

1 Ensemble Storm Surge Modelling of the Goro Lagoon (Adriatic 2 Sea, Northern Italy)

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10 Key Points:

- 11 • Storm surge forecast skill depends mainly on initial and lateral open boundary condition uncertainties,
12 including the tidal components.
- 13 • EPS members derived from different large scale ocean models, atmospheric forcing forecasts and an ad-hoc
14 perturbations of the river runoff.
- 15 • Development of an ensemble weighting method provides an improved ensemble mean forecast skill suitable
16 for operational systems.

17 Abstract

18 We developed a storm surge Ensemble Prediction System (EPS) for the Goro lagoon (GOLFEM-
19 EPS) in the Northern Adriatic Sea. The lagoon is threatened every year by storm surge events with
20 consequent risks for human life and economic losses. We show the advantages and limitations of an
21 EPS with 45 members, using a very high-resolution unstructured grid finite element model. For five
22 recent storm surge events, the EPS generally improves the forecast skill on the third forecast day
23 compared to just one deterministic forecast, while they are similar in the first two days. A weighting
24 system is implemented to compute an improved ensemble mean. The uncertainties regarding sea level
25 due to meteorological forcing, river run-off, initial and lateral boundaries are evaluated, and the
26 different forecasts are used to compose the EPS members. We conclude that the largest uncertainty
27 is in the initial and lateral boundary fields at different time and space scales, including the tidal
28 components.

29 Plain Languages Summary

30 Storm surges are extreme events generated by strong winds, low atmospheric pressure, tides and
31 possibly other non-local phenomena. The Goro Lagoon, on the Italian side of the northern Adriatic
32 Sea, is subject to storm surge, especially when a south-easterly wind (locally named Scirocco) occurs.
33 We developed an ensemble system, called GOLFEM-EPS, to forecast with a numerical model the

34 sea level in the Goro lagoon and the adjacent areas. The “ensemble” approach consists in running a
35 high number of forecasts (the “members”, 45 in this work) with different conditions in order to obtain
36 different estimates and account for errors and inaccuracies in the model set-up and in the forcing data.
37 GOLFEM-EPS generally improves the forecast skill on the third day of forecast while it is similar in
38 the first two days to the reference forecast. The uncertainty connected to river-run off, meteorological
39 forcing, initial and boundary conditions is evaluated. Initial, lateral boundary conditions and tidal
40 components provide the largest uncertainty to the system.

41 **1 Introduction**

42 The operational forecast of sea level (SL) is a widely developed service used to prevent flooding and
43 storm surge hazards that represent a potential threat for human life and activities (Chaumillon et al.,
44 2017; Forzieri et al., 2016). However, the forecast lead time is affected by the limited predictability
45 of the atmospheric forcing and the uncertainties regarding the initial conditions, as well as lateral
46 boundary forcing specifications.

47 Addressing the problem of storm surge forecast reliability involves recasting the single, deterministic
48 forecast in probabilistic terms (Gneiting and Katzfuss, 2014). Atmospheric seasonal and sub-seasonal
49 forecasting systems feature several Ensemble Prediction Systems (EPSs), while EPSs are still in their
50 infancy for short term ocean forecasting and coastal forecasting.

51 The notion of ensemble forecasting was first proposed by Lorenz (1963), who demonstrated the
52 sensitivity to initial conditions for a simple non-linear system. In the 1960s it was already clear that
53 there was a “limit of deterministic predictability” in weather forecasting (Palmer, 2018). During the
54 1980s and 1990s ensemble weather forecasting systems were developed leading to an operational
55 system at ECMWF (European Medium Range Weather Forecast, Palmer et al., 1992; Molteni et al.,
56 1996; Buizza, 2019) and at NMC (National Meteorological Center; Toth and Kalnay, 1993). A further
57 development was the concept of multimodel ensemble and superensemble (Krishnamurti et al., 2000).
58 Considering outputs from different models to create an ensemble system limits the systematic errors
59 that can affect each individual model. Another application of a multimodel uncertainty estimation is
60 used for IPCC climate projections (IPCC, 2021).

61 In oceanography, the multimodel super-ensemble concept was applied for the Mediterranean Sea SST
62 forecasting by Pistoia et al., (2016) using a multiple linear regression technique applied to a multi-
63 physics and multi-model dataset. The Mediterranean Sea was the subject of early ensemble systems
64 for the determination of the ocean response to surface wind uncertainty (Pinardi et al. 2008, 2011;
65 Milliff et al., 2011).

66 The first storm surge EPS for coastal systems was made operational by Flowerdew et al., (2009) with
67 further verification of the results in Flowerdew et al., (2010) where the sensitivity of the surge forecast
68 to meteorological forcing and initial conditions was studied. A recent study by Biolchi et al. 2022,
69 applies EPS techniques for a coastal Early Warning System (EWS) employing a morphodynamic
70 model. A multimodel storm surge EPS is operational in the North Sea, combining a series of storm
71 surge forecasting systems using a Bayesian model average (BMA) to weight each individual forecast
72 (Beckers et al., 2008). The same methodology was applied in the western Mediterranean (Pérez et al.,
73 2012). A multimodel EPS approach was also developed for the Adriatic Sea by Ferrarin et al., (2020),
74 where several operational forecasting systems were used to generate a SL ensemble mean (EM) and
75 to assess its uncertainty. Outside Europe, a multimodel EPS has been applied in the New York coastal
76 area (Liberto et al., 2011).

77 In this study we focus on the development of an EPS methodology for a limited area, coastal model
78 at very high resolution. The novelty is that we explore a methodology to create a set of ensemble
79 members to tackle the specific coastal modelling uncertainties. In coastal domains, the dimension of
80 the domain, the bathymetry, the type of lateral boundary conditions (Chu, 1999), the tidal signal from
81 the lateral boundaries as well as the atmospheric forcing and the river runoff may all represent a
82 source of uncertainty. The physical parametrizations and the specific numerical schemes used in the
83 ocean model add further uncertainty to the system.

84 In the Adriatic Sea, storm surges are more common when Scirocco winds (south easterly) blow for
85 several days (Orlić, Kuzmić, and Pasarić 1994). However, Bora winds (north easterly), which usually
86 have the largest amplitude, are the most threatening, especially if concomitant with high tides and
87 preceded by Scirocco winds (Lionello et al., 2021).

88 Seiches can also be generated in response to the winds. The Scirocco blowing over the Adriatic Sea
89 can trigger the fundamental mode of seiches with a period of 21.2 *hr* and a decay time of 3.2 *days*
90 (Cerovečki et al., 1997) and amplitude rising up to 50 cm (Godin and Trotti 1975). Hence, seiches can
91 contribute to high SL values if they overlap with a storm surge (Vilibić, 2006; Bajo et al., 2019). The
92 second and third modes of Adriatic Seiches have a 10.7 *hr* and 6.7 *hr* period respectively (Raicich,
93 1999) and a smaller amplitude.

94 This study focuses on the Goro Lagoon (Fig. 1), which is exposed to storm surges that threaten the
95 towns around the lagoon (Bondesan et al., 1995). In November 1966, a dramatic flood (Garnier et al.,
96 2018) caused by a persistent Scirocco wind, caused severe damage to buildings, roads and cultivated
97 lands. In Goro town almost 80 families were moved away from their homes. In October 2018, another
98 Scirocco event caused flooding in the Goro harbour. Thus, we tried to define an EPS that could

99 potentially be beneficial to the local population if made operational and converted into an early
100 warning decision support system.

101 The forecasting model is a baroclinic very high-resolution model (GOLFEM) described in Maicu et
102 al., (2021). We tested the EPS methodology considering five recent extreme events, using forcing
103 from different meteorological and ocean operational models for initial and lateral boundary
104 conditions, together with river discharge perturbations. We assessed the sources of uncertainties along
105 with the performance of the ensemble considering specific ensemble mean algorithms.

106 In Section 2 the storm surge, high SL events and the circulation model are described. Section 3 defines
107 the ensemble methodology. The results are shown in Section 4. Section 5 contains summary and
108 conclusions.

109 **2 Data and Methods**

110 **2.1 Sea Level Extreme Events in the Goro Lagoon**

111 The GOLFEM-EPS area of interest is represented in Fig. 1. It contains the whole Goro Lagoon
112 together with the Po River branches of Goro and Volano. The bathymetry of the lagoon is shallow,
113 about 1.50 m on average and it gently slopes to the continental shelf of the northern Adriatic Sea. The
114 lagoon has a wide opening of about 4 km and is thus exposed to sea level anomalies entering from
115 the open Adriatic Sea.

