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A BENCHMARKING EXERCISE ON ESTIMATING EXTREME ENVIRONMENTAL CONDITIONS: METHODOLOGY & BASELINE RESULTS

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ABSTRACT

A wide range of methods have been proposed for the derivation of environmental contours for marine structures that must meet reliability targets. An environmental contour is a set of joint extremes of environmental conditions associated with a target return period. In general, environmental contour methods help with the prediction of some future critical combinations of environmental conditions (e.g., wind, waves, current) at a location of interest based on a limited dataset, thus allowing designers to ensure a prescribed structural reliability. In fact, some of these contour methods are specifically recommended by technical specifications and standards as part of a design process. This paper outlines the rules and procedures for a collaborative benchmarking exercise – focused on open comparison – in which researchers are invited to develop and present their own contour derivation approaches based on common datasets that will be available to all. Hindcast and observational datasets are considered and two exercises are planned: One focuses on applying environmental contour methods to a wide range of datasets and the other focuses on uncertainty characterization. Besides describing the benchmark's methodology, this paper presents baseline results of computed contours following current recommendations. The overall goals of this endeavor are: (i) to work towards the development of more robust statistical models and contour construction methods, (ii) to encourage increased discussion in the international research community and among practitioners, and (iii) to support ongoing efforts to improve technical specifications and standards.

INTRODUCTION

Environmental contours are used to define a set of extreme environmental conditions for which an engineering system can be evaluated. These conditions describe the environment at a given deployment location and may include any combination of environmental descriptors such as wave height, wave period, wave direction, wind speed, wind direction, current speed, and current direction. To analyze a design (or multiple designs), engineers consider the structural response of the system subject to these conditions. Compared to its alternative, the full seastate approach, the environmental contour method is a simplified and quick method.

The environmental contour method has been applied for the analysis of ships [1], offshore oil and gas structures [2, 3], offshore wind turbines [4, 5], and wave energy converters (WECs) [6, 7]. A proposal to consider joint distributions of environmental variables in design, the so-called design curve, was formulated

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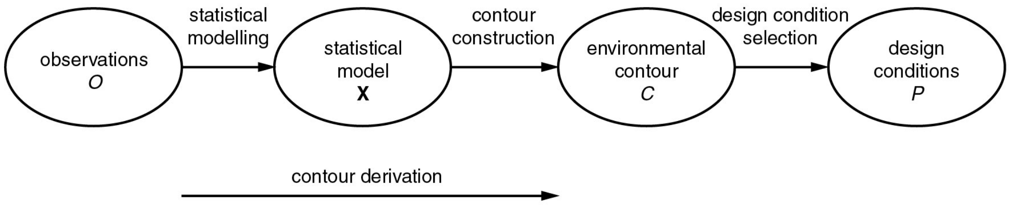

Figure 1. DESCRIPTION OF THE ENVIRONMENTAL CONTOUR METHOD AND OPERATIONAL DEFINITIONS FOR ASSOCIATED TERMS. THE METHOD COMPRISES THREE DISTINCT STEPS: STATISTICAL MODELLING, CONTOUR CONSTRUCTION AND DESIGN CONDITION SELECTION. THIS BENCHMARKING EXERCISE FOCUSES ON CONTOUR DERIVATION, WHICH INCLUDES STATISTICAL MODELLING AND CONTOUR CONSTRUCTION.

by Haver [8]; later, Winterstein *et al.* [9] formally introduced the notion of environmental contours, based entirely on structural reliability principles. In general, the environmental contour method involves three steps: (i) establishing a statistical model that characterizes the environment based on a sample of environmental states ("statistical modelling"), (ii) computing the environmental contour based on that statistical model ("contour construction") and (iii) selecting discrete points along the contour for subsequent use in the design process ("design condition selection"; Figure 1). In this paper, we will use the term "contour derivation" to describe the combination of statistical modelling and contour construction.

Various model structures for the method's first step, statistical modelling, have been proposed. They range from full joint distribution models based on the conditional modelling approach [8–11] to copula models [12–14], models derived from applying principal component analysis [15] and joint distributions derived from multivariate kernel density estimation [16, 17]. The second step, contour construction, can be carried out with a variety of different methods as well. Researchers need to first choose a definition for multivariate exceedance and then apply an efficient numerical method to construct the desired contour. Currently, probably the most popular method to construct an environmental contour is based on the definiton proposed by Winterstein *et al.* [9], who defined multivariate exceedance based on hyperplanes in the standard normal space (inverse first-order reliability method; IFORM). However, in the last six years, researchers have proposed a variety of different definitions for the construction of an environmental contour [18–21]. The final step, that of selecting individual environmental states ("design conditions") along the contour, is also important and is generally determined by best practices for the specific system under consideration.

