



A Review on the Application of Machine Learning Methods in Tropical Cyclone Forecasting

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At present, there is still a bottleneck in tropical cyclone (TC) forecasting due to its complex dynamical mechanisms and various impact factors. Machine learning (ML) methods have substantial advantages in data processing and image recognition, and the potential of satellite, radar and surface observation data in TC forecasting has been deeply explored in recent ML studies, which provides a new strategy to solve the difficulties in TC forecasting. In this paper, through analyzing the existing problems of TC forecasting, the current application of ML methods in TC forecasting is reviewed. In addition, the various predictors and advanced algorithm models are comprehensively summarized. Moreover, a preliminary discussion on the challenges of applying ML methods in TC forecasting is presented. Overall, the ML methods with higher interpretation, intervention and precision are needed in the future to improve the skill of TC prediction.

Keywords: tropical cyclone, machine learning, genesis, track, intensity, disastrous weather

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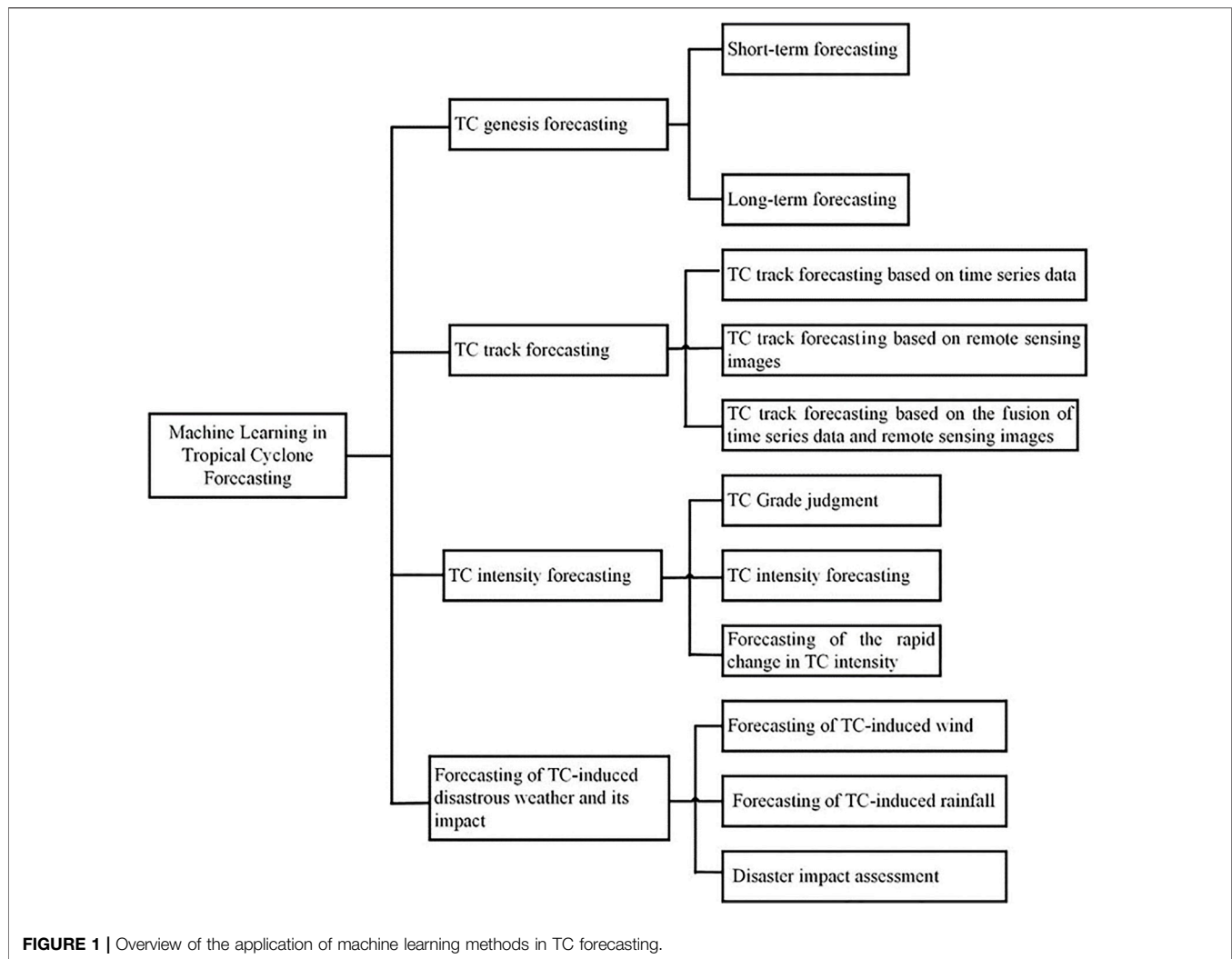
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INTRODUCTION

Tropical cyclone generates over the tropical or subtropical oceans, and it is a kind of extreme weather regime that can cause tremendous loss of human lives and social property through excessive torrential rainfall, flash flood, huge waves and storm surges. Genesis, track, intensity and disastrous weather are the key issues in TC operational weather forecast. At present, the numerical model is still the dominant way to forecast TC, and its ability mainly depends on the parameterization of physical processes within TCs. However, the performance of TC prediction is restricted by the complex dynamical mechanisms and the diverse influence factors, and still needs to be improved (Ma, 2014).

In recent years, major advances in TC forecasting have been made in TC track prediction. But, there still exist challenges in predicting anomalous motions (Dong, 2021) and making long-term track forecasting (Emanuel, 2018). In order to solve such problems, the application of ML methods has gradually become a hot spot. For example, they are used to explore the values of satellite data (Hu et al., 2017; Zhang et al., 2017; Chen et al., 2018; Pradhan et al., 2018; Kim M. et al., 2019; Qian et al., 2021), radar data (Chen X. P. et al., 2020; Huang et al., 2021) and surface observation data (Mercer and Grimes, 2015) in TC forecasting.

As the core technology of Artificial Intelligence (AI), the basic principle of ML is to give data to computers and let them infer rules from it, so that machines can explore the potential values of data and automatically improve their performances (Zhou, 2006). The ML can be divided into supervised learning and reinforcement learning according to whether the assignment needs to obtain experience through the interaction with environment (Cui et al., 2019). ML methods can be used to realize the feature selection (Kim and Choi, 2007), clustering (Melnikov et al., 2020), and regression/classification (Suykens and Vandewalle, 1999), which are thought to be beneficial to TC forecasting (Chen R. et al., 2020).



In this study, we will review the current applications of ML methods in the forecasting of TC genesis, track, intensity and disastrous weather and summarize the existing problems. Then, various predictors and advanced algorithm models are comprehensively summarized (Figure 1). The remainder of this paper is organized as follows. The application of ML methods in the forecasting of TC genesis, track and intensity is reviewed in sections 2–4, respectively. Section 5 reviews the forecasting on TC disastrous weather and its impact. Finally, the conclusions and discussion are given in section 6.

