



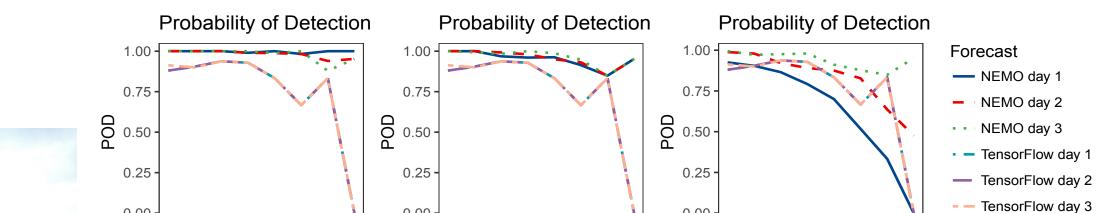
Ensemble and Deep Learning Approach to Storm Surge modeling in the Northern Adriatic

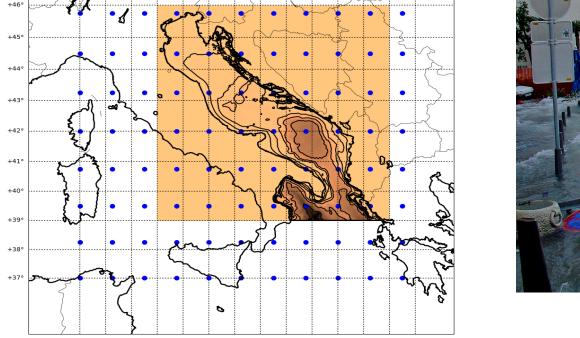
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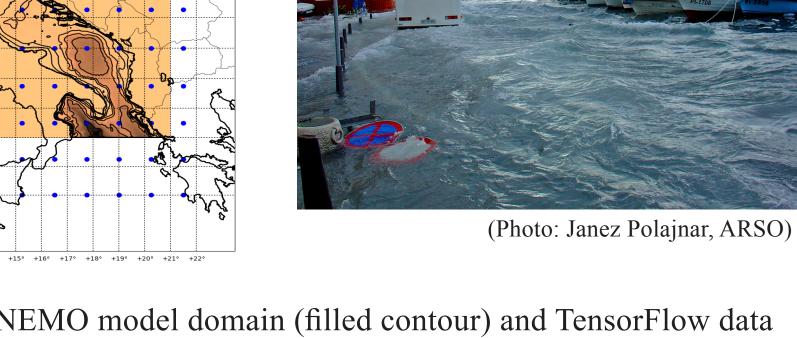
e present results from two distinct strategies for storm surge modeling in the northern Adriatic Sea. First approach consists of **high** resolution ensemble numerical storm surge modeling, based on forcing from a NWP ensemble. Second approach employed was a **Deep Learning** model for sea surface height (SSH) in Koper, Slovenia.

