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Evaluation of open photovoltaic and wind production time series for Norwegian locations

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ABSTRACT

We investigate the accuracy of wind and photovoltaic time series in individual systems in Norway. To study the accuracy of the available open data sets, we compare the measured production from individual photovoltaic- and wind power plants to the open time series from Renewables.ninja and EMHIRES. Additionally, we try to adjust the wind speed based on the average wind speed from Global Wind Atlas 3.0 and Norwegian water resources and energy directorate's Wind Map to try to achieve more accurate wind speed time series that take into account the local wind conditions, since they are not well represented in the large resolution of the MERRA-2 data set used by Renewables.ninja. The results for photovoltaic production time series are promising, the correlation between production obtained from Renewables.ninja and measured production is above 0.72 and maximum capacity factor difference of 2.5%. For the case of wind production, production time series show considerable deviations depending on the specific wind farm (correlation between 0.51 and 0.91 depending on the case and year). Additionally, the adjustments only improve the time series in some of the wind farms, whereas in others the results are even less accurate than the Renewables.ninja time series compared to the measured data.

1. Background

Power generation from renewable energy sources (RES) is fundamental for achieving the transition to a low emission energy system. The variable and non-dispatchable nature of key technologies such as wind and photovoltaic (PV) energy production imposes challenges on both existing and future energy systems. To better account for variation, detailed time series of RES production are increasingly used in modelling to estimate the need for flexible solutions such as storage or extra capacity. High quality data are needed for these analyses, also for potential locations where no historical data is available. Using satellite data with long time series solves many of these problems. Two openly available sources of such data covering all European countries are European Meteorological derived high resolution renewable energy source generation (EMHIRES), published by the European Comission [1–3], and Renewables.ninja, published by ETH Zürich and Imperial College London, [4,5].

However, the accuracy of the data must be assessed before drawing strong conclusions from analyses. As shown for example in Ref. [6], with focus on Germany, the error present in reanalysis methods with high resolution and high RES presence can cause a considerable effect on investment and dispatch decisions in the energy system. Additionally, studies like [7] show the importance on studying possibilities for good, local PV quality in northern regions. In the article [8], the data quality of EMHIRES and Renewables.ninja is compared with measured data from producers for several European countries, though not including any of the Nordic countries. In the article [9], the solar radiation estimation of several data set calculated from satellite data is compared with measured solar radiation from 31 locations in Norway, where 4 of the locations are above 65°N. The study showed that there generally is an overestimation of solar radiation in reanalysis and an underestimation in satellite methods for the Norwegian locations. The article did not include the Modern-Era Retrospective analysis for Research and Applications Version 2 (MERRA-2) satellite data in the comparison, used by Renewables.ninja.

There is generally a lack of open high-quality data sets for representative PV and wind production in the Nordic countries. Solar radiation instead of production data was used by Ref. [9] in

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their comparison. Radiation data are openly available from Meteorologisk institutt (MET) [10] or Norsk institutt for bioøkonomi (NIBIO) [11] for locations covering most of Norway. The Research Center for Sustainable Solar Cell Technology (FME SuSolTech) [12] has started collecting and publishing live measured PV data [13] from systems in Norway. As for wind, Wind Europe [14] provides hourly production on a national aggregated level.

The contribution of this article is to expand on earlier studies and to study the accuracy of open satellite based data where there is available measured data for the Nordic countries, not previously covered, and also from specific locations in Norway. The measured data is either provided aggregated from a Transmission System Operator (TSO) or from individual wind farms and PV installations. The accuracy is studied by comparing the data series for each location.

This article is organised as follows: The data sources are described in section 2, first the satellite based data sets in section 2.1, followed a description of the production data used for comparison in section 2.2. The availability and accuracy of open data for wind and PV production is analysed at national level in Norway, Sweden, and Denmark. The methods used to compare accuracy are described in section 3, followed by a comparison of country level aggregated time series in section 4. Section 5 compares data from selected locations in Norway with the corresponding locations from the Application Programming Interface (API) of Renewables.ninja. Additionally, we study adjustments to overcome local wind conditions. In Section 6, the results of PV and wind production analyses are discussed and we draw conclusions about the accuracy of data and adjustments for individual PV and wind farms in Norway.

2. Data sources

We consider two open data sets, from EMHIRES and Renewables.ninja, described in more detail in Section 2.1 below. These data are compared with national production data where available from official sources, or by other available data sets used for benchmarking.

2.1. Open data

2.1.1. EMHIRES

The EMHIRES data set is published by the European Comission and covers European countries [1–3]. The data set is based on Modern Era Retrospective-Analysis for Research and Applications 1 (MERRA-1), which has a resolution of 0.5° by 0.66° (corresponding to approximately 50 by 50 km) [15].

For wind production, the EMHIRES data set includes hourly onshore wind capacity factors for the years 1986–2015. It is validated against actual wind power generation output from TSOs in 2015. The following bidding zones are covered: NO1-5, SW1-4, DK1-2, as well as 6 zones in Italy. Offshore wind capacity factors are included for countries Belgium, Germany, Denmark, UK, and Netherlands. For PV production, EMHIRES provides hourly capacity factors from 1986 to 2015.

2.1.2. Renewables.ninja

The other open data source is Renewables.ninja, published by ETH Zürich and Imperial College London [4,5], and available both as pre-computed data sets and through an API to get data for specific locations and where details about production technology may be specified.

When downloading data from Renewables.ninja, for PV, one may select a version based on satellite data from either Surface Solar Radiation Data Set - Heliosat (SARAH), by the European Organisation for the Exploitation of Meteorological Satellites (EUMETSAT) for 1985–2016 [16], or MERRA-2, [17]) with reanalysis from National Aeronautics and Space Administration (NASA) for 1985–2015. Wind data is only available based on the MERRA-2.

SARAH data set has a grid resolution of 0.05° by 0.05° (corresponding to 5 by 5 km. MERRA-2 data set has a grid with a resolution of 0.625 by 0.5° (corresponding to approximately 50 by 50 km). SARAH has a higher spatial resolution, giving more accurate hourly variation, in particular on site level. The advantage is less visible for national level due to evening out site variations. MERRA-2 seems to be more stable due to less lacking data, making MERRA-2 more suitable for long-term studies. A comparison of capacity factors based on SARAH and MERRA-2 shows that MERRA-2 predicts higher capacity factors for Nordic countries and lower capacity factors for Mediterranean countries than SARAH (1.2% higher for Norway). While SARAH has higher resolution, it does not cover latitudes outside ± 65°, which leaves northern parts of the Nordics outside, making data based on MERRA-2 results a better fit for long term analysis of Nordic countries.

The time resolution of the Renewables.ninja data set is 1h and the data set is available for 19 years (2000–2018) using the MERRA-2 data set. This is the maximum amount of years available by Renewables.ninja's API at their website. Through the API, wind technology may be specified in terms of hub height, turbine producer and version, while queries for PV data specify tilt (horizontal – vertical), azimuth (compass direction), system losses and the possibility of tracking (1 or 2 axes).

2.2. Production data

We compare national time series from both EMHIRES and Renewables.ninja with official data from Norway, Sweden and Denmark where available, the data sets are described in more detail in the following:

2.2.1. Norway

Due to the lack of official data for PV production in Norway, we used PV production data from a selection of locations that was provided by sources in collaboration with the Institute for Energy Technology (IFE) and FME SuSolTech [13]. The average of the Norwegian producers was compared with the national aggregated values from EMHIRES and Renewables.ninja.

Data from five PV systems in Norway were used to study the accuracy of Renewables.ninja's data sets, four systems located in the southern part of the country (bidding zones NO1 and NO2) and a fifth located in the northern city of Tromsø (NO4). The basic characteristics of these installations are described in Table 1: PV system name, data availability (number of months, years available), bidding zone where it is located, installed capacity and the azimuth and tilt angles. Extra information about the data source, the exact location (when not anonymised) and altitude is located in the Table 9 in Appendix A.

National aggregated wind generation for Norway was obtained from Norges vassdrags-og energidirektorat (NVE, in English The Norwegian Water Resources and Energy Directorate) [18].

2.2.2. Sweden

Hourly national PV generation can be downloaded from Svenska Kraftnät [19]. Yearly generation values are provided by the International Renewable Energy Agency (IRENA) [20] and Statistikdatabasen [21] (with the same values). The total installed capacity of PV systems connected to the grid are from IRENA [20] (2010–2018) and Statistikdatabasen [22] (in this second case only from years 2016–2018), both providing different values, as seen in Table 2. Additionally, there is an apparent mismatch between the capacity

Table 1
PV systems used for data comparison and basic information. The data availability is 2014–2017 for Evenstad, 09.2014–12.2017 for anonymous, 2016–08.2017 for IFE wall, 2014 for Agder Energy and 2018 for UIT-Tromsø.

PV System	Bidding Zone	Capacity (kWp)	Azimuth (°)	Tilt (°)
Evenstad	NO1	70,380	170	35
Anonymous	NO1	18	110	10
IFE wall	NO1	1.3	193	90
Agder Energy	NO2	5	200	20
UIT - Tromsø	NO4	6.09	180, 210[a]	20, 30, 40 60, 90[b]

[a] 18 panels are south oriented (180° azimuth) whereas 3 are south-west oriented (210° azimuth). All panels are equal (290W).
[b] 2 panels with 20° tilt, 4 with 30° 10 with 40°, 2 with 60° and 3 with 90°. All panels are equal (290W), where 6 of the panels with 40° tilt and 180° azimuth are installed vertically and the rest are horizontally.

Table 2
Values of installed capacity and yearly generation in Sweden.

