Screening Global Solar and Wind Energy Investment Potential Accounting for Drought and Surplus

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Abstract

Climate-induced variability of solar and wind energy impacts renewable electricity scaling. Long duration renewable energy droughts, i.e., extended periods of renewable supply deficits, lead to contract penalties or use of thermo-electric sources, while long duration surpluses result in curtailment or in low energy prices and revenue. We present the first global assessment of the implied financial risk for solar and wind deployment due to droughts and surpluses. A seasonally varying threshold is identified at each location to represent reliable contractible production. Cumulative deficits and surpluses and their durations relative to this threshold are identified as proxies for financial investment risk. We consider co-variations in solar and wind outputs to identify their potential for amplifying or buffering deficits/surpluses. Strategic regions for contractible wind and solar energy potential and associated drought/surplus severity and duration are identified globally to inform future investments and risks.

1) Introduction

Renewable energy growth is essential for decarbonizing the electricity sector [1], but climate-driven variability of renewable energy is seen as a significant factor for scaling [2,3]. Global installed capacities of wind and solar energy have grown significantly. According to the Global Wind Energy Council (GWEC), the share of wind global power capacity increased from 2% to 8%, and newly installed photovoltaic capacity reached 345.8 GW in 2023, accounting for three-quarters of global renewable energy capacity additions that year [4]. Regions with high penetration of solar and wind have already experienced concerns with grid reliability and market price collapse due to spatiotemporal variability in wind and solar energy [5]. Accounting for climate variability in electricity supply is critical to meet large-scale integration goals for global emissions reduction [3,6]. Regions with high penetration of solar and wind have experienced curtailment, and zero or negative prices during periods of excess supply [7–9]. Excess supply above a guaranteed or reliable forward contract can lead to a collapse in spot market or day ahead electricity prices, or to a curtailment of production, thus diminishing assumed returns on investment. In 2024, examples of curtailment include Germany (3.5% of its wind energy generation, totaling around 8,000 GWh [10,11]); Chile (5909 GWh of solar and wind, an increase of 121% over the previous year, and nearly 50% at some PV plants, resulting in significant losses for investors[12]); the UK (8.3 terawatt-hours (TWh) of wind-generated electricity, accounting for nearly 10% of total wind production at direct costs of around £393 million[13]); and California (1,180 hours of negative electricity prices, accounting for about 13% of the year, with the median negative price around –$17 per megawatt-hour (MWh), nearly double the –$10/MWh in 2023[14]).

Similarly, long duration deficits or energy droughts[15] from contracted supply can exceed the capacity of existing battery storage and can lead to penalties on the contract, or the use of alternate, more expensive and carbon emitting electricity sources. In October-November 2024, Germany experienced its worst wind drought over the past 3 years, with a reduction of approximately 25% in produced electricity, and a substantial increase in gas-fired electricity production, from 5.34 terawatt-hours (TWh) in October to 9.55 TWh in November [16]. Thus, both long-duration deficits and surpluses influence the financial viability and environmental outcomes of large-scale renewable energy installation and motivate the need for a joint analysis of the conditions that lead to higher or lower renewable energy production relative to expectation.

To address supply reliability issues, measures such as regional grid interconnection [17], storage technologies, and backup generation systems have been adopted [18]. Grid interconnection helps balance the uneven availability of renewable energy across regions by sharing power resources [19,20]. Battery storage smooths supply by offloading renewable power during excess periods for future use during shortages [19–21]. Current battery storage capacity can only mitigate shortages up to several hours [21]. Hydropower and pumped storage units offer renewable energy storage and operation, but their availability is limited. Backup generation systems, such as those powered by chemical fuels [20], hydrogen [22], or ammonia [23], can provide reliability for longer periods, and surplus renewable energy could be used to generate these fuels. However, platforms for these solutions are still nascent, and their cost profiles relying on surplus energy are not well established. Thermal power plants are difficult to ramp up quickly[24]. In some cases, this has led to higher carbon emissions than before the adoption of renewable energy [25]. Overcapacity, i.e., installing more solar and wind, offers a partial solution to energy droughts, but its provision increases the potential for periods of surplus production with an associated price decline, thus reducing their financial efficacy.

The frequency and severity of deficits and surpluses influences the economics of the energy system and determines investment returns. . Renewable energy droughts and surpluses emerge as critical factors in addition to the base energy potential for a region [26].

A global assessment of the impact of climate variability on renewable energy droughts and surpluses is needed to understand the potential for scalability. Current studies analyze energy droughts [15,27–30] but not surpluses. Given this background, we address the following questions in this paper:

1. What are the characteristics of the spatial distribution of wind and solar energy droughts and surpluses across global land areas? What is the severity and duration of these surpluses and deficits?
2. Which regions exhibit spatiotemporal complementarity such that wind and solar resources surplus/drought are negatively correlated, buffering their mutual variability? Which regions show amplified risk for joint wind/solar drought or surplus?

3. Where should future renewable energy investments be placed globally, considering local energy potential and variability?

