Article

Storm Surge Prediction Based on Long Short-Term Memory Neural Network in the East China Sea

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Abstract: As an area frequently suffering from storm surge, the Yangtze River Estuary in the East China Sea requires fast and accurate prediction of water level for disaster prevention and mitigation. Due to storm surge process being affected by the long-term and short-term correlation of multiple factors, this study attempts to introduce a data-driven idea into the water level prediction during storm surge. By collecting the observed meteorological data and water level data of 12 typhoons from 1986 to 2016 at the Lusi tidal station of Jiangsu Province, China near the north branch of the Yangtze River Estuary, a Long Short-Term Memory (LSTM) neural network model was constructed by using multi-factor time series to predict the water level during the storm surge period. This study concludes that the LSTM model performs precisely for 1 h prediction of water level during the storm surge period and it can provide a 15 h prediction of water level within a limited error, and the prediction performance of the LSTM model is visibly superior to the four traditional ML models by 41% in terms of Accuracy Coefficient.

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Keywords: storm surge prediction; long short-term memory; neural network

1. Introduction

Storm surge is a complex atmosphere-ocean coupled process which is characterized by the sudden occurrence of rising water and waves. It is widely known that the estimated maximum wind speed is a vital indicator of storm damage [1–3], because strong winds accompanied with low atmospheric pressure can push the water to pile up above normal levels [4]. Typhoons or hurricanes are the most energetic atmospheric force acting on coastal and estuarine waters and thus are the most serious natural disaster among marine disasters, which would cause significant changes in hydrodynamics like water level or storm surge [5–8]. Due to the warmer sea surface water [9–11] induced by the trend of climate warming in recent years, typhoon average intensity is expected to increase by 14% over the Northwestern Pacific by 2100 [12]. Sea level rise is considered as an important factor of storm surge. The sea level rise projected in this century by many researchers [13,14] will aggravate the threat from storm surge flooding, and the effects of sea level rise need to be considered to deal with the influence of climate changes on coastal areas. Storm size, which is usually represented by the radius of maximum windspeed, is another factor that is less focused on. Irish et al. (2008) analyzed the observed historical storm data along with the idealized numerical simulation data to find that storm surge increases with storm size, especially for the case of intense storms on very shallow slopes [15].

China is one of the nations most prone to suffer from storm surge, as more than one-third of its coastal cities are located in the high-risk zones [16]. When storm surge coincides with high astronomical tides, exceptional high water levels can occur near the mouth of estuaries and rivers [17], which can cause dike overflowing, seawall failure and

salinity intrusion, resulting in a large economic loss [18] and a huge impact on water supply. Therefore, it is necessary to carry out research on observation and prediction of storm surge.

Observations and numerical simulations have been the main ways to investigate the storm surge in the estuary area. A number of numerical simulation models have been developed to improve the forecasting of storm surge. Lin et al. [19] coupled a statistical/deterministic hurricane model with the hydrodynamic model SLOSH to predict and assess the risks of New York area. They used this model to generate a large number of synthetic surge events and the model can be extended to consider the effect of future climate change. Yin et al. [20] used FVCOM to simulate the direct landing typhoon and the offshore northward typhoon and found the responses of storm surge to the representative tracks and storm timing in the Yangtze River Estuary. Shi et al. [21] developed a storm surge model established by ADCIRC and simulated the inundation caused by typhoon and applied an effective tool for predicting the risk of storm surge.

