DELWAVE 1.0: Deep-learning surrogate model of surface wave climate in the Adriatic Basin

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Abstract. We propose a new point-prediction DEep Learning WAVe Emulating model (DELWAVE) which successfully emulates the behaviour of a numerical surface ocean wave model (SWAN) at a sparse set of locations, thus enabling numerically cheap large-ensemble prediction over synoptic to climate timescales. DELWAVE training inputs consist of 6-hourly surface COSMO-CLM wind fields during period 1971 - 1998, while its targets are significant wave height, mean wave period and mean wave direction. Testing input set consists of surface winds during 1998-2000 and cross-validation period is the far-future climate timewindow of 2071-2100. DELWAVE is constructed to have a convolution-based atmospheric encoder block, followed by a temporal collapse block and finally a regression block. Random importance-sampling was performed to better model underpopulated tails of variable data distributions. Detailed ablation studies were performed to determine optimal performance regarding input fields, temporal horizon of the training set and network architecture. DELWAVE reproduces SWAN model significant wave heights with a mean absolute error (MAE) between 5 and 10 cm, mean wave directions with a MAE of 10°-25° and mean wave period with a MAE of 0.2 s. DELWAVE is able to accurately emulate multi-modal mean wave direction distributions, related to dominant wind regimes in the basin. We use wave power analysis from linearized wave theory to explain prediction errors in the long-period limit during southeasterly conditions, indicating, as expected, that non-local generation of swell poses a more difficult challenge during long-fetched Scirocco than during cross-basin Bora flow. We present a storm analysis of DELWAVE, employing threshold-based metrics of precision and recall to show that DELWAVE reaches a very high score (both metrics over 95%) of storm detection. SWAN and DELWAVE time series are compared against each other in the end-of-century scenario (2071-2100), and compared to the control conditions in the 1971-2000 period. Good agreement between DELWAVE and SWAN is found when considering climatological statistics, with a small ($\leq$5%), though systematic, underestimate of 99th percentile values. Compared to control climatology over all wind directions, the mismatch between DELWAVE and SWAN is generally small compared to the difference between scenario and control conditions, suggesting that the noise introduced by surrogate modeling is substantially weaker than the climate change signal.

1 Introduction

The multi-decadal characterisation of wave climate is a primary requirement for a number of applications. Coastal erosion, particularly in sandy, low-lying beaches, is largely dominated by wave-induced sediment transport at multiple time scales, with a short-term response at the seasonal, or even at the event scale, mainly given by cross-shore fluxes, and a long-term response at the annual to decadal scale resulting from the modulation of long-shore sediment fluxes and their spatial gradients (USACE, 2002). In transitional environments, wave climate can significantly affect morphodynamic processes both directly, by locally reworking morphological features such as shoals and salt marshes (Friedrichs, 2011), or indirectly, by controlling the potential sediment supply from the open coast (Di Silvio et al., 2010; Tognin et al., 2021). Wave climate is also an important factor controlling the safety and durability of human infrastructures, along the coast as well as offshore. Not least, in the framework of an ever-increasing demand for energy availability, particularly from renewable sources, information on wave climate and its variability is crucial for assessing the feasibility and improving the design of wave energy converter facilities (Astariz and Iglesias, 2015).

In recent decades, the progressively deeper understanding of the physical mechanisms underlying wave dynamics, together with an increasing availability of computational power, have contributed making wave modelling the reference tool for a number of applications at different scales, from short-term forecasting to multi-decadal hindcasting and climate predictions (Cavaleri et al., 2007; Morim et al., 2020). Nonetheless, surface ocean wave modeling in particular is very numerically expensive. This is related to the fact that surface waves typically span deeply subgrid short spatial and temporal scales which are very far from being resolved in most ocean general circulation models. Modeling surface waves therefore typically translates into solving evolution equations of the directional wave-energy spectrum, requiring direction and frequency discretization at each model grid point, thus inflating computational demand. Furthermore, notwithstanding the continuous improvements, and particularly when dealing with long-term projections, numerical modelling maintains an intrinsic uncertainty at different levels. This impacts the very evolution of the global climate but also the propagation of the climate signal through different scales and systems, as well as the numerical description and parameterization of the processes involved. Part of this uncertainty can be addressed by means of an ensemble approach, in which multiple model descriptions are provided by considering different physical characterisations and different composition of the modelling chain (Parker, 2013). This approach comes at the cost of multiplying, usually by a factor of order 10, the requirements for computational power and data storage. This tends to limit the feasibility of extensive studies on future wave climate, particularly at the regional to local scale, and can require some heavy trade-off in terms of resolution, geographical and temporal coverage, or size of the model ensemble.

Deep learning has shown a great potential to address these issues without hindering performance. It has found its way across multiple fields of science, including machine vision, natural language processing, and, more recently, in various subfields of meteorology (Janssens and Hulshoff, 2022; Beucler et al., 2021; Rasp et al., 2018) and oceanography (Barth et al., 2022; Sonnewald et al., 2021; Boehme and Rosso, 2021; Žust et al., 2021; Mallett et al., 2018). With particular reference to wave dy-

namics applications, James et al. (2018) proposed a machine learning system for predicting the steady-state response of the sea state in a coastal area to a given wind configuration, whereas Rodriguez-Delgado and Bergillos (2021) developed a framework for propagating onshore the open-sea information on incoming waves for renewable energy production purposes. In specific cases and for specific tasks deep learning methods have been shown to achieve state-of-the-art performance while keeping numerical costs low. This allows for performance gains which are often welcome, especially when considering computational requirements of classical geophysical numerical models on high spatial resolutions and on climate timescales.

In this paper we present a newly developed deep learning method, named DELWAVE, for emulating, at a computational price smaller by several orders of magnitude, non-stationary modelled surface sea states in response to given wind fields. The study site is the Adriatic Sea, a 200 km wide and 800 km long elongated epicontinental basin in the north-central Mediterranean. It is surrounded from all sides by the mountain ridges (Apennines in the west, Alps in the north and Dinaric Alps in the east) which topographically constrain winds over the basin (Figure 1). From the modelling point of view, this condition requires a high-resolution description of the atmospheric dynamics and a fine tuning of the physical parameterizations both at the air-sea and at the land-sea interfaces (Cavaleri et al., 2018). Dominant wind-wave forcings consist of the cold northeasterly Bora and warmer southeasterly Scirocco winds. Bora events are predominantly winter (November through March) occurrences of cross-basin continental air flow through the Dinaric orographic barriers over the Adriatic Sea. Scirocco is on the other hand a southerly wind transporting warm and moist air masses from northern Africa over the Adriatic, which can persist for several days and is channeled by the Apennines and Dinaric alps into an along-axis wind with a fetch much longer than in case of Bora. Wave dynamics in the Adriatic Sea are thus controlled by short-fetched wind seas and long-fetched swells, occasionally coexisting, propagating over a broad and shallow continental margin, and characterised by different multi-decadal trends (Pomaro et al., 2018) and possibly different responses to climate change (Bonaldo et al., 2020). As a typical example of some major challenges associated with wave modelling in semi-enclosed and coastal seas, the Adriatic Sea appears as a suitable testing site for wave model emulation within the DELWAVE framework.

DELWAVE is based on well established network architecture components, adapted to the field of wave forecasting, and it is benchmarked against SWAN performance, both models being forced by the COSMO-CLM atmospheric climate model of the far future (2071-2100) climate in the Adriatic basin (Bonaldo et al., 2020). The paper is organized as follows. Classical geophysical models, COSMO-CLM for atmosphere and SWAN for surface wave modeling, are described in Section 2. DELWAVE deep network is thoroughly discussed in Section 3. Results and the far future climate simulations are presented in Section 5.

2 Numerical Models and Datasets

The wind and wave fields used as a reference for this application were retrieved from the numerical modelling chain described by Bonaldo et al. (2020) for the projection of future wave climate in a severe climate change scenario.
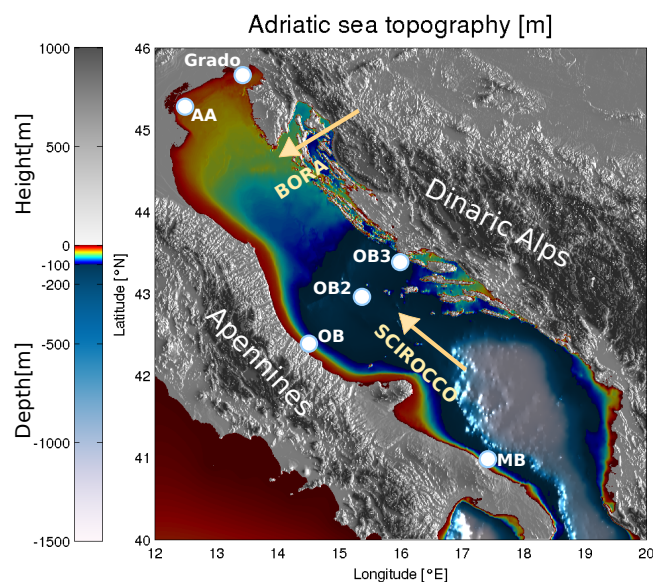
Figure 1. Topography and bathymetry of the Adriatic region. Abbreviations used on the map are as follows: AA - Acqua Alta tower, OB (2,3) - Ortona Buoy (2,3), MB - Monopoli Buoy. Directions of Bora and Scirocco are marked with beige arrows. The image was created by the authors based on EMODnet bathymetry data, available at https://portal.emodnet-bathymetry.eu/ (last access: 8 June 2022) and Copernicus European Digital Elevation Model, available at https://land.copernicus.eu/imagery-in-situ/eu-dem/eu-dem-v1-0-and-derived-products/eu-dem-v1.0 (last access: 8 June 2022).

