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The climatological renewable energy deviation index (CREDI)

Laurens P Stoop[1,2,3,*], Karin van der Wiel[4], William Zappa[3], Arno Haverkamp[3], Ad J Feelders[1] and Machteld van den Broek[5]

[1] Information and Computing Science, Utrecht University, Utrecht, The Netherlands
[2] Copernicus Institute of Sustainable Development, Utrecht University, Utrecht, The Netherlands
[3] TenneT TSO B.V., Arnhem, The Netherlands
[4] Royal Netherlands Meteorological Institute (KNMI), De Bilt, The Netherlands
[5] Faculty Technology, Policy, and Management, Delft University of Technology, Delft, The Netherlands
[*] Author to whom any correspondence should be addressed.

E-mail: laurens.stoop@tennet.eu

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Abstract

We propose an index to quantify and analyse the impact of climatological variability on the energy system at different timescales. We define the climatological renewable energy deviation index (CREDI) as the cumulative anomaly of a renewable resource with respect to its climate over a specific time period of interest. For this we introduce the smooth, yet physical, hourly rolling window climatology that captures the expected hourly to yearly behaviour of renewable resources. We analyse the presented index at decadal, annual and (sub-)seasonal timescales for a sample region and discuss scientific and practical implications. CREDI is meant as an analytical tool for researchers and stakeholders to help them quantify, understand, and explain, the impact of energy-meteorological variability on future energy system. Improved understanding translates to better assessments of how renewable resources, and the associated risks for energy security, may fare in current and future climatological settings. The practical use of the index is in resource planning. For example transmission system operators may be able to adjust short-term planning to reduce adequacy issues before they occur or combine the index with storyline event selection for improved assessments of climate change related risks.

1. Introduction

The energy system is changing. This is due to the increased deployment of renewable energy generators, like wind turbines and solar panels; changes in electricity demand, from increased use of heat pumps and electric vehicles; and climatic changes influencing the weather dependent parts of the system. It is crucial to understand the full dynamics of the (future) energy system, both for policy making and energy security reasons [1].

Knowing the impact of and link between the energy system and weather-related variability on daily to inter-annual and decadal timescales is vital for robust design and planning of future energy systems [1–3]. Meteorological variability leads to temporal variability. Not only in renewable energy production, but also in energy demand, changing the way energy systems have to be operated and controlled [1].

Energy system models are vital to capture the impact of this variability [4]. However, their complexity results in high computational burdens that grows exponentially with the simulation period [1, 5–8]. Incorporating large climate datasets that capture energy-meteorological variability in *operational hourly* energy system models is thus, as of yet, unfeasible [1, 7, 9]. Even so, understanding the scale of this variability, can aid system operators in their task to ensure both short- and long-term energy security [1, 7, 10]. Therefore, alternative approaches are needed to assess energy-meteorological variability [1, 11]. While a number of methods exists to model and/or select challenging high impact events using basic statistical principles (e.g. [10, 12–18]), we aim to define a physics based and intuitive to understand metric

