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WIND ENERGY SCIENCE DISCUSSIONS

Methodology for the analysis of the effect of precipitation on wind farm performance

Maria Aparicio-Sanchez[1], Irene Eguinoa[1], Elena Cantero-Nouqueret[1], Alvaro Olcoz-Alonso[1]

[1]National Renewable Energy Centre (CENER), Sarriguren, Spain

Correspondence to: María Aparicio (maparicio@CENER.com)

Abstract. Wind turbines are exposed to rainfall, which has a long-term impact through erosion, and numerous studies have investigated the consequences of leading-edge erosion (LEE) on wind turbine blades. However, the potential effects of precipitation on turbine performance and on the experimental evolution of wakes have not yet been thoroughly analyzed. This paper presents a new methodology to study the impact of precipitation using experimental operational data. The methodology includes the necessary data processing, the definition of relevant meteorological parameters, and appropriate analysis methods. A commercial wind farm is evaluated following the proposed methodology, identifying differences in behavior between dry and rainy conditions at both the individual turbine level and the wind farm and wake levels, while accounting for the quantity and distribution of the available data.

1 Introduction

The exploitation of operational data from wind farms is becoming a fundamental tool to improve plant and asset management (Pillay et al., 2025; Schreiber et al., 2020). Considering these operational data, it has been possible to move from an evaluation of assets based on generic turbine and ambient data to considering site-specific conditions in which the wind turbines operate. The wind industry is leveraging the value of data to understand physical impacts and, in later stages, develop models to reduce uncertainty. All the available information makes it possible to analyze the effect of certain situations both on the operation of the wind farm, and on the wind turbines individually.

The effect of rain in terms of its impact on performance and asset management has not been addressed in depth to date (Abolude & Zhou, 2018; Corrigan & Demiglio, 1985; Gahlot et al., 2022). The literature has focused on assessing the effects of leading-edge erosion, rather than identifying whether rainfall itself modifies the behaviour of wind turbines. Some authors (Hasager et al., 2020; Maulana et al., 2024) have even studied the impact of leading edge erosion on wind farm control design and performance. Studies have also been conducted on whether the presence of wind farms modifies precipitation at nearby locations (Al Fahel & Archer, 2020).

LES simulations have indicated that rainfall reduces the wind speed within the sweep region of the wind turbine (Yang et al., 2024). Reducing the uncertainty of the effect of rainfall is one of the key points within the AIRE project (AIRE).

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The present study develops a methodology to carry out the assessment of rainfall impact on wind farm performance based on available operational data (rain measurements and typical 10-min SCADA), applying it to a commercial operating wind farm as case study and analysing how considering or not considering precipitation affects characteristic variables of wind energy. Once the impact of rainfall is identified, the wind farm simulation setup could be adapted to estimate wind farm performance more accurately. Some of the alternatives to improve the simulation that are evaluated in this study are modifications in input data or model parameters depending on the presence of rainfall. The modifications that are evaluated in the simulations include the wake parameters and other input data such as power curves or the heterogeneous map of the site.

The remainder of the manuscript is as follows. Sect. 2 briefly describes the approach followed. Sect. 3 introduces the wind farm where the methodology has been tested, while Sect. 4 focuses on the specific steps of the data analysis applied to that wind farm. Finally, conclusions are drawn in Sect. 5.

2 Methodology description

This work deals with the development of a methodology for the associated operational analysis, since it has not been addressed in the state of the art specifically for precipitation and there are many constraints related to the data that must be considered: types of available data, quality of the data, sample size, etc. For the sake of readability, the steps are defined in Sect. 4 in parallel with the study of a commercial operational wind farm, introduced in Sect. 3, where the different issues in the process are addressed, and the suggested procedures are verified.

This methodology is developed to analyze the impact of precipitation on a wind farm using SCADA data, i.e. the minimum available data. In addition to the usual SCADA data with ten-minute statistical information on meteorological signals and wind turbine operation, a signal identifying the precipitation is required (either included in the SCADA or form another external sensor, but located at the site under study). For wind farm analysis, information allowing wake simulation (power curve and thrust coefficient CT data from turbine models) is also required, as well as information on the location of each wind turbine.

After a preliminary data processing, the analysis is considered into three different levels:

- Meteorological characteristics: independent analysis of meteorological signals.
- Wind turbine performance: individual analysis by wind turbine and comparison of the performance in all of them.
- Wind farm analysis: the focus of this approach is on the comparison between SCADA data and wind farm simulations.

3 Site description

The wind farm area, situated in France, encompasses a non-complex region at 1100 m a.m.s.l. (above mean sea level). It benefits from the wind regime of the mistral, particularly favourable for wind energy applications. The area is mainly composed of cultivated fields, and a forest on its western part. Figure 1 shows the wind farm, which is composed of 4 wind turbines (red dots) and a 79 m meteorological mast (purple dot). It is surrounded by two neighbouring wind farms northwest (blue dots) and

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southeast (green dots), with 9 and 5 wind turbines, respectively.

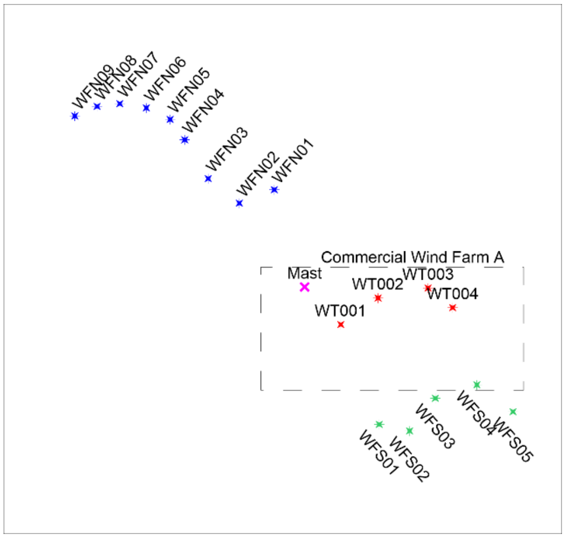

Figure 1: Location and overview of the wind farm. Wind farm turbines (red) and meteorological mast (purple), northwest (blue) and southeast (green) neighbouring wind farms.

The meteorological mast is located 550 m northwest of the first wind turbine from the wind farm. Near the mast, the terrain is open pasture for at least 3 km from west to east but there is a forest area at 400 m at south direction.

