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## Directional and frequency spread of surface ocean waves from SWIM measurements

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1                    **Directional and frequency spread of surface ocean**  
2                    **waves from SWIM measurements**

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8                    <sup>4</sup>ACRIS-ST

9                    **Key Points:**

- 10                    • The SWIM ocean wave spectrum is the narrowest and the most peaked for sit-  
11                    uations with waves close to the fully development stage
- 12                    • For the Southern Ocean conditions, it is found that SWIM directional spread at  
13                    the dominant frequency varies according to the wave development stage.
- 14                    • Compared to the MFWAM model, the SWIM observations indicate narrower and  
15                    more peaked omni-directional spectra but similar directional spreads of the dom-  
16                    inant waves in well-developed sea state conditions.

**Abstract**

The China France Oceanography Satellite (CFOSAT) launched in 2018 now routinely provides directional ocean wave spectra at the global scale. It consists of analyzing the normalized radar cross-section measured by the near-nadir pointing Ku-Band real-aperture scanning radar SWIM (Surface Waves Investigation and Monitoring). The significant wave height, dominant wavelength and direction are provided as the main parameters, but here, we analyze additional parameters, namely the frequency width of the omni-directional spectra, the directional spread of the dominant waves, and the related Benjamin-Feir index. This latter was proposed in the literature to estimate the probability of extreme waves. We discuss the geographical distributions of these parameters, their relation with sea-state conditions, and their similarities and differences with respect to the same parameters obtained from the MFWAM numerical wave model and buoy data. We find that the SWIM omni-directional spectra are narrower and more peaked than the model spectra and that these differences are more obvious in the high sea-state conditions encountered in the Southern Ocean. We find that under the intense conditions of the Southern Ocean, the SWIM directional spread at the peak is the smallest for swell, the largest for young wind seas, and takes intermediate values for mature wind seas. The directional Benjamin-Feir index is similar for SWIM and MFWAM, but this is mainly due to compensating effects in the parameters contributing to this index. The results indicate that these shape parameters may be used in the future to better describe the wave space-time evolution.

**Plain Language Summary**

The France Oceanography Satellite CFOSAT was launched in 2018. It routinely provides for all ocean basins detailed information on the ocean waves, namely the distribution of wave height with direction and wavelength (or wave frequency), obtained from radar measurements. In this study, we analyze several parameters which quantify how the energy spreads around the dominant frequency and the dominant wave propagation direction of the waves. Several of these parameters are also combined to estimate an index, which characterizes the probability of occurrence of extreme waves. To our knowledge, it is the first time that such parameters are accessible from space observations at the global scale. In the paper, we discuss the geographical distributions of these parameters, their relation with sea-state conditions, and their similarities or differences with respect to the same parameters obtained from a numerical wave prediction model and from buoy observations. We find that compared to the satellite observations, the model indicates narrower and more peaked distributions of energy in frequency, and we propose some explanations on this. Overall, the results indicate that these shape parameters from satellite observations may be used in the future to further understand or validate the physical processes impacting the evolution of waves during growth order decay.

**1 Introduction**

Ocean surface waves are commonly described by their directional density spectrum of height, which characterizes the distribution of wave energy as a function of wave frequency (or wave number) and wave propagation direction. However, in both numerical modelling studies and observation analyses, the full information of directional spectra is seldom discussed. Apart from significant wave height, which is widely used to characterize or forecast the total energy of waves, the mean or peak period and the mean or peak directions are the parameters most often used in these studies. This reduces the information on directional spectra to only few parameters, whereas information on directional spread or frequency spread contains useful information.

66 Most of the numerical models developed for describing or forecasting the evolution  
 67 with time and space of the waves over the globe or at the regional scale are based on a  
 68 spectral approach also called phase-averaged approach (Komen et al., 1994; Tolman &  
 69 Chalikov, 1996; The SWAN Team, 2010). Basically, these models solve the wave energy  
 70 or the wave action conservation equation discretized in wave frequency and wave direc-  
 71 tion intervals, with source and sink terms separated in three, namely the wind input term,  
 72 the dissipation term and the non-linear interaction between waves. During the last two  
 73 decades, most of these models have reached an appropriate degree of maturity to pro-  
 74 vide a fairly good agreement with respect to in situ and satellite observations, for the  
 75 main parameters of the sea-state, namely the significant wave height, the mean direc-  
 76 tion and the mean period (The WISE Group et al. (2007); Bidlot (2017), and ECMWF  
 77 reports<sup>1</sup>). However, uncertainties on these parameters still remain in certain conditions,  
 78 in particular those strongly forced by the wind like in the Southern Ocean (Aouf et al.,  
 79 2021; Young et al., 2020) or within tropical storms (Fan et al., 2020). Furthermore, the  
 80 dominant wave period from the models still shows important biases with respect to ob-  
 81 servations (see ECMWF reports). The results from Stopa et al. (2015) also show that  
 82 for the model Wave Watch 3 (WW3), the directional spread parameter is in general not  
 83 consistent with buoy observations regardless of the model parameterization.

84 The successive improvements of numerical models are most often defined and as-  
 85 sessed through comparisons of the significant wave height. Models may be satisfying in  
 86 terms of significant wave height (or integrated wave energy), but their good performance  
 87 may hide some unsatisfying behavior of the energy distribution in wave frequency or wave  
 88 direction (Rogers & Wang, 2007). The reason of this is probably due to the fact that,  
 89 since the 90s, model assessment at the global scale is mainly based on space-borne al-  
 90 timeter observations. These latter provide the significant wave height but no informa-  
 91 tion on wave direction nor wave frequency. In consequence, the model improvements or  
 92 tunings are not strongly constrained by parameters other than significant wave height.  
 93 This can induce some artificial shortcomings on the physical parameterizations of the  
 94 models. It is known from theory and academic numerical tests that the shape of the wave  
 95 spectra in frequency and direction is highly sensitive to the physical parameterization  
 96 of the models (e.g., Zieger et al., 2015; Alves & Banner, 2003), and to numerical simpli-  
 97 fications in the non-linear interaction term (Gagnaire-Renou, 2009; Rogers & Van Vled-  
 98 der, 2013; Zieger et al., 2015; Forristall & Greenwood, 1998; Rogers & Wang, 2007), but  
 99 there are only very few studies which have used the spectral shape information to ad-  
 100 just and validate the numerical models in their operational version.

101 Alleviating such shortcomings with in situ measurements as reference is not triv-  
 102 ial because appropriate observations are scarce. Indeed, although systematic in situ ob-  
 103 servations from wave buoys or wave gauges also provide wave spectra as main informa-  
 104 tion, most of these systems provide only the non-directional frequency spectra and the  
 105 spectral resolution is rather poor. Only a few of them provide directional information.  
 106 Mean or peak period and mean or peak direction are the parameters most often acces-  
 107 sible to compare with the model results. Also, most of the observations are located close  
 108 to the coasts, so that it may be insufficient to use these in situ observations to fully tune  
 109 or validate the models.

110 Among the satellite observation techniques, two of them are appropriate to pro-  
 111 vide detailed information on ocean wave spectra. The high resolution images provided  
 112 by Synthetic Aperture Radars (such as on ERS1, ENVISAT, Radarsat, Sentinel 1A/1B)  
 113 can be inverted to provide wave spectra (e.g., Kerbaol et al., 1988). But it is well-known  
 114 that they have important limitations because they cannot detect waves with wavelengths

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<sup>1</sup> see ECMWF reports at [https://www.ecmwf.int/en/forecasts/charts/catalogue/w\\_wave\\_intercomparison?facets=undefined&time=2018123000,0,2018123000&area=All%20stations%20combined&statistics=Bias](https://www.ecmwf.int/en/forecasts/charts/catalogue/w_wave_intercomparison?facets=undefined&time=2018123000,0,2018123000&area=All%20stations%20combined&statistics=Bias)



115 shorter than about a cut-off limit of about 200 m particularly when waves propagate along  
 116 the satellite track (Alpers & Brüning, 1986). This azimuth cut-off induces a distortion  
 117 of the wave directional spectrum, mainly along the range direction. Furthermore, today,  
 118 none of these satellite missions provide wave spectra over the full globe, because SAR  
 119 are also used in moderate or low resolution modes for other applications close to the sea-  
 120 ice and to the continents. Since 2018, the new satellite called CFOSAT with its SWIM  
 121 instrument onboard dedicated to wave measurements (SWIM= Surface Waves Investi-  
 122 gation and Monitoring) provide directional spectra of ocean waves for waves between 70  
 123 and 500 m in wavelength (Hauser et al., 2017, 2020). Hauser et al. (2020) analyzed the  
 124 performance on the wave height, dominant wave direction and dominant wavelength mainly  
 125 through comparisons between SWIM data and model outputs, where the model used was  
 126 the MFWAM wave prediction model, i.e. the French version of the ECMWF WAM model.  
 127 This study showed that except for waves which propagate in a  $\pm 15^\circ$  sector along-track,  
 128 the main parameters are in good agreement with the MFWAM model.

129 In spite of their limitations, it was proved that wave direction and wavelength of  
 130 swell partitions estimated from SAR observations (from Sentinel-1A/1B) can significantly  
 131 improve the model results in terms of wave height when they are assimilated in the model  
 132 (Aouf et al., 2016). The MFWAM model now operationally assimilates these SAR ob-  
 133 servations. First tests of SWIM data assimilation also show a significant impact on the  
 134 model results when the assimilation process includes the wave direction and wavelength  
 135 of the dominant waves (Aouf et al., 2021). This is a way to better constrain the model  
 136 with directional observations in addition to the sole significant wave height.

137 To go a step further, and in particular to help identifying or correcting the model  
 138 inaccuracies, it is necessary to use additional metrics, such as those characterizing the  
 139 spectral shape (Resio et al., 2016). The most natural ones are those related to the width  
 140 of the omni-directional spectrum and the directional spread of the waves around their  
 141 mean direction. One aim of the present paper is therefore to present and discuss such  
 142 spectral shape parameters estimated from the SWIM data.

143 Another motivation for studying with more details the frequency and directional  
 144 spread of the wave spectra is related to the needs for better characterizing or forecast-  
 145 ing the probability of extreme waves (or freak waves). Using statistical simulations Socquet-  
 146 Juglard et al. (2005) show that in the uni-directional case, the spectral development of  
 147 long waves due to the modulation instability is significantly dependent on the initial spec-  
 148 tral width in frequency and on the significant steepness. Janssen and Bidlot (2009) and  
 149 Mori et al. (2011) show analytically how the kurtosis in the wave height distribution can  
 150 be related to spectral parameters. In order to characterize the excess of kurtosis, they  
 151 propose two parameters, namely the Benjamin-Feir instability index (BFI) in the uni-  
 152 directional case and a two-dimensional version of it, called  $BFI_{2D}$ . BFI is proportional  
 153 to the ratio of significant steepness to the spectral bandwidth in frequency (see Equa-  
 154 tion 8 in Section 2.5), whereas  $BFI_{2D}$  takes into account in addition, the directional spread  
 155 of the waves. Although prognostics values on maximum heights are today currently pro-  
 156 vided as products of numerical wave models (Janssen & Bidlot, 2009; ?, ?), the param-  
 157 eters on which they are based (spectral frequency width, BFI, directional spread,  $BFI_{2D}$ )  
 158 still need to be fully assessed.

