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Maybe less is more: Considering capacity factor, saturation, variability, and filtering effects of wave energy devices

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ABSTRACT

While a great deal of research has been performed to quantify and characterize the wave energy resource, there are still open questions about how a wave energy developer should use this wave resource information to design a wave energy converter device to suit a specific environment or, alternatively, to assess potential deployment locations. It is natural to focus first on the impressive magnitudes of power available from ocean waves, and to be drawn to locations where mean power levels are highest. However, a number of additional factors such as intermittency and capacity factor may be influential in determining economic viability of a wave energy converter, and should therefore be considered at the resource level, so that these factors can influence device design decisions. This study examines a set of wave resource metrics aimed towards this end of bettering accounting for variability in wave energy converter design. The results show distinct regional trends that may factor into project siting and wave energy converter design. Although a definitive solution for the optimal size of a wave energy converter is beyond the reaches of this study, the evidence presented does support the idea that smaller devices with lower power ratings may merit closer consideration.

1. Introduction

The amount of power in ocean waves has inspired generations of engineers to develop machines that might capture this power and apply it towards practical problems. In certain parts of the world's oceans, and at certain times of the year, the amount of power passing through a 1 m span can exceed 500 kW. To put this in perspective, a higher-end photovoltaic solar panel with a 1 m characteristic dimension might be rated at 500 W.

It is logical that broad measures of wave power, such as annual average power, are considered as a first priority. Naturally, studies and public resources highlighting such wave power metrics abound (see, e.g., [1–3]). In fact, utilization of annual average wave power levels have traditionally driven interest in developing wave energy converters (WECs) for high energy locations, such as the United Kingdom.

Higher average wave power levels have historically been treated as highly desirable. This seems natural, especially given the emphasis on levelized cost of energy (LCOE). However, LCOE is widely acknowledged to have shortcomings [4–6]–in fact some studies have considered this specifically for wave energy [7,8]. Additionally, LCOE estimates, particularly those for emerging renewable energy generation technologies, often have large uncertainties [9].

Broadly speaking, LCOE is the ratio of costs to energy generated. Digging somewhat deeper, we see how the rated capacity and the capacity factor (the ratio of average power to the rated power) interplay with costs to affect LCOE.

$$
\begin{aligned}
LCOE &= \frac{\text{(lifetime costs)}}{\text{(energy generated during lifetime)}} \\
&= \frac{\text{(capital costs)} + \text{(operational costs)}}{\text{(rated capacity)} \cdot \text{(capacity factor)} \cdot \text{(lifetime length)}}
\end{aligned} \tag{1}
$$

It follows that given a larger average power input from the waves, a WEC will generate more power and have a lower LCOE. However, as will be a major focus of this study, the variability in the ocean wave resource will often mean that devices designed with the largest waves in mind may be forced to accept low capacity factors.

Although a "dollars-and-cents" metric like LCOE would seem to give the final verdict on a generation technology's viability, this is an oversimplification of the drivers at work upon a modern electrical grid. Quoting directly from the US Energy Information Administration (EIA): "LCOE does not capture all of the factors that contribute to actual investment decisions, making the direct comparison of LCOE across technologies problematic and misleading as a method to assess the economic competitiveness of various generation alternatives" [6]. As noted throughout literature [10–13], variability is a critical factor in determining the real market value of all energy generation technologies. Accordingly, an analysis based solely on LCOE will often tend to

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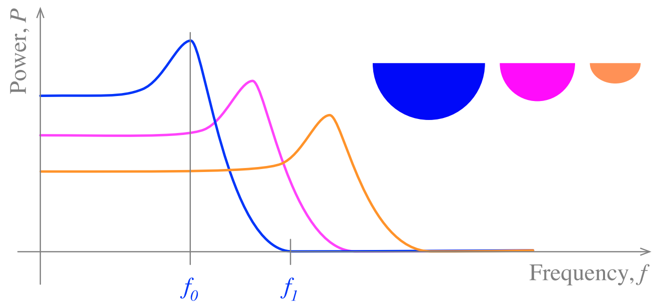

Fig. 1. Power responses of three theoretical hemispherical single-body heaving WECs of different sizes (large: blue, medium: magenta, small: orange).

over-estimate the market viability of variable renewable energy (VRE) generation [10]. Thus, it follows that using an estimate of LCOE that does not factor in the effects of variability will lead to suboptimal design solutions and/or siting decisions. Accordingly, other metrics such as levelized avoided cost of electricity (LACE) [6] and value factor [11] can be used to complement LCOE.

Another oversight implicit in favoring high average wave resource power levels is the omission of how costs will be affected. An increase in average annual power generation may very well come at the cost of additional structural reinforcements, a larger generator, and heavier moorings. Maintenance and operational costs may also increase to counteract higher levels of fatigue. This is especially true for many wave energy sites, where the annual power distribution skews strongly to the right as a result of winter storms [2,14]. As a wise engineer once said, "there is no free lunch," every benefit will have some finite cost—the balancing of these finite benefits and costs is, perhaps, the essence of engineering design. The benefit of capturing the most powerful ocean waves may not be worth the cost.

Finally, we must consider the inherent oscillatory nature of ocean waves. Unlike other generation technologies, WECs are generally designed as resonant systems, and their ability to generate electricity is based entirely on their ability to resonate in response to a given sea state [15], this effect cannot be ignored. In this respect, it is convenient to consider a WEC as a low-pass filter.[1]

A conceptual example of this low-pass filter concept is shown in Fig. 1. Consider, for example, three hemispherical single-body heaving WEC devices of varying scale. The blue WEC is the largest, followed by the magenta, and the orange, which is the smallest. Fig. 1 shows illustrative frequency responses for the power produced by these three conceptual WECs.

Each of these WECs exhibits the same low-pass filter response trend (with the addition of a resonant peak). The largest device, shown in blue, produces its maximum amount of power at resonance, which is shown in Fig. 1 as f_0. To the left of this resonant peak (at lower frequencies), the power response asymptotes to a finite value. To the right of the resonant peak (at higher frequencies), the power asymptotes to zero—no power can be generated from these high frequency waves, as they are filtered out by the WEC. The smaller WECs will generally absorb less power from a given frequency, but can absorb power over a larger range of frequencies.

Thus, we can say that the blue WEC in Fig. 1 operates well for waves with frequencies in the range $[0 : f_1)$, with the best performance near f_0. Similar stories can be told for the magenta and orange WECs in Fig. 1. However, because they are smaller, the magenta and orange WECs' resonant peaks, and the frequencies at which power vanishes, are higher.

It is clear to see from Fig. 1 that the orange WEC can absorb power over the broadest range. However, the blue WEC resonates at a lower frequency—resonance at this lower frequency may be desirable since higher power levels occur in low frequency waves. Conversely, if waves are of too high a frequency ($f > f_1$) no power can be absorbed. This example is extremely simplistic, and without more information it is impossible to say whether one should build the blue, magenta, or orange WEC. Nonetheless, we can see that the frequency (or period) of the waves will strongly affect WEC performance/design, and should therefore be considered in our assessment.

Note also that other WEC archetypes (e.g., oscillating water columns, flapping devices) may have different characteristic dynamics (e.g., bandpass) [16]. Even a single heaving body WEC may exhibit a band-pass nature once the power take-off dynamics are incorporated to consider electrical power [17]. Additionally, factors such as stroke limitations are not necessarily well-capture by the low-pass filter analogy. For simplicity, we consider only the simple low-pass filter to represent a single body heaving WEC in this study, but other response types are relevant depending on the device structure and should be considered in the future.

Even though it is overly simplistic, the "which WEC should we build?" question provides a useful lens through which to consider wave resource characterization. Traditionally, many developers and policy makers have been drawn to the enormous amounts of energy available in large amplitude low frequency waves, and this has necessarily driven many design and siting decisions towards large WECs deployed in energetic sites. While we cannot conclusively answer the "which WEC should we build?" question, this paper presents some compelling evidence to challenge the idea that a WEC must capture the largest waves to be successful, and in fact suggests that the opposite may be true—maybe, less is more.

