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Andrea Ruju and Francesco Viola, ***An assessment of the impact of boundary conditions in dynamical downscaling techniques for fetch-limited waves***

published by Taylor & Francis in *Coastal Engineering Journal* on 2024Sep 2024 (Early Access),

available at:

<http://www.tandfonline.com/10.1080/21664250.2024.2399393>.

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The publisher's version is available at:

<http://dx.doi.org/10.1080/21664250.2024.2399393>

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An assessment of the impact of boundary conditions in dynamical downscaling techniques for fetch-limited waves

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ARTICLE HISTORY

Compiled September 19, 2024

ABSTRACT

The handling of boundary conditions (BCs) is a key issue for the development of dynamical downscaling techniques in which nearshore wave models require the definition of the sea conditions at the offshore boundaries. This study addresses the implications of using simplified BCs represented by bulk or partitioned wave parameters with respect to using the complete information from directional wave spectra. As a large-scale model, we used WAVEWATCH III (WW3) running over the Mediterranean Sea, forced by ERA5 winds and providing the wave BCs for the small-scale SWAN model. One year of measured directional wave spectra from three deepwater buoys allowed the assessment of the WW3 model accuracy. The nested SWAN model simulations propagated the wave field over three nearshore areas. The accuracy of these small-scale simulations was assessed through the comparison of computed results with wave measurement datasets from buoys deployed outside the surf zone. Being the wave conditions dominated by unimodal seas, modest differences of error metrics are found between the datasets forced by different types of BCs, suggesting that the use of BCs derived from integrated bulk wave parameters appears an acceptable choice for site characterized by fetch-limited waves. Conversely, focusing the attention on multimodal sea conditions, an accurate definition of wave BCs achieved by the use of the directional wave spectra or, in alternative, by the reconstruction of wave spectra from partitioned wave parameters becomes crucial for nearshore wave predictions.

KEYWORDS

boundary conditions; dynamical downscaling; multimodal seas; wave modeling; fetch-limited waves

1. Introduction

Wind-generated waves relentlessly shape worldwide shorelines by driving nearshore circulation and transporting sediment in shallow water (Fredse and Deigaard 1992; Kamphuis 2010). Under extreme storms, waves can constitute a threat for waterway operations, can induce overtopping on coastal infrastructures, erode beach dunes and cause inundation of low-lying regions (Athanasίου et al. 2022; Serafin, Ruggiero, and Stockdon 2017; De Leo et al. 2019; Stokes et al. 2021). Global wave model predictions are needed for wave hindcast and forecast purposes (Sartini, Besio, and Cassola 2017; Lira-Loarca et al. 2022; Amarouche, Akpinar, and Semedo 2022). Despite significant

improvements of state-of-the-art global wave models running on supercomputers (Ras-
 cle and Ardhuin 2013; Stopa et al. 2019; Alday et al. 2022), their spatial resolution
 is usually too coarse in the nearshore region where bathymetric features, shoreline
 geometry and local atmospheric forcing drive significant small-scale wave transforma-
 tions (Crosby, O’Reilly, and Guza 2016; Erikson et al. 2018; Wandres, Espejo, and
 Damlamian 2023). To resolve this issue, a downscaling technique able to provide high-
 resolution information from low-resolution deep-water wave data is required.

A proper characterization of wave transformations in the nearshore relies on down-
 scaling approaches to obtain high-resolution wave data from coarse global model out-
 puts. Three main approaches exist to downscale deep-water waves to the nearshore.
 The first approach is represented by a dynamical downscaling in which process-based
 numerical models simulate wave propagation in coastal areas (Erikson et al. 2015;
 Bellotti, Franco, and Cecioni 2021; Wandres, Espejo, and Damlamian 2023; Agulles
 and Jordà 2024). This approach contemplates a small-scale wave model with a fine
 grid that is nested within the coarse grid of a large-scale wave model. The second
 technique is constituted by the statistical downscaling in which small-scale informa-
 tion comes from empirical relationships between large-scale and nearshore variables
 (Camus et al. 2014; James, Zhang, and O’Donncha 2018). Finally, the third approach
 is the hybrid downscaling that reduces the computational cost of the dynamical down-
 scaling by combining it with the statistical approach (Antolínez et al. 2018; Erikson
 et al. 2018; van Vloten et al. 2022; Espejo et al. 2023; Crosby et al. 2023). In contrast
 with data-driven approaches, the dynamical downscaling technique uses process-based
 high-resolution numerical models nested into larger-scale models. As the dynamical
 downscaling technique makes use of numerical models based on the physics of the pro-
 cesses instead of data-driven algorithms, this approach appears as the most rigorous
 and trustworthy between the three methods mentioned above (Crosby, O’Reilly, and
 Guza 2016; Crosby et al. 2023). Nevertheless, beside on the accuracy of large-scale
 model outputs, the accuracy of coastal wave model simulations relies on a proper of
 definition of boundary conditions.

The management of boundary conditions (BCs) is a key issue in the development
 of dynamical downscaling techniques, in which information from large-scale models is
 transferred to regional and local scales. Coastal wave modeling addressed by means of
 spectral wave models requires the definition of the sea conditions at the offshore bound-
 aries of the numerical domain (Olabarrieta et al. 2012; Crosby, O’Reilly, and Guza
 2016; Bellotti, Franco, and Cecioni 2021). Global hindcast and forecast wave mod-
 els run by large research institutions provide open-access publicly available databases
 (Ravdas, Zacharioudaki, and Korres 2018; Zacharioudaki, Ravdas, and Korres 2020)
 usually constituted by bulk and partitioned wave parameters. Whereas directional
 wave spectra are seldom available, mainly due to huge storage requirements (Kumar
 et al. 2017; Hegermiller et al. 2017). Focusing on long-fetch Pacific waves, Kumar et al.
 (2017) reported that the reconstruction of BCs from partitioned wave parameters pro-
 vide accurate regional wave estimates and, therefore, it should be preferred to the use
 of BCs proceeding from integrated bulk wave parameters. Although there is a general
 consensus among scientists that an exhaustive description of BCs achieved through
 directional wave spectra is overall desirable for dynamical downscaling (Cagigal et al.
 2021; Espejo et al. 2023; Crosby et al. 2023), the studies addressing a sensitivity anal-
 ysis that quantitatively considered the implications of different BCs derived from bulk
 or partitioned wave parameters are scarce and they have mainly dealt with long-fetch
 waves (Kumar et al. 2017), whereas less attention has been devoted to the management
 of BCs under fetch-limited wave conditions.

This study explores how the handling of wave BCs proceeding from large-scale wave models can affect the accuracy of nearshore wave simulations within a dynamical down-scaling routine under fetch-limited wave conditions typical of the Mediterranean Sea. A multi-scale wave modeling approach over the entire Mediterranean Sea carried out with the WAVEWATCH III (WW3) model forced by ERA5 winds (Belmonte Rivas and Stoffelen 2019; Hersbach et al. 2020) provided the wave BCs for the small-scale SWAN model. One year of measured directional wave spectra from three buoys deployed in deep waters allowed the assessment of the WW3 model accuracy in terms of bulk and partitioned wave parameters. The nested SWAN wave model simulations, also under the effect of ERA5 winds, propagated the wave field over three nearshore areas located in the Western Mediterranean, taking the BCs from the large-scale WW3 model. Three different types of BC were tested in order to assess how they can impact the accuracy of wave results in the nearshore. The first and more rigorous BC is represented by the full 2D spectra extracted along the open boundary directly from the WW3 output. The reconstruction of wave spectra from windsea and swell partition parameters leads to the second BC. Finally, the third BC is represented by wave spectra reconstructed from integrated bulk wave parameters with a standard directional spread value. The small-scale simulations with different BCs gave rise to three datasets, one dataset for each BC. The assessment on the impact of different BCs was carried out by comparing computed data with one-year wave measurements from nearshore buoys deployed outside the surf zone.

The paper is organized as follows. Chapter 2 describes the measurements, the numerical models together with the spectral partitioning technique. Chapter 3 reports the main results and the assessment of model accuracy. Chapter 4 discusses the results while conclusions are listed in chapter 5.

2. Methods

2.1. Measurements

In this work we used wave data measured by three wave buoys moored in deep waters and three wave buoys deployed in the nearshore. The three deepwater buoys (Revellata, Alistro and Porquerolles) belong to the Candhis Cerema monitoring system and, as of the present writing, they are operational, lying in the Western Mediterranean Sea. They were chosen because, besides bulk wave parameters, they provide directional wave spectra. Moreover, they are characterized by different fetch sizes and orientations, leading to heterogeneous wave conditions. The measured wave spectra have a sampling time step of 1/2 hour and are made up of 72 directions with a $\Delta\theta$ of 5° and 40 frequencies with a range extending from 0.025 to 0.5 Hz. With the purpose of including a wide range of wave conditions and address seasonal variability, this work analysed a dataset covering a 12-month period. The period considered spans from the 1th of January 2021 to the 31th of December 2021.

[Figure 1 about here.]

In addition to the deep-water buoys, this work takes advantage of three wave buoys deployed in the nearshore of three Mediterranean areas characterized by different wave climates: Palma, Espiguette and Bastia. As of the present writing, Palma and Espiguette are in service, whereas Bastia ceased taking measurements in 2008. These buoys are (or was in case of Bastia) moored outside the surf zone in water depths

ranging between 17 and 32 m providing bulk wave parameters with a sampling time step of 1/2 hour. This study took the data from Palma and Espiguette buoys covering the entire year 2021. However, as the Bastia buoy data do not cover the year 2021, we took for this buoy the one-year period from the 1th of January 2007 to the 31th of December 2007. Figure 1 shows the geographical settings with the locations of the deep water and nearshore wave buoys. Table 1 lists the main physical parameters recorded by the three deepwater and three nearshore buoys. The last column of Table 1 presents the percentage of multimodal conditions identified with the procedure described in the following section.

[Table 1 about here.]

2.2. Spectral partition and multimodal seas

The technique of spectral wave partitioning allows the identification of individual wave systems coexisting at the same time but forced by different meteorological inputs along their traveling paths. Nowadays, in addition to bulk wave parameters, global datasets usually provide information of wave partition parameters (Zacharioudaki, Ravdas, and Korres 2020). In this way, the dataset available to the public combines a reasonably good characterization of the wave field with a reduction of the data storage space that would be required by full 2D wave spectra (Kumar et al. 2017). As one BC considered in this work (the second one) involves the spectrum reconstruction from wave partition parameters provided by the large scale WW3 simulation, this section briefly describes the technique used for spectral partitioning.

