An autopilot for energy models

GIS-based automatic generation of input data for energy system models

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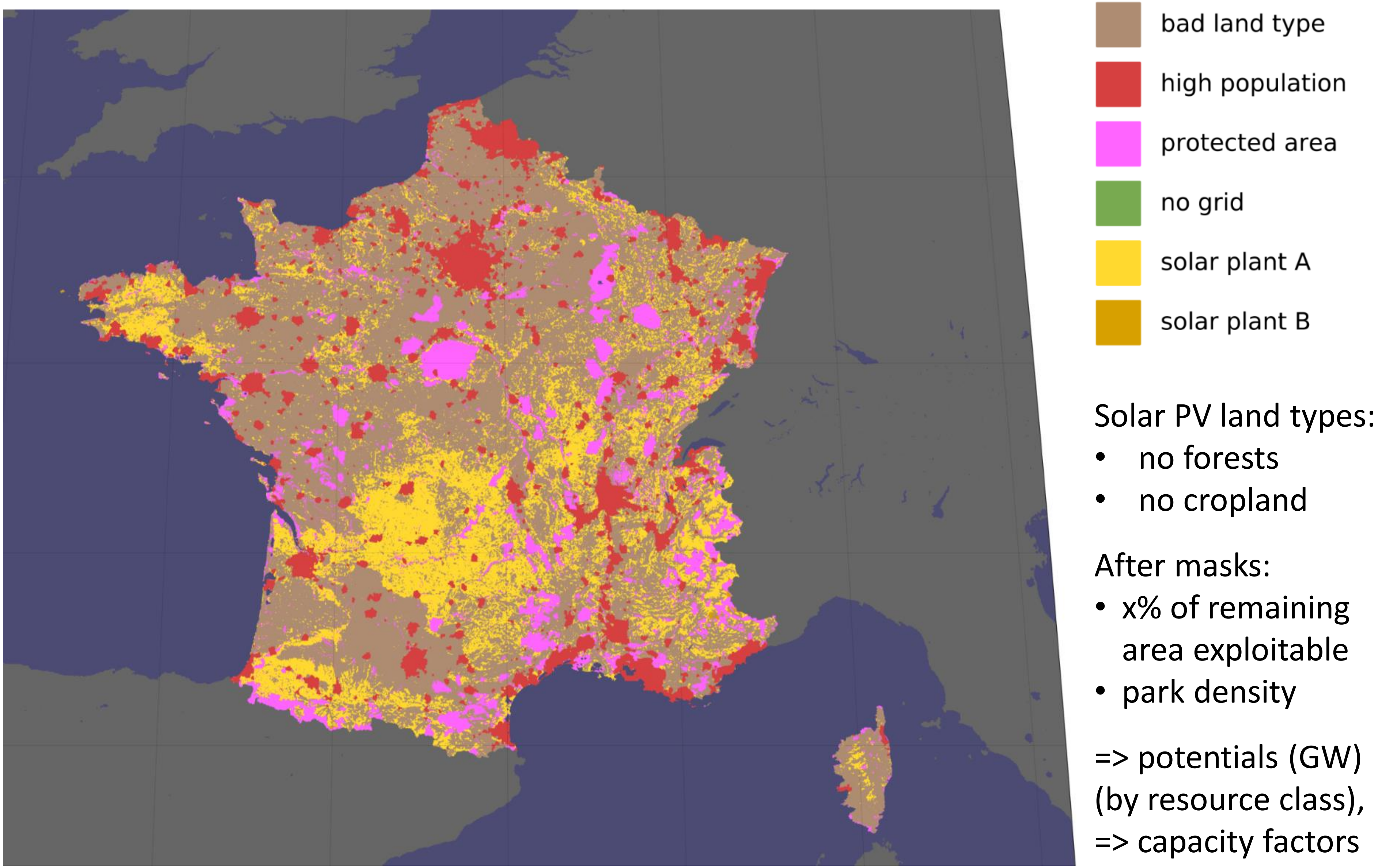
Long-term goal & current status

- GOAL:
  - generate all location-dependent input data for energy models
  - consistent “top down” GIS approach for arbitrary world regions
  - use public datasets and open-source the code
- STATUS:
  - wind & solar: complete
  - synthetic electricity demand: complete
  - hydropower: complete, but may add alternative version
- TO DO:
  - bioenergy, geothermal, pumped hydro, carbon storage
  - improve estimation and representation of global power grid
  - installed capacity in existing plants, fossil energy costs

Two packages

- GIS: “GlobalEnergyGIS“ (name may change)
  - User input: region definitions and GIS parameters
  - Calculates renewable potentials & hourly capacity factors (per region and resource class)
  - Synthetic hourly electricity demand using machine learning
  - Uses ERA5 reanalysis (solar, wind & temperature data) and other publicly available global datasets
- Companion model: “Supergrid” (name will change)
  - A simple capacity expansion model of a generic electricity system (greenfield, one year with hourly resolution)
- Written in julia.

Land masks for solar PV plants



Solar PV land types:

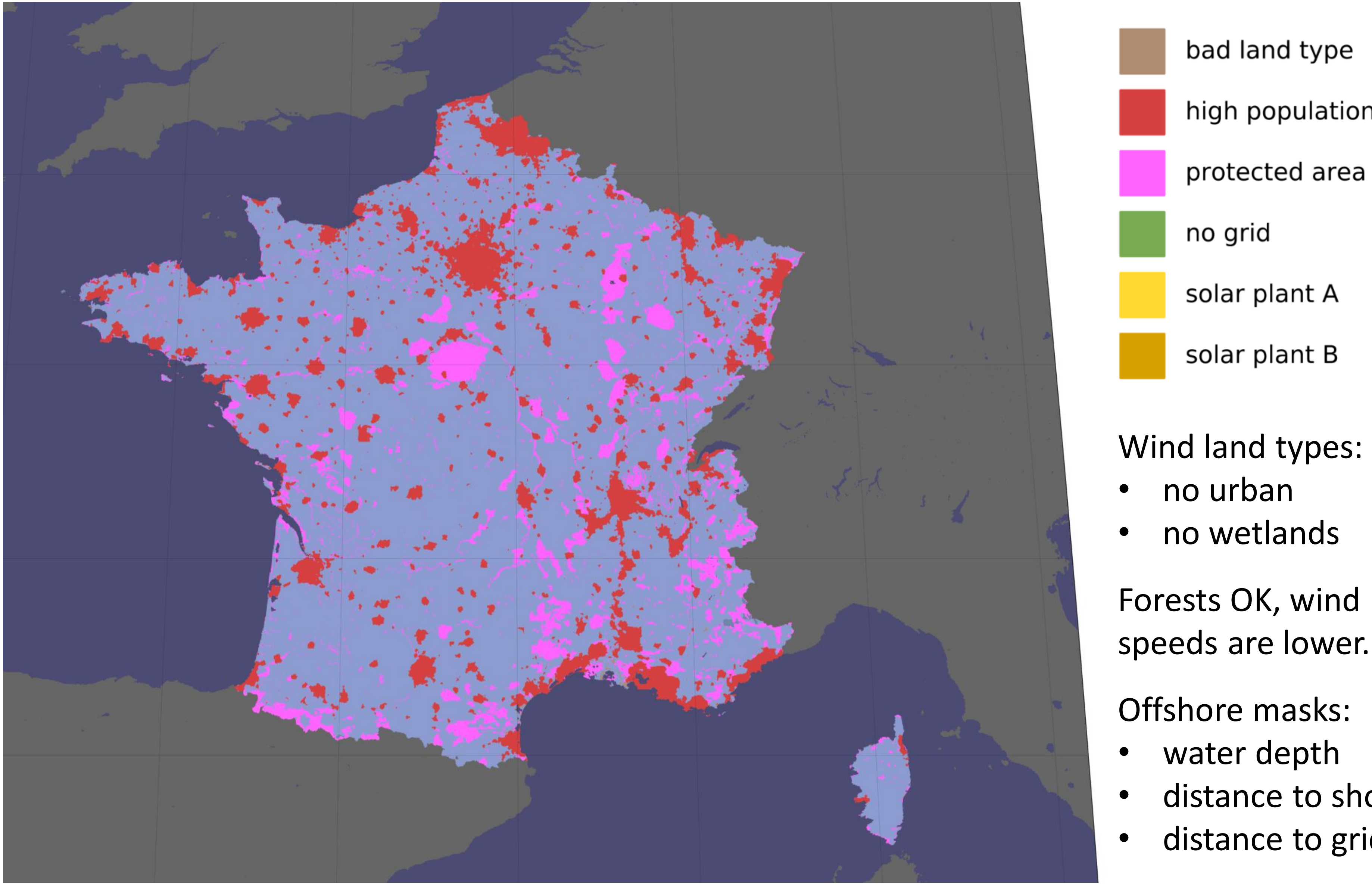
- no forests
- no cropland

After masks:

- x% of remaining area exploitable
- park density

=> potentials (GW) (by resource class),
=> capacity factors

Land masks for wind farms



Wind land types:

- no urban
- no wetlands

Forests OK, wind speeds are lower.

