

COASTAL FLOODING RISK ASSESSMENT BY A NEURAL NETWORK APPROACH

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An effective system of coastal flooding forecasting in the case of storm is essential to mitigate coastal risks for the population living in low-land coastal zones (<10 m above MSL). Nowadays, predictions of coastal flooding are usually carried out by adopting nested numerical models. However, the models adopted to obtain the data in the nearshore area require high computational costs, which are often too demanding and not viable for large scale forecasting. Data-driven models, such as Artificial Neural Networks (ANNs) can help to solve the problem as they can map complex nonlinear relationships between input and output variables once a suitable dataset of process realizations is available. In the present study a forecasting model for coastal flooding based on ANNs, in which the input data are the offshore wave characteristics from large scale model and the output results are the flooded areas, is proposed. These outputs provided a straightforward prediction of the area interested by coastal flooding during storms. Here an application of the model to assess the flooding risk in the village of Granelli, in the Southeast of Sicily (Italy) is presented.

Keywords: Early warning system, Wave propagation modelling, Flood modelling, SWAN, Xbeach

Introduction

Coastal zones are more densely populated than inland areas and they exhibit higher rates of population growth and urbanization (Small and Nicholls, 2003; Neumann *et al.*, 2015). More in details, it has been estimated that at a global scale the population living in lowland coastal zones (elevation lower than 10 m) is more than 600 million (around 10% of the world's population and 13% of the world's urban population) (McGranahan *et al.*, 2007).

At the same time, such zones are exposed to several hazards. Storms, erosion, ecosystem losses and flooding are the main examples. The latter is considered as the major risk due to the potential losses it can inflict in human, environmental and economic terms (Coquet *et al.*, 2019). Moreover, because of expected climate changes, projections of a sea level rise from 0.5 m to 1.8 m by 2100 (Kopp, 2014; Le Bars *et al.*, 2017) are estimated, which, in turn, significantly will increase the exposure to flooding.

To reduce the risk in coastal areas, institutional, structural and preparedness measures can be adopted. Preparedness measures require mainly the improvement of the monitoring and forecasting systems and the development of an alert network. These aspects represent the necessary components for the development of an Early Warning System, namely a system which allows for a timely prediction of an adverse event so that Authorities can undertake the necessary actions to avoid or minimize the risk (Basher, 2006).

Nowadays, several organizations (i.e., European Centre for Medium-range Weather Forecasts-ECMWF, National Oceanic and Atmospheric Administration - NOAA, etc.) provide hindcast and forecast data related to offshore wave characteristics, while predictions of coastal flooding are usually estimated by adopting nested numerical models which simulate hydrodynamic processes taking place in the nearshore area.

A reliable and effective early warning system of coastal risks requires a system able to ensure: (i) high precision in the reconstruction of nearshore hydrodynamic and morphodynamic processes; and (ii) low computational times to minimize the impact of the event on the population.

Unfortunately, the typical approach for coastal flooding prediction requires high computational costs, which is often too demanding and not viable for large scale forecasting system (Poelhekke *et al.*, 2016; Harley *et al.*, 2016; Cheung *et al.*, 2003). A way to overcome these limits is the creation of a database of the flooded areas related to predetermined offshore wave climates. Operationally, the flooded areas are estimated for several offshore probable scenarios. Therefore, once the offshore wave characteristics are known, it is possible to query such a database to estimate the corresponding coastal flooded areas.

However, although the database may be very detailed it will not be able to process all the offshore wave conditions that can occur at a site. For such a reason, in the present study, Artificial Neural Networks (ANNs) were used. ANNs are mathematical/computer models characterized by structures and calibration processes that are inspired by the behavior of the human brain and which can map complex relationships between variables. In coastal engineering, neural networks are widely used in

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several fields (Jain and Deo, 2006) as, for example, for the prediction of environmental parameters (e.g. wave characteristics, wind data, tide data, etc...) (Perez *et al.*, 2015; Lee, 2012) or as support for the estimation of quantities such as wave reflection or wave overtopping for the design process (Formentin *et al.*, 2017).

