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Artificial neural network for tsunami forecasting

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ABSTRACT

This paper presents a data-driven approach for effective and efficient forecasting of tsunami generated by underwater earthquakes. Based on pre-computed tsunami scenarios as training data sets the Artificial Neural Network (ANN) is used for the construction of data-driven forecasting models. The training data comprised spatial values of maximum tsunami heights and tsunami arrival times (snapshots), computed with process-based TUNAMI-N2-NUS model for the most probable ocean floor rupture scenarios. Validation tests demonstrated that with a given earthquake size and location, the ANN method provides accurate and near instantaneous forecasting of the maximum tsunami heights and arrival times for the entire computational domain.

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1. Introduction

Over the past few decades, accurate process-based tsunami propagation models have been developed and thoroughly tested. Most advanced models require significant computational resources at fine grid resolutions; hence, they cannot be used for operational tsunami forecasts due to relatively long computational time required. Accurate and computationally fast data-driven methods are found to be able to mimic pattern of training data sets, which make them ideal for real-time operations. The use of data-driven methods can be extended to replace accurate but computationally demanding process-based tsunami propagation models by means of training data-driven models with a large number of pre-computed tsunami scenarios.

The simplest data-driven tsunami forecast system consists of a database of pre-computed scenarios and a case selection routine with a conventional interpolation algorithm such as those proposed in Whitmore and Sokolowski (1996). In this method, the closest matching event from the database is identified by comparing the pre-computed scenarios with measured wave characteristics near the earthquake epicenter. Other researchers have proposed different approaches such as inversion methods by Wei et al. (2003) and Lee et al. (2005). These methods were constrained by the assumption of the tsunami wave propagation being linear to perform linear superposition of pre-computed data. Barman et al. (2006) used the ANN method in the prediction of the tsunami arrival time in the Indian Ocean. Srivichai et al. (2006) used the general regression neural network (GRNN) method to forecast tsunami heights. This method allows the application of nonlinear process-based tsunami models to build a database of scenarios, but the application was limited to only a few predefined discrete observation points.

Recently, the Center for Tsunami Research/National Oceanic and Atmospheric Administration (NOAA) has reported exploratory work to use EOF as a tool for tsunami model data analysis Burwell and Weiss (2006), Weiss (2007) and a related application of empirical orthogonal function processing which allows for short-term tidal predictions at tsunami buoy locations with the precision of more advanced methods and with minimal a priori knowledge about tidal dynamics is given by Tolkova (2008).

Wei et al. (2008) outlines NOAA forecasting methodology applying to the August 15, 2007 Peru tsunami. In this method, real-time tsunami data from a deep-ocean tsunami detection buoy were used to produce initial experimental forecasts within two hours of tsunami generation and comparison with real-time tide gage data showed accurate forecasts.

Dao et al. (2008) have developed a POD-based data-driven model for the quick and accurate prediction of maximum wave heights and arrival times of an earthquake-generated tsunami at all grid nodes in the entire domain of interest, provided that the initial location and magnitude of tsunami are given.

In this paper, we present the applications of the ANN technique for a rapid and accurate prediction of maximum wave heights and arrival times for any location in the computation domain without the need to solve the underlying governing partial differential equations (PDE). The well-trained ANN models are able to closely mimic the performance of the nonlinear model TUNAMI-N2-NUS within seconds.

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2. Tsunami propagation model

The tsunami propagation model used in this paper is originated from TUNAMI-N2 which was developed at the Disaster Control Research Center (Tohoku University, Japan) through the Tsunami Inundation Modeling Exchange (TIME) Program, Goto et al. (1997). TUNAMI-N2 code has been improved by the authors Dao and Tkalich (2007) to capture the effects of Earth's curvature, Coriolis force, and wave dispersion to simulate transoceanic tsunami propagation. The original nonlinear shallow water equation model (NSWE) is reformulated as:

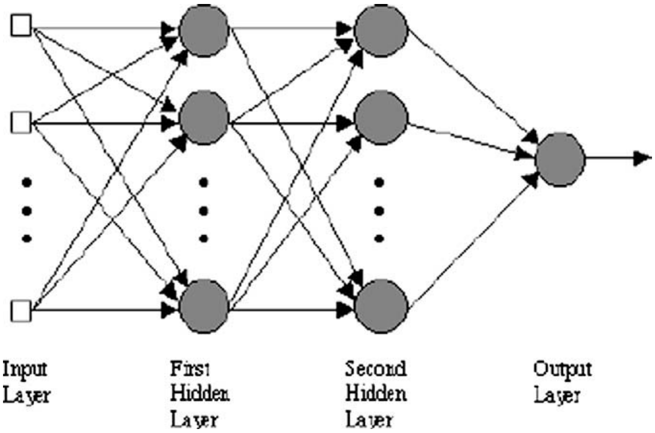

Fig. 1. Schematic diagram of a 2-hidden layer perceptron.