Offshore masks:

- water depth
- distance to shore
- distance to grid

Hydropower based on Gernaat et al. 2017

nature energy
ARTICLES
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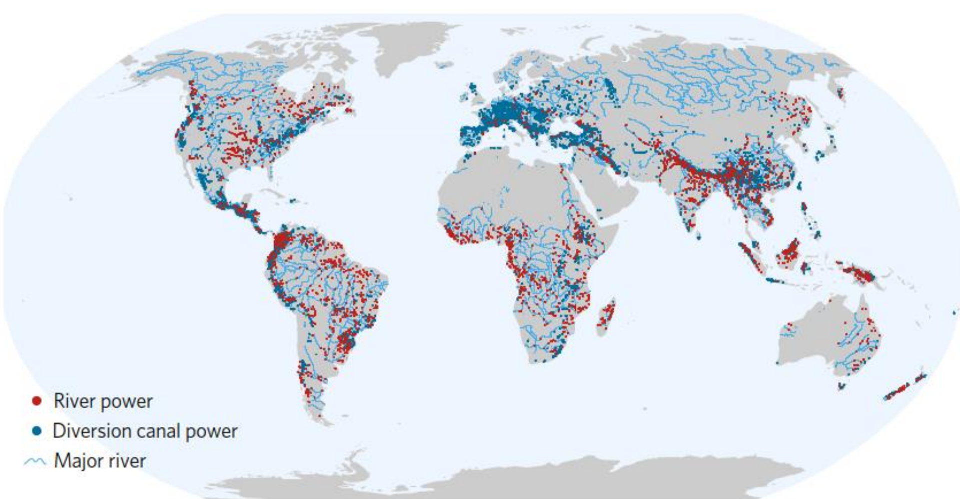
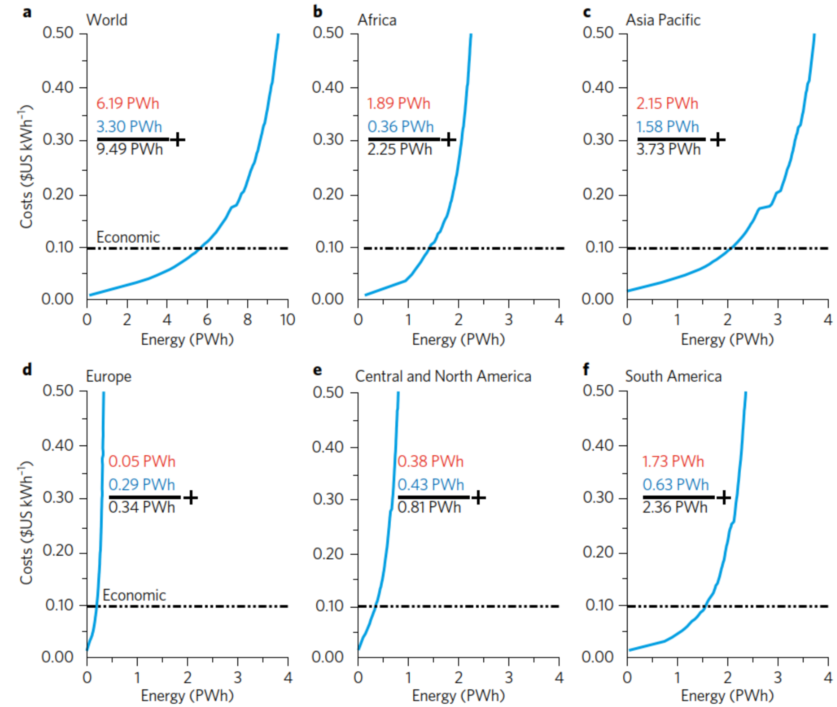
High-resolution assessment of global technical and economic hydropower potential

David E. H. J. Gernaat[1,2]*, Patrick W. Bogaart[2], Detlef P. van Vuuren[1,2], Hester Biemans[1,3] and Robin Niessink[1,2]

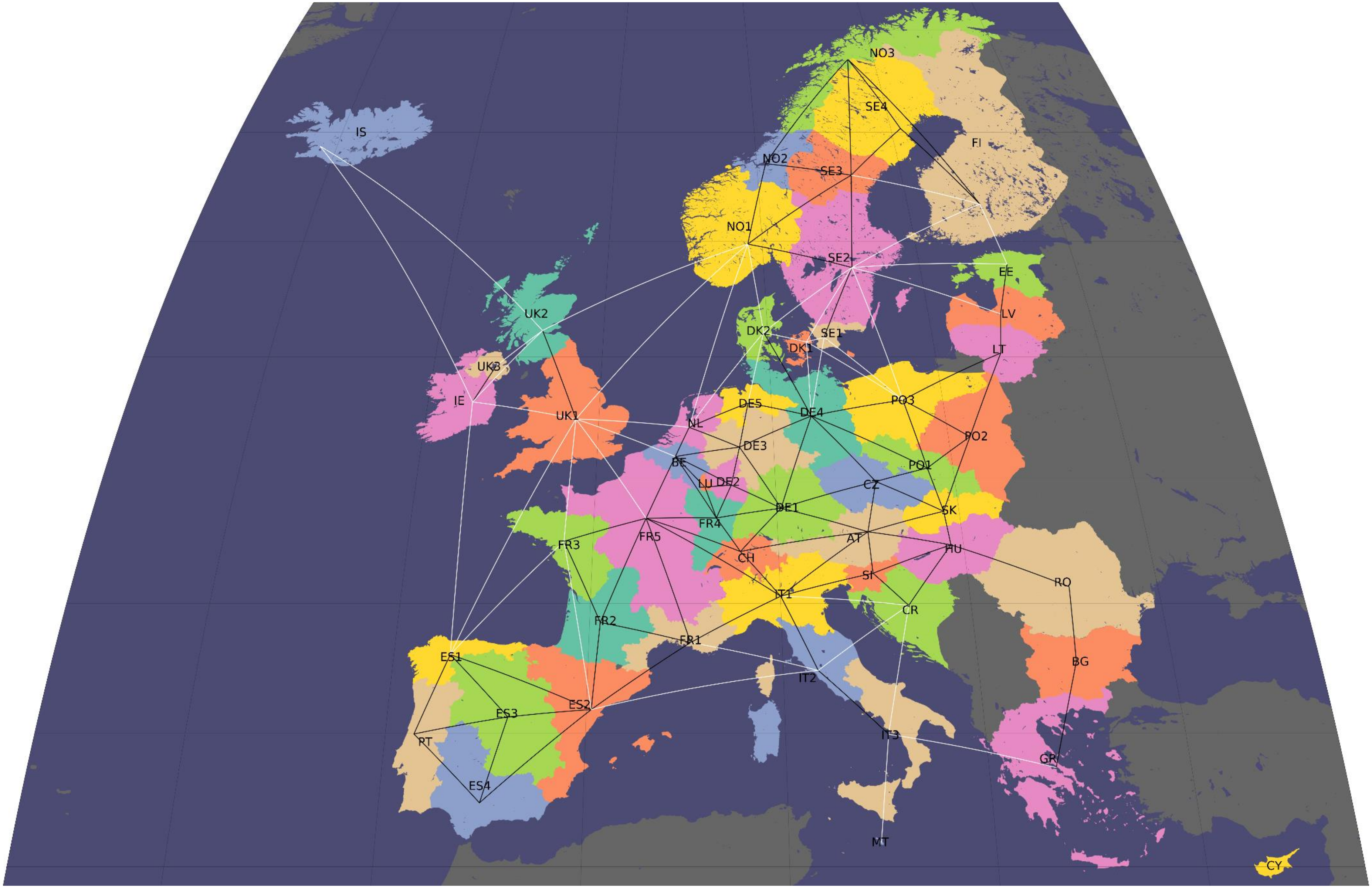
Hydropower is the most important renewable energy source to date, providing over 72% of all renewable electricity globally. Yet, only limited information is available on the global potential supply of hydropower and the associated costs. Here we provide a high-resolution assessment of the technical and economic potential of hydropower at a near-global scale. Using 15″×15″ discharge and 3″×3″ digital elevation maps, we built virtual hydropower installations at >3.8 million sites across the globe and calculated their potential using cost optimization methods. This way we identified over 60,000 suitable sites, which together represent a remaining global potential of 9.49 PWh yr⁻¹ below US\$0.50 kWh⁻¹. The largest remaining potential is found in Asia Pacific (39%), South America (25%) and Africa (24%), of which a large part can be produced at low cost (<US\$0.10 kWh⁻¹). In an ecological scenario, this potential is reduced to 5.67 PWh yr⁻¹.





