Webservice support information

Summary

This document describes the support information and methodologies that were used to produce the results shown in the Clim2Power webservice. It helps the user better understand where the results come from and how they were produced.

You may skip to the part which interests you the most by clicking on the menu below:

Overview of the information explained:

1 Overall Methodological Approach

The Clim2power project created a pipeline of different models and analytical approaches that translate the climate data (seasonal forecasts and long-term climate projections) into indicators useful for end-users (**Erreur ! Source du renvoi introuvable.**).

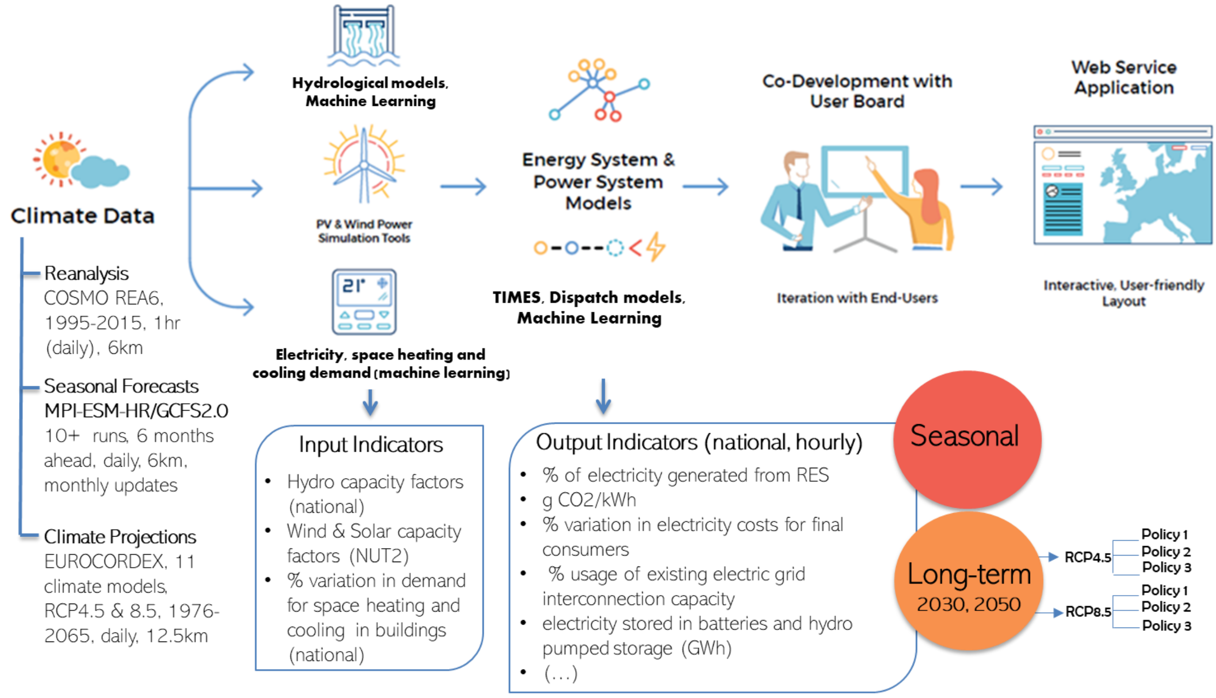

Figure 1 – Overview of the considered approach in Clim2power project

The project makes use of **seasonal climate forecasts** from GCFS - German Climate Forecast System, which are monthly updated and downscaled to 6km (complemented with a set of reanalysis for 1995-2015). The **long-term climate projections** are from EUROCORDEX for 11 climate models and two representative concentration pathways scenarios (RCP4.5 & 8.5) with a spatial resolution of 12.5km.

These are translated to timeseries of maximum **capacity factors for RES energy from hydro, wind power, and solar PV** using different approaches, namely machine learning and statistical methods. This information is aggregated per NUT2 regions of Europe (circa 263) and for 96 maritime regions.

The **impact of temperature on the demand for heating and cooling** (and electricity) is estimated using a machine learning approach.

Finally, **energy system and power models** are used to produce the Clim2power output indicators. For the long-term analysis, a new bottom-up optimisation eTIMES-EU energy system model (Loulou and Labriet, 2008) was used. Because TIMES models are mainly adequate to support decision and investments (e.g. more adequate for long-term climate projections), the seasonal analysis was made with the dispatch model DISPA-SET (Quoilin et al., 2016) to assess the optimal operation of electricity generation at seasonal level. Typical results from both these models are: installed capacity, generation portfolio, electricity prices and CO_2 emissions, among other.

All components are integrated in a **web-service application** inspired by (Ranchin, n.d.). Development is founded on an iterative stakeholder-guided approach, closely integrating target markets in the development process, in line with (Giannini et al., 2016; Lourenco et al., 2015; Reinecke, 2015).

2 Climate data

2.1 Seasonal forecasts

2.1.1 Climate forecasts

Within Clim2Power we use climate forecasts to predict anomalies in meteorological variables for the upcoming months.

To do so, the German Climate Forecast System (GCFS2.0) is run, it is based on the Earth system model of the Max Planck Institute for Meteorology (MPI-ESM-HR, Müller et al. (2018)). The model has different components (see Fig. 1). The atmosphere is coupled with land, ocean and sea-ice. This configuration results in a spatial resolution of ~100 km.

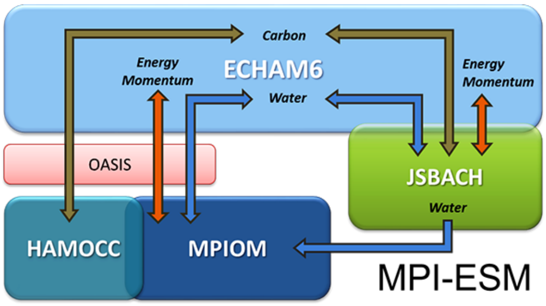

Figure 2: Earth system model MPI-ESM. The atmosphere (ECHAM6) is coupled to the ocean (MPIOM) and sea ice. Land-vegetation is represented by JSBACH, bio-geochemical processes by HAMOCC (Source: MPI-M).

Climate forecasts are being initialized with the observed state of the Earth system, which is realized by performing a so-called assimilation run. Beside this, an ensemble of possible initial conditions is generated: In the atmosphere, a parameter in the uppermost atmospheric layer responsible for the air diffusion is disturbed to create different solutions. In the ocean, so-called bred vectors lead to the growth of the most unstable mode of the temperature and salinity fields over the whole ocean depth, which are then applied as disturbances to the assimilated climate conditions. For details of GCFS2.0, also see:

https://www.dwd.de/DE/leistungen/jahreszeitenvorhersage/jahreszeitenvorhersage_start.html

2.1.2 Clim2Power downscaling approaches

Within Clim2Power, two different methods are used to generate seasonal forecasts on a high-resolution grid. Spatially highly resolved data is incessant for the hydrological modelling of river basins. A flow chart of the downscaling procedures can be seen in Fig. 3. As a first step, a pure remapping to the COSMO-REA6 grid (~ 6km) took place for the whole of Europe. For precipitation, we chose an area conserving interpolation method, all other variables were bilinearly interpolated to the target grid. For all temperature related variables, a height correction was applied in addition.

Beside this, a statistical downscaling method (EPISODES, Kreienkamp et al. (2018)) was applied for the case study regions in Germany-Austria (Danube) and Portugal (Duoro). A local reference data set (here: COSMO-REA6 European reanalysis) is used to retrieve the high-resolution information. EPISODES takes the large-scale circulation of the forecast and searches for analogue days in an historical archive. Based on those data points, a linear regression between predictor and predictand is performed. To translate the results to the highly resolved grid, a weather generator is applied.

The resulting data of both methods is converted to a CMOR (Climate Model Output Rewriter) data structure and transferred to DWD's ESGF node.

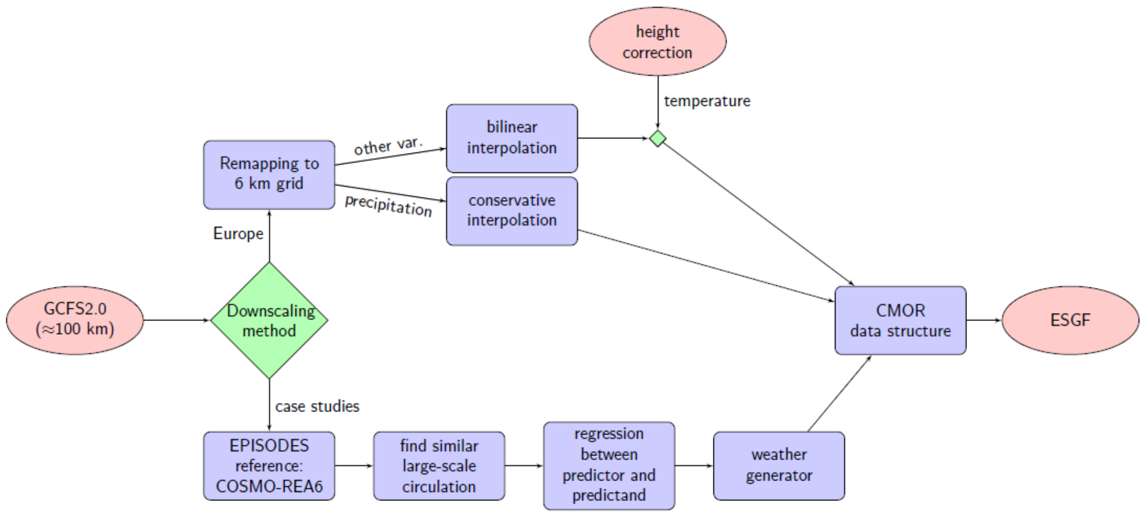

Figure 3: Downscaling of the seasonal forecasts in the Clim2Power project. For the European case study we use a simple remapping procedure, for the case studies in Austria and Portugal, a statistical downscaling method (EPISODES) is applied. All output is converted to a common data structure (CMOR) and delivered via ESGF.

2.1.3 Evaluating skill of the forecasts

An approach to measure how well a model performs is to run it for the past and compare the results to observations (or reanalyses). GCFS2.0 was run in this so-called hindcast mode from 1990-2017 for every start month. In Clim2Power, we analyse start months February, May, August and November, corresponding to the four seasons of a year. For the evaluation of the forecasts, we use the COSMO-REA6 regional reanalysis, which is available from 1995-2018 (Bollmeyer et al. 2015).

