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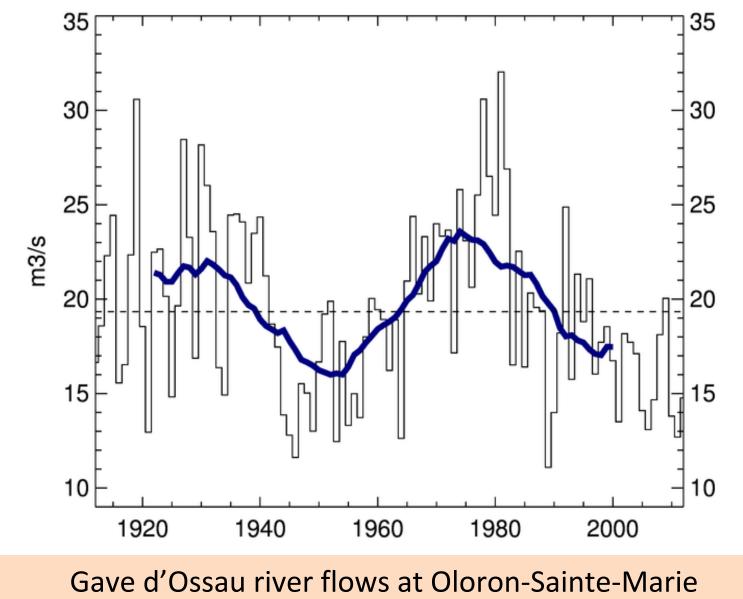


Capacity of climate models to capture multi-decadal hydrological variations over France

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Context: observed multi-decadal variations in river flows over France



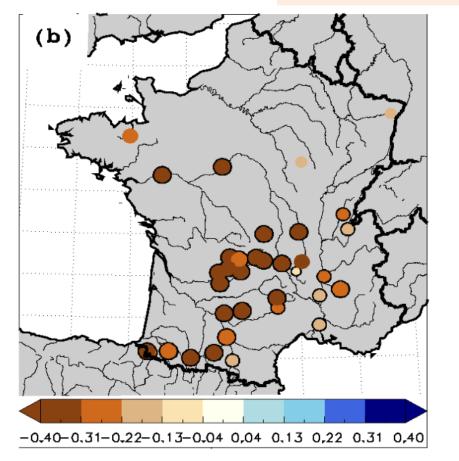
Annual mean. Thick line: low-pass filtered series

Context: role of spring precipitation

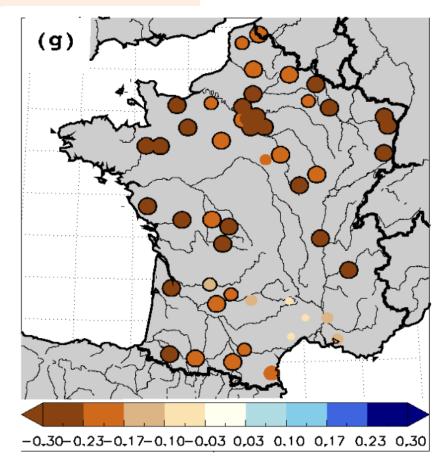
Relative differences, spring

1938/1958 – 1965/1985

Detrended variables



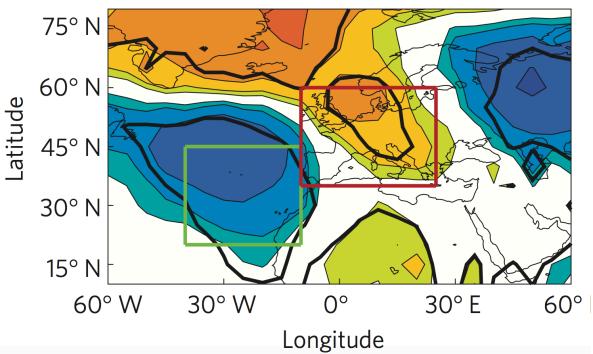
River flows (no unit)



Precipitation (no unit)

Boé and Habets (2014)

O: significance avec p<0.1



MAM ('31 to '60)-('64 to '93)

