XVIII International Conference on Hyperbolic Problems
Theory, Numerics, Applications
Málaga, June 20-24, 2022

# Use of neural networks for tsunami maximum height and arrival time predictions

Juan F. Rodríguez*, Jorge Macías*, Marc de la Asunción*, Manuel J. Castro* and Carlos Sánchez-Linares*.

Operational TEWS play a key role in reducing tsunami impact on coastal populated areas around the world in case of tsunami. Traditionally, these systems in the North-East Atlantic, the Mediterranean, and connected Seas (NEAM) region have relied in the implementation of *Decision Matrices*. The very short arrival times of the tsunami waves from generation to impact in this region have made it not possible to use real time on the fly simulations to produce more accurate alert levels. In these cases, when time restriction is so demanding, the alternative to the use of Decision Matrices is to use data sets of precomputed tsunami scenarios. In this paper, we propose the use of neural networks (NN) to predict the tsunami maximum height and arrival time in the context of TEWS. The numerical code Tsunami-HySEA, developed by the EDANYA group at the University of Málaga, Spain, has been used for generating the large set of tsunami simulations required to train the NN model[6, 4].

Tsunami-HySEA implements the 2D nonlinear shallow-water system on lat-lon coordinates:

$$
\text{(1)} \qquad \begin{cases}
\partial_t h + \dfrac{1}{R\cos(\varphi)}\Big(\partial_\theta q_\theta + \partial_\varphi(q_\varphi \cos(\varphi))\Big) = 0, \\[2mm]
\partial_t q_\theta + \dfrac{1}{R\cos(\varphi)}\partial_\theta\left(\dfrac{q_\theta^2}{h}\right) + \dfrac{1}{R}\partial_\varphi\left(\dfrac{q_\theta q_\varphi}{h}\right) - 2\dfrac{q_\theta q_\varphi}{Rh}\tan(\varphi) + \dfrac{gh}{R\cos(\varphi)}\partial_\theta h = \dfrac{gh}{R\cos(\varphi)}\partial_\theta H, \\[2mm]
\partial_t q_\varphi + \dfrac{1}{R\cos(\varphi)}\partial_\theta\left(\dfrac{q_\varphi q_\theta}{h}\right) + \dfrac{1}{R}\partial_\varphi\left(\dfrac{q_\varphi^2}{h}\right) + \dfrac{(q_\theta^2 - q_\varphi^2)}{hR}\tan(\varphi) + \dfrac{gh}{R}\partial_\varphi h = \dfrac{gh}{R}\partial_\varphi H,
\end{cases}
$$

where $R$ is the radius; $(\theta, \varphi)$, the longitude and latitude; $g$, the gravity; $h$, the thickness of the water layer; $H$, the bottom depth; $q_\theta = hu_\theta$ and $q_\varphi = hu_\varphi$, with $u_\theta$ and $u_\varphi$ the longitudinal and latitudinal velocities averaged in the normal direction. The Okada model [9] is used to compute the initial seafloor deformation caused by the earthquake.

Tsunami-HySEA uses a discretization of the nonlinear 2D shallow-water system with a second-order Finite Volume method that is well-balanced for water at rest on the sphere. The use of lat-lon coordinates introduces an extra difficulty in the design of the well-balanced method due to the new geometry terms[2]. Tsunami-HySEA is currently being used in the TEWS of several countries (as Spain, Italy or Chile), and it has been widely tested and benchmarked [6, 7, 8].

Machine Learning (ML) techniques are spreading rapidly and are being used in all fields of research and, in particular, in tsunami modelling (see for example [1, 10, 11, 3, 5]). In this paper, Multi-Layer Perceptron (MLP) neural networks will be used to forecast results of tsunami maximum height and arrival time at certain points in Chipiona-Cádiz coast (south-western Spain). First, we have considered single models and they have produced good results. Then, ensemble techniques have also been considered and implemented. These ensemble techniques try to combine different single models in order to reduce the variance, obtaining in many cases better predictions.

In this work, the Horseshoe fault has been chosen as area where the generating earthquake takes place. This means that we are designing a NN model for tsunamis generated in this area and triggered by this particular fault. The results obtained confirm that deep learning is a good tool for predicting the maximum height and the arrival time of a tsunami at several points simultaneously. The NN models generated in the present work provide predictions for maximum height and arrival time for the Horseshoe fault in the Atlantic with errors smaller than 6 cm for the maximum height and 212 s for the arrival time.

*Grupo EDANYA, Universidad de Málaga, Málaga, Spain. Email: juanrg@uma.es

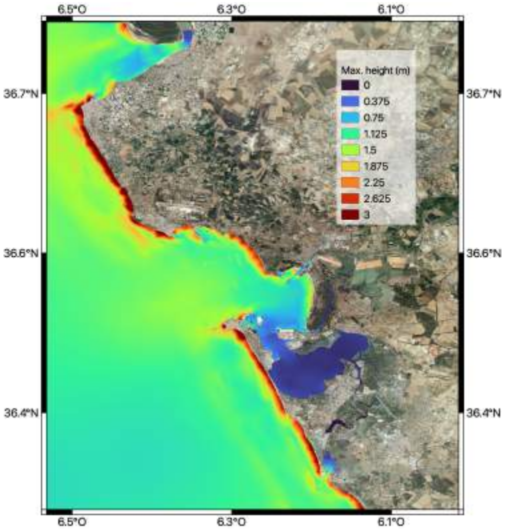


Figure 1: Maximum height for a simulated event on Horseshoe fault. The spatial resolution is 40 meters.

