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C3S Energy: A climate service for the provision of power supply and demand indicators for Europe based on the ERA5 reanalysis and ENTSO-E data

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Abstract

The EU Copernicus Climate Change Service (C3S) has produced an operational climate service, called C3S Energy, designed to enable the energy industry and policymakers to assess the impacts of climate variability and climate change on the energy sector in Europe. The C3S Energy service covers different time horizons, for the past 40 years and the future. It provides time series of electricity demand and supply from wind, solar photovoltaic and hydropower, and can be used for recent trends analysis, seasonal outlooks or the assessment of climate change impacts on energy mixes in the long term. This article introduces this service and the resulting dataset, with a focus on the design and validation of the energy conversion models, based on ENTSO-E energy data and the ERA5 climate reanalysis. Flexibility and coherence across all countries have been preferred upon models' accuracy. However, the comparison with ENTSO-E data shows that the models provide plausible energy indicators and, in particular, allow comparing climate variability effects on power demand and generation in a harmonized manner all over Europe.

KEYWORDS

climate services, Copernicus Climate Change Service, energy conversion models, Europe, renewable energy

1 | INTRODUCTION

The power sector is exposed to weather and climate variability at all timescales, with impacts on both demand and supply (Dubus et al., 2018). This will become more and more relevant for the energy sector as the share of renewable generation increases, mainly from wind and solar energy together with hydropower (Bett & Thornton, 2016; Dubus et al., 2018). And the recent implementation of key policy acts such as the European Green Deal and, more recently, the Inflation Reduction Act from the United States of America, will only accelerate this trend.

The transition towards a more environmentally friendly electricity supply system has been the subject of numerous integration studies, which evaluate the feasibility of a European power system with large shares of renewable generation (ADEME, 2016, 2022; Bloomfield et al., 2021; Bruninx et al., 2015; RTE, 2022; Silva et al., 2018; Silva & Burtin, 2015). Similar studies have been carried out for other regions of the world (Craig et al., 2018; Denholm et al., 2022; DOE, 2020; Elliston et al., 2013; Huva et al., 2016; Wang et al., 2018). In general, such studies design and evaluate different electricity mix scenarios (i.e., the combination of different electricity generation technologies aiming to supply a given electricity demand) in terms of their technical and economic feasibility.

However, climate variability and climate change impacts are either not addressed or only partially. For instance, ADEME (2016) used only 7 years of historical data, which is too short to capture year-to-year climate variability. Silva et al. (2018) used 31 years of wind and solar generation reconstructed past data from the ERA-Interim reanalysis (Berrisford et al., 2009); despite the reasonable temporal coverage, this reanalysis offers limited spatial and temporal resolutions (Boilley & Wald, 2015) (circa 79 km and 3-h, respectively) and requires bias adjustment (Jones et al., 2017). In addition, it is common for such studies to require energy modellers to be versatile, collecting, processing and modelling different data sources, weather and energy variables, and energy conversion models. This is further highlighted in Craig et al. (2022), where a community of practice in energy–climate modelling points out some disconnections between the energy and climate modelling communities that compromise the interdisciplinarity required for producing valuable and reliable studies.

Climate change impacts on hydro, wind and solar power generation have been studied by several authors (Bartók et al., 2019; Jerez et al., 2015; Tobin et al., 2015; Van Vliet et al., 2016), but currently, these studies do not provide open and easily accessible datasets. As a result, energy modellers cannot easily leverage on these analysis to take into consideration the effect of climate change in their energy mix studies. Ideally, to study the climate impacts on the European power system, energy datasets, which are coherent, using homogenized and long-term climatic data sources and energy conversion models, would be needed. This should be done on a continental scale in order to study the possible (dis)balancing effects on a large area (Europe in this case).

In the past few years, several datasets have been developed to address this need: The EMHIRES (Gonzalez et al., 2016, 2017) and Renewables. Ninja (Pfenninger & Staffell, 2016) datasets, in particular, provide time series of renewables capacity factor for European countries covering the last three decades, but they focus only on wind and/or solar generation, whereas hydropower has been addressed only recently by the Joint Research Centre[1] and no data are available for electricity demand in the extent described here. In addition, these databases do not integrate the expected impact of climate change on the renewable energy sources (RES) power generation time series. Currently available datasets therefore present some limitations, for instance too short or incomplete datasets (e.g., demand or hydro is missing), or no systemic approaches between demand and supply from various sources. This leads to a situation where prospective studies focus only on a subset of RES and calculate their own generation time series (those for which researchers have experience or easier access to raw data). In addition to the seemingly unnecessary duplication of effort, having disparate ad hoc approaches to producing input energy data makes it difficult to cross-compare the outcomes of such studies. There is, thus, a need for a unified dataset including all relevant energy variables (wind, solar PV, hydro and demand) and timescales (from historical to climate projection) to allow enough flexibility to easily integrate them in any prospective power system analysis.

This article aims to describe the historical climate of the components of the C3S Energy (C3S-E) data service, an operational data service providing a unified and coherent portfolio of electricy demand and supply time series covering the European Union illustrating the impact of climate variability. C3S-E is implemented under Copernicus Climate Change Service (C3S) and addresses the above-stated needs of a broad range of users from the energy sector, ranging from policymakers to energy modellers or service providers. An overview on the C3S-E data service is provided in Section 2. The different data sources and the energy models are detailed in Section 3. The validation of these models over the historical stream is presented in Section 4. Strengths and weaknesses of our approach as well as possible improvements and extensions are finally discussed in Section 4.

2 | THE COPERNICUS CLIMATE CHANGE ENERGY (C3S-E) SERVICE: AN OVERVIEW

The Copernicus Climate Change Service (C3S—https://climate.copernicus.eu/) was launched in 2015 to lead and

[1]See the JRC Hydropower database (https://data.jrc.ec.europa.eu/dataset/52b00441-d3e0-44e0-8281-fda86a63546d), JRC-EFAS-Hydropower (https://doi.org/10.5281/zenodo.4086004) and this set of inputs/outputs for European power modeling including hydropower (https://data.jrc.ec.europa.eu/dataset/221c6cf4-98c0-4793-8e3a-78820377387f).

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coordinate development of climate service infrastructure and underlying data provision mainly at the European level. The Sectoral Information System (SIS) component of C3S makes use of the C3S climate data to meet the requirements of users, with a specific focus on purveyors and policy makers. The SIS includes various sectors, of which energy is a prime example. The datasets produced by the EU C3S Energy operational service (C3S-E) are designed to fulfil the needs of end users, be it, for example, analysts who want to understand the impact of climate on energy operations, management and planning, or energy modellers, who can benefit from a user-friendly data service ready to be used for their power assessment studies. It builds on the previous C3S data service, produced by the European Climatic Energy Mixes (Troccoli et al., 2018) and Climate4Energy (C4E) projects, updating both the underlying climate data and the energy models.

C3S-E covers three dimensions (Figure 1): it brings together electricity demand with wind, solar and hydropower generation (physical dimension), for three climatic streams (e.g., temporal dimension): historical (from 1979 to present), seasonal forecasts (from present to 6 months ahead) and projections under different Intergovernmental Panel on Climate Change greenhouse gases emission scenarios. A range of spatial scales is available

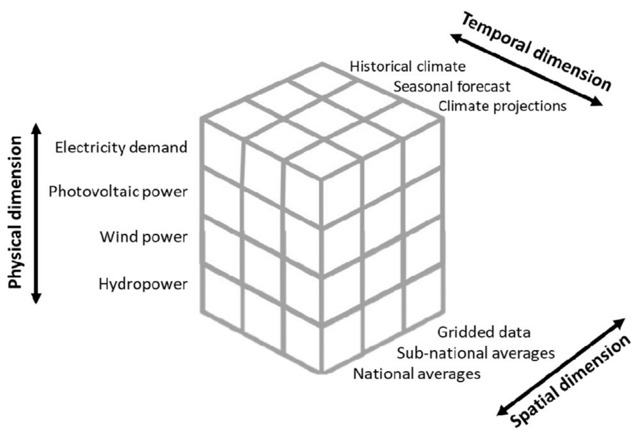

FIGURE 1 The C3S Energy operational service data cube representing the availability of energy datasets for each source (physical dimension), climate streams (temporal dimension) and geographical aggregation (spatial dimension). Note that although all these elements are available from the C3S Energy operational service, in this article we present only the historical stream. It is important to note that this paper will focus only on the historical climate stream. Indeed, energy conversion models are a core part of C3S-E and, given the reduced uncertainty of ERA5 compared with other climate data, the evaluation of the historical stream is the most suited to validate the energy model used. The applications of these energy models with seasonal forecasts and climate projections are to be discussed in a future publication.

(spatial dimension): at a grid resolution of 25 km, but also as subnational (NUTS2) and national (NUTS0) aggregates (Eurostat, 2016). Additionally, national (MAR0) and regional (MAR1) maritime regions have been defined for offshore wind energy (Saint-Drenan, Troccoli, & Dubus, 2020), since no such aggregation regions are defined by Eurostat.

