# Assessing the storm surge model performance: What error indicators can measure the skill?

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**Abstract.** A well-validated storm surge numerical model is crucial, offering precise coastal hazard information and serving as a basis for extensive databases and advanced data-driven algorithms. However, selecting the best model setup based solely on common error indicators like RMSE or Pearson correlation doesn't always yield optimal results. To illustrate this, we conducted 34-year high-resolution simulations for storm surge under barotropic (BT) and baroclinic (BC) configurations, using atmospheric data from ERA5 and a high-resolution downscaling of the Climate Forecast System Reanalysis (CFSR) developed by the University of Genoa (UniGe). We combined forcing and configurations to produce three datasets: 1) BT-ERA5, 2) BC-ERA5, and 3) BC-UniGe. The model performance was assessed against nearshore station data using various statistical metrics. While RMSE and Pearson correlation suggest BT-ERA5, i.e. the coarsest and simplest setup, as the best model, followed by BC-ERA5, we demonstrate that these indicators aren't always reliable for performance assessment. The most sophisticated model BC-UniGe shows worse values of RMSE or Pearson correlation due to the so-called "double penalty" effect. Here we propose new skill indicators that assess the ability of the model to reproduce the distribution of the observations. This, combined with an analysis of values above the 99th percentile, identifies BC-UniGe as the best model, while ERA5 simulations tend to underestimate the extremes. Although the study focuses on the accurate representation of storm surge by the numerical model, the analysis and proposed metrics can be applied to any problem involving the comparison between time series of simulation and observation.

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## 1 Introduction

In coastal areas, accurately depicting storm surges is paramount for effective risk assessment, preparedness, and mitigation
35   strategies, as they can lead to coastal erosion, inundation, and infrastructure damage, and threaten important cultural heritage
sites (Reimann et al., 2018; Vousdoukas et al., 2022). Storm surges arise from the interaction between the atmosphere and
the sea. Essentially, the atmosphere exerts forces on the water body, causing sea levels to rise due to low atmospheric
pressure systems and strong wind fields (Pirazzoli & Tomasin, 2022). The atmospheric pressure effect, known as the inverse
barometer effect or static amplification, typically contributes 10 to 15% of the total storm surge magnitude (World
40   Meteorological Organization, 2011). The second and more significant part of the storm surge, called dynamic amplification
or wind setup, arises from tangential wind stress associated with the weather system's wind field acting on the ocean surface
(Chaumillon et al., 2017).

Numerical simulations play a pivotal role in unraveling the complexities of physical phenomena, such as storm surges (Park
45   et al., 2022). They offer invaluable insights into various processes and greatly contribute to building extensive databases for
further analysis and comprehension. Concerning storm surges, this refers to a complex oceanographic phenomenon that
demands accurate oceanic and atmospheric data for precise representation. Due to diverse orographic configurations,
atmospheric models often exhibit significant errors, necessitating the utilization of local-scale models with high resolution
(Umgiesser et al., 2021). Additionally, the intricate coastal and bathymetric features and interactions pose challenges for
50   existing hydrodynamical models to fully capture the relevant dynamics, partly due to their low resolution (Mentaschi et al.,
2015; Toomey et al., 2022).

On the other hand, the utilization of unstructured grid models enables a more accurate portrayal of coastal dynamics,
considering the intricacies of bathymetry and shoreline configurations (Federico et al., 2017). This approach offers the
55   advantage of employing higher resolution at the coastlines while maintaining more modest resolution in deeper waters
(Ferrarin et al., 2019). Unstructured meshes offer flexibility in resolving basin geometry, allowing for local refinement of
computational domains to simulate regional dynamics on a global mesh with coarse resolution. This flexibility is particularly
valuable for coastal applications, where computational domains encompass complex coastlines and varying scales, ranging
from basin size to details of river estuaries or riverbeds (Danilov, 2013). Over recent years, unstructured grid models have
60   increasingly emerged as alternatives to regular grids for large-scale simulations (e.g. Mentaschi et al., 2020; Muis et al.,
2016; Vousdoukas et al., 2018; Fernández-Montblanc et al., 2020; Saillour et al., 2021; Wang et al., 2022; Zhang et al.,
2023; Mentaschi et al., 2023), with established circulation unstructured models like ADCIRC (Luettich et al., 1992; Pringle
et al., 2021), the Finite-Volume Coastal Ocean Model (FVCOM, Chen et al., 2003), the Semi-implicit Cross-scale
Hydroscience Integrated System Model (SCHISM, Y. Zhang & Baptista, 2008; Y. J. Zhang et al., 2016), the System of

65  HydrodYnamic Finite Element Modules (SHYFEM, Umgiesser et al., 2004; Bellafiore & Umgiesser, 2010; Micaletto et al.,

2022), the model TELEMAC (Hervouet & Bates, 2000), Delft3D (Deltares: Delft, 2024), among others.

In this study we developed numerical simulations of storm surge on the Northern Adriatic Sea, with the aim to generate a

long-term database of storm surge focused on the accurate representation of extreme values. The Northern Adriatic Sea is a

70  semi-enclosed body of water characterized by intricate bathymetry. The region's coastline exhibits distinct features, with the

western coastline being relatively smooth and sandy, while the eastern coastline is fragmented and rocky, dotted with

numerous islands. Both bathymetry and the configuration of the coastline significantly influence the physical processes

occurring along the coast (Bellafiore & Umgiesser, 2010). The semi-enclosed nature of the Adriatic Sea predisposes it to

experiencing intense storm surge events, leading to anomalous increases in sea level. These events are typically driven by

75  local low-pressure system cyclogenesis and the associated strong winds, which are influenced by the region's orographic

features (Umgiesser et al., 2021).

The application of numerical tools to study storm surges in the Northern Adriatic Sea has garnered significant attention over

the years, primarily due to its status as a high-risk area with unique cultural and environmental heritage, as well as significant

80  economic activities (Ferrarin et al., 2020). Previous efforts in this field have included predictive models projecting future

storm scenarios (Yu et al., 1998), long-term numerical simulations (Lionello et al., 2010), analyses of storm events and use

various atmospheric forcings (De Vries et al., 1995; Zampato et al., 2006; Medugorac et al., 2018), investigations into

seiches influence and data assimilation impacts (Bajo et al., 2019), and storm surge ensemble prediction systems for lagoons

(Alessandri et al., 2023).

