

KNMI
Ministerie van Infrastructuur en Waterstaat

TU Delft

A Neural Network Approach to Extreme Sea Level Prediction

DigiShape Day | 19-11-2026

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Introduction







Why?

- Maintenance during storm season → need for sea level forecasting with longer lead times

→Ensemble forecast needed due to natural variability of weather

→Computation times of numerical models are too long for this

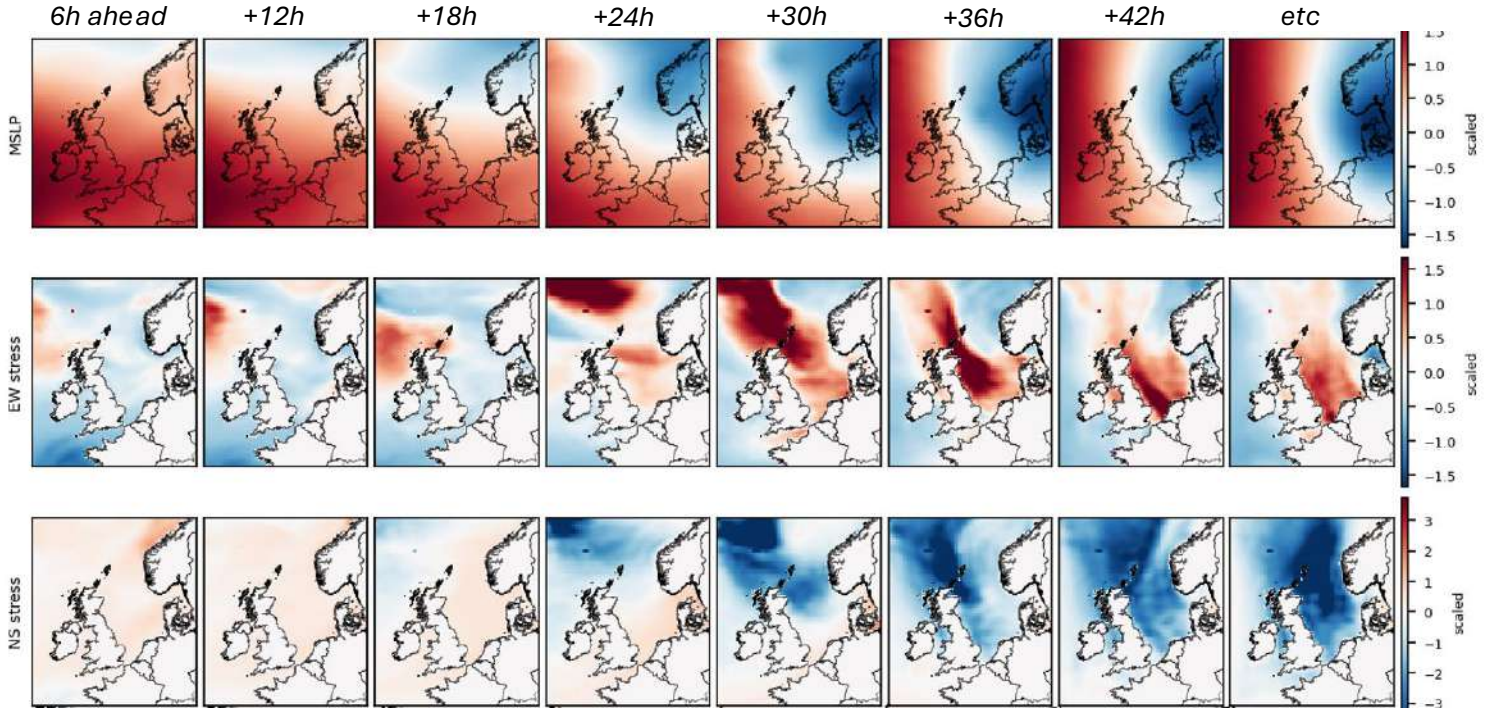
Objective:

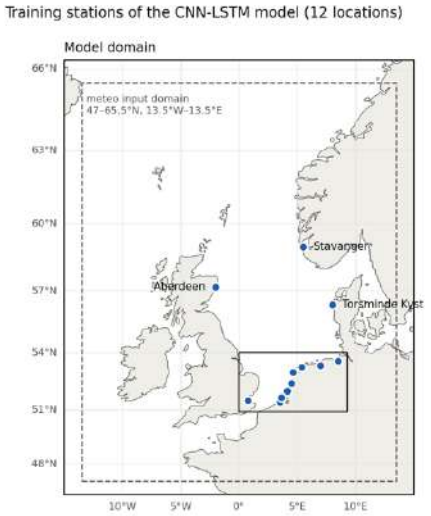
- Fast predictions of sea level time series
- Ensemble forecasting
- Focus on stormy conditions

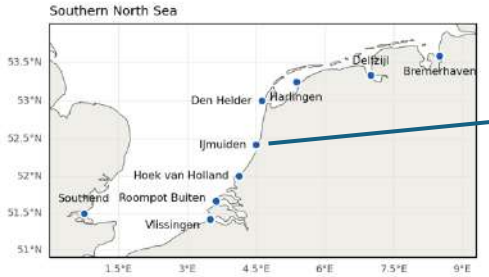
How?

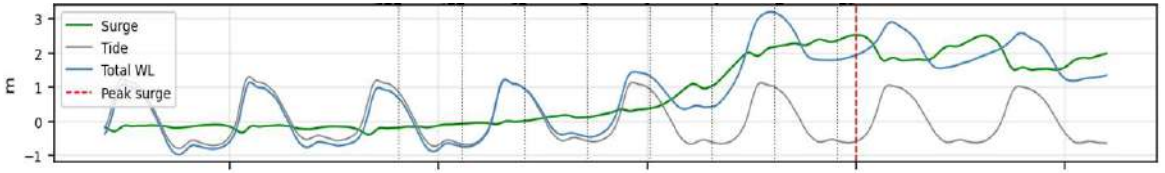
Input:
Spatial fields of mean sea level pressure & wind stress components for 6-hourly time steps

Meteo forecast





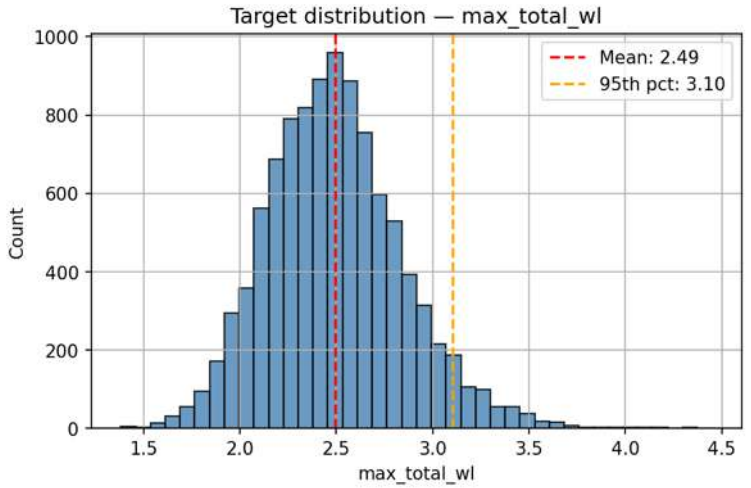




Output:
Time series of residual surge for 10-minute time steps

Data

- Meteo fields from SEAS5 seasonal ensemble forecast by ECMWF
  - Initiated every month since 1981 with 25 or 51 ensemble members → ~9,000 synthetic years of data
  - Resolution: 6-hourly, 0.25°
- KNMI modeled corresponding sea levels using DCSM5-WAQUA
- Training dataset: selection 10,000 storm events based on sea level return periods for locations along North Sea coasts