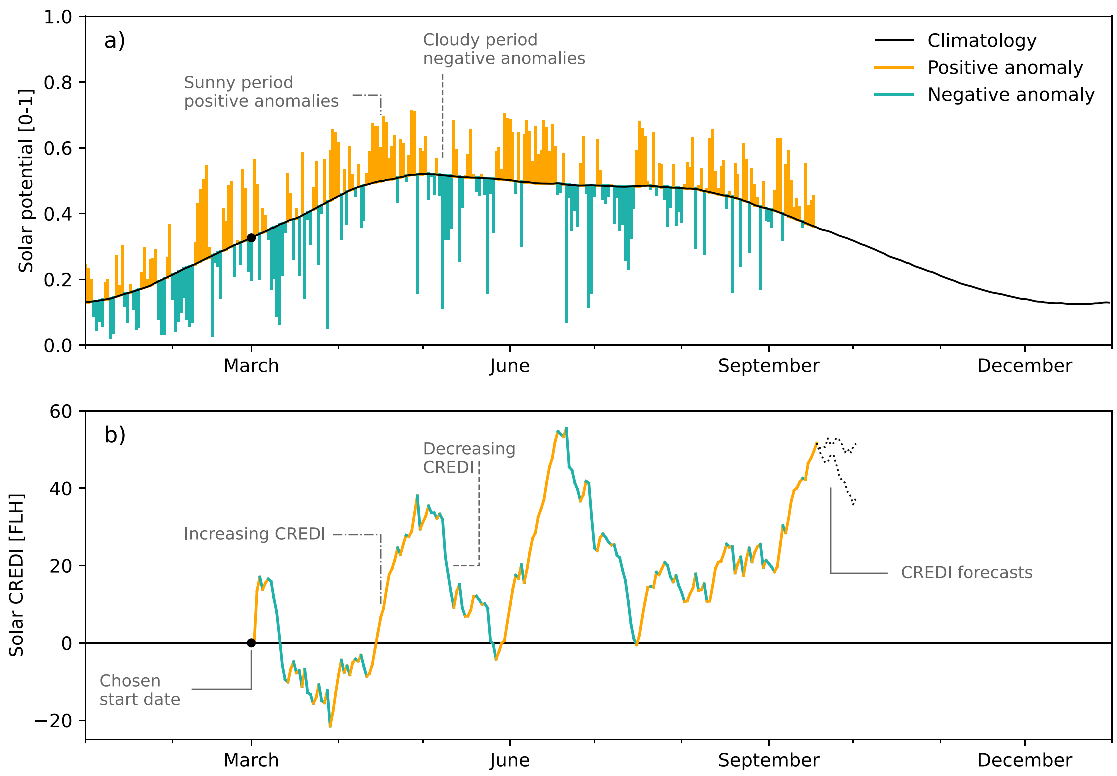

Figure 1. Illustration of climatological renewable energy deviation index. Given the climate of a renewable resource (black line in panel (a)), the instantaneous anomaly can be calculated (orange/teal bars in panel (a)). Positive anomalies (orange) increase, and negative anomalies (teal) decrease the index, which starts at zero at the start of period of analysis (panel (b)). The illustration shows solar potential anomalies for 2021 with respect to a 1991–2020 climate, and the SOLAR CREDI with a starting point at 1 March. Two meteorological forecast ensemble members converted to CREDI are shown to indicate a use-case for grid-operators.

to quantify energy-meteorological variability across timescales.

In developing this metric, we were inspired by the hydrological sciences. For drought monitoring, a number of indices have proven useful for both scientific assessment and operational use. These drought indices, such as the climatological water balance (CWB; [19, 20]), the standardised precipitation index (SPI; [21]), and the standardised precipitation-evapotranspiration index (SPEI; [22]), are based on precipitation deficits (anomaly of precipitation, or anomaly of the difference between potential evapotranspiration and precipitation) and are used to assess the temporal development of dry or wet periods. Furthermore, they have been used to assess the influence of inter-annual to multi-decadal variability, and of climate change on the temporal variability of hydrological drought (e.g. [23–26]). As Allen and Otero [18] showed, some aspects of these indices and their use in assessing hydrological variability can be transferred to the energy-meteorological domain. However, where Allen and Otero [18] developed direct analogues of the SPI and SPEI metrics using probabilistic descriptions, we took inspiration from aspects of these metrics, their use in operational applications, and combined this with the need for physically grounded storylines in energy system operation.

We define the climatological renewable energy deviation index (CREDI) as the cumulative anomaly of a renewable resource with respect to its climate over a specific time period of interest (figure 1). Given this definition, this study addresses the following considerations: (a) how do you define the climatic behaviour of a highly variable renewable resource, like wind or solar? and (b) how do you analyse the CREDI score at different timescales; like (sub-)seasonal, annual, or multi-decadal?

The paper is structured as follows. In section 2, we define the hourly rolling window climate and the index. In section 3, we indicate the data used. In section 4, we analyse the index at different timescales and discuss the best starting point. In the section 5 we discuss our definition of the index. Finally, in section 6, a synthesis of our findings is presented and potential use cases in research and/or operational application are outlined. Supporting information (SI) with additional figures and observational analysis is available online.

2. Definition of the climatic characterisation and index

Within the atmospheric sciences the climate of a region is defined as the statistical-mean weather conditions prevailing in that region [27]. The

