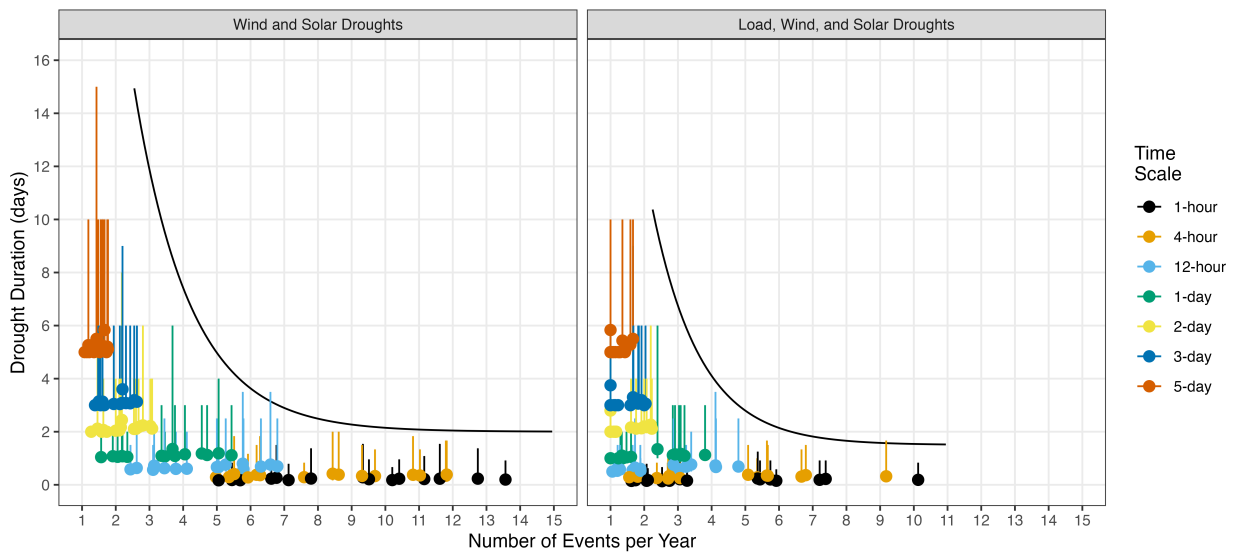


1 Graphical Abstract

2 **Standardized Benchmark of Historical Compound Wind and Solar Energy Droughts**
3 **Across the Continental United States**

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6 Highlights

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- 11 • Standardized multi-scale energy drought analysis using 40 years of data for the CONUS using
12 2020 wind and solar infrastructure at the balancing authority scale.
- 13 • A standardized metric for comparing the magnitude of compound energy droughts is devel-
14 oped.
- 15 • The longest compound energy droughts can last from 16 to 37 continuous hours while the
16 longest daily droughts can last up to 6 days.
- 17 • The longest compound hourly energy droughts occur in Texas while the longest daily droughts
18 occur in California.
- 19 • Compound energy drought are partially connected with peak load events.
- 20 • This study serves as basis to develop local storage strategies that are critical for a decar-
21 bonized grid.

Standardized Benchmark of Historical Compound Wind and Solar Energy Droughts Across the Continental United States

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Abstract

As we move towards a decarbonized grid, reliance on weather-dependent energy increases as does exposure to prolonged natural resource shortages known as energy droughts. Compound energy droughts occur when two or more predominant renewable energy sources simultaneously are in drought conditions. In this study we present a methodology and dataset for examining compound wind and solar energy droughts as well as the first standardized benchmark of energy droughts across the Continental United States (CONUS) for a 2020 infrastructure. Using a recently developed dataset of simulated hourly plant level generation which includes thousands of wind and solar plants, we examine the frequency, duration, magnitude, and seasonality of energy droughts at a variety of temporal and spatial scales. Results are presented for 15 Balancing Authorities (BAs), regions of the U.S. power grid where wind and solar are must-take resources by the power grid and must be balanced. Compound wind and solar droughts are shown to have distinct spatial and temporal patterns across the CONUS. BA-level load is also included in the drought analysis to quantify events where high load is coincident with wind and solar droughts. We find that energy drought characteristics are regional and the longest droughts can last from 16 to 37 continuous hours, and up to 6 days. The longest hourly energy droughts occur in Texas while the longest daily droughts occur in California. Compound energy drought events that include load are more severe on average compared to events that involve only wind and solar. In addition, we find that compound high load events occur more often during compound wind and solar droughts than would be expected due to chance. The insights obtained from these findings and the summarized characteristics of energy drought provide valuable guidance on grid planning and storage sizing at the regional scale.

Keywords: energy droughts, compound energy droughts, renewable energy

49 1. Introduction

50 Hydrologic droughts bring to mind dry soils, low flows and withering crops spanning large
51 geographic regions, lasting months or years, affecting entire populations. While energy droughts
52 from renewable sources occur on a much shorter time scale, they can span similarly large geographic
53 regions as both are fundamentally driven by meteorology. Energy droughts result in energy price
54 spikes that cascade into large-scale power grid impacts such as blackouts, brownouts, and acute
55 carbon emissions from thermoelectric plants that provide for the lost generation [1, 2, 3]. As
56 intermittent renewables continue their rapid expansion in a decarbonized grid, the impacts of
57 energy droughts on the power grid’s reliability, economic performance and greenhouse gas emissions
58 is increasing and thus needs more understanding [4].

59 Although transmissions can alleviate the stress of a drought of a predominant renewable re-
60 source in one particular region [5, 6], coincident droughts that involve multiple renewable resources
61 such as wind, solar and hydro are of particular concern for their potential grid impacts. These
62 coincident, or compound energy droughts can be defined for any two or more variables, though
63 typically wind and solar are of the most interest due to their extensive adoption and growing in-
64 tegration into grids across the world [7, 8, 9, 10, 2, 11, 12]. In Germany, these compound drought
65 events are common enough that the word *dunkelflaute* has come to describe their impact to the
66 grid [13].

67 Drought events involving only sources of energy production are known as energy production
68 droughts [2]. Energy supply droughts involve use of load, typically determined from the net load or
69 the load after subtracting wind and solar production. In some cases, energy supply droughts may
70 be statistically significant but have no actual impact on the grid. For example, during a period of
71 high hydro generation, wind and solar could be in drought conditions yet still be curtailed, giving
72 the drought little or no impact. By including load in the definition of drought we are able to assess
73 the frequency, duration, and magnitude of drought events that have a greater chance of impacting
74 the grid.

75 Previous studies have focused on general meteorological drivers for energy droughts [14, 1, 15,
76 16, 17], or specifically on the reliability of complementary renewable systems [18, 19, 20]. Other
77 studies have looked at energy droughts and the complementarity of wind and solar in Europe
78 [21, 7, 22, 23, 10, 2, 24, 25, 1, 26, 11], Latin America [27, 8] and Africa [28]. Relatively few

79 studies have focused on North America. [12] examined weekly droughts for a region encompassing
80 most of western North America, finding that compound wind and solar droughts were most likely to
81 occur in the winter under specific atmospheric circulation patterns. [29] demonstrated summertime
82 meteorological drivers of relevance to renewable energy supply and demand. [30] examined wind
83 and solar energy droughts separately for California and the Western Interconnection, finding that
84 few daily-timescale droughts last longer than 7 days. [31] developed a space-time simulation model
85 that generates fields of hydroclimatic data used in energy drought analysis, and applied their model
86 to Texas.

