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Evaluating complementarity: A review of metrics and their implications for hybrid renewable energy systems

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HIGHLIGHTS

- Multiple metrics for renewable energy complementarity are reviewed and compared.
- No metric fully captures all relevant complementarity dimensions.
- Metrics for >2 sources tend to overestimate complementarity.
- Recommend multi-metric purpose-driven selection for robust evaluation.

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ABSTRACT

With larger shares of renewable energy sources in the generation mix, their inherent variability and intermittency increasingly challenge power system stability. One strategy to mitigate the variability of renewable energy sources is to co-locate complementary energy sources. This article reviews the concept of renewable energy complementarity, with a particular focus on metrics for complementarity assessment. Twelve distinct metrics are identified and classified into four groups: statistical, fluctuation-based, event-based, and effectiveness metrics. Of the reviewed articles, approximately one-third employed the Pearson correlation coefficient, and more than half focused on wind-photovoltaic (PV) combinations. The identified metrics are compared in this study using both synthetic test data and meteorological reanalysis data. Our analysis reveals that metrics designed for more than two sources tend to overestimate complementarity, and no single metric consistently captures all relevant aspects. We recommend the combined use of multiple metrics, chosen for the intended application, to ensure a robust and transparent assessment.

1. Introduction

The transition to renewable energy sources (RESs) is a critical component of global efforts to mitigate climate change and reduce dependence on fossil fuels. There are various technologies of variable renewable energy sources (VRESs) being deployed, such as wind, solar, tidal, and marine energy sources, each with distinct generation profiles, geographical constraints, and operational characteristics [1]. Each of these types of VRESs, however, shares the attribute that they are driven by, or affected by, highly variable weather patterns [2].

One approach to mitigating problems associated with variability is integrating several VRESs with complementary characteristics. In recent years, several studies have highlighted the benefits of integrating multiple VRESs to achieve a more reliable and consistent energy supply. For instance, a recent study found that combining offshore wind, floating photovoltaic (PV) and wave energy may reduce the hourly variability by 20 % compared to offshore wind [3]. Co-locating energy sources can also lead to economic benefits. Brown et al. [4] found that the overall electricity system cost in the US can be reduced by 0.8 %–2 % by employing hybridized PV and wind power installations.

A recent review emphasizes the importance of addressing complementarity and spatial-temporal dependence in modeling variable renewable energy systems [5]. Similarly, a study by the National Renewable Energy Laboratory (NREL) [6] discusses the potential of hybrid power plants that combine wind, solar, and hydropower to reduce variability and increase capacity factors. In the context of wave and wind energy, several case studies have demonstrated the advantages of co-locating these technologies. For example, combined wave, wind, and solar energy

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Nomenclature

ρ	Density
d	Distance between ranked observations
H_s	Significant wave height
T_e	Wave energy period
v	Velocity
α	Weight parameter
γ	Per unit step change
κ	Time-complementarity index
μ	Mean value
ϕ	Total variation complementarity index
ρ_p	Pearson correlation coefficient
σ	Standard deviation
$k(\mathbf{c})$	Total temporal complementarity index
n	Number of observations
P	Power
r	Normalized mean absolute deviation complementarity index
r_s	Spearman correlation coefficient

offshore multi-source parks have been suggested as a means to increase energy yield and smooth power output [7]. Additionally, co-locating wave energy with offshore wind has shown potential for cost reductions and more sustainable use of marine resources [8].

Much of the research is focused on assessing combinations of certain VRES technologies, such as wind power or solar PV, or addressing the complementary nature of VRESs in a specific geographical region. In recent years, several studies have advanced the understanding of VRES complementarity. For example, a planning methodology that combines wind and solar to better match electricity demand has been proposed [9]. As the field has evolved, some studies have shifted towards examining practical implementation aspects, including the integration of hybrid power generation systems into existing power grids [10]. Moreover, some real-world applications are in operation or under construction. For example, Haringvliet Zuid in the Netherlands is a combined wind–PV park constructed in 2020 [11]. In 2025, a park consisting of 700 MW PV and 300 MW wind power will be taken into operation in China [12]. In India, the massive project Gujarat Hybrid Renewable Energy Park is under construction. When finished, the rated capacity will amount to 30 GW of combined wind and PV [13].

Despite growing interest, there is no standardized approach to quantify complementarity. Existing studies employ diverse metrics, ranging from correlation coefficients (CCs) [14] to complementarity indices [15], often tailored to specific regions or resources. The lack of comparability limits the ability to generalize findings. The review by Jurasz et al. [16] greatly contributed to insights on how to properly assess energy complementarity, but since its publication, several additional metrics have been proposed. Furthermore, no study has compared the numerical values of the metrics used to quantify energy complementarity, so a focused review of available metrics is needed. This review aims to address this gap by extending the body of reviewed metrics and delivering both a qualitative and quantitative comparison of the metrics used in the scientific community. By doing so, we can gain valuable insights into the potential benefits and challenges of integrating these VRESs. We aim to contribute to the broader effort to develop flexible and resilient renewable energy strategies that can adapt to regional resource profiles, policy goals, and infrastructure constraints.

1.1. Concept and dimensions of complementarity

Complementarity refers to the situation where two or more elements enhance each other's qualities. In the context of renewable energy, this could be exemplified by the seasonality of wind speeds and solar irradiation in high-latitude regions [17]. Solar irradiation is highest during summer months, whereas wind speeds and air density are higher during winter months. Thus, co-located wind and solar power pose the possibility of lowering the seasonal variation of energy generation. During short time scales, this effect is not nearly as prominent, however. Another, less obvious example, is the combination of wind power and wave power. Wind-driven waves are highly correlated with wind speeds with a time lag [18], which could be utilized, for example, to increase the accuracy of short-term forecasting of combined wave–wind power. In general,

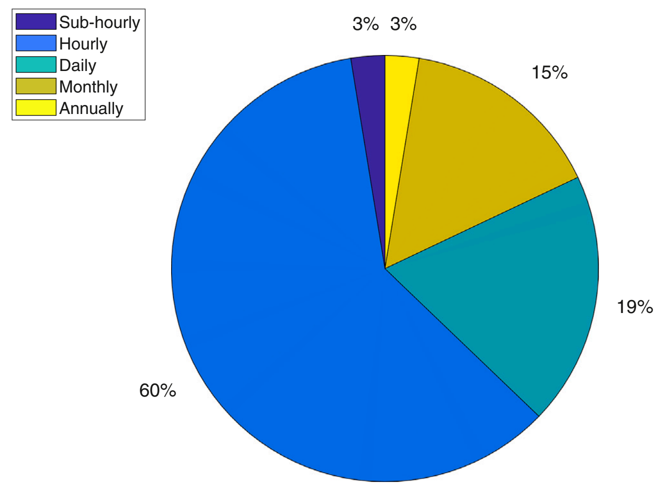

Fig. 1. Highest temporal resolution in the reviewed studies. Most studies using high temporal resolution have also analyzed longer time scales.

complementarity can be measured by any means of increased aspects of quality. However, in the application of renewable energy, the vast majority of the literature is focused on variability aspects such as variance or fluctuations.

One key aspect when addressing complementarity is to analyze desired outcomes. The example with seasonality of wind and solar power in high-latitude countries is, even though pedagogical, not entirely beneficial. The general electricity consumption in these regions is higher during the colder winter months, which coincides with the seasonal profile of wind power. The benefit of adding solar power to generate a smoother seasonal profile could therefore be argued to be minimal, even though statistical metrics might indicate very high seasonal complementarity.