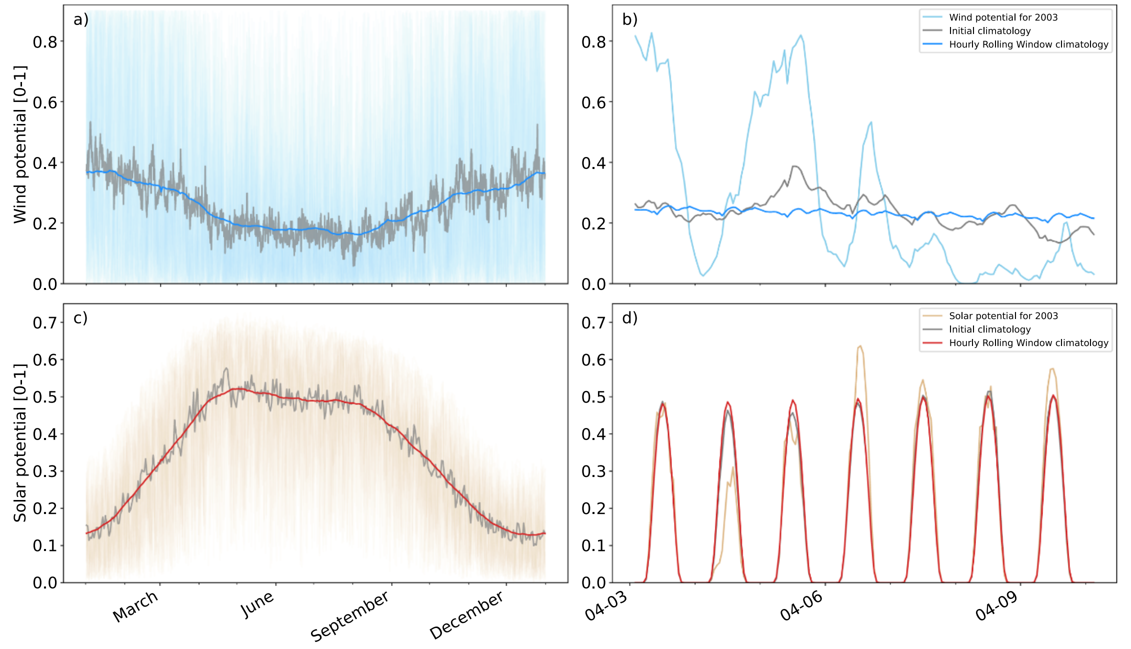

Figure 2. Comparison of different methods for computing the climate of the potential generation for wind (top), and solar (bottom), for the period 1991–2020. Figures (a) and (c) show the hourly generation potentials for each year in this period (light blue for wind and orange for solar), the simple average-based climate (grey, see main text for details) and the hourly rolling window climate (blue and red, for wind, solar, respectively). Figures (b) and (d) show the same, but specifically for the period 3–10 April 2003. For clarity only 13:00 for each day of the year is shown in figure (c).

World Meteorological Organization (WMO; [28]) has a standardised method for calculation of the *climatological normals*, which comes down to calculating monthly or daily mean values over a 30-year period. The climate, or mean expected behaviour, of renewable resources could be defined similarly. However, monthly or daily climatological values are not suitable due to the highly variable nature of renewable resources like wind and solar energy, and the need to balance the power grid at shorter timescales.

We can distinguish four relevant timescales that cover the main modes of energy-meteorological variability. Namely:

1. annual to decadal timescales: variability caused by interactions in the coupled ocean-atmosphere-system, e.g. modes of variability like the El-Niño-Southern Oscillation (ENSO; [29]) or the North Atlantic Oscillation (NAO; [30]),
2. seasonal timescale: variability caused by the revolution of the Earth around the Sun and the directly related variation of the solar declination angle,
3. sub-seasonal timescale: variability caused by the cumulative interplay at various timescales, associated with the passing of weather systems and the changes in their persistence and occurrence,
4. daily timescale: variability caused by the revolution of the Earth around its axis, and the directly related times of sunrise, sunset, and the solar elevation angle.

When studying the generation potential of wind or solar, all these timescales of variability should be considered.

2.1. A climatology of renewable resources and the use of hourly rolling windows

The highly variable nature of the wind and solar resources makes that a straightforward 30-year daily mean does not result in a useful definition of their climate (see SI section A). The same holds for an initial estimate by averaging each ordinal hour over 30 years (figures 2(a) and (c)). Though this simple average-based climatology does capture the mean expected behaviour on annual timescales, the random fluctuations from day-to-day and hour-to-hour cannot be explained by physical processes in this climatological definition. To remove these random fluctuations more data would be needed to obtain the desired, physical, smooth , but physical, climatology. However, considering a period longer than 30-years is ineffective, as climate change would start to influence the result [28]. Applying a simple running mean to this simple average-based climate timeseries is undesirable, as that would remove the diurnal cycle, which has a physical origin and is of large importance for our application in the energy sector.

We therefore define an *hourly rolling window* climate, meaning that we first group the same time of day, and then, for each 'hour-of-the-day'-group, we apply a 30-year running mean (see SI section A.2). The hourly rolling window climate (C) of a renewable resource potential P for hour-of-the-year h is computed by:

$$C_P(h) = \frac{1}{n}\sum_{y=1}^{n} \sum_{h' \in \{h+24d\}_{d=-\Delta}^{d=+\Delta}} \frac{P(y,h')}{2\Delta+1}, \quad h = 1,2,\ldots,8760 \tag{1}$$

where n is the number of years, h is the hour of the year from 1 to 8760, Δ is half the window size (days) and $P(y,h')$ is the generation potential for hour h' of year y. In line with [27] an unweighted average and $n = 30$ years are used. See figure 2 for a comparison between the different methods.

It should be noted that two details where omitted in formula (1). First, the hour-of-the-year is cyclic in nature, meaning that the first hour of year y follows the last hour of year $y-1$. While this is implemented, for reasons of clarity this is not included. Second, to deal with leap years, we discard 29 February when computing the climatology. The climatology of each hour of the day for 29 February is then defined by the mean value of that hour of the day of 28 February and 1 March. This addresses the lack of data for 29 February and keeps a simple formalism.

The choice for the size of the rolling window is somewhat arbitrary. Sensitivity tests indicate that the window size should be bigger than 20 days to smooth any remaining nonphysical day-to-day variability, but smaller than 60 days to avoid over-smoothing the annual cycle (SI section A.3). Within this range the exact size of the window does not affect the use of the index. Here, we choose a window size of 40 days.

By using the hourly rolling window climate, both the importance of the various timescales and the need for more data points to get a smooth climatological function are addressed. It is essential that the climatological definition used in the calculation of the deviation index for wind or solar energy is physical (i.e. does not contain random fluctuations), such that anomalies represent variability due to the weather, decoupled from the climate.