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In this study, the numerical simulations are based on a long-term ocean circulation downscaling carried out with the

SHYFEM model, which is an unstructured-grid finite element hydrodynamic open-source code that solves the Navier-Stokes

equations with hydrostatic and Boussinesq approximations (Umgiesser et al., 2004; (Micaletto et al., 2022). The model has

been already implemented in operational (Federico et al., 2017) and relocatable (Trotta et al., 2016) forecasting framework,

90  and for storm surge events (Park et al., 2022; Alessandri et al., 2023). The simulations consider different setups to explore

the influence of different atmospheric forcings and model configurations on the model's skill. Regarding model

configurations, both barotropic and baroclinic simulations were conducted to compare potential differences between these

two widely used approaches, as covered in the literature for the proper representation of storm surge (e.g. Weisberg &

Zheng, 2008; Staneva et al., 2016; Hetzel et al., 2017; Ye et al., 2020; Muñoz et al., 2022). Furthermore, we focus on the use

95  of different metrics and their ability to provide reliable indications of the model's performance, which is an essential aspect

in assessing model skill and to select the best model configuration. In addition to classical metrics such as the Pearson

correlation coefficient and Root-Mean Squared Error (RMSE), two customized versions of the Mean Absolute Deviation

(MAD) are introduced. These tailored metrics incorporate observed and simulated percentiles, ranging from 0 to 100%, to ensure accurate representation of extreme values during the performance evaluation.

The paper is organized as follows. Materials and methods are described in Section 2, including the description of the two atmospheric databases considered for the simulations, the model setup, and the procedures to carry out the performance evaluation. Section 3 shows the main results of the comparisons between observed and simulated storm surge. The paper continues with a discussion of the results on Section 4. Finally, the conclusion show on Section 5 summarizes the key points of the study.

## 2 Materials and methods

### 2.1 Atmospheric forcing

In this study, we utilized two distinct atmospheric databases to force the circulation model, incorporating mean sea level pressure and wind fields. The first database is ERA5, the fifth generation of reanalysis data generated by the European Centre for Medium-Range Weather Forecasts (ECMWF). ERA5 builds upon the Integrated Forecasting System (IFS) Cy41r2, which became operational in 2016, providing hourly output with a horizontal resolution of 0.25°x0.25° for atmospheric variables (Hersbach et al., 2020). ERA5 is relatively high resolution and accurate for a global reanalysis, although it is known to be affected by negative biases at high percentiles, particularly when is compared with measured wind speed (Pineau-Guillou et al., 2018; Vannucchi et al., 2021; Benetazzo et al., 2022; Gumuscu et al., 2023).

Since ERA5 is relatively coarse for local studies and exhibits significant underestimation of extremes, we employed an alternative approach using a high-resolution (3.3 km) atmospheric downscaling developed by the University of Genoa (UniGe). Wind forcing was derived from 10 m wind fields via the Weather Research and Forecast (WRF-ARW) model v3.8.1, allowing for improved representation of small-scale forcings and physics. The computational domains comprised a 10 km resolution grid covering the Mediterranean, Northern Africa, and Southern Europe (A10), and a 3.3 km grid over the Tyrrhenian Basin and Northern Adriatic basin (A3), nested within A10. Initial conditions were obtained from the Climate Forecast System Reanalysis (CFSR) data, known for reliability but occasionally underestimating extreme events (Saha et al., 2010). WRF simulations were conducted for 24 hours with hourly outputs, employing established physical parameterization schemes to ensure accuracy across various atmospheric conditions. For further details, readers are referred to (Mentaschi et al., 2015).

### 2.2 Model setup

The SHYFEM model utilizes staggered finite elements in an unstructured Arakawa B horizontal grid, with the vertices of the triangle elements referred to as nodes. Vectors (velocity) are calculated at the center of each element, while scalars

(temperature, salinity, and water levels) are determined at nodes (Federico et al., 2017). The unstructured grid for the
130  simulations in this study was generated using the OceanMesh2D tool (Roberts et al., 2019) with a horizontal resolution of 3
km on the open ocean boundary and 50 m nearshore (Fig. 1.a). The General Bathymetric Chart of the Oceans (GEBCO)
dataset (Weatherall et al., 2015) was used, incorporating a high-resolution coastline from the European Environmental
Agency. However, due to identified overestimations in water depth in the Venice and Marano lagoons from GEBCO
bathymetry, adjustments were made based on the contributions from Fagherazzi et al. (2007), Lovato et al. (2010), Zaggia et
135  al. (2017) for the Venice lagoon and Petti et al. (2019) and Bosa et al. (2021) the for the Marano lagoon.
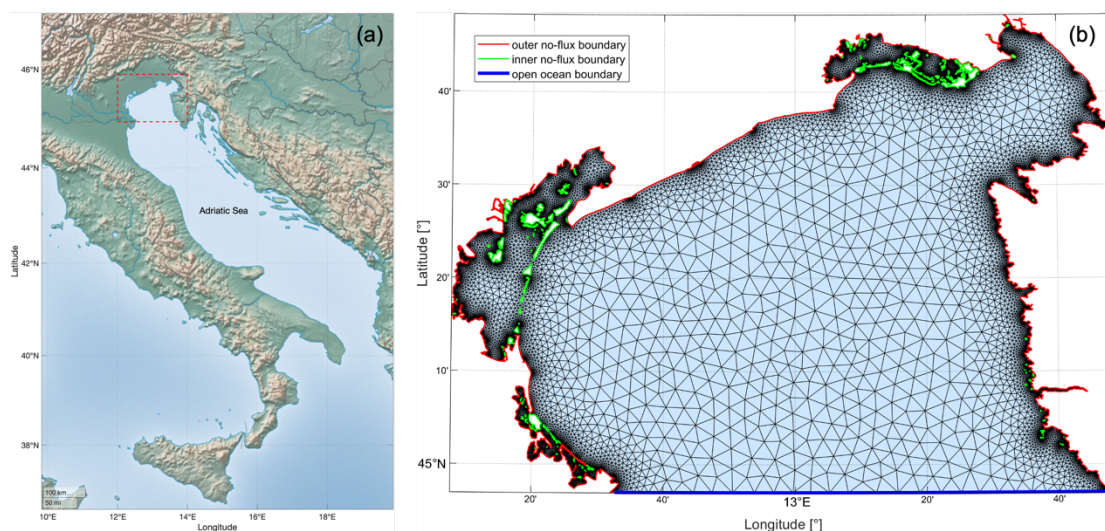
**Figure 1: (a) Location of study area, marked with dashed red line; (b) Unstructured grid for study area, in which the blue line represents the location of the open boundary condition, the red line the coastline, and the green lines the coastline formed by islands.**

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As initial and open ocean boundary conditions, sea level residuals, current velocity, temperature, and salinity from the
Copernicus Mediterranean Sea Physics reanalysis (Escudier et al., 2021) were considered. Tides with hourly resolution from
the Finite Element Solution (FES) 2014 (Lyard et al., 2021) were also included to account for the total sea level in the
simulations.