To consider this fundamental question about WEC size and design, and also to generally provide developers with means of assessing local wave resources in practical terms that can better reflect LCOE and other determinants of economic viability, this paper presents a series of wave resource metrics. In particular, we focus on metrics that can inform us about intermittency, variability, capacity factor, and frequency band. To contextualize these otherwise unfamiliar numbers, we present regional and global distributions for these metrics.

First, in Section 2, we present a review of literature on wave resource characterization, with particular interest paid to similar studies in which the concepts of variability, saturation, and resonance are studied. Next, some basic concepts of the methods employed in this study are summarized (Section 3). Results produced by these methods are presented in Sections 4–6; further discussion is presented in Section 7 and conclusions are drawn in Section 8 and Section 9.

2. Review of previous work

Information on the wave energy resource is critical to the success of the marine energy industry, informing regional energy planning, project siting and development decisions, and conceptual WEC design. International standards have established key resource summary metrics, e.g., annual average power, spectral width, directionality and energy period, as well as attributes of these metrics, e.g., their spatial and temporal distribution and variability, their frequency of occurrence, including their extreme quantiles [18]. The establishment of standard resource metrics and attributes enable comprehensive and consistent assessment of the opportunities, constraints and risks for regional energy planning, WEC siting and project development, and conceptual WEC design.

A large number of studies have performed theoretical wave resource assessments globally [2,3,19–23], nationally [24–32], regionally [33–53], and for specific test sites [54–61]. Generally, most of these studies

[1] Hagerman and Scott [1] considered a similar concept, but called WECs high-pass filters based on their cancellation effect on the ocean waves and considered the filter effect of WECs in terms of wave amplitude, not frequency. Here, we concentrate on the WEC system and prefer to consider the low-pass filtering effect on the energy absorbed by the WEC from the waves.

do indeed consider variability, often by presenting monthly average power levels (see, e.g., [21]). However, such a presentation may not be directly actionable for a WEC designer looking to make design and/or siting decisions.

Assessments of the technical or technically recoverable wave energy resource (see, e.g., [3]), which factors in the conversion limitations of WEC technologies, e.g., thresholds for minimum, rated and maximum operating capacities, and component efficiencies, have also been performed. However, assessment of the technically recoverable resource remains highly subjective, with most studies using the power matrices of specific WEC technologies, where the question is posed in terms of choosing a siting location, not necessarily quantifying the technically recoverable resource [16,62,63]. Given the wide range of WEC concepts, the results of such an approach will be highly dependent on the device selected.

Over the last decade, metrics indicating the temporal variability of the wave power have been examined in different time scales. Cornett [2] parameterized the temporal variability of the global wave power using simple metrics that can be mapped to describe its geographical distribution, e.g., coefficient of variation (COV), monthly and seasonal variability indicating maximum range of monthly and seasonal mean power to the annual mean power. Many studies utilized these metrics to assess the temporal variability of the wave power [19,20,24,25,34,35]. Lower variability levels in the wave resource are desirable, as they may enable lower intermittency and high capacity factor levels while also decreasing demands on the device design.

The energy period, a measure of variance-weighted mean period of a given sea state recommended by the International Electrotechnical Commission (IEC) [18], is typically assessed in wave energy resource characterization studies. A series of statistics for the energy period, e.g., mean, standard deviation, median, 10th percentile, 90th percentile, maximum, minimum, are often examined to characterize the temporal variability (see, e.g., [43]). Recently, Ahn, Hass, and Neary [64] proposed metrics characterizing power-weighted peak period over a particular time period—this weighting approach has the advantage of improving resolution where spectral energy is highest [24].

Hagerman and Scott [1] mention the importance of wave period, but did not explicitly account for it in their analysis. Ahn, Hass, and Neary [64] developed wave energy classification systems based on frequency filtered (resolved) wave power as well as the total wave power, e.g., class of total wave power and class of wave power within the dominant period bands. A more recent study also developed a method for classifying wave energy sites [65], which also includes factors to account for spectral range.

A number of studies [24,25] have investigated temporal variability of the frequency filtered wave power for US coastal waters. Yang, García-Medin, Wu, and Wang [43] presented a characterization of wave resource based on results from a recent high resolution hindcast modeling effort [66]. This study reports IEC specified parameters as well as the local bathymetry for the US West Coast.

Temporal variability of both energy demand and supply can have an important effect on technology deployment. Additionally, the spatial location of electrical generation capacity has important implications for transmission networks. In some cases, e.g., [3,67], researchers have considered the national/region electricity demand in relation to the wave resource. An analysis considering temporal variations in energy demand and energy supply from different VREs was recently employed to assess the potential deployment of hydroelectric, solar, and wave energy for a small remote Canadian community [68]. Similarly, Fairley, Smith, Robertson, Abusara, and Masters [69] considered the value of using an increasing number of wave energy sites to smooth electricity supply on a timescale of hours to days.

Table 1
Key parameters of the present and previous global wave resource studies.

	Spatial res.	Temporal res.	Period of rec.
Present study	(0.5°, 0.5°)	1 h	2011–2020
Gunn and Stock-Williams [3]	(0.5°, 0.5°)	3 h	2005–2011
Arinaga and Cheung [21]	(0.5°, 0.5°)	1 h	2000–2009
Cornett [2]	(1.25°, 1.0°)	3 h	1997–2006
Reguero, Losada, and Méndez [20]	(1.5°, 1.0°)	1 h	1948–2008

3. Methods

3.1. Data source

Data for this study was sourced from the WaveWatch III (WW3) Global Wave Model (`ww3_global`) run by the Pacific Islands Ocean Observing System (PacIOOS) at University of Hawaii for the US National Oceanic and Atmospheric Administration (NOAA) [70]. This data was generated using a WW3 model with a grid spaced every half degree of latitude and longitude (roughly 50 km). Hourly bulk spectral wave parameters for a total of nine years, beginning from July 1, 2011 were used. Atmospheric forcing for this wave model relies on the National Centers for Environmental Prediction Global Forecast System weather model at approximately 50 km resolution.

Arinaga and Cheung performed a more general wave resource assessment using a similar dataset [21]. Other relevant global wave resource assessments are listed in Table 1. Note that the dataset used in this study is too short to capture changes in the wave climate due to global climate change and long term periodic variations (e.g., El Niño/La Niña); these phenomena have been considered in other studies (see, e.g., [20,70,71]).

3.2. Wave power metrics

The `ww3_global` wave resource model's peak period, T_p, and significant weight height, H_{m0}, were used in this analysis. The significant wave height is defined by the zeroth-moment of the spectral energy density distribution.

$$H_{m0} = 4\sqrt{m_0} \tag{2}$$

The n^{th} spectral moment is defined as

$$m_n = \int S(\omega)\omega^n \, d\omega, \tag{3}$$

where S is the spectral energy density (with units of $\frac{\text{length}^2}{\text{frequency}}$) and ω is the radial frequency. The peak period is the period with the largest value of spectral energy (i.e., the peak in the spectral energy distribution).

$$T_p = \left[\frac{1}{2\pi} \arg\max_{\omega} S(\omega)\right]^{-1} \tag{4}$$

The wave energy flux in deep water per a unit of wave front is given by (see, e.g., [72]).

$$J = \frac{1}{2}\rho g^2 \int \frac{1}{\omega} S(\omega)\, d\omega. \tag{5}$$

To calculate J in terms of bulk parameters, it is also convenient to define the energy period:

$$T_e = \frac{2\pi}{\omega_e} = 2\pi \frac{m_0}{m_1}. \tag{6}$$

The introduction of the energy period and some manipulation of (5) allows us to rewrite the equation for wave power as

$$J = \frac{1}{64\pi}\rho g^2 H_{m0}^2 T_e \tag{7}$$

It is often useful to know when working with sea water to find the wave power in units of kW/m, one may reduce (7) to $J \approx \frac{1}{2} H_{m0}^2 T_e$.