2.2. The CREDI

We define the CREDI to be the cumulative anomaly of a renewable resource with respect to its climate over a specific time period of interest from a chosen starting point in two steps (figure 1). First, we determine the anomaly of a renewable resource, as the difference between the hourly generation potential of that resource and its climate (i.e. its expected value), taken from the computed hourly rolling window climate. Second, from an initial chosen starting point we sum these anomalies over a time period of interest.

More formally: let $P(y,h)$ denote the generation potential for ordinal hour h of year y, and let $C_P(h)$ denote the climate for ordinal hour h for that potential P. The anomaly $A_C(y,h)$ of a renewable resource for ordinal hour h of year y is then defined as:

$$A_C(y,h) = P(y,h) - C_P(h). \tag{2}$$

The CREDI over a given period of time is defined as the cumulative sum (or running total) of A_C over that period. For example, if we align the starting point with the start of the year, the CREDI on the ith hour of that year (y) is:

$$\text{CREDI}(y,i) = \sum_{h=1}^{i} A_C(y,h), \quad i = 1,2,\ldots,8760. \tag{3}$$

When interpreting the index, the following should be considered. A change in CREDI over time is an indication of either an excess or deficit of the renewable resource potential with respect to its climatic normal (figure 1(b)). A stable CREDI over a period indicates nominal renewable resource potential with respect to its climate.

Specifically, the CREDI score has the unit full load hours (FLH) and at a given time informs the user of the cumulative surplus or deficit generation potential over the period considered with respect to its nominal behaviour. So given a fixed time window, the distribution of the CREDI score calculated then provides insight into the properties of a connected storage unit, like the (dis-)charge potential. FLHs depend on the installed capacity, therefore if the installed capacity of a resource is known or assumed, the index allows for direct assessment of the storage volume and power needed to always generate nominally within the fixed time window used.

For clarity, when the index is applied to a specific resource, we first refer to the resource before the index acronym is given. For example, the WIND CREDI refers to an assessment of the CREDI of wind energy potential, and similarly for solar.

2.3. The use of storylines in analysing CREDI

The index can be used to assess the temporal development of anomalous renewable energy generation. In line with the application of hydrological drought indices, a physical storylines approach [31, 32] could be used. This approach can use regional climate change information while avoiding the strict limitations of a normal confidence-based approach applied in climate science. Storylines can be used to gain more insight into the driving processes, identify event analogues, and investigate similar events in alternative energy systems or under future climate conditions. Utilising these insights in, for example, resource adequacy assessments or system design studies, will likely lead to a more robust energy system.

Selection of relevant events can be based on historical adequacy assessments (like the [33] Adequacy Outlook). As shown by Van der Wiel *et al* [12, 32], event analogues can then be found in large energy-climate datasets that incorporate climate change [1, 11]. By studying these analogues the physical processes and likelihood of these events can be assessed.

To demonstrate the index at different timescales and to highlight relevant considerations in the application of the CREDI, we selected the years 1996, 1998, 2003 and 2016 as storylines. The year 1996 was chosen specifically, as one of the most challenging years for resource adequacy in the Netherlands and Germany in a future net-zero emission energy system [33, p 56]. In the analysis of the potential for hydrogen generation from wind, 2003 and 2010 where found to be anomalously low [33, pp 58–61]. Both 1998 and 2016 where chosen as they represent the most anomalous years of the index for solar and wind, respectively.

3. Data

We used the preliminary 4th version of the Pan-European Climate Database to demonstrate the CREDI in this paper (PECDv4.0; [11]). This database, developed by Copernicus Climate Change Services (C3S) in cooperation with the European Network of Transmission System Operators for Electricity (ENTSO-E) will be the new standard database used for all common transmission system operator (TSO) studies. The full database will be openly available as part of the new C3S-Energy dataset, expected in late 2023 (https://climate.copernicus.eu/energy/).

To showcase the developed index all figures show data from the preliminary PECDv4.0 of the northern region of the Netherlands. This region is the NUTS statistical region 'NL1' and covers the provinces of Groningen, Friesland and Drenthe, see: https://en.wikipedia.org/wiki/NUTS_statistical_regions_of_the_Netherlands.
While the region is named 'NL01' in the PECD dataset, the NUTS-code is used here. While we focus in the main paper on the NL1 region, in the supplement we show additional regions reflecting some of the diversity within Europe. Further details in SI section F.

4. Application of the CREDI at different timescales

In this section we show the application of the index at decadal, seasonal and sub-seasonal timescales in the context of modelling future energy systems. The considerations associated with choosing a starting point for the CREDI calculation is especially relevant at (sub-)seasonal timescales, and will be discussed.

On daily timescales the weather is extremely variable, but it depends on local conditions and short-term battery storage comes into play [34]. For most regions the maximum cost-effective storage based on the surplus charging capacity from wind and/or solar is in the order of 8 h to 4 days [34–36]. For these reasons, we make no assessment on daily timescales here. However, due to the relevance of short-term events for the energy system, an example of a eight-day study window in CREDI is provided.