The met mast is 79 m height lattice structure, with six measurement levels oriented to 110º and 290º. Wind speed is measured at six levels (30 m, 50 m, 70 m, 78 m and 82.3 m, two anemometers at this last level), wind direction at three levels (50 m, 70 m and 77.5 m), 2 temperature sensors (5 and 76.5 m), 1 pressure sensor (5 m), 1 rain gauge (10 m) and 1 humidity sensor (76.5 m).

Figure 2 shows test site measurements timeline. The extensive measurement period (EMP) ran from May 2017 to May 2023 comprising 6 years of measurements from the SCADA data and 28 months from meteorological mast. The Intensive Observational Period (IOP), when all sensors had concurrent measurements, lasted for 12 months from January 2019 to December

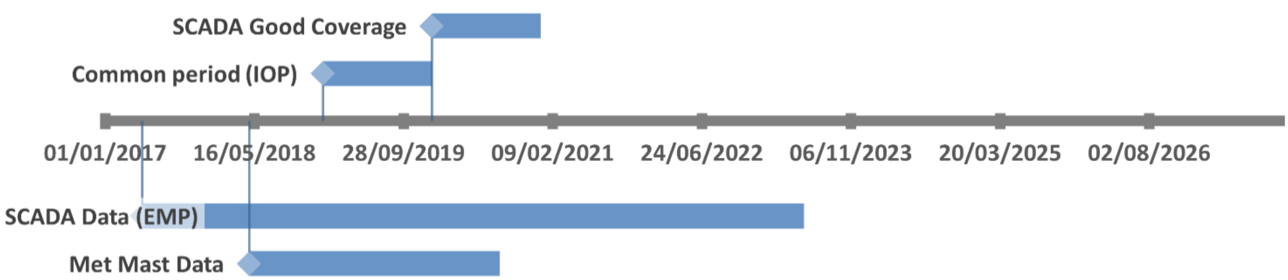

Figure 2: Test site timeline with measurement periods.

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4 Dataset analysis

The steps of the methodology presented in Sect. 2 are applied to the study of the wind farm described in Sect. 3. This makes it possible to address all the practical issues in the process and to verify the suggested procedures of the methodology.

4.1 Data processing

First, a preliminary data processing is necessary to prepare the data for the analysis. This step includes cleaning and curation that means processing raw SCADA data to obtain clean data; operational and meteorological identification methods, these are used to generate additional signals that are useful for the analysis. Finally, the complete dataset is filtered according to the rainfall data.

4.1.1 Cleaning process

This step is compulsory to ensure data quality for both meteorological and operational data, as well as additional sensors related to precipitation. The verifications are carried out both at individual turbine level and at the wind farm level. This process includes the verification of:

- Additional variables, which have been calculated from the available information and operational states identification: air density, yaw misalignment, turbulence intensity, . . .
- Extreme values for relevant signal statistics (maximum, minimum, average and standard deviation). They are used to ensure the consistency of the original and calculated data.
- Power curve verification, taking into account the operational identification.
- Turbulence curve vs wind speed, ensuring results are within normal limits.
- Wind roses and wind distributions.

During the process, original data are corrected where necessary or discarded if their quality is not sufficient.

4.1.2 Operational and meteorological identification

Based on the available information from the SCADA, an identification of the operational states of each wind turbine at each sample has been carried out. The identification of the operational states of the wind turbines is crucial for the analysis of the wind farm. However, the information may not be directly available through the SCADA and then must be obtained implicitly through other operational variables.

Four operational states have been identified in this analysis, according to the operation in the time interval under consideration (10 minutes):

- Production pure normal: the wind turbine has been producing without stops or derating.
- Production pure derating: the wind turbine has been in derating during the whole interval.
- Production partial: there have been moments of production combined with stopping and/or derating.95

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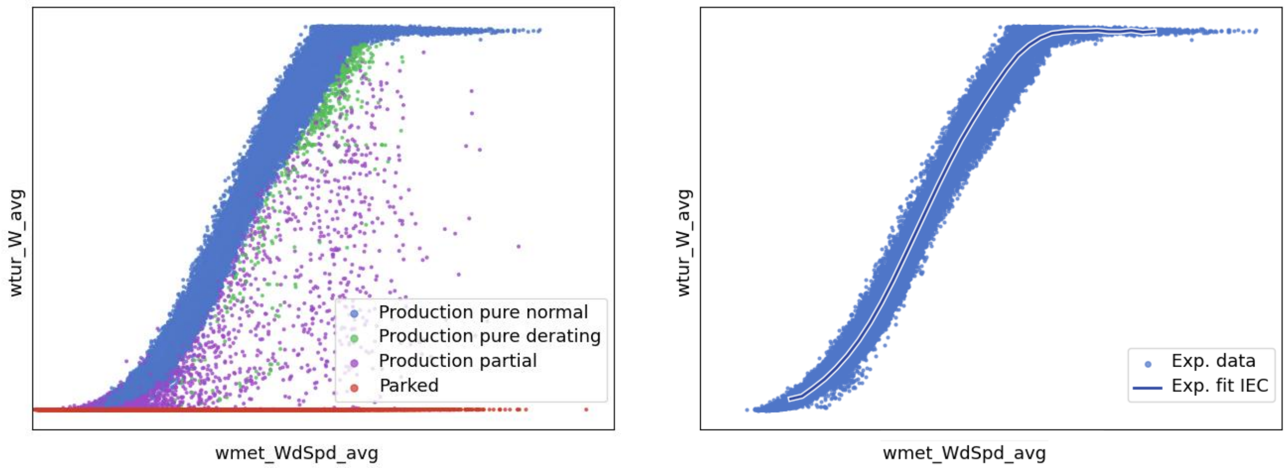
- Parked: the wind turbine has been stopped (either idling or standstill) during the entire interval.

As a mere example, Figure 3 (a) shows for wind turbine WT002 how these four operational states have been identified and how (see Figure 3 (b)) this influences the obtained power curve. The power curve is postprocessed (fit according to IEC 61400-12-1 (International Electrotechnical Commission, 2017)) from samples identified as production pure normal conditions.



(a) (b)

Figure 3: Average power production versus average wind speed for WT002: (a) classification by operational state and (b) data filtered for production pure normal conditions (scatter and IEC fit power curve).