An approach like the one proposed here was introduced by Sahoo and Bhaskaran (2019), who used the ANN for the prediction of storm surge and onshore flooding. In such a work, pre-computed scenarios of storm tide and inundation data were used to train ANN model. The scenarios were defined for various combinations of cyclone track, wind speed, translation speed, angle of approach, and tidal amplitudes. In the present study, the ANNs are used for the prediction of the coastal flooding due to the combined effect of wind waves and storm tide, for this reason, the selected input variables are the offshore wave characteristics and water level. The proposed approach was applied to the village of Granelli, which belongs to the municipality of Pachino, on the Southeast side of Sicily (Italy). The study area covers a surface of 1.40 km², comprise between two headlands (Castellazzo and Gratticelle). Most of the area considered is characterized by an elevation over the mean still water level less than 3 m. The high exposition to coastal flooding risk of the investigated area is confirmed by the analysis based on a new climate model for weather prediction set up by the National Agency for New Technologies, Energy and Sustainable Economic Development, which has allowed estimating that Granelli is one out of seven sites in Italy that could be entirely lost due to flooding by 2100 (Antonioli *et al.*, 2020).

The work is organized as follows. The next section describes the methodology adopted to build the flooding area database and to calibrate the ANN. Then, the data used as input for the calibrated ANN are described and the results of the coastal flooding risk assessment are discussed. Finally, the main findings of the present study are summarized.

Creation of a database of the flooded areas

The training data of the neural network were obtained by using two state-of-the-art nested numerical models: SWAN (Simulating Waves Nearshore) and Xbeach.

SWAN is a third-generation wave model, developed by Delft University of Technology (Booij *et al.*, 1999), which computes random, short-crested wind-generated waves in coastal regions and inland waters. The model is based on the wave action balance equation with sources and sinks.

Xbeach is a two-dimensional model used for the computation of nearshore hydrodynamics and of the morphodynamic response of beaches during storm-events (Roelvink *et al.*, 2015). The model allows users to include two different options for wave boundary conditions in the model: spectral conditions or not spectral condition. In the present study we applied the first option using the wave spectra estimated by SWAN at the seaward boundary. The hydrodynamics processes were simulated using the short-wave averaged modes (surf beat) where the short-wave variations on the wave group scale and the long waves associated with them are resolved. The simulations were performed assuming negligible the effects of wave-current interaction (Marino *et al.*, 2020a; Marino *et al.*, 2020b) and considering a fixed bottom.

The morphology of the seabed was obtained from the charts of the Italian Navy Hydrographic Institute and from a specific in situ bathymetric survey. The emerged beach was reconstructed using the DTM provided by the Sicilian Region, which is characterized by a 2x2 m spatial resolution.

The SWAN computational domain (see Figure 1) was discretized using an unstructured grid. For the present case, the computational domain was discretized with 5563 nodes and 10719 triangular elements. The grid resolution has been assumed constant for depths shallower than 50 m and deeper than 100 m, while it varies linearly in range 50-100 m. Accordingly, the mesh sizes are 400 m for the depths shallower than 50 m, and 1000 m for the depths deeper than 100 m, and vary linearly between 400 m and 1000 m for the depths in the range of 50-100 m.

The lateral boundaries of the Xbeach domain are characterized by a length of 1686 m, while the seaside and the land side boundaries are characterized by a length of 3700 m. On the seaside boundary, the cells have a width both in the y and x directions equal to 10 m; on the land side contour, the cell width in y is 10 m, while it is reduced to 2.5 m in the x direction.

Figure 2 shows the calculation domain used for the simulations conducted at the Granelli beach. The figure also shows the location of section 1 in which the time-series of the moving waterline was recorded. Such data were used to compare the results of Xbeach with the empirical model proposed by Stockdon *et al.* (2006).

Several sea states were simulated to obtain an adequate dataset for the training of the neural network. More in details, 1680 sea states were selected characterized by:

1. wave height in the range of 2-8 m, with a resolution of 0.5 m;
2. wave period in the range of 5-15 s, with a resolution of 2.5 s;
3. wave direction in the range of 120- 270°N, with a resolution of 10°;
4. mean sea level in the range of 0.0-0.50 m, with a resolution of 0.25 m.