159 Finally, directional spreading is important not only to better understand, model  
 160 and forecast the evolution of surface waves, but also because it impacts the Stokes drift,  
 161 which in turn is playing an important role in the ocean mixing in the upper layers (Webb  
 162 & Fox-Kemper, 2015).

163 Considering the issues on the knowledge of spread parameters, our goal in this pa-  
 164 per is to present and discuss the spectral shape of the wave spectra obtained from the  
 165 analysis of the CFOSAT/SWIM observations at the global scale. In order to discuss the  
 166 quality or limit of these estimations, we compare them to numerical model and buoy data.

167 The model considered here is the MFWAM, the French version of the WAM model. The  
 168 paper is organized as follows. In Section 2, we describe the SWIM, MFWAM and buoy  
 169 data sets and recall the definition of the spectral parameters used in the analysis. We  
 170 also present in this section, the wind and wave height conditions of the subsets of data  
 171 considered in this study. In Section 3, we present the spectral shape parameters (direc-  
 172 tional and frequency spread,  $BFI_{2D}$ ) at the global scale, we discuss their geographic dis-  
 173 tributions, the relations between the different parameters and the comparison between  
 174 observed and modeled parameters. In Section 4, a focus is made on results obtained in  
 175 the Southern Ocean, a region of very high waves, strongly forced by stormy winds. From  
 176 this subset of observations, we also discuss the possible reasons of the differences between  
 177 the model and the observations. Section 5 summarizes the main results and conclusions.

## 178 2 Dataset and wave spectral parameters

### 179 2.1 SWIM dataset

180 The SWIM instrument deployed on board CFOSAT since October 2018, is a wave  
 181 scatterometer with six radar-beams rotating around the nadir axis at small incidences  
 182 ( $0^\circ$ ,  $2^\circ$ ,  $4^\circ$ ,  $6^\circ$ ,  $8^\circ$ ,  $10^\circ$ ). Using the concept of real-aperture scanning radar, SWIM pro-  
 183 vides measurements in all azimuth directions, which allows to estimate directional wave  
 184 spectra. The measurement principle of the concept is explained in Jackson et al. (1985a)  
 185 whereas the space-borne configuration with SWIM is detailed in Hauser et al. (2017).

186 The wave products are distributed by the CNES (Centre National d’Etudes Spa-  
 187 tiales) mission center; they consist in directional ocean wave spectra of wave cells of about  
 188 70 km per 90 km on each side of the satellite track (Hauser et al., 2017). The SWIM spec-  
 189 tra are provided in the wavenumber domain from 0.013 rad/m and 0.28 rad/m which  
 190 corresponds to the wavelength domain [22, 500] m. When converted in frequency by as-  
 191 suming the dispersion relationship in deep water, this wavenumber domain corresponds  
 192 to the frequency domain from 0.056 Hz and 0.26 Hz. SWIM wave spectra are provided  
 193 with a  $180^\circ$  ambiguity for the wave propagation direction and their angular discretisa-  
 194 tion is  $15^\circ$ .

195 Hauser et al. (2020) published the first analysis of the SWIM geophysical products. They  
 196 compared to the MFWAM model wave parameters, such as significant wave height, dom-  
 197 inant wavelength and direction. They concluded that with an updated speckle noise cor-  
 198 rection, the main parameters of the SWIM spectra are in reasonable agreement with the  
 199 same parameters obtained from the MFWAM model and from in situ observations. A  
 200 limitation was however found when waves propagate in a direction close to the satellite  
 201 track. It is due to an inaccurate correction of speckle noise in this direction. They also  
 202 concluded that the  $10^\circ$  beam gives the best results compared to the MFWAM data and  
 203 to in situ observations. For this reason, in the present study, we only use the wave spec-  
 204 tral information from the  $10^\circ$  incidence beam. Moreover, the data set used here corre-  
 205 sponds to the updated version of the processing (version 5). This update concerns the  
 206 optimized speckle noise correction as presented in Hauser et al. (2020), and the appli-  
 207 cation of a normalisation on the spectral energy by using the significant wave height (SWH)  
 208 from the nadir beam:

$$209 \quad S(i_k, i_\phi) = \left( \frac{4}{SWH} \right)^2 \sum_{i_k=0}^{Nk-1} \sum_{i_\phi=0}^{N\phi-1} S_{pm}(i_k, i_\phi) dk(i_k) d\phi(i_\phi) / k(i_k) \quad (1)$$

210 With  $S(i_k, i_\phi)$  the wave slope spectrum, and  $S_{pm}(i_k, i_\phi)$  the modulation spectrum. This  
 211 version is the one adopted to produce the operational products since October 12, 2020  
 212 and used to reprocess the SWIM data set since the beginning of the mission.

213 For the analysis presented below, the original SWIM spectra expressed as a func-  
 214 tion of wavenumber have been converted as frequency spectra assuming the deep water  
 215 dispersion relationship.

216 SWIM first order parameters such as significant wave height, dominant wavelength  
 217 and dominant direction are calculated by the operational processor on the 2D polar wave  
 218 slope spectra.

219 The data set chosen for the analysis covers a 13 day period (i.e. a full orbital cy-  
 220 cle of CFOSAT), and extends from the 10th to the 22th of September 2019. Observa-  
 221 tions over land and sea-ice have been filtered out. This global dataset represents 67 981  
 222 measurement points. All these samples are used for comparisons with model data. By  
 223 comparison, a co-location with 43 buoys over 8 months of data represents only 6000 sam-  
 224 ples and much less diversity in terms of wave conditions (see Section 3).

## 215 2.2 MFWAM dataset

226 In this study, SWIM data are compared to MFWAM model data. The MFWAM  
 227 wave model is the French version of the third generation WAM model. It is based on the  
 228 ECMWF version (referred as ECW AM-IFS-38R2) with a parameterization taken from  
 229 the ST4 version of the WW3 model (Ardhuin et al., 2010). The MFWAM products used  
 230 here have a grid resolution of 10 km, are driven by 3-hourly winds from the IFS-ECMWF  
 231 atmospheric system and are co-localised to the closest point from the SWIM measure-  
 232 ment point. Wind information is also available in the MFWAM products. Wave/current  
 233 interactions are taken into account with daily surface currents provided by the global  
 234 PSY4-CMEMS ocean forecasting system. The MFWAM wave spectra are discretized in  
 235 24 directions between  $0^\circ$  and  $360^\circ$ , which corresponds to directional bins of  $15^\circ$ , and 30  
 236 frequencies starting from 0.035 Hz to 0.58 Hz (1300 m to 5 m of wavelength). In its op-  
 237 erational version as used here, the MFWAM model assimilates in real-time the signif-  
 238 icant wave height from various altimeter missions, and the directional information from  
 239 Sentinel 1A and 1B SAR images. The MFWAM wave parameters are provided in out-  
 240 put of the Météo-France operational processor. The peak periods are converted to peak  
 241 wavelengths, assuming the deep water dispersion relationship.

## 242 2.3 Buoy dataset

243 Additional comparisons have been made with the buoys from the National Data  
 244 Buoy Center (NDBC). We have selected 43 buoys moored at more than 60 km from the  
 245 coasts to avoid coastal contamination in SWIM data. Buoys are located along the Pa-  
 246 cific and Atlantic coasts of North America, around the archipelago of Hawaiï, in the Gulf  
 247 of Mexico, in the Caribbean Sea and along the east coasts of the archipelago of The An-  
 248 tilles. Significant wave heights, dominant periods and directions are provided in the data  
 249 files. The dominant wavelength is then calculated from the dominant period consider-  
 250 ing the dispersion equation and taking into account the depth provided in the buoy data.  
 251 Wave height omnidirectional spectra are also provided in the buoy data over the frequency  
 252 range [0.02, 0.485] Hz. In our analysis of the spectral shape with frequency we have re-  
 253 duced this frequency range to the same interval as the one relative to SWIM. To esti-  
 254 mate the directional spread, we have used the Fourier coefficient parameters provided  
 255 in the buoy data files (Section 2.5).

256 The comparisons between the SWIM and the buoy data have been made over a pe-  
 257 riod of 8 months between April 26 and December 31, 2019. For the comparison, the max-  
 258 imum distance accepted between SWIM and the buoy was chosen as 100 km and the  
 259 maximum time lapse as 30 min. As the buoy are moored relatively close to the coasts,  
 260 SWIM wave spectra expressed as a function of wavenumber have been converted into

261 frequency wave spectra using the dispersion relationship considering the depth given in  
 262 the buoy data.

## 263 2.4 Overview of wind and wave height conditions for the global anal- 264 ysis

265 Figure 1 shows the significant wave height from the SWIM 10° incidence beam and  
 266 the wind speed used for the forcing of the MFWAM model. The global conditions ob-  
 267 served during this period show high sea states in the Southern Ocean with wind speed  
 268 reaching 18 m/s and significant wave heights higher than 5 m. Similar conditions of high  
 269 wind speed and wave height are also observed along the North American and the Green-  
 270 land coasts, as well as in the Gulf of Alaska and Bering strait. Along the US coasts the  
 271 high wind and wave conditions are due to the passage of the hurricane Humberto be-  
 272 tween 16 and 19 September 2019. Moreover, close by the Greenland coasts, along shore  
 273 winds stronger than 20 m/s were observed between the 18th and 22th September 2019.

274 Figure 2 is a two-dimensional histogram representing the occurrence of a given sig-  
 275 nificant wave height for a given wind speed as derived from the MFWAM wind and wave  
 276 parameters. The black curves reported in Figure 2 correspond to the relations derived  
 277 from the Elfouhaily et al. (1997) wave spectrum under young, mature and developed con-  
 278 ditions (wave age of 0.5, 1, 1.2 respectively). Over the 13 days period, the majority of  
 279 situations correspond to significant wave heights between 1.5 m and 3 m and wind speeds  
 280 projected along the wave direction between 5 m/s and 11 m/s. Based on the significant  
 281 wave height to wind speed relationship for wind-sea, Figure 2 indicates that the major-  
 282 ity of samples correspond to fully developed wind sea or swell conditions.

283 In order to clarify the discussions of the results, SWIM and MFWAM spectra have  
 284 been classified in different categories of sea-state according to the inverse wave age  $\Omega$   
 285 defined as classically as:

$$286 \Omega = \frac{U_{10} \cos(\theta_{wind} - \theta_{waves})}{c_p} \quad (2)$$

287 Where  $c_p$  is the phase velocity,  $U_{10}$  is the wind speed at 10 m,  $\theta_{wind}$  is the wind direc-  
 288 tion to the north and  $\theta_{waves}$  is the wave propagation direction to the north. The inverse  
 289 wave age is calculated using the MFWAM data.

290 According to the inverse wave age values, we established three sea state categories:  
 291 the swell, the young and the mature wind sea. The swell category lists the ocean wave  
 292 spectra with  $\Omega$  lower than 0.84 (which corresponds to cases with wave age greater than  
 293 1.2). Ocean wave spectra with  $\Omega$  higher than 1 form the young wind sea category. And  
 294 cases with  $\Omega$  between 0.84 and 1 are considered as mature wind sea. Over 67981 co-location  
 295 points, 63300 are swell conditions, 1809 are young wind sea situations and 2872 are ma-  
 296 ture wind seas. Note however that when a sample belongs to one of this class, this does  
 297 not mean that sea-state is pure swell or pure developed wind sea. Using the swell and  
 298 wind sea partitioning of the MFWAM model spectra we have estimated the statistics of  
 299 dominant swell, dominant wind sea and of mixed conditions, based on the ratio of swell  
 300 or wind-sea energy to the total energy. If we consider that a ratio of 0.70 indicates the  
 301 predominance of one particular system, we find that swell predominates in 50% of the  
 302 cases, wind sea predominates in 5% of the cases, and mixed sea conditions are found as  
 303 the complementary, i.e. in 45% of the cases.