87 Although energy droughts have been a focus in the aforementioned studies, none of them employ
88 a standardized definition of drought. There are variations in the time scales applied, drought
89 thresholds, and seasonality considerations when defining droughts. The lack of standardization
90 prevents the ability to measure energy droughts and link them to their impact on the power grid
91 as well as understanding the opportunities to design and site short to long term duration storage
92 technologies. In this paper we adopt the standardized energy drought indices introduced by [32]
93 and inspired by the indices used in hydrology and climatology [33].

94 The time scale of a drought is strongly related to the frequency and duration of drought
95 events [33]. Most previous studies use a single time scale to discuss energy droughts (typically
96 1-day or 1-week). In this study we look at several time scales ranging from 1-hour to 5-days
97 specifically designed around the management of hydropower and other potential storage resources.
98 Energy drought studies typically define droughts as consecutive periods of low or no production.
99 This definition is complicated somewhat when looking at sub-daily scales due to regular overnight
100 periods with no solar production. Some special consideration for these periods is necessary.

101 In this study we examine energy droughts across the Continental US (CONUS) at the Balancing
102 Authority (BA) scale. The wind and solar are considered "must-take" by the power grid at the BA
103 scale. Because of the intermittency, solar and wind are also considered non-dispatchable through
104 the transmission system. This scale is similar to countries and provinces and is strategic in that
105 wind, solar and load need to be balanced prior to understanding transmission needs. This spatial
106 scale was chosen for its application to future studies examining storage siting, sizing and operational
107 guidance to accommodate droughts and address reliability requirements in conjunction with the
108 role of transmission. The goals of this study are to (1) develop the first CONUS-scale assessment

109 and benchmark of energy droughts for the current (2020) infrastructure of wind and solar power
110 plants and (2) characterize the frequency, duration, and intensity of energy droughts including their
111 temporal and spatial distribution to inform power grid planning studies – specifically storage versus
112 transmission in long term planning studies. By utilizing actual wind and solar plant configuration
113 data from the U.S. Energy Information Administration (EIA) we get a view that is as representative
114 as possible to actual conditions. The analysis is based on the contemporary (2020) wind and solar
115 fleet and 40 years of historical weather (1980-2019). Future studies will look at future infrastructure
116 and weather conditions.

117 **2. Data**

118 *2.1. Wind and Solar Generation Data*

119 We utilized the simulated plant level solar and wind generation data produced as part of [34].
120 The dataset includes hourly wind and solar generation for all EIA-860 2020 plant locations [35]
121 using weather from 1980-2019 [36]. The reader is referred to that paper for full details, but a brief
122 summary of the approach is summarized here.

123 The wind and solar generation is based on meteorological data from the Thermodynamic Global
124 Warming (TGW) simulation data [37, 38]. TGW is dynamically downscaled based on ERA5 bound-
125 ary conditions [39]. The dataset includes historical simulations and future projections, but for this
126 study we only utilized the historical data (1980-2019). All meteorological variables are available at
127 1/8th degree (12km) resolution. Surface variables such as solar radiation and surface temperatures
128 are available hourly, while upper level atmospheric variables such as wind and pressure are available
129 3-hourly. All 3 hourly variables were linearly interpolated to hourly. Upper-level atmospheric data
130 that is only available at specific pressure levels was interpolated to the appropriate turbine hub
131 heights of each wind power plant.

132 Downward shortwave solar radiation, also known as Global Horizontal Irradiance (GHI), is an
133 available variable from TGW. Diffuse solar radiation was produced using the simulated GHI and
134 the DISC model [40, 41]. DISC has known biases when used under clear sky conditions so bias
135 correction was applied to the final solar generation data.

136 One potential challenge in utilizing the TGW data is the uncertainty around the capability of
137 the 1/8th degree TGW data to accurately capture cloud radiative effects – the impact of clouds

138 on the amount of longwave (LW) and shortwave (SW) radiation that reaches the surface. At this
139 resolution the majority of clouds, and thus their resulting impacts on surface radiation, must be
140 parameterized in the model that produced the TGW data. The parameterization of cloud radiative
141 effects is scale dependent [42]. Furthermore, the strongest shortwave cloud radiative effects come
142 from shallow cumulus clouds which are not resolved at this scale (e.g., [43]). Collectively this
143 means that the surface SW and LW radiation in the TGW data may be biased. To account for the
144 biases in the solar radiation data, National Solar Radiation Database (NSRDB) data was collected
145 at every plant location and run through identical solar generation models [44]. Bias correction was
146 then applied to the generation data [34]. Bias correction typically lowered the solar generation by
147 approximately 10%.

148 Using the TGW meteorology data, hourly wind and solar generation profiles were produced
149 across the CONUS for every wind and solar plant that is listed in the EIA-860 2020 database [35].
150 Power plant configurations were developed using EIA-860 data. These plant configurations along
151 with the TGW meteorological data were used as inputs to the NREL reV model [45, 46] to produce
152 hourly generation data for each plant.

153 *2.2. Load Data*

154 To characterize energy supply droughts we produced historical hourly total load projections that
155 correspond temporally and spatially to the wind and solar generation data. Loads were produced
156 using the Total ELectricity Loads (TELL) model which downscales simulated annual state-level
157 electricity demands to an hourly resolution [47, 48]. The input data to TELL is hourly time series of
158 meteorology from the same TGW dataset that underpins the wind and solar generation simulations.
159 TELL then uses the hour-to-hour variations in weather to model total load for each BA. Because
160 they are based on the same hourly gridded meteorology forcing the load, the simulations from
161 TELL and the wind and solar generation simulations are temporally and spatially coincident.

162 Over the 40 year historical period of the data, load has had an upward trend due to rising
163 population and, more recently, electrification. To account for such an upward trend, each year of
164 data was normalized by subtracting the annual mean and dividing by the annual standard deviation
165 for each Balancing Authority (BA). BAs are North American energy regions that are required to
166 balance total generation with load locally before relying on neighboring interconnected regions.
167 There are 69 BAs across the U.S. (as of 2020) which are equivalent to countries or sub regions in

168 other continental bulk power grids. The per-year per-BA load normalization allows for every year's
169 load to be analyzed equally and consistently using a percentile based threshold, described in the
170 next Section 3.

171 *2.3. Hourly BA-level Generation Data*

172 Plant-level wind and solar generation data were aggregated by BA. Due to the intermittency of
173 the resources, hourly wind and solar datasets are typically described either in MWh or with capacity
174 factors. In this study, generation is expressed as a capacity factor which is total generation divided
175 by total plant capacity. Only those BAs that had a minimum of 5 wind and solar plants were
176 included so that the results are not unduly influenced by a single plant. This resulted in 15 BAs
177 for this analysis that span the CONUS (Figure 1). The BAs cover most of the CONUS except
178 for the southeast region due to lack of wind plants. The 2020 fleet includes 2,817 solar plants and
179 1,151 wind plants (Table 1). The final dataset used in the analysis thus consists of hourly wind
180 and solar generation and coincident total load for each BA from 1980-2019 (40 years) for 15 BAs.

181 **3. Methodology**

182 Energy droughts have multiple definitions in the literature, but generally the goal is the same
183 in every definition: to define a period of time during which variable energy generation is low. The
184 definition is dependent on the threshold that is used to flag a low period as well as the resolution
185 of the input data. Definitions in the literature tend to look at daily data, but given that we have
186 hourly data it is possible to look at a variety of time scales from sub-daily to multi-day. This range
187 of resolutions aims to address specific temporal scales in bulk power grid operations, specifically
188 to address the need and optimal dispatch of sub-daily storage and management of longer duration
189 storage. Energy production droughts are those which only involve low energy production, in this
190 case wind and solar. A production drought might not have any grid impacts if load is low. Energy
191 supply droughts incorporate energy demand into the definition and quantify drought severity in
192 terms of demand or load shortfall.