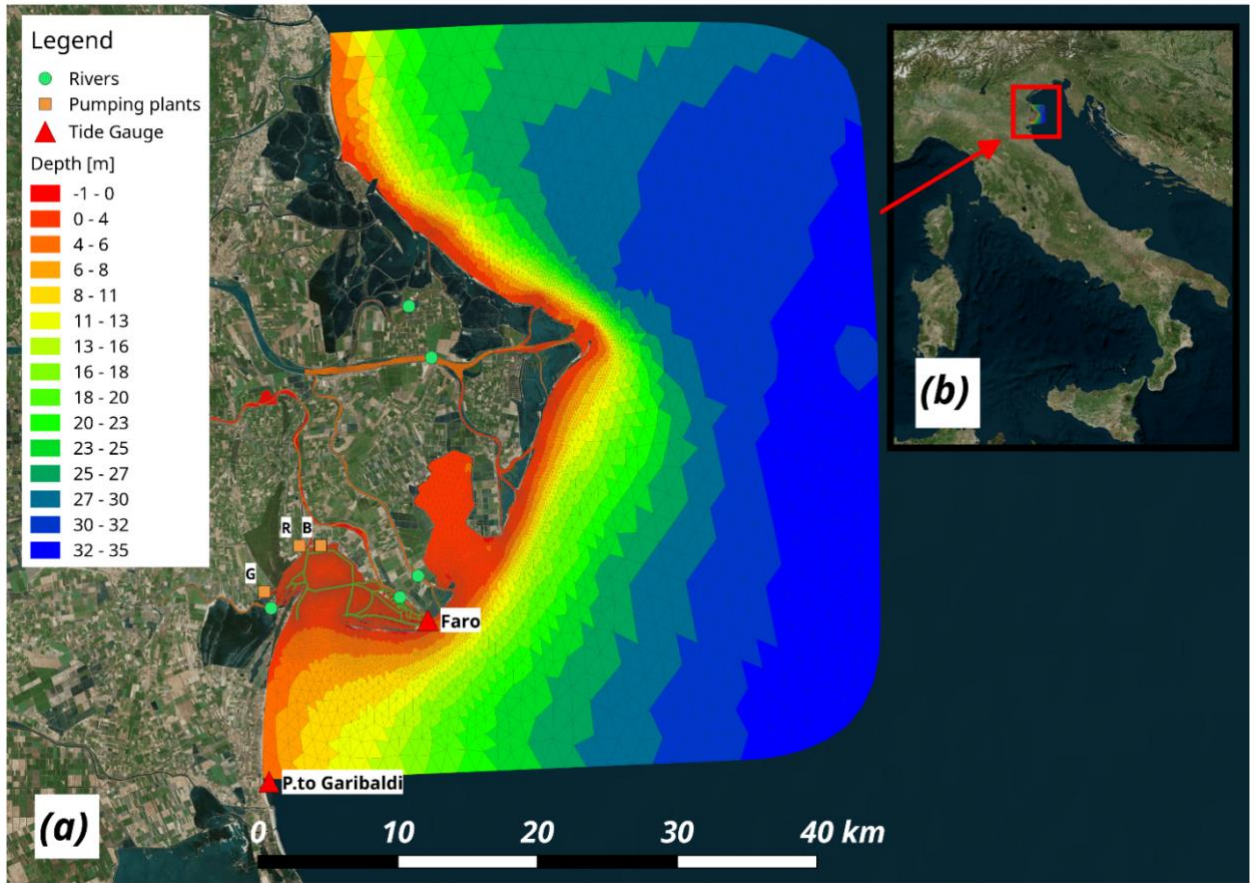


Figure 1: (a) Bathymetry and coastlines of the Goro Lagoon. The red triangles indicate the position of Faro and Porto Garibaldi tide gauges. The green circles indicate the position of rivers, starting from the south-west, the Po di Volano, the Po di Goro, the Po della Donzella, the Po di Pila and the Po di Maistra. The orange squares represent the three pumping plants discharging in the Goro lagoon: (G) Giraldi, (R) Romanina, and (B) Bonello. (b) The domain position in the Adriatic Sea (source map: OpenStreetMap).

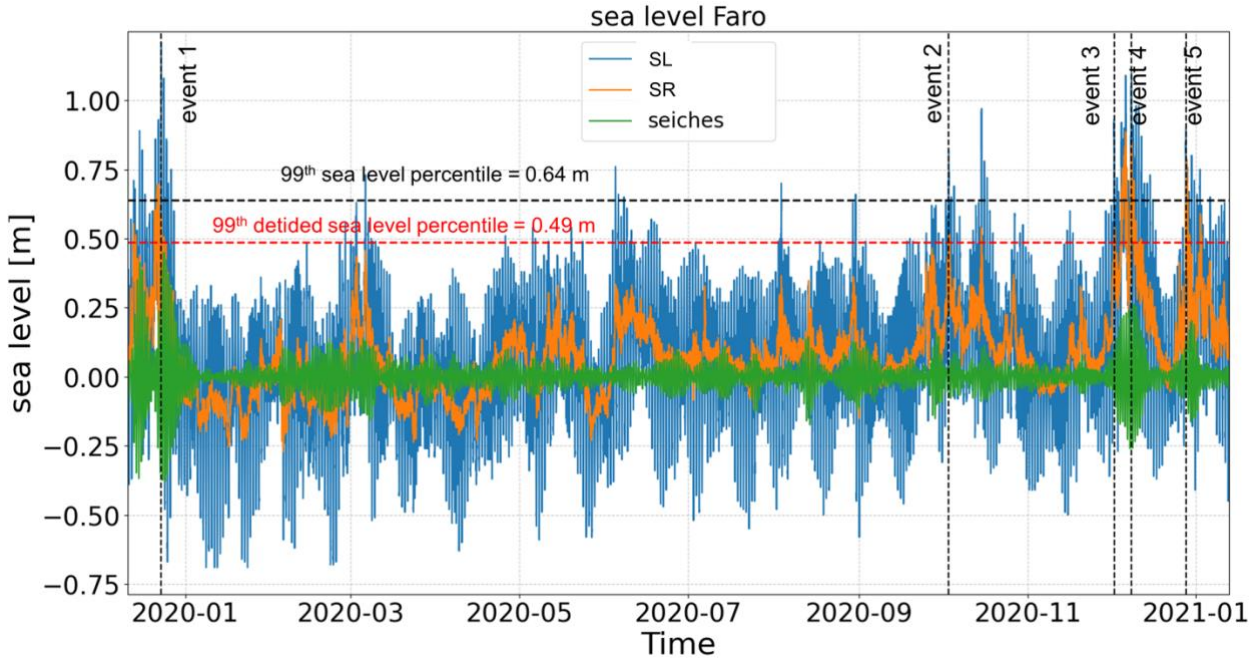
All the extreme events used in this work were collected from Perini et al. (2020, 2019), which details the extreme events and their impacts on the ER coast. Sea level observations collected at Faro and Porto Garibaldi (Fig. 1) are available every 10 minutes, thus giving a very good determination of extremes. Table 1 describe the five tide events from both Porto Garibaldi and Faro tide gauges.

Fig. 2 shows the sea level observations at Faro (from late 2019 to early 2021), together with the surge residual (SR, orange line) and the fundamental and second seiche mode contribution to SL (green line).

SR is calculated from SL using a de-tiding procedure described in the Appendix A. The residual signals only conserve the surge contribution due to local wind, atmospheric pressure, and large scale non-tidal remote forcing. Likewise, the tidal filter is used to compute the contribution of the seiches. The filter is inverted and the frequencies of the seiches are the only ones retained in the computation. The events listed in Table 1 all have a non-negligible surge component.

The time of the peak sea level recorded for each event is indicated by the vertical dashed lines. The horizontal dashed lines indicate the 99th percentile of the sea level, in black for the SL data (0.64 m)

135 and in red for the SR time series (0.49 m) considering all the data available starting from April 2016.
 136 Considering percentiles between 95 and 99 is quite common in extreme value analyses of the sea
 137 level (Wahl et al., 2017; Kirezci et al., 2020). In this work the 99th percentile is just taken as a
 138 reference threshold for the considered events. The same percentile computation was also done for the
 139 Porto Garibaldi station, where data are available starting from July 2009. The values found were 0.7
 140 m and 0.53 m for the SL and SR respectively. It is worth noting that all the peak events considered
 141 for this work exceed both the observed SL and SR 99th percentile.



142
 143 Figure 2: SL observations (blue), SR (orange) and seiches (green) at Faro (see Fig. 1 for reference position). The vertical black dashed
 144 lines indicate the 5 extreme events considered in this paper. The horizontal dashed black and red lines indicate the 99th percentile of
 145 the SL and SR, respectively.

EVENT NO.	DATE	PORTO GARIBALDI TIME(UTC), SL(M), SR(M)	FARO TIME(UTC), SL(M), SR(M)	IMPACTS	PREVAILING WINDS
1	2019-12-23	07:40 -> 1.17, 0.56	07:50 -> 1.21, 0.60	Uniform large impacts	NW
2	2020-10-03	10:50 -> 0.86, 0.51	10:30 -> 0.82, 0.51	No impacts	SE
3	2020-12-02	08:20 -> 1.02, 0.61	08:30 -> 0.93, 0.54	Uniform large impacts	N-NE
4	2020-12-08	15:30 -> 1.06, 0.96	15:10 -> 1.10, 0.85	Ferrara province	E-SE
5	2020-12-28	08:30 -> 0.90, 0.72	09:00 -> 0.90, 0.78	Minor impacts Volano	SE

146 Table 1: The five events analyzed in this study, with date, hour, max observed sea level (SL) and max observed surge residual (SR) at
 147 P.to Garibaldi and Faro (Fig.1). Impacts and prevailing winds for each event are also indicated (NW-North Westerly; SE-South
 148 Easterly; N-NE-North-North Easterly; E-SE- East-South Easterly; SE- South Easterly).