According to Portilla, Ocampo-Torres, and Monbaliu (2009), partitioning refers to the process leading to the detection of wave systems from a directional wave spectrum. Whereas, labeling is defined as the attribution of a wind-sea/swell tag to each partition. In this work, the partitioning algorithm used the watershed technique based exclusively on the morphological features of the spectrum (Hanson and Phillips 2001). Once the partitioning algorithm has been performed, each partition of the wave spectrum can be characterized by partition bulk parameters, such as the significant wave height H_s , mean period T_m and mean direction θ_m .

[Figure 2 about here.]

Labeling was instead carried out by looking at environmental parameters and physical characteristics of wave systems. The information from the spectral shape of wave systems in combination with wind data allows the categorization into either wind-sea or swell (Portilla, Ocampo-Torres, and Monbaliu 2009). The wind-sea region of the spectrum is that region that receives a positive wind input. Following Komen, Hasselmann, and Hasselmann (1984), a positive wind-input term occurs for wave packets that satisfy:

$$\beta \frac{u_{10}}{c} \cos(\theta - \phi) > 1, \quad (1)$$

where u_{10} is the wind speed 10 m above the water level, c is the phase speed of the wave packet, θ is the wave direction, ϕ is the wind direction and β is the age factor. β is usually treated as a calibration parameter (also called multiplier). Large values of β allow old wind states to be still considered under the influence of the wind. According to Tracy, Devaliere, and Hanson (2007), we set β equal to 1.7 to include old wind states

147 into the wind-sea region. It is worth mentioning that 1.7 is also the default value for
 148 β adopted in WW3 v6.07.

149 The wind sea fraction of each partition is (Tracy, Devaliere, and Hanson 2007):

$$W = \frac{E_w}{E}, \quad (2)$$

150 in which E is the total wave energy of the partition and E_w is the energy of the
 151 region of the spectrum under the direct influence of the wind (see Equation 1). W
 152 tends to 0 for pure swell systems while values close to 1 characterize pure wind-sea
 153 partitions. In this work, if W is larger than a cutoff value the partition was labelled
 154 as wind-sea. According to Hanson et al. (2009), the cutoff values was set to 0.33. This
 155 work performed wave partition on both measured and computed wave spectra taking
 156 advantage of the wavespectra library (<https://github.com/wavespectra>, last access: 13
 157 November 2023). The output of the algorithm is a set of wave systems made up of
 158 a single wind-sea partition (if present) followed by a maximum of three swell wave
 159 partitions.

160 Once the partitioning routine has been carried out, it is possible to discriminate
 161 between unimodal and multimodal sea conditions. In this work, a sea state was defined
 162 as multimodal if it contained at least two different wave systems with a partition H_s
 163 larger than 0.5 m and partition mean directions more than 75° apart. This definition
 164 aligns with the one put forth by Amrutha and Kumar (2021) for crossing and opposing
 165 multimodal seas. Figure 2 shows an example of the output of the wave partition
 166 routine carried out at the Porquerolles buoy under a multimodal sea state. As expected,
 167 the wind-sea partition extends over high frequencies and is characterized by a mean
 168 direction that is close to the wind direction. The two swells have similar T_m values.
 169 The secondary swell is heading offshore and it is likely to be the result of shoreline
 170 reflection. The 1D frequency spectra has a double-peaked shape with the two swells
 171 forming the low-frequency peak and the wind-sea raising the secondary high-frequency
 172 peak.

173 **2.3. Wave models**

174 The WW3 model (Tolman et al. 2019) ran over the Mediterranean Sea forced by
 175 winds from the ERA5 global reanalysis dataset (Belmonte Rivas and Stoffelen 2019;
 176 Hersbach et al. 2020). ERA5 has hourly output and a horizontal spatial resolution
 177 of 0.25° . Belmonte Rivas and Stoffelen (2019) assessed the accuracy of the ERA5
 178 wind dataset and found an improvement in model predictive skill over the previous
 179 reanalysis products. With the main aim of simulating wave processes with different
 180 spatial scales, we adopted a multi-grid approach in which a large coarse grid with
 181 a spatial resolution of 0.01667° (18.5 km) extended over the entire Mediterranean
 182 basin, and a nested grid with a spatial resolution of 0.00417° (4.6 km) covered the
 183 coastal seas surrounding the islands of Sardinia and Corsica, the Balearic archipelago
 184 and the southern Europe coastline from Liguria to Catalonia. The fine grid extended
 185 over a region between the shoreline and 58 km offshore where the spectral boundary
 186 conditions from the parent grid were imposed, see Figure 3. The location of the nodes
 187 of the coastal grid was chosen so that it overlaps that of the CMEMS (Copernicus
 188 Marine Environmental Monitoring System) grid dataset (Ravdas, Zacharioudaki, and
 189 Korres 2018). Both coarse and fine grid simulations ran over the bathymetry obtained
 190 using the ETOPO 2022 (Global Relief Model) dataset (NOAA 2022). The wave model

was set up with 32 frequency bins and 24 directions. The frequency range extends from 0.04 to 0.768 Hz, whereas wave directions are 15° spaced.

[Figure 3 about here.]

Nonlinear quadruplet wave interactions were computed with the Discrete Interaction Approximation (DIA) method. We used and tested the package ST6 (Rogers, Babanin, and Wang 2012; Zieger et al. 2015) which is designed for the parameterization of wind input, wave breaking and swell dissipation. ST6 is a state-of-the-art source term package that have been proven skillful under different sea conditions (Umesh and Behera 2020; Ruju et al. 2020; Kalourazi et al. 2021; Soran, Amarouche, and Akpınar 2022). Liu et al. (2019) successfully calibrated the source terms of the ST6 package under different weather conditions and found a set of parameters that have been included as default parameters in WW3 v6.07. A key parameter in the ST6 package is the coefficient CDFAC that represents a multiplier on the wind drag coefficient and allows to correct a bias in the input wind. Aydoğan and Ayat (2021) found that, forcing the SWAN model with wind data from ERA5, the ST6 parameterization with the debias coefficient CDFAC in the range 1.07-1.15 leads to the highest accuracy of wave height prediction in the Black Sea. Table 2 lists the ST6 parameter set-up adopted in this study. The two values of CDFAC tested has been chosen within the ranges already considered by Zieger et al. (2015) and Aydoğan and Ayat (2021). Besides the already mentioned CDFAC parameter, a_1 and a_2 are coefficients related to local and cumulative dissipation terms. Moreover, p_1 and p_2 control the strength of wave dissipation. Finally, Υ is a wind-scaling factor relating the wind speed u_{10} with the friction velocity u_* ; see the WW3 manual (Tolman et al. 2019) for an exhaustive explanation of these terms.

[Table 2 about here.]

WW3 ran over two 12-month periods. The first one goes from the 1th of January 2021 to the 31th of December 2021 and it is the period in which wave measurements are available from the three deep-water buoys and from two nearshore buoys (Palma and Espiguette). The second period spans from the 1th of January 2007 to the 31th of December 2007, that is when the third nearshore buoy (Bastia) provided wave observations.

Nearshore wave propagation was addressed by means of SWAN model (Booij, Ris, and Holthuijsen 1999) simulations nested into the WW3 simulations. SWAN ran over three nearshore areas with a numerical domain extending from the shoreline up to approximately the shoreward limit of deep water (depth in the order of 100 m). In fact, it is a common practise among coastal engineers and modelers to initialize nearshore wave models in the region where wave propagation starts to be significantly affected by the presence of bottom (see for instance Agulles and Jordà (2024)). Consistently with the WW3 simulations, ERA5 winds represented the atmospheric forcing while the parameterization ST6 addressed the wave breaking dissipation processes. The ST6 packages adopted by both SWAN and WW3 shared the same set of parameters (default parameters in WW3 v6.07). The rectangular SWAN computational grids were built using the EMODNet bathymetry dataset, with a spatial resolution of 1/8 arc minute of latitude (231 m), see Figure 4. EMODNet combines a large number of bathymetric datasets with an effort to provide an harmonised Digital Terrain Model (DTM) for the European sea regions. Consistently with the WW3 settings, wave spectra in SWAN were defined by 24 direction bins and 32 frequencies, ranging from 0.04 Hz to 0.768 Hz.

Each directional sector is 15° wide. The SWAN runs covered the same time periods of WW3 simulations. The entire year 2021 was simulated over the Palma and Espiguette areas. Whereas, for the reasons explained before, the run in Bastia area covered the year 2007.

2.4. Boundary conditions

Wave boundary conditions (BCs) were time- and space-varying along the open off-shore sides of the SWAN grid (see Figure 4). Three different types of wave BCs were considered in this study.

The first one is the most rigorous one; it uses the 2D directional spectra directly from the output of the WW3 simulations. The dataset with this BC was labelled as NS and being the most accurate is taken as the benchmark dataset. In the second BC, labelled as NP, wave spectra were reconstructed from the parameters of three wave partitions (one wind-sea and two swells) obtained via the partitioning technique from the WW3 output at the offshore boundary of the nested grid. Each resulting BC spectrum S was the sum of the three partition spectra S_i that adopted a JONSWAP shape with the WW3-computed peak-enhancement parameter and cosine-squared directional spread:

$$S(f, \theta) = \sum_{i=1}^{i=3} S_i(f, \theta). \quad (3)$$

According to Romano-Moreno et al. (2022), the peak enhancement factor γ of the JONSWAP spectrum was computed from the spectral shape parameter κ (Rice 1944). An alternative way to compute γ would be to find the value that leads to the best fit between the JONSWAP spectrum and the WW3 frequency spectrum (Mazzaretto, Menéndez, and Lobeto 2022). However, here we preferred to calculate γ from κ as the latter is not associated to any parametric spectral shape. The third boundary condition, named NI, used the computed bulk wave parameters H_s , T_p and θ_m to reconstruct the BC directional spectra with a JONSWAP shape. In this case the peak-enhancement parameter was set to 2. The BC spectra adopted a fixed value of the directional spread equal to 25° in the construction of the JONSWAP spectrum. The values of the peak-enhancement parameter and the bulk directional spread represent common observed values found in literature (Guedes Soares 1984; Kumar et al. 2017; Hegermiller et al. 2017; Mazzaretto, Menéndez, and Lobeto 2022). It is worth mentioning that, as a consequence of the spectrum recomposition from wave systems, the second BC (NP) is the only one that does not guarantee the conservation of the energy levels of the original spectrum. For this reason, according to Espejo et al. (2023), when using this BC we corrected H_s so that $H_s^2 = \sum H_{si}^2$.