Thus, as mentioned, this service aims to translate climate variables in user-needed variables relevant for power systems, namely time series for: electricity demand, and wind, solar and hydropower generation. Both the climate input and the employed energy conversion models used to generate these time series are described in the following section. Conclusions of prospective studies and analysis can be affected by input RES data (Kies et al., 2021). Based on this finding, a better understanding of the source of variability of energy variables evaluated from climatic data is essential. In this context, the philosophy of the C3S-E is to apply the same energy conversion, aggregation and evaluation methods to different climatic data and energy conversion systems to allows consistent study with respect to climatic data sources, temporal and spatial scales as well as energy sources. The novelty of our approach therefore lies on this harmonized methodology more than on the conversion model themselves.

Additionally, it must be acknowledged that the generated data aim to illustrate the plausible impacts of climate variability on the European power system but may not be suited for operational activities: the ambitioned scale, in space, time and energy sources, required the consideration of simplified assumptions and models (discussed in more detail in Section 3.3).

3 | METHODS: DESCRIPTION OF THE INPUT DATA AND ENERGY CONVERSION MODELS

As mentioned in the end of the previous section, this article focuses on the generation of historical time series of electricity demand and supply and the energy conversion models involved. This set of models—some physical, others data driven—have been developed and calibrated for the historical climate stream, which are then applied to the remaining streams. Additionally, even if the available data for model validation and training (when required) do not cover the whole historical stream (from 1979 onwards), once a model is set up, the full period of climate data is used to reconstruct the energy variables.

A more detailed discussion on the seasonal forecast and climate projection streams, along with their evaluation, will be provided in a future publication.

3.1 | Climate data

The climate data for the C3S-E historical stream come from the ERA5 reanalysis (Hersbach et al., 2020), provided by the European Centre for Medium-Range Weather Forecasts (ECMWF). It consists of a gridded dataset covering the globe, which seeks to reconstruct the past climate through the assimilation of observations in physical numerical models. Compared with ERA-Interim, which the previous C3S data service relied on Troccoli et al. (2018), ERA5 provides a more detailed spatial and temporal resolution (31 km and 1-h) and is less affected by bias.

The ERA5 data are used in its original state, except for an interpolation onto a regular 0.25 degree grid as well as the country averaging (NUTS0 or NUTS2). The specific climate variables used to develop C3S-E are:

- air temperature (at 2 m height);
- precipitation;
- downward solar surface radiation (also known as Global Horizontal Irradiance);
- wind speed (at both 10 and 100 m heights).

It is important to note that while for air temperature and wind speed ERA5 provides instantaneous hourly values (at the hour), for precipitation and solar radiation these are cumulative (over the previous hour).

3.2 | Energy data

Being part of the Copernicus services, C3S-E aims at providing free and open access energy indicators. One of the major requirements in developing and assessing the modelling here involved was to identify adequate data, which were freely available, in order to fulfil with this open access policy. Considering the scope of this work, this meant finding data that: (i) cover all European countries; (ii) have physical relevance both in space and time for the different target variables (demand and wind, solar and hydro generation) and (iii) have sufficient temporal data coverage to train and validate models.

The above-stated requirements are quite demanding; for this work, the databases from the European Network of Transmission System Operators for Electricity[2] (ENTSO-E) were deemed most suitable. In this work, we have mainly used the demand and generation data provided by ENTSO-E in two different repositories: the Power Statistics[3] (ENTSO-E PS hereafter) and the Transparency Platform[4] (ENTSO-E TP hereafter).

ENTSO-E PS compiles electric demand (also called load), generation, capacity and transmission data provided by the member TSOs from various countries. Although discontinued in 2019, its 'Monthly Hourly Load Values' data were considered for electricity demand due to its comprehensive temporal coverage (going back as far as 2006 for some countries). On the other hand, ENTSO-E TP is an operational service put in place in 2015 to provide high-quality and timely available data to the energy markets' participants[5] (going back as far as 2015 and not for every country). The renewable installed capacity (with yearly resolution) and electricity generation (hourly) time series considered in this work were obtained from this platform. Hirth et al. (2018) and Morrison (2018) describe, analyse and discuss this platform and the methodology used to create its datasets, as well as issues and limitations. Some of these issues and limitations are further discussed in Section 4.

Figure 2 provides a visual summary of all the countries (identified using their ISO 3166-1 alpha-2 code) for which the energy variables were collected and, then, modelled in the C3S-E data service. More details about the availability of each variable are given in Section 3.3.

3.3 | Description of the energy conversion models

Throughout this section, the suite of models that leverage the ENTSO-E data service are presented and described in detail. These address electricity demand and five electricity generation sources: wind on- and offshore; solar photovoltaics (PVs); and hydropower from reservoirs and run-off-river. As mentioned in the previous section, the models described here have been set up using the ERA5 climate reanalysis and ENTSO-E data from 2006 onwards for demand, and from 2015 onwards for generation. Table 1 shows the climate variables which have been used to compute each energy indicator.

These energy indicators are provided as mean power (in MW) and energy (in MWh), with the two being equivalent for an hourly timescale. Due to data and modelling restrictions, electricity demand and hydropower generation are only modelled at country level. In contrast, the wind and solar PV generation are calculated on a 0.25° grid, as

[2]The ENTSO-E is an association of 43 electricity transmission system operators (TSOs) from 36 countries across Europe, established by the EU in 2009. https://www.entsoe.eu.

[3]https://www.entsoe.eu/data/power-stats/.

[4]https://transparency.entsoe.eu.

[5]This service follows the requirements imposed by the EU regulation 543/2013. http://eur-lex.europa.eu/LexUriServ/LexUriServ.do?uri=OJ:L:2013:163:0001:0012:EN:PDF.

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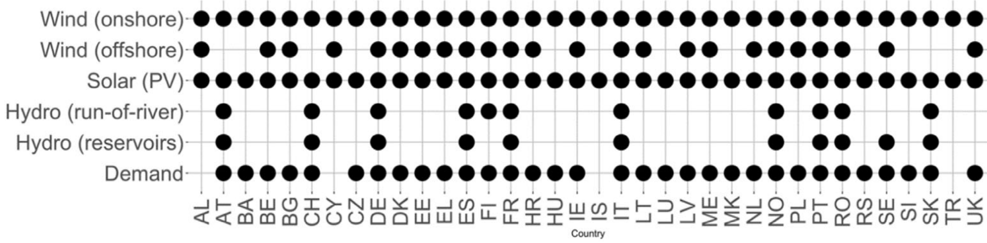

FIGURE 2 Summary of the countries and energy variables available in the C3S-E data service. Countries are identified by their international ISO 3166-1 alpha-2 code.

TABLE 1 Energy indicators provided by C3S Energy, and climate variables used to derive these.

	Electricity demand	Wind on- and offshore	Solar photovoltaics	Hydropower reservoir and run-off-river
Air temperature at 2 m	X		X	X
Global horizontal irradiation	X		X	
Wind speed at 10 m	X			
Wind speed at 100 m		X		
Precipitation				X
Calendar data	X		X	

well as aggregated per NUTS2 and NUTS0 (or MAR0 and MAR1 for offshore wind).

It is also important to note that the main goal of C3S-E is to enable users to easily model and assess the effects of climate variability and climate change on electricity consumption and generation. Thus, to isolate, even if not completely, these climate-related components, the renewable power time series are converted into capacity factors CFR (i.e., normalized according to the installed capacity). The installed capacity data from ENTSO-E TP, but also from other common sources, has a yearly resolution. To consider a progressive capacity deployment, the yearly values were linearly interpolated to daily/hourly values; while this step certainly introduces some uncertainty in the capacity factor estimates, it avoids the presence of considerable jumps in capacity when changing from December 31 to January 1 of each year. On the demand side, the long-term trend due to, for example, economic growth or population change, is removed. Then, once the models are set up, one can easily re-introduce generation capacity evolution or energy consumption trends by adding these external factors to the modelled climate-dependent part of demand and supply.

Although the following subsections aim to describe the different energy conversion methods considered in this work, these can be summarized as:

- Electricity demand: Generalized Additive Model described in Section 3.3.1;
- Hydropower: Random Forest, described in detail in Ho et al. (2020) and summarized in Section 3.3.2;
- Solar power: a physical model, described in detail in Saint-Drenan et al. (2018) and summarized in Section 3.3.3;
- Wind power: a basic, standard model described in Section 3.3.4.