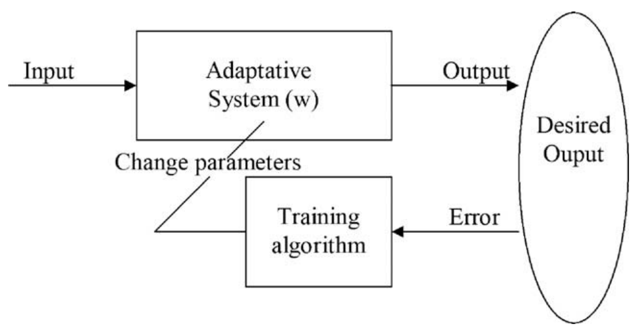

Fig. 2. Schematic diagram of back-propagation ANN.

$$\frac{\partial \eta}{\partial t} + \frac{1}{R\cos\phi}\left[\frac{\partial M}{\partial \lambda} + \frac{\partial (N\cos\phi)}{\partial \phi}\right] = 0 \quad (1)$$

$$\frac{\partial M}{\partial t} + \frac{1}{R\cos\phi}\frac{\partial}{\partial \lambda}\left(\frac{M^2}{D}\right) + \frac{1}{R}\frac{\partial}{\partial \phi}\left(\frac{MN}{D}\right) + \frac{gD}{R\cos\phi}\frac{\partial \eta}{\partial \lambda} + \frac{\tau_x}{\rho} = (2\omega\sin\phi)N + \frac{gD}{R\cos\phi}\frac{\partial h}{\partial \lambda} + \frac{1}{R\cos\phi}\frac{\partial D\psi}{\partial \lambda} \quad (2)$$

$$\frac{\partial N}{\partial t} + \frac{1}{R\cos\phi}\frac{\partial}{\partial \lambda}\left(\frac{MN}{D}\right) + \frac{1}{R}\frac{\partial}{\partial \phi}\left(\frac{N^2}{D}\right) + \frac{gD}{R}\frac{\partial \eta}{\partial \phi} + \frac{\tau_y}{\rho} = -(2\omega\sin\phi)M + \frac{gD}{R}\frac{\partial h}{\partial \phi} + \frac{1}{R}\frac{\partial D\psi}{\partial \phi} \quad (3)$$

Here, λ is the longitude and φ is the latitude; the radius and the angular velocity of the Earth are given by $R = 6378.137$ km and $\omega = 7.27 \times 10^{-5}$ rad/s, respectively; the total water depth is $D = h + \eta$, where h is the still water depth and η is the sea surface elevation; M and N are the water velocity fluxes in the x- and y-directions; the terms τ_x and τ_y (related to Manning's roughness) represent the bottom friction in the x- and y-directions; ψ is the linear dispersion potential.

The initial condition of a tsunami is prescribed as a static instantaneous elevation of sea level identical to the vertical static coseismic displacement of the sea floor, as given by Mansinha and Smylie (1971) for inclined strike-slip and dip-slip faults. Initial sea surface deformation due to multiple and non-simultaneous ruptures is calculated by repeating the fault model of Mansinha and Smylie (1971) for each individual rupture, and the resulting surface deformation is linearly added to the current sea surface. A moving boundary condition is applied for land boundaries to al-

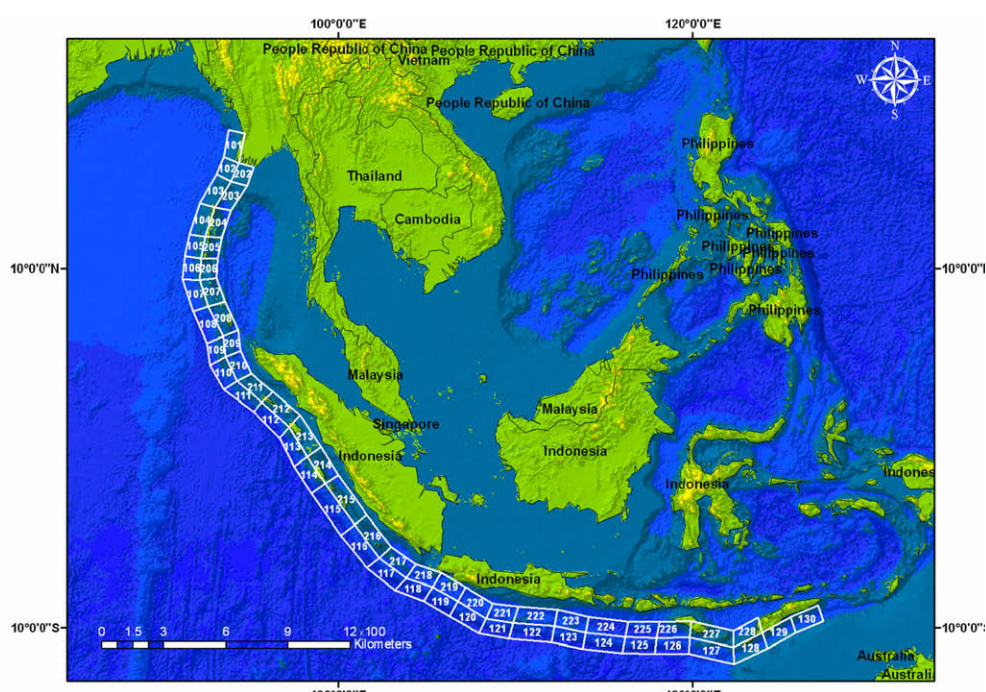

Fig. 3. Segmentation of the Sunda Arc. The entire trench is divided into 30 pairs of boxes.

low for run-up calculation, and free transmitted wave is applied at the open boundaries. The modified version of TUNAMI-N2 (named TUNAMI-N2-NUS) is thoroughly verified using test cases, laboratory experiments and real cases and is subsequently applied to scenario-based tsunami modeling in the Indian Ocean, Dao and Tkalich (2007), Tkalich et al. (2007), Dao et al. (2008).