Except for dataset NS in which the BC wave spectra were taken directly from WW3, all datasets relied on the JONSWAP shape for the BC preparation routine. The fitting of the wave spectrum with a synthetic shape is still an open research topic. Mazzaretto, Menéndez, and Lobeto (2022) assessed the suitability of the JONSWAP spectral shape on coastal areas and found that JONSWAP performs well in the Mediterranean Sea, although with a peak-enhancement factor γ lower than the standard value of 3.3. This is in agreement with Guedes Soares (1984) and Kumar et al. (2017) who provided γ values equal to 2. Akbari, Panahi, and Amani (2020) suggested that the primary system of a double-peaked spectrum can be fitted with a Gaussian model while the JONSWAP spectrum can fit the secondary systems. Consistent with Mazzaretto, Menéndez, and

281 Lobeto (2022), in this study we adopted a JONSWAP shape to reconstruct both the
 282 total spectrum and the spectra of the wind-sea and swell partitions.

283 [Figure 4 about here.]

284 2.5. Error metrics

285 The WW3 and SWAN model performance was assessed by comparing the simulated
 286 datasets with the datasets from buoy observations in deep water and in the nearshore,
 287 respectively. We adopted normalized statistics with the main aim of comparing a
 288 large range of wave conditions. The normalized root-mean-square-error NRMSE and
 289 normalized bias NB were defined as follows:

$$\text{NRMSE} = \sqrt{\frac{\sum (O_i - M_i)^2}{\sum O_i^2}}. \quad (4)$$

290

$$\text{NB} = \frac{\sum (O_i - M_i)}{\sum O_i}. \quad (5)$$

291 where O_i and M_i are the observed and modelled variables.

292 Elshinnawy and Antolínez (2023) employed the 2π angle for the error metrics nor-
 293 malization of the mean direction θ_m . In this work we decided to avoid the normalization
 294 of the error metrics for θ_m , being the range of this variable confined between 0 and
 295 360° . Therefore, the normalization procedure does not seem to bring additional insight
 296 for the interpretation of the results regarding mean wave direction. The root-mean-
 297 square-error RMSE and bias B for θ_m were computed as:

$$\text{RMSE}_{\theta_m} = \sqrt{\frac{\sum (O_i - M_i)^2}{N}}, \quad (6)$$

298

$$\text{B}_{\theta_m} = \frac{\sum (O_i - M_i)}{N}, \quad (7)$$

299 where N is the number of observations. Wave sea states with a measured H_s smaller
 300 than 0.5 m were discarded from the dataset used for the computation of error metrics.

301 Taylor diagrams were used in this work to summarize the predictive skills of model
 302 datasets in comparison to the observed dataset. The correlation coefficient R and
 303 the standard deviation σ_o and σ_m of, respectively, observed and predicted data were
 304 computed as follows:

$$R = \frac{\sum (O_i - \bar{O})(M_i - \bar{M})}{\sqrt{\sum (O_i - \bar{O})^2} \sqrt{\sum (M_i - \bar{M})^2}} \quad (8)$$

305

$$\sigma_o = \sqrt{\frac{1}{N} \sum (O_i - \bar{O})^2} \quad (9)$$

$$\sigma_m = \sqrt{\frac{1}{N} \sum (M_i - \bar{M})^2} \quad (10)$$

in which the overbar $\bar{\cdot}$ denotes the mean value and N is the number of data points.

3. Results

3.1. Waves in deep water

Figure 5 depicts the polar plots of the bulk and partition T_m versus θ_m classified into three H_s classes measured at the three deep-water wave buoys. Only partitions with H_s larger than 0.5 m are displayed. At each buoy, bulk mean wave directions tend to spread on a 180°-wide sector, according to shoreline orientation. On the other hand, windsea and swell partitions tend to cluster around preferred directions. This is particularly evident at La Revellata buoy where, although sea states with mean wave direction from North-West are well represented, no windsea or swell partition shows this direction. The Alistro buoy reports the smallest bulk and swell wave periods, possibly as a result of the site exposure characterized by short fetches that limit the swell development especially in the North-East direction (see Figure 5g). Wind-sea periods are similar at the three buoys, with slightly smaller values recorded at the Revellata buoy, likely due to the local wind climate. It is worth noting that offshore-directed first and secondary swells (from the sector 90-135°) are not unusual at the Revellata buoy. These wave systems travelling offshore might be the result of coastal reflection of long-period waves under energetic conditions. Offshore swell directions are found also at Porquerolles buoy but only for secondary swells.

[Figure 5 about here.]

Table 3 lists the error metrics of the computed results versus the deep-water measurements. Three outputs are compared: CMEMS refers to the freely available Copernicus wave reanalysis product (MEDSEA_MULTIYEAR_WAV_006_012) while ST6.1 and ST6.2 are the outputs of the WW3 simulations carried out with different settings in the parameterization of wind input, wave breaking and swell dissipation. ST6.1 and ST6.2 datasets use the ST6 parameterizations (Rogers, Babanin, and Wang 2012; Zieger et al. 2015) with CDFAC equal to 1.1 and 1.2, respectively. The three datasets have comparable error metrics of H_s , T_m and θ_m . The CMEMS dataset, used as a reference, gives slightly smaller errors for H_s and θ_m , but larger errors for T_m . ST6.2 performs better than ST6.1, partially balancing the ERA5 wind underestimation reported by previous research (Amarouche, Akpinar, and Semedo 2022; Lodise et al. 2024). The underestimation of H_s at La Revellata and Alistro buoys is likely to be the result of the ERA 5 wind speed bias in some parts of the Mediterranean, including the Ligurian sea (Cavaleri and Sclavo 2006). ST6.2 is used for consistency in the following analyses of this paper.

[Table 3 about here.]

The ability of the WW3 model simulations setup with the ST6 parameterization (dataset ST6.2) to describe the evolution of the spectral partitions at Porquerolles buoy is shown in Figure 6. We provide here a qualitative assessment through the comparison

of time series of total, wind-sea and swell 1 partitions. A more comprehensive analysis
 is beyond the scope of the present work. Note that Figures 6a and 6b only show ERA5-
 computed winds (no measurements). In fact the deep-water buoys are not equipped to
 measure wind data and ERA5 winds represent the forcing used in the wave partition
 routine. The time series of Figure 6 shows four main storms that at their peaks are
 driven by local winds. At the storm peaks, the values of H_s exceeding 3 m are on
 the order of the $H_{s,95}$ of that site, as shown in Table 1. The abrupt H_s variations
 observed in the wind-sea and swell 1 partitions for both measured and computed data
 are likely to be the result of the sea fraction W , see Equation 2, that crosses the
 threshold value and thus yields a switch of the label of the most energetic partition
 of the spectrum. A noticeable discrepancy imputable to the model is the absence of
 energy in the computed swell partition during the occurrence of the most energetic
 storm of Figure 6. In fact, between the January 13th and 15th the buoy record shows
 a moderate swell from East that is not reproduced by the model. The inspection of
 the computed wave spectra (not shown) suggests that the absence of the first swell
 partition is not due to the partition routine but is actually the consequence of the lack
 of energy carried by wave packets proceeding from East. Being the direction of the
 measured first swell partition nearly 180° apart from the bulk mean wave direction, it
 is plausible that this wave energy is the result of wave reflection at the shoreline that is
 not well reproduced by the model. Considering that in this case the measured primary
 swell contains low energy (H_s is 0.38 m) and that possible inaccuracies in predicting
 wave energy reflection at the shoreline should have a limited impact on incoming wave
 energy in the nearshore, we do not investigate this issue any further. Overall, despite
 minor discrepancies, the model correctly reproduces the growth and the drop of the
 four main storms, with their wind-sea and swell partitions, displayed in Figure 6.

[Figure 6 about here.]

3.2. *Waves in the nearshore*

The SWAN model runs were nested into the WW3 simulations (dataset ST6.2), de-
 scribed in the previous section. In these nearshore simulations, we kept the same
 wave breaking parameterization (ST6 with CDFAC equal to 1.2) used in WW3 and
 the same atmospheric forcing (winds from ERA5). Even considering the mentioned
 improvements of ERA5 with respect to its predecessor datasets, it is expected that
 its relatively coarse horizontal resolution may lead to a reduction of the accuracy
 prediction on semi-enclosed regional seas and in coastal water where orography and
 land-water transition can produce local disturbances to the wind field (Mentaschi et al.
 2015). The reproducibility of ERA5 winds was checked by comparing wind predictions
 with the data measured by Palma buoy (the only one between the three coastal buoys
 used in this study providing wind data). The analysis proposed by Heidarzadeh et al.
 (2021) is shown in Figure 7 in which the time series of wind speed measured by Palma
 buoy are compared with wind speed predicted at the buoy location and wind speed
 predicted at the neighboring ERA5 grid points. Although Palma buoy provided 7
 months of wind data in 2021, from June to December, Figure 7 shows only 8 days to
 increase readability. The ERA5 wind data at Palma buoy location show a reasonably
 good agreement with observations (NRMSE = 0.35), although an underestimation of
 wind magnitudes (NBIAS = -0.24) is observed. The magnitude of this underestimation
 is consistent with the analysis provided by Aydoğan and Ayat (2021) who reported
 10–24% underestimation for ERA5 wind speed in comparison with in-situ wind mea-

surements in the Black Sea. Wind directions are characterized by a RMSE of 39° with virtually negligible bias ($\text{BIAS} = -1^\circ$). As expected, in general terms, predicted winds over wet grid points have larger magnitude than winds predicted over land. Still considering potential issues in coastal waters, the present analysis gives confidence in the use of ERA5 winds as a forcing for the wave model.

[Figure 7 about here.]

Computed outputs were compared with bulk wave parameters measured by the three nearshore buoys (Palma, Espiguette, Bastia). We considered here three datasets resulting from the different types of wave BCs described in section 2.

Table 4 lists the error metrics of bulk wave parameters in the nearshore resulting from the different BCs used. Since Palma buoy does not provide T_p observations, T_p values are calculated from the Espiguette and Bastia data only.

[Table 4 about here.]