Based on the definition provided in [16], complementarity can be described in the spatial, temporal, or spatio-temporal sense. The spatial sense of complementarity refers to how energy sources spread over larger geographic areas may benefit from each other. Spatial complementarity is mostly applicable to grid-connected distributed generation since a transmission system is needed to utilize the complementarity. One example of spatial complementarity is the idea of complementing the highly positively correlated North Sea offshore wind with offshore wind located by the coastline of Norway [19].

In the temporal sense of complementarity, VRESs in approximately the same location are analyzed in time. The temporal dimension of complementarity varies greatly depending on the time scale. Fig. 1 shows the time scales used in the reviewed articles. The predominance of hourly data resolution likely stems from the fact that most reanalysis datasets for meteorological observations, such as ERA5 [20] and MERRA2 [21], provide hourly resolved variables.

The spatio-temporal dimension combines temporal and spatial effects. One example of this is the investigation of how the temporal anti-correlation between wind and solar decreases over distance [17].

2. Method

2.1. Search strategy

To ensure a broad coverage of metrics, the search engines ScienceDirect, Scopus, and Google Scholar were used. After an initial search with the keywords *"complementarity"* and *"energy complementarity"* and publication year after 2008, 98 articles were selected for screening. In this stage, articles that either provided a method of assessing renewable energy complementarity or assessed renewable energy complementarity were selected for the review. Additionally, we examined references in the reviewed articles and included those studies that fit into the scope of the review. After this stage, a total of 80 peer-reviewed published studies made up the foundation of the review.

2.2. Data for comparative analysis

In order to compare the quantitative metrics, the synthetic test data shown in Fig. 2 was generated. The data shown in Fig. 2a)–d) represent scenarios for the combination of two sources, and the data shown in Fig. 2e)–h) represent scenarios for a combination of three sources. To facilitate a meaningful comparison, the data representing scenarios for three sources were created to mimic the behavior of the respective test data representing scenarios for two sources.

The scenarios represented in Fig. 2a) and e) show scenarios where the sources exhibit similar behavior, but with a time shift, leading to a smoother aggregated power output. The time series

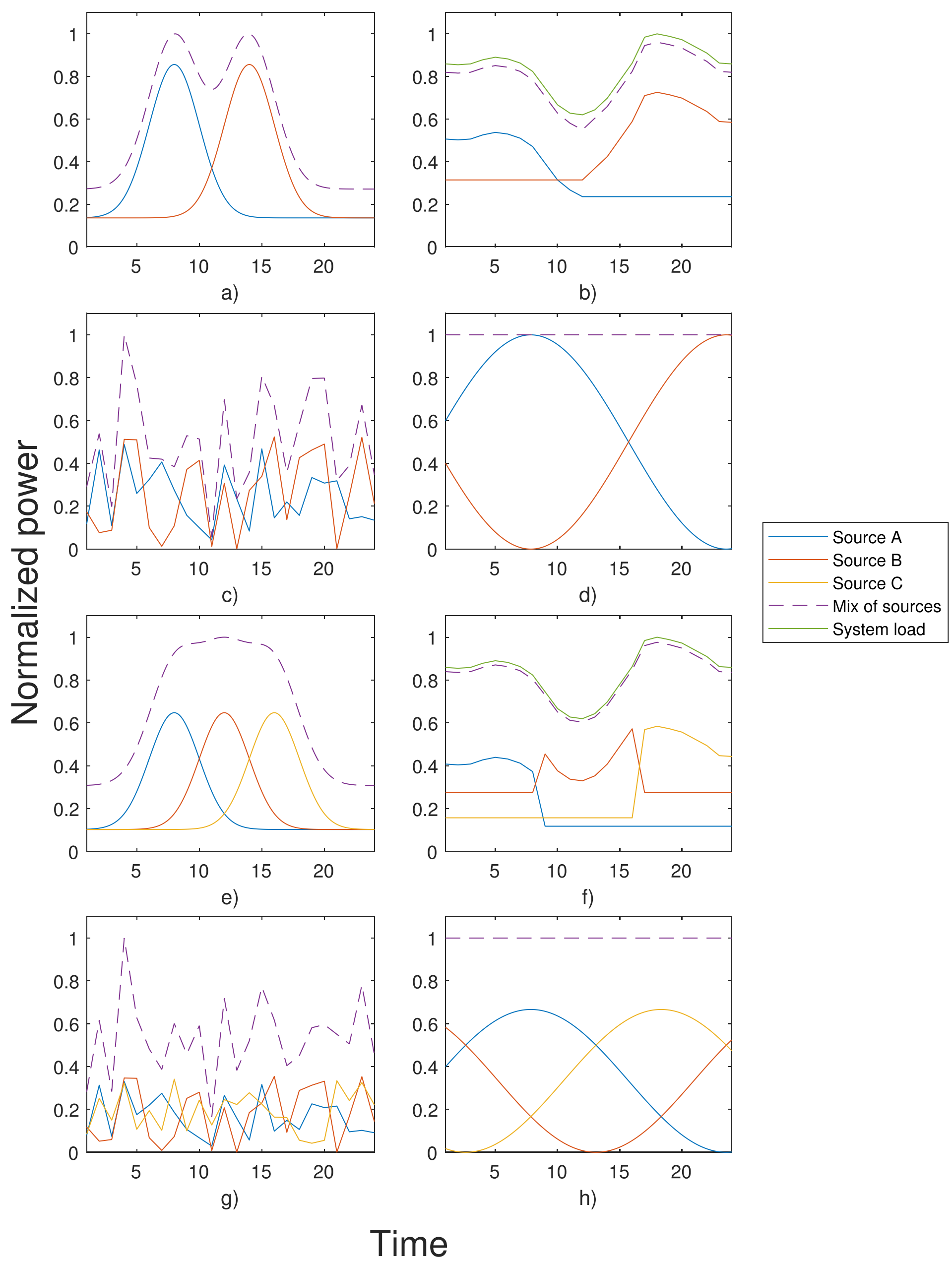

Fig. 2. Synthetic data used for metric comparison. The series represent time shift with power smoothing for two sources in a) and three sources in e), load following appearance for two sources in b) and three sources in f), un-correlated random time series for two sources in c) and three sources in g), and, joint constant output for two sources in d) and for three sources in h).

were generated using the probability density function of a normal distribution.

The data shown in Fig. 2b) and f) represent scenarios where the sources exhibit no obvious relationship, but together have a similar pattern to a generic load profile. The data were created to mimic the appearance of a typical duck–curve profile.

The series shown in Fig. 2c) and g) are samples drawn from uniformly distributed, uncorrelated ($|\rho_p| < 0.05$) variables. They are included to show a scenario where there is no apparent complementarity.

The data shown in Fig. 2d) and h) represent scenarios where the sources together form a constant output. The data were generated using phase-shifted sine waves.

In addition to the synthetic test data, the metrics were compared using meteorological reanalysis data from ERA5 [22]. Time series of wind power density, wave power density, and solar irradiance are used to showcase the outcomes of the metrics when applied to realistic renewable energy data. The analysis is conducted using hourly resolved variables, for the year 2024.

The power density per square meter of swept area (W/m^2) of wind is calculated as

$$P_{wind} = \frac{1}{2}\rho_{air}v^3, \tag{1}$$

where ρ is the air density and v is the wind speed.

Assuming deep water conditions, the energy flux per unit of wave crest length (W/m) is calculated as

$$P_{wave} = \frac{\rho_{water}g^2}{64\pi}T_e H_s^2, \tag{2}$$

where T_e and H_s are the wave energy period and significant wave height, respectively.