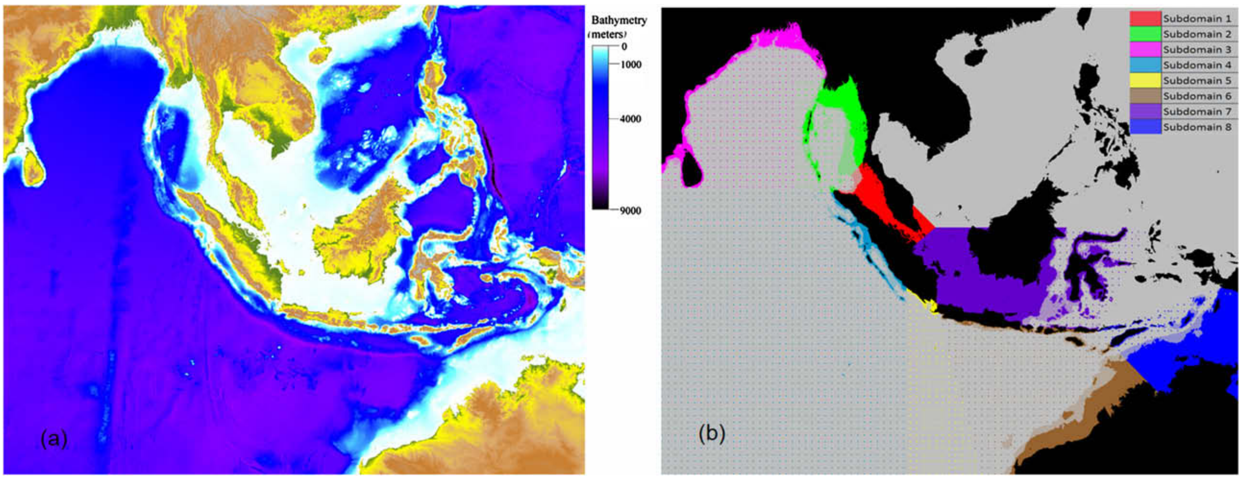

Fig. 4. (a) Bathymetry of the study area and (b) domain decomposition and reduction of number of TUNAMI-N2-NUS gridpoints for ANN training.

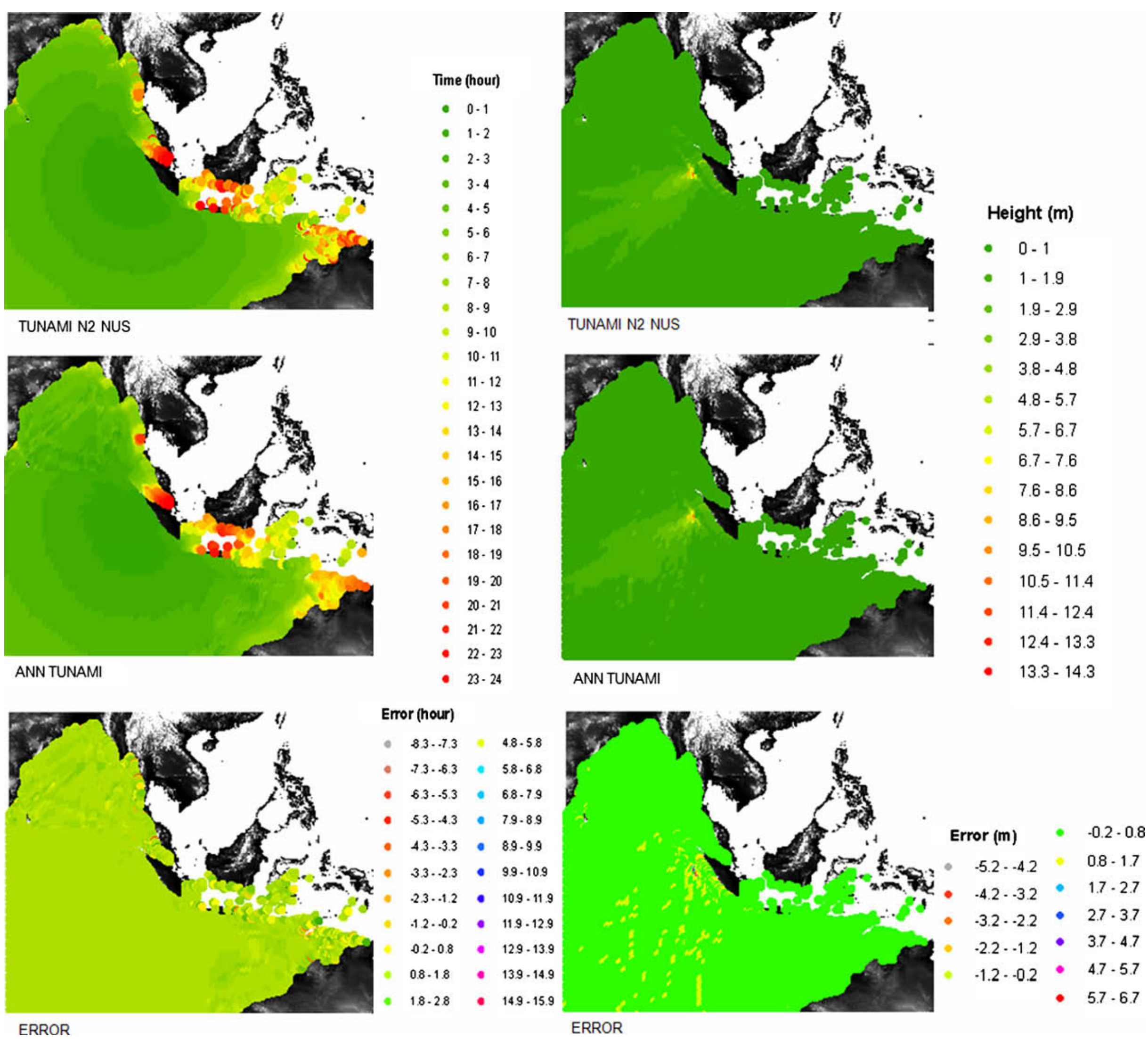

Fig. 5. Arrival times and maximum wave heights resulting from hard- and soft-computing: validation set, earthquake occurs in Box 114, dislocation 26 m.

