Reanalysis of Ocean Model-based Dynamic Topography Utilizing Deep Neural Network and Geoid-referenced Observations

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Dynamic topography (DT) represents a more realistic quantification of sea level and this results in a better understanding of ocean currents and the transport of heat, salt, and other properties of the ocean. DT can be calculated by oceanographic approaches (e.g. using hydrodynamic models) or by geodetic approaches (using satellite altimetry and high-resolution geoid and/or geoid-referenced tide gauges). Hydrodynamic models (HDM) whilst a valuable and reliable source of sea level data, due to their mathematical nature may often deviate from reality due to: (i) errors and limitations in the model and the forcings used and (ii) vertical reference datum differences. These HDM flaws can be overcome by utilizing recent advances made in computing, especially machine learning-based data assimilation techniques, along with a synergistic combination of different data sources results in the determination of a more accurate DT. As a result, this study develops a method to reanalyses the DT of hydrodynamic model and its errors using deep-neural-network-based algorithms by combining in-situ observations (i.e. 50 tide gauges), HDM, and along-track satellite altimetry observations. The method is tested for the entire Baltic Sea for the period 2017-2021.

The method employed consisted of using a multivariate deep neural network that was trained to simulate the model error in time and space with respect to tide gauge observations. For this purpose, the model error with respect to tide gauges was divided into train and test sets in both time and space domains, and the reanalysis model performance was examined by satellite altimetry-derived dynamic topography. The results of the reanalysis demonstrated a residual standard error of 3.8 cm and a coefficient of determination of 0.75 on average. However, the results also reveal temporal and spatial discrepancies and inconsistencies among the data sets. For instance, a large discrepancy between HDM and SA data in the eastern part of the Gulf of Finland is observed that probably points to problems in the geoid model; in the area, we lack sufficient data to compute and validate the geoid.

Keywords: Dynamic topography, Geoid, Deep learning, Data assimilation, Ocean model, Hydrogeodesy, Baltic Sea