

Dear Editor,

Please find the attached authors' responses to the anonymous reviews.

A track changes version of the manuscript is also attached, highlighting all the changes made in response to the reviewers' comments.

On behalf of all the authors, sincerely,

Lojze Žust

## Authors' response to Anonymous Referee #1

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We thank the reviewer for their time and comments that helped us to improve the paper. Responses to individual comments are provided below point-by-point. We also paste the text to reflect the changes to the manuscript.

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**Comment 1:** The authors tend to apply the HIDRA model for business forecasting. However, the input for the model contains the atmospheric data in the future. Please clarify the datasource in the business forecast process.

**Response:** Thank you for pointing this out. As is usual in supervised learning, HIDRA was trained on past atmospheric model forecasts and sea level data. The HIDRA training data is composed of two parts: (a) the atmospheric part consists of past forecasts from a single member of ECMWF model ensemble, and (b) the sea level training data consists of tidal and residual sea levels from 24 hours prior to the forecast obtained from observations in Koper. For operational forecast, starting at time  $t_0$ , the following datasets will be employed:

- The atmospheric data: ECMWF ensemble forecast (the same ECMWF product as in training data) for time interval  $[t_0, t_0 + 72 \text{ hours}]$ . This data is available at the time of the forecast from ECMWF operational service.
- Sea Level data: tidal and residual data for the time interval  $[t_0 - 24 \text{ hours}, t_0]$ . This data is also available at the time of the forecast, assuming that the tide gauge in Koper works as expected, which is a reasonable assumption, given the redundancy in the design (the gauge consists of three independent bottom-mounted pressure gauges).

All the data required for HIDRA forecasting will be available for operational forecasts every day. To make this clear, the following text in the Conclusion,

*“HIDRA outperforms the current operational NEMO setup and is therefore an appropriate candidate for Agency’s operational pipeline.”*

was re-written into:

*“HIDRA outperforms the current operational NEMO setup and is therefore an appropriate candidate for Slovenian Environment Agency’s operational pipeline. HIDRA integration should be straightforward since ECMWF ensemble predictions and tide gauge sea level data are available at the Agency every day in real time for operational forecasting.”*

**Comment 2:** The authors declare “Extending the historical horizon beyond 24 hours did not significantly affect the prediction accuracy”. Please give a concise description of how to find the trade-off between the model forecast accuracy and the computing resource.

**Response:** To improve the insight into the trade-off, we conducted an additional experiment in which HIDRA was re-trained and tested for different values of historic horizon  $T_{\min}$ . The results are shown in Table 1. We find that increasing the historic horizon beyond 24h does not yield measurable improvements in prediction accuracy while increasing the number of parameters in the lower layers and negatively impacting the computational performance. For this reason we decided to set  $T_{\min} = 23$ .

	MAE [cm]	RMSE [cm]	Bias [cm]	Likelihood	CPU time [s]
<b>Overall</b>					
HIDRA <sub>12</sub>	5.3	7.0	<b>-0.2</b>	0.0440	<b>0.17</b>
HIDRA <sub>24</sub>	4.9	<b>6.4</b>	-0.4	<b>0.0470</b>	0.19
HIDRA <sub>36</sub>	<b>4.8</b>	<b>6.4</b>	-0.9	0.0455	0.21
HIDRA <sub>48</sub>	<b>4.8</b>	<b>6.4</b>	-0.6	0.0438	0.23
<b>Storm surge events</b>					
HIDRA <sub>12</sub>	11.7	13.9	-11.2	0.0220	<b>0.17</b>
HIDRA <sub>24</sub>	<b>10.3</b>	12.9	-9.3	<b>0.0253</b>	0.19
HIDRA <sub>36</sub>	10.7	13.2	-9.8	0.0245	0.21
HIDRA <sub>48</sub>	10.4	<b>12.8</b>	<b>-9.1</b>	0.0251	0.23

Table 1: HIDRA performance for different historic horizons in terms of mean absolute error (MAE), root mean squared error (RMSE) and model bias. CPU execution time (on a single core) per example is also reported. Performance for the atmospheric tide is provided as reference.

This experiment is now described along with the Table 1 in a new section in the manuscript (Section 4.1.1: Influence of the historic horizon):

*”We first analyze the influence of the HIDRA historic horizon defined by the parameter  $T_{\min}$  (see Section 3). Table 1 summarizes the performance of HIDRA with  $T_{\min} \in \{11, 23, 31, 47\}$ , which translates to historic horizons of 12, 24, 36 and 48 hours. Increasing the historic horizon from 12 to 24 hours significantly improves the prediction accuracy (9% reduction in RMSE error), however, further increases of the historic horizon (i.e., to 36 or 48 hours) do not show measurable benefits. Note that the execution time increases with the length of the historic horizon due to a substantial increase of parameters on the input layer. For this reason, we use a historic horizon of 24 hours ( $T_{\min} = 23$ ) as the best trade-off in the remaining analysis.”*

**Comment 3:** In Equation (1), there is a “20” on the “sum” signal, which represents the different spatial position on the feature maps, which is confusing that where this value comes from. Please clarify the changes of the feature maps during the fore-propagation process in the Figure. 3, especially in Figure 3 (a). Such as marking the size of the convolution kernel and the output size in the red boxes.

**Response:** Thank you for directing our attention to this issue. We agree that it is not immediately clear that the “20” in the spatial position sum follows from the input feature maps are of size  $4 \times 5$ . To address this, we now make the indexing in equation (1) explicit. In particular, the equation

$$\mathbf{f}_t = \text{ReLU} \left( \sum_{i=1}^{20} \mathbf{F}_t^{(i)} \mathbf{w}_t^{(i)} \right) \quad (1)$$

is now changed to

$$\mathbf{f}_t = \text{ReLU} \left( \sum_{i=1}^4 \sum_{j=1}^5 \mathbf{F}_t^{(i,j)} \mathbf{w}_t^{(i,j)} \right), \quad (2)$$

where  $(i, j)$  denotes the spatial coordinates of the feature map and spatial weights. We believe this is more precise and easier to follow.

Next, we address the comments regarding Figure 3a. We updated Figure 3 in the manuscript and made the annotations in the figure (see Figure 1) and the caption consistent with the text in the paper’s body. The Atmospheric Spatial Encoder now contains the standard markings of ResNet stages as well as the output feature map size for context. The previous caption of Figure 3

*“The proposed HIDRA architecture. A convolutional Atmospheric Spatial Encoder (ASE) extracts spatial atmospheric features from each time-step. Atmospheric and sea level temporal features are encoded by respective Temporal Encoder blocks, fused and passed to the fully-connected Residual Regression Block to predict the residuals along with their uncertainties. The trainable blocks are denoted by red color.”*

was changed to

*“The proposed HIDRA architecture. A convolutional Atmospheric Spatial Encoder (ASE) extracts spatial atmospheric features from each time-step. Atmospheric and sea level temporal features are encoded by respective Temporal Encoder blocks, fused and passed to the fully-connected Residual Regression Block to predict the residuals along with their uncertainties. With  $n$  we denote the number of filters or units of the block. The trainable blocks are colored red. The structure of the bottleneck blocks used in the ASE is presented in Figure 4.”*

Furthermore, we present the structure of the Bottleneck blocks in an additional figure (see Figure 2), which also details the convolutional parameters (kernel sizes, stride) and output feature map sizes.

**Comment 4:** Line 298: results  $\rightarrow$  result

**Response:** Thank you for for spotting the grammar mistake. The manuscript was updated as suggested.



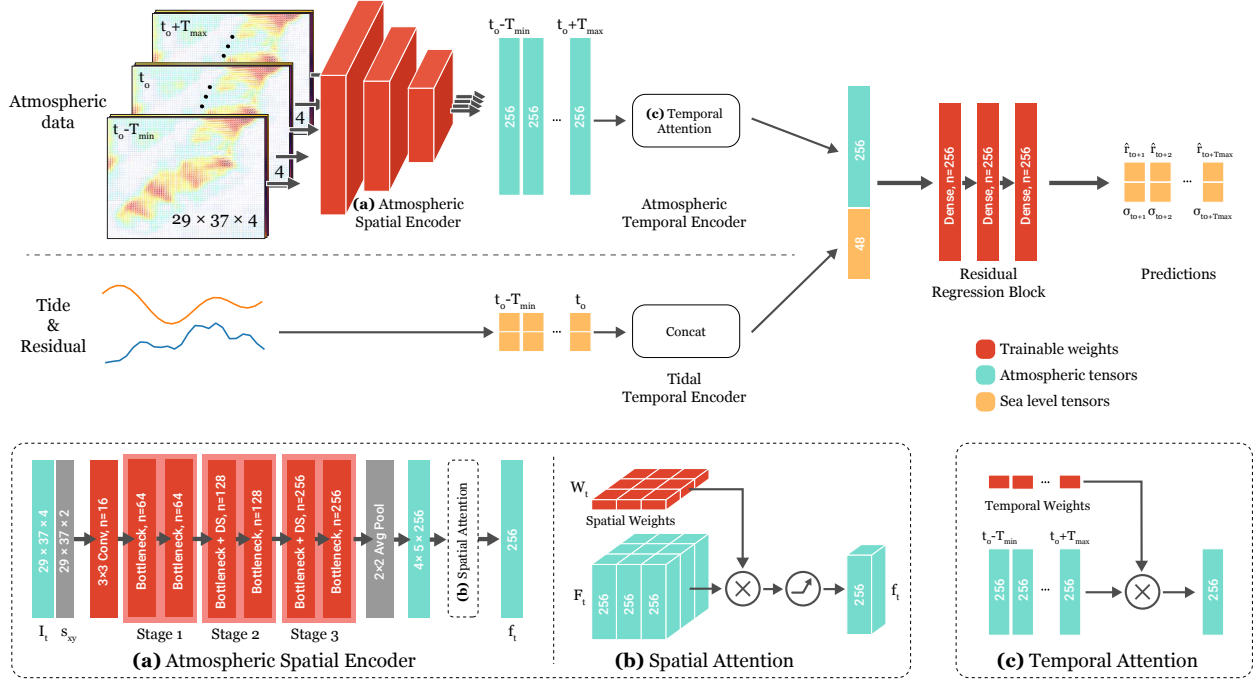


Figure 1: The proposed HIDRA architecture. A convolutional *Atmospheric Spatial Encoder* (ASE) extracts spatial atmospheric features from each time-step. Atmospheric and sea level temporal features are encoded by respective Temporal Encoder blocks, fused and passed to the fully-connected *Residual Regression Block* to predict the residuals along with their uncertainties. With  $n$  we denote the number of filters or units of the block. The trainable blocks are colored red. The structure of the bottleneck blocks used in the ASE is presented in Figure 2.

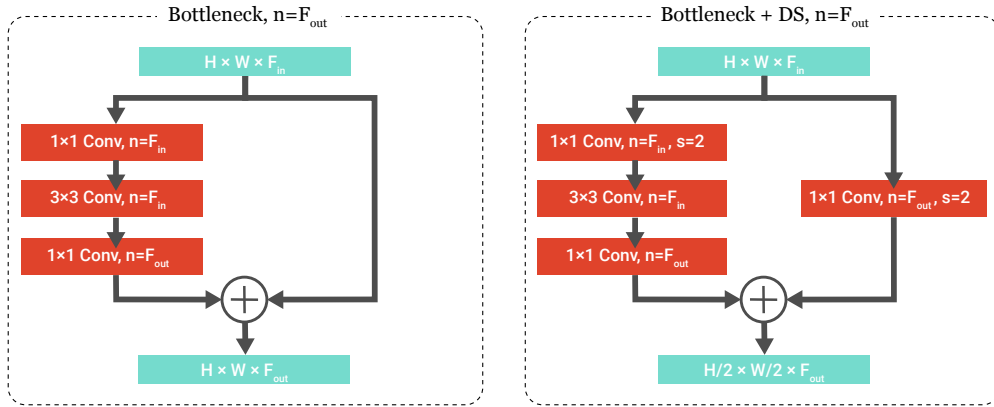


Figure 2: Structure of the bottleneck blocks used in the Atmospheric Spatial Encoder (Figure 1). The bottleneck block takes a feature map with depth  $F_{\text{in}}$  as the input and outputs a feature map with depth  $F_{\text{out}}$ . A regular bottleneck block (left) retains the spatial dimensions of the feature maps, while the downsampling (DS) bottleneck block (right) uses strided convolutions to reduce the spatial dimensions in half. We denote the number of convolutional filters by  $n$  and the stride parameter by  $s$ .

## Authors' response to the Anonymous Referee #2

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We thank the reviewer for their time and comments that helped us to improve the paper. Detailed responses to individual comments are provided below point-by-point. We also paste the text to reflect the changes to the manuscript. In summary, two major changes have been made in line with the reviewer's suggestions:

- We have turned off the wind stress parametrization and repeated training and analyses with wind-only input data. Results with raw wind input is indeed better than with the wind stress transformation. We now use raw wind input during training. The manuscript has been modified accordingly.
  - We have performed another sensitivity study to check the information redundancy in sea level pressure / wind input data. The HIDRA model was re-trained with wind-only and pressure-only inputs. The best results are obtained when both inputs are provided to HIDRA indicating complementarity of the two inputs and ability of HIDRA to compensate for any potential redundancy.
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**Comment 1: This manuscript proposed a model named HIDRA based on a deep learning network to forecast the sea level in the Adriatic. This is a good try and shows the deep-learning-based model has a good future in ocean environment research and forecasting. This work is worthwhile and the manuscript is well-written in general.**

**Response:** We thank the reviewer for the encouraging comment.

**Comment 2: However, there are still several critical issues to be clarified. The Large and Pond parameterization is suitable for calculating the wind stress over the open sea with deep water. In other words, this scheme cannot use in this study. As the data is the basic and core of machine learning, the authors should find another scheme to redo this work.**

**Response:** We thank the reviewer for this insight. Indeed, Large and Pond formulation has its limits, but is often applied in oceanography as a tradeoff between complexity and accuracy. In our case it is worth pointing out that this particular parametrization was not chosen to most concisely represent the vertical momentum flux at the sea surface (which would admittedly require more complex schemes and more data), but to merely introduce the nonlinear wind stress dependence on the wind. Thus our reasoning was that this would make learning the relationships between the atmospheric conditions and tide gauge sea level easier for the deep network.

