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Data article

SOWISP—A retrospective high spatial and temporal resolution database of the installed wind and solar PV power in Spain

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ABSTRACT

The proposal of new energy systems based on renewable energies requires thorough research in order to derive technically reliable and economically sustainable systems. One of the key inputs of such research is constituted by reliable databases of renewable resources. Despite the great effort of the scientific community in recent years, most current databases are far from optimal. Although some databases are based on real data, they lack adequate spatial resolution and/or temporal coverage. Other databases are obtained by estimating renewable energy potential from meteorological reanalysis; however, these estimates are subject to high uncertainty. One of the main problems when building these renewable resource databases is the lack of actual values of installed capacity. In this study we present the SOlar and Wind Installed Spanish Power (SOWISP) database. SOWISP provides the actual installed capacity of wind and photovoltaic solar energy in each Spanish town, with a monthly resolution, and covering the period of 2015–2020. SOWISP has been developed and validated based on a careful and thorough compilation of different public databases. It covers the need for a publicly available database with sufficient spatial and temporal resolution suitable for the analysis of energy systems. Moreover, SOWISP, along with other freely available datasets, supports many modern applications. In addition, a Python package (available on GitHub) was developed for managing this database.

1. Introduction

Energy and power systems of numerous nations around the world are undergoing a transition from a very high dependence on fossil fuels to an increasing dependence on renewable sources (IRENA, 2017). This transition is fostered not only by the climate change threat but also by the level of development of renewables. Notably, wind and solar photovoltaic (PV) energies play a central role in this transition, given the high level of technical and economic competitiveness reached by these energies (IRENA, 2020; IEA, 2020). European Union policy seeks to achieve the target of 32% in the European electricity consumption coming from renewable resources by 2030 (European Comission, 2018). In Spain, this objective will be achieved by installing about 25 GW and 20 GW of additional solar PV and wind power, respectively, along the present decade (MITECO, 2019). Nevertheless, the transition to the new energy systems poses a formidable challenge, since the new systems should be technically reliable and economically sustainable. Many factors, such as the weather dependence of renewables, makes the design of these new systems a complex task. In recent years, very sophisticated energy and power system models have been proposed to help with this task (Müller et al., 2018). These models allow optimizing the new systems accounting for renewable energies, weather dependence, energy costs, demand variability and power transmission restrictions, among other aspects (Ringkjb et al., 2018). One of the very key inputs of these models is a suitable renewable energy resources database. In order to produce significant results, the databases should, ideally, extend over long periods and have a relatively high spatial and temporal resolution. In addition, another desired characteristic of these databases is to be publicly available. This will warrant the reproducibility of the results and, therefore, will boost the impact of the research.

Significant efforts have been made in recent years to generate such databases, particularly for European countries. One example is the European Network of Transmission System Operators for Electricity (ENTSO-E), which provides actual power generation and installed capacity of all relevant technologies for European countries (Hirth et al., 2018; ENTSO-E, 2022). Other authors have proposed the use of reanalysis-derived databases. Reanalyses provide all the relevant meteorological information for energy and power systems analysis such as wind speed, solar irradiation, or temperature. Then, a suitable model can be used to transform the meteorological data into suitable energy variables (solar/wind power generation/capacity factors, electricity demand, etc.). In this way, the University of Reading provides

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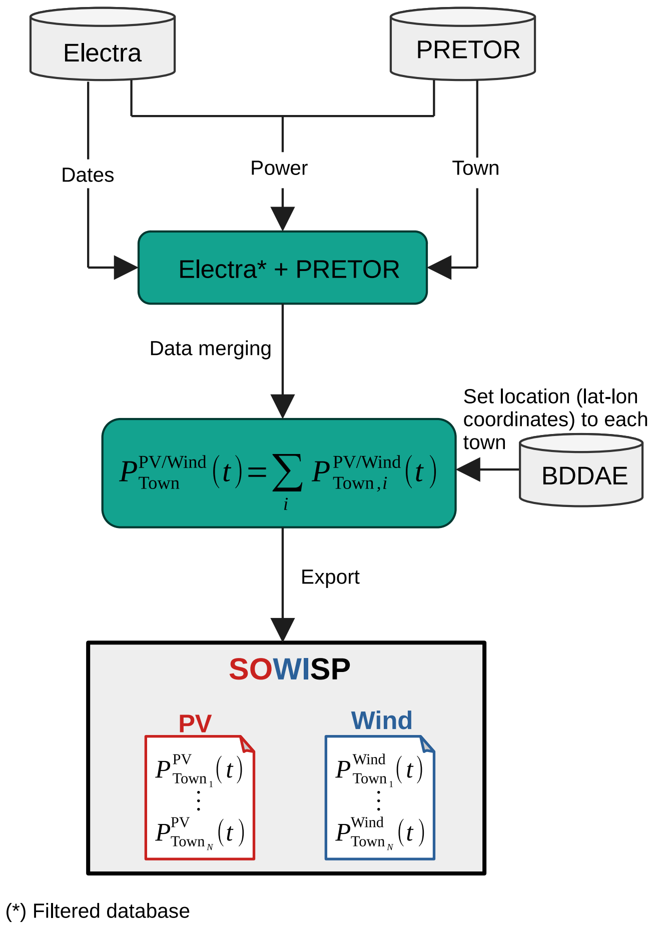

Fig. 1. Outline of the SOWISP building procedure.

nationally aggregated and sub-national time series of demand and wind/solar PV power capacity factors, for European countries extending several decades back (Bloomfield and Brayshaw, 2021; Bloomfield et al., 2022). Another dataset is the Renewables.ninja web application (Pfenninger and Staffell, 2016; Staffell and Pfenninger, 2016), which provides time series of simulated wind and PV capacity factors, at an hourly resolution, of all European countries simulated from historical weather conditions. Finally, another example is the EMHIRES database (Gonzalez-Aparicio et al., 2016, 2017), produced by the Joint Research Centre, which, unlike other databases, provides data at NUTS 2 regional level (ISO 3166-2) for all European countries.

Despite the great effort made by the scientific community, most of the current databases of renewable energy resources have a limited value for energy system analysis. The development of this type of database faces many obstacles. One of the most relevant barriers is the scarcity of actual values of installed capacity with high spatial and temporal resolution. Installed capacity allows converting capacity factors to power generation and vice versa, both of which are important for power system analysis. Notably, capacity factors are key parameters for the analysis of the role of renewables in power systems, although power generation values are necessary for the study of the power transmission requirements in these systems. Therefore, the absence of installed capacity values limits the value of renewable energy resource databases.