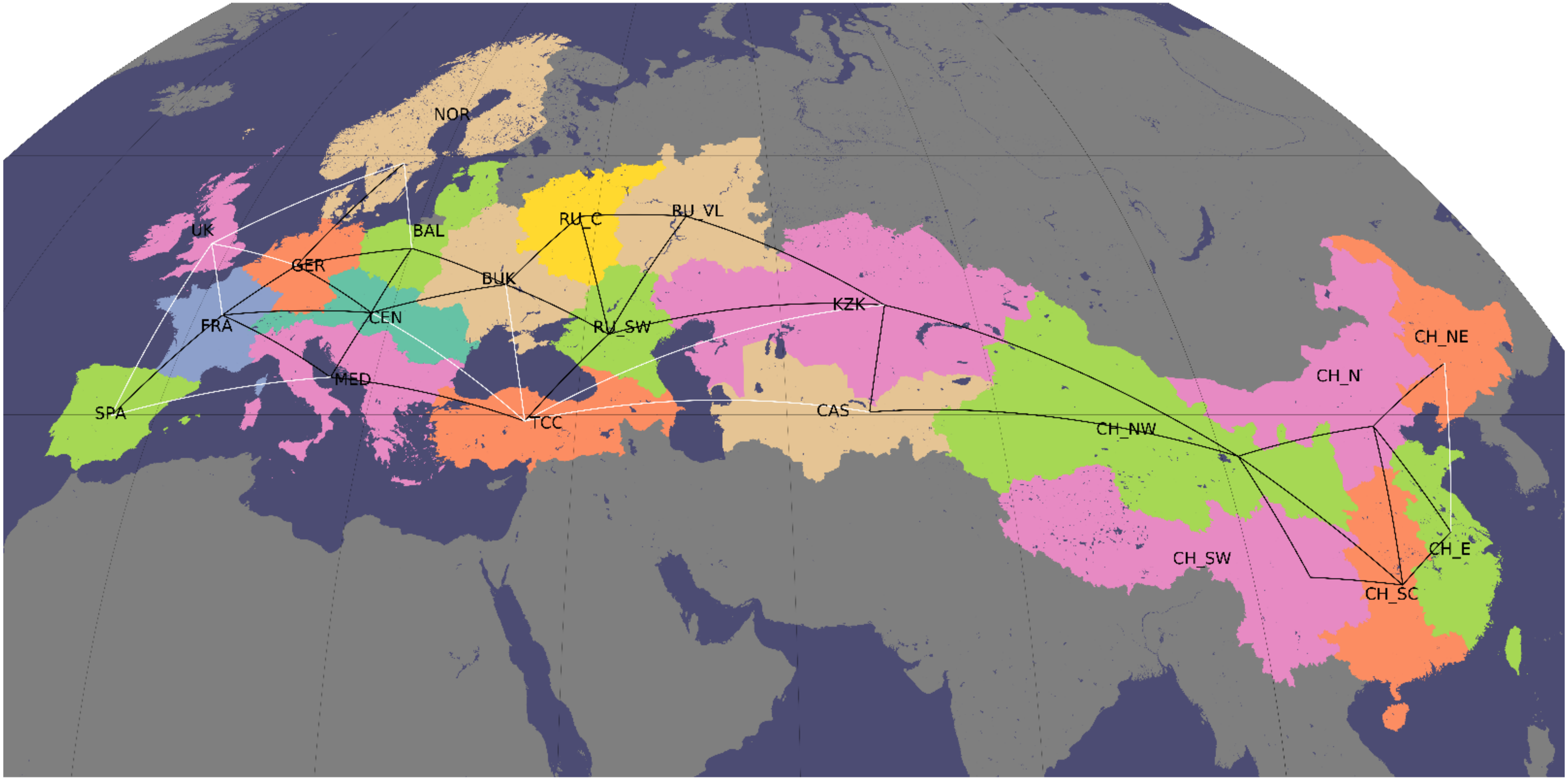
- 60 000 locations (existing & potential capacity)
- annual generation, cost, storage size, monthly inflow

Europe54 (NUTS borders)

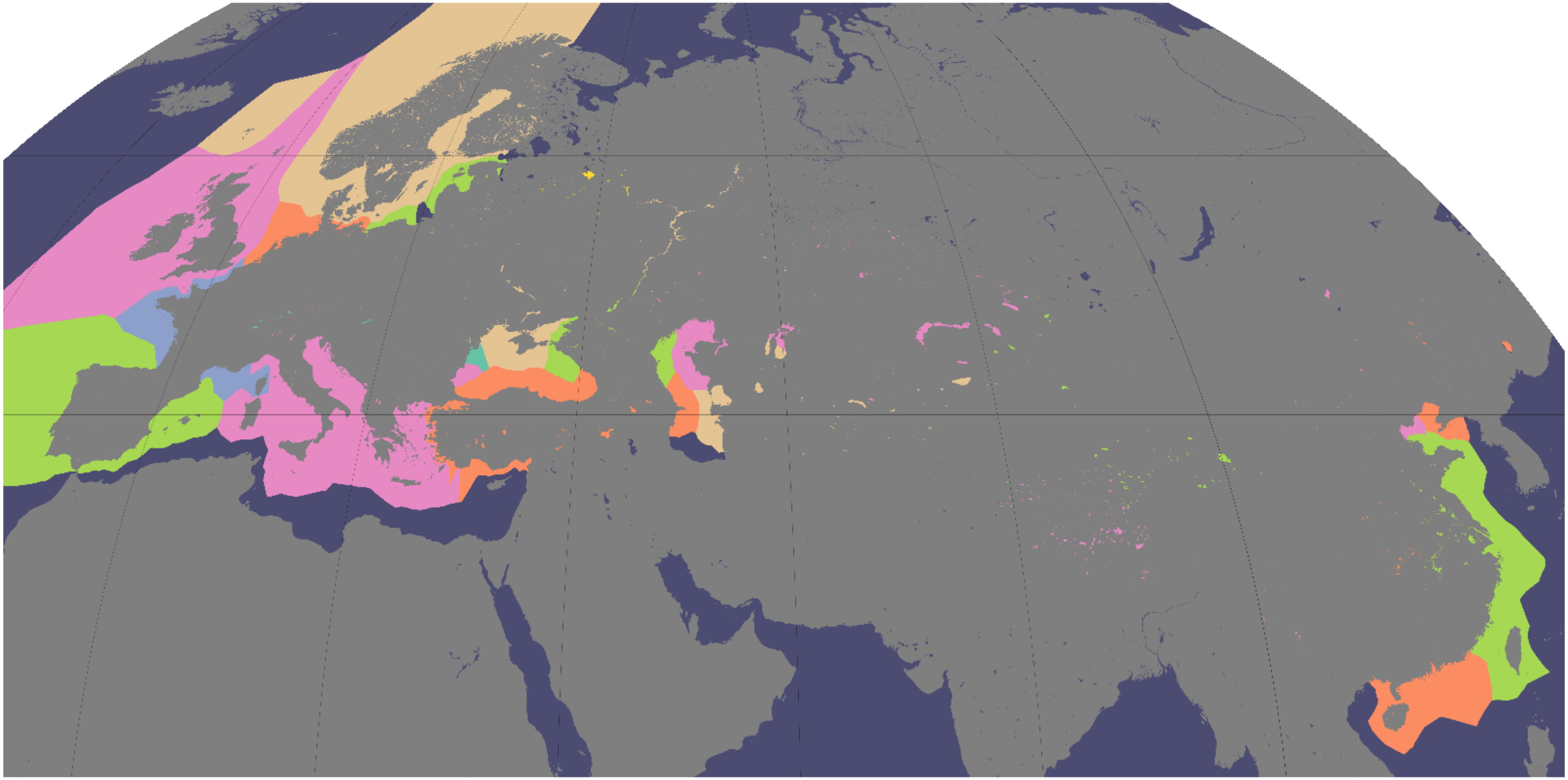


Europe54 offshore

Eurasia21 (GADM borders)



Eurasia21 offshore



ERA5 reanalysis dataset

- Meteorological reanalysis from ECMWF
  - European Centre for Medium-Range Weather Forecasts
  - reanalysis = consistent global dataset, based on observations and running the forecast model forward & backward
- Five downloaded variables
  - wind: u- & v-components of wind speed
  - solar: SSRD (total insolation) & FDIR (direct insolation)
  - temperature (for synthetic demand)
  - spatial & temporal resolution: 31 km, 1 hour
- "Pretty big data"
  - 28 GB raw data per variable per year (140 GB total)
  - after discarding remote ocean data, wind direction and compression: 30 GB total per year (for global data)

