Title:

A Methodology Towards Realistic Absolute Dynamic Topography in the Baltic Sea Using a Synergy of Marine Geoid and Sea Level Data Sets

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Name of Academic Institution: Tallinn University of Technology

Level of study or work: research
(Bachelor thesis, master, research, project, etc.)

Information about you (and your team):
I am a fourth-year PhD candidate in geodesy group at the Dept. of Civil Engineering and Architecture of Tallinn University of Technology. I have been conducting my research study under the supervision of Prof. Artu Ellmann and Dr. Nicole Delpeche-Ellmann. My PhD topic combines geodesy and oceanography, and our goal is to integrate different sea level sources relative to a particular geoid model (that is, an equipotential surface of the Earth's gravity). By doing so, we can attain a remarkable level of accuracy and consistency in the determination of high-resolution sea levels. The results are practical for various applications, such as forecasting, coastal management, and navigation.

Area of interest

(Identifying the problem, explain why it is important and the current relevance of the topic, up to 250 words)

The synergy of various sources of sea level data, such as tide gauges (TG), satellite altimetry (SA), hydrodynamic models (HDM), Global Navigation Satellite Systems tide buoys, and airborne laser scanning, is vital to understand the marine environment in the expanding blue growth economy. This synergistic combination of diverse data sources allows determination of accurate and precise sea level from coast to offshore. This accuracy and consistency are of utmost importance for a wide range of applications, including navigation, climate change, engineering, coastal management. The challenge is the fusion of these sea level sources is not that straightforward, for several limitations exist such as: (i) different spatial and temporal resolutions; (ii) different vertical reference datums are utilized, and (iii) different errors are present based on the method of data collection (Jahanmard et al., 2021 and 2022).
Our motivation is to transfer datasets to a joint geodetic reference surface, in which a high-resolution geoid model plays the role of a critical component in linking different data sources. As a result, the determination of an accurate, high-resolution absolute dynamic topography by combining model and observations in a particular geodetic height system can be possible using a deep learning (DL) approach.

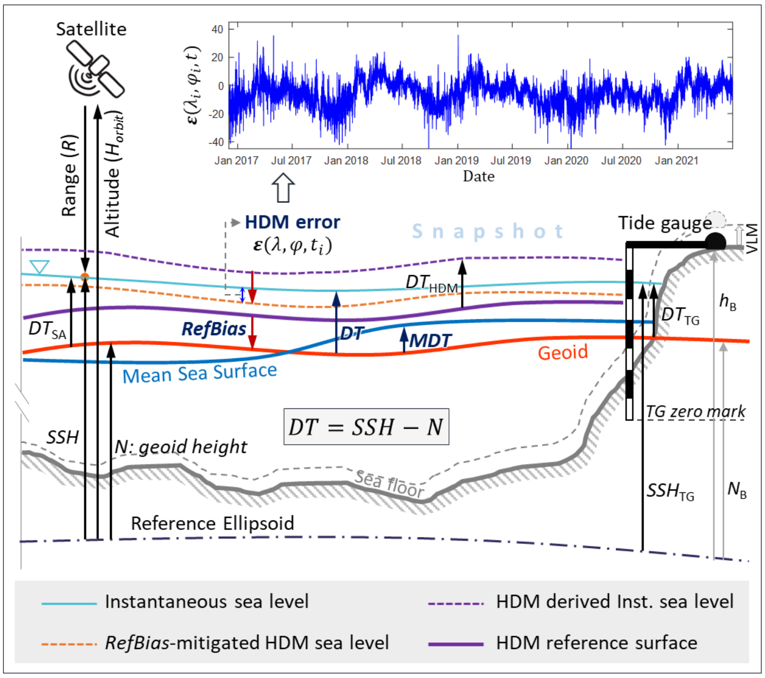

Fig. 1: A schematic diagram of interrelation between different data sources, hydrodynamic parameters, and vertical reference surface

Approach to the problem

(Describe your methodology or technology and how it will solve the problem you identified, up to 300 words)

HDMs typically lack a well-defined vertical reference (Jahanmard et al., 2022). Though HDMs use spherical coordinates in their setup, they implicitly use a vertical coordinate system representing constant geopotential (W). Thus, the term 'dynamic topography' is appropriate for modelled sea level; however, the value of W is undisclosed. Additionally, HDMs can contain errors stemming from topography, computational errors, time steps and modelling discretization, limitations in model resolution and parameterization schemes, and uncertainties in boundary conditions and forcing inputs. Hence, combining the modelled and observed sea levels in terms of absolute value is challenging.