## 304 2.5 Spectral shape parameters

305 As mentioned in the introduction, we propose to study integrated spectral param-  
 306 eters that are less reported in the literature than the first order parameters, but very im-  
 307 portant to assess model performances (Rogers & Van Vledder, 2013; Gagnaire-Renou,  
 308 2009). These parameters characterize the energy distribution in frequency ( $\sigma_f$ ) and di-

309 rection ( $\sigma_\phi$ ), the "peakedness" of the omni-directional spectrum ( $Qp$ ) and the Benjamin  
310 Feir Index (BFI).

311 In the literature, there are several definitions to characterize the distribution in fre-  
312 quency as reported by Saulnier et al. (2011). In this study, the spectrum bandwidth is cal-  
313 culated by the frequency spread, noted  $\sigma_f$  and defined by the Blackman and Tukey (1959)  
314 formulation:

$$315 \quad \sigma_f = \frac{\left[ \sum_{f_{\min}}^{f_{\max}} F(f) df \right]^2}{\sum_{f_{\min}}^{f_{\max}} F^2(f) df} \quad (3)$$

316 where  $F(f)$  is the omnidirectional wave height spectrum.  $f_{\min}$  and  $f_{\max}$  define the fre-  
317 quency domain for the frequency spread calculation:  $f_{\min} = 0.056$  Hz and  $f_{\max} = 0.28$   
318 Hz. As  $\sigma_f$  measures the spectrum bandwidth in frequency, large values of  $\sigma_f$  indicate broad  
319 spectra.

320 In order to characterize the spectral peakedness, we also estimate the Goda param-  
321 eter as introduced by Goda (1976) and noted  $Qp$ . Its formulation is:

$$322 \quad Qp = \frac{2 \sum_{f_{\min}}^{f_{\max}} f F^2(f) df}{\left[ \sum_{f_{\min}}^{f_{\max}} F(f) df \right]^2} \quad (4)$$

323 This parameter is an indicator of how sharp is a spectrum. Large values of  $Qp$  indicate  
324 sharp spectra around the dominant energy peak. For this study, the frequency spread  
325 and  $Qp$  parameter are calculated over the same frequency domain  $[f_{\min}, f_{\max}]$  for SWIM  
326 and MFWAM. Note that  $Qp$  and  $\sigma_f$  vary in the opposite way: large values of  $\sigma_f$  which  
327 indicate broad spectra correspond to low values of  $Qp$ , and the other way around for nar-  
328 row spectra. Although initially defined for narrow-band single mode spectra (as several  
329 other width definitions based on spectral moments), it was shown by Rao (1988) that  
330 the Goda "peakedness" parameter can be considered as an appropriate parameter to char-  
331 acterize the spectral width because, due to its dependence on the square of the frequency  
332 spectrum, it is mostly sensitive on the spectral shape near the dominant peak. To fur-  
333 ther asses this statement, we have carried out additional tests on synthetic spectra, by  
334 simulating bimodal spectra with two gaussian shapes of same variance separated in fre-  
335 quency. The main result is that when increasing from 0.5 to 1 the energy ratio of the  
336 second to first peak, it changes  $\sigma_f$  by more than 25% whereas it only marginally affects  
337  $Qp$  (change of 5%). Actually, in case of bimodal spectra,  $Qp$  takes a value close to that  
338 of the most energetic peak (and not much affected if both peaks are of similar amplitude),  
339 whereas  $\sigma_f$  increases rapidly as the second peak is increased and reaches an asymptotic  
340 value.

341 The directional spread  $\sigma_\phi$  and the mean direction  $\phi_{\text{mean}}$  are calculated using the  
342 first pair of the Fourier coefficients  $a_1(f)$  and  $b_1(f)$ :

$$343 \quad \sigma_\phi(f) = \sqrt{2 \times \left( 1 - \sqrt{a_1(f)^2 + b_1(f)^2} \right)} \quad (5)$$

$$344 \quad \phi_{\text{mean}}(f) = \arctan \left( \frac{b_1(f)}{a_1(f)} \right) \quad (6)$$

345 The expressions for  $a_1(f)$  and  $b_1(f)$  are those proposed by Longuet-Higgins et al. (1963)  
346 and recalled by Kuik et al. (1988) or Pettersson et al. (2003) among others. For SWIM  
347 and MFWAM we have calculated  $a_1(f)$  and  $b_1(f)$  from the directional spectra, whereas  
348 for the buoy data we have directly used the Fourier coefficients provided in the NDBC  
349 buoy files. The directional spread at the dominant wavelength of the spectrum is ana-  
350 lyzed in Section (3.2) whereas in Section (4.3) we present results on the directional spread  
351 as a function of the normalized frequency  $f/f_p$ , where  $f_p$  is the frequency at the energy

352 peak of the spectrum. Note that if one considers that the directional distribution can  
 353 be represented by a shape in  $\cos^{2s}$  as proposed by e.g Mitsuyasu et al. (1975) then  $s$  and  
 354  $\sigma_\phi$  are related by:

$$355 \quad \sigma_\phi = \sqrt{\frac{2}{s+1}} \quad (7)$$

356 The last parameter investigated in this study is the directional version of the Ben-  
 357 jamin Feir Index (BFI) introduced by Mori et al. (2011). BFI has been proposed in the  
 358 literature as an appropriate indicator of non-linearities of wave interactions and prob-  
 359 ability of occurrence of extreme waves in the case of unidirectional seas (Janssen & Bid-  
 360 lot, 2009):

$$361 \quad BFI = k_0 \sqrt{m_0} Qp \sqrt{2\pi} \quad (8)$$

362 With  $k_0$  the mean wavenumber and  $m_0$  the 0th order moment of the energy of the den-  
 363 sity spectrum. BFI is proportional to  $Qp$  and to the significant wave slope :  $k_0 \sqrt{m_0}$ . Its  
 364 values span between 0 and 1, and the highest it is, the highest is the kurtosis of the prob-  
 365 ability density function (pdf), i.e the highest is the probability of occurrence of extreme  
 366 waves. This parameter does not include the directional effects whereas it was shown by  
 367 Mori et al. (2011) that the directional spread impacts the excess of kurtosis of the pdf  
 368 wave heights. For a given value of BFI, an increase of the directional spread reduces the  
 369 excess of kurtosis. Therefore, Mori et al. (2011) introduced an extension of BFI, named  
 370  $BFI_{2D}$ , in order to include the directional effects. Its formulation is:

$$371 \quad BFI_{2D} = \frac{BFI}{\sqrt{1 + \alpha_2 R}} \quad (9)$$

372 Where the constant  $\alpha_2$  is equal to 7.10 (fitted from numerical simulations by (Mori et  
 373 al., 2011)) and  $R$  measures the importance of directional width compared to the frequency  
 374 width:

$$375 \quad R = \frac{1}{2} \sigma_\phi^2 \pi Qp^2 \quad (10)$$

### 376 **3 Results on the shape parameters at the global scale**

377 In this Section we discuss the shape spectrum parameters and the Benjamin-Feir  
 378 Index at the global scale. Because the wave conditions corresponding to the co-located  
 379 SWIM/buoy data set are rather limited (small significant wave heights and short wave-  
 380 lengths), the comparison of SWIM to buoy parameters is mainly used in the following  
 381 to explain some of the differences between SWIM and MFWAM in these conditions.

#### 382 **3.1 Frequency shape parameters**

383 Figure (3a) shows the geographic distribution of the SWIM frequency spread calcu-  
 384 lated with Equation 3. When comparing to sea state conditions illustrated in Figure  
 385 1, one can see that the smallest values of  $\sigma_f$  (typically less than 0,10 Hz) are encoun-  
 386 tered mainly in regions of high winds and high significant wave heights such as in South-  
 387 ern Ocean or along the coasts of Alaska or Greenland. This is rather counter intuitive  
 388 because these regions are characterized by wave actively forced by the wind and we may  
 389 expect broader spectra in these conditions than in those dominated by swell. But ac-  
 390 tually, these regions where the smallest values of  $\sigma_f$  are encountered, correspond to wind-  
 391 waves close to the fully developed stage. Hence, the frequency spread is relatively small  
 392 compared to young seas, and these latter are relatively rare at the global scale (see Fig-  
 393 ure 2).

394 Large values of  $\sigma_f$  (typically between 0.17 and 0.18 Hz) are found either along the  
 395 Equatorial band, and in some areas of the central and eastern parts of the North Pacific  
 396 as well as in enclosed oceanic basins (e.g. Gulf of Mexico, Mediterranean Sea, South China  
 397 Sea). In most of these regions, the significant wave height is low (less than 1.8 m, see



Figure (3a)). Especially for situations in enclosed oceanic basins, these large values of  $\sigma_f$  are due to the presence of spurious energy peaks at the lowest frequency in the SWIM wave height spectra (Tourain et al., 2020). These spurious peaks appear at the lowest frequency in the spectra, due to the amplification of the remaining noise floor at low frequency (i.e. low wavenumber  $k$ ), even if the noise floor is close to zero in the wave slope spectra. To convert wave slope to wave height spectra we apply a division by  $k^2$  which dramatically amplifies small remaining noise when it is present at low frequencies.

The results obtained for  $\sigma_f$  with the MFWAM model are illustrated in Figure 3b as a geographical map. As for the SWIM results,  $\sigma_f$  values are the smallest in the regions of fully developed wind-waves (Southern Ocean, Greenland and Alaska coastal regions), whereas large values of  $\sigma_f$  are found along the Equatorial band, in the central and eastern part of the North Pacific. In these regions, MFWAM gives larger values of  $\sigma_f$  than SWIM. These relatively large values are partly due to the presence of mixed sea conditions. Indeed, the study of the ratio of swell and wind sea energy to the total energy indicates the presence of mixed sea conditions in these regions which impact the  $\sigma_f$  value. In opposite, regions of enclosed oceanic basins (e.g. Mediterranean Sea, Gulf of Mexico), are characterized by intermediate values of  $\sigma_f$  for MFWAM, smaller than in the case of SWIM. As mentioned above, the presence of a spurious energy peak impacts the  $\sigma_f$  value in these low sea state conditions.

Table 1 presents the mean and median values of SWIM  $\sigma_f$  by category of sea-state conditions (swell, young wind sea or mature wind sea, see Section 2.4). Overall, the swell conditions correspond to the smallest  $\sigma_f$  whereas, young wind sea correspond to the broader spectra, but note that in each category, mixed sea cases may also exist. The statistics for MFWAM results are also presented in Table 1. They indicate that for both mature wind sea and swell conditions, MFWAM spectra are broader than the SWIM spectra in average. In opposite in the young wind sea cases, MFWAM spectra are narrower than the SWIM spectra probably because of the spurious peaks on SWIM spectra as mentioned previously. This is confirmed by a complementary analysis carried out by comparing SWIM data to buoy data (see below discussion on Figure 4).