SE PV	2016	2017	2018
Installed capacity (MW, Statikdatabasen)	140.03	230.99	411.06
Installed capacity (MW, IRENA)	153	402	492
Yearly generation (GWh)	143	230	391
Capacity factor (Statikdatabasen)	0.12	0.11	0.11
Capacity factor (IRENA)	0.11	0.07	0.09
Capacity factor (Svenska Kraftnät)	0.04	0.04	0.04
SE Wind onshore	2016	2017	2018
Installed capacity (MW)	6434	6611	7300
Yearly generation (GWh)	15479	17609	16623
Capacity factor	0.27	0.30	0.26
SE Wind offshore	2016	2017	2018
Installed capacity (MW)	6434	6611	7300
Yearly generation (GWh)	15479	17609	16623
Capacity factor	0.34	0.38	0.38

factor calculated with yearly values and from the time series from Ref. [19]. Using yearly values to calculate the capacity factor would yield over 10% in most cases, see Table 2. Using the PV production time series with hourly resolution from Svenska Kraftnät [19] (and installed capacity from Statistikdatabasen [22]), gives very different results, with average yearly capacity factors around 4%, which is too low for PV even in northern latitudes, as pointed out in Ref. [8]. These mismatches do not happen with wind, where the yearly capacity factors are very close: the values from Svenska Kraftnät [19] for the years 2016, 2017 and 2018 are 0.276, 0.302 and 0.261 respectively, and those from IRENA 0.275, 0.304 and 0.260. This situation of too low PV production was confirmed by Svenska Kraftnät by email correspondence, and the cause of it is not known for sure: it could be the still small installed capacity that makes that the numbers reported are not yet consistent. Another possibility for this low average capacity factor is the date of the installed capacity, either if it is counted at the beginning or at the end of the year (in Table 2 it is counted with production and capacity from the same year). Either way, the capacity factor is still way below the expected 10% (7.23% if generation is calculated from 2018 and installed capacity from 2017). As of 2016, only 6% of the grid-connected PV installations in Sweden were ground mounted parks delivering directly to the grid [23], the rest was roof-mounted systems providing electricity to the building before the surplus is sold to the grid. The production then downloaded from Ref. [19] could then be only the part of the PV power production exported to the national grid.

Wind generation time series for the whole country can be downloaded from Svenska Kraftnät [19]. Installed wind capacity can be found in IRENA [20] and Statistikdatabasen [22], both providing the same values and obtaining capacity factor values typical for wind technology (for example when compared with Danish values). For onshore technology, see Table 2.

2.2.3. Denmark

PV generation time series for the whole country can be downloaded from Energinet [24], but the values are partly estimated (a comment on the website mentions “production is to some extent estimated”). Installed capacity of PV systems can be found in IRENA [20] (total country values) and Energinet [24] (installed capacity per municipality per month, 2016–2019). Capacity factor seems consistent and realistic, with values over 10%, as shown in Table 3 (using IRENA national values).

Wind generation time series for the whole country can be downloaded from Energinet [25]. Installed wind capacity can be found in IRENA [20] (total country values) and Energinet [24] (Installed capacity per municipality per month, 2016–2019). These values also summed up in Table 3, using IRENA national values.

3. Quality evaluation

We mostly follow the approach of Moraes et al. [8] in comparing the match between data sets. We concentrate on comparing the duration curves of the production, the correlations between hourly time series for each year, and also investigate some of the measures of the distribution in time of production.

The production time series will be analysed in the form of capacity factor to be able to compare different plants with different sizes, both for the case of PV and wind. Capacity factor is defined as the ratio of net electricity generated for a given time period to the total energy that could have been generated if that plant would have operated at full capacity during the same period of time. Thus, Equation (1) gives the definition of capacity factor.

$$CF = \frac{E_{out}}{\Delta t \cdot P_{inst}}, \tag{1}$$

where CF is the capacity factor for a given period (for a hourly time series it is referred thus as hourly capacity factor, for yearly values as yearly capacity factor etc.), E_{out} is the energy generated by the PV

Table 3
Values of installed capacity and yearly generation in Denmark.

DK PV	2016	2017	2018
Installed capacity (MW)	851	906.4	998
Yearly generation (GWh)	743.8	751.5	953
Capacity factor	0.10	0.10	0.11
DK Wind onshore	2016	2017	2018
Installed capacity (MW)	3975	4226	4410
Yearly generation (GWh)	8132	9600	9269
Capacity factor	0.23	0.26	0.24
DK Wind offshore	2016	2017	2018
Installed capacity (MW)	1271	1297	1358
Yearly generation (GWh)	4650	5180	4630
Capacity factor	0.42	0.46	0.39

system or wind farm during the given time unit. Δt is the time period considered and P_{inst} the system's installed capacity.

The yearly duration curve represents the capacity factor for each hour during the year, sorted by capacity factor in descending order. The duration curve facilitates comparison of the distribution of production between high-production periods (to the left) and low-production periods (to the right) when plotted together, as well as clearly identifying higher or lower production overall between similarly shaped duration curves. Duration curves with very different shape or level may indicate that the underlying data needs to be checked further, as demonstrated by Ref. [8]. Determining which measures to use to judge whether data from different sources match well can be tricky if they scores vary between measures. We find that the duration curves enables comparison of several aspects simultaneously by visualizing both overall production level and distribution over the hours in a year, as both are important when the production profile will be used to determine e.g. capacities and need for flexibility.

In addition, several measures for distribution in time have been considered. Most importantly, we compute and compare the Pearson correlation between hourly time series for capacity factors. As these correlation number can be difficult to interpret without context, note that [8] highlight correlations from some of the least matching time series in their Fig. 1 around 0.58, to some of the best matching time series around 0.98 for the comparison with German TSO values.

Following [8], we also provide analyses for weekly cumulative production and distribution between cumulative production during what they consider the warm season (summer) from April 16 to October 15 and the cold season (winter) from October 16 to April 15. This is particularly interesting for PV where production is expected to vary a lot between the seasons in Nordic countries due to the high latitude.

To analyse deviations from producer data at local level, three different parameters will be calculated for the PV systems and wind farms: Mean Absolute Error (*MAE*), Root Mean Square Error (*RMSE*) and the difference between average capacity factor per year (CF_{Diff}). *MAE* is calculated as shown in Equation (2):

$$MAE = \frac{\sum_{i=1}^{n} |CF_i^{RES.ninja} - CF_i|}{n}, \tag{2}$$

where $CF_i^{RES.ninja}$ is the capacity factor from the Renewables.ninja data series per period i (in this case 1 h), while CF_i is the producer's capacity factor per period i. The total number of capacity factor values per year is defined as n (for a normal, non-leap year it would be 8760 h). Similarly, *RMSE* is calculated per year using Equation (3):

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n} (CF_i^{RES.ninja} - CF_i)^2}{n}}. \tag{3}$$

Finally, average capacity factor difference is calculated as the difference of the producer and Renewables.ninja average capacity factors, as described in Equation (4):

$$CF_{Diff} = \frac{\sum_{i=1}^{n} CF_i^{RES.ninja}}{n} - \frac{\sum_{i=1}^{n} CF_i}{n}. \tag{4}$$

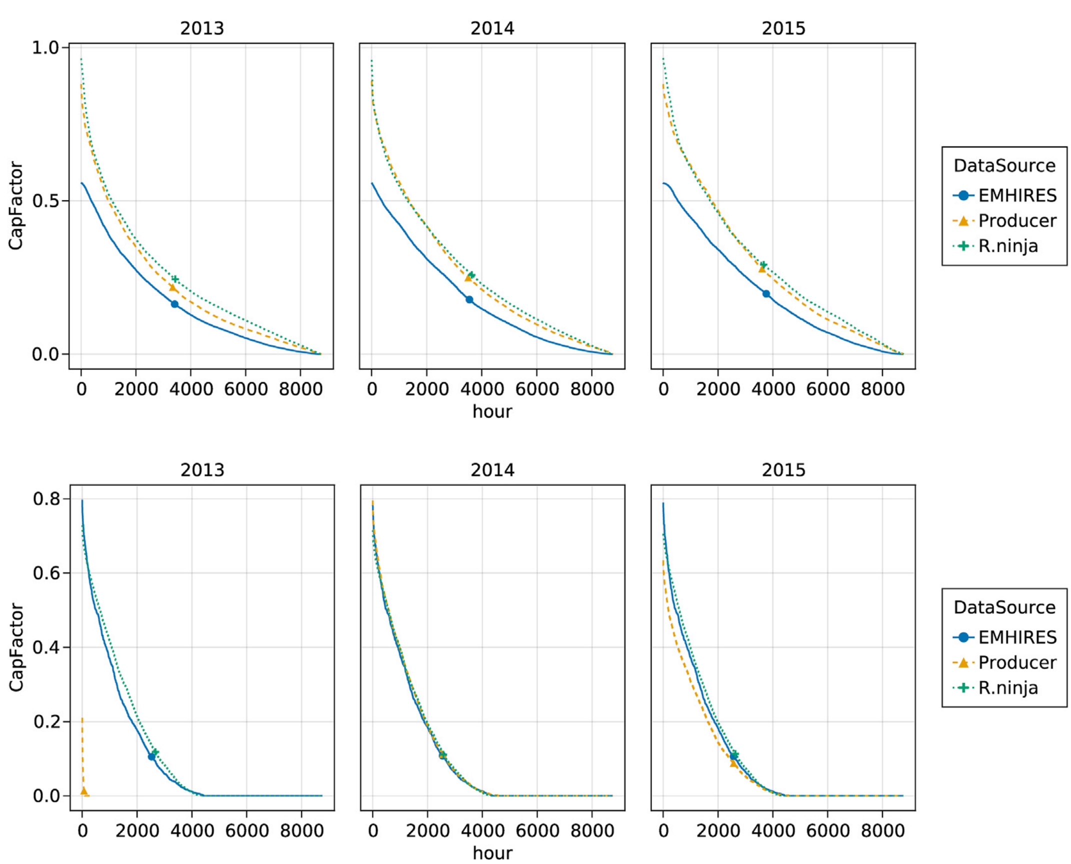

Fig. 1. Duration curves for aggregated production for Denmark (DK), comparing producer data with EMHIRES and Renewables.ninja data series. Wind production in top panel, Solar Power in lower panel.

