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Development of Real Time Storm Surge Forecasting Using Artificial Neural Network

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ABSTRACT: In the present study, the real time storm surge forecasting system is described, which is operated along the Tottori coasts, Japan. Within the system, the 3 hourly forecasting models based on feedforward neural network predict time series of the storm surge heights under the warning of Japan Meteorological Agency. The forecasting models are trained by the input and output data sets combined with the parameters and the storm surges of the historical typhoons and the modeled typhoons in the present and future climates that the storm surges in the different climates are calculated by directly inputting the typhoons into the coupled model of surge, wave and tide. It is found that the accuracy of the predicted surge heights are gradually decreased as increasing the forecasting time span. Therefore, it should be improved as refining a structure of the feedforward neural network.

Keywords: Storm surge, Neural network, Real time forecasting, Climate change

1 INTRODUCTION

Storm surge is a severe disaster along coasts due to a tropical cyclone (hereafter, so-called TC), resulting in flooding in low-lying areas and damage in structure as well as life loss. If the storm surge is forecasted before a typhoon makes an influence on the coast, it will be helpful for decision makers to make a decision of the evacuation warning and execution.

The majority of efforts have been made on the real time storm surge forecasting at the coast, however it is still difficult to predict the accurate real time surge at the specified site because information of TCs is insufficient to provide the detailed TC's parameters to the real time storm surge forecasting system. In general, the storm surge height at the coast is highly sensitive to the TC's parameters of track, radius from the TC's center to the maxima wind speed, moving speed and position. However, these TC's parameters are one of the predictions and have uncertainty in reliability.

In recent studies, an artificial neural network has been implemented to forecasting of surges, wave, tsunamis and tides in Coastal Engineering. A feedforward neural network (hereafter, so-called FNN) classed from the artificial neural network is a nonlinear function of its inputs (Dreyfus, 2002). In the real time storm surge system, a supervised training of FNN is essential in order to forecast the storm surge come from the complex physical process, which is the algorithmic procedure whereby the parameters of the neurons of the network are estimated. For the supervised training, the parameters of a tropical cyclone and its storm surge at the coast are generally used (Kim and Matsumi, 2014). FNN is advantageous to the operation time that it is dramatically fast to predict the storm surge in comparison with a system based on a physics-based numerical model, if the real time system is constructed once.

For the real time forecasting an uncertain relationship between the storm surge and the information of TC's parameters should be defined at the specified area in order to forecast a storm surge during a future event. Structures of the artificial neural network are not well known as well. In addition, the prediction of FNN, which is trained from the information of TC's parameters and storm surges, is a way of interpolations. Therefore, FNN is not able to forecast a storm surge generated by an extraordinary tropical cyclone that it is not included in the training data sets or scenarios for FNN in developing the real time storm surge system.

In the present study, we present the development of the real time storm surge forecasting system based on the feedforward neural network at Sakai Minato, which is trained from the parameters and storm surges observed from the historical typhoon along the Tottori coasts, Japan and obtained from the projection data of the present (1978-2008) and future (2075-2099) climates.

2 THE REAL TIME STORM SURGE FORECASTING SYSTEM

2.1 *Overview of forecasting system*

Figure 1 shows the schematic diagram for the framework of the real time storm surge forecasting system operated by Chukoku Regional Development Bureau, Ministry of Land, Infrastructure, Transport and Tourism, Japan. As seen in Figure 1, the forecasting system will be operated under a warning of Japan Meteorological Agency (JMA) when a typhoon will generate the storm surge at Sakai Minato. With the warning, the system starts to collect the necessary components observed at every meteorological stations and the surge height at Sakai Minato. These are used as the compositions of input data sets in FNN at every time. During the operation, the pre-developed FNN will be served, which is trained by the prequalified combination of the meteorological and hydrodynamic components throughout the sensitivity study (Kim and Matsumi, 2014). The present system consists of 3 hourly forecasting FNNs that these are independently and individually developed at t + 0h, t + 3h, t + 6h, t + 9h, t + 12h, t + 15h, t + 18h, t + 21h, t + 24h, t + 27h and t + 30h. Within the framework, every individual forecasting model concurrently predicts the storm surge at the corresponding time under the warning of JMA that the typhoon will approach to the Tottori coasts. Therefore, it is expected that the short-term forecasting will supplement an accuracy of the long-term forecasting in the real time storm surge forecasting system.

