

## Highlights

### **Reducing RES Droughts through the integration of wind and PV**

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- RES droughts are analysed using 45 years of hourly wind and PV generation data
- RES droughts from C3S-Energy and ERA5-Atlite datasets are compared
- Adding PV to a wind-dominated system reduces RES drought frequency and duration
- Validated RES datasets are crucial to accurately identify RES drought extremes

# Reducing RES Droughts through the integration of wind and PV

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## Abstract

The dependence of renewable energy sources (RES) such as wind and photovoltaic (PV) systems on the weather poses a critical challenge for energy systems. This study investigates the impact of targeting a balanced distribution of wind and PV capacity on reducing periods of low renewable generation, known as RES droughts. Three different RES models are used to estimate the capacity factors for different installed capacities of wind and PV energy. The skill of the RES models is quantified by comparing capacity factor time series to observed data. Their skill at representing RES droughts is also quantified. The RES models are used to generate a 45-year hourly time series of RES generation, enabling analysis of the frequency, duration and return periods of RES droughts at a climatological scale. Results show the importance of using an accurate, validated RES model for RES drought risk assessment. The addition of PV capacity to a wind-dominated system results in a large reduction in the frequency and duration of RES droughts, as well as reducing seasonal drought patterns. These findings underscore the importance of diversification in RES capacity to enhance energy security and resilience.

**Keywords:** RES Drought, Wind Power, Solar PV Power, Renewable Energy Sources, Return Periods

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## 1. Introduction

The EU aims to generate at least 69% of its electricity from renewable energy sources (RES) by 2030, up from 41% in 2022 (EuroStat, 2023). While this transition is essential for reducing greenhouse gas emissions, it also highlights the challenge of managing the variability of weather-dependent energy sources such as wind and photovoltaic (PV) power. This challenge is compounded by the increasing electrification of energy sectors, which places greater demand on the power system and makes it more sensitive to meteorological conditions (Bloomfield et al., 2016, 2021; van der Wiel et al., 2019). Periods of low renewable generation, known as *Dunkelflaute* or RES droughts, pose significant risks to system adequacy and energy security, emphasizing the need for a resilient energy system to meet both growing electricity demand and decarbonization targets.

This study focuses on Ireland, a region with a strong reliance on wind power, which has ambitious targets for PV power expansion. This case study provides valuable insights into the potential benefits of diversifying the renewable energy mix on RES droughts. The performance of different RES models are compared, and a 45-year time series of RES generation is produced. The results highlight the role of increased PV capacity in reducing RES drought risks, offering insights for policymakers and energy planners.

For this study, a RES drought event is defined as occurring when the average capacity factor (CF) remains below a fixed threshold for a given duration, following the methodology used in other research (Kaspar et al., 2019; Ohba et al., 2022; Mockert et al., 2023; Mayer et al., 2023). Alternative methods exist for defining RES droughts. One approach uses relative CF thresholds that change over the year to account for seasonal variations in renewable energy generation (Raynaud et al., 2018; Rinaldi et al., 2021; Gangopadhyay et al., 2022; Allen and Otero, 2023; Kapica et al., 2024). Another common method relies on percentile-based thresholds, where drought events are defined by identifying periods of unusually low generation relative to historical production levels, typically based on the lowest production percentiles (Bracken et al., 2024; Allen and Otero, 2023). Additionally, some studies combine these definitions with metrics that incorporate the demand side of energy consumption, analysing the balance between supply and demand during drought periods (Raynaud et al., 2018; Rinaldi et al., 2021;

Allen and Otero, 2023; Bracken et al., 2024). In this paper, the focus is exclusively on energy generation, and a fixed threshold approach to define RES droughts is used, which facilitates consistent inter-comparison between scenarios with different installed wind and PV capacities.

RES droughts are identified using onshore wind and PV CF time series. In this study, three different datasets are used, all of which are driven by ERA5 data (Hersbach et al., 2020). Two of the datasets are part of C3S Energy (C3S-E), an energy-based operational dataset produced by the EU Copernicus Climate Change Service (Dubus et al., 2023; Copernicus Climate Change Service (C3S), 2020). One of the C3S-E datasets provides CF time series aggregated at the national scale, while the other provides the CF time series at each grid point, at the ERA5 resolution of  $0.25^\circ$ . The third dataset was generated using the Atlite model (Hofmann et al., 2021), which converts the ERA5 atmospheric data to a generation time series using specified wind turbine and PV panel models. Atlite is an open-source tool developed by PyPSA (Hofmann et al., 2021) and is widely used for estimating wind and PV generation (Mockert et al., 2023; Li et al., 2023; Parzen et al., 2023; Ali Khan Niazi and Victoria, 2023).

The datasets used in this study are detailed in section 2, which describes their characteristics and relevance for evaluating RES droughts. Section 3 outlines the RES models used to simulate wind and PV generation and provides the methodology for defining and identifying RES drought events, including the thresholds and metrics applied. In section 4, the models are first verified against observed energy data to assess their accuracy, followed by an analysis of RES drought occurrences for two scenarios with different ratios of installed wind to PV capacities. Finally, section 5 offers a discussion of the results in the context of energy reliability and future planning, followed by the main conclusions and recommendations for further research.

## 2. Data

This study uses publicly available datasets to construct and validate the models for estimating the CF of wind and PV energy. The primary data sources include: EirGrid and SONI, the transmission system operators (TSO) for the Republic of Ireland and Northern Ireland, respectively; the ERA5 reanalysis dataset; and the C3S-E datasets.

### 2.1. Wind and PV Capacity and Availability

EirGrid, the TSO for the Republic of Ireland, and SONI, the Northern Ireland TSO, provide detailed datasets on all wind and PV farms across the island of Ireland (Republic of Ireland and Northern Ireland) from 1990 to the present (EirGrid & SONI). These datasets include information such as each farm’s installed capacity, name, and connection date. To enhance the accuracy of this data, the longitude and latitude for each farm were manually determined through online searches. For simplicity, this data will be referred to as originating from EirGrid, as all-island data was directly obtained from EirGrid, and the combined regions of the Republic of Ireland and Northern Ireland will be referred to as Ireland throughout the remainder of this document.