Composite anomalies of SLP in MAM between positive and negative phases of the AMV Sutton and Dong (2012)

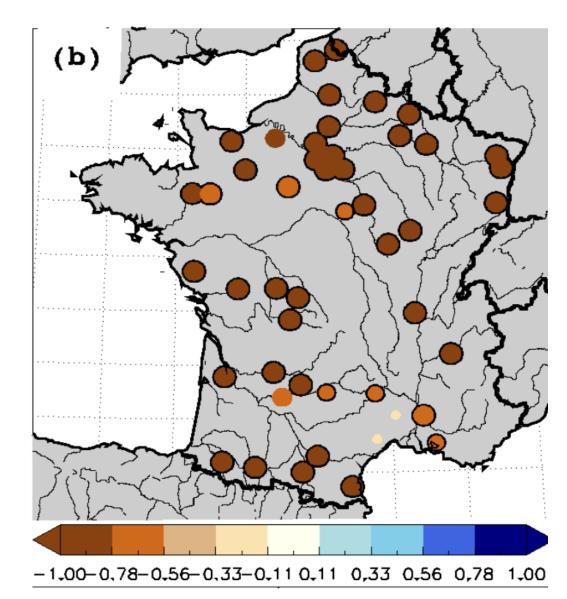
=> The Atlantic Multi-decadal Variability (AMV) may influence the western European climate in spring through changes in atmospheric circulation (*Sutton and Dong, 2012*).

SLP index to capture the potential impact of the AMV on atmospheric circulation:
=> Spatial averages of SLP Red – Green boxes above

Context: origin of multi-decadal variations in spring precipitation

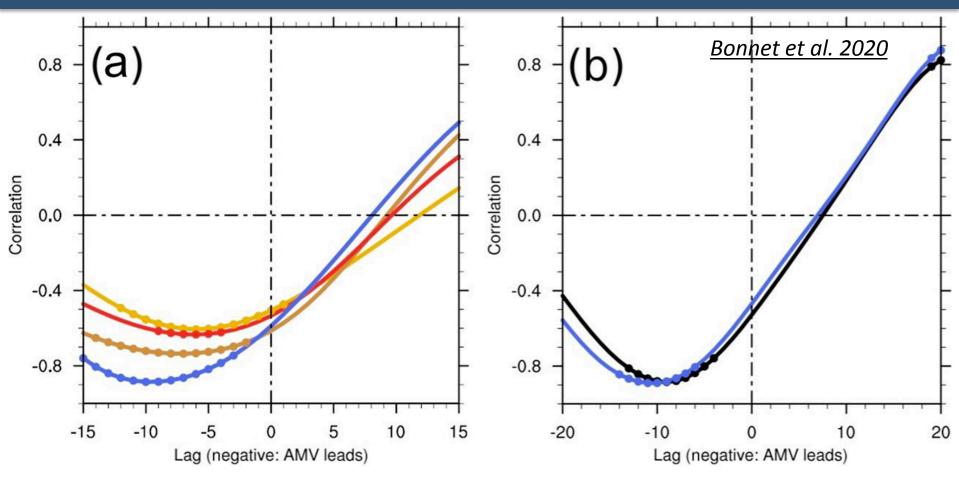
Correlation SLP index / precipitation Low-pass filtered series, detrended MAM 1910-1991