We use global land-area, hourly data at a 0.5-degree latitude/longitude resolution from the [ERA5 reanalysis datasets](). The downward surface solar radiation and the 100m u- and v-components of wind were extracted, covering the period from January 1, 1940, to February 29, 2024. The zonal (u) and meridional (v) wind components were combined to get the vector amplitude of the hourly wind velocity, and the associated wind kinetic energy. The hourly data were aggregated to daily values at each location. Since our primary interest is in comparing the relative suitability of regions based on reliable availability and variability, we directly use solar energy and wind kinetic energy data in our analysis, instead of assuming a specific panel or turbine design.

We consider the q^{th} percentile (results are presented for q=25%) of the daily wind or solar energy for each calendar month at a location as a potential threshold that could be used to define a seasonally variable (100-q)% reliable, firm price contract at that. Energy production below this threshold would then constitute a deficit that must be made up from other sources or face a penalty for contract non-performance. Correspondingly, energy production above this threshold is not contracted and would be sold on the spot or day-ahead market, which may discount the value of the energy. We define drought or surplus duration and severity relative to this threshold at each location as follows:

- Identify each drought or surplus event for each historical month, and its severity and duration. Define the daily cumulative deficit Def_{kjt} and surplus Sur_{kjt} as:

$$Def_{kjt} = \left(0, E_{jt} - T_{j*}^{q} + Def_{kjt-1}\right)$$

$$Sur_{kjt} = \left(0, E_{jt} - T_{j*}^{q} + Sur_{kjt-1}\right)$$

  Where k is the deficit or surplus event index, j is the calendar month, and t is the day; E_{jt} is the energy produced; and T_{j*}^{q} is the q^{th} percentile of daily energy E_{j*t} produced in the calendar month j*. DD_{jk}= Duration of the k^{th} deficit event in month j, and DS_{jk}= Duration of the k^{th} surplus event in month j.

- The drought/surplus of concern is then recorded for each month as the maximum cumulative deficit D_{j*} or surplus for that calendar month, and the corresponding durations are noted.

$$D_{j*} = max_k(Def_{kjt}) \qquad\qquad S_{j*} = max_k(Sur_{kjt})$$

- We normalize these statistics by using a ratio of these values to the time-varying threshold at each location. This allows us to decompose the evaluation of the potential contractible energy production at each site, represented by T_{j*}^q from its variability, represented by the maximum monthly cumulative deficits and surpluses. This scaled measure then permits a comparison of the surplus/drought risk over the period of record, across all locations.

$$RD_q = \frac{D_{j*}}{T_{j*}^q} \qquad RS_q = \frac{DS_{j*}}{T_{j*}^q}$$

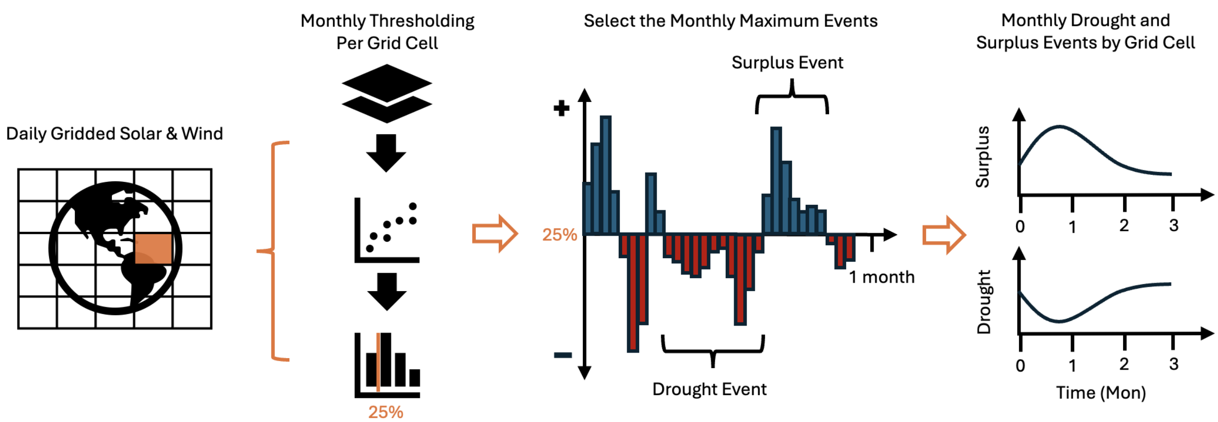

Fig. 1 Flowchart for defining global energy surplus and drought events.

For each calendar month, cumulative deficits and surpluses relative to the qth percentile of daily energy data are computed for each deficit/surplus event and the event with the maximum severity of surplus or deficit for that month is selected. This severity is scaled by the qth percentile of daily energy production for that calendar month for that location. The timing of all events is recorded for the evaluation of potential buffering or compounding of the risk at and across locations.