Seasonal forecasts should always be considered as deviations from a climatological mean state. According to this, we analyse the correlations of the anomalies the model predicted versus the observed anomalies. As a measure for that, we use the Anomaly Correlation Coefficient (ACC). Fig. 4 shows as an example ACC values for the remapping data set over Europe and the statistically downscaled seasonal forecasts over Portugal and the German-Austrian region of the variable temperature at surface. ACC depends on start month and region as well as on lead time and variable. In the specific case shown (Fig. 4, middle panel), GCFS2.0 forecasts for late spring temperature performed well in central Europe but poorly over western Europe. This is highlighted as well in the downscaled forecasts (Fig. 4, left and right). While the skill does not change, the structures are better resolved, as seen for Germany (Fig.3 right).

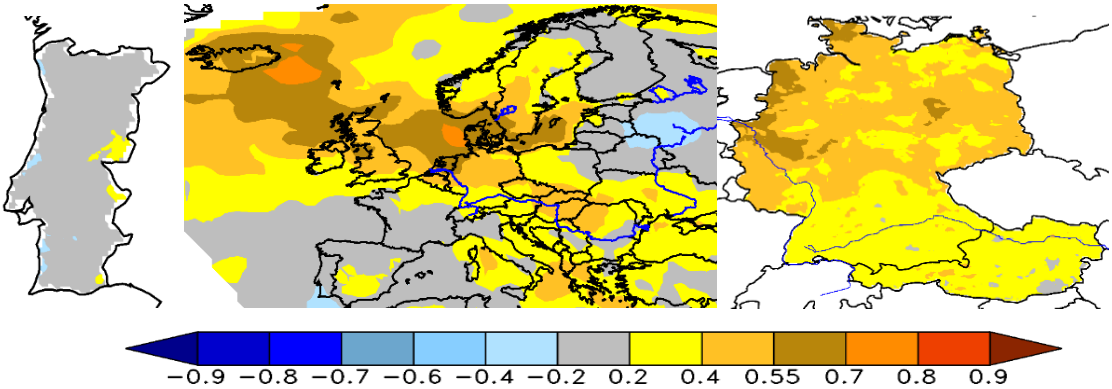

Figure 4: For evaluation of the model, seasonal forecasts were run for the past ("hindcasts"). The displayed Anomaly Correlation Coefficient (ACC) states, how well the forecasts performed compared to observations (here: COSMO-REA6 reanalysis). Shown are the hindcasts of start month February with month 3-5 analysed. The left and the right panel show the results of the statistical downscaling for Portugal (left) and Germany-Austria (right). The panel in the middle shows ACC for the remapped data instead.

2.2 Climate projections

In terms of climate projections data, sixteen combinations of global and regional climate models (respectively GCM and RCM) were explored using simulations made available by the World Climate Research Programme's CORDEX initiative (www.euro-cordex.net). Further information on EURO-CORDEX can be found in. e.g. (Giorgi et al., 2009; Jacob et al., 2014). The spatial scale of the simulations available is 0.11° (around 12.5 km) and 0.44° (around 50 km). Nevertheless, the latter was disregarded taking into account the recognised added value of the higher-resolution dataset (EUR-11) regarding the local-scale climate features of the studied areas. Out of the whole GCM–RCM combinations, some were not available for all the selected variables and scenarios. For selecting the RCMs to be studied, the full set of RCMs was analysed over the Europe domain, in such a way that models with a lower degree of satisfaction simulating the climate of our study regions could be excluded (Carvalho et al., 2019). From the models that perform adequately, a subset of 11 was identified such that each RCM is as "independent" as possible from the other RCMs as in Table 1.

Table 1 – List of climate models generating the climate projections and scenarios used

Regional Climate Model	Driving GCM (Global Climate Model)	Short name	Short code
CLMcom-CCLM4-8-17	CNRM-CERFACS-**CNRM-CM5**	**CLM_CNRM-CM5**	A45. A85
CLMcom-CCLM4-8-17	ICHEC-**EC-EARTH**	**CLM_EC-EARTH**	B45. B85
SMHI-RCA4	ICHEC-**EC-EARTH**	**SMHI_EC-EARTH**	C45. C85
DMI-HIRHAM5	ICHEC-**EC-EARTH**	**DMI_EC-EARTH**	D45. D85
KNMI-RACMO22E	ICHEC-**EC-EARTH**	**KNMI_EC-EARTH**	E45. E85
IPSL-INERIS-WRF331F	IPSL-IPSL-**CM5A-MR**	**IPSL_CM5A-MR**	F45. F85
SMHI-RCA4	IPSL-IPSL-**CM5A-MR**	**SMHI_CM5A-MR**	G45. G85
KNMI-RACMO22E	MOHC-**HadGEM2-ES**	**KNMI_HadGEM2-ES**	H45. H85
SMHI-RCA4	MOHC-**HadGEM2-ES**	**SMHI_HadGEM2-ES**	I45. I85
MPI-CSC-REMO2009	MPI-M-**MPI-ESM-LR**	**MPI_MPI-ESM-LR**	J45. J85
DMI-HIRHAM5	NCC-**NorESM1-M**	**DMI_NorESM1-M**	L45. L85

Moreover, each of these combinations corresponds in fact to two climate RCP scenarios, namely RCP4.5 and RCP8.5, hereafter mentioned as a combination of the individual letter for each model combination and 45 or 85. While the combinations agree on the overall mean climatology. differences can be pronounced over local regions, and different variables can respond differently (see Figure 5 for precipitation anomalies over Europe for all 11 climate models combinations available in EURO-CORDEX). Although averaging across different climate models is quite common, this is difficult to interpret and might lead to misleading and physically meaningless results. In particular, averaging models may cause effects of smoothing the spatially heterogeneous patterns of climate variability across Europe, as well as their temporal variability.

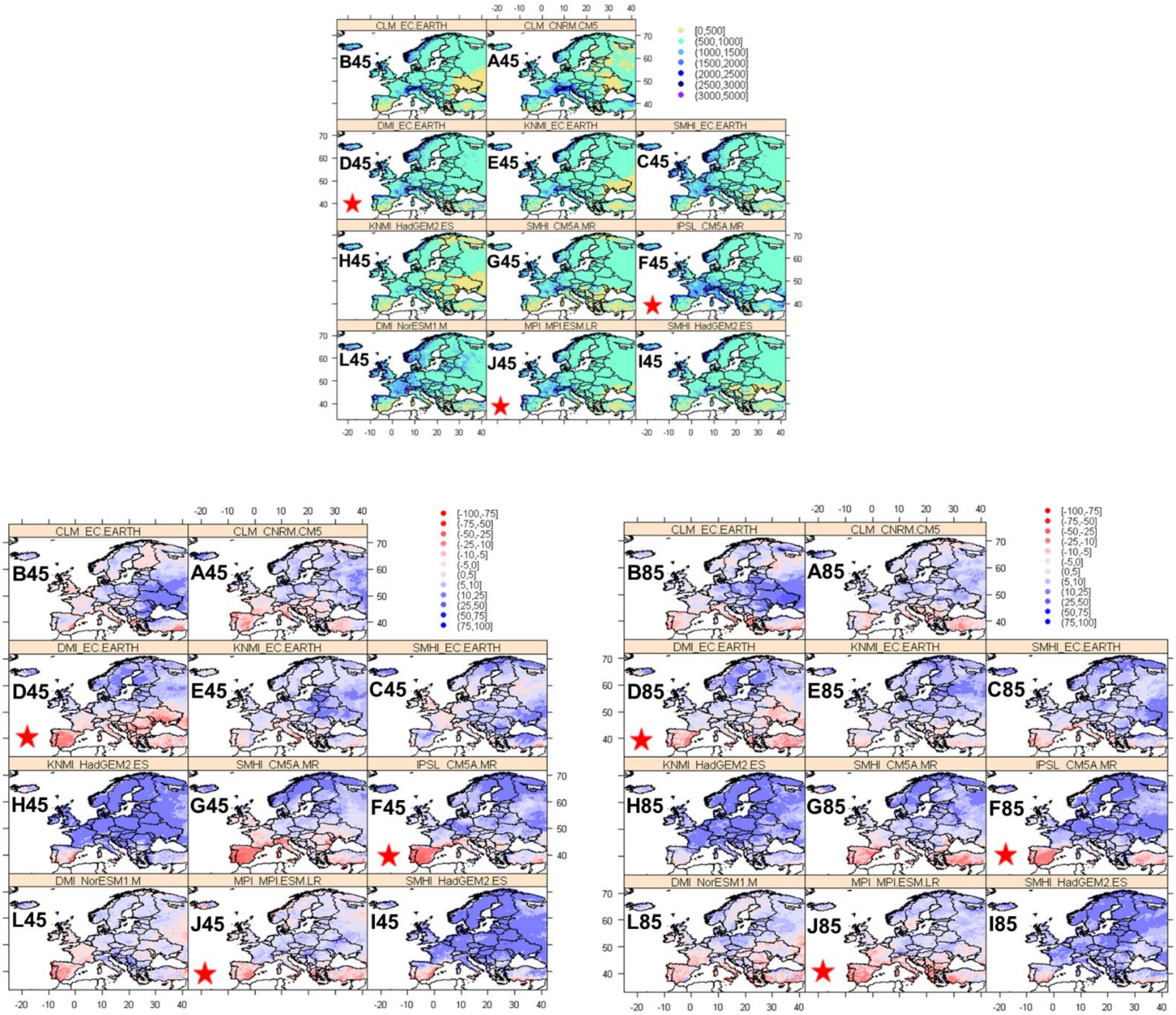

Figure 5 - Annual mean precipitation (mm) for the historical period (1976-2005) (upper figure) and anomalies (%) for the near future (2016-2045) based on 11 selected GCM–RCM combinations under RCP4.5 (bottom left figure) and 8.5 (bottom right figure).

