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Variations in return value estimate of ocean surface waves - a

study based on measured buoy data

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- 7 Abstract. An assessment of extreme wave characteristics during the design of marine facilities not only helps to
- 8 ensure its safety but also the economic aspects. In this study, return levels for different periods are estimated
- 9 using Generalized Extreme Value (GEV) and Generalized Pareto Distribution (GPD) based on the waverider
- 10 buoy data spanning for eight years. The analysis is carried out for wind-sea, swell and total significant wave
- 11 heights separately. Seasonality of prevailing wave climate is also considered in the analysis to provide return
- 12 levels for short-term activities in the location. The study shows that Initial Distribution Method (IDM)
- 13 underestimates return levels compared to that of GPD. Maximum return levels estimated by GPD corresponding
- 14 to 100 years is 5.83 m for monsoon season (JJAS), and corresponding pre-monsoon (FMAM) and post-monsoon
- 15 (ONDJ) values are 2.66 m and 4.28 m respectively. Intercomparison of return levels by block maxima and r-
- largest method for GEV theory shows that maximum return level for 100 years is 7.24 m by r-largest series
- 17 followed by monthly maxima (6.18 m) and annual maxima (5.78 m) series. The analysis is also carried out to
- 18 understand the sensitivity of the number of observation for GEV annual maxima estimates. It indicates that the
- 19 variations in the standard deviation of the series caused by changes in the number of observation are positively
- 20 correlated with the return level estimates.
- 21 Keywords: surface waves, return period, Extreme value distribution, design wave height, north Indian Ocean

22 1. Introduction

- 23 Coastal zones are relatively dynamic than rest of the regions due to numerous natural as well as anthropogenic
- 24 activities. Events such as extreme waves, storm surges, and coastal flooding make large catastrophes in the
- 25 coastal region. Various marine activities like the design of coastal and offshore facilities, planning of harbor
- 26 operations, and ship design require detailed assessment of wave characteristics with certain return periods
- 27 (Caires et al., 2005; Menéndez et al., 2009; Goda et al., 2010). Generally, Extreme Value Theory (EVT) is used
- 28 for determination of return levels by adopting statistical analysis of historic time series of wave heights obtained
- from various sources such as in-situ buoy measurements (eg.: Soares and Scotto, 2004; Mendez et al., 2008;
- Viselli et al., 2015), satellite data (eg.: Alves et al., 2003; Izaguirre et al., 2010), and hindcasted or reanalysis
- data by numerical models (eg.: Goda et al., 1993; Caires and Sterl, 2005; Teena et al., 2012; Jonathan et al., 2014). EVT consists of two type of distributions viz. Generalized Extreme Value (GEV) family which includes
- 33 Gumbel, Frechet, and Weibull distributions (Gumbel, 1958; Katz et al., 2002) and Generalized Pareto
- Distribution (GPD) which incorporates Peak Over Threshold (POT) approach (Pickands, 1975; Coles, 2001).
- 35 GEV distribution by annual maxima (AM) observations (Goda et al., 1992) is one of the widely used methods in
- 36 the Extreme Value Analysis (EVA). The main difficulty with using this method is that the unavailability of a
- 37 reliable observation at a location of interest. To overcome the data scarcity, different alternatives has been used

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- 38 by various authors such as Initial Distribution Method (IDM) in which the distribution of data as such is used
- 39 (Alves and Young, 2003), r-largest approach (Smith, 1986), where a number of largest observation from a block
- 40 of period are considered rather than one observation used in AM method. POT method (Abild et al., 1992) gives
- 41 a good number of observations available for the analysis. GPD are another class of distribution introduced by
- 42 Pickands (1975) and is used by several authors like Caires and Sterl (2005) and Thevasiyani et al. (2014). Teena
- 43 et al. (2012) and Samayam et al. (2017) have carried out the EVA of ocean surface waves in the northern Indian
- 44 Ocean based on wave hindcast data and ERA-Interim reanalysis data.
- 45 Most reliable source of ocean wave data is buoy measurements, and it can be used for EVA (Panchang et al.,
- 46 1999). In this paper, data from a directional waverider buoy located in the central western shelf of India is used.
- 47 Seasonality is one of the important aspects of climate data and therefore, it should be incorporated in the EVA
- 48 of waves especially in a region like the Arabian Sea. Seasonal analysis of the extremes helps for the planning of
- 49 short-term marine activities like offshore explorations, maintenance of coastal facilities, etc. In the present
- 50 paper, the EVA is carried out by following both the GEV and GPD methods considering wind-sea, swell and
- 51 total significant wave height (Hs) separately. The IDM and POT methods are used for total wave height
- 52 analysis, and block maxima (annual and monthly maxima) and r-largest method are used in wind-sea and swell
- 53 height analysis.

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- 54 The paper is organized as follows. Section 2 deals with data and methodology used in the analysis. It also
- 55 presents the threshold selection adopted in the study and Sect. 3 explains the results obtained in the analysis
- 56 categorized into seasons using total Hs data and comparison of return level estimation by different GEV
- 57 approaches using wind-sea and swell height data. A case study is also included in the section for realizing the
- 58 uncertainty related to observations in AM approach when limited number of observations are available. Section
- 59 4 provides the concluding remarks.