3.3.1 | Electricity demand

Generalized additive models (GAMs) were chosen as the preferred approach to model electricity demand. GAMs are a generalization of linear models but can embed non-linear (analytical) functions to capture the relationship between the predictors and the target variables (Hastie & Tibshirani, 1986; Wood, 2017). They are well known methods for load forecasting (Fan & Hyndman, 2012; Goude et al., 2014; Pierrot & Goude, 2011), and have been successfully used in the GEFCOM2012 forecasting competition (Nedellec et al., 2014), since they are easy to interpret, fast to run and can adapt to different datasets. The data used here are from the ENTSO-E PS, namely the 'Monthly Hourly Load Values' described in Section 3.2. The demand models have been developed at

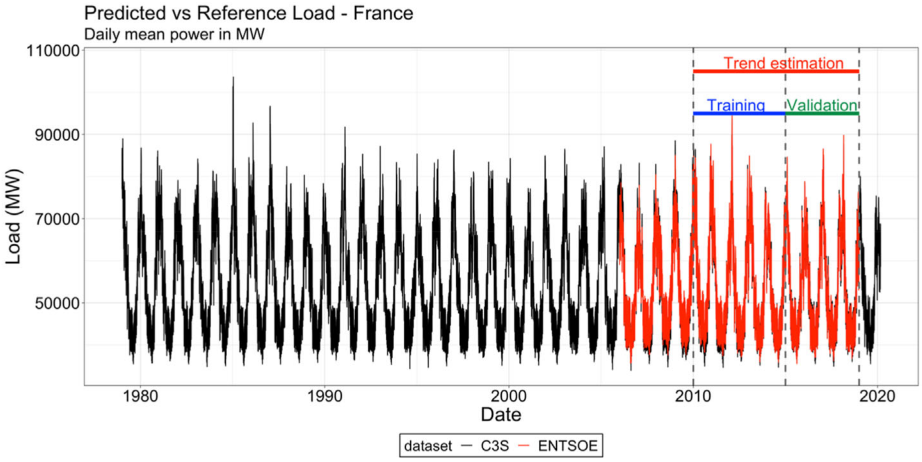

FIGURE 3 Electricity demand model set-up steps. Case of France. Demand is expressed as the daily mean power (in MW).The red curve corresponds to the ENTSO-E PS data. The black curve is the C3S-E reconstructed demand. The red, blue and green horizontal lines represent respectively the trend estimation, training and validation period duration.

country (NUTS0) level and daily time resolution. One GAM has been built for each country of Figure 2, except Albania, Cyprus, Iceland and Turkey, for which not enough data were available in the ENTSO-E database.

A broad selection of predictors was set up:

- country-averaged daily temperature;
- country-averaged daily solar radiation;
- country-averaged daily wind speed at 10 m;
- relative time of the historical period (variable between 0 and 1, which increases linearly from the beginning to the end of the period under consideration);
- relative time of the year (from 0 to 1 between start and end of year, repeated for every year);
- calendar data, flagging, through Boolean markers, bank holidays and the preceding/following day, the day of the week, the time of the year (season, month).

The climate variables can also be combined. For instance, a term can be added to consider GHI only in winter days. Last, but not least, one or several smoothed temperatures over a few days can be considered, to account for the delayed effect of outside air temperature on electricity demand, mainly because of buildings' inertia. The choice to use combined variables and smoothed temperatures is made by iteration, in order to minimize the residuals of the model.

The modelling approach is the same for all the 32 countries considered, as described below. Only the start and end dates of the training and validation periods differ, based on ENTSO-E data availability and quality. The process consists of four steps, as described in Figure 3 for the case of France:

1. A first GAM estimates the trends on the longest possible period. These trends can have three different origins: non-thermal, heating-related or cooling-related. Data from ENTSO-E generally start in 2006, but for most countries, data reliability is questionable before 2010. Dismissing this initial period also avoids taking into consideration the data in 2008/2009, which should be significantly conditioned by the global financial crisis. These trends are then removed, making that the resulting time series has no multi-annual trend, with a constant annual mean value equivalent to that of the start of the training period. Figure 3 identifies the time period for trend estimation through a red horizontal line.
2. The previously mentioned time interval is then divided into two: a training period (2010–2014) and a verification period (2015–2018). A new GAM model is trained over the first half.
3. The model built in step 2 is then applied on the verification period (2015–2018 for France, green horizontal line on Figure 3).
4. Then, the full ERA5 data are used with the GAM parameters obtained at step 2 to reconstruct the full ERA5 temporal coverage, corresponding to the whole time series shown in black in Figure 3. The black curve of Figure 3 is the final product that is provided for each country.

3.3.2 | Hydropower generation

Spatio-temporal modelling of hydropower generation at a pan-European scale is a considerably challenging task, since it would in principle require an extensive amount of information, such as river flow data measured at the inlet of hydropower plants, the technological characteristics of these plants, the management strategies implemented in plants with reservoir (e.g., if it is used for balancing, for seasonal storage, and if it is part of a set of multiple plants in the same basin). Moreover, to calibrate and assess the quality of any approach, it should be validated against operational data (e.g., measured generation time series).

Pragmatically, gathering such an exhaustive amount of data and at spatial scale as broad as the whole European continent is unfeasible. Thus, for the C3S-E data service, the approach described in Ho et al. (2020) was selected. It provides estimates of both reservoir- and run-of-river-based hydropower generation, aggregated at country level and daily time resolution, for the 12 countries with the largest installed capacity: Austria (AT), Switzerland (CH), Germany (DE), Spain (ES), France (FR), Italy (IT), Norway (NO), Portugal (PT), Romania (RO), Sweden (SE) and Slovakia (SK); from these, only Sweden and Finland are disregarded for run-of-river.

The methodology is based on the random forest machine learning approach and uses country aggregated predictors from ERA5, namely air temperature and total precipitation (c.f. Table 1). For each predictor, contemporary and lagged values up to 200 days were considered.

3.3.3 | Solar power generation

Classical approaches to estimate the solar PV power generated in a region from meteorological data require the knowledge on the detailed characteristics of each plant, which are most often not publicly available and are excessively numerous to be modelled individually.

The approach used for C3S-E, and described in detail in Saint-Drenan et al. (2018), aims to obtain the best possible estimate of power generated in any region without having to pursue this exhaustive data collection. It is based on a single-plant PV model coupled with a statistical distribution of the prominent plant characteristics. It follows the assumption that aggregated PV power generated in a region is the sum of the normalized outputs of all plants with characteristics A_i multiplied by their proportion w_i out of the whole set of plants installed in the considered region:

$$\mathrm{CF}_{\mathrm{PV}}(x,t) = \sum_{i=1}^{n} w_i f_{\mathrm{CF}}(x,t,\mathrm{G}(x,t),\mathrm{T}_a(x,t),A_i), \quad (1)$$

where CF_{pv} (x, t) is an estimate of the mean capacity factor of all PV plants located at x at time t $[W/W_p]$. G (x, t) is the global horizontal irradiance (GHI) received at x and t [W/m^2]. $T_a(x,t)$is the air temperature at x and t [°C]. f_{CF} is the single PV plant energy conversion model used to calculate the PV capacity factor $[W/W_p]$.

The function f_{CF} in Equation (1) represents a single-plant model, which needs to be chosen prior to the implementation of the proposed approach. Here, the plant characteristics (A_i) considered consist of the module tilt angle and azimuth angle. There are two steps for the implementation of the regional PV model: (1) the choice of the reference configurations; and (2) the estimation of the weights w_i.

The reference configurations have been chosen on the basis of the statistical analysis of circa 30,000 PV installations, having selected 13 configurations as a compromise between modelling accuracy and computational demand, ensuring model tractability. As detailed in Saint-Drenan et al. (2018), the weights have been derived from the above-mentioned statistical analysis and by a simple geography-dependant parameterization allowing to generalize the characteristics of the German installation to any region in Europe. The generalization was validated using aggregated PV power production from France.

3.3.4 | Wind power generation

To overcome the lack of data and complexity needed to run a wind power physical model, the approach used in C3S-E assumes a single wind turbine model, with a fixed hub height, homogeneously deployed on a regular grid. Similar approaches have been used in other studies such as in Jerez et al. (2015), since it does not require any assumption or data relative to the exact location of wind turbines, and what their evolution will be in the future. The only exception is that C3S-E considers a different turbine model for the onshore and offshore wind power, based on the actual trend in wind turbine installation and expert advice: the Vestas V135/3450 (3.45 MW) for onshore; and the Vestas V164/8000 (8.0 MW) for offshore wind.

