Classification and Identification of Renewable Energy Droughts in the United States

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***Abstract*—Renewable resource droughts, defined as significantly reduced wind and solar power generation periods, present challenges to power system reliability and stability. This study proposes two strategies and suggests their related metrics to identify and classify renewable resource drought events based on severity and duration. The focus of this study is on identifying wind generation droughts across U.S. states, utilizing over 80 years of ERA-5 weather dataset. The results provide valuable insights for optimizing renewable energy integration and strengthening system resilience to renewable resources variability.**

***Index Terms*—variable renewable energy, wind resource drought, renewable energy generation, weather impact**

I. Introduction

Integrating renewable energy sources, particularly wind and solar, is essential for transitioning to a sustainable, low-carbon future. However, these sources' inherent variability and intermittency present significant challenges to grid stability and reliability. A critical concern in this context is the occurrence of prolonged periods with significantly reduced renewable energy output, commonly referred to as "renewable resource droughts" or "energy production droughts." Such droughts can lead to energy shortages, particularly in systems with high renewable energy penetration [1]. As reliance on wind and solar energy is increasing, the risk of these droughts poses a critical challenge to power system reliability and stability. This requires comprehensive analysis and mitigation strategies to ensure the supply and demand balance and power system reliability.

Reference [2] outlined multiple criteria to identify energy shortages, considering aspects like shortage duration, actual megawatt (MW) output, and the geographic scope of impacted regions. These definitions underscore the diverse interpretations and analyses of energy droughts. Various definitions and methods for identifying renewable energy droughts have been presented in the literature with most of the references using daily averages of historical data as in [3], [4], [1], [5] and identifying droughts by resource availability falling below a specific threshold of the historical average values over a given time duration. reference [6] set the drought threshold at 20% of the daily mean wind speed for their analysis of wind droughts in Poland. Resource [7], on the other hand, examines longer-period droughts, utilizing thresholds based on weekly-scale data for wind and solar resources. The methodologies employed in these studies also vary significantly, with some relying on direct weather measurements, such as wind speeds [1], [6], [8], [9], while others use power outputs of renewables based on their input-output models that convert wind speed data into power generation estimates through power curves. For instance, [10] defines power curves in supplemental materials, while [11] and [12] use ERA5-calibrated wind speeds adjusted for turbine classes to optimize generation potential. These differences in thresholds, data sources, and modeling approaches highlight the need for standardized definitions and methods to enhance comparability and applicability across studies.

Most of the references that use mean values in the literature use daily or weekly averages. However, a perspective that can be gained from meteorological studies is using historical climatological data to calculate "hourly normals" for variables such as wind speed, temperature, and cloud coverage [13]. This method offers a structured framework for analyzing variability and identifying patterns in conditions that strongly influence renewable energy outputs. Other approaches to identifying energy droughts include methods traditionally used in meteorological analysis, such as standardized indices. Examples include the Standardized Renewable Energy Production Index (SREPI) and the Standardized Residual Load Index (SRLI) [2]. These indices are inspired by well-established tools for monitoring meteorological droughts, such as the Standardized Precipitation Index (SPI) [14] and the Standardized Precipitation-Evapotranspiration Index (SPEI) [15].

Despite the advancements in indices and methods to identify energy droughts, there remains a lack of detailed analysis specific to US regions with high renewable energy penetration. This includes limited research on the duration, intensity, and drought severity classification. Furthermore, existing studies often overlook region-specific drought characteristics and the cumulative effects of recurring drought events. Addressing these gaps is essential to develop effective mitigation strategies and enhance power system resilience.

This study proposes two complementary strategies and suggests their related metrics to identify and classify renewable resource drought events based on severity and duration, focusing on wind resource droughts within U.S. states, which is chosen as a convenient framework for comparisons with available data. States with higher renewable energy penetration are emphasized to highlight scenarios of low-generation conditions, evaluating droughts' duration, severity, and potential impacts on the power system. While the analysis is state-based, we acknowledge the limitations of using predefined geographic boundaries. Mean-based and SREPI methods are applied to identify severe and extreme events, providing critical insights for enhancing system resilience and reliability.

