Environmental Research Letters

Estimation of global coastal sea level extremes using neural networks

Estimation of Global Coastal Sea level extremes using Neural Networks

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Abstract. Accurately predicting total sea-level including tides and storm surges is key to protecting and managing our coastal environment. However, dynamically forecasting sea level extremes is computationally expensive. Here a novel alternative based on ensembles of artificial neural networks independently trained at over 600 tide gauges around the world, is used to predict the total sea-level based on tidal harmonics and atmospheric conditions at each site. The results show globally-consistent high skill of the neural networks (NNs) to capture the sea variability at gauges around the globe. While the main atmosphere-driven dynamics can be captured with multivariate linear regressions, atmospheric-driven intensification, tide-surge and tide-tide non-linearities in complex coastal environments are only predicted with the NNs. In addition, the non-linear NN approach provides a simple and consistent framework to assess the uncertainty through a probabilistic forecast. These new and cheap methods are relatively easy to setup and could be a valuable tool combined with more expensive dynamical model in order to improve local resilience.

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Submitted to: *Environ. Res. Lett.*

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1. Introduction

Predicting accurately the sea water level variability from short to large time scales is of great importance for coastal communities. The range of impacts and challenges is broad, ranging from harbour management (where minimum water level is required to allow ships to enter the harbour) to life-threatening natural disasters or long-term sea level rise leading to loss of land availability and fertility for agriculture. Coastal flooding due to storm surges is considered as one of the biggest sources of casualties during tropical cyclones; storm surges have large social, economic and environmental impacts[1, 2, 3, 4]. Therefore, timely and accurate prediction of sea-level variability and extremes is crucial for global coastal resilience.

Deterministic numerical models have proven to be powerful tools for predicting sea variability. In particular they are effective for simulating storm surge propagation and impacts, and facilitate understanding of the complex physical processes associated with the storms [5, 6, 7, 8, 9, 10, 11]. However, they are relatively expensive and complex to set up and run operationally, with associated additional computation costs if ensemble forecasts are required for analysis of risk or variability.

More generally, machine learning approaches and particularly deep learning have shown huge potential in pattern recognition for a wide range of applications. Recently, these techniques have emerged in climate, meteorological and oceanographic fields with convincing results. For example, convolutional neural networks have been trained to predict variations in the El Ninõ/Southern Oscillation (ENSO) with skill superior to state-of-the-art dynamical forecast systems[12]. Machine learning algorithms have also been used to aggregate "best-estimate" forecasts from an ensemble for the predictions of ocean waves[13]. Neural networks have also successfully been used to bias-correct measurements leading to more homogeneous climate data records[14].

In sea level and tide processes, regressions have been used to infer meteorological impacts on sea water level and storm surges[15, 16]. Regression models have also been successfully driven by offshore gauge data in New York[17] and statistical models have

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29 been applied to estimate extreme storm surges and associated return periods[18], or
30 as bias-correction to water level predictions along US East Coast[19, 20]. The latter
31 have shown similar performance compared to deterministic hydrodynamic models in
32 capturing extremes in some cases. More recently, storm surges hindcasts in estuarine
33 ports of the UK have been possible using artificial neural networks leading to accurate
34 forecasting coastal flooding [21]. Neural networks have also been used for tide predictions
35 at Mangalore, India[22], and along the Swedish coast to analyse long sea level records[23]
36 where higher performance was obtained when local sea level forcing was prescribed
37 (compared to linear models).

38   The aim of this study is to describe a general non-tuned machine learning
39 framework, based on neural networks, and apply this around the globe with
40 demonstrable skill in predicting non-tidal sea level residuals and extremes. The
41 manuscript is structured as follows. Section 2 presents the GESLA tide-gauge data and
42 associated pre-processing, the neural network ensemble, and the split between training
43 and test sets as well as the scoring probabilistic measure. The first part of Section 3
44 shows the key results of the study based on performance statistics for over 600 gauges
45 around the world while the second part focuses on two particular regions with contrasting
46 behaviours. Finally, Section 4 discusses the results, the benefits and limitations of the
47 approach, and the future steps.

48 2. Methods

49 2.1. Global Extreme Sea Level Analysis dataset - GESLA

50 The Global Extreme Sea Level Analysis database (GESLA version 2 [24]) provides
51 unified high-frequency (15 min to 1 hour temporal resolution) quasi-global coastal sea
52 level water information. Only public data (around 1070 gauges) are used in the present
53 study. While data have been standardised, a simple but strict methodology was applied
54 to pre-process each gauge in a systematic and reproducible manner. The key aspect

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55 of this stage was the elimination or reduction of potential issues arising from spurious

56 data (e.g. temporal or reference height shifts) as well as removing long-term trends.

57 An example of the pre-processing stage is illustrated in Supplementary Figure 1. The

58 following steps were sequentially applied to each gauge:

- 59 • Data from 1980 to 2015 are included and overlaps with the atmospheric reanalysis
- 60   (see 2.2),

- 61 • For simplicity, only gauges with scheduled hourly, data are processed (as this only
- 62   excluded 21 gauges). However, if the time steps are not constant and the percentage
- 63   of time steps equal to the statistical mode is less than 95%, the gauge is rejected;

- 64 • Sections are defined as time-series records where breaks are less than 7 days long;

- 65 • A yearly moving average is computed on each section;

- 66 • Given a record that is N years long, tidal harmonic analysis is computed yearly
- 67   (going backwards) from the most recent one-year period, using the open-source
- 68   *pytides* python module[25]. The analysis outputs 37 complex constituents per year
- 69   (Sa, Ssa, Mm, MSF, Mf, 2Q1, Q1, rho1, O1, M1, P1, S1, K1, J1, OO1, 2N2, mu2,
- 70   N2, nu2, M2, lambda2, L2, T2, S2, R2, K2, 2SM2, 2MK3, M3, MK3, M4, MS4,
- 71   S4, MN4, M6, N6, M8);

- • Spurious years in harmonic analysis are identified by separately inspecting just the
  M2 and K1 constituents. A gauge year can be rejected by either constituent if it
  exceeds a threshold separation from the mean (see e.g. Fig S1b). The procedure is
  as follows: an average complex value is calculated from N yearly values (red square).
  The average separation from this mean is calculated ($\bar{\epsilon}$) over N years. The complex
  difference (ϵ_{year_i}) for each year from the mean is independently assessed and the
  gauge year is rejected if

$$\epsilon_{year_i} > max\left(3cm, min\left(5cm, 10\%\,\bar{\epsilon}\right)\right)$$

72 (e.g. green diamonds). This procedure ensures the rejection is based on the relative

73 size of the separation from the N-year mean whilst preventing rejection for very

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74   small amplitudes.