2. Data and Methodology

- 61 Data used in the analysis is obtained from Datawell directional waverider buoy deployed off Honnavar
- 62 (14.304°N,74.391°E) at a water depth of 9m. The half hourly sampled data covers the period from March 2008
- 63 to February 2016. The waves at the location show strong intra-annual variations due to the prevailing wind
- 64 system during monsoon and non-monsoon seasons (Sanil Kumar et al., 2014). To understand the local and
- 65 remote influences on the design wave characteristics, we did analysis on Hs of wind-sea, swell and total waves
- 66 separately. The season wise study is also carried out since it will provide insight to the design wave heights for
- 67 short-term coastal activities.
- 68 EVA is carried out by following GEV Distribution model and POT method in which exceedance over a reliable
- threshold wave height can be fit into GPD. In POT method, distribution of excess, x, over a threshold u is
- 70 defined as:

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$$F_u(y) = \Pr\{x - u \le x | x > u\} = \frac{F(x) - F(u)}{1 - F(u)}$$
 (1)

- Where y=x-u. Pickands (1975) shows that distribution function of excess. $F_u(y)$, for a sufficiently high
- 73 threshold *u* converges to GPD having CDF as:

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$$G(x; k, \alpha, \beta) = \{1 - \left(1 - k\frac{x - \beta}{\alpha}\right)^{1/k}\}$$
 $k \neq 0$ (2)

$$75 \qquad \qquad = 1 - e^{-(x-\beta)/\alpha} \qquad \qquad k = 0$$

76 GEV has cumulative distribution function (CDF) as:

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$$F(X) = \exp\left\{-\left(1 - k\left(\frac{X - \beta}{\alpha}\right)^{1/k}\right\} k \neq 0$$
 (3)

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$$\exp\left\{-\exp\left(-\frac{x-\beta}{\alpha}\right)\right\} k = 0$$

- 79 Where α is scale parameter in the range of α >0, β is the location parameter with possible values of $-\infty < \beta < \infty$
- 80 and k is the shape parameter in the range of $-\infty < k < \infty$. GPD can be further categorized into three distributions
- based on its tail features. When k=0, GPD corresponds to an exponential distribution (medium-tailed or Pareto I
- 82 type) with mean α ; when k>0, GPD is short-tailed also known as Pareto II type; when k<0, distribution takes the
- 83 form of ordinary Pareto distribution having long-tailed distribution (also known as Pareto III type). Parameter
- 84 estimation and statistical distribution fitting are carried out by using WAFO (Brodtkorb et al., 2000) developed
- by Lund University, Sweden.
- 86 The analysis is carried out by using the wind-sea, swell and total Hs data covering ~ 8 years (2008-2016). GPD
- 87 method is used for seasonal analysis of different time period data series. GEV method is used for inter-
- 88 comparison of return level estimation among wind-sea, swell and resultant data sets by extracting different
- 89 block maxima series viz. seasonal maxima which contain highest observations from each season; monthly
- 90 maxima contain one highest observation from each month, and annual maxima. The parameters are estimated
- 91 using PWM method since the data set duration are very limited, and PWM method holds good results compared
- 92 to other methods such as Maximum Likelihood (ML) method (Hosking et al., 1985).
- 93 To study the uncertainties related to the length of the observation, we extracted 3, 6, 12 and 24 h data series
- 94 from the half hourly original data and carried out EVA. Since the wave climate in the study location strongly
- 95 characterized by the prevailing seasonal behavior of wind system, we took further consideration of uncertainties
- 96 related to a seasonal aspect of wave climate by extracting three seasonal data, viz., pre-monsoon (FMAM),
- 97 monsoon (JJAS) and post-monsoon (ONDJ) seasons.

2.1 Threshold selection

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The major drawback of EVA using block maxima method, especially the annual maxima (AM), is that it do not consider the significant amount of observations which are closely related to storm features of the data set. Those omissions of observation would make variations in the final results of EVA to a great extent especially in the case when EVA is done for a very limited data set. EVT is based on one of the hypothesis that the observations under consideration are independent and identically distributed (Coles, 2001). In the case of ocean wave observations, we can expect its identical status for a large extent. Since POT approach re-samples the data over a threshold value, establishing identical and independence among the re-sampled observation is a tedious task. A suitable combination of threshold and minimum separation time between the re-sampled observations must be taken into account to establish independence among the observations.

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108 The average duration of tropical storms in the Arabian Sea is 2-3 days (Shaji et al., 2014). So, in the present 109 analysis, we fixed minimum 48 hours of separation time in between two consecutive storm peaks to ensure the 110 independence of data points for the analysis. Then selected a tentative threshold value in such a way that there 111 must be at least 15 peak values per year on average. That resulted at least 120 data points in each sub data sets 112 used for the seasonal analysis. The resulting data series are used in further POT analysis. Further adjustment of 113 the threshold is carried by Sample Mean Excess (SME) plots and Parameter Stability plots (PS plot). From these plots, we selected probable four thresholds and fitted corresponding GPD. A final threshold value is chosen by 114 115 analyzing results obtained in different Goodness of Fit (GOF) tests such as Kolmogorov-Smirnov (KS) test,

Anderson-Darling (AD) test and Cramer-von Mises (CM) test (Stephens, 1974; Choulakian et al., 2001).

The distributions used in the analysis is validated using graphical tools like Quantile-Quantile (Q-Q) plots and CDF plots. In addition to above graphical tools, we checked the reliability of chosen thresholds for POT method by using different GOF tests such as KS, AD and CM tests (Table 1). p-value>0.05 indicates the selected distribution does not show a significant difference from the original data within 5 % significance interval.

