Analyzing the Applicability of Random Forest-Based Models for the Forecast of Run-of-River Hydropower Generation

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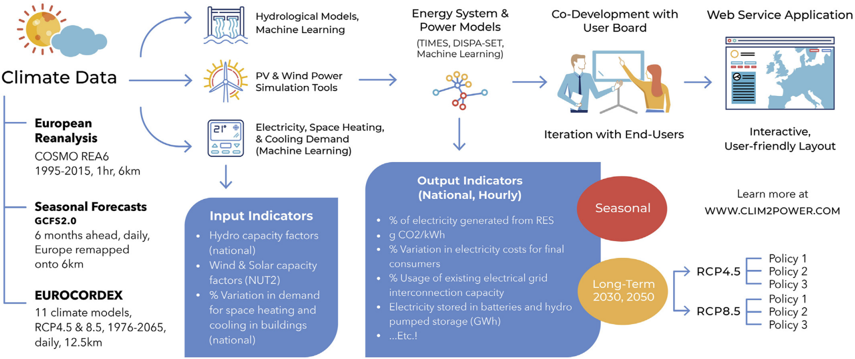
Séminaire public TTI.5
19 September 2022

Clim2Power



Thanks to: Sofia Simões, About the Clim2Power Project, 4th European Climate Change Adaptation conference, Lisbon.

Why is this relevant?

Climate is already affecting the power sector

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System operating at reduced capacity due to low wind speeds and unplanned power plant outages

Jillian Ambrose

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What is the sensitivity to climate variability of the pathways for a carbon neutral power sector in 2030/2050?

Hydropower production

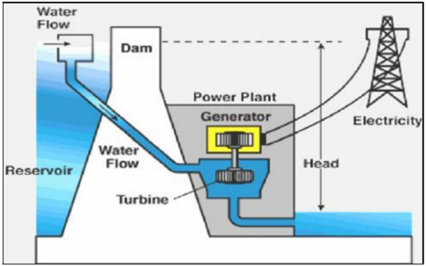
- Hydropower is the world's most dominant source of renewable electrical energy.
- It has been identified as highly valuable for climate mitigation due to its low carbon footprint, high generation efficiency, reliability, and flexibility.
- Installed hydropower capacity continues to grow quickly with the aim at decreasing carbon-based or nuclear power generation.
- During 2020, an additional 21 GW of installed hydropower capacity was added worldwide (3 GW in Europe).

Country	**INST CAP***[MW]	**TOT GEN** [TWh]
Norway	29334	141.69
Spain	20294	33.34
France	16947	64.84
Italy	14900	47.62
Austria	8160	42.52

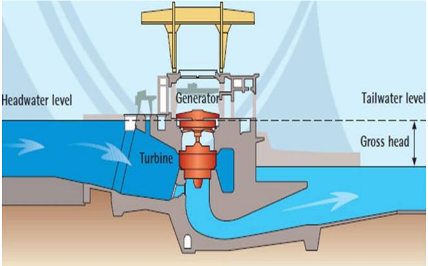
Table: Top five countries by installed hydropower capacity (2020) (*) excluding pump-storage systems. Data from ENTSO-E platform.

Hydropower generation

Reservoir (HRes)



Run-of-River (HRoR)



Our challenge

Translating time series of daily climate data (air temperature and precipitation) into time series of daily hydropower capacity factor at country level for all Europe.

$$\text{Capacity factor} = \frac{\text{Power Generated}}{\text{Installed Capacity}}$$

Main 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

Translating time series of daily climate data (air temperature and precipitation) into time series of daily hydropower capacity factor at country level for all Europe.

$$\text{Capacity factor} = \frac{\text{Power Generated}}{\text{Installed Capacity}}$$

Traditional methods:

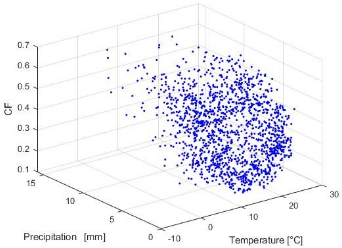
- Hydrological models
  - Require several inputs (e.g., climate data and physiographic information of the power plants locations).
  - For every location of interest, when all these data are available and the model parameters are calibrated, hydrological models accurately represent the rainfall-runoff 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.