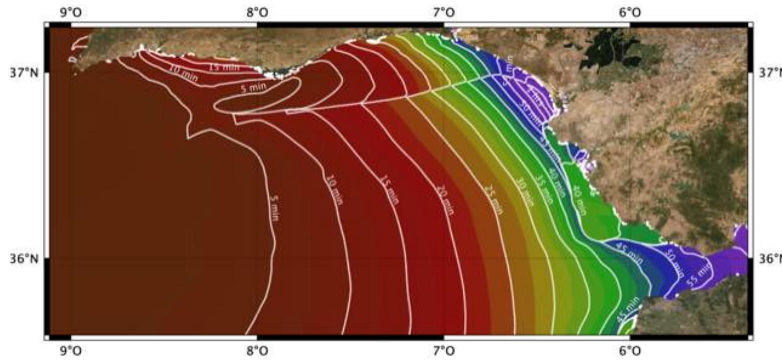


Figure 2: Arrival times splitted by minutes for a simulated event on the fault. The spatial resolution is 320 meters.

## Acknowledgements

This work has been funded by "Innovative ecosystem with artificial intelligence for Andalusia 20205" project of CEI Andalucía Tech and University of Málaga, UMA-CEIATECH-05. The numerical results presented in this work have been performed with the computational resources provided by the Spanish Network for Supercomputing (RES) grants AECT-2020-1-0009 and AECT-2020-2-0001. This research was also partially funded by the European Union's Horizon 2020 Research and Innovation Program under grant agreement No 823844 (ChEESE Center of Excellence, www.cheese-coe.eu) and partially supported by the Spanish Government and FEDER through the coordinated Research project RTI2018-096064-B-C1, the Junta de Andalucía research project P18-RT-3163 and the Junta de Andalucia-FEDER-University of Málaga Research project UMA18-FEDERJA-161.

## References

[1] M. de la Asunción. Prediction of Tsunami-HySEA inundation results using deep learning. *(Submitted to Advances in Engineering Software)*.

[2] M.J. Castro, S. Ortega, and C. Parés. Well-balanced methods for the shallow water equations in spherical coordinates, *Computers & Fluids*, 157, 196-207, 2017. [doi:10.1016/j.compfluid.2017.08.035].

[3] A. Fauzi, N. Mizutani. Machine Learning Algorithms for Real-time Tsunami Inundation Forecasting: A Case Study in Nankai Region. *Pure and Applied Geophysics 177*, 2020, 10.1007/s00024-019-02364-4.

[4] J.M. González, M.J. Castro, J. Macías, M. de la Asunción, S. Ortega, C. Parés. Tsunami-HySEA: A numerical model developed for Tsunami Early Warning Systems (TEWS). *Progress Industrial Mathematics: Success Stories*, *Springer International Publishing*, 2020, pp. 209–226.

[5] C. Liu, D. Rim, R. Baraldi, R. Leveque. Comparison of Machine Learning Approaches for Tsunami Forecasting from Sparse Observations, *Pure and Applied Geophysics 178*, 2021, pp 5129–5153.

[6] J. Macías, M.J. Castro, S. Ortega, C. Escalante, J.M. González-Vida. Performance benchmarking of Tsunami-HySEA model for NTHMPs inundation mapping activities, *Pure and Applied Geophysics 174(8)*, 2017, pp 3174–3183. `https://doi.org/10.1007/s00024-017-1583-1`.

[7] J. Macías, M.J. Castro, C. Escalante. Performance assessment of the Tsunami-HySEA model for NTHMP tsunami currents benchmarking, Laboratory data, *Coastal Engineering 158*, 2020, `https://doi.org/10.1016/j.coastaleng.2020.103667`.

[8] J. Macías, M.J. Castro, S. Ortega, J.M. González. Performance assessment of Tsunami-HySEA model for NTHMP tsunami currents benchmarking, Field cases, *Ocean Modelling 162*, 2020, `https://doi.org/10.1016/j.ocemod.2020.101645`.

[9] Y. Okada. Internal Deformation Due to Shear and Tensile Faults in a Half-Space. *Bulletin of the Seismological Society of America 92(2)*, 1992, pp 1018–1040.

[10] M. Romano, S.Y. Liong, T. Vu, P. Zemskyy, C. Doan, M. Dao, P. Tkalich. Artificial neural network for tsunami forecasting, *Journal of Asian Earth Sciences 36*, 2009, pp 29–37, `https://doi.org/10.1016/j.jseaes.2008.11.003`.

[11] M.J. Song, Y.S. Cho. Modeling Maximum Tsunami Heights Using Bayesian Neural Networks. *Atmosphere 11* 2020, `https://doi.org/10.3390/atmos11111266`.