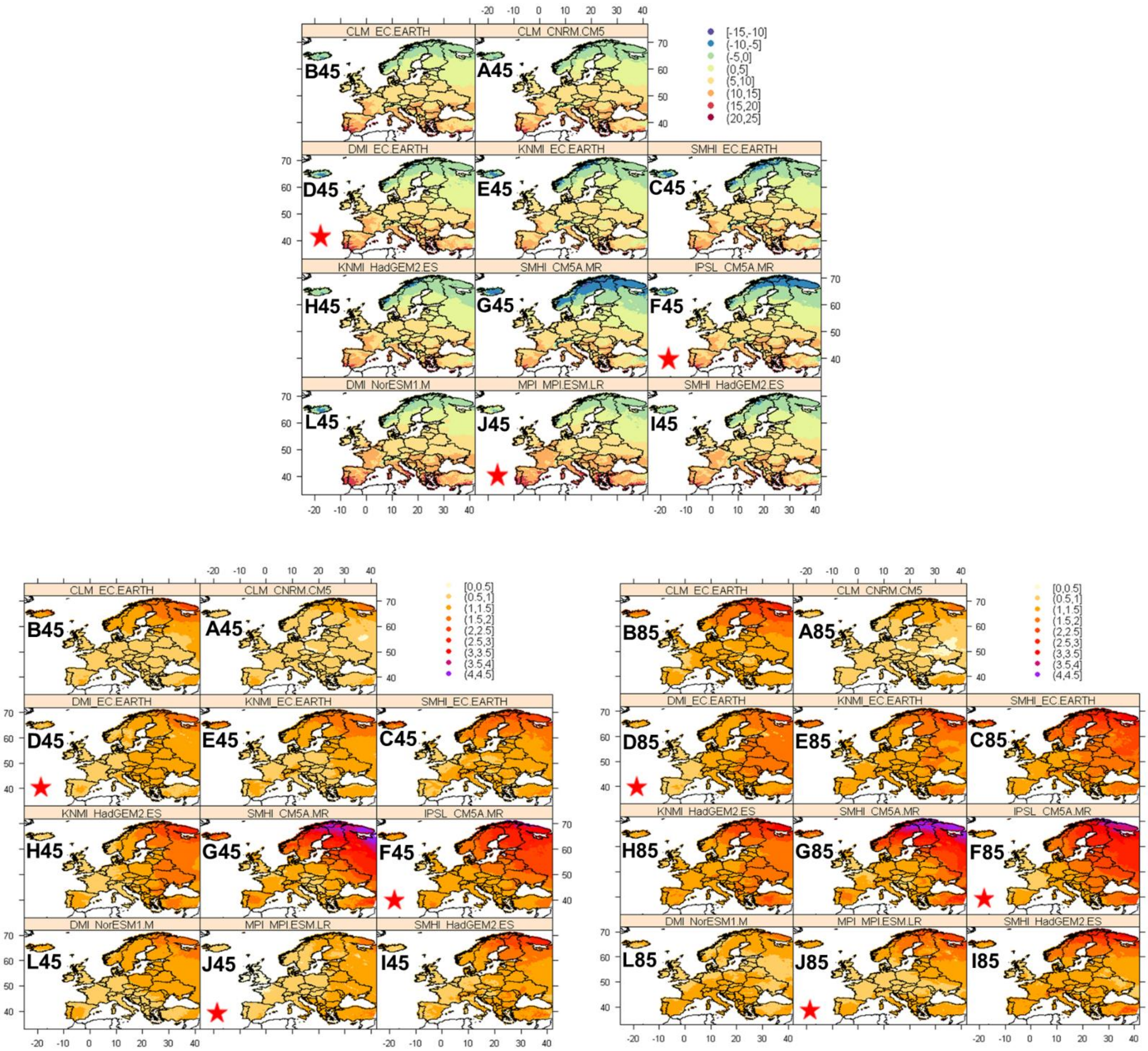

Figure 6 - Annual mean temperatures (ºC) for the historical period (1976-2005) (upper figure) and anomalies (%) for the near future (2016-2045) based on 11 selected GCM–RCM combinations under RCP4.5 (bottom left figure) and 8.5 (bottom right figure). The climate projections considered in this paper are signalled with a star symbol.

One of the key aspects considered in this dataset preparation was the model time horizons (near future and mid-century), as well as spatial dimensions. A forecast can be assessed regarding the future projections (e.g. hotter or colder than average season in the future) and looking at how that relates to the conditions in the past. The choice of spatial resolution may depend on the issue and variables being addressed. For example, too little resolution can fail to capture the small-scale variability of orographic precipitation, whereas too much resolution can cause the model to become computationally impracticable. A spatial scale of 0.11° (around 12.5 km) was expected to adequately fit the requirements of this research. However, at this stage the 0.11° scale was found too large for eTIMES-EU. The uncertainty associated with spatial scale should though be kept in perspective given other uncertainties affecting climate projections.

It is important to mention that climate projections are not an estimation of the year-to-year or season-to-season climate variables. Instead, they are estimations of the average conditions over decades. The 11 GCM-RCM combinations (i.e. 22 climate projections) considered are identified in Figure 5 and Figure 6 regarding precipitation and temperature anomalies for the near-future when compared with the historic time-series of 1976-2005. It becomes clear that they represent different possible future trends regarding climate evolution, from having a drier Portugal with less 50% precipitation (e.g. F45 scenario), or no change from the past (e.g. J45) or even an increase up to 20% of precipitation in the north of the country (e.g. H45). Indeed, despite the updated and detailed information on climate projections estimated from GCMs/RCMs, considerable uncertainties are involved, either resulting from the unknown future evolution of GHG concentrations and other forcing agents of the climate system, as well as climate model simplifications of the chaotic behaviour of the climate system (Knutti and Sedláček, 2013; Prein and Gobiet, 2017; Stocker et al., 2013).

3 Translating climate data into capacity factors

3.1 Solar and wind capacity factors

For the calculation of solar PV capacity factors (or CF) the model f_{PV} developed in ECEM project (Saint-Drenan et al., 2018) was used. In this approach, the cumulated PV power generation of every plant included in a raster cell is evaluated as a function of the known meteorological parameters by means of a physical approach. The total PV power generated in an area is estimated as the weighted sum of the values of the PV power generation obtained for different parameter sets A_i:

$$P_{PV}(x.t) = \sum_{i=1}^{n} w_i \, f_{PV}(x.t.\mathrm{GHI}\,(x.t).\mathrm{Tamb}(x.t).A_i) \quad (1)$$

Where

P_{pv}(x.t) is an estimate of the power produced at time t by all PV plants located at x [W/W_p]

GHI (x.t) is the global horizontal irradiance at time t and location x [W/m^2]

Tamb(x.t) is the air temperature at time t and location x [°C]

f_{PV}(…) is a function representing the PV model used to calculate the normalized PV power [W/W_p]

A_i represents the set of plant parameters needed by the PV model

w_i is the probability of occurrence of a parameter set A_i

In Eq. 1, the parameter set Ai represents the input parameters of a model f_{PV} accounting for the characteristics of a PV plant (e.g. module orientation angles. temperature coefficient). A single PV power calculation is thus conducted for each configuration. The total PV power is then obtained by a weighted sum of the power value evaluated for each configuration. the weights being the share of plants with a configuration set A_i in the total capacity.

As detailed in (Saint-Drenan et al., 2018), the PV system model is chosen to best compromise between a limited number of unknown and a good accuracy. To this end, state of the art models have been selected in the literature and the less important parameters set to representative values. The parameters Ai has been selected using a parameterisation depending on the geographically varying optimal tilt angle.

For wind CF (onshore and offshore), a similar approach to that adopted in the NINJA (Pfenninger and Staffell, 2016), EMHIRES (Gonzalez Aparicio et al., 2016) and ECEM projects has been used. The power production of each turbine installed in Europa has been calculated based on information provided by thewinpower.net database and model wind speed. The wind curve has been generated using the approach described in (Saint-Drenan et al., 2019). Finally, attention has been paid in choosing a model setup allowing a fast calculation. This has been achieved by using a LUT approach. More information on this approach can be found in (Saint-Drenan, 2019).

These wind and solar PV capacity factors are then aggregated per NUT2 regions of Europe (circa 263) and, for the case of wind offshore, 96 maritime regions (obtained by intersecting the International Hydrographic Organization sea limits and Exclusive Economic Zones areas) as in Figure 7. The consideration of maritime region for the spatial aggregation of RES time series has been made to include offshore wind energy. The definition of these areas has been jointly developed in the C2P and C3S energy projects.

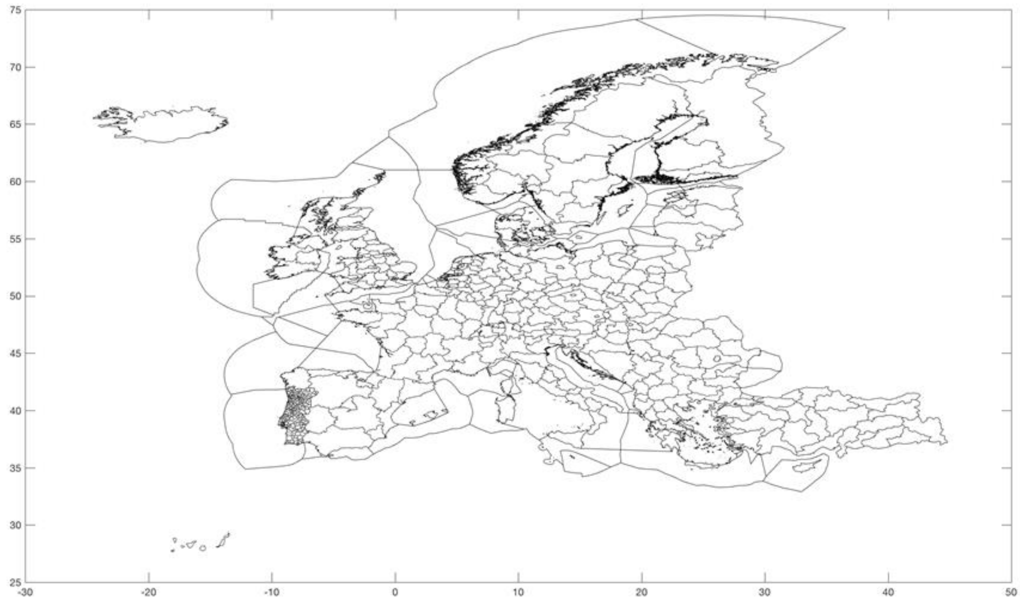

Figure 7 – Spatial disaggregation of the wind and PV capacity factors at NUT2 regions

3.2 Hydropower capacity factors

To translate climate data into potential hydropower production at the country level, machine learning (ML) techniques were used. The workflow of ML procedure is given in Figure 8.

