Application of an artificial neural network to generate wave projections at southern African coasts

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Motivation

In the past decades, the co-occurance of storm surges, wind waves, heavy precipitation and resulting runoff led to critical high water levels at the coasts of southern Africa and as a consequence to property damage and loss of human life. As these compound events at southern African coasts are dominated by wind waves, it is of great importance to investigate the regional wave climate with focus on wave forcing and the origin of wave energy. The understanding of the processes enables us to improve our future wave climate projections and, in a next step, drives flood risk assessment forward.

Model Chain

The aim of this study is the application of a hybrid approach to estimate future wave climate and to downscale the waves to the coast.

First, we use mean sea level pressure data as input for an artificial neural network (ANN) to predict offshore wave data (blue point in fig. 1).

Second, we apply the numerical wave propagation model SWAN to transform the offshore waves nearshore (green point in fig. 1). Due to computational limitations we only transform a selection of waves to the coast and then use radial bias functions for reconstructions of complete nearshore time series.

The focus of this poster is the prediction of offshore waves by the ANN.

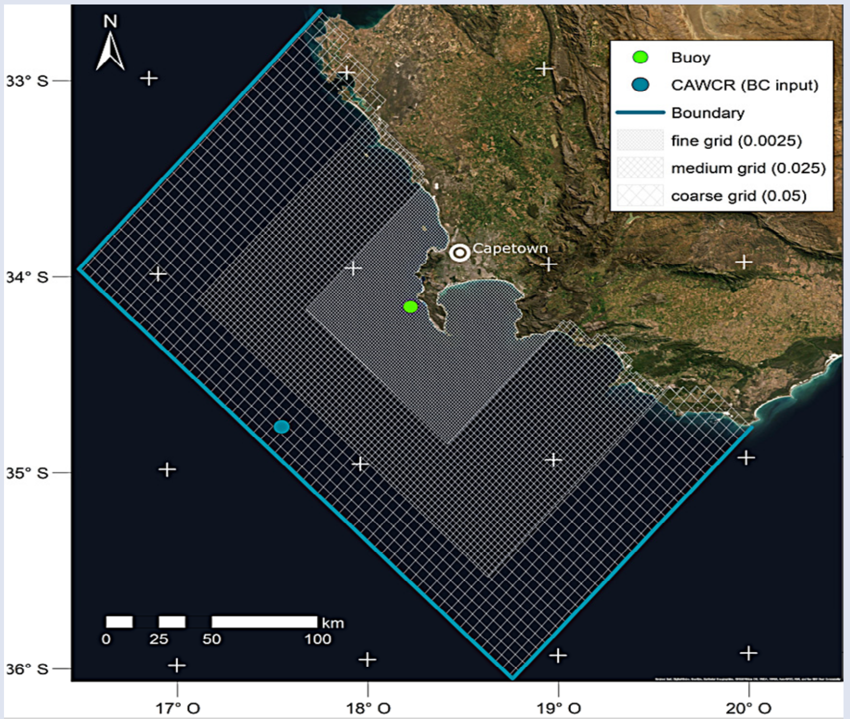

Figure 1: Nested model domains of numerical wave propagation model SWAN with offshore boundary condition (blue) and target point (green).

Mean sea level pressure fields

Offshore wave data

Selection of 1000 sea-states by maximum dissimilarity algorithm

Wave transformation of sea states to the coast by SWAN model

Reconstruction of a time series from transformed sea-states by radial bias functions

Nearshore wave data

Flood risk assessment

Training/Past	Artificial neural network	Prediction/Future
Input data Mean sea level pressure (NCEP/NCAR Reanalysis)		**Input data** Mean sea level pressure (Projections from a downscaled atmospheric model by HZG)
Response data Waves (CAWCR wave hindcast)		**Response data** Future waves

Input data
- mean sea level pressure from NCEP/NCAR reanalysis
- area from 20°S 50°W to 60°S 115°E (yellow rectangle in fig. 2)
- grid size 2.5°
- time period 2000 to 2009
- 6 hourly time steps