75   • The total water signal is re-interpolated over a constant 1h time vector based on

76   the original temporal resolution excluding rejected periods of data;

77   • Finally, only gauges with over 3 (not necessarily contiguous) years of data are kept,

78   with at least 2 years for training and one year for testing the model.

79   At the end of this process, 621 gauges remain and are used in this study. They provide an

80   extensive coverage of the coastlines worldwide. The non-tidal residual is computed as the

81   difference between the observations and the harmonic tide prediction (computed from

82   all remaining sections). The objective was to implement a reasonably simple, robust

83   and consistent pre-processing methodology to objectively deal with the large amount of

84   data available. However, one could define different thresholds or apply different type of

85   pre-processing to the gauge; exploratory analysis suggests that this would not impact

86   the key results of this study.

87   *2.2.   High Resolution Atmospheric and Ocean Wave Reanalysis - ERA5*

88   To assess the impact of atmospheric and ocean wave processes on the non-tidal

89   residual, an ensemble of hourly physical predictors are extracted from the high-resolution

90   atmospheric reanalysis ERA5 of ECMWF[26]. These are pre-processed over three length

91   scales:

92   **Local** - 10 m wind components and mean sea level pressure at 0.25^o resolution as well

93   as significant wave heights (including wind waves and swell) and peak periods (at

94   0.5^o resolution) at the closest grid point from the gauge;

95   **Neighbourhood** - spatially accumulated precipitation in a 3.5^o box centred on the

96   gauge;

97   **Regional** - maximum and minimum wind speed components, maximum wave heights

98   and minimum mean sea level pressure in a 5° box centred on the gauge.

99   In addition, proceeding 3h gradients of all the atmospheric predictors are computed

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100 to capture late intensification / de-intensification (for example a low pressure system

101 developing rapidly) as well as for the harmonic tidal level.

102 *2.3. Machine Learning*

103 Each gauge is modelled independently using artificial Neural Networks (NNs). Each

104 NN is composed of 3 hidden layers of 48 neurones. The input layer has 33 nodes

105 (one for each environmental predictor described in previous sections combined with 7

106 hourly time steps of harmonic tide), and the outer layer has a single node providing

107 the non-tidal residual target. While a sigmoid activation function is used for the last

108 layer, the hidden layers consists of Leaky ReLU activation functions[27] combined with

109 batch normalization layer to normalise the activations[28]. The NN had just under

110 7000 trainable parameters and its schematic view is provided in Supplementary Figure

111 2. Finally, an Adam solver[29] is used to minimise the root mean square error between

112 non-tidal residual predictions and observations; the NN is fitted for 150 iterations or less

113 if the errors is not reduced within 10 consecutive iterations. Due to the large number

114 of gauges available, this configuration has been lightly tuned on three random gauges

115 (namely, a few combinations of the number of neurones, number of hidden layers and

116 type of activation) and then applied to the full set without further adjustment.

117　　　For each gauge, the test set consists of the most recent year of recorded data (8784

118 time steps) while the rest is part of the training set. Therefore depending on the gauge,

119 the training set extends from 2 years to 32 years permitting an analysis of the impact

120 of the training size on the performance. Figure 1a shows the number of gauges as a

121 function of the length of the training data.

122　　　An ensemble of 20 Neural Networks (NNs) is trained at each gauge location to

123 generate a probabilistic forecast. Each NN is fitted using 50% of the training set,

124 randomly sampled. While a larger ensemble would have improved our probabilistic

125 forecast, 20 members were chosen as a pragmatic balance between computational cost

126 (over 12000 NNs have been fitted in this study) and variability in the predictions.

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127   All data (features and targets) have been standardised and normalised. The

128 Neural Networks (NNs) are built with the *Keras* Python module[30] interfacing with

129 *Tensorflow*[31] while processing was mainly done with the *Scikit-Learn* packages[32].

130 The neural networks have the traditional structure, where each node is connected to

131 every node of the next layer. The temporal evolution of sea water level and non-tidal

132 residual is continuous. Recurrent layers (such as Long Short-Term Memory, LSTM

133 layers [33]) can be used to capture the dynamics of temporal processes. An LSTM

134 neural network structure was implemented and tested for a few gauges but it did not

135 lead to significant improvements of the predictions, and therefore a more simple and

136 traditional structure was kept in this study. Finally, as a baseline, an ensemble of multi-

137 variate linear regressions are fitted and used for predicting sea water level in the same

138 manner as the neural networks for comparison; again for the linear regression no time

139 series model was used.

140   Note that the neural network described above did not converge for 11 randomly-

141 located gauges. Given the global coverage and the large number of gauges, these

142 11 gauges have been removed and no further investigation were carried out on these

143 particular gauges.

144 *2.4. Continuous Ranked Probability Score*

145 To assess the skills of the probabilistic predictions, a Continuous Ranked Probability

146 Score (CRPS) is computed, with units cm. In weather forecasting, this is a common

147 qualitative measure of performance for probabilistic forecasts comparing a distribution

148 with observations [34, 35, 36].

149   The CRPS is defined as a quadratic measure of the difference between predicted,

150 $H^p(\eta_r; t)$, and observed, $H^o(\eta_r; t)$, cumulative density functions (CDF). The quadratic

151 measure is integrated over all possible residuals, z, and then averaged over time t to

152 give a CRPS for each gauged location:

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$$CRPS = \frac{1}{N} \sum_{t=1}^{N} \left(\int_{\eta_r > -\infty}^{\eta_r < \infty} [H^p(\eta_r; t) - H^o(\eta_r; t)]^2 \, dz \right),$$

153 where for each gauged location: $H^p(z;t)$ denotes the probability of an anomaly less

154 or equal to η_r being *predicted* at time t; and $H^o(\eta_r;t)$ is step-function, denoting the

155 probability of an anomaly less or equal to η_r being *observed* at time t.

