EGU22-10179
https://doi.org/10.5194/egusphere-egu22-10179
EGU General Assembly 2022

Estimating Time Series of Tsunami Inundation using One-Dimensional Convolutional Neural Networks for Early Warning.

Patricio A. Catalan[1], Jorge Núñez[1], Carlos Valle[2], Natalia Zamora[3], and Alvaro Valderrama[4]
[1]Universidad Técnica Federico Santa Maria, CIGIDEN, Departamento de Obras Civiles, Valparaiso, Chile
[2]Universidad de Playa Ancha
[3]Barcelona Supercomputing Center
[4]Universidad Técnica Federico Santa Maria,

Tsunamis have the potential to cause widespread damage and loss of life over large swaths of coastal areas. To mitigate their effects, both in the long term and during emergency situations, an accurate, detailed and timely assessment of the hazard is essential. Here, an enhanced method for estimating tsunami time series using a uni-dimensional convolutional neural network model is presented, with the aim of reducing the time and computing capacity required by a high-resolution numerical modeling. While the use of deep learning for this problem is not new, most of existing research has focused on the determination of the capability of a network to reproduce inundation values. However, for the context of Tsunami Early Warning, it is equally relevant to assess whether the networks can predict the absence of inundation. Hence, the network model was adjusted for the bays of Valparaíso, Viña del Mar and Coquimbo in central Chile, based on a set of 6800 scenarios with Mw 8.0-9.2. Tentative models were trained with time series from low- and high-resolution numerical modeling, to recreate the tsunami time series of control points on land. The objective was to reproduce the inundation high resolution time series, when the network was fed with low resolution offshore data. The approach considered 1075 (15%) scenarios to test the model, and 5783 (85%) scenarios to adjust (train and validate) the model. Different performance metrics are employed, particularly the RMSE measured with respect to peak flow depth and arrival times. Critically, the number of false alerts and alerts not issued was analyzed, which was considered a relevant performance owing to the wide range of magnitudes tested that led to an unbalance between scenarios that inundate and the ones that not. A notable outcome in this study shows the network is capable of reproducing inundation, either for small or large amplitudes, and also of no inundation. To further assess the performance, the model was tested with three existing tsunamis and compared with actual inundation metrics at three cities with different hydrodynamic response. The results obtained are promising, and the proposed model could become a reliable alternative for the calculation of tsunami intensity measures (TIMs) in a near to real time manner, with a network model forecasting where sea surface and geodetic data are not readily available, as occurs in many countries. This could complement existing early warning systems to reduce uncertainties involved in the decision making process.