193 *3.1. Energy Droughts - Sub-Daily to Multi-Day*

194 To define energy droughts we adopt the indices introduced by [32]. Standardized indices offer
195 a consistent scale that enables the comparison of droughts both within a single study and across

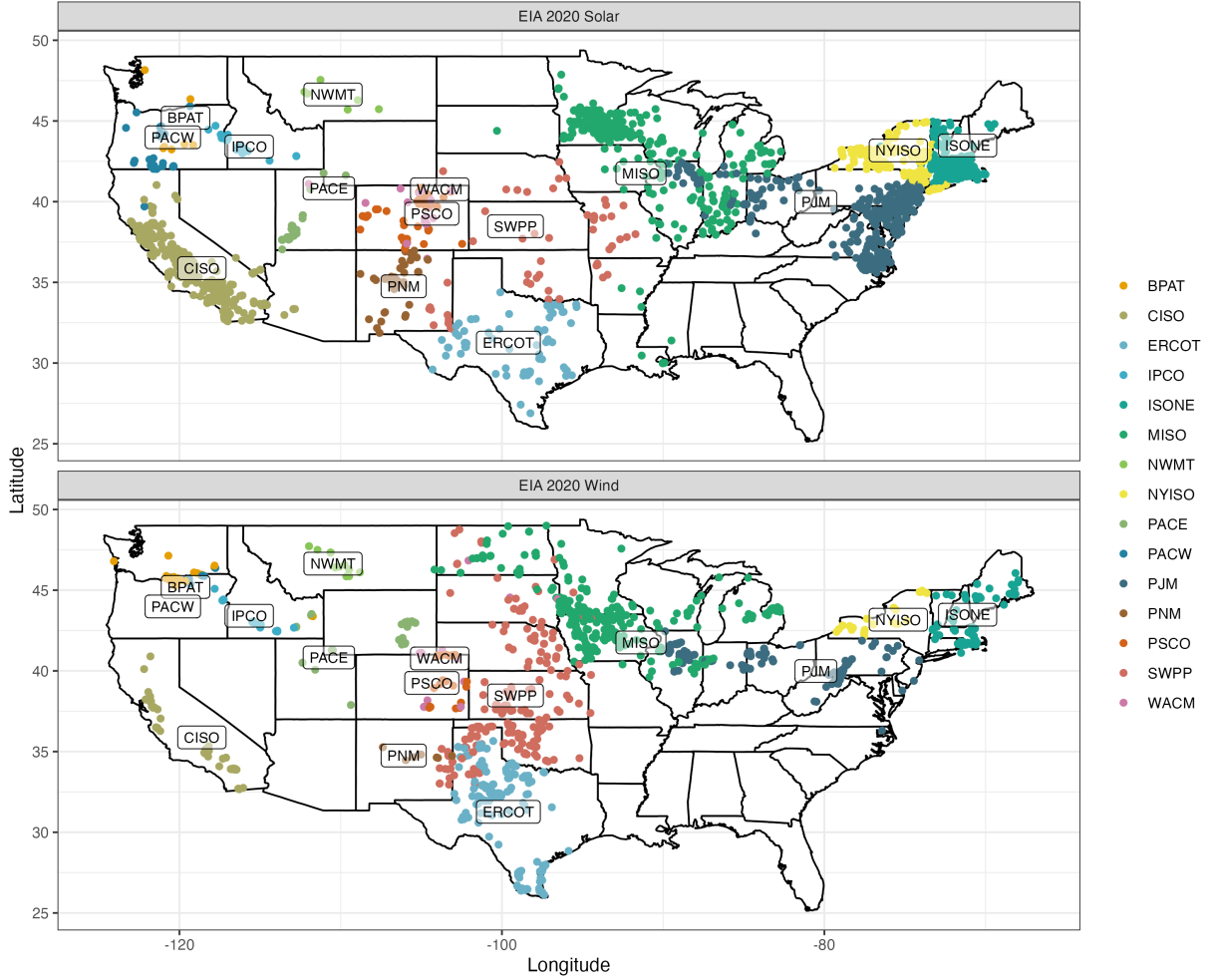


Figure 1: Wind and solar plant locations for each BA in the CONUS that contains at least 5 wind and solar plants.

196 multiple studies, and bring the definition of energy droughts in line with other fields such as hydro-
 197 ology and climatology. For wind and solar, the index introduced by [32] is called the standardized
 198 renewable energy production index (SREPI)

$$\text{SREPI}(P_t) = \Phi^{-1} \left(\frac{1}{n+2} \left[1 + \sum_{i=1}^n \mathbb{1}\{P_i \leq P_t\} \right] \right)$$

199 where P_t represents the solar or wind production at time t , Φ^{-1} is the standard normal quantile
 200 function, n is the number of points in a particular period of interest, $\mathbb{1}$ is the indicator function
 201 which returns 1 if the bracketed expression is true, 0 otherwise. The $n+2$ and $1+$ terms are
 202 plotting position adjustments so that the empirical cumulative distribution will never equal 0 or

| BA Code | BA Name | Solar Plant Count | Wind Plant Count | Solar Capacity (MW) | Wind Capacity (MW) |
|---------|--|-------------------------|------------------------|---------------------------|--------------------------|
| BPAT | Bonneville Power Administration | 11 | 29 | 88 | 3398 |
| CISO | California Independent System Operator | 572 | 125 | 14789 | 5836 |
| ERCOT | Electric Reliability Council of Texas, Inc. | 76 | 163 | 4864 | 27753 |
| IPCO | Idaho Power Company | 20 | 33 | 318 | 717 |
| ISNE | ISO New England Inc. | 518 | 82 | 1528 | 1504 |
| MISO | Midcontinent Independent Transmission System Operator, Inc. | 545 | 401 | 2056 | 26101 |
| NWMT | NorthWestern Energy | 6 | 16 | 17 | 453 |
| NYISO | New York Independent System Operator | 226 | 33 | 664 | 1989 |
| PACE | PacifiCorp - East | 34 | 30 | 1286 | 2690 |
| PACW | PacifiCorp - West | 29 | 19 | 294 | 694 |
| PJM | PJM Interconnection, LLC | 644 | 129 | 4557 | 10159 |
| PNM | Public Service Company of New Mexico | 51 | 7 | 370 | 1066 |
| PSCO | Public Service Company of Colorado | 68 | 28 | 519 | 4491 |
| SWPP | Southwest Power Pool | 55 | 224 | 393 | 24267 |
| WACM | Western Area Power Administration Rocky Mountain Region | 26 | 17 | 192 | 782 |

Table 1: Balancing Authorities used in this study along with the number of wind and solar plants per BA and the installed capacity of wind and solar as of 2020.

203 1, for which cases the indices are not well defined [32].

204 For load, the index is known as the standardized residual load index (SRLI)

$$\text{SRLI}(P_t) = \Phi^{-1} \left(\frac{1}{n+2} \left[1 + \sum_{i=1}^n \mathbb{1}\{L_i \leq L_t\} \right] \right)$$

205 where L_t represents the residual load at time t . We define residual load in this study as load
206 minus wind and solar production. In the analysis residual load is expressed as a fraction of the
207 maximum residual load in the period so that the load data is on the same scale as the wind and
208 solar capacity factors.