The assumption of homogeneous spatial distribution of the installed capacity can be considered strong. It was motivated by two factors: (i) it ensures methodological coherence with PV, for which, contrary to wind, it is not easy to geolocate the fleet of generators; (ii) the hypothesis of spatially constant installed capacity was found to be reasonable for aggregated capacity factors at national level in previous works (Pierro et al., 2022; Saint-Drenan et al., 2018). Results described in Section 4.2 show that this assumption only has a visible impact for specific areas where the resource is very particular, and no plant is installed (e.g., mountains). In the latter case, the exclusion of the regions not relevant for RES installations would be need. The corresponding power curves are given in Figure 4. The power output for each grid point is calculated based on the following steps:

1. Retrieve wind speed components U and V (horizontal wind towards east and north, respectively) at 100 m.

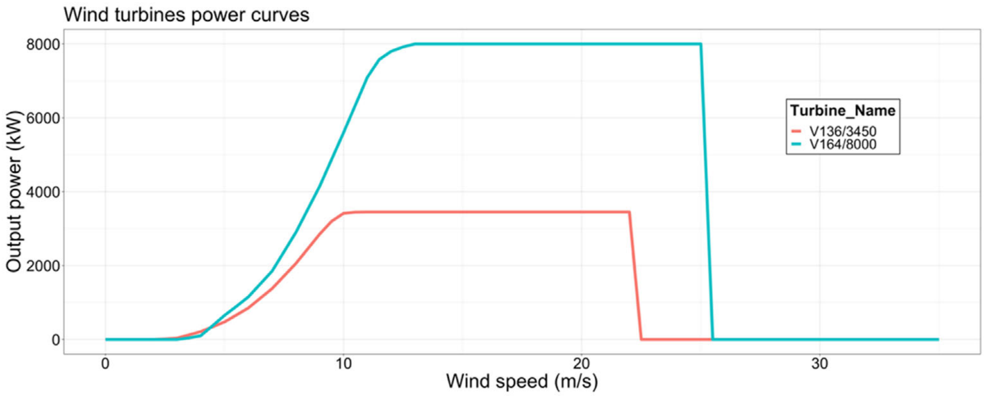

FIGURE 4 Selected onshore (red) and offshore (blue) wind turbine power curves.

Calculate the wind speed norm, based on its components: $\mathrm{WS} = \sqrt{(U^2 + V^2)}$;

2. Compute the power output P (i, j, t), using WS and the turbine's power curve, where i, j and t are, respectively, the longitude, latitude and time step.
3. Compute the capacity factor relative to the maximum power output of the wind turbine (which was already mentioned).

While this method dismisses some relevant elements like the spatial distribution of wind turbines and some loss factors (e.g., electrical losses, wake effects), it can easily reproduce the climate-driven variability of the wind capacity factor driven by changes in wind speed.

4 | RESULTS: VALIDATION OF THE C3S-E ENERGY INDICATORS

Before presenting the validation, it is important to recall the context of C3S-E. The energy models have been designed to be applied in any European region, providing energy indicators that are consistent and coherent in space and time, taking into account different kinds of climatic data (reanalysis, seasonal forecasts and projections), although this work only discusses the historical climate.

Additionally, these models were sought not necessarily for having the best reported accuracy but, instead, for their ability to adapt to often constrained input data. This is important to stress, since C3S-E handles simultaneously with coarse data availability and a vast spatial and temporal coverage, in different timescales, as well as with a variety of electricity sources.

Thus, the validation presented here is aimed at assessing the plausibility of the models output rather than demonstrating that the C3S-E approach outperforms individual models from the literature. And, in fact, this is not sufficient for operational application, as plausibility is key for scenario design and testing. Possible and planned improvements to the models are discussed in Section 5.

4.1 | Reference dataset

As described in Section 3.2, the ENTSO-E datasets (PS and TP) are, to our knowledge, the only source of homogenous energy data available for all European countries. While they provide a very good reference for C3S-E purposes, these datasets nonetheless present some drawbacks as explained in Hirth et al. (2018) and Morrison (2018). The most problematic issues for C3S-E are the following:

i. Record length and quality differ among countries. There is no easily accessible documentation on the reporting and processing methodologies applied to the data, which may change over the years, creating inconsistencies. Discontinuities that can be only explained by a change in the processing method have been identified for a few countries, and some countries have a non-negligible amount of missing or notoriously erroneous data. In addition, the PS dataset was discontinued in November 2019, and the only data available for demand then come from the TP (some inconsistencies between PS and TP were also identified).
ii. Inconsistencies were also found between the ENTSO-E TP and other reference datasets, in particular for the first years of data of the former. It can also happen that the actual generation is not consistent with the installed capacity.

The installed capacity from ENTSO-E TP indeed shows strong deviations from alternative data sources for several countries. Figure 5 shows for instance the difference between the installed PV capacity reported in ENTSO-E TP and in Eurostat for a few selected countries.

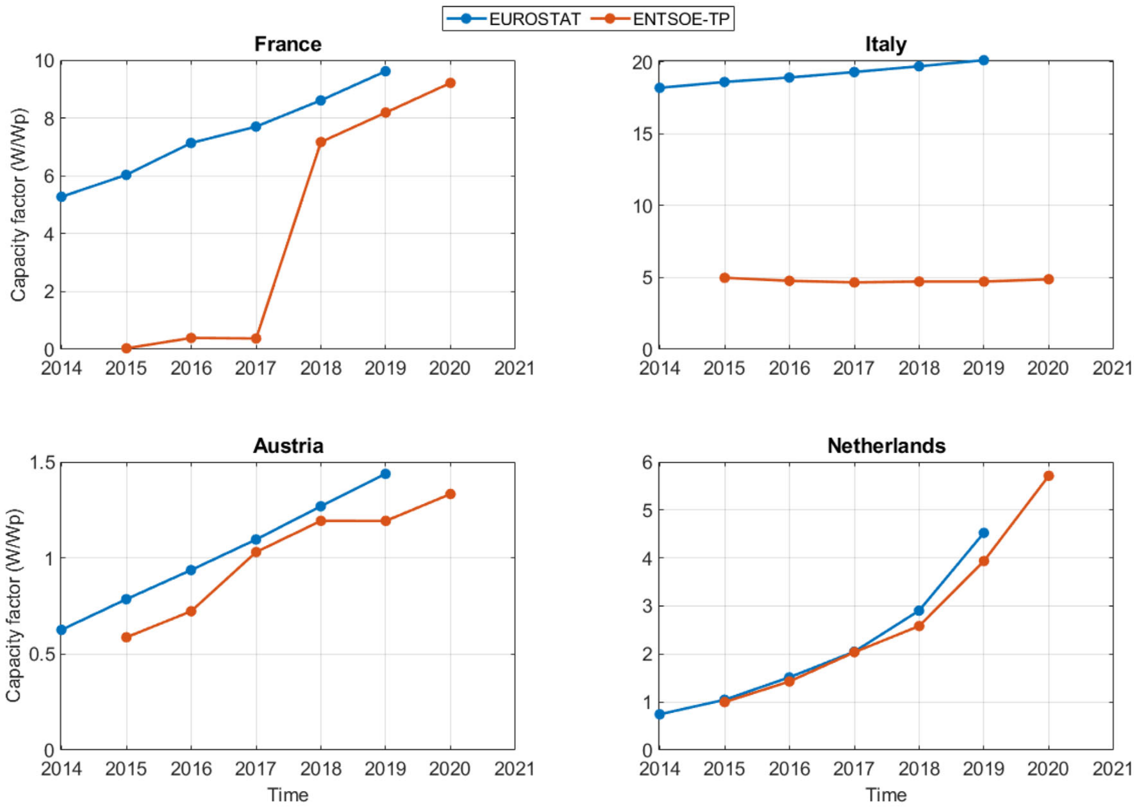

FIGURE 5 Installed capacity for solar power in selected European countries from the ENTSO-E Transparency Platform (ENTSO-E TP) and Eurostat official EU statistics.

The large differences between the two datasets illustrate the uncertainty on the installed capacity, which represents an important problem for the validation of the capacity factors. The installed capacity of all technologies considered in this study is given in Table S1.

Various factors explain the differences between the installed capacity databases: (i) the existence of different categories of installations (e.g., installations benefiting from the feed-in tariff, direct sales installations, etc.); (ii) the fact that the different data sources do not consider exactly the same production units (some considered only units with installed capacity greater than 1 MW for instance) and (iii) the difficulty of monitoring very large fleets of installation (there are more than one million PV systems in Germany). The above-mentioned issues are unavoidable considering the complexity of energy data regulation as well as technical constraints related to the reporting of the RES installations, especially in periods marked by a strong increase of the installed capacity. Although data must be used with caution, it should be noted that the situation is improving constantly, driven by efforts of TSOs and ENTSO-E to improve data sharing and data quality, and also by feedback from end users. Strategies for evaluating capacity factors despite the uncertainty of installed capacity are presented in the next section.

4.2 | Validation results

The main goal of this service is to provide capacity factor and energy generation time series for electricity demand, hydropower, wind power and solar PV. Additionally, such time series are provided at three different spatial scales: gridded values (for wind and solar only); and the corresponding aggregation at NUTS0 (wind, solar, hydropower and demand) and NUTS2 (wind and solar) levels.

Nonetheless, verifying the quality of the outputs of C3S-E is of essence to ensure their plausibility and reliability. Thus, in this section, we use various metrics to evaluate and compare the quality of the modelled variables. The Pearson correlation coefficient is the most used measure in this work for the following reasons:

1. It is scale-independent and, thus, less sensitive to errors associated with the installed capacity (since it allows comparing variables with different scales, e.g. capacity factor or power output).
2. It measures the covariance of two variables, so is particularly suitable to assess the capability of the proposed models to reconstruct and capture the variability of the energy variables, one of the aims of the C3S-E dataset.
3. It is well known and widely used.