O: signif. avec p<0.1



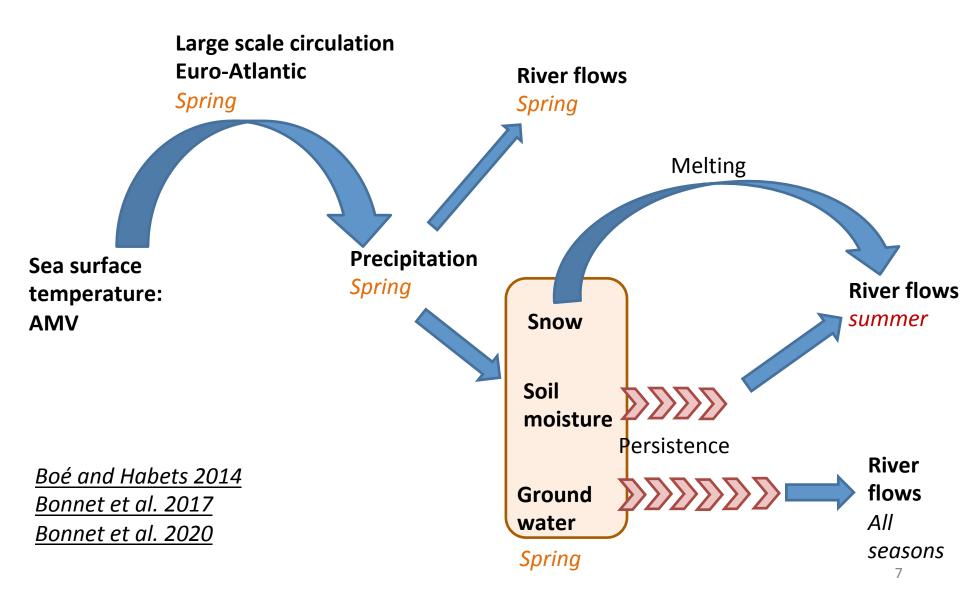
Boé and Habets (2014)

Context: role of the AMV and going further back in time

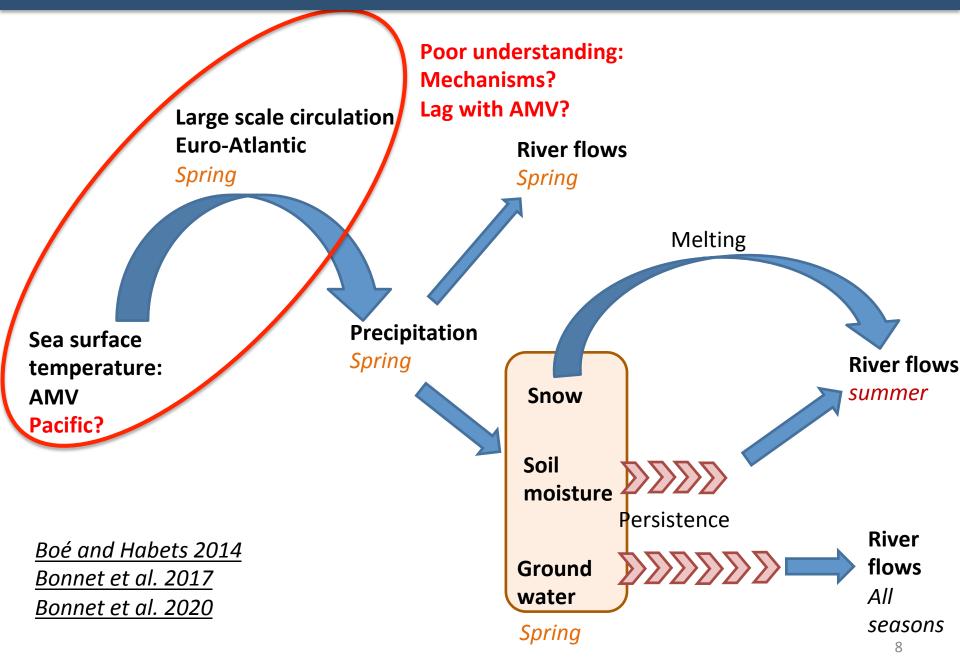


Lagged correlations (lag in years):

(a) Paleoclimate AMV index (*Wang et al. 2017*) & spring precipitation at Paris: 1780–1889, 1890–1989, 1779–1989. Observed AMV index and MAM precipitation, 1882–1979.
(b) Observed AMV index & spring river flows at Paris from (blue) hydrological analysis (black) observations, 1882–1979.
Low-pass filtered series (21-year Lanczos filter). Points: significant correlations (p < 0.05)