The workflow for identifying energy drought and surplus events is illustrated in Fig. 1. We consider the spatiotemporal overlap of wind and solar droughts and surpluses to identify regions where complementary pairing of wind and solar supply systems can mitigate or compound risks using correlation analyses. Finally, by integrating resource potential as indicated by T_{j*}^q, with the risk measures RD_q and RS_q, of drought and surplus events, we classify the world into "Energy

Investment Zones." This classification, considering resource availability and maximal droughts and surpluses over the period of record, provides a measure of the risk-balanced suitability of each location.

2) Main Findings

2.1) Classification of Investment Potential for Solar and Wind Energy

Each location was classified follows (see Fig. 2) for each season:

- Zone 1 (Highly Suitable Development Area): High energy potential (in the top 25% of all sites based on the 25^{th} percentile of daily energy potential), normal deficit and surplus ratio (not in the top 25% of these ratios across all sites);
- Zone 2 (Moderately Suitable Development Area): High energy potential and high deficit or surplus ratio (in the top 25% of sites for these ratios);
- Zone 3 (Low Suitable Development Area): Normal energy potential and normal deficit ratio;
- Zone 4 (Unsuitable Development Area): Normal energy potential and high deficit or surplus ratio.

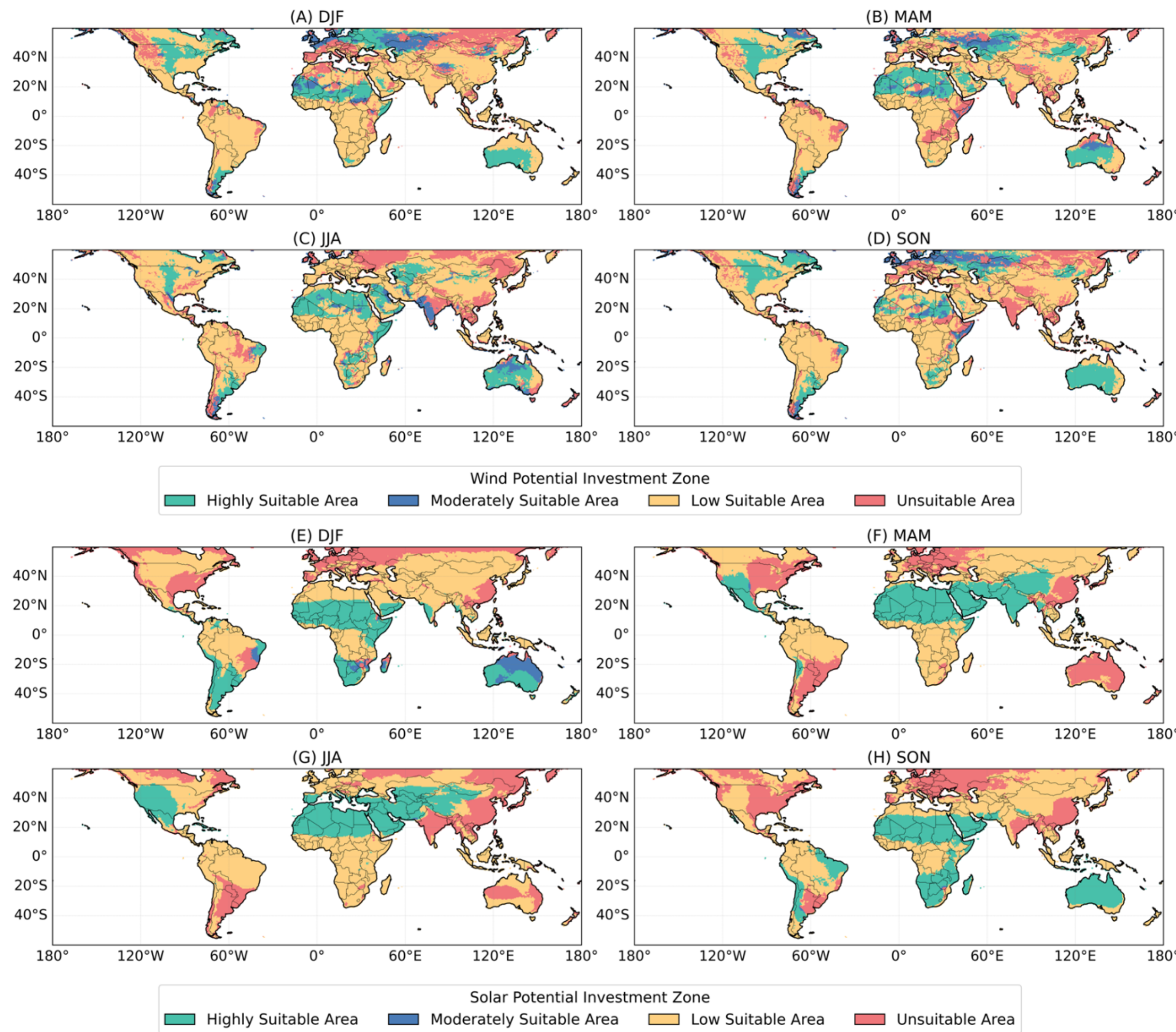

Fig. 2 Seasonal, spatial distribution of wind/solar potential investment zone. A-D wind potential investment zone; E-H solar potential investment zone.

