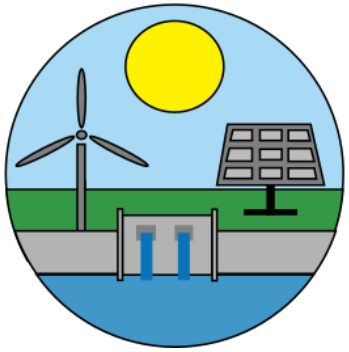

AI for smart and climate resilient energy systems: the challenges of learning and forecasting hydropower production time series at local and global scale in Europe

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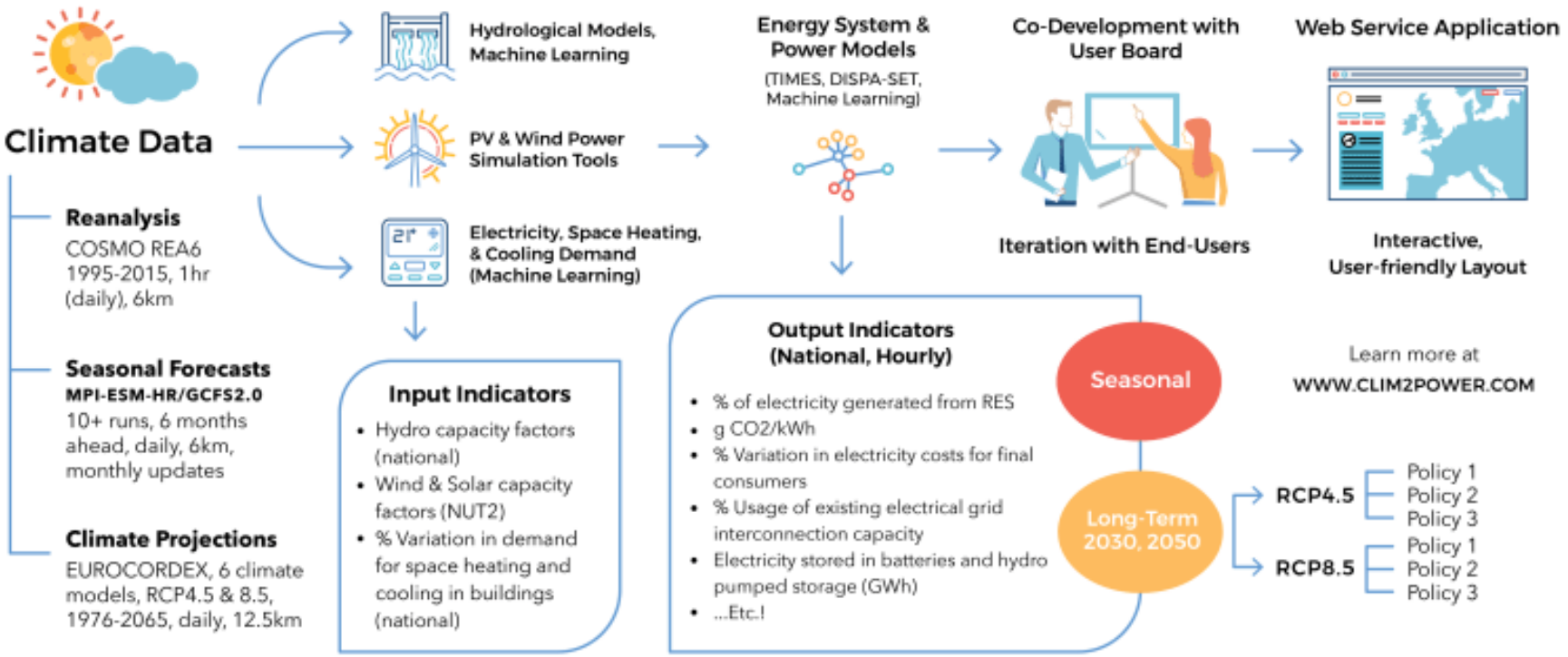
SophIA Summit 2020
19 November 2020

The European project: Clim2Power



Promoting RES

- Electricity generation from renewable energy sources (RES) needs to increase significantly to achieve the long-term objectives of the European Community strategy, which called for fully decarbonized power generation by 2050. This means that more than 80% of the European electricity will be produced by RES.