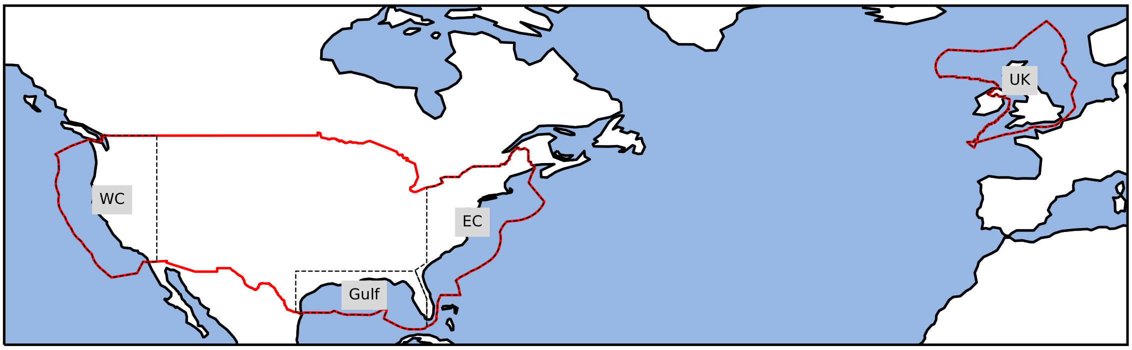

Fig. 2. Regional boundaries considered in analyses (WC: United States West Coast, GC: United States Gulf Coast, EC: United States East Coast, UK: United Kingdom).

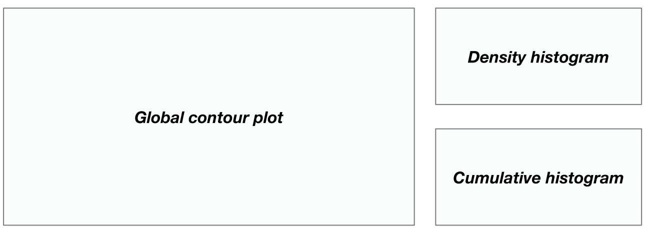

Fig. 3. Illustration of plot configuration commonly used herein.

Returning to the dataset at hand, we must recall that the `ww3_global` wave resource model has provided the peak period, not the energy period as now appears in (7). To infer the energy period from the peak period requires an important assumption about the spectral shape. For example, if the spectrum follows the Pierson–Moskowitz distribution, the relationship is [73].

$$T_e = 0.858 \cdot T_p \tag{8}$$

If the spectrum follows a JONSWAP form, the relationship becomes a function of the peakedness factor γ [73].

$$T_e = T_p \left(0.8255 + 0.03852\gamma - 0.005537\gamma^2 + 0.0003154\gamma^3\right) \tag{9}$$

However, since peakedness is not reported in the `ww3_global` dataset and the Pierson–Moskowitz spectrum is the preferred choice for mean sea states [74], we use the relationship given by (8) for the present analyses. Further appreciation for the effects of using different spectral periods in quantifying wave power can be had from a study on this subject performed by Cahill and Lewis [75].

The large scale of data involved in this analysis necessarily presents a set of computational challenges. Some details on the data processing techniques applied in this study are summarized in Appendix.

3.3. Regional analyses

To provide more focused results, global analyses in this study are accompanied by results for specific regional areas within sovereign state economic exclusion zones (EEZs) as set down by the United Nations Convention on the Law of the Sea in 1982. A nation's EEZ stretches 200 nautical miles (370.4 km) from the coastline. Specifically, we consider the US EEZ in three components: East, West, and Gulf Coasts, along with the UK. These regions and their abbreviations are shown in Fig. 2.

Additionally, it is helpful to introduce the plotting layout shown in Fig. 3, which will be utilized throughout this paper. For a given metric, e.g., median power, the left hand plot illustrated in Fig. 3 will show a global spatial distribution contour plot. To contextualize the values in the spatial contour plot, the empirical probability distribution (histogram) and cumulative distribution are shown on the right hand side of the composite figure.

To provide a more tangible example, and to begin thinking about the wave energy resource in more concrete terms, we can consider Fig. 4, which shows the median wave power over time. The contour plot on the left hand side of Fig. 4 shows how the median wave power is spatially distributed across the globe, with the highest levels of median power occurring towards the poles. The histograms on the right hand side of Fig. 4 show the overall distribution of this power. Globally, we can see that median power levels are widely distributed, with some sites having median power levels up to 110 kW/m. Note however that power levels greater than 100 kW/m are exceedingly rare, occurring in less than 2% of locations globally. These results are similar to other global WW3 hindcast studies [2,3], despite different model resolutions and time periods.

Comparing the median wave power in the EEZ regions defined in Fig. 2, we can see why so much interest has been given to wave energy in the UK, as it has the highest median power levels of the regions considered (up to 50 kW/m). At the other end of the spectrum, the Gulf Coast has much lower power levels—no median power level in the Gulf exceeds 5 kW/m. However, as previously discussed in Section 1, we should look more deeply at the resource characteristics before passing judgment on which of these resources is more desirable.

4. Power variability

As discussed in Section 1, the variability of ocean wave power over time is generally undesirable. If we were to imagine the ideal wave power resource, it would have zero variability: the available power from the ocean would be the same every hour of the day and every day of the year. This would enable a WEC to achieve zero variability. Realistically, we know that this will never be the case.

Nonetheless, it is useful to consider the relative variability of the wave power resource. Fig. 5 shows the standard deviation of wave power taken over time (σ). Further inspection of Fig. 5 reveals some interesting trends. Considering the contour plot on the left hand side of Fig. 5, we can immediately see how the North Atlantic and the Southern Ocean have high levels of variability.

Considering the US and UK EEZs, we see that the Gulf Coast has the lowest variability and the waters to the west of the UK have very high variability. These regions can most easily be compared via the histograms on the right hand side of Fig. 5. It is somewhat surprising to note that the variability in power is mostly similar between the East and West Coasts, even though the median power levels on the West Coast are often twice that seen in the East Coast region. From the histograms in Fig. 5, we can note that the East Coast region's variability levels are quite low compared with the rest of the globe—the wave power variability in the Gulf Coast is even lower (but median wave power is also low in the Gulf).

Thinking further along the same lines about an ideal wave energy source, we would desire not only low variability, but likely also high

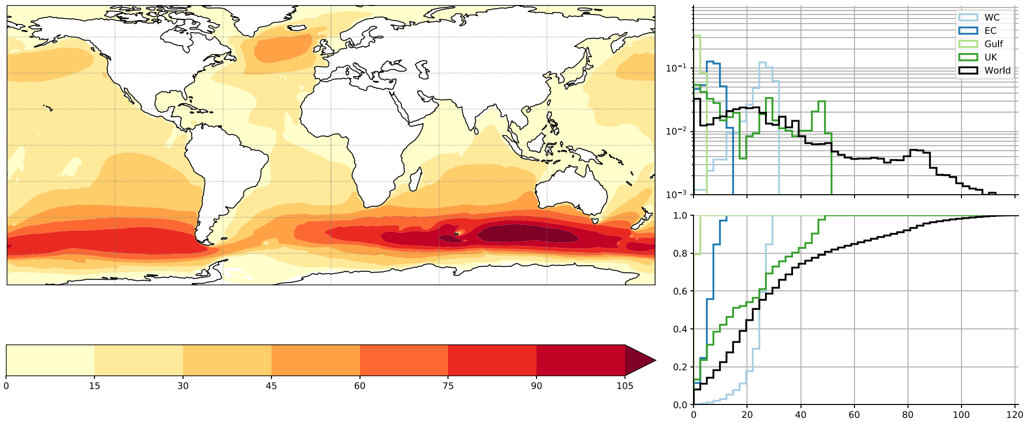

Fig. 4. Median power, ν_J [kW/m].

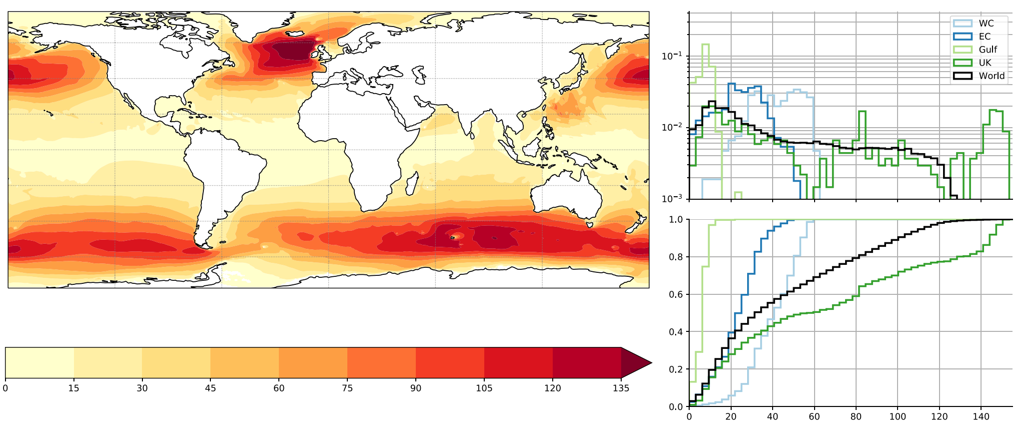

Fig. 5. Power standard deviation, σ_J [kW/m].