209 It is necessary when applying these indices to select a period of interest, which is used to
210 construct the empirical distribution functions and compute the indices. We elect to define the

211 distributions across all years of data, by week of the year, and by hour of the day in the case
 212 of sub-daily droughts. This approach has the benefit of revealing abnormal sub-daily to sub-
 213 seasonally drought conditions in all seasons, instead of only occurring where both wind and solar
 214 are seasonally low and addressing the need for other types of multi-season storage technologies or
 215 thermo-electric plants like nuclear technologies for base load.

216 With the indices for load, wind and solar computed we turn to the definitions of energy droughts.
 217 In this study, we define two types of droughts - production and supply: Wind and Solar (WS) and
 218 Load, Wind, and Solar (LWS) respectively. We presently have not included hydropower as the
 219 time scales involved are much longer and can be addressed with cross-seasonal water management
 220 in future studies. WS droughts occur when both wind and solar SREPI values fall below -1.28 for
 221 the entire drought period, which corresponds to the 10th percentile or below of production in both
 222 resources. The drought may last 2 hours or more¹. LWS droughts use the same definition for wind
 223 and solar but add in a third criteria where the SRLI must also fall above 1.28 for the entire drought
 224 period (which corresponds to a 90th percentile threshold for load). According to the thresholds in
 225 [32], this would be classified as a Moderate drought. Drought definitions are summarized in Table
 226 2. Sensitivity analysis for the 10th percentile threshold is presented in the supplemental materials
 227 (Figure A.7 and Figure A.8).

| Drought type | Drought definition |
|----------------------------|--|
| Wind and Solar (WS) | $SREPI(W_t) < -1.28$ and $SREPI(S_t) < -1.28$ |
| Load, Wind and Solar (LWS) | $SRLI(L_t) > 1.28$ and $SREPI(W_t) < -1.28$ and $SREPI(S_t) < -1.28$ |

Table 2: Definitions for WS and LWS droughts. $SREPI(W_t)$, $SREPI(S_t)$ and $SRLI(L_t)$ indicate the wind, solar and load index values at time t , respectively.

228 We compute energy droughts for seven time scales: 1-hour, 4-hour, 12-hour, 1-day, 2-day, 3-day,
 229 and 5-day. When utilizing time scales of greater than one hour (4-hour or more), the energy is
 230 totaled over the period and the threshold is applied to the aggregated data. This allows for the
 231 possibility that not every hour during a drought period falls below the threshold. For time scales
 232 of less than one day (1-, 4- and 12-hour), one should keep in mind that the nighttime period has no
 233 solar generation. We allowed the nighttime period for solar to function as a wild card, i.e. droughts

¹We excluded droughts lasting only 1 hour due to excessive noise in the data, all other time scales the droughts can last 1 timestep or longer

234 that start before the nighttime where the wind is still below the threshold, are allowed to continue
 235 overnight.

236 3.2. Drought Frequency, Duration and Magnitude

237 In order to identify potential grid impacts and to inform grid planning, specific information
 238 about drought frequency, duration, and magnitude are necessary. Frequency is defined as the
 239 average number of droughts in a year across the 40 year historical record. Duration is defined
 240 by the number of consecutive timesteps falling below (or above in the case of load) the percentile
 241 threshold, multiplied by the timestep length.

242 Drought magnitude for a single variable is defined by the summation of the absolute value of the
 243 index (SREPI or SRLI) over the drought period [32]. This definition works well for single variable
 244 droughts when using a single time scale, but is not suitable to compare droughts across different
 245 time scales and between different compound drought events (WS vs. LWS). For example, shorter
 246 time scales will tend to have higher drought magnitude simply due to having more timesteps. In
 247 addition, compound droughts with more variables will appear to have a larger magnitude due to
 248 more variables being added up each timestep. For these reasons, we found it necessary to modify
 249 the definition of drought magnitude slightly. For compound droughts we define the magnitude
 250 to be the sum of average of the absolute values of the indices involved in the drought, effectively
 251 providing a single average drought magnitude that is on the same scale as the original indices. Given
 252 n variables each corresponding to a standardized index in I_1, \dots, I_n , respectively, the compound
 253 drought magnitude (CDM) is defined as

$$\text{CDM} = \frac{1}{nD} \sum_{j=t}^{t+D-1} \sum_{k=1}^n |I_k|$$

254 where CDM is the compound drought magnitude, t is the first timestep of the drought, D is the
 255 drought duration. For example, for a LWS drought,

$$\text{CDM}_{\text{LWS}} = \frac{1}{3D} \left[\sum_{j=t}^{t+D-1} | \text{SREPI}(W_j) | + | \text{SREPI}(S_j) | + | \text{SRLI}(L_j) | \right]$$

256 For WS droughts this can be easily modified by excluding the SRLI term and dividing by 2 instead
 257 of 3.

258 4. Results

259 4.1. Duration

260 WS drought duration is of particular interest for grid resource planning and storage sizing.
261 Figure 2 shows empirical cumulative distribution functions (CDFs) of drought duration of the
262 entire historical record for 3 time scales. 1-hour droughts are those in which every subsequent hour
263 consistently measures below the 10th percentile threshold; This is useful for applications to sub-
264 daily unit commitment. 1-day droughts are those with consecutive days in which the total energy
265 falls below the threshold for each successive day; they are intended for applications to day ahead
266 market and unit commitment. 3-day droughts are determined similarly to 1-day droughts and are
267 intended for managing longer term storage and daily resources with limited ability to recharge
268 daily. We note that all the BAs show remarkable similarity in the duration of droughts across all
269 time scales as shown by similar CDF shapes. 1-hour WS droughts in the CONUS never last more
270 than about 1.5 days, with the longest drought of about 37 hours occurring in Texas (ERCOT).
271 The shortest 1-hour maximum duration across BAs is roughly 16 hours in California (CISO). The
272 1-hour drought duration across the CONUS is strongly driven by the solar variability which is in
273 turn driven by cloud variability – droughts based solely on wind exhibit much longer durations
274 (not shown). For 1-day and 3-day time scales, California (CISO) exhibits the longest duration of
275 WS droughts at 6 days and 9 days, respectively. BPAT in the Pacific Northwest has the shortest
276 maximum duration at about 2 days and 3 days, respectively. In general, CISO stands out as the
277 BA with the longest duration of droughts at 1-day time scales or longer and ERCOT tends to have
278 the longest droughts at shorter time scales.

279 4.2. Compound Drought Magnitude

280 In the methodology section we introduced the CDM metric with the ability to compare droughts
281 across time scales and when using different number of variables such as WS (production) vs. LWS
282 (supply) droughts. Figure 3 shows the CDM for all BAs across all time scales. All BAs are grouped
283 together for a particular time scale to show the utility of the CDM metric. Clearly LWS droughts
284 are higher in magnitude than WS droughts across all time scales. This finding is significant and
285 indicates that on average wind and solar droughts that co-occur with high loads are more severe
286 than those that occur otherwise. This may be due to WS droughts occurring more often during