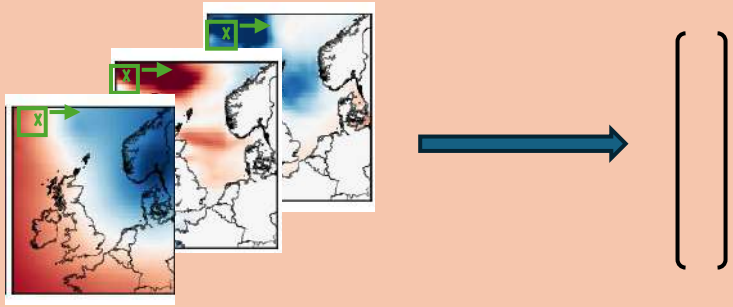
787 events with water levels > NAP+3m at Hoek van Holland

CNN-LSTM:
Spatiotemporal meteo fields → time series of residual surge

Encoder: Reads the input and compresses it into compact summary

- **Input:** 6-hourly meteo fields x 3 variables (MSL & wind stress components)
- **CNN:** extract key spatial patterns, turns each map into small vector
- **LSTM:** reads those vectors per time step, builds running memory

→ Compact representation what happened in what sequence → passed to decoder



Decoder: Generates output using encoders' summary

- Maps to one target value per time step and station
- One shared encoder-decoder for all stations
- At every 10-min target time step, it is fed predicted tidal signal **+ Timmerman surge approximation**
- Static attributes: longitude, latitude, bathymetry
- **Residual training:** target = nontidal residual (NTR) – timmerman surge → model only has to learn what Timmerman model gets wrong

Timmerman surge model

Time lag [h] between wind in section *v* and surge at coastal location:

~0.01 h/km x distance

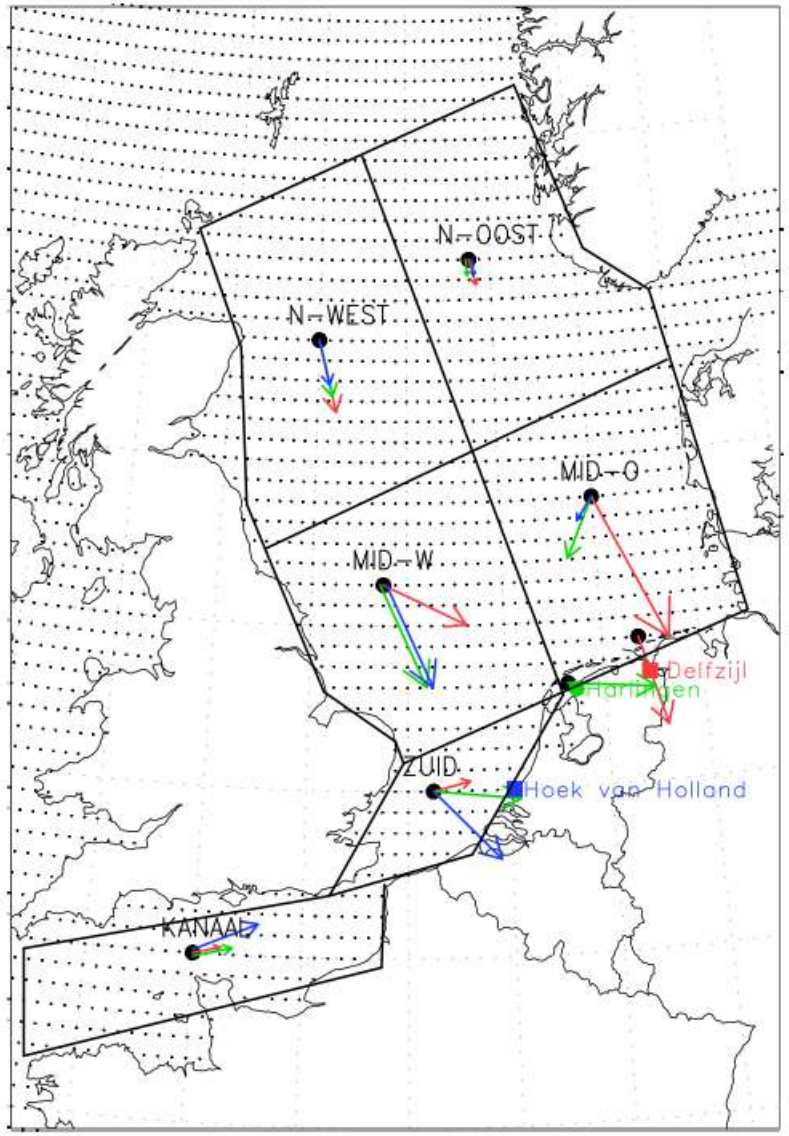
Angle of direction [°N] between section *v* and coastal location

$$S_T(t + \Delta T_v) = 0.01(1013 - \mathrm{MSLP}) + \sum_{v=1,8} C_d(U_v) A_v \{U_v \cos(\gamma(U_v) - \beta_v)\}^2$$