4. National aggregates

We first evaluate how well the national aggregates from national sources match data from EMHIRES and Renewables.ninja with an emphasis on results from Norway. A summary of comparisons for Sweden and Denmark is also included.

4.1. Norway

For Norway, EMHIRES underestimated the production for both PV and wind, see Fig. 3, while the match is better for Renewables.ninja, though overestimating the wind production. For PV, Renewables.ninja underestimates national capacity factors, but shows a better match in the shape of duration curves and has smaller deviation than EMHIRES. Also seasonal and weekly profiles match better for Renewables.ninja, seen in Fig. 4. When comparing the aggregated producer data with these two data sets, the correlation is higher between producer and Renewables.ninja's data (e.g. 0.7 EMHIRES vs 0.88 Renewables.ninja, 0.53 vs. 0.88), see Fig. 6 for detailed results. In conclusion, for Norway Renewables.ninja provides a better match with production data, actually better than expected, and it seems better than several countries evaluated by Ref. [8].

4.2. Sweden

For Sweden, the problems related to PV generation data are obvious in the duration curves (lower panel of Fig. 2), where the reported production is much lower than both time series from EMHIRES and Renewables.ninja, making it difficult to conclude on the quality of either.

Swedish wind power generation seems to be generally underestimated by Renewables.ninja, while maintaining a similar distribution between low-production periods and high-production periods (top panel of Fig. 2), suggesting it could achieve good matching by scaling. EMHIRES, on the other hand, tends to overestimate the share of high-production periods, and underestimating the share of low-production periods, supporting the overall impression that Renewables.ninja provides better data than EMHIRES for Nordic countries. Fig. 5 shows a graphic comparison between national, yearly capacity factor values for Denmark and Sweden to see the differences between the available sources.

4.3. Denmark

For Denmark, the time series for PV production are largely in agreement with reported numbers for Denmark, see Fig. 1. For 2014 the duration curves almost completely overlap, while for 2015 both Renewables Ninja and EMHIRES estimate higher production overall. Since the production data for Denmark are based on estimates, we are however reluctant to draw strong conclusions.

The duration curves for Danish onshore wind production show a generally good match between reported production from Denmark with a tendency of Renewables.ninja towards overestimating production, particularly in low-production periods. The EMHIRES wind production estimates are substantially lower for all three production years. Note that EMHIRES numbers are for unspecified wind production, and even larger discrepancies must be expected for Offshore wind production.

Again it is difficult to draw strong conclusions for PV, but

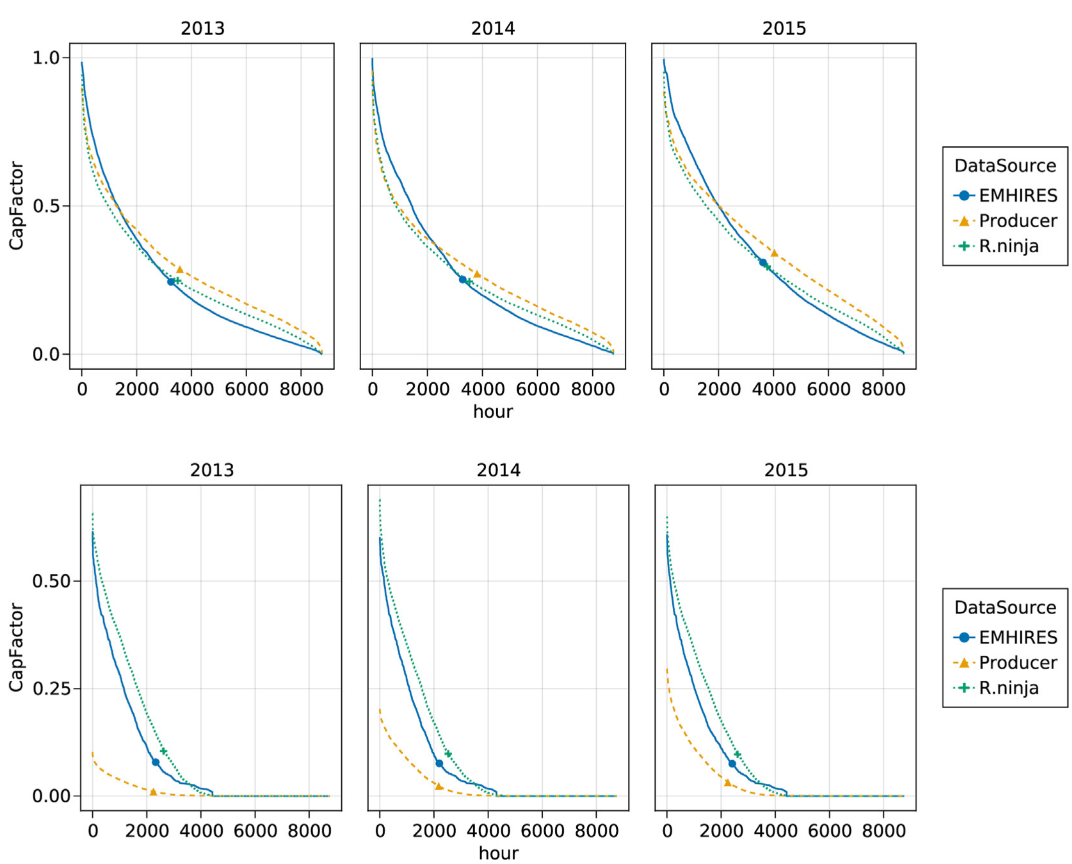

Fig. 2. Duration curves for aggregated production for Sweden (SE), comparing producer data with EMHIRES and Renewables.ninja data series. Wind production in top panel, Solar Power in lower panel.

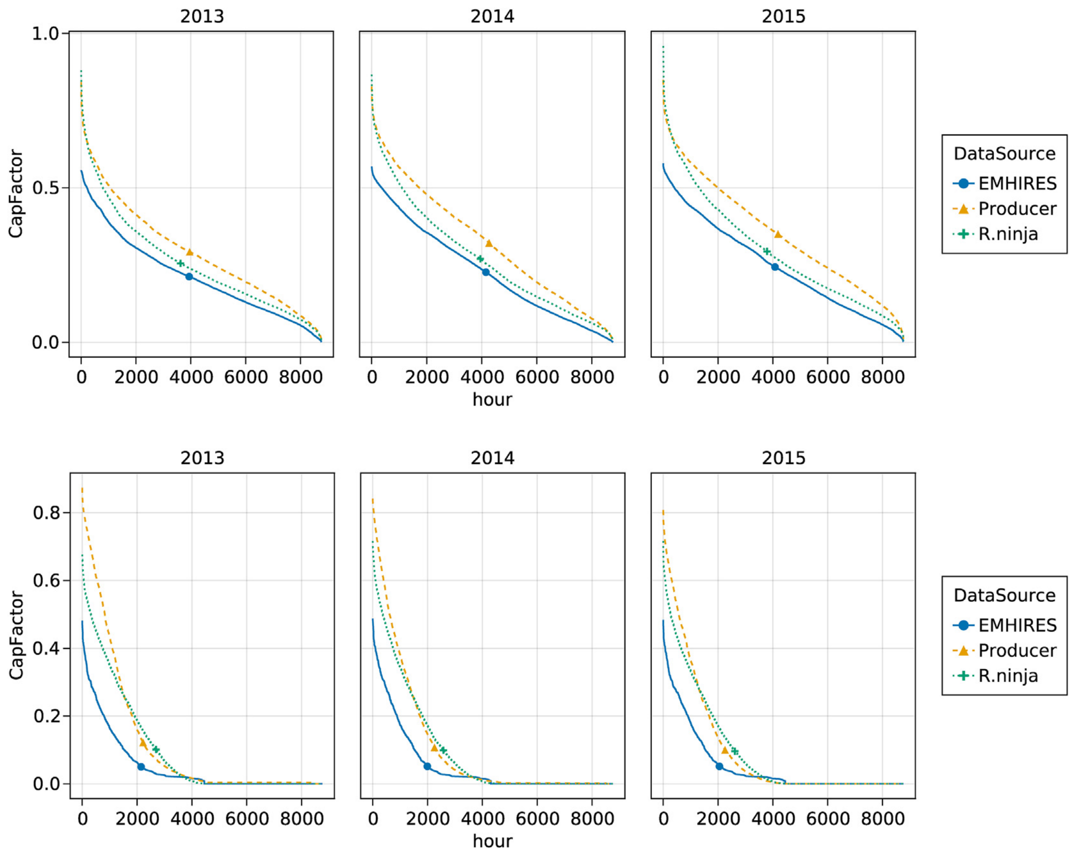

Fig. 3. Duration curves for aggregated production for Norway (NO), comparing producer data with EMHIRES and Renewables.ninja data series. Wind production in top panel, Solar Power in lower panel.

Renewables.ninja again provides more accurate estimates for wind power production.