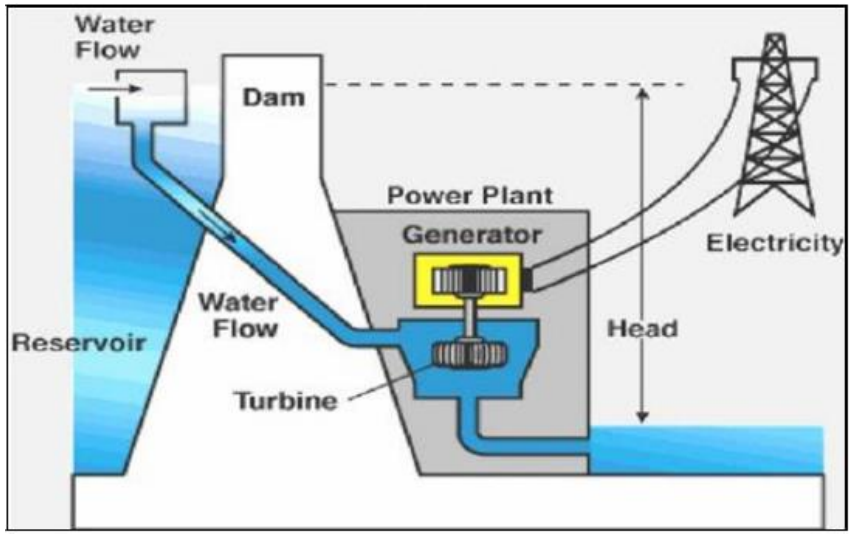
- The growth of the renewables share in the existing grids will require a more flexible and smarter management of the electric power system.

How to promote the penetration of the environmentally-friendly energy sources?

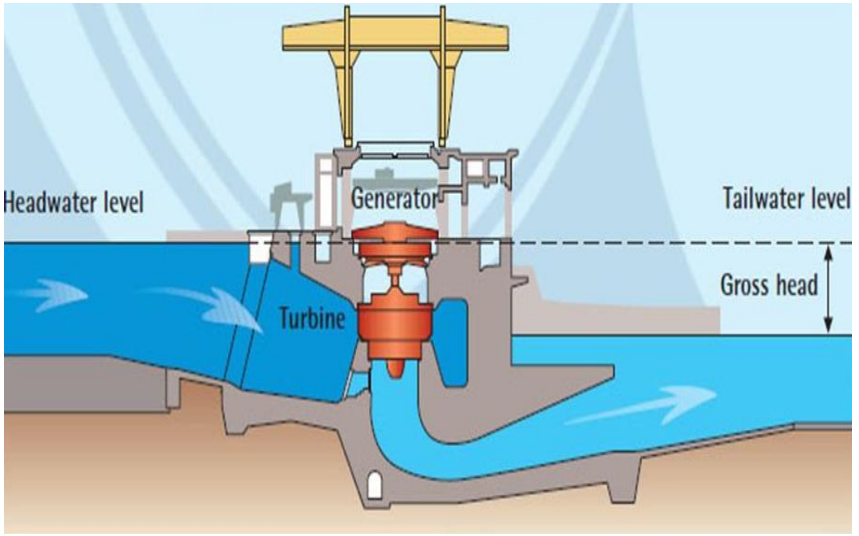
- Develop a prediction model to forecast the RES availability based on possible scenarios of weather conditions.

Hydropower generation

Reservoir (HRes)



Run-of-River (HRoR)



Our challenge

Translate daily time series of climate data (air temperature and precipitation) and (residual) electricity demand
into daily time series of hydropower generation capacity factor at country level for all Europe.

Difficulties:

- It is necessary to capture the complex relationship between the availability of water and the generation of electricity, by considering the coexistence of several spatial and temporal scale conditions.

- Run-of-river hydropower (HRoR) is limited by the flow of the river in which the power plants are located. Moreover, the water flow is a *nonlinear* function of the climate variables and the physical characteristics of the river basins.