The numerical simulation for the typhoon storm surge is time-consuming in most cases, while the emergency response to the disaster caused by storm surge requires a fast and reliable model for predictions of storm surge height so as to mitigate the environmental, social and economic damages. Machine Learning (ML) is a suitable surrogate method to ease the computational burden of physical process-based model [22]. ML refers to the method of learning general rules from limited observational data, and using these rules to make prediction or inferences [23]. Generally, ML algorithms are divided into three categories, i.e., Supervised Learning, Unsupervised Learning, and Reinforcement Learning [24,25]. Supervised Learning (e.g., Bayesian Ridge Regression, Linear Regression, Elastic Net, Support Vector Machine, Gradient Boosted Decision Tree, XGBoost, and Neural Networks) aims to establish the relationship between the sample characteristics and labels, and each sample in the training set has a label. The relationship trained by a Supervised Learning algorithm is used either for predicting categorical values (i.e., classification tasks), or for predicting continuous values (i.e., regression tasks). Unsupervised Learning refers to learning of valuable information from training samples without labels, which is often used to identify patterns in big data or abstract low-dimensional representation of big data. Reinforcement Learning is a ML algorithm that carries out learning through interaction, in which agents use learning strategies to maximize rewards or achieve specific objectives in the process of interacting with the environment.

With the boost of data abundance and computer power, ML has shown huge potential in climate, meteorological and oceanographic fields with satisfying results [26], and further applied to morphodynamics [27]. In terms of the application of ML, especially Neural Networks in Tropical Cyclone (TC), it covers the meteorological prediction of TC [23], the oceanographic prediction responding to the meteorological action [22], and the morphodynamical prediction responding to the oceanographic action [27]. The meteorological prediction involves the genesis forecast, the track forecast and the intensity forecast of TC. The genesis forecast of TC includes short-term forecast [28–34] which is defined as predicting whether TC precursors will evolve into TCs, and long-term forecast [35–39] which is defined as predicting the numbers of TCs in vulnerable areas for the upcoming TC season. The track forecast of TC investigated by many researchers focuses on the improvement of path prediction [40,41], valuable predictor selection for building ML-based forecast models [42–44] and similarity search by which forecasters find similar historical TC cases to achieve the final forecast goal [45–53]. The intensity forecast of TC is usually concentrated on predicting the maximum wind speed or minimum sea level pressure at the center of a TC [54–56]. The oceanographic prediction responding to the meteorological action of TC using Neural Networks involves the prediction of storm surge [26,57–59], extreme waves [60–65], etc. The morphodynamical prediction responding to the oceanographic action of TC applies Neural Networks to sandbar movement [66–68], seasonal beach profile changes [69], and longshore sediment transport [70,71]. In addition to TC prediction, Neural Networks has been widely applied in the prediction of tidal level [72–75], wave height [61,76] and coastal floods [77]. Compared with conventional method for tidal level

prediction (harmonic analysis), the excellent nonlinear problem processing capability of Neural Networks solves the environmentally influenced noises of seasonal effects and TC-induced surge superposed on the astronomical tide level series [75]. Many studies have attempted single-layer Neural Networks or multi-layer Neural Networks (known as Deep Neural Networks, DNN) to predict tidal levels or storm surges [58,78–80]. Since tidal levels and storm surges are varying with time, Recurrent Neural Networks (RNN), as a branch of Neural Networks, is a preferable option with better capability of predicting time series. Long Short-Term Memory (LSTM) proposed by Hochreiter and Schmidhuber [81] is a state-of-art development of RNN, whose disadvantages, including the disappearance or the explosion of gradient when dealing with long sequence data, are overcome [82,83]. As a favorable method for the description and prediction of time series, it is wide applied in multiple scientific and engineering fields, e.g., text recognition [84], speech recognition [85], handwriting recognition [86], trajectory prediction [87], disease diagnosis [88], stock analysis [89], oil production [82], and electricity price [90]. LSTM is also employed to predict tidal level [73,75]. However, when it comes to dealing with the sea level during the typhoon period, which is composed of the pure tidal level and the intense typhoon-induced nonlinearity, it becomes complicated for prediction. Hence, it is an optional idea, which is implemented in this research, to take the meteorological data along with the total water level composed of the pure tidal level and the typhoon induced storm surge as the input for the LSTM model.