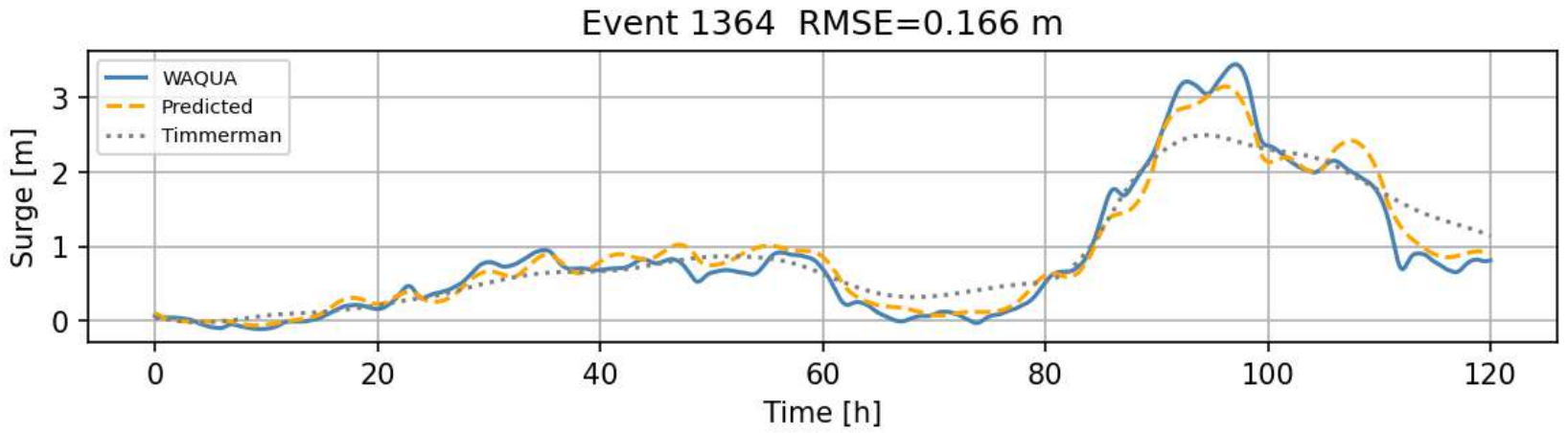
Multiplication factor representing contribution of section *v*

Direction of isobars in section *v*

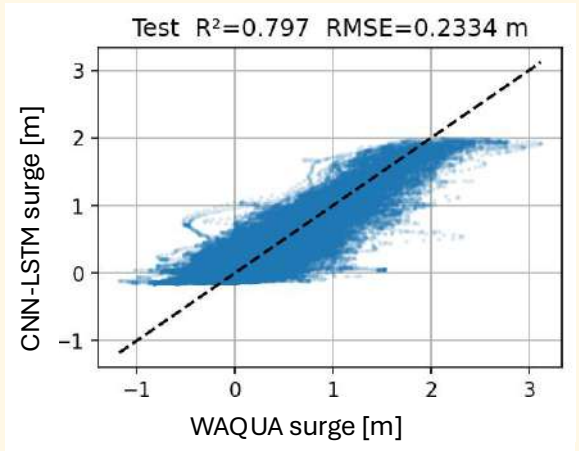
Target = $\mathrm{surge}_{\mathrm{WAQUA}} - \mathrm{surge}_{\mathrm{Timmerman}}$



Results – Time series of nontidal residual at Hoek van Holland



Excl. residual learning using Timmerman model:



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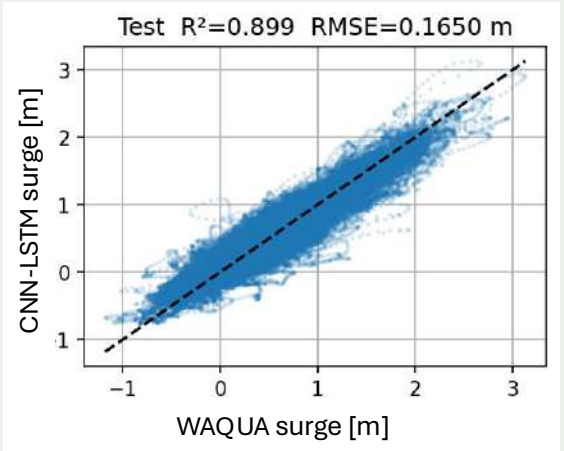
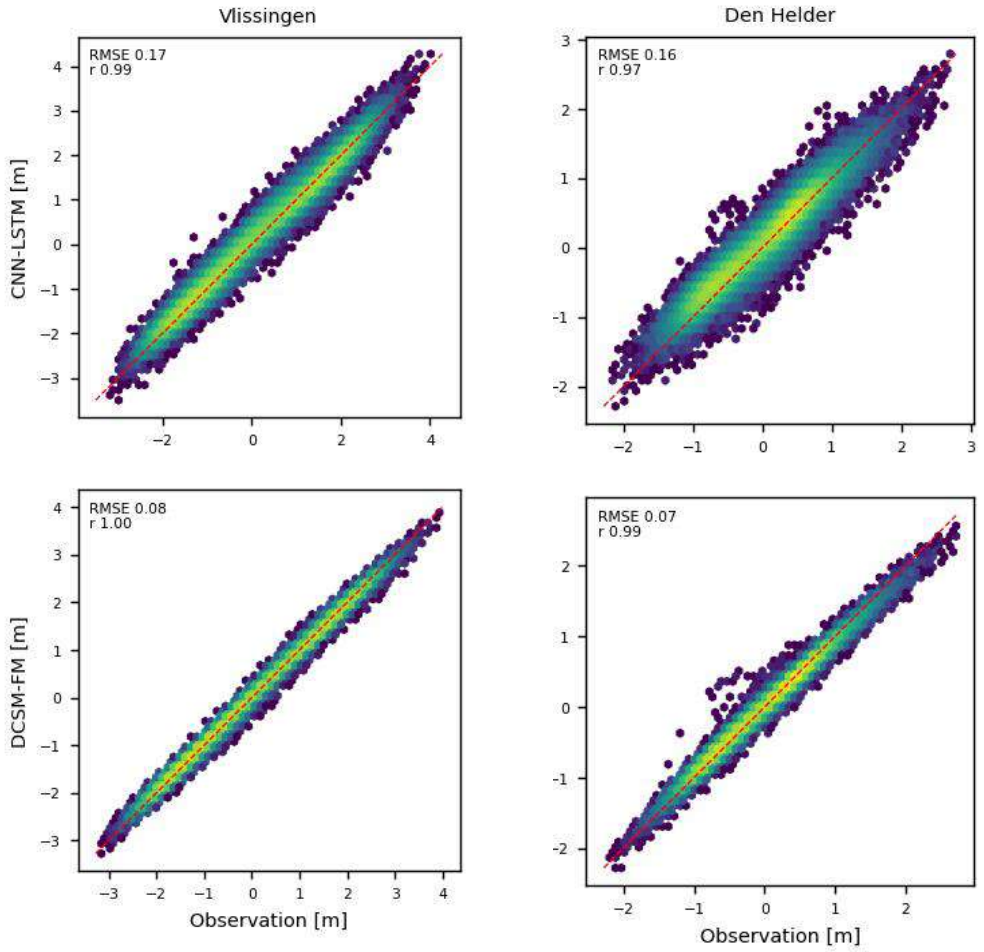
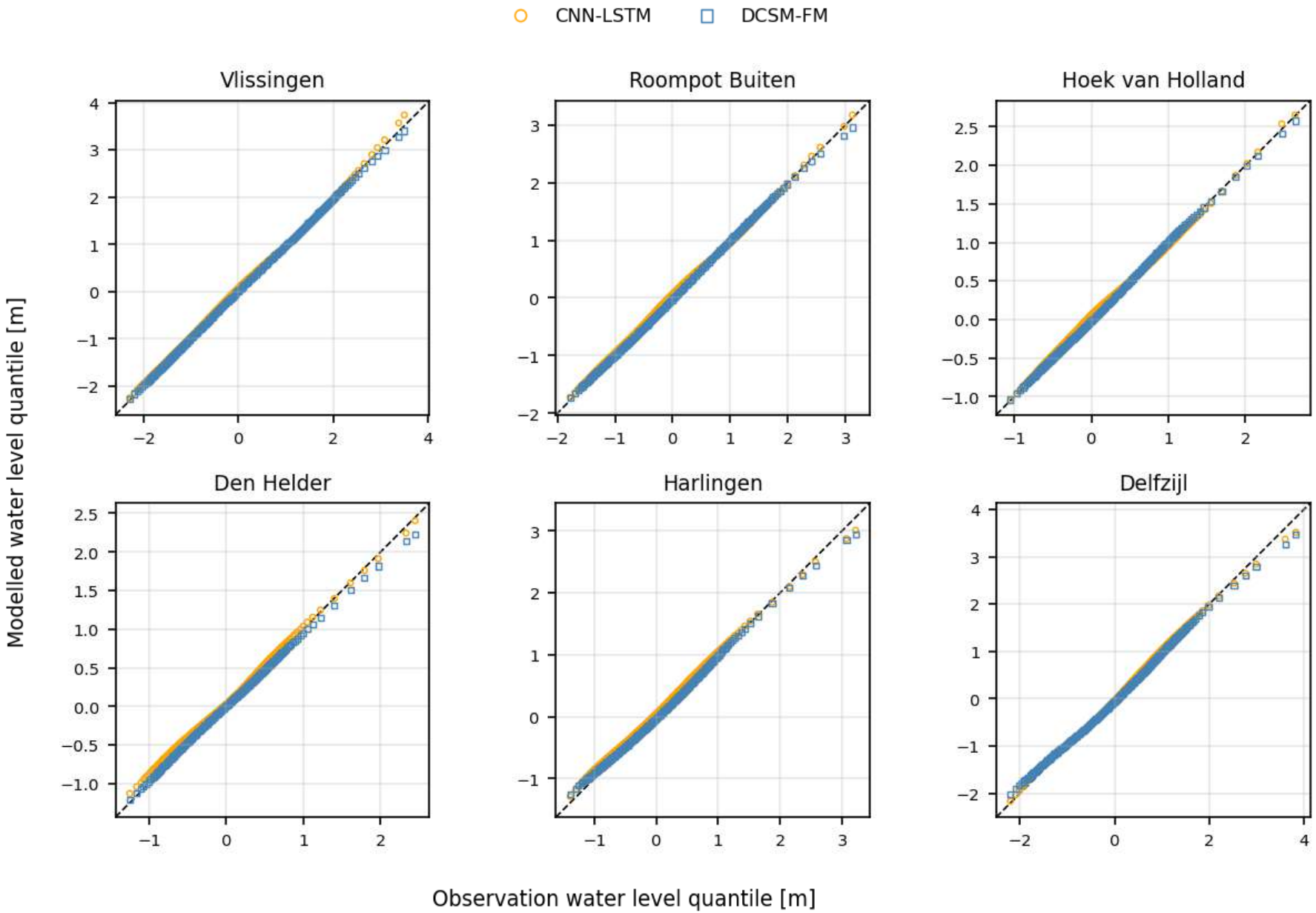