The statistics on the differences between SWIM and MFWAM  $\sigma_f$  values are illustrated in Figure 4a with the histogram of  $\sigma_f$  differences (SWIM-MFWAM) as a function of the significant wave height. Figure 4 shows the statistics of differences between SWIM and buoy data. In the mean, the difference between SWIM and MFWAM is small but systematically negative, with a mean value of -0.010 Hz, and a root mean square difference (RMSD) of 0.023 Hz. For values of  $H_s$  greater than about 2 m, the mean difference is clearly negative (SWIM values smaller than MFWAM values). For the smallest  $H_s$  values (less than about 2 m), although the largest occurrence is for negative differences, the number of points with positive differences is also significant. At these small  $H_s$ , positive differences are also found with respect to the buoy values (Figure 4b). Therefore, it is likely that the positive differences between SWIM and MFWAM at low  $H_s$  indicate non reliable values from SWIM, probably due to the spurious peaks in the SWIM spectra in these conditions. In opposite, for the negative differences, SWIM  $\sigma_f$  smaller than MFWAM values, there is no evidence that SWIM results should be questioned. The same trend is also found when we analyze the histogram of differences as a function of the dominant wavelengths (not shown): there is a clear negative mean difference between SWIM and MFWAM  $\sigma_f$  values for all peak wavelengths above 100 m. The histograms of differences have also been analyzed for mixed sea conditions only (not shown) and the negative mean difference is also observed. Hence, for all conditions except for the cases of small  $H_s$  and/or short dominant wavelengths, we can conclude that there is a systematic positive bias of MFWAM  $\sigma_f$  with respect to  $\sigma_f$  from SWIM, i.e. the model spectra are systematically broader than the SWIM spectra. This conclusion is further assessed in Section 4 with the analysis of the Southern Ocean data set.

Figure 5a shows the Goda peakedness factor  $Qp$  from SWIM. It shows that maximum values (around 2.4) are encountered in the high sea-state regions (the same as those with low  $\sigma_f$  values). In opposite, in the areas of low significant wave height (enclosed ocean basins and some areas in the open ocean),  $Qp$  shows the lowest values (around 1.0). These are the regions where we mentioned here above that SWIM spectra may be polluted by spurious peaks at low frequency. So, results from SWIM must be considered with caution in these regions. In almost all other regions,  $Qp$  takes intermediate values. The comparison with the results from MFWAM (Figure 5b) shows that  $Qp$  values from SWIM are larger than those from MFWAM in average. In the areas of strong winds and high significant wave heights, such as in the Southern Ocean or along the Greenland or Alaska coasts, this overestimation by SWIM is particularly obvious.

Table 2 shows the statistical results by category of sea-state conditions (young wind sea, mature wind sea and swell), for both SWIM and MFWAM results. For young and mature wind sea cases, MFWAM values are larger than SWIM ones, whereas the opposite is true for swell conditions. For MFWAM, the mean and median values of  $Qp$  values decrease from young wind sea to mature wind-sea and from mature wind-sea to swell. For SWIM, the young wind-sea  $Qp$  is in-between values for swell and mature wind sea. It is likely that this is due to the limitations of SWIM already mentioned for the young wind-sea cases which predominantly correspond to low significant wave height and short wavelength conditions. For SWIM, similarly to MFWAM, swell cases show the smallest peakedness parameter among all the cases. Again, it must be noted that this analysis does not distinguish mixed sea cases, but as explained in Section 2.5,  $Qp$  is expected to be less sensitive to bimodal spectra than  $\sigma_f$ .

Figure 6a shows the histogram of SWIM-MFWAM differences for  $Qp$  as a function of the significant wave height. For  $H_s$  lower than about 1.8 m, we observe a large scatter, and a systematic negative difference between SWIM and MFWAM values (bias of -0.20). As mentioned above, these points correspond to situations of low sea-state in enclosed seas where the SWIM data are probably affected by spurious energy peaks which appear at low frequency (long wavelength). The same type of difference is also found from the comparison of SWIM with the NDBC buoy data set (Figure 6b). This seems to indicate that SWIM spectral shape must be analyzed with caution in these situations. On the other hand, for wave heights larger than about 1.8 m, there is a systematic positive bias of 0.14 (0.29) for SWIM with respect to MFWAM. As evidenced with the results presented in Table 2, these larger values of  $Qp$  for SWIM with respect to MFWAM are associated to swell cases and mature wind sea in areas strongly forced by the wind (e.g. Southern Ocean).

### 3.2 Directional spread

Figure 7a shows the geographical distribution of the SWIM directional spread  $\sigma_\phi$  estimated at the frequency peak of each spectrum. According to this map the directional spread at the peak of the spectrum is minimum ( $15^\circ$ - $25^\circ$ ) in the regions of high sea states like in the Southern Ocean, along the coasts of Alaska, Greenland and North America. Elsewhere, the directional spread takes values from about  $25^\circ$  to  $60^\circ$  without any clear relation with the  $H_s$  map (Figure 1a) nor with the map of dominant wavelengths (not shown).

$\sigma_\phi$  estimated from MFWAM is shown in Figure 7b. As for SWIM, in regions of active generation,  $\sigma_\phi$  also indicates relatively narrow spectra. This is again counter intuitive but is confirmed by the mean and median values estimated when sorting the data set by sea-state categories (Table 3). At the global scale the narrower spectra are observed for the mature wind sea conditions for both SWM and MFWAM whereas young wind sea conditions correspond to the broader spectra.



500 Moreover, MFWAM data shows narrow spectra not only in the active generation  
 501 regions but also in other areas like west of Chile, west of Africa and in the Gulf of Ben-  
 502 gal whereas, SWIM values are large. After analyzing the maps of SWIM and MFWAM  
 503 dominant wavelengths (not shown), we could identify that these differences correspond  
 504 to locations where SWIM dominant wavelengths are significantly smaller than those from  
 505 MFWAM. Comparing the ratio of the swell and the wind sea energy to the total energy  
 506 of the spectrum, we find that mixed sea conditions are mostly present in these areas, ac-  
 507 cording to the MFWAM data. The presence of mixed sea in these regions can explain  
 508 the different identification of the dominant wave system between SWIM and MFWAM  
 509 and induce differences in the directional spread. Indeed, smaller dominant wavelengths  
 510 and broader directional distributions at the peak of the spectrum are observed for SWIM  
 511 compared to MFWAM. Significant differences are also observed in enclosed seas and near  
 512 the coasts. In these areas it seems to be a limitation of SWIM because of the presence  
 513 of a spurious peak as mentioned above. The comparison of Figures 7a and 7b also shows  
 514 some large negative differences in the directional spread between SWIM and MFWAM  
 515 in the Mid-Pacific Ocean. According to MFWAM one can find mixed sea conditions in  
 516 this region but these cases are not associated to any significative differences in dominant  
 517 wavelengths between the two sets of data.

518 Figures 8a-b highlight the problem of mis-association between SWIM and MFWAM.  
 519 Indeed, the MFWAM histogram indicates a larger density of points for cases with dom-  
 520 inant wavelength around 250-300 m than SWIM. However, the mean directional spreads  
 521 at these long wavelengths are of the same order of magnitude for SWIM and MFWAM  
 522 ( $25^\circ$ ). At shorter wavelengths (lower than 200 m), the average value of the SWIM  $\sigma_\phi$   
 523 ( $45^\circ$ ) is higher compared to MFWAM ( $30^\circ$ ). Which means that in average, situations  
 524 with relatively short dominant wavelengths (like young wind sea conditions) are more  
 525 spread in direction than MFWAM.

526 Figure 9a shows the histogram of the differences between SWIM and MFWAM for  
 527 the directional spread, as a function of the SWIM significant wave height. In spite of the  
 528 visual aspect of Figure 9, the SWIM to MFWAM differences are almost similar for small  
 529 and large significant wave heights (less or greater than 1.8m): bias of about  $4^\circ$  and RMSD  
 530 of  $15^\circ$  to  $18^\circ$ . At small  $H_s$ , the upward part of the scatter plot (positive bias) is partly  
 531 due to the mis-association of the dominant wavelengths of SWIM and MFWAM spec-  
 532 tra as mentioned above and partly due to the limitations of SWIM partition at small  $H_s$   
 533 as evidenced in Figure 9b obtained from the SWIM to buoy comparison. Even if the num-  
 534 ber of co-located points is less in Figure 9b than in Figure 9a, one can see that there  
 535 is also a positive bias of SWIM with respect to buoy data (mean of about  $3^\circ$ ), with how-  
 536 ever an important scatter (RMSD of about  $21^\circ$ ). Even if small, this positive bias for SWIM  
 537 directional spread compared to both MFWAM and buoy data, and the relatively large  
 538 value of RMSD indicate that one must remain cautious on the SWIM results in these  
 539 regions of enclosed seas and coastal zones.

540 Table 3 shows that for all categories, MFWAM values are slightly smaller than those  
 541 from SWIM, meaning a larger directional spread from SWIM than from MFWAM in the  
 542 mean. The maximum difference ( $\sim 8^\circ$ ) is for the young wind sea. As mentioned above,  
 543 it is clear that at the global scale, the mature wind sea conditions correspond to the nar-  
 544 rower spectra for SWIM and MFWAM. This is not really expected from the literature  
 545 (the swell systems are always mentioned as corresponding to the narrowest angular spread  
 546 conditions), but we will see in Section 4.3 that when we limit our analysis to the South-  
 547 ern Ocean area, the results are slightly different.

### 548 3.3 Benjamin Feir Index

549 As mentioned in Section 2.5, the  $BFI_{2D}$  is an appropriate indicator of non-linearities  
 550 of wave interactions and probability of occurrence of extreme waves. Figure (10a) shows

551 the spatial distribution of  $BFI_{2D}$  calculated with the SWIM data. As could be expected,  
 552 the Southern Ocean, the region along the Greenland coasts and the Gulf of Alaska are  
 553 the areas where  $BFI_{2D}$  values are the highest. This is also the case for BFI (not shown  
 554 here).

555 The comparison of  $BFI_{2D}$  calculated with SWIM and MFWAM data shows a very  
 556 good agreement (Figure 10b) with a mean bias equal to  $-7 \cdot 10^{-3}$  and a RMSD equal to  
 557  $2.1 \cdot 10^{-2}$ . In opposite to the BFI comparison (not shown here), there is no overestima-  
 558 tion of the SWIM  $BFI_{2D}$  compared to the MFWAM  $BFI_{2D}$ . This can be explained by  
 559 the fact that  $BFI_{2D}$  is expressed as a function of BFI and of the R coefficient (Equations  
 560 9 to 10), both dependent on the  $Qp$  parameter. Comparison of the R coefficient between  
 561 SWIM and MFWAM indicates an overestimation of SWIM (not shown here). This is due  
 562 to larger values of  $Qp$  and, to a lesser extent, to the largest values of  $\sigma_\phi$ . Hence, it turns  
 563 out that for  $BFI_{2D}$  from SWIM compared to MFWAM, the overestimation of BFI which  
 564 appears at the numerator is compensated by the overestimation of R which is at the de-  
 565 nominator. Although the mean difference between SWIM and MFWAM for  $BFI_{2D}$  is  
 566 very small, it does not result from a good agreement between SWIM and MFWAM but  
 567 from a compensation effect between BFI and the R coefficients. We will see below that  
 568 the same result is found for the case of the Southern Ocean where  $\sigma_\phi$  values are simi-  
 569 lar for SWIM and MFWAM. This means that this compensating effects is mainly sup-  
 570 ported by  $Qp$ .