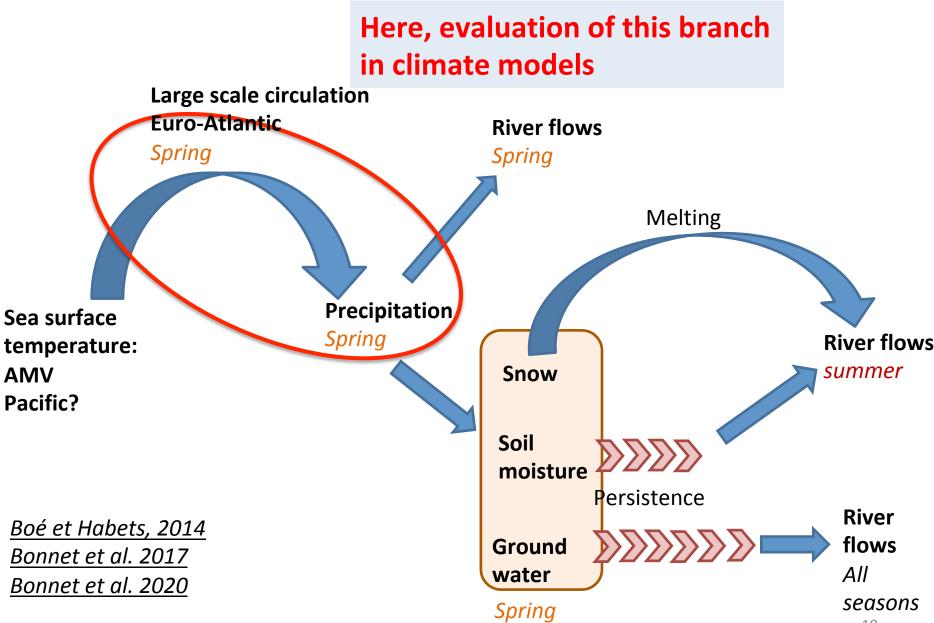


In summary, mechanisms of multi-decadal hydrological variations in France

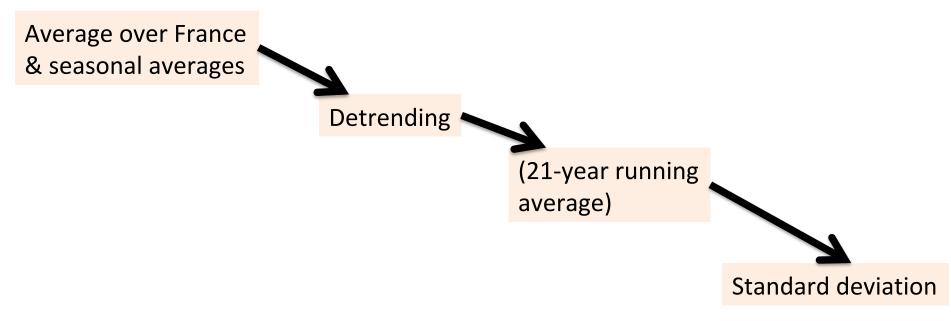


Do new generation climate models correctly capture the multi-decadal variability of the hydrological cycle in France?

=> And therefore: are models able to capture correctly the uncertainties due to internal variability in future climate projections?



✓ 30 CMIP6 models: historical and piControl simulations
 ✓ Observations: CRU-TS 1901-2014

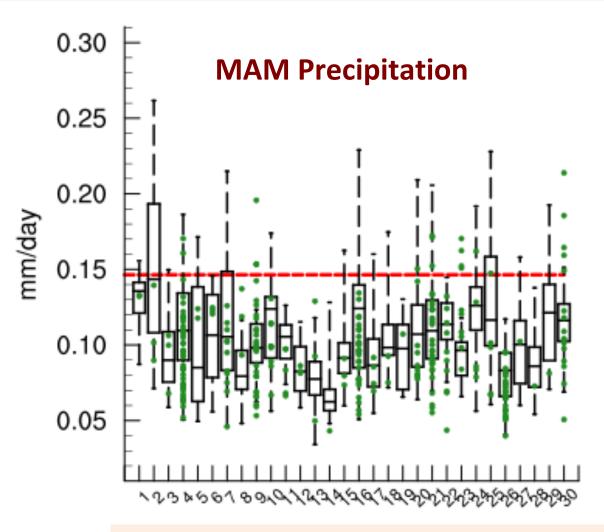


> Historical simulations:

same as obs. for all members on 1901-2014

> piControl simulations:

same as obs for all 114-year periods (with overlap)