4.1.3 Filtering

For the rain study, three datasets are created using filters based on precipitation information when available:

- rain: dataset filtered for values of "Rainfall average" higher than 0
- no rain: dataset filtered for values of "Rainfall average" equal to 0
- complete: includes all data

Table 1 shows the number of 10-minute samples in the study period for each turbine individually (data used for the study of meteorological conditions) and for the wind farm.

It should be noted that the complete dataset also includes samples without information about rain conditions. For the analysis of the turbine performance, the data are additionally filtered for normal operating conditions. Finally, the number of samples for the wind farm analysis is significantly lower because the wind farm simulations require synchronized normal production states for all wind turbines.

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Table 1 Classification of atmospheric stability adapted from.

ID	All data	no rain	rain
WT001	145937	99454	20185
WT002	155089	100978	19933
WT003	154556	100867	19507
WT004	69031	35638	6220
Wind farm analysis	26252	15770	2875

Initially, several variables were proposed to ideally classify the data and analyze their correlations with rainfall in greater detail, namely: air density, wind direction, wind shear, turbulence intensity, and wind speed. However, they are ultimately not used in the case study due to the insufficient data, as binning the data by including more classification variables drastically reduced the number of samples per bin. Therefore, these variables have not been used to divide the dataset, but they are considered during the analysis process instead to evaluate their effect and separate it from the impact of precipitation.

4.2 Meteorological characteristics

In this section, the effect of precipitation is analyzed in terms of meteorological magnitudes. Different variables are compared to see if a different behaviour is detected depending on the precipitation. Figure 4 shows the analysis performed on the turbines.

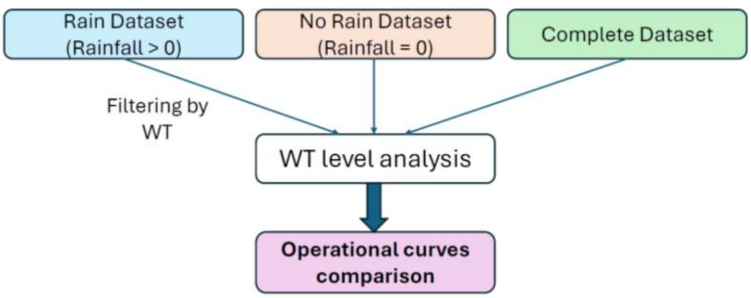

Figure 4: Diagram of rain impact analysis at wind turbine level.

4.2.1 Wind speed distribution analysis

The average wind speed distributions have been obtained for the different wind turbines and the three datasets. As an example, the distributions are shown in Figure 5 for wind turbine WT002, for the complete dataset (a), no-rain dataset (b) and rain dataset (c), and taking into account the turbine operational states.

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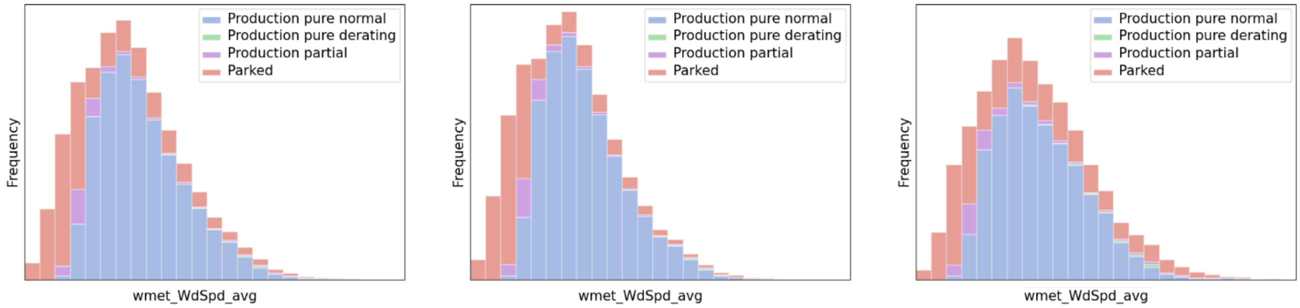


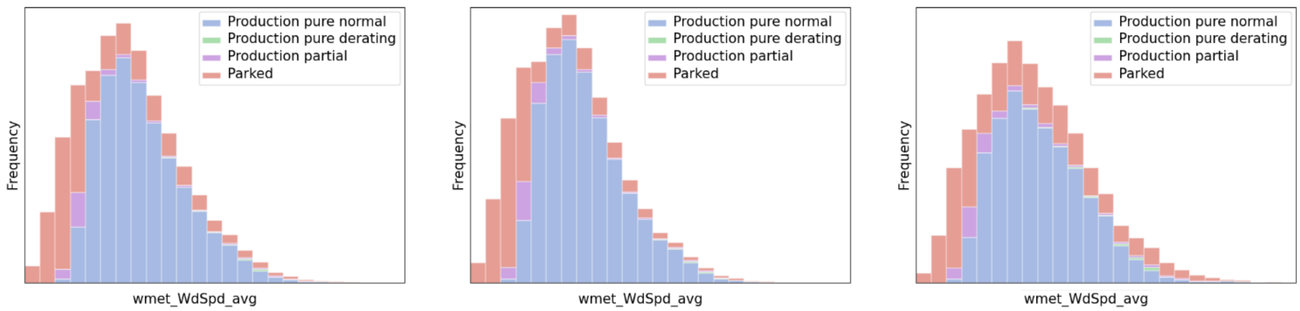
(a) (b) (c)

Figure 5: Wind speed distribution and operational states for WT002: (a) Complete dataset, (b) no-rain dataset and (c) rain dataset.

It is evident that the performance for the complete dataset and the no-rain dataset are similar. The highest differences between them are related to the operational states. For high wind speeds, the complete dataset shows lower contribution of production pure normal operation. The performance of the rain dataset is clearly different to the rest: the distribution is displaced to higher wind speeds, the variance is higher, and there are higher percentages of parked conditions at speeds above cut-in wind speed.

4.2.2 Wind roses analysis

The wind roses are shown in Figure 6, (a) for the full dataset, (b) for the no-rain dataset and (c) for the rain dataset, again for WT002. It can be observed that the distribution of occurrences and the prevailing wind directions depend on precipitation. Similar trends are observed for the rest of wind turbines in the wind farm.