For wind, Zone 1 is primarily distributed across northern Africa, most of Australia, Uruguay, and central North America where energy potential is high and variability is low throughout the year. Russia appears in DJF. For solar, Zone 1 is concentrated in central and southern Africa as well as parts of the Middle East, exhibiting stability and high potential across different seasons. Seasonally, Western N. America (MAM, JJA), S. Asia (MAM) and Australia (SON) are also in Zone 1. These areas provide stable power generation with low need for storage or grid adjustments.

Zone 2 would need augmentation by storage systems, long-distance transmission networks, or complementary energy technologies to mitigate risks associated with variability. For solar, Zone 2 appears only in the DJF season, in northern Australia, southern Africa, and parts of eastern Brazil.

For wind, Zone 2 is found in Russia (DJF, MAM, SON), Western India (JJA), and Argentina (all seasons).

Zones 3 is prevalent across much of the world for both wind and solar, for all seasons, in part due to the criteria used for classification. With lower deficit ratios, it is suitable for development when investment costs are moderate.

For wind, Zone 4 includes eastern Russia/Siberia, the Himalayas, Southern and Central Europe (SON, DJF), E. Africa (MAM), S.E. Asia (MAM, JJA) and India (MAM, SON). For solar, Zone 4 includes eastern North America (except JJA), Paraguay (except DJF), East Asia, and southern South America (MAM, JJA).

The seasonal and spatial variations in the classification can be marked. For example, much of Australia is classified as Zone 4 during the MAM season, but as Zone 1 during SON, for solar energy. Interestingly, much of Australia is classified as Zone 1 for wind for all seasons, suggesting either a choice of wind, or complementary buffering for solar in MAM. Similarly, significant negative correlations for wind deficit – solar surplus in parts of Europe (DJF, SON) and western North America (DJF, MAM, SON) suggest that the deployment of both resources can overcome a Zone 4 seasonal classification for one resource.

Note that these are subjective classifications intended to present a global view. Given that economic values and use cases change with time and space, instead of making assumptions as to these values for a global analysis, we provide the detailed data and source codes for our analysis at https://github.com/Ivyzhangmj/Mengjie-Screening-Global-Solar---Wind-Energy-Investment-Potential-Accounting-for-Drought-and-Surplus. These could be used to zoom into a desired location/region, specify the criteria for thresholding and receive a time series of deficit/surplus duration and severity to use directly with custom analyses of wind and solar locally or regionally.

2.2) Reliable wind and energy potential and deficit/surplus patterns

The annually averaged 25th percentile (computed by calendar month) and the corresponding average deficit and surplus ratios are presented in Fig. 3, with the corresponding seasonal versions presented in Fig. S1.

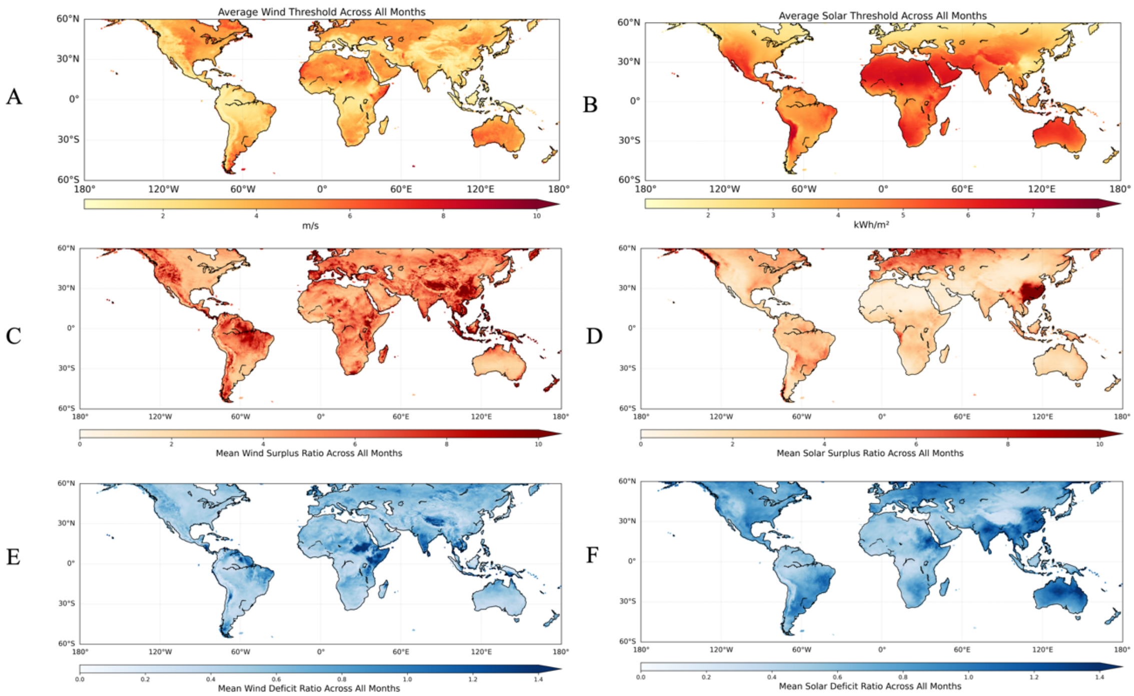

Fig. 3 Spatial distribution of the average daily 25th percentile threshold across all months for wind and solar, and the corresponding average deficit and surplus ratios. A-B daily 25th percentile threshold averaged across all months for wind and solar; C-D average surplus ratios for wind and solar surplus, E-F average deficit ratios for wind and solar, respectively.