## 571 4 Focus on the Southern Ocean

### 572 4.1 Comparisons of SWIM and MFWAM shape parameters

573 The Southern Ocean is the only ocean connected to the three main oceans in the  
 574 world: Pacific, Atlantic and Indian and it plays a non-negligible role on the Earth's cli-  
 575 mate. This region is dominated by strong westerly winds, with almost unlimited fetches  
 576 (Young et al., 2020). In winter, the wind speed reaches high values of the order of 20 m/s  
 577 or locally more (Young et al., 2020). These intense winds and unlimited fetch conditions  
 578 generate extreme sea states. This is one of the reason why we focus here our analysis on  
 579 SWIM and MFWAM data in the Southern Ocean (latitudes between  $-40^\circ$  and  $-70^\circ$ ). The  
 580 other reason is that in this region, the limitations of SWIM are the smallest because in  
 581 these high significant wave height situations, the SWIM measurements are of the high-  
 582 est quality (negligible effect of a potential spurious peak, minimum impact of the speckle  
 583 noise). Moreover for this data set, there is a good agreement between SWIM and MFWAM  
 584 for the dominant wavelengths (mean values of 219 m for SWIM and 236 m for MFWAM),  
 585 with limited number of cases where there is a mis-association of the dominant wave sys-  
 586 tems between SWIM and MFWAM. For the period of investigation, the mean signifi-  
 587 cant wave height in the considered area is 4.3 m which is twice the mean  $Hs$  at the global  
 588 scale.  $Hs$  values range between 1 m and 11 m.

589 Figure (11) shows the comparisons of the frequency and directional spread,  $Qp$  and  
 590  $BFI_{2D}$  between SWIM and MFWAM. The frequency spread (Figure 11a) is clearly larger  
 591 for MFWAM than for SWIM data, with a mean difference of 0.015 Hz, larger than at  
 592 the global scale (0.010 Hz). Moreover, in contrary to the comparison at the global scale,  
 593 in the Southern Ocean the scatter remains limited because most of the situations encoun-  
 594 tered in this area have high significant wave heights. Correlatively, the comparison of  $Qp$   
 595 in Figure (11b) shows that SWIM values are larger than those from MFWAM, with a  
 596 bias between SWIM and MFWAM of 0.26. It indicates that SWIM spectra are more peaked  
 597 than the MFWAM spectra. So, SWIM and MFWAM wave spectra significantly differ  
 598 in their omni-directional shape with broader and less peaked spectra for MFWAM as com-  
 599 pared to SWIM.

600 An overestimation of the frequency spread of model spectra with respect to obser-  
 601 vations has already been mentioned in several studies. From comparison between MFWAM  
 602 results with buoy and KuROS airborne radar data (KuROS is a concept similar to SWIM),  
 603 Le Merle et al. (2019) concluded on the same kind of overestimation of the model fre-  
 604 quency spread compared to buoy and radar observations in fetch limited conditions in  
 605 the Mediterranean sea. Several authors have also discussed in the past, that the frequency  
 606 width of the modelled wave spectrum is highly sensitive to the way the non-linear in-  
 607 teractions are taken into account (Rogers & Van Vledder, 2013; Gagnaire-Renou, 2009;  
 608 S. Hasselmann & Hasselmann, 1985a, 1985b). Here, we find that spectra from the MFWAM  
 609 model are systematically broader than the SWIM spectra. As MFWAM uses the Dis-  
 610 crete Interaction Approximation -DIA- to represent the non-linear interactions, it is pos-  
 611 sible that this is due to this approximation. Such bias in frequency spread was also ev-  
 612 idenced in S. Hasselmann and Hasselmann (1985b) on few test cases. More recently, Annenkov  
 613 et al. (2021) shows with academic tests, that in fully developed conditions they obtain  
 614 closer values of  $Qp$  with observations using the Zakharov-Kolmorov approach instead of  
 615 the classical representation of non linear interactions by the DIA.

616 The comparison on the directional spread calculated at the peak frequency (Fig-  
 617 ure 11c) shows that for this parameter, there is a good agreement between SWIM and  
 618 MFWAM with a mean bias of  $0.4^\circ$  and a RMSD of  $12^\circ$  which is less than at the global  
 619 scale. So, although the wave evolution modeled by MFWAM seems to produce wave spec-  
 620 tra which are too broad in frequency compared with the observations, this does not seem  
 621 to affect the directional spread in the conditions encountered in the Southern Ocean. This  
 622 is due to the fact that, even if mixed sea conditions are present, wind sea and swell sys-  
 623 tems propagate in the same directions in average. This has been checked when analyz-  
 624 ing the directional wave spectra in this region.

625 The  $BFI_{2D}$  comparison (Figure 11d) indicates a good correspondance between SWIM  
 626 and MFWAM (mean difference of 0.0031). As mentioned in Section 3.3, the rather small  
 627 difference between SWIM and MFWAM  $BFI_{2D}$  is in fact due to a compensating effect  
 628 of larger values of BFI and R (Equation 10) parameters from SWIM compared to MFWAM.  
 629 Moreover, in the case of the Southern Ocean data set, the larger values of R for SWIM  
 630 compared to MFWAM are mainly due to the  $Qp$  factor and not to the directional spread.

## 631 632 633 **4.2 Frequency spread according to sea state categories**

634 In this section, the distributions of the frequency spread and the  $Qp$  parameter are  
 635 estimated and compared for each sea state category. Similarly to the analysis at the global  
 636 scale, sorting the data according to the 3 classes of inverse wave age does not exclude  
 637 that there are mixed sea situations in certain areas or periods. For the Southern Ocean,  
 638 we have verified that over our data set (16667 samples) swell remains dominant (i.e. con-  
 639 tributes to more than 70% of the total energy in the spectrum) in 50% of the cases, whereas  
 640 wind waves are dominant (i.e. their energy contributes to more than 70% of the total  
 641 energy in the spectrum) in 8% of the cases. The remaining (42%) may be mixed seas,  
 642 according to MFWAM. By analyzing the directional wave spectra in this region, we could  
 643 check that these situations of mixed seas correspond to wind sea and swell propagating  
 644 in the same directions. Figure (12) shows the histograms of the frequency spread for SWIM  
 645 and for MFWAM data. The frequency spread is calculated for each individual omni-directional  
 646 spectrum over the dimensional frequency vector. The mean and median values of the fre-  
 647 quency spread distributions are reported in Table 1. In the case of SWIM, the mean and  
 648 median frequency spread are the smallest for swell conditions (mean and median values  
 649 of 0.097 and 0.093 Hz, respectively) and the largest in young wind sea conditions (mean

and median values of 0.110 Hz and 0.108 Hz, respectively), with intermediate values in mature wind sea conditions (mean and median values of 0.098 Hz and 0.092, respectively). The frequency spread from MFWAM is significantly broader than that from SWIM in all conditions. The largest differences are for the swell conditions (mean value of 0.109 Hz). This confirms the results discussed in Section 3 from the global data set, but extends the results to the young wind sea cases, which are here not affected by uncertainties at low significant wave heights of SWIM spectra.

Figure (13) shows the distributions of the Goda peakedness factor for SWIM (a) and for MFWAM (b) data. The mean and median values of the  $Qp$  parameter distributions are reported in Table 2. For SWIM, the smallest mean values are found for the swell category ( $Qp = 2.00$ ), the largest for the mature wind seas category ( $Qp = 2.11$ ) and intermediate values are found for young wind sea category ( $Qp = 2.07$ ). When considering the median instead of the mean values, the ranking is the same:  $Qp$  values are the smallest for swell, and the largest for the young wind sea, whereas intermediate values are found for young wind sea (Table 2). Hence, with the SWIM data, we find that the mature wind sea cases have sharper omni-directional spectra than both the swell and young wind sea cases. The conclusion is slightly different with the MFWAM distributions, which indicate that the largest values are found for the young wind sea, the smallest for swell and intermediate values for mature wind seas. In addition, the most significant difference is that swell spectra from MFWAM are much less sharp than SWIM spectra (mean value of  $Qp$  is 1.76 for MFWAM instead of 2.00 for SWIM). For young and mature wind sea cases, MFWAM mean values of  $Qp$  are also significantly smaller for MFWAM than for SWIM. As mentioned above, one explanation could be the use of the DIA to represent the wave-wave non linear interactions in the MFWAM model. Indeed, our results can be compared to those of Rogers and Van Vledder (2013) who showed by comparing simulated spectra to wave buoy spectra, that the DIA tends to produce underestimated values of  $Qp$  compared to those obtained from the buoy measurements. This underestimation does not exist any more when Rogers and Van Vledder (2013) use the exact formulation of the non-linear interactions in their model. Note however that in our case, the underestimation of  $Qp$  from model with respect to observations is evidenced for all conditions of young wind sea, mature wind sea and swell, although this difference is less obvious for the wind sea cases.

### 4.3 Directional spread of mean ocean wave spectra

In this section the directional spread is investigated as a function of the adimensional frequency ( $f/f_p$ ) for mean spectra estimated for both SWIM (Figure 14a) and MFWAM (Figure 14b). Mean spectra are calculated for each sea state category. In order to estimate these mean spectra, individual wave spectra are transformed before averaging to express them as a function of the adimensional frequency vector:  $f/f_p$ , where  $f_p$  stands for the peak frequency. Moreover, the individual directional spectra are rotated in direction in order to set the mean wave propagation direction along the north direction. These spectral transformations allow to force all the spectra used in the averaging procedure, to have their maximum matching each other in direction and adimensional frequency.

The results from the SWIM spectra (Figure 14a) show that the minimum of directional spread is found at  $f/f_p=1$ . This is in agreement with many other experimental results obtained in wind wave conditions as mentioned by Forristall and Ewans (1998) in his review and also described by Mitsuyasu et al. (1975); Ewans (1998); Babanin and Soloviev (1998); Hwang et al. (2000); Pettersson et al. (2003); Romero and Melville (2010). D. E. Hasselmann et al. (1980) and Donelan et al. (1985) found slightly different position of the minimum of the directional spread (1.05  $f_p$  in the former case, and 0.95 in the latter case). With our data set the resolution in frequency is not sufficient to conclude more precisely about this position. From the SWIM spectra we find that the min-

imum value of the directional spread is weakly dependent on sea-state conditions with broader distributions for young wind sea (around  $33^\circ$ ) and narrower distributions for mature wind sea ( $29^\circ$ ) and swell ( $27^\circ$ ) conditions. Mitsuyasu et al. (1975); Donelan et al. (1985) and Romero and Melville (2010) also found such a small sensitivity with wave age whereas almost all the other authors mentioned here-above could not evidence such a trend with wave age. Figure (14b) shows that for MFWAM, the direction spread slightly decreases with wave development (smaller for swell and mature wind sea than for young wind sea) however it has to be noted that for MFWAM, the position of the minimum of the directional spread varies significantly with the sea-state category: it occurs at  $f/f_p = 0.8$  to  $f/f_p = 0.9$  for swell cases but at  $f/f_p > 1$  for wind waves and intermediate values for mature wind waves. MFWAM differs on this point from SWIM and from other experimental results of the literature, but on the other hand MFWAM and SWIM minimum angular spread are very similar. This shows that MFWAM is able to reproduce the observed angular spread near the peak. This is consistent with the results of Rogers and Wang (2007) who showed that in spite of the numerical simplification of the representation of the non-linear interactions in the SWAN model, the directional spreading near the peak frequency is quite close to that of buoy estimates.