2.1 Atmospheric Climate Model COSMO

90 The wind fields used for the present applications were retrieved from an implementation of the Regional Climate Model (RCM) COSMO-CLM (Bucchignani et al., 2016), the climate version of the operational forecast model COSMO-LM (Steppeler et al., 2003), implemented over Italy and central Europe at a 0.0715° horizontal resolution (approximately 8 km, total 224 × 230 grid points), forced by the General Circulation Model (GCM) CMCC-CM (Scoccimarro et al., 2011). In that implementation the analysed period spanned from 1971 to 2100 reproducing first the CMIP5 historical experiment in the 1971-2005 period, and
95 subsequently parting into two independent runs representing respectively the IPCC RCP4.5 (intermediate) and RCP8.5 (severe) scenarios. The evaluation of the model showed particularly good skills in reproducing the climatic features of air temperature and precipitation over Italy (Bucchignani et al., 2016; Zollo et al., 2016). A subsequent focus on the wind fields over the Adriatic sea (Bonaldo et al., 2017), whose reproduction is a challenging task also for hindcast and operational models due to the geometry of the basin and its complex coastal orography, highlighted outstanding skills for both intensity, although with
100 some tendency to overestimate mean wind energy, and direction. Most interestingly for ocean modelling applications, COSMO-CLM proved capable of capturing the bimodality of Bora (north-easterly) and Sirocco (south-easterly) in the northernmost part of the basin, impossible to reproduce for previous climate models (Bellafiore et al., 2012). In a recent work (Benetazzo et al.,

2022) COSMO-CLM was also used to quantile-adjust near-surface wind speeds from ECMWF ERA5 reanalysis, thus merging the accuracy of the former with the higher temporal resolution and the synchronization with observed variability of the latter.

105 For the wave modelling experiment described by Bonaldo et al. (2020) and for the present work the COSMO-CLM wind fields over the Adriatic Sea were retrieved for two 30-year periods in control conditions in the recent past (CTR, 1971-2000) and in the future in a severe RCP8.5 climate scenario (SCE, 2071-2100).

2.2 Wave Model SWAN

The modelling run described by Bonaldo et al. (2020) and providing wave data for this application was ~~thus~~ implemented

110 in SWAN with reference to the Adriatic Sea in the CTR and SCE periods. SWAN provides a phase-averaged description of wind-generated sea states by solving a non-stationary wave action balance equation (Booij et al., 1999):

$$\frac{\partial N}{\partial t} + \frac{\partial c_x N}{\partial x} + \frac{\partial c_y N}{\partial y} + \frac{\partial c_\sigma N}{\partial \sigma} + \frac{\partial c_\theta N}{\partial \theta} = \frac{S_w}{\sigma} \qquad (1)$$

N represents the action density, namely, the wave energy density divided by the relative frequency, and t is time. The propagation of N (second to fifth term in Eq. 1) is described in 2-D space (x and y, expressible in both Cartesian and spherical

115 coordinates, with speed respectively c_x and c_y), and spectral space (radian frequency σ, relative to a frame moving with the ocean current, and angle θ normal to the wave crest, speed respectively c_σ and c_θ). S_w represents sources and sinks of wave energy density associated with generation, dissipation, and non-linear wave-wave interactions.

For the application presented here, the domain was discretised into an orthogonal curvilinear structured grid with horizontal

120 resolution ranging from approximately 2 km in the northern region to 8-10 km in the southeasternmost part of the study area. Calm conditions were prescribed at the open boundary at the Otranto Strait, where waves generated within the basin were nonetheless permitted to radiate out of the domain. This assumption was made necessary by the lack of available wave fields consistent with the atmospheric forcing at the Mediterranean scale, but the validation confirmed that no major drawbacks in the results could be found beyond 100-200 km from the boundary. Wave spectra were discretised into 25 logarithmically-distributed

125 frequencies ranging between 0.05 and 0.5 Hz and 36 directional sectors, whereas the timestep was set to 360 s. The bathymetry was reinterpolated from a 1-km resolution dataset used in previous applications (Benetazzo et al., 2014; Bonaldo et al., 2016) and obtained by merging recent surveys in the shallow northern basin and in the southern continental margin into previous basin-scale information. Sea level rise between the CTR and SCE period was taken into account by increasing the water depth in the latter scenario by 0.70 m, based on estimates by Antonioli et al. (2017), for the sake of simplicity uniformly distributed

130 throughout the domain. As wind forcings from COSMO-CLM were provided with 6-hourly timestep, the same interval was maintained for the output, in which the main spectral parameters were saved for each grid point and the full spectra were saved for approximately 600 points along the Adriatic coast. The model validation was based on directional wave recordings from three observatories off the Italian coast along the main axis of the basin, namely the Acqua Alta oceanographic tower (AA,
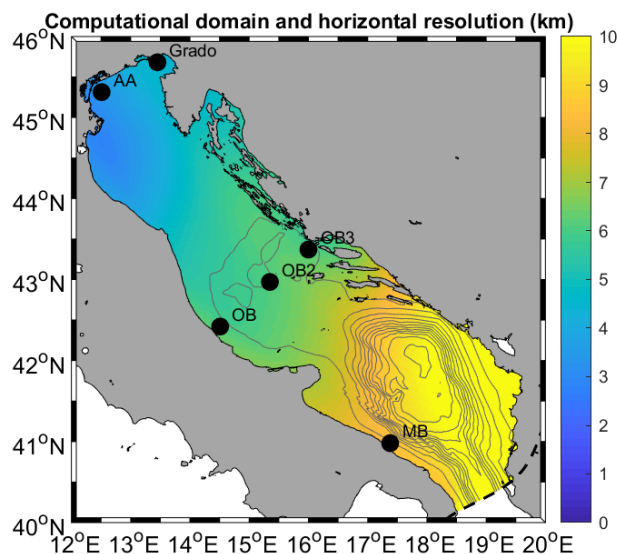
Figure 2. Geographical domain, validation stations and locations considered in SWAN and DELWAVE modeling.

12.51 °E, 45.31 °N, see Pomaro et al. 2018), and the Ortona and Monopoli buoys (respectively OB, 14.51°E, 42.42°N, and

135 MB, 17.38°E, 40.98°N, Figure 2).

The comparison against observational data (carried out in statistical terms, as climate models are not synchronised with observed variability) was focused on significant wave height (H_S) and mean direction showed overall satisfactory performances for the SWAN implementation. The reported tendency of COSMO-CLM to overestimate mean wind energy had actually a moderate impact on wave modelling, being partially compensated by other factors such as the southern boundary conditions

140 and some residual limitations in reproducing orographic jets, and its more marked effect was a partial overestimate of significant wave height statistics in the southernmost regions of the basin.

The end-of-century projections in a severe climate change condition outlined a composite scenario. While H_S in mean and stormy conditions appeared to decrease in most of the basin and for most directions, the effect of storms from the southern

145 quadrant (southwest to southeast) on the northern Adriatic Sea resulted expected to intensify. This result, interpreted as a consequence of a northbound shift of the storm tracks (Trenberth et al., 2003; Giorgi and Lionello, 2008) in the Mediterranean region, was shown to have significant implications for the coastal regions. Besides the obvious impact of stronger storms where this will happen, and besides the baseline sea level rise exacerbating the effect of storms even when their intensity are expected to decrease (Lionello et al., 2017), the spatial variability in the impact of climate change will result in a modification of the

150 patterns of energy fluxes onto and along the Adriatic coast, thus modifying the sediment transport rates and gradients and ultimately coastal morphodynamic processes.

2.3 Training and evaluation datasets

Training and the application of DELWAVE was based on basin-wide wind fields from COSMO-CLM and pointwise wave time
series at six locations exposed to different wave climates (Figure 2). AA (12.51 °E, 45.31 °N), OB (14.51 °E, 42.42 °N), and
MB (17.38 °E, 40.98°N) which coincide with the observation points used for the SWAN model validation in Bonaldo et al.
(2020) and are representative of nearshore conditions respectively along the northern, central and southern Italian coast. Grado
(13.45 °E, 45.68 °N) lies at the edge of the gulf of Trieste in the northernmost end of the Adriatic Sea, facing south and is
partially sheltered by the Istrian peninsula. OB2 (15.35 °E, 42.97 °N) and OB3 (16.00 °E, 43.37 °N) are located along an ideal
transect off Ortona respectively in the middle of the basin and along the Croatian coast. Wind fields are provided as six-hourly
meridional and zonal components, whereas wave data, also six-hourly, are given in terms of significant wave height (H_S),
mean wave direction (d), and energy period ($T_{m-1,0}$). The model data from the control (CTR) period (1971-2000) were used
for the network training, whereas future scenario (SCE, 2071-2100) data were used as a reference for assessing the network
skills, particularly in terms of its capability to capture the features of the climate signal.

3 DELWAVE

In this section we present our DEep Learning WAVe Emulator (DELWAVE). DELWAVE is constructed from three logically
separate parts. We proceed by providing an overview of the model input fields. Following that, we describe the DELWAVE
architecture in detail and further argument specific model architecture decisions using ablation studies.