The power density of solar irradiance is simply defined as the global horizontal irradiance (GHI), which is in the unit of W/m^2. The power densities have been calculated with hourly resolution for one year. The power densities are not directly comparable since they are in different units or refer to different areas (swept area for wind and surface area for solar), therefore, the resulting power density time series was normalized by its maximum value. In this sense, the relative variations can be used to assess the complementarity.

3. Metrics for complementarity

One key question in the field of renewable energy complementarity is how to quantify the complementarity. In this section, well-used, established, or especially promising metrics for complementarity are presented. The metrics are divided into statistical (metrics derived from statistical distributions), fluctuation-based, event-based, and effectiveness metrics. Additionally, alternative means of assessing complementarity that fall outside of these categories are presented. These metrics are the prominent ones that are used based on a review of relevant scientific literature. There are, however, several niche metrics used for one specific study that are not included in the review.

In Fig. 3, an overview of the metrics found in the literature is presented. From the overview, it is clear that correlation-based metrics are the most commonly used metrics.

3.1. Statistical metrics

3.1.1. Correlation

By far, the most commonly employed metric for complementarity is the CC [16]. Often when referring to correlation, one is referring to Pearson's CC, ρ_p, which is the covariance of two variables scaled by their standard deviation, σ, as described in Eq. (3).

$$\rho_p = \frac{cov(X,Y)}{\sigma_x \sigma_y} \tag{3}$$

Several studies have assessed complementarity solely via Pearson CC. A well-studied case is the combination of wind and solar power, which

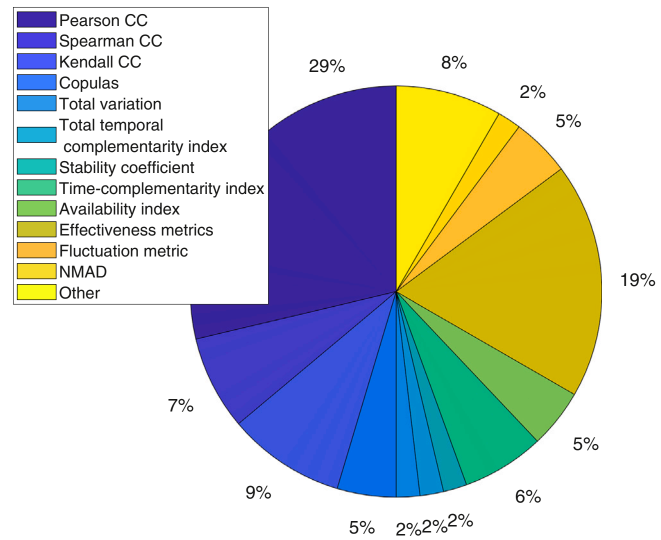

Fig. 3. Overview of used metrics in the literature. NMAD stands for normalized absolute deviation.

has been studied on the hourly [23–27], daily [28–30], and monthly [31,32] time scales. Pearson CC has also been used to assess the complementarity of solar power and hydropower [33], wind and hydropower in Brazil [34], and PV systems with varying tilt and azimuth angles [35].

Pearson CC only measures the linear relationship between the variables. Non-linear relationships can be better identified using Spearman's rank CC [36], r_s, which is calculated as

$$r_s = \frac{cov(R(X), R(Y))}{\sigma_{R(X)}\sigma_{R(Y)}}, \tag{4}$$

where $R(X)$ and $R(Y)$ are ranks of X and Y. When no tied ranks exist, the coefficient can be calculated as

$$r_s = 1 - \frac{6\sum d_i^2}{n(n^2-1)}, \tag{5}$$

where d_i is the difference between the two ranks at each observation, and n is the number of observations.

Spearman correlation has also been frequently applied to the case of wind and solar power [37–40], though it has been shown that Spearman and Pearson CCs in this application yield similar results [41,42].

For datasets containing many tied ranks, Kendall's CC, τ, may be more suitable to measure the relationship [36]. Even though both Kendall and Spearman CCs can be used to describe non-linear relationships, they can only describe monotonic relationships between two variables [43].

Several studies have used Kendall's CC, arguing that it is necessary due to the non-normality of the studied variables [44–50]. It is worth noting that to draw a strong conclusion about the population from which the data was sampled, the requirement of normality should be met, but Pearson's CC is still computable and provides information on the linear relationship of the variables [51]. Studies that have employed both Pearson's CC and Kendall's CC have observed very similar results [52,53].

All CCs can take values between -1 and 1, where -1 means perfect opposing trends, 0 indicates no dependencies, and 1 represents a perfect positive trend. Even though correlation is limited to two variables, there are possibilities to analyze scenarios with more than two sources. For example, by creating correlation matrices [54,55] or by generating pairwise correlation maps [14].

Table 1
Tail dependence and use cases for various copulas.

Copula	Tail dependence	Use case
Gaussian	None	General symmetric dependence
t-Copula	Both tails	Joint extreme events
Clayton	Lower tail	Joint low outcomes
Gumbel	Upper tail	Joint high outcomes
Frank	None	Moderate, symmetric dependence

3.1.2. Stability coefficient

The widely used metric stability coefficient, c_{stab}, was proposed by Sterl et al. [56]. The metric is based on the coefficient of variation (CoV), which is the standard deviation, σ, normalized by the mean value, μ, as

$$CoV = \frac{\sigma}{\mu}. \tag{6}$$

The stability coefficient is calculated as the reduction in CoV due to hybridization compared to stand-alone. In [56], a mix of wind power and solar power is compared to stand-alone solar power, and the coefficient is calculated as

$$c_{stab} = 1 - \frac{CoV_{mix}}{CoV_{solar}}. \tag{7}$$

This metric is particularly useful when retrofitting an additional energy source into an existing generating unit, as the existing generating unit would then constitute the base case and the additional one to assess (compare to CoV_{solar} in [56]). The measure, however, is sensitive to proportions used, as for example 10 % of one source and 90 % of another will yield a completely different result than 50 % / 50 %.

The stability coefficient will by definition be ≤1. A value of 0 indicates that the co-location does not improve balancing, and 1 indicates perfect balancing [56]. If the generation mix has a larger CoV than the compared base case, the stability coefficient will be negative. In a study comparing stability coefficient with statistical correlation, it was argued that the stability coefficient is likely a better indicator of complementarity than correlation in regions with large variation in wind capacity factors, and high shares of PV generation [52].

3.1.3. Copulas

To analyze dependencies beyond what CCs capture, various copula functions can be employed. A copula $C(x, y)$ relates the joint cumulative density function (CDF) $H(x, y)$ of the marginal CDFs $F(x)$, $G(y)$ as [57]

$$H(x, y) = C[F(x), G(y)]. \tag{8}$$

Several different copulas exist. The Gaussian copula has no tail-dependency, and therefore is useful when the variables are jointly normal or have symmetric relationships. The Frank copula does not have tail dependency either, and is good for analyzing the centers of the distributions [58,59]. Clayton copulas have a strong lower tail dependency, and Gumbel copulas have a strong upper tail dependency. These copulas are therefore useful when analyzing joint weak or high outcomes, such as energy droughts and extreme events [60]. The t-Copula is dependent on both upper and lower tails, which makes it suitable for analyzing both extreme events at once [61]. Conceptually, copulas are similar to the conditional relative frequency distributions proposed in [3]. Even though copulas are an excellent tool to analyze dependencies between variables, they lack the ease of numerical evaluation compared to correlation. An overview of considerations for the various copulas is found in Table 1.