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Two model configurations were considered: a) barotropic (BT) and b) baroclinic, employing 33 vertical levels with layer
thickness of 1 m up to 10 m depth and then 2 m up to a maximum depth of 60 m (BC). To determine vertical viscosities and
diffusivities, we utilize a k-ε turbulence scheme derived from the General Ocean Turbulence Model (GOTM) model
(Burchard & Petersen, 1999). For wind stress at the air-sea interface a constant wind drag coefficient of $2.5 * 10^{-3}$ was
150  employed, following the works from Orlić et al. (1994) and Zampato et al. (2007). The bottom stress is determined through a
quadratic formulation, where the bottom drag coefficient is determined by the logarithmic formulation and varies with water
depth as specified in Maicu et al. (2021). In this logarithmic formulation, the roughness length remains constant at 0.01 m.

The simulation period extends from 1987 to 2020, with hourly output. Three combinations of atmospheric forcing and
155  configuration are considered here: 1) barotropic forced by ERA5 (BT-ERA5), 2) baroclinic forced by ERA5 (BC-ERA5),
and 3) baroclinic forced by UniGe (BC-UniGe).

## 2.2 Model performance evaluation

The model output was compared with observations from tide gauges located in the Northern Adriatic Sea. The observational
data were acquired from Italian National Institute for Environmental Protection and Research (ISPRA), the Civil Protection
160  of the Friuli-Venezia Giulia Region, and Raicich (2023). Table 1 summarizes the locations considered, and the available
time spans for comparison that match with the simulation timespan. Fig. 2 shows the locations considered for comparison
between measured and simulated storm surges, together with the bathymetry used for the simulations.

| Location | Lon [°] | Lat [°] | Start date | End date |
|---|---|---|---|---|
| ISMAR-CNR research platform "Aqua Alta" (hereafter CNR platform) | 12.53 | 45.31 | 01-01-1987 | 31-12-2020 |
| Punta della Salute | 12.33 | 45.43 | 01-01-1987 | 31-12-2020 |
| Caorle | 12.86 | 45.59 | 01-01-2000 | 31-12-2020 |
| Grado | 13.38 | 45.68 | 01-01-1991 | 31-12-2020 |
| Monfalcone | 13.54 | 45.78 | 01-01-2008 | 31-12-2020 |
| Trieste | 13.76 | 45.64 | 01-01-1987 | 31-12-2020 |

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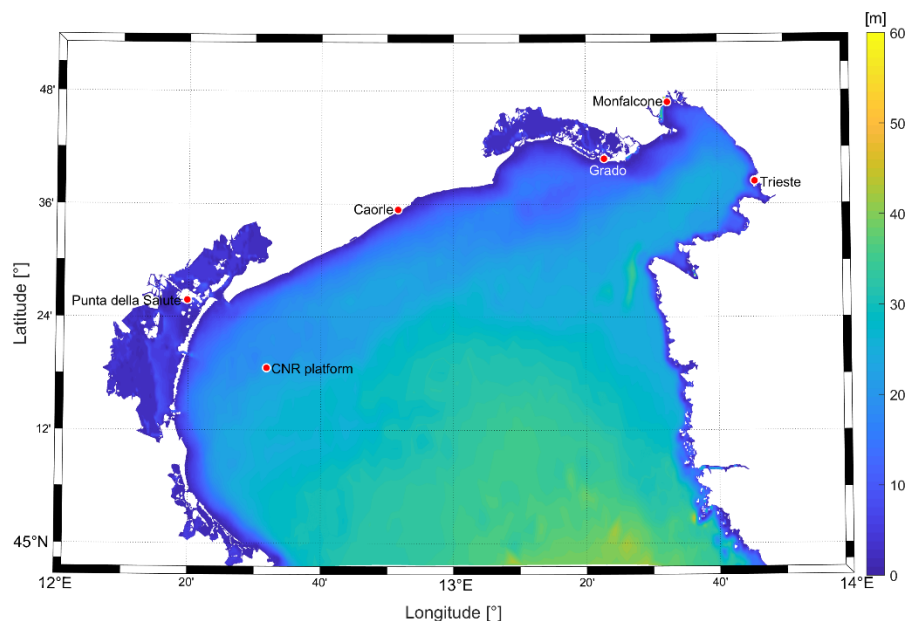
**Figure 2: Tide gauges locations and bathymetry (depth values on positive).**

Both the model output and the observations were processed as follow to enable their intercomparability. To start, both
170  measurement and simulation were centered with a zero mean and then detrended. This approach mitigates possible effects of
unmodulated land motion (Chepurin et al., 2014) and ensures that extreme values across the years can be considered as
homogeneous and can be compared despite relative sea level changes (Ferrarin et al., 2022). Harmonic analysis was
performed for each calendar year on the detrended sea levels using the T-Tide MATLAB package (Pawlowicz et al., 2022),
and the non-tidal residual was obtained as the arithmetic difference between sea level and tides (Tiggeloven et al., 2021).
175  Performing yearly harmonic analysis reduces timing errors that could cause tidal energy to seep into the non-tidal residual
(Merrifield et al., 2013).

Finally, to obtain the pure storm surge (hereafter also called "surge"), a low-pass filter is applied to the non-tidal residual,
following the work from Park et al. (2022). In this study, we consider a cut-off period of 13 hours for the filter based on the
180  mixed-semidiurnal tidal regime around the Northern Adriatic Sea (Lionello et al., 2021).

The performance evaluation of the simulations relies on the computation of statistical metrics of hourly data, which
encompass the entire dataset, as well as values exceeding the 99th percentile from the cumulative distribution of measured
data at each location. The following metrics are considered:

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Pearson correlation:

$$\rho = \frac{1}{N-1}\sum_{i=1}^{N}\left(\frac{S_i - \mu_S}{\sigma_S}\right)\left(\frac{O_i - \mu_O}{\sigma_O}\right) \tag{1}$$

Where $S_i$ and $O_i$ are the ith simulated and observed data respectively, $N$ is the sample size, $\mu$ and $\sigma$ are the mean and standard deviations of $S$ and $O$. A value closer to one identifies a better performance.

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Root-Mean Squared Error (RMSE):

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(S_i - O_i)^2} \tag{2}$$

A value closer to zero indicates a better performance.

195 Bias:

$$Bias = \bar{S} - \bar{O} \tag{3}$$

Where $\bar{S}$ and $\bar{O}$ are the average simulation and observation values respectively. A value closer to zero identifies a better performance, negative values indicate underestimation, and positive values indicate overestimation from the simulations. Given that both observed and simulated data were detrended and had their mean removed, bias was solely applied to the

200 analysis of values exceeding the 99th percentile.

Slope of linear fit between observations and simulation:

$$S = m\,O + b \tag{4}$$

Where the slope is given by the coefficient $m$. A value closer to one indicates a better performance.