The spreadsheet available from the EirGrid website contains two key variables: generation and availability. Generation is the energy that a RES farm actually contributed to the grid, which may include limitations introduced by the TSO to maintain grid stability, such as constraints and curtailment. Availability represents the energy that would have been generated from a RES farm if no grid constraints had been applied, making it representative of the weather-related response. Generation and availability values are available from 2014 onward for wind power and from 2018 onward for PV power, although PV availability data only became present in the Republic of Ireland in 2023. This study focuses on availability for all analyses.

### 2.2. Atmospheric Variables

Atlite and C3S-E datasets are driven by the ERA5 reanalysis (Hersbach et al., 2020), produced by the European Centre for Medium-Range Weather Forecasts (ECMWF). This global gridded dataset provides hourly atmospheric variables from 1940 to the present at a horizontal resolution of  $0.25^\circ$ . It is widely used for estimating PV and wind energy (Mockert et al., 2023; Dubus et al., 2023; Brown et al., 2021; Otero et al., 2022). Table 1 lists the ERA5 variables used by Atlite and C3S-Energy.

### 2.3. C3S Energy

The EU Copernicus Climate Change Service developed the C3S-E renewable energy dataset for Europe (Dubus et al., 2023), using ERA5 atmospheric variables and weather-to-energy models. This dataset provides hourly CF for wind and PV energy from 1979 to the present. The data are available on the same grid as the ERA5 data, which has a horizontal resolution of  $0.25^\circ$ . The

Table 1: ERA5 variables used to calculate wind and PV generation

ERA5 name	variable
100 metre zonal and meridional wind speed	$u_{100}, v_{100}$
2 metre temperature	$t2m$
Surface net solar radiation	$ssr$
Surface solar radiation downwards	$ssrd$
Top of atmosphere incident radiation	$tisr$
Total sky direct solar radiation at surface	$fdir$

time series are also available for download at two aggregated scales: regional (NUTS 2) and national.

The C3S-E dataset estimates wind energy using wind speeds at 100 metres ( $u_{100}, v_{100}$ ) and a standard turbine model, the Vestas V136/3450, with a fixed hub height of 100 meters. This choice is based on expert advice and the trend in wind turbine installation. The PV generation model used by C3S-E uses two ERA5 variables: surface solar radiation downwards ( $ssrd$ ) and air temperature ( $t2m$ ). PV generation is calculated multiple times, using the same model with different azimuth and tilt angles. The results are aggregated based on a statistical distribution of the module angles based on the geographical location (Saint-Drenan et al., 2018).

### 3. Methods

This study uses three datasets to analyse RES droughts across the island of Ireland. Data downloaded from C3S-E were used to obtain two datasets: one based on national-level data (C3S-E N), and another on grid-level data (C3S-E G). The third dataset was computed using the Atlite model (Atlite).

#### 3.1. C3S-Energy National

For national-level analyses, the aggregated CF time series provided by C3S-E were used at two levels: Republic of Ireland (NUTS0: IE) and Northern Ireland (NUTS2: UKN0). These are based on the assumption by C3S-E that RES generation occurs at every ERA5 grid point in Ireland. We computed a weighted average of these, based on the installed capacity of each one, to represent the total CF for Ireland.

### 129 3.2. C3S-E Gridded

130 The gridded dataset from C3S-E was used to create CF datasets which  
131 account for the location of RES farms in Ireland. A list of the RES farms in  
132 Ireland was compiled, including each farm’s latitude, longitude and installed  
133 capacity. Using these coordinates, the nearest grid point on the C3S-E grid  
134 was identified for each farm. The CF values from the C3S-E dataset corre-  
135 sponding to these grid points were retrieved. A weighted average of the CF  
136 values was calculated, with the installed capacity of each farm serving as the  
137 weight, to construct the CF time series for Ireland. This process resulted in  
138 a time series of RES generation for each energy source (wind and PV) for  
139 Ireland, which takes the location of the RES farms into account.

### 140 3.3. Atlite

141 Atlite transforms weather data into energy data using the gridded ERA5  
142 data and the locations of existing RES farms, as described in C3S-E G.  
143 ERA5 data for wind speed at 100 metres ( $u_{100}$ ,  $v_{100}$ ) are used to calculate  
144 wind generation, while the ERA5 radiation variables ( $ssr$ ,  $ssrd$ ,  $tisr$ , and  
145  $fdir$ ) and air temperature ( $t2m$ ) are used to calculate PV generation. A  
146 key distinction between C3S-E and Atlite lies in their representation of wind  
147 turbines and PV panels. This study identifies the most appropriate wind  
148 turbine power curve to use from the 121 power curves made available by  
149 Renewables.ninja (Staffell and Pfenninger, 2016). The selection of a specific  
150 wind turbine and PV panel characteristics is further discussed and explained  
151 in section 4.1.

### 152 3.4. Energy Scenarios

153 In addition to analysing wind and PV generation separately, a combined  
154 CF was computed for each model by averaging wind and PV generation,  
155 weighted by their installed capacities at the end of 2023 (5.9 GW for wind  
156 power and 0.6 GW for PV power). This configuration is referred to as the  
157 91W-9PV scenario, reflecting the distribution of 91% wind and 9% PV ca-  
158 pacity. Given that PV capacity in Ireland is low in 2023, and to explore how  
159 a more balanced distribution of wind and PV capacities might impact RES  
160 droughts, this study also considered a second scenario, referred to as 57W-  
161 43PV, where the installed PV capacity is assumed to increase to 8.6 GW,  
162 while wind capacity rises to 11.45 GW. These values are based on targets  
163 outlined in the roadmap published by the 2024 Climate Action Plan (Gov-  
164 ernement of Ireland, 2023). This study does not include offshore wind in the

analysis. Recent reports suggest that even by 2030, Ireland is unlikely to have any significant new offshore wind farms, with projected offshore capacity expected to remain near zero using realistic scenarios (Sustainable Energy Authority Ireland, 2024).

New time series were generated for both the Atlite and C3S-E G PV models, incorporating a revised distribution of installed capacity across Ireland as specified in the roadmap. For wind power, the CF time series remains unchanged, as significant shifts in the location of wind farms are not expected. In total, twelve CF time series were analysed in this study, six for individual wind and PV CF (three models for each source) in the 91W-9PV scenario, and an additional six time series that include the combined CF for 91W-9PV and 57W-43PV scenarios across the different models.