156 Intuitively, an ensemble producing a wide range of outcomes or an ensemble with a

157 mean significantly different from the observed values would be heavily penalised while

158 a narrow ensemble centred on the observations would lead to a better score. The

159 CRPS is computed for the one year test period as well as for 95th percentile extreme

160 values (surge). While a 20-member ensemble is not extensive, using a CRPS metric

161 is a better validation approach compared to using the mean or median where the

162 information contained in the ensemble is mainly lost. The CRPS are computed using

163 the *properscoring* Python library.

164 3. Results

165 *3.1. Global skills of the NN*

166 The CRPS is computed for the observed non-tidal residual to provide a baseline metric

167 for the signal not captured by the astronomical harmonic analysis. The harmonic

168 analysis does not aim (and has not been designed) to capture this kind of variability;

169 the non-tidal residual simply provides a first-order baseline for comparison based on a

170 37 constituents harmonic analysis and it is expected than any method should capture

171 parts of the non-tidal signal. The boxplot summarising this baseline skills per number

172 of training years as well as their global distribution for the extreme values (over the 95th

173 percentile anomaly) are presented in Figure 1c (yellow box) and Figure 2a, respectively.

174 The length of the time series has a weak impact on the CRPS, which ranges from 15 to

175 25 cm on average. Figure 2a illustrates the spatial variability of the CRPS with larger

176 value in mid latitudes due to consistent winter storms and larger tides compared to

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177 tropical regions.

178 The NNs consistently capture the non-tidal residual due to the effect of atmospheric

179 forcing as well as tide-tide interactions and tide-surge interactions with a mean CRPS

180 of around 10 cm (Fig. 1c - blue box). The CRPS for outlier gauges with large non-

181 tidal residual can be improved from over 50 cm to around 25 cm. Figure 1b shows

182 the percentage of non-tidal residual (baseline) captured in the NN predictions ranging

183 from 30 to 60% on average. While longer training period improves the skills, it appears

184 that after 6 years of training data, the performance remains fairly stable. While for

185 any gauge, the NN captures the non-tidal residual (Fig. 2b), the skill varies spatially

186 (Figure 3a). It is mainly due to the ease of improving a bad skill compared to reducing

187 already good skills (lower than 10 cm).

188 While the NN approach leads to high skill in reconstructing extremes of non-tidal

189 residual, it is worth considering how a multivariate linear regression would perform in

190 comparison. Figure 3b shows the percentage improvement between the two methods.

191 While tropical regions show the lowest improvements using a NN (10-20%), the skills

192 at higher latitude improves by up to 50% with clear regions of the globe emerging as

193 Europe, West coast of North America, Alaska, Chinese Coast, North Australia and the

194 Northern coastline of Japan (facing the Sea of Japan). Except one point in the Canary

195 Islands, the NN outperformed the regression anywhere else; this might be due to a fitting

196 issue at this particular site (not investigated).

197 Supplementary Figures 3, 4 and 5 highlight similar results for the whole 1 year

198 test time series. The skill improvements is not as high as for the extremes but is still

199 significant and systematic. The Baltic sea regions can be pointed here as a region of

200 lower skill improvement from the regression to the NN. This is potentially due to the

201 long time scale sea-level variability that is not included in the predictors used, due

202 to seasonally integrated winds and salinity changes[37]. Similar performance are also

203 obtained for the lowest levels (5th percentile, lowest level being of importance for harbour

204 management) and the 99th percentile (not shown) of the non-tidal residual.

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²⁰⁵   Predicting the full range of non-tidal residuals is key for a broad range of

²⁰⁶ applications. However assessing the skill of the models in stressed conditions is also

²⁰⁷ of relevant importance. While the usual extreme statistics cannot be applied to this

²⁰⁸ study (the test sets bbeing only one year at each gauge), looking at the most extreme

²⁰⁹ skew surges within over 600 gauges highlights the capability of the models. Figure 4

²¹⁰ shows the 20 largest skew surges in the test set. Predictions of these large skew surges

²¹¹ are almost always under-estimated compared to observations, but the neural network

²¹² ensemble shows some skill in capturing them (over 2/3 of the signal) and systematically

²¹³ outperforms the multivariate linear regression. Note that the present neural network

²¹⁴ and training set have been designed to predict the complete time series and not only the

²¹⁵ extreme storm surges; therefore the training set is highly unbalanced such that extremes

²¹⁶ are seen as outliers which penalises the model predictions (more details on the impact

²¹⁷ of the the training set are provided in discussion).

²¹⁸ *3.2. Time series at two particular locations*

²¹⁹ The previous section focus on time-averaged skills in capturing the non-tidal residual.

²²⁰ However, it is difficult to assess the highly-complex time variability of this residual.

²²¹ Therefore, two gauges have been selected for a more detailed investigation for their very

²²² different characteristics:

²²³ • *Anchorage* (149.89W / 61.24N - around 14 years of training data - Supp. Fig. 6a),

²²⁴   Alaska, USA, located at the end of the Cook inlet and protected from the open

²²⁵   ocean. Due to its location, Anchorage is not exposed to extreme surges (less than

²²⁶   1 m in the test year) but the time series exhibits significant tide-related variability

²²⁷   not captured by the harmonic analysis with this constituent set (Fig. 5a),

²²⁸ • *Dunkirk* (2.37E / 51.05N - also around 14 years of training data - Supp. Fig. 6b.

²²⁹   This gauge was used in the light tuning, mentioned in the method section), North

²³⁰   France, located in the English channel, on the North Sea side. For Dunkirk gauge,

²³¹   the test year includes the winter 2013-2014 when severe winterstorm Xaver (Dec.