3. Results and Discussion

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3.1 Long-term statistical analysis of total Hs

The mean wave climate at the study location is characterized by annual mean Hs of 1.04 m. Maximum Hs of the data is 4.75 m and the highest wind-sea, and swell Hs are 4.29 m and 4.28 m respectively. Statistical analysis of Hs was carried out by considering the seasonal characteristics of the wave climate. In order to study the seasonal aspects of the return level estimation, the data is grouped into three different seasonal series, viz. FMAM, JJAS and ONDJ seasons in addition to full-year data. Since the study location is located off the central west coast of India, the wave climate shows distinct variability throughout a year. Previous studies like Anoop et al. (2015) reported that average Hs attains its peak around 3 m during JJAS and FMAM season is relatively calm (0.5-1.5 m) compared to that (1.5-2 m) in ONDJ. The seasonal analysis is carried out using Hs data following both the GEV and GPD methods. Here, Initial Distribution Method (IDM) is considered in GEV method rather than block maxima (Mathiesen et al., 1994). One of the challenging tasks for GPD modeling is the selection of a suitable threshold value. The threshold should be high enough for observations to be independent and data after POT must have enough number of observations left inorder to converge POT into GPD. SME plots and PS plots are used to select a range of initial thresholds. On analyzing the resultant GPD fit for those thresholds, final thresholds are chosen by the help of GOF tests which are presented in Table 1. Figure 1 and Table 2 shows the estimated parameters using PWM method for both GEV and GPD. It is clear that shape parameters in both cases are negative indicating the models are Type III distribution for GPD and Weibull distribution for GEV respectively. Table 2 also shows the RMSE in the chosen model for each data series with estimated CDF. It is evident that JJAS season has lesser RMSE (~0.07 m on average) when considering GPD model. While in the case of GEV model, full year data series has lesser RMSE (~0.02 m on average). ONDJ season shows a higher discrepancy in both cases resulting an average RMSE of 0.31 m and 0.54 m for GPD and GEV respectively. Figure 2 shows a typical SME and PS plots used for choosing a range of thresholds before fixing final threshold for POT analysis on each series. In this particular case (6 h data series of FMAM season) a range of thresholds

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from 1.10 m to 1.32 m were selected, and the final threshold of 1.19 m was fixed on analyzing the GOF test

results (Table 1).

147 3.1.1 Full year

148 Here, we considered full year data series without dealing with seasonality and both the GEV and GPD are used 149 in the analysis. Initially, a range of thresholds from 2.5 to 3.4 m was selected, and further adjustment of 150 threshold is carried out by analyzing the GOF test results. Table 1 shows the selected thresholds and 151 corresponding GOF test results for each series in the full year data analysis. It is clear that the selected 152 thresholds are in good agreement with GOF test results. Both KS test and CM test gives p-value > 0.45. 153 Moreover, both CDF plots and Q-Q plots (see Figure 3: first and second rows, respectively) show selected GPD 154 models made a good performance for the particular POT series. After acquiring best fit model, return levels 155 (Table 3) were estimated for 10, 50 and 100 years. The GPD model estimates 10-year return level smaller than 156 that of maximum measured total Hs value by an extent of 5 to 15 %. Underestimation of 10 to 25 % from the 157 maximum measured value was reported by Samayam et al. (2017) compared to the 36-years and 30-years return 158 levels based on ERA-Interim reanalysis data for deep waters around Indian mainland. The initial distribution 159 approach clearly underestimates the return levels such a way that even 100 years return level does not cross the 160 highest observation (4.75 m) in the data and the largest 100 years return level is reported as 4.38 m when dealing with half-hourly data series. The large number of observations having very low Hs in the data series 161 162 used in the analysis lead to the underestimation in the initial distribution method. Whereas, GPD model 163 estimated 5.38 m and 5.83 m as 50 and 100 years return levels respectively which is comparable with Teena et 164 al. (2012) estimation at a location in the eastern Arabian Sea. When considering different time interval data, 165 both 6 and 12 h data series estimates lower return levels compared to other series. It is evident that there are 166 uncertainties related to the sampling interval adopted for the return value estimation. The standard deviation for 167 GPD estimation when considering different time intervals is 0.57 m which is highest among the other seasonal 168 data. GEV estimation reports even lesser spreading of return levels with 0.16 m standard deviation.

3.1.2 Pre-monsoon season

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The data of February to May constitute the pre-monsoon data set. This is the calmest season in the study location with maximum and average Hs of around 1.94 m and 0.73 m. Using SME and PS plots, a range of thresholds from 1.1 m to 1.35 m are selected for each time series and fitted corresponding GPD by using resultant POT. The final threshold selected by the help of GOF tests is presented in Table 1. KS and CM tests gives p-value more than 0.43 and 0.45 respectively on an average (Table 1). Since the p-values are more than 0.05, the chosen POT is not significantly different from the time series data. CDF plots and Q-Q plots (Fig. 4) for the different data series of the season illustrate the reliability of chosen model. Return levels for different return periods using a particular GPD are presented in Table 3. GEV estimation exhibit same characteristics of underestimation as shown in the full year analysis. Average 100 years return levels estimation using different time interval data attained only 1.77 m which is less than the highest observed data point in the season, whereas, GPD reports 100 years return level of 2.49 m. Time interval analysis for the season exhibits least discrepancies among the return level estimations compared to other seasons. Standard deviations of 0.11 m and 0.08 m for GPD and GEV estimations respectively were observed for 100 year return levels considering different time series data.

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3.1.3 Monsoon season

185 Monsoon season data set covers observations from June to September and this season is characterized by rough wave climate at the study location. Hs of 4.75 m and 1.77 m are recorded as maximum and average during the 186 187 season. A range of thresholds (2.7 to 3.6 m) are selected for preliminary GPD fitting as a result of interpreting 188 SME and PS plots of each data series, and corresponding final thresholds were selected after clarifying with 189 GOF test results (Table 1). Both KS and CM tests report p-value > 0.75 indicating that the resulting POT for 190 selected threshold converges into GPD. CDF and Q-Q plots in Fig.5 shows the credibility of adopted threshold 191 value. Return levels for distinct return period were estimated using resultant POT. Table 3 provides 10, 50 and 192 100 years return period values estimated using GPD and GEV models. For half hourly data, GPD projects 5.65 193 m as 100-year return level, whereas GEV underestimates to 4.39 m. While considering different time interval 194 data, GPD model shows 0.36 m standard deviation among the return levels for different time interval data. Both 195 the 6 and 12 h series gave lower return levels compared to other series.