It is important to note that the specific capacity values used in this study are illustrative and are not intended to reflect precise future realities. Instead, they serve to explore the impact of transitioning from a wind-dominated system (91W-9PV) to a more evenly distributed system (57W-43PV). This approach allows for a comparative analysis between the two scenarios, assessing how the balance of RES capacity affects the occurrence of RES droughts.

### 3.5. *RES Drought Definition*

In this study, a RES drought event was defined as occurring when the 24-hour moving average of CF remains below a fixed threshold of 0.1 for a period of longer than 24 hours. The choice of this threshold is somewhat arbitrary, but aligns with similar studies on low renewable energy production (Kaspar et al., 2019; Ohba et al., 2022; Mayer et al., 2023). By using a 24-hour moving average, fewer but longer-lasting events were captured compared to using the raw CF time series, which can be more sensitive to short-term fluctuations. A fixed threshold approach was chosen in this study to enable consistent inter-comparison between datasets.

The moving average approach smooths out short-term fluctuations, so that brief periods above the threshold do not interrupt an otherwise continuous low-CF period (Fig. 1). This means that a single hour above the threshold does not "break" a drought event if it is surrounded by prolonged low-generation hours. As a result, fewer but longer-lasting drought events are identified, which may better reflect real-world conditions where energy supply constraints persist over extended periods.



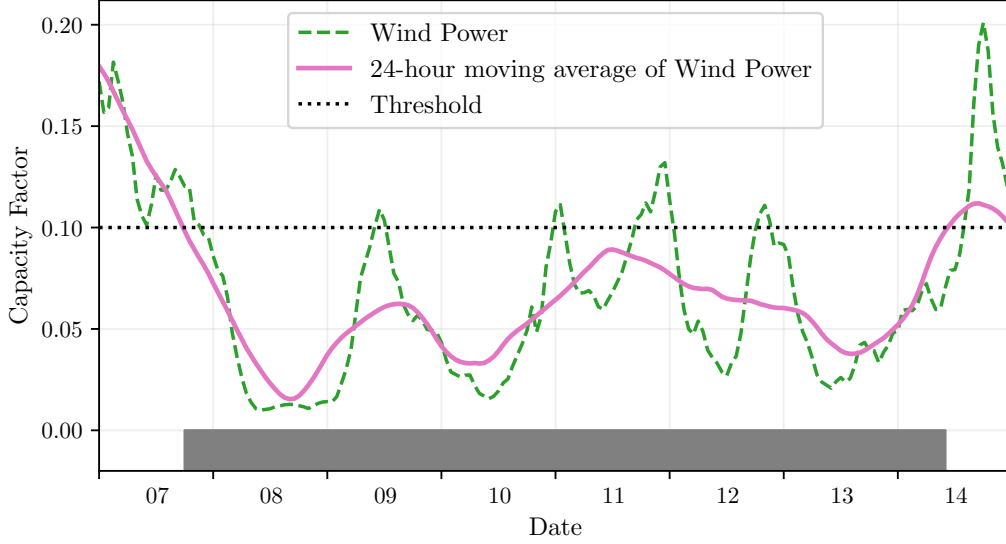


Figure 1: Wind time series of CF (green) and its 24-hour moving average (pink) from the 7th to the 15th of July 2021. The black dashed line indicates the CF threshold. The grey bar shows the period identified as a wind drought under our definition

## 4. Results

### 4.1. Verification

The accuracy of the datasets used in this study was verified, before continuing to the analysis of RES droughts. For the verification process, time-varying values of installed capacity were used to account for changes in RES development over the verification period. This step allowed us to assess how well the datasets represent the production of renewable energy by comparing them against observed data.

#### 4.1.1. Wind Energy

The C3S-E datasets use the Vestas V136/3450 wind turbine power curve, (Fig. 2a). The Atlite model allows the user to specify the power curve. We considered the 121 power curves available for download from Renewables.ninja (Staffell and Pfenninger, 2016). For each power curve, Renewables.ninja also provides four associated smoothed power curves. The smoothing is done using a Gaussian filter with different standard deviations that depend on the wind speed. A separate wind CF time series for Ireland was generated for each of the wind turbine power curves and smoothing levels.

217 The performance of each CF time series was then assessed based on four  
 218 skill scores: correlation coefficient (CC), root mean square error (RMSE),  
 219 mean bias error (MBE), and area under the curve. The area under the curve  
 220 was calculated from histograms of the hourly CF values for the most recent  
 221 decade, 2014-2023. Based on these metrics, the most representative power  
 222 curve for Ireland was the Enercon E112.4500 power curve with the  $0.3w$   
 223 smoothing filter.

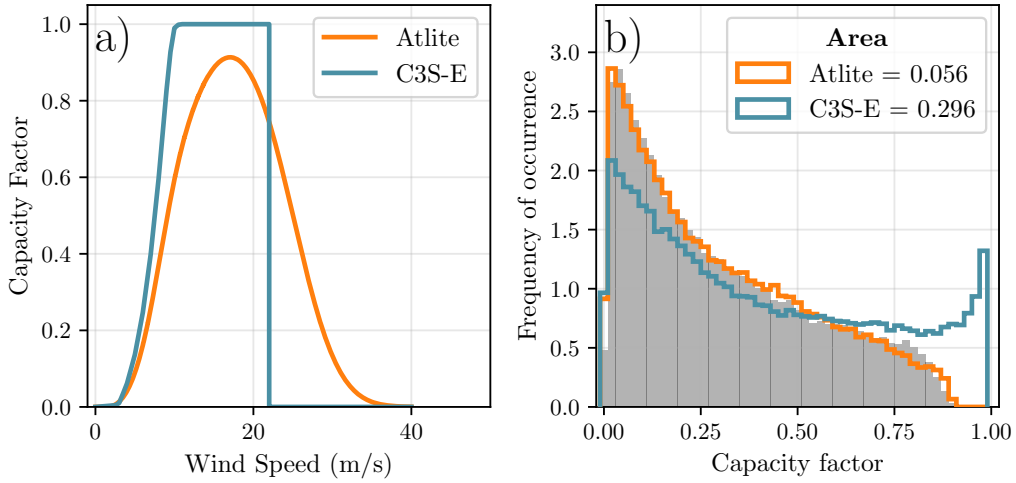


Figure 2: a) Power curves of the Enercon E112.4500 with a  $0.3w$  smoothing filter used by Atlite (orange) and the Vestas V136/3450 used by C3S-E (blue) b) Histograms of wind CF for Ireland from Atlite (orange), C3S-E (blue) and Observed (shaded)

224 The smoothing of the wind turbine power curve represents losses associ-  
 225 ated with each turbine, as well as losses such as wake effects between turbines,  
 226 which are important when modelling wind energy on larger spatial scales.  
 227 The histogram in Fig. 2b shows that the C3S-E power curve tends to under-  
 228 estimate low CF values and overestimate higher ones, whereas the smoothed  
 229 Atlite power curve more closely follows the recorded wind availability data  
 230 from EirGrid.