While there is a great variety of methods to derive an environmental contour in the academic literature, practitioners might follow guidance provided in standards such as DNV-RP-C205:2017 [22] as well as NORSOK N-003 [23]. In the design process for offshore wind turbines, the international standard IEC 61400-3 [24] requires designers to define severe sea states by selecting joint values of the significant wave height and wind speed with a recurrence period of 50 years. The standard recommends use of the IFORM for that task. Similarly, the standard IEC TS 62600-2 [25], which outlines the design process for WECs as well as tidal and ocean current energy converters, utilizes sea states from environmental contours.

Previous efforts to compare contours have provided useful findings. Leira [26] considered a series of stochastic models for use in developing environmental contours. Manuel *et al.* [14] provided procedures for constructing contours using variables' joint dependence structures based on copula definitions as well as Rosenblatt and Nataf transformations. In addition, Manuel *et al.* quantified the associated uncertainty in constructed contours resulting from limited data. Other authors examined different definitions for multivariate exceedance and, consequently, different contour construction methods, given the same statistical model. Such comparative studies were conducted, for example, by Vanem and Bitner-Gregersen [27], Haselsteiner *et al.* [20], Chai and Leira [21] and Wang *et al.* [28]. Although these studies provide many useful insights, a benchmark problem that is open to everybody and that lays out a clear methodology for comparison, could provide the basis for more systematic and complete results.

To better understand the performance of different environmental contour methods, this paper outlines the methodology for a benchmarking exercise that is proposed. Various methods to characterize the environment and to derive environmental contours will be applied to a selected set of offshore system deployment locations. The different methods will be evaluated based on a series of metrics, with the goal of open comparison and the development of new ideas in the field. We designed the format of the exercise such that all environmental contour methods that have been proposed in the past can be employed and evaluated. Consequently, apart from welcoming all possible types of statistical modeling approaches, participants are free to use their desired definitions for multivariate exceedance and associated numerical computation techniques.

METHODOLOGY

The following sections describe the decision process used to define the organization and structure of the environmental contour comparison exercise. Given that the definition of such a benchmarking exercise is far from straightforward, these sections serve as an explanation of the thought process of the organizers. We identified the following important concepts, which we would like to consider:

1. **Predictive power:** In application, an environmental contour is generally used to better understand the potential loading on a structure over some long design life (e.g., 25 years), while relying on less data (from, say, 15 years). Therefore, the constructed contour must have some predictive power and the capability of being used, by extrapolation, for design periods longer than the data sample.
2. **Site-specific data:** Bathymetry, weather, nearby geography, and large-scale metocean phenomena (e.g., currents, trade winds), all combine to give a specific character to the metocean conditions at a given location. An environmental contour method must be flexible enough to capture the site-specific dependence structure in a dataset, while not "overfitting" to the data.
3. **Uncertainty in relation to limited datasets:** When considering the ultimate design load of a structure, uncertainty in this load is just as important - perhaps more important - than the derived load itself. Given the typically limited nature of recorded measurements for metocean data, it is clear that a method's associated level of uncertainty, given a limited data record, is an important consideration. The uncertainty needs to be characterized or quantified to the extend possible.
4. **Defining multivariate extremes:** An environmental contour represents the definition of a set of multivariate extremes. In comparison with univariate extremes, multivariate extremes can be defined in multiple ways, and researchers have proposed various definitions in the context of the environmental contour method. A comparison between environmental contours, that are based on different statistical models and on different definitions for multivariate exceedance, is difficult because of these alternative definitions.

In the design of this comparison exercise, we have attempted to consider all of these concepts outlined previously. The following sections lay out the process used to determine the structure of this contour comparison effort. First, we considered the datasets to be included in the comparison. Next, although somewhat tied to the selection of datasets, we define a set of comparison methods and metrics.

Datasets

We considered three high-level categories of datasets for the benchmark: (i) real datasets from wave buoys and wind measuring masts, (ii) hindcast datasets created by models of wind-wave interaction, and (iii) synthetic datasets sampled from pre-defined distributions (not known to the participants).

When selecting datasets for this effort, one important consideration was the eventual evaluation and comparison of contours produced by participants. It is desired to have some sort of blind validation, in which participants produce their results, which can then be evaluated against a ground truth. There are a number of ways in which this can be accomplished for the present study, all with some deficiencies.

If real data, measured by buoys and offshore stations, are used, one can potentially withhold some subset of the data. For example, if a wave buoy has 25 years of data, we could provide 10 years of data, withholding 15 years of data. To provide a blind evaluation, a 25 year contour produced by a participant can be compared with one based on all of the available 25 years of data. On the surface, this seems like a rational approach; however, given the stochastic nature of the system considered, those 25 years of data represent only a single realization, of which an infinite number are possible. Nonetheless, this remains an attractive approach, as working with real data is generally preferable, when available. Another issue with using real data is the limited nature of recorded measurements, which are often available for a much shorter period than the return period of interest.