4.1. Annual to decadal variability in CREDI

At annual to decadal timescales the index can be used to assess the impact of large scale oscillations in the ocean and atmosphere on the availability of a renewable energy resource. These long-term deviations from the climate are relevant, e.g. because they offer sources of meteorological predictability [37, 38], or because stakeholders look at 10 year time periods to estimate return of investments [33].

Over the past 30 years, large inter-annual variation is observed in the WIND CREDI (figure 3(a)). The cumulative effect of variations at seasonal scales resulted in higher than expected wind generation potential from 1991 to 2002, while from 2010 onwards WIND CREDI declined indicating lower than expected wind generation potential. These general variations are in line with those found by Stoop *et al* [15] and Wohland *et al* [39].

Similarly, the SOLAR CREDI shows inter-annual variability. From 1991 to 2003 SOLAR CREDI shows a general decrease, indicating less than average potential generation from solar. Within this period, a strong reduction in the periods 1993–1995 and 1998–2002 is observed (figure 3(b)). In the period 2005–2018, SOLAR CREDI is flat, showing that the solar potential was as expected from climate. After this period a steady increase in the SOLAR CREDI is observed, indicating higher than expected potential generation.

The values of SOLAR CREDI are generally lower than those of the WIND CREDI. This is directly related to the diurnal cycle, which by definition gives zero solar potential at night and low values in the morning and evening. Consequently, the sum of the anomalies over a given period is smaller than for wind potential, which has values for all 24 h in a day.

Finally, while the impact of the relative observed variability depends on the ratio of installed capacities, we observe that the inter-annual energy-meteorological variability is mainly driven by the wind resource in the analysed region (i.e. the northern of the Netherlands). And though the WIND and SOLAR CREDI s show strong anti-correlated behaviour during some years (e.g. from 1991 to 2002), in others this is not the case (e.g. from 2004 to 2005). At decadal timescales, wind and solar balance the system somewhat, but they are not suited to fully negate the variability of their counterpart.

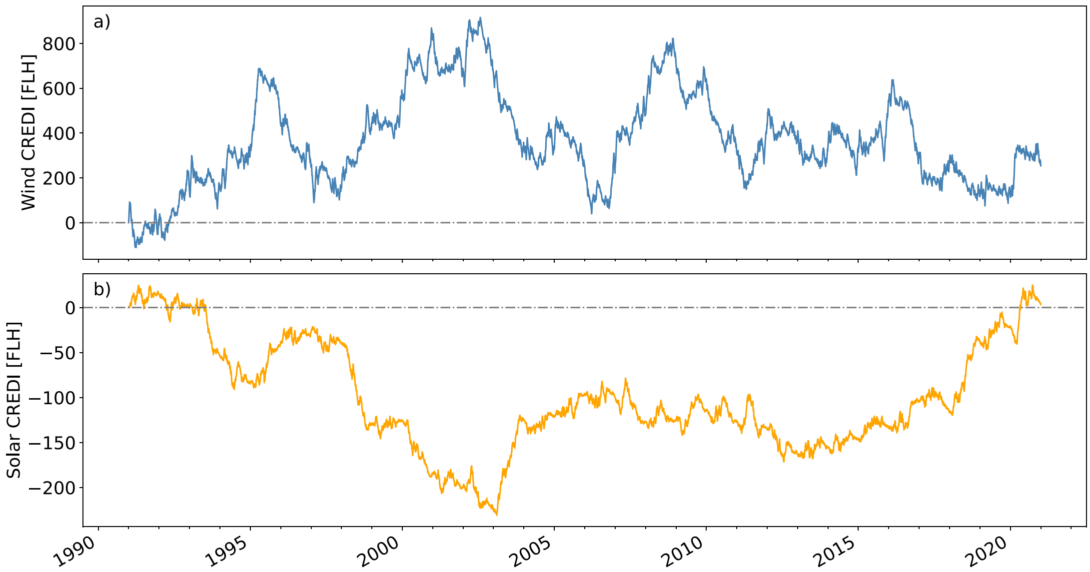

Figure 3. Hourly wind (a) and solar (b) CREDI over the period 1991–2020 for 'NL1'. As the climate was calculated over the same period, by definition the CREDI sums to zero over the full period.