3.2. Fluctuation based metrics

A common argument against correlation and variance-based methods is that the variance is a measure of statistical spread rather than actual deviations. For example, outliers heavily influence the variance, which might not necessarily be the case in an energy balancing situation. The metrics in this subsection are all based on the residual values of fluctuations.

3.2.1. Total variation

Cantor et al. [62] introduced a metric based on the concept of total variation. The total variation, $\bigvee$, of a time series, f, with n data points can be calculated as

$$\bigvee_a^b f = \sum_{k=0}^{n-1} |f(t_{k+1}) - f(t_k)|. \tag{9}$$

Conceptually, the total variation is the sum of all changes between time steps in a time series. Therefore, a constant series will have a total variation of zero, and all non-constant series will have non-zero total variation. The authors [62] argue that some of the downfalls of CCs, such as non-linear trends and magnitude of variations, are overcome using total variation. The complementarity index, ϕ, is calculated as in Eq. (10).

$$\phi(f_1, f_2) = 1 - \frac{\bigvee_a^b (f_1 + f_2)}{\bigvee_a^b (f_1) + \bigvee_a^b (f_2)} \tag{10}$$

The index ϕ can take values between 0 and 1, where 0 indicates no complementarity and 1 represents perfect complementarity, which can only occur when $f_1 + f_2$ is constant. The metric can be expanded for any number of sources [63].

3.2.2. Normalized mean absolute deviation

The metric based on need for energy storage (NFES) introduced in [64] is calculated in a similar manner to variance, σ^2, but with absolute value of deviation instead of squared values. The metric NFES is in essence the same as normalized mean absolute deviation (NMAD), calculated for a variable x as

$$NMAD = \frac{\sum |\bar{x} - x_i|}{\bar{x}}. \tag{11}$$

The complementarity of variables, here X and Y, due to hybridizing energy sources can be calculated as in Eq. (12). The result indicates how much the NMAD has been reduced due to hybridization, compared to the NMAD of stand-alone installations.

$$r = 1 - \frac{NMAD(\alpha X + (1-\alpha)Y)}{\alpha NMAD(X) + (1-\alpha) NMAD(Y)} \tag{12}$$

The interpretation of r is the reduction of NMAD due to the co-location of the energy sources. A value of 0 indicates no benefit, and 1 implies perfect balancing. A negative value indicates a worsened situation, where the NMAD has increased due to the co-location of the energy sources.

3.2.3. Fluctuation rates

There are several metrics based on fluctuation rates [65,66], but this description is based on the work by Han et al. [67]. The fluctuation ratio (FR) of an energy source is calculated as

$$FR = \frac{1}{n-1} \sum_{i=1}^{n-1} |\gamma_i|, \tag{13}$$

where γ_i is the per unit step change in power output, calculated as

$$\gamma_i = \frac{P_{i+1} - P_i}{P_{cap}}, \tag{14}$$

where P_{cap} denotes the rated capacity and P_i the power output at time step i. A lower FR value indicates a more stable and less variable power output.

In [67], the FR of a combined power (FROC) generation is defined as

$$FROC = \frac{1}{n-1}\sum_{i=1}^{n-1} |\gamma_i^c|. \tag{15}$$

The per unit time step is calculated as

$$\gamma_i^c = \frac{\alpha_1\gamma_i^1 + \alpha_2\gamma_i^2 + \cdots + \alpha_k\gamma_i^k}{\alpha_1 + \alpha_2 + \cdots + \alpha_k}, \tag{16}$$

where α_k represents the proportion of the kth energy source.

The fluctuation ratio of independent power generation (FROI) is calculated as

$$FROI = \frac{\alpha_1 FR^1 + \alpha_2 FR^2 + \cdots + \alpha_k FR^k}{\alpha_1 + \alpha_2 + \cdots + \alpha_k}, \tag{17}$$

where FR^k is the fluctuation ratio of the kth energy source. Finally, the complementarity metric complementary rate of fluctuation (CROF) is calculated as

$$CROF = 1 - \frac{FROC}{FROI} \tag{18}$$

The authors also suggest using ramp rates (RRs) in a similar manner [67]. The complementary rate of ramp rates (CROR) is calculated as

$$CROR = 1 - \frac{RROC}{RROI} \tag{19}$$

where the ramp ratio of the combined power generation is $RROC$ and $RROI$ for the independent energy sources. Both $CROF$ and $CROR$ are between 0 and 1, where 1 indicates perfect complementarity and 0 indicates no complementarity.

3.3. Indices

3.3.1. Total temporal complementarity index

As correlation is inherently limited to measuring the relationship between two variables, it is not directly possible to use it when analyzing more than two energy sources. Canales et al. [68] therefore proposed the total time complementarity index, k, which can be used to assess the complementarity between three sources.

Firstly, a vector consisting of pairwise CCs between all variables (here x,y, and z) is constructed as in Eq. (20).

$$\mathbf{c} = \rho_p^{xy}\widehat{xy} + \rho_p^{yz}\widehat{yz} + \rho_p^{zx}\widehat{zx} \tag{20}$$

Based on compromise programming, the distance from the optimal point is calculated as

$$L_p(\mathbf{c}) = \left[\sum_{k=1}^{n} \alpha_k^p \left|\frac{f_k^{best} - f_k(\mathbf{c})}{f_k^{best} - f_k^{worst}}\right|^p\right]^{1/p}, \tag{21}$$

where α_k^p is an optional weight parameter. The optimal value, f_k^{best} is -1, and the worst value, f_k^{worst} is 1. The authors [69] suggest choosing $p = 1$, as it leads to a linear assessment of the results.

As shown in [70], a proper normalization of $L_p(\mathbf{c})$ is

$$k(\mathbf{c}) = \begin{cases} \frac{2.25 - L_p(\mathbf{c})}{1.5} & 0.75 \le L_p \le 1.5 \\ \frac{3 - L_p(\mathbf{c})}{3} & 1.5 < L_p \le 3 \end{cases}, \tag{22}$$

where $k(\mathbf{c})$ is the time complementarity index. The index can take values in the range $[0, 1]$ where 1 implies maximum complementarity, and 0 implies maximum similarity.

3.3.2. Time-complementarity index

The time-complementarity index, κ, was first introduced by Beluco et al. [71]. The index is defined as

$$\kappa = \kappa_t\kappa_e\kappa_a, \tag{23}$$

where κ_t is a partial time-complementarity index, κ_e is a partial energy-complementarity index, and κ_a is a partial amplitude-complementarity index. The proposed index is defined for hydropower and solar energy, but is expressed in a technique-neutral manner in this article.

The partial time-complementarity index describes the time interval between the minimum availability of two energy sources. If the interval is one half period, κ_t takes the value of 1, and if the minimum values coincide, the value is zero. The index is calculated according to Eq. (24), where $d_{x,y}$ is the number of the day of minimum availability of energy from source x and y, and $D_{x,y}$ is the number of the day of maximum availability.

$$\kappa_t = \frac{|d_x - d_y|}{\sqrt{|D_x - d_x||D_y - d_y|}} \tag{24}$$

The partial energy-complementarity index, κ_e, is calculated as

$$\kappa_e = 1 - \sqrt{\left(\frac{E_x - E_y}{E_x + E_y}\right)^2}, \tag{25}$$

where $E_{x,y}$ stands for energy generation during some time period. This index measures the difference in average energy generation. If the averages of the two sources are close, the index is close to one. If the average values differ, the index becomes smaller and approaches zero for very large differences.