TC GENESIS FORECASTING

TC genesis is referred to as a process through which a tropical disturbance rapidly develops into a warm-core, cyclonic system with sustained winds (Gray, 1968, 1998). The TC can be identified and tracked through the criteria of co-located high values of low-level vorticity, low surface pressure values, elevated temperatures aloft, and high 10-m wind speed maintained for a specified duration of time (Knutson et al., 2007; Ullrich and Zarzycki,

2017). Traditionally, the forecasting procedures are based on a multi-variable set of physical conditions based on known properties of TCs. The physical conditions can be predicted by numerical models. Recently, more advanced numerical models, such as the Global Environmental Multi-Scale Model, Global Forecast System, Navy Operational Global Atmospheric Prediction System and United Kingdom Met Office global model, have been applied in operational forecasting of TC genesis (Halperin et al., 2013). Although this prediction method is based on physical interpretations, it has some limitations, such as poor understanding of TC genesis and huge computational costs (Chen R. et al., 2020). The used statistical relationship between the probability of TC genesis and large-scale environmental predictors is too simple to describe the actual situation accurately (Chaudhuri et al., 2017). At present, TC genesis forecasting can be carried out by combining ML methods with traditional methods. According to the forecast leading time, the TC genesis forecasting can be divided into short-term forecasting and long-term forecasting (Table 1). Aimed at predicting seasonal generation frequency of TC, long-term forecasting usually uses large-scale environmental

TABLE 1 | Machine learning in TC genesis forecasting.

Tasks	Algorithms	References
Short-term forecasting	decision tree logistic regression random forest AdaBoost	Zhang et al. (2015); Park et al. (2016) Wijnands et al. (2016) Ahijevych et al. (2016) Zhang et al. (2019)
Long-term forecasting	decision tree, random forest and support vector machine support vector regression multiple linear regression	Kim et al. (2019a) Richman and Leslie (2012); Wijnands et al. (2014); Richman et al. (2017) Nath et al. (2016)

field information to establish the statistical relationship between environmental factors and the active frequency of TCs, and further constructs the genesis potential index (GPI) (Chen, 2018). The selection of large-scale environmental factors, such as low-level vorticity, convective instability, ocean mixed layer depth/temperature, vertical wind shear, absolute vorticity, relative humidity, etc. (Gray, 1968; Emanuel and Nolan, 2004; Camargo et al., 2007; Zhao et al., 2012), plays a key role in long-term forecasting. For short-term forecasting, there are preconditions of tropical disturbances or tropical cloud clusters existing over tropical ocean surface, and then an algorithm is used to determine whether they will develop into a TC (Chen, 2018). The existence of tropical disturbances or tropical cloud clusters is often identified according to the state of atmospheric variables (wind field, vorticity field, etc.) (Fu et al., 2012; Peng et al., 2012) and the brightness temperature data of satellite cloud images (Hennon and Hobgood, 2003; Hennon et al., 2011).

Short-Term Forecasting

To forecast whether the tropical disturbance can develop into a TC, many studies have devoted to finding the optimal predictors and algorithms. For example, Zhang et al. (2015) built a decision tree (DT) model (Safavian and Landgrebe, 1991) based on the C4.5 algorithm to classify tropical disturbances in the Northwest Pacific. They found that the maximum relative vorticity, sea surface temperature, precipitation rate at 800 hPa, the average divergence at 1,000–500 hPa and temperature anomaly at 300 hPa are essential predictors to distinguish whether the tropical disturbance can develop or not. Compared with the numerical methods with a hit rate of less than 50% (Halperin et al., 2013), the DT method with a higher hit rate (64%) has excellent performance in the short-term (24–48 h) TC genesis forecasting. Wijnands et al. (2016) used the logistic regression prediction model to select the short-term predictors for TC genesis. The results showed that 600 hPa potential vorticity, 925 hPa relative vorticity and 200–700 hPa vertical wind shear are key predictors.

In addition to reanalysis data and simulation data, satellite data has been used in several studies to forecast TC genesis. With the aid of the circular variance and a spatial pattern analysis program tool, Park et al. (2016) used the WindSat remote sensing images of ocean surface wind and precipitation to quantify the predictors in the DT algorithm, and then they established a new forecast model of TC genesis. Moreover, they further pointed out that the symmetry and intensity of circulations are the most

important parameters that characterize the development of tropical disturbance.

In recent years, significant advances in prediction algorithms have also been made. For example, Ahijevych et al. (2016) used the Random Forest (RF) algorithm to make the probability forecast of the genesis of mesoscale convective systems. Zhang et al. (2019) evaluated the performance of the linear, non-linear and non-linear ensemble classification algorithms on TC genesis forecasting, and they found that the AdaBoost, a non-linear ensemble classification algorithm, has significant higher forecast accuracy than the traditional methods based on the genesis potential index (**Figure 2**). Similar to Park et al. (2016), Kim M. et al. (2019) adopted eight predictors from the WindSat observed ocean surface wind and precipitation in the Northwest Pacific, and compared the detection skill for TC genesis using the models based on three different ML algorithms i.e., DT, RF and support vector machines (SVM) (Suykens and Vandewalle, 1999), and a model based on linear discriminant analysis. They highlight that ML approaches can provide an improved skill for detecting TC genesis compared with conventional linear approaches.

Long-Term Forecasting

The long-term forecast aims to predict the seasonal genesis frequency of TCs. The traditional methods use a set of interrelated predictors through linear statistics to predict the TC frequency in the next quarter. However, the relationship between predictors and TC genesis does not satisfy the assumption of standard prediction technique. Therefore, scholars regarded seasonal-scale TC forecasting as a regression problem and tried to use ML methods to build some newer model. In particular, the Support Vector Regression (SVR) algorithm has been widely used. Richman and Leslie (2012) extended the traditional multiple linear regression method and introduced the quasi-biennial oscillation (QBO) into the SVR model to predict the genesis frequency, spatial distribution and seasonal intensity variation of TCs. The results showed that the prediction accuracy of the improved SVR model was 40% higher than that of the traditional multiple linear regression model and 121% higher than that of the SVR without QBO. On this basis, Wijnands et al. (2014) and Richman et al. (2017) further improved the SVR model with reduced the seasonal forecasting errors of TCs. Nath et al. (2016) selected five large-scale climate variables, namely 500 hPa geopotential height, 500 hPa relative humidity, sea level pressure, and 700 hPa and 200 hPa zonal wind in the previous month, as potential predictors