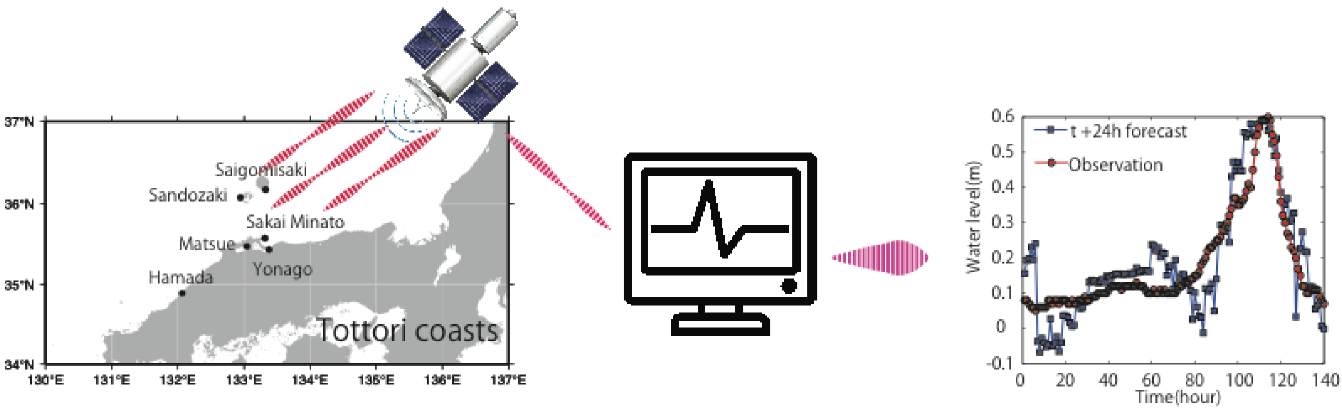


Figure 1. Schematic diagram for the framework of the real time storm surge forecasting system.

2.2 *Description of feedforward neural network*

The feedforward neural network (FNN) used in this study is described as a set of neurons, where the information flows from the inputs to the outputs. FNN consists of a single layer of the input, a single layer of the hidden neuron and a single layer of the output with a log-sigmoid activation function.

For the inputs, the hourly measurements of the surge height at Sakai Minato, the sea level pressures (5 stations), the depression rates of the sea level pressures (5 stations) and the position of the typhoon (longitude and latitude) are combined for the input layer. This combination is based on the consequence introduced by Kim and Matsumi (2014). The number of neurons in the hidden layer is of the same number of the components in the input layer: 13 neurons. The surge height of t + ah at Sakai Minato is the parameter in the output layer, where a is the forecast time span.

For training FNN, we followed the method used in Kim and Matsumi (2014). That is to say, the back-propagation optimization technique is applied to estimate the weights of the neurons in the network. Among the back-propagation algorithms, the Levenberg-Marquardt algorithm was chosen because of the computation time and memory size. The Bayesian method is employed to avoid a large number of meaningless computations as well as the insufficient training.

2.3 *Historical typhoon*

For the historical typhoons, we gathered the measured parameters during Typhoon Maemi (2003), Megi (2004) and Songda (2004) that these generated the storm surge at Sakai Minato as seen in Figure 2. The parameters of the storm surge, the sea level pressure, the depression rate of the sea level pressure and the typhoon's position for Typhoon Maemi and Songda are composed into the input data sets together with those of the modeled typhoon in the present and future climates. The parameters for Maemi are used to validate the trained FNN.