A second option for conducting blind evaluations is to use synthetic data. By providing samples to participants from some known, but not disclosed, distribution, an absolute evaluation can be made. This approach is more ideal in terms of evaluation, since it is straightforward to define the correct contour given a known or assumed exact distribution. However, this approach is somewhat hampered by the challenge of choosing a distribution. Ideally, this distribution should very closely mirror those seen in real data, but the required statistical modelling of the environment is an open research problem that we want to address in this benchmark.

Hindcast data represent something of a middle ground between the two former options, that of real data and of a predefined joint distribution. Hindcast data usually cover longer periods than real data, but are associated with a modeling error.

Comparison methods & metrics

The manner in which contours are to be compared is another important factor. It can be interesting, and in fact helpful, to perform a simple visual comparison of a set of overlaid contours. From this, one can intuitively see how different contours behave. However, it would also be useful to have some quantitative means for performing a comparison.

Based on these considerations, we have selected the following methods and metrics for comparing contours that will be used in two exercises, Excercise 1 (E1) and Exercise 2 (E2).

Qualitative methods:

Simple overlay (E1) - We will plot the different contours together for visual comparison.

Uncertainty overlay (E2) - We ask participants to resample 1000 times from a dataset, apply their contour derivation method 1000 times, and plot the resulting 1000 contours in an overlay for visual uncertainty characterization.

Quantitative methods:

Points outside the contour (E1) - We will count the points that lie outside the contours. Note that due to the different definitions for exceedance in environmental contour methods, the number of expected points outside the contour will be different among the methods.

Maxima (E1) - In each dimension, we will record the maxima predicted by the contours and those observed in the measurement or hindcast sample.

Confidence intervals (E2) - We ask participants to compute a 95% confidence interval of their environmental contour based on 1000 samples that were resampled from a given dataset (further details are given in section "Exercise 2: Uncertainty characterization").

Note that the methods and metrics above are not proposed to justify a basis for a definitive scoring. Instead, they strive to provide a limited, but practical, means of comparison. Thus, while the metrics do not necessarily represent a perfect set of tools for ranking the performance of any given contour, we believe that in the absence of better alternatives, these metrics provide a good means for open comparison, which is the aim of this exercise.

EXERCISES & ORGANIZATION

Exercise 1: Provided datasets and desired contours

After consideration of these options, the mixture of datasets specified in Table 1 were selected. Thus, we will consider six total cases: three measured datasets (A, B, and C) and three hindcast datasets (D, E, and F). Figure 2 shows a map of locations for these datasets.

The real datasets are taken from three locations along the eastern coast of the United States. These are each located off the coast of Maine, off the coast of Florida, and in the center of the Gulf of Mexico. In each case, 10 years worth of hourly wave data collected from National Data Buoy Center (NDBC) buoys operated by the U.S. National Oceanic and Atmospheric Administration (NOAA) will be used in the exercise. We preprocessed NDBC's original datasets to provide participants consistent time series of significant wave height H_s and zero-up-crossing period T_z. Participants will be asked to derive 1-yr and 20-yr environmental contours of these two variables. Roughly 10 years of additional data will be retained to use in comparing the contours.

The hindcast datasets are from the North Sea, with one of the three datasets each located nearest to Germany, the UK, and Norway, respectively. In these cases, 25 years of hourly data from the coastDat-2 hindcast [29] will be provided. Two variables, near-surface wind speed U_{10} and significant wave height data H_s will be used. The wind speed variable U_{10} is computed to represent a 10-minute mean value, measured 10 m above sea level. Participants will be asked to derive 10-yr and 50-yr environmental contours of the significant wave height and the near-surface wind speed.

Figure 2 also shows scatter plots of the datasets to be provided. It is clear that the datasets contain unique characteristics. The wave datasets (A, B, and C) exhibit markedly different patterns, with bimodal characteristics evident in datasets A and B. In the wind-wave datasets (D, E, and F), we see that the observed maximum wave height at a given wind speed interval varies greatly between the datasets. For wind speeds $< 10\,\mathrm{m\,s^{-1}}$ the observed highest significant wave height varies between 5.4 m (dataset D) and 10.6 m (dataset F).

Exercise 2: Uncertainty characterization

Uncertainty characterization of environmental contours is a second part of this benchmark. We selected the wave-wind dataset D for this exercise and ask participants to compute 50-yr contours based on (a) a 1-yr sample, 8,766 data points, (b) a 5-yr sample, 43,830 data points and (c) a 25-yr sample, 219,150 data points. To characterize uncertainty, participants should follow the uncertainty characterization method based on hindcast data described by Gramstad *et al.* [30]. The method can be described as follows:

1. Set the index, $i = 1$.
2. Resample Y (1, 5 or 25) years of data from dataset D (resulting in sample O_i).
3. Fit the model structure that you used in Exercise 1 to the sample O_i (resulting in the statistical model $\mathbf{X}_i$).
4. Compute a 50-yr contour with the same method that you used in Exercise 1 based on the statistical model $\mathbf{X}_i$ (resulting in environmental contour C_i).
5. If $i < 1000$: Increase the index i and repeat steps 2-4.