II. Methodology

A. Data Preparation

The impact of weather on the electric grid is usually studied based on the outputs of renewable generators. However, if the weather measurements are directly used as input to operation studies such as Optimal Power Flow (OPF), they can provide a more detailed calculation for each renewable generator and track quick weather changes. Reference [16] introduced a strategy for directly incorporating weather measurements into the OPF framework using established methods like Newton-Raphson, while minimizing any significant increase in the problem's complexity. To estimate the hourly capacity of renewable generation, this study employs weather data—including temperature, wind speed, wind direction, dew point (for humidity), radiation, and cloud coverage—collected from numerous weather stations. The specific weather data utilized in this study consists of high-resolution, hourly measurements from European Centre for Medium-Range Weather Forecasts (ECMWF) Re-Analysis fifth generation ERA5 [17] with weather stations at each 0.25 degree latitudes and longitudes across the continental United States from 1940 to 2023 [18], [19]. Weather measurements are associated with electrical generators by leveraging the geographic coordinates of both generators and weather stations, linking them based on proximity. [16]. Weather data for power system studies have been converted to a new data format called PWW, and the files containing all relevant weather data from 1940 to the present have been generated and made available at [20] website.

The location and capacity of generators in the United States and their types are available in publicly available yearly datasets from the U.S. Energy Information Administration (EIA-860) [21]. The dataset includes key characteristics of the generators, such as wind generators model classes, and details, such as tilt angle for solar cells. This data allows for grouping individual wind turbines and solar cells at a location with similar characteristics, which are further classified into power plants and their geographical location. Of note is that since real-world power grid information is considered Critical Energy Infrastructure Information (CEII), this work uses the synthetic copper plate model generated using EIA-860 data to get the renewable energy generation outputs that are mapped to the synthetic generator locations [22]. Power flow weather (PFW) models are also created to model the relationship between the input weather measurements and output power data [23]. PFW models are based on the types and models of renewable resources from EIA-860 data. The data has also been validated at [24] to ensure that the PFW models reflect the weather-related impacts on the power grid.

B. Renewable Resource Drought Identification Strategies

This work proposes two analytical methods for drought identification. The first strategy is based on historical means of each hour over 83 years of data, and the second strategy that we propose is based on statistical normalization using the Standardized Renewable Energy Production Index (SREPI). Each method offers distinct insights into renewable energy droughts: the mean-based approach emphasizes seasonal change across the year and hourly changes across each hour of each day in a year, while SREPI-based analysis captures deviations from typical generation patterns for the overall dataset.

The mean-based drought classification approach evaluates current wind generation compared to long-term averages, applying percentage thresholds to assess how the current sample compares to all historical values at that time. On the other hand, the SREPI-Based Analysis approach leverages historical wind generation data to detect anomalies by comparing current output with a normalized distribution. This method is valuable for identifying statistically significant deviations from expected production levels and particularly useful for pinpointing rare but impactful low-generation events.

The following subsections provide detailed descriptions of each methodology, highlighting their computational steps, classifications, and respective advantages for identifying and categorizing renewable energy droughts.

C. Yearly Mean-Based Drought Classification

The first methodology, which is more commonly used for drought identification, is based on daily and hourly averages of historical data as explained in [13]. The proposed approach finds the average renewable output values at each hour of each day over the year. When each new sample is compared to the average value at the same time of the year, using percentage-based thresholds, specific thresholds are assigned to identify droughts if the comparison is below specific values of renewable generation. This method compares observed values to a defined percentage of the mean for a given day and hour, effectively capturing both seasonal and daily variations.