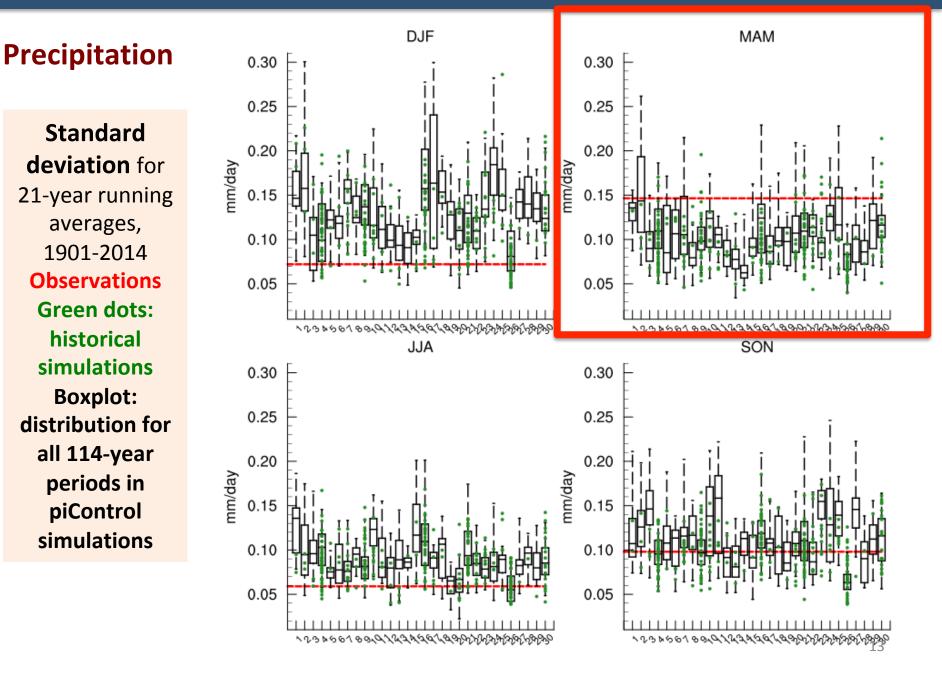


Note: detrending has little impact

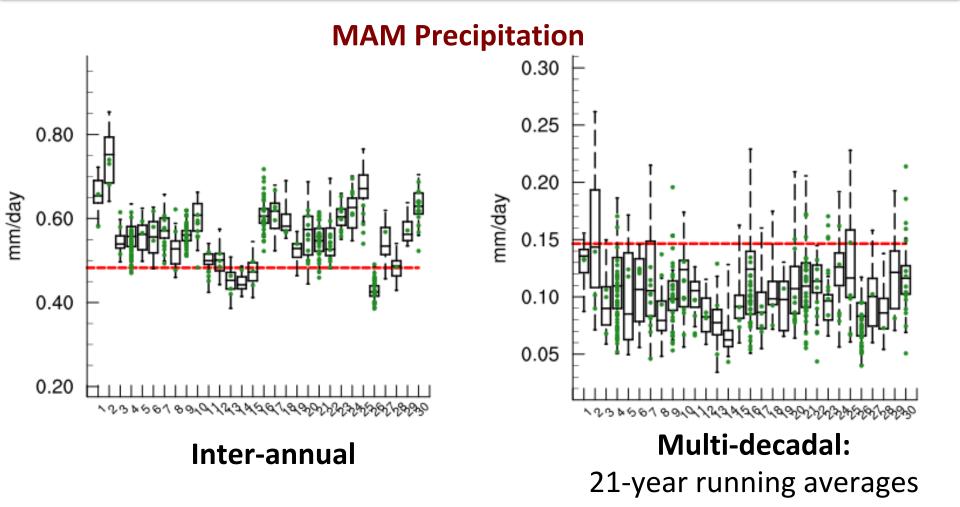
=> Only 7% of historical members (from 8 models) with larger standard deviation than observed