3. Artificial neural network in tsunami forecasting

3.1. General description

ANN is a powerful data modeling tool that is able to capture and represent complex input/output relationships. According to Haykin (1994), ANN is a massively parallel distributed processor that has a natural propensity for storing experimental knowledge and making it available for use. ANN is known to have the ability to represent both linear and nonlinear relationships and to learn these relationships directly from the data being modelled. It has been proved mathematically that ANNs are universal computing machines capable of arbitrary nonlinear function approximation provided they are given sufficient training data, Hornick et al. (1989). They can be evaluated based on physical model outcomes and experimental/field data can be further integrated in order to enhance their performance. The application of ANN to simulation and/or forecasting problems can now be found in various disciplines. In water resources, for example, the applications date back to early 90s and have increased exponentially since the late 90s, e.g. French et al. (1992), Hsu et al. (1995), Campolo et al. (1999), ASCE Task Committee on Artificial Neural Networks in Hydrology, (2000a,b), Liong et al. (2000), Hu et al. (2001). Maier and Dandy (2000) provide a comprehensive review of 43 papers dealing with the use of ANNs for the prediction and forecasting of water resources variables, as well as a useful protocol for developing such models. In oceanography, their applications began later, e.g. Vaziri (1997), Tsai and Lee (1999), Lee and Tanaka (2002), Supharatid (2003).

In this study the most popular ANN method is used, namely multilayer perceptron, MLP (Bishop, 1995; Reed and Marks, 1999; Fausett, 1994), and back-propagation, BP (Rumelhart et al., 1986). The network attempts to map correctly the input to the output using data computed with process-based TUNAMI-N2-NUS model for the most probable ocean floor rupture scenarios so that the trained network can later be used in the applications to produce the desired output.

A graphical representation of an MLP is shown in Fig. 1.

As seen in Fig. 1, the inputs are fed into the input layer and are multiplied by interconnection weights as they are passed from the input layer to the first hidden layer. Within the first hidden layer, they are summed, and then processed by a selected nonlinear activation function.

As the processed data leaves the first hidden layer, it is again multiplied by interconnection weights, summed and then processed by the second hidden layer. Finally, the data are multiplied