196 3.1.4 Post-monsoon season

197 Post-monsoon season constitutes data from October to January months of the year and the observed maximum 198 Hs in this season is 2.41 m. The majority of observations during this season lies below the average value of Hs. 199 Only 32 % of the observations lies above 1.13 m and 8 % of the data are above 1.5 m. Hence, selecting the best 200 threshold for the season was more difficult. GPD was fitted for a range of thresholds (0.7 to 1.3 m) selected 201 from SME and PS plots corresponding to each series. Most suitable thresholds were selected after checking the 202 goodness of GPD (Table 1). The GOF test results show that the ONDJ series holds maximum uncertainties on 203 threshold selection due to lower p-values for KS test ranges from 0.13 to 0.48 and 0.19 to 0.45 for CM test 204 respectively. Figure 6 shows the CDF and Q-Q plots. GEV and GPD estimation for post-monsoon season show 205 very large difference among return levels (Table 3). The average percentage difference between 100 years return 206 values obtained from GEV and GPD estimations is more than 60%. It shows that GEV model clearly 207 underperforms during ONDJ season when initial distribution methods were adopted. Highest return level 208 reported by GPD model is 4.28 m, whereas GEV estimated about 2.3 m for the season. ONDJ accounts standard 209 deviation of 0.30 m and 0.13 m for GPD and GEV estimation, respectively, while using different sampling 210 intervals.

3.2 Long-term statistical analysis of wind-seas and swells

In this section, we relayed on GEV method based on block maxima. For that purpose, we extracted total, wind-sea and swell Hs data into different block maxima viz. monthly, seasonal and annual maxima series. Two seasonal maxima series is considered in such a way that one includes highest two observations in a season and another one consist of highest observation from each season. So monthly maxima series includes 96 data points. Both seasonal maxima series (seasonal maxima 1 and 2) consist of 24 and 48 data points respectively. Annual maxima series covers 8 data points. Table 4 shows the estimated return levels corresponding to various return periods. It is clear that both seasonal maxima series provides highest return levels for total Hs (6.61 m and 7.24 m) and swell Hs (5.95 m and 6.35 m), whereas wind-sea Hs is 6.19 m when annual maxima series is considered. But the annual maxima series provides an abnormal result for 100 years return level estimation (Figure 7). The GEV-AM model also shows underestimation of 10-year return level compared to the maximum measured data.

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We did a separate analysis of the annual maxima series to get insight into the abnormal results observed for wind-sea data series. Here, we considered four unique series of different length by taking annual maxima observations from 2008 to 2016. That is, first series (S1) consist of 5 data points (2008-2012) and second series (S2) consist of 6 data points (2008-2013) and so on. The density plots showing the probability for different wave height class is presented in Fig. 8 along with the corresponding GPD fit. We calculated the standard deviation for each series and the percentage difference between each series with the parent series (S0). The result shows that return levels are positively correlated with standard deviation (Table 5). In the case of total Hs, the correlation between the changes in standard deviation and the corresponding changes in 100-year return levels are 0.997, whereas for wind-sea and swell, it is 0.964 and 0.647 respectively. Annual maxima of wind-sea (4.29 m) for the year 2015 made an abrupt change in the standard deviation of the series by about 0.46 m which is more than 17 % of the average of the series excluding 2015. So, the 100 years return level for wind-sea overshoot for about 6.16 m making 66 % difference from return value obtained for S3 series. In this case study, the length of the special series under consideration does not influence on the estimated return levels. That is, in the case of total Hs series, 100 years return levels for S1 series is greater than both S2 and S3 series. Same characteristics can be seen in the case of swell Hs also. Therefore, return levels for annual maxima by GEV model have greater influence over how a single data point, i.e. the annual maxima, alter the standard deviation of the series rather than the changes in the length of the series.

4. Conclusion

Long-term statistical analysis of extreme waves is carried out based on GEV and GPD models using measured buoy data from March 2008 to February 2016. Return levels are calculated for resultant, wind-sea and swell Hs separately. The analysis is also conducted for data under three different seasons. The parent data are resampled into 3, 6, 12 and 24 hourly series and estimated the discrepancy in return level estimation. Selection of appropriate thresholds for POT method is justified using different GOF tests results. Analysis of the total Hs shows that IDM approach underestimates return levels for different seasons compared to corresponding GPD. The 100 years return level estimated by IDM are almost comparable with corresponding GPD estimation for ten years period, but there is a significant difference in the return level estimates when considering different sampling intervals. Maximum return levels are obtained while considering half hourly series for different seasons except pre-monsoon season where 12 hourly data estimated highest return level. IDM estimates largely underestimates return levels for the post-monsoon season since majority of the observation in this season lies away from its tail of the distribution.

Long-term statistics of wind-sea and swell data are calculated by GEV model following block maxima and r-largest methods. Annual maxima and monthly maxima are considered for block maxima series, and two seasonal maxima series are considered for the r-largest method. It is shown that these methods give higher return levels than GPD models. The r-largest method provides 7.24 m as 100-year return level when compared to 6.03 m of GPD model. The sensitivity analysis of GEV-AM model shows that change in the standard deviation of data series under consideration makes discrepancies in the return level estimates rather than a change in the length of the series. Both GEV and GPD models underestimates 10-year return levels compared to maximum measured data.

