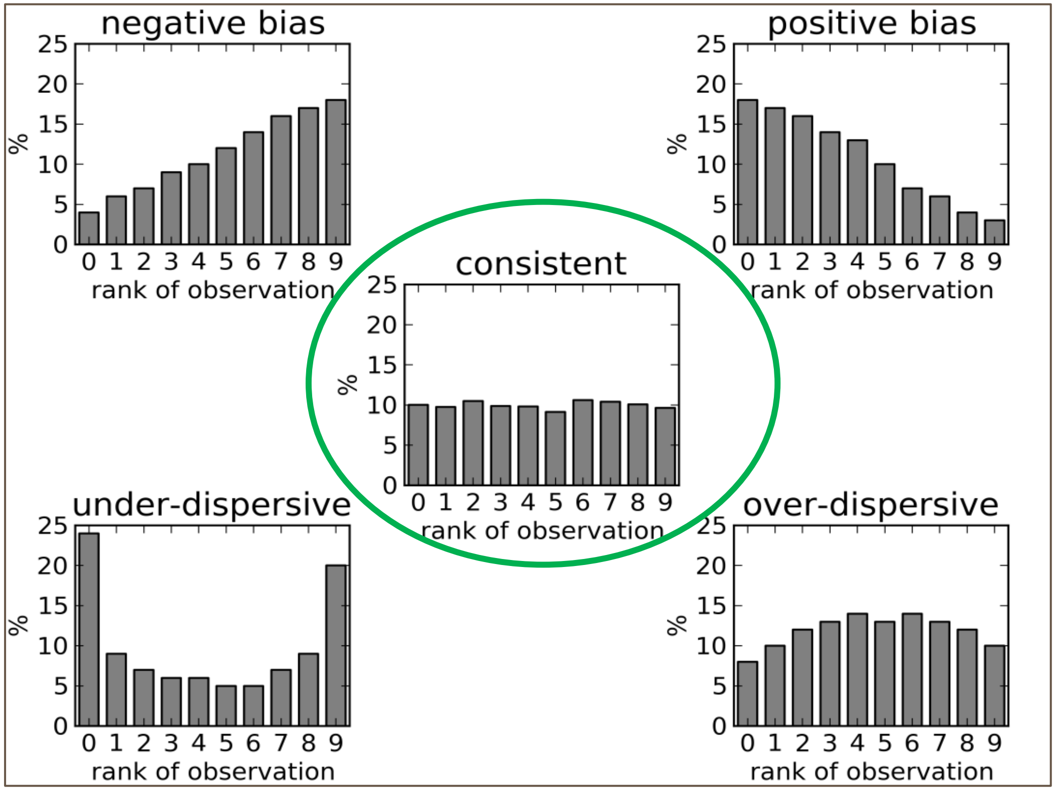


61 ESP scenario years

4. Results

4. Results

Talagrand Diagrams are used to analyse the percentiles for all years.

