Deep learning of dynamic sea-level variability to investigate the relationship with the floods in Gothenburg

Omid Memarian Sorkhabi (✉ omidmemaryan@gmail.com)

University of Isfahan

Research Article

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Posted Date: April 15th, 2021

DOI: <https://doi.org/10.21203/rs.3.rs-422515/v1>

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Deep learning of dynamic sea-level variability to investigate the relationship with the floods in Gothenburg

Omid Memarian Sorkhabi

(omidmemoryan@gmail.com)

Department of Geomatics Engineering, Faculty of Civil Engineering and Transportation, University of Isfahan,
Isfahan, Iran.

Abstract

It is important to study the relationship between floods and sea-level rise due to climate change. In this research, dynamic sea-level variability with deep learning has been investigated. In this research sea surface temperature (SST) from MODIS, wind speed, precipitation, and sea-level rise from satellite altimetry investigated for dynamic sea-level variability. An annual increase of 0.1°C SST is observed around the Gutenberg coast. Also in the middle of the North Sea, an annual increase of about 0.2°C is evident. The annual sea surface height (SSH) trend is 3 mm on the Gothenburg coast. We have a strong positive spatial correlation of SST and SSH near the Gothenburg coast. In the next step, dynamic sea-level variability is predicted with long short term memory. Root mean square error of wind speed, precipitation, and mean sea-level forecasts are 0.84 m/s, 48 mm, and 2.4 mm. The annual trends resulting from 5-year periods show a significant increase from 28 mm to 46 mm per year in the last 5 year periods. The rate of increase has doubled. The wavelet can be useful for detecting dynamic sea-level variability.

Keywords: Dynamic Sea-level, Sea-level, floods, Gothenburg

Introduction

It is important to study the relationship between floods and sea-level rise due to climate change. Research has shown that rising sea-level increase flooding in coastal cities [1-5]. The storm Sven struck the southern parts of Sweden with wind gusts of hurricane force and increased water levels high above normal (122 cm above-average sea-level on December 2013) [6]. This highlights the importance of examining the relationship between sea-level rise and floods. In this research, dynamic sea-level variability with deep learning has been investigated.

Artificial intelligence is a very wide field, and based on the purpose of the problem, we must select and develop its type [7]. As a subset of artificial intelligence, machine learning (ML) algorithms create a mathematical model based on sample data or training data for predicting or making decisions without obvious planning [8]. Machine learning is the scientific study of algorithms and statistical models used by computer systems that benefit from patterns and inferences to perform tasks instead of using explicit instructions. Deep learning (DL) is a subset of ML. In DL, the network input is affected by the previous input, and thus almost a memory is created in the neural network [9]. So deep learning is not limited to deep learning nonlinear hierarchical features [10]. It can also be used to learn long nonlinear time dependencies in sequential data. In a long short-term memory (LSTM) recursive neural network, the network is able to

decide on the maintenance of current memory through the introduced gateways. Intuitively, if the LSTM unit detects an important feature in the input sequence in the initial steps, it can easily transmit this information over a long distance, thus receiving and maintaining such potential long-term dependencies. Having a longer-term memory has a stabilizing effect because even if the network fails to understand its recent history, it is still able to complete its prediction by looking back [11].

In this research SST, wind speed, precipitation, and sea-level rise investigated for dynamic sea-level variability on the Gothenburg coast. In the next step, dynamic sea-level variability is predicted with LSTM-DL.

Results

Modis sea surface temperature (SST) and altimetry sea surface height (SSH) data processed for the North Sea from 2000 to 2019, the results of which are shown in Figure 1. To examine more accurately, we estimated the annual linear trend. An annual increase of 0.1°C is observed around the Gutenberg coast. Also in the middle of the North Sea, an annual increase of about 0.2°C is evident. The annual SSH trend is 3 mm on the Gutenberg coast. We have a strong positive spatial correlation of SST and SSH near the Gothenburg coast. This result is not a model and climate projection.

Figure 1. MODIS SST, annual SST, and SSH and spatial correlation between SST and SSH

We used CMIP5 wind speeds from 2006 to 2100. 300 hidden layers of LSTM are used for learning and forecast. Figure 2 shows the deep learning of wind speeds with the forecast value in blue and orange, respectively. Figure 3 shows the root mean square error (RMSE) of the wind speed forecast. The RMSE of wind speed forecast is 0.84 m/s.