Data in Table 4 reveal that there is only minimal differences between the three datasets in terms of errors of H_s , T_m and T_p . The difference in NRMSE of H_s between the datasets remains smaller than 2%. Slightly more consistent discrepancies reside in θ_m errors where the use of the less accurate BC of dataset NI leads to a 13% RMSE increase with respect to dataset NS (from 22.08° to 24.93°). A second evidence from Table 4 is the strong underestimation of T_m by all datasets. In fact, regardless of the BC used, all datasets in this work underestimate T_m in the nearshore. This drawback of the numerical approach occurs more evidently in coastal waters, despite the fact that both WW3 and SWAN shared the same package ST6 with the same settings. In fact, although also WW3 underestimated T_m , the bias values are not as large as those of SWAN. Values of the CDFAC parameter larger than 1 have the purpose of balancing the wind speed biases of ERA5. In fact, although ERA5 represents a state-of-the-art wind dataset with acknowledged accuracy (Belmonte Rivas and Stoffelen 2019), Cavaleri and Sclavo (2006) and Amarouche, Akpınar, and Semedo (2022) reported an underestimation of ERA5 wind speed in the Mediterranean Sea, especially in the Ligurian basin. It is worth noting that the underestimation affected only T_m , while T_p was properly addressed by SWAN, without appreciable bias. This outcome suggests that the T_m bias may be the result of the effect of the wind input source term that transfers too much energy into the high-frequency tail of the wave spectrum. In fact, it is acknowledged that parameterization ST6 yields a rapid wave growth for young seas (Zieger et al. 2015). Changing the CDFAC of the ST6 parameterization from the value of 1.2 to lower values, of about 1, yielded a slight mitigation of the T_m underestimation (not shown in this work). Nevertheless, consistently with the large-scale WW3 simulations we kept the value of CDFAC equal to 1.2 also in SWAN.

Given the small differences found between the error metrics of the three datasets obtained considering the entire range of wave conditions, we focus now our attention on multimodal sea states. As stated in section 2, we label a sea state as multimodal if at least two wave partitions with H_s larger than 0.5 m are more than 75° apart. We look if this condition is satisfied at a grid node located in the middle of the offshore boundary segment of the numerical domain. Therefore, we check if this condition is satisfied in deep water and we make no assumption in the nearshore, where refraction processes are expected to reduce wave directional spreads.

Figure 8 and 9 allow the visualization of different types of wave BCs along the open boundary and the implications for nearshore wave propagation. They compare the H_s field from datasets NS and NI computed by SWAN under two multimodal sea

conditions occurred, respectively, at Bastia and Espiguette. The polar plots in panel a) show the BC directional wave spectra of dataset NS, proceeding directly from the WW3 simulation. Whereas the BC wave spectra in panel b) are reconstructed from the bulk wave parameters of the WW3 simulation (dataset NI). The multimodality of incoming waves is evident in Figure 8a in which the wave BCs along three sides of the boundary are characterized by a main wave partition from South-West accompanied by at least one secondary partition from North-East. Figure 8b shows how dataset NI, including bulk wave parameters only, misses the information from secondary wave systems. In this multimodal sea state, dataset NI provides slightly larger H_s values in the nearshore area and at the buoy location (measured $H_s=0.90$, H_s from NS=0.86m, H_s from NI=1.00m). On the other hand, Figure 9 shows that, for this multimodal wave condition at Espiguette, dataset NS yields a slightly larger H_s value than dataset NI. Moreover, dataset NS gives more southern-oriented waves with the mean wave direction parameter that varies from 108° for dataset NI to 118° for dataset NS (measured mean wave direction equal to 126°).

[Figure 8 about here.]

[Figure 9 about here.]

Figures 10 and 11 show the histograms of error metrics at the three nearshore buoys resulting from the three datasets. Each panel discriminates between the error metrics resulting from the totality of wave conditions and those obtained considering multimodal sea states only. In general terms, except for NRMSE of H_s at Bastia, multimodal conditions yield larger errors both in terms of H_s and θ_m . This is a predictable outcome since multimodal sea conditions are characterized by complex spectral shapes with multiple and heterogeneous wave systems coexisting at the same time, see Figures 8 and 9. Moreover, under multimodal conditions, the differences in terms of H_s accuracy among the datasets become more evident. Combining the data from the three buoys, dataset NI has a H_s NRMSE of 0.24, that is 20% larger than that of the reference dataset NS (NRMSE=0.20). Observing the bias values plotted in Figure 11 we can note that, including the data from the three buoys, SWAN tends to underestimate H_s considering all wave conditions (see also Table 4). Nonetheless, H_s under multimodal sea states is overestimated. Data suggest that NP dataset provides slightly lower H_s than the other datasets. The results of Figure 10 are confirmed by the Taylor diagrams of Figure 12. Including all wave conditions at the three nearshore buoys, Figure 12a shows minor differences in the statistical error metrics associated to the three datasets. Nevertheless, when focusing of multimodal sea states, dataset NI leads to a lower correlation coefficient with respect to dataset NS, thus attesting poorer prediction skills (Figure 12b).

[Figure 10 about here.]

[Figure 11 about here.]

[Figure 12 about here.]

Although the BC spectra of the different datasets are build so that the total energy at the boundary remains unchanged with same H_s , see Espejo et al. (2023), different spectral shapes can yield different amounts of the total energy that actually enter the numerical domain. In fact, the offshore components of the wave spectrum do not participate to the energy balance within the numerical domain. A more comprehensive

insight into the implication of imposing different incoming spectral shapes on the boundary can thus be obtained by looking at the wave energy entering the numerical domain. The wave energy flux E_f across a boundary section with normal n is computed as:

$$E_f = \rho g \int_{n-\pi/2}^{n+\pi/2} \int_{f_1}^{f_N} S(f, \theta) c_g(f) df d\theta, \quad (11)$$

in which ρ is the density of sea water, g is the gravity acceleration, $S(f, \theta)$ is the directional spectrum and $c_g(f)$ is the group velocity of the wave component with frequency f , according to linear theory. Equation (11) refers to the flux across a grid cell lying on the boundary. Summing up the fluxes of the boundary cells of the domain and dividing by their number leads to the energy flux across the entire open boundary, expressed in watts per meter. Figure 13 shows the scatter plots of the incoming wave energy flux of datasets NP and NI versus the reference dataset NS. At each buoy, the slope of the regression line lower than 1 and the negative NB values indicate that dataset NP brings lower E_f levels than NS under both all and multimodal conditions. In general terms, the BC associated with NP leads to smaller incoming energy fluxes at the boundary. The opposite occurs for dataset NI that tends to raise the incoming E_f with respect to dataset NS (see also Figure 8). The consequences of this trend at the offshore boundary of the numerical domain can be observed in nearshore parameters, especially on the wave energy flux E_f . In fact, the bias of E_f of dataset NI is significantly larger than that of NS (NB=0.21 for NS and NB=0.27 for NI) under multimodal wave conditions. In contrast, dataset NP tends to reduce bias values of E_f (NB=0.18 for NP). The significant wave height H_s seems to be less affected, as we observe that NS and NI bring similar H_s bias values (NB=0.07 for both datasets, see also similar NB values in Table 4 considering the totality of wave conditions). However, the same trend in bias discrepancies associated with different datasets observed for E_f can be found also for H_s if we focus on the most energetic wave conditions, for instance if we consider only H_s larger than 1 m. This suggests that the differences in incoming wave energy fluxes at the offshore boundary have a stronger impact on energetic sea states. Finally, it is worth mentioning that the most energetic conditions at Bastia are likely to be multimodal but the same does not happen at Palma and Espiguette, where the most energetic sea states are unimodal.

[Figure 13 about here.]

We conclude this section with the assessment of longshore wave energy flux estimates at the nearshore buoy locations. The most widely used model for estimating total longshore sediment transport rate is the CERC formula (USACE 2006) that assumes that the total longshore sediment transport rate is proportional to longshore energy flux. Therefore, accurate estimates of the longshore component of the wave energy flux are necessary to quantify longshore sediment transport and thus morphodynamic beach evolution (Fredsøe and Deigaard 1992; Kamphuis 2010). As coastal engineering studies dealing with beach erosion often rely on dynamical downscaling techniques, it appears of interest to investigate the implications of different BCs on longshore energy flux estimates. The longshore component of the energy flux is calculated as:

$$E_{fl} = \frac{\rho g}{16} H_s^2 c_g \sin(2\alpha), \quad (12)$$

where c_g is computed from the peak period T_p and α is the wave angle of incidence with respect to the line perpendicular to the shoreline. Figure 14 shows the scatter plots of the longshore wave energy fluxes of the three datasets versus those measured by waves buoys at the nearshore sites. NRMSE of E_{fl} are larger than those of other parameters, such for instance H_s , see Table 4. This is an expected result, being E_{fl} proportional to H_s^2 , with the exponent that amplifies the error magnitudes. Considering the results combining the different locations and considering the totality of wave conditions, the different datasets bring modest differences of NRMSE (less than 5 %). This is consistent with Table 4 that does not provide significant error differences between the three datasets. Focusing the attention on multimodal sea states, the normalized errors significantly rose from the value of 0.70 of dataset NS to the values of 0.84 of dataset NI.

[Figure 14 about here.]

4. Discussion

This paper aims to shed some lights on how the handling of wave boundary conditions (BCs) can affect the accuracy of nearshore wave simulations within a dynamical downscaling routine. The adoption of a WW3 grid that lies over the CMEMS grid allowed us to place ourselves in the same situation of coastal practitioners and scientists that need to deal with a downscaling wave problem starting from the availability of the CMEMS wave reanalysis product (Sanchez-Arcilla et al. 2021), but with the advantage of having also the directional spectra available from the large-scale wave model. Thanks to the directional spectra from WW3, we performed a comprehensive analysis considering the three BCs described in section 2.

A non-exhaustive list of recent publications dealing with wave downscaling problems is shown in Table 5. In general, omitting minor discrepancies in data processing and wave spectrum reconstruction, these types of BCs can be brought back to the three BCs considered in the present work: BCs from directional spectra (NS), BCs derived from wave partitioned wave parameters (NP) and BC derived from integrated bulk wave parameters (NI). Although the scientific community agrees that the use of directional wave spectra from large-scale models is overall desirable for dynamical downscaling problems, Table 5 shows that scientists are nowadays used to adopt different types of BCs, mainly depending on data availability and specific project goals.

[Table 5 about here.]

