











# Clim2Power

### Next Generation Challenges in Energy-Climate Modelling

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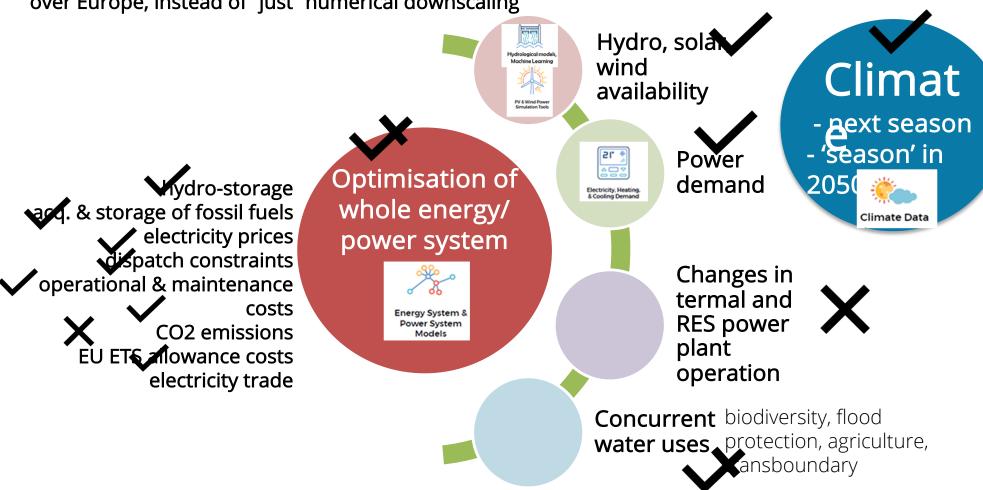




#### Where we stand - nutshell

#### **Objectives:**

- making energy and power models respond to climate variability
- statistical meaningfull approach to enhance the predictive skill of the current models over Europe, instead of "just" numerical downscaling





### Clim2Power Pipeline

#### **UNCERTAI**







PV & Wind Power Simulation Tools



Energy System & Power System \_ Models



TIMES, Dispatch models, Machine Learning





Iteration with End-Users

#### Web Service Application



Interactive, User-friendly Layout

### 51. **\***

Electricity, space heating and cooling demand (machine learning)

#### nonths Input Indicators

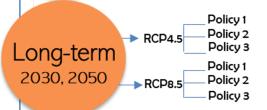
- Hydro capacity factors (national)
- Wind & Solar capacity factors (NUT2)
- % variation in demand for space heating and cooling in buildings (national)

#### Output Indicators (national, hourly)

- % of electricity generated from RES
- q CO2/kWh
- % variation in electricity costs for final consumers
- % usage of existing electric grid interconnection capacity
- electricity stored in batteries and hydro pumped storage (GWh)

• (...)