- The impact of the weather variables on the runoff may occur with a certain *delay*, whose determination depends on physically based phenomena (e.g., melting snow–local temperature).

Our challenge

Translate daily time series of climate data (air temperature and precipitation) and (residual) electricity demand
into daily time series of hydropower generation capacity factor at country level for all Europe.

Traditional methods:

- Hydrological models:
  - Require several inputs (e.g., climate data and physiographic information of the power plants locations).
  - For every location of interest, when all these data are available and the model parameters are calibrated, hydrological models accurately represent the rainfall-runoff relationship.
  - Finally, the transformation from the river runoff to hydropower production requires additional information about the power plants under investigation (e.g., hydraulic head.).

- Long term calendar mean:
  - with the multiplication of extreme weather events occurring in the last years and predicted in many climate future scenarios, this approach becomes too conservative and risks to mask the climate change effects.

Our proposal

We want to build a model at the aim of providing an overview of the change in the European hydroelectricity generation due to different climate scenarios.

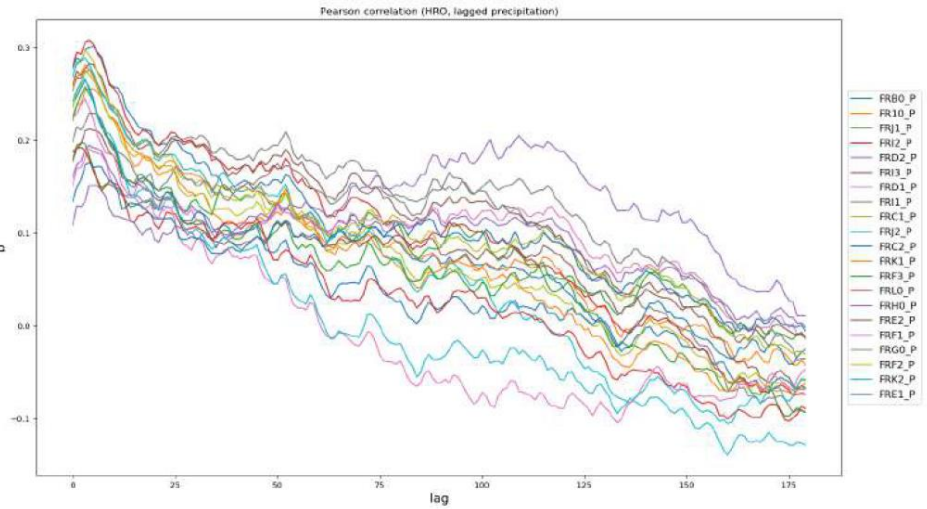
We are not interested in providing detailed results in terms of local hydropower production, but we wish to have information about the variability of the hydropower production at country level and European regional level subject to future climate changes.

MACHINE LEARNING

Machine Learning for EU hydropower CF prediction

HRoR	HRes	Predictor	Spatial scale	Source (Training)	Source (Forecast)
X	X	**Temperature** (it also includes lagged time series)	NUTS2	C2P	C2P
X	X	**Precipitation** (it also includes lagged time series and accumulation)	NUTS2	C2P	C2P
X		**Load**	NUTS0	ENTSO-E	C2P
	X	**Residual-Load-Curve**	NUTS0	ENTSO-E	C2P

Response	Spatial scale	Source (Training)
HRoR	NUTS0	ENTSO-E
HRes	NUTS0	ENTSO-E



Machine Leaning

Response	Spatial scale	
HRoR	NUTS0	Seasonal forecasts Long-term projections
HRes		

Choice of the ML algorithm

We tested the performance of several ML algorithms:

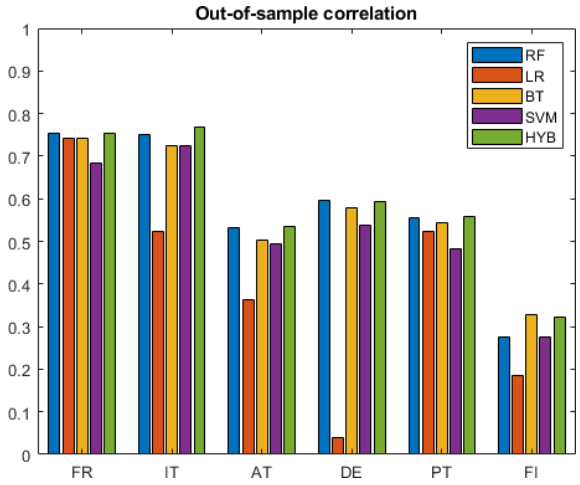
- Random Forest
- Boosted Decision Trees
- Linear Regression
- Support Vector Machine
- Hybrid algorithm

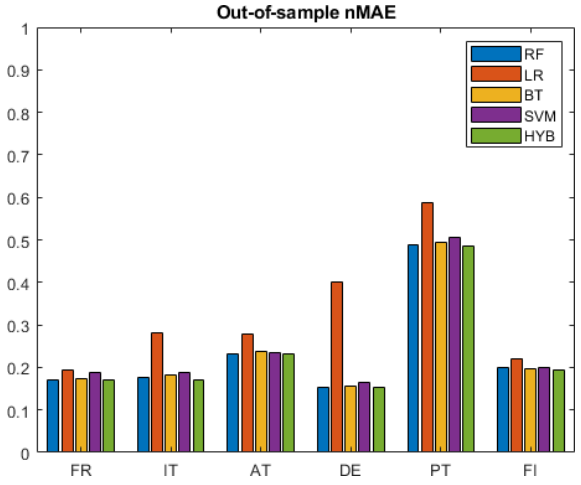
2015	2016	2017	2018	2019

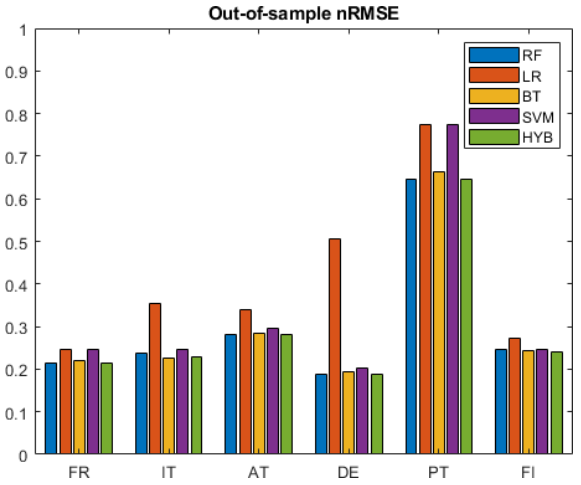
	Training set
	Testing set

Perfomance evaluation

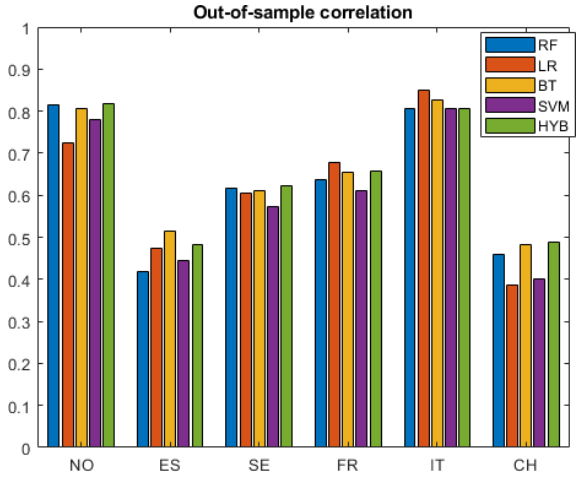
Run-of-River (HRoR)