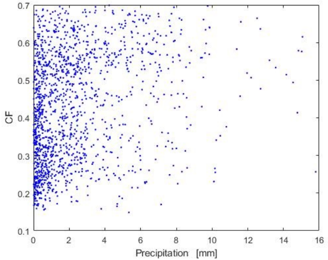
France

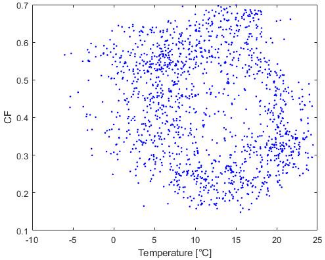
Historical daily data

Data (1 Jan 2015 – 30 Apr 2018):

- Capacity factor (national average)
- Precipitations (national average)
- Temperature (national average)

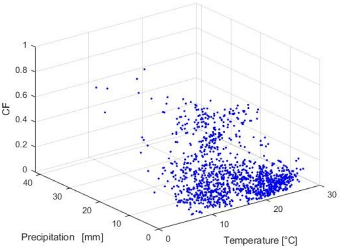


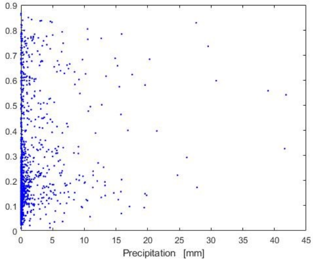


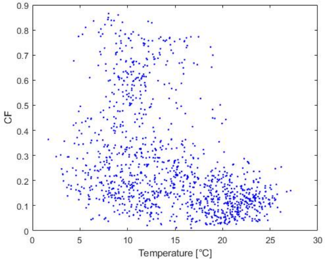


Data (1 Jan 2015 – 30 Apr 2018):

- Capacity factor (national average)
- Precipitations (national average)
- Temperature (national average)





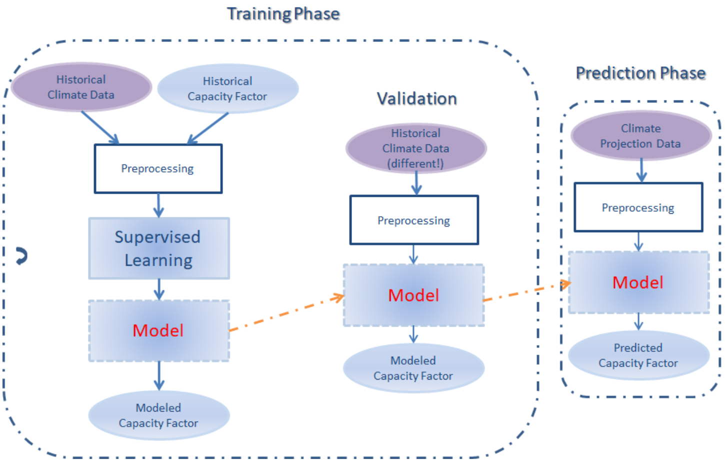


Our proposal

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.

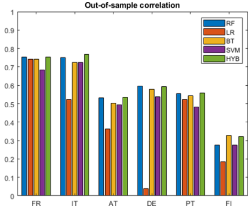
We are not interested in providing detailed results in terms of local hydropower production, but we wish to have information about the variability of the hydropower production at country level and European regional level subject to future climate changes.

Machine learning workflow

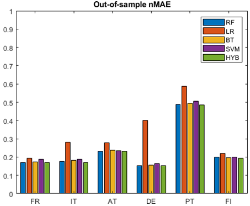


Choice of the ML algorithm: 5-fold cross validation

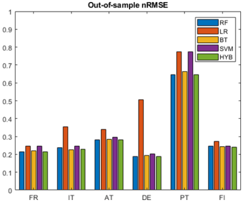
- Training period: 2015-2019
- Data aggregated at country level