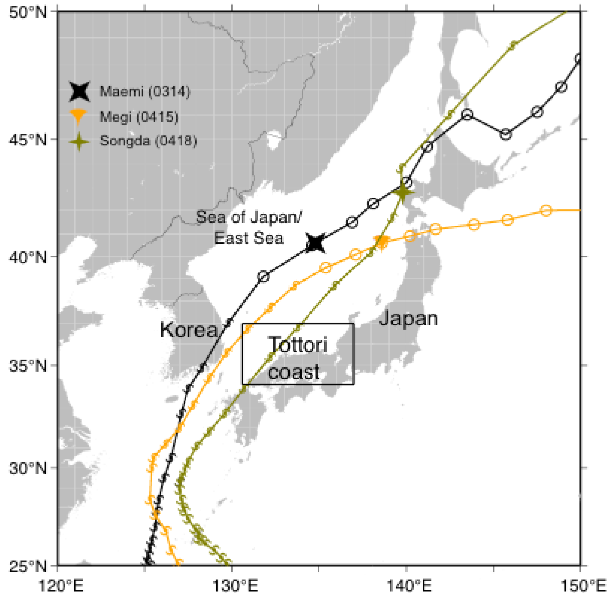
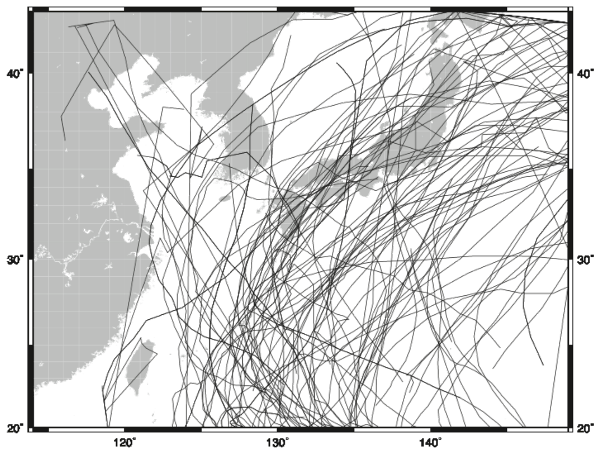
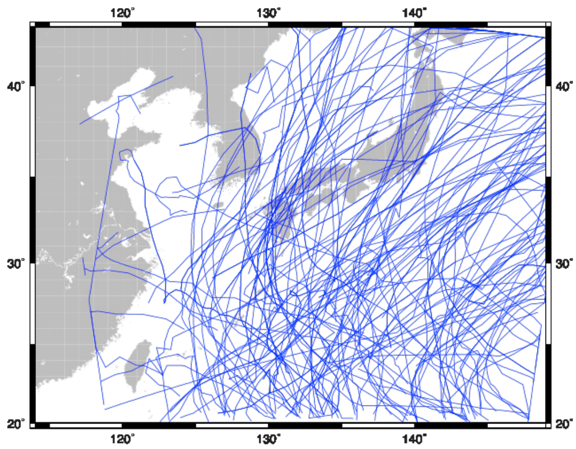


Figure 2. Historical typhoon's tracks used for training and validation.



(a) the present climate



(b) the future climate

Figure 3. Modeled typhoon's tracks in the present and future climates for training.

2.4 *Climate projection typhoon Modeled typhoon in the present and future climates*

2.4.1 *Modeled typhoon in the present and future climates*

In order to supplement the lack of typhoons for training FNN, we have used the modeled typhoons in the present and future climates projected by the atmospheric general circulation model (AGCM). Meteorological Research Institute of Japan Meteorological Agency (MRI) have developed and operated MRI-AGCM 3.1S and 3.2 models, which are contributed to IPCC fifth assessment report. MRI-AGCM is one of state-of-the-art GCMs with a 20 km mesh in the horizontal resolution in the global domain (Kitoh et al., 2009). In the experimental frame, three climate periods of 1979-2008, 2015-2039 and 2075-2099 were conducted with different sea surface temperatures in the bottom boundary conditions in the MRI-AGCM. The climate projections followed the scenario of A1B. The detailed descriptions are addressed in Yasuda et al. (2014).

In this study, we used the projected typhoons for two climates of the present (1979-2008) and future (2075-2099) climates as shown in Figure 3 for the training data of FNN. According to Yasuda et al. (2014), the similar number of tropical cyclones for the present climate in the area of 0° - 60° N and 100° - 180° E were projected in comparison with the historical ones. The annual average numbers of tropical cyclones in the present climate and the history are 22 and 26, respectively. These standard deviations are 6 and 4. The annual average number of tropical cyclones in the future climate is 19 and its standard deviation is 7.