The wave input at the seaside boundary was defined using the JONSWAP (Joint North Sea Wave Project) spectrum. The spectrum was discretized into 36 directions and 40 frequencies in a range of 0.04–0.5 Hz, which corresponds to range of 2–25 s in terms of time.

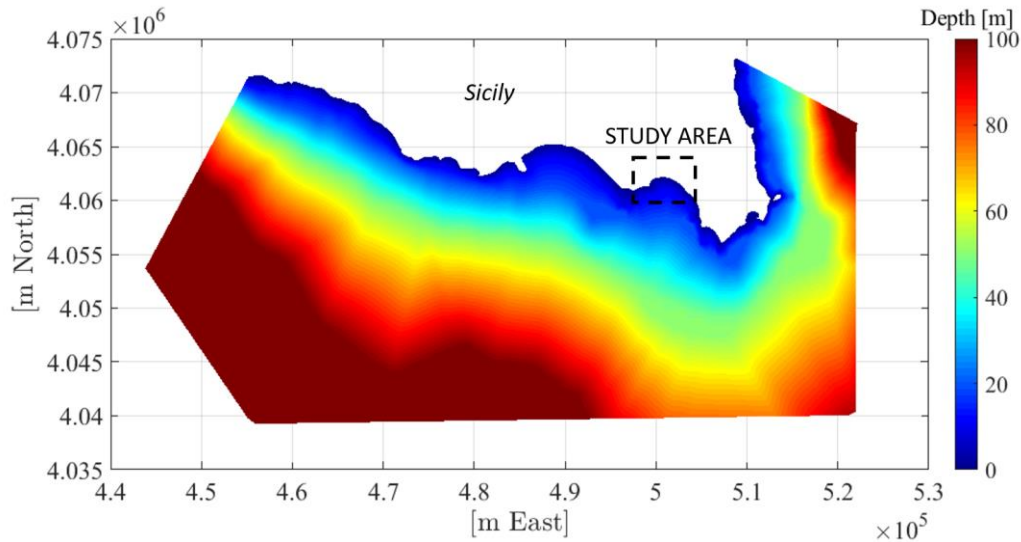


Figure 1. Computational domains and bathymetry adopted for the numerical simulations using SWAN.

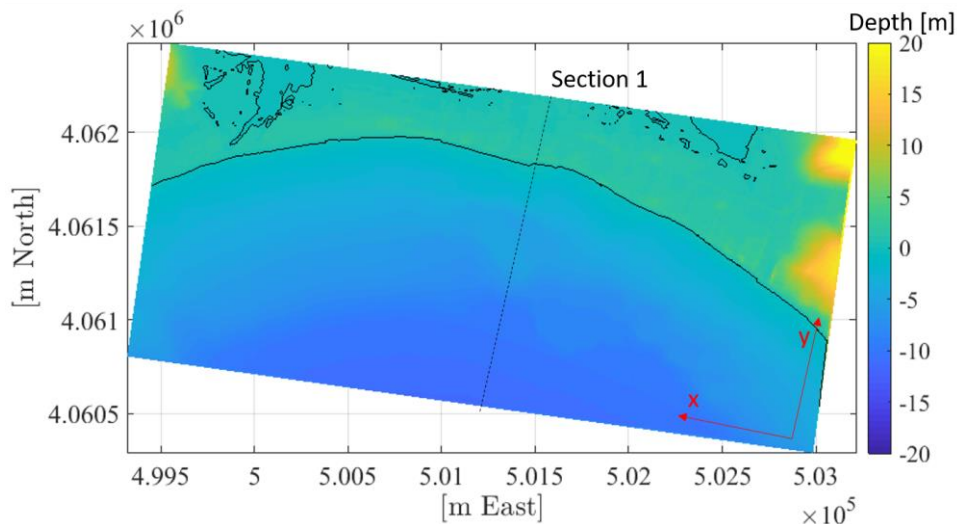


Figure 2. Computational domains and bathymetry adopted for the numerical simulations using Xbeach. The dashed line individuates the section 1 in which the waterline position was recorded.