At the annual scale, Africa (especially North), the Middle East, Australia, Western North America, N.E. Brazil, Peru, Bolivia, South Asia, and Tibet have the best potential for reliable solar energy. Remarkably, China, where significant solar resources have been deployed, has not only a lower solar energy potential but is marked by a high potential for both solar surpluses and deficits. A similar situation holds for Europe. A high potential for deficits exists in S and SE Asia, Australia, and N.E. Brazil. The corresponding story for wind has much less spatial continuity. Still, generally N. and E. Africa, midwestern N. America, S.E. Latin America, Russia and Australia emerge as the best locations based on the 25th percentile threshold magnitude for daily wind energy. Solar deficits can be more severe than those for wind, particularly in East Asia, southern Africa, and eastern North America, where deficit ratios exceed 1.2. Wind surplus events are stronger globally and distributed across a broader geographic range than solar surplus events. Thus, significant asymmetries in the spatial and temporal distribution of wind and solar droughts and surpluses are revealed. Given that the financial implications of surpluses and deficits are quite different, an investor would need to apply those as a value function to these asymmetric distributions. Many locations demonstrate very high wind surplus and deficit ratios, suggesting that the distribution of wind energy is fat-tailed. Hence, relying solely on the wind could require much more long-duration energy storage or alternate sources in many areas.

We present the spatial distribution of the annual maximum ratio in Fig. S2. Overall, the spatial pattern of the annual maximum ratio closely resembles that of the annual mean ratio. For surplus events, the maximum ratio exceeds the mean by more than five times in regions such as East Asia, northern Africa, South America, and western North America. For deficit events, the difference is even more pronounced, with eastern Africa and parts of India showing maximum deficit ratios exceeding the mean by more than nine times.

Seasonal analyses are presented in the supplement Fig. S3 through S4. The main observation is that both the 25th percentile threshold and the associated deficit and surplus ratios can vary significantly across seasons for most locations. Australia's solar deficit ratio is significantly lower during SON (spring) than the annual average, whereas Europe experiences more severe deficits in all seasons. Southern North America exhibits a noticeable increase in solar surplus during DJF (winter), whereas, in China, both solar deficit and surplus ratios remain high across all seasons, indicating persistent high variability in energy availability. Similarly, solar energy in Europe exhibits high deficit and high surplus ratios in the same season. Seasonal variations in wind ratios are less pronounced than for solar. Some regions experience high deficit and surplus ratios for a particular energy type, such as solar energy in East Asia and wind energy in Eastern South America in the same season.

The durations associated with the largest cumulative deficit for each calendar month were averaged seasonally and are illustrated in Fig. 4, with the maximum duration presented in Fig. S6. Similar to the ratio, the spatial distribution of maximum duration closely resembles that of the mean duration for each season. In regions where the mean duration exceeds 5 days, the maximum duration can be up to four times greater than the mean. For wind, the spatial pattern of deficit duration generally matches the seasonal pattern for the deficit ratio, for all the seasons, i.e., longer droughts correspond to the highest severity. However, for solar, there is not always a good correspondence between the deficit duration (Fig. 4) and the deficit ratio (Fig. S3) for most locations and seasons. For instance, N. Africa/Middle East has relatively low solar deficit ratios in each season, but long durations are associated with these deficits. In contrast, S. Asia has high solar deficit ratios in JJA and SON and correspondingly longer drought durations in those seasons, and N. America has high solar deficit ratios in most seasons but with short deficit durations.