The amplitude-complementarity index, κ_a, accounts for the values of differences between the maximum and minimum of the energy availability. If the sources have identical differences, the index will take the value of 1. If the differences are not equal, the index will be between 0 and 1, where 0 implies no complementarity. The amplitude-complementarity index is calculated as [71,72]

$$\kappa_a = \begin{cases} 1 - \frac{(\delta_x - \delta_y)^2}{(1-\delta_y)^2}, & \delta_x \le \delta_y \\ \frac{(1-\delta_y)^2}{(1-\delta_y)^2 + (\delta_x - \delta_y)^2} & \delta_x \ge \delta_y \end{cases}. \tag{26}$$

The difference between maximum and minimum energy availabilities, $\delta_{x,y}$, is calculated as in Eq. (27) where $E_{d,\max}$ is the maximum daily energy availability, $E_{d,\min}$ is the minimum daily energy availability, and, E_{dc} is the average daily energy availability.

$$\delta = 1 - \frac{E_{d,\max} - E_{d,\min}}{E_{dc}} \tag{27}$$

The index is relatively well-used in the literature, and has been used to assess the complementarity of hydro and solar [15,73], wind and solar [74], and the combination of hydro, wind, and solar [75].

One study [76] compared the index to Pearson CC and concluded that the results are similar in the temporal dimension, but argued that the index provides a more accurate overall complementarity description due to the other dimensions. The index is designed for smoothed annual profiles and is therefore not directly applicable to hourly or other time series [71].

3.4. Event based metrics

3.4.1. Availability index

The index proposed in [77] focuses on the availability of energy resources. It should be noted that neither the original source [77] nor the studies included in the review that employed the metric [78–81] have decided to assign the index a specific term, but for the sake of distinguishing the metrics it is referred to in this review as the availability index. The availability index evaluates the percentage of time that one source generates above a certain threshold level, while the other source generates below a certain level. The index is in its general form expressed as in Eqs. (28) and (29) [81].

$$xCy = \frac{Nr.\,of\ hours\,(x > x_{threshold}\ and\ y < y_{threshold})}{Total\ nr.\,of\ hours} \tag{28}$$

$$yCx = \frac{Nr.\,of\ hours\,(y > y_{threshold}\ and\ x < x_{threshold})}{Total\ nr.\,of\ hours} \tag{29}$$

The index is only applicable to pairwise combinations and is suitable for analyzing reduced periods of energy droughts. The index ranges from 0 to 1, where 0 indicates no complementarity and 1 signifies that one source consistently exceeds the threshold while the other remains below it.

3.4.2. Generation deficiency

The metrics R_{DGDE} and R_{DGDH} are metrics of generation adequacy, and specifically increased generation adequacy due to co-location of VRESs [82]. The rate of multi distributed generation deficiency of energy (R_{DFDE}) is calculated as,

$$R_{DGDE} = \frac{2 \cdot K_{MDGDE}}{K_{SDGDE_1} + K_{SDGDE_2} + \cdots + K_{SDGDE_n}}, \tag{30}$$

where K_{MDGDE} is the difference between energy generation from multiple sources and the load, and K_{SDGDE} is the difference between energy generation from a single source and the load. A smaller value of R_{DGDE} indicates higher complementarity. The authors also suggest an analogous implementation of the rate of distributed generation deficiency of hours (R_{DGDH}), where hours of energy deficiency are calculated instead of energy deficiency. The authors point out that a smaller value of R_{DGDE} and R_{DGDH} indicates higher complementarity [82].

3.5. Effectiveness metrics

An alternative approach to quantifying complementarity of VRESs is to measure some quality of hybridized energy sources and compare it to the non-hybridized case. This connects to the general definition of complementarity, where two or more elements improve each other's qualities [84]. Some examples of such qualities are utilization degree of cable capacity [64,83], economic payback time [85], ability to generate accurate forecasts [86], and avoided CO_2 emissions [87].

Other relevant qualities to address are those especially pertinent for power system integration of VRESs, related to intermittency, uncertainty, and balancing requirements. Closely related reliability metrics that have been addressed in this manner are capacity credit [3], effective load carrying capability (ELCC) [88,89], loss of load probability (LOLP) [90], and resource adequacy [91]. For an accurate determination of these metrics, certain data of the power system are required, such as the existing generation fleet and outage and reliability data on the additional generation units. However, simplified methods can serve as a practical foundation for comparing hybridized and non-hybridized solutions.

Other methods which do not require extensive power system modeling or simplifications are, for example, the concept of daily guaranteed delivery [92], load-following capability [93], and periods of energy droughts [94–96]. These concepts often require the load profile of the system, which in large parts of the world is accessible at aggregated levels.

For power systems with hydropower as a balancing resource, complementarity can be measured through decreased need for hydro storage for certain combinations [97,98]. In the absence of hydropower, the general need for balancing resources can be quantified [99].

What could be thought of as the ultimate quality to measure would be the total system cost for different combinations, as in [100]. System cost approximations are, however, difficult to accurately project and are associated with large uncertainties such as future needs for balancing requirements, discount rates, and politics.

Quantifying complementarity based on some effectiveness metric is versatile in the sense that it is possible to choose quality aspects freely, but not fully transparent since often only the chosen quality is shown, whereas other qualities might be worsened. An effectiveness metric can take any value depending on the problem formulation. Therefore, it is important to provide guidance on the interpretation of the metric when using effectiveness metrics and to provide a transparent explanation of the applied methodology. A common approach to increase transparency is to combine effectiveness metrics with established metrics. For example, energy droughts [101,102], ELCC [89], LOLP [103], hydro storage need reduction [97] and economic metrics [10,104] have been used in combination with Pearson CC, which provides a more thorough analysis.

3.6. Other methods

It is not uncommon to assess complementarity without explicitly assigning a value or number, particularly in combination with a quantitative method. For example, with clearly anti-correlated trends, it may be effectively conveyed via a figure showing clearly opposing trends [105,106]. A more in-depth graphical assessment can be made via duration curves, where each time state is sorted from low to high or vice versa. Via duration curves, periods of, for example, energy droughts can be observed [107].

Case studies based on optimization methods fall outside the scope of this review, but are still worth mentioning. For a specific region, optimization studies can, for example, be formulated to find a generation mix with an acceptable capacity factor and minimal variance [9,108].

4. Comparative evaluation of metrics

4.1. Quantitative comparison

In this section, applicable metrics are compared using the synthetic test data presented in Section 2. The metrics that can be applied to an arbitrary number of sources have been used for all the scenarios, whereas metrics specifically designed for two or three sources have been applied to applicable scenarios.

4.1.1. Metrics for two sources

In the following sections, each case will be referenced by its alphabetical label. The numerical value of each applicable metric for two sources can be found in Table 2. The interpretation of each metric is divided into four equal regions, namely weak, moderate, strong, and very strong complementarity. Values indicating no or negative complementarity are displayed as none. Classification of metrics, such as for example correlation in this manner, is rather arbitrary and should be used sparingly [51], but it is used here for comparing the outcomes of all metrics.

The resulting complementarity analysis from Pearson, Spearman, and Kendall correlation yields similar results except for scenario a). Since the data is non-linear, Spearman and Kendall likely provide a more accurate description of the correlation. However, as the data is also non-monotonic, no conclusions can be drawn from these values. By applying the logic of splitting the data as suggested in [36] into the monotonic region, all CCs are < -0.9. As all metrics imply none to moderate complementarity, this points to the importance of careful consideration. The actual complementary region is more or less missed by all metrics, but could be of importance.