It is well-known that the Yangtze River Delta area, as one of the most important regions of China, is highly developed in economy and densely populated. However, it is vulnerable to coastal disasters such as typhoon, therefore it is vital to make fast disaster warning to reserve time for preparation of disaster prevention measures. In this research, a fast early-warning system based on a LSTM model for water level prediction of storm surge at Lusi tidal station, Jiangsu Province, China near the Yangtze River mouth was established. The LSTM model was trained by the time series of water level based on 12 typhoons affecting the Yangtze River Delta area from 1986 to 2016. This paper was organized as follows: Section 2 explains the relevant theory of the applied models. Section 3 gives the specific workflow to establish the LSTM prediction model and the model results are analyzed. Section 4 extends the prediction time of the LSTM model and then compares four other ML models with the LSTM model. Section 5 summarizes the main conclusions.

2. Methods

The forerunner of LSTM neural network is Recurrent Neural Network (RNN) [91], which is the evolution of Multi-Layer Perception and is capable of processing sequential data due to its short-term memory ability. The memory ability is realized by the so-called hidden state h which is transmitted from the former hidden layer cell to the next which is the major improvement to Feedforward Neural Network [92]. A traditional RNN structure whose hidden layer is unfolded into a full network is shown in Figure 1a, and the formulas correspondingly are shown as follows:

$$h_t = f(Uh_{t-1} + Wx_t + b), \quad (1)$$

$$y_t = Vh_t, \quad (2)$$

where x_t is the input, y_t is the output, h_t is the hidden state which is transmitted to the next hidden layer cell. The subscript t denotes the time step. f is the nonlinear activation function which is typically applied with tanh. U , W , b and V are the hyperparameters to be calibrated.

The cycle of the hidden state can store the information of the previous step to keep the dependency between the hidden layer cells, and it can improve the ability of learning and extracting characteristics from the sequential data. However, the long-term dependence problem [93], e.g., the vanishing or exploding of the gradient during the back-propagation calculation, cannot be well-solved. Therefore, LSTM neural network is proposed to improve

RNN with the Gating Mechanism [81], selectively adding new information and forgetting previously accumulated information. The structure of LSTM is more complicated compared with RNN and is shown in Figure 1b.

Figure 1. The typical structure of (a) traditional RNN and (b) LSTM.

Compared with RNN, LSTM neural network [82,83], as shown in Figure 2, introduces a new internal state c_t , which delivers information linearly to the next hidden layer cell and outputs information nonlinearly to the hidden layer's external state h_t (which is analogous with the hidden state h_t in RNN). c_t and h_t are expressed as follows:

$$c_t = f_t \cdot c_{t-1} + i_t \cdot \tilde{c}_t, \quad (3)$$

$$h_t = o_t \cdot \tanh(c_t), \quad (4)$$

$$\tilde{c}_t = \tanh(W_c x_t + U_c h_{t-1} + b_c) \quad (5)$$

where c_t is the internal state. f_t , i_t , o_t are the three gates to control the path of information transmission. The subscript t denotes the time step. $\tilde{c}_t$ is the candidate state through the nonlinear activation function $\tanh$. U , W , b and V are the hyperparameters to be calibrated and the subscript c represents $\tilde{c}_t$.

LSTM neural network introduces Gating Mechanism to control the path of information transmission, i.e., forget gate, input gate, and output gate. The formulas of these three gates are expressed as follows:

$$f_t = \sigma(W_f x_t + U_f h_{t-1} + b_f), \quad (6)$$

$$i_t = \sigma(W_i x_t + U_i h_{t-1} + b_i), \quad (7)$$

$$o_t = \sigma(W_o x_t + U_o h_{t-1} + b_o) \quad (8)$$

where f_t is the forget gate to control how much information needs to be forgotten about the internal state c_{t-1} of the previous time step. i_t is the input gate to control how much information needs to be saved about the candidate state $\tilde{c}_t$ of the current time step. o_t is the output gate to control how much information about the internal state c_t needs to be output to the external state h_t at the current time step. U , W , b , and V are the hyperparameters to be calibrated and the subscripts f , i and o represent forget gate, input gate and output gate,