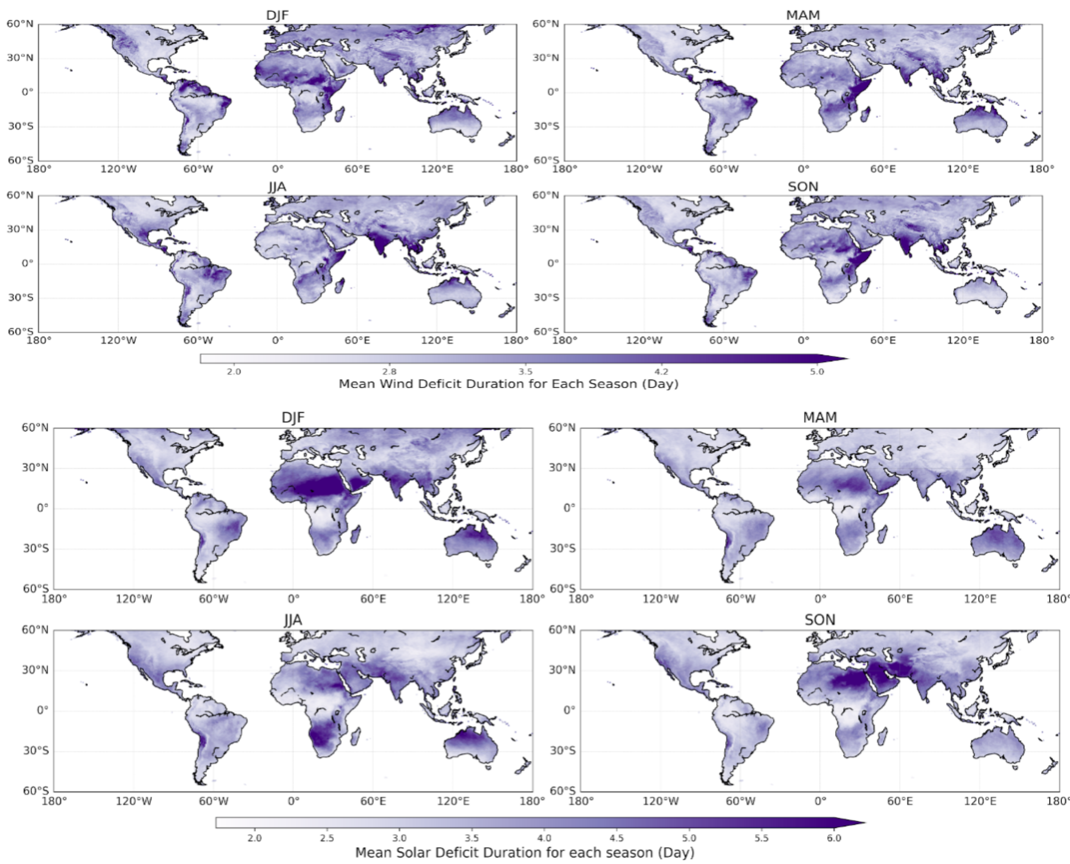

Fig. 4 Mean Wind (upper 4 quadrants) and Solar (lower 4 quadrants) Deficit Durations by Season.

2.3) The Complementarity of Wind and Solar Deficit and Surplus Events

The simultaneous occurrence of solar and wind deficits can challenge renewable energy systems that try to incorporate both elements to buffer variability in supply. When both energy sources experience shortages at the same time, the reliability of the energy supply decreases. Conversely when a deficit matches a surplus in the other resource, risks are buffered.

The correlation between solar and wind deficits across all months is presented in Fig. 5. East Africa and parts of N.E. Brazil stand out as areas where solar and wind deficits are positively correlated, indicating a high risk of a joint deficit in these regions.

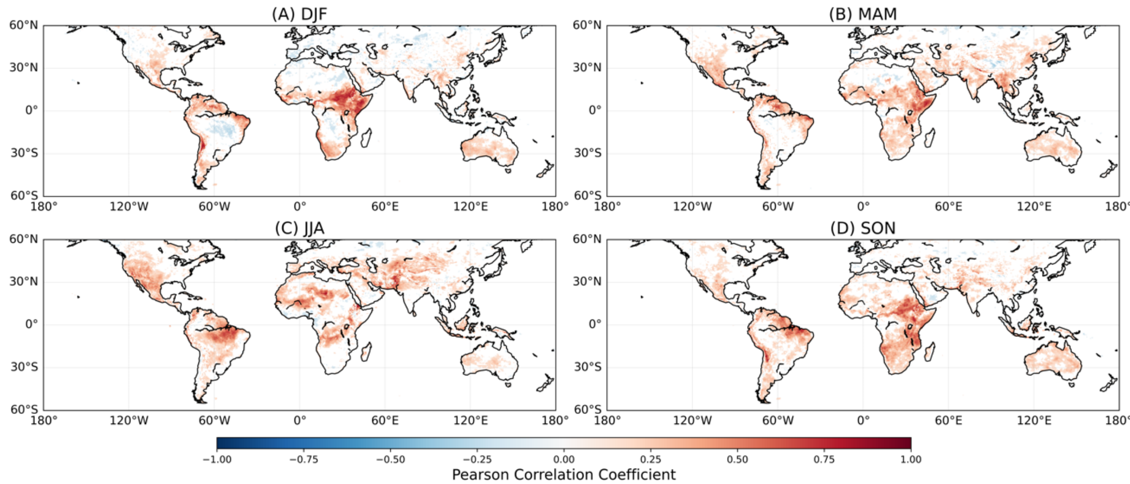

Fig. 5 The Correlation of wind and solar deficit by season for each location

The potential for buffering deficits in one resource by a surplus in the other is illustrated in Fig. 6 and S7 (by season). A positive correlation is favorable for buffering the deficit. North Africa, Australia, and Western N. America emerge as regions with a higher potential for such buffering. Buffering of solar deficits by wind surplus appears feasible in central Africa and Australia. Seasonal buffering in central Africa for solar deficits happens primarily in DJF. Similarly, in western North America, the correlation between wind deficits and solar surpluses weakens significantly during JJA compared to other seasons.