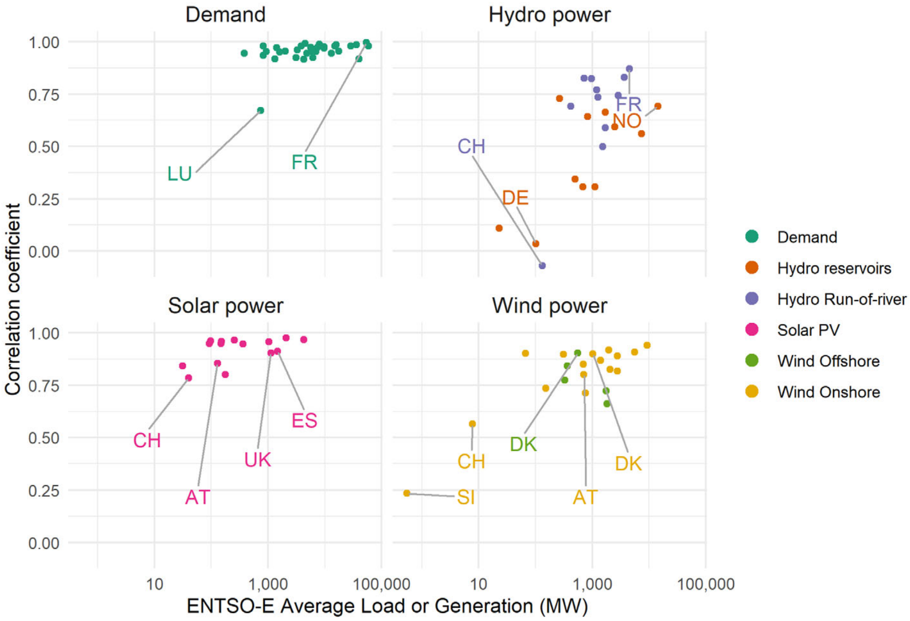

FIGURE 6 Correlation coefficient of the C3S-E data as a function of the average load or generation provided by ENTSO-E. Correlation coefficient values are given in Tables S2 and S3. Labelled countries are more explicitly discussed in the following sections.

When possible, we have also considered other error metrics such as the mean absolute error (MAE), the mean absolute percentage error (MAPE) or the normalized MAE (nMAE, here relative to the average demand/generation) to describe the error using the same unit measure as the energy variable.

As the models are different from one another for demand, wind, solar and hydro, slightly different approaches were necessary. For wind and solar, we used physical models that are unsupervised by observations. Therefore, the validation was done on all the ENTSO-E available period (2015–2019 included). For demand, the validation period is in general 2015–2018, as explained in Section 3.3.1 and shown in Table S3. For hydropower, different training and validation were tested, and the one reported here is based on a leave-one-out cross validation in which the model is iteratively trained over 3 years and validated over the fourth year available on the 2015–2019 interval.

An overview of the correlation coefficient of the different models, computed on the validation period, is given by Figure 6 (the values can be found in Tables S2 and S3). Results show, overall, a good degree of correlation between the reconstructed variables and the ENTSO-E data. For demand, the only exception is Luxembourg, due to issues in the data available to train the model. Hydropower shows better results for run-of-river than reservoir-based. This is expected: the former is more directly driven by climate variability, while the latter is more dispatchable and, thus, embeds a reservoir management strategy. For reservoirs, it can also be argued that C3S-E data can be integrated in energy modelling frameworks, which integrate a dispatch optimization component to derive their own dispatched hydropower generation time series.

Additionally, Figure 6 highlights how model performance is linked to a country's average generation (which is correlated to the installed capacity). It can be discussed how a low installed capacity will correspond to a low number of plants in a given region, making regional- or country-level averages less representative, while reducing the smoothing effect of spatial averaging. Another explanation is that the signal-to-noise ratio is smaller for countries with little installed capacity.

To complement this, we show in Figure 7 the scatter plots for three selected countries at the maximum available temporal resolution (daily for hydropower and demand, hourly for wind and solar). This figure highlights three main aspects of all models: (i) an overall good fit with the observations, despite the simplifications and assumptions made in the modelling; (ii) a significant dispersion in the results and (iii) some issues, especially for wind power. The low correlation coefficient in the modelling of hydropower reservoir in Germany (DE) is due to the low installed capacity.

The issues reflect both the simplifications made in the models, but also the lack of quality of some data in the ENTSO-E database. More details are given in the next sections for each energy variable, and possible improvements are discussed in Section 5.

4.2.1 | Electricity demand

The demand models performance can be evaluated during the three building steps (trend estimation, training and validation). Table 2 gives the error metrics of the

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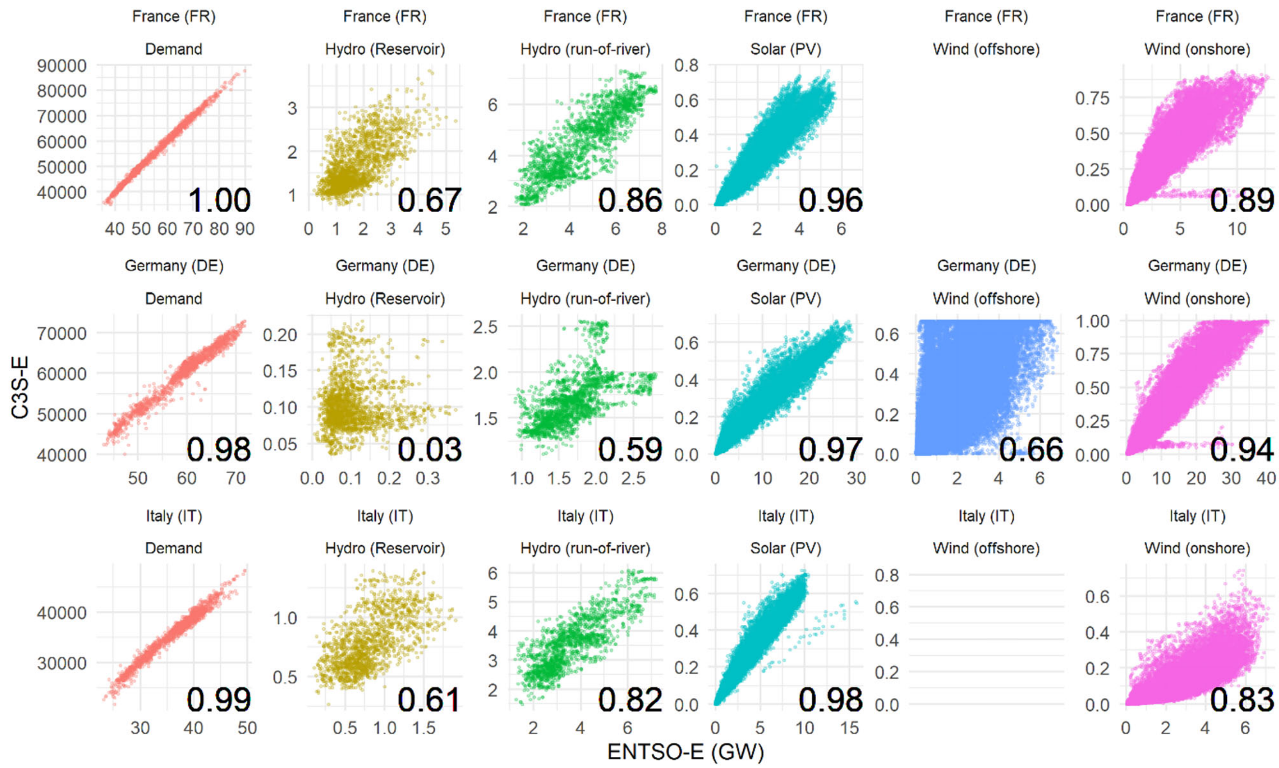

FIGURE 7 Validation scatter plots for three countries (FR, DE and IT). Hydropower and demand data have daily resolution while wind and solar are hourly. The number in the bottom-right corner of each plot is the corresponding correlation coefficient. On the *y*-axis, generation values are shown for demand and hydropower, while for PV and wind the capacity factor is considered.

TABLE 2 Demand model performance for France, for the three steps described in the text and previous figures.

Step	RMSE (MWh)	MAPE (%)
Trend estimation	18,21	1.04
Training	18,19	1.02
Validation	20,06	1.17

model for France for each of the three periods displayed in Figure 3. The most significant metrics are the validation errors, calculated on an independent period when the models parameters have been determined after trend estimation and training. For the case of France, the MAPE is 1.17%, which is higher but very close to what is generally obtained with operational demand forecasting models.

Table S3 provides the exact periods of training and validation for all the countries, as well as the corresponding metrics (RMSE, MAPE and correlation coefficient with ENTSO-E PS data).

Figure 8 shows the MAPE of the simulated demand with respect to ENTSO-E PS data, for all the 32 countries. Red bars are for the model parameters estimation period, while blue bars are for the independent validation period. Overall, all models show a good accuracy, with validation MAPE lower than 2% for 23 countries out of 32. The worst results are obtained for Switzerland (CH), Luxembourg (LU), Macedonia (MK) and United Kingdom. For these countries, the most likely reason for the poor quality of the reconstruction lies in the quality of the ENTSO-E data, as individual countries' data show (not shown here).