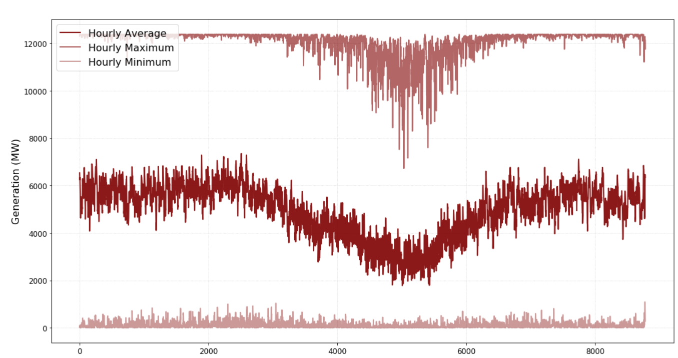

Fig. 1. Iowa mean yearly variation for wind generation

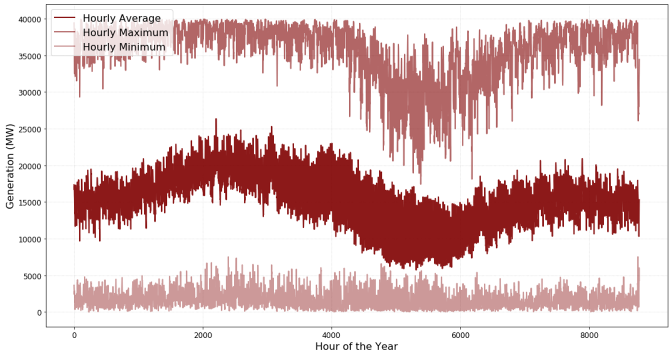

Fig. 2. Texas mean yearly variation for wind generation

Figures 1 and 2 show the hourly average, minimum, and maximum of historical data over 83 years for Iowa and Texas, respectively. This mean-based approach enables a nuanced classification of renewable energy droughts considering different regional and seasonal patterns.

Generation output data are grouped by the same hour and day across all 83 years to compute historical averages, providing a consistent baseline for assessing deviations.

$$N_{h,d} = \frac{\sum_{y=1}^{Y} X_{h,d,y}}{Y} \tag{1}$$

Where $N_{h,d}$ is a long-term average ("hourly normal") for a specific hour h on a given day d, $X_{h,d,y}$ is observed value for hour h, day d, and year y and Y number of years used for the calculation.

Underperformance is assessed by comparing generation levels to the mean using fixed thresholds: 25%, 15%, and 5%. Binary indicators mark when wind generation falls below each threshold, while drought duration is calculated by grouping consecutive drought hours. Severity levels are classified relative to the mean: "Level A" (above 25%) - normal condition, "Level B" (15–25%), "Level C" (5–15%), and "Level D" (below 5%). Metrics for this approach are detailed in Table I. This method provides a straightforward and operationally relevant approach for detecting how each sample falls above or below the related historical mean, which is especially useful in contexts of seasonal and daily patterns.

TABLE I
Classification of Wind Energy Droughts Based on Severity and Duration

Severity / Duration	$15\% \leq$ Mean $\leq 25\%$	$5\% \leq$ Mean $\leq 15\%$	Mean $\leq 5\%$
12-24 hours	Level B Short-Term Drought	Level C Short-Term Drought	Level D Short-Term Drought
24-48 hours	Level B Medium-Term Drought	Level C Medium-Term Drought	Level D Medium-Term Drought
More than 48 hours	Level C Long-Term Drought	Level B Long-Term Drought	Level D Long-Term Drought

D. SREPI-Based Analysis

The second proposed methodology utilizes the SREPI evaluation approach, to identify deviations from historical renewable generation patterns by applying statistical normalization. This approach offers significant advantages by leveraging the full historical distribution of renewable energy generation data rather than focusing solely on averages or fixed thresholds. This methodology enables granular, hour-by-hour analysis and standardized anomaly detection, ensuring robustness against variations and outliers in data.

The main difference between the SREPI-based strategy and the mean-based strategy lies in its approach to data analysis. While mean-based methods focus on summary statistics (such as averages or standard deviations) for each hour of the historical year, the SREPI approach provides a more granular analysis by considering the entire historical distribution of renewable energy generation.

SREPI is calculated for each hour of the day by comparing the observed wind generation value to the cumulative distribution function (CDF) of the historical data. The CDF represents the probability that a random variable (in this case, wind generation) will take a value less than or equal to a specific value. It effectively shows how the observed value ranks relative to the historical data distribution. Once the CDF value is determined, it is transformed into a standardized SREPI score using the inverse normal distribution. This transformation maps the CDF values to a normalized scale, allowing for consistent and interpretable comparisons of deviations across different time periods and datasets:

$$\text{SREPI}(P_t) = \Phi^{-1}\left(\frac{1 + \sum(\text{Wind Generation} \leq P_t)}{n+2}\right) \tag{2}$$

Where P_t is the observed wind generation at time t, and Φ^{-1} represents the inverse normal distribution.