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Additionally, with the aim of considering the representation of extremes by the simulations, we introduce two new metrics based on customized versions of the Mean Absolute Deviation (MAD):

MAD of the percentiles (MADp):

210 $$MADp = \overline{|S_{prc} - O_{prc}|} \tag{5}$$

Where $S_{prc}$ and $O_{prc}$ are the simulation and observation percentile values, considered from 0 to 100%, every 1%. The MADp metric provides a comprehensive assessment of simulation model performance by comparing percentile values derived from simulations ($S_{prc}$) with those observed ($O_{prc}$). This evaluation encompasses the entire distribution, from the lowest to the highest percentiles, allowing to gauge the model's accuracy across a range of scenarios. MADp is particularly

215 valuable for its sensitivity to systematic errors, such as persistent underestimation of high percentiles, which can significantly impact the reliability of simulation results. By penalizing these systematic errors, MADp highlights areas where improvements in the simulation model are necessary to better align with observed data. Lower MADp values indicates closer agreement between simulations and observations.

220    Corrected MAD (MADc):

$$MADc = \overline{|S - O|} + MADp \qquad (6)$$

In this indicator we exploit the ability of the "traditional" MAD to capture the model's skill but reduce its strong penalization of the phase error or timing error (i.e. the reproduction by the model of peaks shifted in space-time) by adding the MAD (MADp) on the percentiles previously defined. MAD measures the average absolute difference between simulated and
225    observed values, while MADp evaluates the average percentage deviation between them. By combining these two components, MADc provides a comprehensive evaluation of the simulation model's performance, considering both the magnitude and percentage deviations. A lower MADc value indicates better agreement between simulated and observed values, reflecting higher accuracy and reliability of the simulation model.

## 3 Results

230    The performance evaluation shows that, if the model performance is assessed in terms of Pearson correlation and RMSE, the surges simulated with the ERA5 forcing fit better to the measured data (Fig. 3). The Pearson correlation coefficients obtained range between 0.8 and 0.9 in all locations for the three simulations, with maximum of 0.842 with BT-ERA5 in Grado (Fig. 3.d). Regarding the RMSE, mean values of 0.077 m for BT-ERA5, 0.075 m for BC-ERA5, and 0.079 m for BC-UniGe were obtained, with a minimum of 0.072 m (BT-ERA5 in Grado, Fig. 3.d) and a maximum of 0.094 m (BC-UniGe in Monfalcone,
235    Fig. 3.e). Despite the aforementioned, the best performance is achieved by BC-UniGe in the linear fit slope, with values above 0.8 in all locations and a maximum of 0.869 in Monfalcone (Fig. 3.e). For this parameter, the less favorable performance is obtained with BT-ERA5 in all locations.