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Skill Comparison Metrics







Ocean model ensemble

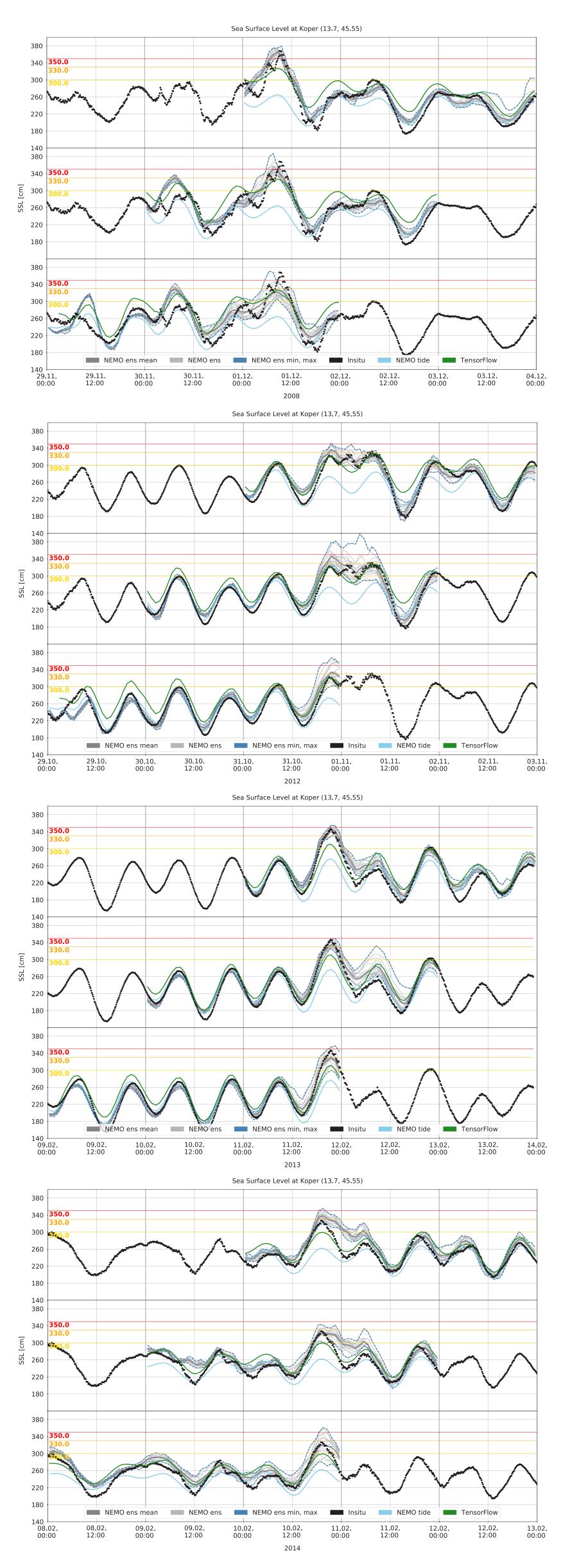
The ocean model ensemble members were NEMO general circulation models with resolution of 1/72degrees over the Adriatic basin and 31 horizontal partial-step vertical z levels.

NEMO model atmospheric forcing consists of a spread-conserving 17-member subset of a 52-member ECMWF ensemble. All NEMO members obtain lateral boundary conditions at the open boundary from CMEMS MFS. TPXO8 tides are applied at the open boundary.

Additional reference tidal setup of NEMO was run on the same grid with no atmospheric forcing and TPXO8 tides (from OTPS tidal inversion model) at the open boundary.

Figure 1. Left: NEMO model domain (filled contour) and TensorFlow data points (blue dots). Right: Storm surge in Piran on 01. 12. 2008