3.1 Model input fields

3.1.1 Wind field

The input (wind) fields described in Section 2 have a spatial dimension of 90 by 89 and are represented at each timestep as a
three dimensional tensor of dimensions $[2, 90, 89]$, where the first dimension corresponds to either u or v components of the
wind vector. The initial wind input tensor consists of a temporal sequence of three dimensional tensors mentioned above, and
we denote the temporal input slices as I_l^t. Here the exponent t signifies the timestamp of the wind field and the subscript l the
location for which we are predicting.

3.1.2 Location encoding

DELWAVE atmospheric input is further complemented by a spatial encoding matrix which introduces positional information to
the network. Location encoding takes the form of a sparse matrix with values corresponding to a radially symmetric Gaussian
distribution with variance of 20, normalized to the interval $[0, 1]$, centered at the location of the prediction point. This Gaussian
location encoding field is then added to the input tensor I_l^t, increasing its dimension to $[3, 90, 89]$. Gaussian encodings of
all stations are illustrated in Figure 3. This input provides the necessary information for the model to distinguish between
the different locations for which we request surface wave predictions. Indeed, without this encoding the model did gravitate
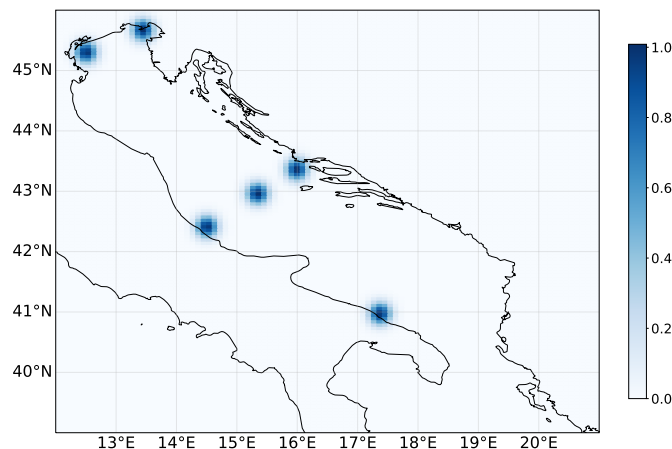
Figure 3. Training location encoding at each point consists of a radially symmetric Gaussian distribution around the location of the training point. The values are scaled to the interval $[0,1]$. Note that while all training points are depicted here, only a single Gaussian, i.e. the one corresponding to the training location, is used during training at that location.

towards an average prediction for all stations, as it was unable to differentiate between the inputs. Additionally, as the encoding is passed to the network in terms of a "spatial hint" the network gravitates towards extracting spatial information in the vicinity of the spatial encoding.

Next, a coordinate grid-encoding matrix (not shown), monotonously encoding each grid point with a unique value between 0 and 1 for each of the 90 by 89 grid points, is further added the input tensor, bringing the dimension to $\dim(I_l^t) = [4, 90, 89]$. The grid encoding matrix aims to help convolutional layers to encode spatial information, since convolutions are by design location agnostic. In our case, the location of wind feature typically matters since it determines the wind fetch, therefore an encoding of this sort is beneficial.

3.1.3 Temporal extent

Surface wave field at a specific location consists of the local wind sea and of the incoming swell, generated remotely in the hours preceding forecast time t. Consequently predictions at time t require additional wind inputs from times preceding t. The number of preceding timesteps was estimated using deep-water dispersion relation for gravity waves $\omega^2(k) = gk$ and corresponding wave phase speed $c_f = \omega/k = (g/k)^{1/2} = (g\lambda/2\pi)^{1/2}$. Using an estimate of surface wave wavelength $\lambda = 40$ meters, indicates that such waves traverse basin scale distances in about a day and a half. We consequently estimate that the wave field at a given location can be influenced by remotely generated swell over distances, traversed by swell waves in about 1 to 1.5 days, corresponding to about $10-14$ timesteps in three-hourly resolution input. We rounded this down to 10 temporally preceding timesteps.

We therefore take 10 preceding wind inputs from consecutive time instants leading up to t, namely $[I_l^{t-10}, I_l^{t-9}, \ldots, I_l^{t-1}, I_l^t]$, totaling in 11 wind tensors, concatenated into the final input tensor structure with dimensions $\dim(I_l^t) = [11, 4, 90, 89]$.
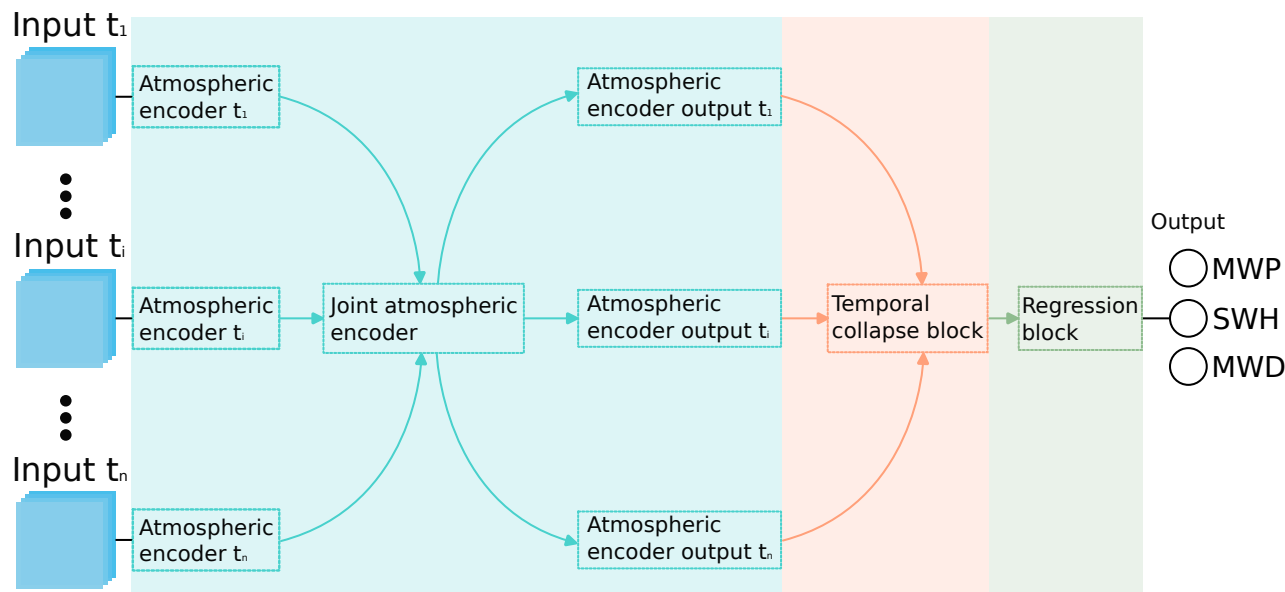
Figure 4. DELWAVE architecture overview. The network is comprised of three logically distinct sections. Each section is denoted using a different color. The information in the network flows from left to right. Inputs t_i denote the n timesteps passed to the network, while MWP, SWD, and MWD denote mean wave period, significant wave height, and mean wave direction, respectively.

To sum up, we end up with 11 timesteps of 4 fields (zonal wind, meridional wind, Gaussian station location encoding, linear grid encoding) over a spatial grid of 90×89 cells.

3.2 DELWAVE model architecture

205 DELWAVE is composed of three logically distinct components, each responsible for a specific processing task, as depicted in Figure 4. The atmospheric encoder is responsible for encoding the input fields for each timestep into latent vectors. These vectors are then passed to the temporal collapse block where they are merged into a single latent vector, attenuated based on the temporal importance of the individual inputs, as explained in subsection 3.2.2 bellow. Finally, the regression block transforms this latent vector into the three required outputs. Individual blocks are described in more detail in the following subsections.

210 ### 3.2.1 Atmospheric encoder block

The atmospheric encoder block, displayed in Figure 5, is constructed from three sub-components: the per input atmospheric encoder, the joint atmospheric encoder, and the output atmospheric encoder.

Input atmospheric encoder: The input atmospheric encoder encodes each timestep individually before passing them the joint atmospheric encoder. Each input field has its own input atmospheric encoder block. This is to ensure that the initial 215 processing of the wind field with the location encoding is unique to each timestep. The per-timestep encodings of spatial
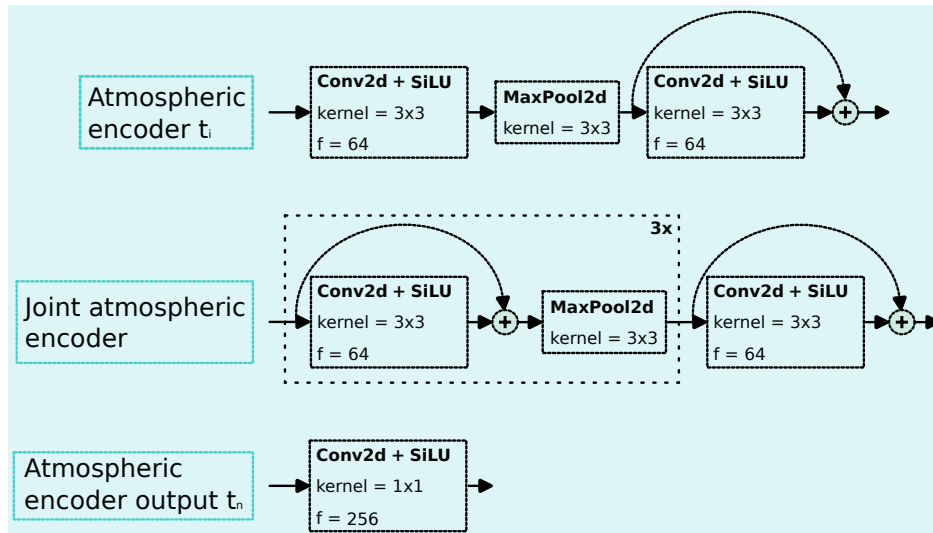
Figure 5. DELWAVE atmospheric encoder block sub-components. Each sub-component is shown in a separate row. The variable f denotes the number of output features of that operation and kernel denotes the kernel size of the convolution operation. Stride is always one for the convolution layers and two for the max pool layers.

locations might be important for predicting wave characteristics at different timesteps, therefore per input encoders add to the flexibility of the model being able to adapt to such requirements. However, using completely separate encoders for each timestep would result in slow, hard to scale architectures with overfitting issues. Therefore, a shallow initial encoder structure for each timestep is a good compromise between the two approaches.