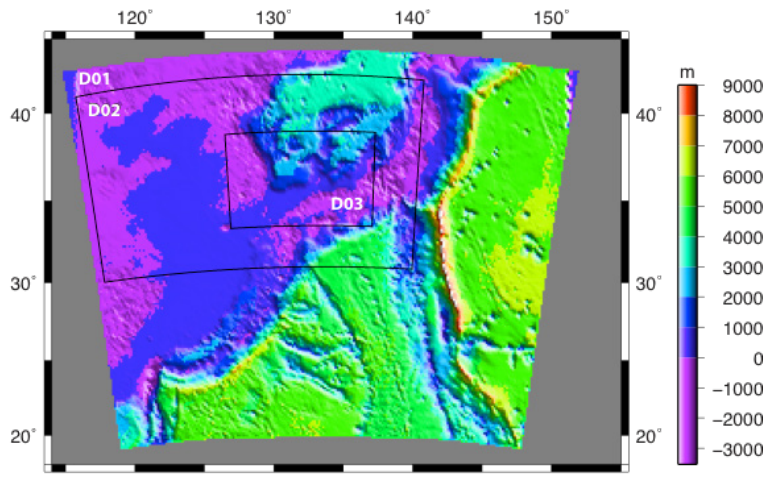
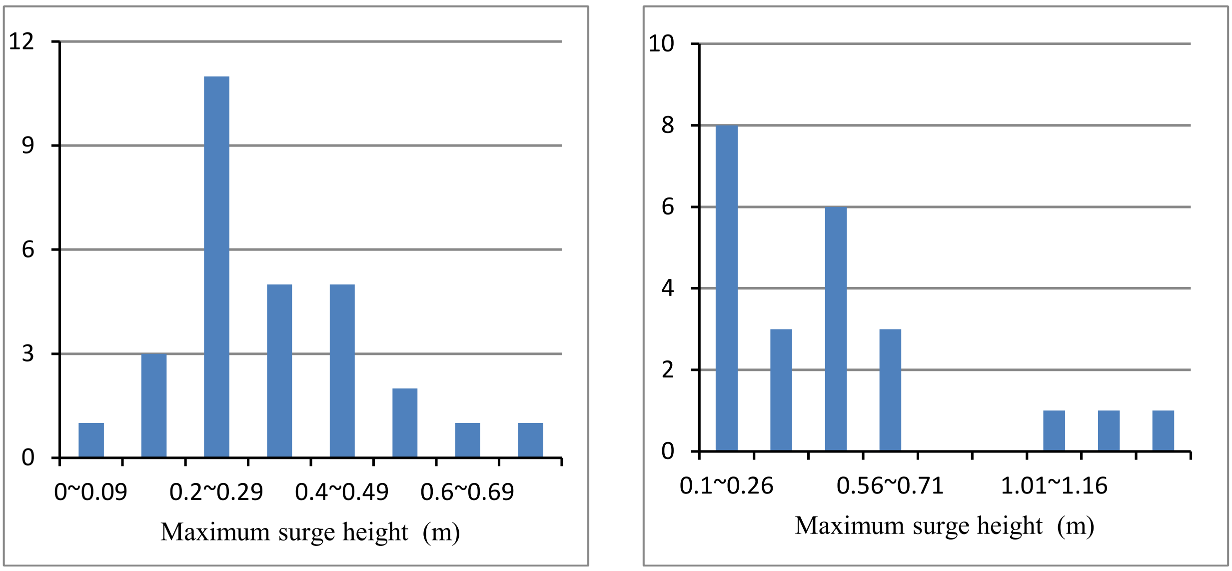


Figure 4. Computational regions downscaling from 12 km to 1.3 km for the storm surge simulation.