149 2.2 The circulation model

150 GOLFEM is the implementation of the SHYFEM model (Umgiesser et al., 2004; Bellafiore et al.,
 151 2010, Micaletto et al., 2022) in the Goro Lagoon. SHYFEM is an open-source
 152 (<https://github.com/SHYFEM-model/shyfem>) unstructured grid baroclinic ocean model that solves

the primitive equations for the ocean under Boussinesq and hydrostatic approximations. It has been already applied in operational (Federico et al., 2017) and relocatable (Trotta et al., 2021) forecasting systems, and for storm surge events (Park et al., 2022). GOLFEM has been extensively calibrated, validated and described in Maicu et al. (2021). GOLFEM is nested in large scale ocean models and is forced by atmospheric numerical weather prediction fields. The river runoff is also imposed as a lateral open boundary condition. All the ocean and meteorological products characteristics used to initialize and force the different members are described in the next section and are summarized in Table S1 of the Supporting information (SI).

2.3 Nesting in large scale circulation models

GOLFEM-EPS is nested within five ocean larger scale circulation models. Starting with the largest, the Copernicus Marine Service global model (Le Traon et al., 2019), offers daily global forecasts (hereafter referred to as GLOBAL; Lellouche et al., 2018) with a horizontal grid resolution of $1/12^\circ$ (~ 8 km) and 50 vertical levels. It uses the SAM-2 data assimilation scheme, based on a reduced-order Kalman filter. It is forced at the surface with ECMWF meteorological fields. On a daily basis, the GLOBAL operational system provides a 10 day forecast (daily output), and every week it computes the best analysis for the previous 14 days.

The Copernicus Marine Service Mediterranean Sea model (Clementi et al., 2017, 2021, hereafter MED-MFC) is a coupled current-wave model of the Mediterranean Sea and the adjacent Atlantic area. It is composed of the general circulation model NEMO (Nucleus for European Modelling of the Ocean-NEMO; Madec, 2008) and coupled 2-way with the third-generation spectral wave model WaveWatchIII (Tolman, 2009). The horizontal grid is at $1/24^\circ$ resolution (~ 4 km), with 141 unevenly vertical z levels. The analyses and forecasts are forced by ECMWF atmospheric fields and use climatological discharges from 36 rivers, including the Po. The model uses a 3D variational data assimilation scheme to correct the model output. The eight major tidal constituents were recently added providing a different forecasting and analysis current model, hereafter called MED-MFC-T.

ADRIAC is an Adriatic Sea scale forecasting model operational at the Hydro-Meteo-Cimate Service of the Regional Agency for Prevention, Environment and Energy of Emilia-Romagna, Arpae-SIMC (Bressan et al., 2017). It is based on the COAWST model (Warner et al., 2010) which is a coupled ocean-atmosphere-wave-sediment transport model. The ocean part is simulated with the ROMS model (Shchepetkin and McWilliams, 2005) at a resolution of about 1 km and 30 σ -layers. Hourly discharge data from the Po are used, while a climatology is used for the other 48 Adriatic rivers. Initial and boundary conditions are provided by the MED-MFC model for currents, salinity, temperature, and sea level. Tides (eight components: K1, O1, P1, S1, K2, S2, M2 and N2) are given

186 at the Otranto strait computed by the TPXO model (Egbert and Erofeeva, 2002). Meteorological
187 forcing is provided by COSMO-2I and COSMO-5M models (Gastaldo et al., 2021; Steppeler et al.,
188 2003; COSMO-newsletter, 2004). ADRIAC provides three day forecasts per day, with a one-day
189 spin-up, using the analyses of the meteorological forcing and boundary conditions.
190 ADRIAROMS is another operational model based on ROMS model and implemented by Arpae-
191 SIMC (Russo et al., 2013). It covers the entire Adriatic basin with a horizontal resolution of about 2
192 km and 20 σ -layers. Initial and boundary conditions are provided by CMEMS MED-currents. Tides
193 (four components: K1, O1, S2, M2) are computed and provided by TPXO to the Otranto strait.
194 Meteorological forcing is provided by the COSMO-5M model. Rivers are the same as in ADRIAC.
195 ADRIAROMS provides a three-day hourly forecast with a one-day spin-up as for ADRIAC.

196 **2.4 Meteorological forcing fields**

197 Three operational meteorological products are used as input fields by the circulation model to
198 compute momentum, heat and water fluxes at the air-sea interface via bulk formulas (Maicu et al.,
199 2021). The ECMWF weather forecast fields are based on the deterministic high resolution global
200 model at 12.5 km of nominal resolution (ECMWF-IFS; Owens and Hewson, 2018). It provides 10-
201 day forecast fields every three hours for the first three days and 6 hours for the subsequent days.
202 COSMO-5M is a regional operational meteorological model (Garbero and Milelli, 2020). It is based
203 on the COSMO model (Steppeler et al., 2003) and covers the Mediterranean region. It has a horizontal
204 resolution of about 5 km and 45 vertical layers. It is initialized by the deterministic analysis of
205 COMet-LETKF (the model used by the Italian air force) and takes the ECMWF-IFS fields as
206 boundary conditions. It runs twice per day, at 00 and 12 UTC providing a 72-hour forecast (hourly
207 output). The COSMO-5M input fields are given at hourly frequency for 3 forecast days.
208 COSMO-2I is the highest resolution operational weather forecast model (Gastaldo et al., 2021)
209 covering the Italian domain. It is nested in COSMO-5M. The initial state is computed from the
210 KENDA-LETKF system (Schraff et al., 2016; Gastaldo et al., 2021), and has a resolution of ~ 2.2
211 km and 65 vertical layers. It provides a *48 hr* forecast (hourly output) and two forecasts per day at 00
212 and 12 UTC.

213 **2.5 River Runoff Conditions**

214 The hourly discharge from the Po River is measured by Arpae at Pontelagoscuro. At the eastern side
215 of the Goro lagoon (Fig. 1), the Po of Goro runoff is computed as a percentage of the Pontelagoscuro
216 discharge values, based on a repartition equation that fits data from Arpav (2012). At the western side
217 of the lagoon, the Po of Volano runoff is provided as the sum of all the pumping plant discharges
218 which constitute the final flow of the Po of Volano. The runoff is imposed as a lateral boundary

condition. In addition to the two Po branches, three pumping stations were considered for the freshwater discharge in the lagoon. Three simulations were performed: one with the nominal discharge of the Po of Volano, Po of Goro and the three pumping plants, and two others were defined by adding and subtracting 30% of the discharges.

3 The Ensemble Prediction System

3.1 The Ensemble Methodology

GOLFEM-EPS has 45 members. The GOLFEM-EPS members are composed of a suitable combination of atmospheric and ocean models and perturbations to the river flow (Table 2).

227

Meteorological models	River runoff	Ocean Models				
		ADRIAC	ADRIAROMS	MED-MFC	GLOBAL	MED-MFC-T
COSMO 2I	Data	Exp-1	Exp 10	Exp 19	Exp 28	Exp 37
	-30 %	Exp 2	Exp 11	Exp 20	Exp 29	Exp 38
	+30 %	Exp 3	Exp 12	Exp 21	Exp 30	Exp 39
COSMO 5M	Data	Exp 4	Exp 13	Exp 22	Exp 31	Exp 40
	-30 %	Exp 5	Exp 14	Exp 23	Exp 32	Exp 41
	+30 %	Exp 6	Exp 15	Exp 24	Exp 33	Exp 42
ECMWF	Data	Exp 7	Exp 16	Exp 25	Exp 34	Exp 43
	-30 %	Exp 8	Exp 17	Exp 26	Exp 35	Exp 44
	+30 %	Exp 9	Exp 18	Exp 27	Exp 36	Exp 45

Table 2: EPS members with the relative meteorological and ocean forcing and river perturbations.

The EPS methodology is shown in Fig. 3: one day before the start of the forecast, GOLFEM-EPS is initialized and forced with surface analysis fields and lateral analysis boundary conditions from the circulation model outputs. Starting from the initial time of the forecast, always set at 00:00 UTC, forecast lateral boundary conditions and surface meteorological fields are used for a three days forecast, up to +72 hr. ADRIAC and ADRIAROMS models do not have an operational data assimilation scheme. For ADRIAC and ADRIAROMS the analyses are thus simulations forced by meteorological and open ocean lateral boundary analyses. Since COSMO-2I provide only a 48 hr forecast, from +48 hr to +72 hr, the meteo fields from COSMO-5M are used.

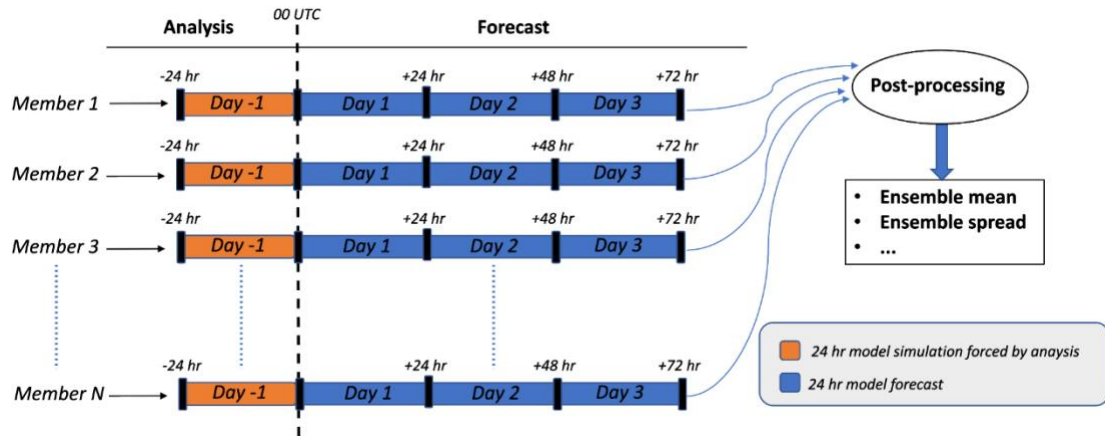


Figure 3: The GOLFEM-EPS modelling scheme. The post-processing creates ensemble mean, ensemble spread and the weighted ensemble mean.