This procedure will lead to 1000 different environmental contours. Then, use these 1000 contours as follows: (i) plot them in a single figure and (ii) compute a 95% confidence interval. For the latter, compute the median contour, the 2.5th percentile contour and the 97.5 percentile contour.

Confidence intervals in two dimensions can be defined in various ways. For comparability, please construct them as follows:

1. Set the origin $\mathbf{x_0} = (x_{0,v}, x_{0,hs})$ to be at the mean of dataset D: $\mathbf{x_0}$=(7.95 $\mathrm{m\,s^{-1}}$, 1.53 m).

Table 1. OVERVIEW OF THE PROVIDED DATASETS, WHICH ARE AVAILABLE AT HTTPS://GITHUB.COM/EC-BENCHMARK-ORGANIZERS/EC-BENCHMARK. WE DOWNLOADED THE BUOY DATA FROM HTTPS://WWW.NDBC.NOAA.GOV AND GATHERED THE HINDCAST SAMPLES FROM THE COASTDAT-2 DATASET [29].

Dataset	Data source	Site	Provided data	Retained data	Env. contour
A	NDBC 44007 moored buoy	43.525 N 70.141 W (off Maine coast)	10 years (82,805 data points)	92,515 data points	1 year H_s-T_z, 20 years H_s-T_z
B	NDBC 41009 moored buoy	28.508 N 80.185 W (off Florida coast)	10 years (83,917 data points)	91,403 data points	1 year H_s-T_z, 20 years H_s-T_z
C	NDBC 42001 moored buoy	25.897 N 89.668 W (Gulf of Mexico)	10 years (81,749 data points)	93,571 data points	1 year H_s-T_z, 20 years H_s-T_z
D	coastDat-2 hindcast sample	54.000 N 6.575 E (off German coast)	25 years	25 years	1 year H_s-U_{10}, 50 years H_s-U_{10}
E	coastDat-2 hindcast sample	55.000 N 1.175 E (off UK coast)	25 years	25 years	1 year H_s-U_{10}, 50 years H_s-U_{10}
F	coastDat-2 hindcast sample	59.500 N 4.325 E (off Norwegian coast)	25 years	25 years	1 year H_s-U_{10}, 50 years H_s-U_{10}

2. Define a set of lines $\mathbf{L} = \{L_j\}_{j=1}^{180}$ at angles $\theta \in [0, 360\,\text{deg})$. Each line starts at the origin $\mathbf{x_0}$ and has an angle θ relative to the abscissa; θ increases in counter-clockwise direction. Construct lines at $\theta = \text{atan2}[\sin(\theta^*)t_2, \cos(\theta^*)t_1]$ where t_1 and t_2 are the ranges of the dataset D's wind speed and significant wave height: $t_1 = 29.23\,\text{m}\,\text{s}^{-1}$, $t_2 = 10.57\,\text{m}$, $\theta^* = \{0\,\text{deg}, 2\,\text{deg}, 4\,\text{deg}, 6\,\text{deg}, ..., 358\,\text{deg}\}$.
3. Find the intersections between each contour C_i and each line L_j. This leads to 1000 points of intersection for each line[1]. Let $\boldsymbol{I_j} = \{I_{j,i}\}_{i=1}^{1000}$ be the list of points of intersections that corresponds to line L_j.
4. Order each list of points of intersections by the distance between the intersection and the origin such that $I_{j,i=1}$ is the point that is closest to the origin and $I_{j,i=1000}$ is the point that is farthest away from the origin.
5. Construct the $P \in \{2.5, 50, 97.5\}$th percentile contour by connecting all intersections with index $i \in \{25, 500, 975\}$.

How to participate

We will officially announce the benchmarking exercise at the OMAE 2019 conference, in June 2019. Interested participants can enter the benchmark until March 31, 2020. We plan to showcase the results in a special session at the OMAE 2021 conference. Optionally, participants may choose to present the results of their own efforts with the benchmark problem at the OMAE 2020 conference. In summary, the benchmark study will be announced at OMAE 2019; results from participating teams may be optionally presented at OMAE 2020 and results of the benchmark study including all participants' work will be be presented at OMAE 2021.