232 2013) crossed Northern part of the North Sea and led to significant surges all along 233 the North Sea coast [38]. This was also the highest sea water level anomaly in our 234 15-year period at Dunkirk (around 2.5m while the highest peak in the 14 training 235 years was 2.2 m). Finally, the storm occurred far away from Dunkirk where pressure 236 and wind speed did not show any exceptional values but the surge wave travelled 237 around the North Sea, making an interesting and challenging case for the NN (Fig. 238 5b).

239 Figure 5 shows a few weeks of non-tidal residual at each selected gauge. The 240 multivariate regression captures fairly well the long-term smoothed variability at 241 Anchorage (Fig. 5a) but cannot capture the high-temporal variability induced by 242 complex tides in the Cook inlet that were not computed in the tidal harmonic analysis; 243 the ensemble variability is also almost non-existent. On the other hand, the NN ensemble 244 captures efficiently the variability (with some spread) leading to a good CRPS (9 cm 245 versus 21 cm for the regression over the one year test window). A Fourier transform is 246 applied to the one-year signal (Fig. 6a), highlighting the compelling skill of the NN to 247 capture the energy of the system at all time scales while the regression underestimates 248 by an order of magnitude the energy for time scales lower than a day. This shows the 249 capacity of a non-linear NN to predict tide-tide interactions or tide components not 250 included in the harmonic analysis.

251 Similar conclusions are obtained at Dunkirk. While the extreme storm surges 252 induced by storm Xaver (around 6th December 2013) are under-estimated (and so is the 253 previous peak in late November), the prediction is more accurate than the one predicted 254 with a regression. For comparison, the Met Office CS3x deterministic forecast[39] also 255 under-estimates the peak by around 75 cm (Fig. 5b). Over the test year, the NN CRP 256 scores 8 cm and 18 cm for the mean and 95th percentile when the regression gets 13 cm 257 and 32 cm. As for the Anchorage, the energy is well captured by the NN at this gauge 258 except the two smaller peaks for periods of around 3 h 40 min and 4 h 50 min. For 259 periods longer than 1 day, the energy is slightly under-estimated by both the regression

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260 and the NN. This highlights skills into predicting sea water anomaly and particularly

261 extreme events using a simple NN forced by a small range of atmospheric and wave

262 data.

4. Discussion and Conclusion

264 An ensemble of NNs have been built for over 600 tide gauges spread around the world in

265 order to predict the non-tidal residual (total sea water level minus an harmonic analysis

266 based on 37 constituents), in term of general behaviours as well as extremes events. The

267 results presented in this study have highlighted the global skill of NNs in capturing non-

268 tidal residual variability and extremes, systematically outperforming predictions based

269 on multivariate linear regressions (in term of CRPS but also in term of correlations).

270 Due to the large amount of available data, the same simple pre-processing and neural

271 network structure were applied to each gauge. A higher level of data quality control

272 or gauge-by-gauge NN tuning could have been applied, and better performances would

273 then be expected. However, analysis and pre-processing requiring localised intervention

274 was not the aim of the study.

275   While it was expected that the non-linearity of the NN would play a key role

276 in predicting extreme events through environmental forcing, the results have shown

277 an even better performance of the NNs in their ability to represent tide-tide non-

278 harmonic interactions, treat noise, and express uncertainty. Similar advantages are

279 also reported in the application of Bayesian approaches to the study of tidal currents

280 [40]. Traditional harmonic and response methods [41, 42] have successfully been used

281 for decades to predict tidal amplitudes across the world; however the advent of easily

282 accessible meteorological data combined with novel applications of methods (for example

283 neural networks, as in this study), could offer a new avenue for improving predictions

284 by capturing non-linear processes.

285   The model has also shown significant skill in reconstructing extreme surges but still

286 lacks accuracy in the strongest events, in capturing the peak elevation (Fig 4 and Fig 5b

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287 for example). This is partially due to the training data. Extremes can be seen as outliers

288 and are only a fraction of the training set. The machine learning technique minimises

289 a cost function (here, root mean square errors) which generalises common behaviours,

290 and is not well designed for outliers. This leads to bias in the performance toward

291 the average dynamics and not towards the extreme anomalies (positive or negative).

292 Therefore the capability at predicting extremes could be improved by using a differently

293 balanced training set[43]. As a simplistic example, one can draw a similar amount

294 of training data in regular bins covering the range of outcomes (using sampling with

295 replacement technique for bins with a very small amount of data); this leads to a more

296 balanced training set. Supplementary Figure 7a illustrates the impact of the training

297 set on the model skill at Dunkirk (during storm Xaver in 2013). The NN now captures

298 the amplitude of the peak on the 5th December as well as the deterministic CS3x model,

299 and the peak on the 6th December almost perfectly. The mean of the NN ensemble

300 with a balanced training set is 50 cm higher than the unbalanced result. As seen in

301 Supplementary Figure 7b, in term of energy, the balanced training set is in much better

302 agreement with data for a period longer than 12 hours but it penalises the weaker period

303 where the energy in-between peaks is over-estimated. In terms of CRPS, the mean score

304 decreases by less than 1 cm while the extremes (95th percentile) score improves by 6 cm.

305 This type of model can be a great tool alongside a deterministic numerical model

306 to improve coastal resilience and potentially set-up warnings in the future as they can

307 also be used to solve classification problems instead of regression ones (as done in the

308 present work) enabling an outcome such as *low risk*, *high risk* and *extreme risk* for

309 example. It was shown here that only a couple of years of training data were enough to

310 get reasonable skills, and there is not significant skill improvement in 30 years training

311 data compared to 6-7 years. In addition, though not shown, even old data collected

312 in the past could be used for present forecasts as long as reference levels have been

313 corrected.

314 So far the present work has not be extended to locations with no data and the

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315 next step would be to built a globally connected tool to predict non-tidal residuals

316 spatially. In addition a better representation of the regional / global atmospheric forcing

317 might help to improve skill. This could be achieved via dimensionality reduction of

318 environmental information based on unsupervised learning such as principal component

319 analysis or auto-encoder. Finally, investigating more in depth the impact of using a more

320 complex neural network structure adapted to time series (Long- Short Term memory for

321 example) could also be of interest in the future. Setting up high-resolution full physics

322 numerical models in complex inshore regimes is time and computationally expensive

323 and requires physical expertise. These new types of machine learning approaches are

324 appealing for informing stakeholders where there is no capacity for implementing such

325 deterministic weather - surge forecasting systems.