(a) $R = \frac{cov(\bar{y}, \hat{y})}{\sigma_{\bar{y}} \sigma_{\hat{y}}}$

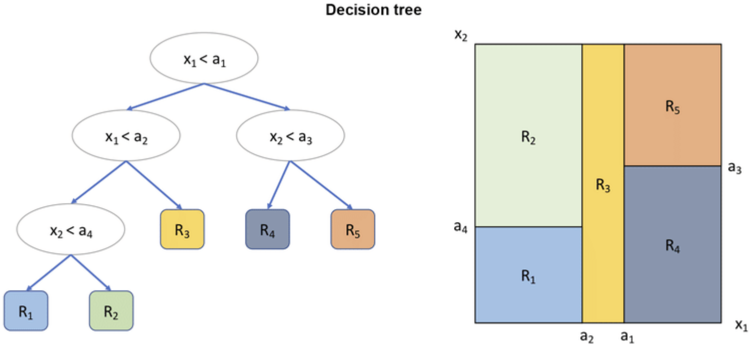


(b) $nMAE = \frac{\sum_{i=1}^{M} |\hat{y}_i - \bar{y}_i|}{\sum_{i=1}^{M} \bar{y}_i}$

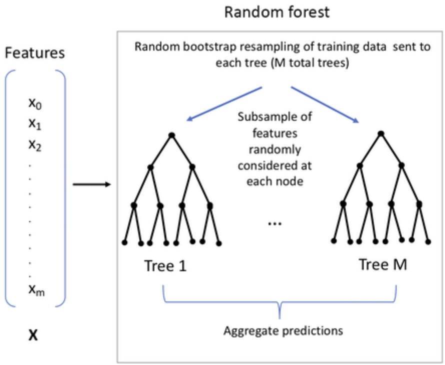


(c) $nRMSE = \frac{RMSE}{\frac{1}{M} \sum_{i=1}^{M} \bar{y}_i}$

Random Forest: basic element



Random Forest



Model definition via predictors selection

Predictors	**M1 (avg)**	**M2 (NUTS2)**	**M3 (avg+NUTS2)**
Temperature			
sync	✓	✓	✓
lagged (opt)	✓	✓	✓
Precipitation			
sync	✓	✓	✓
lagged (opt)	✓	✓	✓
accum (opt)	✓	✓	✓

Available data over the period 1-Jan-2015 to 31-Dec-2019.

Optimal lags

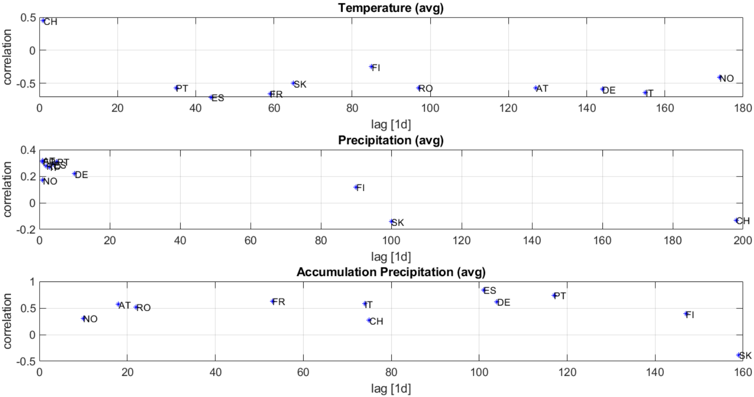
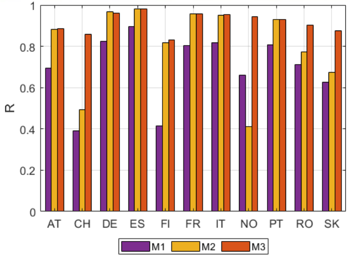
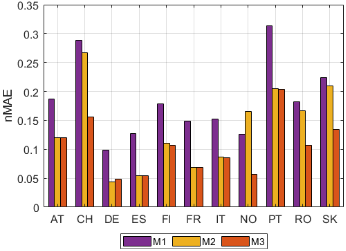


Figure: Optimal lag and corresponding maximum value of correlation for each country.