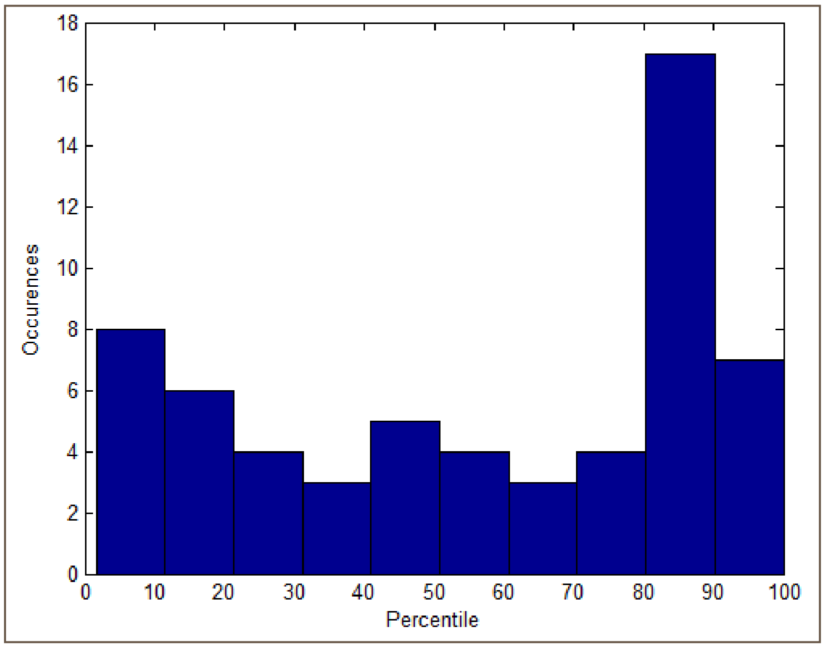


From www.interchopen.com

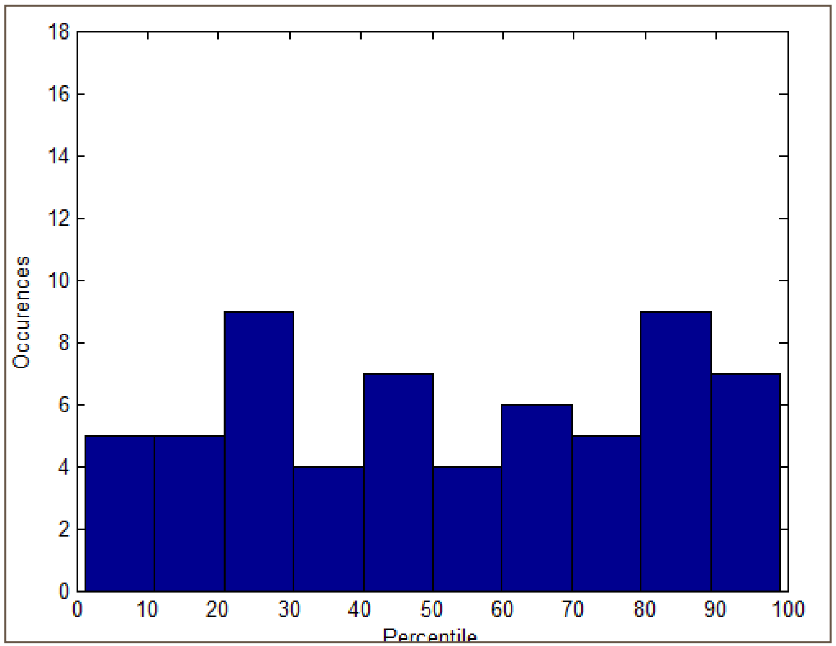
4. Results

Before and after correction for the 61 years – start date January 1st.

Before (no correction)



After (with correction)



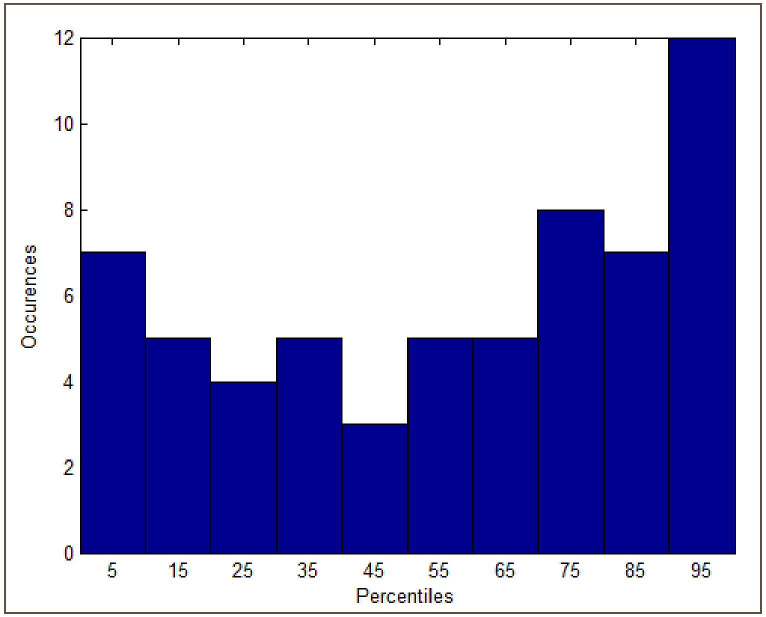
Under-dispersed
(non-uniform)

Consistent
(uniform)