220   **Joint atmospheric encoder:** The joint atmospheric encoder is the primary extractor of important wind field features. It is shared between timesteps, since we care to locate important wind features independently of the time at which they occurred. For example, a specific wind pattern can occur at different timesteps. Therefore, we can use the same wind pattern detector to locate and recognize the pattern irrespective of the time of occurrence. The approach of weight sharing between timesteps also reduces the computational complexity, the number of required parameters, and acts as a regularizing method preventing

225   overfitting.

    Output atmospheric encoder: The output atmospheric encoder selects wind features important for each timestep. This is achieved with a convolution filter with a kernel size of one, signifying a linear combination of the input features. The resulting per-timestep tensors of dimension $[b, 256, 4, 4]$, where b denotes the batch size, are summed across their last two dimensions, resulting in a 256 dimensional vector as the final output of this layer. These vectors serve as latent, high dimensional weather

230   descriptors for individual timesteps and encode weather information at each timestep.
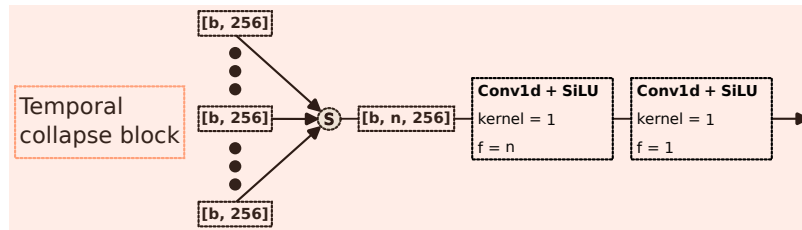
Figure 6. DELWAVE temporal collapse block. The variable n denotes the number of time steps used to train the model, b denotes the batch size, The n weather feature vectors of dimension $[b, 256]$ are stacked into a single tensor which is then reduced to a single 256 dimensional vector by passing through the convolutional operations. Stride is always one for the convolution layers.
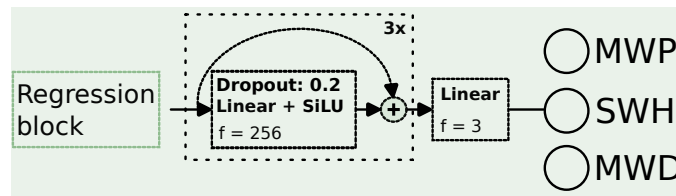
Figure 7. DELWAVE regression block reduces the output of the temporal collapse block into the final outputs: MWP, SWH, and MWD. The regression is conducted by a cascade of three dense skip connections followed by the final dense connection with three outputs.

3.2.2 Temporal collapse block

The temporal collapse block, displayed in Figure 6, collects the individual atmospheric vectors and encodes them into a single 256 dimensional vector. This is achieved using one dimensional convolutions in conjunction with the SiLU (Hendrycks and Gimpel, 2016) activation function. The first block produces a new set of combined temporal features vectors by leveraging the temporal nature of the tensor, using convolution. The second block reduces these temporal feature vectors into a single vector by means of a linear combination.

3.2.3 Regression block

Finally, the regression block, displayed in Figure 7, comprises of consecutive fully connected layers with skip connections. This block produces the final outputs: MWP, SWH, and MWD. Dropout with a removal probability of 0.2 is applied between each fully connected layer, except the last two (the output layer and the penultimate layer).

3.3 Training protocol

The CTR period was used for training while the SCE period was used for testing the final, developed model. The CTR data was further split into two parts: the actual training dataset (CTR_{trn}) and the validation dataset (CTR_{vld}). CTR_{trn} contains the first 80 percent of the training data, while CTR_{vld} contains the remaining 20 percent. The data for each station and for each
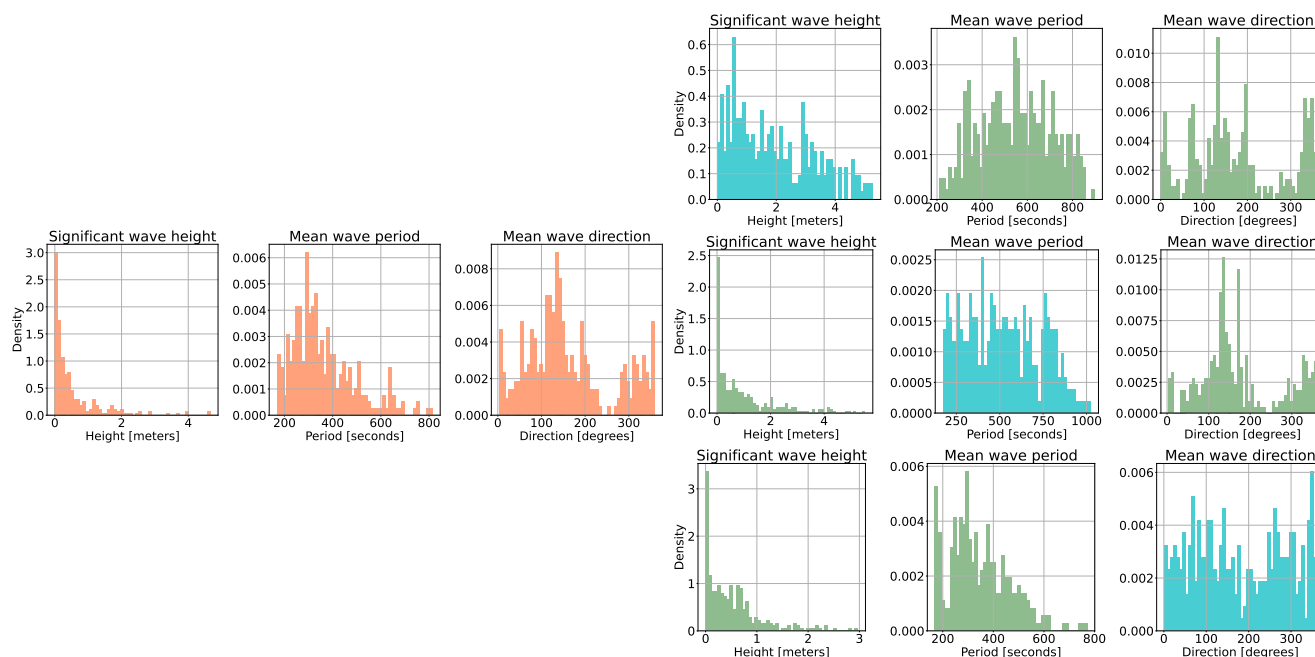
Figure 8. Random importance-sampling's effect on the batch constitution over training. The row on the left with orange columns represent the distributions of all three target variables in a random training batch without importance-sampling. The right three rows display importance-sampled batches, each row belonging to a specific variable that was importance-sampled. The histograms colored in blue contain those variables that were importance-sampled. Importance-sampling results in more uniform distributions for the sampled variables, which indicates a more equal sampling of the target variable realization space.

variable (significant wave height, mean wave period, mean wave direction) is separately normalized to exhibit zero mean and variance one. Prior to the normalization we log-transform significant wave heights by $\ln(\text{SWH} + 1)$. We give arguments for this transformation in the following paragraphs. Then at each training iteration a random batch of training samples is collected and the model loss function, the root mean squared error, is optimized with respect to these batches.

To better model distributionally underrepresented values of the target variables we employ random importance-sampling. We illustrate random importance-sampling in Figure 8. If we observe the distributions of the three target variables in a randomly sampled batch we can see that these are skewed. For example, in Figure 8, the significant wave height is distributed similarly to a left slanted gamma-like distribution with a very long tail. Therefore, the model is not exposed to the tail of the distribution frequently which inhibits efficient training in that part of the distribution. This results in systematic errors, where the regression accuracy for significant wave height drops with increasing height. This is understandable as samples with wave heights above two meters constitute only a small fraction of the dataset.

Our implementation of importance-sampling is conducted on-the-fly at batch acquisition. The reasons we do this on-the-fly as opposed to conducting this statically (oversampling before training and saving the new samples on disk) is this: oversampling highly skewed distributions to a point of close uniformity would require a large amount of additional samples. Since we had

limited disk space this was not an option. Therefore, we implemented single variable importance sampling that over-samples one of the target variables at random for a given training batch. However, when we over sample one of the variables, the remaining usually remain biased. We can observe this effect in the skewed green histograms in Figure 8, while the blue histograms are more uniform. To alleviate this issue, we alternated the sampling between the three target variables randomly to eliminate single variable importance sampling bias.

Furthermore, we alternated between regular sampling and importance-sampling, where every second batch was randomly importance sampled. This compromise offered the best performance out of the two approaches. We believe that this is due to the majority of data taking on only a small subset of values, thus these values influence the loss more than the rare events. This is especially true for significant wave heights where only five percent of all samples across all stations exhibit wave heights above two meters.