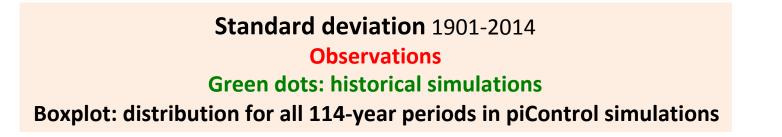
Standard deviation for 21-year running averages, 1901-2014 Observations Green dots: historical simulations Boxplot: distribution for all 114-year periods in piControl simulations

Multi-decadal variability in CMIP6 models: precipitation, all seasons

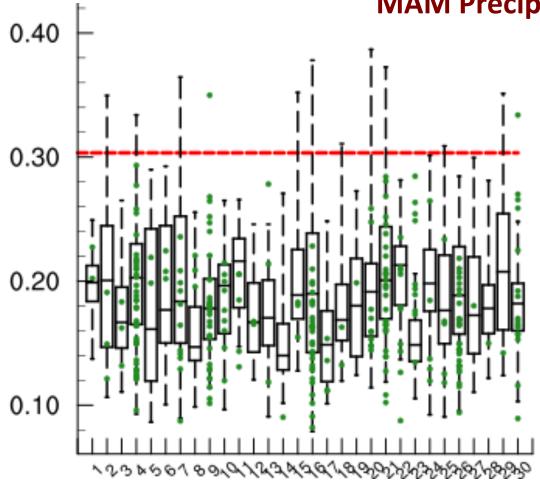


Multi-decadal versus inter-annual variability in spring precipitation





Multi-decadal versus inter-annual variability in CMIP6 models



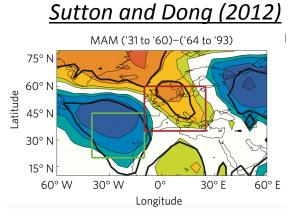
MAM Precipitation

=> Only 0.7% of historical members (from 2 models) with larger ratio of standard deviation than observed

Ratio of standard deviation multi-decadal/inter-annual 1901-2014 Observations Green dots: historical simulations

Boxplot: distribution for all 114-year periods in piControl simulations

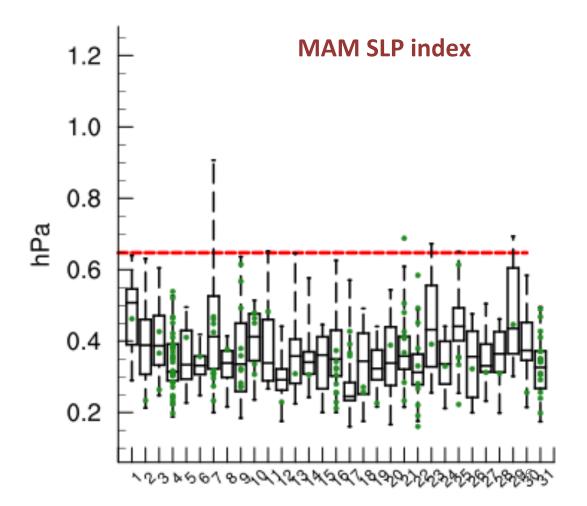
Multi-decadal variability of SLP in CMIP6 models: spring



Red - Green

Sea level pressure index that captures the impact of large scale circulation on precipitation at multi-decadal time-scale in spring

Standard deviation 1901-2014, 21-year running mean Observations Green dots: historical simulations Boxplot: distribution for all 114-year periods in piControl simulations



Multi-decadal versus inter-annual variability in CMIP6 models: SLP index in spring