Synthetic demand using machine learning

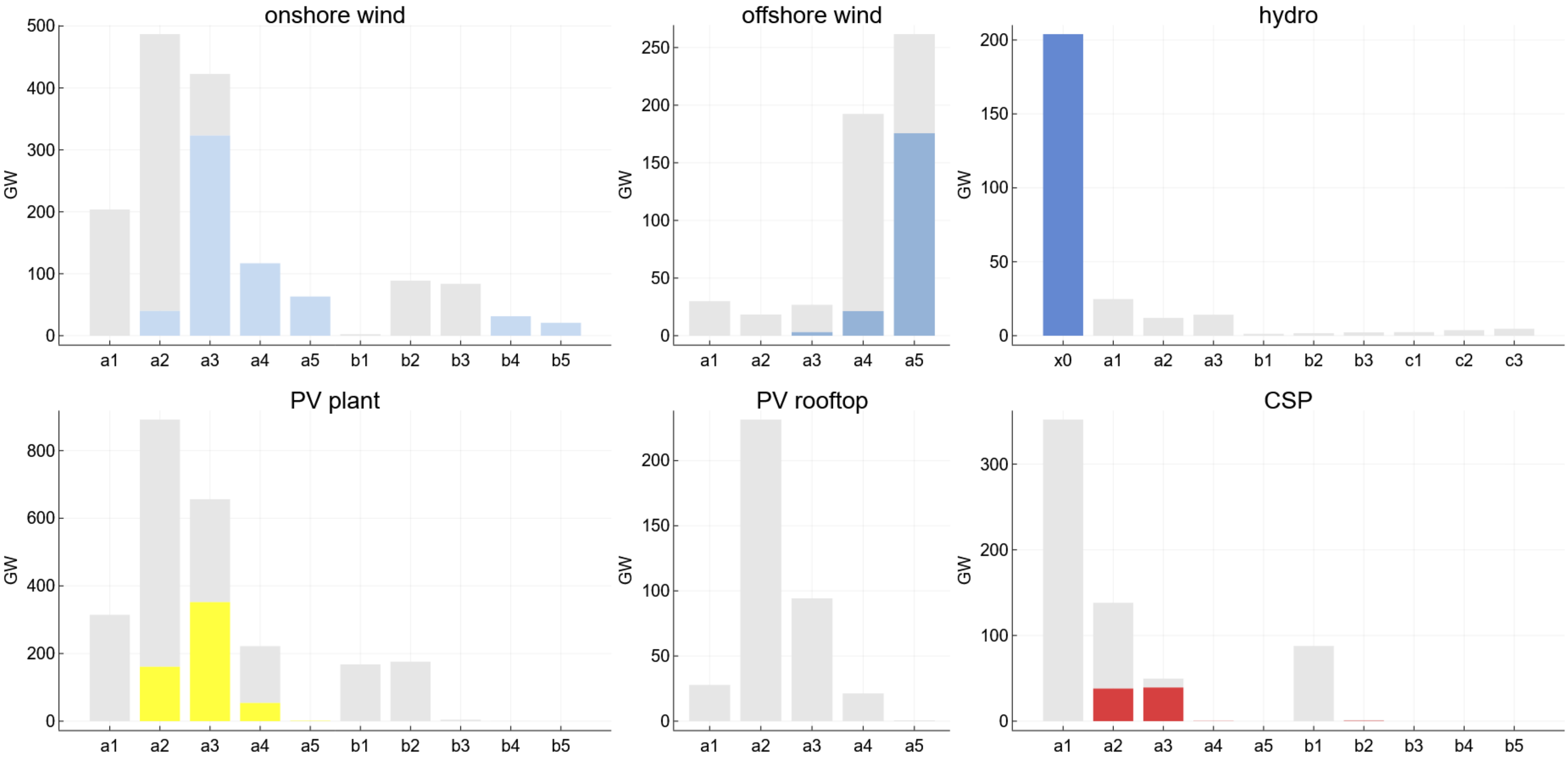
- rationale: we need hourly electricity demand for any world region – but hard to find outside of OECD
- assume annual (mean) demand known (based on SSP 2)
- use **gradient-boosted tree regression** to predict variations around the mean
- train the model on hourly demand data for 44 countries
- cross-validation: to predict demand in country X, use ***only*** data from other 43 countries

Independent variables for machine learning

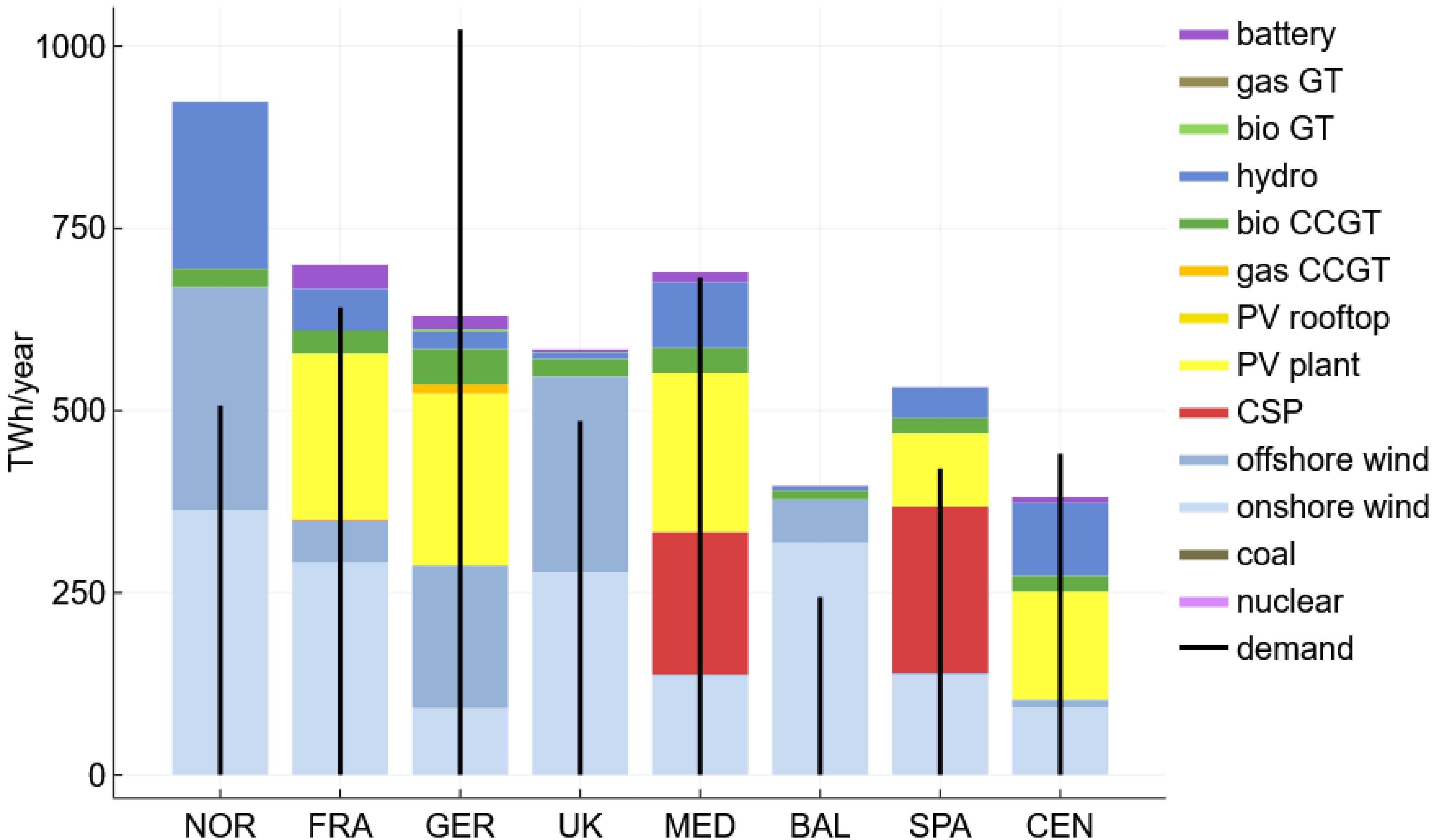
- Calendar variables
  - local hour of day, weekday/weekend
- Temperatures on different time scales
  - hourly average temperature of top 3 urban areas
  - average monthly temperature in the top urban area and temperature-ranked month of year (seasonal indicators)
  - annual mean, high and low temperature levels (variability indicators)
- Economic indicators
  - annual GDP per capita, annual electricity demand per capita
- ==> 10 variables in total