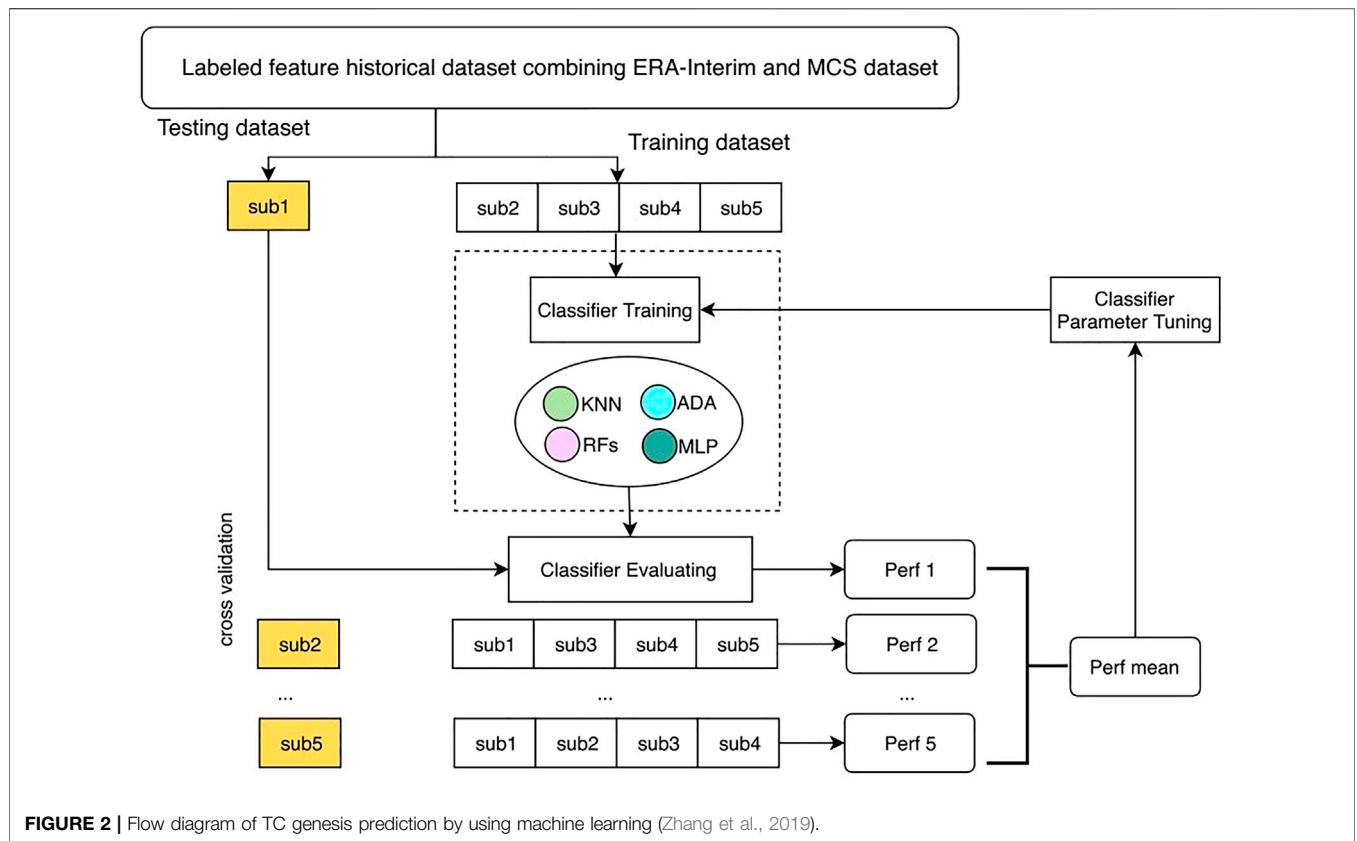


FIGURE 2 | Flow diagram of TC genesis prediction by using machine learning (Zhang et al., 2019).

TABLE 2 | Machine learning algorithms used in TC track forecasting.

Tasks	Algorithms	References
TC track forecasting based on time series data	linear regression algorithm stepwise regression algorithm neural network artificial neural network principle component analysis, genetic algorithm and neural network algorithm support vector machine gradient boosting decision tree K-means cluster analysis dynamic fuzzy clustering method recurrent neural network long short-term memory neural network	Neumann and Hope (1972) Chen et al. (1999a) Shao et al. (2009) Wang et al. (2011) Huang and Jin (2013) Song et al. (2005); Lv et al. (2009) Tan et al. (2021) Camargo et al. (2007); Yu et al. (2017); Wang et al. (2019) Li et al. (2008) Dong and Zhang (2016); Alemany et al. (2018); Kordmahalleh et al. (2016) Gao et al. (2018)
TC track forecasting based on remote sensing images	neural network convolutional neural networks	Lee and Liu (2000); Kovordá and Roy (2009) Sophie et al. (2020)
TC track forecasting based on the fusion of time series data and remote sensing images	convolutional long short-term memory network integrated neural network	Shi et al. (2015); Kim et al. (2019b) Giffard-Roisin et al. (2020); Dong (2021)

of TC activities. Also, they used the multilayer perceptron, radial basis function (RBF) and generalized regression neural network algorithm to predict the seasonal TC activities over the North Indian Ocean. The results showed that all three algorithms performed well, and the performance of the multilayer perceptron model is better than that of the RBF and the generalized regression neural network model.

TC TRACK FORECASTING

Although there have been decent advances in TC track forecasting in recent years, difficulties still exist in predicting anomalous tracks and making longer-term forecasting (Dong, 2021). In early studies, the models for predicting TC tracks were mainly built by comprehensively using thermal-dynamic

knowledge and analyzing the characteristics of complex terrain and coastlines in coastal areas. However, these characteristics were often extracted subjectively, so the methods are less efficient and objective, depending on forecasters' experience. With the development of ML methods and the enrichment of computing resources, automatic extraction of the temporal and spatial characteristics from big data has been realized, and efficient and accurate prediction of TC track may be achieved (**Table 2**).

TC Track Forecasting Based on Time Series Data

The historical TC best track data are typical time series data. As early as in 1972, for the TC track forecasting in the Atlantic, Neumann and Hope (1972) used linear regression algorithms to construct regression equations and built a TC track forecast model named "Climatology and Persistence" (CLIPER). Chen et al. (1999) used the stepwise regression algorithm instead of linear regression algorithm to eliminate independent variables that are not significant to regression equations. Due to the complexity and nonlinearity of the physical processes affecting TC tracks and the interactions among these processes, besides linear regression and stepwise regression algorithms, many studies adopted nonlinear algorithms such as the neural network, SVM and artificial neural network to predict TC tracks. For instance, Shao et al. (2009) established a TC track forecast model by selecting the factors with high correlation as the independent variables of the model based on the forward feedback back propagation (BP) learning algorithm. The mean absolute errors of predicted moving distance in BP neural network model at 24, 48 and 72 h are respectively 40.8, 8.1 and 16.9 km lower than those of the CLIPER model. Wang et al. (2011) broke the bottleneck of subjectively-constructed predictors and used the nonlinear characteristics of the artificial neural network to automatically construct predictors for TC track forecasting. On this basis, Huang and Jin (2013) further integrated the Principal Component Analysis (PCA), genetic algorithm and neural network algorithm to establish a regional TC track ensemble forecast model, which has good promotion and application values. Due to fewer predictors and shorter leading time of TC track forecasting, the SVM algorithm, which excels in dealing with small samples, high-dimensional pattern recognition and nonlinear complexity, performs better than traditional numerical predictions and nonlinear regression algorithms (Song et al., 2005; Lv et al., 2009). As a new statistical regression/classification technique, ensemble learning is more effective than single learning in non-linear regression and multi-scale approximation problem, and is widely applied in many fields (e.g., Tian et al., 2012; Huang et al., 2018; Pradhan et al., 2018). Aiming to improve the level of TC track forecasting, a novel ensemble learning method based on DT and boosting skill, called gradient boosting decision tree, was proposed (Tan et al., 2021). Compared with the CLIPER model, the TC track predicted by the new model is more robust and accurate.