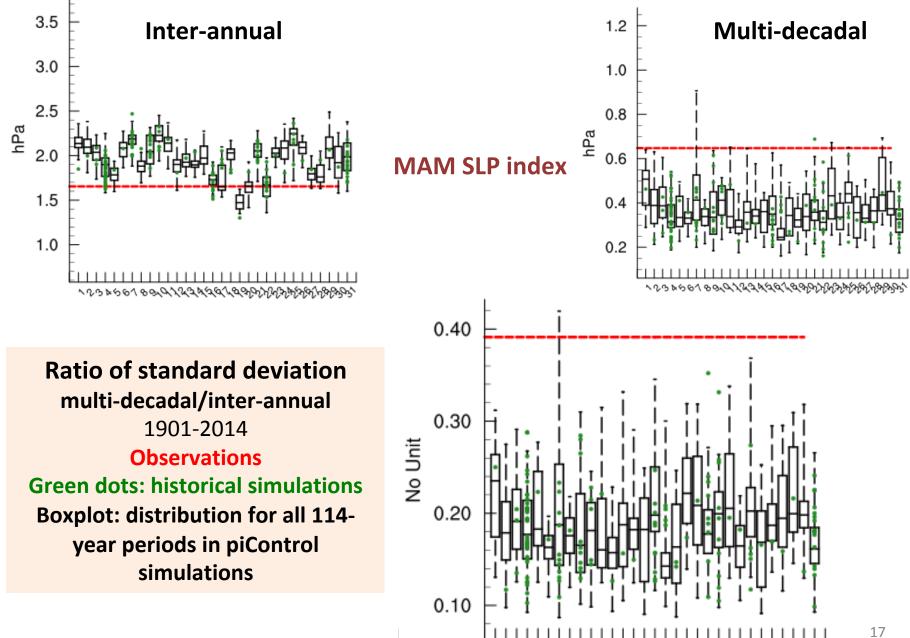
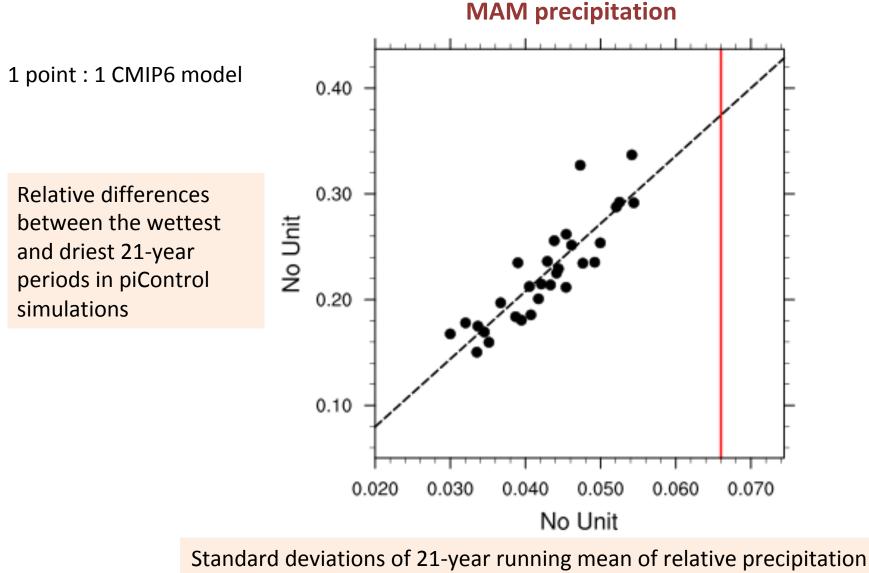


Illustration of potential impacts on uncertainties in hydrological projections



piControl simulations and observations 1901-2014

Difficulties to evaluate internal low-frequency variations in climate models:

✓ Short instrumental period, major sampling uncertainties

✓ Difficulty to estimate robustly the forced signal (small here for spring precipitation) to extract internal variations in the observations and in the models with few historical members

The use of piControl simulations may be interesting, but:

 the external signal should be correctly taken care of in the observations
 it is hypothesized that there is no interaction between

-it is hypothesized that there is no interaction between forced and internal variability

- In many climate models, it is highly unlikely to see multi-decadal variations in spring precipitation as large as observed on 1901-2014, even if most models overestimate the inter-annual variability.
- This is related to an underestimation of the multi-decadal variability in large-scale atmospheric circulation over the North Atlantic / Europe sector at multi-decadal time scales

=> The uncertainties in projected hydrological changes over France due to internal variability might be underestimated (either directly in climate models, or based on off-line hydrological modelling after either dynamical or statistical downscaling)

- Next step: to understand why multi-decadal variability in large scale atmospheric circulation in spring is underestimated in models.
 - Bad representation of the teleconnection between AMV and sea level pressure?
 - Interestingly, some difficulties in CMIP5 climate models to capture spatial and temporal properties of the AMV (Qasmi et al. 2017)