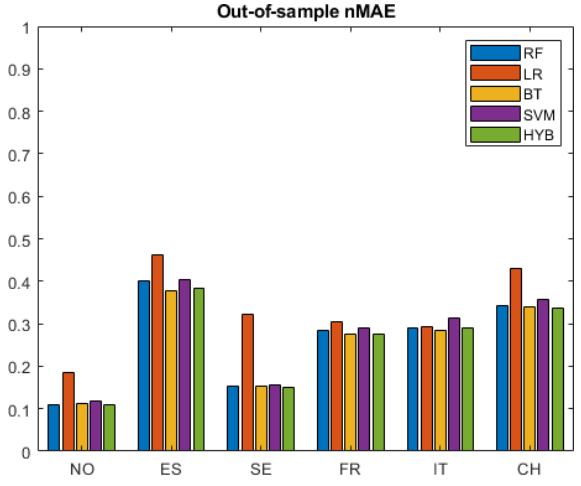


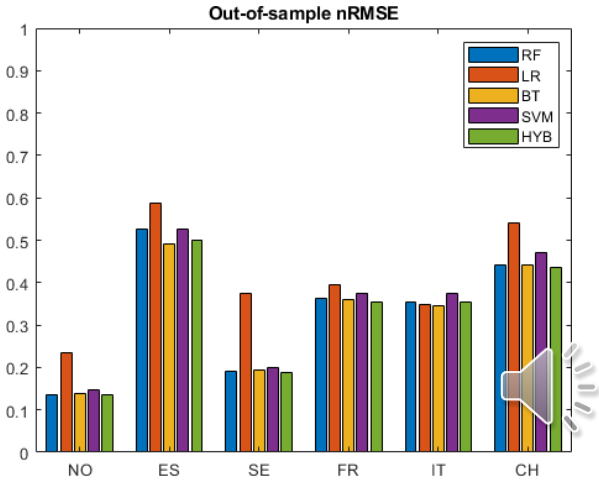




Reservoir (HRes)





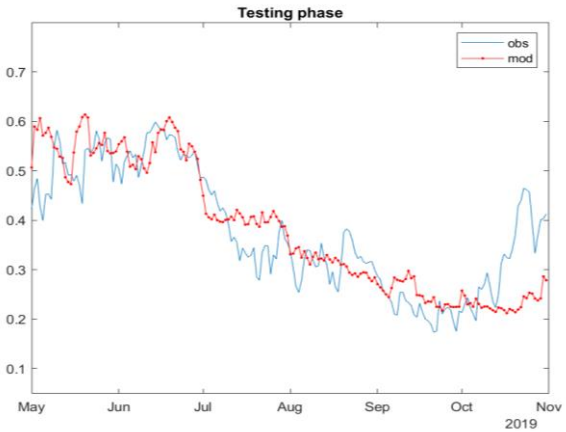


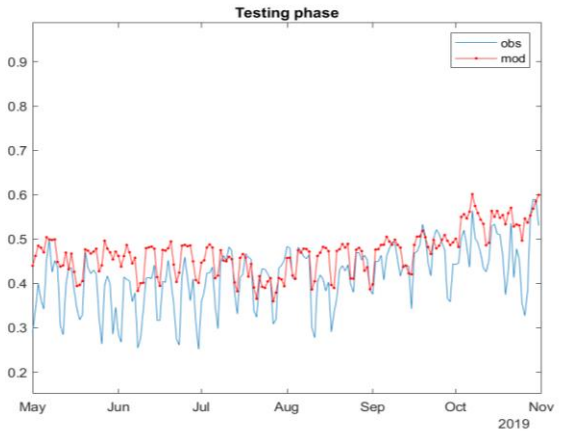
Choice of the ML algorithm

- Random Forest showed to have the best performance in all the evaluative criteria (R, nMAE, nMAPE) for more that 60% of the EU countries, of which 90% are the countries mostly contributing to the European hydropower generation.