TC track forecasting can also be regarded as a classification issue. In the Northwest Pacific, Camargo et al. (2007) used the

shape and movement parameters of TC tracks to conduct the K-means cluster analysis (Krishna and Narasimha, 1999), and they pointed out that TC tracks in this region are mainly "westward" and "turning" types. Similarly, Yu et al. (2017) and Wang et al. (2019) also used the K-means cluster analysis to study the TC recurvature tracks. Their results showed that frequency of TCs with "western recurvature" tracks had an increasing trend in the past 2 decades. Before recurvating, the right-turning TCs tend to move northwestward, while the left-turning TCs mainly move northward. Li et al. (2008) adopted a dynamic fuzzy clustering method to investigate the TC tracks in the South China Sea from 1960 to 2002. Also, they surveyed the TC-related factors, namely circulation, physical factors and motion characteristics, and then they established a forecast model for summer TC tracks in this region based on the multiple regression algorithm.

Deep Learning (DL) methods, which can efficiently extract the nonlinear features, are used to investigate the highly nonlinear atmospheric systems such as TC. For example, the recurrent neural network (RNN) (Dorffner, 1996) can effectively extract the temporal features from continuous data, so it has been widely used in TC track forecasting (Dong and Zhang, 2016; Alemany et al., 2018). Kordmahalleh et al. (2016) employed a sparse recurrent neural network based on the dynamic time warping to forecast TC tracks in the Caribbean Sea and indicated this network is particularly suitable for modeling of hurricanes which have complex systems with unknown dynamics. The dynamic time warping can be used to recognize similar TCs so that the RNN can extract common features. However, this method is not suitable for non-single-track TCs. Alemany et al. (2018) considered all types of TC tracks and used the RNN to forecast them. Unlike traditional methods which directly predict latitudes and longitudes, Alemany et al. (2018) divided the Atlantic Ocean into $1^\circ \times 1^\circ$ grids and numbered the grid points. The wind speed, latitudes, longitudes, travel angles and TC grid numbers were used as inputs, which can effectively reduce the recursive error transfer caused by direct prediction. The RNN performs better in short-term forecasting but not very good for long-term forecasting. Another important method, long short-term memory neural network (LSTM) (Hochreiter et al., 1997) was developed in 1997. Gao et al. (2018) used the TC best track data to train and optimize the LSTM-based deep neural network (DNN), and the results showed that the LSTM has a better performance in TC track forecasting with the leading time of 6–24 h.

TC Track Forecasting Based on Remote Sensing Images

Forecasting TC tracks using ML methods are not only affected by the characteristics of historical TCs, but also by spatial factors. Compared with time-series data, remote sensing images contain more rich spatial information. Early in 2000, Lee and Liu (2000) proposed a TC automatic identification and track mining system based on the neural network, and the forecast errors of this system were reduced by 30% and 18% compared with the one-way interactive TC model and track forecast system, respectively.

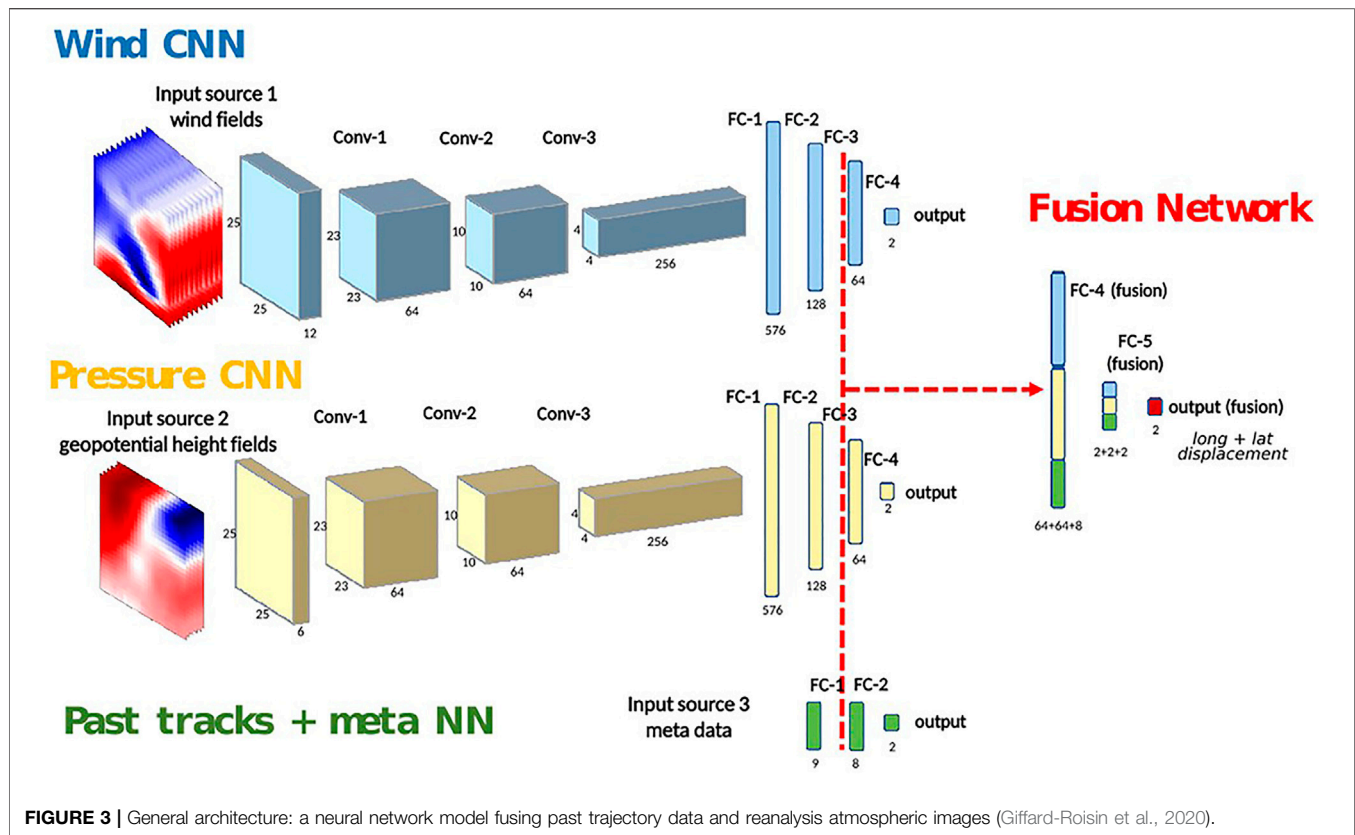


FIGURE 3 | General architecture: a neural network model fusing past trajectory data and reanalysis atmospheric images (Giffard-Roisin et al., 2020).