The scatter plots of simulated versus actual load for the period (2015–2018) are presented in Figure 9 for four countries and in Figure S3 for all countries. Overall, there is a very good fit between reconstructed and reported values in the ENTSO-E database. Such good performance is mainly due to the fact that demand depends foremost on calendar information due to its seasonal, weekly and daily variations; the climate dependence varies from country to country.

Overall, the good performance of the GAM models lies in practice in three main aspects: (i) the quality of the training data from the ENTSO-E database; (ii) the degree of dependence of demand on the climate parameters and (iii) the expert knowledge put in the model parameters definition. Aspect (ii) refers to the fact that some countries have more direct dependence of their demand on climate parameters, the most important one being

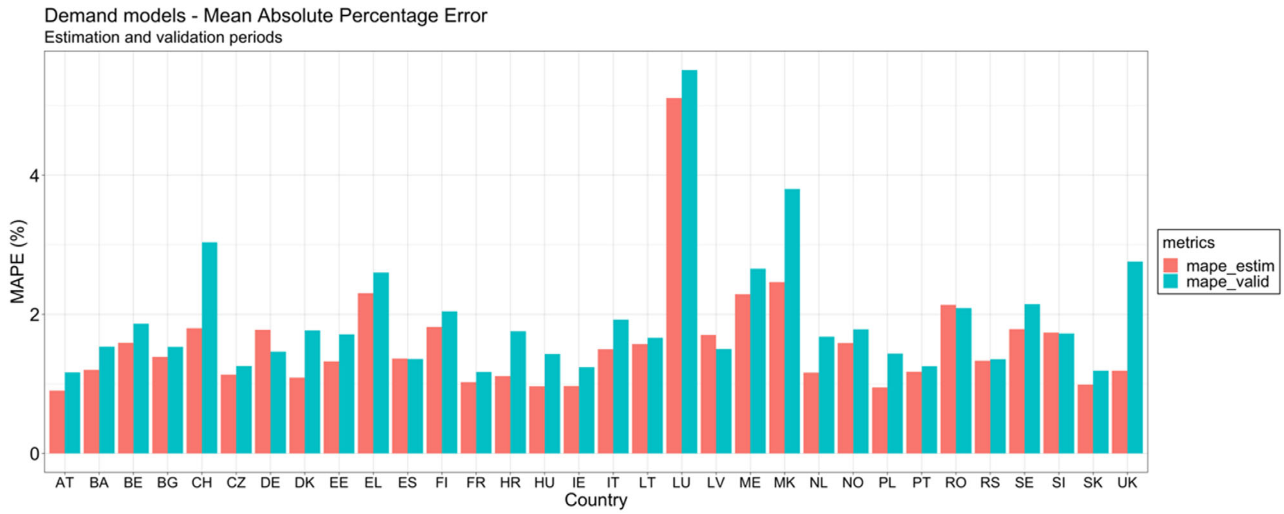

FIGURE 8 Mean absolute percentage error (MAPE) of demand models calculated on the verification period (optimized for each country). Red bars denote the MAPE of the estimation period, and blue bars for the validation period.

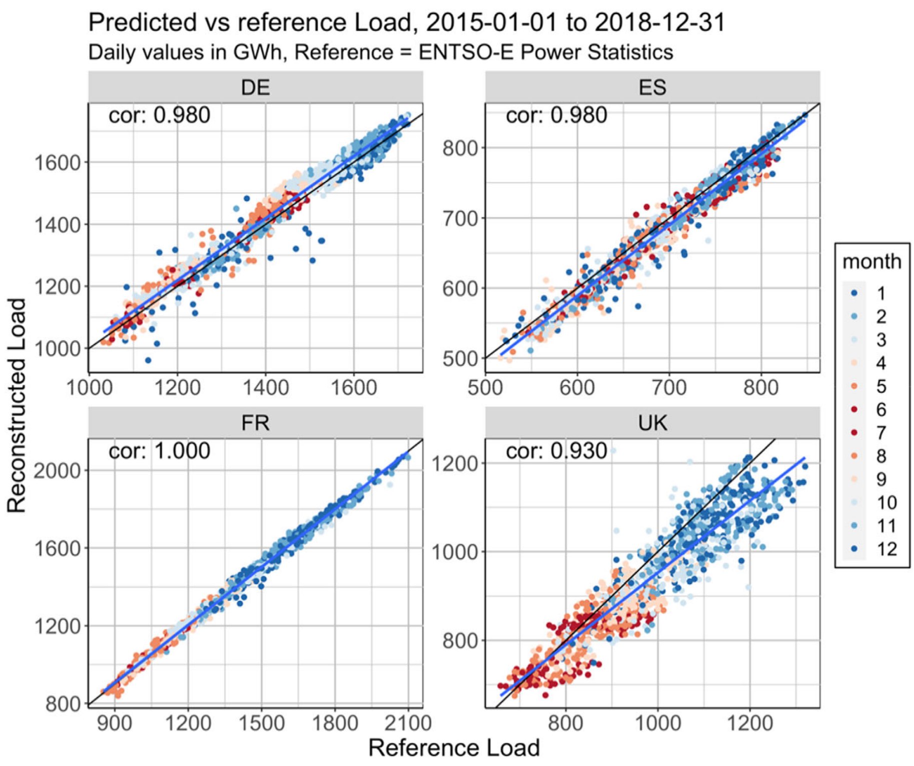

FIGURE 9 Scatter plots of simulated versus reference demand on the period 2015–2018 for four countries. The dots' colour refers to the months, with reddish colours for summer months, and bluish colours for winter months. Correlation coefficients are indicated on each country's panel.

temperature. France is the perfect example of this, as winter peak demand dependence is around 2400 MW per degree Celsius. This is the highest dependence in Europe, representing 60% of the total sensitivity of demand on temperature. For those countries where climate data play a significant role, point (iii) above relates to the degree of sophistication that was put into each model.

It has to be reminded that the simulated electricity demand has been detrended in the first step of the model set-up. Therefore, the final data from 1979 to present reflect the variability due to the climate variables (and calendar data) only, and not the evolution of other exogenous factors such as population changes and economic activity growth. The average level of demand, for instance expressed as an annual mean, is then similar to that of the end of the training period. Should a particular user be interested to reconstruct actual demand (including population and GDP effects for instance), they should rescale

TABLE 3 Summary error table for reservoir hydropower.

Country	Correlation coefficient	MAE (MW)	Average generation (2015–2019, MW)	nMAE (%)
NO	0.69	1966	14,389	13.7
SE	0.56	1204	7440	16.2
ES	0.59	878	2494	35.2
FR	0.66	472	1702	27.7
CH	0.31	441	11,122	39.3
IT	0.64	212	827	25.6
RO	0.31	261	690	37.8
AT	0.34	201	501	40.1
PT	0.73	130	266	48.9
DE	0.04	53	102	52
SK	0.11	12	23	52.2

Note: Values are sorted by the average generation observed in the ENTSO-E dataset.

TABLE 4 Summary error table for run-of-river hydropower.

Country	Correlation coefficient	MAE (MW)	Average generation (2015–2019, MW)	nMAE (%)
FR	0.87	576	4548	12.7
IT	0.83	592	3648	16.2
AT	0.74	508	2897	17.5
DE	0.59	240	1694	14.2
FI	0.5	266	1545	17.2
NO	0.74	151	1274	11.9
RO	0.77	209	1210	17.3
ES	0.82	158	977	16.2
PT	0.82	241	722	33.4
SK	0.69	91	423	21.5
CH	−0.07	82	132	62.1

Note: Values are sorted by the average generation observed in the ENTSO-E dataset.

the present data using, for instance, actual mean annual values of demand, which can be obtained from Eurostat or the World Bank.

4.2.2 | Hydropower

As said in Section 3.3.2, modelling of hydropower has been particularly challenging, mostly due to the lack of data and information for calibration and validation. A more extensive discussion of the results can be found in Ho et al. (2020). Tables 3 and 4 show the correlation coefficient, MAE and the nMAE (relative to the average generation on the entire period) for all the countries with hydropower capacity.

In general, models perform better for hydropower run-of-river than for reservoir hydropower, mainly because the majority of hydropower run-of-river plants are mostly non-dispatchable, depending then mainly on the meteorological conditions. On the other hand, reservoir power plants are most often dispatchable, meaning that their generation planning is done taking into account the power system conditions (e.g., prices, balancing needs), which is disregarded in C3S-E. There is a positive association between the correlation coefficient and the country-level hydropower installed capacity, which can be seen in Figure 6 and also in Tables 3 and 4.