Fig. 4 shows the GOLFEM-EPS basin average kinetic energy (KE) for one member simulation (exp-1) initialized three days and one day before the nominal start of the forecast. The KE is initially zero for both simulations (all simulations are initialized with a zero-velocity field). After about 14 hours the simulations were found to reach a similar KE. This explains the choice of only one day as a spin-up time for the forecast, which is a reasonable time for the ocean limited-area domains. It is also well known that the spin-up time decreases with the scale of the implemented computational domain, and one day of spin-up has also been used by authors dealing with very limited coastal models (Gaeta et al., 2016).

The GLOBAL and MED-MFC products are provided without tides. In the case of non-tidal models, the tidal sea level is extracted from the TPXO model and added to the GOLFEM open boundaries. Despite the importance of baroclinic pressure gradients during storm surge events (Staneva et al., 2016), preliminary simulations have compared the sea level of baroclinic and barotropic runs, highlighting only a negligible difference, probably due to the very small and shallow areas considered. We argue that for SL forecasts, the baroclinicity may be site-by-site dependent. However, building a multi-hazard system means that all processes need to be considered from the start. Incremental improvements will thus be made, also considering the progress in SL forecasting.

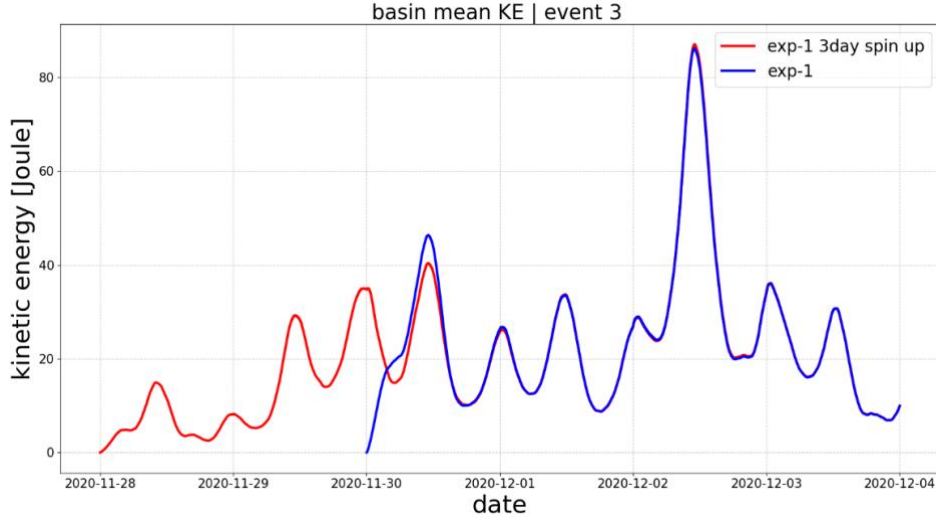


Figure 4: Mean basin kinetic energy of exp-1 considering one (blue) and three (red) days of spin-up.

3.2 Ensemble Mean

The ensemble forecast is usually considered to be a better estimate of the forecast since the members sample the probability distribution function of the forecasts. However, interpreting multiple forecasts can be complex, so very often the Ensemble Mean (EM) is used for the sake of simplicity.

Using the notation of Salighehdar et al. (2017), a forecast matrix is defined as $X = \{x_i^j\}_{(i,j) \in \{1, \dots, T\} \times \{1, \dots, m\}}$ where T and m are the forecast lead time and the total number of forecasts available respectively. The point x_i^j thus represents the sea level or surge at time i predicted by member j . The EM produced by an EPS is denoted by a vector F_i of all times i . The EM is a simple average of the member forecasts defined as:

$$F_i = \bar{x}_i = \frac{1}{m} \sum_{j=1}^m x_i^j \quad (1)$$

In this case each member has the same weight. However, during extreme events, when usually the forecast uncertainty is greatest, this may not be the best solution. Another method is to evaluate the weights of each member based on the performance achieved during a training period. Here the correlation method is tested to compute a Weighted EM (WEM). In addition, only a subset k of the m members can be considered to compute a better average. The first k forecasts are chosen based on the performance during the training period. However, selecting the value of k is subjective. The specific WEM methodology is detailed in Appendix B.

275 **4 Results**

276 **4.1 EPS Skill**

277 The SL and SR are shown for events 2, 3 in Fig. 5 and events 4 and 5 in Fig. 6. We will discuss event
278 1 in the last part of this section. The thick green line (exp-1) is the member forced by the highest
279 resolution models (Adriac and COSMO-2I; see Table 2). This is the deterministic reference model.
280 The thick black and orange lines are the EM and WEM, respectively. Qualitatively the deterministic
281 forecast overestimates the SR in two out of the four events.

282 The ensemble spread grows and peaks at the time of the extreme event. This is another benefit of the
283 EPS which alerts the forecaster of the possibility of a large event even if not capturing the correct
284 amplitude. For SR, the maximum spread is at the peak of the event with values of 4.5, 7, 7 and 12 cm
285 for event 2, 3, 4 and 5, respectively. Interestingly, in event 2 one of the members forced by
286 ADRIAROMS overestimates the SL at the peak time (see the upper light green line in Fig. 5b), as do
287 other members with the same nesting model (not shown). Since no overestimation is observed in the
288 SR (Fig. 5a) the error may be attributed to a wrong tidal signal provided by ADRIAROMS.

289 The performances of individual members during the forecast time are summarized for each event
290 with Taylor diagrams (Figs. 7 and 8). An evident feature is the grouping of members with the same
291 ocean initial and lateral boundary conditions. This is even clearer when the SL is considered (Figs.
292 7b,d and 8b,d). If SR is considered (Figs. 7a,c and 8a,c), for each group there is a smaller dispersion
293 due to the different meteorological forcings and to a lesser extent, due to the different river forcing.
294 The initial/lateral boundary conditions (including the tidal forcing) therefore seem to be the greatest
295 source of uncertainty (both for SR and SL), followed by the meteorological forcing and river forcing.

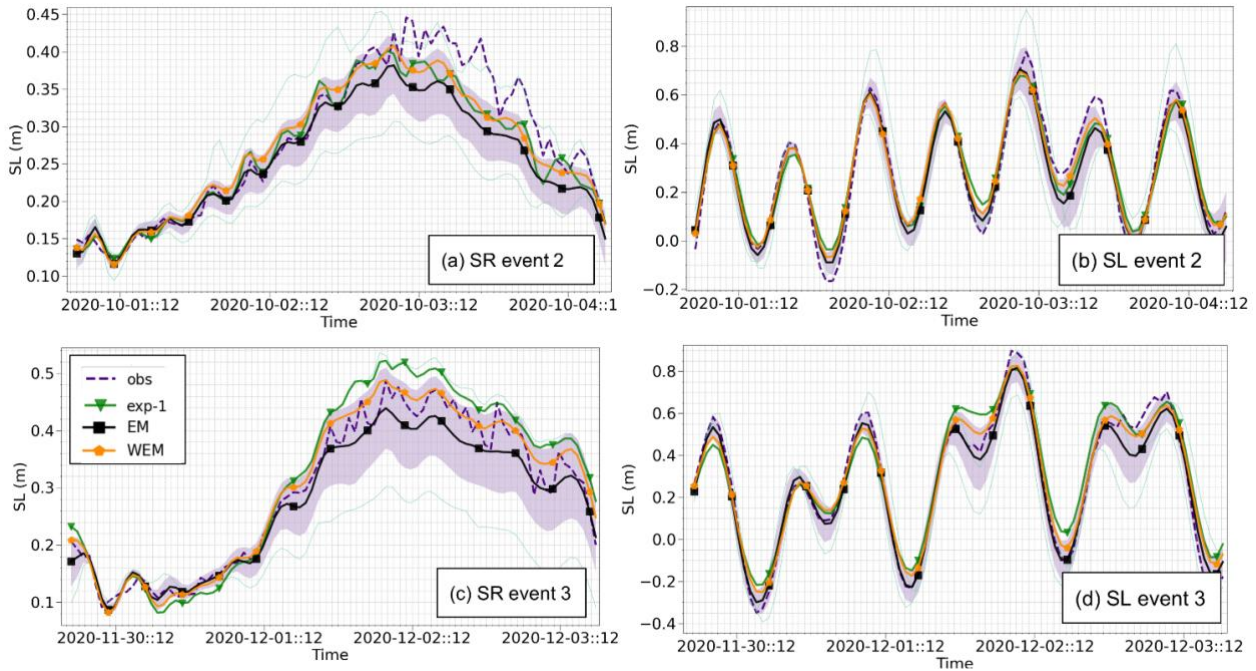


Figure 5: SR (left column) and total SL (right column) forecast comparison at Faro for event 2 (a,b) and event 3 (c,d). The green line shows exp-1 considering the reference deterministic forecast as described in Table 2. EM and WEM indicate the Ensemble Mean and the Weighted Ensemble Mean. The light green lines represent the members with maximum and minimum sea level values during the storm surge peak. The shaded areas are the ensemble spreads.