Alday et al. (2022) suggested that the generation of BCs at a global scale is one of the most important factors on shorelines exposed to waves from the North Atlantic. Kumar et al. (2017) and Ricondo et al. (2023) recalled the importance of using partitioned (rather than bulk) wave information to reconstruct the directional spectrum as open boundary conditions in regional wave modeling studies. Our work differs from that of Kumar et al. (2017) in two main aspects. Firstly, the nested numerical domains considered in our study were smaller and we imposed the BCs at water depths on the order of 100 m. In fact, whereas Kumar et al. (2017) investigated the implications of using different types of BCs for regional wave model applications (nested grid size in the order of 100 km), this study carried out a local wave downscaling (nested grid size in the order of 10 km) in which incoming waves at the offshore boundary are expected to have experienced a significant sheltering effect due to the nearby coastline geometry

that limits the width of the fetch. Moreover, in contrast with long-fetch Pacific waves, limited Mediterranean fetch extensions lead to less developed sea conditions.

Bellotti, Franco, and Cecioni (2021) used the SWAN model to dynamically downscale the ERA5 wave dataset and assemble a nearshore wave database with high spatial resolution along a stretch of the Western Italian coast. In that study, the dynamical downscaling was carried out forcing the nearshore model with JONSWAP spectra built from the ERA5 bulk wave parameters. The authors commented that, being the wave conditions in the area mainly unimodal, using directional spectra as boundary conditions would not significantly affect their results. The results presented in our work partially confirm the Bellotti, Franco, and Cecioni (2021)'s intuition as we have found only minor error differences among datasets associated with different BCs. In fact, when the totality of incoming wave conditions are considered, more rigorous BCs did not yield appreciable accuracy improvements in terms of wave height and longshore wave energy flux. More appreciable discrepancies were found in the wave direction prediction, with the boundary condition NI that led to an error increase of 13% with respect to the benchmark dataset NS.

The modest differences of error metrics between the three considered datasets dominated by unimodal sea conditions suggest that the use of BCs derived from wave partitions or directly from the directional wave spectra becomes crucial under multimodal sea conditions. However, as said, multimodal sea conditions are found to be rare at the three deepwater Mediterranean wave buoys considered here. Therefore, taking into account long time series characterized mainly by unimodal conditions, the use of BCs derived from integrated bulk wave parameters appears an acceptable approach. In fact, the advantages of forcing the nearshore model with a BC considering the real shape of the spectrum are likely to be hidden by other prevailing sources of uncertainties, such as poorly-resolved offshore wave spectra, biases in the wind dataset, model parameterization limitations and inaccuracies in the bathymetry database (Campos et al. 2019; Alday et al. 2022; Alonso and Solari 2021; Crosby et al. 2023; Agulles and Jordà 2024).

The benefit of using more detailed BCs, such as those linked with datasets NS and NP, becomes more apparent if we focus on multimodal sea states only. In this case, BCs derived from bulk wave parameters (dataset NI) resulted in an accuracy decrease, with the error ratio between the NI dataset and the reference dataset NS being 1.2 for significant wave height, 1.22 for mean wave direction, and 1.20 for longshore energy flux. The analysis of the incoming wave energy flux at the offshore boundary shows that the BC derived from bulk wave parameters tends to increase the amount of wave energy that enters into the numerical domain (see the positive slope of the regression line in Figure 13 showing the relationship between the energy fluxes from dataset NI and dataset NS). On the other hand, the accuracy deterioration brought by the dataset NP with respect to the dataset NS was of limited magnitude, with minor error discrepancies (the error increase was within 2% for significant wave height, mean wave direction and longshore energy flux). Therefore, the use of BCs derived from directional wave spectra or from the reconstruction of wave spectra from partitioned wave parameters becomes crucial for achieving an accurate nearshore wave predictions under multimodal sea conditions. The quantification of the importance of the BC preparation for the dynamical downscaling of the wave field in a semi-enclosed basin for fetch-limited waves can be considered a contribution of the present study. In an attempt to expand the scope of the current contribution, still bearing in mind the required caution, we can state that BCs derived from bulk wave parameters can be confidently used in wave downscaling routines only on those sites that are characterized

by a wave climate dominated by unimodal sea conditions. While wave downscaling routines on those sites in which multimodal sea conditions occur frequently need BCs that retain the information of wave partitions and thus derived from directional spectra or, alternatively, from partitioned wave parameters.

5. Conclusions

This paper reports the analysis of the impact of different types of wave boundary conditions (BCs) in a dynamical downscaling approach under fetch-limited wave conditions. One-year long spectral wave data proceeding from deepwater buoys allowed the validation of the large-scale WW3 simulations. SWAN model runs nested into the WW3 simulations provided three datasets (one dataset for each BC) over three different nearshore areas located in the Mediterranean Sea. The first BC was represented by the directional wave spectra extracted directly from the WW3 output (dataset NS). The reconstruction of wave spectra from wave partition parameters led to the second BC (dataset NP). The third BC was represented by wave spectra reconstructed from integrated bulk wave parameters (dataset NI). The benefit of using more rigorous and complex boundary conditions was assessed by comparing computed wave parameters with wave measurements in the nearshore. This work dedicates special attention to multimodal sea states in which wave systems with different characteristics coexist at the same time.

The one-year long records of three deep-water buoys located in Western Mediterranean showed sea states that were dominated by unimodal conditions, whereas multimodal conditions only occurred on limited time spans (between 3 and 11% of the time). WW3 simulations forced with ERA5 wind data reproduced the main wave evolution observed at the deep-water buoys. With the ST6 parameterization CDFAC parameter value equal to 1.2, we achieved error metrics of the same order of magnitude of those of the publicly available CMEMS dataset. One-year long datasets computed with SWAN and proceeding from the three tested BCs yielded modest differences in error metrics in terms of wave height and longshore energy flux in the nearshore. More appreciable discrepancies were observed in the direction prediction, with the less rigorous boundary condition NI that led to an error increase of 13% with respect to the benchmark dataset NS. The modest differences of error metrics between the three considered datasets suggest that the use of BCs derived from integrated bulk wave parameters appears an acceptable approach for sites in which incoming wave conditions are dominated by unimodal sea states, such as the three Mediterranean sites taken into account in this work.

Narrowing the attention on multimodal sea states only, dataset NI overall yielded larger errors on significant wave height, mean wave direction and longshore energy fluxes with respect to the datasets NS and NP. Moreover, data suggest that dataset NI can increase the wave energy that enters into the numerical domain. We observed an error increase, with respect to the reference dataset NS, of 20% in terms of significant wave height and 22% in terms of mean wave direction. Dataset NI also brought a significant accuracy deterioration of longshore energy flux predictions, with normalized error values that rose from 0.70 of dataset NS to 0.84 of dataset NI. Conversely, the accuracy deterioration brought by dataset NP with respect to dataset NS was of limited magnitude, with minor error discrepancies. This outcome suggests that an accurate definition of wave BCs achieved by the use of the directional wave spectra or, in alternative, by the reconstruction of wave spectra from partitioned wave parameters

669 becomes crucial for nearshore wave predictions under multimodal sea conditions.

670 Acknowledgement(s)

671 This study has been conducted using E.U. Copernicus Marine Service Informa-
672 tion. The authors thank the developers of the scientific package wavespectra
673 (<https://github.com/wavespectra>). Alain Le Berre of CEREMA is acknowledged for
674 providing the directional wave spectra of the deep-water buoys. We thank the two
675 reviewers for providing a timely review of this work.

676 Disclosure statement

677 No potential conflict of interest was reported by the authors.

678 Funding

679 This work has been financially supported by MUR (Ministero dell’Università e della
680 Ricerca of Italy) under PON “Ricerca e Innovazione” 2014-2020 (D.M. 1062/2021),
681 Azione IV.6, grant number 04-G-14285-1.

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Table 1. Physical parameters at the deepwater and nearshore buoys. The last column lists the percentage of multimodal MM conditions recorded at the deepwater buoy locations.

Buoy	lon [°]	lat [°]	depth [m]	$H_{s,50}$ [m]	$H_{s,95}$ [m]	% MM
Deep water						
Revellata	8.65	42.57	130	0.76	2.83	11
Alistro	9.64	42.26	120	0.53	1.47	3
Porquerolles	6.20	42.97	90	0.83	2.42	6
Nearshore						
Palma	2.70	39.49	30	0.29	1.12	-
Espiguette	4.13	43.43	32	0.50	1.70	-
Bastia	9.45	42.67	17	0.28	1.20	-

Table 2. ST6 parameterization settings in WW3.

	a_1	p_1	a_2	p_2	Υ	CDFAC
ST6	4.75E-6	4	7E-5	4	32	1.1, 1.2

Table 3. Error metrics of WW3-computed output in deep water

	H_s		T_m		θ_m	
	NRMSE [-]	NB [-]	NRSME [-]	NB [-]	RSME [$^\circ$]	B [$^\circ$]
Revellata 02B04 - Depth = 130m						
CMEMS	0.22	-0.16	0.16	0.01	16.85	2.67
ST6.1	0.26	-0.24	0.12	-0.04	19.48	3.43
ST6.2	0.22	-0.18	0.12	-0.02	19.39	3.32
Alistro 02B05 - Depth = 120m						
CMEMS	0.21	-0.08	0.16	-0.09	28.78	-0.68
ST6.1	0.28	-0.21	0.16	-0.12	29.22	1.03
ST6.2	0.25	-0.15	0.15	-0.09	29.30	1.02
Porquerolles 08302 - Depth = 90m						
CMEMS	0.18	-0.02	0.12	-0.07	25.61	3.34
ST6.1	0.19	-0.08	0.12	-0.07	28.90	7.43
ST6.2	0.19	-0.01	0.11	-0.05	28.85	7.37
All buoys						
CMEMS	0.19	-0.05	0.14	-0.07	26.11	1.94
ST6.1	0.23	-0.15	0.13	-0.08	27.43	4.54
ST6.2	0.21	-0.08	0.12	-0.06	27.42	4.48

Table 4. Error metrics of SWAN-computed results proceeding from different boundary conditions in shallow water.

	H_s		T_m		T_p		θ_m	
	NRMSE	NB	NRSME	NB	NRSME	NB	RSME	B
	[-]	[-]	[-]	[-]	[-]	[-]	[°]	[°]
All buoys								
NS	0.19	-0.04	0.19	-0.15	0.18	0.01	22.08	-5.73
NP	0.19	-0.06	0.20	-0.16	0.18	-0.00	22.51	-6.62
NI	0.20	-0.05	0.19	-0.15	0.19	-0.01	24.93	-8.49

Table 5. Recent studies dealing with wave downscaling categorized based on the adopted boundary condition (BC) technique.