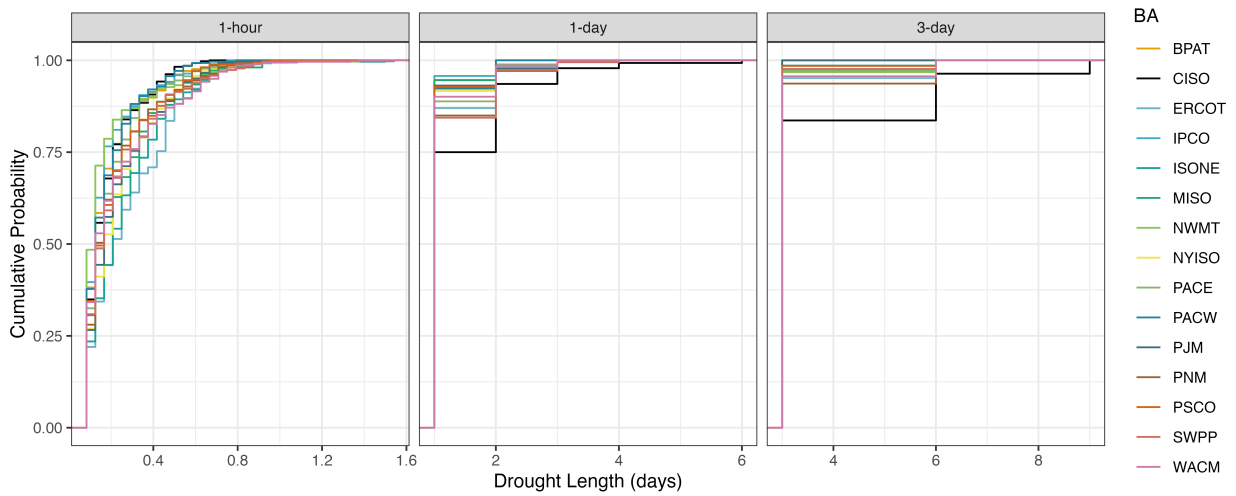


Figure 2: Empirical CDFs for WS drought duration, for 1-hour, 1-day and 3-day time scales. CISO is highlighted in black as it tends to be the BA with the longest duration droughts at time scales longer than hourly.

287 extreme temperature conditions when load is high. More research is necessary to determine the
 288 specific meteorological mechanisms, but this statistical finding may be of interest to grid planners.
 289 Also of note, there is a minor decrease in the magnitude of both LWS and WS droughts as time
 290 scale increases. At longer time scales the criteria for droughts is harder to satisfy so those droughts
 291 that do meet the criteria tend to be less severe.

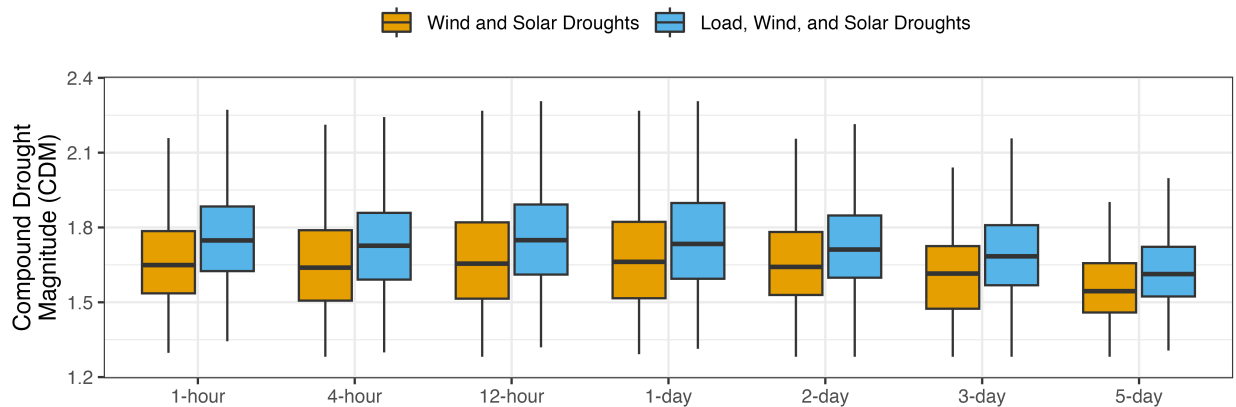


Figure 3: CDM for WS and LWS droughts for all BAs across all time scales.

292 4.3. *Spatial distribution of frequency and maximum duration*

293 Figure 4 shows the frequency and maximum duration of droughts in all the BAs included in the
294 study for a 1-hour and 1-day time scale. The size of the dots indicates the number of events per
295 year and the color indicates the maximum drought duration observed during the historical period.
296 1-hour droughts exhibit some spatial grouping in terms of drought duration, such as the Rocky
297 Mountains, and across the north. Daily droughts also show a clear spatial pattern. Duration tends
298 to be shorter (0-2 days) in the northern BAs and longer in the southern BAs (2-4 days), with
299 CISO again standing out as having the longest duration droughts (4-6 days). The most frequent
300 1-hour droughts (9-13 per year) occur in the central and Rocky Mountain regions, while the least
301 frequent droughts occur in the northern regions (5-9 per year). A similar spatial pattern is present
302 in the 1-day droughts with the most frequent events (4-6 per year) occurring in the central and
303 Rocky Mountain regions and the least frequent events (2-4 per year) occurring in the northern
304 regions. This result is somewhat counter-intuitive as one might expect that regions with less solar
305 production, simply due to higher latitude or climatological conditions, might have more frequent
306 droughts. In this study, energy droughts are only identified when solar and wind production
307 is abnormally low for a particular period of the year, effectively excluding seasonal signals. In
308 regions where low solar production is typical, it is more difficult to have abnormally low conditions
309 compared to regions where high production is normal, and thus there are less frequent sub-seasonal
310 droughts.

311 4.4. *Seasonal Distribution of Droughts*

312 Figure 5 shows the seasonal distributions of daily energy droughts for each BA. Most BAs do not
313 exhibit a strong seasonal drought signal, except for CISO where droughts are far more common in
314 the summer months. Drought duration also does not exhibit a strong seasonal distribution. These
315 results indicate that in most BAs across the CONUS (except CISO), compound WS droughts have
316 an approximately equal probability of occurring in any season. It is worth noting that the lack
317 of seasonal signal in most BAs is expected and certainly related to the way droughts are defined
318 in this study. We chose to use a moving threshold that changes based on the week of the year.
319 If droughts were defined based on a single yearly threshold, then they would occur most often at
320 the time of the year when the wind and solar were both climatologically lowest and would impact
321 different storage technologies (seasonal). When defined using a fixed threshold droughts tend to

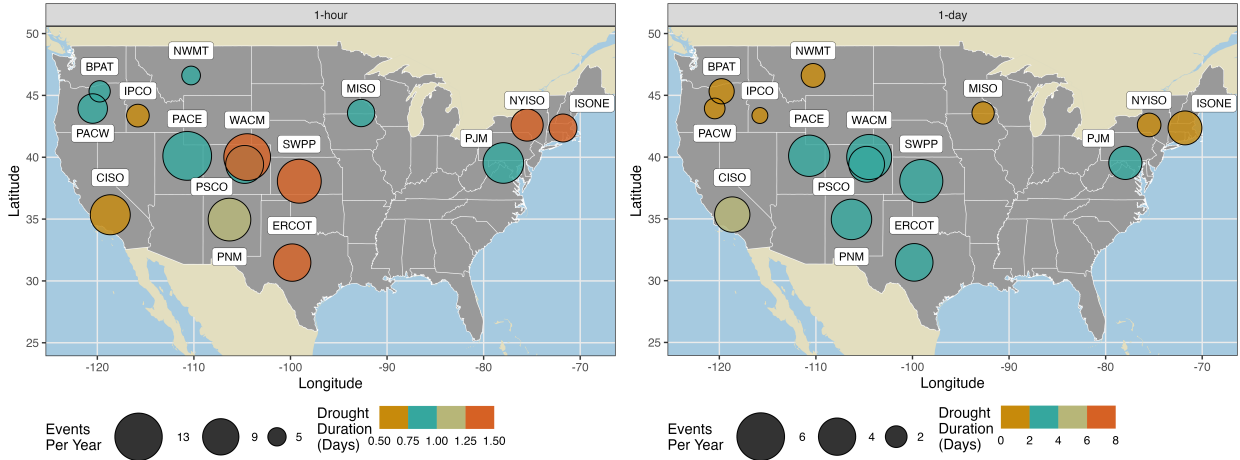


Figure 4: Hourly (left panel) and daily (right panel) droughts. The maximum drought duration is indicated by the bubble color and the the drought frequency is indicated by the size of the bubble. Note the scale of the drought frequency is different in each panel.