However, following the referee's insight, we have performed a number of new experiments. In particular, HIDRA was re-trained with using the raw wind instead of Large and Pond parametrization. The prediction performance did not change overall, which means that the network is capable of modeling, at some level, how wind translates into vertical momentum flux. We did notice that the

prediction performance on storm surges did improve on average by approximately 1 cm. These results will be added to the revised manuscript as a separate subsection in the “Hidra Architecture Analysis” Section 4.1. For convenience we include the new subsection below:

*“We proceed to inspect the impact of Large and Pond parametrization which might oversimplify the wind stress dependence on the wind. To this end we consider another variant of HIDRA, which uses raw wind instead of wind stress. Results in Table 7 show that, overall, the performance between the two wind-input variants is indistinguishable. However, on storm surges, using raw wind reduces the RMSE by approximately 1 cm when compared to the setup which uses wind stress. It appears that HIDRA is capable of extracting the information important for sea level prediction during storm surges also directly from the raw wind.”*

**Table 7.** Performance of HIDRA variants with different wind and pressure input configurations. HIDRA<sub>0</sub> uses the wind stress, HIDRA<sub>wnd</sub> uses the raw wind, HIDRA<sub>no\_wnd</sub> does not use wind inputs and HIDRA<sub>no\_prs</sub> uses the wind stress, but not the air pressure. Performance of the astronomic tide is provided for reference.

	MAE [cm]	RMSE [cm]	Bias [cm]	Likelihood
<b>Overall</b>				
HIDRA <sub>0</sub>	<b>4.9</b>	<b>6.4</b>	-0.4	<b>0.0470</b>
HIDRA <sub>wnd</sub>	<b>4.9</b>	<b>6.4</b>	<b>0.2</b>	0.0465
HIDRA <sub>no_wnd</sub>	5.3	7.1	-0.3	0.0434
HIDRA <sub>no_prs</sub>	5.3	7.0	-0.1	0.0451
Reference (tide)	12.1	15.7	-2.4	-
<b>Storm surge events</b>				
HIDRA <sub>0</sub>	10.3	12.9	-9.3	0.0253
HIDRA <sub>wnd</sub>	<b>9.3</b>	<b>11.6</b>	<b>-7.8</b>	<b>0.0274</b>
HIDRA <sub>no_wnd</sub>	13.7	16.5	-12.9	0.0192
HIDRA <sub>no_prs</sub>	11.6	14.0	-10.8	0.0225
Reference (tide)	49.6	50.4	-49.6	-

**Comment 3:** In fact, the wind is associated with sea level pressure and latitude (Coriolis force). For the Adriatic, the difference of wind in different locations due to Coriolis force can be ignored, which means the wind is almost determined by sea level pressure. So, wind stress has included information on sea level pressure. I think it’s double-counted when the authors used wind stress as well as sea level pressure.

**Response:** Thank you for the comment. Indeed, winds in the Adriatic basin have a substantial geostrophic component. But we would like to note that the two strongest winds, Bora and Scirocco, can also have a significant non-geostrophic contribution (orographic channeling, non-linear wave breaking, density-driven flows during weak Bora episodes etc., e.g. Pasarić et al., 2007, <https://angeo.copernicus.org/articles/25/1263/2007/>; Grisogono and Belušić, 2009, <https://onlinelibrary.wiley.com/doi/10.1111/j.1600-0870.2008.00369.x>). In such cases the wind field can exhibit cross-isobaric flow and reflects other constraints beyond the geostrophic equilibrium.

Thus, to explicitly verify the potential effect of the information redundancy between the wind and air pressure inputs, we trained several additional variants of HIDRA. One that used wind input but not pressure, and another that used the air pressure but not the wind. Results show that performance drops by approximately 10% when excluding either wind or air pressure, implying that the network

accounts for potential redundancy and capitalizes on the complementary information encoded in both inputs. These results will be added in the revised manuscript as a separate subsection in the “Hidra Architecture Analysis” Section 4.1. For convenience we include the new subsection below:

*“Bora and Scirocco characteristics in the Adriatic basin are often determined through an interplay of geostrophic, orographic and other influences (Pasarić et al., 2007; Grisogono and Belušić, 2009). At other times however, non-geostrophic effects may play a lesser role and the wind field is largely determined by the pressure field. To investigate potential information redundancy between the wind and pressure inputs, two HIDRA variants were trained: one which did not use the wind input and another which used the wind, but not the pressure. Results in Table 7 show that removing either wind or air pressure input leads to an approximately 9% increase of RMSE. HIDRA seems to compensate for potential redundancy in the inputs and capitalizes on the fact that wind in the basin is not entirely pressure driven. In any case using both inputs is preferred.”*

**Table 7.** Performance of HIDRA variants with different wind and pressure input configurations.  $HIDRA_0$  uses the wind stress,  $HIDRA_{wnd}$  uses the raw wind,  $HIDRA_{no\_wnd}$  does not use wind inputs and  $HIDRA_{no\_prs}$  uses the wind stress, but not the air pressure. Performance of the astronomic tide is provided for reference.

	MAE [cm]	RMSE [cm]	Bias [cm]	Likelihood
<b>Overall</b>				
$HIDRA_0$	<b>4.9</b>	<b>6.4</b>	-0.4	<b>0.0470</b>
$HIDRA_{wnd}$	<b>4.9</b>	<b>6.4</b>	<b>0.2</b>	0.0465
$HIDRA_{no\_wnd}$	5.3	7.1	-0.3	0.0434
$HIDRA_{no\_prs}$	5.3	7.0	-0.1	0.0451
Reference (tide)	12.1	15.7	-2.4	-
<b>Storm surge events</b>				
$HIDRA_0$	10.3	12.9	-9.3	0.0253
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$HIDRA_{no\_wnd}$	13.7	16.5	-12.9	0.0192
$HIDRA_{no\_prs}$	11.6	14.0	-10.8	0.0225
Reference (tide)	49.6	50.4	-49.6	-

**Comment 4: Topography is important for the sea level, besides the wind stress (or sea level pressure). Therefore, topography should also be considered in the HIDRA model.**

**Response:** We agree that topography affects the sea level dynamics and is imperative for sea level prediction in physical models. We would nevertheless like to point out that topography is constant and does not change with time, thus it is not necessary to provide it explicitly as an input parameter to HIDRA. Note that HIDRA is not a dynamical model which would have to explicitly take into account the complex per-point topography interaction. Rather, interactions between dynamic spatially-varying and static elements (like topography), relevant for sea level prediction accuracy, are *learned implicitly* by the deep neural network from the vast amount of data. To achieve this in HIDRA, the spatial encoding is enforced by providing the normalized spatial coordinates as part of the input to the network (x and y input channels), thus allowing the learning algorithm to make such spatially-dependent relations.

Furthermore, HIDRA predicts the sea level for a single specific location, taking into account the past sea level measurements from that location (Koper tide gauge). These measurements already reflect Adriatic basin bathymetry: sea level experiences topographic amplification due to shallowness in the north, resonant amplification due to forcing frequency being close to the basin seiche frequency, and also reflection due to the closure of the basin in the north. All these bathymetry effects are already implicitly contained in the observations that the network receives as the input. In fact, our experiments show that HIDRA can respond in a manner that consistently reflects these bathymetric constraints, for example that it amplifies the signal in the basin seiche  $(21.5 \text{ hr})^{-1}$  frequency band during a Scirocco event.

**Comment 5: Line 327, the description is inaccurate. Usually, the regional ocean model, especially the coastal model, can simulate the sea level including the tidal directly by using the water level boundary condition.**

**Response:** Thank you for pointing this out. The description will be updated by including NEMO configuration namelist into the paper supplement (the parameter space of the NEMO model is too large to be completely covered in the descriptive text). We also agree that regional ocean models can simulate sea level (including tides) via open boundary conditions.

As pointed out by the referee, tides are not included in the forcing of the current NEMO setup. This decision is partly based on the fact that we have a tide-gauge in Koper and we can analyze the tidal constituents for Koper directly from the local observations, which seemed to be the most straightforward way of obtaining tides in Koper. We have however in the past compared full (with tides on open boundaries) NEMO sea-levels to the setup presented in this paper. The main result (unpublished) was that sea level from NEMO with tides at the open boundary offers comparable, but somewhat worse representation of observed total sea levels than the non-tidal setup of NEMO with tides computed on the Koper tide gauge.

Furthermore, as explained in the paper, HIDRA is using tidal sea-levels and residuals obtained from the Koper tide-gauge. Allowing NEMO and HIDRA to use the same tidal signal allows for more consistent comparisons of their performance. We have therefore chosen not to include tidal forcing at NEMO open boundary (in the Ionian Sea) in this study, but to obtain the tidal part of the sea level signal from local observations.

**Comment 6: Moreover, the authors cannot claim HIDRA is better than NEMO because they only compared with results from only one NEMO configuration they used. If the NEMO is tuned carefully, maybe the results are better. In fact, the NEMO in the storm surge events seems better than HIDRA.**

**Response:** We thank the reviewer for this comment. We agree -- there certainly exists a possibility that a better tuned setup of NEMO would produce better results. For example, assimilation of sea level data might be of substantial benefit and our current setup does not have it. Therefore, we must certainly clarify that we do not claim that HIDRA is better than NEMO in general - but rather that HIDRA does compare favorably with the only specific operational setup of NEMO at our disposal.

To make the manuscript more consistent with the referee's arguments, we have amended the manuscript to be very specific that we are referring to the specific operational setup of NEMO at Slovenian Environment Agency. We however fear that a stand-alone NEMO setup sensitivity study would diverge too far from the scope of our paper, which is to present a numerically cheap machine learning architecture which can compete with (and most often outperform) a much more complex and numerically demanding general circulation model.

Minor comments:

**Comment 7: How to deal with the land points in this study is missed.**

**Response:** HIDRA does not distinguish between wet and dry points - it focuses on the synoptic pattern of surface meteorological fields. It does however receive spatial encoding of atmospheric fields (x and y input channels). Again, as in topography, ECMWF land/sea mask is a constant field and as such cannot profoundly impact gradient descent during the learning process. To make this clearer, the following sentence was added to the manuscript:

*“Atmospheric fields over land and sea are treated in the same manner, i.e. while HIDRA does receive an explicit spatial encoding of atmospheric fields (Section 3.1.1), it does not employ a land/sea mask.”*

**Comment 8: Why did the authors select the 29x37 for the atmospheric tensor?**

**Response:** The spatial size is specific to the input ECMWF ensemble grid. The ECMWF ensemble forecast over the domain of the study contains 73x57 grid points. As described in Section 2.3, we further downscale the data by a factor of two and end up with a grid of dimensions 37x29. Following the standard convention, spatial maps are represented as height-first tensors, thus 29x37. To clarify the origin of the atmospheric tensor dimensions we changed a line in Section 2.2 to

*“... In this study, the following forecast fields were subset to the Adriatic basin, [represented by a 73x57 spatial grid](#) (see Figure 2) ...”*

and a line in Section 2.3 to

*“The data is standardised and global average pooling is used to reduce the dimensionality of the atmospheric data -- spatial dimension of the data in samples is [reduced in half, from 73 x 57 points to 37 x 29 points](#), and the temporal dimension is reduced by a factor of 4.”*

**Comment 9: It's better to give a table for the HIDRA and NEMO configuration**

**Response:** As pointed out in our response to Reviewer's Comment 5, we now include the NEMO configuration namelist in the supplementary material. Apart from the architectural design of HIDRA specified in Figure 3, the only free parameters are the learning rates and batch sizes summarized in the last paragraph of Section 3.1.4.

# HIDRA 1.0: Deep-Learning-Based Ensemble Sea Level Forecasting in the Northern Adriatic

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<sup>2</sup>Slovenian Environment Agency, Group for Meteorological, Hydrological and Oceanographic Modelling, Ljubljana, Slovenia

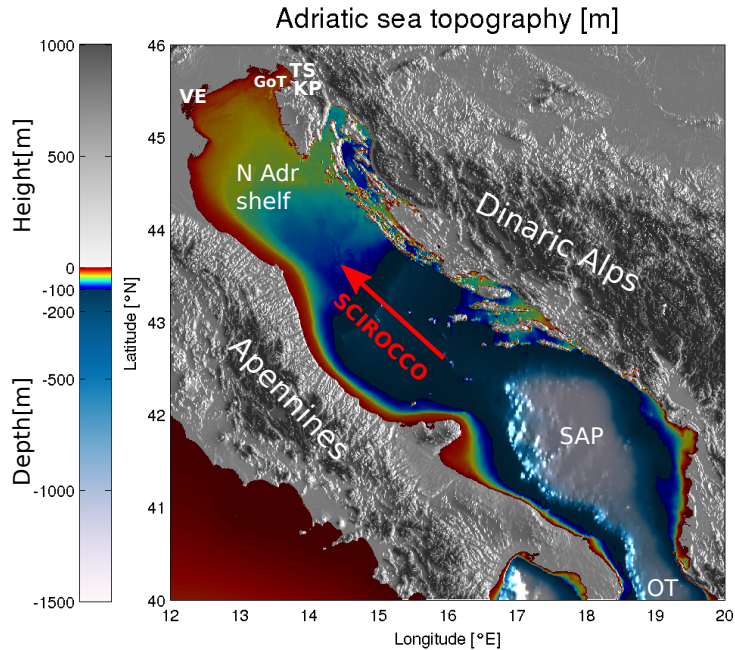
<sup>3</sup>National Institute of Biology, Marine Biology Station, Piran, Slovenia

**Correspondence:** Lojze Žust (lojze.zust@fri.uni-lj.si)

**Abstract.** ~~Complex interactions~~ Interactions between atmospheric forcing, topographic constraints to air and water flow, and resonant character of the basin, make sea level modeling in Adriatic a ~~particularly~~-challenging problem. In this study we present an ensemble deep-neural-network-based sea level forecasting method HIDRA, which outperforms our setup of general ocean circulation model ensemble (NEMO v3.6) for all forecast lead times and at a minuscule fraction of the numerical cost (order of  $2 \times 10^{-6}$ ). HIDRA exhibits larger bias but lower RMSE than our setup of NEMO over most of the residual sea level bins. It introduces a trainable atmospheric spatial encoder and employs fusion of atmospheric and sea level features into a self-contained network which enables discriminative feature learning. ~~The~~ HIDRA architecture building blocks are experimentally analyzed in detail and compared to alternative approaches. Results show ~~individual~~-importance of sea level input for ~~accurate~~-forecast lead times below 24 h and ~~of the importance of~~ atmospheric input for longer ~~time leads~~ lead times. The best performance is achieved by considering the input as the total sea level, split into disjoint sets of tidal and residual signals. This enables HIDRA to optimize the prediction fidelity with respect to atmospheric forcing, while compensating for the errors in the tidal model. HIDRA is trained and analysed on a ten-year (2006-2016) timeseries of atmospheric surface fields from a single member of ECMWF atmospheric ensemble. In the testing phase, both HIDRA and NEMO ensemble systems are forced by the ECMWF atmospheric ensemble. Their performance is evaluated on a one-year (2019) hourly time series from tide gauge in Koper (Slovenia). Spectral and continuous wavelet analysis of the forecasts at semi-diurnal frequency  $(12 \text{ h})^{-1}$  and at ground-state basin seiche frequency  $(21.5 \text{ h})^{-1}$  is performed ~~by a continuous wavelet transform~~. The energy at the basin seiche in the HIDRA forecast is close to the observed, while our setup of NEMO underestimates it. Analyses of the January 2015 and November 2019 storm surges indicate that HIDRA has learned to mimic timing and amplitude of ~~resonant sea level excitations in the basin~~ basin seiches.