(a) (b) (c)

Figure 6: Wind roses for WT002: (a) Complete dataset, (b) no-rain dataset and (c) rain dataset.

4.2.3 Air density effect

Air density significantly impacts wind turbine performance; it is directly proportional to the power available in the wind. Denser air means more energy can be extracted, and this density changes with pressure and temperature. Density is not a value that appears in the original wind farm SCADA data, but it can be calculated from the air temperature and pressure recorded at each wind turbine.

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Figure 7 shows the air density distribution for the different datasets: complete, rain and no rain. The boxplot shows the median (green horizontal line), mean (green triangle) and inter-quartile range (25th–75th percentiles), while whiskers extend to the 1st and 99th percentiles. The difference shown in air density between datasets was minimal (<1%) and is not considered to reach practical significance for the wind turbine performance.

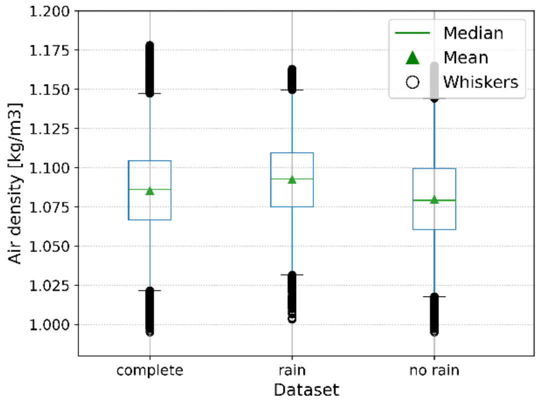

Figure 7: Air density distribution (WT002) for the different datasets.

4.2.4 Turbulence intensity effect

The effect of the turbulence intensity in the power curve has been a topic of interest for the wind energy and it has been extensively studied by the industry and the academia (Bardal & Sætran, 2017; Malik & Bak, 2025; Saint-Drenan et al., 2020). The first option for the methodology is to include the turbulence intensity in the binning process in order to analyze the effect of this variable combined with the precipitation. However, the specific dataset used as case study could not be split into different levels of turbulence intensity due to the insufficient amount of data for the analysis.

Figure 8 shows the reference turbulence intensity values for each of the three datasets at each of the four wind turbines in the wind farm. It can be seen how the turbulence intensity is higher in rainy than in non-rainy conditions in the four wind turbine positions.

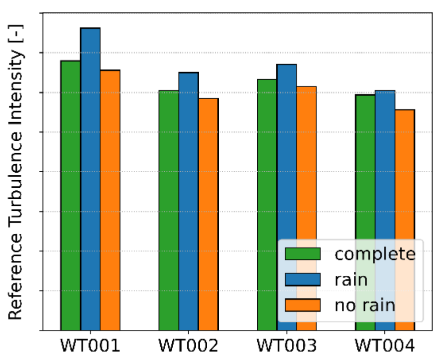

Figure 8: Differences in reference TI for different datasets by wind turbine: complete (green), rain (blue) and no-rain (orange) datasets.

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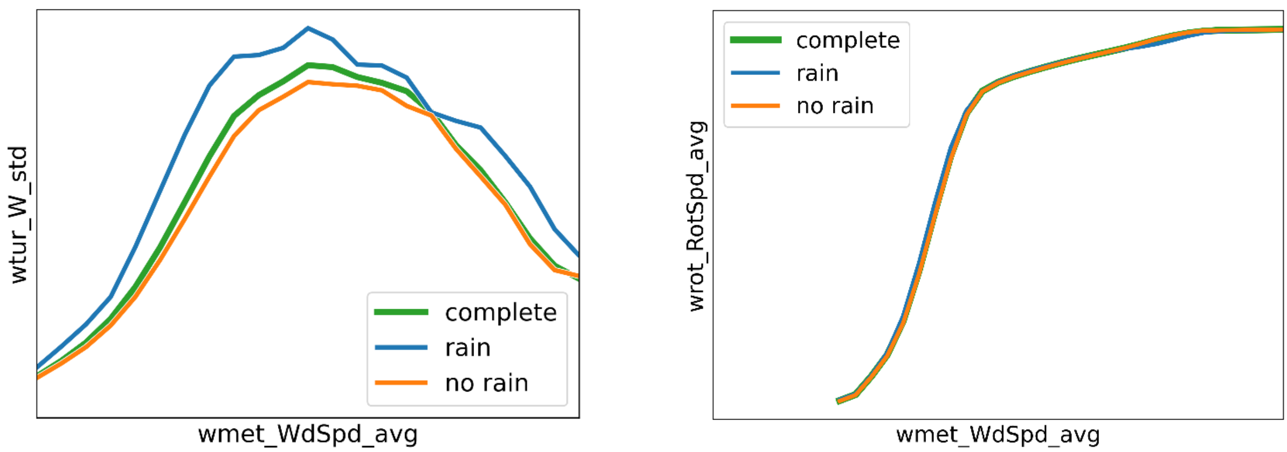
4.3 Analysis of rain impact on wind turbine performance

The analysis of the performance of wind turbines is focused on pure normal production state. Consequently, the previous datasets (complete, rain and no rain) are filtered in order to evaluate the normal production state samples.

The statistics of operational signals are included in the analysis. In terms of standard deviation of power production (Figure 9 (a)) the behaviour observed for the rain dataset is coherent with the increase of turbulence intensity with respect to the other datasets. Regarding the average rotational speed in the rotor (Figure 9 (b)), the curve for the data set with rain is slightly displaced to the left with respect to the other curves and slight differences are observed at higher speeds (close to rated wind speeds).



(a) (b)

Figure 9: (a) Standard deviation of power production, and (b) average rotor speed vs wind speed for different datasets: complete (green), rain (blue) and no rain (orange).

The measured IEC fit power curve for the various datasets shows differences for the rain dataset in Figure 10 (a): higher power values for the lowest wind speeds and lower values for higher wind speeds. However, this behaviour is similar to the effect of the turbulence intensity could have.