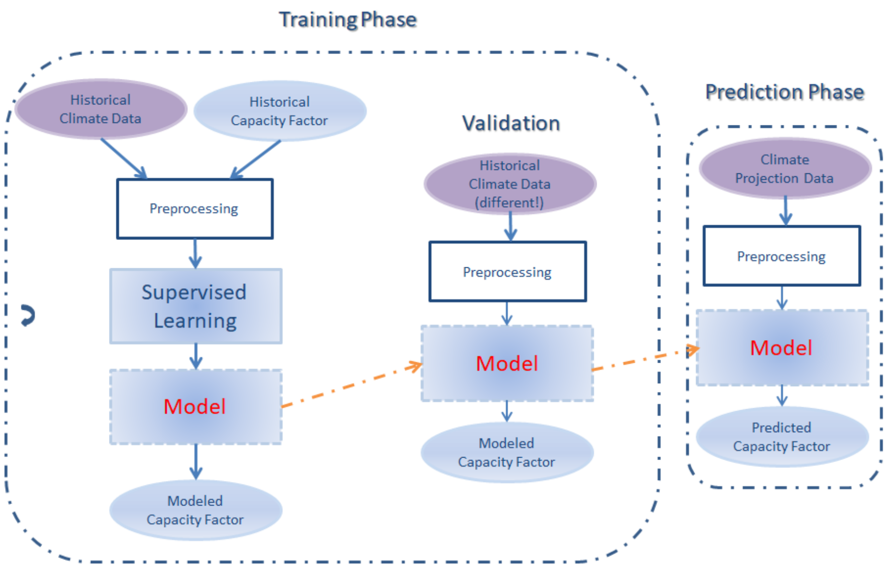

Figure 8: Machine learning workflow

The procedure starts by training a so-called (supervised) learner with a set of data including the observed outcome and feature measurements. This leads to building a prediction model, which enables predicting the unobserved outcome based on a different set of input features. A good learner is one that accurately predicts this outcome. In the statistical literature, the features are often called the predictors or the inputs, whereas the outcomes are called the responses or the outputs.

In the case of the present project, the main input features are the daily time series of air temperature and precipitation aggregated at NUTS2 level. We build two different models: one to be used for the prediction of the daily national run-of-river hydropower (HRoR) CF and one dedicated to the prediction of the reservoir-based hydropower (HRes) CF.

For the training and validation phases of the ML models, observed climate and energy data are required. In particular,

- climate data include the daily time series of precipitation and air temperature remapped to the 6 km COSMO-REA grid. Reanalysis climate data covering the period 1995-2019 are provided by one of the Clim2Power partners, Deutscher Wetterdienst (DWD) (DWD, 2019). Moreover, in order to take into account the temporal delay between the meteorological event and the corresponding hydropower production, suitable temporal shifts applied to the time series of precipitation and air temperature were also considered;
- historical data of hydropower production aggregated at a country level are from the ENTSO-E Transparency Platform (ENTSO-E, 2019), where energy generation data are systematically collected at hourly time resolution starting from 1 January 2015 to the current days.

Moreover, for building the model of the HRoR, we also include the daily national load. This choice is due to the fact that many HRoR plants are located downstream of Res plants, which largely affect the river flow and, consequently, the generation in the HRoR plants. Instead, for building the model of the HRes, we include the daily time-series of the national Residual Load Curve (RLC) which is computed by subtracting from the demand, the values of hydro, PV, and wind power. This choice is related to the fact that HRes plants are activated for meeting peak demand situations, as they are more responsive than other generation sources and can be started or stopped within a very short time.

In order to select the ML technique that provides the best performance, five well-established ML algorithms were tested: Linear Regressor, Support Vector Machine, Boosted Ensemble of Trees, Random Forests (RF) and Artificial Neural Networks (ANN) (Hastie et al., 2009). The first four regression methods were implemented in the Statistics and Machine Learning Toolbox 11.4, while the ANN was in the Deep Learning Toolbox 12.0 in MATLAB® R2018b.

In the validation phase, the output model (HRoR CF or HRES CF) was compared with observed data and the performance of the five algorithms was measured in terms of correlation coefficient, adjusted coefficient of determination, mean absolute and mean square percentage errors. This comparison indicated that the models based on Random Forests (RF) exhibit the best performance (e.g. correlation coefficient in the validation phase equal to 0.86 for France, 0.90 for Portugal and 0.95 for Spain).

Once a model has been trained and validated, it can be used to perform a prediction of the response; this is the ‘prediction phase’ in the scheme in Figure 8. At this aim, we feed our model with the seasonal predictions (resp., the long-term projections) of all the required predictors. This allows us to obtain the seasonal predictions (resp., the long-term projections) of the hydropower CF.

It is important to mention that even if ML does not require numerous diverse inputs for building an approximate model between climate variables and hydropower, on the other hand, a large quantity of historical observed data would be necessary for opportunely training the learners and improve the model accuracy and response to extreme events. Although the historical dataset at our disposal is relatively small, our models are able, in general, to reproduce the climate impact on the hydroelectricity production, although some extreme events are still difficult to be predicted. Nevertheless, we are confident that the validity of our approach still holds, and it will improve with the increase of historical data.

3.3 Impact of temperature in demand

The impact of future temperatures on the demand for electricity was computed at country level and for each long-term time-series of climate variables also using machine learning techniques. Hourly demands were estimated using a two-stage approach: (i) quantifying structural changes expressed as the percentage of demand allocated to each time step and (ii) applying these structural changes to exogenously specified future demands in a second stage (Figure 9).

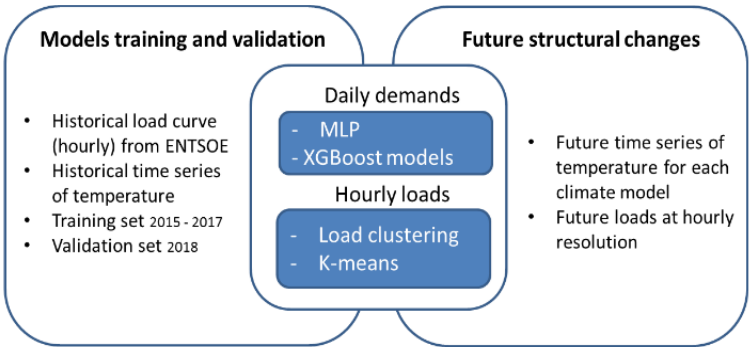

Figure 9 - Structural change model

Figure 9 describes the methodological approach used to estimate climate induced structural changes in the load curve of electricity demand for each country. Based on historical temperature time series and hourly load values from ENTSO-E, was firstly built an estimator of future daily demands using two ML techniques: neural networks and XGBoost (Chen and Guestrin, 2016) using 2015, 2016 and 2017 data for model training and 2018 data for the test.

To obtain hourly load curves, was used a load profiling approach to identifying typical load curves for each season, weekday and holidays. The K-means algorithm (Jin and Han, 2010) was used as classifier to define a set of clusters explaining more than 90% of the variance. Each load profile is described by the hourly % of the average daily load. Applying the model to the future times-series provided by each climate model, it is possible to compute hourly structural changes per country for each consistent climate scenario. Figure 10 shows the results for the countries of FR, PT, SE and DE. The approach finds the number of load patterns that captures the way electricity is consumed at daily level. In Figure 10 each line is a cluster that describes one representative load profile for the considered country. The number of clusters depends on the number of profiles needed to explain most of the variance.

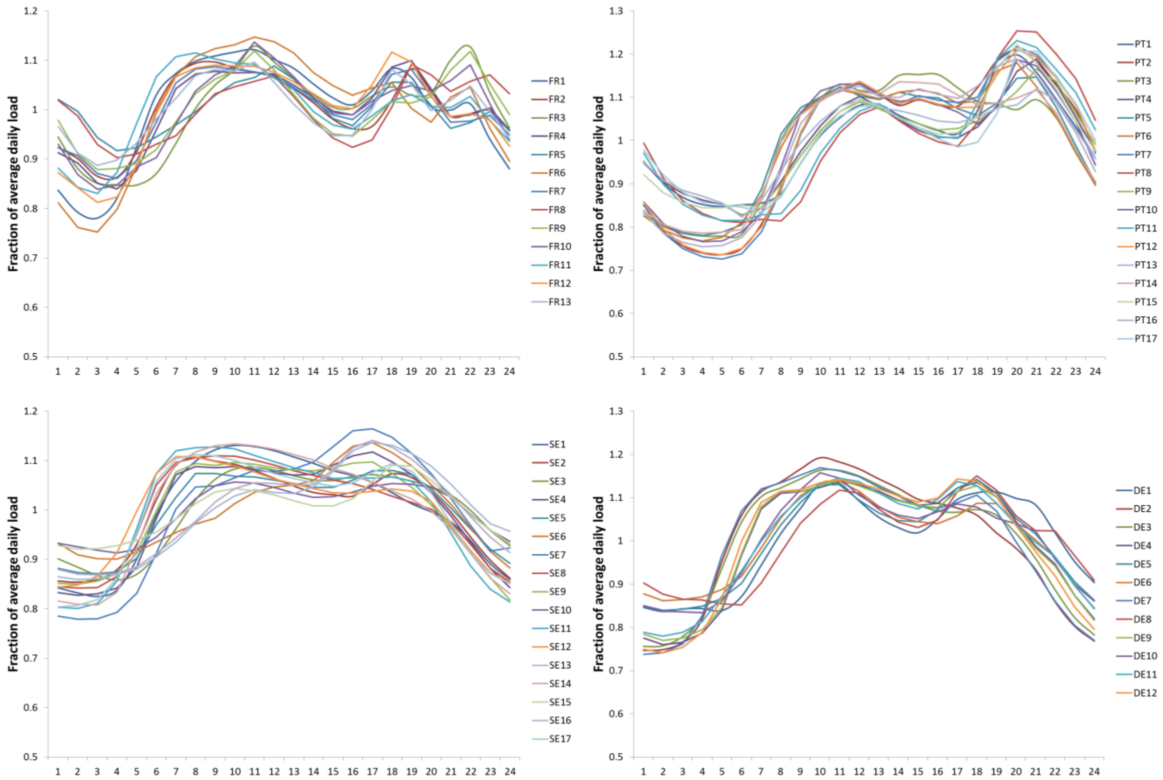

Figure 10 - Hourly load profile clusters for 4 countries: FR. PT. SE. DE

It should be noted that by using models trained on past data, this approach of structural changes assumes that observed temperature dependencies can provide meaningful information for the future. This assumption ignores the possible future changes in the role of electricity for heating and cooling, which could occur due to higher deployment of electric heat pumps and/or electric vehicles. Basically, these hourly load profiles can have a different shape in 2030 and 2050. To somewhat reduce the effect of this assumption, structural changes were applied to the projected demand of the EU Reference scenario considering the effect of electric vehicle's electricity demand. The structural allocation of the electric vehicle demand is the same across all the scenarios and corresponds to the dynamic management of the charging for the "Crescendo" scenario (RTE, 2019).

4 Output indicators

4.1 Seasonal results – DISPA-SET model

The hourly power demand and capacity factors for solar, wind and hydropower were input into a Dispa-SET model developed for the whole of Europe. Dispa-SET is an open-source unit commitment and optimal dispatch model suited to study the balancing of European power grids. Dispa-SET is mainly developed within the Joint Research Centre of the EU Commission, in close collaboration with the University of Liège and the KU Leuven (Belgium). More information on the model can be obtained here: http://www.dispaset.eu/en/latest/.