The main reason for the lack of actual installed capacity data is that energy yield and power system data usually belong to private companies, or to government institutions which cannot provide them due to legal restrictions. Some private companies provide commercial datasets of relevant technologies (e.g. The Wind Power and Wiki-Solar) covering even entire countries. However, these datasets, although useful, are mainly meant for commercial purposes, providing information of only certain types of plants (usually large plants), and lack independent evaluation analysis studies. An additional obstacle is related to the compilation of the necessary data, particularly for solar PV energy. There are a large number of solar PV installations (solar PV plants, small farm, self-consumption systems) in many countries. Among the renewable resource databases mentioned above, only ENTSO-E provides public actual values of installed capacity. Although valuable, this dataset has a poor spatial and temporal resolution (mainly annual national aggregated values of installed capacity are provided). The use of such a national-aggregate value in energy modeling may provide misleading results, particularly when used to estimate future renewable generation in countries with a high spatial variability of the resources (Frysztacki et al., 2021). To cope with the low temporal resolution (annual update), common practices are the use of a fixed value for a specific date (Pfenninger and Staffell, 2016; Victoria and Andresen, 2019) or the use of a linear interpolation between two consecutive values (Pierro et al., 2022). Nevertheless, these approaches may provide misleading results during periods of important relative changes of the installed capacities, as is the case of many Spanish regions along the year 2019.

Therefore, the development of enhanced databases of installed capacity with a high spatial and temporal resolution is a key element to produce reliable results from energy system analysis regarding the energy transition. Since the development of comprehensive facility databases has become a highly time-demanding process, several initiatives have appeared in the last few years. In this regard, Stowell et al. (2020) proposed creating an open database of the PV installation across the UK (several hundreds of thousands). This database is based on a crowd-sourcing campaign, being compatible with continual updating to track the rapid growth in PV. Two other important crowd-sourcing initiatives have been proposed in the last years, aiming at promoting open source and, specifically, open data for energy modeling: the open energy modeling initiative (Openmod) and the Open Power System Data platform (Wiese et al., 2019).

In this framework, this study presents the SOWISP (SOlar and Wind Installed Spanish Power) database, with the aim of contributing to the energy transition. Notably, SOWISP provides the actual wind/solar PV installed capacity of the wind/solar PV plants operating and connected to the power grid, as well as the corresponding town of Spain in which each of them is associated, with the median size of these towns being around 43 km^2. This database has a monthly resolution and covers the period of 2015–2020. The database was developed and validated based on a thorough and exhaustive compilation of publicly available information collected from different sources. A special characteristic of SOWISP is that it contains simultaneous information of both wind and solar PV energies actual plants. This is particularly relevant for energy system analysis. To the best of the author's knowledge, SOWISP dataset contains data in greater detail than any previous similar dataset of this type released for Spain and, for any other country in the world. SOWISP covers the need for a publicly available database with enough high spatial and temporal resolution suitable, among other purposes, for the development of renewable energy resource databases and energy systems analysis. However, the SOWISP database, given its characteristics and the availability of complementary open source datasets, supports other modern applications, as discussed in the final part of this work.

This paper is organized as follows. The primary data sources used in the development of SOWISP are presented in Section 2, along with the data-processing procedure. Section 3 addresses the data quality control and the database validation. Section 4 provides a description of the database records. Section 5 describes a set of potential usages of the dataset. Finally, Section 6 presents the SOWISP_lib library developed to promote the use of the new database.

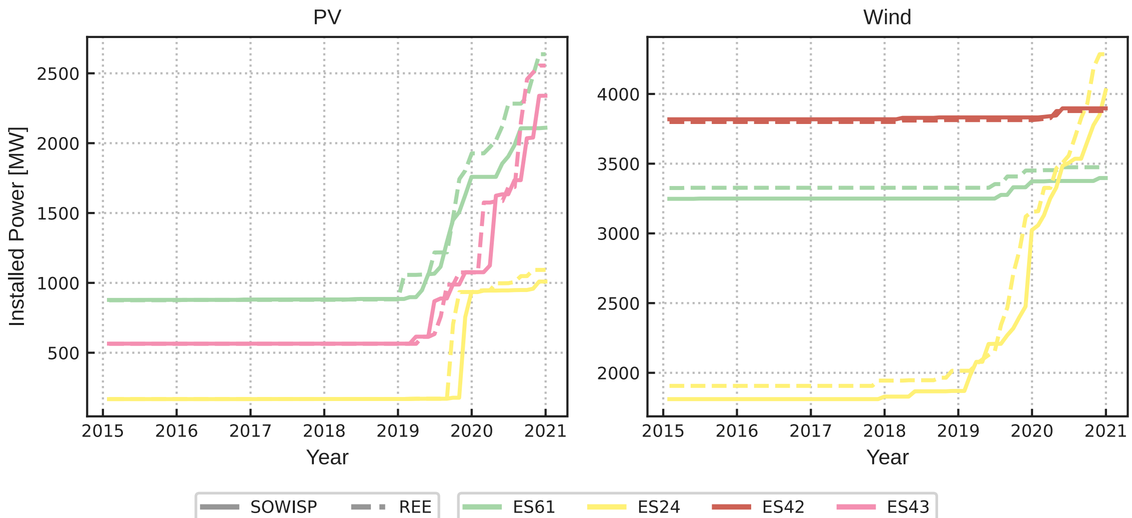

Fig. 2. Monthly values of installed power for the period of 2015–2020 as derived from SOWISP (solid line) and provided by REE (dashed line), for both PV (left plot) and wind power (right plot). Values are displayed for four NUTS 2 regions; namely: ES24 (Aragon, yellow), ES42 (Castilla-La Mancha, brown), ES43 (Extremadura, pink) and Andalucía (ES61, green). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

Table 1
Relative differences (in %) between the values of the solar PV installed power values as derived from the SOWISP and REE databases. Values are displayed for each NUTS 2 region at the end of each year of the study period (2015–2020). Positive values indicate that the SOWISP data are greater than the REE data.

NUTS_2	20151231	20161231	20171231	20181231	20191231	20201231
ES11	−1.93	−1.92	−1.68	−1.59	−1.46	−1.32
ES12	−12.88	−12.88	−6.62	−4.93	−0.98	−0.98
ES13	2.10	1.15	2.05	2.05	2.05	2.95
ES21	−3.15	−3.17	−2.82	−2.57	−1.34	−0.05
ES22	−0.85	−0.54	−0.53	−0.29	−0.58	−0.02
ES23	−0.15	−0.15	−0.15	−0.15	−0.13	−0.13
ES24	−0.23	−0.23	−0.06	−0.06	−0.01	−7.62
ES30	−2.02	−2.03	−1.75	−1.63	−1.56	−1.51
ES41	−0.35	−0.35	−0.34	−0.34	−1.23	−6.21
ES42	−0.35	−0.36	−0.34	−10.82	−0.18	−3.35
ES43	0.20	0.20	0.20	0.20	0.11	−8.46
ES51	−0.04	0.17	0.17	−1.41	−3.05	−4.89
ES52	0.08	0.05	0.09	0.11	−0.01	−8.75
ES61	0.31	0.31	0.32	0.32	−8.74	−19.97
ES62	−2.35	−2.34	−1.98	−1.96	−0.78	−0.68

Table 2
As in Table 1 for wind technology.