GitHub repository: We will use the repository "ec-benchmark" that is available at `https://github.com/ec-benchmark-organizers/ec-benchmark` as a hub for the organization of the benchmark. There, participants will find up-to-date information and can use "Issues" to openly discuss any questions that may arise.
Provided datasets: The six datasets are available in the repository's folder "datasets".
Submission: Participants must provide CSV files for each contour. In Exercise 1, only submissions that contain all twelve contours listed in Table 1 will be considered. CSV files should use the format that is described in the "ec-benchmark" repository. Participants of the uncertainty quantification exercise must additionally submit three CSV files for each of the three cases (1 year data, 5 years data, 25 years data; a total of nine CSV files). In each case, one CSV file should contain the median contour, one CSV file the 2.5th percentile contour and one CSV file the 97.5th percentile contour. Extensive examples are available at the "ec-benchmark" repository. One can either participate only in Exercise 1, only in Exercise 2 or in both.
Optional: To aid in future usage, consider coding your method in Python and submitting it along with your results. Then, your work (with proper attribution) will

[1] In cases where one line intersects with one contour at multiple points special care is necessary. Either use the point of intersection that has the highest distance to the origin and discard the other points (this procedure is used by the authors) or define your own procedure and describe it in detail.

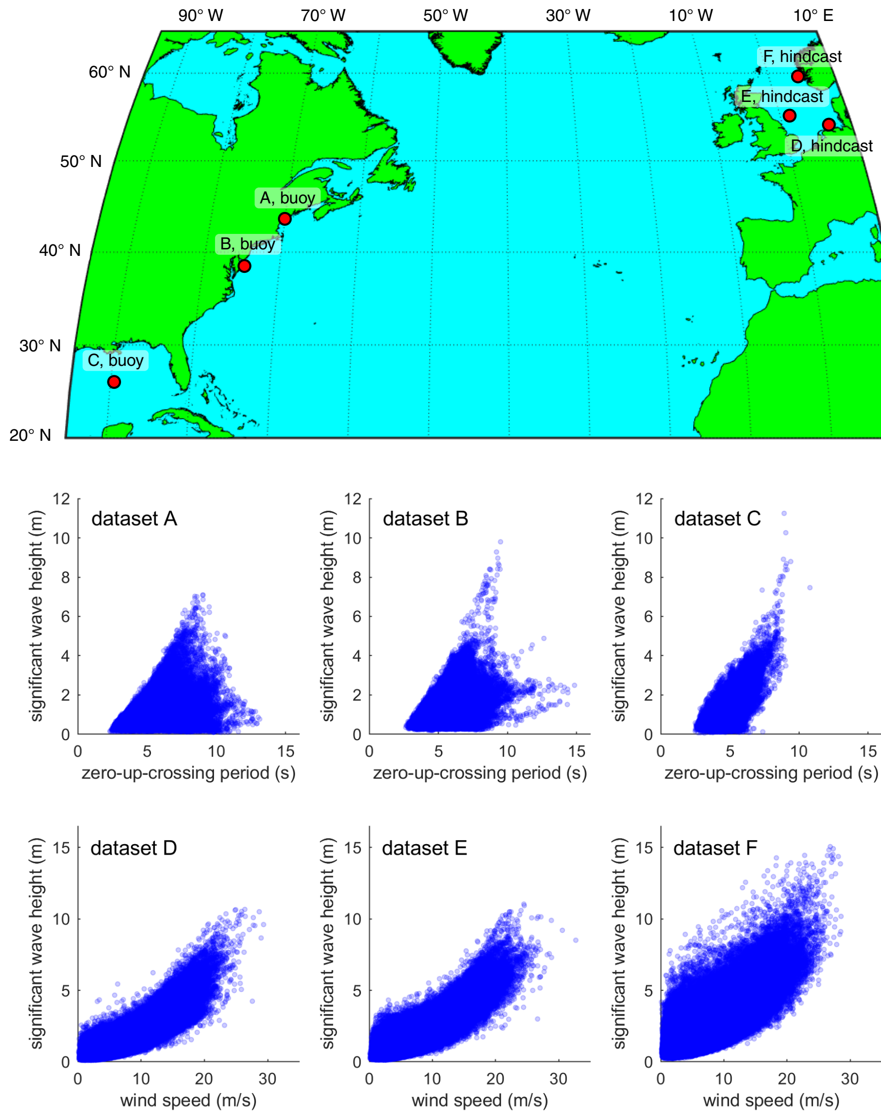

Figure 2. UPPER: MAP OF DATASET LOCATIONS. LOWER: SCATTER PLOTS OF THE DATASETS.

be permanently available as open-source software in the "ec-bechmark" repository. Additionally, if desired, your code could possibly be integrated into the "viroconcom" software-package that provides various methods to compute environmental contours.

How to enter: Submissions must be sent to the email address provided at the "ec-benchmark" repository.

BASELINE RESULTS: MODELS & CONTOURS

Methods

To illustrate the benchmark's methodology and provide baseline results, we fitted the statistical model structures that are currently recommended by the certifying organization DNV GL in their recommended practice DNVGL-RP-C205:2017 [22] to the six datasets. Consequently, we used a conditional model structure based on a 3-parameter Weibull distribution and a log-normal distribution to model the sea states of datasets A, B and C. Similarly, we used a 3-parameter Weibull distribution and a 2-parameter Weibull distribution for the wind-wave joint model of datasets D, E and F.