The alternative option for cases with limited data and evident differences in terms of turbulence intensity is to use the procedure included in IEC 61400-12 Annex M for the normalisation of power curve data according to the turbulence intensity. This method normalises power curve data to a reference turbulence

intensity, and can be applied to the different datasets with and without rain events, in order to compare the power curve results using equivalent turbulence intensity level. Figure 10 (b) shows such normalised results (zero turbulence intensity) for the three datasets for wind turbine WT002. The differences observed in the measured power curve at low wind speeds for the rain dataset (Figure 10 (a)) have been reduced in the normalised curve. Consequently, these differences in the IEC fit power curve were directly explained by the effect of the turbulence intensity. However, the normalised TI results obtained for the specific rain dataset show a behaviour that differs from the other power curves close to rated wind speed. Similar trends are observed

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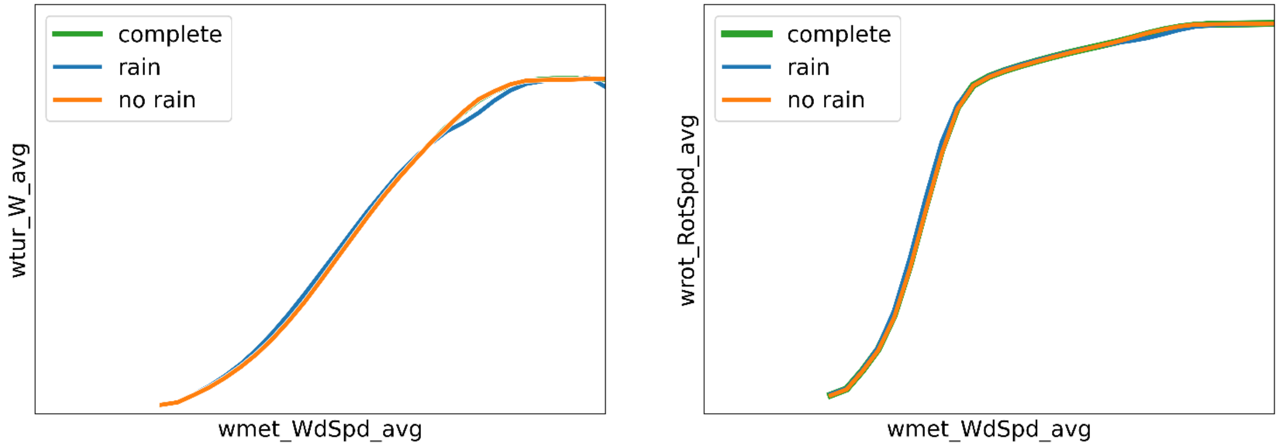
for the rest of wind turbines in the wind farm. Therefore, it is clear that the behaviour of the turbines analyzed is different depending on the datasets, i.e. on the rain conditions, and this effect is not directly related to the effects of concurrent turbulence intensity change.



(a) (b)

Figure 10: Power production for wind turbine WT002: (a) IEC fit; (b) TI0 power curve. Complete (green), rain (blue) and no-rain (orange) datasets.

4.4 Analysis of rain impact at wind farm level

The analysis at wind farm level is based on the comparison between the real data of the wind farm and the results from simulations to analyze a potential impact of rain on wake effect. A parametric study has been carried out, see Figure 11, to evaluate whether an impact is observed in the results for the datasets considered, with different data according to rainfall. The analysis focuses on identifying whether wake simulation should be performed similarly for the different datasets according to rainfall. The wind farm model parameters that have been taken into account for the simulation can be divided into groups:

- **Parameters related to the characterisation of the flow map in the wind farm**. The baseline scenario is performed assuming homogeneous flow (same wind speed, wind direction for all wind turbine positions). Heterogeneous flow refers to the wind conditions being non-uniform across the entire wind farm area. The heterogeneity is influenced by terrain, vegetation and atmospheric conditions. The methodology for obtaining the heterogeneous map is described below.
- **Wind turbine power curve impact**. Based on the previous conclusions of the turbine-level study, a comparison is considered necessary between the two power curves considered for the simulation, namely:
    - Power and thrust coefficient curves from wind turbine manufacturer (OEM).
    - Measured IEC power curve and CT curves. The thrust curve has been considered equivalent to that from the manufacturer, since there is no information available to estimate it from operation.

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- **Wake deficit parameters**. The default parameters for the wake deficit model (default FLORIS parameters for 'Gauss' velocity deficit model) are used for the basic analysis and then the impact of the calibration of these values is analyzed.

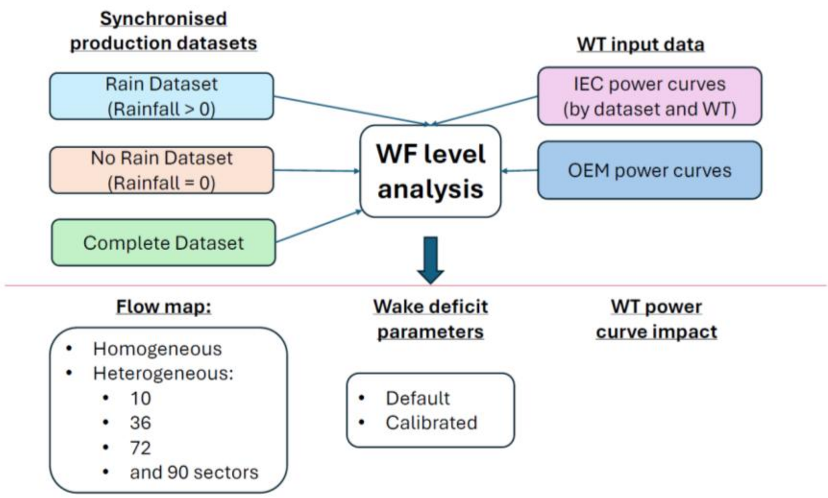

Figure 11: Diagram of rain impact analysis at wind farm level.

4.4.1 Heterogeneous map characterisation

Methods have already been developed in the literature and studies have been conducted demonstrating the importance of characterising both the heterogeneity of the flow and the parameters of the wake models to ensure that the wind farm simulation accurately represents reality (Braunbehrens et al., n.d.). In this case, the methodology developed has split the two effects, which are characterised independently. The heterogeneity of the flow is characterised by taking a wind direction of the reference wind farm (usually the average of all turbines), then filtering when each turbine is in free-stream conditions, using Frandsen's theoretical affection model (Frandsen, 2007) and according to the reference direction. This allows the analyzed flow to be independent of the wake parameters, which can be characterised at a later stage.