Thereafter, Kovordá and Roy (2009) extracted Dvorak features (Dvorak, 1975) from remote sensing images of meteorological satellites and input the data, such as TC locations and maximum wind speed, into the neural network to predict TC tracks. This method improved the forecast accuracy by about 30% compared with the numerical model in Guam. In addition, the neural network represented by the convolutional neural networks (CNN) (Lecun et al., 1989; Ji et al., 2013) can effectively extract the spatial features from the data. Sophie et al. (2020) fused the extracted nonlinear features with latitudes and longitudes of TCs, wind speed and air pressure based on the CNN algorithm. The results indicated that the method better predicted the TC tracks over the Eastern Pacific and the Atlantic Ocean and well retained the TC three-dimensional features. Moreover, this method can forecast the genesis of a TC in a few seconds, which is an important asset for real-time forecasts compared to traditional forecasts.

TC Track Forecasting Based on Fusion of Time Series Data and Remote Sensing Images

Some studies have shown that the TC track sequence is not a fixed-length vector but the time series data with indefinite length (Jia et al., 2007). However, the CNN (Zeiler and Fergus, 2014), which is good at image processing, is unable to characterize the spatial information in the temporal dimension. Additionally, LSTMs perform well in time series forecasting (Staudemeyer

and Morris, 2019). However, TC track forecasting requires too many prediction factors and relies on a long period of past states, resulting in that the LSTM is also hard to achieve the desired predictions in terms of temporal-spatial issues (Wang, 2020). Shi et al. (2015) added convolution operations to extract spatial features while ensuring the extraction of temporal features, and they proposed a convolutional long short-term memory network (ConvLSTM), which successfully combined the time series analysis capability of the LSTM and the image recognition capability of the CNN. After that, ConvLSTM was combined with atmospheric reanalysis data for TC track forecasting and achieved relatively better performance (Kim S. et al., 2019). By fusing past trajectory data and reanalysis atmospheric images (wind and pressure 3D fields), a neural network model was proposed by Giffard-Roisin et al. (2020) to estimate the longitude and latitude displacement of TCs (Figure 3), which is an important asset for real-time forecasts compared to traditional forecasts. At present, in order to solve the problems in anomalous track prediction, such as sudden changes in moving speed, turning and even stagnation, Dong (2021) built an integrated neural network prediction model for TC tracks by using TC data with multiple modes.

TC INTENSITY FORECASTING

Limited by the available observations and technologies, it has been a long-standing challenge in tropical meteorology to make

TABLE 3 | Machine learning in TC intensity forecasting.

Tasks	Algorithms	References
TC grade judgment	multiple logistic regression, support vector machine and back-propagation neural network convolutional neural networks-DeepMicroNet Two-dimensional and three-dimensional convolutional neural networks multi-layer deep convolutional neural network	Chen et al. (2018) Wimmers et al. (2019) Lee et al. (2019) Pradhan et al. (2018); Cui et al. (2020)
TC intensity forecasting	back-propagation neural network partial least squares regression support vector machine and genetic algorithm decision tree logistic regression and bayesian network deep convolutional neural network ResNet deep learning convolutional neural network-long short-term memory network deep neural network-long short-term memory network shallow learning and DL algorithms DL convolutional neural network- DeepMicroNet DL-based method augmented- DeepTCNet	Baik and Paek (2000) Zhou (2014) Gu et al. (2011) Gao et al. (2016) Rozoff and Kossin (2011) Pradhan et al. (2018) Qian et al. (2021) Chen et al. (2019b) Zahera et al. (2019) Jiang et al. (2018) Wimmers et al. (2019) Zhou and Tan (2021)
Forecasting of the rapid change in TC intensity	C4.5 recurrent neural network support vector machine decision tree	Zhang et al. (2013) Chandra and Dayal (2015) Mercer and Grimes (2015) Gao et al. (2016)

accurate estimates of TC intensity (e.g., Landsea and Franklin, 2013; Knaff and Sampson, 2015). As early as in the 1970s, Dvorak (1975) established a TC intensity prediction technology based on statistical estimation by using satellite cloud images to identify and detect TCs, which has become a common TC intensity estimation method used by official meteorological agencies (Xu et al., 2015). However, it is highly subjective in determining the cloud feature indexes, so its forecast accuracy depends on forecasters' experience. To increase the objectivity and automation of infrared-based TC intensity analysis, advanced versions of the Dvorak technique (e.g., Olander and Velden, 2007, 2019) and many other algorithms (e.g., Kossin et al., 2007; Ritchie et al., 2012; Fetanat et al., 2013) have been introduced. However, most of these algorithms have been proven to be less reliable than the Dvorak technique due to the limited availability of effective features extracted from satellite data by these traditional algorithm-based techniques (e.g., Demuth et al., 2004, 2006; Jiang et al., 2019; Zhou and Tan, 2021). At present, Satellite Consensus technology, a weighted consensus algorithm, which is designed to optimize the strengths of multiple infrared-based and microwave-based technique, is the most accurate method in TC intensity estimation (Velden and Herndon, 2020). More and more studies have taken advantages of ML methods in image recognition and classification to conduct TC intensity estimation (Girshick et al., 2014; Krizhevsky et al., 2017; Zhong et al., 2017). These studies mainly focus on three aspects: TC grade judgment, TC intensity forecasting and TC rapid change forecasting (Table 3).

TC Grade Judgment

ML algorithms mainly use satellite data to judge the grade of TCs. As early as in 2003, an ML algorithm was applied in the cloud classification using GOES images, and TC intensity estimations

(Richardson et al., 2003). Chen (2018) treated the prediction of TC grade as a classification issue. In addition, by using the multiple logistic regression, SVM and back-propagation neural network as classifiers, they performed predictions with the multispectral images captured by the Fengyun-4 meteorological satellite. Wimmers et al. (2019) explored the possibility of estimating TC intensity from satellite images by using the CNN-DeepMicroNet. Two-dimensional and three-dimensional CNNs were used by Lee et al. (2019) to analyze the relationship between multispectral geosynchronous satellite images and TC intensity, and this method had better performance than the existing CNN-based models and the models with single-channel images. Based on the advanced geosynchronous radiation imager data from the second-generation geostationary meteorological satellite (Fengyun-4A), Pradhan et al. (2018) and Cui et al. (2020) established a multi-layer deep CNN model with multidimensional nonlinear processing ability and algorithm stability to conduct TC intensity estimation. Their results showed higher accuracy and lower root-mean-square errors.

TC Intensity Forecasting

In 2000, Baik and Paek (2000) used the back-propagation neural network algorithm to forecast TC intensity based on various data, such as the TC location and intensity, and NCEP/NCAR reanalysis data. Zhou (2014) developed a forecast model to improve the prediction of TC intensity over the Northwestern Pacific based on the partial least squares regression, which considers multiple factors such as climate background, water vapor, environmental airflow and TC structure. Gu et al. (2011) built an SVM-based TC intensity forecast model and used a genetic algorithm to optimize the model parameters in order to achieve desired results at the leading time of 12, 24 and 48 h. Gao

et al. (2016) introduced the averaged ocean temperature from the surface down to 100 m to improve the model performance on TC intensity forecasting at the leading time of 24 h based on the DT algorithm. The results indicated that such method performed well in predicting TCs with a rapid intensification (RI) process.