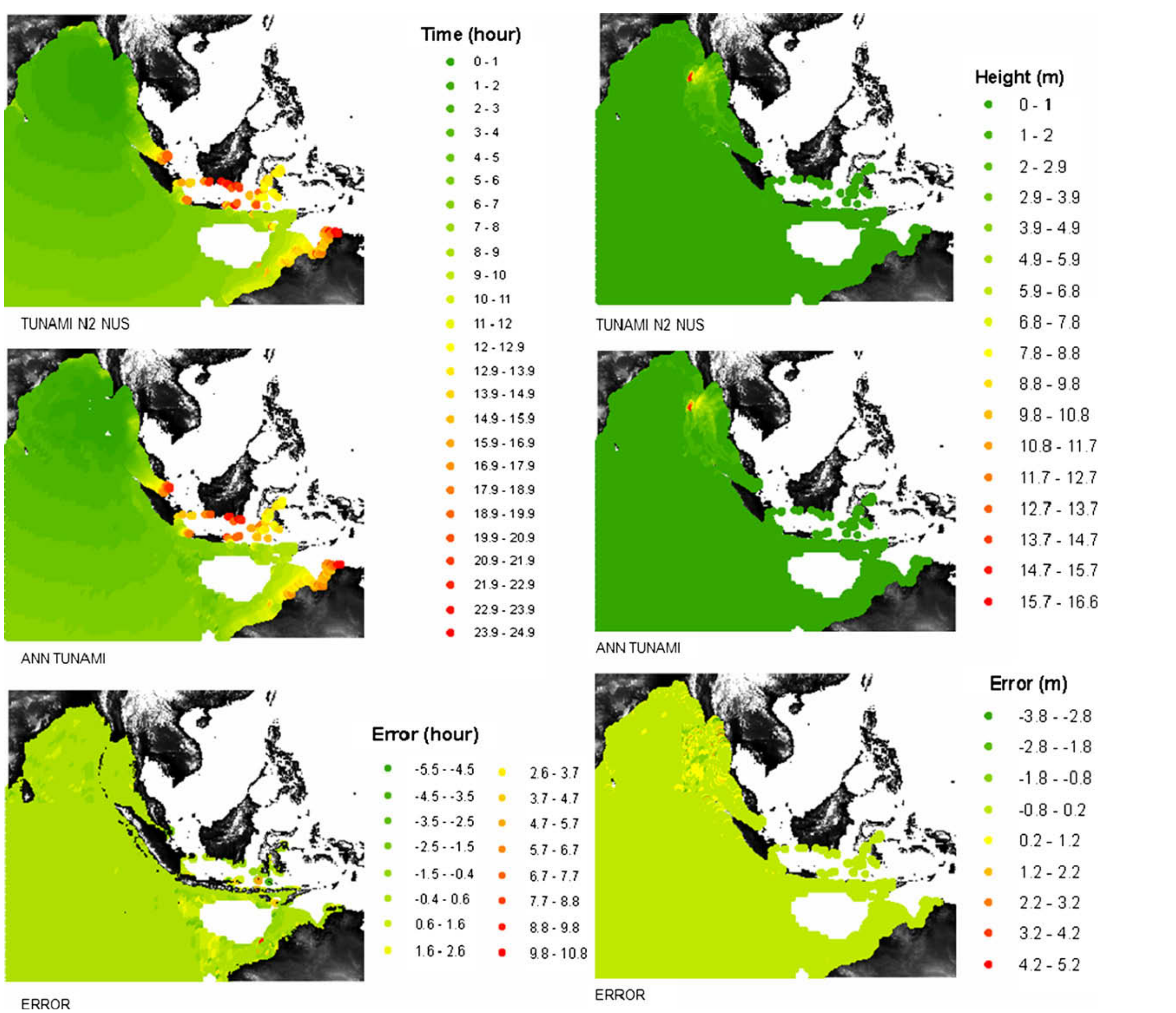

Fig. 6. Arrival times and maximum wave heights resulting from hard- and soft-computing: validation set, earthquake occurs in Box 203, dislocation 35 m.

by interconnection weights and processed one last time within the output layer to produce the neural network output.

With back-propagation (see Fig. 2), the input data are presented repeatedly to the neural network. With each presentation, the output of the neural network is compared to the desired output and an error is computed. This error is then fed back (back propagated) to the neural network and used to adjust the weights such that the error decreases with each iteration and the neural model becomes closer to produce the desired output. This process is known as training.

3.2. ANN application for tsunami forecasting

In this section, ANN is applied to mimic the data produced by a tsunami model TUNAMI-N2-NUS. The training, testing and validation data sets of ANN were simulated by TUNAMI-N2-NUS.

Maximum wave heights and tsunami arrival times at selected grid points in the study areas form the data sets. The neural network software used is Matlab Neural Network toolbox. Two case studies have been conducted. The first case includes the Indian Ocean, Andaman Sea and Singapore waters which are vulnerable to tsunamis generated by subsea earthquakes at the Sunda Arc. The second area includes the South China Sea and Singapore waters which are affected by tsunamis from the Manila Trench. ANN models are constructed each for the Sunda Arc and Manila Trench.

In order to carry out this study, plausible models for the rupture geometry and slip of these two subduction zones are used. The rupture models have been developed at the Tropical Marine Science Institute as part of the Operational Tsunami Prediction and Assessment System (OTPAS) project. These models were derived from geodetic and seismic data and based on fault geometry, aerial maps and historical earthquake data, and have subsequently been adapted for use in the TUNAMI-N2-NUS and ANN models in order to simulate tsunamis using various slip magnitudes.

In this paper, ANN model is demonstrated for the Indian Ocean region which involves the earthquakes from the Sunda Arc. The study area is bounded by longitude 77.7739–136.64598° and latitude −23.371–24.27116°. The subduction zone is segmented into pairs of boxes (as shown in Fig. 3) which represent the fault planes.