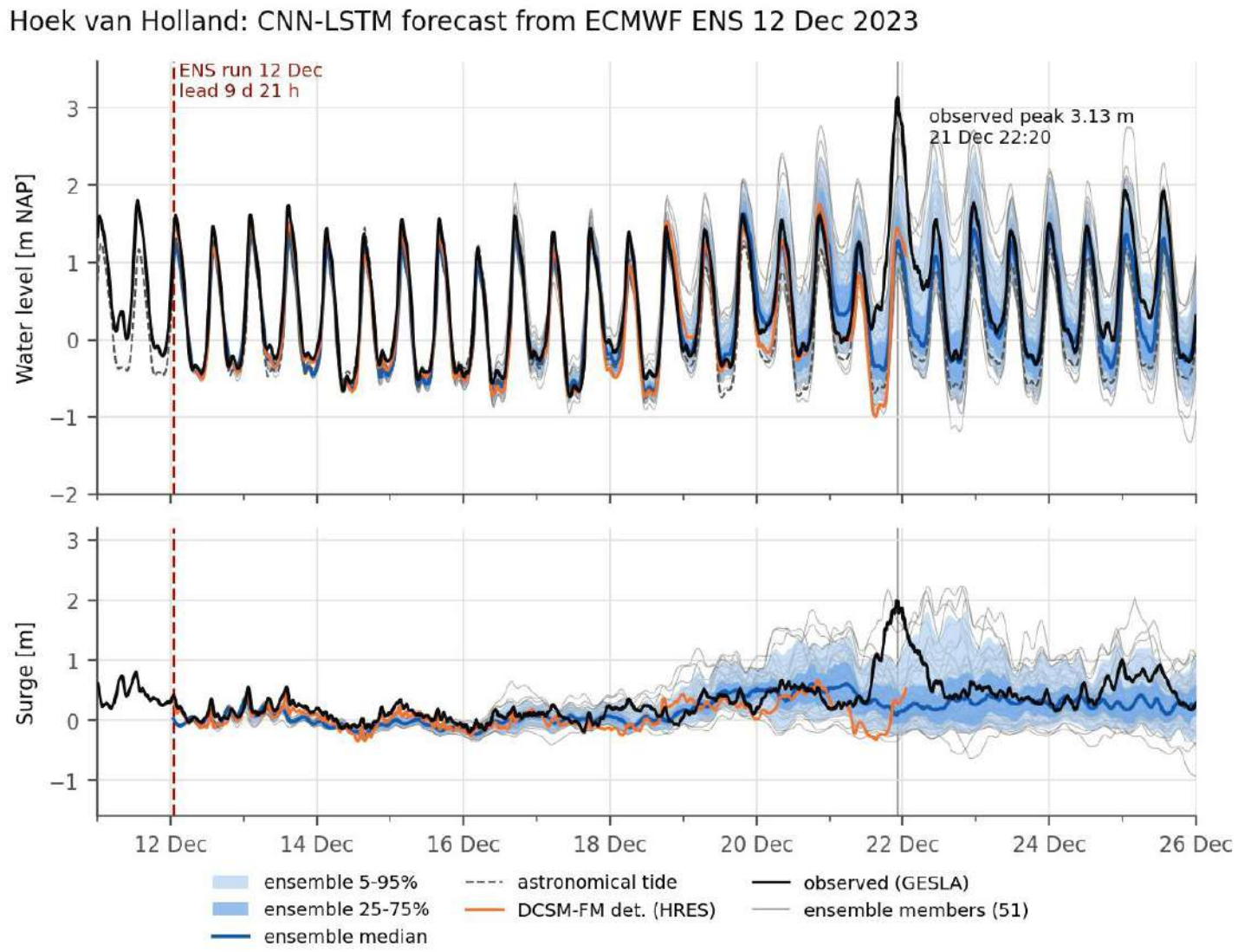
Results – Comparison to observations and DCSM-FM

- Model is trained on coarse data
- How does the model perform compared to DCSM-FM and observations?
- Meteo input from ERA5 (1980-2023, downgraded to SEAS5 resolutions)
- U-tide for astronomical tide prediction




CNN-LSTM
DCSM-FM
Vlissingen
Roompot Buiten
Hoek van Holland
Den Helder
Harlingen
Delfzijl
Modelled water level quantile [m]
Observation water level quantile [m]

Application in ensemble forecasting



It takes 7–9 minutes to produce a 15-day forecast for all 51 members and all 12 stations.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Thank you for your
attention