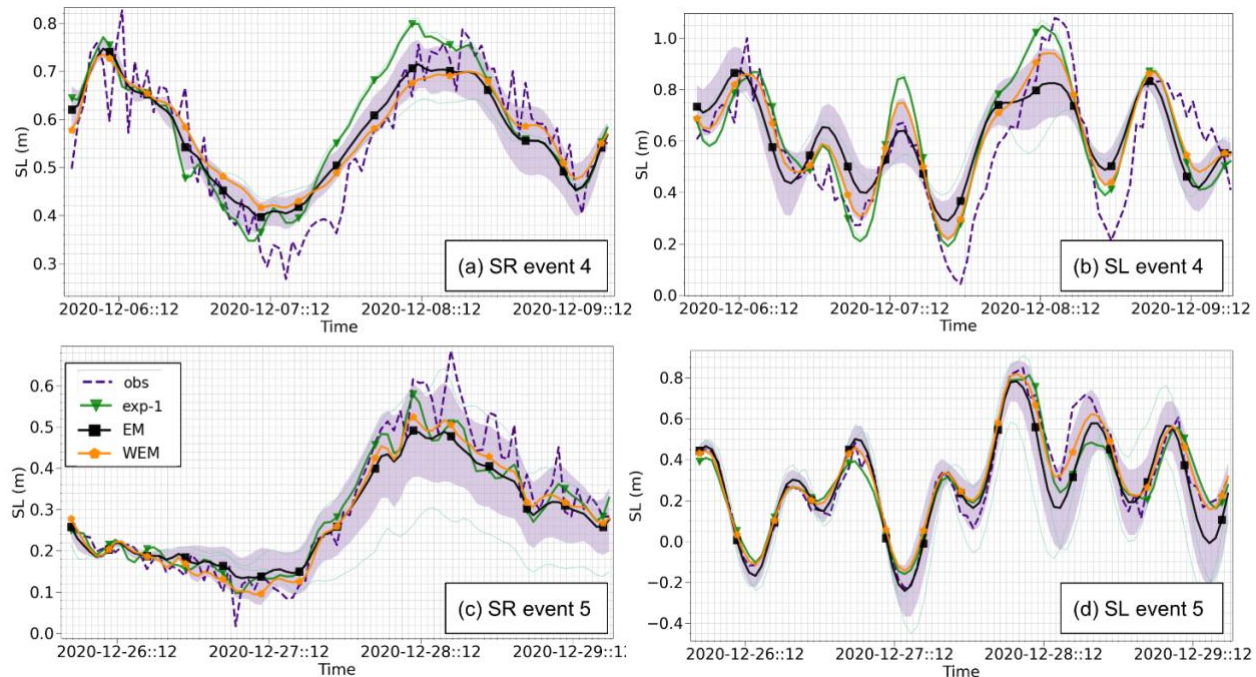


Figure 6: As in Fig. 5 but for event 4 (a,b) and event 5 (c,d).

In both events 2 and 3, the maximum surge occurred with the maximum tidal amplitude, with some impacts at the level of the coast. Conversely, event 4 reached the peak during a tidal minimum. A spectral analysis of the observed sea level revealed that there was a high contribution from the fundamental Adriatic seiche (~ 0.25 m), as shown in Fig. 2. The coincidence of remotely forced

coastally trapped sea level maxima with tidal and local wind forcing has also been examined in detail for the US East Coast (Park et al., 2022). A correlation between the arrival time of remote signals was found to be the most important predictor of sea level extremes.

The Taylor diagrams provide an indication of the members that most contribute to build the final WEM for each event. In most cases members initialized/forced with MED-MFC-T (from exp-37 to exp-45) show the best scores (ρ between 0.95 and 0.99; ~ 0.7 for event 1 SR) followed by members initialized/forced with ADRIAC (exp-1 to exp-9; ρ between 0.85 and 0.95; ~ 0.5 for event 1 SR) and MED-MFC (exp-19 to exp-27; ρ between 0.85 and 0.99; ~ 0.7 for event 1 SR). Members initialized/forced by ADRIAROMS (exp-10 to exp-18) usually show the worst performance (ρ between 0.3 and 0.95; $\sim 0.1 - 0.2$ for event 1 SR) together with the members initialized/forced by the GLOBAL product (exp-28 to exp-36; ρ between 0.4 to 0.9; ~ -0.4 for event 1 SR).

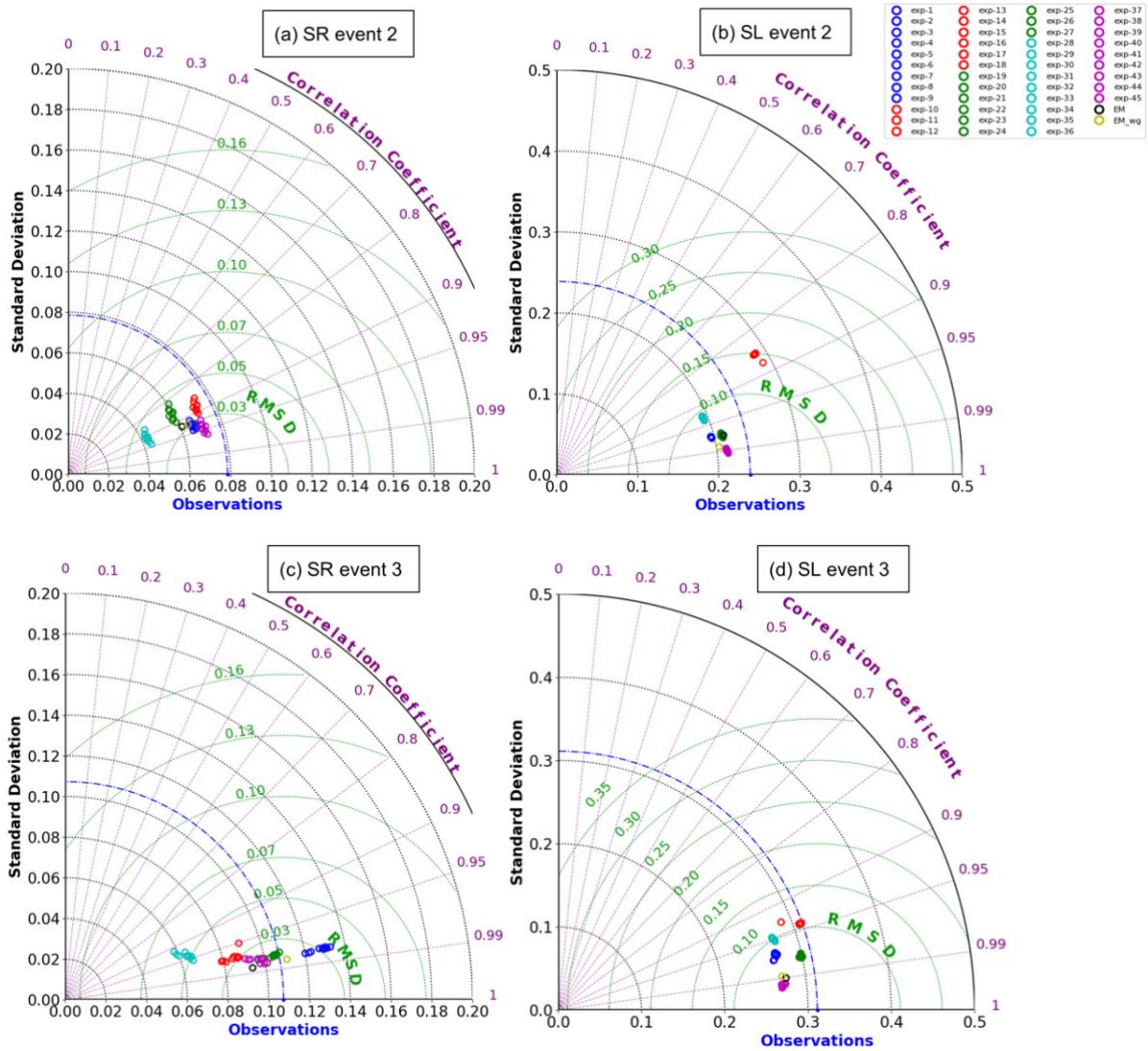


Figure 7: Taylor diagrams for SR and total SL for event 2 (a,b) and event 3 (c,d).