NUTS_2	20151231	20161231	20171231	20181231	20191231	20201231
ES11	−4.77	−4.83	−4.82	−4.73	−4.27	−4.80
ES12	0.00	0.00	0.00	0.00	0.00	0.00
ES13	−0.01	−0.01	−0.01	−0.01	−0.01	0.00
ES21	−0.59	−0.59	−0.59	−0.59	−0.59	−0.59
ES22	−12.23	−11.98	−11.84	−11.84	−10.86	−9.05
ES23	0.00	0.00	0.00	0.00	0.00	0.00
ES24	−4.98	−4.98	−5.91	−7.19	−4.18	−6.04
ES41	−1.39	−1.42	−1.38	−1.38	−1.28	−1.90
ES42	0.51	0.51	0.51	0.51	0.51	0.46
ES43	0.00	0.00	0.00	−100.00	0.00	0.00
ES51	3.61	3.61	3.61	3.42	3.42	3.42
ES52	−0.34	−0.34	−0.34	−0.34	−0.34	−0.32
ES61	−2.33	−2.33	−2.33	−2.33	−2.25	−2.23
ES62	−0.00	−0.00	0.00	0.00	0.00	0.00

2. Data description and methods

2.1. Data sources

SOWISP was built based on the analysis and compilation of three public databases: Electra (MITECO, 2022a), PRETOR (MITECO, 2022b) and BDDAE (IGN, 2022). Electra and PRETOR provide information associated with actual electricity generators connected to the Spanish power grid. SOWISP does not include small PV self-consumption systems, although it should be mentioned that the installed power of such systems in Spain in the analyzed period is very limited and their contribution to the solar PV generation is negligible. Furthermore, concentrating solar power (CSP) plants have not been included in SOWISP, but information of plants currently operating in Spain can be obtained from (https://www.protermosolar.com). It is important to mention the limited perspective of future developments of this technology for power generation in Spain (MITECO, 2019; IEA, 2022). Both Electra and PRETOR are managed by the Spanish Government, as part of the initiative of transparency and openness of relevant governmental data to citizens and companies for their free reuse. The information provided by Electra and PRETOR is complementary, making both databases necessary in the process for creating SOWISP. Thus, while Electra contains, for each wind farm/solar PV plant, information about the installed power and the grid connection/disconnection dates, it does not provide information about their locations. For its part, PRETOR provides information about installed power and the town where the plants are associated, although it does not contain the grid connection/disconnection dates. The third database employed in this study, i.e., BDDAE, was created and managed by the Spanish National Geographic Institute (IGN). It consists of shapefile maps with the border lines of different territorial units. Additionally, this shapefile contains the information to place each location into their corresponding NUTS 2 and NUTS 3 territory units, as defined at the ISO 3166-2 for Spain. This information is used to obtain aggregated values of installed power at these levels, as explained in detail in Section 2.2. It should be highlighted that all these files were downloaded manually.

2.2. Data processing

The starting point in the building process of SOWISP was a thorough comparative analysis of Electra and PRETOR, due to a lack of public information describing these databases. The content of all columns in each database was carefully studied in order to identify which of them can contribute to creating SOWISP. Interestingly, it was found that two databases were associated with different administrative procedures and their records were updated at different rates for each NUTS 3 region. An important issue was to identify the updating time period of each database and region. The great delay in the updating time for some regions limited the release of SOWISP to the period of 2015–2020.

```
>>> print(SOWISP_wind)
         Town   Area  Latitude  Longitude  NUTS_2  NUTS_3  InsPowMW_20150131  ...  InsPowMW_20201231
0      Abadín  196.0     43.37      -7.49    ES11   ES112            208.860  ...            243.510
1        Abla   45.2     37.16      -2.77    ES61   ES611             38.000  ...             38.000
2     Ablitas   77.5     41.96      -1.59    ES22   ES220              0.000  ...             41.580
3    Abrucena   83.7     37.13      -2.83    ES61   ES611             12.000  ...             12.000
..        ...    ...       ...        ...     ...     ...                ...  ...                ...
203    Hellín  781.7     38.46      -1.67    ES42   ES421             49.500  ...             49.500
..        ...    ...       ...        ...     ...     ...                ...  ...                ...
499       Zas  133.4     43.09      -8.93    ES11   ES111              0.000  ...             24.000
500    Zestoa   43.7     43.24      -2.24    ES21   ES212              0.004  ...              0.004
501  Zierbena   12.2     43.35      -3.09    ES21   ES213             10.000  ...             10.000
502     Zújar  102.1     37.57      -2.85    ES61   ES614             34.000  ...             34.000
[503 rows x 78 columns]
```

Fig. 3. SOWISP record example for the wind technology.

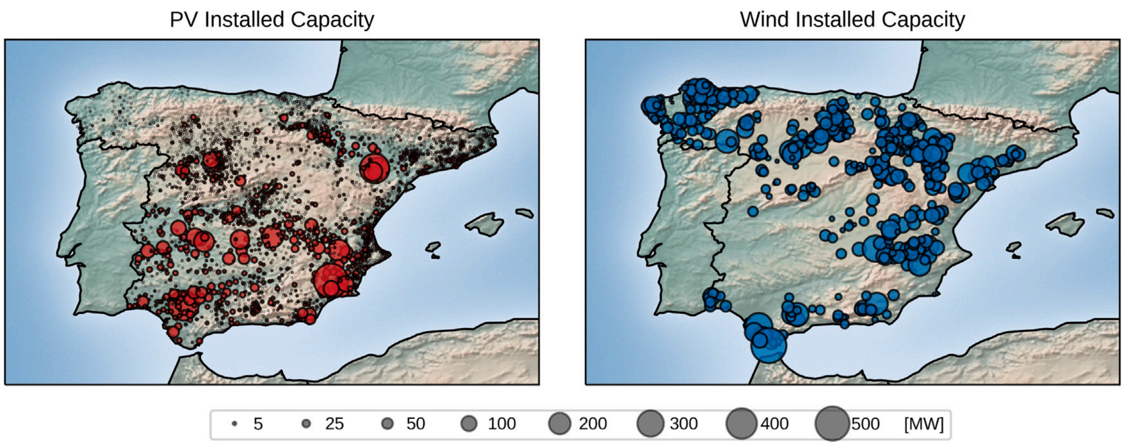

Fig. 4. Locations of the solar PV and wind plants of the SOWISP database as by December 2020. The size of the points represents the installed power, according to the scale shown at the bottom.