For both SWIM and MFWAM, there is a marked broadening of the angular distribution on each side of its minimum position. At frequencies higher than about  $1.2 f_p$ , SWIM spectra do not show any dependence with sea-state categories (swell or wind sea), in opposite to the case of the MFWAM mean spectra. On this point, SWIM spectra are in good agreement with the results from the literature (Mitsuyasu et al., 1975; D. E. Hasselmann et al., 1980; Ewans, 1998; Babanin & Soloviev, 1998), whereas MFWAM spectra are not. At frequencies smaller than  $f_p$ , both SWIM and MFWAM indicate a broadening towards the smallest frequencies and wider spectra for young wind sea than for mature wind sea and swell. The difference between the three categories is however more pronounced on MFWAM than on SWIM spectra. At these normalized frequencies less than 1, this dependence of angular spread with the wave development was also found by Mitsuyasu et al. (1975); D. E. Hasselmann et al. (1980); Babanin and Soloviev (1998), but not observed by Ewans (1998).

Finally, it is interesting to note that the trend of the angular spread variation with  $f/f_p$  is significantly different between the SWIM and the MFWAM spectra. Whereas for SWIM, the trend is steeper towards the low frequencies than towards the high frequencies, in agreement with most of the above-mentioned results from the literature, the results obtained from MFWAM spectra show a rather symmetric trend towards the high and low frequencies.

In summary, we find that for the SWIM data the behavior of the angular spread with the normalized frequency and with the wave development are in good agreement with the literature whereas the spectra from the MFWAM model show some differences on several points (position in frequency of the minimum, trend with the normalized frequency and trend with wave development at high frequencies). On the other hand, the minimum values of the directional spread close to the frequency peak of the spectrum are very similar for SWIM and MFWAM. Considering every spectra in each categories of wave development, both SWIM and MFWAM mean spectra are slightly broader than the typical values found for the literature. For swell conditions our results indicate a mean angular spread of  $32^\circ$  and  $33^\circ$  for respectively SWIM and MFWAM (Table 3), whereas typical values as reported by Mitsuyasu et al. (1975) correspond to  $18.7^\circ$  (using Equation 7 to convert the  $s$  exponent into  $\sigma_\phi$  values). Similarly, wind sea conditions for our data set correspond to mean directional spread between  $31^\circ$  and  $37^\circ$  (larger values for young wind sea conditions, and SWIM values larger than MFWAM - see Table 3) whereas values reported by Mitsuyasu et al. (1975) correspond to about  $23^\circ$ . However, because of the lack of independent co-located in-situ observations in the situations encountered



754 in the Southern Ocean, it is difficult to conclude whether this difference is due to the speci-  
755 ficity of the data set or to another reason.

## 756 5 Discussion and conclusion

757 We have presented above an analysis of shape parameters of ocean wave spectra  
758 obtained from the observations of the SWIM instrument on-board CFOSAT. To our knowl-  
759 edge it is the first time that global statistics and maps of spectral shape parameters and  
760 Benjamin-Feir Index are provided from satellite observations. For most of the open ocean  
761 conditions (significant wave heights larger than 1.8 m and wavelength larger than 70 m,  
762 which corresponds to 73% of the dataset), we can conclude that SWIM provides consis-  
763 tent values of these parameters with sensitivity of these parameters with the sea state  
764 condition, compatible with what we know from the literature.

765 The analysis with co-located observations of SWIM and buoys (8 months of co-located  
766 points for 43 NDBC buoys) allows to conclude that SWIM parameters are biased in con-  
767 ditions of low significant wave height ( $H_s < 1.8$  m) and short dominant wavelength ( $\lambda_p <$   
768 70 m). We attributed this to the frequent occurrence of a spurious peak at the very low-  
769 est frequencies of the SWIM spectra, which modifies the shape of the spectra and may  
770 dominate in these conditions.

771 For the other conditions, the comparison of the parameters derived from SWIM  
772 to those derived from the MFWAM model, using exactly the same frequency interval and  
773 the same expressions for both sources of information, indicates systematic positive dif-  
774 ferences for the peakedness parameter  $Qp$  (sharpest spectra for SWIM), and negative  
775 differences for the frequency spread (narrowest spectra from SWIM). These differences  
776 are more marked in extreme conditions like those encountered in the Southern Ocean.  
777 By analyzing the data sorted according to the sea-state development stage, we could con-  
778 clude that these differences are the most significant in swell and mature conditions.

779 Concerning the angular spread of the dominant waves, the main conclusion comes  
780 from the Southern Ocean data set because in this data set, there is less uncertainty on  
781 the determination of the dominant energy peak and on its association between SWIM  
782 and MFWAM data sets. For this subset of data, SWIM spectra show clearly that the  
783 narrowest spectra are obtained for swell components, and the broader for young sea com-  
784 ponents. Compared to MFWAM, the results are not very different. However, SWIM spec-  
785 tra are slightly broader in cases of young wind sea (about  $37^\circ$ ) compared to MFWAM  
786 (about  $33^\circ$ ). When converted into a  $2s$  exponent in the  $\cos^{2s}$  expression, these values  
787 lead to an exponent  $2s$  between 6 and 8 for the MFWAM values and between 8 and 10  
788 for the SWIM values. In both cases, this is larger than the classical values of 2 or 4 which  
789 are often found in the literature.

790 Using global data sets and a single version of the model it is difficult to formally  
791 conclude on the causes of the differences on frequency distribution, especially for the neg-  
792 ative bias at low and high  $H_s$ . The complementary comparison of SWIM and buoy data  
793 over 8 months of NDBC buoy observations do not help to conclude either, because the  
794 large majority of co-located data between SWIM and buoy corresponds to low sea-state  
795 and short wavelengths of the dominant waves. However, provided that we exclude these  
796 situations, we think that a possible reason may come from the model which uses, as all  
797 similar operational 3rd generation wave models, the Discrete Interaction Approximation  
798 -DIA- (S. Hasselmann & Hasselmann, 1985a) to represent the energy transfer by non-  
799 linear interactions between waves. According to K. Hasselmann (1962), Babanin and Soloviev  
800 (1998), Romero and Melville (2010), the non-linear interactions between quadruplets of  
801 ocean waves, with different wavenumbers and direction is a dominant mechanism which  
802 must be invoked to explain the transfer of energy between directions and between wavenum-  
803 bers. Although its representation by the DIA gives satisfactorily numerical results in terms

804 of total energy (or significant wave height), it was previously shown (e.g., Rogers and  
 805 Van Vledder (2013) with his study with the SWAN model) that the frequency width of  
 806 the omni-directional spectrum is broader and in less agreement with buoy observations,  
 807 when this approximation is used than when the exact solution (exact NL) is implemented.  
 808 However, for practical reasons, the exact solution cannot yet be implemented in oper-  
 809 ational global numerical models. Therefore, some authors are looking for alternative phys-  
 810 ical solutions to represent the wave-wave interactions (e.g., Annenkov & Shrira, 2001,  
 811 2006, 2018; Annenkov et al., 2021) which would overcome this practical impossibility while  
 812 providing wave spectra shapes in agreement with observations. Although promising, the  
 813 approach needs to be validated with observations. It is the aim of future studies to con-  
 814 tribute to this kind of study by analyzing SWIM data sets in specific situations.

815 Finally we have shown in this paper that SWIM observations can be used to pro-  
 816 vide an index to characterize the deviation from a Gaussian shape of the wave height  
 817 distribution, and hence the probability of occurrence of extreme waves. The BFI and  $BFI_{2D}$   
 818 indexes can both be estimated by SWIM and used either for prediction purposes or for  
 819 climatological surveys.

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**Tables**

Table 1: Mean and median values of frequency spread distributions for SWIM and MFWAM

	Global scale				Southern Ocean			
	SWIM		MFWAM		SWIM		MFWAM	
	Mean	Median	Mean	Median	Mean	Median	Mean	Median
Young Wind sea	0.137	0.143	0.133	0.129	0.110	0.108	0.119	0.111
Mature wind sea	0.126	0.129	0.128	0.127	0.098	0.092	0.104	0.098
Swell	0.122	0.126	0.133	0.131	0.097	0.093	0.109	0.105

Table 2: Mean and median values of  $Qp$  parameter distributions for SWIM and MFWAM

	Global scale				Southern Ocean			
	SWIM		MFWAM		SWIM		MFWAM	
	Mean	Median	Mean	Median	Mean	Median	Mean	Median
Young Wind sea	1.82	1.73	2.35	2.24	2.07	2.04	2.05	2.09
Mature wind sea	1.87	1.80	2.06	2.04	2.11	2.09	2.00	2.04
Swell	1.74	1.64	1.66	1.61	2.00	1.96	1.76	1.76

Table 3: Mean and median values of directional spread distributions for SWIM and MFWAM

	Global scale				Southern Ocean			
	SWIM		MFWAM		SWIM		MFWAM	
	Mean	Median	Mean	Median	Mean	Median	Mean	Median
Young Wind sea	40.0	39.8	31.8	31.0	36.6	35.4	33.4	31.8
Mature wind sea	36.5	35.0	31.1	30.2	32.5	31.2	30.6	29.2
Swell	39.0	38.7	34.7	31.5	32.2	30.0	33.3	30.4

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**Figures**

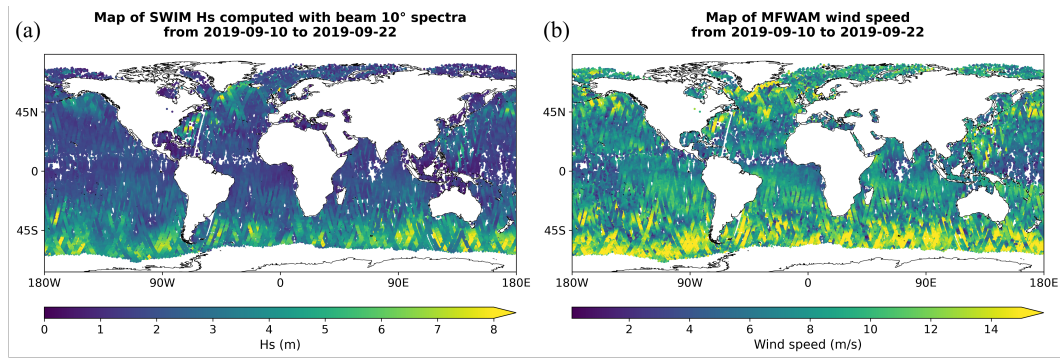


Figure 1: Maps of (a) the significant wave height from SWIM, and (b) the wind speed from the MFWAM model during the period 10-22 September, 2019.