respectively. The nonlinear activation function σ is the sigmoid function which enables values between 0 and 1, and it is expressed as:

$$\sigma(x) = \frac{1}{1 + e^{-x}}, \quad (9)$$

From the flow chart of LSTM neural network in Figure 1b, the computational process is as follows: firstly, the external state h_{t-1} of the previous time step and the input x_t of the current time step are used to calculate the three gates f_t , i_t , o_t and the candidate state $\tilde{c}_t$; secondly, the forget gate f_t and the input gate i_t are integrated to update the internal state c_t ; finally, combined with the output gate o_t , information about the internal state c_t is passed to the external state h_t .

In addition to the LSTM neural network method, several other ML methods, i.e., Bayesian Ridge Regression (BRR), Gradient Boosted Decision Tree (GBDT), Linear Regression (LR) and Support Vector Regression (SVR), are used in this research as a comparison group. BRR, based on Bayesian knowledge, is aimed to solve the problem of multicollinearity in linear regression, and to serve the purpose of estimating regression coefficients and selecting variables [94]. GBDT is a suitable method for classification and regression problems, which uses decision stumps or regression trees as weak classifiers [95]. LR is the most basic and widely used model in ML and statistics, which is a regression analysis to model the relationship between independent variables and dependent variables. SVR is also widely used as another type of ML approach, which finds a line or a hyperplane in a higher dimension to fit the data [96]. The ML models were constructed based on scikit-learn [25] that is a simple and efficient tool for ML, readers can refer to it for more detailed information of the four ML methods used in this study.

Figure 2. The detailed structure of LSTM.

3. Experimental Process and Result Analysis

3.1. Study Area and Data Collection

This research focuses on the Yangtze River Delta Region, which is located in the lower-middle reaches of the Yangtze River near the East China Sea as shown in Figure 3. The

Yangtze River Delta Region covers an area of $3.58 \times 10^5 \text{ km}^2$ including Shanghai, Jiangsu, Zhejiang and Anhui, where the total population reaches up to 227 million. The Yangtze River Delta is one of the regions in China with the most active economic development, so it has created nearly a quarter of China's total economy with less than four percent of the country's land area. Due to the coastal location, the Yangtze River Delta has been suffering from multiple disasters, especially typhoons and the resulting storm surge. Hence it is necessary to provide a fast prediction for the water level, which usually exceeds the safety threshold during the typhoon period. In this research, the LSTM model was trained for typhoon water level prediction by the observation data which is derived from the oceanic and meteorological observation station at Lusi Port of Jiangsu province near the north branch of the Yangtze River. The data were collected during the 12 typhoon-induced storm surges occurred from 1986 to 2016 and their tracks are shown in Figure 3. In particular, the oceanic and meteorological sample data of Typhoon No. 1410 in 2014 are shown in Table 1. ML algorithms require large amounts of data as training sets for higher reliability. Air pressure, wind speed, wind direction and water level are set as the main training input factors. Typhoon central pressure, central wind speed, moving speed, and moving direction are set as related auxiliary reference factors.

Figure 3. The East China Sea with the tracks of 12 typhoons from 1986 to 2016. The yellow line represents the track of Typhoon No. 1410 in 2014 and the white lines represent the tracks of the rest 11 typhoons. The time interval between contiguous dots is 6 hours.

3.2. Data Processing and Model Setting

First, it is vital to preprocess the data by normalization or standardization methods for data correlation analysis and network training because the magnitudes of the original data

are usually different. Here the standardization method is utilized, and the formulas are as follows:

$$x'_i = \frac{(x_i - \bar{x})}{S_d}, \quad (10)$$

$$S_d = \sqrt{\frac{\sum_{i=1}^n (x_i - \bar{x})^2}{n - 1}} \quad (11)$$

where x'_i is standardized data, x_i is original data, $\bar{x}$ is the mean of original data, and S_d is the standard deviation of original data.