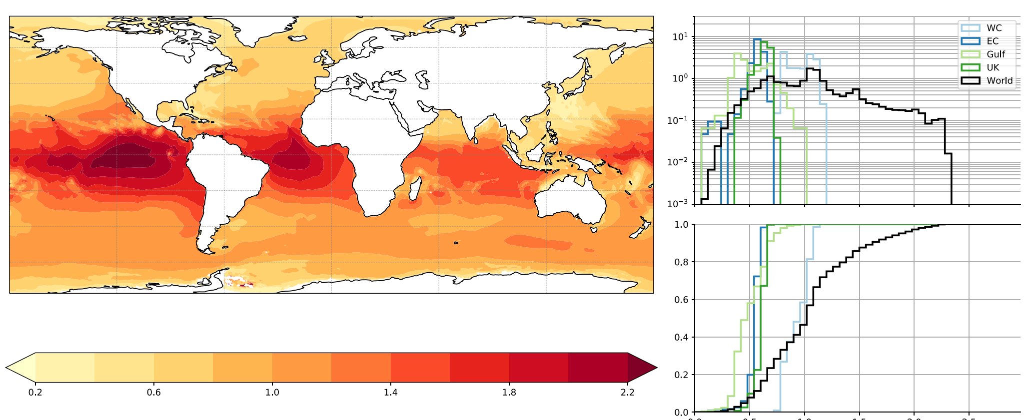

Fig. 6. Power inverse coefficient of variation, $CV_J^{-1} = \frac{\mu_J}{\sigma_J}$ [ ].

levels of power. The coefficient of variation is the ratio of standard deviation to mean. If we invert this quantity, we have a metric that is positively proportional to power level and inversely proportional to power variability.

$$CV^{-1} = \frac{\mu}{\sigma} \tag{10}$$

Here, μ is the mean power over time.

Fig. 6 shows the global distribution of this inverse coefficient of variation. From the histograms in Fig. 6, we can see that the metric has a fairly normal distribution, with CV^{-1} ranging from 0.1 to 2.5 and where values above 1 are in the upper half of the distribution. Many of these higher inverse coefficient of variation levels occur in equatorial waters. The southern US West Coast is also observed to be attractive in terms of this metric. The geographical trend of the inverse coefficient of variation (CV^{-1}) shown in Fig. 6 maintains large similarities with the trend observed by Cornett [2] and Reguero, Losada, and Méndez [20], which each considered the coefficient of variation.

Once we admit that any real wave power resource will have some finite level of variability, we can also think about how we would prefer for that variability to be distributed. Nonparametric skew is a metric

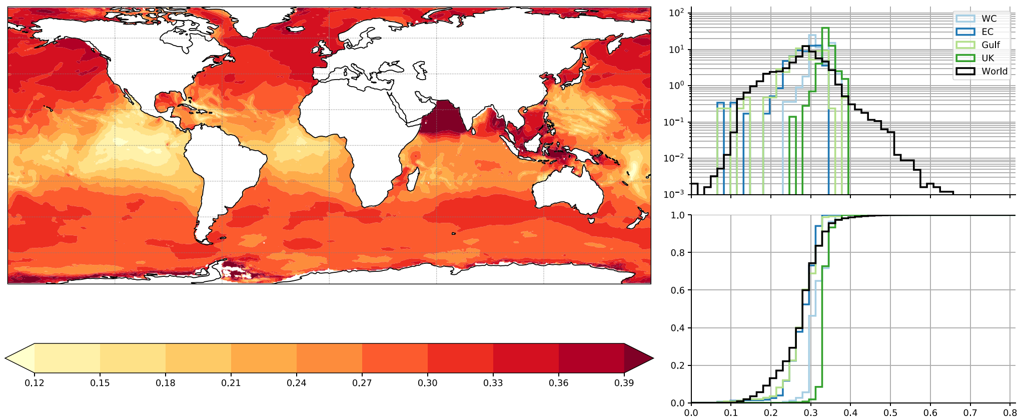

Fig. 7. Wave power distribution non-parametric skew, S_J [ ].

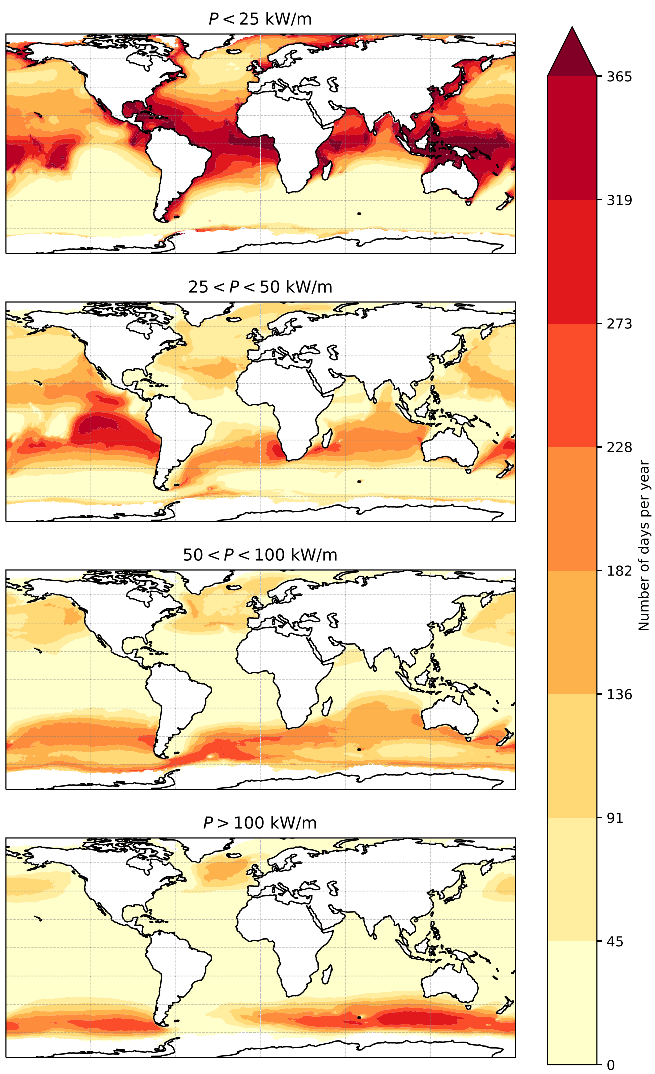

Fig. 8. Mean number of days per year with power in set of bins $[0, 25, 50, 100, \infty]$ kW/m.

used to understand this aspect of a distribution.

$$S = \frac{\mu - \nu}{\sigma} \tag{11}$$

Here, ν is the median over time.

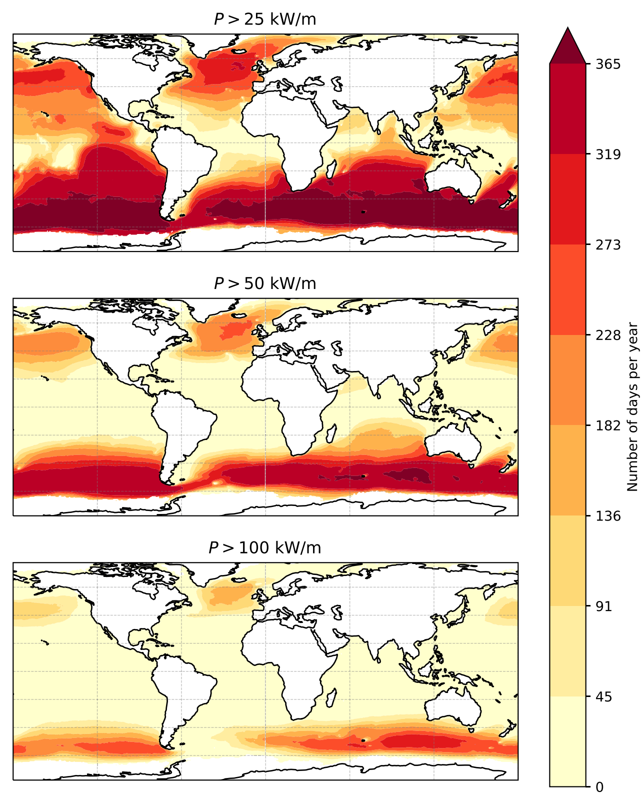

Fig. 9. Mean number of days per year with power above thresholds of $[25, 50, 100]$ kW/m.