NS
Stokes et al. (2021)
Alday et al. (2022)
Valiente et al. (2023)
Wandres, Espejo, and Damlamian (2023)
NP
Alonso and Solari (2021)
Ruju et al. (2022)
Espejo et al. (2023)
Ricondo et al. (2023)
NI
Bellotti, Franco, and Cecioni (2021),
De Leo et al. (2022),
Agulles and Jordà (2024),
Lucio et al. (2024)



Figure 1. Geographical settings and buoy locations. Panel a) shows the deep-water buoys location: Revellata, Alistro and Porquerolles. Panels b), c) and d) show the nearshore buoy locations: Palma, Espiguette, Bastia. Depth values are placed over the isobath lines.

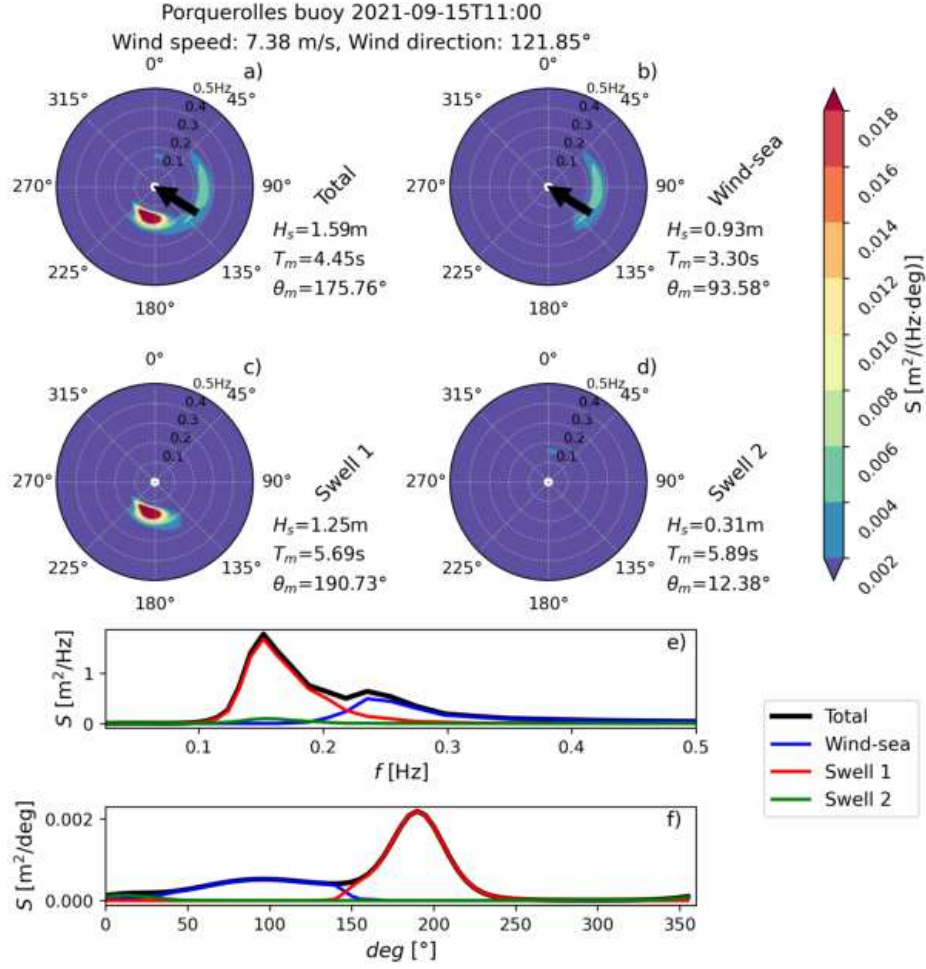


Figure 2. Example of output of the spectral partition routine at Porquerolles buoy. a) 2D spectrum, b) wind-sea partition, c) swell 1 partition (most energetic swell wave system), d) swell 2 partition (second-most energetic swell wave system), e) 1D frequency spectra, f) 1D directional spectra. The arrows in panels a) and b) indicate the wind direction.

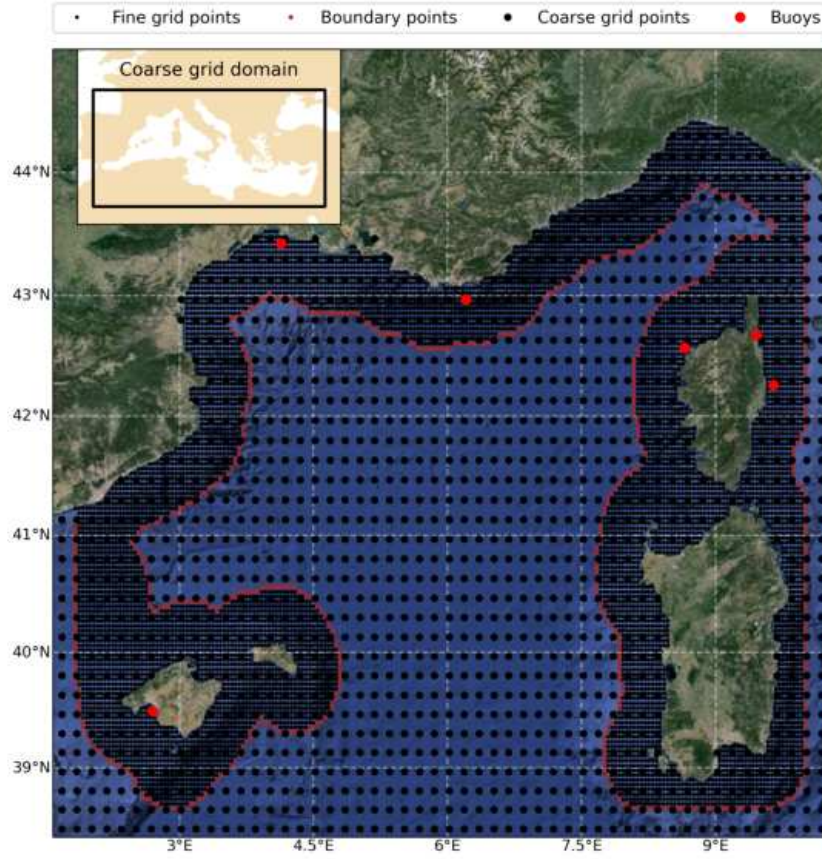


Figure 3. Detail of the WW3 coarse and fine grids. The red points indicate the deepwater and nearshore buoy locations. The large black dots indicate the grid points of the coarse grid. The small black and brown dots represents, respectively, the grid points and the boundary points of the fine grid. The box in the upper-left corner shows the coarse grid domain extending over the entire Mediterranean basin.

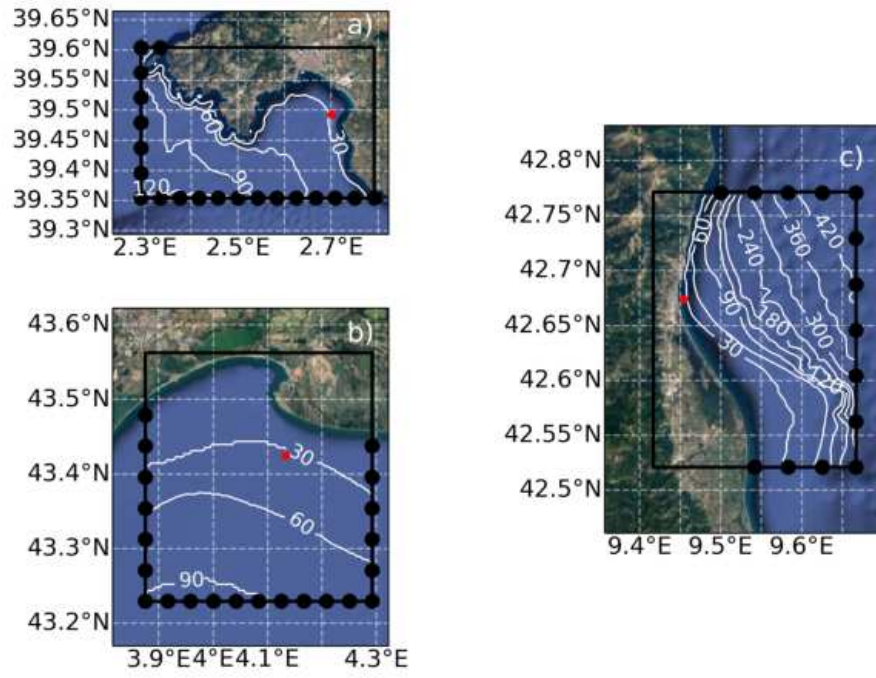


Figure 4. Extension of SWAN grids (black line). Boundary conditions are imposed on the locations indicated by the black points. a) Palma, b) Espiguette, c) Bastia. Depth values are placed over the isobath lines.

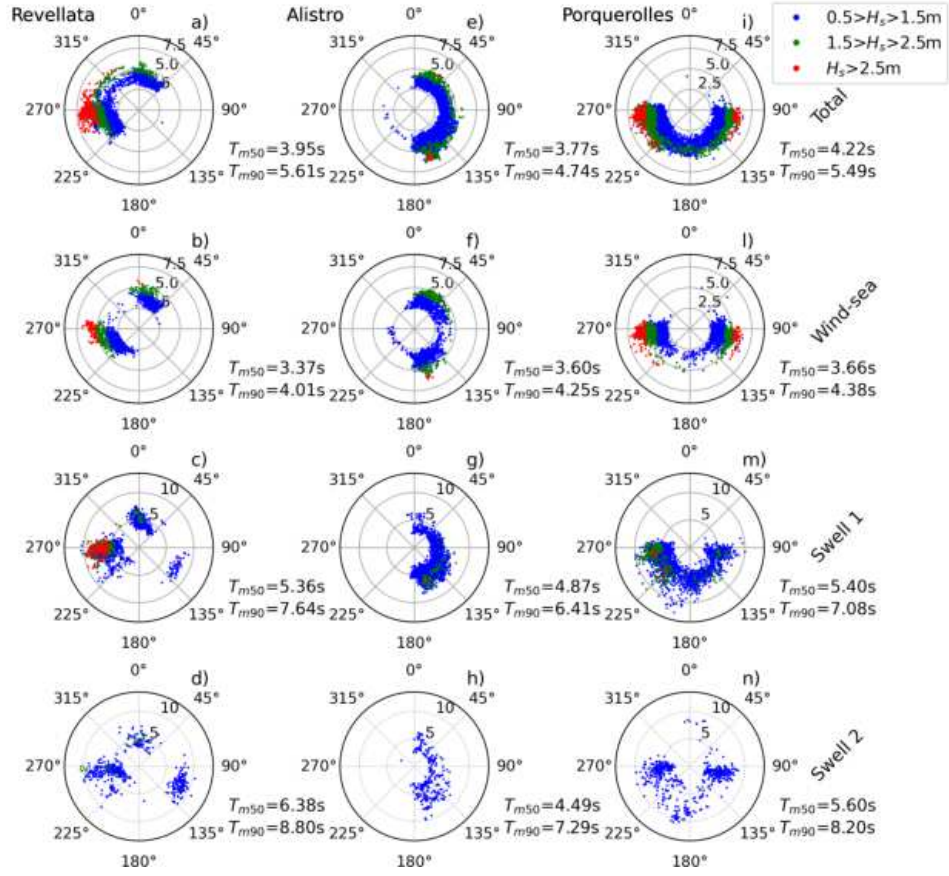


Figure 5. Polar plots of mean wave periods T_m at the three deep-water buoys. The color indicates the class of H_s . Total: a), e) and i). Wind-sea partition: b), f) and l). First swell partition: c), g) and m). Second swell partition: d), h), n).