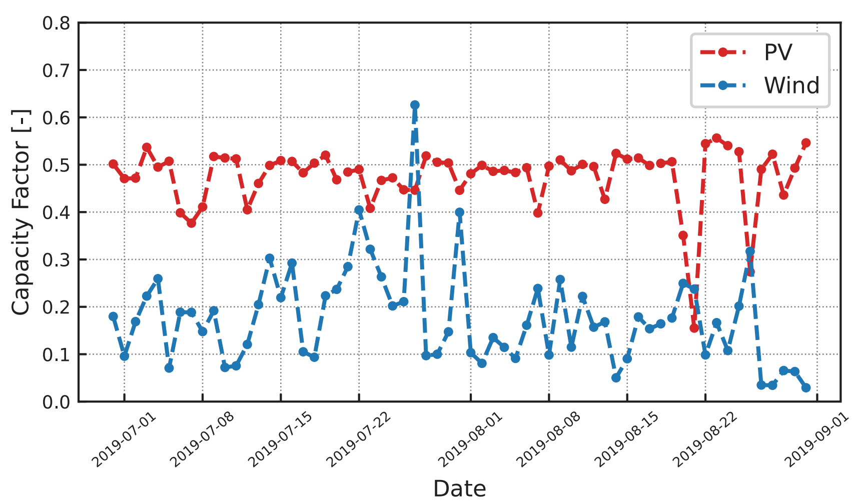

Fig. 5. Daily values of the wind and solar PV capacity factor time series for NUTS 3 region ES421 along the period July to September 2019.

Future updates of SOWISP are planned, once additional information for the last years is available for all the regions.

Additionally, numerous mismatches were detected related to relevant information of the solar PV and wind plants. These discrepancies range from general aspects, such as divergences in the number of recorded plants at certain locations or duplicated information, to more specific problems related to the Identification (ID) code of the same plants at the two databases. It should be noted that the ID code was the only common information of the plants in both datasets and it was used for cross referencing purposes. Thus, an exhaustive analysis was conducted in order to detect and correct the inconsistencies in the ID nomenclature. Additional problems were found regarding the ID code formats. ID codes are formed by the combination of letters, numbers, empty spaces and different symbols ("/", "-", etc.) favoring the appearance of numerous misspelling problems affecting the implementation of a general methodology. Once these problems were corrected, a supervised procedure was conducted to derive the SOWISP database, outlined in Fig. 1.

The first step of the procedure was to select useful records in both databases. To this end, the Electra database was used to select records corresponding to wind/solar PV plants having a grid connection/disconnection date or, alternatively, having the date the plant was included in the database. Only these records that have the corresponding installed power and ID code (along with the connection/disconnection

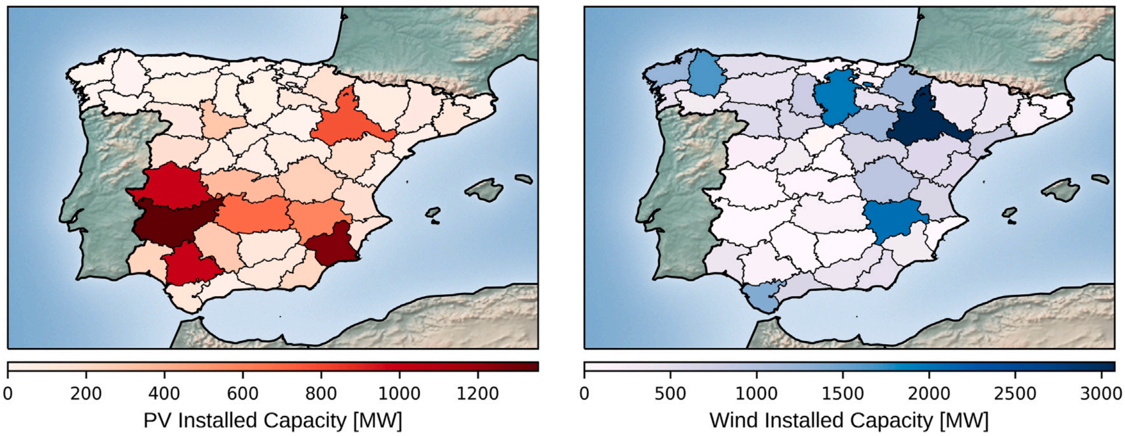

Fig. 6. Wind and solar installed power (in MW) at NUTS 3 level, for both PV and wind energies, as by December 31 2020.

date) were further considered. On the other hand, the spatial information (town and NUTS territory units), the installed power and the ID code were extracted for all the facilities registered in PRETOR. In the next step of the procedure, the ID codes were used to match records in both databases. The corresponding records were compared and only wind/solar PV plants appearing in both databases and containing the same actual installed power information were further considered. This process involved a quality control of the original databases and contributed to the reliability of the SOWISP dataset. This part of the procedure is of special relevance to establish common criteria for the two different technologies and to automate the procedure for a large number of regions.

In the following step, since the actual latitude and longitude coordinates of each wind/solar PV plants are unknown, it was assumed that the facilities are located within the administrative boundaries of the town with which they are associated in the PRETOR dataset. Thus, the total installed power of each town for a specific date, $P_{\text{Town}}^{\text{PV/Wind}}(t)$, was calculated as the sum of the installed power of all the corresponding wind/solar PV plants. At this step, only those wind/solar PV plants that were connected to the grid during the corresponding time step t (one month) were considered. The procedure was repeated for each month throughout the period of 2015–2020. It is important to highlight the relevance of this procedure regarding solar PV energy. Due to administrative issues, the splitting of large PV plants into artificial 100-kW-size plants was a common practice in Spain. Consequently, the original databases contain numerous records corresponding to plants located at the same location with 100 kW installed power. As a result of this aggregation procedure, the number of records corresponding to solar PV plants was reduced from 59,386 to 3899 "locations". Similarly, the number of wind farm records decreased from 1205 to 503 locations.

Finally, once the total installed power of each town was calculated, the latitude–longitude coordinates of the geographical centroid of the town was computed from the corresponding shapefile in the BDDAE database. For each town, the wind/solar PV installed power was considered to be allocated at this centroid. Finally, the processed information was exported to a Comma Separated Values (CSV) file, which is described in Section 4.