Renewable potentials (GW) in Europe

Results from GIS (gray) & energy model (colored)

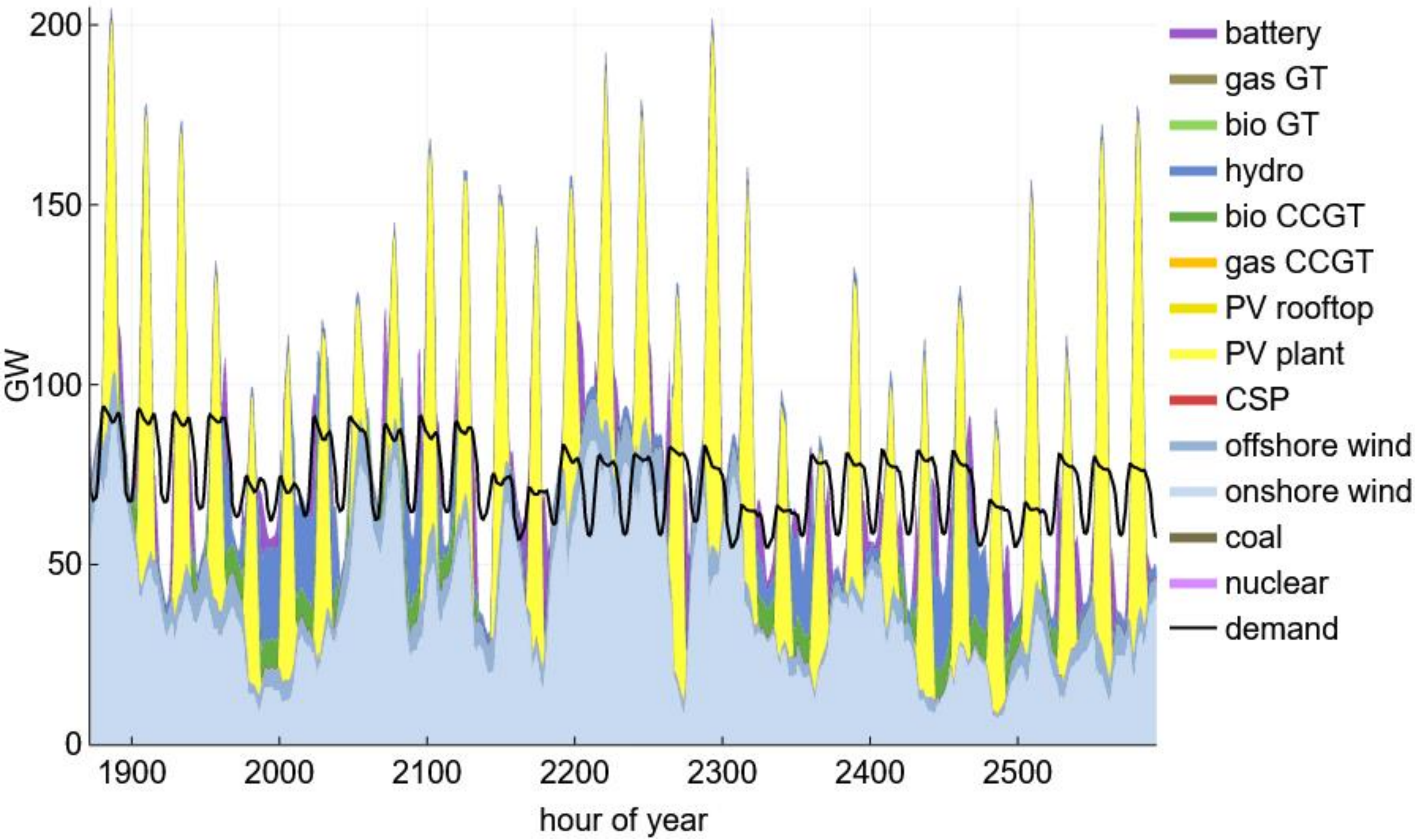


Electricity mix (Europe8)



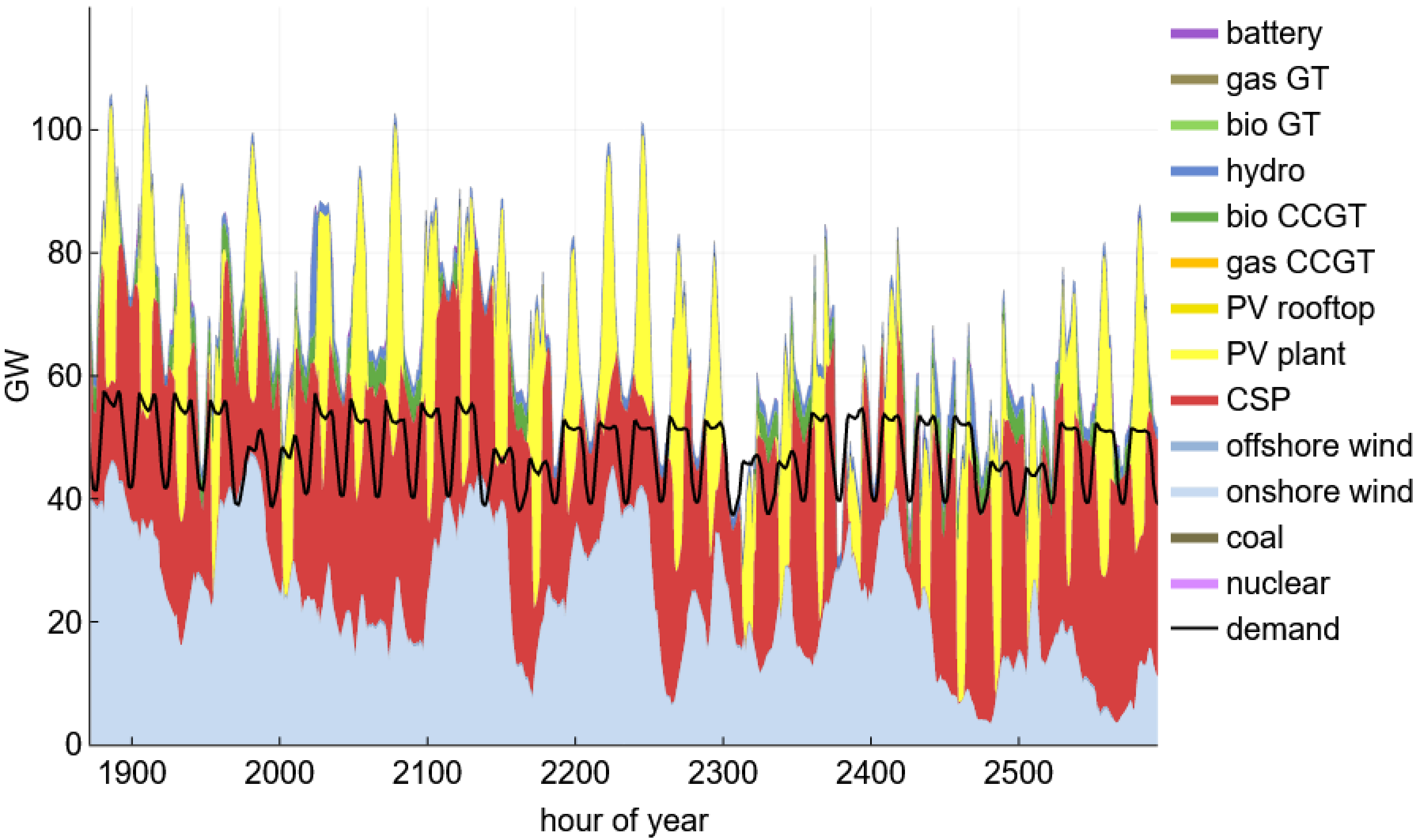
One month of electricity generation in France