In the case of scenario b), all statistical metrics imply strong complementarity, whereas only NMAD implies strong complementarity of the fluctuations-based metrics. The implementation of total variation and CROF is very similar, which is why it is expected that they yield the

Table 2
Numerical results of the example complementarity characteristics in Fig. 2a)–d) for the reviewed metrics. Mod. = Moderate, V. str = Very strong.

	a)	b)	c)	d)
Pearson CC	−0.27 (Mod.)	−0.71 (Strong)	0.00 (None)	−1.00 (V. str.)
Spearman CC	0.09 (None)	−0.80 (Strong)	0.03 (None)	−1.00 (V. str.)
Kendall CC	0.14 (None)	−0.65 (Strong)	0.01 (None)	−1.00 (V. str.)
Stability coefficient, source A as base case	0.39 (Mod.)	0.61 (Strong)	0.17 (Weak)	1.00 (V. str.)
Stability coefficient, source B as base case	0.39 (Mod.)	0.59 (Strong)	0.36 (Mod.)	1.00 (V. str.)
Total variation	0.31 (Mod.)	0.00 (None)	0.27 (Mod.)	1.00 (V. str.)
NMAD	0.30 (Mod.)	0.66 (Strong)	0.31 (Mod.)	1.00 (V. str.)
CROF	0.31 (Mod.)	0.00 (None)	0.28 (Mod.)	1.00 (V. str.)
Availability index, A complements B	0.25 (Weak)	0.00 (None)	0.17 (Weak)	0.50 (Mod.)
Availability index, B complements A	0.25 (Weak)	0.58 (Mod.)	0.25 (Weak)	0.27 (Mod.)

Table 3
Numerical results of the example complementarity characteristics in Fig. 2e)–h) for the reviewed metrics.

	e)	f)	g)	h)
Total temporal complementarity index	0.56 (Weak)	0.93 (V. str.)	0.50 (None)	0.99 (V. str.)
Stability coefficient, source A as base case	0.46 (Mod.)	0.79 (V. str.)	0.38 (Mod.)	1.00 (V. str.)
Stability coefficient, source B as base case	0.46 (Mod.)	0.46 (Mod.)	0.53 (Strong)	1.00 (V. str.)
Stability coefficient, source C as base case	0.46 (Mod.)	0.79 (V. str.)	0.31 (Mod.)	1.00 (V. str.)
Total variation	0.58 (Strong)	0.54 (Strong)	0.31 (Mod.)	1.00 (V. str.)
NMAD	0.37 (Mod.)	0.77 (V. str.)	0.46 (Mod.)	1.00 (V. str.)
CROF	0.58 (Strong)	0.51 (Strong)	0.36 (Mod.)	0.95 (V. str.)

same result. The implementation is somewhat similar to NMAD, but differs in the calculation of the final metric, which is why the final results are different. The event-based metric availability index has conflicting results, where source B moderately complements A but not the other way around.

All metrics imply none to moderate complementarity for scenario c). Since this data is included on the basis that it should not exhibit any obvious complementary traits, it is possible that metrics that imply moderate complementarity tend to overestimate complementarity on certain occasions. All metrics except for the availability index indicate near perfect complementarity for scenario d), since the availability index is not focused on variance or fluctuations, unlike the other metrics.

Apart from Spearman and Kendall correlation, the metrics NMAD and stability coefficient (with B as base case), as well as total variation and CROF, yield similar results. The latter is expected since they are very similarly formulated mathematically. The similarity of NMAD and stability coefficient across the cases is most likely due to chance, since the implementation of these metrics differs significantly.

4.1.2. Metrics for three sources

The results of the metrics applicable to three sources are shown in Table 3. For scenario e), only the total temporal complementarity index indicates weak complementarity. Similar to scenario a), these variables are non-monotonic and non-linear, so it is expected that the correlation-based complementarity index will fall short. Other metrics imply similar results, but total variation and CROF show slightly higher complementarity than the rest. Conversely, for scenario f), total variation and CROF, as well as stability coefficient with B as base case, imply lower complementarity than all other metrics.

Similar to scenario c), scenario g) is expected not to exhibit complementarity. Nevertheless, all metrics except for the total temporal complementarity index imply moderate to strong complementarity, which may suggest a tendency to overestimate complementarity among the metrics. For the perfectly opposing scenario in case h), all metrics lead to the same conclusion of very strong complementarity.

Across all cases, the stability coefficient with A and C as bases yields similar results to NMAD. As in the case with two sources, this is most likely by chance rather than a systematic effect. The very similar results from total variation and CROF are again expected as they follow the same logic also for more than two sources.

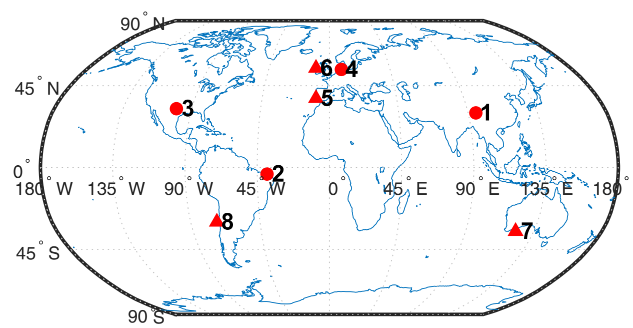

Fig. 4. Overview of the examined locations.

4.2. Quantitative comparison with meteorological data

Eight locations, shown in Fig. 4, were chosen to highlight different aspects of renewable energy temporal complementarity and how they are captured by the various metrics. For the locations numbered 1 to 4, the complementarity of power density of wind and solar irradiance has been assessed, and in locations numbered 5–8, wave energy is included in the mix.

South China (location 1) has been shown to exhibit weak positive correlation of hourly PV and wind power [50] due to the region's topography. Brazil (location 2) is a rather well-studied region in the context of energy complementarity [75], and location 3 in the USA is interesting due to the large number of wind farms in the area [109]. Co-located PV and wind generation in Northern Germany (location 4) have been shown to be promising [61].

For locations numbered 5–8, the power density of wind, wave, and solar irradiance has been analyzed. Even though the literature on the combination of the three is rather scarce, the combination has been shown to exhibit complementary traits around Ireland (location 6) [63] and the Portuguese nearshore area (location 5) [80]. Australia (location 7) and Chile (location 8) have been shown as promising locations for wave power installations [110,111].

In Table 4, the calculated metric values for locations 1–4 are presented, while the corresponding results for locations 5–8 are shown in Table 5. The obtained CC values are consistent with previously reported

Table 4
Resulting complementarity metric values for locations 1 to 4.

	1	2	3	4
Pearson CC	0.05 (None)	0.06 (None)	0.21 (None)	−0.12 (Weak)
Spearman CC	0.09 (None)	0.13 (None)	0.23 (None)	−0.10 (Weak)
Kendall CC	−0.10 (Weak)	0.06 (None)	0.16 (None)	−0.07 (Weak)
Stability coefficient, solar as base	0.13 (Weak)	0.13 (Weak)	0.06 (Weak)	0.38 (Mod.)
Stability coefficient, wind as base	0.23 (None)	0.28 (Mod.)	0.41 (Mod.)	0.21 (Weak)
Total variation	0.05 (Weak)	0.11 (Weak)	0.05 (Weak)	0.10 (Weak)
NMAD	0.01 (Weak)	0.09 (Weak)	0.00 (None)	0.26 (Mod.)
CROF	0.05 (Weak)	0.11 (Weak)	0.05 (Weak)	0.10 (Weak)
Availability index, solar complements wind	0.26 (Mod.)	0.34 (Mod.)	0.34 (Mod.)	0.14 (Weak)
Availability index, wind complements solar	0.00 (None)	0.01 (Weak)	0.00 (None)	0.05 (Weak)

Table 5
Resulting values of complementarity metrics for locations 5 to 8.