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- 264 References
- 265 Abild, J., Andersen, E. Y., and Rosbjerg, D.: The climate of extreme winds at the Great Belt, Denmark, J. J
- 266 Wind Eng Ind Aerod., 41(1), 521-532, 1992.
- 267 Alves, J. H G M., and Young, Ian R.: On estimating extreme wave heights using combined Geosat,
- Topex/Poseidon and ERS-1 altimeter data, Appl Ocean Res, 25(4), 167-186, 2003.
- 269 Anoop, T. R., Kumar, V. S., Shanas, P. R., and Johnson, G.: Surface wave climatology and its variability in the
- 270 north Indian Ocean Based on ERA-interim reanalysis, J. Atmos. Ocean. Technol., 32(7), 1372-1385.
- 271 http://doi.org/10.1175/JTECH-D-14-00212.1, 2015.
- 272 Brodtkorb, P.A., Johannesson, P., Lindgren, G., Rychlik, I., Rydén, J. and Sjö, E.: WAFO a Matlab toolbox for
- analysis of random waves and loads, Proc. 10th Int. Offshore and Polar Eng. Conf., Seattle, USA., Vol III, pp.
- 274 343-350, 2000.
- 275 Caires, S., and Sterl, A.: 100-year return value estimates for ocean wind speed and significant wave height from
- 276 the ERA-40 data, J Climate., 18(7), 1032-1048, 2005.
- 277 Choulakian, V. and Stephens, M.A.: Goodness-of-Fit Tests for the Generalized Pareto
- 278 Distribution, Technometrics., 43, 478–484, 2001.
- 279 Coles, S., Bawa, J., Trenner, L., and Dorazio, P.: An introduction to statistical modeling of extreme values,
- Springer-Verlag, London., UK., 205pp, 2001.
- 281 Goda, Y., Hawkes, P., Mansard, E., Martin, M. J., Mathiesen, M., Peltier, E., and Van Vledder, G.:
- 282 Intercomparison of extremal wave analysis methods using numerically simulated data, Proc. WAVES'93, New
- 283 Orleans, USA, 963-977, 1993.
- 284 Goda, Y., Kudaka M., and Kawai.H.: Incorporation of Weibull distribution in L-moments method forregional
- 285 frequency of peaks-over-threshold wave heights, Proceedings of 32nd international conference on coastal
- engineering., ASCE, 2010.
- 287 Goda, Y.: Uncertainty of design parameters from viewpoint of extreme statistics, J Offshore Mech Arct., 114(2),
- 288 76-82, 1992.
- 289 Gumbel, E. J.: Statistics of extremes, Columbia Univ. Press., New York, 1958.
- 290 Hosking, J. R. M., Wallis, J. R., and Wood, E. F.: Estimation of the generalized extreme-value distribution by
- the method of probability-weighted moments, Technometrics., 27(3), 251-261, 1985.
- 292 Izaguirre, C., Mendez, F. J., Menendez, M., Luceño, A., and Losada, I. J.: Extreme wave climate variability in
- 293 southern Europe using satellite data, J Geophys Res., 115(C4), doi:10.1029/2009jc005802, 2010.

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- 294 Jonathan, P., Randell, D., Wu, Y., and Ewans, K.: Return level estimation from on-stationary spatial data
- exhibiting multidimensional covariate effects. Ocean Eng., 88, 520-532, doi:10.1016/j.oceaneng.2014.07.007,
- 296 2014.
- 297 Katz, R. W., Parlange, M. B., and Naveau, P.: Statistics of extremes in hydrology, Adv Water Resour., 25(8-12),
- 298 1287-1304, doi:10.1016/s0309-1708(02)00056-8, 2002.
- 299 Mathiesen, M., Goda, Y., Hawkes, P. J., Martín, M. J., Peltier, E., and Edward, F.: Recommended practice for
- 300 extreme wave analysis, J Hydraul Res, 32:6, 803-814,1994.
- 301 Méndez, F. J., Menéndez, M., Luceño, A., Medina, R., and Graham, N. E.: Seasonality and duration in extreme
- value distributions of significant wave height, Ocean Eng., 35(1), 131-138, 2008.
- 303 Menéndez, M., Méndez, F. J., Izaguirre, C., Luceño, A., and Losada, I. J.: The influence of seasonality on
- 304 estimating return values of significant wave height, Coast Eng., 56(3), 211-219, doi:
- 305 10.1016/j.coastaleng.2008.07.004, 2009.
- 306 Panchang, V., Zhao, L., and Demirbilek, Z.: Estimation of extreme wave heights using GEOSAT measurements,
- 307 Ocean Eng., 26(3), 205-225, doi:10.1016/s0029-8018(97)10026-9, 1999.
- Pickands, J.: Statistical inference using extreme order statistics, Ann Stat., 3,119–131, 1975.
- 309 Samayam, S., Laface, V., Annamalaisamy, S. S., Arena, F., Vallam, S., and Gavrilovich, P. V.: Assessment of
- 310 reliability of extreme wave height prediction models. Nat. Hazards Earth Syst. Sci., 17, 409-421, 2017
- 311 Sanil Kumar, V., Shanas, P. R., and Dubhashi, K. K.: Shallow water wave spectral characteristics along the
- 312 eastern Arabian Sea, Nat Hazards., 70(1), 377-394, doi:10.1007/s11069-013-0815-7, 2014.
- 313 Shaji, C., Kar, S.K., and Vishal, T.: Storm surge studied in North Indian Ocean: A review, Indian J Geo-Mar
- 314 Sci., 43(2)125-147, 2014.
- 315 Smith, R. L.: Extreme value theory based on the r largest annual events, J Hydrol., 86(1-2), 27-43,
- 316 doi:10.1016/0022-1694(86)90004-1, 1986.
- 317 Soares, C. G., and Scotto, M.: Application of the r-largest-order statistics for long-term predictions of significant
- 318 wave height, Coast Eng., 51(5-6), 387-394, doi:10.1016/j.coastaleng.2004.04.003, 2004.
- 319 Stephens, M. A.: EDF Statistics for Goodness of Fit and Some Comparisons, J Am Stat Assoc., 69(347), 730-
- 320 737, doi:10.1080/01621459.1974.10480196, 1974.
- 321 Teena, N. V., Sanil Kumar, V., Sudheesh, K., and Sajeev, R.: Statistical analysis on extreme wave height. Nat
- 322 Hazards., 64(1), 223-236, doi:10.1007/s11069-012-0229-y, 2012.
- 323 Thevasiyani, T. and Perera, K.: Statistical analysis of extreme ocean waves in Galle, Sri Lanka. Weather Clim.
- 324 Extrem., 5-6, 40-47, doi:10.1016/j.wace.2014.07.003, 2014.