4.4. Summary

To summarise, the evaluation of national production time series from EMHIRES and Renewables.ninja showed that the latter provided more exact results when compared to real aggregated data from wind and PV producers. As Renewables.ninja was most promising, in particular for Norway, we selected Renewables.ninja for further investigation of individual locations for wind and PV production time series for individual systems in Norway, which can be used to construct data for representative regions.

5. Local generation

In this section, we focus on local PV systems and wind farms and will study the possibilities to obtain production time series from Renewables.ninja for individual systems. A common use-case is to evaluate the production potential of individual locations or regions where there may or may not be previously installed generation capacity. The Norwegian bidding zones (NO1−NO5) are natural regions to evaluate, considering both potential for wind power production, as well as PV power production for those same areas for typical orientations and inclinations. To achieve this goal, we compare historical production from existing PV systems and wind farms with data from Renewables.ninja. For the wind farms, we also adjust the average wind speed with additional sources to represent local variations before comparing with producer data. Through this approach, the accuracy of the available data sets from Renewables.ninja can be evaluated and one can easily generate production data for specific regions or bidding zones.

5.1. Local PV production

We compare the measured time series from the systems presented in Table 1 with satellite data from PV production from Renewables.ninja, in order to see how precise and accurate the data set is for individual locations. The system losses given as input to the Renewables.ninja API are estimated as 10% for all PV systems.

Correlation values for yearly capacity factors, *CF*, shown in Table 4, represent the accuracy of Renewables.ninja to the measured productions. The values range from 0.72 to 0.94, which are reasonable values for a data set such as Renewables.ninja, although not as good as the best matching time series evaluated by Moraes et al. [8]. The hourly *CF* distribution show how Renewables.ninja's PV production is compared to producer data by the hour. An example of two analysed solar systems, one in the southern part of the country (IFE, NO1, top panel) and one in the north (UIT - Tromsø university, NO4, lower panel), is shown in Fig. 7. Renewables.ninja tends to estimate a larger amount of hours with low capacity factor, and thus fewer hours with large production.

To show the error distribution of the time series obtained from Renewables.ninja we use violin plots [26]. These are shown in Fig. 8 and they display the probability density of the hourly capacity factor difference between Renewables.ninja values $CF^{RES.ninja}$ and producer data CF (i.e. $CF^{RES.ninja} - CF$). The plots also mark the median value of the values with a horizontal line. The plot for the IFE PV system in 2015 deviates in shape from the rest of the yearly values because the available data is below one month (from the 8th

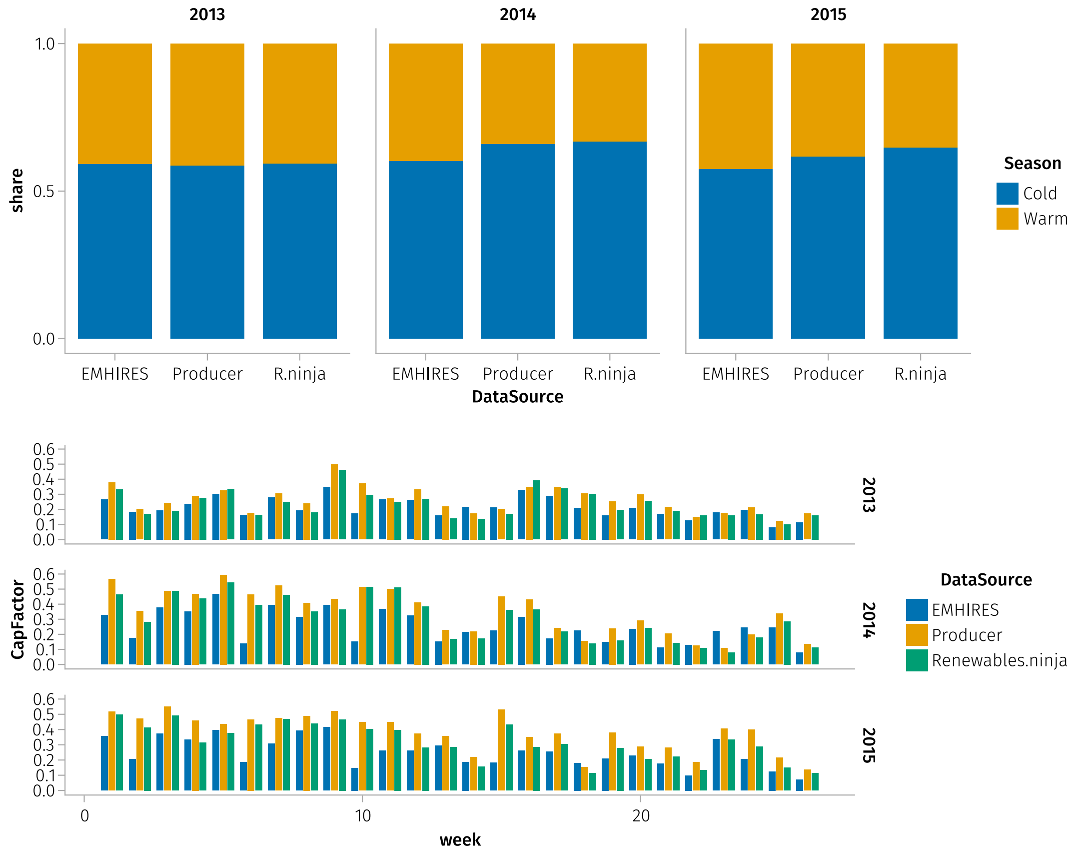

Fig. 4. Examples of Seasonal Wind production in Norway: In top panel distribution of production during warm season vs cold season. Lower panel shows weekly average wind production for weeks 1 thru 26. Renewables.ninja estimates often seem closer to producer numbers than EMHIRES estimates.

to 31st of December). In general, the distribution is concentrated around the median, with few, but present extreme values (above $+0.6$ and below -0.6 deviations in some cases). From all the PV systems IFE presents a slightly less concentrated distribution around the median, that is, the capacity factor difference density increases between $+0.1$ and -0.1 compared to the other systems. On the other hand, Agder, Evenstad and Tromsø present slightly larger extreme values, both positive and negative maximum deviations.

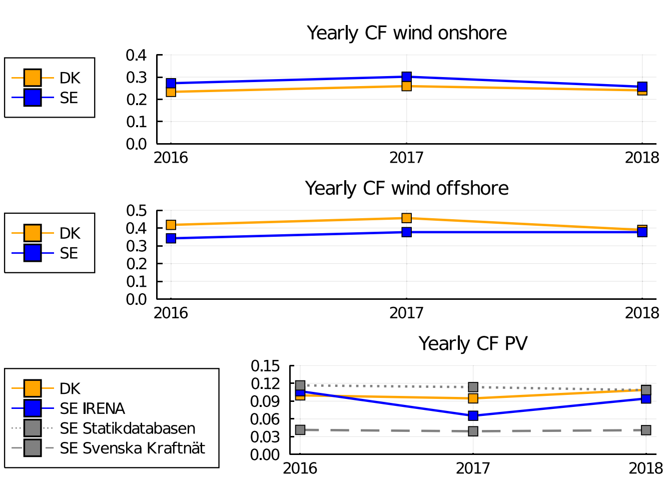

Fig. 5. Yearly capacity factor comparison for national values of wind onshore, offshore and PV in Sweden and Denmark. Several sources are shown if the values are not consistent across them.

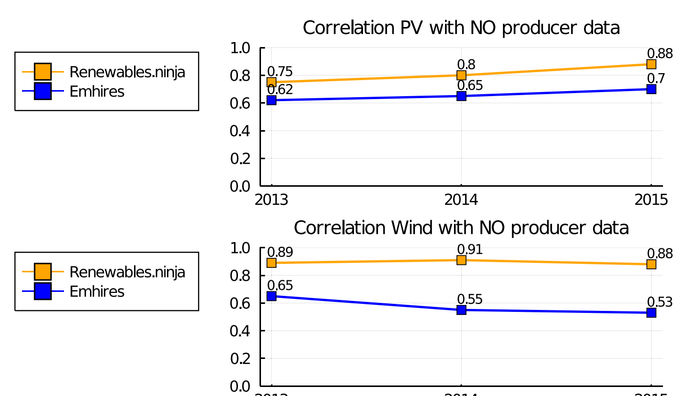

Fig. 6. Correlation values comparing aggregated national data from EMHIRES and Renewables.ninja against average of Norwegian producer data.

Table 4
Correlation values (Renewables.ninja values respect to producer) per year of the analysed PV systems.