Table 1. Oceanic and meteorological sample data during Typhoon No. 1410.

Date	Time	Water Level (cm)	Wind Direction (°)	Wind Speed (m/s)	Atmospheric Pressure (hPa)	Typhoon Central Location	Typhoon Central Pressure (hPa)	Max Wind Speed (m/s)
24 July 2014	0:00	142	91	10.8	995.2	26.1° N 118.4° E	988	25
24 July 2014	1:00	214	102	11.3	994.2	26.2° N 118.1° E	988	25
24 July 2014	2:00	315	104	9.3	993.3	26.4° N 118.1° E	988	25
24 July 2014	3:00	411	105	10.7	992.2	26.7° N 118.1° E	988	25
24 July 2014	4:00	475	108	9	991.5	27.0° N 118.0° E	988	25
24 July 2014	5:00	486	13	15	991.3	27.2° N 118.0° E	988	25
24 July 2014	6:00	460	14	16.2	991.2	27.5° N 118.0° E	988	25
24 July 2014	7:00	408	354	15.2	991.3	27.7° N 117.9° E	988	25

After standardization, the processed data which avoids the influence of abnormal and extreme values is good for ML training. The restore of the standardized data can be implemented according to the inverse function of the formulas above. The dataset was made in the way that the meteorological data and the water level data during the storm surge from the previous time period were selected as input, and the water level data of the next time step were selected as output. More detailly, the input data was divided into data slices by a sliding window of 24 h and then the 24-h data slice was used to predict the next 1 h, 3 h, 7 h, and 15 h of water level data respectively. The dataset was divided into a training set by 80% and a testing set by 20% and the number of the training cycle is 100. The testing set is used to train the LSTM model and the testing set is used for prediction.

3.3. Model Evaluation

In order to effectively evaluate the predicted results under different ML models, Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and Accuracy Coefficient (ACC) are employed as the evaluation indexes for different models.

Mean Absolute Error (MAE), which is used to evaluate the closeness between the predicted data and the observed data. The smaller the value is, the better the fitting result. Root Mean Squared Error (RMSE), which is used to calculate the square root of the mean of the sum of the squares of the errors between the predicted data and the observed data. The smaller the value of RMSE, the better the fitting result. Accuracy Coefficient (ACC), which is 1 minus the absolute error between the predicted data and the observed data. The larger the value of ACC, the better the fitting result. The formulas of MAE, RMSE, and ACC are expressed as follows:

$$MAE = \frac{1}{n} \sum_{i=1}^n |X_i^p - X_i^o|, \quad (12)$$

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (X_i^p - X_i^o)^2}, \quad (13)$$

$$ACC = 1 - \frac{\sum_{i=1}^n \frac{|X_i^p - X_i^o|}{X_i^p}}{n}, \quad (14)$$

where X_i^p and X_i^o are the i th predicted value and the i th observed value of n samples, respectively.

In practice, the peak value of the water is usually the key criterion for marine management departments to judge whether it is necessary to enter the state of alert or disaster relief. Hence, the maximum difference between the modelled and observed values of at the water level peak is taken into consideration for analysis below.

3.4. Model Results of LSTM

The 12 processes of storm surge with the meteorological data (air pressure, wind speed, wind direction) and the water level data which were recorded at Lusi tidal station in Jiangsu Province, China from 1986 to 2016 are used to train the hyperparameters of the LSTM model. Although some scholars used neural network to predict the time-varying storm surge which is calculated by subtracting the astronomical tidal level from the total water level [57], the data used in this study is the total water level including the pure astronomical tidal level and the typhoon-induced water level due to that the key criterion usually considered by the marine management departments is the total water level, especially the peak water level prone to exceed the warning limit.