322 occur more often and with longer duration in the fall and winter though the timing does vary
 323 substantially between BAs (Figure A.9).

324 4.5. WS vs. LWS Droughts

325 In order to summarise the average behavior of WS and LWS droughts, Figure 6 displays average
 326 frequency (events per year) and duration of droughts in days for all 15 BAs. The left panel shows
 327 WS droughts and the right panel shows LWS droughts. About half as many LWS droughts tend
 328 to occur each year compared to WS. While a decrease in frequency is expected due to the extra
 329 load criteria placed on the drought definition, this reduction in frequency is smaller than expected
 330 if high load events were independent of WS droughts. Given the 90th percentile threshold used in
 331 the definition of LWS droughts, we would expect the frequency of LWS droughts to drop by 90%
 332 if the WS droughts were equally distributed across all potential load values. The fact that the
 333 frequency of events instead only drops by 50% suggests that the WS droughts preferentially occur
 334 during periods of high loads.

335 In Figure 6, 1-hour and 4-hour time scale droughts have nearly indistinguishable average du-
 336 rations, while other time scales tend to cluster just above the minimum duration possible. The
 337 vertical lines from each point span from the minimum drought duration to the maximum, indi-
 338 cating that the drought duration distributions are highly skewed. The durations do not exhibit

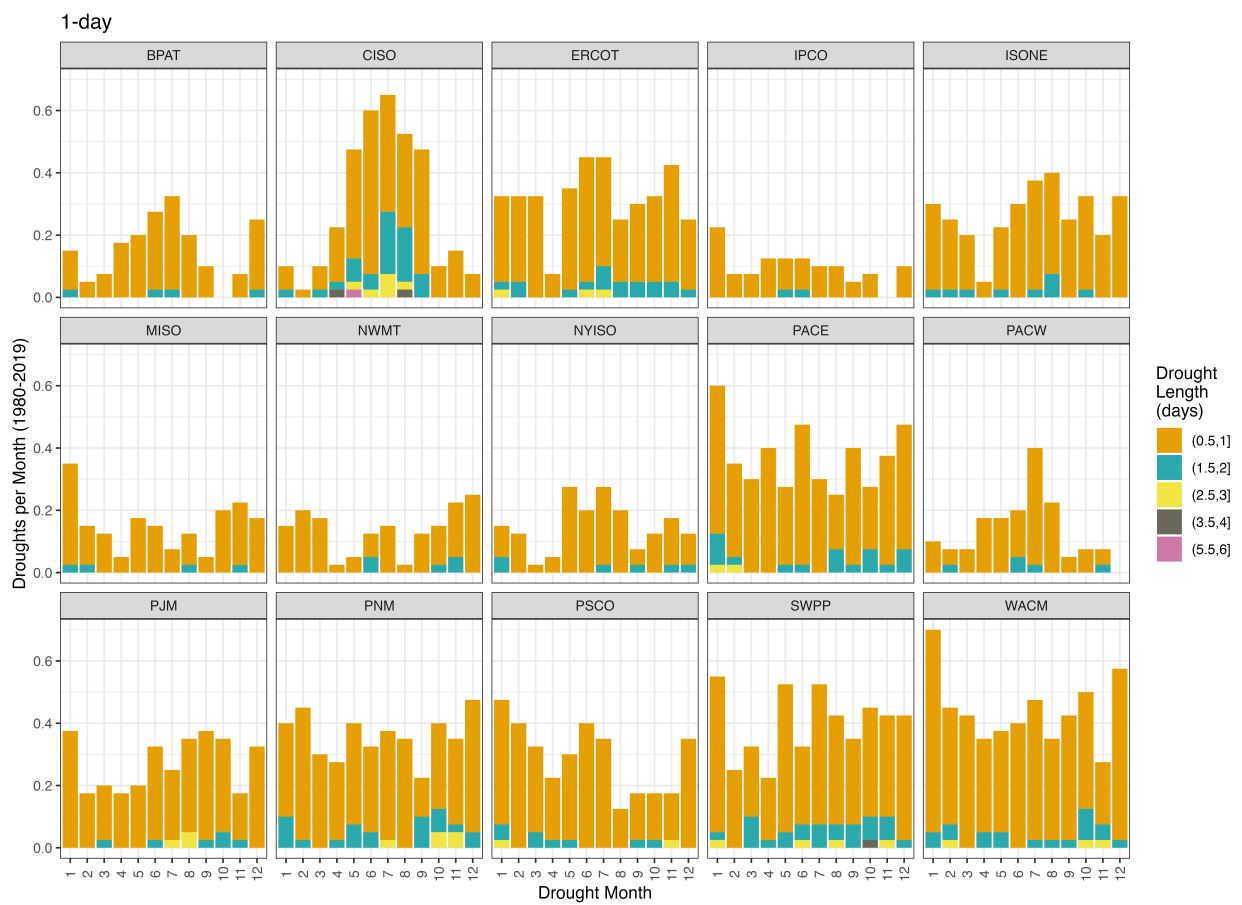


Figure 5: Seasonal distributions of energy droughts. The bar heights indicate the frequency of droughts in a particular month (average number of droughts per year). The color indicates the drought duration.

339 significant differences between WS droughts and LWS droughts.

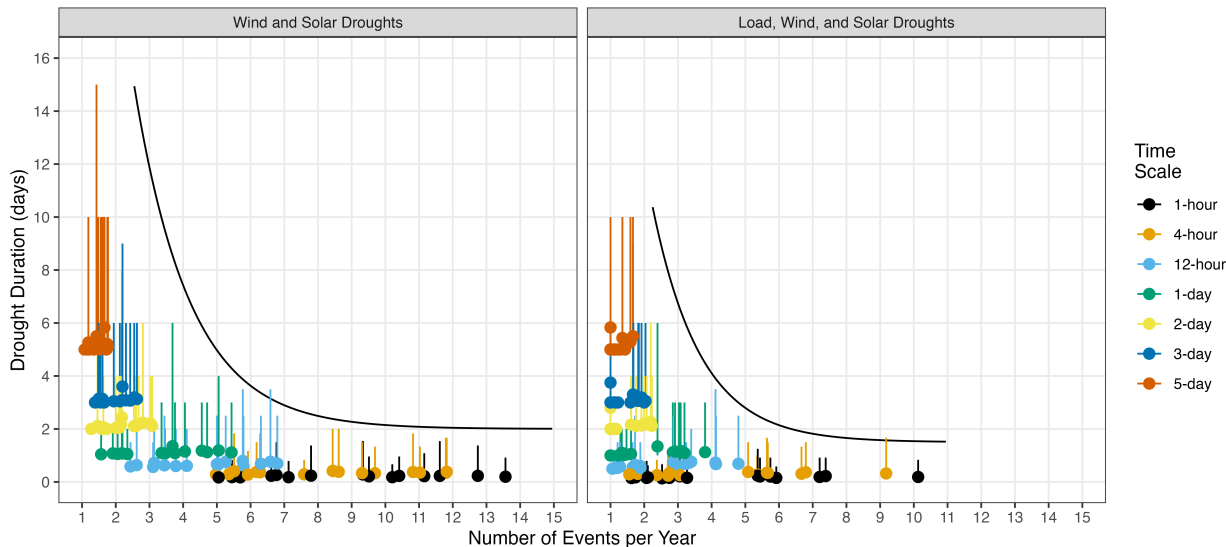


Figure 6: Magnitude, duration and frequency of energy droughts for all BAs and aggregation periods. WS droughts are shown in the left panel and LWS droughts in the right panel. The points indicate the mean drought duration for a BA at a given time scale, the vertical lines indicate the range of drought durations from the min to the max observed duration in the 40 year period. The curved line is an exponential curve meant to illustrate a rough upper bounding region for the data.