Figure 10 can help to explain the low performance in some cases, where there is a clear discrepancy of models' performance depending on the year. A similar figure for

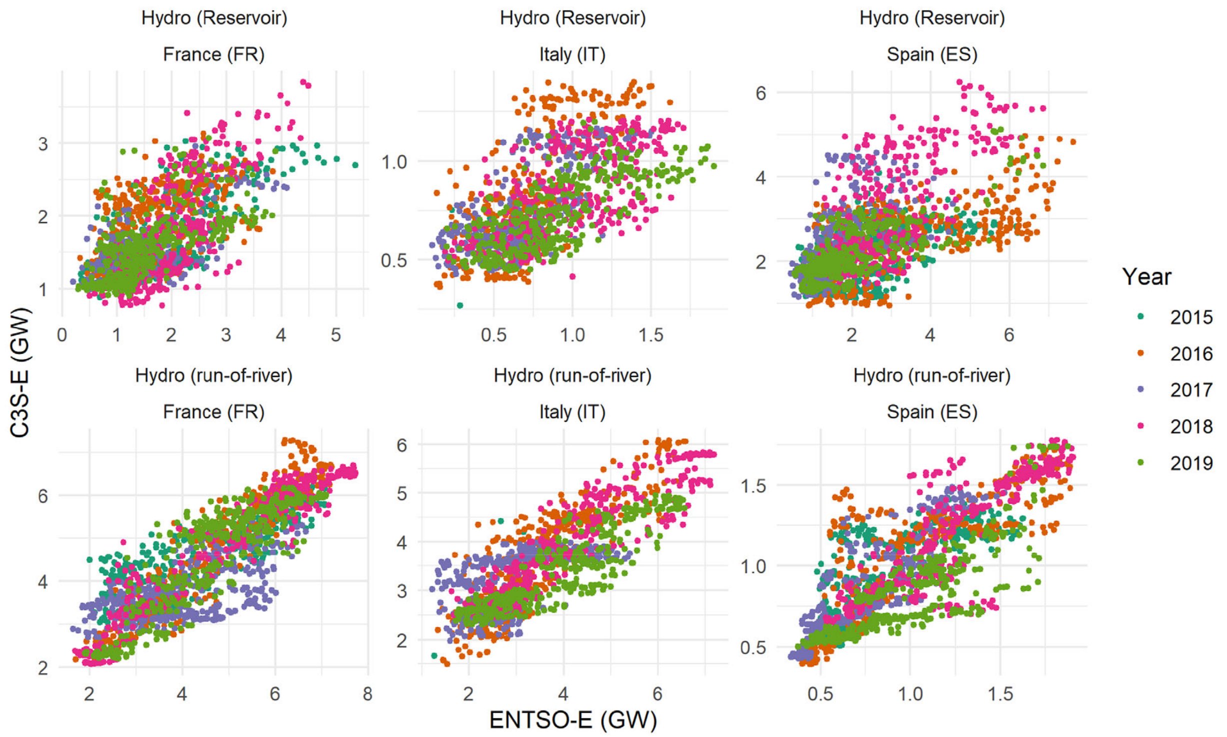

FIGURE 10 Hydropower scatter plots for three selected countries. The colour represents the modelled year. The scatter plots for the other countries are available in the Supplementary Section.

all countries is available as Figure S4. This might be caused by changes in installed capacity in those countries. As described in the methodology, the hydropower model assumes a fixed total installed capacity for each country in order to assess solely the impacts of climate conditions on hydropower. In reality, the installed capacity may change over time, by adding new power plants or removing old power plants from the electricity grid, resulting in an underestimation or overestimation of the model over time, respectively.

4.2.3 | Wind power

As mentioned in Section 4.1, an issue to be dealt with when comparing model output with ENTSO-E data is the lack of information on the installed capacity. The resulting uncertainty hinders a detailed quantitative analysis of the model error. Thus, a qualitative analysis is conducted by representing in Figure 11 the model output (capacity factor) for onshore wind power as a function of the ENTSO-E power data where the colours of the scatter points represent the year. The actual installed capacity increasing with time, we observe the slope of the scatter points in Figure 11 decreasing with time. This effect is particularly observable in the four selected countries. For the Netherlands, a problem related to the installed capacity is visible for the year 2019, which confirms the issue previously discussed in Section 4.1. A similar figure for all countries is available as Figure S5 for onshore wind power and Figure S6 for offshore wind power.

We can observe for some countries, for instance, Denmark (but also Belgium and the Netherlands, see Figure S5), a saturation of the capacity factor when the wind speed exceeds the nominal wind speed of the chosen reference wind turbines (the nominal wind speed is the value over which the power production is maximum, hence corresponding to a capacity factor of 1.0). This effect is a direct consequence of the chosen modelling approach (use of a single wind turbine). It is particularly marked in small countries where the chosen power curve differs from that of the prevailing wind turbines. Denmark and the Netherlands are two pioneer countries in wind energy. As a result, a large proportion of their park contains old turbines, with a lower hub height and a smaller nominal power than the ones chosen here and presented in Section 3.3.4. It is therefore obvious that the representativity of a modern wind turbine used in our model is limited for those countries. The spatial extension of a country is also playing a role in the presence of such effects in the country average: indeed, the larger the averaging area, the more such effects will be smoothed out during the aggregation. In countries like the Netherlands and Denmark, the smoothing effect is limited and the

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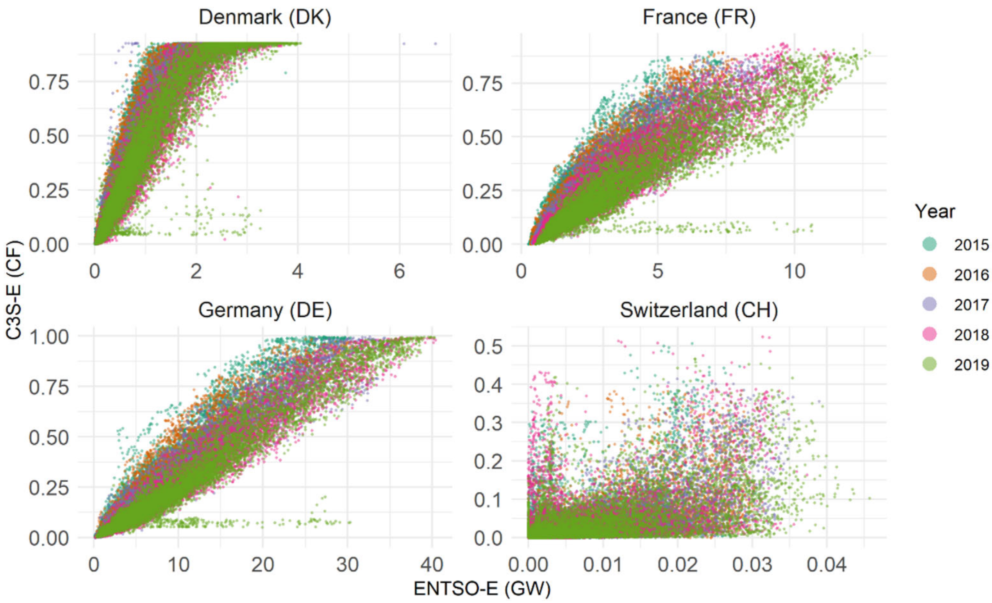

FIGURE 11 Scatter plot for onshore wind in four selected countries. The C3S-E capacity factor is represented against ENTSO-E TP actual generation. Dots' colour correspond to different years.

saturation is observable. A further reason may lie in the fact that ERA5 has some biases in wind speed as shown for instance in Jourdier (2020), with overall an overestimation in Northern Europe, and an underestimation in the South. The positive wind speed bias in the North artificially leads to an overestimation of the capacity factor for the Netherlands and Denmark. Yet, possible simulation errors due to bias in ERA5 are difficult to diagnose due to the uncertainty on the installed capacity and will be investigated in detail in the future.

Correlation coefficients for Switzerland and Austria (0.56 and 0.80 respectively) are low in comparison with the performances obtained for other countries (see correlation coefficients in Table S2). These below-average scores can be explained by the chosen calculation method. The spatial distribution of the installed capacity being not available for this analysis, we assumed a homogeneous distribution of the capacity over the territory. It was shown by Saint-Drenan et al. (2018) that this assumption is tractable for France and Germany but not for countries located in the Alpine region where weather conditions are very different between the mountains and the plains. As in practice, there is little or even no RES capacity installed in mountainous areas, the assumption of uniform geographical distribution leads to large estimation errors. This issue is planned to be fixed in future versions where a more sophisticated aggregation approach will be implemented, using more realistic wind farms location assumptions.

With exception of the cases detailed in this section, most values of the correlation coefficients are greater than 0.8 for all countries, which is a very encouraging result that supports the plausibility of our onshore wind power model. The model might however be improved in three ways: first, by considering actual wind farms characteristics (location, technology, hub height...); second, by using a more realistic approach for the spatial distribution of the installed capacity; and third, by applying a bias adjustment to the ERA5 wind speed data.

4.2.4 | Solar PV

The same validation procedure used for onshore wind has been applied to the outputs of the solar PV model. The scatter plots representing the output of our model against power data provided by ENTSO-E are displayed again for four selected countries in Figure 12. A similar figure for all countries is available as Figure S7. As mentioned previously, the colour of the scatter points represents the year. This representation is used to avoid the uncertainty on the installed capacity in the validation.