Fitting was performed with the module viroconcom (version 1.2.0) of the software ViroCon [31]. We used a multi-step fitting approach, similar to that of Li *et al.* [11]. First, the marginal distribution was fitted. Second, n distributions for the conditional variable (T_z or V) were fitted based on n sub-samples, each holding the conditional variable's values within a specified H_s-interval. The interval size was 0.5 m and only sub-samples that held at least 10 data points were considered. Third, the dependence functions were fitted to the parameters of the n distributions. Marginal distribution fitting (steps 1 and 2) was performed using maximum likelihood estimation (via viroconcom that uses the distribution fitting implementation from the Python package scipy [32]). Dependence function fitting (step 3) was performed using non-linear least squares (via viroconcom that uses scipy's function `curve_fit`).

Then we constructed IFORM contours [9] based on the fitted models via the implementation in viroconcom. This procedure led to a baseline for Exercise 1.

Similarly, we provide baseline results for Exercise 2. The DNV GL model structure was fitted to 1000 bootstrap samples from dataset D resulting in 1000 statistical models. Then we constructed 1000 50-yr IFORM contours based on these models and computed the 95% confidence interval. Note that in the presentation of these baseline results we do not use the retained fractions of the datasets (meaning that we used only the subsets of data that are available to the participants for both, statistical modelling and in plotting of the results).

Results

Table 2 presents the fitted statistical models. Interestingly, the fitted dependence functions often had a first coefficient with value zero (8 of 12 dependence functions). It was zero in all σ-dependence functions of the lognormal distribution [$\sigma(h_s) = c_4 + c_5 \exp(c_6 h_s)$; $c_4 = 0$; datasets A, B, C] and zero in all α_v-dependence functions of the 2-parameter Weibull distribution [$\alpha_v(h_s) = c_7 + c_8 h_s^{c_9}$; $c_7 = 0$; datasets D, E, F].

The computed environmental contours capture the data's dependence structure to some extent (Figure 3). All environmental contours are exceeded by multiple data points. This is not necessarily expected since the contour's return period is longer than the time duration of the sample (20-yr contour vs. 10-yr sample for datasets A-C and 50-yr contour vs. 25-yr sample for datasets D-F). All contours except the 20-yr contour based on dataset A are exceeded at various distinct regions in the variable space. For example, the 50-yr wind-wave contour of dataset D is exceeded in regions of high wind speed and medium wave height, regions of high wind speed and high wave heights and regions of low wind speeds and low wave heights.

The baseline results for the uncertainty characterization exercise are presented in Figure 4. As the bootstrap sample's duration increases from 1 to 5 and finally 25 years, the variability between the environmental contours decreases. This is apparent in the overlay plots and in the decreasing width of the confidence intervals (Figure 4).

Exercise 1's baseline contours can be reproduced by running the Python files `e1_baseline_dataset_a_to_c.py` and `e1_baseline_dataset_d_to_f.py` that are available in the benchmark's repository. Similarly, the baseline results for Exercise 2 can be reproduced with the file `e2_baseline.py`.

CONCLUSIONS

The proposed comparison exercise is intended first and foremost to further the state-of-the-art in modelling the uncertain metocean environment and in constructing environmental contours by bringing together researchers working in this area. It is with this goal in mind that we have defined the two exercises described in this paper. We hope that the benchmark will result in increased interest and communication among researchers in this area.

The proposed benchmark will be limited in a number of ways. As discussed, the metrics proposed here to aid in the comparison do not offer a means for providing any final objective rankings on contour methods. However, we believe they can provide some instructive insights that may lead to future research ideas. Likewise, with the wide variety of methods, each comprising many subtle steps that impact the shape of a contour, it is clear that the exercise will consider only a subset of the many possible contours that could be derived.

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Table 2. BASELINE STATISTICAL MODELS. THE MODEL STRUCTURE FOLLOWS THE RECOMMENDATIONS IN DNVGL-RP-C205:2017 [22].

Dataset	Significant wave height			Zero-upcrossing period, log-normal distribution					
	3-p. Weibull distribution			$\mu(h_s) = c_1 + c_2 h_s^{c_3}$			$\sigma(h_s) = c_4 + c_5 \exp(c_6 h_s)$		
	α_{hs} (scale)	β_{hs} (shape)	γ_{hs} (location)	c_1	c_2	c_3	c_4	c_5	c_6
A	0.944	1.48	0.0981	1.47	0.214	0.641	0.00	0.308	-0.250
B	1.14	1.60	0.188	1.41	0.234	0.581	0.00	0.241	-0.200
C	1.16	1.56	0.0566	1.24	0.300	0.600	0.00	0.155	-0.161
				Wind speed, 2-p. Weibull distribution					
				$\alpha_v(h_s) = c_7 + c_8 h_s^{c_9}$			$\beta_v(h_s) = c_{10} + c_{11} h_s^{c_{12}}$		
				c_7	c_8	c_9	c_{10}	c_{11}	c_{12}
D	1.58	1.41	0.102	0.00	7.58	0.520	0.00	3.89	0.497
E	1.86	1.49	0.122	0.00	7.40	0.525	0.00	3.89	0.398
F	2.57	1.55	0.225	0.00	5.77	0.561	1.97	0.279	1.27