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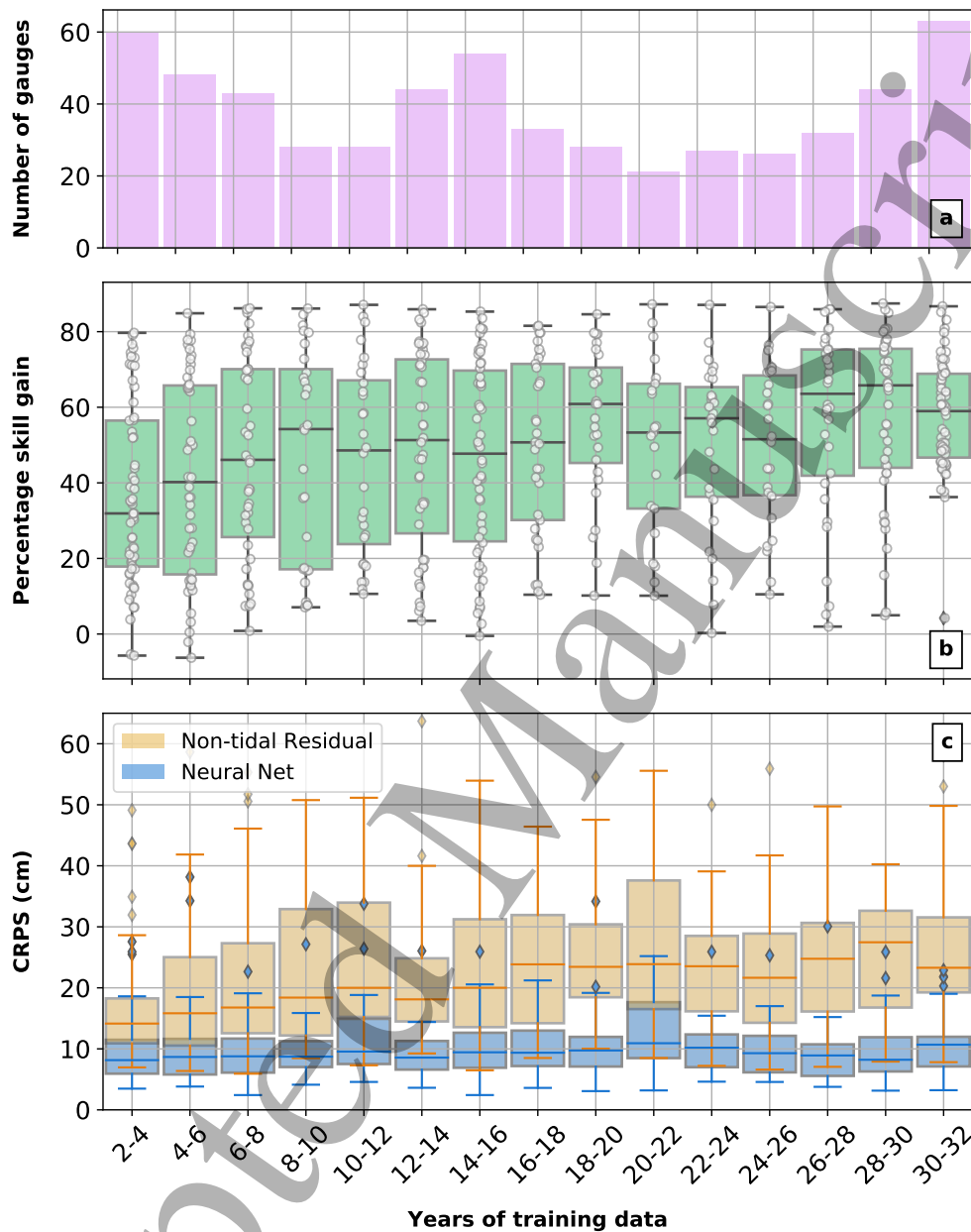*Estimation of Global Coastal Sea level extremes using Neural Networks* 20