Thresholds for energy production droughts are defined based on the SREPI values as outlined in [2]. A drought is identified when the SREPI falls below -1.28, indicating conditions outside the normal range, classified as "Level A". Normal conditions are defined as SREPI values greater than -1.28, reflecting generation within the typical historical range. "Level B" droughts are classified for SREPI values between -1.64 and -1.28, representing a noticeable decline in generation with a 10% probability of occurrence. "Level C" droughts correspond to SREPI values between -1.96 and -1.64, indicating significant underperformance with a 5% probability. "Level D" droughts are identified for SREPI values below -1.96, reflecting rare events of extreme underperformance with a 2.5% probability.

Beyond simply analyzing generation output, it is crucial to incorporate event duration into the evaluation. Of primary interest are events with prolonged durations, as these have the most substantial implications for energy systems. To classify these events effectively, in addition to severity levels based on SREPI, drought events were categorized into short-term, medium-term, and long-term durations with corresponding ranges of 12–24 hours, 24–48 hours, and more than 48 hours, resulting in the classification presented in Table II.

TABLE II
CLASSIFICATION OF WIND ENERGY DROUGHTS BASED ON SREPI SEVERITY AND DURATION

Severity / Duration	-1.64 $\leq$ SREPI $\leq$-1.28	-1.96 $\leq$ SREPI $\leq$-1.64	SREPI $\leq$-1.96
12-24 hours	Level B Short-Term Drought	Level C Short-Term Drought	Level D Short-Term Drought
24-48 hours	Level B Medium-Term Drought	Level C Medium-Term Drought	Level D Medium-Term Drought
More than 48 hours	Level B Long-Term Drought	Level C Long-Term Drought	Level D Long-Term Drought

For both methodologies, the primary focus of this study is on ”Level C” long-term events and ”Level D” medium- and long-term drought events.

III. CASE STUDY AND RESULTS

The generation output was calculated based on the 2023 EIA-860 generation data. Wind drought statistics were analyzed for each state, focusing on the frequency, duration, and deviation from the expected average generation output during prolonged drought events. The analysis centers on zones where wind generation capacity comprises a substantial portion of the overall generation capacity. In this study, each state's installed wind generation capacity was compared with its net summer capacity - the maximum output of all types of generating equipment during summer peak demand (Table III). States in which wind power represents more than 25% of the total generation capacity are of specific interest.

TABLE III
WIND INSTALLED CAPACITY, NET SUMMER CAPACITY, AND PERCENTAGE BY STATE

State	Wind Installed Capacity (GW)	Net Summer Capacity (GW)	Percentage (%)
IA	12.98	22.71	57.2
KS	9.11	19.20	47.4
ND	4.33	9.40	46.1
SD	3.16	6.80	46.4
NM	4.41	10.72	41.1
OK	12.25	31.69	38.6
NE	3.52	10.78	32.7
WY	3.23	10.19	31.7
MN	4.97	17.84	27.8
CO	5.38	19.54	27.5
TX	40.30	155.01	26.0

A. Mean-Based approach for wind generation

Mean-based approach results were analyzed, looking at the times when generation output is lower than 25, 15, and 5 % compared to the mean value. Across the studied dataset, ”Level D” scenarios happened two times in Nebraska and once in Kansas and Wyoming (Table IV).

Then durations of these drought events were analyzed to understand the persistence of low-generation periods under each threshold (Table V).

TABLE IV
48 HOURS AND LONGER WIND DROUGHT DURATION OCCURRENCES FOR SELECTED STATES, LOWER THAN 25, 15 AND 5% OF MEAN

State	Less than 25% Mean	Less than 15% Mean	Less than 5% Mean
CO	26	2	0
IA	97	19	0
KS	79	21	1
MN	102	30	0
ND	67	9	0
NE	83	26	2
NM	35	9	0
OK	110	15	0
SD	91	22	0
TX	16	0	0
WY	85	18	1

TABLE V
LONGEST WIND DROUGHT DURATION FOR SELECTED STATES, LOWER THAN 25, 15 AND 5% OF MEAN

State	Less than 25% Mean	Less than 15% Mean	Less than 5% Mean
CO	73 h	61 h	37 h
IA	126 h	82 h	39 h
KS	129 h	104 h	76 h
MN	137 h	103 h	44 h
ND	93 h	62 h	44 h
NE	131 h	78 h	52 h
NM	137 h	103 h	44 h
OK	142 h	97 h	47 h
SD	160 h	133 h	39 h
TX	69 h	44 h	13 h
WY	98 h	93 h	57 h

The most severe wind drought event recorded in Kansas lasted 76 hours, with a mean threshold value below 5% and wind generation output near zero. This event began on February 25, 2003, at 10:00 PM and persisted until March 1, 2003, at 1:00 AM, Fig. 3.