The results of simulation performed with Xbeach were compared with the empirical method proposed by Stockdon *et al.* (2006). The latter method is a simple parameterization which provides useful predictions of extreme setup and runup on natural beaches. This method includes foreshore beach slope, offshore wave height, and deep-water wavelength. For the comparison, the output data of Xbeach (setup and runup) were extracted along the section 1, whose more offshore point is at $x=501351$ m and $y=4060520$ m and the more onshore point is at $x=501558$ m and $y=4061993$ m (see Figure 2).

As it can be seen in Figure 3, the correspondence between the numerical model and the empirical model is quite good. However, for some extreme events, it can be noted that the method of Stockdon *et al.* (2006) provides lower values than those estimated by Xbeach. The mean error between the two model was equal to 0.004 m and 0.02 m for the setup and the runup, respectively. The root mean square

discrepancy between the two sets of data was equal to 0.09 m and 0.27 m for the setup and the runup, respectively.

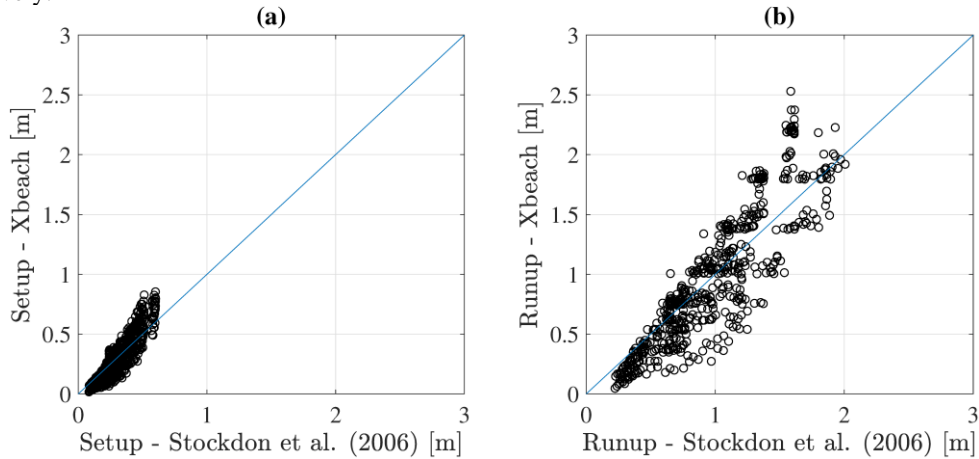


Figure 3 Comparison between wave setup and wave runup estimated using both the numerical model Xbeach and the empirical model proposed by Stockdon et al (2006).

Figure 4 shows six sectors (A1-A6) in which the village of Granelli was divided according to the population density. The results on flooded surface areas within such sectors have been used to train the ANNs, as discussed in the next section.

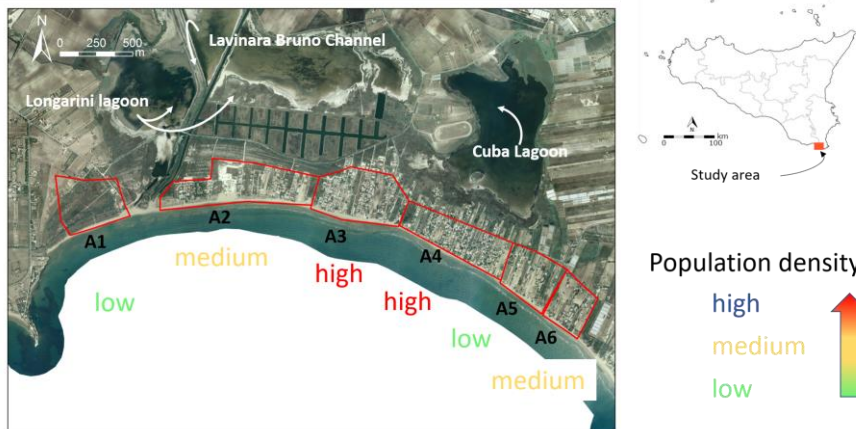


Figure 4 Population density and location of the six sectors (A1-A6) in which the village of Granelli was divided according to the population density.