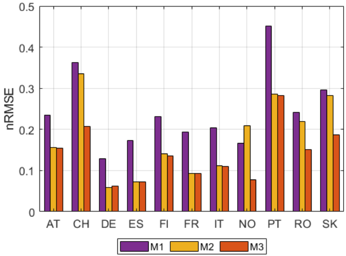
Models comparison: 5-fold cross-validation



(a) R

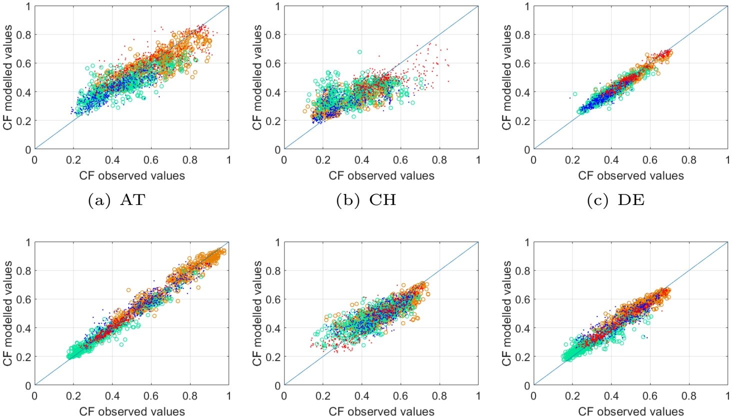


(b) $nMAE$



(c) $nRMSE$

Model M3

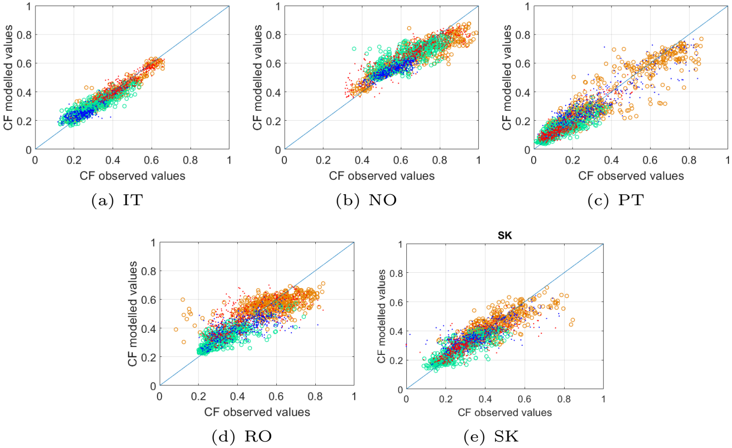


(a) AT (b) CH (c) DE

(d) ES (e) FI (f) FR

Figure: Scatter plot of the modeled and observed capacity factors. We indicate with blue dots the values in the period December–January–February (DJF), with orange circles the values in the period March–April–May (MAM), with red dots for June–July–August (JJA) and, finally, with green circles for September–October–November (SON).

Model M3



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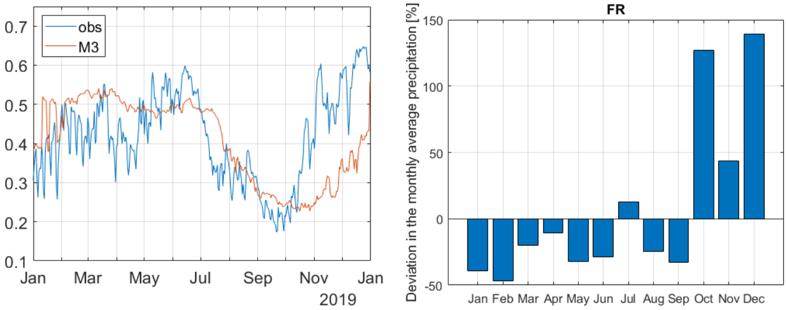
Can we use M3 for prediction?

France: Autumn's heavy rainfall

- Training period: 2015-2018
- Testing period: 2019 (R = 0.44, nMAE = 0.22, and nRMSE = 0.28.)



(a) (b)

Figure: (**a**) Time series of the observed and modelled capacity factor over the test year 2019, with training set over 2015–2018. (**b**) Deviation of the monthly average precipitation in 2019 from the monthly average precipitation in the four previous years.