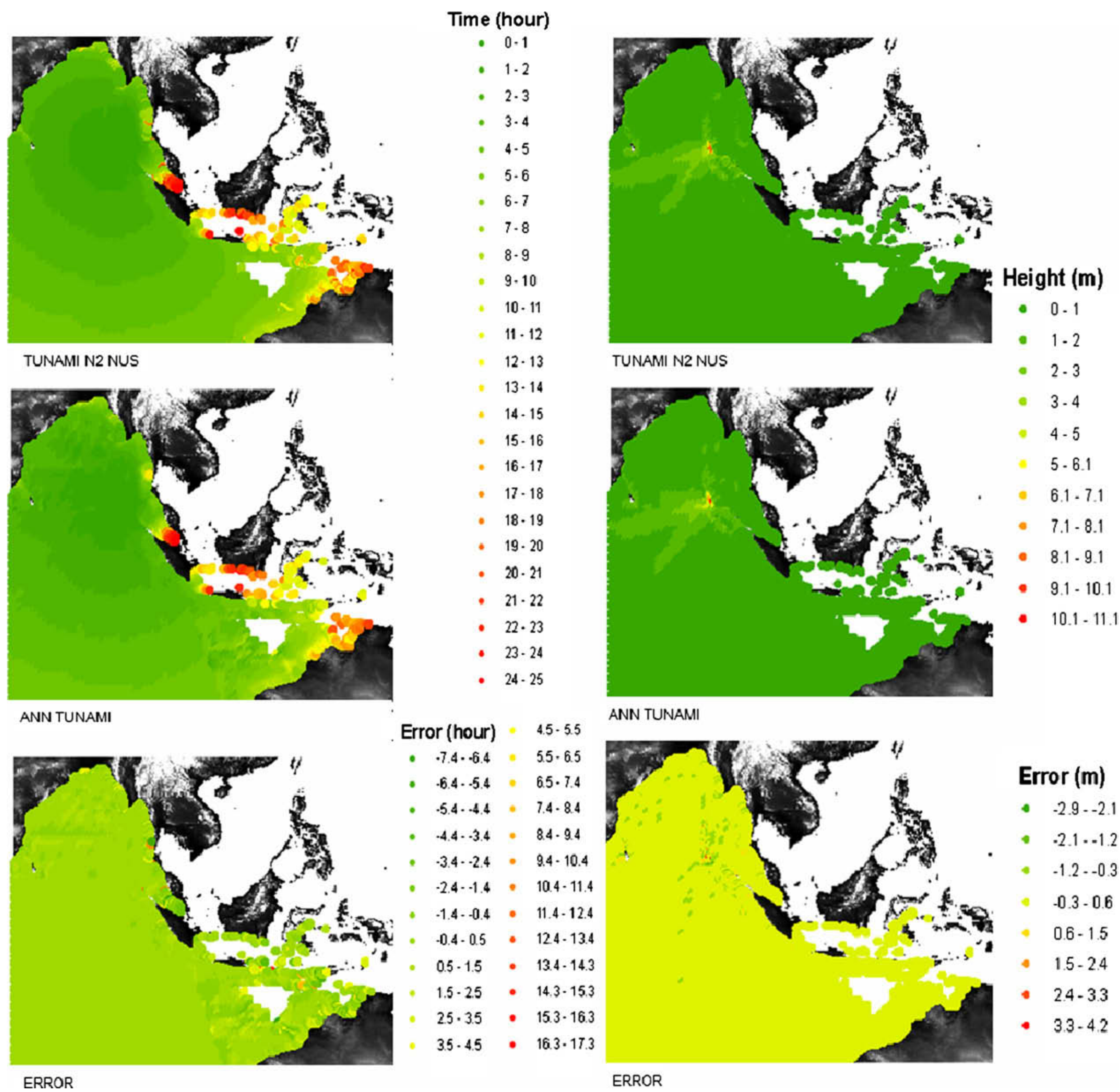

Fig. 7. Arrival times and maximum wave heights resulting from hard- and soft-computing: validation set, earthquake occurs in Box 208, dislocation 25 m.

The segmentation of a subduction zone is first used by NOAA (Titov et al., 2005). A thorough and complete database of the fault parameters (i.e., magnitude, location, dimension of the fault, strike and dip, rake, slip, etc.) was developed for each of these boxes. This database is used as references for the estimating of actual fault parameters which are empirically calculated from the sizes and locations of occurring earthquakes.

To consider the largest number of plausible tsunami events, a database of rupture scenarios is built based on probable permutations of boxes involved in the rupture scenarios. However, to prevent the number of scenarios from growing too large, only certain permutations are chosen. For instance, the following scenarios are selected for the Sunda Arc: every single box (boxes 101–130 and boxes 202–228) ruptures with four different slip magnitudes (10m, 20m, 30m and 40m).

The TUNAMI-N2-NUS grid size is two arc minutes (∼4 km). This translates into 2,526,810 grid points in the domain. TUNAMI-N2-NUS outputs the maximum wave height and wave arrival time at every of the grid points. This challenges the ANN training with a very large computing resource issue. The domain is divided into eight subdomains to reduce the total number of grid points in each subdomain. Grid points in a subdomain are further eliminated to increase the efficiency of the ANN training. The reduction in the number of grid points is performed predominantly in the deep water regions where the wave evolution is much linear and is less concerned in the forecast. No reduction is made, however, in the region close to the coasts where the forecasted tsunamis are greatly concerned. The following criteria are used in reducing the number of grid points for ANN: (i) no reduction is considered for the regions where depths are less than 200 m; (ii) for regions with depths between 200 m and 1000 m every other grid point is discarded in both x- and y-directions; and (iii) for regions with depths greater than 1000 m, only every 20th grid point is retained. These criteria emphasize the results in the coastal areas.

The maximum wave height and wave arrival time in each subdomain will form the training sets for the ANNs. The abovementioned sub-division and reduction also improve the performance of the trained ANN models since they will learn to predict the maximum wave height and wave arrival time in regions with more similar characteristics.

Fig. 4 shows the bathymetry of the study domain, the sub domains and the reduced grid points used for ANN models.