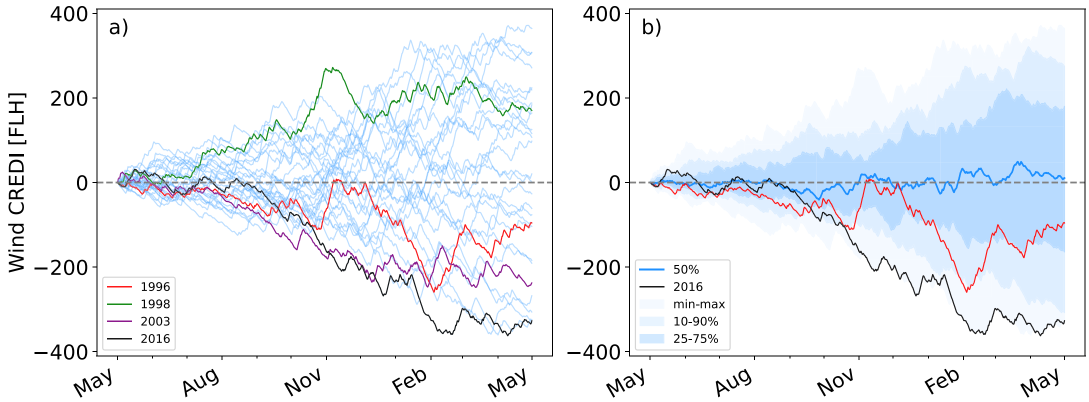

Figure 4. Hourly WIND CREDI per analysis year over the period May 1991 to April 2021 for 'NL1'. Figure (a) shows the specific progression of WIND CREDI for each year (blue lines). Figure (b) shows the distribution of the WIND CREDI for each hour of the year, namely the 50th percentile (blue line), the 25–75, 10–90 percentile and min-max range (shaded blue, see legend). Four exemplary storylines are shown, namely 1996 (red), 1998 (green), 2003 (purple) and 2016 (black).

4.2. Seasonal variability in CREDI

When assessing the seasonal energy-meteorological variability using the CREDI, the starting point determines the way the temporal development of the index is perceived. In line with definitions of hydrological drought, the starting point determines the separation between energy surplus (wet) and deficit (dry) years. As the index is intended to capture the energy-meteorological variability, the start date is picked such that the biggest range if CREDI at the end of, and throughout, the year is observed.

Comparing CREDI starting points for each month of the year, we found that these should *not* be the same for wind and solar (SI section B). We use May 1st as the starting point for wind, as it gives the widest distribution of the index at the end of the analysis window in this particular region. For solar no clear distinction is found between a December or January starting point, we chose to use January 1st here.

For the yearly WIND CREDI, it is obvious that an individual year can either be anomalously positive or negative, and that variations throughout a year are large (figure 4(a)). This results in a wide range of yearly storylines. The 25%–75% spread of the index grows to ±180 FLH over a year (figure 4(b)). The most extreme negative year in the period considered for WIND CREDI was 2016. In that year, from about September onwards, the wind potential was almost consistently below expected with 350 less FLHs at the end of the analysed period.

As an example of the use of WIND CREDI for storyline analysis we look at 1996. From May to

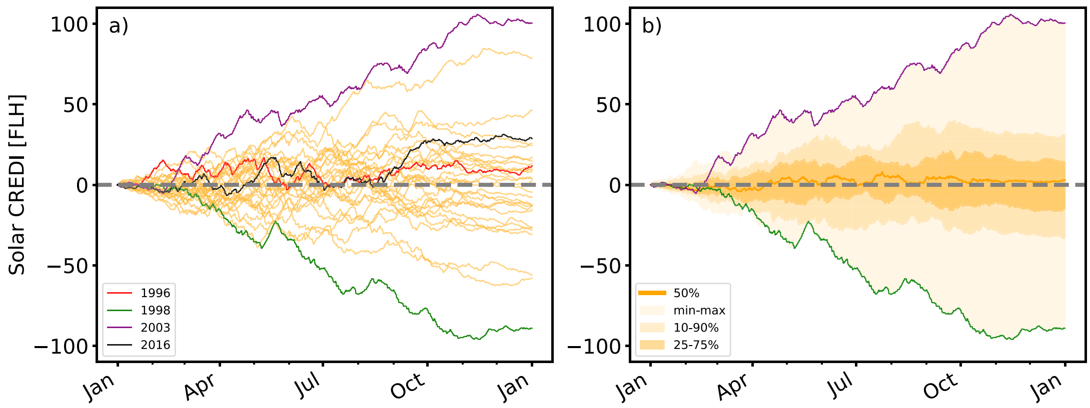

Figure 5. Hourly SOLAR CREDI per year over the period 1991–2020 for 'NL1'. As shown in figure 4, but the SOLAR CREDI is shown in orange hues.