Location	2013	2014	2015	2016	2017	2018
Agder	0.88	–	–	–	–	–
Anonymous	–	0.82	0.94	0.92	0.93	–
Evenstad	–	0.74	–	0.72	–	–
IFE	–	–	0.38	0.84	0.82	0.9
Tromsø	–	–	–	–	–	0.75

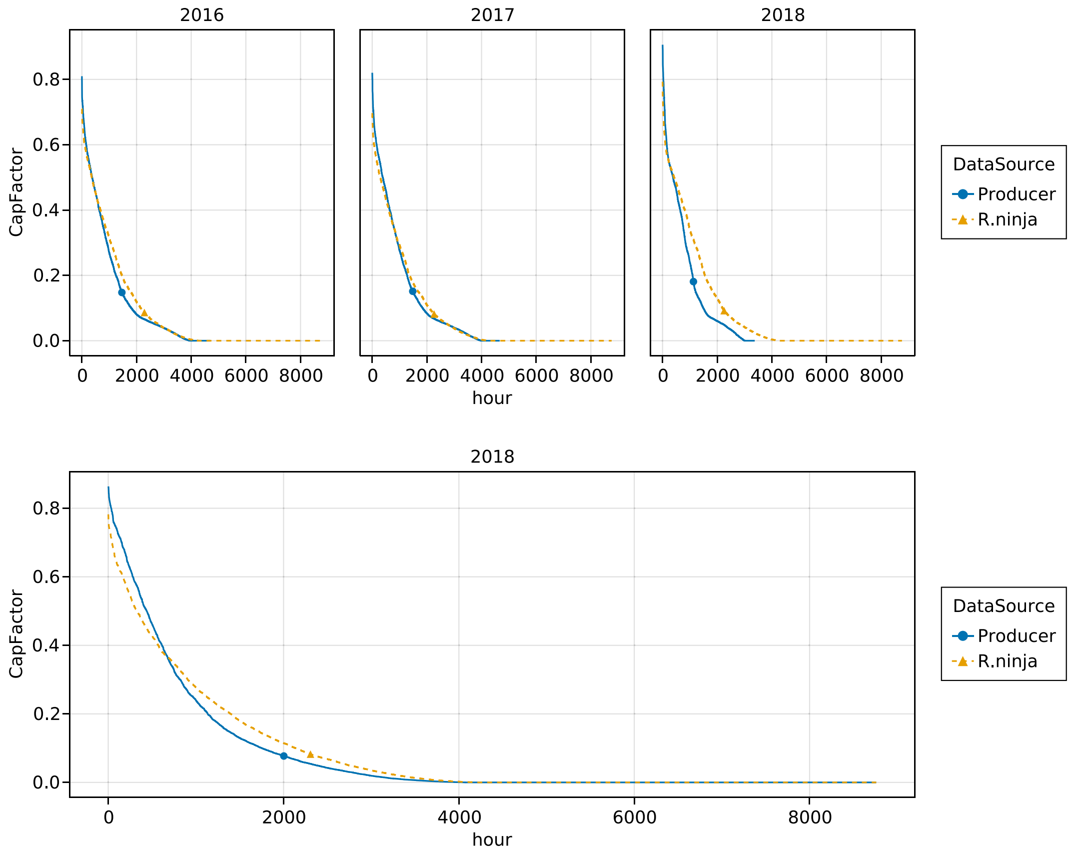

Fig. 7. Duration curves comparing producer data with the Renewables.ninja (R.ninja) data series for two analysed PV systems in southern Norway (IFE wall, above) and in northern Norway (Tromsø University, UIT, below).

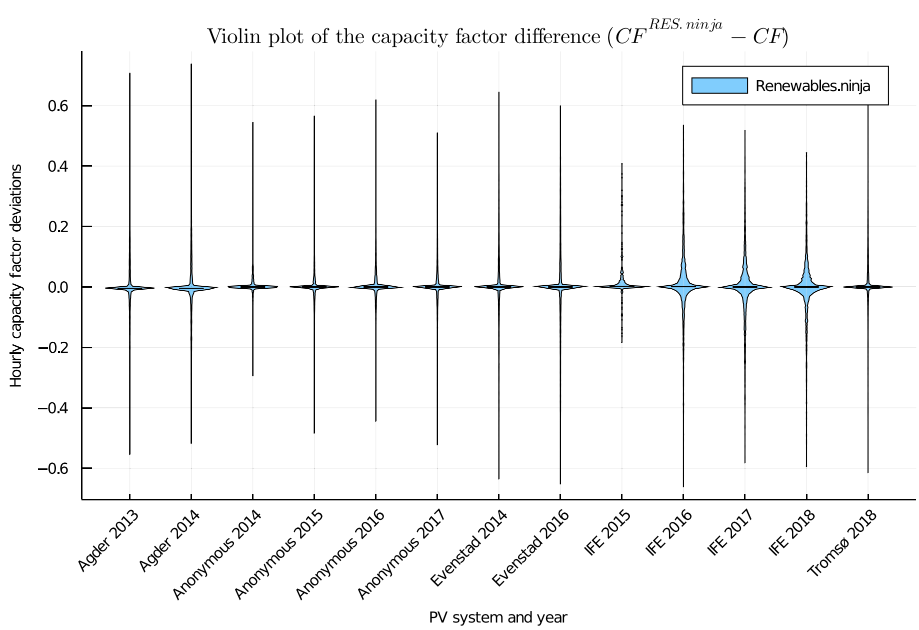

Fig. 8. Violin plot for several wind parks and years for the hourly capacity factor difference between Renewables.ninja and producer's data. The short, horizontal line represents the median value of the hourly capacity factor difference distribution for each plot.

The yearly values of the considered error parameters (*MAE*, *RMSE* and CF_{Diff}) are displayed in Fig. 9. *MAE* is below 7.58% for all analysed PV systems. Interestingly, the PV systems in Agder and Evenstad, with larger *MAE* and *RMSE* (with values of 5.63% *MAE* and 10.17% *RMSE* for Agder in 2014 and 7.58% *MAE* and 13.98% *RMSE* for Evenstad in 2016) have relatively low differences in average capacity factor, CF_{Diff} (−0.17% for Agder in 2014 and 0.71% for Evenstad in 2017), comparable with the other systems, where the largest CF

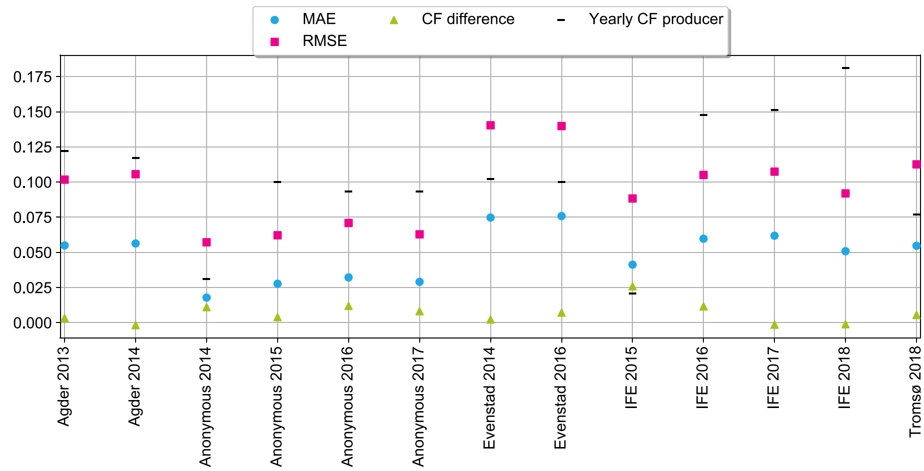

Fig. 9. Comparison of producer data with the different Renewables.ninja data series, showing mean absolute error, root mean square error and difference in average capacity factor together with the average yearly capacity factor of producer data.

difference is found in Anonymous in 2016 (1.19%). This indicates that this last parameter cannot be used alone to show the accuracy of Renewable ninja's data set. This type of situation shows, again, that production is over-estimated for periods with low *CF* in the satellite data and it is under-estimated in periods with *CF* closer to the maximum. This can be observed in Fig. 9, where Renewables.ninja overestimates the amount of hours for lower capacity factors than ca. 0.35 for Tromsø and ca. 0.55 for IFE in 2018 and underestimates those above those values. However, the CF difference is, despite the different hourly CF distribution profiles, 0.55% for Tromsø 2018 and 0.11% for IFE in that same year. Thus, the error is somehow compensated along the year in some years and PV systems, as it can be observed in most of the PV systems with larger MAE and RMSE (like Agder in 2013 and 2014, Evenstad in 2014 or IFE in 2017).

Given these results, Renewables.ninja provides relatively high correlations (from 0.72 to 0.94) for individual PV systems, considering the northern location of the power systems and that they are individual. For comparison, the German correlation of Renewables.ninja Merra and TSO data was 0.95 for the period 2012–2014 in Ref. [8]. Considering error parameters (and that systematic local effects occur from shadows caused by local objects or snow and it is hard to discover in an aggregated data set), it can be said that the Renewables.ninja data set, with the resolution provided by MERRA-2 for PV production, is able to provide practical and fast time series that can be used to estimate local, and thus regional, PV electricity production, especially where the time series' high resolution accuracy is not critical. Nevertheless, one needs to be aware of the limitations presented above.

5.2. Local wind production

To generate time series from satellite data for local wind production in Norway, we have selected a group of wind farm locations in the most relevant bidding zones of the country for this study. NVE [18] provided data and time series from several wind farms in Norway to analyse the accuracy of the Renewables.ninja data set. A list of the selected wind farms is shown in Table 5 with basic information including bidding zone, installed capacity and average hub height of the wind farm. The wind farms are located in the Norwegian bidding zones NO2 (south-west), NO3 (centre) and NO4 (north), which are the ones with larger onshore wind installed capacity and generally better wind conditions. Extra information regarding exact satellite location and turbine models is shown in A, in Table 10. The capacity factor of the provided data for the available years (mostly from 2015 to 2017) is compared with the data set of Renewable ninja, and with the adjusted data set using local average wind speeds from GWA 3.0 and NVE Wind Map.

Table 5
Wind farms used for data comparison with basic data: region or bidding zone where it is located, installed capacity and average hub height of the wind park.