231 The effect of the difference between the power curves is also visible in  
 232 Fig. 3, which shows a density plot of wind CF values. The two C3S-E datasets  
 233 are shown to overestimate the observed CF, whereas the Atlite model is in  
 234 good agreement with the observed data. The skill scores presented in Table 2  
 235 show that Atlite performs better than the C3S-E datasets for all of the skill  
 236 scores.

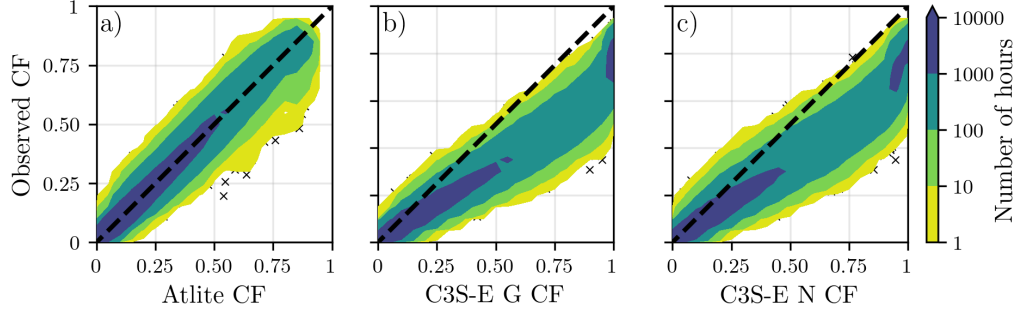


Figure 3: Wind CF density plot of the observed CF (vertical axes) and modelled (horizontal axes) CF data for the a) Atlite, b) C3S-E G and c) C3S-E N models

	Atlite	C3S-E G	C3S-E N
<b>CC</b>	0.981	0.972	0.970
<b>RMSE</b>	0.045	0.177	0.162
<b>MBE</b>	-0.003	0.137	0.121

Table 2: Skill scores for wind power for the three datasets compared to observed data

237 Fig. 4 shows the average annual number of wind drought events during  
 238 the 2014 to 2023 validation period. The figure reveals that Atlite presents  
 239 the best overall agreement with the observed frequency and duration of wind  
 240 drought events. This pattern is particularly evident for shorter-duration  
 241 events, which are the most frequent.

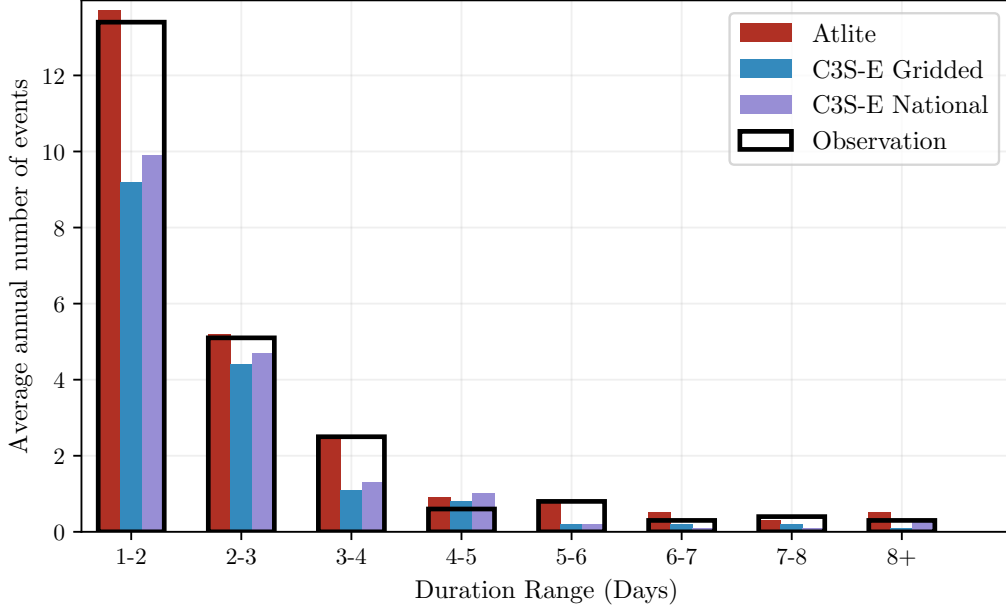


Figure 4: Average annual number of wind drought events for Atlite (red), C3S-E G (blue), C3S-E N (purple), and the observed data (black outline). The wind droughts are identified from 2014 to 2023, considering the actual capacity of the system at any given time

#### 242 4.1.2. PV Energy

243 The Atlite model allows the user to select certain PV panel characteristics.  
 244 In this study, the three PV panel types available in the Atlite model were  
 245 considered (CSi, CdTe, Kaneka). Following the same methodology as in the  
 246 previous section, the three available models were compared using four skill  
 247 scores (CC, RMSE, MB, and area under the curve). Based on the best-  
 248 performing metrics, the Breyer PV panel model was selected (Beyer et al.,  
 249 2004), using the Kaneka Hybrid panel option. For all PV farm locations, the  
 250 azimuth angle is fixed at  $180^\circ$  (due south), and the optimal tilt angle option  
 251 is applied.