	5	6	7	8
Total temporal complementarity index	0.56 (Weak)	0.44 (None)	0.41 (None)	0.47 (None)
Stability coefficient, solar as base	0.44 (Mod.)	0.41 (Mod.)	0.38 (Mod.)	0.52 (Strong)
Stability coefficient, wind as base	0.47 (Mod.)	0.38 (Mod.)	0.26 (Mod.)	0.36 (Mod.)
Stability coefficient, wave as base	0.34 (Mod.)	0.33 (Mod.)	0.34 (Mod.)	0.11 (Weak)
Stability coefficient, wind as base	0.23 (None)	0.28 (Mod.)	0.41 (Mod.)	0.21 (Weak)
Total variation	0.12 (Weak)	0.11 (Weak)	0.17 (Weak)	0.13 (Weak)
NMAD	0.33 (Mod.)	0.28 (Mod.)	0.24 (Weak)	0.33 (Mod.)
CROF	0.12 (Weak)	0.11 (Weak)	0.17 (Weak)	0.13 (Weak)

results for these locations [50,61]. Overall, the findings indicate none to weak complementarity, which aligns with earlier studies. However, no clear pattern emerges from the employed metrics regarding which locations exhibit a higher degree of complementarity. As the metrics capture different aspects of complementarity, the results suggest that certain complementary characteristics may be enhanced in some areas, while others are more pronounced in other areas. This observation further underscores the importance of employing multiple complementarity metrics to achieve a comprehensive assessment.

For locations 5–8, the employed metrics similarly do not provide a definitive ranking of the most favorable site. Nevertheless, the general trend indicates that the complementarity among wave, wind, and solar resources tends to be higher than that between wind and solar alone. As shown in Table 3, metrics applied to combinations of more than two sources often indicate a higher degree of complementarity, which may partly result from methodological overestimation rather than a true increase in resource complementarity. Consequently, it remains uncertain whether the wave–wind–PV combination genuinely exhibits superior complementarity or if this is an artifact of the employed metrics.

4.3. Qualitative comparison

One common ground for all statistically-based metrics is that they stem from well-established equations related to statistical distributions, which is not the case for the fluctuation-based metrics. The benefit of using metrics with a well-established mathematical framework is the possibility of relating the metric to other results. For example, with known variances and correlation, it is easy to calculate the variance of every scaled combination as in Eq. (31).

$$var(\alpha X + \beta Y) = \alpha^2\sigma_X^2 + \beta^2\sigma_Y^2 + 2\rho_p^{X,Y}\alpha\sigma_X\beta\sigma_Y \tag{31}$$

No such analytical expression is derived for the metric of total variation, CROF or NMAD. Instead, the metric must be calculated for the aggregated time series and compared to the non-aggregated time series, which is straightforward using computational software. If, however, only the underlying statistical distribution of the variables is known, metrics such as correlation or the stability coefficient can be calculated directly.

One benefit of the fluctuation-based metric is the ability to assign a physical meaning to the metric. For example, in [64], NMAD describes the percentage of energy that would need to cycle through an energy storage system to achieve constant power output. When variance or standard deviation is calculated, each observation is squared, whereas in total variation, CROF and NMAD only the absolute value of the deviation is used in the calculations. Therefore, in the context of energy, the absolute values of the deviations can be interpreted as energy surplus or excess in the unit of energy, but variance-based metrics are a measure of the data spread in the unit of energy squared. Even though standard deviation has the same unit as the data, variance is the basis for calculations, which is why it is not directly possible to assign a physical meaning to the figure.

The event-based metrics differ somewhat from the statistical and fluctuation-based metrics since the metrics are not directly related to the general variability of the VRESs. Event-based metrics and effectiveness metrics share the trait that the interpretation is very simple—the metric can tell exactly how much hybridization has improved the situation. The drawback is that by using such specific metrics, comparison between other studies becomes more difficult. Additionally, traits that are not included in the analysis might be worsened. For example, two sources might together significantly reduce periods of energy droughts, but in other periods pose significant variability with high ramp rates, which would not be shown.

Conversely, indices such as the total temporal complementarity index [68] and the time-complementarity index [71] are excellent for comparison between studies, regions, and sources but lack precision in representing complementarity. Creating an index that captures all of the possible complementary traits and ranks these would likely be impossible, especially since different complementary traits are of varying usefulness in different power systems.

A summary of the different considerations for each metric is found in Table 6.

5. Discussion

5.1. Applications across renewable energy sources

When applying a complementarity metric for VRESs, there are some special considerations that are beneficial to take into account for certain combinations of VRESs. An overview of various combinations found in the scientific literature is provided in Fig. 5. It should be noted

Table 6
Comparison of different metrics for analyzing energy resource complementarity.

Metric	Key references	Computational complexity	Interpretability and transparency	Strengths	Limitations
Correlation	[17,36,43]	Built-in function in most software	Weak physical meaning; statistical	Well-known; easy to communicate	Only pair-wise; ignores variation magnitude
Total temporal complementarity index	[69,70]	Similar to correlation	Weak physical meaning	Handles > 2 sources	No general method for > 3; ignores variation magnitude
Copulas	[58–61]	From marginal distributions	Weak physical meaning; detailed statistical view	Captures non-linear trends; more info than correlation	Difficult to compare and quantify
Total variation	[62]	Simple; established concept	Strong physical meaning (base units)	Includes variation magnitude; scalable	Ignores capacity factor; needs proportions
Stability coefficient	[56]	Simple; well-known concept	Weak; variance-based	Good for adding a source to a system	Can yield contradictory results
NMAD	[64]	Simple; needs custom functions	Strong physical meaning (base units)	Includes capacity factor; scalable	Needs proportions
CROF	[67]	Simple; needs custom functions	Strong physical meaning (base units)	Works for multiple sources	Ignores capacity factor
Availability index	[77]	Simple implementation	Direct meaning	Easy to calculate and explain	Can contradict; needs threshold
Generation deficiency, R_{DGDE}	[82]	Simple implementation	Strong physical meaning	Useful for off-grid sizing	Limited for utility-scale use
Time-complementarity index	[71,72]	Moderate	No direct physical interpretation	Includes several aspects	Only for smoothed annual profiles
Effectiveness metrics	[3,83,112,113]	Context-dependent	Physical interpretation by design	Describes co-location impact; scalable	Less transparent; reduces comparability

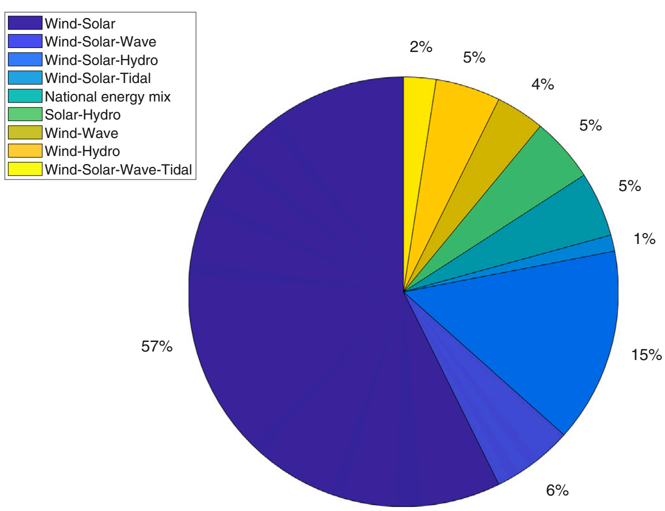

Fig. 5. Overview of studied renewable energy resource combinations.

that real-world practical examples for utility-scale hybrid parks almost exclusively combine wind power and solar PV.