## 20 1 Introduction

Climate change is inducing sea level rise, adversely affects coastal ecosystems, economies and civil safety. In the shallow Northern Adriatic, low sea levels influence port activities and inhibit marine cargo while high sea levels cause substantial coastal flooding, inundation and erosion (Ferrarin et al., 2020), thus presenting a serious threat to Venice, Chioggia, Piran and other coastal towns and businesses in the region. Low sea levels predominantly occur when periods of high atmospheric



**Figure 1.** Adriatic basin topography and bathymetry. ~~Abbreviations~~ The following abbreviations are as follows used: TS - Trieste, KP - Koper, GoT - Gulf of Trieste, VE - Venice, N Adr Shelf - Northern Adriatic Shelf, SAP - Southern Adriatic Pit, OT - Otranto Strait. Direction of Scirocco is marked with a red arrow. ~~The image was created by the authors based on EMODnet bathymetry data, available at <https://portal.emodnet-bathymetry.eu/> (last access: 27 October 2020) 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: 27 October 2020).~~

25 pressure coincide with spring tide sea level minimums. High sea levels typically occur as storm surges during passages of atmospheric cyclones which manifest themselves as substantial air pressure lows and related winds over the basin. Reliable and timely sea level forecasting is thus a crucial element of early warning systems for mitigating the flooding consequences.

Adriatic Sea has an elongated basin with northwest-southeast orientation, lies in the Northern Central Mediterranean, and connects to the eastern Mediterranean basin through the Otranto strait at its southern end (see Figure 1). ~~Surrounded from all~~  
 30 ~~sides by mountain ridges – the Alps in the north~~ The basin lies embedded between the Alps (to the north), the Apennines in the west (to the west) and Dinaric Alps in the east (to the east) – it spans a 800 km long and 200 km wide area. The ridges significantly influence the basin circulation through topographic ~~air flow control, most notably during strong wind episodes of the northeasterly Bora and the southeasterly Scirocco~~ control of the air flow, especially during wind events of Bora (northeasterly wind) and Scirocco (southeasterly wind). Scirocco, predominantly directed along the basin long axis, is among  
 35 the main drivers of the Adriatic storm surges. Northern Adriatic shelf is closed at its northern end and is the shallowest part of the Adriatic basin. Storm surges in this part are consequently most pronounced, causing substantial coastal flooding, inundation and erosion (Ferrarin et al., 2020).



The elongated basing results in seiches with a fundamental period of 21.5 h (and first excited mode period of 10.9 h) (Cerovecki et al., 1997; Medvedev et al., 2020). Diurnal and semi-diurnal tides enter the Adriatic through the Otranto Strait and force the basin close to its ~~resonant frequencies with both seiches resonantly amplified (Medvedev et al., 2020)~~eigen-periods (Medvedev et al., 2020). Both seiches and tides are resonantly and topographically amplified in the shallow northern Adriatic. In Northern Adriatic, crest-to-trough range of tidal sea level movement can reach up to ~~1-meter~~1.5 m (and up to 10 ~~cm/s~~ in current speed (Cosoli et al., 2013)). In absence of strong winds, this signal dominates the sea level dynamics. During storm surges however, tides are generally too weak to be dominant but remain a crucial part of the total sea level signal. Moreover, since Adriatic seiches decay on scales of several days, seiches and tides may continue to reinforce (or diminish) ~~the surges~~each other for several days.

The resonant character and high sensitivity to temporal phase lag between tides and seiches make Adriatic sea levels prediction ~~challenging with a challenge for~~ deterministic numerical ocean models. Even modest modeling errors in the timing, intensity or trajectory of an atmospheric cyclone, often lead to substantial modeling errors in the predicted sea level. Introduction of atmospheric numerical forecast ensembles has thus enabled implementation of operational sea surface height forecast systems that yield probabilistic forecasts along with error variance estimation, which show promise world-wide, see *i.e.* (Ferrarin et al., 2020; Bernier and Thompson, 2015; Mel and Lionello, 2014; Bertotti et al., 2011).

These systems, however, often involve a high computational cost, usually requiring running tens of runs of basin scale numerical ocean models (each forced by a different member of the atmospheric ensemble) each day (or even several times per day). Ensemble numerical modeling is therefore prohibitively demanding for many operational or civil rescue services that lack access to dedicated high-performance computing facilities.

Machine-learning-based ensemble modelling offers a possible solution to the challenges described above. Even though training a machine-learning model may involve substantial amount of training data and computational resources, the subsequent forecasting – even ensemble forecasting – is numerically cheap enough to be executed in some cases instantaneously on a standard personal computer. Early approaches employ classic machine learning methods (Imani et al., 2018) or shallow fully-connected neural networks (Pashova and Popova, 2011; Karimi et al., 2013) for daily or hourly sea level forecasting. The reported results show promise in sea level prediction, but fall short with simplistic architectures that ignore the atmospheric forcing. Ishida et al. (2020) attempt to improve the dynamics of hourly scale sea level forecasts by using a long short-term memory (LSTM) network, which are well established methods for sequence modelling and time-series prediction. The network considers several atmospheric variables (wind speed and direction, sea level pressure, air temperature) as well as relative positions of the Sun and the Moon and annual global air temperatures as the input. Empirically, the short-term sea level prediction of one hour in the future is improved compared to older approaches. While predictions farther into the future could be achieved by iterative auto-regression, the errors would likely exponentially increase. A longer prediction horizon is considered by Braakmann-Folgmann et al. (2017), who apply a combination of recurrent neural networks (LSTMs) and convolutional neural networks to model monthly spatial sea level time series. This is one of the first works that considers both spatial and temporal aspects of the input data, however, predictions are made at a much coarser temporal resolution than that considered in this paper. A higher temporal resolution is considered by Hieronymus et al. (2019), which is the most closely

related work to ours. Autoregressive neural networks are used to model the sea level time-series with addition of atmospheric forcing reduced by empirical orthogonal function (EOF) decomposition. For northern Adriatic, Venice lagoon specifically, artificial neural networks have already been shown to be useful at modelling numerical model errors in sea level prediction (Bajo and Umgiesser, 2010).

In this work we propose ~~HIDRA~~HIDRA – a HIgh-performance Deep tidal Residual estimation method using Atmospheric data. ~~HIDRA~~HIDRA is a novel deep learning architecture which employs tidal and atmospheric forcing contributions for accurate sea level predictions. The model is trained end-to-end with discriminative feature extraction as part of the learning to maximize the forecast accuracy and to compensate for the inaccuracies of the astronomical tide estimates. HIDRA is benchmarked against the operational general circulation model ensemble, based on NEMO v3.6 engine (Madec, 2008), which is run daily at the Slovenian Environment Agency (ARSO).

The remainder of the paper is structured as follows. The input sea level and atmospheric data, and the datasets used in this study are described in Section 2. The HIDRA architecture, ~~the~~our NEMO ocean model setup and the ensemble structure are presented in Section 3. Section 4 reports a detailed analysis of the HIDRA architecture and empirical comparison to the NEMO system on a challenging setup. Conclusions are drawn in Section 5.

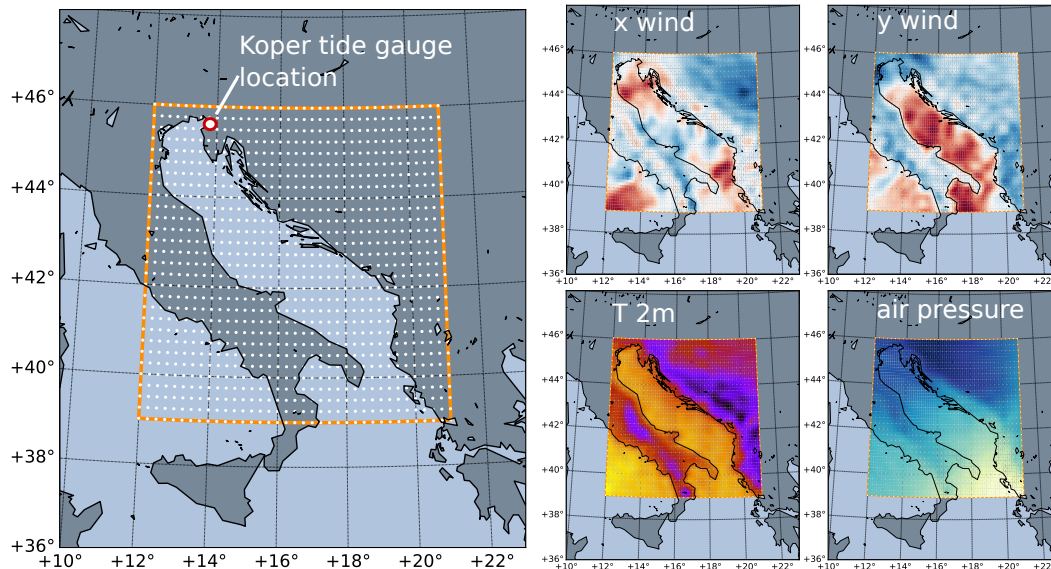
## 2 Sea Level and Atmospheric Data

### 2.1 Sea Level Data

Sea surface height (SSH) measurements were obtained from the Koper Mareographic Station (45°33' N, 13°44' E; see Figure 2 for location), which is operated by the Slovenian Environment Agency (ARSO). The measurements are acquired by a bottom-mounted pressure gauge in ten minute intervals, which are subsequently quality controlled at ARSO. The tidal part of the sea level ~~dynamics~~ is independent from ~~the~~ atmospheric forcing and can be approximated by tidal models. We analyzed the tidal contribution to Koper SSH using the Tidal Analysis Program for Python TAPPY (Cera, 2011). ~~The tidal~~Tidal contribution is estimated from a 20-year hourly time-series of Koper SSH for the period between January 1995 and September 2014. ~~The tidal~~Tidal constituents are then used to estimate past and future tidal values. The residual sea level is defined in this paper as the arithmetic difference between the total and the tidal sea level.

### 2.2 Atmospheric Data

Atmospheric data is obtained from Ensemble Prediction System (EPS) of the European Centre for Medium-Range Weather Forecasts (ECMWF). The data comes as an ensemble of fifty integrations of global atmospheric models (Leutbecher and Palmer, 2007). Ensemble forecasts have a 0.125° arc degree spatial (zonal and meridional) resolution and a 3-hour temporal resolution. In this study, the following forecast fields were subset to the Adriatic basin, represented by a 73 × 57 spatial grid (see Figure 2): (i) 10-meter zonal and meridional winds, (ii) mean sea level pressure and (iii) air temperature at 2 metres. The forecasts were linearly interpolated to hourly timesteps to match the SSH temporal resolution. Atmospheric fields over land and



**Figure 2.** Left: NEMO ocean model domain (orange rectangle) and ECMWF ensemble grid points (white dots). Every second ECMWF grid point is displayed for clarity. Koper tide gauge location is marked with red-white circle. Right: four ECMWF atmospheric fields are extracted over the region at each time-step: zonal (x) and meridional (y) wind stress, air temperature at 2 meters and surface air pressure.

105 sea are treated in the same manner, i.e. while HIDRA does receive an explicit spatial encoding of atmospheric fields (Section 3.1.1), it does not employ a land/sea mask.

Direct wind influence on the ocean is exerted through vertical momentum transfer or wind stress. ~~We thus compute at each time-step the wind stress from the ECMWF predicted wind velocity, where the~~ Configurations with both raw wind and wind stress were tested to obtain optimal neural network configuration. Whenever wind stress was used, turbulent momentum transfer (wind drag) coefficient was computed using the Large and Pond parametrization (Large and Pond, 1981). Note that the purpose of wind stress parametrization in this study is not to most concisely represent the vertical momentum flux at ocean surface (which would require more complex schemes), but merely to introduce to the neural network the nonlinear wind stress dependence on the wind to assist its learning process.

110

### 2.3 Evaluation datasets

~~The atmospheric and the~~ Atmospheric and sea level data described in previous sections were used to create a dataset for years 115 2006–2016. The first 80% of the dataset is used for training (70%) and validation (10%), while the last 20% (September 2014 - December 2016) is used for testing. The data is standardised and global average pooling is used to reduce the dimensionality of the atmospheric data – spatial dimension of the data in samples is reduced in half, from  $73 \times 57$  points to  $37 \times 29$  points, and the temporal dimension of atmospheric data is reduced by a factor of 4. Sea level data retains 1-hour resolution. An additional

test-only dataset for the year 2019 was constructed in the same manner and was used for comparison of [our setup of NEMO](#) and HIDRA prediction performance.

Oversampling is applied to the training data to improve the prediction accuracy of the rare storm surge events. The training dataset is split into two subsets by thresholding the residuals at 40 cm. Storm surges ([residual](#) > 40 cm) represent approximately two percent of the data. During training the samples are randomly sampled from each of the two subsets with equal probability.