Neural Network Calibration

Fully connected single hidden layer feed forward ANNs have been used (see Figure 5). The input nodes provide information on the storm wave characteristics and mean sea level to the network. The hidden nodes compute the parameters of the ANNs and transfer information from the input nodes to the output nodes. The output nodes predict the flooded areas.

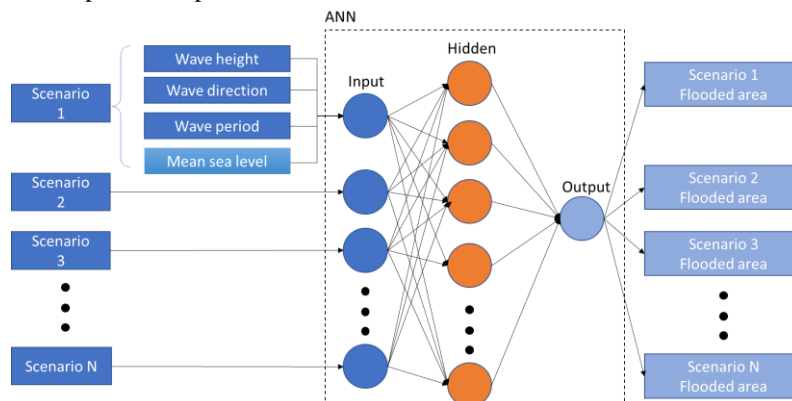


Figure 5 Structure of the artificial neural network used for the prediction of the flooded areas.

According to population density (Figure 4), the village of Granelli was divided into six areas. For each area, several configurations of ANN were analyzed by changing the number of the nodes in the hidden layer. In particular, the numbers of nodes considered are: 1, 5, 10, 20, 40, 80, 100, 200 and 500. The calibration of the ANNs was carried out by means of the early stopping method. In this method, the data is divided into three subsets. The first subset is the training set, which is used for computing the gradient and updating the network weights and biases. This analysis was carried out by means of the Matlab function *trainlm* which updates weight and bias values according to Levenberg-Marquardt optimization. The second subset is the validation set. The error on the validation set is monitored during the training process. When the validation error increases for a specified number of iterations, the training is stopped, and the weights and biases at the minimum of the validation error are returned. The last subset is the test set which is used both to check the network generalization and to identify the neural network configuration which best describes the function between the input data and the output data. According to this method, the whole dataset of scenarios (consisting of offshore wave characteristics, mean sea level data as well as flooded areas) was split into three subsets: 60 % for the training set, 20% for the validation set, and 20% for the test set. The optimal numbers of the nodes in the hidden layer were estimated by comparing the flooded areas estimate by ANN and those estimated by using Xbeach.

Coastal flooding risk assessment through the ANN

To estimate the flooded areas for the select site, the wave characteristics (significant wave height, peak period, and direction) and storm tide (i.e the sum of the storm surge and astronomical tide) must be known. For the select site, there are no measuring stations for wave or tide. For this reason, the ERA5 dataset created by ECMWF was used. ERA5 is the fifth generation ECMWF atmospheric reanalysis of the global climate and covers the period from 1979 and continues to be extended forward in near real time. The database provides hourly estimates of many atmospheric, land and oceanic climate variables. Such data were produced using 4D-Var data assimilation in CY41R2 of ECMWF's Integrated Forecast System (IFS), with 137 hybrid sigma/pressure (model) levels in the vertical, with the top level at 0.01 hPa. The wave model is characterized by a spatial resolution of 0.5° both latitude and longitude and a spectral resolution of 24 directions and 30 frequencies. From this dataset, in addition to the characteristics of the wave motion, data relating to wind speed and atmospheric pressure were extracted. These two last variables were used to estimate the storm surge by adopting the empirical methods suggested by the guidelines issued by World Meteorological Organization (Horsburgh and De Vries, 2011). As regards the surge due to the wind, the guideline suggests the relationship proposed by Reid (1956), while the component of the storm surge related to the atmospheric pressure was estimated assuming that a decrease of 1 hPa in atmospheric pressure gives rise to an increase of 1 cm in the water level. The astronomical tide was obtained by the model OSU Tidal Prediction Software (OTIS) created by the collaboration of the Scientists at Earth and Space Research (ESR) and Oregon State University (OSU). The input data of the ANN used in the present study covers the period between 1979 and 2019.