252 The PV installed capacity available on the spreadsheets from EirGrid  
 253 represents the Maximum Export Capacity (MEC) and does not accurately  
 254 reflect the installed PV capacity. To enable actual PV generation potential  
 255 to be modelled correctly, installed capacities were set at 1.4 times the MEC  
 256 values. This scaling factor was estimated by analysing proprietary data from  
 257 individual PV farms provided by EirGrid, which showed that, on average,

258 assuming that the installed capacities of farms exceed their MEC values by  
 259 40% yields the best agreement with the observed availability.

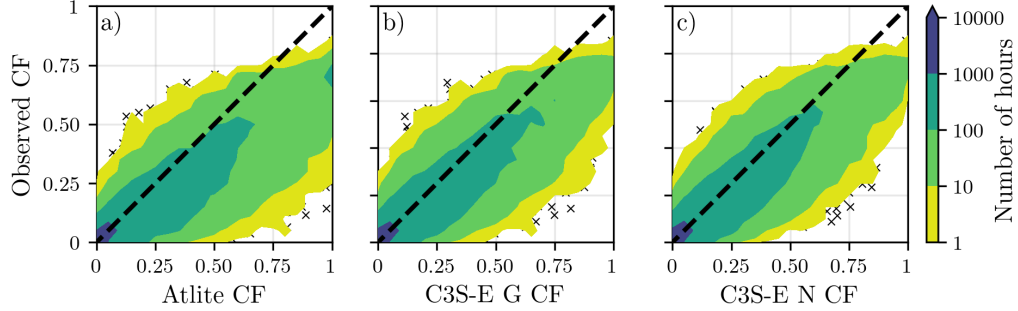


Figure 5: PV CF density plot of the observed (vertical axes) and modelled (horizontal axes) CF series for the a) Atlite, b) C3S-E G and c) C3S-E N models

260 Figure 5 shows that the three datasets have a similar tendency to overesti-  
 261 mate the CF compared to the observed values, especially for high CF values.  
 262 The skill scores presented in Table 3 indicate that C3S-E G performs best  
 263 overall, with the lowest RMSE and a high correlation coefficient, suggesting  
 264 a closer match to observed data. All models show a slight positive bias, with  
 265 Atlite exhibiting a slightly lower correlation and higher RMSE.

	Atlite	C3S-E G	C3S-E N
<b>CC</b>	0.921	0.931	0.931
<b>RMSE</b>	0.119	0.090	0.113
<b>MBE</b>	0.046	0.027	0.021

Table 3: Skill scores for PV CF for the three datasets compared to observed data

266 Fig. 6 shows the number of PV drought events during the 2023 validation  
 267 period across different duration ranges. The figure reveals partial agreement  
 268 between the three datasets and the observed data, with consistent results  
 269 noticed for duration ranges of 1-2, 3-4, 7-8, and 8+ days. However, dis-  
 270 crepancies appear in the other ranges, where the models diverge from the  
 271 observed data. The main challenge in validating PV data stems from the  
 272 recent installation of a large share of Ireland’s PV capacity, leading to un-  
 273 certainties in PV generation data and the actual generating capacity in the  
 274 first few months after each farm is connected. With over 65% of the total

275 PV capacity installed in 2023, these data uncertainties significantly impact  
 276 the ability to perform rigorous validation for PV drought events.  
 277 Nevertheless, the goal of this analysis is to assess the combination of wind  
 278 and PV generation, where the complementary nature of these energy sources  
 279 mitigates the limitations seen in PV-only results.

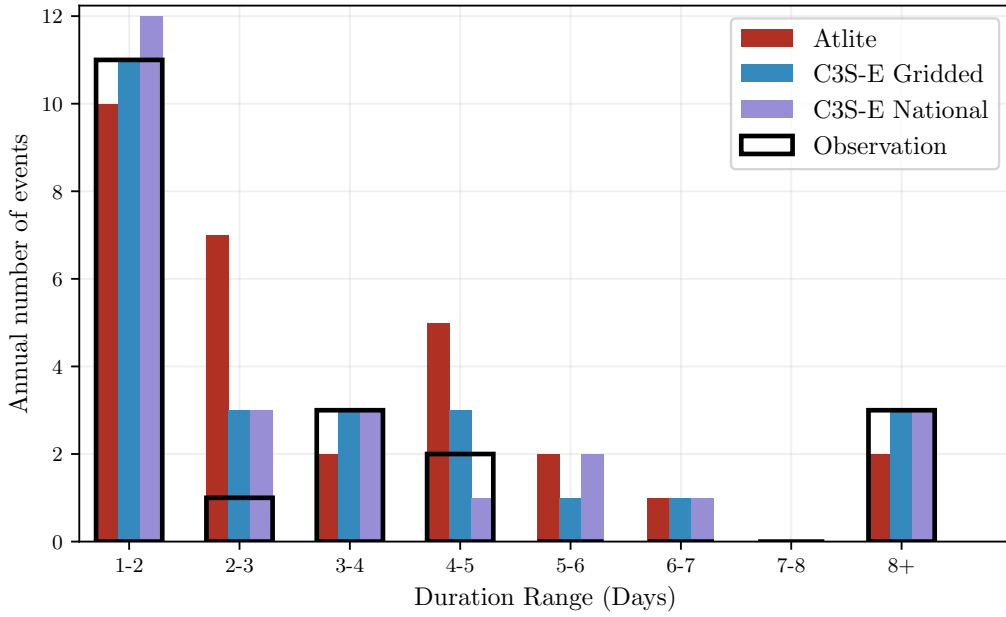


Figure 6: Number of PV drought events for Atlite (red), C3S-E G (blue), and C3S-E N (purple) and the observed data (black outline). The PV droughts are identified for 2023, considering the actual capacity of the system at any given time

## 280 4.2. Analysis

281 In this section, RES drought events are evaluated under two different  
282 scenarios with fixed installed capacities: the 91W-9PV scenario, with 5.9 GW  
283 of wind capacity and 0.6 GW of PV capacity; and the 57W-43PV scenario,  
284 where wind capacity comprises 11.45 GW and PV capacity increases to 8.6  
285 GW. Both scenarios were driven by 45 years of ERA5 data. Using the RES  
286 drought identification process described in Section 3.5, wind and PV droughts  
287 are first analysed separately before presenting the results for combined (wind  
288 + PV) RES droughts under both scenarios.