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the corresponding GPD fit.

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parameters for offshore wind turbines in the Gulf of Maine using a POT method. Ocean Eng., 104, 649-658, 326 327 doi:10.1016/j.oceaneng.2015.04.086, 2015. 328 Figure captions 329 Figure 1: Estimated shape parameters for different seasonal data with different sampling intervals used in a) 330 GEV and b) GPD model. 331 Figure 2: A Typical (a) SME and (b) PS plots used for selecting a range of thresholds required for POT analysis. 332 In this particular case, a range of 1.1 m to 1.32 m was selected. Figure 3: Figure corresponding to full year analysis. (a) to (e) is CDF plots for ½ hourly to 24 hourly data 333 334 respectively, sub-figures, (f) to (g) are corresponding Q-Q plots and (k) to (o) are corresponding return levels estimated using GPD model. 335 336 Figure 4: Same as in Figure 3 but corresponding to pre-monsoon season. 337 Figure 5: Same as in Figure 3 but corresponding to monsoon season 338 Figure 6: Same as in Figure 3 but corresponding to the post-monsoon season. 339 Figure 7: Return levels estimated by GEV model using annual maxima series. 340 Figure 8: Density plots showing the probability for different wave height class. Total, wind-sea and swell Hs are presented in rows wise. Columns correspond to selected number of data points (5 to 8 years). The solid curve is 341

Viselli, A. M., Forristall, G. Z., Pearce, B. R., and Dagher, H.J.: Estimation of extreme wave and wind design

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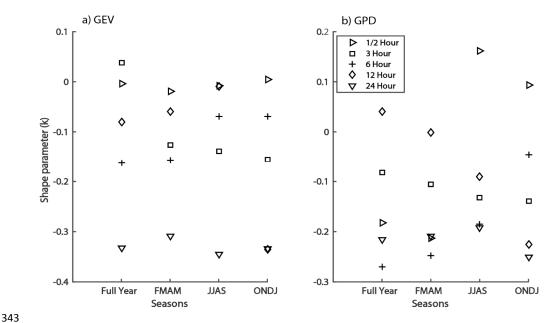


Figure 1: Estimated shape parameters for different seasonal data with different sampling intervals used in a)
GEV and b) GPD model

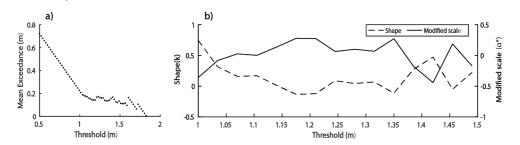


Figure 2: A Typical (a) SME and (b) PS plots used for selecting a range of thresholds required for POT analysis.
 In this particular case, a range of 1.1 m to 1.32 m was selected

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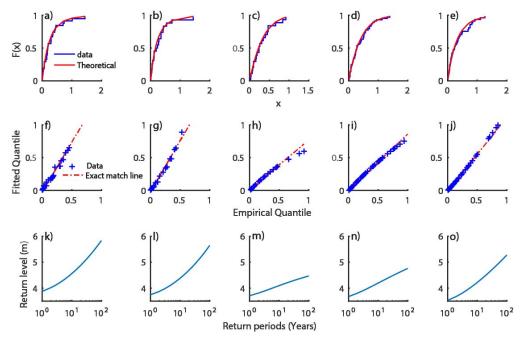


Figure 3: Figure corresponding to full year analysis. (a) to (e) is CDF plots for $\frac{1}{2}$ hourly to 24 hourly data respectively, sub-figures, (f) to (g) are corresponding Q-Q plots and (k) to (o) are corresponding return levels estimated using GPD model

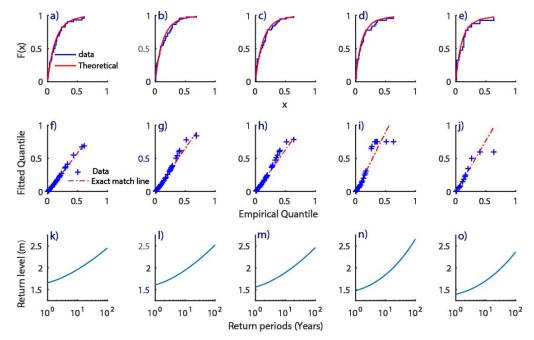


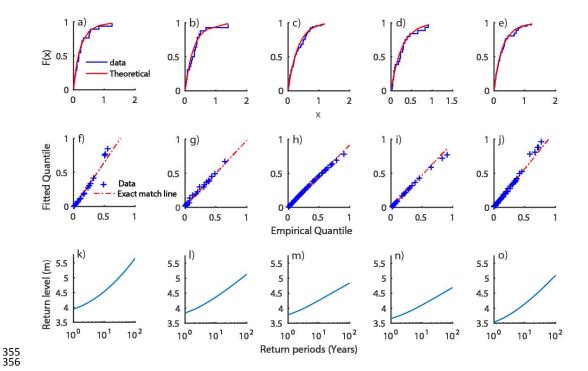
Figure 4: Same as in Figure 3 but corresponding to pre-monsoon season