Results and Comparisons



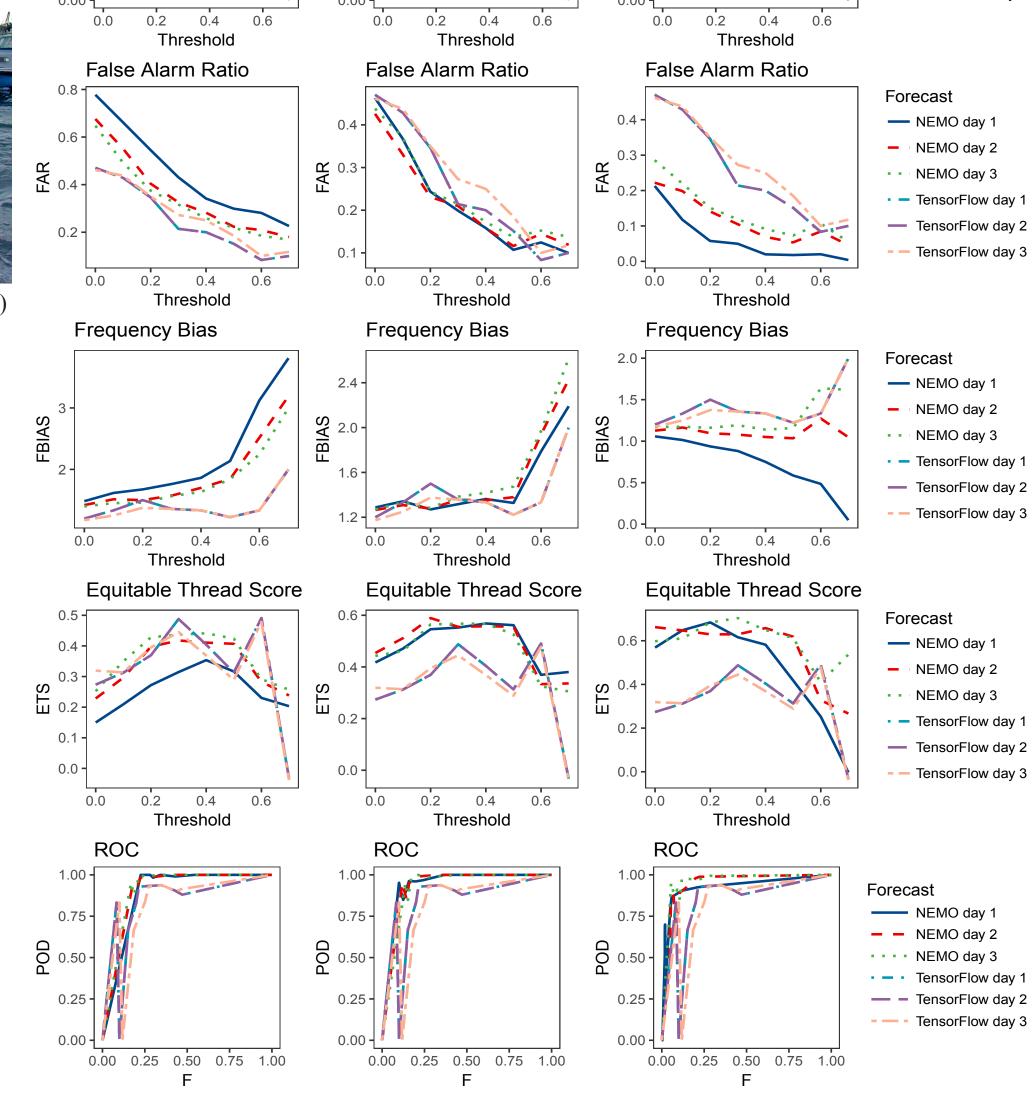


Figure 3. Left column: Skill scores for ensemble maximum. **Center column**: Skill scores for ensemble mean. **Right column**: Skill scores

The NEMO simulations were initialized 5 days prior to the event and restarted each day, hotstarting from previous run and performing a 72 hours SSH forecast.

Deep Learning setup

A convolutional neural network (CNN) was constructed using TensorFlow API. CNN hyperparameters were optimized using a Gaussian process based Bayesian optimization with rectified linear unit (ReLU) activation prescribed in advance. CNN was trained on features below, but excluding the time-windows of each respective event.

for ensemble minimum

Skill score comparison metrics were computed on aggregated NEMO or TensorFlow forecasts from all events. Threshold used is the SSH deviation from mean [m]. The following notation is employed:

• NEMO day 1: NEMO run 48 h prior to event day

- NEMO day 2: NEMO run 24 h prior to event day
- NEMO day 3: NEMO run on the event day

The same notation holds for TensorFlow.

Conclusions

• NEMO is consistently performing better than the employed setups of Convolutional Neural Network. • CNNs consistently exhibit very low probability of detection for the highest storm surge levels, which are by definition statistical outliers.

CNN features [~170 million data points]: • 16 years of 3-hourly MSLP, U10m, V10m, T2m at grid points (blue dots in Figure 1) from ECMWF ensemble.

• 8 h, 12 h, 22 h lags of all of the above data. • Along and across Adriatic axis MSLP gradients

CNN label: SSH from Koper tide gauge.

• Forecast reliability of NEMO simulation runs grows as we approach the event. • Using ensemble mean results in highest ETS score.

• During the storm surge, ECMWF ensembles generate significant spread in the SSH range. • Ensembles and provided forecast variances are key to successful storm surge prediction. • The CNN approach might be improved using more data and with further Bayesian optimization.

Figure 2. NEMO ensemble and TensorFlow forecasts of SSH during several storm surge events.

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