In addition to above regression algorithms, classification algorithms can be well applied in the operational forecast of TC intensity. The National Hurricane Center of the United States used the Statistical Hurricane Intensity Prediction Scheme dataset to analyze the environment around TCs and their satellite inversion characteristics based on the linear discriminant analysis. This method solved the probability of TC sudden change based on the logistic regression and Bayesian network algorithms to predict TC intensity (Rozoff and Kossin, 2011). Pradhan et al. (2018) and Qian et al. (2021) developed a deep CNN and ResNet DL-based TC intensity prediction model using satellite cloud images, which could objectively predict the intensity of TCs with various intensities at different development stages. The root mean square errors (RMSEs) of these two models are 5.5 m s^{-1} and 5.84 m s^{-1} , respectively. Compared with the traditional statistical method for TC intensity prediction using cloud images (Lu et al., 2014), whose RMSE is 7.7 m s^{-1} , the deep CNN and ResNet models have obvious advantages. The TC intensity prediction is not only a temporal issue but also a spatial issue. Therefore, numerous studies have been conducted based on integrated models, such as the CNN-LSTM (Chen R. et al., 2019) and DNN-LSTM (Zahera et al., 2019), which can more comprehensively consider the temporal-spatial relationships of the features of TC formation and can improve the TC intensity forecast.

To improve TC intensity forecast, we should better resolve the heat and momentum exchange at the TC-ocean interface. The major challenge is how to accurately include the effects of ocean in TC forecast models, which requires information not only from historical data but also more importantly from the target TC itself. Two algorithms based on ML neural networks are proposed—the shallow learning and DL algorithms—that can potentially be used in atmosphere-only TC forecasting models to provide flow-dependent TC-induced sea surface temperature cooling for improving TC forecast (Jiang et al., 2018). Furthermore, due to the successful applications of DL in pattern detection, physical parameterization and state prediction (e.g., Rasp et al., 2018; Ham et al., 2019; Reichstein et al., 2019), it is considered to provide insights into TC intensity forecasting. Pradhan et al. (2018) applied DL to estimate TC intensity from infrared imagery. Then, Chen B.-F. et al. (2019) used a larger dataset than Pradhan et al. (2018) and utilized infrared images and passive microwave-retrieved precipitation to train DL models. Wimmers et al. (2019) constructed a DL convolutional neural network model called “DeepMicroNet” to explore the possibility of estimating TC intensity from satellite imagery. However, an independent dataset for evaluation was not used in Pradhan et al. (2018). The optimal estimates of Chen B.-F. et al. (2019) are not available in real time due to the intermittent microwave rain-rate data and post-analysis smoothing required. Therefore, Zhou and Tan (2021) proposed a DL-based method augmented by prior physical knowledge of TC, called “DeepTCNet” (Figure 4), to estimate TC intensity from

satellite infrared imagery. Compared with the unaugmented model, DeepTCNet with auxiliary information of TC fullness yields a 12% performance improvement in estimating TC intensity. The evaluation results showed that the DeepTCNet is in-line with the Satellite Consensus technique but systematically outperforms the advanced Dvorak technique at all intensity scales with an averaged 39% enhancement in TC intensity estimation.

Forecasting of the Rapid Change in TC Intensity

Due to the difficulties in directly forecasting the accurate intensity values, the evolutionary algorithm, particle swarm optimization and DT algorithms (such as the Classification and Regression Trees and the C4.5 algorithm) were used in lots of studies to forecast the change of TC intensity (Zhang et al., 2013; Geng et al., 2015, 2016). However, cases such as the RI process exist during the TC development, making the forecasting of intensity change into a much more challenging task.

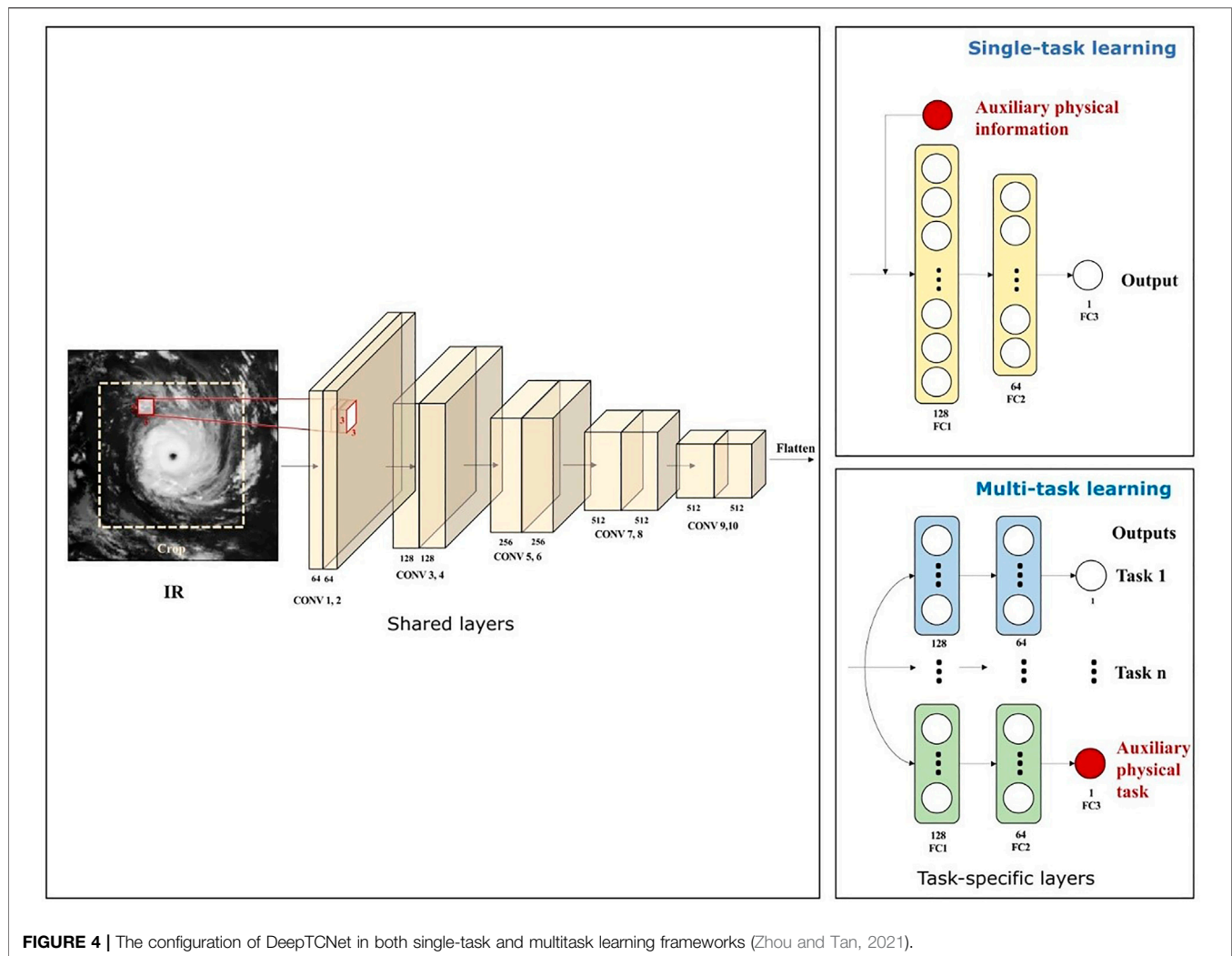
Zhang et al. (2013) and Chandra and Dayal (2015) applied the C4.5 and RNN algorithms to classify the TC intensity changes over the Northwestern Pacific and the Southern Pacific, respectively. Their studies strongly contributed to the development of operational forecast of TC intensity change. Similarly, Mercer and Grimes (2015) used the SVM as the classification algorithm and took the geopotential height, temperature, u - and v -wind components, vertical velocity and relative humidity as the predictors to construct a model. The results suggested that this model was able to distinguish the RI and non-RI cases. In addition, Gao et al. (2016) believed that the sea surface temperature is the key factor for predicting RI cases. Also, they introduced the ocean coupling potential intensity index into the DT algorithm to improve the RI prediction, and this method can effectively reduce the intensity overestimation in the traditional DT model. By combining satellite products and conventional predictors, Su et al. (2020) presented a ML framework to demonstrate the prediction capability of satellite observations of storm internal structures for TC RI forecasting.