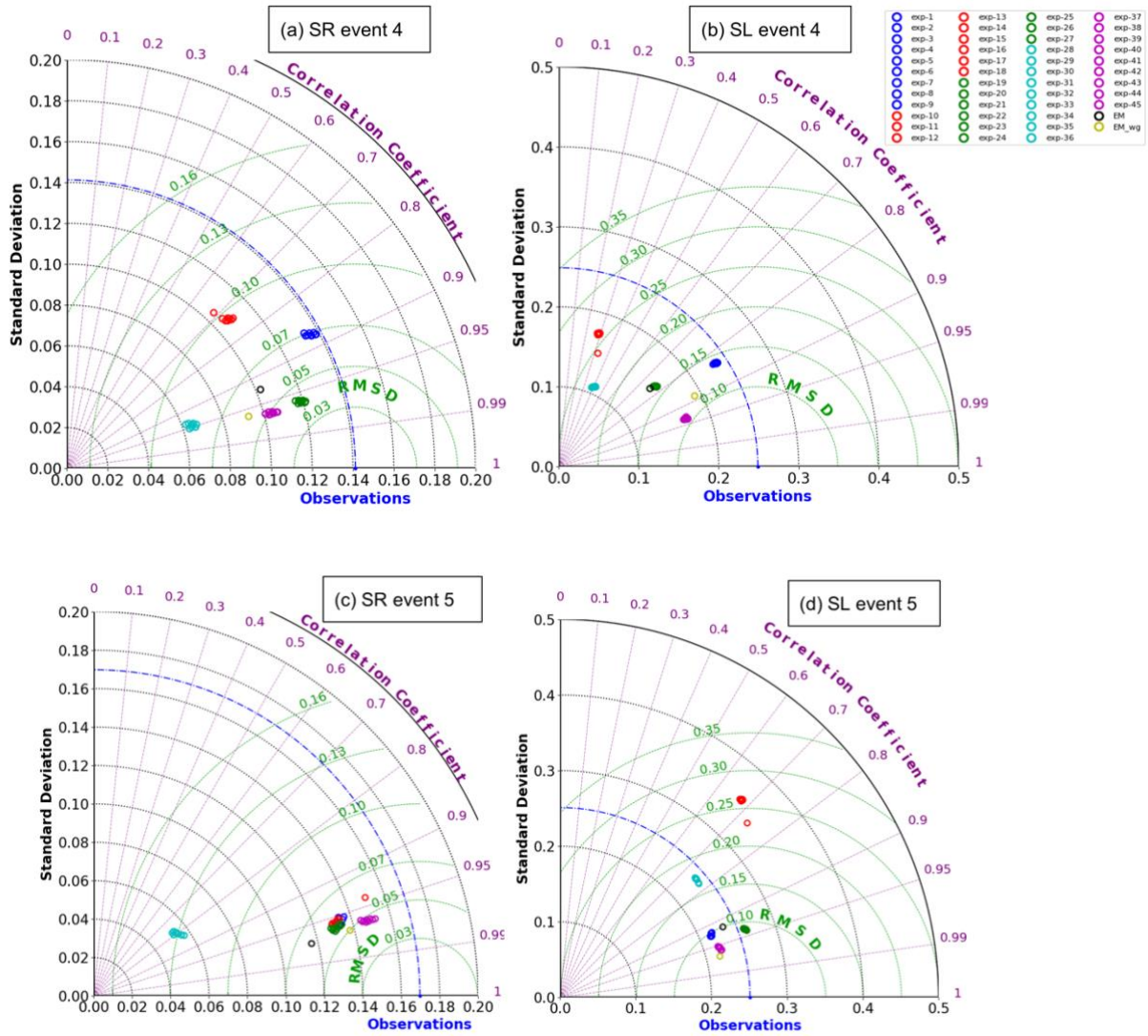


Figure 8: Taylor diagrams for SR and total SL for event 4 (a,b) and event 5 (c,d).

If SL Taylor diagrams are considered, we note again that members forced by MED-MFC-T have the best performance. This suggests that a Mediterranean scale ocean model may be more effective in representing the non-linear interactions that occur between tides, bathymetry and Adriatic basin modes compared to Adriatic scale models (ADRIAC or ADRIAROMS) that imposes TPXO tides at the southern boundary.

Event 1 is a special case because the contribution of the Adriatic Sea seiches reached values close to 40 cm (Fig. 2). Fig. 9a shows that the SL peak coincides with a decreasing SR (Fig. 9a and b). The storm surge is thus generated mainly by the seiches and the tides.

Of the events analyzed, this case shows the worst performance for most of the ensemble members, with a negative correlation for the one forced by GLOBAL (Fig. 9c and d). However, EM and WEM benefit from error compensation and show satisfactory results in terms of SR, although none of the members reproduced the peak of SL occurring on 23 December 2019 at 07:50. This highlights the fundamental importance of tide-seiche resonant phenomena without the contribution from local

338 meteorological forcing and underline some limitation of regional and large-scale ocean models in
 339 simulating such interaction.
 340 The members initialized/forced by the GLOBAL model have usually the worst results. This is not
 341 surprising since the GLOBAL product has the lower resolution and its daily output is not able to catch
 342 appropriately the surge components due to wind during extreme events. Indeed, members forced by
 343 GLOBAL are most of the times excluded by the weighting procedure.

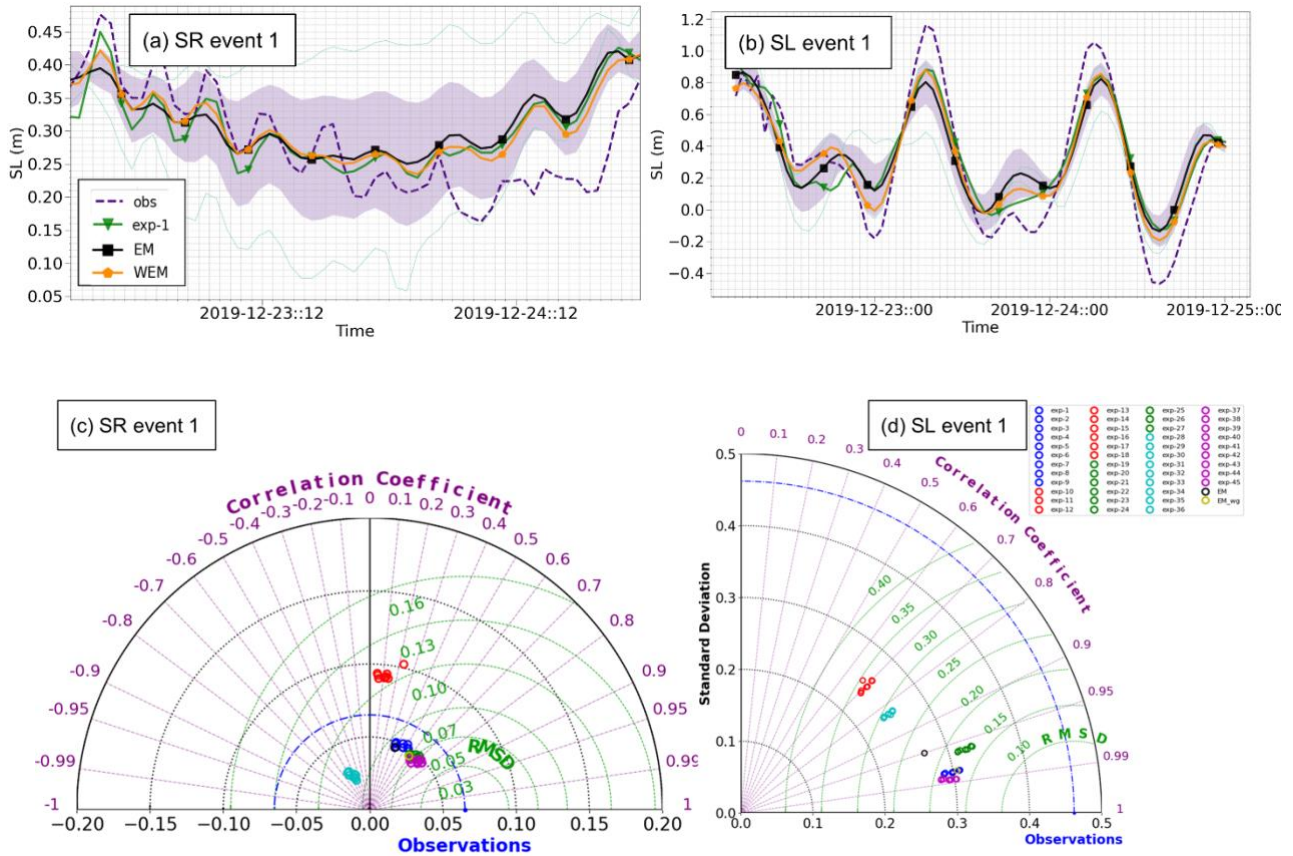


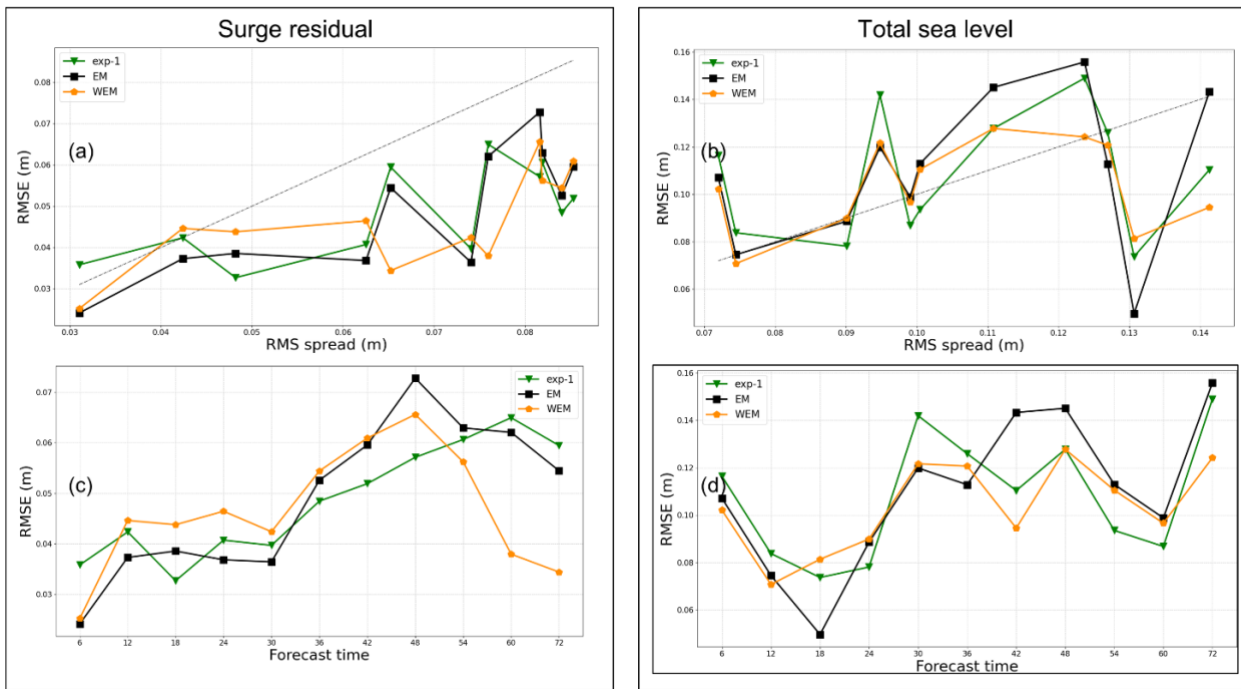
Figure 9: SR (a) and SL (b) forecast comparison for event 1. The light green lines represent the members with maximum and minimum sea level values during the peak. The shaded area is the ensemble spread. Taylor diagrams for SR (c) and SL (d) are also shown.