Ideally, a wave power resource distribution might be negatively skewed—that is with the tail of distribution extending towards zero. This would mean that a WEC device could be designed to target the bulk of the power that occurs at higher levels, with lower power levels occurring in the negatively skewed tail unlikely to cause damage. As it turns out, this situation does not occur in nature, at least not over the long term; in practice, all wave power is positively skewed. Alternatively, if the WEC device can effectively saturate above a certain power level, it may be advantageous to have a positively skewed distribution.

Fig. 7 shows the non-parametric skew of the wave power distribution, where we can see that the skew in power has a fairly normal distribution globally, ranging from 0.1 to 0.4. The distribution is quite

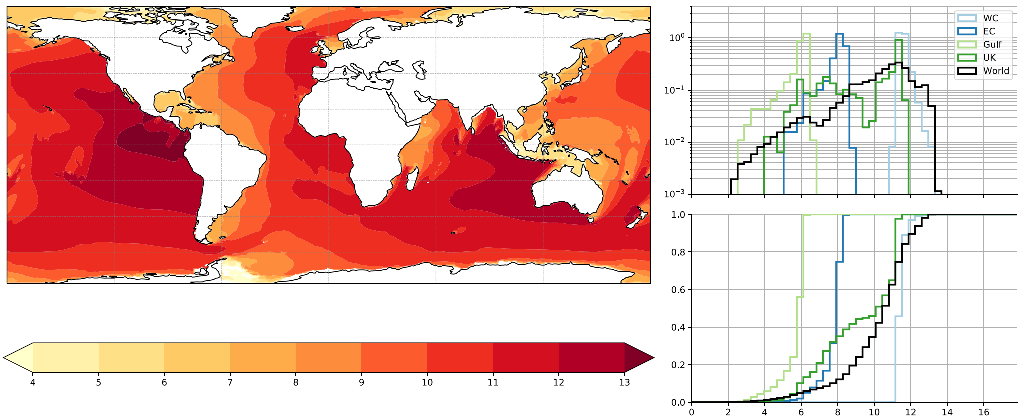

Fig. 10. Power weighted mean of energy period, $\mu_{T_e(J)}$ [s].

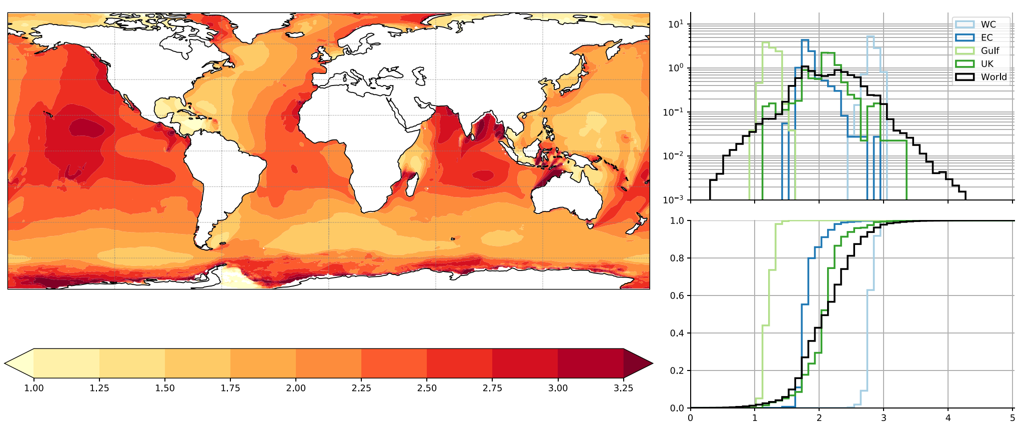

Fig. 11. Energy period standard deviation taken over time, σ_{T_e} [s].

narrow, with a standard deviation of only 0.056. Equatorial waters again look attractive in terms of wave power skew.

It is also interesting to compare the skew shown in Fig. 7 to the standard deviation shown in Fig. 5. While both of these metrics are positively correlated with variability, they do not necessarily show the same trends. For example, we can see that the skew of the wave power distribution in the Gulf Coast region is relatively high, but the standard deviation is fairly low. This may be related to tropical storms, which are relatively rare, but create extreme waves, and may, in turn, extend the positive tail of the wave power distribution.

Another means of looking at the variability of the wave energy resource is to consider the average power level for each day in the year. For instance, we can consider the number of days in a year with power in a certain range, as is shown in Fig. 8. The top-most plot in Fig. 8 shows the number of days in a year (on average) with a mean power less than 25 kW/m. The three lower plots in Fig. 8 similarly show the number of days in power bins of [25, 50], [50, 100], and [100, ∞) kW/m, respectively.

We can see from Fig. 8 just how rare it is to have more than 100 kW/m of power. This finding is in line with conclusions drawn by [65]. Even in the US Pacific Northwest and the North Atlantic, two regions well known for their high levels of wave power, waves with more than 100 kW/m of power occur at best half the year, often much less. The power band with $25 < P < 50$ kW/m appears to be the most broadly persistent throughout the globe. A WEC that can perform well in this $25 < P < 50$ kW/m regime may actually generate more power on average *and* have a higher capacity factor than a WEC targeted at capturing the waves in, e.g., the $50 < P < 100$ kW/m range.

Alternatively, it is also useful to consider thresholds of power instead of bins. Consider, for example, a WEC sized and engineered to generate power in seas with up to 25 kW/m of power and capable of effectively saturating and shedding loads when the power level exceeds 25 kW/m. We could write a piecewise function for the power produced by such a device, P, as

$$P = \begin{cases} f(J) & J < 25 \text{ kW/m} \\ f(J = 25) & J \geq 25 \text{ kW/m}. \end{cases} \tag{12}$$

Fig. 9 shows the average number of days in year in which power is greater than thresholds of 25, 50, and 100 kW/m. Again, we can see just how rare power levels greater than 100 kW/m are. Conversely, if, as imagined, we can design a WEC that performs well whenever the incident wave power is greater than 25 kW/m, this would have many viable deployment locations where such a device might operate at or near rated capacity for 300+ days in an average year.

5. Frequency bands

As discussed in Section 1, wave energy converters can typically only operate well within a limited frequency range. Based on this, we would prefer to have a wave resource where, ideally, waves with a single period occur all year long and carry all of the energy in the sea. Returning again to reality and accepting that real ocean waves carry energy in a range of frequencies, we can think about where the wave power is concentrated (in terms of period) and how much variability there is in that period location.

Taking the first of these concepts (the spectral energy location), one method of assessing the spectral location of wave power is to find the power weighted mean energy period (as was similarly done by [64] for peak period)—this is shown in Fig. 10. Focusing first on the histograms on the right hand side of Fig. 10, we see that wave power is globally distributed across a range of $T_e \in (2, 14)$ s. We can also notice that the global distribution of the power weighted mean energy period has a negative skew, with the higher energy period waves contributing more heavily to the mean.

The regional histograms in Fig. 10 are quite interesting as well. The three US regions show very distinct behaviors, with the Gulf Coast having relatively short period waves (~5.8 s), the East Coast having intermediate period waves (~7.9 s), and the West Coast have relatively long period waves (~11.6 s). The power weighted energy periods in UK EEZ waters span a broader range, which is not surprising when one considers that the UK region includes different coastlines, exposed to distinct fetches.