Figure 2. The deep learning of wind speeds with the forecast value in blue and orange

Figure 3 Forecast and RMSE of the wind speed

We used precipitation National oceanic and atmospheric administration climate data records from 1979 to 2020 for Gothenburg. 300 hidden layers of LSTM are used for learning and forecast. Figure 4 shows the deep learning of precipitation with the forecast value in blue and orange, respectively. The RMSE of the precipitation forecast is 48 mm. Figure 5 shows the RMSE of the precipitation forecast.

Figure 4 The deep learning of precipitation with the forecast value in blue and orange, respectively.

Figure 5 Forecast and RMSE of the precipitation.

We used altimetry to mean sea-level (MSL) from 1993 to 2021. The annual trend of mean sea-level is 3.42 cm/year as shown in Figure 6. To further examine the trend rate of altimetry data, has been processed for 5-year periods, which results are shown in Figures 7 and 8. The sea-level rise rate is accelerating. The annual trends resulting from 5-year periods show a significant increase from 28 mm to 46 mm per year in the last 5 year periods. The rate of the MSL increase has doubled.

Figure 6 Mean sea-level from altimetry and annual trend

Figure 7 5-years mean sea-level trend rate

Figure 8 Time series of 5-years sea-level trend rate

Figure 9 shows the training progress of MSL. 300 hidden layers of LSTM are used for learning and forecast. Figure 10 shows the deep learning with the forecast value in blue and orange, respectively. Figure 11 shows the RMSE of the MSL forecast. The RMSE of MSL forecast is 2.4 mm. The proposed method has provided good accuracy in the studied parameters. By developing the model, better accuracy can be achieved.

Figure 9 Training process of MSL

Figure 10 Deep learning of MSL

Figure 11 Forecast and RMSE of MSL

We used the wavelet to reveal parameters relation sea-level variability. Wavelet coherence is a measure of the correlation between two signals [12]. This method is used for the correlation between signals MSL and SST in the time-frequency domain. Wavelet is useful for analyzing nonstationary signals. The coherence is computed using the Morlet wavelet as shown in Figure 12. In the period of 4 years, we have a high correlation, high energy. The relative phase relation between MSL and SST is shown with arrows; arrows to the right show the same phase. In 4 years from 2008 to 2020 arrows to the right show the same phase. This may be due to the El Nino period.

Figure. 12 SST and MSL wavelet coherence

We simulated the scenario of water rising 5 meters in Gothenburg due to floods and sea-level rise with ArcMap and Landsat image. The simulation shows damage to more than 50% of the city. However, this is a primary scenario and requires modeling of precipitation, river flow, and other parameters.

Figure 13 0-5 m water rise in Gothenburg

Conclusion

Machine learning offers good accuracy in predicting various dynamic sea-level parameters. This method can be improved with development at dynamic sea-level. Also, the effect of different parameters on dynamic sea-level can be investigated (with wavelet). The combination of terrestrial and satellite sensors can increase the temporal and spatial resolution of dynamic sea-level variability.

For future work, three suggestions are presented as follows.

- Study SST, MSL, precipitation, and flood pattern with deep learning for Gothenburg coast
- Study the season variability of SST, MSL, precipitation, and flood with a wavelet and deep learning for Gothenburg coast

Development of the city with distance from coastal areas, construction of dams, and flood barriers, there can be solutions to this problem.

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Figures

Figure 1

MODIS SST, annual SST, and SSH and spatial correlation between SST and SSH. Note: The designations employed and the presentation of the material on this map do not imply the expression of any opinion whatsoever on the part of Research Square concerning the legal status of any country, territory, city or

area or of its authorities, or concerning the delimitation of its frontiers or boundaries. This map has been provided by the authors.

Figure 2

The deep learning of wind speeds with the forecast value in blue and orange

Figure 3

Forecast and RMSE of the wind speed

Figure 4

The deep learning of precipitation with the forecast value in blue and orange, respectively.

Figure 5

Forecast and RMSE of the precipitation.

Figure 6

Mean sea-level from altimetry and annual trend

Figure 7

5-years mean sea-level trend rate

Figure 8

Time series of 5-years sea-level trend rate

Figure 9

Training process of MSL

Figure 10

Deep learning of MSL

Figure 11

Forecast and RMSE of MSL

Figure 12

SST and MSL wavelet coherence

Figure 13

0-5 m water rise in Gothenburg