The model results include dispatched power, the shedded load and the curtailed power generation. The binary variables are the commitment status of each unit. The model considers minimum and maximum power for each unit; power plant constraints as minimum power, ramping limits, Minimum up/down times, start-up, no-load costs; curtailment; pumped-hydro storage and the functioning of non-dispatchable units (e.g. wind turbines, solar PV, run-of-river, etc.), among other. In Clim2power special attention was paid to integrated mid-term scheduling and short-term optimal dispatch considering the available seasonal forecasts.

Within Clim2power Dispa-SET was calibrated for the whole of Europe and each individual country for the year of 2019, using ENTSO-E data. The seasonal analysis results are obtained for each country in Europe for each of the seasonal forecasts considered.

4.2 Long-term Results - eTIMES-EU model

The maximum possible CF and impacts on demand were input into a bottom-up optimisation TIMES energy system model (Loulou and Labriet, 2008). A new TIMES model was developed in Clim2power for the whole of EU covering only the power sector (eTIMES-EU) which, as for any TIMES family models, has intertemporal optimization, and minimizes the total discounted cost. eTIMES-EU has 29 regions, representing all countries in continental European Union (thus, it excludes Cyprus and Malta), plus Norway, Switzerland and Iceland (Table 2).

Table 2 – Considered countries and country groups in eTIMES-EU

Country groups	Group code	Included countries name (and short code)
Alpine Peninsula	ALP	Italy (IT)
British Islands	BIS	Ireland (IE), United Kingdom (UK)
Iberian Peninsula	IBE	Spain (ES, Portugal (PT)
Central West Europe	CWE	Austria (AT), Belgium (BE), Switzerland (CH), Germany (DE). France (FR), Luxembourg (LU), Netherlands (NL)
Central East Europe	CEE	Czech Republic (CZ), Poland (PL)
Nordic & Western Nordic	NWN	Denmark (DK), Finland (FI), Norway (NO), Sweden (SE), Iceland (IS)
Nordic & Eastern Nordic	NEE	Estonia (EE), Lithuania (LT), Latvia (LV)
South Eastern Europe	SEE	Bulgaria (BG), Greece (GR), Croatia (HR), Hungary (HU), Romania (RO), Slovenia (SI), Slovakia (SK)

The model runs in 1- or 5-year time-steps from 2016 to 2060. Each year is disaggregated in 64 time slices, outlining the 4 seasons (DJF, MAM, JJA, SON), 2 typical days (weekdays and weekends) and 8-time sequential day periods (P1 to P8 of 3 hrs each).

eTIMES-EU is supported by a detailed database, with the following main exogenous inputs: (1) electricity demand from the 2016 Energy Reference Scenario (The European Commission, n.d.) and summarised in Table 3; (2) characteristics of the existing and future electricity generation technologies, such as efficiency. stock. availability. investment costs, operation and maintenance costs, and general discount rate of 8%; (3) present and future sources of primary energy supply and their potentials; and (4) policy constraints and assumptions.

Table 3- Evolution of considered electricity demand per group of countries (TWh)

Year/Country group	ALP	BIS	CEE	CWE	EU	IBE	NEE	NWN	SEE
2020	304	361	203	1251	2915	294	25	248	229
2030	314	384	234	1314	3084	304	27	264	242
2040	359	426	258	1383	3317	320	28	281	262
2050	395	472	281	1463	3574	342	31	306	283
Evolution from 2020 to 2050 (%)	*30%*	*31%*	*38%*	*17%*	*23%*	*16%*	*24%*	*23%*	*24%*

4.2.1 Electricity generation technologies

Electricity generation data from (ENTSO-E, 2019) and Eurostat (EUROSTAT, 2018) was used to derive country-specific power balances, which determine the characterisation of power generation technology profiles in the base year. Beyond the base year, possible new electricity generation technologies are compiled in an extensive database with detailed technical and economic features based on (OCDE/IEA, 2016) summarised in Annex 2. CO_2 storage capacity and transport is possible as illustrated by different projects (Global CCS Institute, 2019). The model uses country-specific hydro, wind and solar annual availability profiles (introduced as maximum possible CF) for replicating the year of 2016 as in ENTSO-E Transparency Portal (ENTSO-E, 2019) for the 64 modelled time-slices. Concerning electricity grids, eTIMES-EU considers both import/export processes regarding the existing infrastructures (capacity and flows) and possible new investments based on the TYNDP2016 (ENTSO-E, 2016). These investments are considered only within the 29 modelled countries. There are three levels of electricity voltage and conversion between levels. The electricity trade outside the modelled region is not considered. The internal and external trade maximum capacity hypothesis are key assumptions with potential high impact on the results.

4.2.2 Primary energy potentials and import costs

The model considers current and future sources of primary energy (potentials and costs) and their constraints for each country. The reference fossil primary energy import prices into EU as in (European Commission, 2011) were used (Table 4).

Table 4 - Primary energy import prices into EU considered in eTIMES-EU in EUR_{2010}/PJ

Fuel	2020	2030	2040	2050
Oil	16.33	17.49	19.08	20.52
Gas	8.77	9.06	9.5	9.9
Coal	2.93	3.04	3.09	3.17

A number of assumptions and sources are adopted to derive the RES potentials in the modelled countries for wind, solar, geothermal, marine and hydro, as detailed in Table 5. More details can be obtained in (Simoes et al., 2013) and Annex 1. At this stage, import of biofuels are not considered due to lack of reliable data. The use of biofuels in the base year is calibrated with (Bioenergy Europe, 2019). For the rest of the period, biofuels consumption can grow up to 120% more than used in the base year.

Table 5 - Overview of the technical RES potential considered in eTIMES-EU

RES	Methods	Main data sources	Assumed maximum possible technical potential capacity / activity for Europe+
Wind onshore	Maximum activity and capacity restrictions per country	JRC-EU-TIMES model (Simoes et al., 2013)	282 GW in 2020 and 302 GW in 2050
Wind offshore	Maximum activity and capacity restrictions per country	(Giles Hundleby et al., 2017)	60 GW in 2020 and 271 GW in 2050
PV and Concentrated Solar Power	Maximum activity and capacity restrictions disaggregated for different types of PV and for CSP per country	JRC-EU-TIMES model (Simoes et al., 2013)	620 GW in 2020 and 1 316 GW in 2050 for PV & CSP
Geothermal electricity	Maximum capacity restriction in GW. aggregated for both EGS and hydrothermal with flash power plants	JRC-EU-TIMES model (Simoes et al., 2013)	71 GW in 2020 and 124 GW in 2050
Ocean	Maximum capacity restriction in GW. aggregated for thermal. hydrokinetic. tidal and wave	JRC-EU-TIMES model (Simoes et al., 2013) + own assumptions	691 GW in 2020 and 2050
Hydro	Maximum capacity restriction in GW. further disaggregated for run-of-river and dam plants	JRC-EU-TIMES model (Simoes et al., 2013)	137 GW in 2020 and onwards for run-of-river and lake. 98 GW for dams

4.2.3 Policy assumptions and scenarios

As previously mentioned, 22 climate projections from 2016 till 2050 are modelled. Besides these, it is also modelled a "BASE" scenario and a NEUTR scenario. The BASE scenario is mainly used as a reference case and considers "historic" CF for wind, PV and hydropower, as well as observed load curves for electricity demand. The "historic" CF are the ones for 2016 from (ENTSO-E, 2019), that are maintained till 2050. The NEUTR scenario is identical to BASE, but it includes an ambitious 2050 CO_2

emissions mitigation cap of no emissions from the power sector modelled as a linear trajectory from 2016 emission values. The purpose of this scenario is to test the effect of changing the "historic" CF and demand structure in a highly-RES European power system. The other scenarios are identical to NEUTR, but have CF and modified intra-annual electricity demand structure according to the six considered climate projections.

All of the modelled scenarios have in common the following assumptions:

i) No consideration of the specific policy incentives to RES (e.g. feed-in tariffs, green certificates) since the objective is to assess deployment based solely on cost-effectiveness.

ii) Countries currently without NPP will not have these in the future (AT. PT, GR, IT, DK, HR, NO and IS). NPPs lifetime expansion is authorized till 2040. Until 2025, the model has the choice between investing in a new capacity or extending the life of an existing plant. NPPs in DE are not operating after 2025.

iii) Coal plants in BE are not operating from 2017 onwards.

iv) No new coal plants to be built in AT, BE, CH, DK, FI, IE, IT, PT, UK, LT, LV, EE, LU and IS.

Based on the approach described in the previous section, the eTIMES-EU inputs on maximum possible capacity factors for wind (onshore and offshore).

4.3 Output indicators in the Clim2power webservice

Category	Indicator name	Definition[1]
CO_2 emission	gCO_2/kWh (CO_2 emissions per generated electricity) Mass of CO_2 emissions in each country	The CO_2 emission intensity (g CO_2/kWh) is calculated as the ratio of CO_2 emissions from electricity production (as a share of CO_2 emissions from public electricity and heat production related to electricity production), and gross electricity production.
Renewable energy sources (RES) generation	% of electricity generated from RES	Renewable energy sources considered include wind power, solar power, hydro power, and other RES (bioenergy, geothermal and biomass with carbon capture and storage).
Electricity generation	% of electricity generated from hydropower % of electricity generated from solar % of electricity generated from wind Total of electricity generated from hydropower (TWh) Total of electricity generated from solar (TWh) Total of electricity generated from wind (TWh) Total generated electricity	-

[1] Sources : European Commission and European Environment Agency

5 References and links

Deliverables and information on the project are available on the project's website https://clim2power.com/.

Anderson, M.L., Chen, Z.Q., Kavvas, M.L., Feldman, A., 2002. Coupling HEC-HMS with atmospheric models for prediction of watershed runoff. J. Hydrol. Eng. 7, 312–318.

Añel, J.., Fernández-González, M. Labandeira, X., López-Otero, X., De la Torre, L., 2017. Impact of Cold Waves and Heat Waves on the Energy Production Sector. Atmosphere (Basel). 8, 209. https://doi.org/10.3390/atmos8110209

Behrens, P., van Vliet, M.T.H., Nanninga, T., Walsh, B., Rodrigues, J.F.D., 2017. Climate change and the vulnerability of electricity generation to water stress in the European Union. Nat. Energy 2, 17114. https://doi.org/10.1038/nenergy.2017.114

Bessembinder, J., Street, R., Matthias, T., Baños de Guisasola, E., Decluse, P., Benestad, R., 2012. Guidance to support the identification and assessment of users' requirements. Version 5-10-2012. Brussels.