### Seasonal





Climate Data

(daily), 6km

Seasonal Forecasts

MPI-ESM-HR/GCFS2.0 10+ runs, 6 months ahead, daily, 6km,

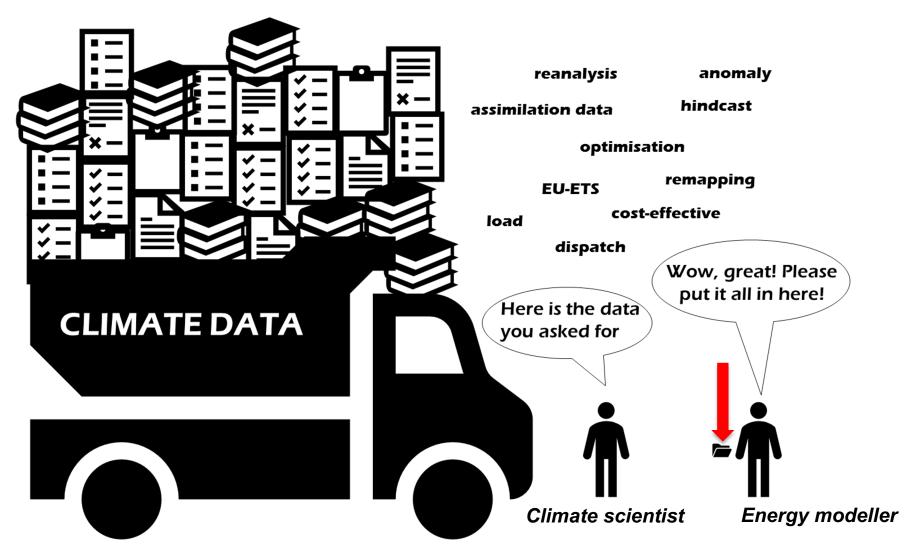
monthly updates

Climate Projections
EUROCORDEX, 11
climate models,
RCP4.5 & 8.5, 19762065, daily, 12.5km



### Lessons learnt







### Challenges / difficulties



- combining expertise of persons with a multi-disciplinary background
- different data demands on the spatial/temporal resolution
- tight/challenging timings for processing the seasonal forecasts and downscaling
- how to assess uncertainty in the modelling cascade
- communicating to users the limited skill of seasonal forecasts over Europe
- process and store the large amount of climate data get familiar with different data types and storage protocols
- computation limits of energy system model for Europe

How useful is C2P to users (which users)? How insights of national case-studies feed the EU analysis? Can we recommend the Seasonal Forecasts for some months/regions?



### Some insights

- many other factors affecting the energy system evolution (technology evolution, market dynamics, policy decision as shutting down nuclear or not, etc.) than climate
- changing with the more clear effects of climate change and increasing shares
  of RES power plants yet climate change trends are still not a very major
  factor how to deal with extreme events in energy models with some degree
  of reliability?
- In energy system modelling we do not quantify risk although climate scientists deal competently with assessing risks and uncertainty, energy systems modellers do not assess uncertainty (or risk). We simply deal with it by creating many scenarios but we cannot attribute a probability to each one of our scenarios
- Increasing substantially our time-slices and geographical disaggregation led to huge computational problems (in fact the models stopped running) - still trying to find solutions for this.
- in the power domain we are lacking a coordinated time series of daily/hourly power outputs for each country in Europe ENTSO-E only has at the moment a 3 year time-series. Thus, integrating bias adjustment from GCM into "bias adjustment" of power plants output becomes a big challenge



#### Some Publications

#### **Published**

- 1. Amorim, F., Simoes, S.G., Siggini, G., Assoumou, E. (2020) **Integrating Climate Variability in energy system models.** Energy (Q1; IF: 5.537) https://doi.org/10.1016/j.energy.2020.118089
- 2. Saint-Drenan, Y.M., Besseau, R., Jansen, M., Staell, I., Troccoli, A., Dubus, L., Schmidt, J., Gruber, K., Simoes, S.G., Heier, S. (2020) A parametric model for wind turbine power curves incorporating environmental conditions. Renewable Energy Journal (157) pp. 754-768 (Q1; IF: 5.439) https://doi.org/10.1016/j.renene.2020.04.123
- 3. Baumgartner, J., Schmidt, J., Gruber, K., Simoes, S.G., Saint-Drenan, Y-M., (2020). Less Information, Similar Performance: Comparing Machine Learning-Based Time Series of Wind Power Generation to Renewables.ninja. Energies 13(9), 2277; https://doi.org/10.3390/en13092277 (Q1; IF: 2.747) https://www.mdpi.com/1996-1073/13/9/2277/htm

#### **SUBMITTED**

- 1. Sessa, V., Assoumou, E., Bossy, M., Carvalho, S. Simoes, S.G. (n.d.) Machine learning for assessing variability of the long-term projections of the hydropower generation on a European scale. Applied Energy (submitted March 2020)
- 2. Simoes, S.G., Amorim, F, Siggini, G., Sessa, V., Saint-Drenan, Y-M., Carvalho, S., Mraihi, H., Assoumou, E. (n.d.) Climate proofing the renewable electricity deployment in Europe introducing climate variability in large energy systems models. Energy Strategy Reviews (submitted October 2019)

#### **UPCOMING**

- 1. Adaptation needs for EU power sector
- 2. Review existing web-based climate services highlight the importance of user-centred approach + integration of transdisciplinary perspectives and cross-disciplinary expertise

























## More on CLIM2POWER:





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