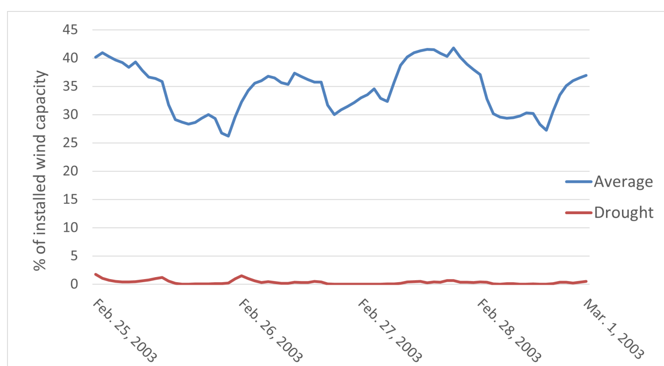

Fig. 3. Level D Wind Drought in Kansas, February 2003 (76 Hours)

Another severe wind drought event happened in Wyoming (Fig.4), starting on January 7, 4 pm, continued till January 12, 12 am, and lasted for 57 hours.

Using a mean-based approach, the longest wind drought durations across selected states were analyzed. Kansas experienced the longest event with generation below 5% of the mean, lasting 76 hours, followed by Wyoming at 57 hours and Nebraska at 52 hours. At the 15% threshold, South Dakota ex-

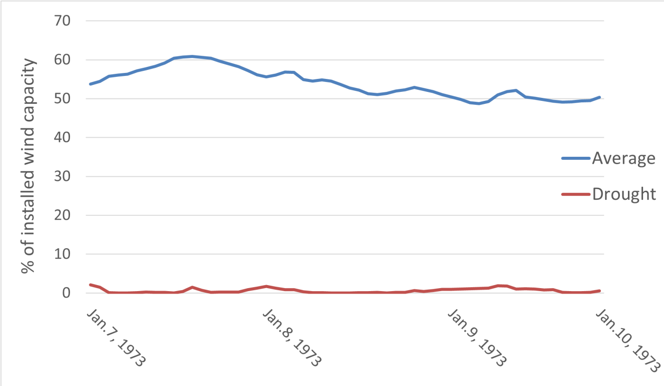

Fig. 4. Level D Wind Drought in Wyoming, January 1973 (57 Hours)

hibited the most prolonged duration at 133 hours, with Kansas and Minnesota also showing extended droughts at 104 and 103 hours, respectively. For events below 25% of the mean, South Dakota again had the longest drought duration at 160 hours, with Oklahoma, New Mexico, and Minnesota showing durations close to 137 hours. These findings reveal substantial variability in wind drought durations across states, identifying regions like South Dakota and Kansas as experiencing more persistent low-generation periods at specific thresholds.

B. SREPI approach for wind generation

SREPI results were also analyzed to assess the frequency, duration, and severity of wind generation drought conditions. Table VI shows wind drought occurrences lasting 48 hours or more across selected states at different SREPI thresholds. Similar to the mean strategy, Kansas exhibits the highest frequency, with 21 events for -1.28 SREPI threshold, 4 events at -1.64 threshold, and 2 events -1.96 threshold. North Dakota, South Dakota, and Texas also show notable counts at -1.28 threshold, but only Kansas and North Dakota reach higher severity levels. Colorado, Wyoming, and New Mexico have few occurrences across all thresholds, indicating less severe drought patterns overall. These results reflect considerable variability in drought severity and frequency across states, with Kansas experiencing the most significant impacts.