Bioenergy Europe, 2019. Bionergy Europe Statistical Report. Brussels.

Bollmeyer, C., J. D. Keller, C. Ohlwein, S. Wahl, S. Crewell, P. Friederichs, A. Hense, J. Keune, S. Kneifel, I. Pscheidt, S. Redl, and S. Steinke. 2015. 'Towards a high-resolution regional reanalysis for the European CORDEX domain', *Quarterly Journal of the Royal Meteorological Society*, 141: 1-15.

Carvalho, S., Fröhlich, K., Ostermoeller, J., Lourenço, T., 2019. Clim2power Deliverable D2.7 Evaluation Requirements of Long-term Climate Data. CLIM2POWER – Translating Climate Data into Power Plant Operational Guidance.

Chen, T., Guestrin, C., 2016. XGBoost: A Scalable Tree Boosting System, in: Proceedings of the 22Nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining, KDD '16. ACM, New York, NY, USA, pp. 785–794. https://doi.org/10.1145/2939672.2939785

CLIM4ENERGY, 2016. CLIM4ENERGY A service providing climate change indicators tailored for the energy sector Website [WWW Document].

Donnelly, C., Ernst, K., Arheimer, B., 2018. A comparison of hydrological climate services at different scales by users and scientists. Clim. Serv. 11, 24–35. https://doi.org/https://doi.org/10.1016/j.cliser.2018.06.002

ECEM, 2016. ECEM European Climatic Energy Mixes Website [WWW Document]. URL http://climate.copernicus.eu/ecem-european-climatic-energy-mixes (accessed 5.26.16).

Emodi, N.V., Chaiechi, T., Beg, A.B.M.R.A., 2019. The impact of climate variability and change on the energy system: A systematic scoping review. Sci. Total Environ. 676, 545–563.

https://doi.org/https://doi.org/10.1016/j.scitotenv.2019.04.294

ENTSO-E, 2019. ENTSO-E European Network for Transmission System Operators Transparency Platform [WWW Document].

ENTSO-E, 2016. Ten-Year Network Development Plan 2016 [WWW Document].

EUPORIAS, 2014. Deliverable D42.1 - Report summarising the (expected) usefulness of selected prototypes. EUPORIAS - European Provision Of Regional Impact Assessment on a Seasonal-to-decadal timescale project.

European Commission, 2018. Communication from the Commission to the European Parliament, the European Council, the Council, the European Economic and Social Committee, the Committee of the Regions and the European Investment Bank — A clean planet for all — A European strategic long. Brussels.

European Commission, 2014. COM(2014) 15 final. Communication from the Commission to the Council, the European Parliament, the Council, the European Economic and Social Committee and the Committee of the Regions. A policy framework for climate and energy in the period from 2020 to 2. European Commission, Brussels.

European Commission, 2011. COM(2011) 885 final. Communication from the Commission to the European Parliament, the Council, the European Economic and Social Committee and the Committee of the Regions- Energy Roadmap 2050. European Commission, Brussels.

European Enviromment Agency, 2019. Adaptation challenges and opportunitiesfor the European energy system - Building a climate-resilient low-carbon energy system. Copenhagen. https://doi.org/10.2800/227321

European Union, 2018a. Directive (EU) 2018/2001 of the European Parliament and of the Council of 11 December 2018 on the promotion of the use of energy from renewable sources.

European Union, 2018b. Directive (EU) 2018/2002 of the European Parliament and of the Council of 11 December 2018 amending Directive 2012/27/EU on energy efficiency. Brussels.

EUROSTAT, 2018. EUROSTAT Energy Statistics [WWW Document].

Giannini, V., Bellucci, A., Torresan, S., 2016. Sharing skills and needs between providers and users of climate information to create climate services: lessons from the Northern Adriatic case study. Earth Perspect. 3, 1. https://doi.org/10.1186/s40322-016-0033-z

Giles Hundleby, Freeman, K., Barlow, M., Blanch, M., Pierre Tardieu, W., Walsh, C., Pineda, I., 2017. Unleashing Europe's offshore wind potential A new resource assessment. Brussels.

Giorgi, F., Jones, C., Asrar, G.R., 2009. Addressing climate information needs at the regional level: the CORDEX framework. Bull. - World Meteorol. Organ. 58, 175–183.

Global CCS Institute, 2019. Facilities- Global CCS Institute [WWW Document].

Gonzalez Aparicio, I., Zucker, A., Careri, F., Monforti, F., Huld, T., Badger, J., 2016. European Meteorological derived HIgh resolution RES generation time series for present and future scenarios EMHIRES dataset Part I: Wind power generation 2016 EUR 28171 EN.

https://doi.org/10.2790/831549

Hastie, T., Tibshirani, R., Friedman, J., 2009. The Elements of Statistical Learning: Data Mining, Inference, and Prediction, 2nd ed. Springer-Verlag, New York, NY, USA.

Jacob, D., Petersen, J., Eggert, B., Alias, A., Christensen, O.B., Bouwer, L.M., Braun, A., Colette, A., Déqué, M., Georgievski, G., Georgopoulou, E., Gobiet, A., Menut, L., Nikulin, G., Haensler, A., Hempelmann, N., Jones, C., Keuler, K., Kovats, S., Kröner, N., Kotlarski, S., Kriegsmann, A., Martin, E., van Meijgaard, E., Moseley, C., Pfeifer, S., Preuschmann, S., Radermacher, C., Radtke, K., Rechid, D., Rounsevell, M., Samuelsson, P., Somot, S., Soussana, J.F., Teichmann, C., Valentini, R., Vautard, R., Weber, B., Yiou, P., 2014. EURO-CORDEX: new high-resolution climate change projections for European impact research. Reg. Environ. Chang. 14, 563–578. https://doi.org/10.1007/s10113-013-0499-2

Jin, X., Han, J., 2010. K-Means Clustering BT - Encyclopedia of Machine Learning, in: Sammut, C., Webb, G.I. (Eds.), . Springer US, Boston, MA, pp. 563–564. https://doi.org/10.1007/978-0-387-30164-8_425

Klein, D.R., Olonscheck, M., Walther, C., Kropp, J.P., 2013. Susceptibility of the European electricity sector to climate change. Energy 59, 183–193. https://doi.org/https://doi.org/10.1016/j.energy.2013.06.048

Knutti, R., Sedláček, J., 2013. Robustness and uncertainties in the new CMIP5 climate model projections. Nat. Clim. Chang. 3, 369–373. https://doi.org/10.1038/nclimate1716

Köppen, W., 2011. The thermal zones of the Earth according to the duration of hot, moderate and cold periods and to the impact of heat on the organic world. Meteorol. Zeitschrift 20, 351–360. https://doi.org/10.1127/0941-2948/2011/105

Kreienkamp, Frank, Andreas Paxian, Barbara Früh, Philip Lorenz, and Christoph Matulla. 2018. 'Evaluation of the empirical–statistical downscaling method EPISODES', *Climate Dynamics*, 52: 991-1026.

Linnerud, K., Mideksa, T.K., Eskeland, G.S., 2011. The Impact of Climate Change on Nuclear Power Supply. Energy Journal, Int. Assoc. Energy Econ. 0, 149–168.

Loulou, R., Labriet, M., 2008. ETSAP-TIAM: The TIMES integrated assessment model Part I: Model structure. Comput. Manag. Sci. 5, 7–40. https://doi.org/10.1007/s10287-007-0046-z

Lourenco, T.C., Swart, R., Goosen, H., Street, R., 2015. The rise of demand-driven climate services. Nat. Clim. Chang. advance on.

Massmann, C., Wagener, T., Holzmann, H., 2014. A New Approach to Visualizing Time-varying Sensitivity Indices for Environmental Model Diagnostics Across Evaluation Time-scales. Environ. Model. Softw. 51, 190–194. https://doi.org/10.1016/j.envsoft.2013.09.033

Müller, W. A., J. H. Jungclaus, T. Mauritsen, J. Baehr, M. Bittner, R. Budich, F. Bunzel, M. Esch, R. Ghosh, H. Haak, T. Ilyina, T. Kleine, L. Kornblueh, H. Li, K. Modali, D. Notz, H. Pohlmann, E. Roeckner, I. Stemmler, F. Tian, and J. Marotzke. 2018. 'A Higher-resolution Version of the Max Planck Institute Earth System Model (MPI-ESM1.2-HR)', *Journal of Advances in Modeling Earth Systems*, 10: 1383-413.

OCDE/IEA, 2016. World Energy Outlook 2016. Paris.

OECD/IEA, 2018. World Energy Outlook 2018. Paris.

O'Higgins, T., 2019. Clim2Power Deliverable 1.4- Final User Requirements.

Pfenninger, S., Staffell, I.L., 2016. Long-term patterns of European PV output using 30 years of validated hourly reanalysis and satellite data. Energy 114, 1251–1265. https://doi.org/10.1016/j.energy.2016.08.060

PLAN4RES, 2019. PLAN4RES - Synergistic Approach of Multi-Energy Models for an European Optimal Energy System Management Tool [WWW Document].

Prein, A.F., Gobiet, A., 2017. Impacts of uncertainties in European gridded precipitation observations on regional climate analysis. Int. J. Climatol. 37, 305–327. https://doi.org/10.1002/joc.4706

Quoilin, S., Kavvadias, I.H.G.K., Zucker, A., 2016. The Dispa-SET model [WWW Document]. Instititue Energy Transp. JRC-European Comm. URL http://dispa-set.readthedocs.io/en/latest/index.html

Rademaekers, K., van der Laan, J., Boeve, S., Lise, W., van Hienen, J., Metz, B., Haigh, P., de Groot, K., Dijkstra, S., Jansen, J., Bole, T., Lako, P., C., K., 2011. Investment needs for future adaptation measures in EU nuclear power plants and other electricity generation technologies due to effects of climate change. Technical Report. Luxembourg.

Ranchin, T., n.d. SoDa Service Knowledge in solar radiation Website [WWW Document]. URL http://www.soda-is.com/ (accessed 6.3.16).

Ravestein, P., van der Schrier, G., Haarsma, R., Scheele, R., van den Broek, M., 2018. Vulnerability of European intermittent renewable energy supply to climate change and climate variability. Renew. Sustain. Energy Rev. 97, 497–508. https://doi.org/10.1016/j.rser.2018.08.057

Reinecke, S., 2015. Knowledge brokerage designs and practices in four european climate services: A role model for biodiversity policies? Environ. Sci. Policy 54, 513–521. https://doi.org/10.1016/j.envsci.2015.08.007

RTE, 2019. Development challenges of the electrical mobility for the powr system [Enjeux du développement de l'électromobilité pour le système électrique].