### 289 4.2.1. Annual Number of RES Droughts

290 The first part of the analysis examines the annual number of RES drought  
291 events across the three datasets. When only wind energy is considered  
292 (Fig. 7a), the number of events decreases as the duration range increases,  
293 with very few events lasting more than seven days. In the case of only PV  
294 energy (Fig. 7b), the number of events also declines as the duration range  
295 extends from one to eight days, followed by a slight increase for longer dura-  
296 tions. This increase is due to extended low-generation periods occurring from  
297 November to March, depending on the dataset. When comparing wind and  
298 PV results (Fig. 7a & b), the median, first, and third quartiles for PV are  
299 consistently higher than or equal to those for wind, across all duration ranges  
300 and datasets. This is due to the typically lower CF of PV power compared  
301 to wind power, especially in a region such as Ireland where solar potential  
302 is limited. PV generation is also zero at night and constrained by the daily  
303 solar cycle, leading to a naturally higher frequency of drought events in PV  
304 compared to wind.

305 Fig. 7c & d show the combination of wind and PV under the two capacity  
306 scenarios. In the 91W-9PV scenario (Fig. 7c), the identified RES droughts  
307 closely match those for wind alone, which is expected due to the dominance  
308 of installed wind capacity. In contrast, the 57W-43PV scenario (Fig. 7d)  
309 shows a clear reduction in the number of drought events across all datasets  
310 and durations, with a decrease of the total number of events of 56% for Atlite,  
311 52% for C3S-E G, and 50% for C3S-E N. This reduction is attributed to the  
312 anti-correlation between wind and PV generation.

313 The median, first, and third quartiles for the Atlite dataset are consis-  
314 tently greater than or equal to those of the other two datasets, regardless of  
315 the duration range or type of renewable energy considered. This difference  
316 arises from the wind turbine power curve model used in the C3S-E datasets,

317 which tends to overestimate the wind CF (Fig. 3). As a result, the overall  
 318 number of RES droughts is underestimated in the C3S-E datasets compared  
 319 to Atlite.

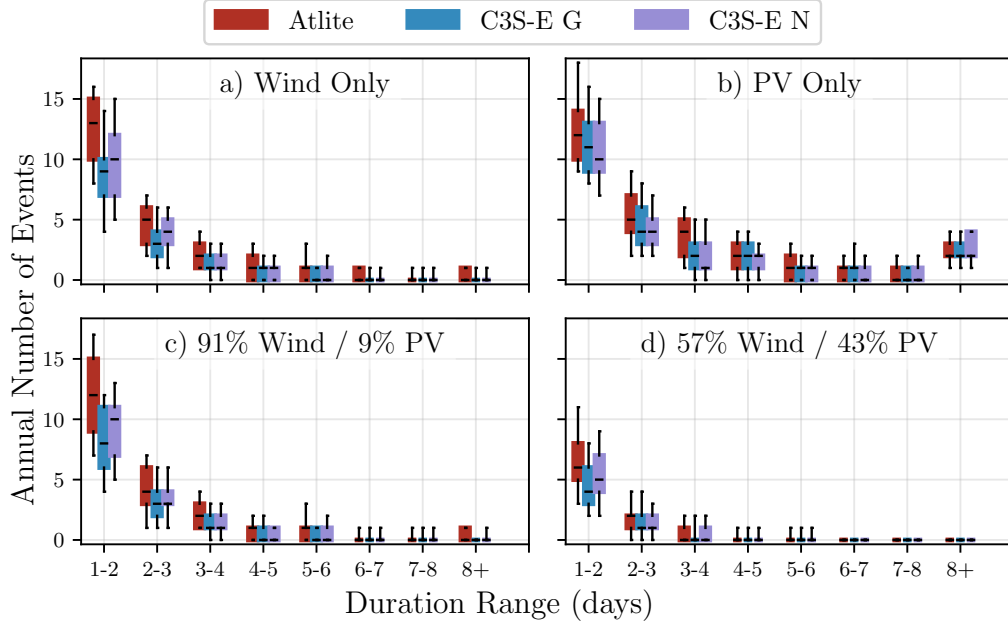


Figure 7: Annual number of RES droughts (from 1979 to 2023) for a) Wind, b) PV, and the combination for the c) 91W-9PV and d) 57W-43PV scenarios for Atlite (red), C3S-E G (blue), and C3S-E N (purple). The x-axis represents duration ranges in days (lower bound included), while the y-axis indicates the annual number of events. The boxes display the first and third quartiles and the median is marked by a black line. The whiskers indicate the 5th and 95th percentiles



#### 4.2.2. Return Periods of RES Drought Duration

The RES drought events identified over the 45-year period were used to calculate the return periods for different RES drought durations. A return period is the estimated average time interval between events of a specified duration or intensity (not to be confused with the frequency of their occurrence within a fixed time frame). Fig. 8 illustrates the return periods for varying RES drought durations, highlighting how often different drought lengths are likely to occur across the datasets. This analysis provides insight into the frequency and likelihood of prolonged low-generation periods, which is crucial for evaluating the potential impact of RES droughts on energy reliability and security of supply.

The duration of wind droughts (Fig. 8a) increases in a log-linear fashion across the three datasets. The log-linear trend indicates a predictable relationship between drought duration and occurrence, with longer wind droughts becoming exponentially less likely as duration increases.

In the case of PV droughts (Fig. 8b), Atlite behaves differently than the two C3S-E datasets. The Atlite results show a log-linear increase but reach higher values in general with the longest event lasting forty days. For C3S-E G and C3S-E N, the duration of PV droughts increases in a log-linear pattern for events lasting less than 16 days. Beyond this duration, there is a sharp rise in drought duration for events up to a one-year return period. This sudden increase reflects the impact of winter on PV generation in Ireland, as PV output often remains below the CF threshold for extended periods during winter months. The difference between Atlite and the C3S-E results arises from differences in the datasets near the threshold of 0.1 CF. Atlite remains slightly above the threshold more frequently during these conditions, leading to shorter, more fragmented drought events. In contrast, C3S-E G and C3S-E N tend to fall below the threshold in similar conditions, resulting in longer continuous drought periods, especially during winter. This sensitivity to the threshold highlights how slight model differences can have substantial effects on drought duration estimates, particularly for PV in low-generation conditions.