3. Data quality control and validation

The SOWISP database was validated using data provided by the Spanish Transmission System Operators, Red Eléctrica de España (hereinafter, REE). REE provides monthly time resolution values of wind/solar PV installed power at NUTS 2 territory levels. Therefore, the evaluation was conducted by aggregating the SOWISP values matching these territory units (Appendix A shows a map of the NUTS 2 and NUTS 3 units). Fig. 2 shows the monthly values of PV and wind installed power derived from SOWISP and provided by REE for four selected Spanish NUTS 2 territory units. In addition, Tables 1 and 2 show the relative differences between the PV and wind installed power values, respectively, at the end of each year of the study period for all regions. In general, as is shown in Fig. 2, two periods are clearly differentiated. In the period between 2015 and 2018, approximately, the installed capacity is almost constant and differences in the installed power values are relatively low. On the contrary, along the period of 2019–2020, a notable increase in the installed capacity can be observed, with some discrepancies in specific periods and regions. For instance, Fig. 2 (left) shows some discrepancies in the PV installed power in the Aragon region (ES24) at the end of the year 2019, and in the Extremadura region (ES43) at the beginning of the year 2020. Similar information can be extracted from Table 1; the relative differences during the period of 2015–2018 are in the range of −3% to 3% for most of the regions. Nevertheless, in the period of 2019–2020, differences greatly increased for certain regions, especially at the end of 2020. Similarly, for wind power (Table 2), relative differences remained almost constant over time, with values ranging from −5% to 5% for all the regions, except Aragon (ES24) and Navarra (ES22). Aragon (ES24) shows error values ranging from −5% to −7%, while Navarra (ES22) shows values ranging from −9% to −12% over the whole study period. In Appendix B, the evolution of PV and wind installed power values along the study period are displayed for all the Spanish NUTS 2 regions. In general, as is shown by these figures and Tables 1 and 2, SOWISP values tend to be lower than REE values for both solar PV and wind power during certain periods, although differences are low in general.

The analysis of the results revealed different sources for the SOWISP errors. The first source of error is constituted by the discrepancies in the number of facilities/plants and the installed capacity. This may explain the bias values (positive and negative) observed for some regions during periods with no changes in the installed capacity. This is the case of the ES22 region (Navarra), which shows an almost constant negative bias value of about 10% (Table 2) caused by certain wind farms that appear in neither Electra nor PRETOR, and, therefore, were not included in SOWISP.

The second source of error is the uncertainty in the connection/disconnection dates registered in Electra, which give rise to mismatches with the values provided by REE. This issue is observed in the PV installed power time series in the region ES24 (Aragon) during the second part of 2019 and in region ES43 (Extremadura) along the first half of 2020 (Fig. 2 left). Additionally, this source of error can also reverse the sign of the bias, such as for the wind power in region ES24 in the first half of 2019.

Finally, the third source of error is the delay in the updating period of Electra and PRETOR databases. Due to this delay, some of the latest facilities added may not be included in the SOWISP database. This source of error is more relevant at the end of the periods with an important number of new facilities added. This is the case of regions ES61, ES43 and ES24 for solar PV (Fig. 2). Therefore, the installed capacity data for this period and regions should be viewed with caution. Different combinations of these sources of errors explain the relative discrepancies observed in Tables 1 and 2 and Fig. 2, as well as in the figures of Appendix B.

4. Records description

As was discussed above, SOWISP provides two CSV files: one for the PV and another for the wind technology. The final database size is around 1.9 MB, which makes it easy to store and manipulate. Both files include the following columns: (1) Town (Spanish name), (2) Area (area of the town, in km^2), (3) Latitude (degrees), (4) Longitude (degrees), (5) NUTS_2 (territory units code), (6) NUTS_3 (territory units code), and from (7) onwards a set of 72 columns with installed power (in MW) at the end of each month for the period from 2015/01/31 to 2020/12/31 in MW (InsPowMW_YYYYMMDD). It should be mentioned that PV power data refer to DC nominal power. Additionally, two files with the same structure but with the time series of the total number of PV and wind systems within each town were created. All these files are available and can be downloaded from the GitHub repository (https://github.com/matrasujaen/SOWISP).

An example of the file for the wind technology in SOWISP, which contains data for the 503 towns (#rows) in Spain with this type of installation, is shown in Fig. 3. Thus, for example, record #203 (row) of this file is associated with the Spanish town of Hellín, a town with an area of 781.7 km^2 located at 38.46°N, 1.67°W (Southeastern Iberian Peninsula), inside the NUTS 3 unit of Albacete (ES421) and Castilla-La Mancha NUTS 2 (ES42). The first value of installed power for this location at date 2015/01/31 is 49.5 MW, and this value remains constant throughout the whole analyzed time period.

Fig. 4 shows the spatial distribution of the PV and wind plants of SOWISP. Both figures are plotted at the end of the year 2020, using the data corresponding to the 'InsPowMW_20201231' column of the solar PV and wind files, as well as the 'Latitude' and 'Longitude' columns values.

5. Potential usages

In this section, some potential uses of SOWISP are discussed, based on the review of works that used similar data sets. It should be noted, however, that the potential applications of this dataset are numerous, only a few of which are mentioned below.

The most immediate application of SOWISP is in studies related to energy system modeling. In this way, the information contained in SOWISP may be used directly as input for these models in order to set the actual installed power. This is relevant, in order to derive meaningful results from the further analysis. These analyses may include validation studies or studies about optimal future power systems with a high share of renewables.

A second application is in the development of enhanced solar PV/wind power generation models, which can be of two types: (1) direct models, obtained by regressing power generation with adequate predictors (solar radiation, wind speed, temperature, etc.); or (2) physical-based models of the relationship between generation and meteorological variables (Yao et al., 2021). Particularly, physical-based models also require information about the characteristics of the wind farm, such as the turbine type and height, or the solar PV plant, such as the tilt and azimuth angles. In order to overcome the lack of these data, approaches such as those used by Monforti and Gonzalez-Aparicio (2017) for wind, and Saint-Drenan et al. (2015) for PV, can be followed. The development and validation of both types of models require meteorological and energy system data, i.e., actual power generation and installed capacity. In this regard, while there are plenty of freely available meteorological datasets related to the wind and solar energies (Yang, 2018; Feng et al., 2019; Bright et al., 2020; Sengupta et al., 2018), there is a lack of actual wind and PV system datasets useful for energy system analysis (i.e., with a high spatial and temporal resolution and covering extensive areas). Enhanced PV/wind power models can be developed by using SOWISP, i.e., actual generation power data, which can be downloaded from REE-ESIOS website following the instructions in the manual included in the SOWISP GitHub, and any set of reanalysis-derived meteorological inputs. A byproduct of these SOWISP-derived power models can be the study of the spatio-temporal variability of the PV and wind power generation. This type of analyses, feasible due to the high spatial resolution of SOWISP, provides estimates of the spatial correlation of the PV/wind generation, from which specific strategies for new plant allocation may be obtained, such as to reduce the PV/wind power generation intermittency (Santos-Alamillos et al., 2014; Jurasz et al., 2020; Mühlemann et al., 2022).