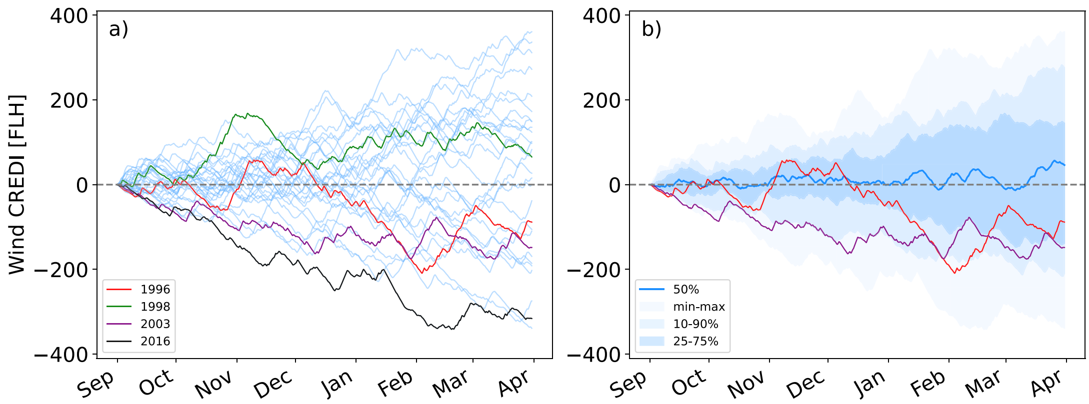

Figure 6. Hourly winter WIND CREDI per season (Sep.–Apr.) for 1991–2021 for 'NL1'. Figure (a) shows the specific progression of WIND CREDI for each summer season (blue lines). In addition, four example storylines are represented, namely those starting in 1996 (red), 1998 (green), 2003 (purple) and 2016 (black). Figure (b) shows two storylines (1996, 2003) and the hourly distribution of the WIND CREDI, namely the 50th percentile (blue line), the 25–75, 10–90 percentile, and min–max range (shaded blue, see legend).

October the index is relatively flat, indicating that the wind potential was as expected from its climate (red line in figure 4(b). Then, a strong reduction is observed in the WIND CREDI from December to the end of January, indicating much lower then average potential generation from wind. Part of this deviation is compensated by higher than normal generation potential in February of 1997.

As noted earlier, values of yearly SOLAR CREDI are smaller than of WIND CREDI (figure 5(a)), with an average spread (25%–75%) of ±18 FLHs, and uncommon spread (10%–90%) of ±35 FLHs spread over a year (figure 5(b)). This indicates that ~18 FLHs of total energy is needed to cover the deficit of the installed solar capacity in 50% of years and ~35 FLHs to cover 80% of years (figure 5).

The most extreme year of high solar potential was 2003; the most extreme year of low solar potential was 1998. Especially 2003 is remembered for its extremely warm and sunny summer [40].

4.3. Sub-seasonal variability in CREDI

At sub-seasonal timescales, similar to seasonal, the start point determines the way the temporal development of the index is perceived. We use 'energy'-seasons to capture the large scale changes on sub-seasonal timescales. For wind we define two seasons of interest: September to March, and April to August. For brevity, only the results found for wind in the winter 'energy'-season are shown here, see SI section C for the other and solar. Alternative definitions of 'energy'-seasons can be relevant, especially for regions that have different sub-seasonal behaviour then the 'NL1'-region shown here.

It is obvious that different years show quite different characteristics (figure 6(a)) and individual winter seasons can differ greatly. As expected, the sub-seasonal timescale is emphasised more. For instance, the anomalous index-development in 1996 described in section 4.2 is more clearly visible. Especially the strong reduction in WIND CREDI from December to the

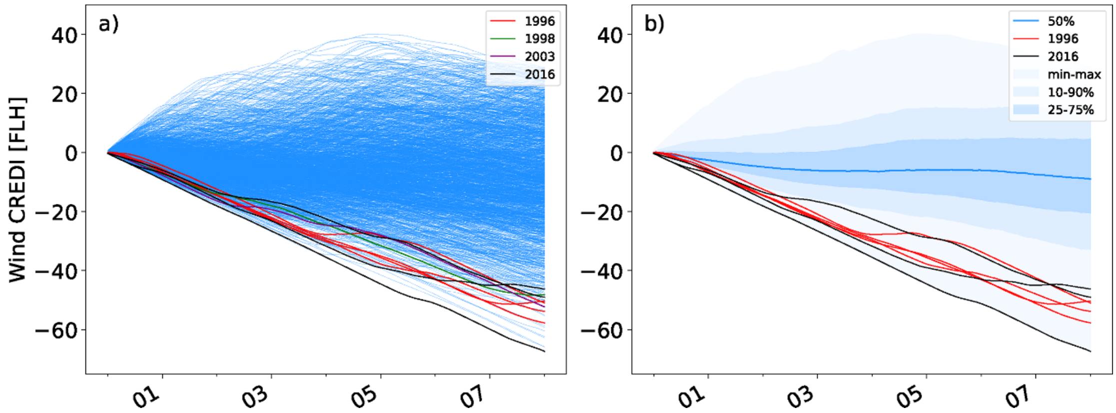

Figure 7. Hourly winter WIND CREDI during 8-days for all events with less then 5 days overlapping in the period May 1991 to April 2021 for 'NL1'. The storylines show the analysis years 1996 (red, 4x), 1998 (green, 1×), 2003 (purple, 1×) and 2016 (black, 3×). Further formatting as shown in figure 6.

end of January stands out as a period of much lower than normal wind generation potential.

4.4. A short-term study window for event-based CREDI

Finally, short-term events, e.g. *Dunkelflautes*, can pose significant risk to highly renewable energy systems [12, 41–44]. A 8-day window for CREDI aligns with previous work [33], and is investigated here, see SI section D for additional figures and the top 50 eight-day events.

For short-term event analysis we do not predefine the start point, all eight-day windows are considered. Overlapping events that share a five or more days, are removed from the analysis. While we only consider the lowest final CREDI value for our event selection, other impact selection methods as described by Van der Wiel *et al* [32] can be used.