For MADp, the best performance is achieved by BC-UniGe in all locations, with a mean value of 0.004 m, while less
240    favorable results are obtained with BT-ERA5, with a mean of 0.011 m. Similar results were obtained for MADc, except in Caorle (Fig. 3.c) and Monfalcone (Fig. 3.e), where BC-ERA5 showed better performance, likely due to overestimation in the mentioned sites. These results underscore the importance of considering percentiles as part of the performance evaluation. BC-UniGe simulations demonstrate an improvement in representing extreme values, showing a better fit of the highest percentiles, which can be noticed in Fig. 4 and Fig. 5. Additionally, these figures indicate that BC-UniGe simulations
245    generate a greater dispersion of information, probably due to a more frequent occurrence of phase error. However, they also exhibit a better fit of the linear regression and a more accurate representation of extreme values compared to BC-ERA5, which fail to represent the most extreme events in each location.
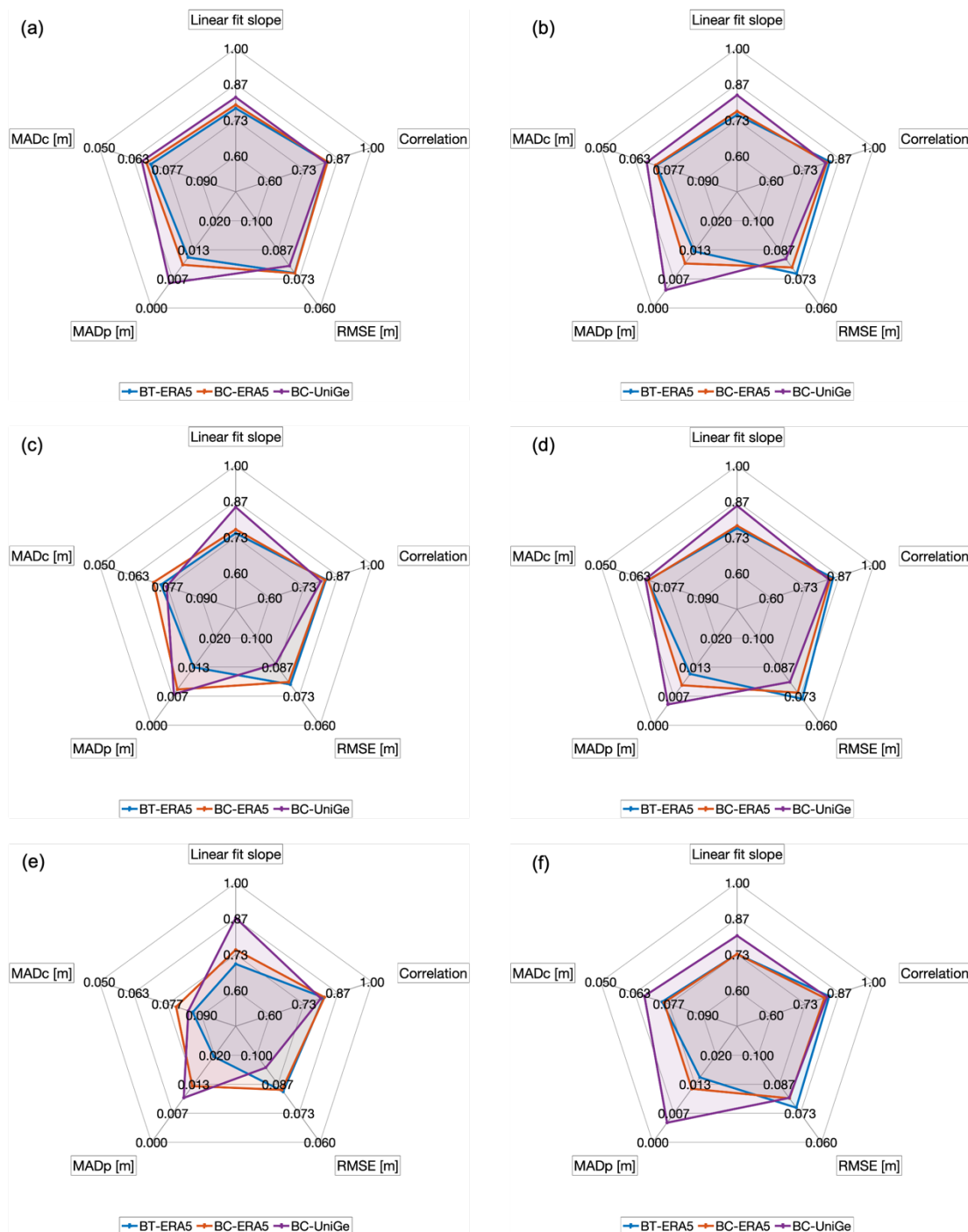
Figure 3: Radar charts of evaluation metrics for the total amount of data in all locations. (a) CNR platform; (b) Punta della Salute; (c) Caorle; (d) Grado; (e) Monfalcone; (f) Trieste. For RMSE, MADp and MADc a reverse axis is used, this ensures that simulations covering a larger area on each metric represent a better performance.
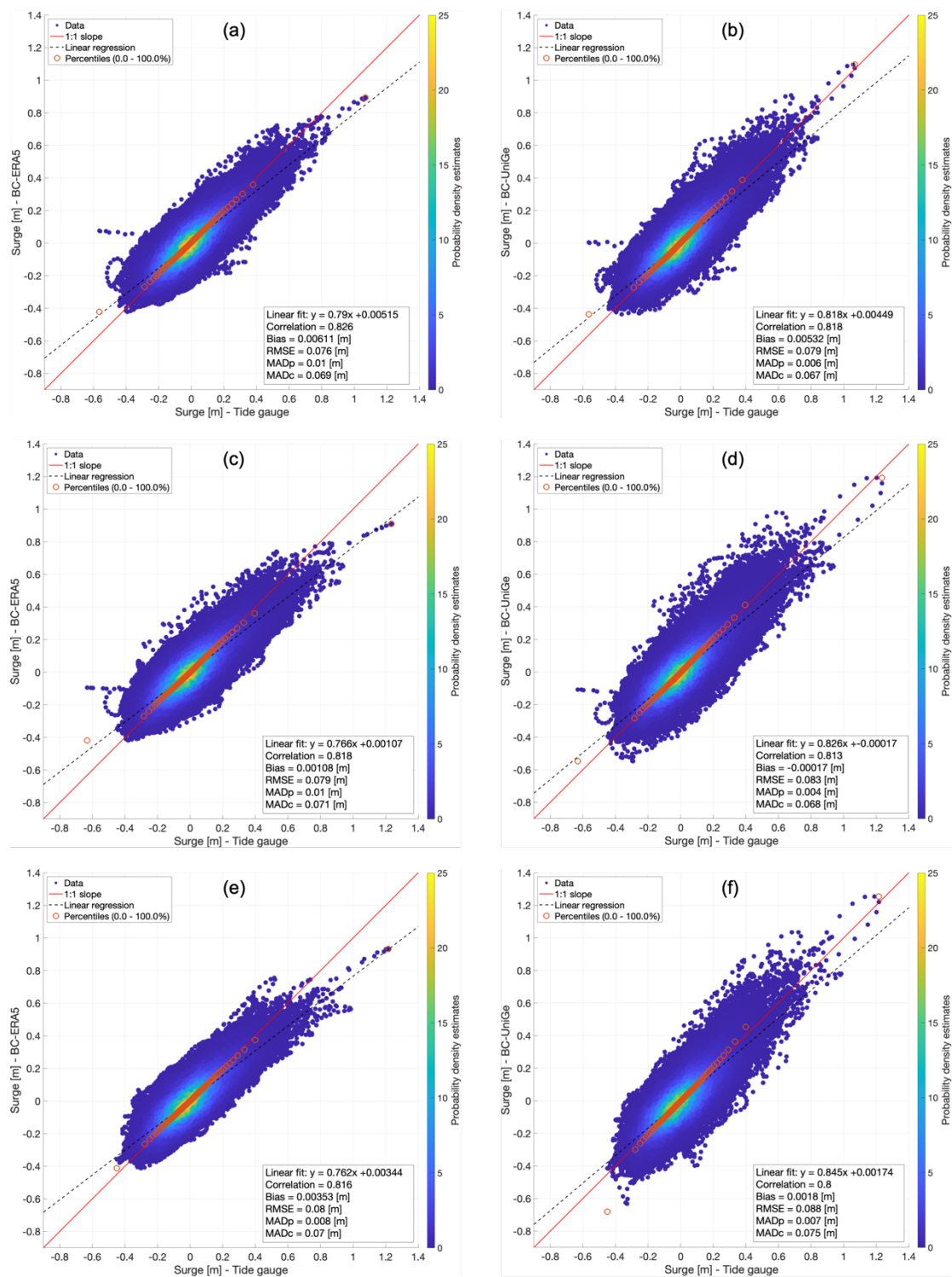
**Figure 4: Scatter plots between tide gauges and baroclinic simulations. CNR platform: BC-ERA5 (a), BC-UniGe (b); Punta della Salute: BC-ERA5 (c), BC-UniGe (d); Caorle: BC-ERA5 (e), BC-UniGe (f).**
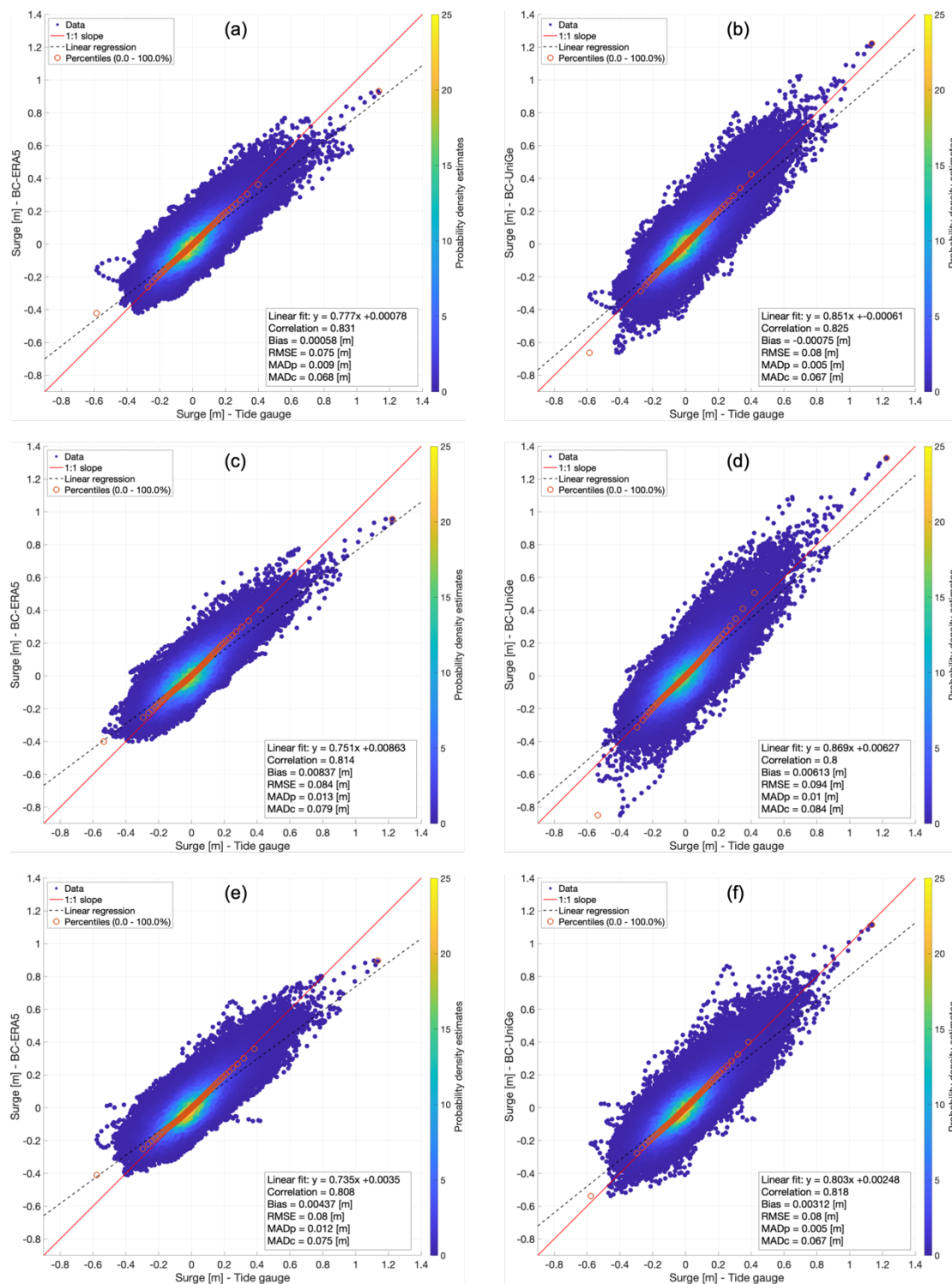
**Figure 5: Scatter plots between tide gauges and baroclinic simulations. Grado: BC-ERA5 (a), BC-UniGe (b); Monfalcone: BC-ERA5 (c), BC-UniGe (d); Trieste: BC-ERA5 (e), BC-UniGe (f).**