(a) the present climate

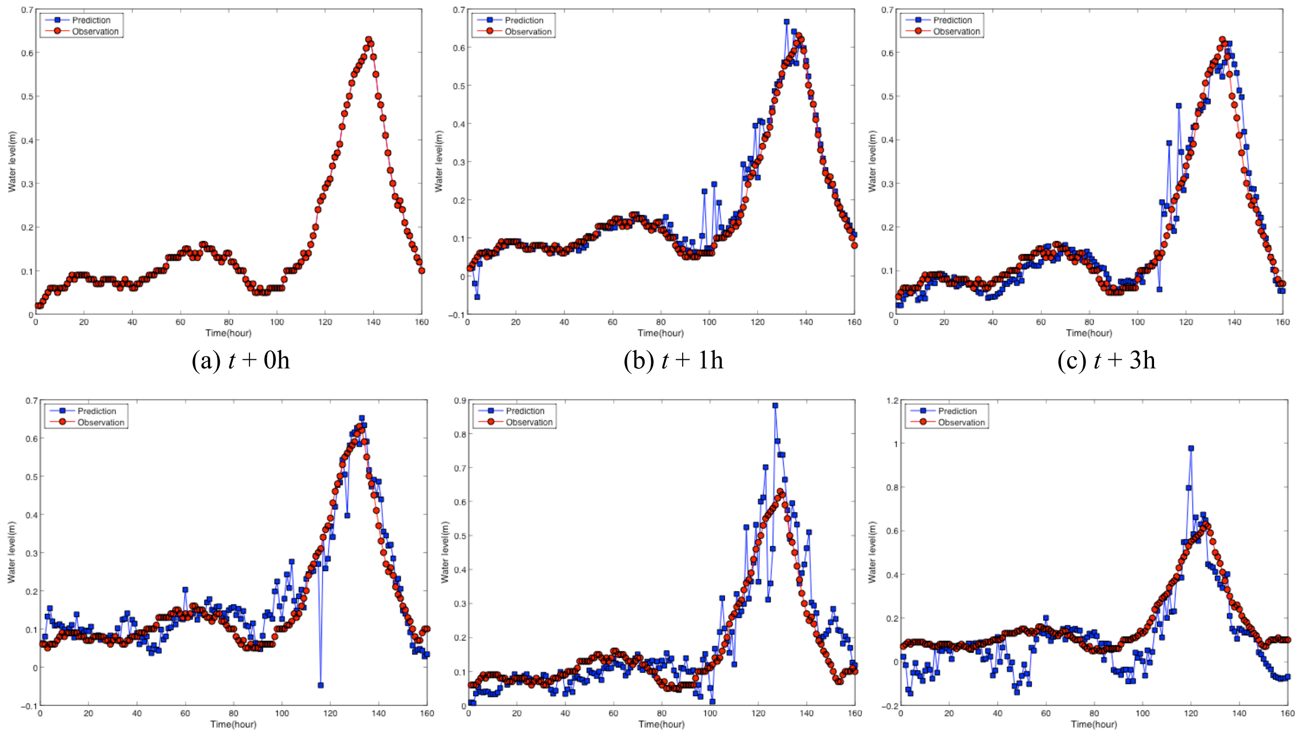
(b) the future climate

Figure 5. The number of annual maximum surge heights in the storm surge simulations under the present and future climates at Sakai Minato.

2.4.2 *Storm surge simulations in the present and future climates*

A series of storm surge simulations have been carried out by directly inputting the output data obtained from two climates into the coupled model of surge, wave and tide (SuWAT) developed by Kim et al. (2008). Figure 4 shows the computational regions, which has three nested domains, downscaling from 12 km to 1.3 km in the grid sizes focusing on the Tottori coasts. The SuWAT model is able to parallelize a nested domain using Message Passing Interface (MPI). In the simulations, only a storm surge mode is used to calculate the storm surge because it can make a fast computing process in SuWAT without coupling with waves and tides. Therefore, in this computation, the detailed physical mechanism of the storm surge is not included: wave-current interaction in the bottom boundary, wave-dependent drag coefficient in the sea surface boundary, wave-induced radiation stress and surge-tide interaction, for instance. More than 218 and 270 tropical cyclone events extracted from the experiments of MRI-AGCM are taken into account in the storm surge simulations.