The above data are grouped by sector, and the ratio between the free wind speeds of each turbine with respect to the upstream turbine of that sector is obtained. When a turbine is affected for the complete sector, the values are filled in by interpolation between neighbouring sectors. Finally, a matrix is obtained with the speed-up factors of all the turbines with respect to the200 turbine considered upstream for all the sectors, and it is transferred to positions around the wind turbines in FLORIS format to carry out the simulation.

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4.4.2 Wind farm simulation set up

Synchronised data in which the turbines are in production pure normal operating conditions have been filtered out, as this is the baseline situation for wake simulation. This filter significantly reduces the number of time series data that can be used for both characterisation and evaluation in the practical case, as can be observed in Table 1. Again, as in the previous section, three different input datasets have been generated for this analysis depending on the rainfall data: complete, rain and no-rain datasets.

From SCADA data, free stream wind speeds, wind directions and turbulence intensities are extracted (according to the heterogeneous map). These series are used for the simulation of the SCADA samples with the wind farm model. For the different combinations of datasets, power curves and number of sectors of the heterogeneous flow (see Figure 11), the process for the wake calculation is similar.

1. The heterogeneous flow of the wind farm is characterised for a determined number of sectors (this step is not necessary when homogeneous flow is considered).
2. From SCADA data, free-stream wind speeds, wind directions and turbulence intensities are extracted according to the heterogeneous map. These series are used as input for the simulation of the wind farm SCADA registries.
3. The comparison of the simulation against the real data is performed through a set of error metrics: Root Mean Square Error (RMSE), mean absolute error (MAE) and bias. These errors are evaluated for individual wind turbines and general at the wind farm level, for both wind speed and power production.
4. Finally, the calibration of the wake parameters is performed, and the metrics evaluation is repeated. The metrics results and additional figures comparing SCADA timestamps against the simulations have been used to evaluate the impact of rainfall, as shown in the following sections.

4.4.3 Flow map results

In order to carry out the impact study of the flow map, simulations with homogeneous flow and with heterogeneous flow. The number of sectors for the characterisation of the flow heterogeneity in terms of wind speed is the parameter for the parametric study, where 10, 36, 72 and 90 sectors are evaluated.

First, the results for the simplest simulation assuming homogeneous flow are obtained. As shown in Figure 12, significant bias errors are observed for both turbines WT001 and WT004. Comparatively, these errors are larger for the rain dataset.

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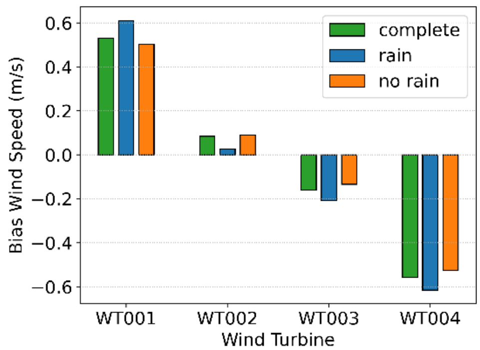
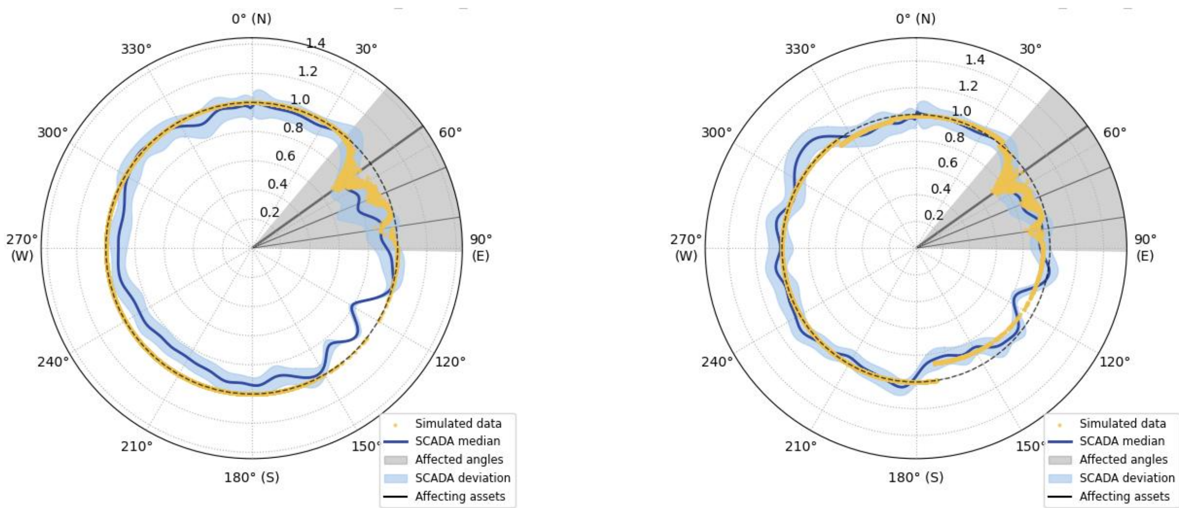


Figure 12: Bias in wind speed by wind turbine for complete (green), rain (blue) and no-rain (orange) datasets.

The affection figures show the normalised wind speed values with respect to the free-stream velocity of the wind farm in radial coordinates (Figure 13 (a)). The angular coordinates correspond to the wind direction. In this case, the simulation (yellow dots) uses a homogeneous map and consequently, the values in the free sectors (white background) are 1.0, while the SCADA spline fit for this turbine shows lower values. It is also observed that these values vary with wind direction, so it is assumed that the heterogeneous flow characterisation (Figure 13 (b)) will need to be divided into several sectors. In general, this homogeneous type of wind farm simulation is not considered valid for the wind farm under study.



(a) (b)

Figure 13: Power production for wind turbine WT002: (a) IEC fit; (b) TI0 power curve. Complete (green), rain (blue) and no-rain (orange) datasets.

By comparing to the previous simulation with homogeneous flow, it is clearly shown that, even using a 10-sector map, the normalised wind speed heterogeneous simulations are closer to the SCADA data than the homogeneous assumption (Figure

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13). The results in terms of RMSE of wind speed for the wind farm (the analysis per wind turbine is not included for the sake of conciseness) can be seen in Figure 14. This figure shows that errors clearly decrease from 10 to 36 sectors and then remain practically the same at 72 and 90 sectors.