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The results of the error metrics for surge values above the 99th percentile, represented using radar charts (Fig. 6), confirm that, in general, better performance is observed with BC-UniGe, while less favorable results are obtained for BT-ERA5. Although the transition from barotropic to baroclinic configuration indicates an improvement in the representation of extremes (Weisberg & Zheng, 2008; Staneva et al., 2016; Hetzel et al., 2017; Ye et al., 2020; Muñoz et al., 2022), the

265 utilization of UniGe forcing represents the best improvement across practically all metrics. Only in Caorle (Fig. 6.C) and Monfalcone (Fig. 6.E) does BC-ERA5 show better correlation and RMSE; additionally, in the latter, MADc exhibits better performance for that simulation, likely due to overestimation of the peaks by BC-UniGe in Monfalcone. In the other locations, it's evident that BC-UniGe performs better in representing the highest storm surge values.

270 In order to show the capacity of the different model configurations to represent certain known storm events at each location, Fig. 7 shows time series of different storm surge events at each location. These extreme events were chosen according to the contributions of Lionello et al. (2012), Medugorac et al. (2018), Ferrarin et al. (2020), Umgiesser et al. (2021), and Giesen et al. (2021). As mentioned before, the incorporation of the UniGe forcing implies a significant improvement in the representation of extreme events, clearly evident in the peak values of the storm surges. Despite, an overestimation of some