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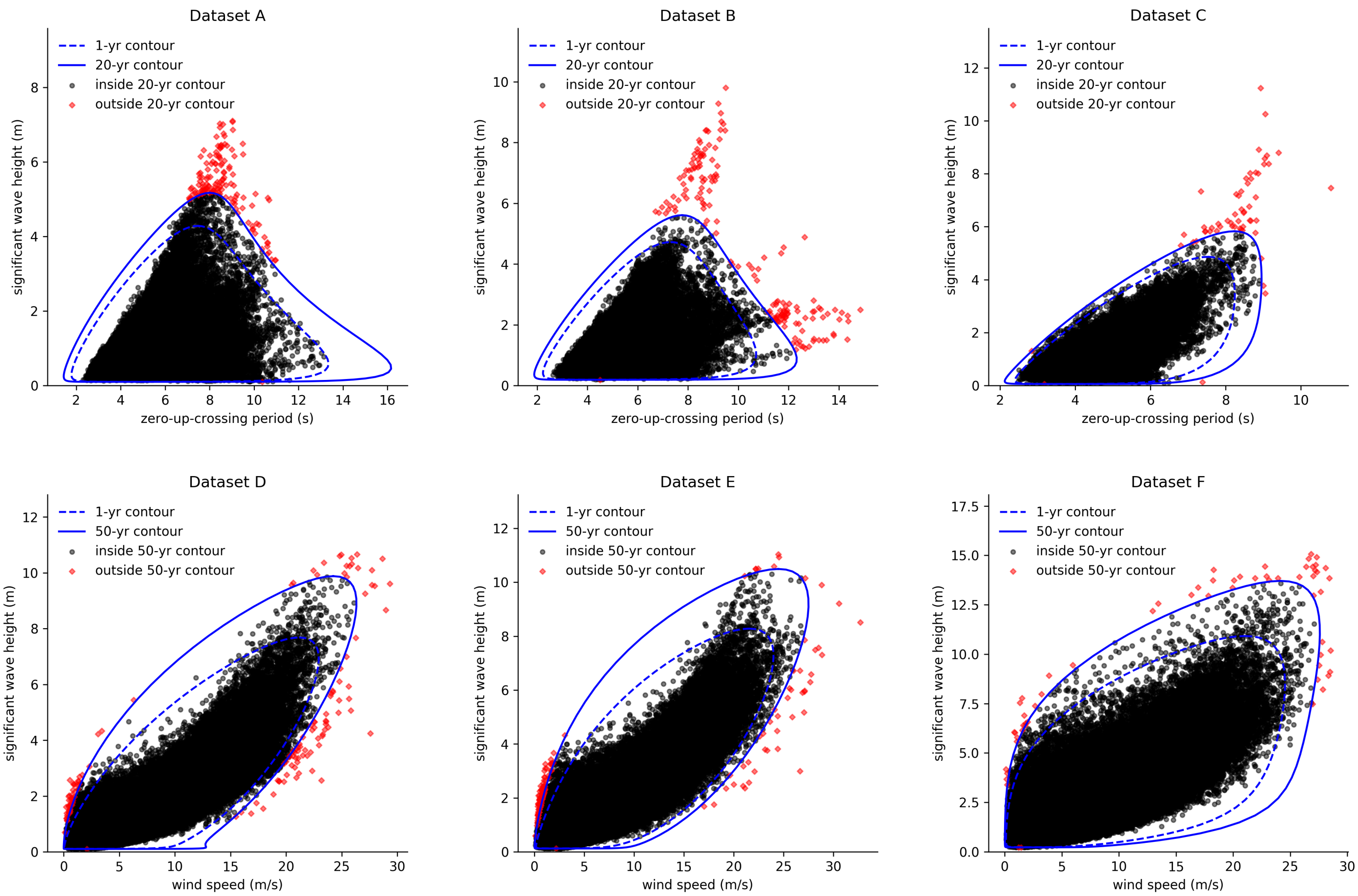

Figure 3. BASELINE ENVIRONMENTAL CONTOURS. THE CONTOURS WERE DERIVED FROM STATISTICAL MODELS THAT ARE CURRENTLY RECOMMENDED (SEE TABLE 2). THE DEFINITION FOR EXCEEDING THE CONTOUR IS BASED ON HYPERPLANES IN THE STANDARD NORMAL SPACE (INVERSE FIRST-ORDER RELIABILITY METHOD). TOP: SEA STATE CONTOURS. BOTTOM: WIND-WAVE CONTOURS. NOTE THAT DATASETS A, B, AND C CONSIST OF 10 YEARS OF DATA WHILE DATASETS D, E, AND F CONSIST OF 25 YEARS OF HINDCAST DATA.