After completing the simulation, we examined the events that those generated the storm surge at Sakai Minato along the Tottori coasts. Then, we gathered time series of the parameters: the storm surges at Sakai Minato, the meteorological data of winds and sea level pressures at 5 stations along the Tottori coasts and the typhoon's position of longitude and latitude in degree for individual event in the different climates. Figure 5 shows the numbers of the annual maximum surge heights at Sakai Minato for the present and future climates. It was found that the climate change is apparent in the storm surge at Sakai Minato as occurring higher the maximum surge heights in the future climate in comparison with those in the present climate. These parameters collected have been used for training the real time storm surge forecasting system based on FNN at each forecasting time.



(a) t + 0h (b) t + 1h (c) t + 3h

(d) t + 6h (e) t + 9h (f) t + 12h

Figure 6. Comparisons of the observed and predicted storm surges at Sakai Minato for forecasting models at t + 0h ~ t + 12h. (clrcle: the observation, square: the prediction).

3 EXPERIMENTS OF FORECASTING

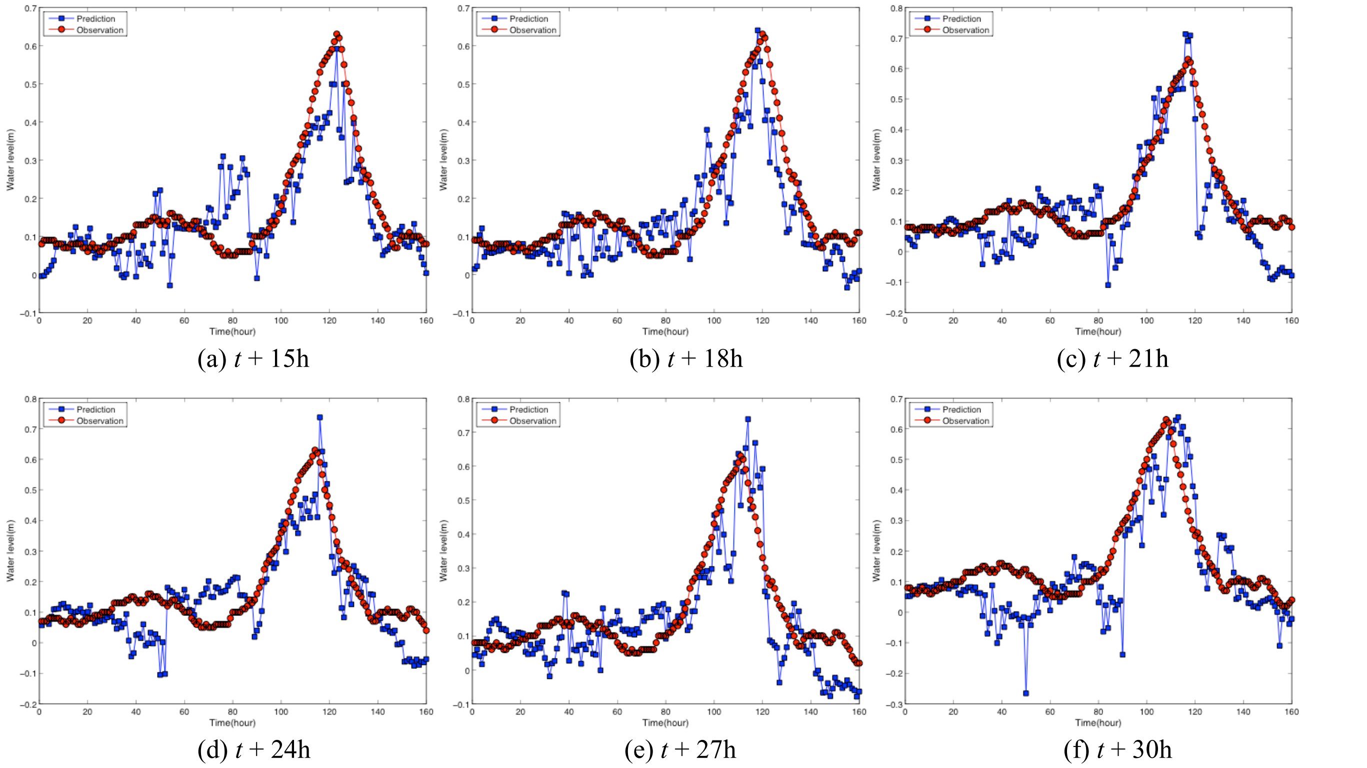
3.1 *Results and discussion*

In this experiments, we made trains of every FNN by 10,000 epochs (iterations) with the input data sets gathered from the historical and projected events. For every FNN, we carried out the 20 runs and examined two statistical indices of the correlation coefficient and the root mean square error between the predicted and observed Maemi surges. It is expected that weighted values in the hidden layers are updated by re-training FNN.