Model results with renewables and demand based on GIS

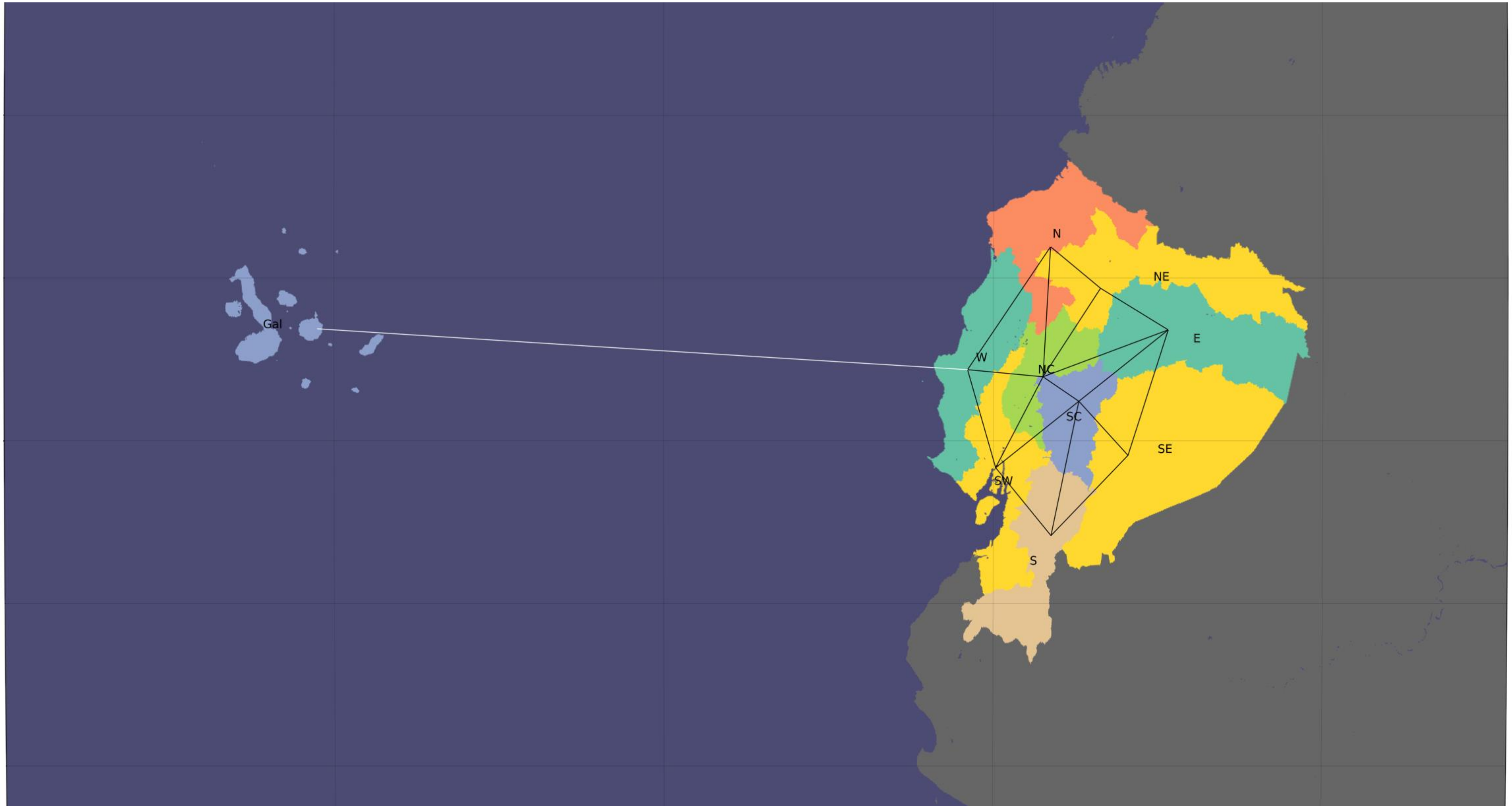


One month of electricity generation in Spain

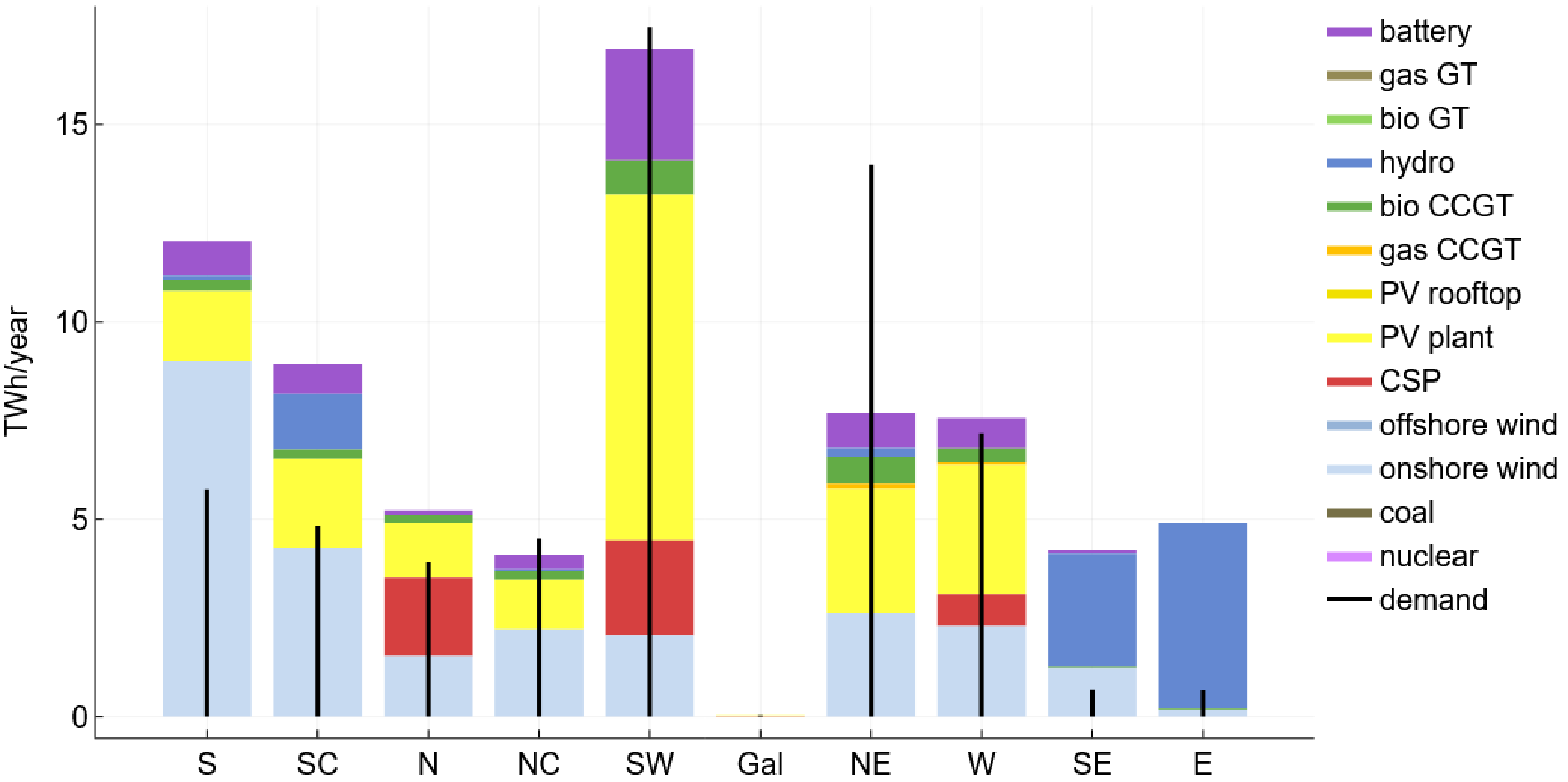
Model results with renewables and demand based on GIS



Ecuador10 (GADM borders)



Electricity mix (Ecuador10)



Thank you!

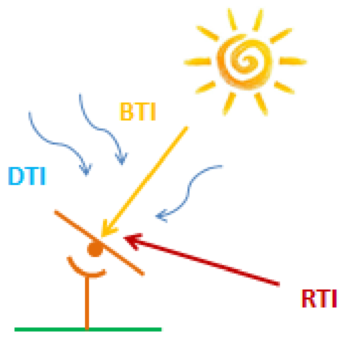
- Github repositories (package names may change):
  - https://github.com/niclasmattsson/GlobalEnergyGIS
  - https://github.com/niclasmattsson/Supergrid
- Online and usable now but not “officially” released yet.
  - README hopefully enough to get anyone started.
  - Need to clean up API, more extensive documentation, etc.
- Paper preprint and supplementary material
  - linked at the top of the GlobalEnergyGIS repo at Github
- Contact me
  - Niclas Mattsson: niclas.mattsson@chalmers.se

Extra slides

Preprocessing of solar variables

ERA5 variables --> output from solar PV & CSP

- Convert SSRD and FDIR --> Global Tilted Irradiance (GTI) and Direct Normal Irradiance (DNI)
- Need solar positions for every ERA5 grid cell and hour, and lots of trigonometry!