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357 Figure 5: Same as in Figure 3 but corresponding to monsoon season

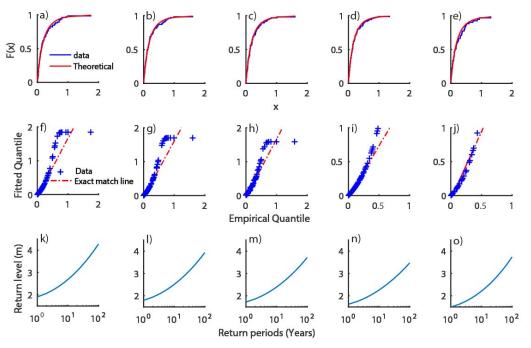


Figure 6: Same as in Figure 3 but corresponding to the post-monsoon season

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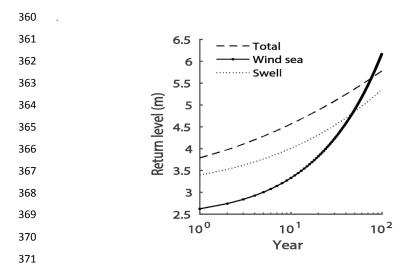


Figure 7: Return levels estimated by GEV model using annual maxima series

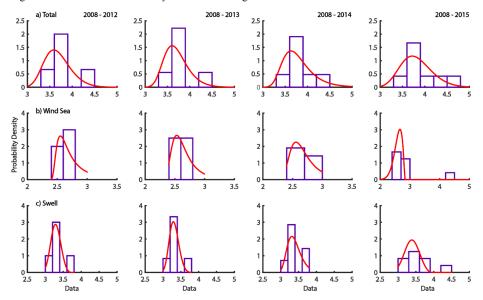


Figure 8: Density plots showing the probability for different wave height class. Total, wind-sea and swell Hs are presented in rows wise. Columns correspond to selected number of data points (5 to 8 years). The solid curve is the corresponding GPD fit

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Table 1: Different goodness of fittests used for selecting threshold values of POT analysis. H =0 indicates the
 test does not reject hypothesis at 5 % significance level (i.e., p-value > 0.05 or test statistics is less than critical
 value) and H=1 indicates hypothesis is rejected

Seasons	Time Interval	· · · · · · · · · · · · · · · · · · ·	Threshold	KS test			CM test				
			(m)	p- value	Test statistics	Critical value	Н	p-value	Test statistics	Critical value	Н
	½ h	4.75	3.31	0.545	0.143	0.246	0	0.425	0.141	0.459	0
	3 h	4.75	3.31	0.549	0.167	0.287	0	0.477	0.126	0.458	0
Full	6 h	4.11	3.19	0.402	0.183	0.281	0	0.490	0.122	0.458	0
Year	12 h	4.11	2.72	0.745	0.092	0.187	0	0.595	0.098	0.460	0
	24 h	4.00	2.74	0.525	0.126	0.213	0	0.739	0.072	0.459	0
	½ h	1.94	1.32	0.952	0.081	0.218	0	0.985	0.027	0.459	0
	3 h	1.88	1.19	0.258	0.126	0.170	0	0.222	0.226	0.460	0
FMAM	6 h	1.83	1.19	0.203	0.151	0.192	0	0.210	0.234	0.460	0
	12 h	1.83	1.19	0.447	0.143	0.227	0	0.446	0.134	0.459	0
	24 h	1.83	1.19	0.296	0.210	0.294	0	0.423	0.142	0.458	0
	½ h	4.75	3.49	0.772	0.132	0.275	0	0.901	0.047	0.458	0
	3 h	4.75	3.36	0.864	0.124	0.287	0	0.794	0.064	0.458	0
JJAS	6 h	4.11	2.94	0.766	0.084	0.174	0	0.758	0.069	0.460	0
	12 h	4.11	3.20	0.890	0.117	0.281	0	0.906	0.046	0.458	0
	24 h	4.00	2.78	0.961	0.070	0.194	0	0.990	0.024	0.460	0
ONDJ	½ h	2.81	1.06	0.131	0.123	0.144	0	0.193	0.247	0.460	0
	3 h	2.61	1.00	0.247	0.106	0.142	0	0.307	0.183	0.460	0
	6 h	2.59	0.98	0.488	0.092	0.151	0	0.451	0.133	0.460	0
	12 h	2.18	0.84	0.197	0.102	0.129	0	0.350	0.166	0.461	0
	24 h	2.18	0.87	0.195	0.155	0.196	0	0.207	0.237	0.460	0

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Table 2: Table showing different parameters and corresponding RMSE of data and estimated CDF used during
 each data series analysis