Then, the best results among the runs are shown in Figures 6 and 7. The t + 0h forecasting FNN predicted well the time series of Maemi surge. As increasing the forecasting time span, an oscillation appears in a time series of predicted surge heights. In addition, it is seen that a predicted surge height suddenly spike at a time. From the forecasting time span of t + 15h to t + 30h, the oscillation seems to become apparent in a time series of predicted surge heights. However, all the forecasting FNNs predicted well the Maemi's maximum surge heights.

The statistical indices are summarized in Figure 8. The correlation coefficients of t + 0h ~ t + 15h forecasting FNNs are gradually decreased from 1 to 0.8. For the t + 18h ~ t + 30h forecasting FNNs, the change of the correlation coefficients is insignificant in the range of 0.9 to 0.8. For the t + 0h ~ t + 15h forecasting FNNs, the root mean square errors are steadily increased from 0 to 0.5. As seen in the correlation coefficient, the errors are also changing in the range of 0.5 to 0.3 in the cases of the t + 18h ~ t + 30h.

These behaviors of statistical indices that long-term forecasting FNNs are inaccurate are quite similar with Kim and Matsumi (2014) even thought in the present study, the training input data are dramatically increased for the FNNs as incorporating the modeled typhoon's parameters and surges in the present and future climates. These results may come from the use of same training processes: the number of epochs, the number of hidden layers and a starting time for forecasting, for instance. In addition, a structure of feedforward neural network should be refined to improve accuracy of forecasting models.



(a) $t + 15$h (b) $t + 18$h (c) $t + 21$h

(d) $t + 24$h (e) $t + 27$h (f) $t + 30$h

Figure 7. Comparisons of the observed and predicted storm surges at Sakai Minato for forecasting models at t + 15h ~ t + 30h. (clrcle: the observation, square: the prediction).

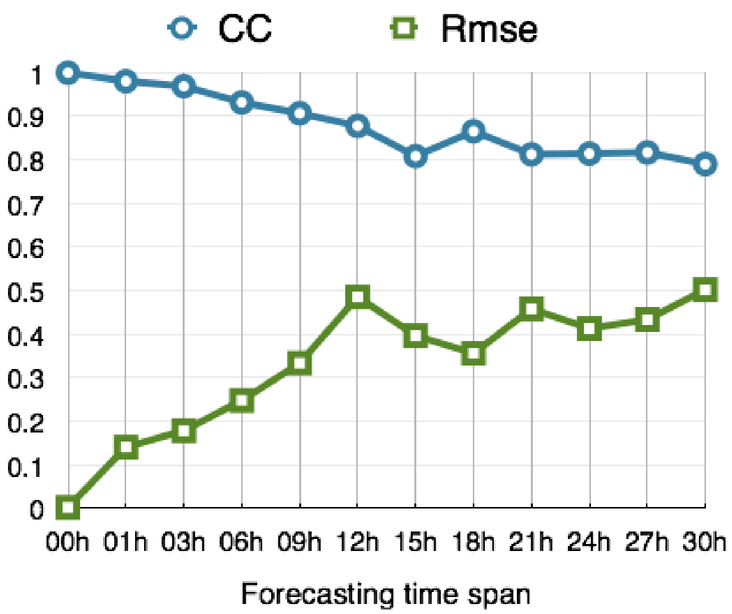


Figure 8. Statistical indices of the correlation coefficient and the root mean square error for the forecasting FNNs.

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