Wind farm	Region	Capacity (MW)	Hub height (m)
Kjøllefjord	NO4	39.1	70
Lista	NO2	71.3	80
Nygårdsfjellet	NO4	32.2	80
Bessakerfjellet	NO3	57.5	64
Skomakerfjellet	NO3	13.2	94
Valsneset	NO3	11.5	64
Raggovidda	NO4	45	80
Mehuken	NO3	25.3	64
Høg Jæren	NO2	73.6	80
Fakken	NO4	54	80
Ytre Vikna	NO3	39.1	64
Hundhammerfjellet	NO3	4.6	64
Hitra	NO3	55.2	80

5.2.1. Comparison with Renewables.ninja

The accuracy of Renewables.ninja data was estimated for the list of individual wind farms in Table 5 in terms of the Pearson correlation efficient between yearly time series of production obtained from Renewables.ninja and the measured production. The time resolution is 1 h using the weather data output from Renewables.ninja, based on MERRA-2 and the Virtual Wind Farm model (VWF, described in Ref. [5]), which transforms the wind data to wind farm power output. Wind speed from Renewables.ninja's was obtained for 19 years (2000–2018), which was the maximum amount of years available by Renewables.ninja's API in their website [27]. The yearly correlation of the measured producer data and Renewables.ninja is shown in Table 6 for the available years of producer data. Observe that, depending on the individual wind farm, very different yearly correlation values are obtained, ranging from 0.51 for Nygårdsfjellet in 2017 to 0.91 for Ytre Vikna in 2015. This may be because MERRA-2 data set used by Renewables.ninja has a relatively large spatial resolution and thus does not represent local wind phenomena well, causing these varying results. Thus, the question arises whether it is possible to make some adjustments to the data from Renewables.ninja to obtain a better

Table 6
Correlation values of Renewables.ninja values without adjustments respect to producer's values per year for all selected wind farms.

Location	2015	2016	2017
Bessakerfjellet	0.83	0.76	0.84
Fakken	0.63	0.63	0.61
Hitra	0.7	0.77	0.79
Høg Jæren	0.85	0.86	0.86
Kjøllefjord	0.82	0.81	0.74
Lista	0.86	0.88	0.88
Mehuken	0.83	0.8	0.84
Nygårdsfjellet	0.52	0.53	0.51
Raggovidda	0.78	0.81	0.81
Skomakerfjellet	–	0.71	0.75
Valsneset	–	0.78	0.8
Ytre Vikna	0.91	0.9	0.9

correlation between producer's and satellite data in individual wind farms. We therefore attempt to adjust for the local wind conditions of individual wind farms to compensate for the low resolution of the MERRA-2 data set, and include the effect of valleys, different surface roughness, irregular terrain around the wind park and other local aspects. We use wind speed, as opposed to calculated production from Renewables.ninja, for these further adjustments and calculate the power production at the hub height and the wind turbine model for each specific site.

5.2.2. Local adjustments of Renewables.ninja

We adjust the average wind speed over the available period obtained from Renewables.ninja (2000–2018) with a more precise local average speed, for example from the newly released Global Wind Atlas (GWA) 3.0 [28] and, in the case of Norway, The Norwegian Water Resources and Energy Directorate (NVE) [29] also provides local average wind speeds. GWA uses a downscaling process to calculate the wind climate data, calculated every 250 m for five heights (10 m, 50 m, 100 m, 150 m and 200 m). The database also provides roughness length values (used also to scale the NVE average speed) and, for the given point, the average speed values are given for a 3 km by 3 km grid based of the percentage of the "windiest areas" included in the wind speed calculation (in this article chosen as 50%). The resolution of the wind speed values in the NVE wind map is 1 km in inland areas. The reason for choosing these two databases was to study if it was possible to develop a methodology for a systematic adjustment of data from Renewables.ninja for wind farms independently of the location (in the case of GWA) or at least for any wind farm in Norway (if the adjustments by NVE Wind Map are more accurate). The adjustments would then cause increased production in case of underestimated wind speed and *vice versa*.

The values in Table 7 do not seem very consistent. The average wind speed from GWA, v_{GWA}, is estimated at 50 m above the ground level and in several cases is very close to or higher than the average wind speed from NVE Wind Map, v_{NVE}, despite the fact that NVE's speed is estimated at 80 m (and therefore one would expect it to be larger). Often, the average speed from Renewables.ninja at hub height, $\bar{v}_{ninja}$, shows considerable discrepancies compared to the adjustment values, such as in Skomakerfjellet or Bessakerfjellet. However, these speeds are located at different heights (and cannot be compared directly), so the main difference between Renewables.ninja and the adjustments will be seen more clearly when calculating errors and average capacity factors (see Table 8).

Equation (5) is used to scale the average speeds up or down to the average hub height of each of the wind farms, and it is based on the logarithmic dependence of wind speed with height, described in Ref. [30] and also used in Ref. [31]:

Table 7
Data used for the Renewables.ninja adjustments, wind speeds at a given height by the sources, roughness length on the wind farm surface and average Renewables.ninja speed at hub height.

Wind farm	**v_{GWA} at 50 m (m/s)**	**v_{NVE} at 80 m (m/s)**	**Roughness length (m)**	**$\bar{v}_{ninja}$ at hub (m/s)**
Kjøllefjord	7.34	8	0.05	7.83
Lista	7.52	8.5	0.2	7.99
Nygårdsfjellet	6.8	6.5	0.05	5.61
Bessakerfjellet	9.57	8	0.05	6.59
Skomakerfjellet	9.06	8.5	0.05	6.99
Valsneset	8.13	8.25	1.5	7.04
Raggovidda	9.32	9	0.05	8.44
Mehuken	10.83	9.75	0.2	8.11
Høg Jæren	7.96	9	0.2	7.57
Fakken	6.46	7.25	0.5	7.08
Ytre Vikna	7.95	8.25	0.05	8.21
Hundhammerfjellet	8.79	7.75	0.5	7.41
Hitra	6.8	7.5	0.05	6.51

Table 8
Comparison of the average wind speed of the original Renewables.ninja (R.ninja) and the two adjustments sources, GWA and NVE Wind Map, scaled at the average hub height of each wind farm (speed in m/s).

Plant Name	R.ninja	GWA	NVE
Kjøllefjord	7.834	7.698	8.390
Lista	7.989	8.160	9.224
Nygårdsfjellet	5.607	7.263	6.942
Bessakerfjellet	6.589	9.912	8.286
Skomakerfjellet	6.986	9.888	9.277
Valsneset	7.036	8.702	8.831
Raggovidda	8.442	9.954	9.612
Mehuken	8.107	11.314	10.186
Høg Jæren	7.571	8.638	9.766
Fakken	7.082	7.119	7.990
Ytre Vikna	8.210	8.234	8.545
Hundhammerfjellet	7.413	9.261	8.165
Hitra	6.507	7.263	8.010

$$v_{hub} = v_{ref} \cdot \frac{ln(h_{hub}/z)}{ln(h_{ref}/z)}, \tag{5}$$

where v_{hub} is the speed at the turbine's hub (at a height h_{hub} over the ground), v_{ref} is the reference speed at a reference height h_{ref} and z is the roughness length in m, defined by the surface type and surrounding landscape, taken from Ref. [28] for the wind farm location, used for both the GWA and NVE adjustments.

Then, the wind speeds, $v(t)$, are normalised with the average wind speed of the data set obtained from Renewables.ninja, $\bar{v}_{ninja}$, and scaled up with the more locally defined average wind speeds (either from GWA or from NVE's Wind Map) escalated to the hub's height, v_{adj}, as it is described in Equation (6):

$$v(t) = v_{ninja}(t) \cdot \frac{v_{adj}}{\bar{v}_{ninja}}, \tag{6}$$

where $v_{ninja}(t)$ are the wind speeds obtained from Renewables.ninja.

To obtain power production from the wind speeds time series we use a turbine power curve, which is dependent on the installed turbine model. The curves were obtained from Refs. [32,33] with 0.5 m/s steps. In order to represent a wind farm, the power curve for a turbine is smoothed following [34]. This assumes that the wind speed in the physical location of the wind farm varies and it is

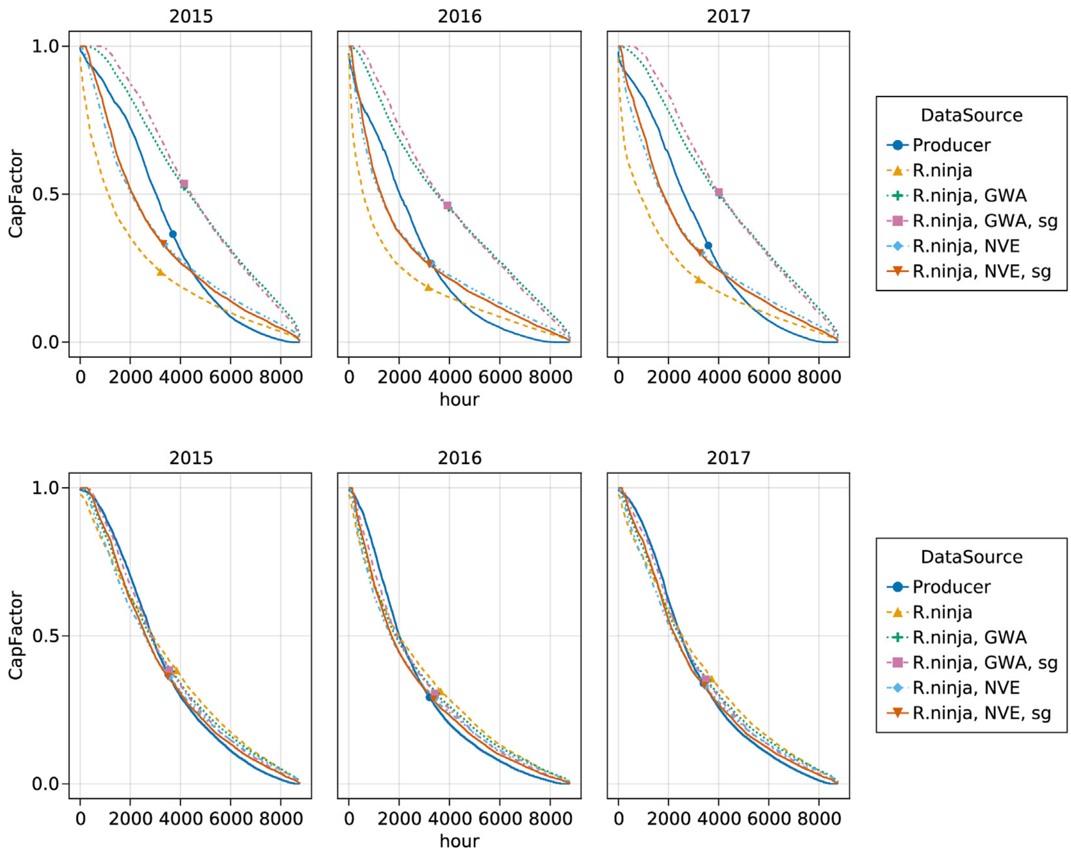

Fig. 10. Duration curves for all time series analysed for the wind farms of Bessakerfjellet (above) and Ytre Vikna (below).