In this study, a DL model is employed to predict HDM modelling errors, which utilizes stacks of dilated causal convolutional layers inspired by WaveNet. This approach allows us to investigate the frequency contents of HDM errors and discover causal relationships between HDM errors and input variables. Also, as TG records are considered the most reliable time series for representing the temporal variation of sea level, the DL model is trained using TGs. However, note that TG stations are spatially sparse, and this limitation disrupts the possibility of feature learning over space and the use of spatial convolutions. Hence, it is crucial for the DL model to effectively generalize over the spatial dimension. This can be attained by carefully selecting appropriate training and test sets and ensuring the model's robustness to spatial variations during the training process using a wrapper-type sequential feature elimination algorithm to select relevant input variables.

Once the HDM modelling errors have been predicted, the corrected HDM can be determined from the original HDM sea level. Consequently, a reference bias (*RefBias*) can also be obtained by comparing the corrected HDM with SA data points for accurately vertically referencing the corrected HDM, where the SA data has been corrected for a particular geoid model.

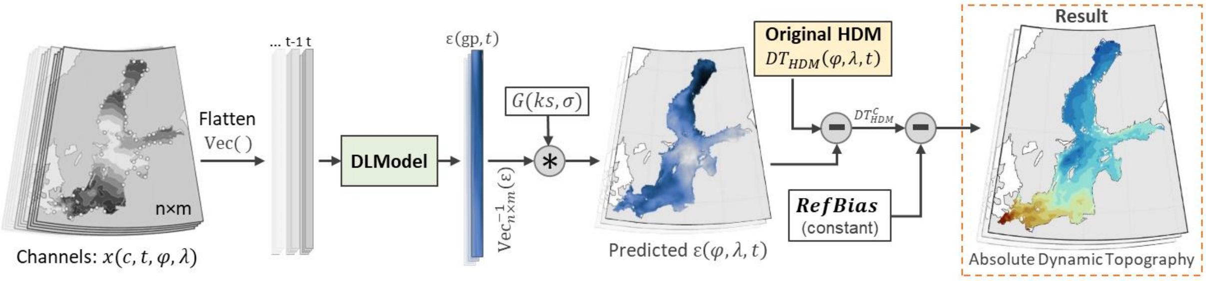

Fig. 2: Implementation of the DL model for correcting the HDM dynamic topography and vertical referencing to a particular geodetic reference frame.

Results, conclusions and next steps

(Present your research results and conclusions of your study, up to 250 words)

The method is tested in the Baltic Sea using the Nemo-Nordic model with 1 NM horizontal resolution, a dense network of fifty TGs, Sentinel-3A satellite altimetry, NKG2015 geoid model, and NKG2016LU land uplift model for the period of December 2016 to June 2021.

The quantification of modelling errors and *RefBias* enabled accurate HDM dynamic topography calculations. The DL-based corrected Nemo-Nordic model agrees with TG records, showing an RMSE of 3.5 cm and a correlation coefficient of 0.98, compared to the original HDM with an RMSE of 7.6 cm and a correlation coefficient of 0.93. The corrected HDM's RMSE relative to the SA measurement significantly improved from 6.5 cm to 4.1 cm on average across the Baltic Sea. Comparison assessment between different data sources also revealed problematic areas in the Eastern part of the Gulf of Finland, the Bothnian Sea, and Southwest Baltic Sea, likely caused by geoid modelling issues. The *RefBias* was calculated as 18.1±2.9 cm using SA data points to reduce the HDM's reference surface to the desired geoid model.

This study demonstrated a promising improvement in the determination of absolute dynamic topography by integrating the hydrodynamic model, tide gauge, satellite altimetry, and marine geoid model. The unification of the vertical reference between the model and observations enhances the effectiveness of data assimilation, enabling the integration of various data sources to accurately determine the absolute dynamic topography. Further studies can be conducted to address and improve the problematic regions by incorporating informative variables into the deep learning model.