Figure 1. Statistics per number of training years for the 95th percentile.
a) Distribution of the number of GESLA gauges, b) percentage skill gain from the non-tidal residual to the neural network predictions and c) the continuous ranked probability score (equivalent to a mean absolute error) for both non-tidal residuals and neural network predictions. The box plots shows the mean, the quartiles and the extend of the distributions excluding outliers (marked as diamonds). Systematic gain of knowledge with the neural network and significant for the full range of training periods.
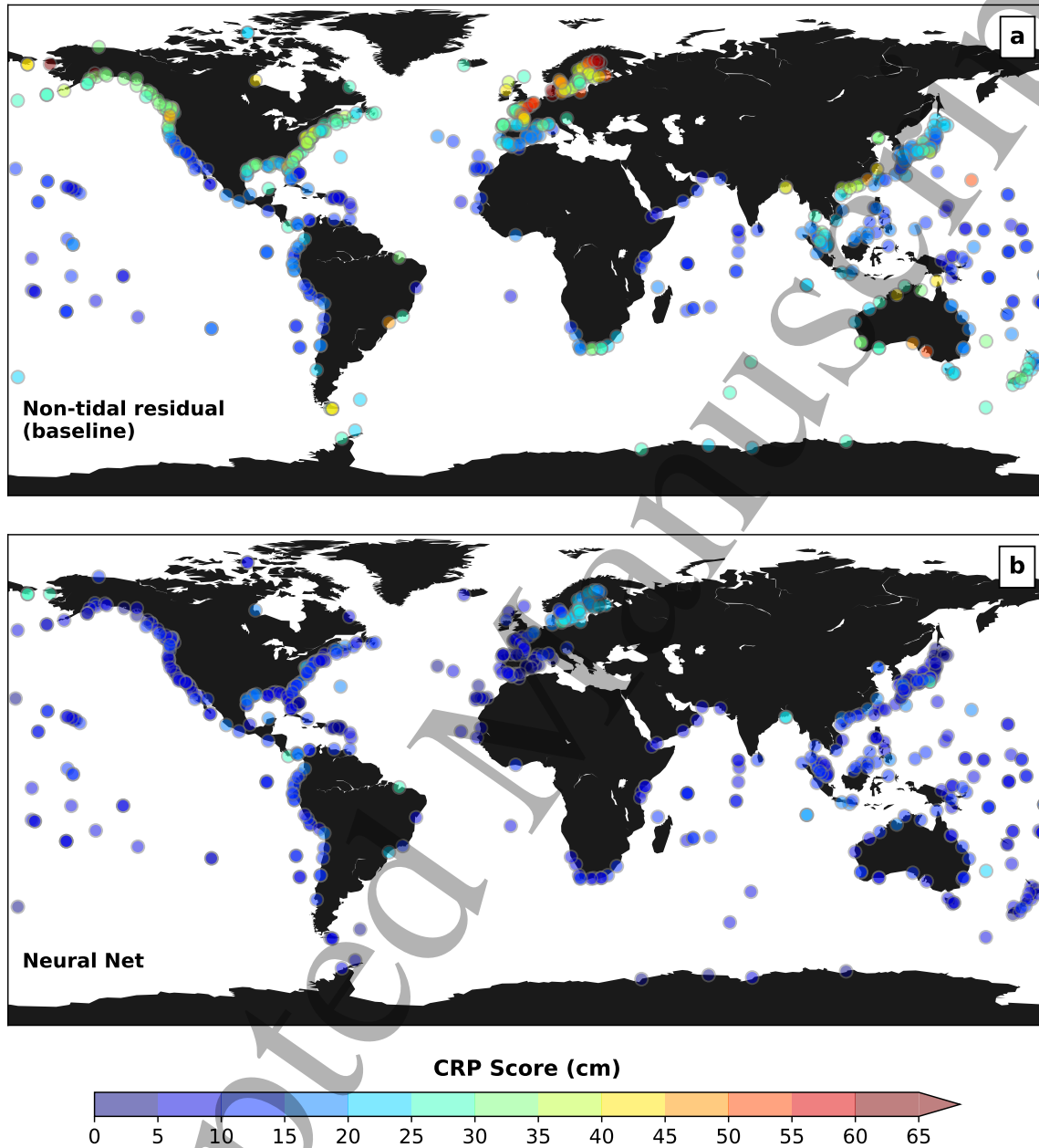
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Figure 2. Continuous Ranked Probability Score for the 95th percentile for each of the 610 GESLA gauges; a) for the non-tidal residual (baseline) and b) for the Neural Network ensemble predictions. Strong reduction of the errors are consistently obtained with the Neural network, particularly in the mid-latitude regions.
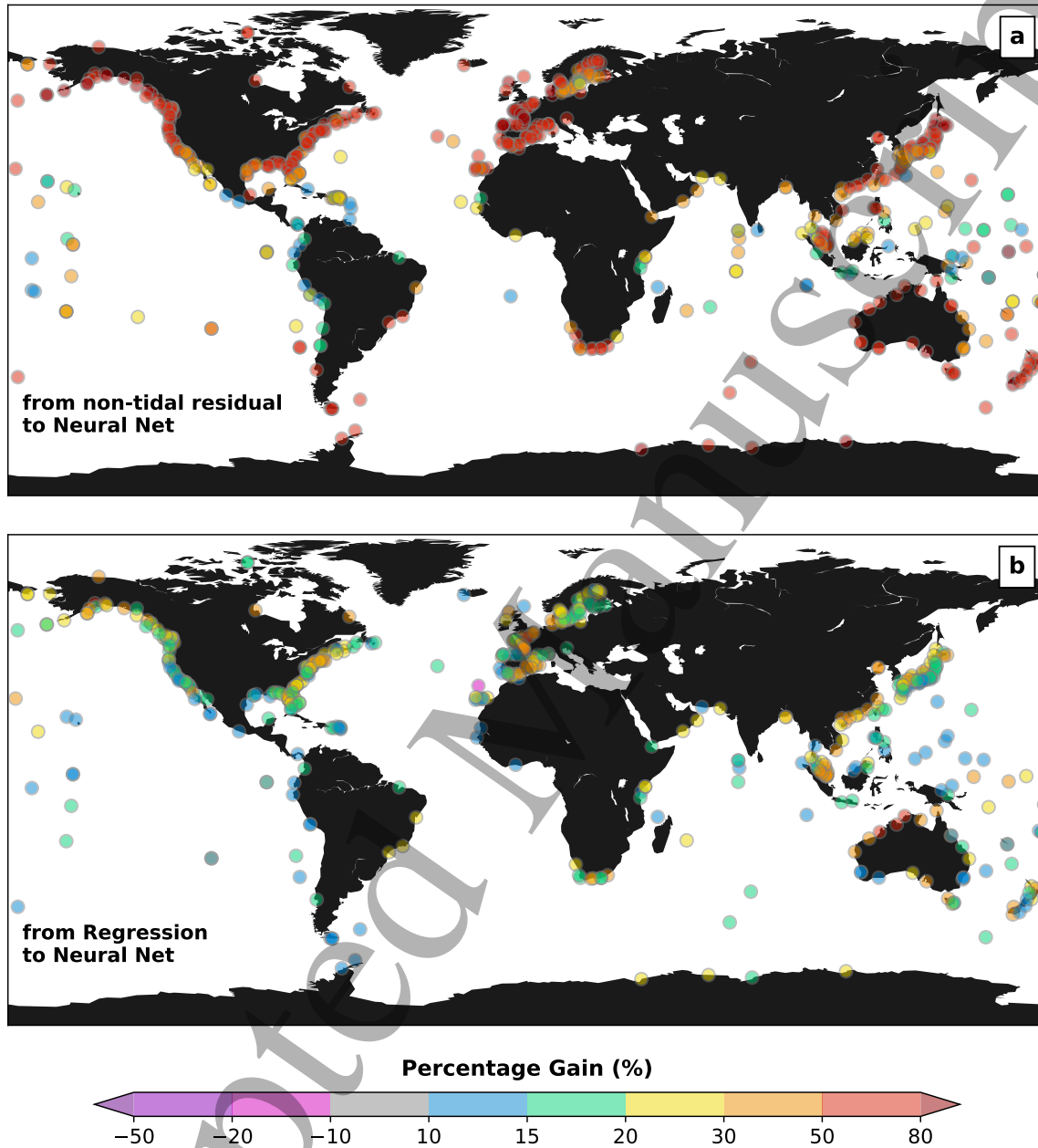
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Figure 3. Percentage improvements between the different methods for the 95th percentile. a) from non-tidal residual to neural network and b) from multivariate linear regressions to neural network. The neural network enhanced systematically the improvement, particularly in regions where tides are large.