Our training took place in two stages. Since we trained our model on the Vega cluster (Institute of Information Science, 2023) we were limited by the maximum time our training could take up. A single run could last up to two days maximum therefore, we first trained our model using the Adam (Kingma and Ba, 2014) solver with default Pytorch parameters, learning rate of $1e\text{-}\,$ and a weight decay of $1e-6$ for two days. Following this period we extracted the model that best performed on the validation dataset, reinitialized the learning procedure with a reduced learning rate of $1e-5$, and retrained for 600 more epochs. We again took the model that best performed on the validation dataset and used it to compute the test dataset results we present in the following sections.

4 Temporal ablation study of the input

In this section, we investigate the impact of the number of timesteps on the performance of the model. Adding multiple timesteps results in inputing more information into the model, therefore training performance might increase. However, due to overfitting this performance might not be reflected in the actual accuracy on unseen data. Therefore, we conducted a preliminary comparison of five DELWAVE variants, each trained with a different number of input timesteps. These variants are DELWAVE_2, DELWAVE_4, DELWAVE_8, DELWAVE_{11}, and DELWAVE_{16}, where the subscript denotes the number of used timesteps. Results of this study are presented in Table 1 and their validation loss during training in Figure 9.

We can observe the diminishing returns nature of adding timesteps beyond the 11th timestep: the performance seems to be roughly identical between the DELWAVE_{16} and DELWAVE_{11}. Note also that DELWAVE_{16} contains more trainable parameters and is also slower to train comapred to DELWAVE_{11}. DELWAVE_{11} exhibits the best performance in four cases, equal to DELWAVE_{16}, followed by DELWAVE_8 with two cases. Similarly, we can observe that after the threshold of 11 time samples is reached we enter the diminishing returns domain, where DELWAVE_{16} offers negligible or even worse performance in some cases compared to DELWAVE_{11}. Therefore, we concluded that DELWAVE_{11} is the most promising network variant for further training.

	AA	MB	OB
DELWAVE$_2$ RMS$_{height}$	0.145	0.134	0.072
DELWAVE$_4$ RMS$_{height}$	0.091	0.078	0.034
DELWAVE$_8$ RMS$_{height}$	**0.065**	0.082	0.033
DELWAVE$_{11}$ RMS$_{height}$	0.067	0.083	**0.032**
DELWAVE$_{16}$ RMS$_{height}$	0.073	**0.079**	**0.032**
DELWAVE$_2$ RMS$_{period}$	98.279	44.930	107.135
DELWAVE$_4$ RMS$_{period}$	82.057	30.432	76.555
DELWAVE$_8$ RMS$_{period}$	50.457	**24.402**	55.783
DELWAVE$_{11}$ RMS$_{period}$	**43.546**	24.407	**55.614**
DELWAVE$_{16}$ RMS$_{period}$	44.056	25.084	58.559
DELWAVE$_2$ RMS$_{direction}$	22.057	69.798	25.836
DELWAVE$_4$ RMS$_{direction}$	19.877	62.432	22.065
DELWAVE$_8$ RMS$_{direction}$	16.504	57.108	19.985
DELWAVE$_{11}$ RMS$_{direction}$	16.775	**54.720**	19.626
DELWAVE$_{16}$ RMS$_{direction}$	**16.270**	55.614	**18.961**

Table 1. Table containing the performance evaluations of DELWAVE which we constructed by varying the amount of timesteps used during training, for three training locations: AA, MB, and OB. RMS denotes the root mean squared error and the best performing (with the lowest RMS) variant is in bold.
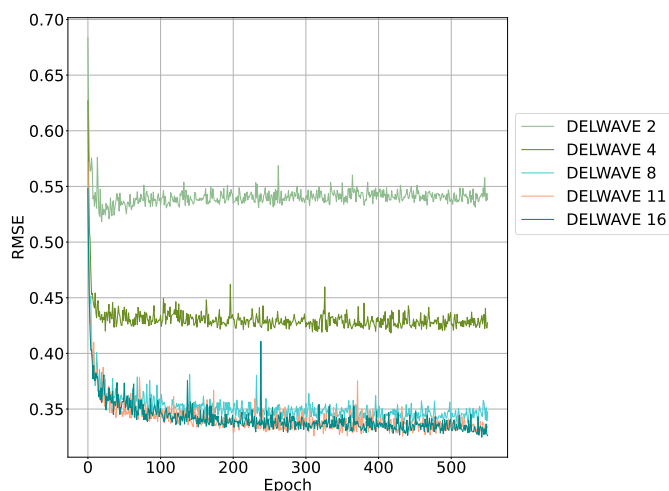
Figure 9. Root mean squared error on the validation dataset (averaged over all three variables) for all DELWAVE temporal ablation variants. The cut off number of epoch is the amount achieved by DELWAVE$_{16}$ in two days of training since it is the slowest of all the variants.

5 Results

In order to assess the potential and the possible limitations of the DELWAVE network, the analysis of the results is divided into three phases. After an overview of the performance of the network in reproducing the main overall properties of the SWAN time series (Sec. 5.1), the analysis will focus on two aspects of particular relevance for practical purposes, namely the capability of reproducing storms (including, but not only, extreme events, Sec. 5.2) and their main properties, and the capability of capturing the main features of the climate change signal (Sec. 5.3).

5.1 Deep Network vs SWAN under far future climate 2071-2100

In this section we present DELWAVE performance during the far future period of 2071-2100, as benchmarked against SWAN simulations. In other words: SWAN simulations represent the ground truth DELWAVE aims to model. Figure 10 depicts DELWAVE-SWAN heatmaps of H_S, d and $T_{m-1,0}$ at the locations of Acqua Alta oceanographic tower (AA) and the Ortona and Monopoli buoys (respectively OB and MB, see Figure 2 for locations). Results for other locations are provided in the Supplementary material.

We will proceed by analyzing DELWAVE performance using three related Figures. Figure 10 depicts DELWAVE predictions for H_S, d and $T_{m-1,0}$ with respect to those from the SWAN model predictions, obtained from the same wind fields, *i.e.* obtained for the same forecasting time window. Figure 11 shows the overlaps of histograms of H_S, d and $T_{m-1,0}$ from both DELWAVE and SWAN model. Note that close overlap of the distribution histograms from both models does not guarantee a good forecast since this overlap does not tell anything about the synchronicity of both forecasts - one therefore needs to view Figure 11 in conjunction with Figure 10. Finally, Figure 11 illustrates how DELWAVE forecasting mean absolute errors change depending on which part of distribution we are modeling. Here mean errors imply error averaging over all the forecasting samples in a specific distribution bin. Consequently the error values are well defined only in the bins containing a large enough (e.g. over 100) number of samples. In what follows we will be basing our remarks on an interplay of messages from all three Figures.

Location AA in the northern Adriatic (off the Venetian shore, see Figure 2 for location) is marked by an excellent performance in H_S and d prediction, indicated by the near linear scatter plot displayed in Figure 10. The same aspect of DELWAVE performance is illustrated via histogram distribution for the same three parameters on Figure 11. d (Figure 11, top row, right column) exhibits two maximums related to two dominant Adriatic winds, northeasterly Bora at roughly $75°$ and southeasterly Scirocco at roughly $135°$. Short wave periods at AA location on the other hand seem to be the hardest to predict, as can be seen ~~from~~ in the left column in either of the Figures 10 or 11. This is to some extent expected: long wave periods correspond to longer waves and consequently windy atmospheric conditions. Short periods on the other hand correspond to calm conditions where the network is essentially modelling low amplitude, short wavelength, stochastic ocean surface behaviour.

Similar observations can be made for OB and MB locations. SWAN H_S is modelled very reliably with DELWAVE. Multimodal direction histograms at all locations are also reproduced to a high degree of accuracy, as can be seen from middle column of Figure 11. On the other hand, the network seems to be struggling to reproduce northerly directions (rougly $0° \pm 10°$)
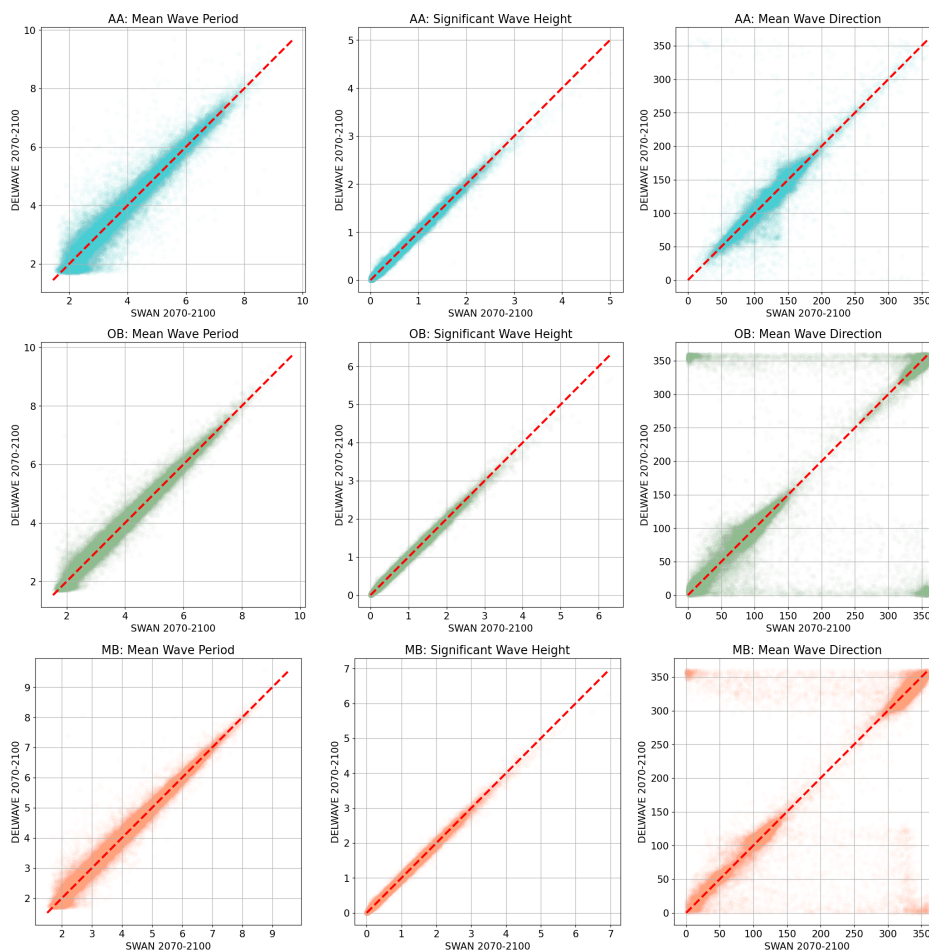
Figure 10. DELWAVE forecasts vs SWAN targets for locations AA (top row), OB (middle row) and MB (bottom row). Mean wave directions are listed in nautical notation ($0° =$ North, $90° =$ East, etc.). Dashed diagonal line indicates a perfect forecast.