HRoR - FR

R = 0.84
nMAE = 0.13
nRMSE = 0.18





HReS - NO

R = 0.66
nMAE = 0.12
nRMSE = 0.15

Valentina Sessa, Edi Assoumou, Mireille Bossy, Sílvia Carvalho, Sofia Simoes. Machine learning for assessing variability of the long-term projections of the hydropower generation on a European scale. 2020. ⟨hal-02507400⟩

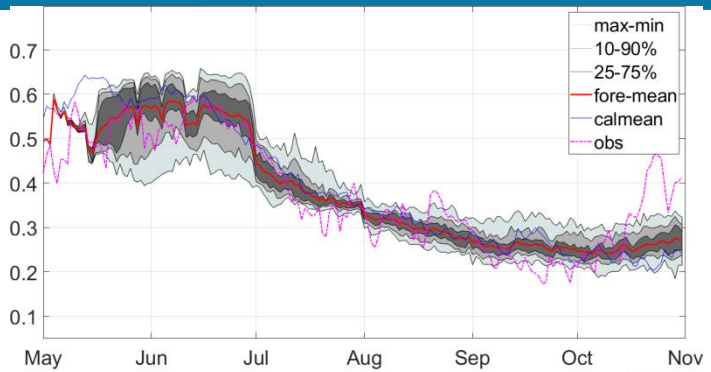
Seasonal forecasts

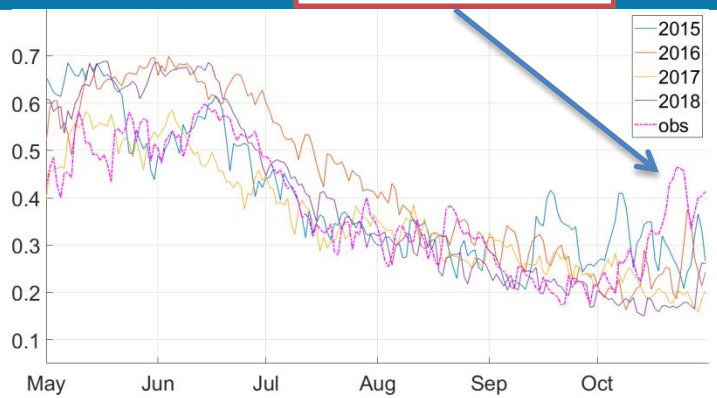
Can we really provided 6 month ahead daily predictions?

season 201905 – HRoR

October 2019 was one of the ten most rainy October months after 1959 (+40%).

FR





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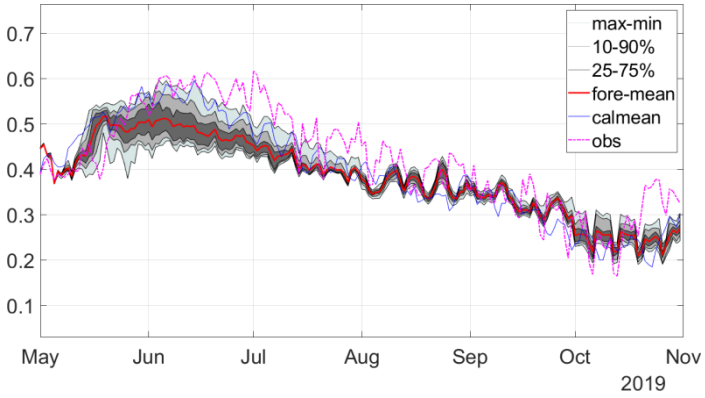