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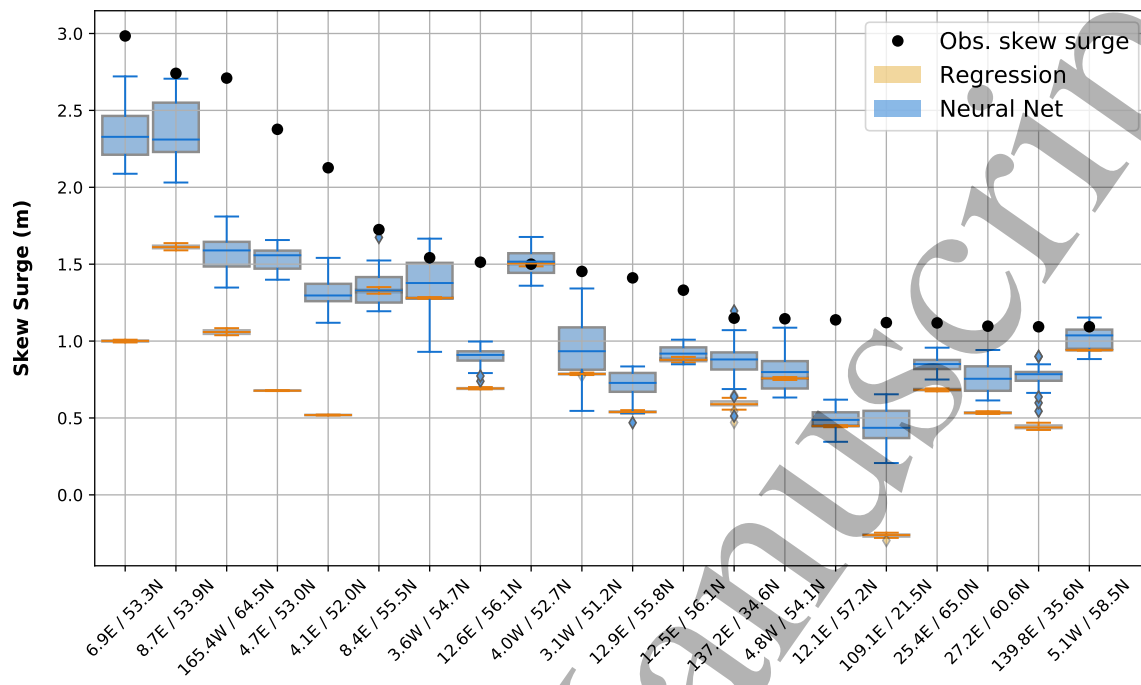

Figure 4. The 20 largest skew surges observed across all gauges in the test set, and the success of the neural net ensemble and regression at modelling them. The skew surges are computed as the difference between the highest water level and the highest harmonic tide level within a 12h window around the maximum non-tidal residual.

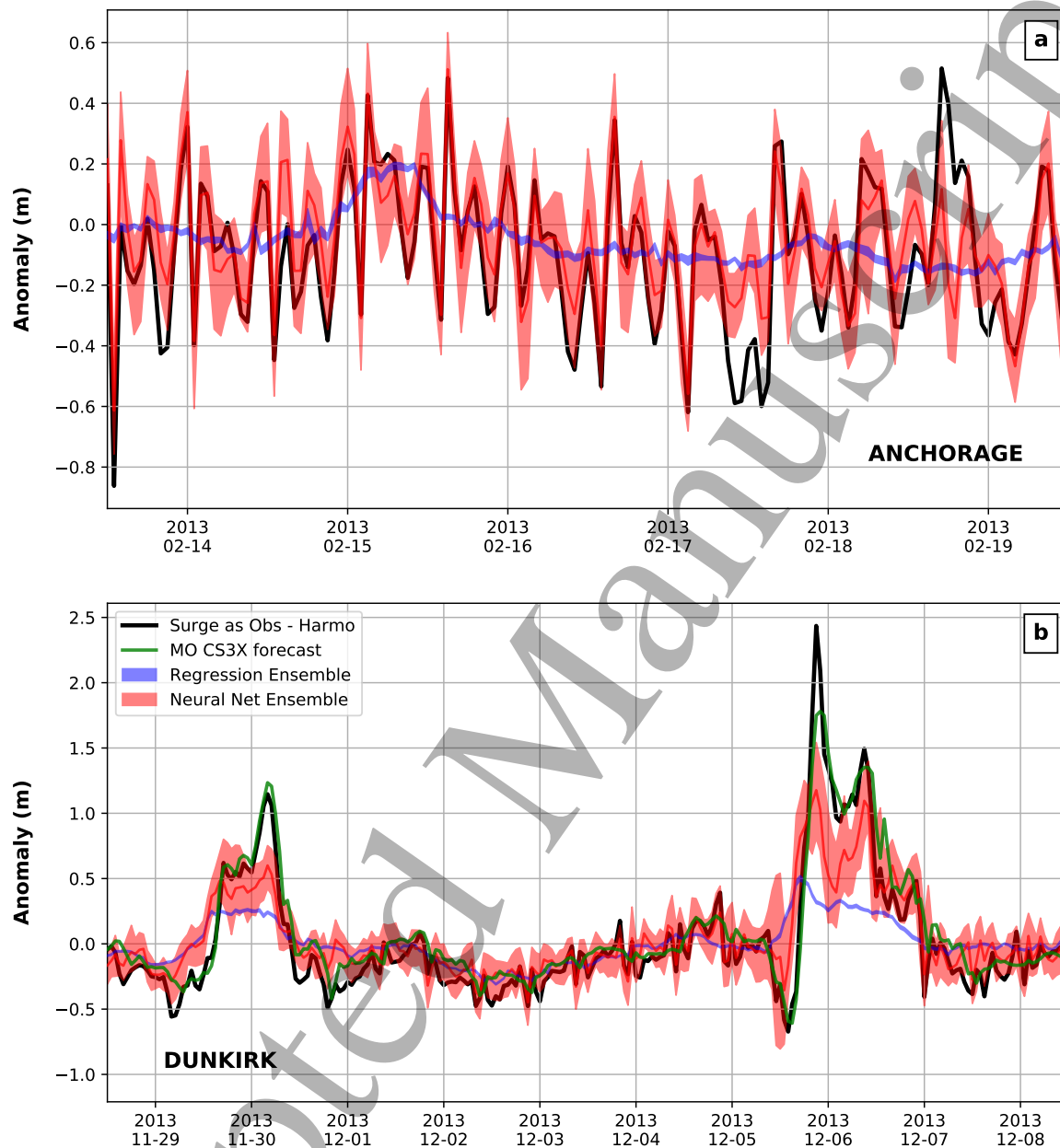*Estimation of Global Coastal Sea level extremes using Neural Networks* 24