As can be seen in Fig. 5, the most studied combination is wind power and solar PV. Both wind power and solar PV have a high degree of maturity, perhaps the highest among RES except for hydropower, which is likely one reason for the popularity of the combination. The other reason is the alluring near-perfect anti-correlated seasonal pattern in temperate climates [45], indicating very high seasonal complementarity. However, on short time scales, such as diurnal and hourly, this effect is negligible [64]. The actual benefits of seasonal anti-correlation are also not obvious. In a scenario of desired near-constant output, the need for long-term balancing resources would in fact be significantly reduced, but balancing resources would still be required for sufficient operation. Both energy sources can also be unavailable for time periods of several days [96], especially prominent during static high-pressure situations known as Dunkelflaute events [114].

Additionally, the benefit of the seasonal anti-correlation diminishes in many regions when applying a load-following based effectiveness metric. In temperate climates, the annual profile of the system load is similar to the annual profile of wind power. Therefore, it is advised not to conclude complementarity solely based on the value of a CC, but also to address the other known issues.

When assessing the complementarity of wave energy, it is natural to first and foremost consider the combination with offshore wind, as offshore wind is the dominant offshore energy source. Generally, the power output of wind and wave power is strongly correlated [18,115]. A simple statistical analysis purely based on the CC would therefore lead to the conclusion that these sources are not complementary, which need not be the case [70]. As an extension, most correlation-based metrics, such as the time complementarity index and stability coefficient, will likely yield similar results. Correlation can be applicable for wind–wave power plants with careful consideration, however. For example, it has been shown that co-locating wave and wind can significantly lower the total downtime and variability, and that this effect is strongest in areas where the power output is weakly correlated [113]. Considering a time-lag, the wave climate in certain locations is strongly correlated to the wind speeds [116]. This could, for example, be used for generating more accurate forecasts for wave power.

Due to the positive correlation, however, it could be more suitable to use effectiveness-based metrics for expressing the complementarity between wave power and other energy sources. It has, for example, been shown that co-locating wave power with offshore wind and solar is favorable in terms of capacity credit [3]. Wave power and offshore wind share other synergies such as common legislative framework, possibly shared maintenance, and leading to an increased space utilization [8]. There are also mechanical advantages, such as the wave energy converters (WECs) sheltering the wind turbines, shown as the shadow effect [112]. It is therefore not adequate to only focus on measures of statistical dispersion, but instead to focus on well-defined metrics for the benefits added when co-locating wave power with other energy sources.

5.2. Implications for power system design and policy

Understanding and quantifying renewable energy complementarity is not only a theoretical pursuit; it also holds implications for the practical design and operation of power systems. This is, however, sometimes overlooked in complementarity assessments. It is relatively simple to conclude that sources with clear anti-correlation are complementary, but if the anti-correlation does not entail any benefits for the power system, it is dubious whether these sources actually are complementary or not. Correlation metrics can still be used in this manner, but instead by assessing the correlation between a generation profile of a hybrid park and the general system load [117,118].

The fluctuation-based metrics share this limitation with correlation-based metrics, but instead penalize variation rather than variance. It can be observed that the power system load has a non-zero total variation, so a zero-valued total variation of a generation profile might not be the most desirable. Alternative implementations of total variation, CROF and NMAD are, however, possible. For example, it is possible to address complementarity by using the metric total variation, but for the residuals of generation and load, or CROF in the same manner. The metric NMAD can be altered to quantify absolute deviations from normalized system load, instead of absolute deviations from the mean [64]. Assessing complementarity in this manner might hinder simple presentation of the results, but could yield a more sound assessment. It also introduces a further difficulty, namely, predicting the future load of the system in the case of proposing future installations.

From the system design perspective, complementarity should play a role in the design. In regulated systems where one actor is responsible for the long-term planning, complementarity analysis would help with the strategic placement of VRESs, benefiting the entire power system. In deregulated market-driven systems, site selection is often governed by practical considerations, such as where permits are issued, and where the local population and government accept construction. In these scenarios, complementarity mainly affects the stipulated grid connection capacity, which could be significantly lower than the aggregated nameplate capacities of the combined resources.

5.3. Research gaps and future directions

Based on the findings in this review, it is evident that multiple metrics are used in the scientific literature as means to assess complementarity. The choice of complementarity metric is often rationalized by common practice or by a critique of a certain aspect of another metric, such as correlation. However, it is dubious whether it is possible to say that any metric more accurately describes complementarity than another, at least if no definition of complementarity is provided. For example, if the desired quality to improve is variance, Pearson CC is an excellent metric for assessing the possibility of decreasing variance. The use of Pearson correlation is often criticized as a complementarity metric, though the critique may be more appropriately directed at the underlying assumption that variance is the quality to be improved. Studies undertaken in the field of renewable energy complementarity should provide a good rationale for the choice of complementarity metric, referring to which quality should be improved and why.

New metrics will undoubtedly be proposed, providing an ever larger variety of available methods. Future proposals are, however, advised to first assess if there are metrics that are applicable to the relevant quality. If there are, and said metric still lacks accuracy, new metrics are sound. The introduction of new metrics simply on the basis of “more accurate assessment of complementarity” should be done sparingly.

When it comes to the application of metrics, an interesting direction for future studies would be to explore under-explored resource combinations and under-explored complementary traits. Emerging resources like wave power and tidal are unlikely to be economically competitive for a long time, but utilization as a complement to established sources such as offshore wind might accelerate the learning curves of these technologies, thus paving the way for a broader and more diverse energy mix.

6. Conclusions

In this article, several complementarity metrics have been reviewed and compared. It is evident from the review that there is a skew towards quantifying complementarity through reduced variability or fluctuations of the aggregated generation profiles, most often using correlation metrics. As discussed in this article, there are many more traits to consider apart from fluctuations and variability, even though it is natural and logical to include these in the complementarity analysis.

It should also be emphasized that all reviewed metrics work for assessing complementarity, and there is no obvious way of concluding that one metric more accurately describes complementarity than another. Pearson CC, for instance, is very effective in quantifying the possibility of reducing variance through combining resources, whereas the availability index clearly shows the possibility of reducing periods of energy droughts. Both are examples of complementarity, and neither describes complementarity better than the other, but they describe certain traits of complementarity better than the other. Therefore, it is essential to first and foremost decide which quality or trait should be improved before trying to quantify complementarity.

However, it is strongly advised to use multiple metrics in complementarity studies. Since the metrics may yield contradictory results (in essence, meaning that one quality is improved and another one could be worsened), a thorough and transparent assessment should reflect this. Certain considerations based on the physical nature of VRES technologies should also be taken into account when selecting complementarity metrics. For wave power, for example, as the wave climate and wind speeds generally are positively correlated, a straightforward correlation-based statistical analysis will indicate that these energy sources are not suitable for co-location. As has been shown in several studies, however, several benefits do exist. Therefore, it is advised to not only focus on statistical measures for wave power, but rather on quality or effectiveness metrics.

Ultimately, a robust complementarity analysis should be guided by a clear definition of the desired outcome and a thoughtful choice of metrics that best capture the relevant qualities. Combining different metrics while acknowledging their limitations will lead to more comprehensive and transparent evaluations of renewable energy resource complementarity.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Data availability

Data will be made available on request.

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