275 surge peaks is also observed in the events chosen at Punta della Salute (Fig. 7.B), Caorle (Fig. 7.C), and Monfalcone (Fig. 7.E) with BC-UniGe. On the other hand, a systematic underestimation of extremes obtained in simulations with ERA5 forcing is notable on every surge peak.
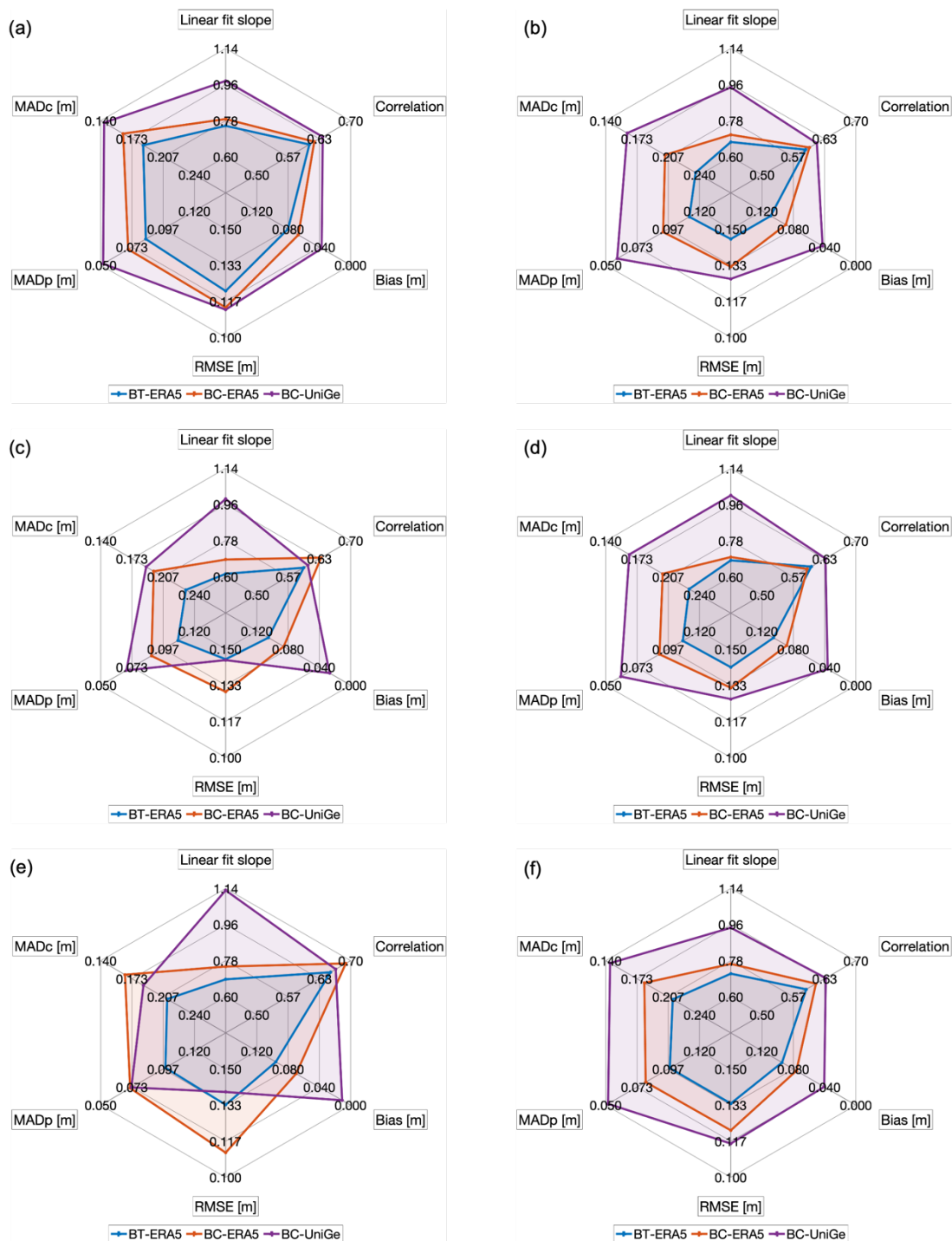
**Figure 6: Radar charts of evaluation metrics for surge values above the 99th percentile of the cumulative distribution at each location. (a) CNR platform; (b) Punta della Salute; (c) Caorle; (d) Grado; (e) Monfalcone; (f) Trieste. Bias is represented by absolute value. Also, for RMSE, Bias, and MADp and MADc a reverse axis is used, this ensures that simulations covering a larger area on each metric represent a better performance.**
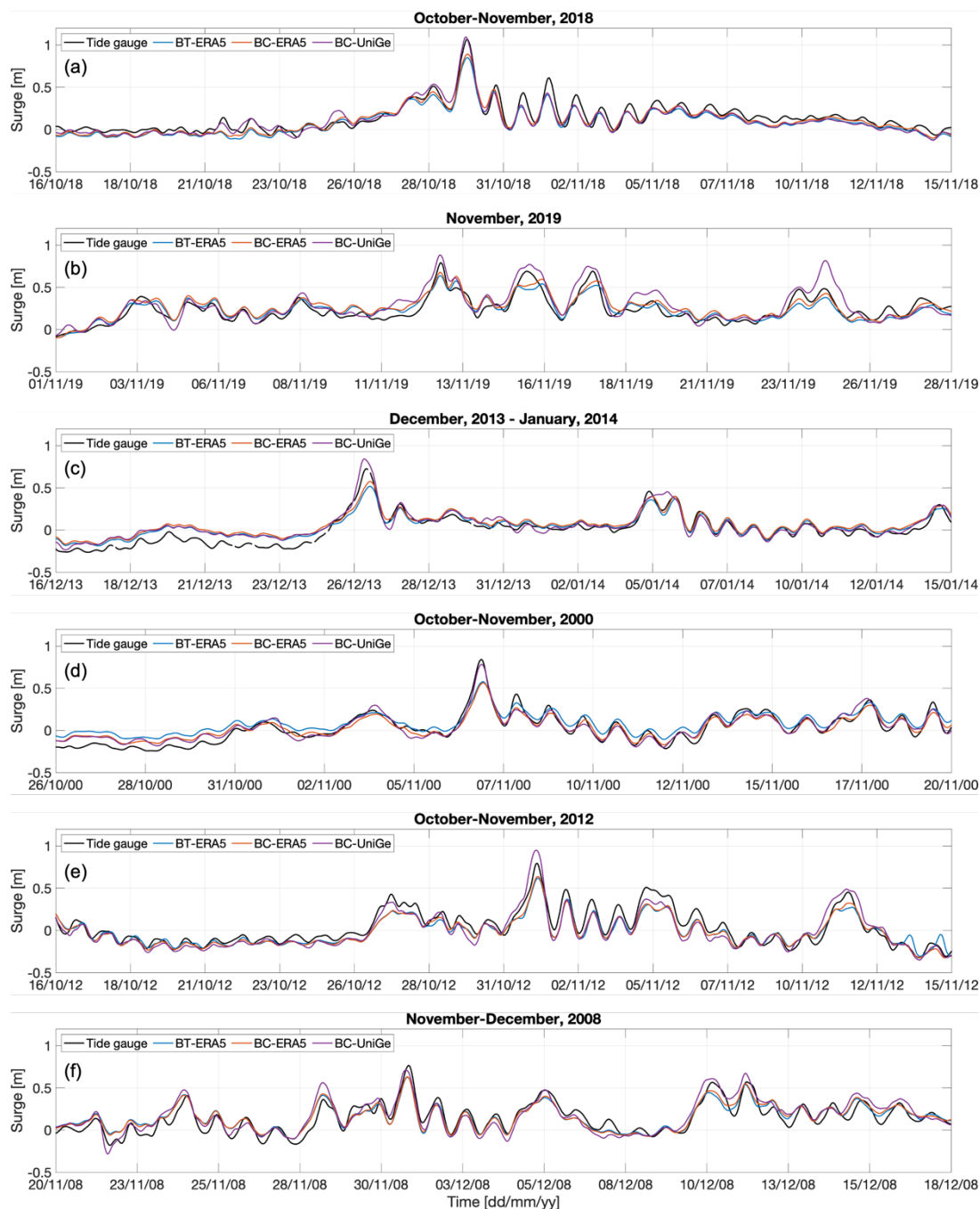
**Figure 7: Time series of different storm surge events in all the locations, tidal gauge versus model. (a) CNR platform; (b) Punta della Salute; (c) Caorle; (d) Grado; (e) Monfalcone; (f) Trieste.**

## 4 Discussion

290    The utilization of different atmospheric forcing databases has revealed significant implications for the representation of storm surges in numerical simulations. Given the direct influence of wind speed and sea level pressure on this phenomenon, as represented in both forcings databases, the resulting model performances present significant differences. While simulations using ERA5 forcing generally show slightly better performance on traditional metrics such as RMSE and Pearson correlation coefficient, a more detailed analysis reveals that using the UniGe forcing results in better performance,
295    especially the extreme values when considering additional metrics.

Simulations using ERA5 forcing tend to underestimate the highest surge values, primarily due to a corresponding underestimation of extreme wind speed by this database, a variable crucially linked to surge amplitude (Campos et al., 2022). Despite this, metrics such as Pearson correlation and RMSE generally indicate better performance for ERA5 simulations.
300    Conversely, the utilization of UniGe forcing shows an improvement in representing the peaks of storm surge events (with the noticeable exception of Monfalcone, where the extremes are overestimated, and where MADp present similar values for BC-ERA5 and BC-UniGe). These results demonstrate that the increase in atmospheric forcing resolution does not consistently translate into better values of all the statistical metrics.