not the same for all individual turbines. Thus, it assumes a normal distribution of the deviations in wind speed over the turbine locations for the hourly wind speed at the wind farm. The parameters of this normal distribution consist of the average wind speed $\mu = -0.15$ m/s[1] and the standard deviation of the wind speeds $\sigma = 2$ m/s. Equation (7) illustrates the wind farm power curve calculation, assuming that the wind speed at every hour follows the normal distribution (i.e. parts of the wind farm have higher wind speed than others).

$$P_{park}(v) = \sum_k \Delta s \cdot p(k) \cdot P_{turbine}(v+k), \tag{7}$$

where $P_{park}(v)$ is the power output at the adjusted wind speed v for the total wind farm, Δs is the discrete step of the power curve (in this case 0.5 m/s). $p(k)$ is the probability of the spatial normal distribution with the previously mentioned μ, σ, in a range k (from -5 m/s to 5 m/s with 0.5 m/s steps, which covers the majority of the normal distribution described above without causing long calculation times). Finally, $P_{turbine}(v+k)$ is the single turbine power output at the speed $v+k$, corresponding with the single turbine power curve of each turbine model, obtained from Refs. [32,33].

The power output of wind speeds in between the 0.5 m/s steps is linearly interpolated to obtain the resulting power, as shown in Equation (8):

[1] μ is a normalised value, meaning that the wind park will have a slightly lower average wind speed (-0.15 m/s than the wind profile) than if only one turbine was installed, due to turbulence and other effects between turbines.

$$P_{park}(v) = P_{park}(v_1) + (v - v_1) \cdot \frac{P_{park}(v_2) - P_{park}(v_1)}{v_2 - v_1} \tag{8}$$

where v_1 and v_2 are the consecutive discrete wind speeds of the wind farm power curve, where the actual speed v has a value in between the two, so that $v_1 < v < v_2$.

5.2.3. Comparison with adjusted wind speed

We calculate new and adjusted capacity factors and compare to see whether the adjustments made were successful: CF_{GWA} for GWA adjustment and wind farm power curve, $CF_{GWA,sg}$ for GWA adjustment and single turbine power curve, CF_{NVE} for NVE adjustment and wind farm power curve and $CF_{NVE,sg}$ for NVE adjustment and single turbine power curve. In Fig. 10, capacity factor duration curve of two of the analysed wind farms are shown (Bessakerfjellet above and Ytre Vikna below), illustrating how the Renewables.ninja values differ significantly in exactitude compared with the producer's value. Also the two adjustments gives opposite results in Bessakerfjellet. While NVE adjusted capacity factor achieve closer values to those provided by the producer, though still underestimating, the opposite is true for GWA adjustment, where production is greatly over-estimated. The different power curves (wind farm vs. single turbine) have less effect on the capacity factor distribution, yielding similar values.

To show the difference distribution of deviations in capacity factor between Renewables.ninja time series ($CF^{RES.ninja}$), both without and with adjustments (the latter defined previously as CF_{GWA} and CF_{NVE}) and producer data (CF), Fig. 11 displays violin plots for a representative selection of the analysed wind farms for the years 2016 and 2017. In this plot only wind farm profiles are

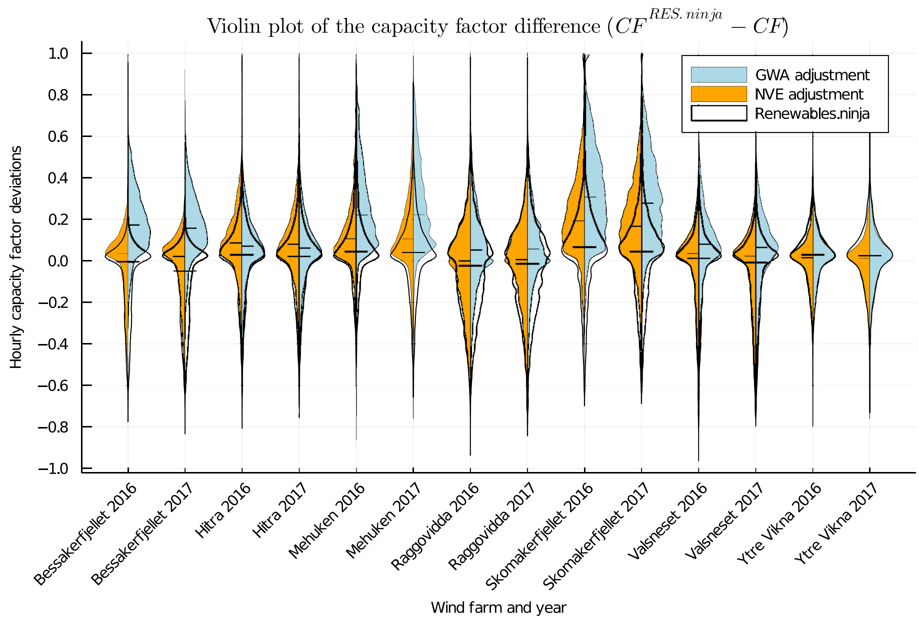

Fig. 11. Violin plot for several wind parks and years for the hourly capacity factor difference between the three studied time series (Renewables.ninja and its adjustments with data from NVE and GWA) and producer's capacity factor. The short, horizontal lines represent the median values of the hourly capacity factor difference distribution for each of the three plots.

considered, no single turbine profiles. The transparent surface delimited with a black line represents the distribution of the difference between Renewables.ninja without adjustments and producers hourly capacity factor. The orange surface (on the left) represents the capacity factor difference distribution between Renewables.ninja time series with the NVE wind speed adjustment and producers data, whereas the blue surface (on the right) considers Renewables.ninja data with GWA adjustment used for the wind speed adjustment. A horizontal line shows the median in each of the three violin plots per wind farm and year.

The adjustment using GWA average wind speeds tends to overestimate the average wind speed and thus wind capacity factor, as it is observed in Bessakerfjellet, Mehuken or Valsneset, where the distribution of positive deviations (that is, hourly capacity factors from generated time series are larger than producer values) expands compared to values without adjustments. The NVE adjustments result in a more moderate distribution change. While it reduces deviation in the case of Ytre Vikna and partially in Raggovidda (by reducing the area of the violin plot), in other cases, like in Hitra, Mehuken or Bessakerfjellet a similar overestimation of production is observed (and thus pushing the violin plot up, increasing positive capacity factor differences). The most extreme case, as anticipated in Fig. 10, is Bessakerfjellet, where the two adjustments produce a notable worsening of the accuracy of the time series.

The error parameters show considerable differences in the adjusted power productions and *CF*, see Fig. 12. It is clear that deviations in wind are larger than in the case of PV, see Fig. 9, reaching *MAE* maximum values of 24.6% for non-adjusted Renewables.ninja values (Nygårdsfjellet in 2017) and 35.8% for some adjustments (Skomakerfjellet in 2017, GWA adjustment and single turbine power curve). Wind farm power curves provide generally lower values in *MAE*, *RMSE* and $|CF_{Diff}|$ (though for some cases like Raggovidda or Valsneset single turbine profiles provide a slightly lower *MAE* and *RMSE* than single turbine power curves, for example for Raggovidda in 2017 MAE is 16.47% with GWA adjusted profile and wind park curve while the single turbine profile provides 16.42% *MAE*. If the two adjusted time series are compared to the errors of the Renewable.ninja's *CF* time series, there is also a result disparity. In some locations and specific years (Nygårdsfjellet, Ytre Vikna, Valsneset, Raggovidda), an error reduction (*MAE* and *RMSE*) can be observed with adjusted wind speeds from GWA and NVE (with a maximum reduction of 0.018 in the case of *MAE* and 0.04 in *RMSE* and up to 0.148 reduction in absolute capacity factor difference). In Bessakerfjellet, the adjusted speed from NVE reduces all yearly *MAE* and *RMSE* while GWA adjustment increases *MAE* and *RMSE*. In other wind farms, for example Mehuken or Skomakerfjellet, both adjustments create considerably larger errors compared to the non-adjusted time series: it is observed a maximum of 16.08% *MAE* and 16.67% *RMSE* higher error compared to Renewables.ninja for Mehuken in 2017 with GWA adjustment (5.39% and 5.88% for NVE for that same year) and a maximum of 17.85% *MAE* and 18.76% *RMSE* larger for Skomakerfjellet in 2016 with GWA adjustment (8.41% and 5.88% for NVE for that same year).