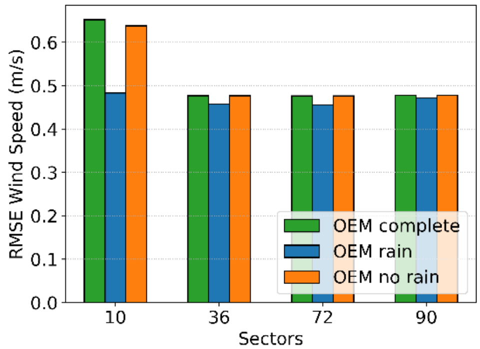

Figure 14: RMSE wind speed vs number of sectors (heterogeneity).

The results in terms of adequate number of sectors are considered site-dependent. For the current case study, it is important to note that the number of samples for the rain dataset is clearly smaller than for the rest (see Figure 15).

The extracted heterogeneous map should resemble the median for the SCADA normalised wind speed at the affection figure. Comparing this line for the different datasets shows that the approximation for the complete and without rain datasets is similar in both cases (see Figure 15 for 36 sectors).

It should be noted that a difference is observed between the SCADA median for these datasets and the one for the rain dataset (Figure 16 (a)) in several directions (60-150 degrees, 300-330 degrees), which coincide with the directions with the lowest number of occurrences in the wind rose (see Figure 6c). The simulation approximates quite well the SCADA data (Figure 16 (b)) for the rain dataset and wind turbine WT003, both in free stream sectors (white background) and affected sectors (grey background).

It has been observed that increasing the number of sectors slightly worsens the results in sectors with less data, as the flow behaviour cannot be characterised with sufficient information. The overall heterogeneous flow trends have been very similar for the datasets regardless of precipitation conditions (especially for the most common wind sectors). It is evident that the number of data in each sector has turned out to play a relevant role, it is also a parameter that differs in the datasets analyzed. However, it has been concluded that the characterisation for all datasets should be 36 sectors (value selected for the next steps in the study), as a trade-off solution with a sufficient number of data to capture the variation trend of the flow heterogeneity, avoiding overfitting.

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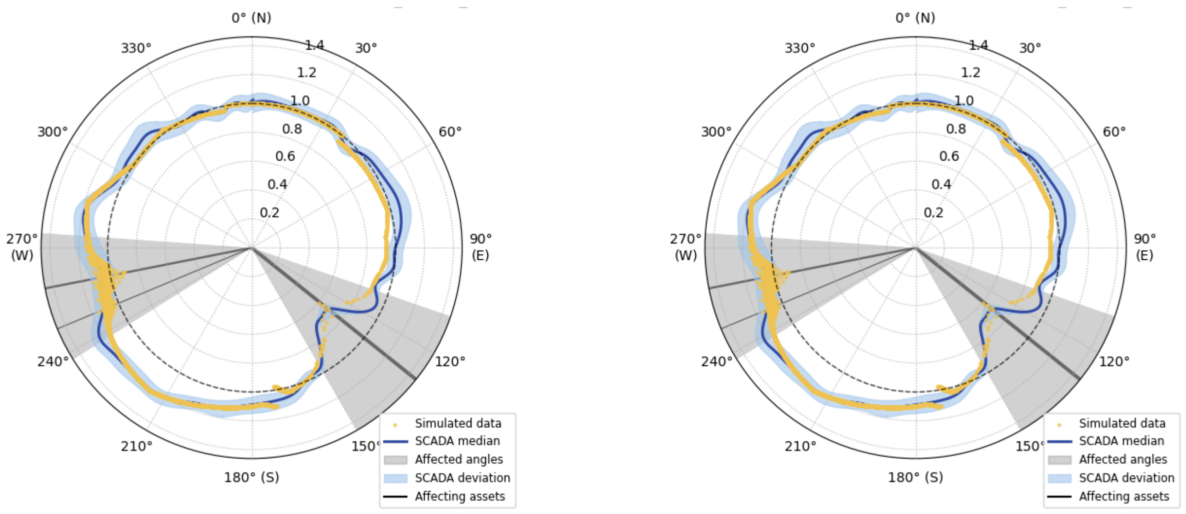
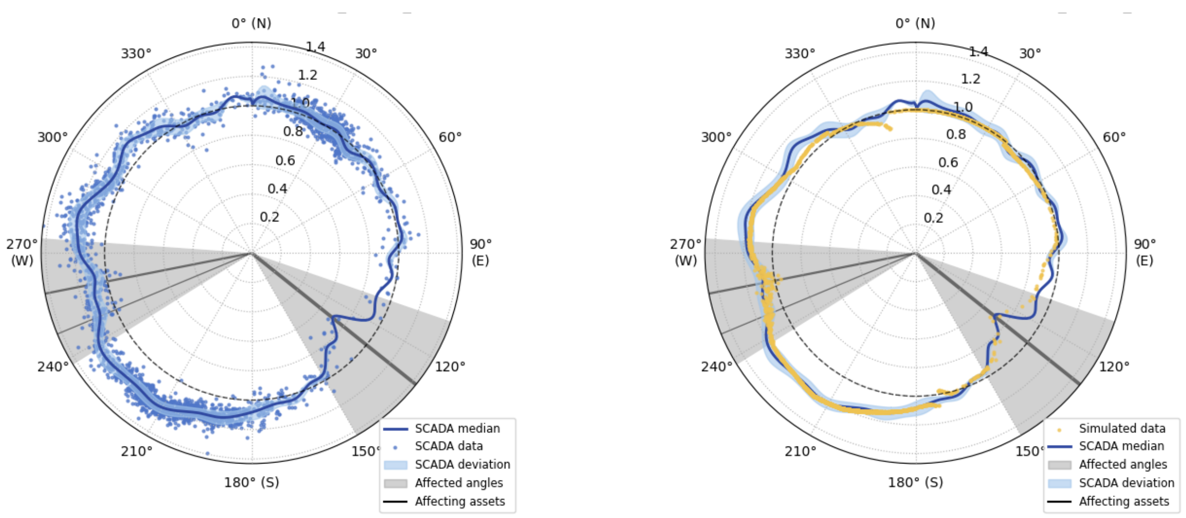


(a) (b)

Figure 15: Normalised wind speed comparison using 36 sectors for heterogeneous flow (wind turbine WT003) with (a) complete dataset and (b) no-rain dataset.