Portugal: trans-boundary challenge

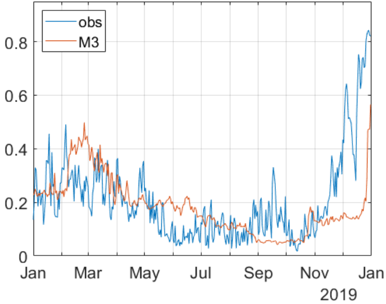
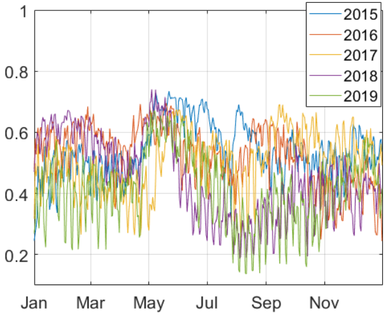
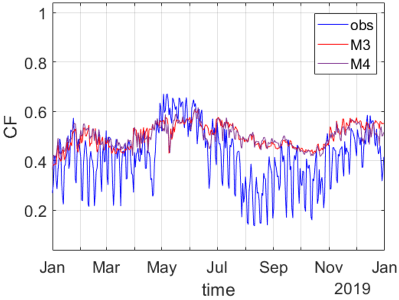


Figure: Time series of the observed and modeled capacity factor over the test year 2019, with training set over 2015–2018.

Finland: is there any hydropeaking effect?



(a) FI



(b) FI

Figure: (**a**) Time series of the observed CF. (**b**) Time series of the observed CF (blue line) along with the time series of CF obtained by models M3 (red line) and M4 (violet line) over the year 2019.

Finland: change in the energy mix

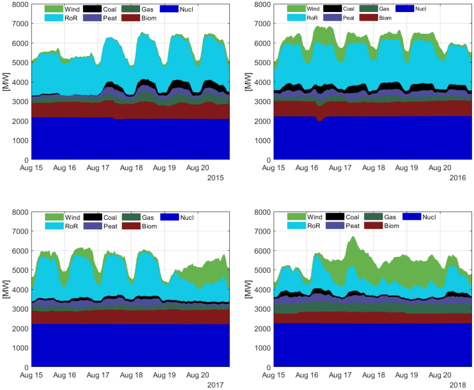
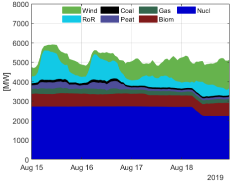


Figure: Comparison of the energy mix in Finland in August.

Installed wind capacity:

459 MW in 2015

1908 MW in 2018



Conclusions

- The growth of the renewables share in the existing grids will require a more flexible and smarter management of the electric power system. $\Rightarrow$ Develop a prediction model to forecast the RES availability based on possible scenarios of weather conditions.
- Machine learning lends itself well for this goal. Our experiments showed that a more accurate model is obtained for our dataset when we introduce a finer spatial resolution for the inputs.
- ML models are easy to be built and require few physical input parameters.
- ML allows modelling the climate dependency of run-of-river hydropower production at the country level.
- The performance varies greatly across countries and seasons. We observed that the current level of accuracy of the ML outputs for all the countries is likely not precise enough to give a strong operational advantage.
- More historical data would be necessary for opportunely training the learners and improve the model accuracy and response to extreme or singular events that have a better probability to be incorporated as the training dataset improves.

Merci! Thank you! Grazie!

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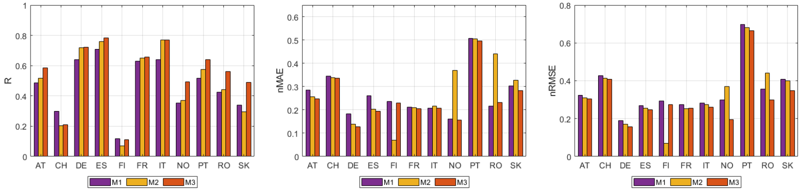
Leave-one-year-out validation

2015	2016	2017	2018	2019



(a) R

(b) nMAE

(c) nRMSE