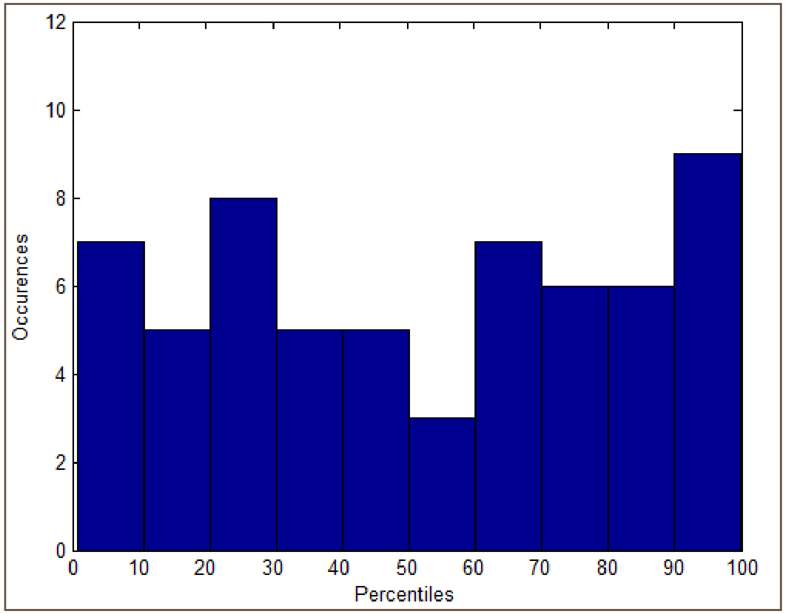
4. Results

Before and after correction for the 61 years – start date February 1st.

Before (no correction)



After (with correction)



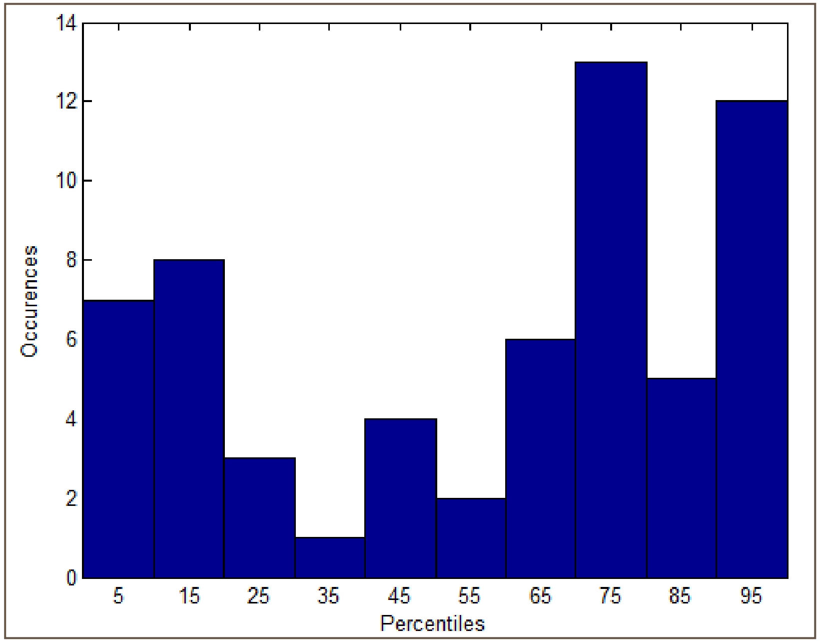
Under-dispersed
(non-uniform)

Consistent
(uniform)

4. Results

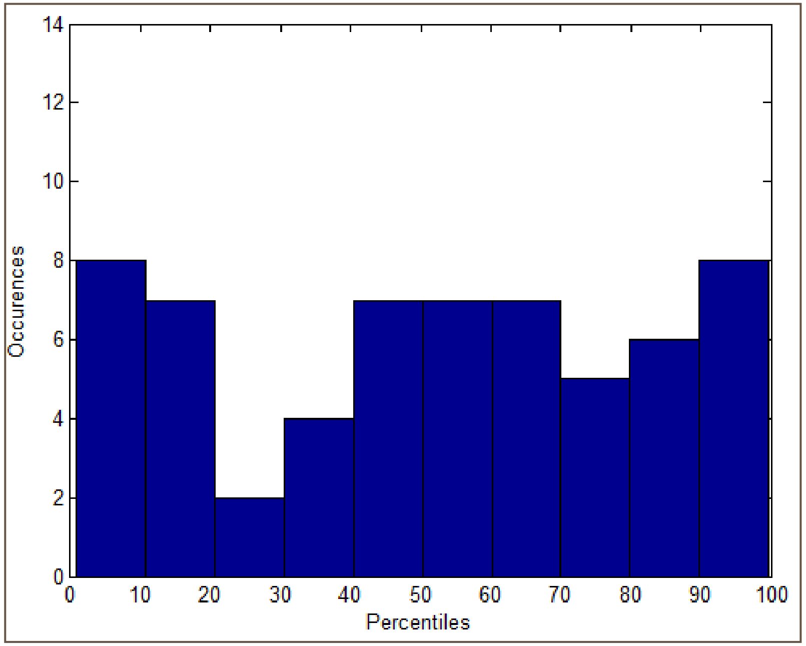
Before and after correction for the 61 years – start date March 1st.