340 5. Limitations and Discussion

341 In this section we discuss some of the limitations of this study and broader implications. First
 342 and foremost, hydropower is not represented in this study. In some regions, like the Pacific North-
 343 west, hydropower is a dominant source of renewable energy such that integrating wind and solar
 344 and mitigating local energy droughts to 6 days is not a major concern. In other regions, hy-
 345 dropower is a conserved resource critical for ramping, energy storage, and mitigating the cost of
 346 additional battery storage to manage wind and solar droughts. In this study we focus on sub-daily
 347 to multi-day droughts without consideration of hydropower since water resources at those scales
 348 can most often be managed to mitigate those droughts if the market incentives are present. For
 349 studies which consider seasonal or longer period droughts, hydropower should be considered.

350 Drought studies at the BA scale are strategic to understand the potential need for local storage,
 351 and innovate on commitment approaches and market incentives. Even though we looked into

352 LWS (supply) droughts, we note that adjacent BAs linked by transmission may display seasonal
353 complementarities and thus reduce the local stress. This research needs to feed into more complete
354 studies where production cost models are involved in evaluating local storage versus transmission
355 with social equity impacts. Those production cost model simulations are resources intensive and
356 our approach identifies events to prioritize.

357 We chose to use a 10th percentile benchmark in this study across wind, solar and load. Although
358 we do provide a sensitivity analysis in the appendix, such thresholds alone may not represent
359 conditions that are extreme enough to stress the grid, even when compound events are considered.
360 Our study could be complemented with thermal derating and forced power outages when reaching
361 certain thresholds which would accentuate the impact of droughts. In that sense, 10 percent is a
362 regional standardized threshold but derating and unit outages could add a different dimension to
363 the overall severity. Finally, the choice to use a fixed or moving threshold has implications that
364 vary by application and by region – a more detailed exploratory analysis should likely consider both
365 approaches. Nonetheless this work represents the first benchmark of standardized contemporary
366 energy production and supply droughts by BA over the CONUS.

367 **6. Conclusions**

368 In this study we present a methodology and dataset for examining compound wind and so-
369 lar energy droughts that have the potential to impact the power grid dynamics and local supply.
370 Specifically we provide the first standardized benchmark of energy droughts in the Continental
371 United States (CONUS). By focusing our results on 15 Balancing Authorities (BAs) with numer-
372 ous utility scale wind and solar plants, we are able to draw conclusions that are applicable to grid
373 planning and storage sizing. BA-level load was included to quantify high residual load coincident
374 with Wind and Solar (WS) droughts, providing a view of the potential impact of compound Load,
375 Wind, and Solar (LWS) events. We utilized a dataset of hourly BA level generation which in-
376 cludes thousands of 2020 infrastructure wind and solar plants. Using this dataset we examine the
377 frequency, duration, and magnitude of energy droughts at a variety of temporal and spatial scales.

378 To classify compound droughts we utilize the standardized renewable energy production index
379 (SREPI) and the standardized residual load index (SRLI). This study is the first application of
380 these indices outside of the original paper focusing on the development of the indices and a case

381 study in Europe [32]. In addition, we introduce a definition of compound drought magnitude
382 (CDM) that is suitable for comparing droughts across different timescales and with any number of
383 variables.

384 WS droughts are typically less frequent and shorter in the northern CONUS compared to other
385 regions. California stands out as having the longest duration droughts at time scales 1-day or
386 longer but having among the shortest duration of droughts at shorter time scales. Droughts in
387 California also show a strong seasonality, tending to occur in the summer, while other BAs tend
388 to show a more even distribution across the year. Adjacent droughts in the Pacific Northwest and
389 Rockies tend to have some of the lowest and highest drought frequencies, respectively. At shorter
390 timescales, eastern BAs have some of the longest drought durations recorded. Existing hydropower
391 resources in the area may be able to mitigate this given the drought durations tend to be low to
392 moderate at longer time scales. ERCOT which covers most of Texas, has limited interconnections
393 with other BAs. It also has some of the longest 1-hour droughts in the record, although at longer
394 timescales the droughts are on the lower end compared to other BAs. This suggests a need for
395 short term storage infrastructure in a decarbonized future.

396 LWS droughts differ from WS droughts notably in the average frequency of events per year, sug-
397 gesting that WS droughts occur preferentially with high load events. Additionally, LWS droughts
398 exhibit higher magnitudes on average than WS droughts. Both of these findings have implications
399 to grid planning and storage sizing. WS and LWS droughts exhibit similar durations across all
400 time scales.

401 The standardized approach in this study supports the synthesis of this type of research at
402 storage and energy system security scales. This research on standardized drought informs research
403 in storage, transmission siting and sizing, characterization of extreme events for climate stress tests
404 and reliability studies. Some potential future work includes i) incorporating derating and forced
405 outages, ii) applications to evolving infrastructure, iii) future climate, and v) future markets since
406 a "must-take" approach in the U.S. may not be appropriate under deep decarbonization scenarios.

407 **7. Data and Code Availability**

408 The energy drought analytics and dataset developed in this paper is available at:
409 <https://zenodo.org/record/8008034>

410 The code used to conduct the analysis and produce the figures is available on GitHub:
411 <https://github.com/GODEEEP/energy-droughts>

412 8. Credit Author Statement

413 Cameron Bracken: Conceptualization, Data curation, Formal analysis, Investigation, Method-
414 ology, Software, Visualization, Roles/Writing – original draft. Nathalie Voisin: Conceptualization,
415 Methodology, Supervision, Writing – review & editing. Casey Burleyson: Data curation, Writing
416 – review & editing. Allison Campbell: Conceptualization, Writing – review & editing. Z. Jason
417 Hou: Conceptualization, Writing – review & editing. Daniel Broman: Conceptualization.

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552 **Appendix A. Supplemental Material**

553 Figure A.7 shows a sensitivity analysis of drought duration by changing the percentile threshold
 554 for the 1-day time scale. The dashed lines show the min and max duration and the solid line is the
 555 average duration.