4.2 Ensemble Member Analysis

Any analysis of an EPS should consider its degree of the over or under-dispersiveness of the members. To do this, we analyzed the root mean square error (RMSE) as a function of the ensemble spread (Figs. 10a and b), aggregating all the events in Porto Garibaldi and Faro, considering 6 h intervals. The RMSE-spread plot provides information on the dispersion of the ensemble members. In an ideal case the RMSE should be linearly proportional to the ensemble spread. Fig. 10a shows that there is a slight over-dispersion of the members for spreads greater than 0.05 cm. This implies that during peak events, there is more dispersion of the ensemble members than expected. We argue that this over-dispersion of the ensemble is due to the very different initial and lateral boundary conditions used. If the SL is considered, over-dispersion appears for spread values greater than 0.13

358 cm, while a slight under-dispersion appears for smaller spread values, probably connected to the tidal
 359 components.

360 The SR RMSE error increases with time up to a maximum at 48 h for EM and WEM. The exp-1
 361 seems to perform slightly better between 36 and 48 *hr*, while after 48 *hr*, both EM and WEM
 362 performances are slightly better. The SL RMSE shows almost a linear increase with time for all
 363 forecasts with slightly better performances for the WEM at the end of the forecast period. The RMSEs
 364 considered for all the forecasts and all events are 5.7, 5.5 and 5 cm for EM, exp-1 and WEM
 365 respectively for SR, while for SL, the RMSEs are 12, 11.5 and 11 cm.



366

367 *Figure 10: RMSE against ensemble spread and forecast time for SR (a,c) and total sea level (b,d). Data are computed aggregating*
 368 *all the events at Porto Garibaldi and Faro stations.*

369 We conclude this section by analyzing the spatial distribution of the ensemble spread at the time of
 370 each peak event, taking into account only the SR. Considering first the river and meteorological
 371 forcing induced ensemble spread, the river run-off has a small influence on the SR ensemble spread
 372 (Fig. 11a), which remains confined at the river mouths along the coast, reaching low values of 0.3
 373 and 0.4 cm. The meteorological forcing leads to a bigger ensemble spread but with a maximum value
 374 of 1-3 cm (Fig. 11b). Although the winds are one of the main drivers of storm surges in the area and
 375 may represent a big source of uncertainty, we argue that the low spread values found here are a
 376 consequence of the small size of the domain, and the fact that the storm surge component due to
 377 remote wind effects is important, as discussed earlier.

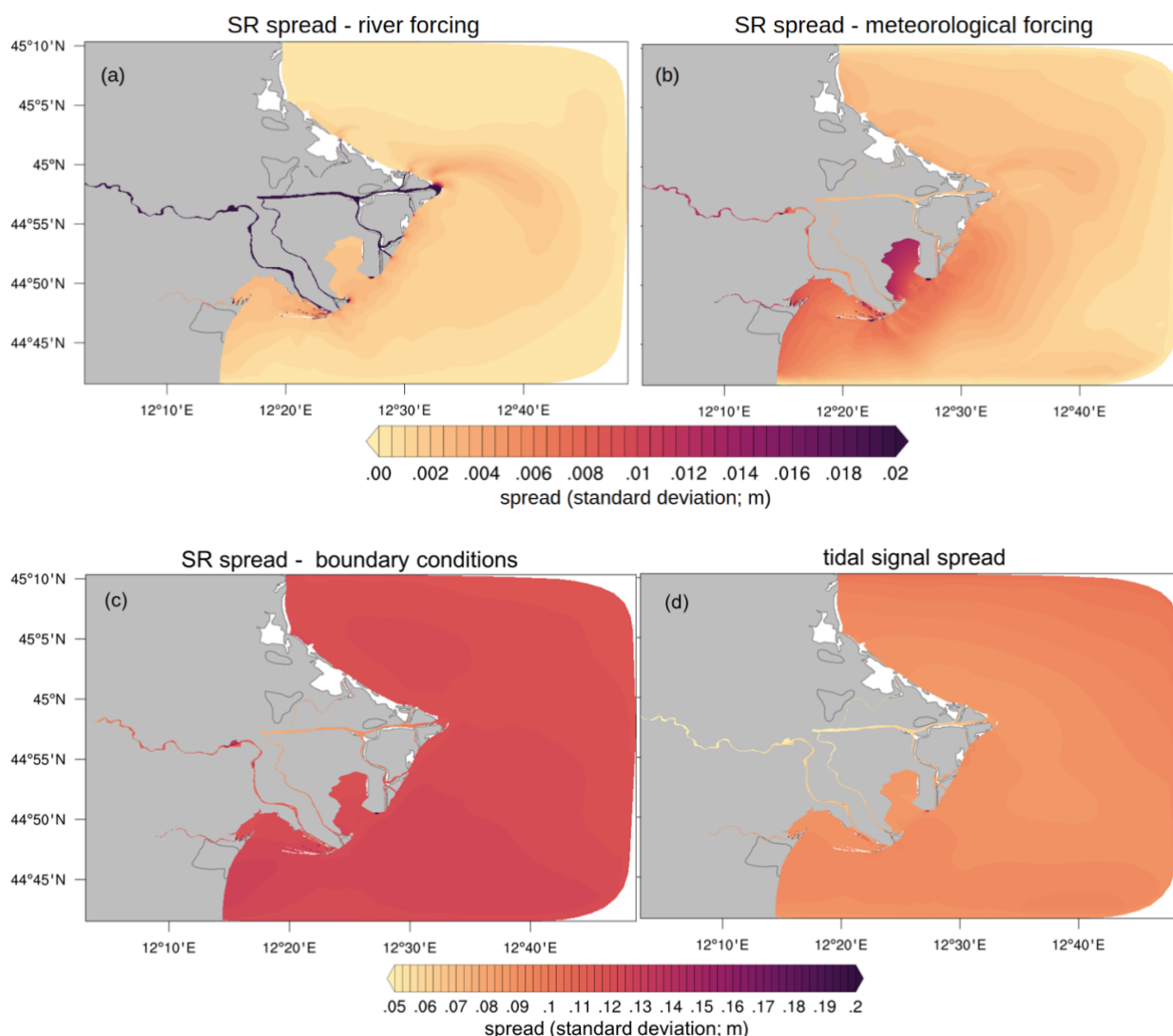


Figure 11: Spread due to river forcing (a), meteorological forcing (b), boundary conditions (c) and tidal signal (d). Data are computed aggregating all the events.

The ensemble spread due to initial and lateral boundary conditions is clearly a dominant contribution (Fig. 11c), exceeding by one order of magnitude the spread due to local meteorological forcing. The SR spread (Fig. 11c) is almost uniform throughout the entire domain with values between 12 and 13 cm. The tidal signal extracted inverting the filtering procedure reveals that the contribution of tides to the sea level spread is of the same order of magnitude (Fig. 11d), with slightly smaller values between 9 and 10 cm. This suggests that both for computational efficiency and system performance, the storm surge EPS implemented in small domains should focus on the initial and lateral boundary condition uncertainties, further substantiating previous results (Chu, 1999).

5 Summary and Conclusions

We designed and developed a coastal Ensemble Prediction System for the Goro Lagoon (GOLFEM-EPS) using a baroclinic very high-resolution unstructured grid model. The EPS is composed of 45

members produced by model forecasts carried out with different meteorological forcing, initial and lateral boundary conditions from coarser resolution ocean models and perturbations to the river discharge. The forecast lead time is 3 days with a one day spin-up in analysis/simulation mode. The total SL RMSE computed at the two reference stations is 11 and 12 cm respectively for WEM and EM, while it is 11.5 cm for the deterministic reference forecast. One case, event 1, showed large errors, due to the specific importance of seiches and tidal elevation in the process and the limitation of the circulation models to reproduce such basin modes and their non-linear interaction with tides. The correct simulation of the tidal phase is also crucial and a way to account for the shifts in the tidal peak is to consider the skew surge (Williams et al., 2016). Such an approach will be further investigated for the domain considered here.