Another important area where SOWISP may be also used is in studies related to the development of improved PV/wind power-forecasting models, aimed at the integration of these energies (Yang et al., 2022). The use of accurate forecasts will be critical as the share of renewables increases in the next years in many countries. One of the challenges identified in this area is related to the so-called "hierarchical forecasting", i.e., the procedures to provide aggregate spatially distributed PV/wind power generation forecasts to obtain valuable forecasts at the utility level (regional/national) (Yang et al., 2021; Pierro et al., 2022). The answer to this question is far from trivial and research in this field lacks adequate datasets, which must include high spatial resolution data as those provided by SOWISP.

As an example of SOWISP uses, solar and wind power capacity factor series were obtained for the Spanish NUTS 3 region ES421. Daily capacity factor values were computed based on installed capacity provided by SOWISP and the hourly generation data provided by REE, which are publicly available. For the sake of completeness, a Portable Document Format (PDF) file describing the procedure for downloading these generation data has been made available on the GitHub repository. The daily generation values were computed as an average of the hourly values. For the solar PV generation only daytime values were used. The daily installed capacity were estimated applying a linear interpolation between two consecutive monthly values from SOWISP. Fig. 5 shows the daily values of solar PV and wind capacity factor time series for the period of July–September 2019.

6. Computer code

In order to manage the new database, a Python library, named as SOWISP_lib, was developed. This library is composed of three functions, which allow: (1) reading the SOWISP database, (2) extracting information at different spatial aggregations (towns, NUTS 2 and NUTS 3), and (3) selecting information for specific time periods or specific dates. Additionally, several examples to create different types of plots, such as that presented in Fig. 4, and tables in $\LaTeX$ format were included. To promote this Python library and facilitate its future use, the library and examples of use are available on the GitHub repository.

An example of how to operate with the SOWISP_lib to aggregate the installed power in each NUTS 3 region and visualize it on a map is described as follows.

In the first step, the required libraries are imported and the paths and dictionaries are defined.

```
import numpy as np
import pandas as pd
import geopandas as gpd
import cartopy.crs as ccrs
import cartopy.feature as cf
import matplotlib as mpl
```

```
from datetime import datetime
from matplotlib import pyplot as plt
import sowisp_lib

sowisp_path = 'YourSOWISPdirectory'
shapefile   = 'example_usages/DATA/shapefiles/
    recintos_provinciales_inspire_peninbal_etrs89.shp'
dict_nuts3  = {'ES111': 'A Coruña', 'ES112': 'Lugo', '
    ES113': 'Ourense', 'ES114': 'Pontevedra', 'ES120': '
    Asturias', 'ES130': 'Cantabria', 'ES211': 'Araba/Á
    lava', 'ES212': 'Gipuzkoa', 'ES213': 'Bizkaia', '
    ES220': 'Navarra', 'ES230': 'La Rioja', 'ES241': '
    Huesca', 'ES242': 'Teruel', 'ES243': 'Zaragoza', '
    ES300': 'Madrid', 'ES411': 'Ávila', 'ES412': 'Burgos
    ', 'ES413': 'León', 'ES414': 'Palencia', 'ES415': '
    Salamanca', 'ES416': 'Segovia', 'ES417': 'Soria', '
    ES418': 'Valladolid', 'ES419': 'Zamora', 'ES421': '
    Albacete', 'ES422': 'Ciudad Real', 'ES423': 'Cuenca'
    , 'ES424': 'Guadalajara', 'ES425': 'Toledo', 'ES431'
    : 'Badajoz', 'ES432': 'Cáceres', 'ES511': 'Barcelona
    ', 'ES512': 'Girona', 'ES513': 'Lleida', 'ES514': '
    Tarragona', 'ES521': 'Alacant/Alicante', 'ES522': '
    Castelló/Castellón', 'ES523': 'València/Valencia', '
    ES611': 'Almería', 'ES612': 'Cádiz', 'ES613': 'Có
    rdoba', 'ES614': 'Granada', 'ES615': 'Huelva', '
    ES616': 'Jaén', 'ES617': 'Málaga', 'ES618': 'Sevilla
    ', 'ES620': 'Murcia'} # required for the above
    shapefile
date_map    = '20201231' # date_format: %Y%m%d
dict_colors = {'PV': 'Reds', 'Wind': 'PuBu'}
```

It should be noted that, in this example code, the shapefile with the NUTS 3 borders provided by the IGN (see Section 2.1) is required. This publicly accessible file is also provided in the GitHub repository mentioned above, although any other shapefile for the NUTS 3 can be employed. In that case, a modification in the code may be necessary.

Thus, the shapefile was loaded and the figure is initialized. Since the figure is composed of two maps, a loop with the two types of technology is deployed. For each iteration, the first step was to load the corresponding SOWISP data, select the date range (in our case, only one date, as it is a map, date_map = '20201231') and group by NUTS 3 level regions. All these steps make use of the functions contained in the SOWISP_lib library.

```
geoDf = gpd.read_file(sowisp_path + shapefile)
geoDf.set_index('NAMEUNIT', inplace = True)
fig   = plt.figure(0, (19.0 / 2.54, 7.5 / 2.54)
    , dpi = 600, clear = True)
ax    = {}
dx    = 0.0 # initial displacement of ax in fig

for tech in ('PV', 'Wind'):
    dfSOWISP = sowisp_lib.read_database(
    sowisp_path + 'SOWISP_' + tech + '.csv')
    dfSOWISP = sowisp_lib.select_date_range(
    dfSOWISP, date_beg = date_map, date_end =
    date_map)
    dfSOWISP = sowisp_lib.group_data(dfSOWISP,
    aggregator = 'NUTS_3')
    dfSOWISP.set_index('NUTS_3', inplace = True
    )
    ax['Map_' + tech] = fig.add_axes([0.02 + dx
    , 0.1, 0.46, 0.95], projection = ccrs.
    PlateCarree())
    ax['Map_' + tech].set_extent([-11.0, 4.5,
    35.0, 45.0], ccrs.PlateCarree())
    cmap = plt.get_cmap(dict_colors[tech])
    ax['Map_' + tech].stock_img()
    ax['Map_' + tech].coastlines(resolution = '
    50m')
    ax['Map_' + tech].add_feature(cf.BORDERS)
    ax['Cbar_' + tech] = fig.add_axes([0.02 +
    dx, 0.15, 0.46, 0.02])
    cbar = mpl.colorbar.ColorbarBase(
        ax['Cbar_' + tech],
        cmap = cmap,
        norm = mpl.colors.Normalize(vmin = 0.0,
     vmax = dfSOWISP['InsPowMW_' + date_map].
    max()),
        orientation = 'horizontal'
    )
    cbar.set_label(tech + ' Installed Capacity
    [MW]', fontsize = 10, family = 'Liberation
    Sans')
    cbar.ax.tick_params(labelsize = 8)
```

Once the SOWISP data were processed, the axis ('ax' in the code) was filled with the spatial information necessary to build this map. In addition, a colorbar was defined, varying between zero and the maximum SOWISP value for the specific type of technology and date.