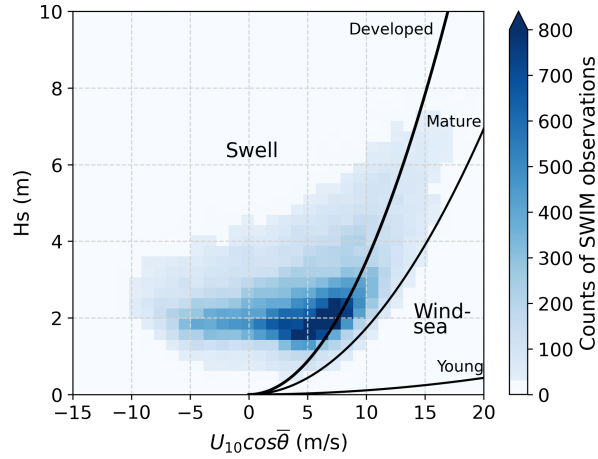


Figure 2: Two-dimensional histogram of the significant wave height  $H_s$  as a function of the wind speed projected along the wave direction from MFWAM. Solid lines describe the variation of  $H_s$  with wind speed at different wave evolution stages according to the Elfouhaily et al. (1997) spectrum. "Young" corresponds to inverse wave age  $\Omega = 2$ , "Mature" corresponds to  $\Omega = 1$ , "Developed" corresponds to  $\Omega = 0.84$ .

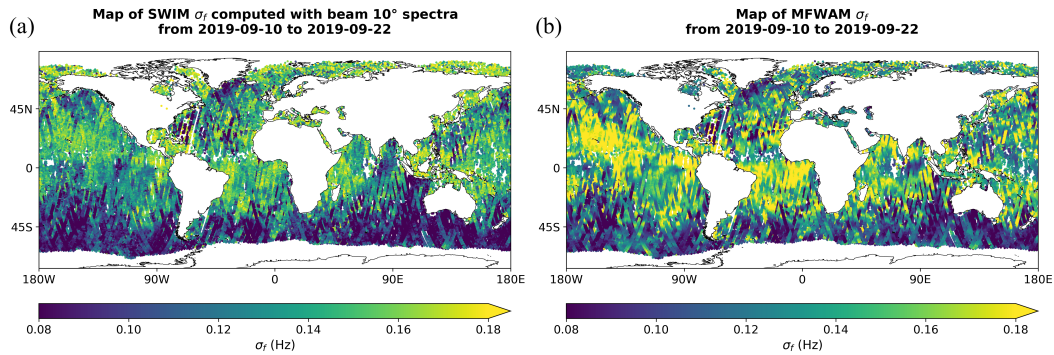


Figure 3: Maps of the frequency spread  $\sigma_f$  calculated with (a) SWIM data and (b) MFWAM data during the period 10-22 September, 2019.

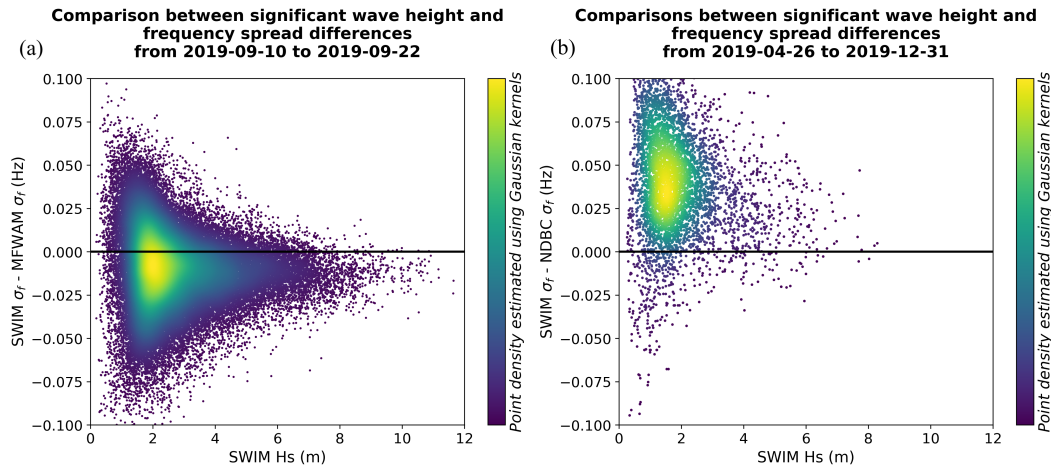


Figure 4: Histogram of the differences of the frequency spread between (a) SWIM and MFWAM and (b) SWIM and NDBC buoys as a function of significant wave height from SWIM.

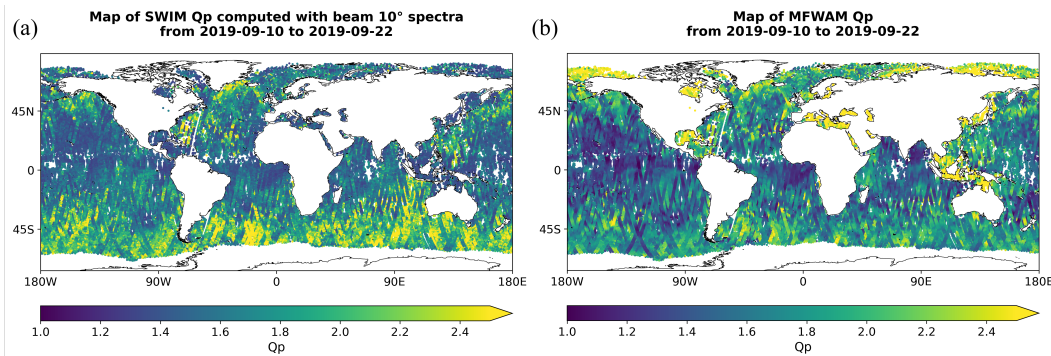


Figure 5: Maps of the Goda peakedness factor  $Q_p$  calculated with (a) SWIM data and (b) MFWAM data during the period 10-22 September, 2019.

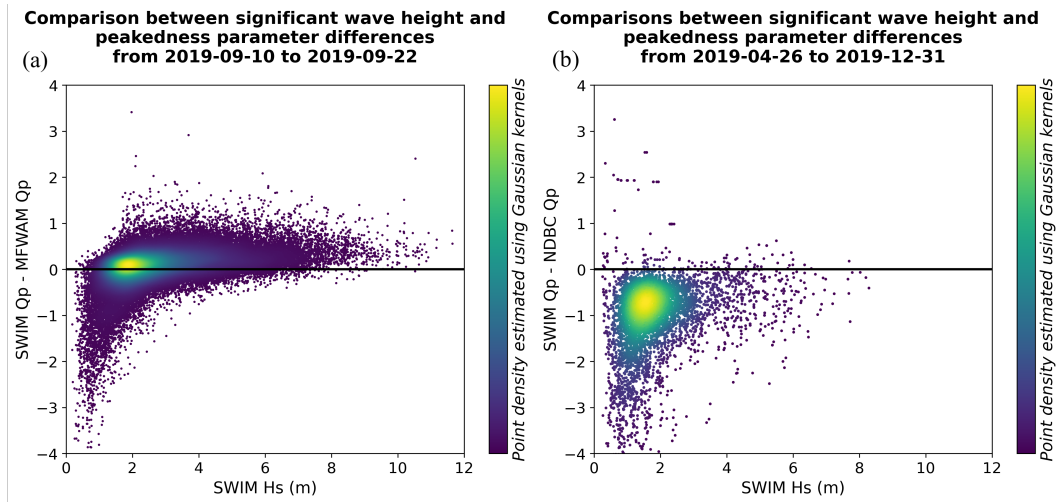


Figure 6: Histogram of the differences of the Goda peakedness factor  $Q_p$  between (a) SWIM and MFWAM and (b) SWIM and NDBC buoys as a function of significant wave height from SWIM.

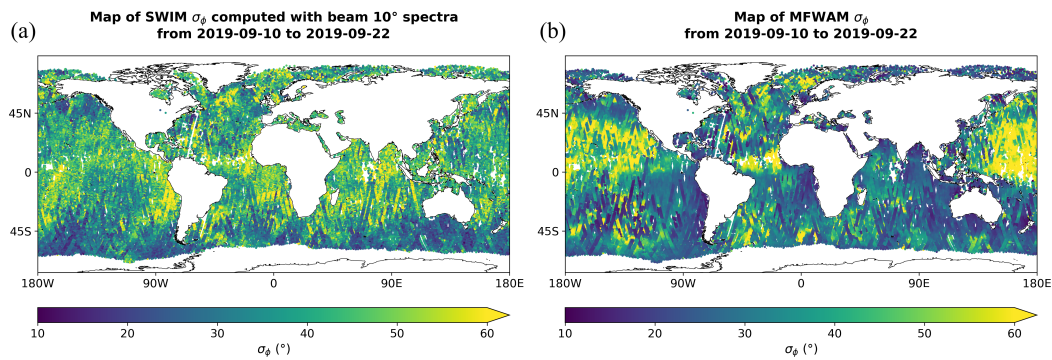


Figure 7: Maps of the directional spread  $\sigma_\phi$  calculated with (a) SWIM data and (b) MFWAM data during the period 10-22 September, 2019.



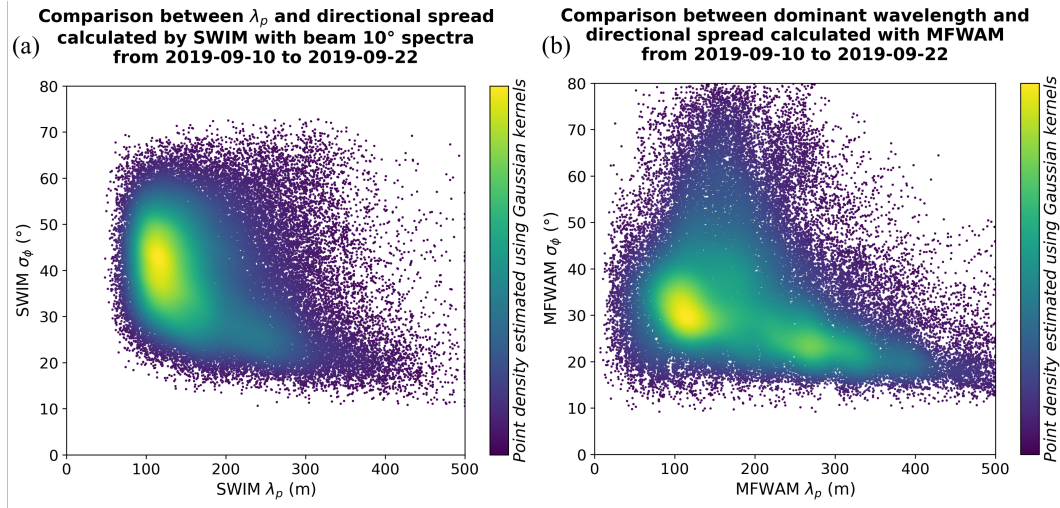


Figure 8: Histograms of the directional spread at the peak of the wave spectrum  $\sigma_\phi$  as a function of the dominant wave length. (a) for SWIM, (b) for MFWAM.