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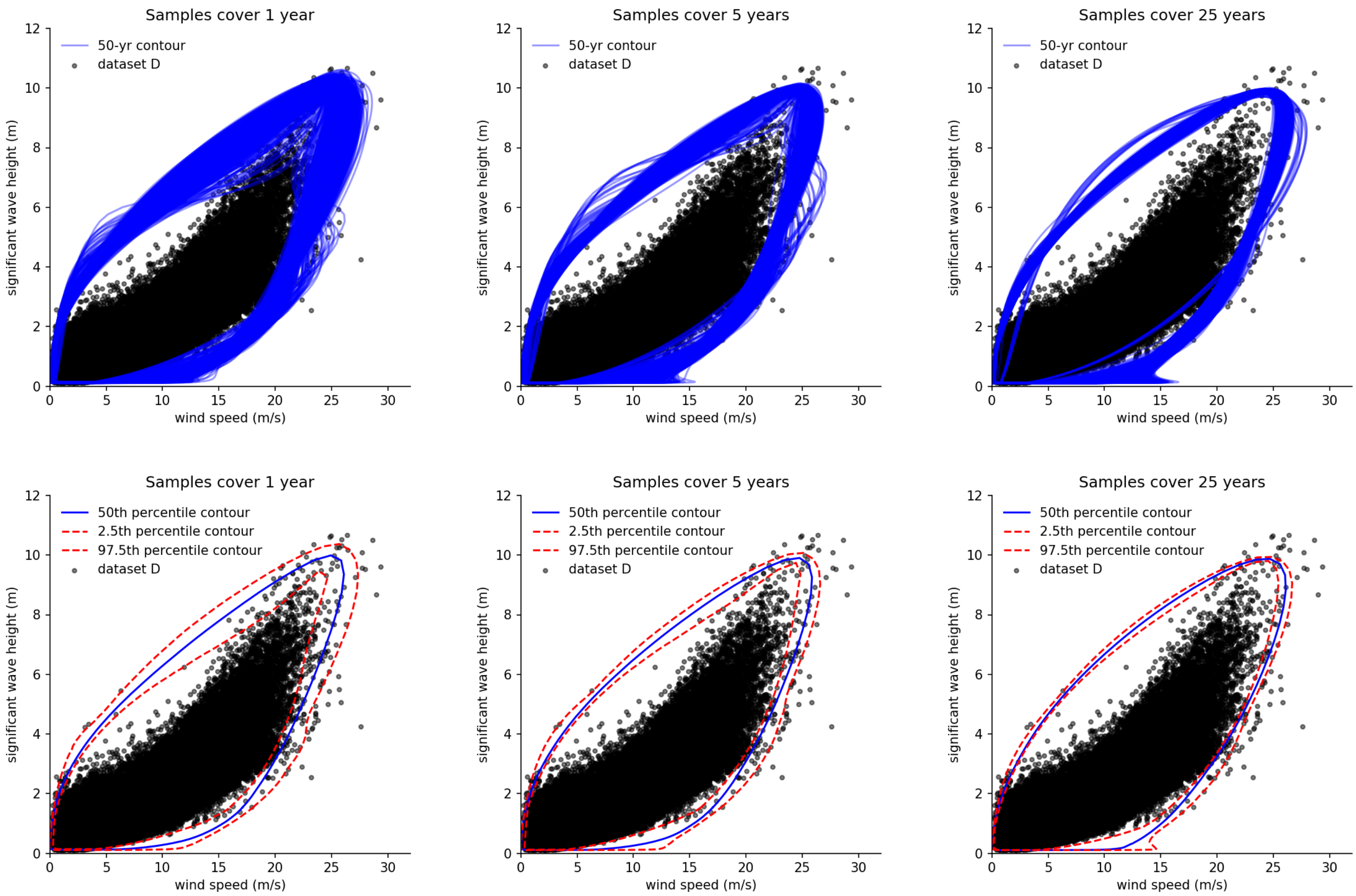

Figure 4. BASELINE RESULTS FOR THE UNCERTAINTY CHARACTERIZATION EXCERCISE. 1000 BOOTSTRAP SAMPLES WERE DRAWN FROM THE HINDCAST DATASET D AND 1000 50-YR ENVIRONMENTAL CONTOURS WERE CONSTRUCTED. THE DATASET CONTAINS 25 YEARS OF DATA. TOP: PLOTS OF ALL ENVIRONMENTAL CONTOURS THAT WERE DERIVED BASED ON SAMPLES THAT COVERED 1 YEAR (LEFT), 5 YEAR (MIDDLE) AND 25 YEARS (RIGHT). BOTTOM: WITH INCREASING SAMPLE DURATION THE CONFIDENCE INTERVAL BECOMES NARROWER.

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