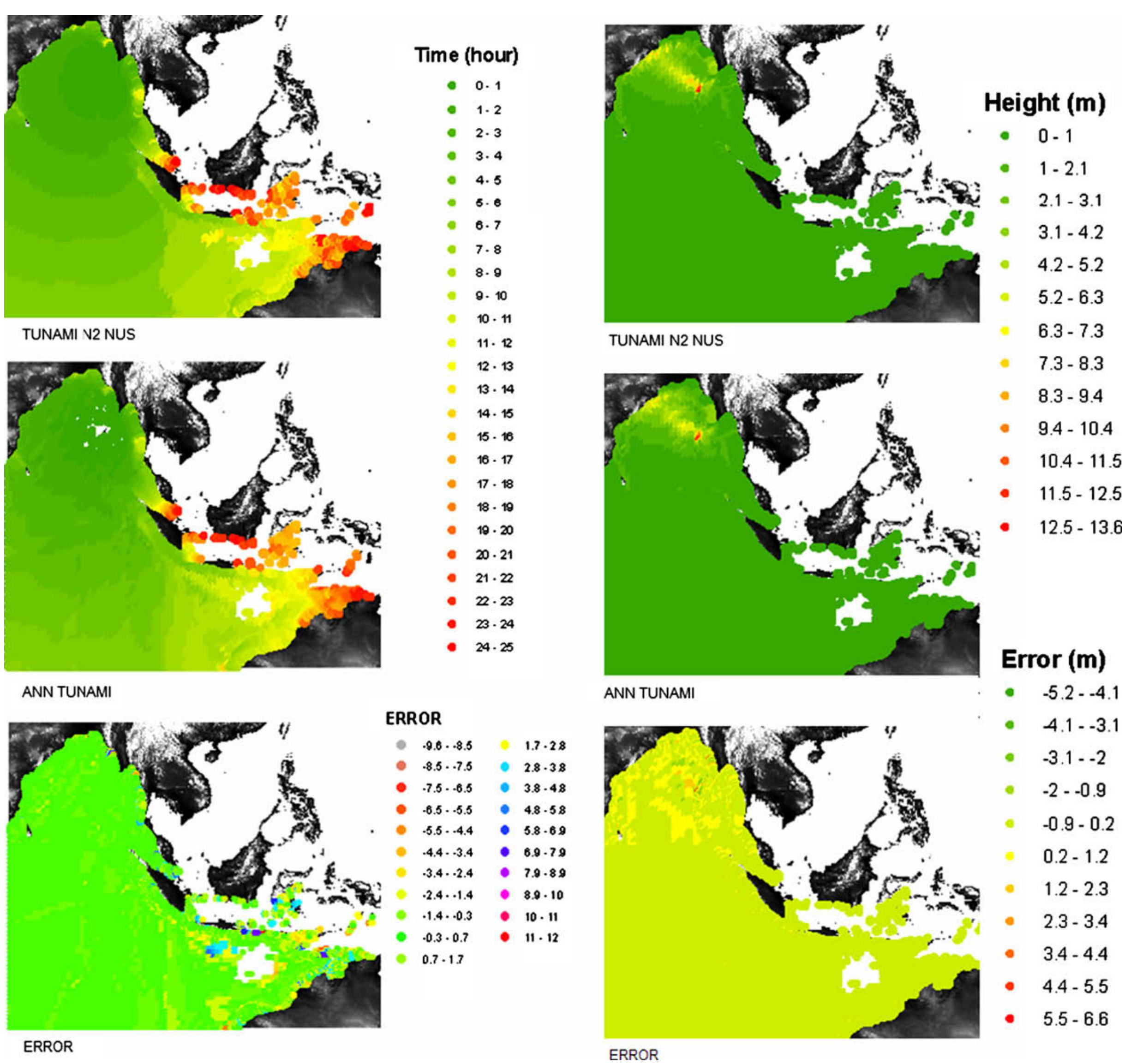

Fig. 8. Arrival times and maximum wave heights resulting from hard- and soft-computing: validation set, earthquake occurs in Box 103, dislocation 35 m.

For each segment/box (boxes 101–130 and 202–228), TUNAMI-N2-NUS is run for four dislocation scenarios (10 m, 20 m, 30 m and 40 m). For each box, two ANN models in each subdomain, one for the maximum wave heights and one for the arrival times, were trained and validated. Validations were conducted for different scenarios in which the dislocation varies between 10 m and 40 m. Here, dislocations of 26 m for Box 114, 35 m for Box 203, 25 m for Box 208, 35 m for Box 103, and 25 m for Box 108 were chosen.

The goodness-of-fit measure used to compare the performance of the ANNs with their TUNAMI-N2-NUS counterpart is the Nash index defined in Eq. (4).

$$r^2 = 1 - \frac{F}{F_0} = 1 - \frac{\sum_{i=1}^{m}(M_i - S_i)^2}{\sum_{i=1}^{m}(M_i - \bar{M})^2} \tag{4}$$

where M is the value from Tunami-N2-NUS, $\bar{M}$ is the mean of M, S is the value predicted by the ANNs, and m is the number of patterns in the training or validation set.

Figs. 5–9 show comparisons of hard-computing (TUNAMI-N2-NUS) and soft-computing (ANN TUNAMI) results for five selected hypothetical earthquakes occurring in five different boxes along the Sunda Arc (box numbers 114, 203, 208, 103 and 108). Discrepancies between the hard- and soft-computing are also illustrated.

Fig. 10 summarizes the number of models in different ranges of Nash index respectively for the wave arrival time and for maximum wave height.

The study shows a reasonably good agreement between the simulations of TUNAMI-N2-NUS and those of ANN for both the arrival time and maximum wave height. As depicted in the respective plots, the error is remarkably small across most of the study area. Only on shallow water close to the coastal areas where the errors seem to be "more" pronounced. The error may, however, be further reduced if the spatial resolution in this region is increased in the TUNAMI-N2-NUS simulation. This means that in the regions where the errors are more pronounced, ANN should be given more patterns to train.

4. Conclusion

The paper presents an effective and efficient data-driven approach, artificial neural network (ANN) used for the prediction of tsunami travel times and maximum wave heights. The forecast re-