Considering Renewables.ninja capacity factor time series alone (i.e. without adjustments), despite having considerable in *MAE* and *RMSE*, yearly average capacity factor differences are below $\pm 2\%$ in some of the wind farms and years. One example is Skomakerfjellet in 2017, with a *MAE* and *RMSE* of 16.29% and 21.5% respectively, but a capacity factor difference of 1.69%. In other cases, the capacity factor difference between the obtained data sets and producer's data are well above or below 0, with a maximum difference of 35.18% for Skomakerfjellet with GWA adjustment and single turbine profile in 2016 and a minimum of -14.89% for Nygårdsfjellet in 2017 (no adjustment).

6. Summary and conclusion

A key part of the future energy system in Europe will be the presence of variable energy production from wind and PV. In order to estimate flexibility and future investments in the energy system, data of good quality is vital. Thus, it is useful to study the data sources available in the individual countries and regions and its accuracy to obtain data sets with acceptable quality standards.

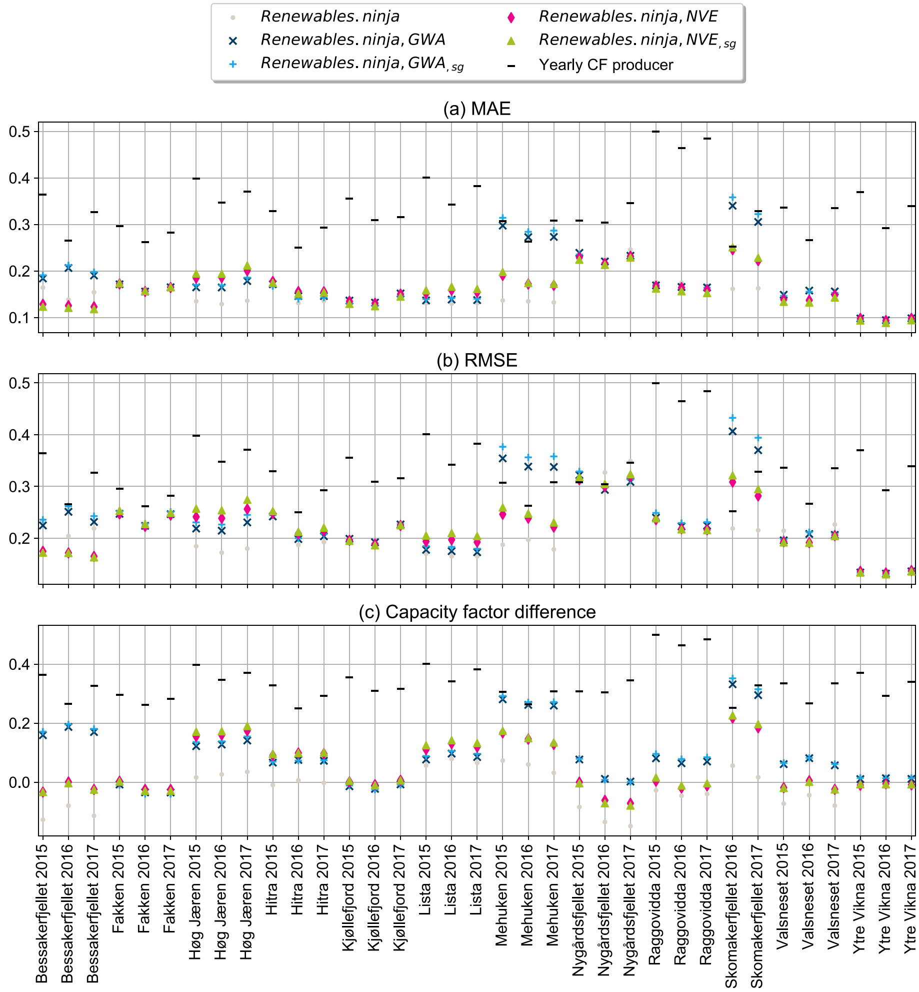

Fig. 12. Comparison of producer data with the different time series analysed (Renewables.ninja and its adjustments with data from NVE and GWA), showing mean absolute error (figure **a**), root mean square error (figure **b**) and difference in yearly average capacity factor (figure **c**). For each of the plots, the average yearly capacity factor of producer data is also plotted.

We supplement existing literature by comparing national data sets for the Nordics, and find that Renewables.ninja provides the estimates that best correspond to the data we collected for these countries, and selected Renewables.ninja for the further investigations.

We also compare individual PV systems and wind farms to study the quality of time series for specific locations to represent production in the Norwegian bidding zones (NO1–NO5). Several measured wind farm production time series in Norway (located in the electricity trade regions NO2–NO4) and PV system production time series (in the regions NO1, NO2 and NO4) were compared to time series obtained from Renewables.ninja.

The results for PV show that the yearly capacities were reasonable compared to similar works for other regions, with a yearly minimum correlation of 0.72 and an a yearly average of 0.844. Additionally, *MAE* was kept below 8%, the maximum *RMSE* was 14% and the maximum yearly capacity factor difference below 3%. We did not observe significant differences in Renewables.ninja accuracy between the PV systems located in the southern part of the country and in the northern PV system located in the city of Tromsø despite the city's high latitude where satellite data may be less accurate.

For wind power, initial analyses showed noticeably low and varying correlation in wind production and the low resolution of the MERRA-2 data set. We developed and tested two different local wind speed adjustments in an attempt to improve accuracy. We used average wind speeds from GWA 3.0 at 50 m's height, and NVE Wind Map average speed at 80 m. After adjusting these two average wind speeds to the average hub height of the wind farm, the wind speed time series from MERRA-2 would be adjusted with these new average speeds. These new wind speed curves were transformed into wind turbine and wind farm power profiles. Unfortunately, the results of the individual locations still vary considerably after these adjustments, and in several cases the adjustments provide opposite results for individual power plants. For example, in the case of Bessakerfjellet, it provides a considerable improvement both in deviations (*MAE* and *RMSE*) and makes the average absolute capacity factor difference very close to zero (between 0.000792 and 0.0341) for the three analysed years with the NVE adjustment. In other cases, however, the adjustments cause a considerable increase in error (most extreme for Skomakerfjellet and Mehuken). Therefore, we cannot generally obtain better time series for Norway using this method. Adjustments based on GWA would be attractive as the method would be applicable anywhere, while the NVE wind speed estimates only cover Norway. We nevertheless find that the adjustments based on NVE wind speed estimates generally provide better results than those using GWA averages.

After analysing the results discussed in Section 5, we conclude that one needs to be wary of Renewables.ninja data sets for individual PV systems and wind farms in Norway. In the case of PV, the correlations, errors and average capacity factor deviation show that data the quality of PV data sets from Renewables.ninja for individual PV systems can be accurate enough when the detail level is not too critical. In the case of wind, however, it can be observed that Renewables.ninja cannot provide low error time series (compared to similar data sets) for Norway for individual wind farms. Moreover, both GWA and NVE adjustments taken into account, local average wind speeds provide inconsistent and contradictory results for the same Norwegian locations (in some cases increasing the error compared with Renewables.ninja) and thus a systematic methodology for all wind regions in Norway could not be successfully applied in this paper. Considering the high variability in accuracy of Renewable.ninja's data set, also when adjusting the average wind speed, we conclude that one should be careful with wind time series from these sources and one has to study each wind farm individually. Fortunately, new wind models with high resolution (e.g. Ref. [35]) and covering specific areas (offshore reanalysis models like [36]) are under development and thus one can expect better alternatives in the near future, as there is a need for good quality estimations of wind energy production.

Credit author statement

M. Muñoz Ortiz: Writing - original draft preparation, Investigation, Software, Formal analysis, Data curation, Visualisation. **L. Kvalbein**: Investigation, Validation, Writing - review & editing. **L. Hellemo**: Conceptualization, Investigation, Formal analysis, Methodology, Software, Data curation, Writing - review & editing, Visualisation.

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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Appendix A. Extra information of the locations

In this appendix extra information of the individual locations selected for the analysis is presented. In the case of PV data, more detailed information (regarding data source, satellite location and altitude) is presented in Table 9. For the case of wind the exact location and turbine model is specified in Table 10.

Table 9
PV systems used for data comparison, the exact location of the first four systems was required to be anonymised

PV System	Data source	Satellite location (Long., Lat.)	Altitude (m)
Evenstad	[37]	Anonymised	259
Anonymous	[38]	Anonymised	80
IFE wall	[39]	Anonymised	100
Agder Energy	[40]	Anonymised	NA
UIT - Tromsø	[41]	69.680084, 18.971774	NA

Table 10
Detailed information of the analysed wind farms including specific location (latitude and longitude, in degrees) and turbine model

Wind farm	Latitude	Longitude	Turbine model
Kjøllefjord	70.9222	27.2819	Siemens SWT 2.3 82
Lista	58.157056	6.7114	Siemens SWT 2.3 93
Nygårdsfjellet	68.5046	17.8722	Siemens SWT 2.3 93
Bessakerfjellet	64.2221	10.3721	Enercon E70 2300
Skomakerfjellet	64.13999	10.269	Vestas V112 3300
Valsneset	63.8190	9.6230	Enercon E70 2300
Raggovidda	70.7632	29.0845	Siemens SWT 3.0101
Mehuken	62.0177	4.9995	Enercon E70 2300
Høg Jæren	58.6427	5.7638	Siemens SWT 2.3 93
Fakken	70.1004	20.1063	Vestas V90 3000
Ytre Vikna	64.9006	10.8919	Enercon E70 2300
Hundhammerfjellet	64.7538	11.3642	Enercon E70 2300
Hitra	63.5195	8.8041	Siemens SWT 2.3 93

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