This spatial trend is consistent with US national scale studies [24, 76]. The wave energy in the Gulf of Mexico is mainly contributed by local wind seas within a narrow frequency band, leading to the consistent energy periods. The wave energy in the East Coast is dominated by two swell systems (i.e., trade wind swells and high-pressure swells) within similar period band, leading to the consistent energy periods. For the West Coast, the long-period westerly swells dominating winter season significantly diminish in summer season, leading to the large seasonal variability in the energy period [76].

Looking at the contour map of power weighted energy period in Fig. 10, we can see how long period waves occur on continental west coasts and shorter period waves along continental east coasts. This trend, where longer period waves occur on west facing coasts—especially in the middle latitudes, is due to the prevailing Westerlies. The negatively skewed nature of the global power weighted energy period distribution is also evident from the contour map in Fig. 10.

It is also useful to consider the variability of the wave period, as this is somewhat indicative of the bandwidth over which the energy occurs.[2] Fig. 11 shows the standard deviation of the energy period. Narrower bandwidths, which are linked to lower levels of standard deviation of energy period, are preferable in terms of WEC device design. The US East Coast and Gulf Coast have relatively consistent energy periods ($\sigma_{T_e} \approx 1.5$ s), whereas the West Coast wave energy period varies much more broadly ($\sigma_{T_e} \approx 2.8$ s).

Recalling the filtering effect introduced with Fig. 1, we would also like to consider the amount of power that is available to a WEC acting as a low-pass filter. As discussed, a WEC of a given size will be able to absorb energy from waves at frequencies below a given threshold (f_1 in Fig. 1). Equivalently, we can consider the amount of power at wave periods *above* different thresholds (since $T = f^{-1}$ we swap the directionality of the expression, i.e., a device will absorb waves with periods $T \geq T_1$). Fig. 12 shows the mean power available for $T_e > [4, 8, 12]$ s. It is not at all surprising to find the highest mean power levels for $T_e > 4$ s, as this necessarily includes the waves in the two upper period bins ($T_e > [8, 12]$ s). While the long period waves have the largest power, they are not always present. Thus, the ability to capture power in the shorter period waves can substantially increase the mean power output of a WEC.

Per the previous discussion on the potential importance of capacity factor, it is also beneficial to ask how many days in a year will a WEC acting as a low-pass filter be able to absorb power. This metric is shown in Fig. 13. The situation illustrated by Fig. 13 is rather dramatic: a small WEC may be able to absorb power many more days in a year than a large WEC. Returning the f_1 coordinate used in Fig. 1, if $f_1 \approx \frac{1}{4}$ Hz, the WEC will likely be capable of absorbing power nearly every day of the year. Conversely, if $f_1 \approx \frac{1}{12}$ Hz the WEC may operate at capacity well less than a quarter of a year.

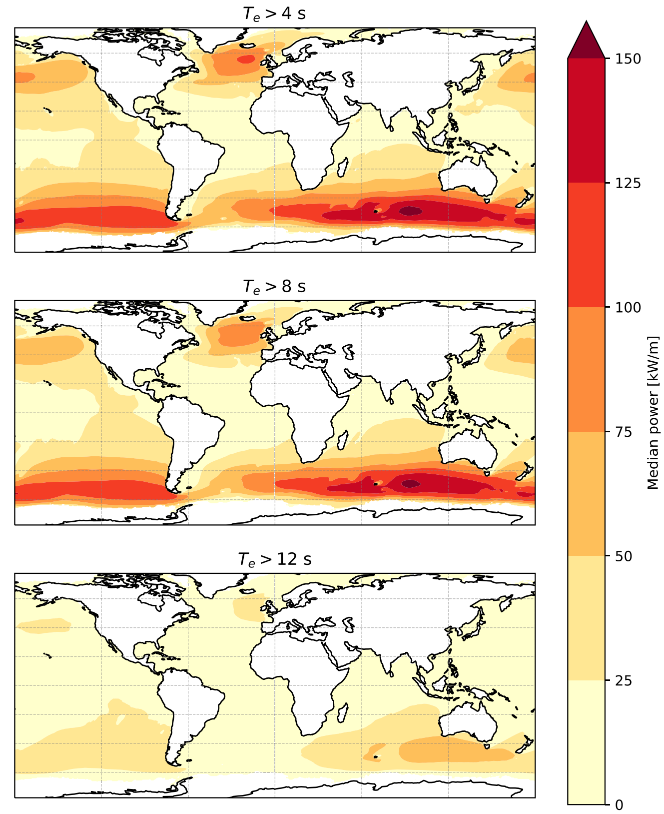

Fig. 12. Mean wave power with $T_e > [4, 8, 12]$ s.

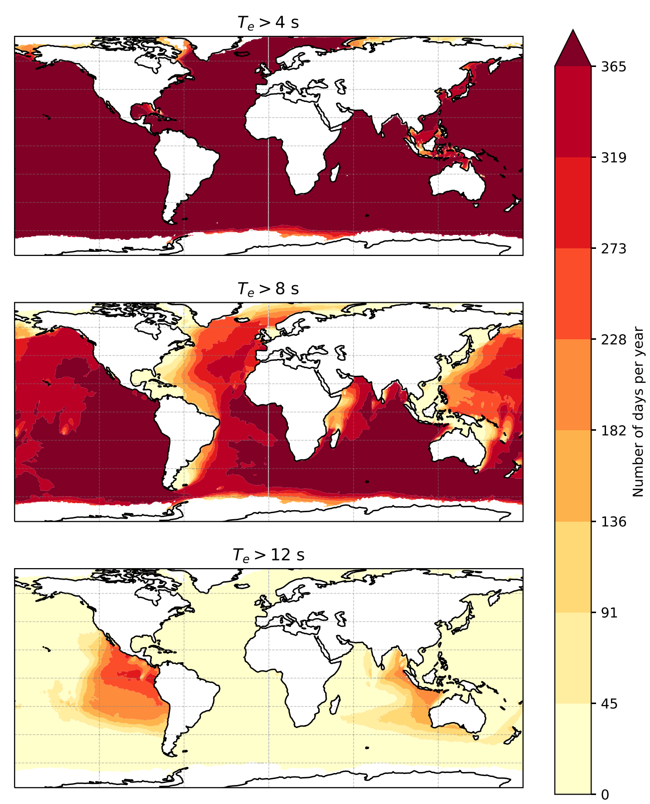

Fig. 13. Mean number of days per year when $T_e > [4, 8, 12]$ s.

[2] Note that the spectral bandwidth could be more directly measured from spectral density, $S(\omega)$. The `ww3_global` `ww3_global` wave resource dataset reports only bulk parameters, not spectral density.