Rübbelke, D., Vögele, S., 2011. Impacts of climate change on European critical infrastructures: The case of the power sector. Environ. Sci. Policy 14, 53–63. https://doi.org/https://doi.org/10.1016/j.envsci.2010.10.007

Ruiz, P., Nijs, W., Tarvydas, D., Sgobbi, A., Zucker, A., Pilli, R., Jonsson, R., Camia, A., Thiel, C., Hoyer-Klick, C., Dalla Longa, F., Kober, T., Badger, J., Volker, P., Elbersen, B.S., Brosowski, A., Thrän, D., 2019. ENSPRESO - an open, EU-28 wide, transparent and coherent database of wind, solar and biomass energy potentials. Energy Strateg. Rev. https://doi.org/10.1016/j.esr.2019.100379

S2S4E, 2019. S2S4E H2020 Project [WWW Document].

Saint-Drenan, Y.-M., 2019. Clim2Power Deliverable D3.2 Simulation framework for bias corrected wind and solar PF for the whole of Europe.

Saint-Drenan, Y.-M., Bessea, R., Jansen, M., Staffell, I., Troccoli, A., Dubus, L., Schmidt, J., Gruber, K., Simoes, S.G., Heier, S., 2019. A parametric model for wind turbine power curves incorporating environmental conditions (submitted). Electr. Eng. Syst. Sci.

Saint-Drenan, Y.-M., Wald, L., Ranchin, T., Dubus, L., Troccoli, A., 2018. An approach for the estimation of the aggregated photovoltaic power generated in several European countries from meteorological data. Adv. Sci. Res. 15, 51–62. https://doi.org/10.5194/asr-15-51-2018

SECLI-FIRM, 2019. SECLI-FIRM - The added value of seasonal climate forecasting for integrated risk management [WWW Document].

SHMI, 2009. The HBV Model [WWW Document]. URL http://www.smhi.se/forskning/forskningsomraden/hydrologi/hbv-1.1566 (accessed 11.14.16).

Simoes, S., Nijs, W., Ruiz, P., Sgobbi, A., Radu, D., Bolat, P., Thiel, C., Peteves, S., 2013. The JRC-EU-TIMES model. Assessing the long-term role of the SET Plan Energy technologies, EUR – Scientific and Technical Research series. https://doi.org/10.2790/97596

Stocker, T.F., Qin, D., Plattner, G.-K., Tignor, M., Allen, S.K., Boschung, J., Nauels, A., Xia, Y., Bex, V., Midgley, P.M. (Eds.), 2013. Climate Change 2013: The Physical Science Basis, Contribution of Working Group I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change. Cambridge University Press: Cambridge, UK and New York, USA.

Street, R., Parry, M., Scott, J., Jacob, D., Runge, T., 2015. A European research and innovation Roadmap for Climate Services. Luxembourg. https://doi.org/10.2777/702151

The European Commission, n.d. EU Reference Scenario 2016 Energy, transport and GHG emissions Trends to 2050. https://doi.org/10.2833/9127

Tobin, I., Greuell, W., Jerez, S., Ludwig, F., Vautard, R., van Vliet, M.T.H., Bréon, F.-M., 2018. Vulnerabilities and resilience of European power generation to 1.5 °C, 2 °C and 3 °C warming. Environ. Res. Lett. 13, 44024. https://doi.org/10.1088/1748-9326/aab211

Tomaszewski, M., Ruszczak, B., 2013. Analysis of frequency of occurrence of weather conditions favouring wet snow adhesion and accretion on overhead power lines in Poland. Cold Reg. Sci. Technol. 85, 102–108. https://doi.org/https://doi.org/10.1016/j.coldregions.2012.08.007

Anderson, M.L., Chen, Z.Q., Kavvas, M.L., Feldman, A., 2002. Coupling HEC-HMS with atmospheric models for prediction of watershed runoff. J. Hydrol. Eng. 7, 312–318.

Bessembinder, J., Street, R., Matthias, T., Baños de Guisasola, E., Decluse, P., Benestad, R., 2012. Guidance to support the identification and assessment of users' requirements. Version 5-10-2012. Brussels.

CLIM4ENERGY, 2016. CLIM4ENERGY A service providing climate change indicators tailored for the energy sector Website [WWW Document]. URL http://climate.copernicus.eu/clim4energy-service-providing-climate-change-indicators-tailored-energy-sector (accessed 11.10.16).

Donnelly, C., Ernst, K., Arheimer, B., 2018. A comparison of hydrological climate services at different scales by users and scientists. Clim. Serv. 11, 24–35. https://doi.org/https://doi.org/10.1016/j.cliser.2018.06.002

ECEM, 2016. ECEM European Climatic Energy Mixes Website [WWW Document]. URL http://climate.copernicus.eu/ecem-european-climatic-energy-mixes (accessed 5.26.16).

EUPORIAS, 2014. Deliverable D42.1 - Report summarising the (expected) usefulness of selected prototypes. EUPORIAS - European Provision Of Regional Impact Assessment on a Seasonal-to-decadal timescale project.

Giannini, V., Bellucci, A., Torresan, S., 2016. Sharing skills and needs between providers and users of climate information to create climate services: lessons from the Northern Adriatic case study. Earth Perspect. 3, 1. https://doi.org/10.1186/s40322-016-0033-z

Loulou, R., Labriet, M., 2008. ETSAP-TIAM: the TIMES integrated assessment model, Part I: Model structure. Comput. Manag. Sci. 5, 7–40. https://doi.org/10.1007/s10287-007-0046-z

Lourenco, T.C., Swart, R., Goosen, H., Street, R., 2015. The rise of demand-driven climate services. Nat. Clim. Chang. advance on.

Massmann, C., Wagener, T., Holzmann, H., 2014. A New Approach to Visualizing Time-varying Sensitivity Indices for Environmental Model Diagnostics Across Evaluation Time-scales. Environ. Model. Softw. 51, 190–194. https://doi.org/10.1016/j.envsoft.2013.09.033

O'Higgins, T., 2019. Clim2Power Deliverable 1.4- Final User Requirements.

OECD/IEA, 2018. World Energy Outlook 2018. Paris.

Quoilin, S., Kavvadias, I.H.G.K., Zucker, A., 2016. The Dispa-SET model [WWW Document]. Institiute Energy Transp. JRC-European Comm. URL http://dispa-set.readthedocs.io/en/latest/index.html

Ranchin, T., n.d. SoDa Service Knowledge in solar radiation Website [WWW Document]. URL http://www.soda-is.com/ (accessed 6.3.16).

Ravestein, P., van der Schrier, G., Haarsma, R., Scheele, R., van den Broek, M., 2018. Vulnerability of European intermittent renewable energy supply to climate change and climate variability. Renew. Sustain. Energy Rev. 97, 497–508. https://doi.org/https://doi.org/10.1016/j.rser.2018.08.057

Ravestein, P., van der Schrier, G., Haarsma, R., Scheele, R., van den Broek, M., 2018. Vulnerability of European intermittent renewable energy supply to climate change and climate variability. Renew. Sustain. Energy Rev. 97, 497–508. https://doi.org/10.1016/J.RSER.2018.08.057

Reinecke, S., 2015. Knowledge brokerage designs and practices in four european climate services: A role model for biodiversity policies? Environ. Sci. Policy 54, 513–521. https://doi.org/10.1016/j.envsci.2015.08.007

Sessa, Valentina, 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⟩

SHMI, 2009. The HBV Model [WWW Document]. URL http://www.smhi.se/forskning/forskningsomraden/hydrologi/hbv-1.1566 (accessed 11.14.16).

Street, R., Parry, M., Scott, J., Jacob, D., Runge, T., 2015. A European research and innovation Roadmap for Climate Services. Luxembourg. https://doi.org/10.2777/702151

van den Hurk, B.J.J.M., Bouwer, L.M., Buontempo, C., Döscher, R., Ercin, E., Hananel, C., Hunink, J.E., Kjellström, E., Klein, B., Manez, M., Pappenberger, F., Pouget, L., Ramos, M.-H., Ward, P.J., Weerts, A.H., Wijngaard, J.B., 2016. Improving predictions and management of hydrological extremes through climate services: www.imprex.eu. Clim. Serv. https://doi.org/10.1016/j.cliser.2016.01.001

van Vliet, M.T.H., Yearsley, J.R., Ludwig, F., Vögele, S., Lettenmaier, D.P., Kabat, P., 2012. Vulnerability of US and European electricity supply to climate change. Nat. Clim. Chang. 2, 676–681. https://doi.org/10.1038/nclimate1546

Wenz, L., Levermann, A., Auffhammer, M., 2017. North{\textendash}south polarization of European electricity consumption under future warming. Proc. Natl. Acad. Sci. https://doi.org/10.1073/pnas.1704339114

Version 1, date of publication: 22/10/2020

Clim2Power

www. facebook.com/Clim2Power

@Clim2Power www.clim2power.com www.linkedin.com/groups/13562960

Contact project coordinator: Sofia Simoes (sofia.simoes@lneg.pt)

6 Annexes

6.1 ANNEX 1 – Considered technical and economic assumptions for the power production technologies

Fuel	Technology	Specific investments costs (overnight) (eur2010/kW)					Fixed operating and maintenance costs (eur2010/kW)					Electric net efficiency (condensing mode) (%)					Tech. life (yr.)	Maximum Capacity factor (%)	CO_2 capture rate (%)	
		2017	2020	2030	2040	2050	2017	2020	2030	2040	2050	2017	2020	2030	2040	2050			2030	2050
Coal	Hard coal / lignite 600 MWel																			
	Supercritical	1700	1506	1506	1506	1506	30	30	30	30	30	40	44	44	44	46	30	80		
	Supercritical+ (post comb./oxyfuelling) capture	5500	4872	4430	4252	4252	35	35	35	35	35	32	38	38	38	42	30	80	89	90
	FB	2457	2098	2005	1973	1940	30	30	30	30	30	40	42	42	42	44	30	80		
	FB + capture	7994	6728	5761	5422	5313	35	35	35	35	35	32	37	37	37	40	30	80	89	90
	IGCC	2407	2133	2005	1962	1962	33	33	33	33	33	40	45	45	45	50	35	80		
	IGCC pre-comb capture	5633	4990	4479	4223	4223	39	39	39	39	39	32	39	39	39	45	35	80	89	90
	CHP BackPressure	3107	2753	2753	2753	2753	55	55	55	55	55	Country specific values					35	Country specific		
Natural Gas	Combined Cycle Small	1104	978	978	978	978	20	20	20	20	20	60	60	63	63	63	35	85		
	Combined Cycle Large	1000	886	886	886	886	18	18	18	18	18	60	60	63	63	63	35	85		
	Combined-cycle+post comb. capture	2985	2645	2389	2261	2261	53	53	53	53	53	54	56	57	57	57	35	85	89	90
	Peak Turbine	220	220	220	220	220	12	12	12	12	12	34	34	34	34	34	30	85		