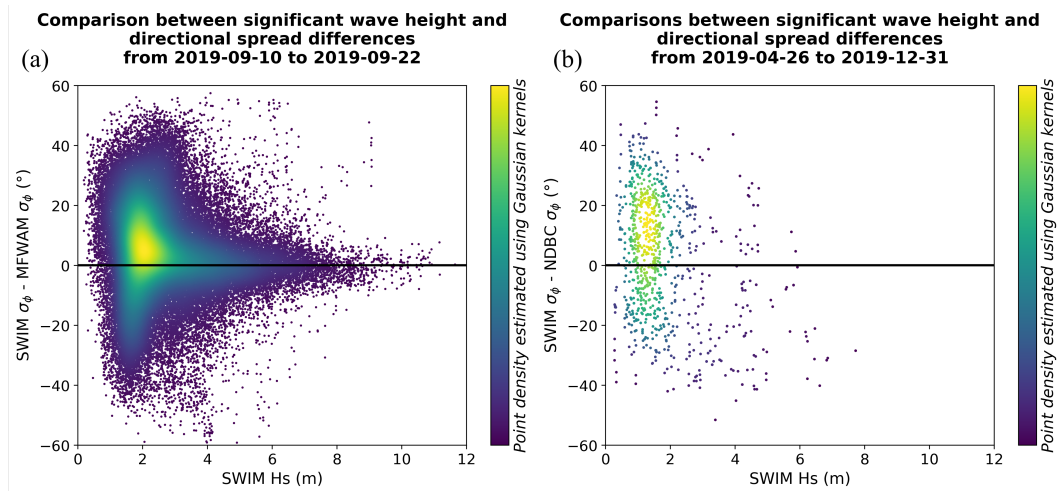


Figure 9: Histogram of the differences of the directional spread  $\sigma_\phi$  between (a) SWIM and MFWAM and (b) SWIM and NDBC buoys as a function of significant wave height from SWIM.



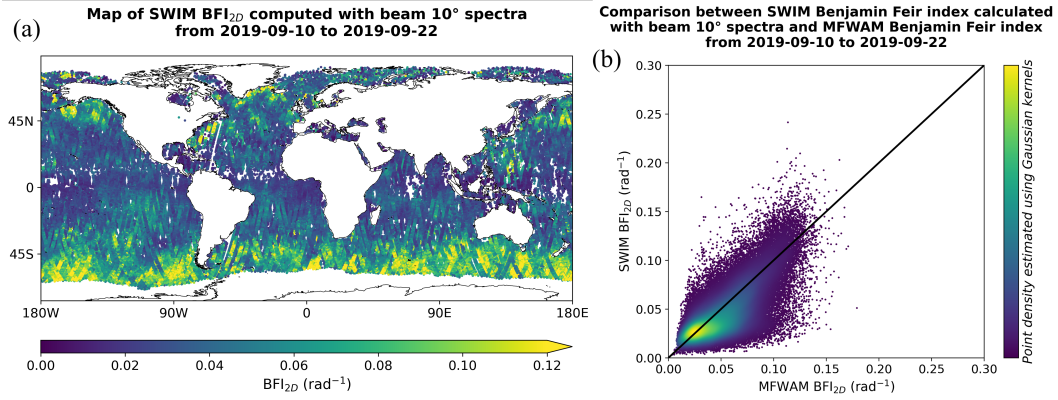


Figure 10: (a): Map of the  $BFI_{2D}$  parameter for SWIM. (b)  $BFI_{2D}$  from SWIM (vertical) compared to  $BFI_{2D}$  from MFWAM (horizontal).

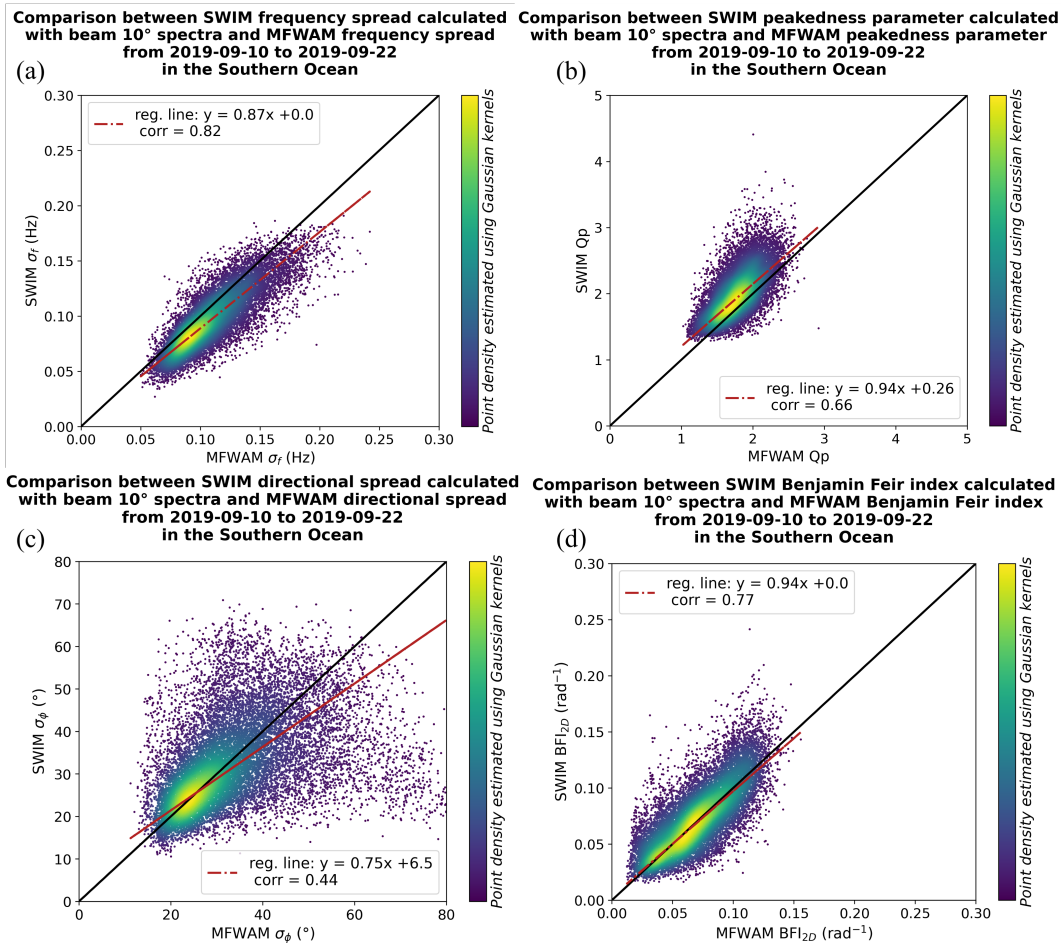


Figure 11: Comparison between SWIM and MFWAM data in the Southern Ocean. (a): frequency spread, (b):  $Q_p$ , (c): directional spread, (d):  $BFI_{2D}$ .

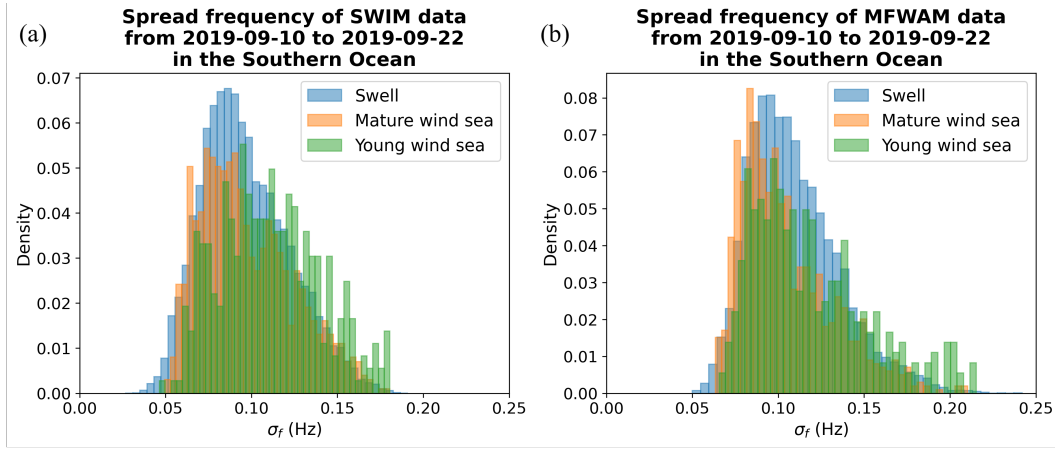


Figure 12: Distributions of frequency spread for individual spectra in the Southern Ocean. (a): for SWIM data, (b): for MFWAM data. The different colors refer to different wave developments: cyan for swell, orange for mature wind sea, green for young wind sea (see text).

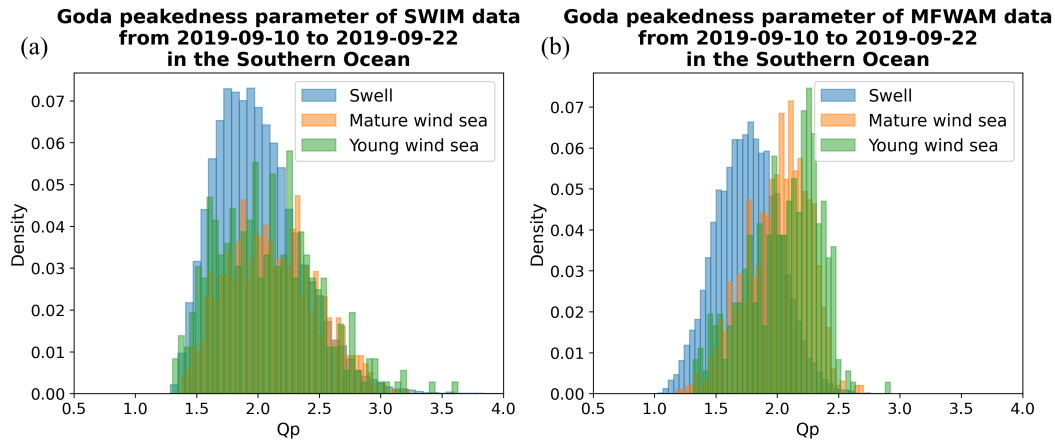


Figure 13: Distributions of the peakness parameter  $Q_p$  for individual spectra in the Southern Ocean. (a): for SWIM data, (b): for MFWAM data. The different colors refer to different sea-state categories: cyan for swell, orange for mature wind sea, green for young wind sea (see text).

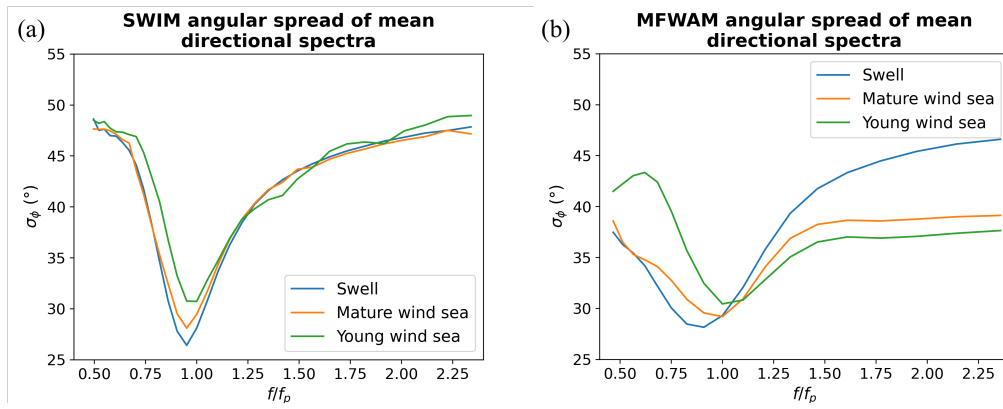


Figure 14: Directional spread as a function of the adimensional frequency for each mean directional spectrum for (a): SWIM , (b): MFWAM. The color code refer to mean spectra estimated for different sea-state category: cyan for swell, orange for mature wind sea and green for young wind sea.