For each sector, Figure 6 shows the ratio between the flooded area and the total area versus a dimensional parameter which is a function of wave characteristics (significant wave height H_{m0} and the wavelength, related to peak wave period, L_p) and the beach slope (β_j). The dot line indicates the limit between the beach and the urban zone.

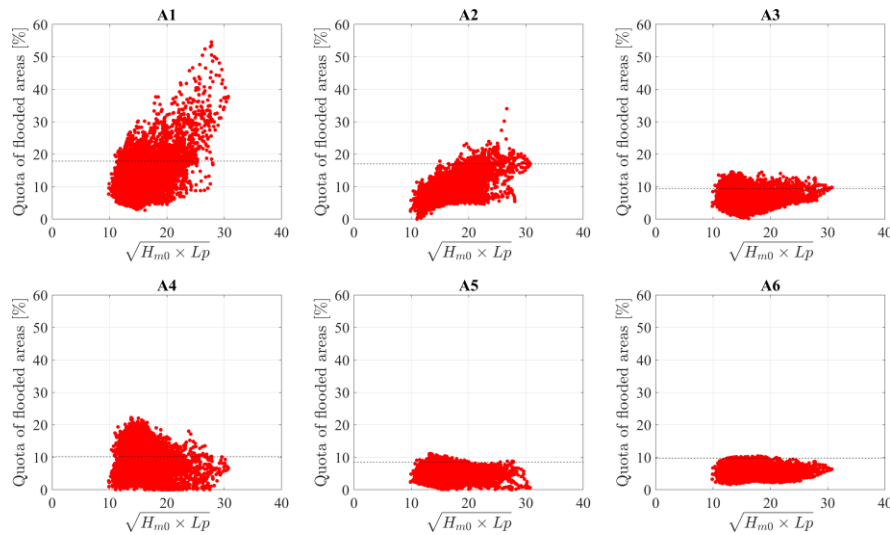


Figure 6 Ratio between the flooded area and the total area versus the dimensional parameter.

As it can be seen from Figure 6, for the areas A2, A5, and A6 a limited number of flooding events was estimated. In these cases, the urban zones are protected by the dunes which reduce the overtopping discharge. Area A1, instead, has a higher number of flooding events but the population density is very low. The annual average number of flood events estimated for such areas are: 32 for A1, 7 for A2, 5 for A5 and 1 for A6. The higher risk for the population due to the flood was estimated for the areas A3 and A4. Indeed, for these two areas, a yearly average number of flood events equal to 27 and 47 was assessed, respectively.

Conclusion

Early Warning Systems can help to mitigate coastal flooding risks. However, typical prediction methods of coastal flooding require too high computational costs, which are incompatible with an effective early warning system.

The proposed strategy couples a database of coastal flooding areas related to predetermined offshore wave climates and the ANNs. Such an approach allows an instantaneous evaluation of coastal flooding which, in turn, permits the Authorities a timely decision for preparing the population in the case of storm.

The calibrated ANNs allowed the reconstruction of the historical data of the flooded areas for the village of Granelli. In particular, the ANN has been used in a back-analysis mode to identify the areas exposed to a higher risk.

Future analyses will be aimed at validating the proposed ANNs through field measurements which will be carried out in the correspondence of flood events.

ACKNOWLEDGMENTS

This work has been partly supported by the project “NEWS - Nearshore hazard monitoring and Early Warning System” (code C1-3.2-60) in the framework of the EU programme INTERREG V-A Italia Malta 2014–2020, the project “eWAS- an Early Warning System for cultural heritage” financed under the program PNR 2015-2020, and by the projects , "Interazione Moto Ondoso - Strutture (IMOS)", and "Valutazione del Rischio Idraulico in sistemi cOmplessi (VARIO), funded the PIACERI programme of the University of Catania.

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