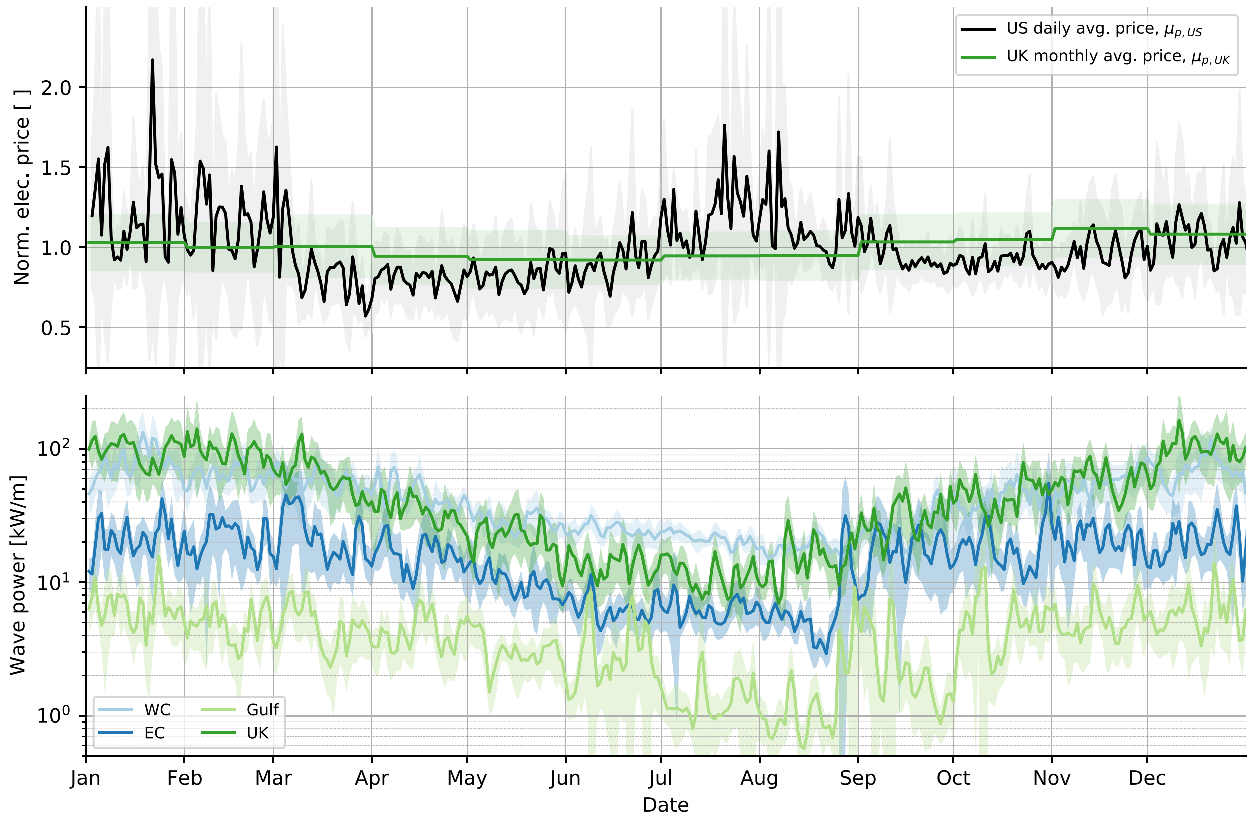

Fig. 14. Mean normalized US and UK electricity wholesale day-ahead price (sources: US Energy Information Administration [77], UK Office of Gas and Electricity Markets [78]) compared with average wave regional resources. Darker curves show average, shaded areas show variability (for electricity price: $\mu_p \pm \sigma_p$, for wave power: $\mu_J \pm \frac{1}{2}\sigma_J$).

6. Correlation with electricity demand

As noted and analyzed by [10–12], the real market value of generated electricity is temporally dependent. More specifically, electricity is a heterogeneous good, both temporally and spatially. Temporal heterogeneity comes from varying demand, which occurs at many different time scales, for example with peak demands occurring within the waking hours of each day and seasonal peaks occurring in both the winter and summer driven by heating and cooling needs [6]. Spatial heterogeneity, which tends to have a smaller effect on price [11], comes from the fact that energy generation does not always take place at the location of consumption, and electrical grids have limited transmission capabilities.

The effects of these heterogeneities are relatively well understood for wind and solar generation technologies [11]. However, wave energy has a unique resource profile: in the northern hemisphere, large waves occur in the winter with smaller waves occurring in the summer. This long twelve-month time scale in wave resource fluctuation means that energy storage technologies, except for perhaps chemical storage and in some cases pumped hydroelectric, will have a large challenge in smoothing the wave energy supply profile (see, e.g., [79]). The good news is that short-term variability in wave power is relatively low.[3]

As shown in Fig. 14, the wave resource and demand for electricity are not necessarily in phase. The upper axes in Fig. 14 show the average normalized US and UK electricity day-ahead wholesale price [77,78]. The US curve is based on nine years of *daily* data; the UK curve is based on nine years of *monthly* data. The lower axes show the regional wave power resources.

Ignoring, for the moment, the matter of spatial heterogeneity and also assuming that the penetration of wave energy on the grid is marginal, we can consider what this potential mismatch between electricity supply and demand may entail for wave energy development. As suggested by [11], we can find the "value factor" for wave energy from the data shown in Fig. 14. This value factor is the simple ratio of the real market value of the electricity at the time and place of generation ($\bar{p}'$) versus the base price of electricity ($\bar{p}$).

$$v = \frac{\bar{p}'}{\bar{p}} = \frac{1}{n\bar{p}} \sum_{i=1}^{n} p_i \, g_i \tag{13}$$

Here, p_i and g_i are the daily electricity price and generation, respectively. A value factor greater than one indicates a resource that is positively correlated with demand, while a value factor less than one would correspond to a resource that is negatively correlated with demand. For context, the average wind and solar value factors reported by [11] for the German electricity market were 0.94 and 1.16, respectively.

If we assume that wave electricity generation will be linearly correlated with the wave resource, we can find the region-specific value factors for each of the regions considered in this study. For the US regions, daily wholesale day-ahead electricity prices were obtained from the US EIA [77]; for the UK, only monthly averages of the wholesale day-ahead electricity prices were available [78]. Using this monthly data for the UK precludes a direct comparison with the value factor of the other regions, since taking temporal averages will, necessarily, drive the value factor towards unity. Another important assumption for these calculations is that the market penetration of wave energy is taken to be negligible (i.e., the contribution of wave power to the grid is so small that variations in the supply of wave power do not affect price).

[3] Because waves provide an oscillatory power input to a WEC (e.g., in a regular wave, the velocity – and therefore mechanical power – of a WEC would be zero twice during the wave period), local energy storage will likely be necessary to smooth the power output from a WEC array.

Table 2
Region-specific value factors for wave energy resource using nine years of data starting January 1, 2011. Yearly value factors are shown in Fig. 15. * Annual energy is considered proportional to average wave power. † UK electricity price data was only available on a monthly basis, and this value factor is therefore not directly comparable with other regions.

Region	Annual energy [*]	Value factor [ ]
WC	4.5e+01	0.978
EC	1.6e+01	1.006
Gulf	4.1e+00	1.032
UK	4.9e+01	1.012†

Taking, for example, the West Coast, the data shown in Fig. 14 give

$$v_{\mathrm{wc}} = \frac{\bar{p}'_{\mathrm{wc}}}{\bar{p}_{\mathrm{wc}}} = \frac{38.30\,\$/\mathrm{MWh}}{44.95\,\$/\mathrm{MWh}} = 0.978. \quad (14)$$

The value factors for each of the regions considered in this study are reported in Table 2.

Note that the value factors presented in Table 2 are computed with nine years of daily electricity price and wave power data, while Fig. 14 shows the yearly averages for these data for clarity. A plot of the yearly regional value factors is shown in Fig. 15. High value factor levels shown in Fig. 15 for the US regions in 2014, 2015, and 2019 are due to spikes in electricity prices in January/December in those years caused by cold weather spells and increased heating demand in the Northeast. These anomalies are evident from the large variability in electricity price shown early in the year in Fig. 14.

From the results presented Table 2, we can see that the wave energy resource tends to have a value factor close to unity. When considered in combination with the well-known predictability of ocean waves [80], these value factors close to unity suggest that WECs may be well suited to providing a base load generator service on an electrical grid. Additional work will be needed to estimate the value factor of a WEC's actual output, which may not be directly correlated to the local wave resource levels.

7. Discussion

As discussed in Section 1 and from the definition of LCOE given by (1), there is a complex interplay between a WEC's rated capacity, capacity factor, and costs—each of these factors are affected by the wave resource. If these factors (rated capacity, capacity factor, lifetime length, and costs) were represented by a hyper-surface, the optimal design in terms of LCOE would lie at their intersection. Thinking beyond LCOE to metrics such as LACE and value factor that better measure the true value of a generation asset, the design problem becomes perhaps more complex, because LACE and value factor consider the coupled interaction of a generating asset with a specific energy grid—one must consider, e.g., a proposed WEC array operating in southern California and how the addition of this array will affect costs within California Independent System Operator (CAISO) system, which coordinates California's bulk electric power system.