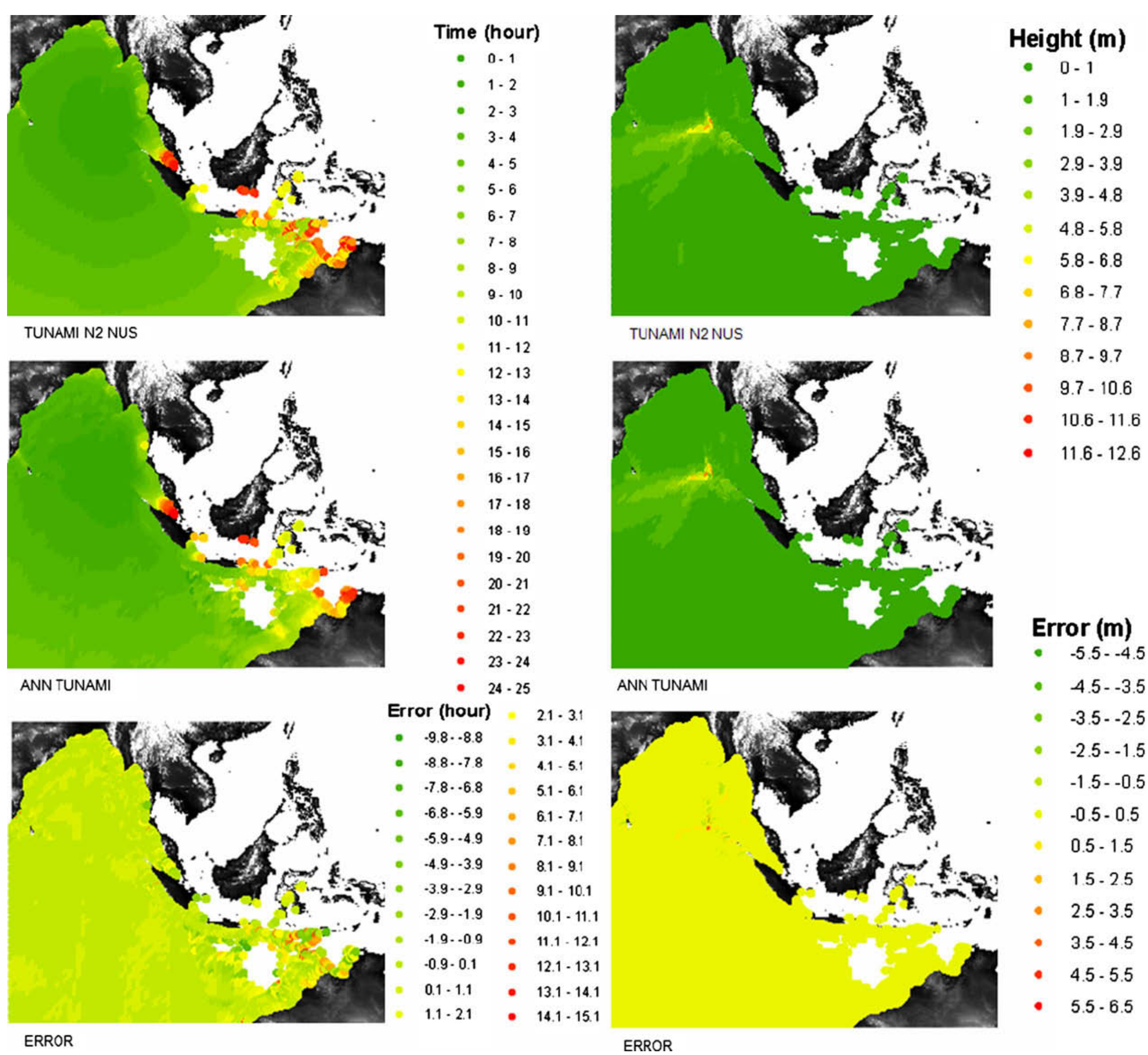

Fig. 9. Arrival times and maximum wave heights resulting from hard- and soft-computing: validation set, earthquake occurs in Box 108, dislocation 25 m.

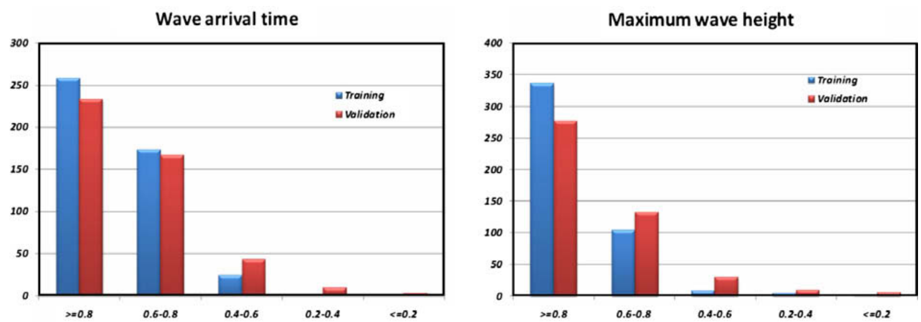

Fig. 10. Number of models in different ranges of Nash index: overall model accuracies.

sults from ANN for some typical fault displacement scenarios are compared with solutions of the deterministic TUNAMI-N2-NUS model.

TUNAMI-N2-NUS is used to generate the maximum wave heights and their respective arrival times of tsunami scenarios from the Sunda Arc. The data obtained are then used to train the ANN models. Validation shows close agreement between results obtained from TUNAMI-N2-NUS and those from the ANN models.

The ANN forecast models require only a few seconds to produce results with accuracies similar to those obtained from a common tsunami propagation model, such as TUNAMI-N2-NUS, requiring tens of minutes CPU time on a standard desktop PC. Moreover, the computation time of ANN is independent of the simulation time of tsunami and spatial resolution of the computational domain. This speed in computation is essential for quick assessments in tsunami disaster management.

The study has additionally shown that the careful selection of input data for the data-driven model drastically improves the accuracy of forecasting. Furthermore, the data-driven models resulting are flexible enough for the user to select multiple faults occurring at any sequence.

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