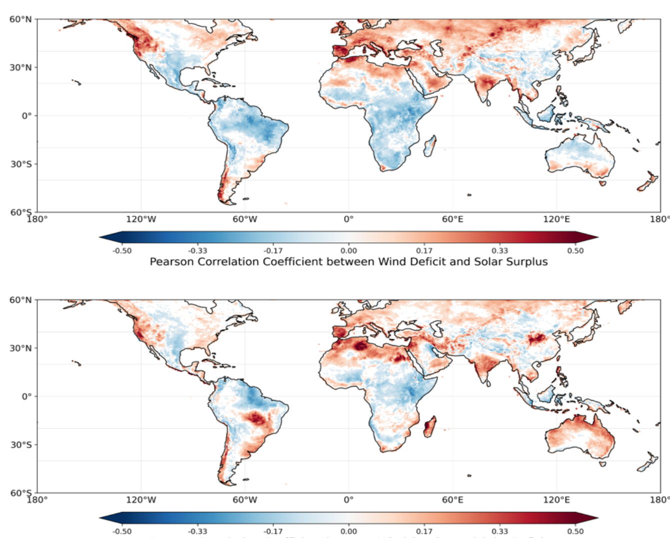

Fig. 6 Correlation of Wind Deficit and Solar Surplus (upper frame), and of Solar Deficit and Wind Surplus (lower frame) across all months. All correlations shown are significant at p=0.1.

To better characterize the spatial variations in the monthly deficits and surpluses, we conducted a Principal Correlation Analysis for each field using correlation as a metric. The leading principal component (PC) of the solar deficit (accounts for ~6% of the global variance) has a correlation of -0.88 with the leading PC of the wind surplus (~10% of the global variance). The leading PC of solar surplus (~18% of global variance) has a correlation of -0.53 with the first wind deficit PC (~5% of global variance) and 0.56 with the 2nd wind deficit PC (~3.5% of the global variance). The spatial patterns associated with these PC's are illustrated in Fig. S8. Consistent with the earlier analyses, the spatial fields for solar surplus and deficit are much more continuous than those for the wind variables. However, prominent correlated patterns are evident in both cases, suggesting that common underlying large-scale climate mechanisms may determine these outcomes.

3) Discussion

Our analyses were motivated in part by news media reports of significant wind energy droughts in Australia and Europe and by negative prices associated with spot market electricity prices in Texas and California - US states with a relatively high penetration of renewable energy sources. Discussions with energy producers revealed a growing concern about revenue assumptions in the payback analyses of large-scale renewable energy projects. These led to questions about the climate-induced financial risk associated with the projects and how these risks could be managed. There is much awareness of the sub-diurnal variability of wind and solar and how to manage that using battery storage or short-term augmentation contracts from other sources. However, the respondents did not have a clear strategy for longer-term variations from a target production level. We probed whether financial hedging strategies (e.g., derivatives, swaps, or options) traditionally used in electricity markets [31] were being leveraged for long-term fluctuations in renewable energy and related cooling or heating demand. While there is emerging academic literature on this topic [32–37], analytics or market activity that relies on these analytics is not prominent, and most of the literature still does not address long-duration droughts or surpluses. Spatio-temporal stochastic modeling and monthly to seasonal predictability of solar, wind and cooling/heating demand provide a foundation for formal modeling of these long-duration anomalies and their impact on regional electricity supply-demand imbalance risks [38–51]. Our analysis provides a screening tool for the relative potential and the relative risks of introducing renewable wind and solar energy in different parts of the world – to facilitate planning activities. More detailed financial, stochastic and predictive modeling could then supplement this screening tool.

An interesting outcome of our analysis is that China, a global leader in wind and solar energy deployment with one of the lowest deployment costs, does not emerge as a highly suitable region for either resource. A similar observation applies to South Asia, where there has been a big push for solar energy. West Asia, North Africa, and Western N. America emerged as highly suitable for solar energy, and deployment in these areas in United States is well below the potential. North Africa, the mid-western United States, Australia, and pockets of mid-latitude land masses in both hemispheres are highly suitable for wind. Land-based wind resources are highly variable compared to solar resources. Much of the percentage growth in electricity development is happening in rapidly industrializing countries where traditional electricity resources are a limiting factor and demands are increasing, given multiple drivers. In these settings, the low levelized energy cost of wind and energy and the independence from a fuel source may be responsible for the rapid deployment, even though the reliability of the resources and the resource potential are lower. Conversely, in the United States, development is typically focused in the areas with the highest potential, and discussing how to achieve high reliability is paramount. It is in this context that the quantification of the financial risks for surplus and deficit may have immediacy, as it provides for an analysis of hedging vs mitigation options, and may open a discussion of potential uses for surplus power that is not 100% reliable.