FORECASTING OF TC-INDUCED DISASTROUS WEATHER AND ITS IMPACT

Given changing climate and continued escalation of coastal population density, the situation of TC inflicting severe economic losses and casualties through strong winds and torrential rain may be further complicated (Czajkowski et al., 2011; Rappaport, 2014). The accurate simulation and forecasting of TC-induced wind and precipitation, as well as disaster assessment (Table 4), can provide important guidance for disaster prevention and mitigation (Lonfat et al., 2007; Needham et al., 2015).

Forecasting of TC-Induced Wind

In 1987, the Joint Typhoon Warning Center (JTWC) used satellite images, remote sensing data and the Dvorak technology (Dvorak, 1975) to retrieve the TC low-level wind



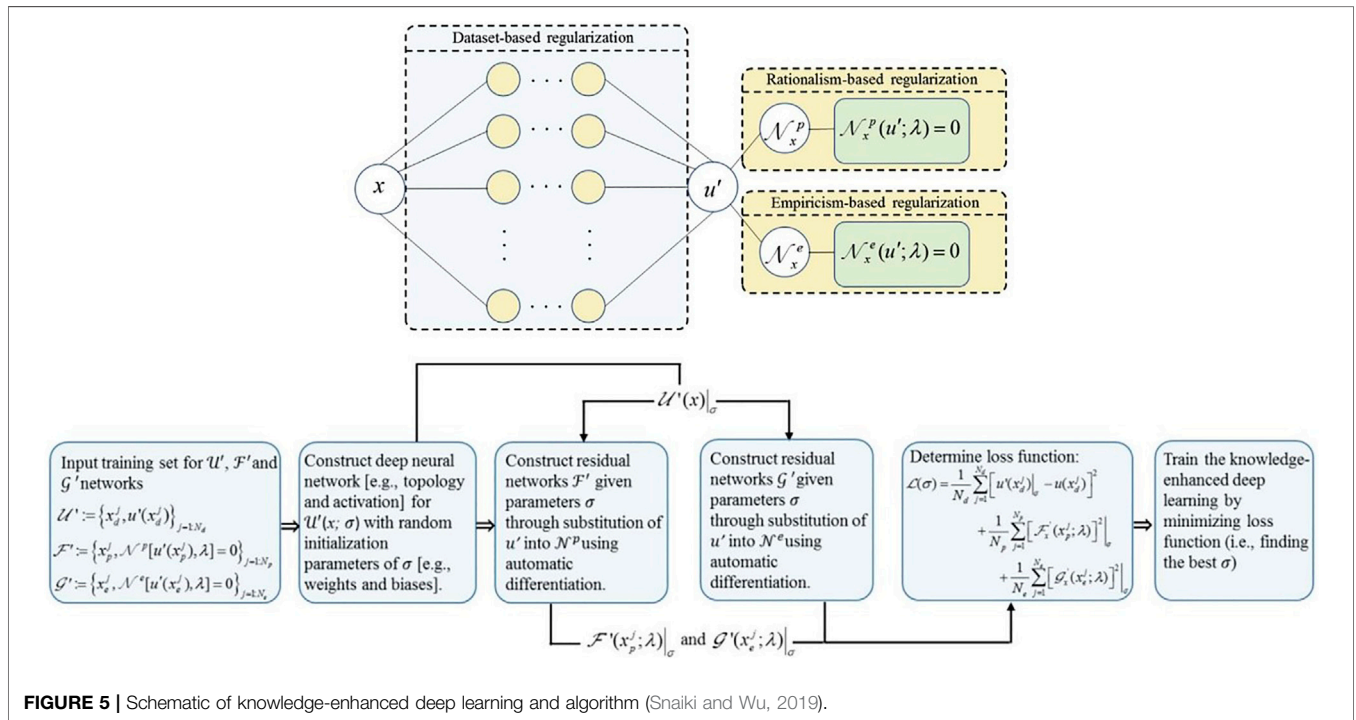
field, while the mid-level and upper-level wind fields were retrieved by the cloud motion wind (Xu and Zhang, 2006). However, since it is difficult to specify the height of cloud motion wind, and the satellite microwave scatterometers are only suitable for low wind speed and gentle wind-speed changes, there are great challenges in the observation and forecast of TC wind field. To forecast the hourly wind speed over offshore islands during TC processes, Wei (2015) developed four kernel-based SVR models, including the RBF, linear, polynomial and Pearson VII universal kernel models, which was proved to be the most accurate one among the kernel-based SVR models. Considering that traditional models based on simple parametric formulations strongly underestimate the full range of TC wind field variability (Uhlhorn et al., 2014; Klotz and Jiang, 2016), Loridan et al. (2017) explored the potential of ML algorithms (RF and quantile regression) as alternatives to simulate the trajectory, intensity and spatial distribution of TC-induced wind.

In particular, with a theorem stating that an artificial neural networks (ANN) with a single layer of enough hidden units can approximate any multivariate continuous function with

arbitrary accuracy (Hornik et al., 1989), ANN has been widely utilized in simulating the wind field inside TCs (Snaiki and Wu, 2019). By integrating TC wind field model, Monte Carlo simulation technique, computational fluid dynamics (CFD) simulation and ANN, a numerical simulation procedure for predicting directional TC-induced wind speed and profiles for sites over complex terrain was proposed (Huang and Xu, 2013). However, limited by the high demand of high-fidelity training datasets for the classical neural networks, the ANN model developed by Huang and Xu (2013) is not comprehensive enough (Snaiki and Wu, 2019). Snaiki and Wu (2019) developed a more general knowledge-enhanced DL algorithm to simulate the spatial distribution of TC-induced wind fields (Figure 5). This algorithm not only efficiently captures the complex dynamics using small datasets, but also accurately predicts TC-induced wind. Moreover, ML methods were used to correct the wind forecasting of numerical weather models. For example, Deng et al. (2018) used the PCA-RBF algorithm to further correct the forecasted wind speed by using the simulated meteorological factors such as temperature, pressure and wind direction. The

TABLE 4 | Application of machine learning in the forecasting of TC-induced disastrous weather and its impact.