### 3 Numerical Models

#### 125 3.1 HIDRA

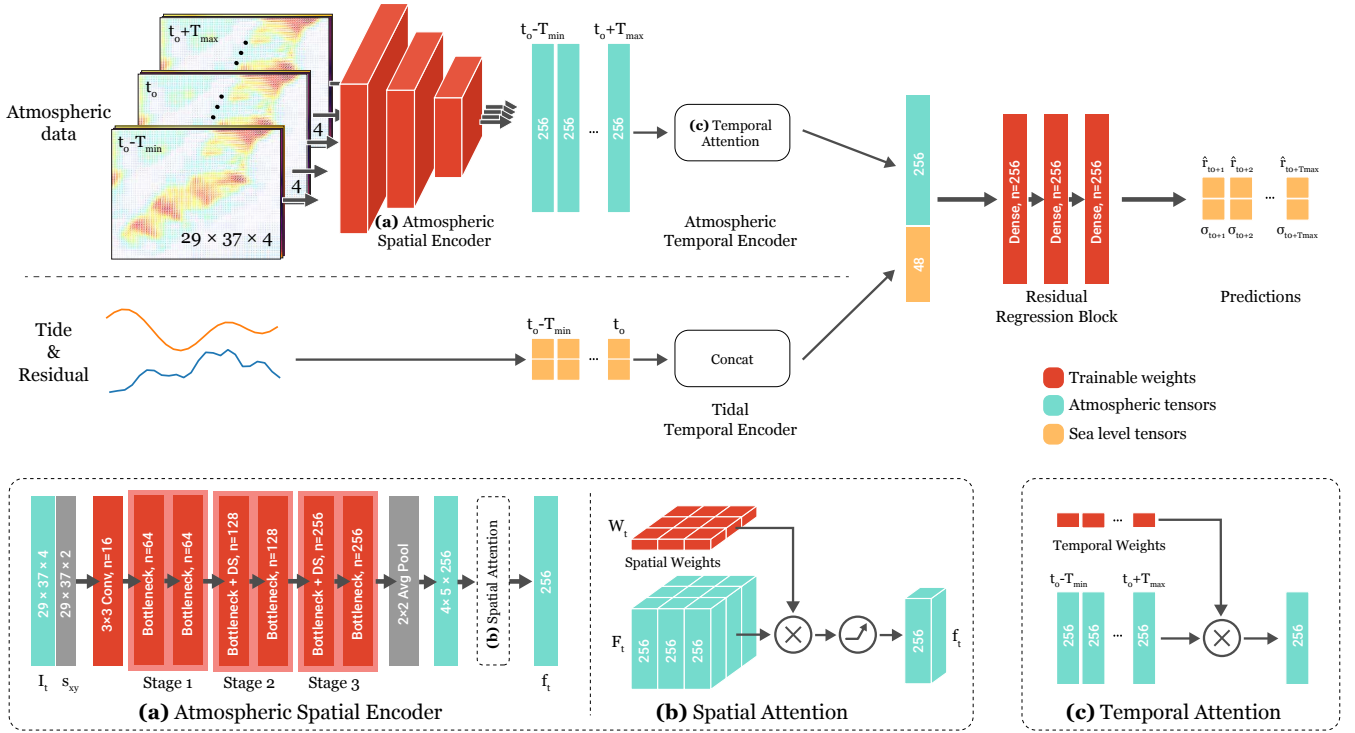
HIDRA (a High-performance Deep tidal Residual estimation method using Atmospheric data) is a deep neural network that predicts future surface height residual values (relative to the tidal model) from the sea level and atmospheric forcing input tensors. The atmospheric state at time-step  $t$  is represented by an atmospheric tensor  $\mathbf{I}_t \in \mathcal{R}^{W \times H \times 4}$ , where  $W = 29$  and  $H = 37$ .  $\mathbf{I}_t \in \mathcal{R}^{H \times W \times 4}$ , where  $W = 37$  and  $H = 29$  are the numbers of domain cells in longitudinal and latitudinal direction, respectively. The third dimension of  $\mathbf{I}_t$  corresponds to the four atmospheric surface input fields: two components of the wind stress, mean sea level pressure and air temperature at 2 m (see Figure 2).

To account for the causal relation between past atmospheric and tidal forcing in the basin and future sea surface heights, HIDRA considers the forcing data over a range of past and future timesteps. In particular, for prediction starting at time  $t_0$ , HIDRA takes as the input atmospheric tensors  $\mathbf{I}_t$  for the interval  $t \in [t_0 - T_{\min}, t_0 + T_{\max}]$  and the tidal and the residual values from the interval  $t \in [t_0 - T_{\min}, t_0]$ , and predicts residual values for the interval  $t \in [t_0 + 1, t_0 + T_{\max}]$ . Here,  $T_{\min}$  defines the number of past hours considered in sea level prediction and  $T_{\max}$  denotes the prediction horizon. In our experiments the predictions are made for 72 hours into the future, thus  $T_{\max} = 72$  h and we have determined [in our preliminary study \(see Section 4.1.1\)](#) that extending the historical horizon beyond 24 hours [did not significantly does not](#) affect the prediction accuracy, thus we set  $T_{\min} = 23$ ,  $T_{\max} = 24$  h. Note that the atmospheric tensor contains future forecasts as well, while the input sea level vectors contain only tides and residuals observed up to the prediction time  $t_0$ .

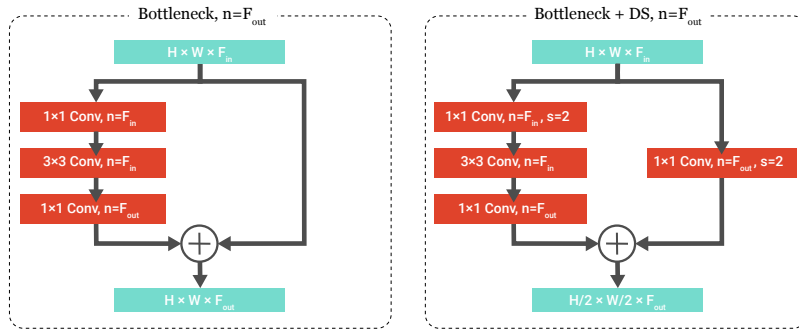
The HIDRA architecture is summarized in Figure 3. Atmospheric tensors from all considered time-steps are individually encoded by an *atmospheric spatial encoder* (ASE) module (Section 3.1.1) and fused by the temporal encoder block (Section 3.1.2) based on the temporal attention mechanism into an atmospheric feature vector. The resulting vector is concatenated with the past tidal and residual measurements. This is followed by a *residual regression block* (Section 3.1.3) to generate the final residual predictions  $\hat{\mathbf{r}}_t$  along with their uncertainties  $\sigma_t$ .

##### 3.1.1 Atmospheric Spatial Encoder

The atmospheric spatial encoder (ASE) encodes the spatially-represented atmospheric data into features, fine-tuned for the task of sea level prediction, i.e., the atmospheric tensor  $\mathbf{I}_t \in \mathcal{R}^{29 \times 37 \times 4}$  for time-step  $t$  is encoded into a feature vector  $\mathbf{f}_t \in \mathcal{R}^{256 \times 1}$ . The ASE architecture (shown in Figure 3a) follows design principles of the ResNet20 v2 convolutional neural network (He



**Figure 3.** The proposed HIDRA architecture. A convolutional *Atmospheric Spatial Encoder* (ASE) extracts spatial atmospheric features from each time-step. Atmospheric and sea level temporal features are encoded by respective Temporal Encoder blocks, fused and passed to the fully-connected *Residual Regression Block* to predict the residuals along with their uncertainties. With  $n$  we denote the number of filters or units of the block. The trainable blocks are denoted by colored red color. The structure of the bottleneck blocks used in the ASE is presented in Figure 4.



**Figure 4.** Structure of the bottleneck blocks used in the Atmospheric Spatial Encoder (Figure 3). The bottleneck block takes a feature map with depth  $F_{in}$  as the input and outputs a feature map with depth  $F_{out}$ . A regular bottleneck block (left) retains the spatial dimensions of the feature maps, while the downsampling (DS) bottleneck block (right) uses strided convolutions to reduce the spatial dimensions in half. We denote the number of convolutional filters by  $n$  and the stride parameter by  $s$ .

150 et al., 2016), which has already demonstrated remarkable performance in image processing tasks. ASE is composed of 22 convolutional layers. Spatial dependence in feature extraction is enforced by concatenating the atmospheric tensor  $\mathbf{I}_t$  with a spatial encoding tensor  $\mathbf{s}_{xy} \in \mathcal{R}^{29 \times 37 \times 2}$ , which contains the  $x$  and  $y$  coordinates (scaled between 0 and 1) of each pixel in the tensor. The augmented tensor is then processed by a convolutional layer with 16 filters of  $3 \times 3$  size, followed by three ResNet20 v2 stages, a spatial pooling layer and a time-dependent spatial attention layer (Figure 3b).

155 Each ResNet stage consists of two residual (bottleneck) blocks, where each block contains three convolutional layers (*i.e.*,  $1 \times 1$ ,  $3 \times 3$  and  $1 \times 1$ ) and a residual connection, which sums the block input with its output. To match the number of output features in the residual connection, the first residual block in each stage uses an additional  $1 \times 1$  convolutional projection. Spatial feature reduction-downsampling (DS) is applied by a stride of length 2 in the first convolutional layer of the second and third stage to increase the effective receptive field of neurons. A ReLU activation layer is appended to each convolutional  
160 layer, except from the first one, are pre-pended by a batch-normalization layer to stabilize the learning.

The output of the last residual block is spatially reduced by half with an average pooling layer, resulting in a feature tensor  $\mathbf{F}_t$  of size  $5 \times 4 \times 256$ . Finally, a time-dependent spatial attention layer produces the final feature vector  $\mathbf{f}_t \in \mathcal{R}^{1 \times 256}$ , which is a weighted sum of spatial positions

$$\mathbf{f}_t = \text{ReLU} \left( \underbrace{\sum_{i=1}^{20} \mathbf{F}_t^{(i)} \mathbf{w}_t^{(i)}}_{\text{spatial position } i} \underbrace{\sum_{i=1}^4 \sum_{j=1}^5 \mathbf{F}_t^{(i,j)} \mathbf{w}_t^{(i,j)}}_{\text{coordinates } (i,j)}, \right) \quad (1)$$

165 where  $\mathbf{F}_t^{(i)}$   $\mathbf{F}_t^{(i,j)}$  is a slice of the feature tensor at time  $t$  at spatial position  $i$ ,  $\mathbf{w}_t^{(i)}$  coordinates  $(i, j)$ ,  $\mathbf{w}_t^{(i,j)}$  is the respective spatial weight and  $\text{ReLU}(\cdot)$  is the ReLU activation function. Note that the weight matrices are temporally dependent, which allows them to focus on different parts of the atmospheric feature maps over time. With the exception of the spatial attention layer, all weights of the ASE network are temporally-independent and are thus shared between all atmospheric input tensors.

### 3.1.2 Temporal Encoders

170 The ASE encodes input sequence of atmospheric tensors into a sequence of atmospheric features. These are stacked into an atmospheric feature matrix  $\mathbf{F} \in \mathcal{R}^{256 \times T_\Delta}$ , where  $T_\Delta$  is the number of time-steps in the atmospheric input tensor  $\mathbf{I}_t$ , and compressed into a single feature vector  $\mathbf{f} \in \mathcal{R}^{256 \times 1}$  by a weighted summation

$$\mathbf{f} = \mathbf{F} \mathbf{w}^T, \quad (2)$$

where  $\mathbf{w}$  is a temporal weights vector which serves as a temporal attention mechanism (Figure 3c) and adjusts the contributions  
175 of different past time-steps to maximize the prediction performance.

The input tidal and residual sequences, each a  $T_{\min} \times 1$  vector, are concatenated with the encoded atmospheric feature vector (2) into the combined temporally-encoded atmospheric and surface height feature vector. This vector is passed to the residual regression block (Section 3.1.3) for the final prediction.

### 3.1.3 Residual Regression Block

180 Probabilistic regression is employed to enable predicting the most likely residual values along with their uncertainties. For each time-step, the mean and variance of a Gaussian probability density function are predicted. The residual regression block output are thus two sequences  $\hat{\mathbf{r}}$  and  $\hat{\boldsymbol{\sigma}}$ , each a  $1 \times T_{\max}$  vector, where  $T_{\max}$  is the prediction horizon. The residual regression block (Figure 3) is composed of three dense fully-connected layers, each consisting of 256 units, followed by a fully-connected layer that maps into two  $1 \times T_{\max}$  vectors for the means  $\hat{\mathbf{r}}$  and standard deviations  $\hat{\boldsymbol{\sigma}}$ . A soft-plus function (Glorot et al., 2011)  
185 is applied to the standard deviation vector to ensure positive values.

### 3.1.4 Network Training

A loss function that takes into account the probabilistic outputs is designed for training HIDRA end-to-end. In particular, a log-likelihood of the ground-truth data (*i.e.*, the residuals series  $\mathbf{r}_{t_0} = \{r_{t_0+\delta}\}_{\delta=0:T_{\max}}$ ), is computed under the sequence of predicted Gaussians (Figure 3,  $\hat{\mathbf{r}}_{t_0}$  and  $\hat{\boldsymbol{\sigma}}_{t_0}$ ) for all training sequences starting at different times  $t_0 \in \mathcal{T}$ . The loss is thus defined  
190 as

$$\mathcal{L}(\mathbf{r}, \hat{\mathbf{r}}, \hat{\boldsymbol{\sigma}}) = - \sum_{t_0 \in \mathcal{T}} \sum_{\delta=0}^{T_{\max}} \log \left( \frac{1}{\hat{\sigma}_{t_0+\delta} \sqrt{2\pi}} \exp \left( - \frac{(r_{t_0+\delta} - \hat{r}_{t_0+\delta})^2}{\hat{\sigma}_{t_0+\delta}^2} \right) \right), \quad (3)$$

where  $\mathbf{r}$  are the sets of training samples, while  $\hat{\mathbf{r}}$  and  $\hat{\boldsymbol{\sigma}}$  are the corresponding HIDRA predictions and their error estimates, respectively.

The network and experiments are implemented using Google’s machine learning library TensorFlow (Abadi et al., 2015).  
195 We use the ADAM optimizer with learning rate of 0.001,  $\beta_1 = 0.9$  and  $\beta_2 = 0.999$  to train the model. The training batch size is set to 64 data samples. The models are trained for 30 epochs, each epoch consisting of 1000 training steps (batches). A computer with a NVIDIA GeForce GTX 980 graphics card was used for model training and evaluation.