As is the case for onshore wind, the chosen aggregation approach yields estimation errors in the Alpine region (Switzerland, Austria) but also in the United Kingdom. Larger estimation errors are also found for Spain. As identified in previous works, errors in Spain are explained by the fact that the ENTSO-E data encompass both PV and CSP (Concentrating Solar Power) while our model only considers PV systems (Saint-Drenan et al., 2018).

Figure 6 shows, in general, good performances. Below-average performance is visible for the Netherlands, whose origin has not been identified so far and is still under investigation. Apart from the above-mentioned cases, the values of the correlation coefficient are above 0.9 for all countries, which indicates that the output of the solar PV model is plausible.

The SPV model might then be improved in two ways: first, as for onshore wind, by improving the assumption

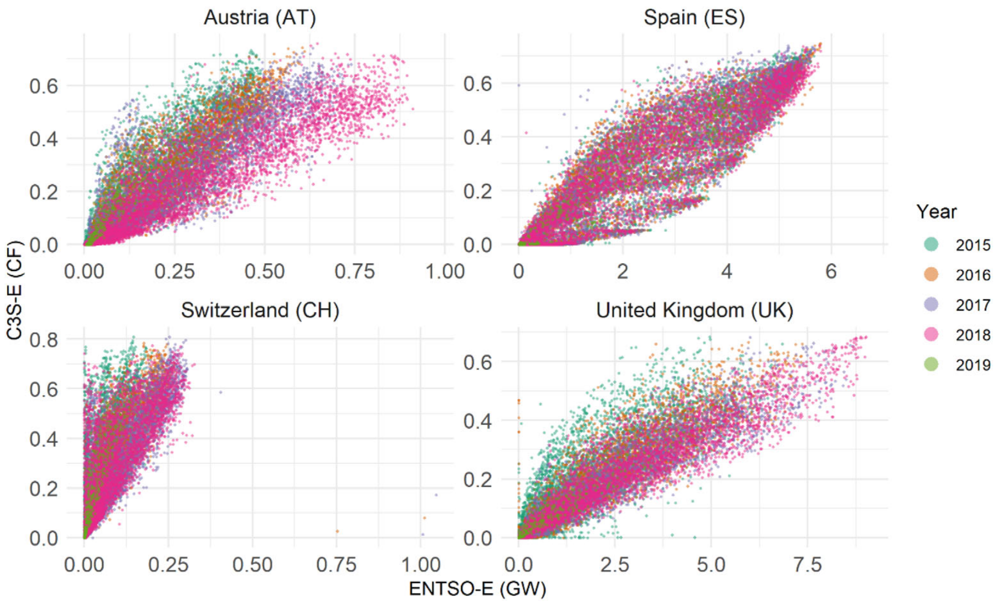

FIGURE 12 Scatter plot for solar PV in four selected countries.

on the spatial distribution of the installed capacity, and secondly, by improving the country-specific model weights to increase the correlation with the ENTSO-E data.

5 | DISCUSSION AND CONCLUSION

The objective of C3S Energy service is to produce a dataset of coherent weather-dependant energy variables for all European countries for different temporal scales: covering the last four decades, for the next 6 months using seasonal forecasts and until the end of the century using climate projections. In this article, we describe the energy conversion models developed to generate this dataset. These are trained and validated against power data from the ENTSO-E databases. This choice was made to cover as many countries as possible, also considering the need to use publicly available data to comply with C3S open access policy.

The validation is conducted using reanalysis data as input to the models. Although not presented here, the same models have also been applied to seasonal forecasts from three of the C3S models (ECMWF, Météo-France and the UK Met Office) as well as to 10 climate projections models from the EURO-CORDEX experiment (Bartók et al., 2019; Jacob et al., 2014) for IPCC scenarios RCP4.5 and RCP8.5.

Of course, the evaluation of the energy dataset derived from reanalysis does not necessarily guarantee performance for the seasonal forecasts and climate projections derived datasets because these have biases. Bias correction have been applied to the climate data from these sources and further verification has been done, using the hindcasts for the seasonal forecasts, and the ERA5 overlapping period (1970–2020) for the projections. The detailed methods and results of the application of the energy conversion models presented here to future climate will be the scope of a future paper.

The extended evaluation that was performed shows that the energy conversion models produce plausible demand and supply data, and in particular they reproduce fairly well the effects of climate variability on electricity demand and generation, noting that validation is hindered by uncertainty in the reference data.

Several causes have been identified to explain the model limitations, and improvement options have been listed, which might be implemented in the near future.

Firstly, energy observations are a key issue in developing and validating such models. The ENTSO-E TP database provides uniform access to data from all European countries only since 2015. The record length is relatively short, especially with respect to the amount of data needed to calibrate statistical models when the interannual variability is large, as is the case for hydropower. In addition, issues were observed in the data and some inconsistencies have also been found. In order to increase the data quality and extend the depth of the archive, it is of utmost importance that significant effort is put in maintaining and improving the collection of, and public access to, improved quality data on energy demand and generation.

Secondly, the ERA5 climate data have been used here without any bias adjustment. Results from other research groups have shown that there are some biases, especially in wind speed. Further developments should implement bias adjustment on wind speed fields, which should significantly improve the wind power estimations.

Thirdly, energy conversion models could be improved. The wind power model is the most basic of all the models used here and could be enhanced for instance by using a more generic and adaptable power curve like in Saint-Drenan, Besseau, et al. (2020). The wind and solar PV power estimations could also be improved by taking into account the actual location of the installed capacity. However, it has to be remembered that the same models are applied for projections until the end of the century, when the location of wind and solar capacity cannot be anticipated. The integration of scenarios taking into account the evolution of the installed capacity may be considered to address this issue. The hydropower model could also be improved, and more collaboration could be sought with hydrological model developers into the future, to possibly find intermediate complexity models, between full hydrological models and the more simple models used here. The demand models could also be adapted to the hourly time resolution, in order to fit the needs of adequacy studies. It could also benefit from direct interactions with national TSOs, in order to refine the model equations based on their expertise of the demand behaviour in their country.

The C3S-E models and dataset are among the first to provide climate-related energy indicators for electricity demand and generation from wind, solar and hydropower for most countries in Europe, in a homogenized way for three different time streams. The originality of this work lies in its availability through open and free access in the C3S Climate Data Store. This is a first stone in building a common framework for climate-related energy modelling activities. Rather than an end-product, the dataset should be seen as the demonstration that it is possible to combine all the necessary elements to provide relevant information to help energy modellers and decisions makers better integrate the effects of climate variability and climate change in long-term energy prospective studies, as well as seasonal outlooks. It provides a strong basis for studying the impacts of climate variability and climate change on current and future energy mixes in Europe, like in Bloomfield et al. (2021). Efforts should be pursued to better identify and meet end-user needs to ensure that the further development of the C3S-E service addresses the challenges raised by climate change and the energy transition. The C3S ecosystem provides an excellent framework for developing these activities, and more collaboration should be sought between climate scientists, climate services developers and energy modellers.

Following the work presented here, a direct collaboration between C3S and ENTSO-E has been established, which aims at developing the new version of the Pan-European Climate Database, the cornerstone of all ENSTO-E's prospective studies, from seasonal outlooks to European Resource Adequacy Assessments (ERAA), to Ten Year Network Development Plans (TYNDP). The project focuses on the historical period and the projections for the next decades, including several improvements in the energy conversion models. In parallel, C3S is also working towards the extension of the current energy service at the global scale, including using some CMIP6 simulations instead of EURO-CORDEX. All these developments target to better answer the needs of a wide community of users, at the European level and worldwide.

AUTHOR CONTRIBUTIONS

Laurent Dubus: Conceptualization (lead); data curation (lead); formal analysis (equal); investigation (equal); methodology (lead); visualization (equal); writing – original draft (equal). **Yves-Marie Saint-Drenan:** Conceptualization (equal); data curation (equal); formal analysis (lead); methodology (equal); validation (lead); visualization (equal); writing – original draft (equal). **Alberto Troccoli:** Conceptualization (equal); funding acquisition (lead); project administration (lead); supervision (lead); writing – review and editing (equal). **Matteo De Felice:** Conceptualization (supporting); data curation (equal); formal analysis (equal); methodology (equal); validation (equal); visualization (equal); writing – original draft (equal). **Yohann Moreau:** Conceptualization (equal); methodology (equal); validation (equal). **Linh Ho-Tran:** Conceptualization (equal); methodology (equal); validation (equal). **Clare Goodess:** Conceptualization (equal); writing – review and editing (equal). **Rodrigo Amaro e Silva:** Writing – review and editing (equal). **Luke Sanger:** Software (lead).

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DATA AVAILABILITY STATEMENT

All processed C3S-E datasets are passed to a publicly accessible drive. Then, as part of a monthly automated procedure, integrated into the Climate Data Store (CDS). The dataset is freely available to download from the CDS[6] to anyone who has a registered account (DOI: 10.24381/cds.4bd77450). In addition to downloading the data from the CDS, users are able to access and plot data via the online visualization tool,[7] made available as part of the CDS toolbox.

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SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

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