		GPD			GEV			
Seasons	Data	k	α	RMSE	k	α	β	RMSE
		(m)	(m)	(m)	(m)	(m)	(m)	(m)
	½ h	-0.182	0.239	0.162	-0.004	0.414	2.459	0.015
	3 h	-0.213	0.219	0.159	-0.019	0.381	2.437	0.019
Full Year	6 h	0.161	0.346	0.110	-0.008	0.418	2.223	0.004
	12 h	0.094	0.420	0.102	0.005	0.416	2.206	0.020
	24 h	-0.082	0.314	0.071	0.037	0.458	2.015	0.060
	½ h	-0.105	0.130	0.037	-0.126	0.115	1.134	0.090
	3 h	-0.132	0.125	0.078	-0.139	0.104	1.143	0.098
FMAM	6 h	-0.139	0.123	0.077	-0.155	0.099	1.147	0.100
	12 h	-0.271	0.095	0.167	-0.162	0.108	0.998	0.125
	24 h	-0.247	0.099	0.082	-0.157	0.114	0.872	0.142
	½ h	-0.184	0.216	0.124	-0.069	0.298	2.782	0.088
	3 h	-0.046	0.280	0.068	-0.069	0.274	2.786	0.074
JJAS	6 h	0.041	0.328	0.051	-0.081	0.288	2.583	0.118
	12 h	-0.002	0.265	0.042	-0.060	0.281	2.598	0.065
	24 h	-0.090	0.267	0.083	-0.009	0.312	2.423	0.007
	½ h	-0.225	0.189	0.393	-0.335	0.117	1.023	0.631
	3 h	-0.215	0.178	0.333	-0.332	0.116	1.025	0.533
ONDJ	6 h	-0.208	0.177	0.284	-0.309	0.114	0.912	0.525
	12 h	-0.192	0.167	0.267	-0.345	0.104	0.911	0.523
	24 h	-0.251	0.183	0.315	-0.334	0.111	0.780	0.498

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Table 3: Estimated return values corresponding to different seasons using total wave height (Hs) following GEV and GPD methods. Here GEV method follows initial distribution approach

Seasons	DATA	GPD			GEV		
		10 Years	50 Years	100 Years	10 Years	50 Years	100 Years
		(m)	(m)	(m)	(m)	(m)	(m)
	½ h	4.52	5.38	5.83	3.40	4.09	4.38
	3 h	4.34	5.18	5.65	3.31	3.98	4.27
Full Year	6 h	4.08	4.37	4.47	3.17	3.88	4.18
	12 h	4.17	4.59	4.76	3.14	3.81	4.10
	24 h	4.18	4.92	5.27	3.00	3.68	3.95
	½ h	1.94	2.29	2.45	1.43	1.71	1.85
	3 h	1.93	2.33	2.52	1.42	1.68	1.81
FMAM	6 h	1.87	2.26	2.46	1.41	1.68	1.81
	12 h	1.82	2.35	2.66	1.29	1.59	1.74
	24 h	1.68	2.12	2.36	1.18	1.48	1.64
	½ h	4.50	5.25	5.65	3.51	4.11	4.39
	3 h	4.34	4.89	5.13	3.45	4.02	4.27
JJAS	6 h	4.24	4.66	4.84	3.29	3.90	4.19
	12 h	4.08	4.51	4.69	3.27	3.83	4.09
	24 h	4.11	4.78	5.10	3.13	3.66	3.89
	½ h	2.64	3.69	4.28	1.41	1.96	2.30
	3 h	2.46	3.41	3.93	1.41	1.95	2.28
ONDJ	6 h	2.35	3.23	3.71	1.28	1.77	2.07
	12 h	2.22	3.03	3.47	1.27	1.77	2.09
	24 h	2.16	3.16	3.74	1.15	1.67	2.00

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Table 4: Return levels estimated by GEV model using total, wind-sea and swell data for different block maximaseries.

-	Total Hs (m)			wind-s	wind-sea Hs (m)			swell Hs (m)		
DATA	10 years	50 Years	100 Years	10 years	50 Years	100 Years	10 years	50 Years	100 Years	
Monthly Maxima	3.22	5.16	6.18	2.45	3.43	3.88	2.92	4.77	5.72	
Seasonal Maxima 1	3.68	5.62	6.61	2.68	3.78	4.29	3.31	5.07	5.95	
Seasonal Maxima 2	3.85	6.07	7.24	2.91	4.32	5.06	3.51	5.40	6.35	
Annual Maxima	4.52	5.36	5.78	3.27	4.86	6.16	3.97	4.83	5.35	

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Table 5: Table showing the result of the case study. Standard deviation (STD) of each data series considered are provided, and percentage difference among the STD of each series with parent series (S0) are given in the brackets. Percentage difference in the corresponding return level estimation also shown in the brackets of respective return periods.

Dataset	Series	Maximum	Standard deviation	Return levels			
	(Years)	observed	(% difference)	10 Years	50 Years	100 Years	
		(m)		(m)	(m)	(m)	
	S1	4.32	0.36	4.24	4.89	5.20	
	(2008-2012)		(21.75)	(6.31)	(9.12)	(10.42)	
	S2	4.32	0.32	4.17	4.67	4.90	
Total	(2008-2013)		(32.68)	(8.07)	(13.66)	(16.34)	
	S3	4.32	0.32	4.23	4.65	4.83	
	(2008-2014)		(34.52)	(6.62)	(14.09)	(17.96)	
	S0	4.75	0.45	4.52 5.36 2.82 2.88 (14.81) (51.29)	5.36	5.78	
	S1	2.80	0.13	2.82	2.88	2.89	
	(2008-2012)		(128.90)	(14.81)	(51.29)	(72.30)	
	S2	2.80	0.14	2.81	2.95	3.00	
Wind-sea	(2008-2013)		(125.06)	(15.00)	(48.96)	(69.16)	
	S3	2.89	0.16	2.89	3.05	3.11	
	(2008-2014)		(114.08)	(12.35)	(45.80)	(66.00)	
	S0	4.29	0.60	3.27	4.86	6.16	
	S1	3.47	0.23	3.65	4.16	4.45	
	(2008-2012)		(48.17)	(8.23)	(14.93)	(18.36)	
	S2	3.47	0.20	3.62	4.01	4.22	
Swell	(2008-2013)		(58.53)	(9.18)	(18.53)	(23.56)	
	S3	3.47	0.22	3.71	4.05	4.21	
	(2008-2014)		(50.80)	(6.62)	(17.53)	(23.97)	
	S0	4.28	0.37	3.97	4.83	5.35	