## 3.2 NEMO Ocean Model

~~A state-of-the-art sea surface level prediction method, General circulation model NEMO v3.6 ocean model (Madec, 2008),~~  
200 ~~(Madec, 2008)~~ is used as a ~~strong~~-baseline for comparison with HIDRA. ~~The NEMO model Detailed configuration namelist of our particular setup described below is available in the supplementary material in the paper.~~

~~Adriatic NEMO model used in this study~~ is set up ~~over the Adriatic basin~~ on a regular ~~longitude-latitude grid~~ (648×504 ~~longitude-latitude cells~~) with a 1°/72 arc-degree horizontal resolution and 31 vertical ~~partial step~~  $z^*$ -levels ~~with partial step~~. The model domain spans 12–21° E and 39–46° N (see Figure 2). In all regions shallower than 2 m, a 2 m depth is enforced.  
205 ~~Baroclinic timestep was set to 120 s. Explicit time-splitting is enforced and barotropic timestep is automatically Barotropic timestep is~~ adjusted to meet Courant-Friedrichs-Lewy stability ~~criterion. The model runs daily condition. This operational suite runs every day~~ at Slovenian Environment Agency (ARSO) High Performance Computing Center and is ~~initialized from the previous operational run~~ ~~hotstarted from the run of the previous day~~. Hourly lateral boundary conditions in the Ionian Sea are taken from the hourly Copernicus CMEMS Mediterranean Sea Analysis and Forecast product. Turbulent ~~heat and momentum~~



210 ~~momentum and heat~~ fluxes across the ~~ocean surface are computed with air-sea interface are parametrized using~~ CORE bulk flux formulation (Large and Yeager, 2004) using ECMWF ensemble atmospheric fields: ~~longwave and shortwave radiation fluxes, 10-meter winds, mean sea level pressure, 2 temperature, relative humidity and precipitation. Rivers are implemented as freshwater release over the entire water column at the discharge location, with runoff values.~~

~~Rivers are modeled as discharge of fresh water at the respective river location~~ as described in Ličer et al. (2016). ~~The model employs~~ Flather boundary condition ~~for barotropic dynamics and determines barotropic dynamics at the lateral open boundary, while~~ Flow Relaxation Scheme (Engedahl, 1995) ~~is applied~~ for baroclinic dynamics and tracers ~~at the open boundary.~~ Lateral momentum boundary condition at the coast is free-slip. Bottom ~~friction is nonlinear with a logarithmic boundary layer boundary layer is logarithmic with nonlinear bottom friction.~~ Lateral diffusion ~~is governed by Laplacian~~ operators for tracers and dynamics ~~are both bilaplacian, acting along, both operating over~~ geopotential surfaces. ~~Vertical diffusion is computed using~~ Generic Length Scale  $k-\epsilon$  ~~turbulenee closure. scheme is used for vertical diffusion. Surface wave mixing is parametrized using~~ Craig and Banner formulation (Craig and Banner, 1994) ~~of surface mixing due to wave breaking is applied as well. The full NEMO configuration namelist is provided as supplementary material (Žust et al., 2021).~~

NEMO was run in this study without tidal forcing and predicts the residual sea level for the entire Adriatic basin with the forecast period set to 72 h (as in HIDRA). In the ensemble simulations, only eight out of fifty ECMWF ensemble members  
 225 were used as forcing to ~~the our~~ NEMO circulation model due to computational constraints. These eight ensemble members were selected from ECMWF ensemble based on the wind strength each member exhibits in the central Adriatic: ECMWF ensemble members were ordered by wind strength in the central Adriatic and then a subset of members was made from the strongest to the weakest member in steps of 6 (*i.e.* integer part of  $50/8$ ). This generates eight possible forcing scenarios in the Adriatic basin while conserving the wind forecast spread of the reduced ensemble. For the  $i$ -th ( $i = 1, \dots, 8$ ) NEMO ensemble  
 230 member run, residual sea level forecast for Koper is extracted from the NEMO basin prediction as a single time-series. This is then added to the tidal time series, obtained via tidal analysis from observations, to obtain the total modeled sea level, which we denote as  $y^{\text{nemo}}(i, t)$ .

Each member of the NEMO ensemble sea level forecast for Koper is further corrected for bias. This is necessary to compensate for the fact that NEMO sea level reflects departures from a local geoid and does not represent the absolute local depth of  
 235 the water, which is also driven by low-frequency processes (like planetary waves in air pressure), which cannot be reflected in the 72 hour run in a regional basin. To obtain the absolute sea level needed by port and civil rescue authorities, the NEMO sea level predictions have to be adjusted to the Koper tide gauge observations.

On the  $n$ -th hour of the forecast day, the model bias with respect to Koper tide gauge observations  $y^{\text{kp}}(t)$  can is estimated as

$$240 \quad \epsilon_n(i) = n^{-1} \sum_{k=1}^n [y^{\text{nemo}}(i, t_k) - y^{\text{kp}}(t_k)]. \quad (4)$$

The  $i$ -th ensemble NEMO prediction time-series  $y^{\text{nemo}}(i, t)$  is then shifted by  $\epsilon_n(i)$  so that the bias of the first  $n$ -hours of the  $y^{\text{nemo}}(i, 1 < t < n)$  with respect to observations is zero. Complete forecast time-series  $y^{\text{nemo}}(i, t)$  will of course still exhibit a non-zero bias. This procedure is applied every hour as new observations from Koper tide gauge arrive. Note that, unlike NEMO



ensemble, HIDRA ensemble does not need any such bias correction, because it already contains local tide gauge information  
 245 through its sea level input in the day prior to the forecast and learns to adjust for the possible bias.

For operational reasons, first daily NEMO sea level ensemble run usually becomes available between 11 00 and 12 00 UTC at the earliest. This means that the earliest bias correction of each day generally takes into account the first 12 hours of tide gauge observations of that day. Raw NEMO time-series from  $i$ -th ensemble member  $y^{\text{nemo}}(i, t)$  therefore gets shifted by  $\epsilon_{12\text{h}}(i)$  to produce the first bias-corrected forecast of that day, i.e.,

$$250 \quad y_{\text{bc}12\text{h}}^{\text{nemo}}(i, t) = y^{\text{nemo}}(i, t) - \epsilon_{12\text{h}}(i), \quad (5)$$

with  $\epsilon_{12\text{h}}(i)$  defined in (4). The bias-corrected NEMO ensemble mean, ensemble maximum and ensemble minimum time-series is then constructed from 12-hour bias-corrected ensemble members at each forecast timestep in an identical fashion as with HIDRA – see (6)-(8). The corresponding time-series are denoted as  $\bar{y}_{\text{bc}12\text{h}}(t)$ ,  $y_{\text{bc}12\text{h}}^{\text{max}}(t)$  and  $y_{\text{bc}12\text{h}}^{\text{min}}(t)$ .

### 3.3 Ensemble Statistics

255 As mentioned in Section 2.2, a total of fifty ECMWF atmospheric ensemble members are available daily. This results in an ensemble of  $n_{\text{ens}} = 50$  sea level forecasts by HIDRA and an ensemble of  $n_{\text{ens}} = 8$  sea level forecasts by NEMO. The ensemble mean time-series is defined as the average over all ensemble members predictions

$$\bar{y}(t) = n_{\text{ens}}^{-1} \sum_{i=1}^{n_{\text{ens}}} y(i, t), \quad (6)$$

where  $y(i, t)$  is the  $i$ -th member. Similarly, the ensemble prediction envelope, i.e., the per-time-step minimum and maximum  
 260 sequence, is defined as

$$y^{\text{max}}(t) = \max_i [y(i, t)], \quad (7)$$

$$y^{\text{min}}(t) = \min_i [y(i, t)]. \quad (8)$$

In the interest of clarity, only ensemble means, maximums and minimums, as defined above, are analyzed in the following (rather than individual ensemble members).

## 265 4 Results and Discussion

Predictions from HIDRA and NEMO are discussed in two sections. Section 4.1 analyzes the influence of atmospheric and sea level input on HIDRA ~~forecasting skill~~ forecasts and concludes with a brief analysis of HIDRA atmospheric encoder design. Statistical and spectral analyses of HIDRA and NEMO predictions are then presented in Section 4.2.

### 4.1 HIDRA Architecture Analysis

270 The HIDRA architecture design choices and their impact on forecast accuracy is analyzed in this section. Forecast accuracy is tested (i) with regard to the prediction lead time, i.e., the number of hours in the future we are forecasting, and (ii) with regard

**Table 1.** HIDRA performance for different historic horizons in terms of mean absolute error (MAE), root mean squared error (RMSE), model bias and likelihood shown separately on all data and on storm surge events. CPU execution time (on a single core) per example is also reported.

	MAE [cm]	RMSE [cm]	Bias [cm]	Likelihood	CPU time [s]
<b>Overall</b>					
$T_{\min} = 12$	5.3	7.0	-0.2	0.0440	0.17
$T_{\min} = 24$	4.9	6.4	-0.4	0.0470	0.19
$T_{\min} = 36$	4.8	6.4	-0.9	0.0455	0.21
$T_{\min} = 48$	4.8	6.4	-0.6	0.0438	0.23
<b>Storm surge events</b>					
$T_{\min} = 12$	11.7	13.9	-11.2	0.0220	0.17
$T_{\min} = 24$	10.3	12.9	-9.3	0.0253	0.19
$T_{\min} = 36$	10.7	13.2	-9.8	0.0245	0.21
$T_{\min} = 48$	10.4	12.8	-9.1	0.0251	0.23

to the sea level residual value, i.e., how far away from astronomical tide lies the sea level. All experiments regarding network design are performed on the Koper test sea level dataset, which spans November 2014 to December 2016.

275 Influence of the historic horizon is examined in Section 4.1.1. Contribution of individual data sources (*i.e.* atmospheric data and sea level history data) is analyzed in Section 4.1.2. The influence of the residual forecasting approach is evaluated in Section 4.1.3. The influence of the proposed atmospheric data encoder in comparison to reconstruction-based empirical orthogonal functions (EOF) is examined in Section 4.1.4, while the influence of the temporal encoder is analyzed in Section 4.1.5.

#### 4.1.1 **Contribution-Influence of Atmospheric and Sea Level Inputs**the Historic Horizon

280 We first analyze the **individual contributions of** influence of the HIDRA historic horizon defined by the parameter  $T_{\min}$  (see Section 3.1). Table 1 summarizes the performance of HIDRA with  $T_{\min} \in \{12, 24, 36, 48\}$ , which translates to historic horizons of 12, 24, 36 and 48 hours prior to the beginning of forecast. Increasing the historic horizon from 12 to 24 hours significantly improves the prediction accuracy (9% reduction in RMSE error), however, further increases of the historic horizon (*i.e.*, to 36 or 48 hours) do not show measurable benefits. Note that the execution time increases with the length of the historic horizon due to a substantial increase of parameters on the input layer. For this reason, we use a historic horizon of 24 hours ( $T_{\min} = 24$ ) as  
285 the best trade-off in the remaining analysis and denote this version as  $\text{HIDRA}_0$ .

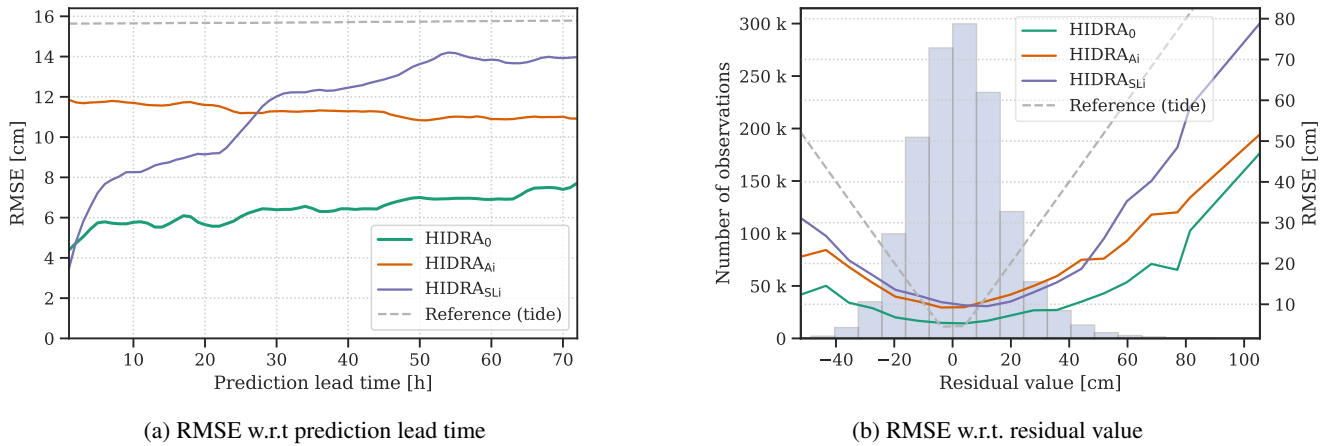
#### 4.1.2 **Contribution of Atmospheric and Sea Level Inputs**

HIDRA uses two input sources: the atmospheric data and the sea level history. **Full** In this study we analyze the individual contributions of both input sources. The full HIDRA model (using both atmosphere and sea level data input, denoted as  $\text{HIDRA}_0$ ) is compared with two single-input-source models: (i)  $\text{HIDRA}_{\text{Ai}}$ , using only atmospheric inputs, and (ii)  $\text{HIDRA}_{\text{SLi}}$ ,

**Table 2.** HIDRA performance for individual input data ~~source~~ sources in terms of mean absolute error (MAE), root mean squared error (RMSE) and model bias. Full HIDRA<sub>0</sub> with both input sources is compared with alternatives that use only atmospheric (HIDRA<sub>Ai</sub>) or tidal forcing (HIDRA<sub>SLi</sub>) as the input. Performance for the atmospheric tide is provided as reference. Performance is reported on all data as well as on storm surge events only.

	MAE [cm]	RMSE [cm]	Bias [cm]	Likelihood
<b>Overall</b>				
HIDRA <sub>0</sub>	<b>4.9</b>	<b>6.4</b>	<b>-0.4</b>	<b>0.0470</b>
HIDRA <sub>Ai</sub>	8.8	11.3	-0.5	0.0315
HIDRA <sub>SLi</sub>	8.6	11.7	3.3	0.0279
Reference (tide)	12.1	15.7	-2.4	–
<b>Storm surge events</b>				
HIDRA <sub>0</sub>	<b>10.3</b>	<b>12.9</b>	<b>-9.3</b>	<b>0.0253</b>
HIDRA <sub>Ai</sub>	20.1	22.5	-19.5	0.0093
HIDRA <sub>SLi</sub>	21.1	25.5	-20.2	0.0134
Reference (tide)	49.6	50.4	-49.6	–

290 using only sea level inputs. In both setups, the network branch responsible for processing the ignored input source is removed. Results are presented in Table 2 and Figure 5.



**Figure 5.** Performance of single-input-source models. Root Mean Squared Error (RMSE) with respect to (a) prediction lead time and (b) residual value bins for different input sources is visualized. The full HIDRA model is compared with single-input-source variants – atmospheric data only HIDRA<sub>Ai</sub> model and tidal data only HIDRA<sub>SLi</sub> model. The RMSE of the astronomic tide is shown for reference.

Table 2 indicates that HIDRA exhibits best performance when using both atmospheric and sea level input and outperforms both single-source variants by a large margin. This holds overall and also within limited time windows during storm surge events (defined as the timestamps where the residual is larger than 40 cm). Removing each source individually leads to a

295 significant performance drop. The RMSE increases by 77% when using only the atmospheric input data ( $HIDRA_{Ai}$ ), while a 83% RMSE increase is observed when using only sea level data ( $HIDRA_{SLi}$ ). This confirms that both input data sources are essential for accurate prediction. Note also that both input data sources have a similar overall contribution to the prediction accuracy.