For the 91W-9PV scenario (Fig. 8c), the return periods mirror those of Fig. 8a, due to the low levels of installed PV capacity. In the 57W-43PV scenario (Fig. 8d), the return periods for RES droughts increase across all durations. For example, the return period for a five-day drought event (shown by the vertical dashed lines in Fig. 8) extends from roughly six months for

the 91W-9PV scenario, to four years for the 57W-43PV scenario in the Atlite dataset, and from about fifteen months to around five years in the two C3S-E datasets.

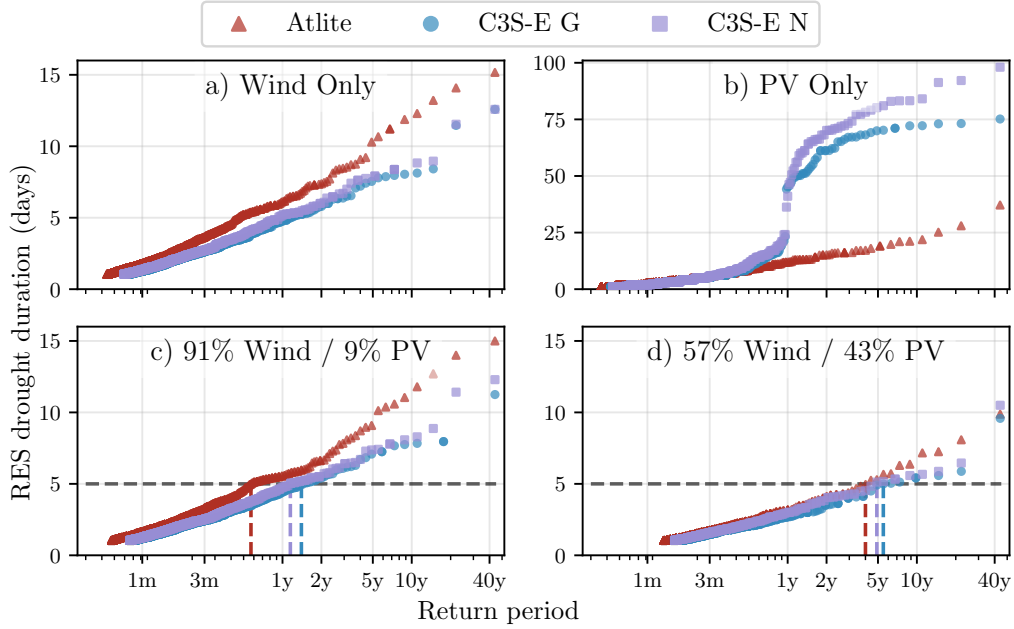


Figure 8: Return periods of the duration of RES droughts (from 1979 to 2023) for a) Wind, b) PV, and the combination for the c) 91W-9PV and d) 57W-43PV scenario, for Atlite (red triangle), C3S-E G (blue circle), and C3S-E N (purple square). The x-axis represents the return period time in a log-scale and the y-axis indicates the duration of RES drought associated with it. The horizontal dashed line marks the 5-day return period, with coloured vertical dashed marking its return period for each dataset

Across Fig. 8a, c, and, d, the return periods in the Atlite dataset are consistently higher than those in the two C3S-E datasets. For instance, in the 91W-9PV scenario (Fig. 8c), an event with a one-year return period lasts six days in the Atlite dataset, compared to only five days in the C3S-E datasets. This difference underscores the importance of model selection when quantifying RES droughts, as each model’s assumptions and parametrisations significantly influence drought duration estimates. Additionally, in all four graphs, the similarity between results from the two C3S-E datasets suggests that assumptions in the Atlite model—such as wind turbine power curve selection and PV panel specifications—have a greater impact on RES drought

370 duration estimates than the precise geographic distribution of RES farms  
371 when studying the return periods of RES droughts.

### 372 4.2.3. Seasonal Distribution of RES Droughts

373 The seasonality of RES droughts was analysed by comparing the percent-  
374 age of hours in each month classified as part of a RES drought.

375 The percentage of hours that are part of a wind drought (Fig. 9a) are  
376 higher in summer than in winter. In the Atlite dataset, for instance, an aver-  
377 age of 24% of hours in summer (June-July-August) are identified as wind  
378 droughts, compared to only 4% in winter (December-January-February).  
379 This seasonal variation is less prominent for the two C3S-E datasets com-  
380 pared to the Atlite one. This difference can be linked to the shape of the two  
381 power curves (Fig. 2). CFs near or under the 0.1 threshold are produced by  
382 higher wind speeds for the Atlite power curve than for the C3S-E one. In  
383 contrast, the results for PV droughts (Fig. 9b) show a higher percentage in  
384 winter, with PV droughts occurring over 60% of the time regardless of the  
385 dataset. The Atlite results show a higher percentage of PV drought hours  
386 for wind, and a slightly lower percentage for PV, compared to the two C3S-E  
387 datasets.

388 Similar to previous results, the 91W-9PV scenario (Fig. 9c) shows pat-  
389 terns comparable to the ones for wind droughts (Fig. 9a). However, in the  
390 91W/9PV scenario, the number of hours classified as RES droughts in sum-  
391 mer decreases slightly compared to the wind-only scenario. This reduction  
392 can be explained by the contribution of PV generation during the summer  
393 months in the 91W-9PV scenario, even though it constitutes only 11% of  
394 total capacity. Since the number of RES drought hours for PV in summer is  
395 near zero, this small contribution has a noticeable impact on reducing over-  
396 all drought hours. In the 57W-43PV scenario (Fig. 9d), all three datasets  
397 show a reduction in monthly RES drought frequency. Annual reductions in  
398 median RES drought frequency are observed across the datasets, dropping  
399 from 14% to 5% for Atlite, from 8% to 3% for C3S-E G, and from 9% to  
400 4% for C3S-E N. The balanced mix of wind and PV power in this scenario  
401 reduces the seasonal signal overall and significantly decreases the percentage  
402 of RES drought hours in the summer.