(a) (b)

Figure 16: (a) Normalised wind speed SCADA data using 36 sectors for heterogeneous flow (wind turbine WT003) and (b) normalised wind speed comparison between simulation and SCADA data (same wind turbine and number of sectors).

4.4.4 Wind turbine power curve impact

As mentioned above, the wind farm simulations are calculated for power curves from the wind turbine manufacturer (OEM) and IEC curves measured on each of the turbines.

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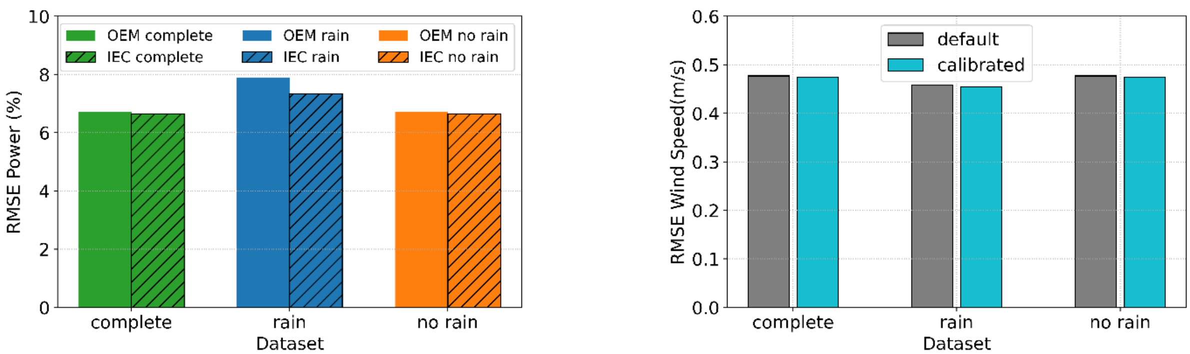
The wind speed results are equivalent even if the power curves are modified, since the wake depends on the thrust coefficient data, which in this case could not be characterised from the data, and implies a limitation of the study. It would be necessary to have an independent thrust coefficient characterisation for the different datasets to assess whether it has an impact at the farm level. The farm simulation results in terms of power additionally depend on the power curves of the turbine models. It is observed that errors in the farm simulation are considerably reduced for the rain dataset by using the measured IEC power curves (Figure 17 (a)). For the other datasets, the error reduction in terms of power is negligible.



(a) (b)

Figure 17: a) Power RMSE for OEM and IEC power curves (36 sectors), (b) Wind speed RMSE for default and calibrated wake parameters (36 sectors).

4.4.5 Calibration of wake model parameters

The calibration is performed using an Powell's minimisation algorithm ((Powell, 1964) by calling the function available in Scipy (Min).that modifies the deficit model values in FLORIS to minimise the wind speed error between simulation and real SCADA data (RMSE for the complete wind farm). This calibration is performed for a set of 90 representative wind directions, this finer sector grid is used in order to better capture the wake behaviour. Wake model calibration serves to improve estimates in the affected sectors, i.e., areas with a grey background in the affection figures (Fig. 13, 15 and 16).

The improvement achieved through calibration is negligible in terms of wind speed RMSE (Figure 17 (b)). The main reason is that the default parameters generate results that are fairly close to the actual behaviour, so the room for improvement has been very small.

This behaviour is similar for the different datasets (rain, no-rain and complete). An obvious limitation is the limited number of samples for studying the wake effects in the rain dataset. For instance, Figure 16 (a) shows a very small number of SCADA samples between 120 and 150 degrees (affected sector).

5 Conclusions

The main output from the study is the development of the methodology for analysis of the precipitation impact on wind farm

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performance. Some conclusions have been reached to this respect.

First of all, it is necessary to have a representative number of samples both for the study of meteorological conditions and for the analysis of the performance of the turbine and the wind farm. Depending on the site climate conditions, i.e. how often it rains, the analysis of rain impact on wind farm performance may therefore require a longer measurement period. Air density and turbulence intensity should be accounted for in the analysis of rain effects, particularly when comparing power curves, as both factors significantly influence the performance of the wind turbines. Normalising power curves to zero turbulence intensity provides a practical approach for facilitating such comparisons by isolating the influence of turbulence.

The characterisation of the heterogeneity of the site could be necessary for a proper wind farm simulation, and the number of wind direction sectors used should be consistent with the SCADA data. This heterogeneous characterisation should be performed independently for the different datasets (complete, rain, no-rain), in order to evaluate whether differences are observed.

Similarly, the calibration of wake parameters independently with the different datasets allows the robustness assessment of such parameters with respect to rainfall.

Other conclusions drawn from the specific analysis of the case study include the following:

The effect of air density in the case study was found to be negligible, with no major differences observed between the rain and no rain datasets. In contrast, turbulence intensity exhibited a more significant impact, as the rain dataset was associated with higher values of mean velocity and reference turbulence intensity.

The effect of the rain can be observed in terms of differences in rotational speed and power production close to rated wind speed. The impact is also observed in power curves normalised to the turbulence intensity (IEC 61400-12 Annex M) in regions close to rated wind speed.

Slight differences have been observed for the heterogeneous maps of the different datasets. Some of the differences may be due to lack of data, especially in wind direction sectors with few occurrences. More data would be required to characterise the heterogeneous flow behaviour within the wind farm in a more reliable manner.

The use of IEC-fitted power curves tailored to each dataset and turbine enhances the power estimation for the wind farm in the case study. Although wake parameter calibration was applied across the different datasets, its impact on the error metrics was found to be negligible in this context.

Given the current scope, the impact observed in this case study cannot be generalised to other sites. Applying this methodology to a larger number of wind farms would be necessary to draw broader conclusions regarding the effects of precipitation on wind turbine and wind farm performance.

Data availability. Original data are confidential and belong to wind farm operator and. Simulated data, comparisons and metrics have been generated by CENER. Simulated data and metric results can be obtained from the author upon request.

Author contribution. MAS is the principal investigator of the project and coordinated the activities and the preparation of the paper. IE aided in the formulation of the scope of the work, ECN and AOA assisted in the measurement post-processing, while the methodology was devised by MAS. MAS wrote the original draft, ECN and AOA helped with the composition of the manuscript while IE contributed, reviewed and edited the final paper.

Competing interests. The authors declare that they have no conflict of interest.

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