While the calculations may be more challenging, estimating LACE for WECs may prove very instructive. Such a factor is particularly important when considering government initiatives, such as renewable energy portfolio standards (RPSs).[4] California, for example, has a RPS program requiring utilities to have 60% retail electricity delivered by renewable sources by 2030 and 100% by 2045. Hawaii has a similar goal of 100% renewables by 2045. New York is aiming for 70% renewables by 2030. The UK has plans to reach net zero emissions by 2050. When faced with the need to meet these requirements while

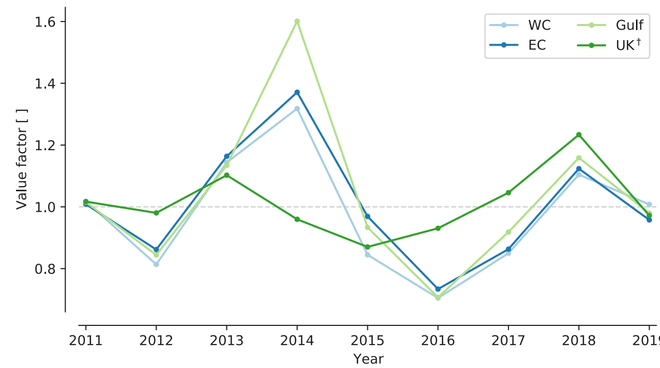

Fig. 15. Yearly value factor estimates based on regional wave resources. †UK electricity price data was only available on a monthly basis, and this value factor is therefore not directly comparable with other regions.

satisfying electricity demand, a utility may very well be willing to adopt generator assets with higher LCOEs if they can help keep the lights on at night when the solar panels are dormant. Extending this concept to a hypothetical WEC, it may actually be beneficial to even increase LCOE, if necessary, in order to increase capacity factor and/or align supply with demand (see Section 6). Note that, as discussed in Section 6, energy storage will factor into these considerations about meeting temporally varying electricity demands.

Some interesting analogs for this concept can be found in wind turbines and photovoltaic solar panels. Wind turbines are rated based on the power they will produce at a design wind speed (generally on the order of 10 to 16 m/s). However, a turbine will, of course, experience a range of wind speeds based on the prevailing weather (broadly speaking, wind speeds tend to follow an exponentiated Weibull distribution [81]), and thus it is typical for wind turbines to have capacity factors on the order of 30%–35%. Likewise, solar panels often have capacity factors of roughly 25% due to clouds and the angle of the sun at the deployment location. Nuclear power plants generally operate a capacity factor near 90%, with the remaining 10% left to spinning reserves [82].

The specific capacity of a wind turbine is the ratio of the rated capacity to the blade swept area, with units, for example, of W/m^2. In the past 20 years, an interesting trend has developed in which wind turbine manufacturers have steadily decreased the specific capacity of their turbines. From 2000 to 2020, the average specific capacity of onshore wind turbines in the United States has decreased from 400 W/m^2 to 225 W/m^2 [83]. While limiting the ability to capture power from the strongest winds, this change has increased capacity factors and average annual energy of wind turbines, while also reducing costs.

Sizing of a device can also affect operational and maintenance costs. An instructive example is the so-called "truck roll" for performing repair work on a solar photovoltaic system [84,85]. Because the costs of a single repair trip are often substantial, it is advantageous to have a more distributed system, with many relatively small individual solar panels and micro-inverters. With this approach, the solar array can continue to provide power as individual elements fail, reducing the need for expensive repair trips. One can imagine the maintenance cost drivers for WEC array, which must be accessed via rented ship time during limited weather windows [86,87], will be similar and perhaps even more important.

8. Key findings

Key takeaways from this study are as follows:

[4] For a listing of RPSs within the United States, see, e.g., https://www.ncsl.org/research/energy/renewable-portfolio-standards.aspx.

- While short term storms can create waves with power greater than 500 kW/m, sites with median wave power levels in excess of 100 kW/m are very rare (less than 2% of locations globally), particularly near-shore (see Fig. 4). Even if a device can be designed to capture power from a storm with power levels on the order of 500 kW/m, the contribution to annual average energy will tend to be small.
- The often large variability (Fig. 5) and positive skew (Fig. 7) of ocean wave power may limit the ability of a WEC with a high power rating to operate at a high capacity factor. This is particularly well illustrated in Fig. 9.
- While, per (7), wave power is positively correlated with period (see Fig. 10), the ability of a device to capture shorter period waves may dramatically increase capacity factor (see Fig. 13).
- Although wave power is lower in summer months (often dramatically so), the relative magnitude and phasing of fluctuations in wave power and electricity prices appear unlikely to have a large adverse effect on the value of wave energy generating assets (see Fig. 14 and Table 2). In fact, the results shown in Table 2 indicate a strong potential for wave energy converters to fill a critical base load generator role.

In summary, while the original allure of wave energy was largely tied to the truly tremendous amount of power carried by ocean waves (see, e.g., Salter's seminal paper [88]), there is increasing reason to believe that the first successful WECs may be better off eschewing the hunt for world's largest waves. A large WEC is certainly better suited to capture the largest waves that carry the highest levels of power, but, due first to the high variability and strong positive skew of ocean wave power and second to the filtering behavior of a WEC, a smaller WEC may actually have better economics in terms of average annual energy, capacity factor, and costs. While a smaller WEC, with a lower power rating, may not be able to go head-to-head with today's 9 MW wind turbines, that smaller WEC may be able to operate at or near capacity for more than 300 days a year, giving it a capacity factor of 80% against the wind turbine's capacity factor of 30%. In addition to having larger capacity factors, smaller WECs may also be more attractive from an O&M perspective. In this respect, WECs may look more like solar panels than wind turbines, with many small units grouped within an array to provide grid-scale power. It may be that, where the economic viability of a WEC is concerned, less is more.

While the consideration of electricity prices in this paper (Section 6) is targeted at grid-scale energy markets, there is increasing interest in using WECs to support autonomous power demand in the ocean. This so-called "powering the blue economy (PBE)" market, supporting remote sensors, recharging of autonomous vehicles, and even potentially supporting aquaculture farms, is considered an attractive niche for WECs [89,90]. With lower power demands and increased emphasis on simplifying deployment and maintenance, it is logical that PBE WECs would be smaller scale. However, per the results of this study, smaller scale devices are also likely to have higher capacity factors and less intermittency, which may be particularly important for a PBE application.

9. Conclusion

This study leverages nine years of global resource data to present a set of metrics for better understanding the wave energy resource. In particular, these metrics are targeted at assessing factors that will directly affect wave energy converter design and profitability, with the aim that the study inform future and ongoing device design. In addition to reporting these metrics globally, regional trends and distributions are shown.

The results of this study show that small lower period waves, which carry lower power levels than larger long period waves, are much more common both spatially and temporally. When one considers the benefits of operating a wave energy converter near maximum capacity for a large fraction of the year, regions that have traditionally not been considered prime wave energy locations, such as the US East Coast and Southern California, show increasing promise. Furthermore, by quantifying the temporal correlation of ocean wave energy resources with electricity prices, our analysis shows that wave energy converters may be well-suited to providing a base load generator service.

Future studies should seek to present direct comparisons between wave energy and other variable energy generation technologies (hydroelectric dams, wind, solar photo-voltaic), with the aim of better understanding the potential market value of wave energy generation, potentially using metrics such as levelized avoided cost of electricity and value factor. Additionally, these future studies should seek to utilize resource data with higher resolutions, which may offer an improved spatial fidelity in the results and also more accurate results overall. Reconsidering some of the trade-offs raised about rated capacity, capacity factor, and costs, it may be possible to make specific design and deployment decisions if the analysis presented in this paper is coupled with a wave energy converter performance model. Such studies would also support development of a technology-agnostic approach to estimating the technically recoverable resource.

CRediT authorship contribution statement

Ryan G. Coe: Conceptualization, Methodology, Software, Formal analysis, Writing - original draft, Writing - review & editing, Visualization, Supervision, Project administration, Funding acquisition. **Seongho Ahn:** Writing - original draft, Writing - review & editing. **Vincent S. Neary:** Writing - original draft, Writing - review & editing. **Peter H. Kobos:** Writing - original draft, Writing - review & editing. **Giorgio Bacelli:** Writing - review & editing.

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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Appendix. Data analysis methods

Data for this study was sourced from the PacIOOS global WWIII model [70].[5] A single Net-CDF file was downloaded for each day's data using PacIOOS's ERDDAP service. In total, the nine years of data used in this study amount to roughly 200 GB of data.

To process this large amount of data, the Python packages `xarray` and `dask` were used to perform calculations. These packages allow for the efficient processing of data that is too large to fit into memory. Data were partitioned into "chunks" of size 24 h × 311 latitude segments × 720 longitude segments, such that a total of 3263 chunks were needed to encompass the entire nine year dataset.

[5] https://pae-paha.pacioos.hawaii.edu/erddap/griddap/ww3_global.html.

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