GTI = DTI + BTI + RTI

GTI: Global Tilted Irradiation
DTI: Diffuse Tilted Irradiation
BTI: Beam (or Direct) Tilted Irradiation
RTI: Reflected Tilted Irradiation

$$\mathrm{GTI} = I^{\mathrm{sun}}_{\mathrm{direct}} + I^{\mathrm{sky}}_{\mathrm{diffuse}} + I^{\mathrm{ground}}_{\mathrm{diffuse}}$$

$$I^{\mathrm{sun}}_{\mathrm{direct}} = \mathrm{FDIR} \cdot R_b = \mathrm{FDIR} \cdot \frac{\cos \mathrm{AOI}}{\cos z} = \mathrm{DNI} \cdot \cos \mathrm{AOI}$$

$$I^{\mathrm{sky}}_{\mathrm{diffuse}} = \mathrm{DHI} \cdot \mathrm{AI} \cdot R_b + \mathrm{DHI} \cdot (1 - \mathrm{AI}) \cdot \frac{1 + \cos \beta}{2}$$

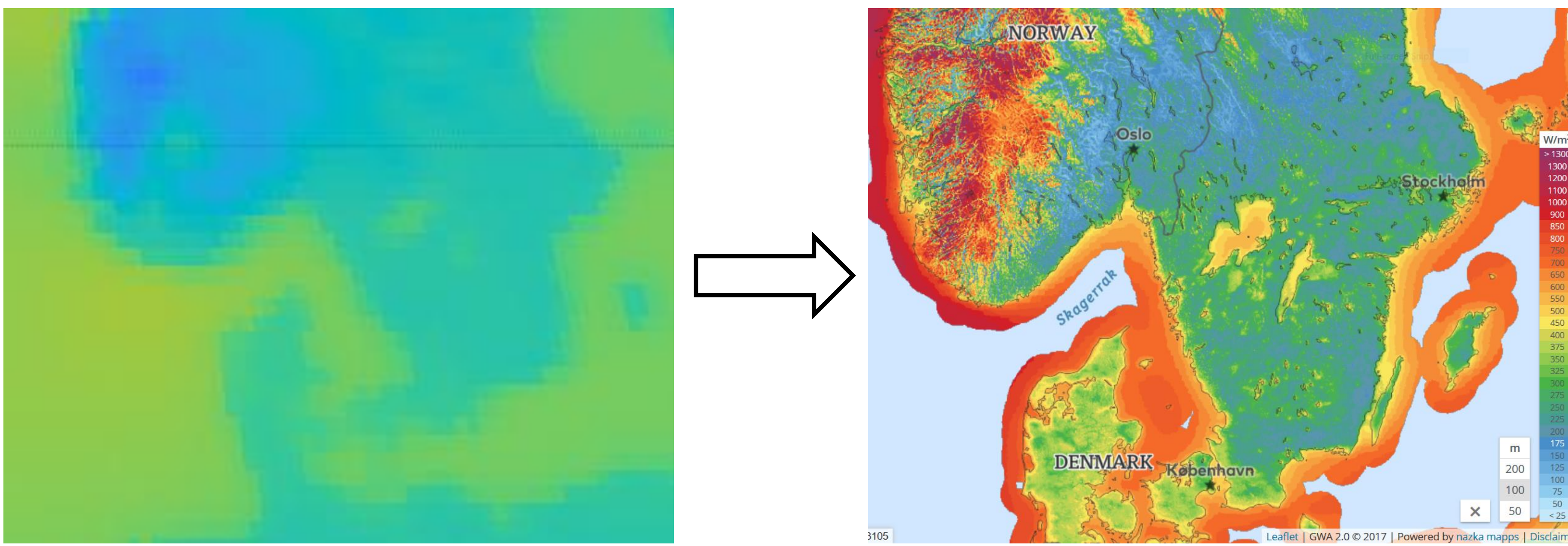
$$I^{\mathrm{ground}}_{\mathrm{diffuse}} = \mathrm{GHI} \cdot \rho \cdot \frac{1 - \cos \beta}{2}$$

$$\mathrm{DHI} = \mathrm{SSRD}, \quad \mathrm{DNI} = \frac{\mathrm{FDIR}}{\cos z}, \quad \mathrm{AI} = \frac{\mathrm{DNI}}{\mathrm{TOA}}, \quad R_b = \frac{\cos \mathrm{AOI}}{\cos z}$$

$$\cos \mathrm{AOI} = \cos z \cos \beta + \sin z \sin \beta \cos(\alpha_{\mathrm{sun}} - \alpha_{\mathrm{pv}})$$

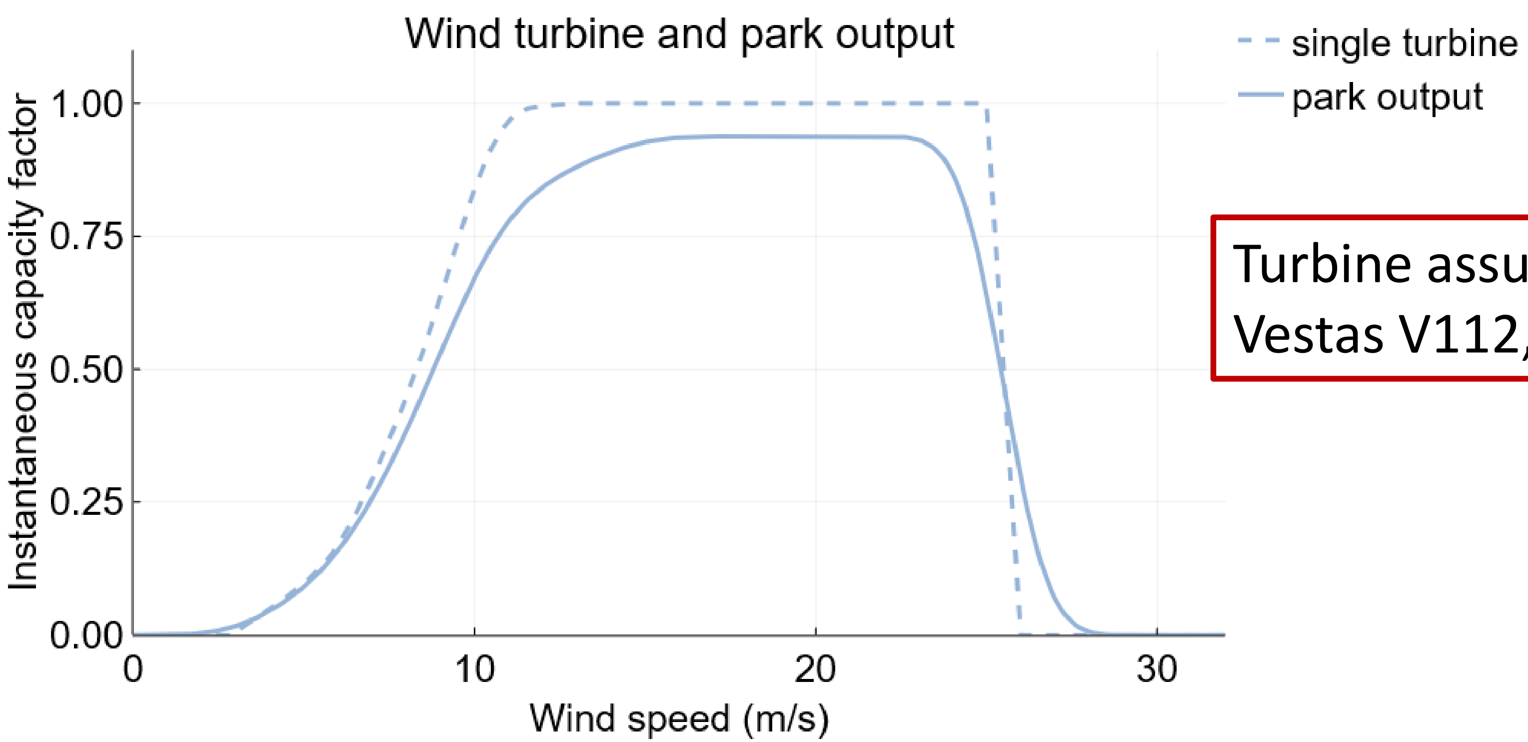
Extra step 1 for wind power

- Rescale ERA5 hourly wind speeds to match annual average speeds from Global Wind Atlas
  - GWA has 1 km resolution, but only average annual wind speeds (i.e. no time series)
  - based on a microscale model of how wind flow is influenced by land cover & topography (by IRENA and DTU)



Extra step 2 for wind power

- Turbine curve: wind speed => capacity factor
  - including wake losses in parks (i.e. turbine “shading”), electrical losses and smoothing of local wind variations