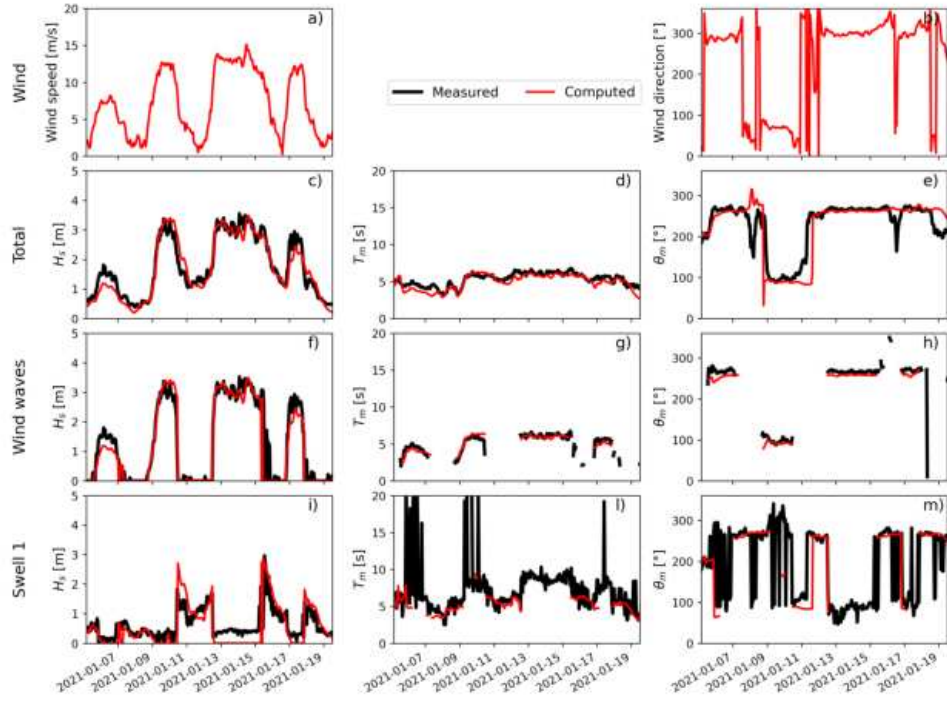


Figure 6. Observed (black line) and predicted (red line) time series of bulk wave parameters (panels c), d), e)) wind partition parameters (panels f), g), h)) and primary swell partition parameters (panels i), l), m)) at the Porquerolles wave buoy during January 2021. Panels a) and b) only show ERA5-computed winds.

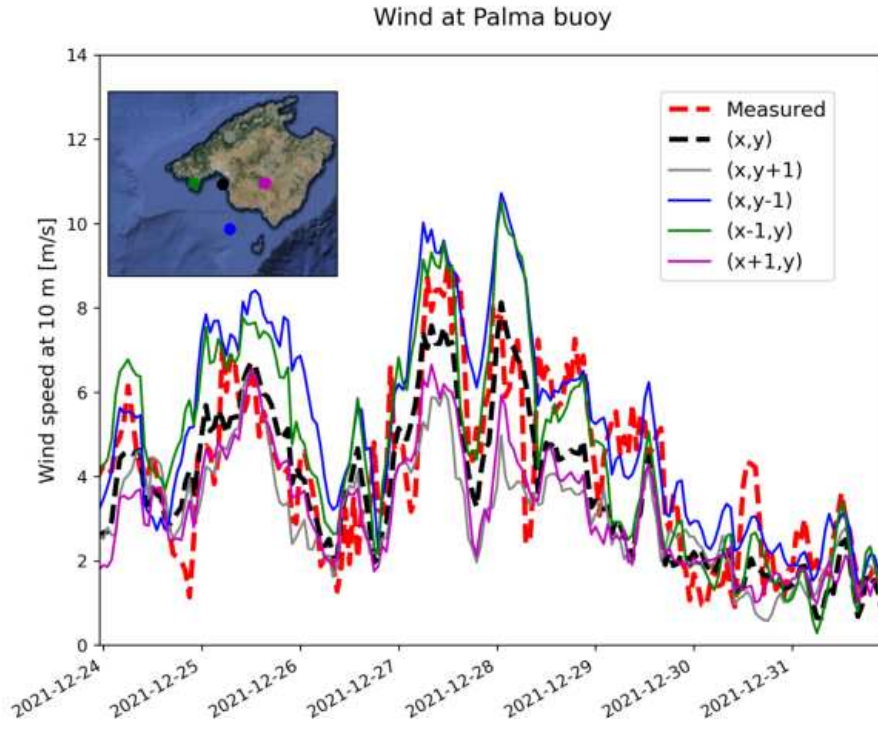


Figure 7. Comparison of 10 m wind speed at Palma buoy. The dashed red line is for the observations, the black dashed line indicates the ERA5 wind at the buoy location and other colors are the values from ERA5 at the neighboring points.

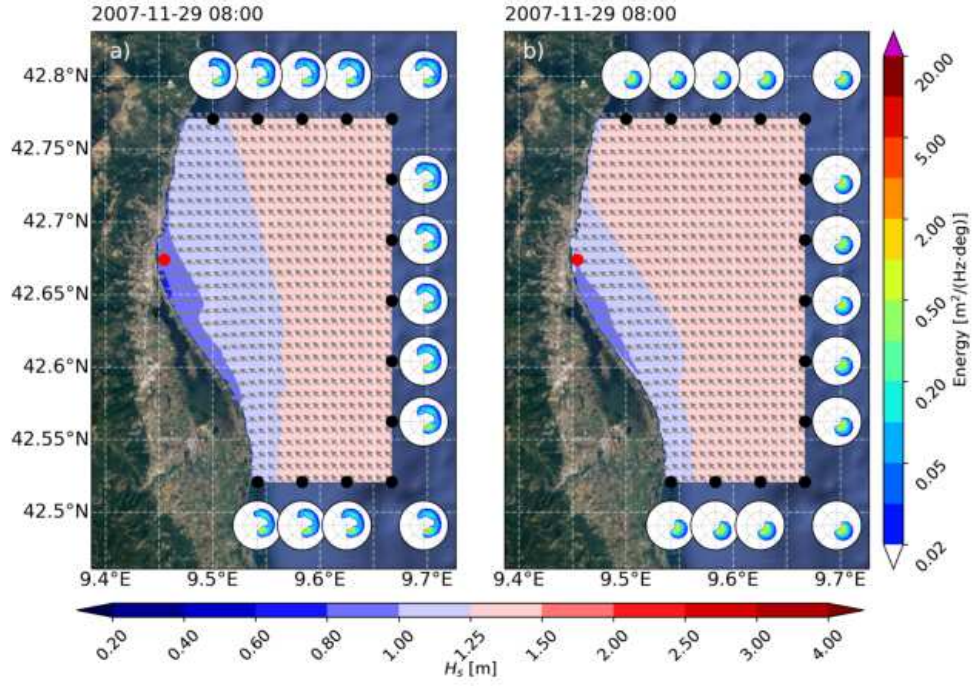


Figure 8. Comparison of H_s field from datasets NS (a) and NI (b) computed by SWAN. Polar plots along the boundary are the BCs from WW3 simulations. The red dot indicates the Bastia buoy location. The grey arrows indicate the mean wave direction.

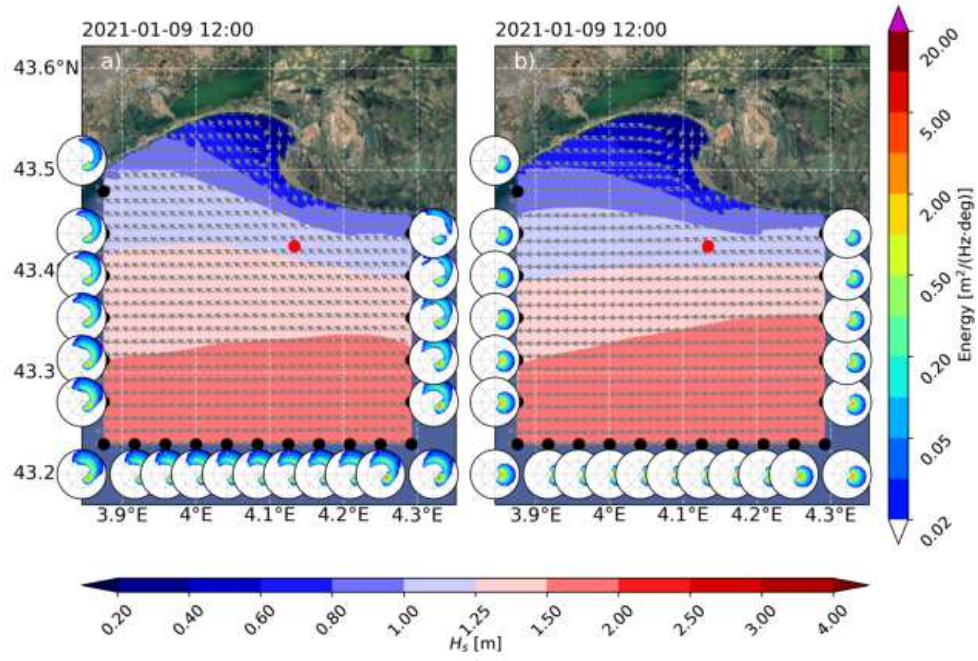


Figure 9. Comparison of H_s field from datasets NS (a) and NI (b) computed by SWAN. Polar plots along the boundary are the BCs from WW3 simulations. The red dot indicates the Espiguette buoy location. The grey arrows indicate the mean wave direction.