Before (no correction)



Under-dispersed (non-uniform)

After (with correction)



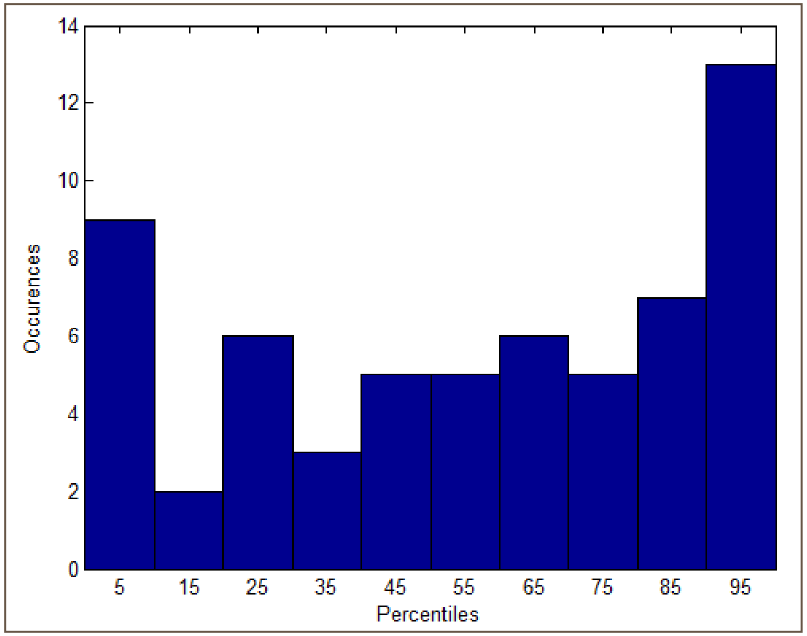
Consistent (uniform)

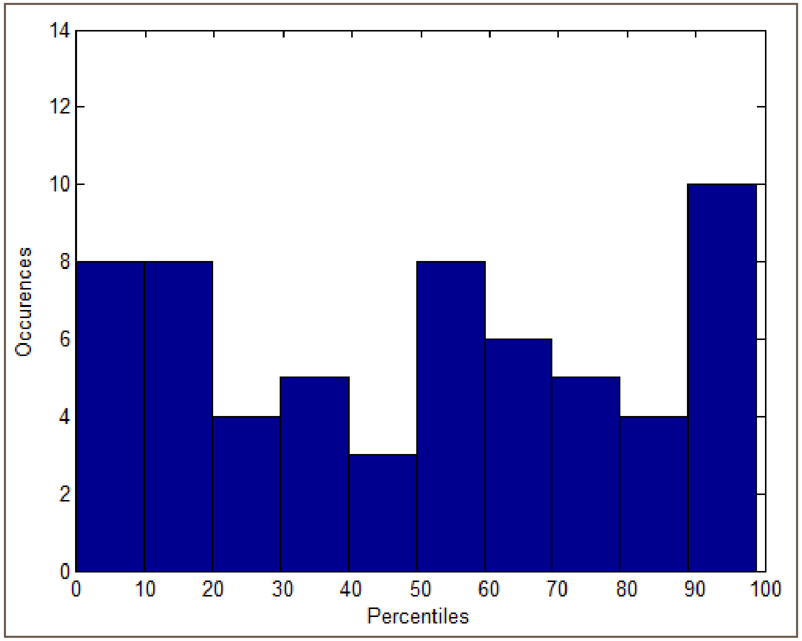
4. Results

Before and after correction for the 61 years – start date April 1st.

Before (no correction)

After (with correction)





Under-dispersed (non-uniform)

Consistent (uniform)

5. Conclusions and future work

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- There is a problem with ensemble under-dispersion during long-term forecasting in winter

- The proposed method seems to add an adequate amount of variability without going into over-dispersion territory.

- The concept can be applied to other periods and contexts, such as rainfall volumes or soil saturation variables.

- If needed, it could be possible to use 2 variables and model variability using bivariate distributions

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