Performance analysis over prediction lead time (Figure 5a) reveals further insights.  $HIDRA_{Ai}$  is very consistent across the entire prediction interval. In fact, the error slightly decreases over time (8% decrease in RMSE over the interval of 72 h).  $HIDRA_{SLi}$ , on the other hand, is a much better sea level predictor in the short-term, but the error increases rapidly over the prediction interval (by 400% over the interval of 72h). Thus, while the sea level data is important for short-term predictions, the atmospheric data is more informative for predictions further into the future.

Grey dashed line in Figure 5 depicts forecast errors of using the astronomical tide values as the surface height predictor. Since tidal forecast is done independently of prediction lead time, its RMSE over prediction time window is simply a root mean square error of the tidal model, plotted as a horizontal line. Bias of the reference tidal model with regard to specific residual bin is, by definition, the negated value of the residual itself, while its RMSE is, again by definition, simply the absolute value of the residual itself. Whenever HIDRA exhibits lower biases or RMSEs than tidal reference model, they are essentially predicting more accurately than a tidal model would. Note that this is the case for all prediction lead times and practically all residual values.

On large residual values that correspond to storm surges (Figure 5b),  $HIDRA_{Ai}$  outperforms  $HIDRA_{SLi}$ , confirming that atmospheric data is essential for accurate storm surge prediction. Both models achieve similar performance on small residual values, and both perform worse than the full model.

### 4.1.3 Influence of Sea Level Input Type

315 HIDRA considers the total sea level information split into the tide and the residual provided as separate input time series, and predicts the residual which is added to the tidal signal to predict the full surface height. To analyze the contribution of different sea level input types, two additional variants were considered: (i)  $HIDRA_{res}$  considered only the residual as the input to predict the future residuals and (ii)  $HIDRA_{sl}$  considered a single total sea level input and predicted the total sea level output.

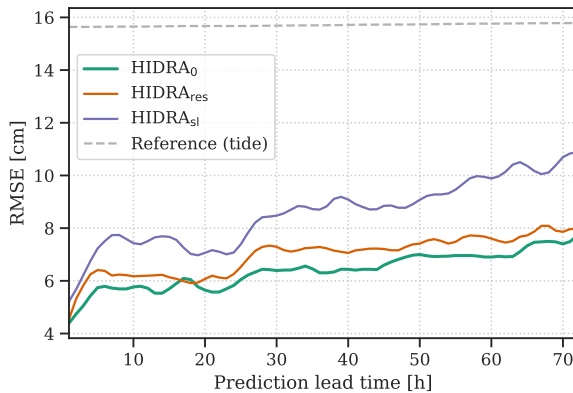
Results are shown in Table 3. Sea-level-only model ( $HIDRA_{sl}$ ) performs significantly worse than  $HIDRA_{res}$  with a 35% increase in RMSE, which speaks in favor of residual prediction over the total sea level. The residuals-only model  $HIDRA_{res}$  also performs slightly worse than the full model, causing an 8% RMSE increase, indicating that tidal information as an additional input provides useful context for improved prediction accuracy.

Performance analysis over different prediction lead times (Figure 6a) shows that the sea-level-only model  $HIDRA_{sl}$  makes much larger errors (41% increase compared to  $HIDRA_{res}$ ) when predicting far into the future (prediction lead time is high), which suggests that the network has trouble predicting the tidal component that far into the future using only the data from the last 24 hours. Comparing predictions over different residual values (Figure 6b) shows a similar situation.  $HIDRA_{sl}$  performs substantially worse (40-50% larger RMSE than  $HIDRA_{res}$ ) for small residual values. This is the range at which the tidal model typically is most accurate and thus provides sufficient information for accurate predictions.

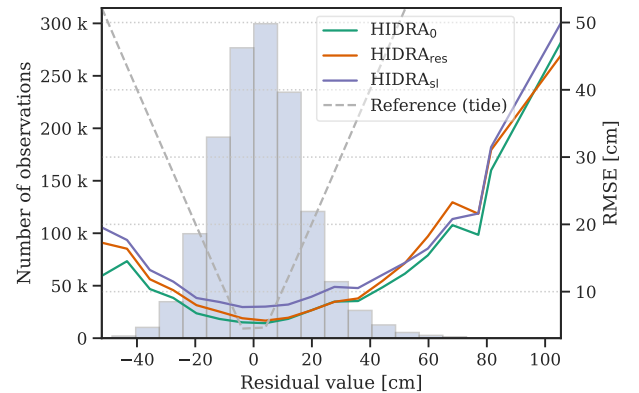
**Table 3.** Performance evaluation of different HIDRA sea level input variants. Results are reported on the entire test set (2014-2016) and separately on storm surge events.

	MAE [cm]	RMSE [cm]	Bias [cm]	Likelihood
<b>Overall</b>				
<b>HIDRA</b> <u>HIDRA</u> <sub>0</sub>	<b>4.9</b>	<b>6.4</b>	-0.4	<b>0.0470</b>
<b>HIDRA</b> <u>HIDRA</u> <sub>res</sub>	5.3	7.0	0.8	0.0443
<b>HIDRA</b> <u>HIDRA</u> <sub>sl</sub>	6.6	8.7	<b>0.2</b>	0.0312
Reference (tide)	12.1	15.7	-2.4	–
<b>Storm surge events</b>				
<b>HIDRA</b> <u>HIDRA</u> <sub>0</sub>	<b>10.3</b>	<b>12.9</b>	<b>-9.3</b>	<b>0.0253</b>
<b>HIDRA</b> <u>HIDRA</u> <sub>res</sub>	11.9	14.4	-11.1	0.0221
<b>HIDRA</b> <u>HIDRA</u> <sub>sl</sub>	11.7	14.4	-9.6	0.0216
Reference (tide)	49.6	50.4	-49.6	–

Note also that although the sea level only model **HIDRA**HIDRA<sub>sl</sub> does not use tidal information, its prediction errors still follow a similar pattern of increasing with growing residual values. This is an interesting **results-result** and shows that the examples belonging to small residual values are inherently easier to predict regardless of whether the tidal estimation is used or not.



(a) RMSE w.r.t prediction lead time



(b) RMSE w.r.t. residual value

**Figure 6.** Performance comparison of HIDRA sea level input variants. HIDRA<sub>0</sub> is compared with residuals only model HIDRA<sub>res</sub>, which does not use the estimated tide signal at the input and the sea level only model HIDRA<sub>sl</sub>, which does not use separate tidal estimation and predicts the entire sea level signal. The RMSE with respect to (a) prediction lead time and (b) residual value bins is reported. The errors of the astronomic tide are presented for reference.

**Table 4.** Comparison of the proposed ASE-based ( $\text{HIDRA}_{\text{A0}}$ ) and the EOF-based ( $\text{HIDRA}_{\text{EOF}}$ ) in terms of overall performance and performance on storm surges. The astronomic tide model performance is reported for reference.

	MAE [cm]	RMSE [cm]	Bias [cm]	Likelihood
<b>Overall</b>				
$\text{HIDRA}_{\text{A0}}$	<b>4.9</b>	<b>6.4</b>	-0.4	<b>0.0470</b>
$\text{HIDRA}_{\text{EOF}}$	5.0	6.6	<b>-0.1</b>	0.0431
Reference (tide)	12.1	15.7	-2.4	–
<b>Storm surge events</b>				
$\text{HIDRA}_{\text{A0}}$	<b>10.3</b>	<b>12.9</b>	<b>-9.3</b>	<b>0.0253</b>
$\text{HIDRA}_{\text{EOF}}$	11.1	13.6	-10.1	0.0225
Reference (tide)	49.6	50.4	-49.6	–

#### 4.1.4 Influence of the Atmospheric Encoder

The role of trainable discriminative atmospheric encoder ASE is analyzed by replacing it with a reconstructive embedding proposed in Hieronymus et al. (2019). A principal component analysis is applied to the atmospheric input to compute a low-dimensional subspace (empirical orthogonal functions, EOFs) that maximizes the data reconstruction. Following Hieronymus et al. (2019), the top three EOF are used in the subspace construction. The input is projected into this subspace producing a low-dimensional signal that is directly used in the HIDRA regression network. The modified HIDRA is denoted by  $\text{HIDRA}_{\text{EOF}}$  in the following.

The HIDRA variants with ASE and with EOF are compared in Table 4. In normal conditions, the EOF-based version ( $\text{HIDRA}_{\text{EOF}}$ ) performs on par with HIDRA using the proposed ASE. The  $\text{HIDRA}_{\text{EOF}}$  RMSE is approximately 3% larger than that of  $\text{HIDRA}_{\text{A0}}$ . However, the difference increases on the less frequent conditions with high residuals (*i.e.* surges) in which the EOF-based version results in a 5% RMSE increase compared to ASE-based version. This supports the choice of using end-to-end learned feature encoder as opposed to a hand-crafted one.

#### 4.1.5 Influence of Temporal Encoders

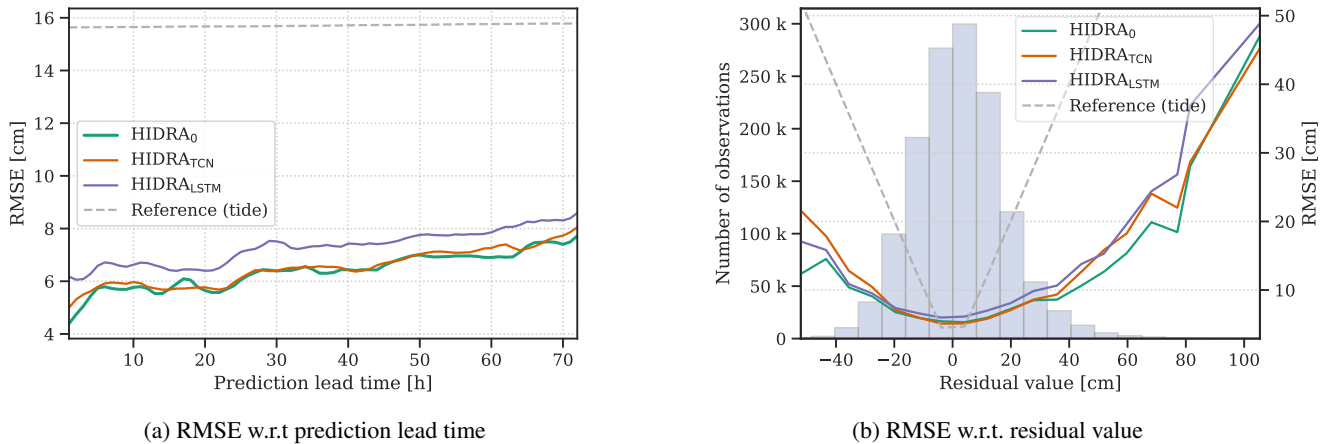
Temporal encoder with temporal attention weights (Section 3.1.2) plays an important part in HIDRA. Two additional variants are created to study alternative choices of feature encoding. The first HIDRA variant ( $\text{HIDRA}_{\text{TCN}}$ ) uses temporal convolutional networks (TCN) (Bai et al., 2018) for encoding the atmospheric and the sea level branch of the network. The atmospheric branch applies three TCN blocks with 128 units, while the sea level branch applies three TCN blocks with 64 units. The second HIDRA variant ( $\text{HIDRA}_{\text{LSTM}}$ ) uses a popular long short-term memory (LSTM) (Hochreiter and Schmidhuber, 1997) networks for temporal encoding. Three LSTM layers are used in both the atmospheric and the sea level branch of the model. Each layer contains 128 units in the atmospheric and 64 in the sea level branch.

Results are reported in Table 5 and Figure 7. Overall,  $\text{HIDRA}_{\text{A0}}$  performs on par with the more complex TCN-based  $\text{HIDRA}_{\text{TCN}}$  (RMSE of  $\text{HIDRA}_{\text{TCN}}$  is 3% larger), while LSTM-based  $\text{HIDRA}_{\text{LSTM}}$  performs worse (RMSE is 14% larger

**Table 5.** Performance of HIDRA model variants using different temporal encoders.  $\text{HIDRA}_0$  model uses fixed temporal attention for the atmospheric data.  $\text{HIDRA}_{\text{TCN}}$  uses TCNs and  $\text{HIDRA}_{\text{LSTM}}$  uses LSTMs to encode temporal features of atmospheric and sea level data. Performance of the astronomic tide is provided for reference.

	MAE [cm]	RMSE [cm]	Bias [cm]	Likelihood
<b>Overall</b>				
$\text{HIDRA}_0$	<b>4.9</b>	<b>6.4</b>	-0.4	<b>0.0470</b>
$\text{HIDRA}_{\text{TCN}}$	4.9	6.6	-0.2	0.0431
$\text{HIDRA}_{\text{LSTM}}$	5.5	7.3	-0.8	0.0461
Reference (tide)	12.1	15.7	-2.4	-
<b>Storm surge events</b>				
$\text{HIDRA}_0$	<b>10.3</b>	<b>12.9</b>	<b>-9.3</b>	<b>0.0253</b>
$\text{HIDRA}_{\text{TCN}}$	13.5	15.3	-13.2	0.0180
$\text{HIDRA}_{\text{LSTM}}$	13.6	16.2	-12.9	0.0188
Reference (tide)	49.6	50.4	-49.6	-

355 than  $\text{HIDRA}_0$  ( $\text{HIDRA}_{\text{TCN}}$ ,  $\text{HIDRA}_{\text{LSTM}}$ ).  $\text{HIDRA}_0$  outperforms both TCN and LSTM-based versions by a solid margin on the storm surge events (31% and 32% RMSE increase, respectively). Furthermore, temporal weights of  $\text{HIDRA}_0$  use very few parameters compared with the other variants (see Table 6) – TCN and LSTM-based variations increase the total model size (including other network layers) by 50% and 150% respectively.



**Figure 7.** Comparison of different temporal encoder variants.  $\text{HIDRA}_0$  is compared with more complex variants using different temporal encoders: LSTMs ( $\text{HIDRA}_{\text{LSTM}}$ ) and TCNs ( $\text{HIDRA}_{\text{TCN}}$ ). The RMSE with respect to (a) prediction lead time and (b) residual values is shown. The prediction errors using the astronomic tide are presented for reference.

#### 4.1.6 Influence of the Wind Input Type and Wind-Pressure Redundancy

**Table 6.** Total number (in millions) of trainable parameters of HIDRA variants with different temporal encoders.

Method	# of parameters
<b>HIDRA</b> <u>HIDRA<sub>0</sub></u>	<b>0.8 M</b>
<b>HIDRA</b> <u>HIDRA<sub>TCN</sub></u>	1.2 M
<b>HIDRA</b> <u>HIDRA<sub>LSTM</sub></u>	2.1 M

**Table 7.** Performance of HIDRA variants with different wind and pressure input configurations. HIDRA<sub>0</sub> uses the wind stress, HIDRA<sub>wnd</sub> uses the raw wind, HIDRA<sub>no\_wnd</sub> does not use wind inputs and HIDRA<sub>no\_prs</sub> uses the wind stress, but not the air pressure. Performance of the astronomic tide is provided for reference.