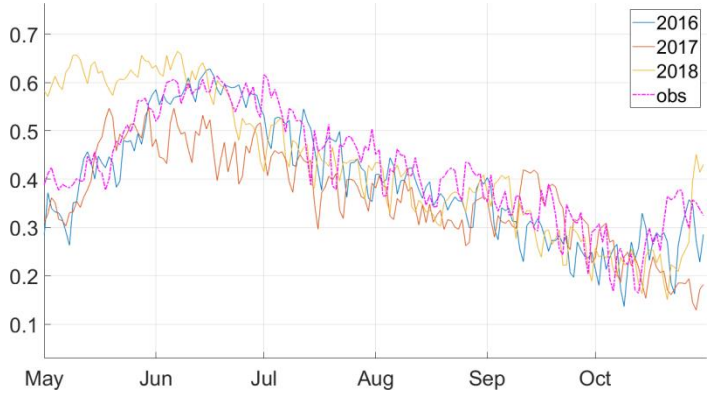

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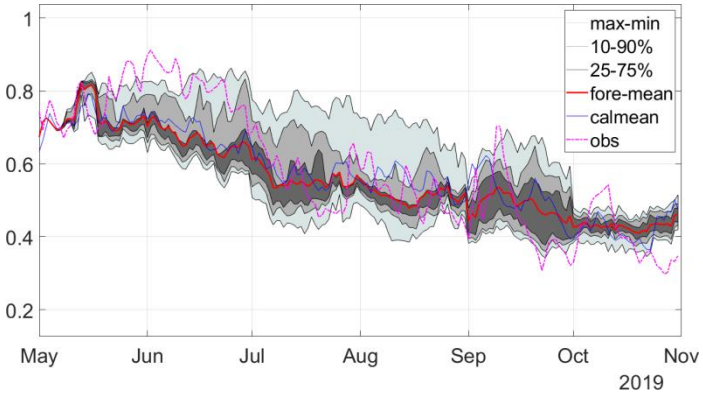
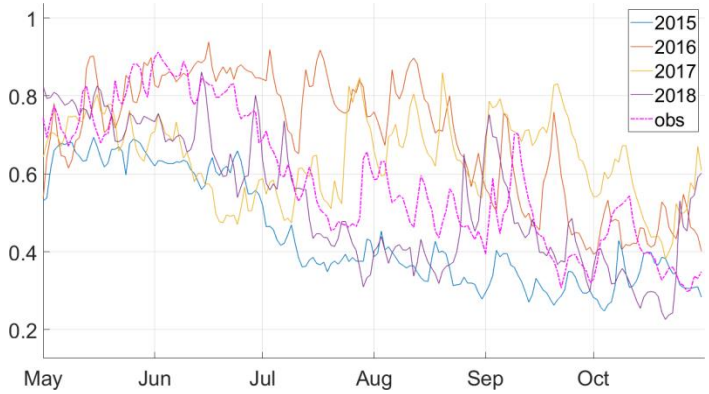
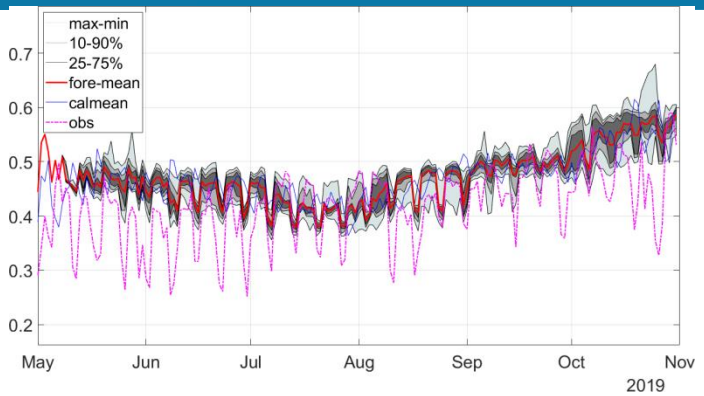
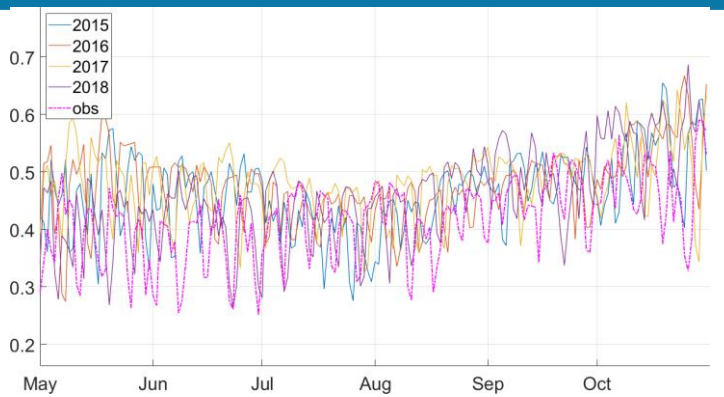