Then, each NUTS 3 region was color-filled with the installed power value associated with the date (in our case, the "InsPow_20201231" column value), taking into account the previously defined colorbar.

```
    for nutId in dfSOWISP.index.values:
        if geoDf.loc[dict_nuts3[nutId]]['
    geometry'].geom_type == 'Polygon': # if it
    is Polygon geom_type, geoms argument must
    be a list
            geomsList = [geoDf.loc[dict_nuts3[
    nutId]]['geometry']]
        else:
            geomsList = geoDf.loc[dict_nuts3[
    nutId]]['geometry']
        ax['Map_' + tech].add_geometries(
            geoms = geomsList,
            crs = ccrs.PlateCarree(),
            facecolor = cmap(dfSOWISP.loc[nutId
    , 'InsPowMW_' + date_map] / dfSOWISP['
    InsPowMW_' + date_map].max()),
            edgecolor = 'black',
            linewidth = 0.5
        )
    dx += 0.5 # increase of ax displacement in
    the fig
```

Finally, the resulting figure was saved in an existing directory, with a specific name, format and resolution. Note that this last piece of information can be easily modified by the user.

```
fig.savefig(sowisp_path + 'example_usages/imgs/
    NUTS_3_map.jpg', dpi = 600)
plt.close(0)
```

Fig. 6 shows the maps generated by the code lines shown above.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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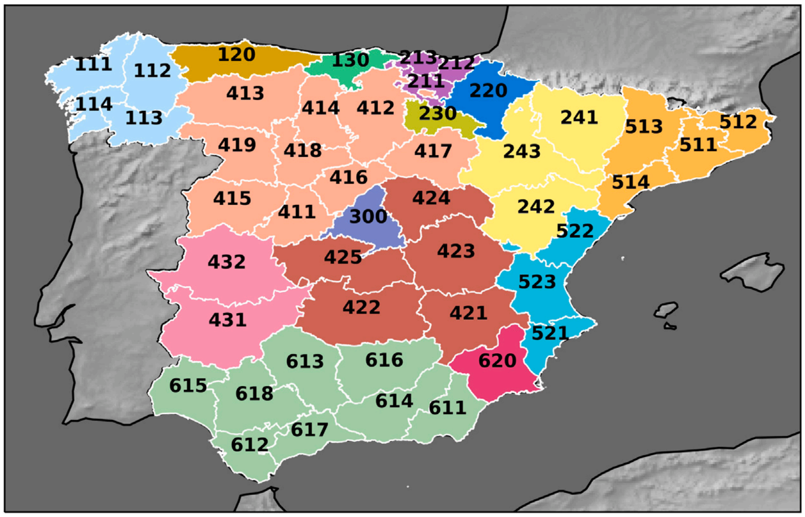

Fig. A.1. NUTS 2 and NUTS 3 regions representation for Spain. Homogeneous colors in the NUTS 3 regions, which are represented by the corresponding code number, are used to represent the NUTS 2 level regions. Note, for the sake of clarity, in the figure, the prefix "ES" was removed from all NUTS 3 level codes. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

Appendix A. Spatial NUTS 3 codes

A map showing the different NUTS 2 and NUTS 3 regions of Spain is displayed in Fig. A.1. Colors are used to indicate the NUTS 3 regions corresponding to each NUTS 2 region (see Table A.1).

Table A.1
NUTS 2 and NUTS 3 codes for Spain.

NUTS_2		NUTS_3	
Code	Region	Code	Region
ES11	Galicia	ES111	La Coruña
		ES112	Lugo
		ES113	Orense
		ES114	Pontevedra
ES12	Principado de Asturias	ES120	Principado de Asturias
ES13	Cantabria	ES130	Cantabria
ES21	País Vasco	ES211	Álava
		ES212	Guipúzcoa
		ES213	Vizcaya
ES22	Comunidad Foral de Navarra	ES220	Comunidad Foral de Navarra
ES23	La Rioja	ES230	La Rioja
ES24	Aragón	ES241	Huesca
		ES242	Teruel
		ES243	Zaragoza
ES30	Comunidad de Madrid	ES300	Comunidad de Madrid
ES41	Castilla y León	ES411	Ávila
		ES412	Burgos
		ES413	León
		ES414	Palencia
		ES415	Salamanca
		ES416	Segovia
		ES417	Soria
		ES418	Valladolid
		ES419	Zamora
ES42	Castilla-La Mancha	ES421	Albacete
		ES422	Ciudad Real
		ES423	Cuenca
		ES424	Guadalajara
		ES425	Toledo
ES43	Extremadura	ES431	Badajoz
		ES432	Cáceres
ES51	Cataluña	ES511	Barcelona
		ES512	Gerona
		ES513	Lérida
		ES514	Tarragona
ES52	Comunidad Valenciana	ES521	Alicante
		ES522	Castellón
		ES523	Valencia
ES61	Andalucía	ES611	Almería
		ES612	Cádiz
		ES613	Córdoba
		ES614	Granada
		ES615	Huelva
		ES616	Jaén
		ES617	Málaga
		ES618	Sevilla
ES62	Región de Murcia	ES620	Región de Murcia

Appendix B. PV and wind installed power by NUTS 2 and NUTS 3 levels

Figs. B.1 and B.2 show the monthly temporal evolution of the solar PV and wind installed power, respectively, as derived from SOWISP and REE databases. Values are displayed along the period of January 2015 to December 2020 for each of the Spanish NUTS 2 regions. The SOWISP values corresponding to each NUTS 3 level are also displayed.