Webservice support information

Fuel	Technology	Specific investments costs (overnight) (eur_{2010}/kW)					Fixed operating and maintenance costs (eur_{2010}/kW)					Electric net efficiency (condensing mode) (%)					Tech. life (yr.)	Maximum Capacity factor (%)	CO_2 capture rate (%)	
		2017	2020	2030	2040	2050	2017	2020	2030	2040	2050	2017	2020	2030	2040	2050			2030	2050
	CHP Int Comb Small	2500	2500	2500	2500	2500	65	65	65	65	65	Country specific value					15	Country specific value		
	CHP Int Comb Medium	1050	1050	1050	1050	1050	45	45	45	45	45						15			
	CHP Int Comb Large	750	750	750	750	750	35	35	35	35	35						18			
	CHP Combined-cycle Small	1521	1347	1347	1347	1347	30	30	30	30	30						35			
	CHP Combined-cycle Large	1300	1152	1152	1152	1152	25	25	25	25	25						35			
Nuclear 1000 MWel	**3rd generation**	6563	5315	5315	5315	5315	39	39	38	38	38	36	36	36	36	36	60	85		
	4th generation				7773	6500				28	28				38	38	60	85		
Wind onshore	**Wind onshore 1 low/2 medium (IEC class III/II)**	1620	1388	1342	1310	1295	40	40	40	40	40	100	100	100	100	100	20	23		
Wind offshore	**Wind offshore 1 low/medium (IEC class II)**	4050	3003	2496	2262	2235	60	60	60	60	60	100	100	100	100	100	20	40		
Hydro	**Reservoir**	2650	2348	2348	2348	2320	45	45	45	45	45	93	93	93	93	93	80	60		
	Run of river small	4429	3924	3924	3924	3878	45	45	45	45	45	93	93	93	93	93	60	60		
	Run of river medium	4164	3689	3689	3689	3646	45	45	45	45	45	93	93	93	93	93	70	60		
	Run of river large	2650	2348	2348	2348	2320	45	45	45	45	45	93	93	93	93	93	80	60		

Webservice support information

Fuel	Technology	Specific investments costs (overnight) (eur2010/kW)					Fixed operating and maintenance costs (eur2010/kW)					Electric net efficiency (condensing mode) (%)					Tech. life (yr.)	Maximum Capacity factor (%)	CO_2 capture rate (%)	
		2017	2020	2030	2040	2050	2017	2020	2030	2040	2050	2017	2020	2030	2040	2050			2030	2050
Solar	Solar PV utility scale fixed systems > 10MW	1800	1329	709	586	532	29	29	29	19	19	100	100	100	100	100	25	25		
	Solar PV roof <0.1 MWp / 0.1-10 MWp	2182	1636	890	736	728	40	40	40	40	40	100	100	100	100	100	25	25		
	Solar CSP 50 MWel	8000	6341	5284	4663	4608	45	45	41	38	38	100	100	100	100	100	25	25		
Biomass	Steam turbine biomass solid conventional	2400	2082	2038	1993	1970	64	64	64	64	64	35	35	35	35	36	35	80		
	Steam turbine biomass solid conventional HT	2400	2082	2038	1993	1970	45	45	45	45	45	38	39	39	39	39	25	80		
	IGCC Biomass 100 MWel			3900	3700	3500	54	54	54	54	54			44	44	49	25	80		
	IGCC Biomass 100 MWel + capture			3900	3700	3500	63	63	63	63	63			38	38	44	25	80	89	90
	CHP IGCC	4680	4146	4146	4146	4146	143	143	124	90	90			37	37	37	25	Country specific		
	CHP Steam Turb condensing	3750	3278	3233	3145	3108	72	72	72	72	72			31	31	31	25			
Geothermal	Hot Dry Rock geotthermal	4900	4341	3960	3561	3189	194	194	175	136	136	20	20	21	22	22	20	85		
Ocean	Wave 5 MWel	6950	5891	4119	3056	3021	160	160	160	160	160	100	100	100	100	100	25	40		
	Tidal energy stream and	5414	4589	3209	2381	2533	92	92	92	92	92	100	100	100	100	100	80	25		

Fuel	Technology	Specific investments costs (overnight) (eur_{2010}/kW)					Fixed operating and maintenance costs (eur_{2010}/kW)					Electric net efficiency (condensing mode) (%)					Tech. life (yr.)	Maximum Capacity factor (%)	CO_2 capture rate (%)	
		2017	2020	2030	2040	2050	2017	2020	2030	2040	2050	2017	2020	2030	2040	2050			2030	2050
	range 10 MWel																			
	Thermal	30000	30000	13000	13000	13000	120	120	120	120	120	100	100	100	100	100	25	91		
	Hydrokinectic	7894	6692	4679	3472	3431	120	120	120	120	120	100	100	100	100	100	25	40		
Biogas	CHP Internal Combustion Small	4000	4000	4000	4000	4000	115	115	115	115	115	34	34	34	34	34	15	Country specific		
	CHP Internal Combustion Large	2350	2350	2350	2350	2350	115	115	115	115	115	39	39	39	39	39	15			
Oil	CHP Internal Combustion Small	2210	1958	1958	1958	1958	65	65	65	65	65	30	30	30	30	30	18	Country specific		
	CHP Internal Combustion Medium	2730	2419	2419	2419	2419	45	45	45	45	45	30	30	30	30	36	15			
	CHP Internal Combustion Large	750	750	750	750	750	35	35	35	35	35	30	30	30	30	42	18			
	Supercritical HFO	1916	1671	1636	1617	1604	21	21	21	21	21	40	44	44	44	46	35	85		
	Supercritical HFO + capture	1413	1342	1264	1264	1215	24	24	24	24	24	32	38	38	38	42	35	80	89	90
	Turb Diesel	910	806	806	806	806	18	18	18	18	18	34	34	34	34	34	35	85		
Waste	Steam	7000	6072	5943	5814	5746	33	33	33	33	33	14	14	14	20	25	20	68		

Webservice support information

Fuel	Technology	Specific investments costs (overnight) (eur_{2010}/kW)					Fixed operating and maintenance costs (eur_{2010}/kW)					Electric net efficiency (condensing mode) (%)					Tech. life (yr.)	Maximum Capacity factor (%)	CO_2 capture rate (%)	
		2017	2020	2030	2040	2050	2017	2020	2030	2040	2050	2017	2020	2030	2040	2050			2030	2050
	CHP Steam Turb Condensing	7450	6511	6423	6290	6216	74	74	74	74	74	14	14	14	25	25	20	Country specific		

6.2 ANNEX 2 - Maximum potential installed capacity for RES electricity power plants per country considered in eTIMES-EU (GW)

Country /Year	Hydropower[a]			PV[b]			Wind onshore[b]			Wind offshore[b]			Ocean[a]		
	2020	2030	2050	2020	2030	2050	2030	2050	2050	2020	2030	2050	2020	2030	2050
AT	8.9	10.0	13.3	73	73	73	11	11	11	0	0	0	0	0	0
BE	0.1	0.1	0.1	52	52	52	8	8	8	2	2	2	0.54	0.54	0.54
BG	2.3	3.0	6.4	149	149	149	53	53	53	0	0	0	0	0	0
CH	13.6	14.3	16.3	20	20	20	1.1	1.1	1.1	0	0	0	0	0	0
CZ	1.1	1.2	1.4	112	112	112	76	76	76	0	0	0	0	0	0
DE	4.5	4.5	4.7	494	494	494	107	107	107	28	28	28	0	0	0
DK	0.0	0.0	0.0	76	76	76	55	55	55	27	27	27	9.29	9.29	9.29
EE	0.0	0.0	0.0	28	28	28	27	27	27	1	1	1	0	0	0
ES	17.0	20.8	34.2	658	658	658	704	704	704	1	1	1	47.63	47.63	47.63
FI	3.2	3.5	4.1	36	36	36	31	31	31	21	21	21	5.54	5.54	5.54
FR	18.5	20.9	28.1	822	822	822	813	813	813	16	16	16	55.88	55.88	55.88
GR	2.7	3.9	10.0	157	157	157	168	168	168	0	0	0	14.44	14.44	14.44
HR	1.8	1.9	2.2	50	50	50	24	24	24	5	5	5	4.81	4.81	4.81
HU	0.1	0.1	0.1	161	161	161	53	53	53	0	0	0	0	0	0
IE	0.2	0.3	0.4	113	113	113	147	147	147	1	1	1	66.6	66.6	66.6
IS	2.0	2.7	6.2	1	1	1	0.303	0.303	0.303	0	0	0	0	0	0
IT	14.3	15.4	18.3	443	443	443	178	178	178	5	5	5	11.59	11.59	11.59
LT	0.1	0.1	0.2	93	93	93	128	128	128	3	3	3	0.07	0.07	0.07
LU	0.0	0.0	0.1	3	3	3	1	1	1	0	0	0	0	0	0
LV	1.6	1.6	1.8	48	48	48	79	79	79	15	15	15	0	0	0
NL	0.0	0.0	0.0	42	42	42	49	49	49	48	48	48	3.71	3.71	3.71
NO	30.4	34.1	45.4	12	12	12	14.31	14.31	14.31	7.3	7.3	7.3	79.2	79.2	79.2
PL	0.6	1.0	3.8	447	447	447	102	102	102	12	12	12	23.4	23.4	23.4
PT	4.7	6.2	12.4	92	92	92	39	39	39	3.38	3.38	3.38	46.8	46.8	46.8

Country /Year	Hydropower[a]			PV[b]			Wind onshore[b]			Wind offshore[b]			Ocean[a]		
	2020	2030	2050	2020	2030	2050	2030	2050	2050	2020	2030	2050	2020	2030	2050
RO	6.6	8.6	16.3	381	381	381	169	169	169	9	9	9	0.18	0.18	0.18
SE	16.4	19.9	32.5	71	71	71	134	134	134	31	31	31	10.8	10.8	10.8
SI	1.3	1.4	1.9	18	18	18	2	2	2	0	0	0	0	0	0
SK	1.6	1.8	2.5	60	60	60	29	29	29	0	0	0	0	0	0
UK	1.9	1.9	2.0	347	347	347	230	230	230	104	104	104	309.6	309.6	309.6

[a] Based on (Simoes et al., 2013); [b] Based on (Giles Hundleby et al., 2017)

[b] Based on (Ruiz et al., 2019)