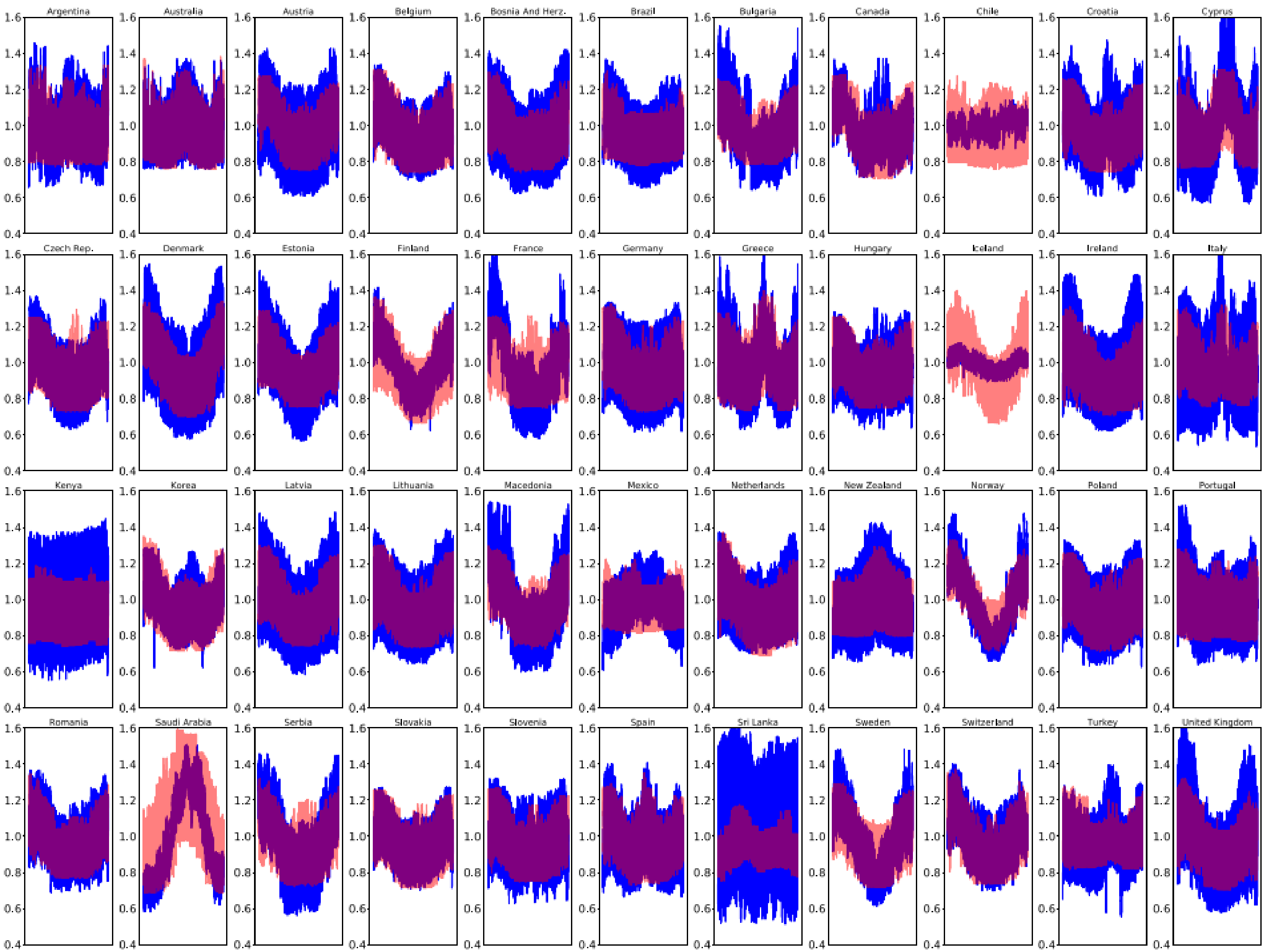


Turbine assumption:
Vestas V112, 3 MW

Machine learning model predicting variation: 1 year

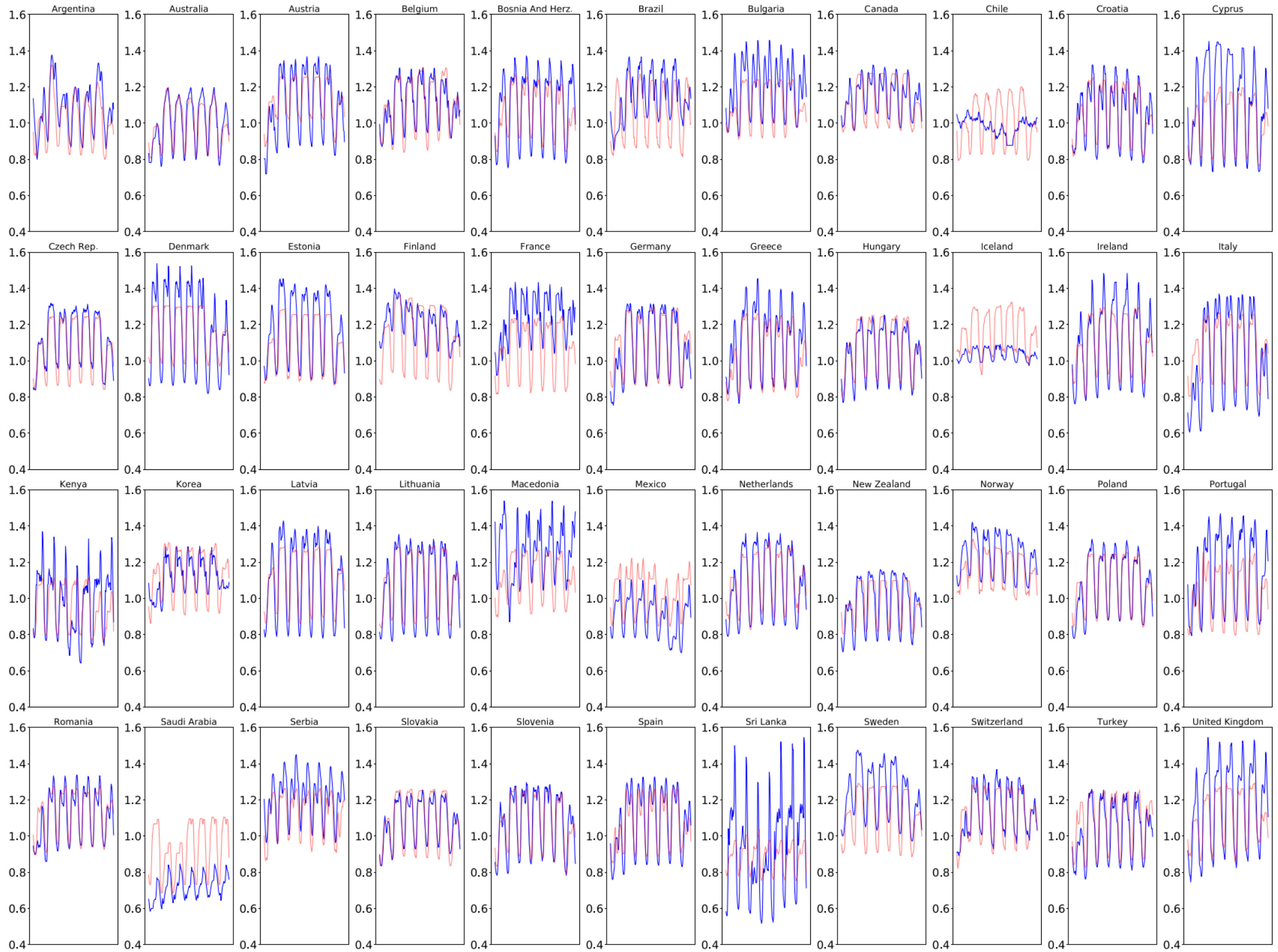
real data

prediction



Machine learning model predicting variation: 1 week in Jan

real data
prediction



GIS potentials

Max capacity (GW) for each region, technology and class

- Use auxiliary GIS datasets to filter allowed grid cells for solar/wind deployment:
  - land cover, population density, protected areas
  - topography (land elevation/ocean depth, distance to shore)
  - proxy for electricity access: gridded GDP >= threshold
  - all datasets have 0.01 degrees resolution (1 km at equator)
- Allocate each cell to class A1-A5 based on annual resource
- Big assumption: assume X % of remaining area available for solar plants/wind parks
  - currently 3% for solar PV, 5% for onshore wind, 33% offshore
- Potential (GW) = X% * pixel area * power density of park
  - Power density: 45 Wp/m^2 for PV, 5 Wp/m^2 for wind, 8 for offshore

GIS capacity factors

for each region, technology, class and hour

- Take acceptable land areas and resource class divisions as determined in previous step (potentials).
- Use reanalysis data to obtain average hourly capacity factors for each resource class and region
  - Two extra steps for wind power, see next slides.
- Aggregation of pixels (belonging to the same class)
  - E.g. hourly output of offshore wind in French Atlantic and French Mediterranean get averaged together into the same time series.
  - Implicit assumption: assume wind/solar parks are deployed uniformly within each resource class of each region
  - Alternatively, we could make additional classes for different subregions (to let the model optimize geographical smoothing).