Again we noted the large weather-caused variability between different eight-day periods (figure 7(a)). The computed spread in figure 7(b) considers events throughout the year. This can also be investigated on a seasonal basis for winter or summer-specific event information, or for shorter or longer events.

The most extreme event is from 16–24 January 2017 and the analysis year 2016 is present three times in the top 50 events. While the specific eight-day event found in TenneT [33] is not the most extreme event, the analysis year 1996 does show up four times in the top 50 events. Indicating that the analysis year 1996 indeed stands out as quite exceptional.

5. Discussion

The presented index is defined as the cumulative anomaly of a renewable resource with respect to its climate. The method of determining the climate is thus vital and, as shown, should take into account the strong diurnal and annual cycle present in renewable energy resources. The calculation of the climate used here has a dependence on the size of the rolling window, which was primarily based on expert judgement. A longer timeseries, covering many decades, could be used for a cross-validation check to obtain the optimum *rolling window* size, but the data source should be selected with great care, due to potential inconsistencies [39, 45, 46]. In previous work a climatic definition on harmonics has been effective [47–49], but we found it unsuitable here (see SI section A.3).

CREDI should not be confused with the standardised energy indices recently introduced by Allen and Otero [18]. While we have been inspired by indices for monitoring hydrological droughts, their standardised energy indices are direct analogues. Meaning that those indices are a pure statistical assessment of the observed variance that rely heavily on the empirical distribution functions used (see section 2 [18], pp 2–3). However, in energy system operation and control, the specific sequence of observations and the deviation with respect to the expected patterns matter. The CREDI presented incorporates these aspects.

When combined with weather forecasts, indices for hydrological drought can help policy makers make early decisions regarding societal risks [23–26]. However, the operation of the electricity grid requires balance on very short timescales [1, 33]. While we presented our index with an hourly resolution, further research is needed to investigate if the CREDI can also be applied on these very short timescales. The examples provided, however, do already show CREDI's usefulness in resilience planning, resource adequacy assessments, and as a metric for selecting events for robustness analysis.

In this introduction of the index, we applied it to the northern region of the Netherlands. However, as shown by Pickering *et al* [50], energy-meteorological variability is strongly region dependent. Therefore, the CREDI should be calculated and analysed for each region separately. Due to the ease of application, and the intuitive analysis and interpretation of the index, this application to other regions is relatively straightforward (see SI section E for a few additional regions).

6. Conclusion

Drawing inspiration from the work on drought monitoring indices, we have presented the hourly rolling window climatology and CREDI. Given the relevance of both the diurnal and annual cycle in meteorology for energy applications, we recommend a simple but suitable definition of the background climate using an hourly rolling window approach. This new index is meant as an analytical method for researchers and stakeholders to help them understand and explain the impact of the variable nature of the weather on the energy system. The index computes the cumulative deviation or anomaly from the climatology for a chosen period.

The index can be used when understanding of energy-meteorological variability is key. For example, the CREDI can be used as part of a resource adequacy analysis from TSOs to identify events which are likely to be a challenge in maintaining security of supply in a (future) power system driven by renewable energy sources. At the same time, the CREDI could be used to assess the volume and power output of back-up resources needed for a given timescale, region, and energy system design. Then, by using the event selection and analysis, as e.g. in Van der Wiel *et al* [32] for hydrological extremes, detailed event descriptions can be developed, systems can be stress tested, and further insight could be gained into energy-meteorological variability.

Data availability statement

The data and code that support the findings of this study are openly available at the following URL/DOI: https://github.com/laurensstoop/CREDI.

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Credit author statement

Conceptualisation, Formal Analysis and Visualisation: LPS, Investigation, Methodology and Writing—Original Draft: L P S, K v d W, Writing—Review & Editing: *All listed authors*, Supervision and Funding acquisition: A J F, M v d B.

Open research

The implementation of the CREDI, its use at different timescales, all code used to generate the figures, the data from the 'NL1' region discussed and the full list of the most extreme short-term events found as presented in this study are available at Github via https://github.com/laurensstoop/CREDI with the MIT license.

The full preliminary dataset of the PECDv4 containing the regional renewable resource potential for other technological definitions of wind and solar, or regions, then used in this study are not available due to ongoing validation. In due time the full PECDv4, including raw gridded and aggregated regional/national renewable resource potentials for a wide range of technological definitions, will be made available as part of the C3S Energy dataset and can be found through https://climate.copernicus.eu/operational-service-energy-sector. The framework describing the new C3S-Energy dataset, part of which is the PECDv4, can be found on: https://climate.copernicus.eu/c3s2412-enhanced-operational-services-energy-sector.

ORCID iDs

Laurens P Stoop https://orcid.org/0000-0003-2756-5653
Karin van der Wiel https://orcid.org/0000-0001-9365-5759
William Zappa https://orcid.org/0000-0001-6810-7224
Arno Haverkamp https://orcid.org/0000-0001-6947-7892
Ad J Feelders https://orcid.org/0000-0003-4525-1949
Machteld van den Broek https://orcid.org/0000-0003-1028-1742

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