season 201905 – HRes

NO





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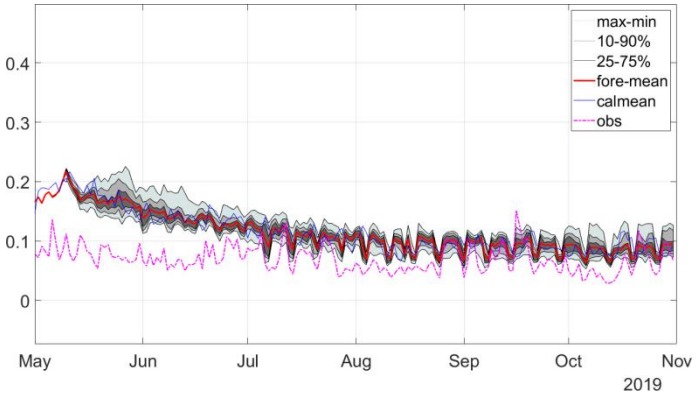

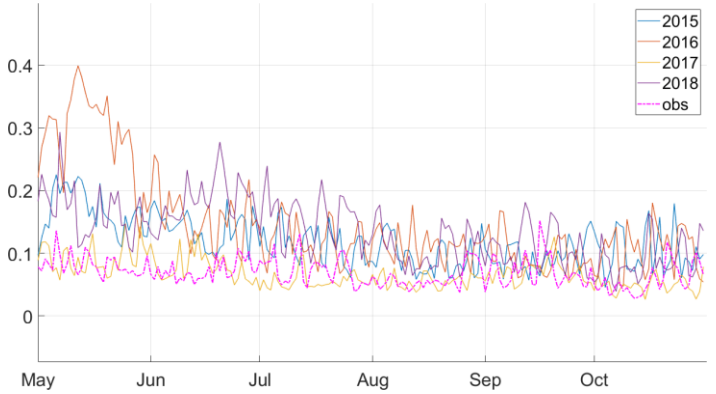

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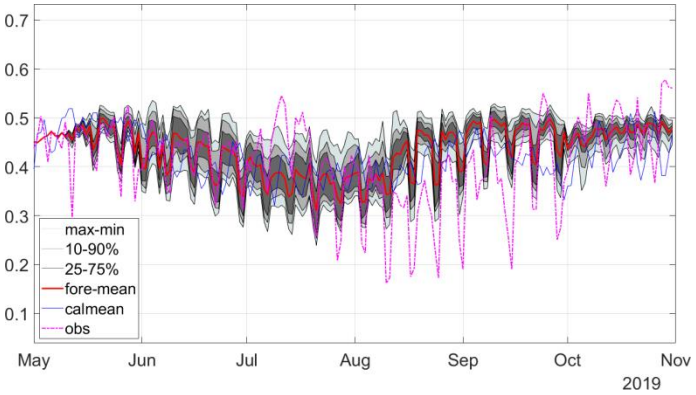

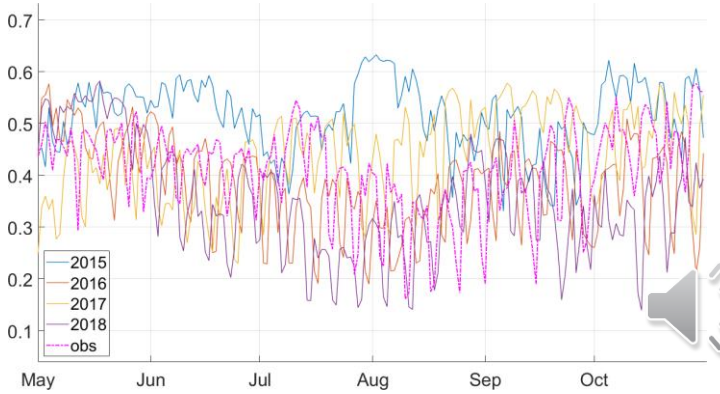

Conclusions

- A greater integration of RES in a smart territory can be promoted by the definition of prediction models able to take into account the climate variability
- Machine learning lends itself well for this goal.
- ML models are easy to be built and require few physical input parameters.
- ML models *mimic* the seasonal behavior of the hydropower production CF. They are still conservative and the historical dataset is too short (from 2015 to current days) to catch extreme events.

Thank you! Merci !

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