Figure 5. Example of time series extracted from the test time period in a) Anchorage, Alaska, USA where strong tidal interactions occurs and b) Dunkirk, North France during a severe winter. The thick line shows the mean of the ensemble. The neural network shows significant skills in predicting the variability and extremes. The green thick line shows the MetOffice deterministic CS3x forecast for the same period for comparison.
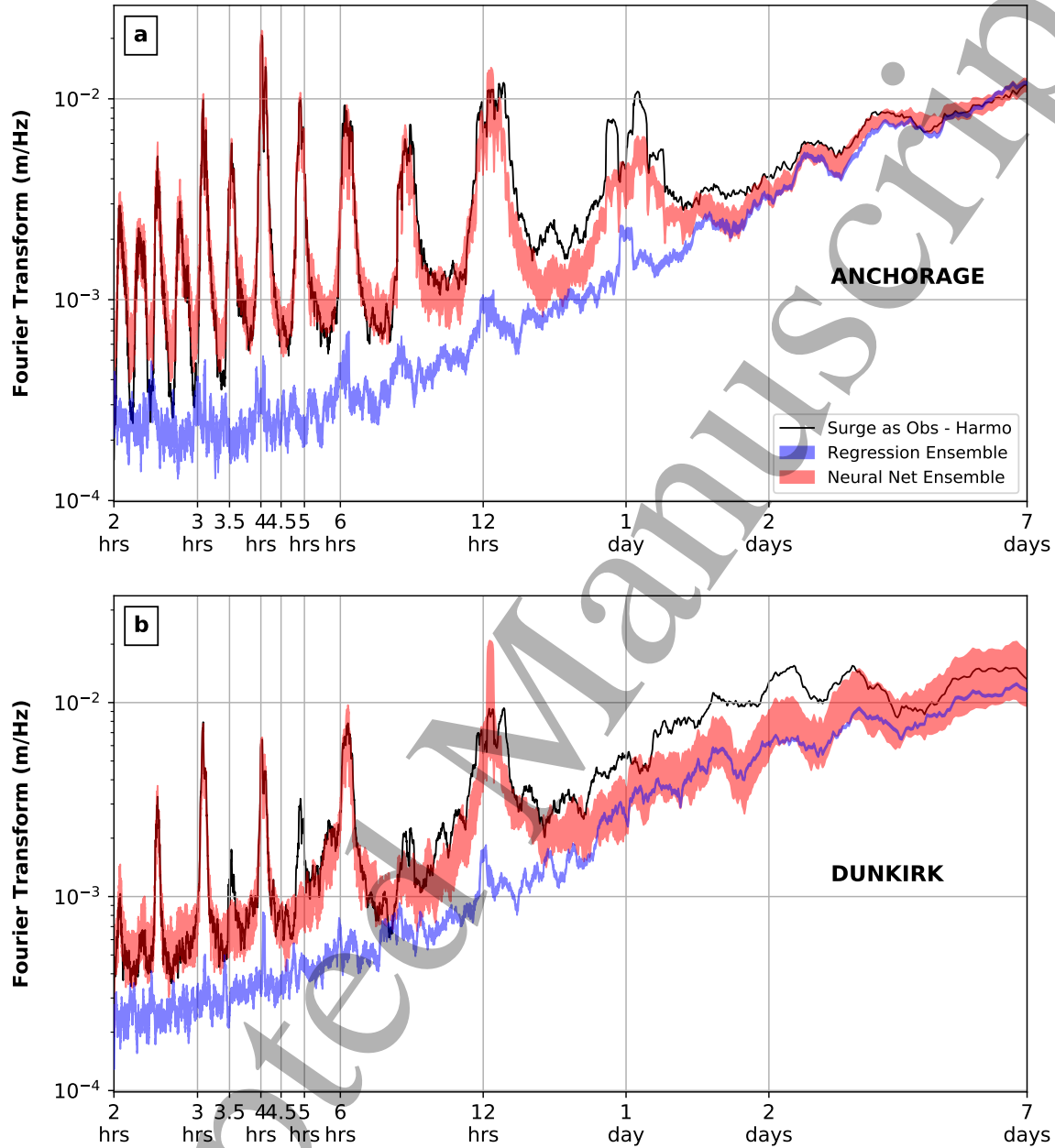
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Figure 6. Energy spectrum extracted from the full test year in a) Anchorage, Alaska, USA where strong tidal interactions occurs and b) Dunkirk, North France during a severe winter. Again the neural network shows high skills at capturing the energy peaks in non-tidal residual.