	MAE [cm]	RMSE [cm]	Bias [cm]	<u>Likelihood</u>
<b>Overall</b>				
<u>HIDRA<sub>0</sub></u>	<u>4.9</u>	<u>6.4</u>	<u>-0.4</u>	<u>0.0470</u>
<u>HIDRA<sub>wnd</sub></u>	<u>4.9</u>	<u>6.4</u>	<u>0.2</u>	<u>0.0465</u>
<u>HIDRA<sub>no_wnd</sub></u>	<u>5.3</u>	<u>7.1</u>	<u>-0.3</u>	<u>0.0434</u>
<u>HIDRA<sub>no_prs</sub></u>	<u>5.3</u>	<u>7.0</u>	<u>-0.1</u>	<u>0.0451</u>
<u>Reference (tide)</u>	<u>12.1</u>	<u>15.7</u>	<u>-2.4</u>	<u>-</u>
<b>Storm surge events</b>				
<u>HIDRA<sub>0</sub></u>	<u>10.3</u>	<u>12.9</u>	<u>-9.3</u>	<u>0.0253</u>
<u>HIDRA<sub>wnd</sub></u>	<u>9.3</u>	<u>11.6</u>	<u>-7.8</u>	<u>0.0274</u>
<u>HIDRA<sub>no_wnd</sub></u>	<u>13.7</u>	<u>16.5</u>	<u>-12.9</u>	<u>0.0192</u>
<u>HIDRA<sub>no_prs</sub></u>	<u>11.6</u>	<u>14.0</u>	<u>-10.8</u>	<u>0.0225</u>
<u>Reference (tide)</u>	<u>49.6</u>	<u>50.4</u>	<u>-49.6</u>	<u>-</u>

360 Bora and Scirocco characteristics in the Adriatic basin are often determined through an interplay of geostrophic, orographic and other influences (Pasarić et al., 2007; Grisogono and Belušić, 2009). At other times however, non-geostrophic effects may play a lesser role and the wind field is largely determined by the pressure field. To investigate potential information redundancy between the wind and pressure inputs, two HIDRA variants were trained: one which did not use the wind input and another which used the wind, but not the pressure. Results in Table 7 show that removing either wind or air pressure input leads to an  
 365 approximately 9% increase of RMSE. HIDRA seems to compensate for potential redundancy in the inputs and capitalizes on the fact that wind in the basin is, in the last instance, not entirely pressure driven. In any case using both inputs is preferred.

We proceed to inspect the impact of Large and Pond parametrization (Large and Pond, 1981) which might oversimplify the wind stress dependence on the wind. To this end we consider another variant of HIDRA, which uses raw wind instead of wind stress. Results in Table 7 show that, overall, the performance between the two wind-input variants is indistinguishable.  
 370 However, on storm surges, using raw wind reduces the RMSE by approximately 1 cm when compared to the setup which uses wind stress. It appears that HIDRA is capable of extracting the information important for sea level prediction during storm surges also directly from the raw wind.



## 4.2 Comparisons between HIDRA and NEMO

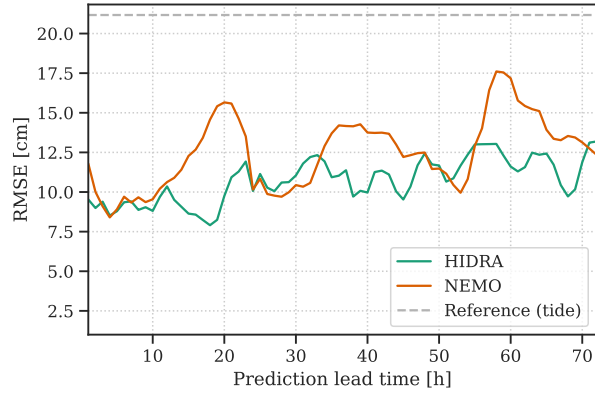
In ~~the usual regional~~ ocean modeling setups, tides are ~~mostly treated strictly separately from the residuals. But in HIDRA,~~  
375 ~~the tide enters the prediction model, and often implemented as open boundary conditions and are treated as an external part~~  
~~of model's sea level response. In HIDRA on the other hand, tides enter the model as information that gets inextricably linked~~  
~~into its residual (i.e. non-tidal part) of prediction:~~ results of Section 4.1.3 show that ~~it including tides~~ improves the prediction  
of the residual ~~itself~~. Thus in HIDRA, the quantity we refer to as the residual, is in fact composed of two ~~entangled~~ parts: the  
atmospheric part of the residual and the error correction of the tidal model. ~~Given a perfect tide model, the latter term would~~  
380 ~~have been zero, and HIDRA's residual would have been solely due to the atmosphere—this is not the case. We nevertheless use~~  
~~the term residual to differentiate it not from the tide, but rather from total sea level.~~ For these reasons we cannot, as is otherwise  
customary in sea level modeling, focus on the verification of the residual part of the ~~total~~ sea level signal. ~~We thus compare~~  
~~HIDRA and NEMO in this section. In this section, we thus compare the best-performing variant of HIDRA from the ablation~~  
~~study (Section 4.1.6) and NEMO~~ on the total sea levels, which, ~~in HIDRA and in NEMO,~~ contain both residuals and tides.

### 385 4.2.1 Overall Performance

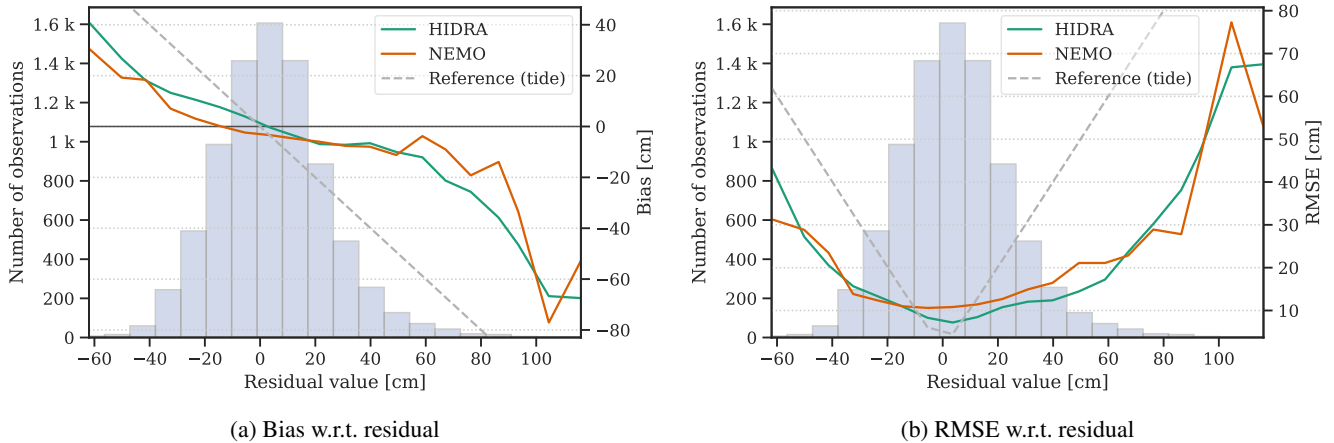
HIDRA and NEMO are compared on the 2019 tide-gauge sea level observations in Koper. While HIDRA enables prediction  
starting at each time-step, NEMO does not, since it runs once per day. The models are thus compared only on the prediction  
windows matching the NEMO runs. The analysis uses the ensemble mean of NEMO members with a 12 h bias correction, i.e.,  
 $\bar{y}_{bc12h}(t)$  defined in (5). The corresponding ensemble mean HIDRA time series are denoted as  $\bar{y}_H(t)$  and the Koper tide gauge  
390 time series are denoted by  $y^{kp}(t)$ .

Results are reported in Table 8. Overall (top panel of Table 8), HIDRA outperforms NEMO, obtaining a lower MAE, RMSE  
and bias. During storm surges (bottom panel of Table 8) HIDRA also outperforms NEMO, but exhibits a larger bias. The  
results visualised with respect to the residual sea level bin in Figure 9 confirm this. To track the prediction error growth with  
prediction horizon, we show RMSE with respect to the prediction lead time in Figure 8. Both NEMO and HIDRA exhibit a  
395 similar RMSE growth trend of approximately +4 cm per 72 h. But NEMO exhibits a higher mean error and a higher error  
variance. HIDRA outperforms NEMO over the entire range of prediction lead times with lower and less volatile errors.

To gain further insights, the NEMO, HIDRA and tide gauge 2019 time-series power spectra were analyzed by computing  
spectral energy densities of the signals over the frequency domain  $(2h)^{-1} - (96h)^{-1}$  (Figure 10). The power spectra were  
computed as absolute values of one-dimensional Fast Fourier Transforms. The tide gauge power spectrum exhibits clear tidal  
400 presence and also a clear peak at the fundamental Adriatic seiche period of 21.5 h. Some higher harmonics are also present in  
the tide gauge spectrum at shorter periods (below 8 h) which are present in NEMO but absent from HIDRA. They are, however,  
less important as they contain at least an order of magnitude less energy than tides or the ground state seiche, which may be the  
reason HIDRA learned to partially ignore it. Both NEMO and HIDRA contain adequate amount of energy at tidal periods. But  
NEMO significantly underestimates the amount of energy contained in the frequency band around the fundamental Adriatic  
405 seiche. HIDRA, on the other hand, contains an adequate, if slightly underestimated, amount of energy in the seiche frequency



**Figure 8.** Performance comparison of HIDRA and NEMO with respect to the prediction lead time. Error of the astronomic tide is presented for reference as a grey dashed line.

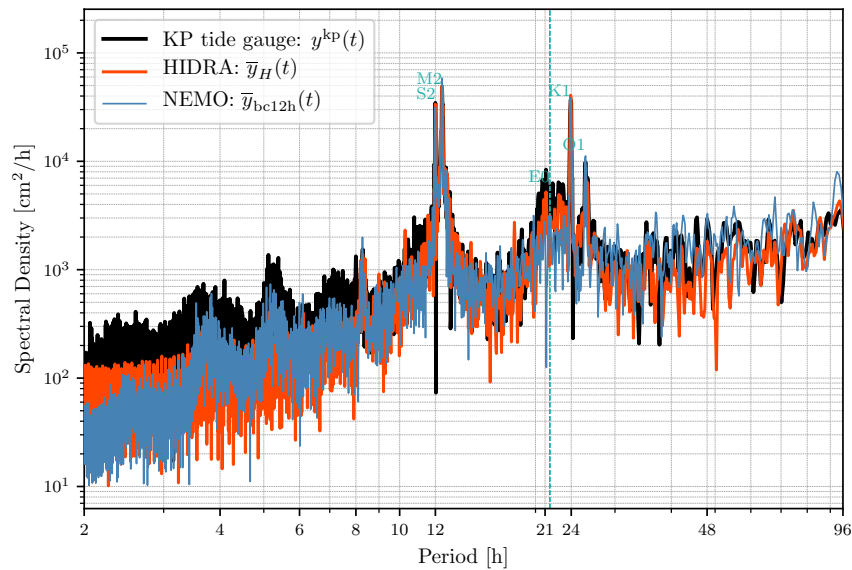


**Figure 9.** Comparison of HIDRA and NEMO over the sea level distribution. Bias (a) and RMSE (b) with respect to the residual value are shown. Error of the astronomic tide is shown for reference.

**Table 8.** Comparison of HIDRA and NEMO on the Koper 2019 test dataset. Overall performance is shown separately from performance during storm surge events. Performance of the astronomic tide is provided for reference.

	MAE [cm]	RMSE [cm]	Bias [cm]	Likelihood
<b>Overall</b>				
HIDRA	<b>8.4</b>	<b>10.9</b> <b>10.8</b>	<b>-0.80</b> <b>2</b>	<b>0.0324</b> <b>0.0323</b>
NEMO	9.5	12.7	-3.0	<b>0.0337</b>
Reference (tide)	16.0	21.0	-4.7	-
<b>Storm surge events</b>				
HIDRA	<b>15.2</b> <b>15.6</b>	<b>19.5</b> <b>20.2</b>	<b>-12.5</b> <b>-13.5</b>	<b>0.0190</b> <b>0.0180</b>
NEMO	17.1	22.4	<b>-9.7</b>	<b>0.0202</b>
Reference (tide)	54.9	56.7	-54.9	-

band. This seems to be a solid argument to claim that the network has learned to mimic the fundamental basin resonant seiche behaviour. However, adequate HIDRA energy content in the  $(21.5\text{h})^{-1}$  frequency band does not in itself mean that Adriatic seiches are excited at appropriate times during storm surge events. To test whether this is indeed the case, inspection of specific storm surge cases is required.



**Figure 10.** Power spectrum of NEMO  $\bar{y}_{bc12h}(t)$  ensemble forecast mean time-series (blue line), HIDRA ensemble forecast mean time-series  $\bar{y}_H(t)$  (orange line) and tide gauge observations time-series  $y^{kp}(t)$  (black line) for year 2019. Turquoise symbols denote spectral peaks due to respective tidal constituent.  $E0$  denotes the spectral peak due to fundamental Adriatic seiche with a period of 21.5 h, also marked with the vertical turquoise dotted line.