Response data
- significant wave height from CAWCR global wave hindcast
- location in front of Cape Town at 34.4°S 17.6°E (blue squares in fig. 2)
- time period 2000 to 2009
- 6 hourly time steps

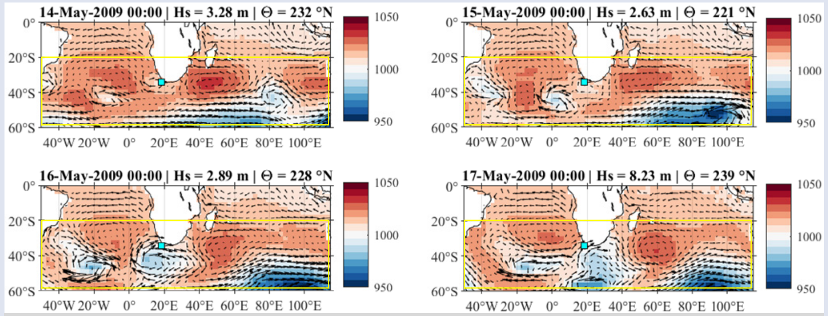

Figure 2: Example of mean sea level pressure (blue to red) with geostrophic wind velocities (black arrows), 3 days before and at the time (17.05.2009 0:00) of an extreme wave event (H_s=8.23m).

Artificial neural network (ANN)

- time delay neural network (see fig. 3)
- 10 hidden layers
- 1 to 21 steps of time delay (6 hours per step)
- Sigmoid transfer fuction inside the hidden layers, linear transfer function inside the output layer
- scaled conjugate gradient backpropagation algorithm
- 70% of time steps for training, 15% for validation 15% for testing

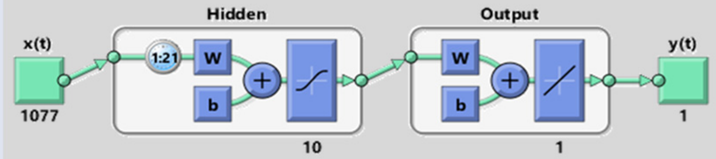

Figure 3: Schematic layout of time delay neural network. x(t) input data, y(t) output data, 1:21 time delay, w weight, b bias.

First training results of the ANN

The ANN is established by the input data mentioned above. Afterwards 6 hourly significant wave heights of 2010 are predicted and compared with the CAWCR hindcast as shown in fig. 4. There is a good agreement for small and large wave heights. The correlation is R^2=0.79 with a RMSE of 0.60m.

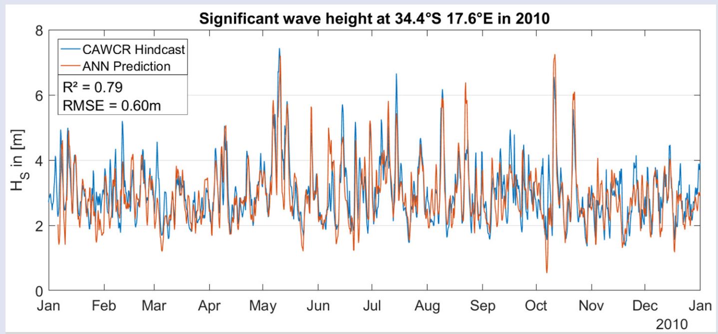

Figure 4: Comparison of significant wave heights from ANN prediction and CAWCR hindcast at 34.4°S 17.6°E (blue squares in fig. 2) in 2010.

Conclusion and Outlook

As shown the ANN is a suitable method to predict future wave hydrographes from mean sea level pressure data. The comparison with the hindcast already shows a high correlation although the training period of 9 years is still small which could be one reason for the elevated RMSE.

In a next step, we will apply a larger training period to the ANN and refine the time delay and the area of wave generation to further improve the predictions. Afterwards we will be able to use robust projections of the mean sea level pressure to estimate future wave hydrographs which in turn will be the input for improved flood risk assessments.

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