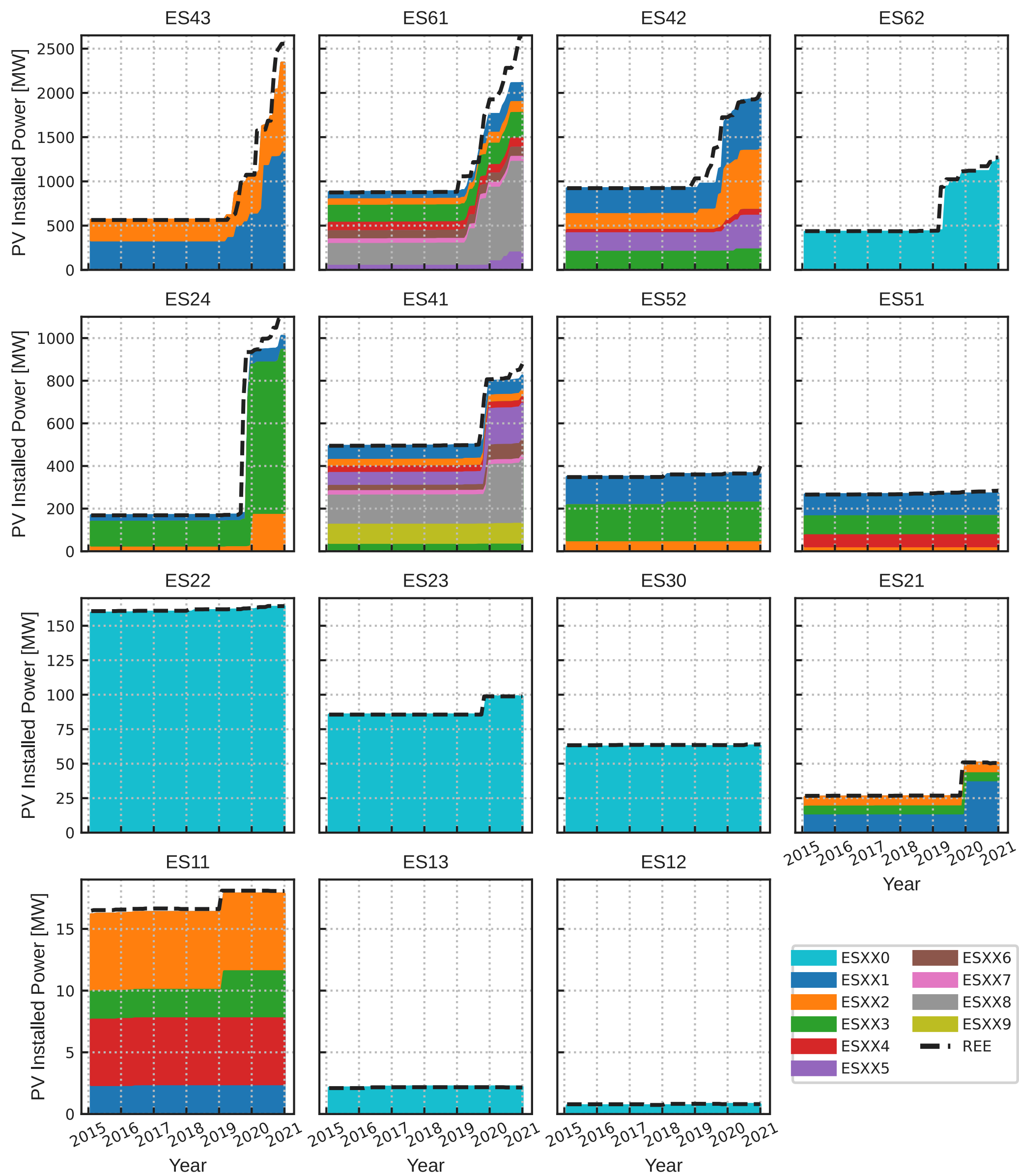

Fig. B.1. Solar PV installed power as derived from the SOWISP (colors) and REE (dashed line) at NUTS 2 levels. Values (in MW) are displayed at monthly time resolution from January 2015 to December 2020. Colors indicate cumulative values of the NUTS 3 regions (derived from SOWISP) for each of the NUTS 2 regions. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

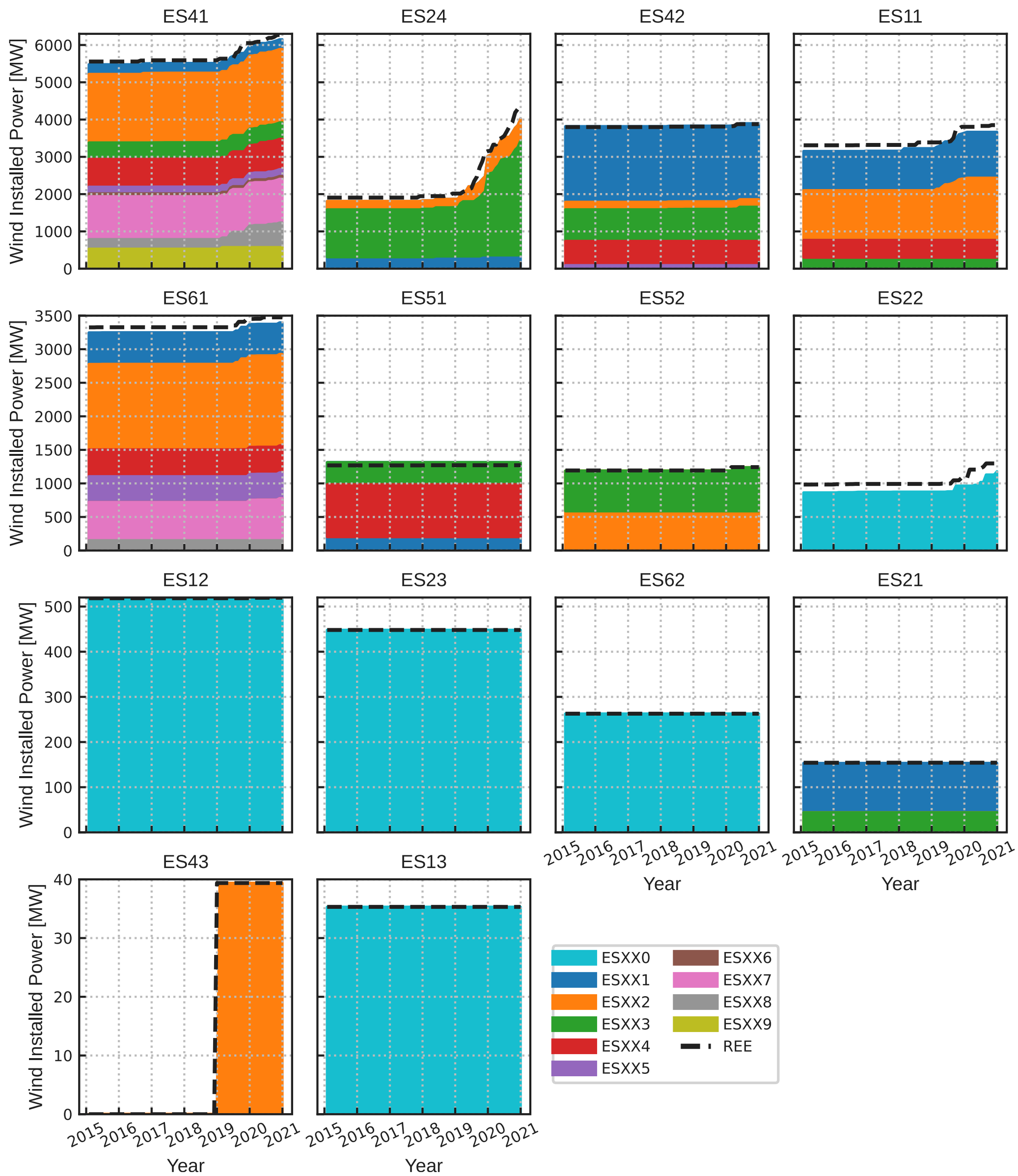

Fig. B.2. As in Fig. B.1 for wind technology.

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