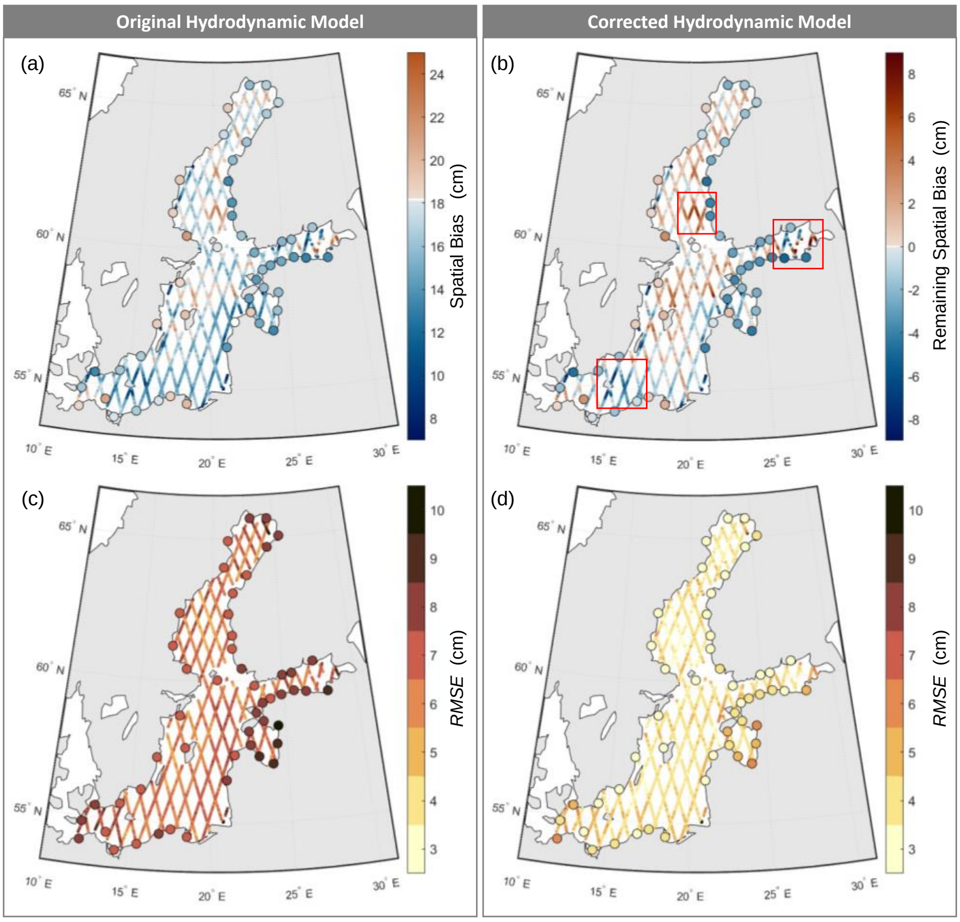

Fig. 3: a) Spatial bias of the Nemo-Nordic model compared to the SA and TG observations. b) Spatial bias of the corrected HDM. The white colour in (a) and (b) has been set on their *RefBias* relative to the SA observations. RMSE of original and corrected HDM are demonstrated in (c) and (d), respectively.

References

(Additional information, publications, or links, up to 200 words)

1. Jahanmard, V., Delpeche-Ellmann, N., Ellmann, A. (2021). Realistic Dynamic Topography Through Coupling Geoid and Hydrodynamic Models of the Baltic Sea. Continental Shelf Research, 222. https://doi.org/10.1016/j.csr.2021.104421
2. Jahanmard, V., Delpeche-Ellmann, N., Ellmann, A. (2022). Towards Realistic Dynamic Topography from Coast to Offshore by Incorporating Hydrodynamic and Geoid Models. Ocean Modelling, 180. https://doi.org/10.1016/j.ocemod.2022.102124
3. Mostafavi, M., Delpeche-Ellmann, N., Ellmann, A., Jahanmard, V., 2023. Determination of Accurate Dynamic Topography for the Baltic Sea Using Satellite Altimetry and a Marine Geoid Model. Remote Sensing, 15(8), 2189. https://doi.org/10.3390/rs15082189
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