For regions classified as Zone 1 and Zone 2, hydropower as a backup, or hydrogen conversion or thermal energy storage may be technologies to buffer the relatively modest variability and provide greater flexibility in energy system adjustments, enabling better management of seasonal or long-term energy fluctuations. For regions with complementary wind and solar potential, joint deployment of wind and solar facilities, development of smart grid technologies, enhancement of energy management and forecasting models, and integration of storage systems can optimize energy utilization efficiency. Investors must also consider financial instruments such as insurance products, derivatives or innovations in forward options to mitigate the cost of acquiring alternative energy sources during periods of energy drought. Characterizing variability in terms of “drought” and “surplus” is a crucial first step in assessing the need for such financial tools. Additionally, how certain regions deviate significantly from target thresholds—is essential for risk assessment. Our analysis used the 25th percentile as a threshold, but alternatives could easily be explored using the tools and data we provide.Given the rapid deployment capabilities of solar energy systems, seasonal forecasts can provide valuable insights for energy investment decisions. For instance, using ENSO to predict wind and solar variability is one of our current research directions, offering a promising approach to enhancing investment resilience in the face of climate variability.

4) Data and Methods

4.1) Climatological Data

We used hourly data at a 0.5-degree latitude/longitude resolution from the ERA5 reanalysis datasets. The downward surface solar radiation and the 100m u- and v-components of wind were extracted, covering the period from January 1, 1940, to February 29, 2024. The u and v wind components were combined to get the vector amplitude of the hourly wind velocity. The hourly data were then aggregated to daily values at each location.

Converting solar radiation to electricity requires multiplication by a scalar representing the efficiency of energy conversion that depends on the specific photovoltaic design. Likewise, converting wind velocity to wind energy requires a transformation that limits wind energy produced from low and high wind, a specification of the wind turbine diameter, and the application of a turbine dependent efficiency factor to the kinetic energy of the wind. Since these factors may vary depending on actual implementation choices, and we are interested in a comparative analysis of different locations, we work directly with the solar radiation and wind velocity to identify potential and variability, fully recognizing that wind energy is a cubic function of wind velocity.

4.2) Defining Renewable Energy Drought and Surplus Events

Defining energy drought and surplus events is quintessential in our analysis. Currently, there is no consensus definition of “energy drought,” and studies have implemented varied methods to identify and quantify energy drought events. For example, Raynaud et al. 2018 defines “Energy Production Droughts (EPDs)” as periods of consecutive days with low energy production, where the total wind and solar energy generation falls below a specific low-production threshold [28]. Rinaldi defines such an “energy drought” threshold as periods when daily energy production is less than 50% of the mean daily value for that day of the year [52]. Conversely, Ohlendorf and Schill 2020 use lower thresholds of 2%, 5%, and 10% to define wind energy drought events that fall below these percentiles [53]. Dijkstra, Bloomfield, and Hunt 2025 define the threshold even lower, with "renewable energy droughts" as periods when wind and solar energy potential is below the lowest 2.5% of the climatological mean [54]. Other studies have adopted more varied methods to define energy droughts. Kapica et al. 2024 defined droughts by setting a threshold, and the duration of the droughts was measured using the sum of binary variables [55]. Allen and Otero 2023 proposed standardized indices based on quantiles, defining droughts by percentiles and quantifying their severity through the sum of the drought index over a given period [15]. Antonini et al. 2024 introduced an energy deficit metric that combines the depth and duration of low wind energy and uses power density, seasonal variability, and climate variability to identify reliable locations for wind power generation [56].

Here, we define energy drought and surplus using a standard thresholding method. Specifically, we approach this by using the q^{th} percentile of the daily wind and the daily solar energy potential at each location and for each calendar month as a threshold for the level of production that could be guaranteed (nominally (100-q)% of the time, assuming that other sources would provide short term backup energy. The variation in this percentile, seasonally and across geography then addresses our first research question. The deficit and surplus metrics were computed by reference to these thresholds as described in the introduction.

4.3) Defining Complementarity and Compound Deficits with Correlation Analysis

Compute the correlation between D_j and S_j for wind and solar at each location to assess the potential that implementation of wind and solar in the grid box has the potential to offset a shortage in either resource in that month. We realize that this indicates the potential to assume some energy storage capacity and does not resolve the timing issues associated with daily or hourly fluctuations.

To quantify the relationship between two series, we employ the Pearson correlation coefficient (r), which measures the linear association between two variables. The Pearson correlation coefficient is computed as follows:

$$r = \frac{\sum(X_i - \bar{X})(Y_i - \bar{Y})}{\sqrt{\sum(X_i - \bar{X})^2}\,\sqrt{\sum(Y_i - \bar{Y})^2}}$$

When calculating compound deficit, X and Y represent solar deficit and wind deficit, respectively. When calculating complementarity, X and Y represent solar deficit and wind surplus or solar surplus and wind deficit, respectively.

The Pearson correlation coefficient ranges from −1 to 1. For compound deficit, when the coefficient is greater than 0, wind and solar deficits tend to co-occur. For Complementarity, when the coefficient is greater than 0, it suggests that the deficit and the corresponding surplus have potential complementarity. Standard significance tests for correlation were employed

The Principal Component Analysis [57] on each data field was computed using the spatial correlation matrix of the field, using standard methods in Python.

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