at this location. This leads to horizontal strips of incorrect predictions displayed in the scatter plot of the right column, middle row in Figure 10 and to a bump in mean absolute error in the histogram displayed at the same location in Figure 11.

Figure 11 also hints at quantitative estimates of DELWAVE performance. When it comes to H_S predictions (middle column)
325 errors at all stations grow with significant wave height from errors below 5 cm for H_S below 1 m to errors of order 10-15 cm for H_S over 3 m. DELWAVE predictions of mean wave direction d (right column) exhibit smallest errors in the directional bins corresponding to prevalent wind patterns. In general directional errors are below $25°$, at AA even lower. High directional errors at $0°$ and $360°$ stem at least partly from algorithms false distinction between $0°$ and $360°$ directions.

Wave period $T_{m-1,0}$ predictions are illustrated in the left column of Figure 11. At all locations, periods below 6 s are
330 captured well by DELWAVE, with prediction errors below 0.25 s. Longer periods, likely corresponding to an incoming swell, however exhibit more diverse behaviour. MB station wave periods seem to be captured more accurately in the long period limit,
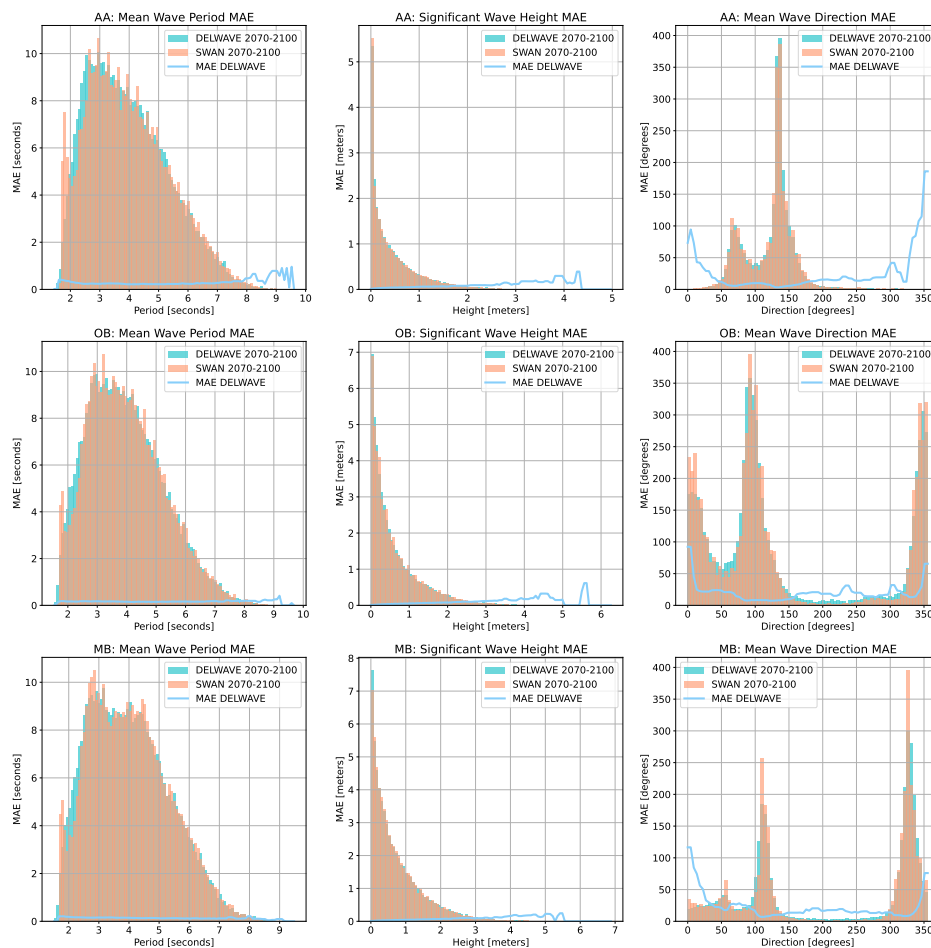
Figure 11. Histograms of DELWAVE-vs-SWAN distributions of H_S (left column), d (middle column) and $T_{m-1,0}$ (right column) from DELWAVE (turquoise bars) and SWAN model (brown bars) during the 2071-2100 timewindow at AA (top row), OB (middle row) and MB (bottom row) location. Light blue lines are scaled on the y axis and depict MAE, averaged over number of samples in each bin.

with forecast error dropping below 0.1 s. At OB station the errors in the long period limit slightly rise, from 0.2 s to 0.3-0.5 s. AA station on the other hand indicates a sharp rise of $T_{m-1,0}$ prediction error which reaches 1 s for period above 8 s.

The error behaviour at the AA station is possibly explained by the differing roles played by the basin geometry, the local wind sea and swell. Station AA is prevalently exposed to northeasterly Bora (blowing from roughly 75°) and to southeasterly Scirocco (blowing from 135°). In case of Bora the fetch is quite limited since Bora is a cross-basin wind. Therefore we do not expect swell to play a major role at AA station during Bora conditions: the wave field at AA station must be determined by local wind conditions. The case of Scirocco is very different. Scirocco is an along-axis wind with the largest fetch in the Adriatic basin. This means that during Scirocco, swell field at AA is determined to a large extent by non-local wind patterns in the south of the basin. Local wind conditions at AA location are furthermore often a poor proxy for winds in the south
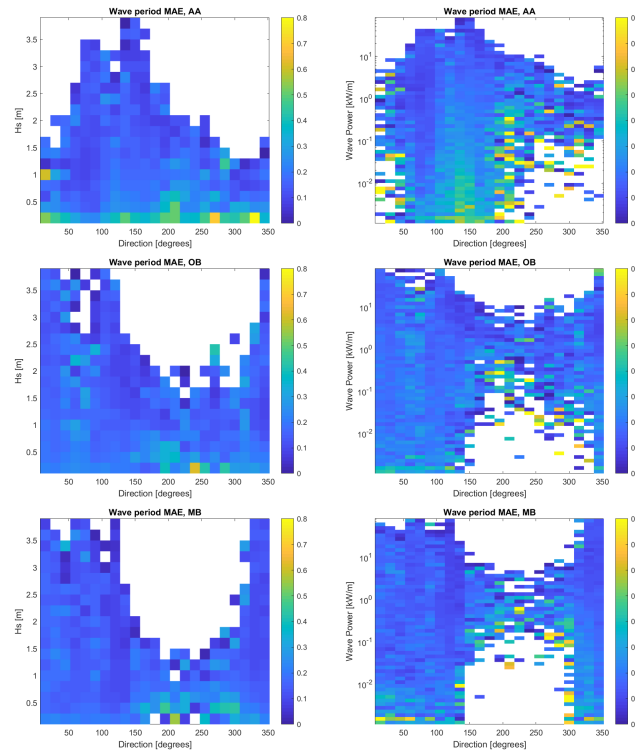
Figure 12. Comparison of wave period (indicated by color) relationship to significant wave height H_s (left column, y-axis) and to wave power (right column, y-axis) at all directions (x-axis) for AA (top row), OB (middle row) and MB (bottom row).

Adriatic. Bora in the north (promoting short fetch and shorter wave periods) coinciding with Scirocco in the south (promoting long period swell arriving at AA) is, for example, not unusual. These circumstances likely pose a challenge for the DELWAVE deep network, resulting in growing errors at longer wave periods (which most likely occur during Scirocco).

This explanation can be further substantiated by comparing wave period MAE to H_s, $T_{m-1,0}$ and wave power. The latter is

345 computed from the linear theory to be

$$P = \frac{\rho g^2}{64\pi} H_s^2 T_{m-1,0}, \tag{2}$$

with ρ being the water density and g the acceleration due to gravity. This comparison is depicted in Figure 12, which corroborates this interpretation and constrains DELWAVE limitations in capturing the basin-scale dynamics.