TABLE VI
48 HOURS AND LONGER DROUGHT DURATION OCCURRENCES FOR SELECTED STATES, SREPI

State	SREPI ≤ -1.28	SREPI ≤ -1.64	SREPI ≤ -1.96
CO	2	0	0
IA	8	0	0
KS	21	4	2
MN	12	0	0
ND	14	2	0
NE	9	1	0
NM	7	0	0
OK	8	1	0
SD	13	1	0
TX	20	0	0
WY	1	0	0

Table VII shows wind drought durations by SREPI thresholds. Kansas records the longest drought at -1.28 threshold with 127 hours, followed by South Dakota with 118 hours. For the -1.64 threshold, South Dakota leads with 81 hours, while Kansas and Montana have 79 and 66 hours, respectively. At -1.96, Kansas had the longest event similar to the mean strategy, with 76 hours. States like Colorado, Wyoming, and New Mexico show shorter durations, generally under 72 hours.

TABLE VII
LONGEST WIND DROUGHTS FOR SELECTED STATES USING SREPI

State	SREPI ≤ -1.28	SREPI ≤ -1.64	SREPI ≤ -1.96
CO	62 h	45 h	25 h
IA	84 h	44 h	37 h
KS	127 h	79 h	76 h
MN	86 h	44 h	39 h
ND	70 h	51 h	38 h
NE	67 h	53 h	37 h
NM	72 h	32 h	25 h
OK	74 h	49 h	33 h
SD	118 h	81 h	36 h
TX	70 h	45 h	41 h
WY	58 h	45 h	21 h

Results for the longest "Level D" drought event in Kansas were identical using both approaches, but with SREPI methodology, an additional long-duration "Level D" event was found, 61-hour drought in September 1942. This is shown in Figure 5.

Fig. 5. Level D Wind Drought in Kansas, September 1942 (61 Hours)

Notable differences were observed for other states, highlighting how the two methods complement each other. In Texas, the mean-based approach identified the longest "Level C" event lasting 13 hours, whereas the SREPI approach revealed a more extended 41-hour "Level D" event, Figure 6.

Conversely, in Wyoming, the mean-based approach detected a 55-hour "Level D" event, while the SREPI approach identified a shorter 21-hour event. Together, these methods provide a more comprehensive understanding of "Level D" wind drought events.

The mean-based approach shows more extended droughts, especially below 25% mean generation, with South Dakota reaching 160 hours and Kansas 129 hours. In contrast, SREPI thresholds show shorter durations, capturing frequent but shorter low-generation periods. In both methods, Kansas and South Dakota show long droughts, yet the mean-based

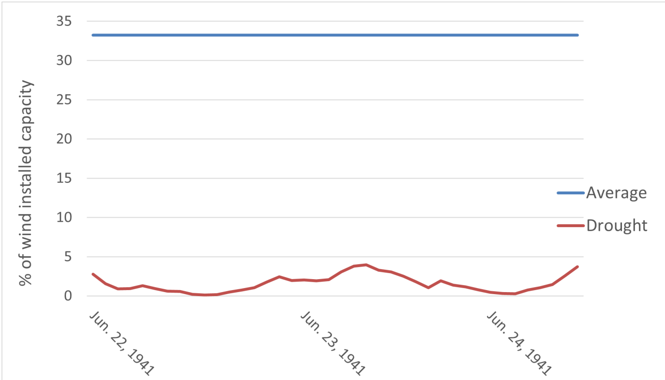

Fig. 6. Level D Wind Drought in Texas, June 1941 (41 Hours)

approach emphasizes less frequent, prolonged events, while SREPI highlights more frequent, shorter droughts. Using both of these proposed strategies provide a more comprehensive picture of wind drought patterns.

IV. Conclusion and Future work

This study analyzed and compared methods for identifying and characterizing extreme renewable drought events, focusing on mean-based thresholds and the SREPI approach. Our findings demonstrate that each method captures distinct aspects of renewable generation underperformance, offering complementary insights into the duration and severity of these events across different states. Based on the wind drought results, numerous severe long-duration droughts were observed, which could pose significant challenges as the percentage of renewable energy in the power grid continues to grow. Future work will focus on moving beyond predefined regions, such as states, by using pattern recognition and clustering techniques to identify actual regions with extreme drought events. This approach will provide a more detailed and dynamic understanding of droughts' spatial and temporal patterns.

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