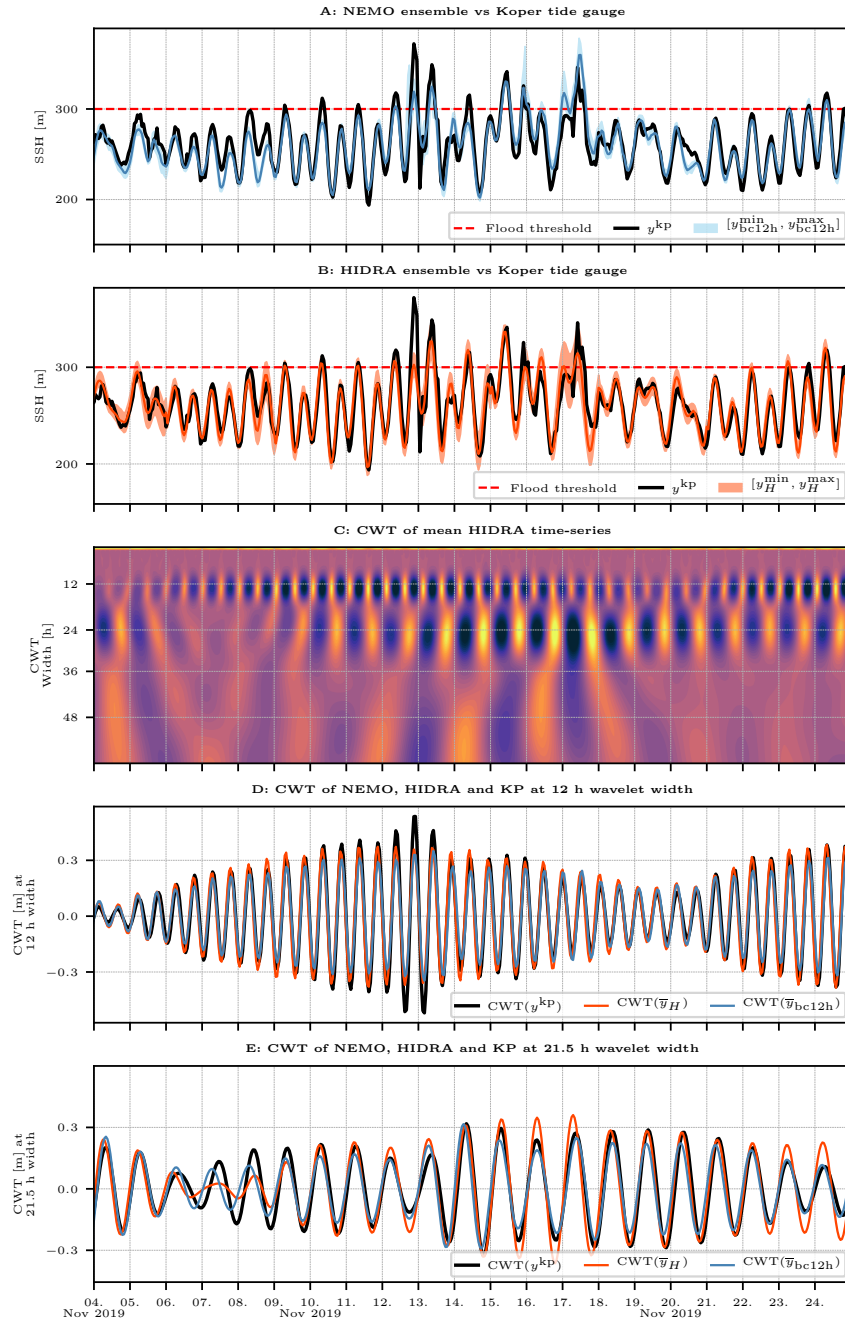
We now proceed to investigate the total sea level time-series predicted by NEMO and HIDRA during specific storm surges by analyzing the total sea level ensemble envelopes from a 12-hour bias corrected NEMO  $\bar{y}_{bc12h}(t)$  and HIDRA  $\bar{y}_H(t)$ . In addition, continuous wavelet transforms (CWT, see *e.g.* Mallat (2009)) over time windows containing the specific storm surges are computed. This allows comparison of the excitation level of specific harmonic contributions to the total sea level during each particular storm surge event. The analysis is focused on the semi-diurnal tidal signal (with periods around 12 h) and on the fundamental seiche period (with a period of 21.5 h). A Morlet wavelet was used for the CWT convolution computation.

We first discuss the historic storm surge flooding event from mid-November 2019. Atmospheric conditions during November 2019 were not remarkable in themselves. Mean sea level pressures were moving between 990-1000 mbar, while Scirocco speeds in Northern Adriatic were measured to be around  $10 \text{ ms}^{-1}$ . However, an unfortunate coinciding of a general low pressure, high neap tide and seiche-inducing high-frequency forcing due to a local pressure low caused one of the worst Northern Adriatic floods in history (Cavaleri et al., 2020). These multifaceted circumstances made forecasting of these floods, using a lower resolution forcing such as ECMWF ensemble, challenging (Cavaleri et al., 2020). This problem is at least partly reflected in the November 2019 forecasts, presented in Figure 11.

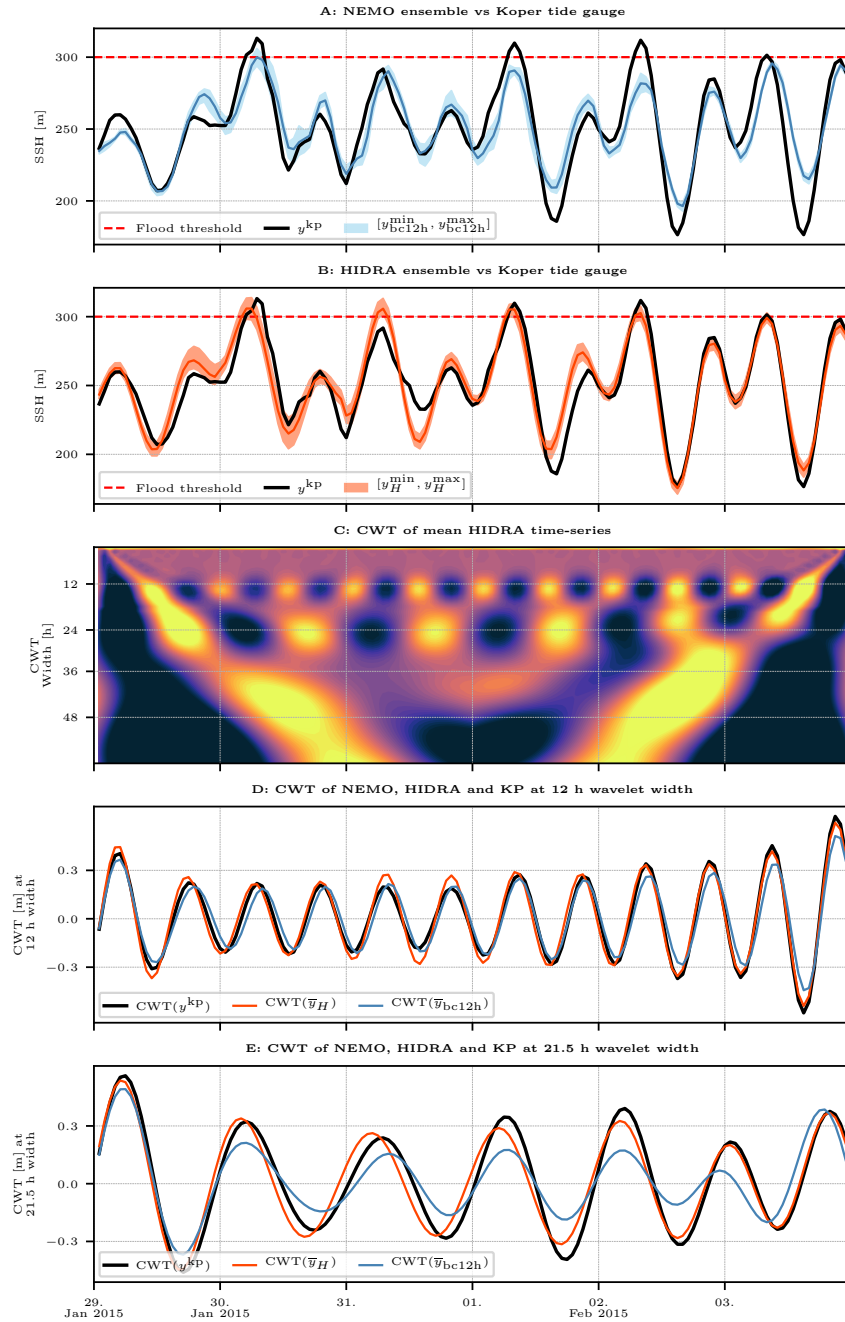
Panel A in Figure 11 depicts NEMO  $\bar{y}_{bc12h}(t)$  mean time-series, together with the  $y_{bc12h}^{\min}(t) - y_{bc12h}^{\max}(t)$  ensemble envelope, while panel B depicts HIDRA predictions. Both NEMO and HIDRA mean time-series seem to underestimate the storm surge peak values. Both ensembles, however, exhibit high forecast spread, with maximums often adequately representing the observed peaks. The first peak on 12th November 2019 is missed by HIDRA, but the subsequent dynamics is better represented in HIDRA than in NEMO. In particular, HIDRA does not exhibit a substantial false positive on 15th November and also overshoots less during the surge of 17th November 2019. Judging from CWT signals of mean ensembles from both HIDRA and NEMO (in panels D and E), HIDRA missing the first peak can be at least partly attributed to underestimation of semi-diurnal tidal signal in the HIDRA forecast. Semi-diurnal tides are ~~better represented in NEMO (panel D) while resonant~~ similarly represented in both models and both underestimate the signal in this band. On the other hand the seiche signal seems better represented in HIDRA (panel E) during the storm surge. Note that HIDRA excites the seiche immediately after the sea level peak on 12th November. NEMO, of course, cannot do this since the seiche period is 21.5 h. Panel D of Figure 11 show that, like NEMO, HIDRA resolves well the low frequency tidal variability between spring and neap tides.

We now move to an event from late January and early February 2015, which turned out to be quite problematic for NEMO to forecast, while HIDRA behaved much better. During this period, Adriatic was impacted by several days of low pressures (990-1000 mbar) and moderate Scirocco (with speeds  $8-12 \text{ ms}^{-1}$ ). These conditions led to a series of moderate storm surges in the Northern Adriatic, as shown in Figure 12.

NEMO ensemble, depicted in Panel A of Figure 12, performs particularly poorly during this time window. While it did predict the first surge on 30th January, the following peaks were underestimated and the crest-to-trough sea level range of NEMO is overall unsatisfactory throughout the time-window. Since the tidal part of the NEMO signal is appropriate (Figure 12, Panel D), the reason for poor forecast seems to lie in insufficient excitation of the fundamental basin seiche, which is



**Figure 11.** Comparison between NEMO (with a 12-hour bias correction) and HIDRA ensembles during a historic surge of November 2019. Panels A and B depict NEMO and HIDRA ensemble predictions for Koper sea level, together with Koper tide gauge time series. Mean values and minimum-maximum ensemble spans are depicted, as defined in Section 3.3. Panel C depicts a CWT of  $\bar{y}_H(t)$  HIDRA mean timeseries. Panels D and E depict a CWTs of Koper tide gauge, HIDRA and NEMO time-series at semi-diurnal (12 h) and E0 (21.5 h) wavelet width respectively. Flooding threshold in the historic coastal town of Piran (Slovenia) is marked by a dashed red line in the top two panels.



**Figure 12.** Comparison between NEMO (with a 12-hour bias correction) and HIDRA ensembles during surge of January and February 2015. Panels A and B depict NEMO and HIDRA ensemble predictions for Koper sea level, together with Koper tide gauge time series. Mean values and minimum-maximum ensemble spans are depicted, as defined in Section 3.3. Panel C depicts a CWT of  $\bar{y}_H(t)$  HIDRA mean timeseries. Panels D and E depict a CWTs of Koper tide gauge, HIDRA and NEMO time-series at semi-diurnal (12 h) and E0 (21.5 h) wavelet width respectively. **Flooding** **Severe flooding** threshold in the historic coastal town of Piran (Slovenia) is marked by a dashed red line in the top two panels.

drastically underestimated in [our setup of](#) NEMO (Figure 12, Panel E). HIDRA yields a more accurate overall forecast in  
445 this case (Figure 12, panel B), and does not underestimate the seiche signal at the  $(21.5 \text{ h})^{-1}$  frequency as much as NEMO.  
Semi-diurnal tidal signal is reasonably well represented in both models (panel D of Figure 12). These performances of NEMO  
and HIDRA are consistent with the power spectrum in Figure 10.

## 5 Conclusions

In this study, we presented HIDRA, a novel deep learning network for sea level modeling in complex environments like the  
450 Adriatic. We describe key HIDRA architecture blocks and discuss several aspects of how [both](#) HIDRA architecture and its  
input [impact-influence](#) its performance. HIDRA outperforms the current operational NEMO setup  ~~,running daily at Slovenian  
[Slovenian Environment Agency \(ARSO\)](#) ,~~ and is therefore an appropriate candidate for [Slovenian Environment](#) Agency’s operational  
pipeline. Furthermore, preliminary tests (not reported in this study) indicate that HIDRA also generalizes well to other geo-  
graphical locations.

455 Last but not least, numerical cost of both setups is vastly different. NEMO ensemble runs require dedicated HPC facilities,  
while the HIDRA ensemble forecast can be executed on a personal computer (even without a dedicated GPU)  ~~.Furthermore,  
[HIDRA exhibits and exhibits an](#)~~ extremely low energy footprint. A single HIDRA run for our requirements takes less than half  
a CPU second per ensemble member, while a full basin NEMO ensemble requires tens of CPU hours per ensemble member –  
a speedup in order of  $0.5 \times 10^6$  times.

460 We believe the presented results are a promising first step. In our future work we plan to focus on improving the performance  
of both HIDRA and NEMO in the tails of the sea level distributions as well as explore other environmental [inputs-input streams](#)  
and architectural designs to further reduce the prediction errors with increasing forecast horizon. We hope this study builds  
a strong case in favor of machine learning capabilities with carefully designed architectures to discern sea level dynamics in  
regional basins and will inspire other groups to consider similar solutions.

465 *Code and data availability.* HIDRA code and data samples are available in the Git repository: <https://github.com/lojzezust/HIDRA> (last  
access: ~~20 October 2020~~ , [5 January 2021](#)). [Persistent version of the HIDRA 1.0 source code is available through](#) <https://doi.org/10.5281/zenodo.4274708> ([Žust et al., 2020a](#)). ECMWF ensemble data are available through the Meteorological Archive and Retrieval Sys-  
tem (MARS), but access is limited to member countries. Sea level datasets employed in this paper are available at [https://doi.org/10.5281/  
zenodo.4106440](https://doi.org/10.5281/zenodo.4106440) (~~last access: 19 October 2020~~) ([Žust et al., 2020b](#)) and NEMO configuration namelist used in the experiments is published  
470 [at](https://doi.org/10.5281/zenodo.4419333) <https://doi.org/10.5281/zenodo.4419333> ([Žust et al., 2021](#)).

*Author contributions.* LŽ and MK designed and implemented HIDRA. ML provided the physics-related background for HIDRA architec-  
ture. AF obtained and preprocessed ECMWF ensemble data. AF and ML implemented NEMO ensemble. ML, LŽ and MK analyzed the  
results and wrote the paper. All authors contributed to the final version of the manuscript.

*Competing interests.* Authors declare no competing interests.

475 *Acknowledgements.* ML wishes to acknowledge financial support of the Slovenian Research Agency (ARRS) project grant J1-9157: "Drivers that structure coastal marine microbiome with emphasis on pathogens – an integrated approach". MK and LŽ were supported in part by the the Slovenian Research Agency (ARRS) basic research project grant J2-2506 "Adaptive deep perception methods for autonomous surface vehicles" and research program P2-0214 "Computer vision". [The paper benefited from comments of two anonymous reviewers.](#)



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