Figure 4 shows the model results of the LSTM model with 1 h prediction time and its ACC value of training set is above 0.95 to guarantee the model precision. The testing set is calculated for prediction of the water level using the hyperparameters derived by training the LSTM model based on the training set. In Figure 4b, the light blue area represents a cold start period of 24 h for testing set calculation and it is not considered into analysis. In terms of the model evaluation for testing set, the values of MAE, RMSE, and ACC are 13.40, 16.28, and 0.95 respectively, as shown in Table 2. The testing set agrees well with the observed water levels. Since the peak value of water level is the most concern during the time series, the differences of each peak value are calculated and the maximum difference is 18 cm circled by the red dash line in Figure 4b. In general, the 1 h prediction ability of the LSTM model performs quite well.

Table 2. Model evaluation of testing set for different models with four prediction times.

Model Evaluation	Prediction Time	LSTM	BRR	GBDT	LR	SVR
MAE (cm)	1 h	13.40	48.80	59.52	48.80	64.08
	3 h	33.59	96.22	102.58	96.62	105.51
	7 h	31.44	83.98	96.37	84.01	89.95
	15 h	40.70	99.25	102.50	99.58	101.61
RMSE (cm)	1 h	16.28	56.13	71.14	56.12	75.45
	3 h	41.06	109.30	125.06	109.89	131.49
	7 h	42.26	98.50	116.13	98.70	110.86
	15 h	66.77	112.91	127.15	113.84	130.96
ACC	1 h	0.95	0.83	0.81	0.83	0.80
	3 h	0.85	0.67	0.70	0.67	0.66
	7 h	0.88	0.71	0.63	0.71	0.68
	15 h	0.86	0.66	0.65	0.66	0.61
Maximum Difference * (cm)	1 h	18	38	173	150	205
	3 h	23	51	129	186	166
	7 h	36	38	172	149	205
	15 h	45	114	188	210	278

*: "Maximum Difference" represents the maximum difference between the modelled and observed values of the testing set at the water level peak.

Figure 4. (a) Model results of the LSTM model with 1 h prediction time, and (b) the zoom-in view of the testing set section where the light blue area is the cold start subset. Red dash line circle represents the maximum difference between the modelled and observed values at the water level peak.

4. Discussion

4.1. Multiple Prediction Times of LSTM Model

In order to investigate the prediction capability of the LSTM model in a longer term, representative prediction times of 3 h, 7 h, and 15 h are selected to train the model and the ACC values of training set are all above 0.85 to ensure the model precision. Figure 5 shows the model results of testing set for the LSTM model with these four prediction times. It can be seen that the time series fit well with the observed values for the testing set morphologically. In terms of the difference between the modelled and observed values of the testing set, the maximum difference increases with prediction time which are 18 cm, 23 cm, 36 cm, and 45 cm at prediction times of 1 h, 3 h, 7 h, and 15 h respectively.

Figure 6 shows the MAE, RMSE, and ACC values of testing set for the LSTM model with 1 h, 3 h, 7 h, and 15 h prediction times. Difference has a consistent augment trend for the maximum difference between the modelled and observed values, i.e., the MAE value increases sharply from 1 h prediction time to 3 h prediction time by 150%, which is followed by a slightly decrease from 3 h prediction time to 7 h prediction time by 6% and a moderately increase from 7 h prediction time to 15 h prediction time by 29%. It might be due to the nature of MAE which is the average of the absolute difference value between the modelled and observed values. The variation of RMSE with the prediction time displays a similar form to MAE while ACC shows an inverse pattern. For simplicity, it is feasible to select one of these three methods to evaluate the model. For example, when MAE is taken as the criterion, its value for 1 h and 15 h prediction times is 13.4 cm and 40.7 cm respectively. Based on the 20-year return period storm surge value of 186.5 cm [97], the percentage error of 1 h and 15 h prediction times are 7% and 22% respectively. Finally, it can be concluded that the LSTM model performs precisely for 1 h prediction of water

level during the storm surge period and it can also provide a 15 h prediction of water level within a limited error.