305    It is important to recognize that identifying the optimal model configuration cannot rely solely on a few statistical metrics. As outlined in section 3 no single simulation emerges as superior across all metrics and locations. While ERA5 simulations may demonstrate better performance on RMSE and correlation, BC-UniGe exhibits superior performance in terms of the slope of the linear fit, MADp and MADc.

310    From an epistemic point of view BC-UniGe is a significantly more sophisticated model compared to BT-ERA5. Not only does it employ a higher resolution forcing. It also takes into account the baroclinicity and the vertical motion within the water column, whereas the barotropic configuration of BT-ERA5 approximates the ocean as a 2D sheet only subject to vertically uniform motions and waves. This suggests that widespread indicators such as RMSE and Pearson correlation, which in this case identify BT-ERA5 as the best model, should not be considered as the sole source of information in model
315    skill assessment, since a higher resolution forcing and a baroclinic setup are known in literature to better capture the variability of the sea levels (Weisberg & Zheng, 2008; Hetzel et al., 2017; Muñoz et al., 2022).

Similar results were found by Zampato et al. (2006) using SHYFEM with three different forcings for wind and atmospheric pressure fields: ECMWF global model, high-resolution LAMI model and satellite QuickSCAT. In this work, the authors
320    found well correlated sea levels with observations near Venice using the ECMWF forcings, but underestimation on highest values. On the other hand, simulations driven by the high-resolution model (LAMI) succeeded in simulating the storm surge,

giving a good reproduction of the sea level peaks. Nevertheless, the correlation with observed data was lower than in the case of ECMWF forcing.

325    The complexity in simulations performance evaluation is echoed in the work of Mentaschi et al. (2013), who caution against over-reliance on metrics like RMSE, NRMSE (Normalized RMSE), and SI (Scatter Index) as indicators of model performance. These metrics may not fully capture the intricacies of natural processes such as atmospheric dynamics, ocean circulation, or wave generation and propagation. These authors mention that the RMSE and its variations tend to assume typical values of the best performance for simulations that underestimate the physical process of interest. The discrepancy

330    between metrics and the representation of extremes highlights the need for a comprehensive understanding of model performance beyond traditional statistical measures.

This results on performance evaluation are usually related to phase error in high-resolution models and RMSE "double penalty". The phase error refers to a discrepancy between the timing or phase of a simulated event and its actual occurrence

335    on measured data. In the context of atmospheric models, phase errors can manifest as delays or advances in the timing of weather events, such as the onset of precipitation, the movement of storm systems, or the arrival of fronts. Double penalty refers to a situation where the errors in the model output are penalized twice, in indicators such as RMSE and MAD, once for missing the observations and again for giving a false alarm (e.g. Gilleland et al., 2009). This is a well-known problem during performance evaluation of numerical models and different contributions have sought to overcome it, with approaches

340    specialized in atmospheric and oceanographic fields (e.g., Ebert & Mcbride, 2000; Zingerle & Nurmi, 2008; Roberts & Lean, 2008; Mittermaier, 2014; Skok & Roberts, 2016; Crocker et al., 2020).

In RMSE, "double penalty" is further amplified compared to MAD, as the penalizations due to the peak mismatch are squared. This means that phase errors have a disproportionately large impact on RMSE. A more sophisticated model may be

345    better able to capture the magnitude of the peaks, but as it is more prone to phase error compared to low-resolution ones this ability will be doubly penalized. This is the reason why a less sophisticated model employing a low-resolution forcing (BT-ERA5) appears to out-perform the other two in terms of RMSE.

In other words, RMSE tends to be better for "blurring" models, whereas high-resolution models, known to be more capable

350    of reproducing small-scale dynamics (e.g. BC-UniGe), perform worse in terms of RMSE due to phase error (Crocker et al., 2020). Although in many aspects, capturing a peak with a phase error is preferable to missing the peak entirely, this does not lead to a reduction in the RMSE.

This limitation of RMSE also impacts the Pearson correlation. Indeed, RMSE can be decomposed into a bias component and

355    a scatter component that depends solely on the Pearson correlation (Mentaschi et al., 2013, equation 8). All these

considerations call for caution when claiming that one model outperforms another one just based on a better value of RMSE or MAD or Pearson correlation.

360   The MADc indicator was introduced here as a possible way to correct MAD to make it less prone to the double penalty effect. The incorporation in MADc of a term that takes into account the distribution of the data (the MAD of the percentiles MADp) rewards the ability of a high-resolution and more sophisticated model to reproduce the variability in the observations without systematic errors. In other words, MADc remains more resilient to phase errors compared to other metrics, ensuring that discrepancies in the timing of events do not unduly influence the assessment of model performance.

## 5 Conclusions

365   In this study we developed high-resolution simulations of storm surge in the Northern Adriatic Sea spanning from 1987 to 2020, using the model SHYFEM, employing different forcing data and physical configurations. The comparative analysis of the results highlights nuanced differences in performance metrics, particularly concerning the representation of the extreme values. Traditional metrics like Pearson correlation and RMSE favor a simulation (BT-ERA5) forced by a coarser database and employing a less sophisticated setup (barotropic). However, a closer examination and the use of different metrics tell a

370   different story and allow to identify a baroclinic model forced by a high-resolution dataset (BC-UniGe) as better able to capture the variability of the water levels and, in particular, the extremes. This is because BC-UniGe is more prone to phase error than BT-ERA5, and is thus doubly penalized in indicators such as RMSE, MAD and Pearson correlation.

The corrected MAD (MADc) introduced in this study comes as a possible way to alleviate the double penalty, by adding a
375   term that rewards the ability of a model to capture the distribution of the observations irrespective of the position of the peaks. In this study MADc is successful in identifying BC-UniGe as the best simulation in most locations. Even though this study has focused on the performance evaluation of storm surge, the analysis and proposed customized metrics (MADc and MADp) can be applied to any problem of validating a numerical model with observations by time-series comparison.

380   These findings suggest that simply having a lower RMSE is insufficient evidence to claim that one model is superior to another. RMSE, MAD and Pearson correlation are valuable indicators but should be used considering their limitations, and complemented by other metrics, qualitative assessment, and expert judgment.

## 6 Author contribution

385 RC carried out the numerical simulations, post processing, performance evaluation of the simulations and prepared the manuscript. LM guided during numerical simulations, post processing, performance evaluation and contributed to the preparation of the manuscript. JA guided and supported numerical simulations. PC contributed to the performance evaluation and with the preparation of the manuscript. AM, FF, IF, and MV contributed during the preparation of the manuscript. MT contributed to the performance evaluation.

## 390  7 Competing interests

Co-author MT is employed by the company HS Marine SrL.

The remain authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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