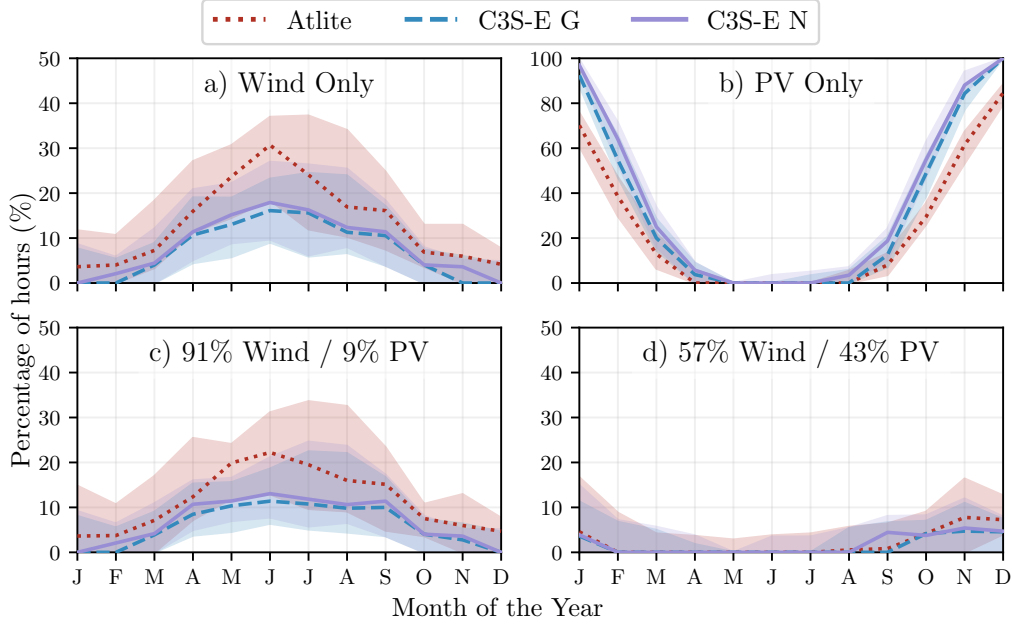


Figure 9: Percentage of hours in a month which are part of a RES drought (from 1979 to 2023) for a) Wind, b) PV, and the combination for the c) 91W-9PV and d) 57W-43PV scenario, for Atlite (red dotted), C3S-E G (blue dashed), and C3S-E N (purple solid). The x-axis represents the month of the year, and the y-axis indicates the percentage of hours. Lines correspond to the median values and the area between the first and third quartiles is shaded.

## 5. Discussion and Conclusions

This study has investigated the ability of three RES models to represent RES droughts: Atlite, C3S-E G, and C3S-E N. One of the most evident differences is how each dataset incorporates the specific locations of RES farms. Both Atlite and C3S-E G consider the locations of wind and PV farms, which should, in theory, provide a more accurate representation of RES generation. While this approach slightly improves PV models, our analysis indicates that for wind energy, the Atlite dataset performs better overall, especially in its close alignment with observed data for wind generation estimates. This finding suggests that, although the inclusion of RES farm locations is beneficial, the accuracy of the RES model is more strongly influenced by underlying model assumptions, such as selecting an appropriate wind power curve.

Atlite shows the best alignment with observed data for wind generation.

416 Differences between the models are smaller for PV, with C3S-G performing  
417 marginally better than the other two. The results show that the two C3S-  
418 E datasets (C3S-E G and C3S-E N) consistently yield similar outcomes,  
419 indicating that their methodological differences have minimal impact. This  
420 distinction was also evident in the analysis, where Atlite reported higher  
421 return periods and a greater number of RES droughts, especially in scenarios  
422 with a balanced share of RES. Again, the results from RES drought modelling  
423 rely more on the precision of the wind power curve and PV panel models  
424 than on the specific locations of RES farms. Atlite’s superior performance  
425 highlights the importance of selecting validated models for assessing RES  
426 drought risks. This careful model selection can better quantify risks, support  
427 effective planning, and avoid the potential underestimation of capacity needs,  
428 which is essential for ensuring energy security.

429 Looking at the 57W-43PV scenario, the analysis showed a significant im-  
430 provement in the management of RES droughts due to the complementary  
431 nature of wind and PV generation. Wind and PV together perform better  
432 in terms of reducing drought frequency and duration than either would in-  
433 dividually, largely because of the seasonal anti-correlation between the two  
434 energy sources. This diversification reduces the seasonal impact on RES  
435 droughts, as PV generation peaks in the summer and wind generation is  
436 more consistent in winter. Ireland currently has a highly wind-dependent  
437 energy system, but with ambitious targets for PV installations in the coming  
438 years, the energy mix is expected to approach a balance between wind and  
439 PV capacity. While this balanced approach offers a more stable and secure  
440 energy supply by mitigating RES drought risks, it is important to note that  
441 having similar wind and PV capacities may not optimise other aspects, such  
442 as annual energy production or meeting nighttime loads. For policymakers,  
443 these findings underscore the importance of meeting these capacity targets  
444 to enhance energy security through diversification. Additionally, the choice  
445 of model for RES drought assessment becomes increasingly critical as more  
446 renewable capacity is integrated into the system.

447 Future work is planned to extend the current analysis. First, climate  
448 projection data will be integrated with different energy scenarios, incorpo-  
449 rating the addition of offshore wind, to better understand how climate change  
450 might affect RES droughts. Second, expanding the geographic domain of the  
451 study to include the rest of Europe would provide a more comprehensive un-  
452 derstanding of RES droughts in an interconnected energy grid. This would  
453 require extensive verification across other European countries, making it a

454 more complex but highly relevant challenge.

## 455 Data Availability

456 The ERA5 data can be obtained from the Climate Data Store (<https://doi.org/10.24381/cds.adbb2d47>). The C3S-E dataset is also available  
457 from the Climate Data Store (<https://doi.org/10.24381/cds.4bd77450>).  
458 Information on wind and PV farms in Ireland can be obtained from the  
459 EirGrid website ([https://www.eirgrid.ie/grid/system-and-renewable](https://www.eirgrid.ie/grid/system-and-renewable-data-reports)  
460 [-data-reports](https://www.eirgrid.ie/grid/system-and-renewable-data-reports)). The Atlite model used in this study is open-source and can  
461 be found on GitHub (<https://github.com/pypsa/atlite>). The data and  
462 code required to reproduce the analysis in this article will be made available  
463 upon acceptance of the manuscript in a public GitHub repository.  
464

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