A post-processing ensemble mean (EM) procedure was carried out and a weighted ensemble mean (WEM) methodology was tested based on the performance of the members during the spin-up which was considered to be equivalent to a training period. Of the 45 members used for the ensemble, most of the variability was reached including only members that differed in initial and lateral boundary conditions. An estimate of the uncertainty due to different initial/lateral boundary conditions, river runoff and atmospheric forcings was provided. A perturbation of $\pm 30\%$ in the river run off was found to contribute with 3-4 mm in the ensemble sea level spread limited to the river mouths. Meteorological forcing had a greater impact of between 1 and 3 cm, while initial/boundary conditions (including tides) provided most of the sea level uncertainty between 9 and 13 cm.

It is found that EM and WEM forecasts have better skill from 48 to 72 *hr* forecast lead time while in the first two days they are equivalent to a single deterministic forecast skill.

The conclusions regarding the skill of WEM or EM for 3 days sea level forecast is probably ultimately connected to the specific model domain size and the specific area dynamics. For general ensemble coastal forecasting, several areas should be tried with the same WEM and EM methodologies. For the Goro Lagoon specifically, different model size domains are needed, and the optimal model domain size should be found in order to obtain a reduced SL forecast error. The limitations in validating the model domain size derive from the small number of observations available which makes it difficult to produce a robust probabilistic verification of the EPS. In the future it is possible that coastal scale altimetry will offer a convenient data set for validation/calibration of a storm surge EPS.

The lesson learnt from this exercise, most probably a generalizable conclusion, is that limited area storm surge forecasting uncertainty is dominated by initial and lateral boundary conditions and by phase/amplitude errors in tidal components. The former are also influenced by remotely forced propagating signals such as seiches for the specific case of the Adriatic but more generally remotely

427 forced circulation signals. Given the necessity of having resolutions of ~100 m at the coasts, we
428 conclude that an EPS might be useful also at the scale of the regional models that embed the limited
429 area coastal models.

430 **Appendix A**

431 **The tidal filter methodology**

432 The surge component (i.e., SR), the seiches and the tides extracted from model results were found
433 using a frequency domain filter procedure based on the Fourier transform. The basic principles of
434 the digital filter used here are described in Thomson and Emery (2014). If we consider a variable
435 $x(t)$ in the time domain t and its transformed $X(f)$ in the frequency domain f found applying the
436 discrete Fourier transform (DFT), the application of the digital filter can be summarized in the
437 following three steps:

- 438 1. Take the DFT, $X(f)$ of the original dataset $x(t)$.
- 439 2. Multiply $X(f)$ by the appropriate frequency response function $W(f)$ or FRF, of a high, low or
440 bandpass filter.
- 441 3. Take the IFT of the results to obtain a filtered dataset in the time domain.

442 The power of this method is its simplicity. Unlike the filters in the time domain that require a
443 convolution (e.g., Doodson filter), in the frequency domain, our solution just entails a simple
444 multiplication

$$445 \quad X'(f) = W(f)X(f)$$

446 **A 1**

447 The filtered time series is then simply found by applying the IFT to $X'(f)$. However, the form of $W(f)$
448 is extremely important in order to have a reliable filter. Ideally the FRF should be near unity in the
449 frequency band to be passed, and zero in the bands to be stopped, with a narrow transition band to
450 prevent contamination by unwanted frequencies.

451 Unfortunately, a very narrow and steep transition band is the main cause of large Gibbs phenomenon,
452 affecting the time series obtained by IFT of $X'(f)$ which manifests itself as large side lobes in the initial
453 and final part of the time series (ringing). The Gibbs phenomenon can be reduced by “tapering” the
454 filter ($W(f)$) with a smooth function to ensure a smooth transition to non-zero Fourier coefficients
455 (Forbes, 1988). We tapered the transition bands using a Tukey window (also called cosine-taper),
456 defined as

457

$$w(x) = \begin{cases} \frac{1}{2} \left\{ 1 + \cos \left(\frac{2\pi}{r} [x - r/2] \right) \right\}, & 0 \leq x \leq \frac{r}{2} \\ 1, & \frac{r}{2} \leq x \leq 1 - \frac{r}{2} \\ \frac{1}{2} \left\{ 1 + \cos \left(\frac{2\pi}{r} [x - 1 + r/2] \right) \right\}, & 1 - \frac{r}{2} \leq x < 1 \end{cases}$$

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A 2

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where x are the L points of the windows, and r is the ratio of the cosine-tapered section length to the entire window length with $0 < r < 1$. A value $r=0.5$ produces a Tukey window where half of the entire window length consists of segments of a phase shifted cosine with period $2r=1$. If $r \leq 0$ a rectangular window is returned, while for $r \geq 1$ a Von Hann window is generated (Bloomfield, 2000).

The energy density spectrum (ESD) of the observed sea level at Faro is shown in Fig. S1 of SI together with the ESD of the filtered signal using the Fourier transform filter. The green line is the FRF which was calibrated to exclude tidal and seiche signals from the time series in order to retain only the surge component. The resulting time series after the filter has been applied is the orange line in Fig. S1 of SI. The FRF can be easily inverted and the windows can be moved if there is a need to focus on particular frequencies (e.g., tides or seiches).

On the other hand, the initial and final parts of the time series must be excluded because they are the ones most affected by the Gibbs phenomenon. If in time domain filters, the initial and final part of the time series are automatically excluded, in frequency domain filters, there is no clear threshold, and which part of the time series should be excluded is subjective. However, Walters and Heston (1982) suggest that in both time domain and frequency domain filters, the same amount of data are lost. The version of the tidal filter used for this work can be found at the Zenodo repository of the Oceanography group of the University of Bologna at the link: <https://doi.org/10.5281/zenodo.6478113>.

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Appendix B

479

The Weighted Ensemble Mean method

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The steps for the WEM are as follows.

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1. First the bias between the model output and observations during the training period in a determined station is removed for each member (this step is also done for the simple average).

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$$B^j = \frac{1}{T} \sum_{i=1}^T (x_i^j - o_i)$$

484

B.1

485 where B^j is the bias for member j . x_i^j is the member j variable value at time i . o_i is the observation at
 486 time i and T is the length of the training period.

487 2. The standard Pearson correlation coefficient, defined by

$$488 \quad \rho_o^j = \frac{\frac{1}{T} \sum_{i=1}^T (x_i^j - \bar{x}^j) (o_i - \bar{o})}{x_{\sigma j} o_{\sigma}}$$

489 **B.2**

490 is computed for each member of the ensemble during the training period, where \bar{x}^j is the mean
 491 value of member j , \bar{o} is the mean observed value, $x_{\sigma j}$ is the model member j standard deviation, and
 492 o_{σ} is the observed standard deviation.

493 3. The forecasts are ranked based on the correlation and the first k members are retained and
 494 used to compute the weights w_j

$$495 \quad w_j = \frac{\rho_o^j}{\sum_{j=1}^k \rho_o^j}$$

496 **B.3**

497 4. the WEM is computed as the weighted average of the selected forecasts

$$498 \quad F_i = \sum_{j=1}^k w_j (x_i^j - B^j)$$

499 **B.4**

500 The accuracy of the member forecasts and of EM and WEM are evaluated by computing the
 501 correlation for the forecast period and RMSE defined by

$$502 \quad RMSE = \sqrt{\frac{1}{N} \sum_{i=1}^N (x_i^j - o_i)^2}$$

503 **B.5**

504 for both SL and SR.

505 The RMSE is evaluated against the ensemble spread computed as the root mean square of the
 506 ensemble variance. For sufficiently large ensemble sizes, the following equation should be
 507 approximately verified (Fortin et al. 2014).

$$RMSE \approx \sqrt{\frac{1}{N} \sum_{t=1}^N s_t^2} = (\overline{s_t^2})^{\frac{1}{2}}$$

B.6

where s^2 indicates the variance of the ensemble.

Taylor diagrams (Taylor, 2001) are produced for chosen events, evaluating the model performances in terms of correlation, standard deviation (σ) and CRMSE (centered root mean square error) defined as

$$CRMSE = \sqrt{\frac{1}{N} \sum_{i=1}^N \left((x_i^j - \overline{x_i^j}) - (o_i - \overline{o_i}) \right)^2}$$

B.7

In eqs. B.5, B.6 and B.7, N is the maximum number of observations in the forecast period.

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Data Availability Statement

Model data of COSMO-5M, COSMO-2I, ADRIAC and ADRIAROMS models were provided by Arpa. Observed Sea level and Po river data were provided by Arpa through the dext3r webapp (<https://simc.arpae.it/dext3r/>). The GLOBAL product was provided by COPERNICUS-CMEMS (<https://marine.copernicus.eu/it>). ECMWF, MED-MFC and MED-MFC-T data were provided by CMCC. The open-source model SHYFEM (version 7_5_70) used in this work is freely available on the Zenodo repository (<https://doi.org/10.5281/zenodo.3833857>). Figures 2, 4, 5, 6, 9 and 10 were made with Matplotlib version 3.4.0 (Caswell et al., 2021; Hunter, 2007), available under the matplotlib license at <https://doi.org/10.5281/zenodo.4638398>. Taylor diagrams of figures 7, 8 and 9 were made with Skillmetrics python package (Rockford, 2016; version 1.1.8). Figure 11 was made with PyNGL (version 1.6.1), a graphical python package developed by the National Center for Atmospheric Research (NCAR). Figure 1 was made with QGIS 3.22 geographic information system.

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