Concentration of the highest values of MAE at low values of H_s and P (left and right columns respectively) confirms that

350 largest errors tend to be associated with low-energy, nearly random sea states, even in the presence of relatively long waves (middle column) along the main basin axis (Scirocco at AA), thus with limited impacts on possible practical applications. It is further worth mentioning that a separate analysis, carried out by independently considering the rising and declining phases of the sea states (not shown), did not exhibit any preferential concentration of the higher values of MAE in either phase. Wave

period error is therefore not systematically larger during either onset or calming of the storm, suggesting that it is not directly related to the sequential and monotonous temporal encoding of inputs within DELWAVE. Had this not been the case, we would have expected some error asymmetry with regard to the timing of the storm.

5.2 Storm analysis

The analysis of the storms was carried out by comparing the DELWAVE results against the SWAN time series during period 2071-2100. For each time series, the storms were identified following the method proposed by Boccotti (Boccotti, 2000), namely (i) finding the events with H_s larger than 1.5 times the mean value $\overline{H_s}$ of each respective series, (ii) merging the events parted by less than 10 hours and (iii) discard those overall shorter than 12 hours. Figure 13 compares SWAN and DELWAVE peak H_s and directions for each storm at AA, OB, and MB (the same is shown for the other locations in the supplementary material), considering separately the whole sets of storms occurring during the period and the annual maxima for each series. While the former provides a broader view on how DELWAVE reproduces the whole meteo-marine climate at each location, the latter aims at assessing its capability of addressing extreme events. The picture is flanked by a quantification of the DELWAVE precision (how many DELWAVE-predicted storms are actually present in the SWAN time series) and recall (how many SWAN-modelled storms are retrieved by DELWAVE). These two metrics are computed as

$$\text{Precision} = \frac{TP}{TP+FP} \ , \ \text{Recall} = \frac{TP}{TP+FN}, \tag{3}$$

where TP, FP and FN denote true positive (storm present in SWAN and predicted by DELWAVE), false positive (storm predicted by DELWAVE but not present in SWAN) and false negative (storm present in SWAN but not predicted by DELWAVE) classifications. Figure 14 shows an example of the application of Boccotti's method to SWAN and DELWAVE storms and the occurrence of false negatives and false positives.

All considered sets exhibit a satisfactory performance with very high scores (Precision, Recall ≥ 0.95) when all the storms are considered. When only annual maxima are taken into account, precision and recall are lower, though fairly high (≥ 0.8), and without an evidently prevailing directional offset. Considering the whole storm sets, most of the false negatives and positives are generally clustered among the weakest events. This can be explained by considering that, for particularly weak or short events, small absolute errors can mean large relative errors. Therefore in small H_s limit, already a small error in the reproduction of H_s can significantly impact whether the criteria for the identification of storms are met or not (Figure 14).

This result seems to be in contradiction with the results for the yearly maxima sets, where prediction and recall scores decrease and the number of false negatives and positives increases. This contradiction is however only apparent and is related to the propagation of H_s prediction errors downstream into the identification of the yearly maxima. More precisely, in this case the mismatch does not seem related to the classification of an event as a storm, but rather to its classification as an yearly maximum: in fact, a slight error in predicting the peak height of storm events can introduce some noise in the ranking of the events, and in particular in the identification of the yearly maxima, leading to a mismatch between DELWAVE and SWAN. Nonetheless, as far as small errors in the prediction of the peak H_s are the cause for this mismatch, even if the events retrieved
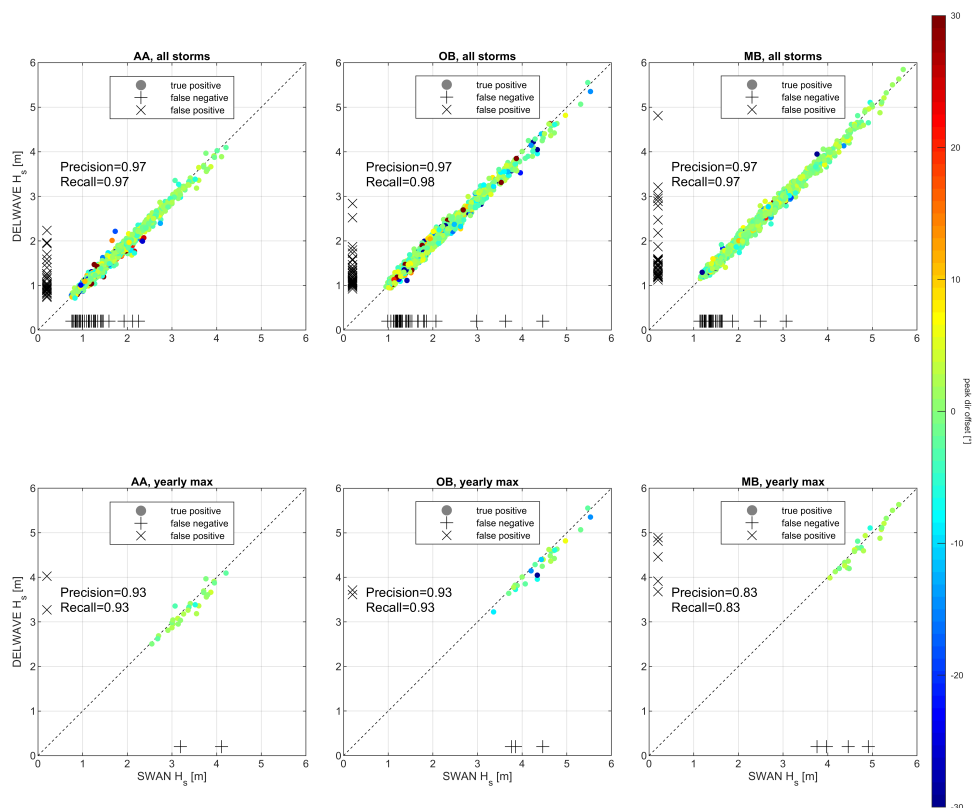
Figure 13. Comparison of SWAN and DELWAVE peak H_s value at AA, OB, and MB during all the storms (top row) and for the annual maxima (bottom row). Dashed diagonal line indicates a perfect match. The colormap represents the directional offset during the peak of each storm. Pluses and crosses along the plot axes represent false negatives (+) and false positives (×).

by DELWAVE are not exactly the ones resulting from the SWAN time series, their properties (or at least their peak H_s) should be quite close, which should be sufficient for most practical applications.

5.3 Climate change features

390   One of the main scopes of DELWAVE is to provide a computationally cheap model emulation system capable of providing large ensemble predictions for wave climate at a multi-decadal scale. This kind of applications is to some extent complementary to the event-scale analysis of single storms, and requires a specific assessment of the network capability of capturing the main statistical features of the climate signal. Figure 15 provides a twofold comparison of the climatological normals of the monthly mean, median and 99th percentile of H_s at AA, OB, and MB (the same values for the other locations are provided
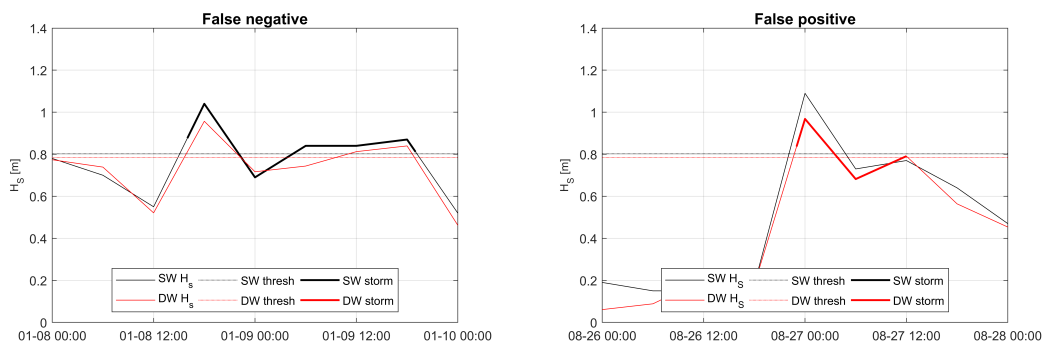
Figure 14. Examples of false negatives (left) and false positives (right) in the identification of storms (thick lines) following the method by Boccotti (2000) in the DELWAVE and SWAN H_S time series (thin lines). Dotted lines represent the reference threshold of $1.5\overline{H_S}$ for each time series.

395 as supplementary material) provided by SWAN and reproduced by DELWAVE. The statistics resulting from the SWAN and from the DELWAVE time series are compared against each other in the end-of-century scenario (2071-2100, SCE), and both are compared against the statistics from the control condition (CTR), available only for SWAN in the 1971-2000 period. The good agreement between DELWAVE and SWAN is confirmed also when considering climatological statistics, with a small ($\leq$5%), though systematic, underestimate of 99th percentile values, reflecting what was discussed in Section 5.1. Compared to

400 the CTR climatologies, the mismatch between DELWAVE and SWAN is generally small compared to the difference between SCE and CTR conditions, suggesting that the noise possibly introduced by the model mimicking is weaker than the climate change signal in the considered locations. Not surprisingly, the only way in which the performance seems partially affected by seasonality is through the modulation of significant wave height and the tendency of the network to underestimate higher (and therefore wintry) values.