Figure 5. Model results of testing set for the LSTM model with (a) 1 h, (b) 3 h, (c) 7 h, and (d) 15 h prediction times. Red dash line circle represents the maximum difference between the modelled and observed values at the water level peak. Light blue areas are the cold start subsets for all prediction times.

Figure 6. Model evaluation of testing set for the LSTM model with 1 h, 3 h, 7 h, and 15 h prediction times.

4.2. Comparison with Other ML Methods

As mentioned before, the most impressive feature of LSTM is the superior ability to deal with the time sequence data to traditional ML methods owing to its nature of long short-term memory. Hence, it is necessary to compare its performance with other traditional ML methods in terms of different prediction times. When training the four models with different prediction times, their ACC values of training set are all above 0.85 to guarantee the model precision. Figure 7 shows the model results of testing set for the BRR, GBDT, LR and SVR models with 1 h, 3 h, 7 h, and 15 h prediction times. For 1 h prediction results, it can be observed from Figure 7a,i that the line shapes of BRR and LR are quite similar with generally the same values of MAE, RMSE, ACC, and maximum difference (listed in Table 2), which is probably because BRR is a variant development of LR. Compared with BRR and LR, the morphology of GBDT and SVR for 1 h prediction result fits worse with the observation data. As the prediction time increases, the performance of the four models gets worse with different characteristics, i.e., the amplitudes of BRR and LR results are much smaller than the observation data and some parts of GBDT and SVR results are out of phase with the observation data and mix with noise.

Figure 7. Model results of testing set for (a–d) BRR, (e–h) GBDT, (i–l) LR and (m–p) SVR with 1 h, 3 h, 7 h, and 15 h prediction times. Red dash line circle represents the maximum difference between the modelled and observed values at the water level peak.

Figure 8 shows the model evaluation of testing set for MAE, RMSE, ACC, and Maximum Difference with 1 h, 3 h, 7 h, and 15 h prediction times. In Figure 8a–c, the variation patterns of MAE, RMSE, and Maximum Difference are consistent for all the five models, i.e., their values increase sharply from 1 h to 3 h prediction time and then increase or

decrease slightly from 3 h to 15 h prediction time. In Figure 8c, variation trend of ACC is on the contrary to the other evaluation metrics. In the four subplots of Figure 8, the evaluation values of LSTM (dark blue line) are separated from the other four models, which indicates that its prediction performance is visibly superior to the four traditional ML models. Taking ACC as the evaluation metric, the average ACC values of LSTM and the traditional ML methods for the four prediction times are 0.89 and 0.7, and therefore LSTM has a superior prediction ability by 27%.

Figure 8. Model evaluation of testing set for (a) MAE, (b) RMSE, (c) ACC, and (d) Maximum Difference with 1 h, 3 h, 7 h, and 15 h prediction times.

5. Conclusions

In this study, an improved version of RNN, i.e., LSTM neural network, is trained to predict the water level during the storm surge period in the East China Sea based on the meteorological and water level data of 12 typhoons from 1986 to 2016. The 1 h prediction ability of the LSTM model performs quite well with the MAE, RMSE, and ACC values of 13.40 cm, 16.28 cm, and 0.95, respectively and the maximum difference between the model prediction values and the observation values is 18 cm during the testing set. When extending the prediction time to 3 h, 7 h, and 15 h and comparing their model results with 1 h prediction time, it can be concluded that the LSTM model performs precisely for 1 h prediction of water level during the storm surge period and it can provide a 15 h prediction of water level within a limited error. In addition, four traditional ML models are trained in the prediction times of 1 h, 3 h, 7 h, and 15 h, and the model results are compared with the LSTM model. Based on the comparison analysis, it indicates that the prediction performance of the LSTM model is visibly superior to the four traditional ML models by 27% in terms of ACC. In general, the LSTM model can help engineers and decision-makers to quickly obtain the warning information of the storm surge in advance based on the reasonable water level prediction and immediately make fast emergency responses.

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