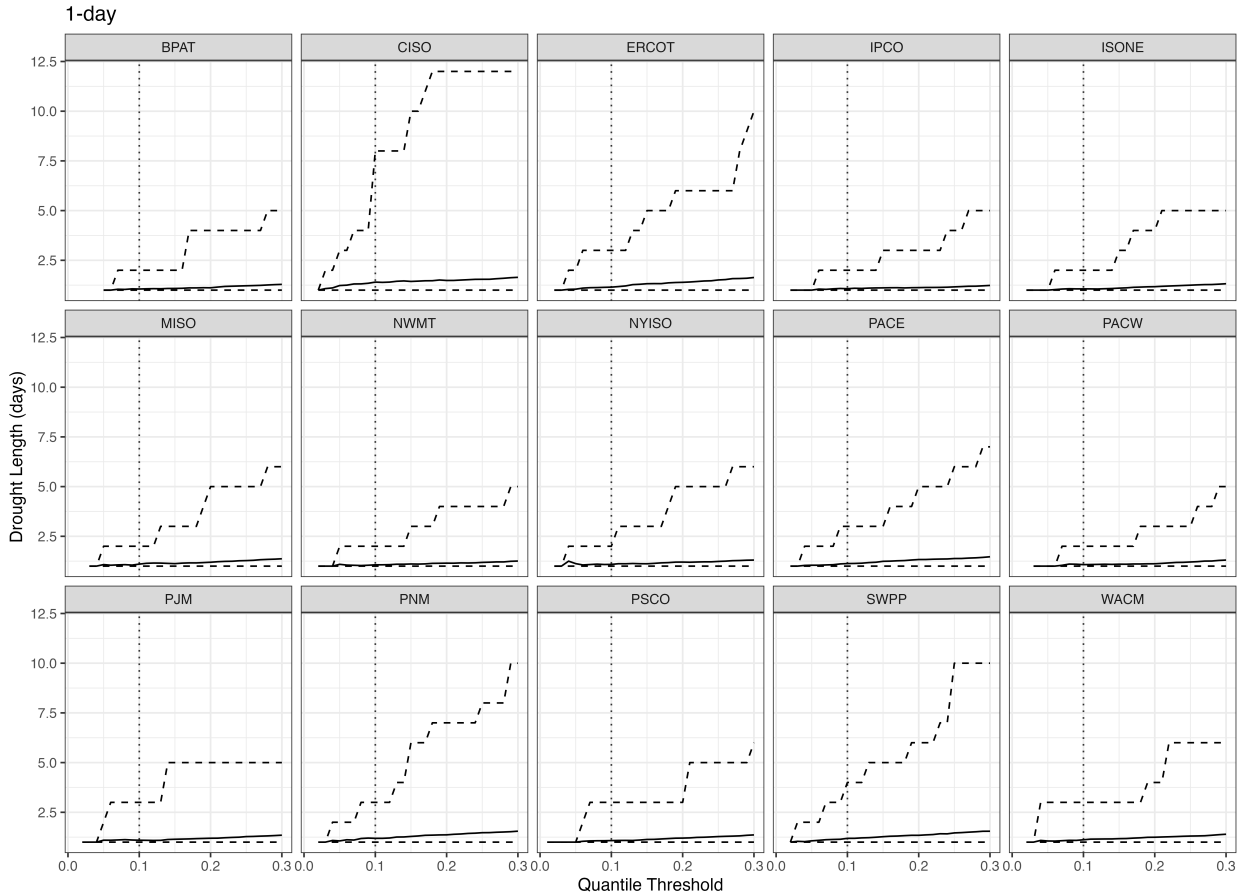


Figure A.7: Sensitivity analysis for drought duration. The dashed lines show the min and max duration and the solid line is the average duration.

556 Figure A.8 shows a sensitivity analysis of compound WS drought magnitude by changing the
 557 percentile threshold for the 1-day time scale. The dashed lines show the min and max magnitude
 558 and the solid line is the average magnitude.

559 Figure A.9 shows the seasonality of 1-day drought frequency defined using a fixed threshold,
 560 as opposed to a moving threshold based on time of the year. There is strong seasonality exhib-
 561 ited in many BAs (eg. CISO, PACW) corresponding to periods where wind and solar are both

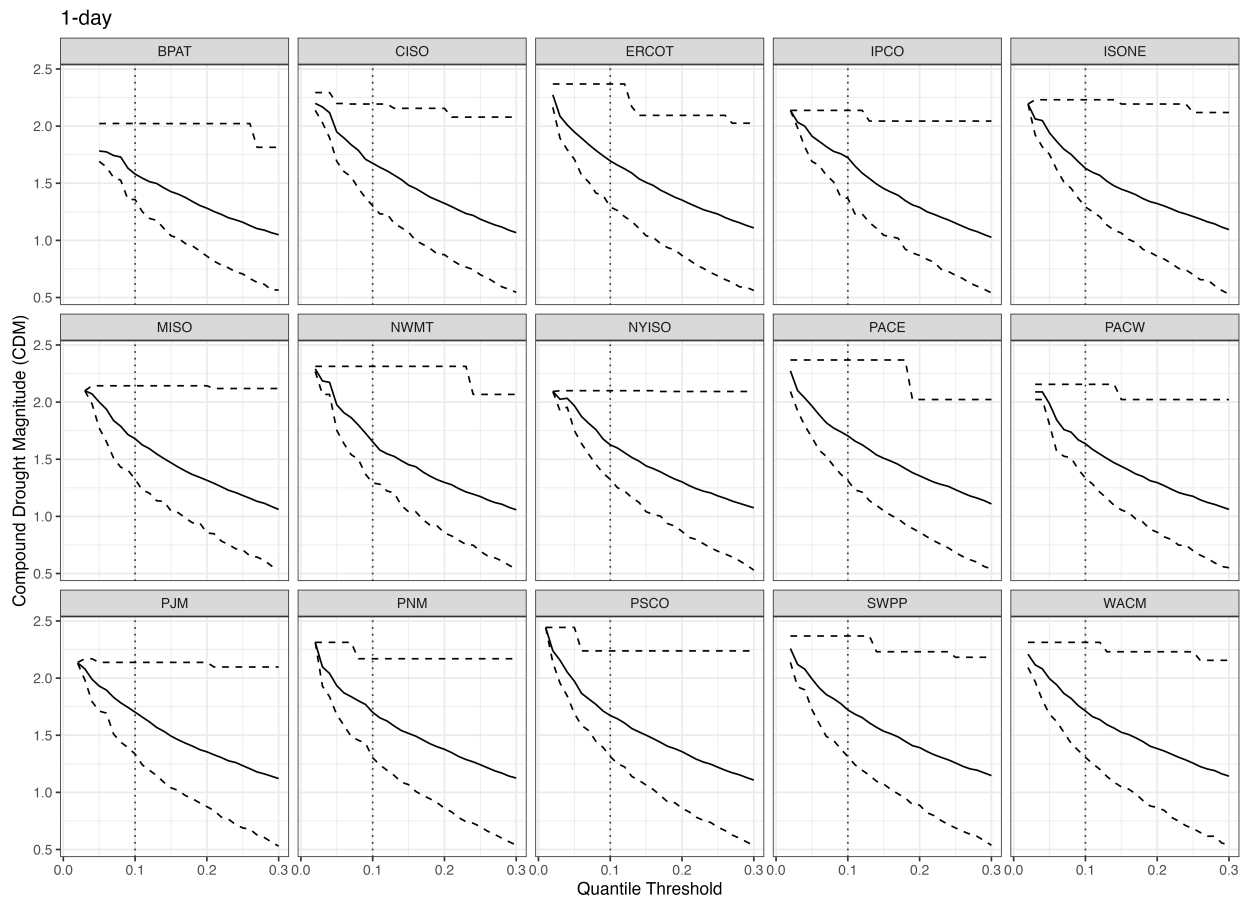


Figure A.8: Sensitivity analysis for drought magnitude. The dashed lines show the min and max magnitude and the solid line is the average magnitude.

562 climatologically low.



Figure A.9: Average number of droughts per month defined using a fixed 10th percentile threshold. Note the y axis is different for each panel.