405 Following a similar approach for the directional wave climate, the linearized wave roses in Figure 16 show that the agreement between DELWAVE and SWAN allows to capture important impacts of climate change in the wave regime not only in absolute terms, but also in response to projected shifts in the wind regimes. This is for instance the case of the slight weakening of Bora (NE) storms associated with an intensification of Scirocco (SE) events in the northern Adriatic Sea in the broader framework of a tendency towards an overall decrease of the storminess in most of the basin, suggested by Bonaldo et al. (2020) and confirmed

410 by the DELWAVE projections.

6 Conclusions

We have presented a new point-prediction deep learning method for surface gravity wave emulation in epicontinental Adriatic basin, which is fast enough to train and apply to be used for large-ensemble prediction over synoptic to climate timescales. DELWAVE input set consists of atmospheric winds during 1998-2000 and cross-validation period is the far-future climate
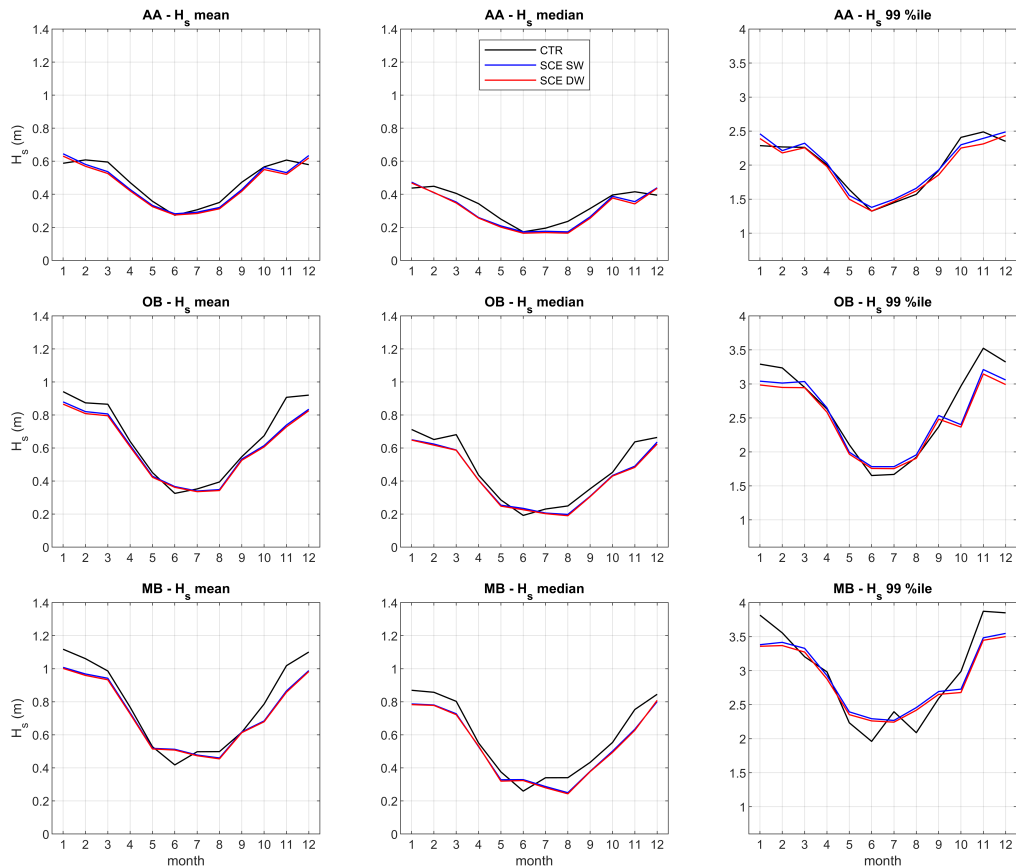
Figure 15. Comparison of SWAN (SW) and DELWAVE (DW) mean, median and 99th percentile H_s climatologies statistics in the future scenario (2071-2100, SCE) against the SWAN-modelled statistics referred to the control period (1971-2000, CTR), respectively at AA, OB, and MB.

timewindow of 2071-2100. We have thoroughly analyzed which architecture yields best results for wave emulation and these efforts led us to presented architecture of a convolution-based atmospheric encoder block, temporal collapse block and finally a regression block. We introduced random importance-sampling for improved modeling of underpopulated tails of variable data distributions. Detailed ablation studies were performed to determine optimal performance regarding input fields, temporal horizon of the training set and network architecture. We demonstrated that DELWAVE reproduces SWAN model significant wave heights with a mean absolute error (MAE) between 5 and 10 cm, mean wave directions with a MAE of 10°-25° and mean wave period with a MAE of 0.2 s. The network is able to accurately emulate multi-modal distributions of mean wave directions, which are related to dominant wind regimes in the basin. An analysis of DELWAVE performance during storms was
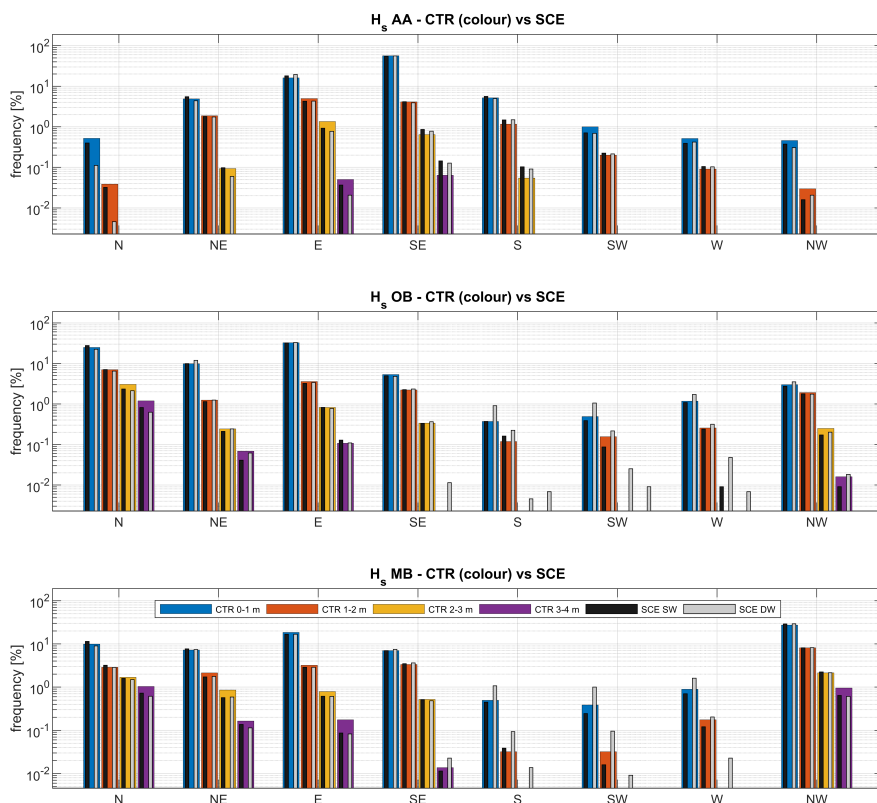
Figure 16. Comparison of SWAN (SW) and DELWAVE (DW) directional H_s statistics in the future scenario (2071-2100, SCE, black and grey bars respectively) against the same quantities modelled by SWAN with reference to the control period (1971-2000, CTR, coloured bars), respectively at AA, OB, and MB.

performed by employing threshold-based metrics of precision and recall. DELWAVE reached a very high score (both metrics over 95%) of storm detection.

425   SWAN and DELWAVE time series are further compared against each other in the end-of-century scenario (2071-2100), and both are compared to control period of 1971-2000. Compared to control climatology over all wind directions, the mismatch between DELWAVE and SWAN is generally small compared to the difference between scenario and control conditions, suggesting that the noise introduced by surrogate modeling is substantially weaker than the climate change signal. There is a number of things we would like to explore further: it is currently not clear how to leverage gaussian (or other) spatial encoding

430 to generate, if possible, reliable predictions for locations which lie outside of the training set. This might open the door for dense predictions of the wave field, at least in the vicinities of input data locations. It would furthermore be interesting to

introduce temporal dependence of the Gaussian variances in the spatial encoding matrix to help the network focus on wider areas of input data as we feed it data from a more distant past.

Future research and potential applications may also focus on the larger scales, for example the entire Mediterranean Sea basin, using high-resolution wind and waves model to boost DELWAVE training. The objective would be to explore the behaviour of numerical and machine learning models in diverse wind and wave regimes, as well as wind and marine storms, which exhibit distinct physical characteristics in a basin with highly diverse morphological and dynamic features.

Last but not least, another promising venue is offered by recent developments in the field of physics-informed machine learning. Here, the solution subspace is further constrained by additional loss terms which nudge the learning process towards physically consistent solutions. Since the physical aspects of wind driven surface gravity waves are known in substantial detail, we expect there to be some immediate benefits to introducing dynamics laws into the training. Last but not least, it would be interesting to study how well the network generalizes to other domains and other models. All these will be topics of further research.

Code and data availability. DELWAVE model code is available publicly on Zenodo: https://doi.org/10.5281/zenodo.7980397. Raw COSMO dataset can be found at the following repository, maintained by CMCC: https://doi.org/10.25424/cmcc-3hph-jy15. Preprocessed COSMO datasets, suitable for DELWAVE input, can be found on the following repository: https://doi.org/10.5281/zenodo.7816888.

Author contributions. PM designed, implemented and tested DELWAVE and all its ablations. ML wrote the initial version of the network. DB and ML contributed to geophysics-related aspects of DELWAVE. DB and AR provided SWAN simulations. PM, DB and ML performed the analyses and wrote the paper. All authors contributed the research plan and to the final version of the paper.

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