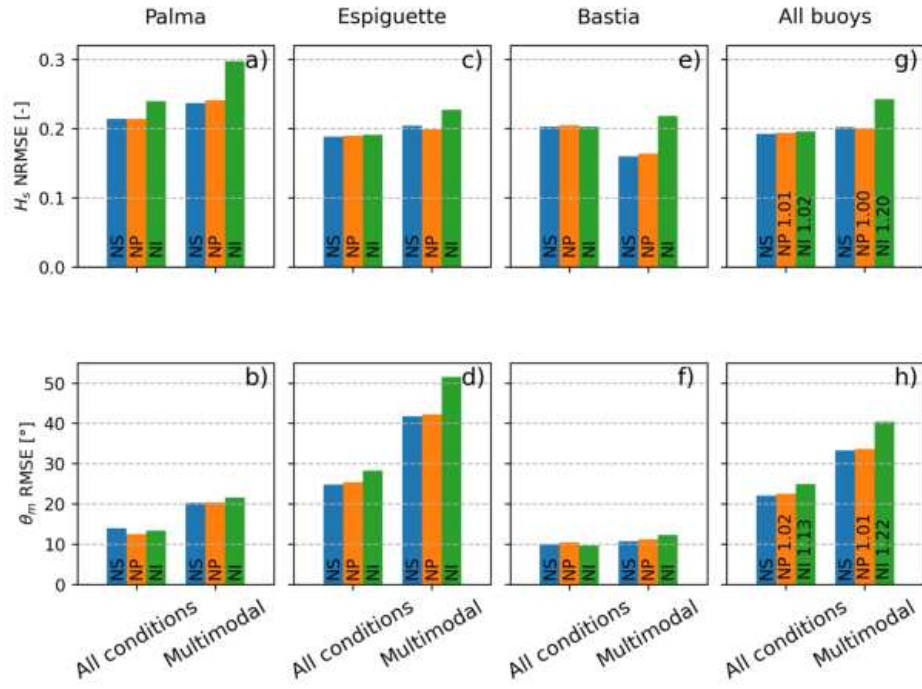


Figure 10. Significant wave height H_s NRMSE and mean wave direction θ_m RMSE metrics of the three datasets in the nearshore. In panels g) and h) the numbers inside the bars of the histogram specify the ratio between the error of the dataset and that of the reference dataset NS.

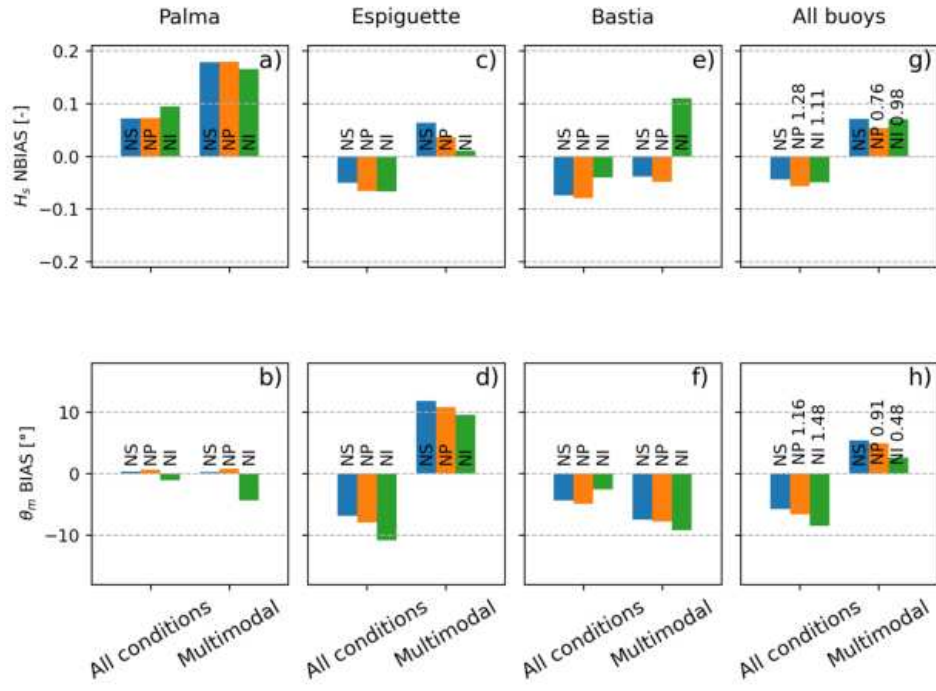


Figure 11. Significant wave height H_s NBIAS and mean wave direction θ_m BIAS metrics of the three datasets in the nearshore. In panels g) and h) the numbers inside the bars of the histogram specify the ratio between the error of the dataset and that of the reference dataset NS.

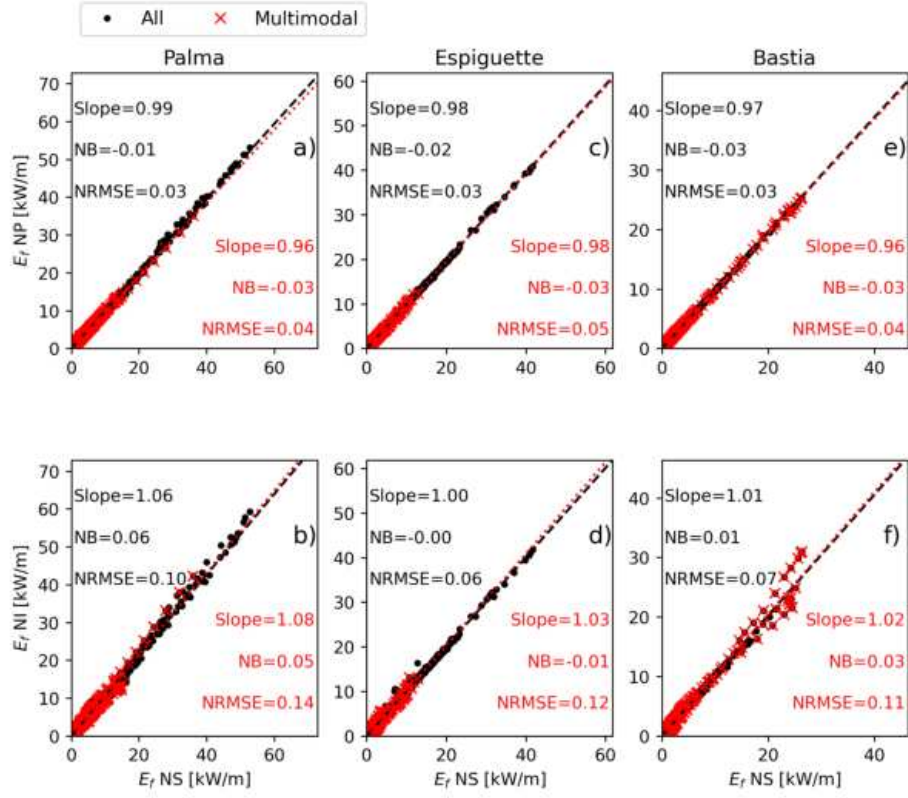


Figure 13. Scatter plots incoming energy flux at the open boundary computed from reconstructed (datasets NP and NI, vertical axis) and directional WW3 (dataset NS, horizontal axis) wave spectra. Black markers indicate all conditions, red markers are for multimodal conditions. The dashed lines represent the best-fit lines.

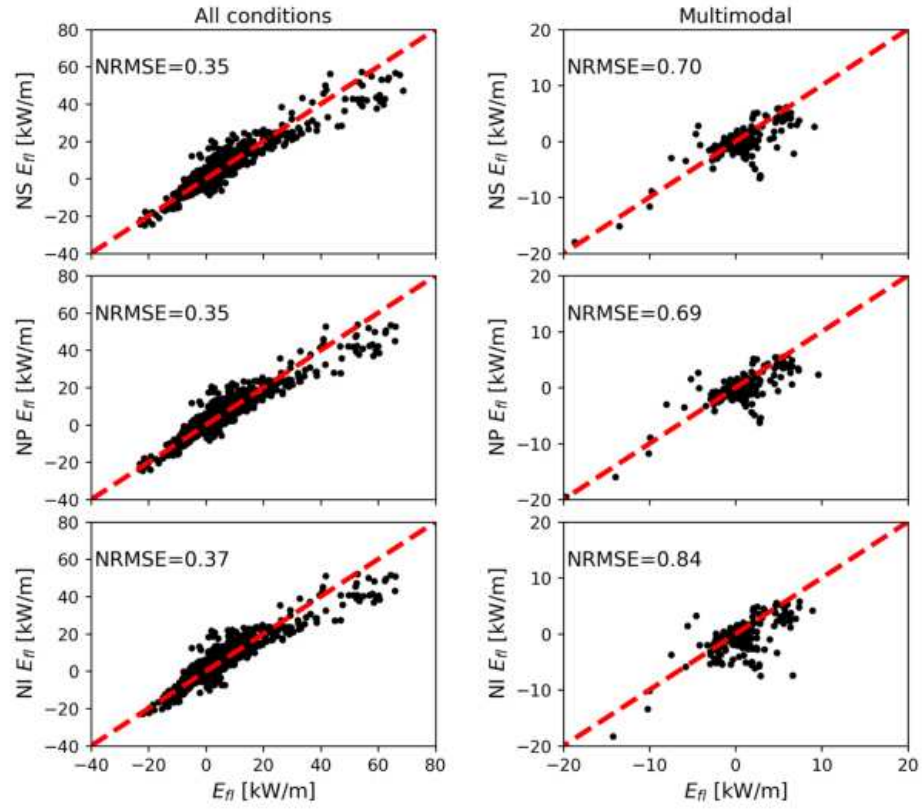


Figure 14. Scatter plots of computed (datasets NS, NP and NI) versus measured longshore energy flux F_{fl} . The red dashed line is the line of perfect agreement.