Tasks	Algorithms	References
Forecasting of TC-induced wind	support vector regression RF and quantile regression artificial neural networks knowledge-enhanced deep learning algorithm principal component analysis-radial basis function least absolute shrinkage and selection operator regression, random forest and deep learning algorithms	Wei (2015) Loridan et al. (2017) Huang and Xu, (2013) Snaiki and Wu (2019) Deng et al. (2018) Sun et al. (2019)
Forecasting of TC-induced rainfall	neural network self-organizing map and multilayer perception networks hybrid neural network back-propagation network and support vector machine support vector machine multi-objective genetic - support vector machine physical-conceptual models - ML methods conceptual rainfall-runoff model - Bayesian artificial neural networks statistical model two-stage forecasting approach integrating numerical and ML-based models	Lin and Chen (2005) Lin and Wu (2009) Lin et al. (2009); Jhong et al. (2016) Lin et al. (2013a) Lin et al. (2013b); Lin and Jhong, (2015) Loukas and Vasiladias (2014); Young and Liu (2015) Humphrey et al. (2016) Huang et al. (2019)
Disaster impact assessment	Hopfield neural network support vector machine decision tree	Chen and Liu (2011) Lou et al. (2012); Pham et al. (2016) Pham et al. (2016)

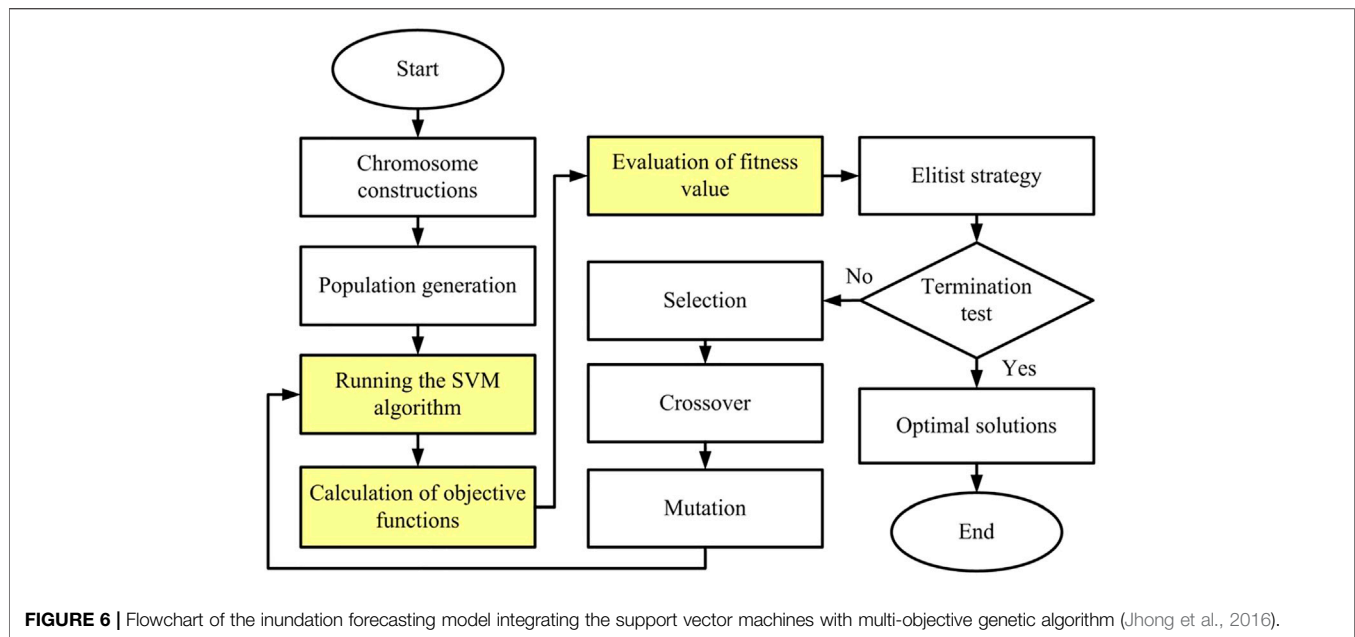


results showed that, compared with the back-propagation algorithm and the least squares SVM algorithm, the PCA-RBF algorithm effectively improved the accuracy of wind speed forecast. Based on the least absolute shrinkage and selection operator regression, RF and DL algorithms, Sun et al. (2019) corrected the 10 m wind speed in North China predicted by the European Centre for Medium-Range Weather Forecasts. The results indicated that the correction effect of these 3 ML algorithms is better than that of the model output

statistics method, especially for the future 8–15 days and the 10 m wind speed in the sea areas and coastal areas.

Forecasting of TC-Induced Rainfall

Early in 2005, Lin and Chen (2005) applied the neural network to forecast TC-induced rainfall. They took TC features and spatial rainfall information as the input of the model and gave reasonable predictions at the leading time of 1–2 h. To break the limitations of single algorithm, Lin and Wu (2009) proposed a hybrid neural



network model for TC-induced rainfall forecasting. The model was composed of the self-organizing map and the multilayer perception network, and it is proven higher prediction accuracy than the traditional neural network method (Lin and Chen, 2005). One of the most important steps in neural network modeling of the TC-induced rainfall forecast is to identify important input variables. The capabilities of multi-objective genetic algorithm (MOGA) to explore and discover Pareto-optimal fronts on multi-objective optimization problems have been well recognized and increasingly applied (Deb et al., 2002; Liu, 2009). Meanwhile, by comparing the hourly TC-induced rainfall forecasting models of back-propagation network (BPN) and SVM, Lin et al. (2009) pointed out that the SVM-based model is more accurate, robust and effective and proved that the SVM has faster training speed and better generalization ability. Based on the above research, several hybrid methods, especially a combination between MOGA and SVM, have been implemented to optimize parameters in TC-induced rainfall forecasting fields (Lin et al., 2013b; Lin and Jhong, 2015). By integrating MOGA and SVM, the biggest advantage of this model is that it can automatically determine the optimal combination of input variables including precipitation. Specifically, by integrating MOGA and SVM, Lin et al. (2013b) and Lin and Jhong (2015) proposed two models to yield accurate forecasts of the spatial distribution of TC-induced rainfall, and to improve the hourly forecast and long lead-time forecast. Furthermore, a large number of scholars have combined physical-conceptual models with ML methods to improve the forecasting of TC-induced rainfall. For example, Loukas and Vasilades (2014), Young and Liu (2015) successively simulated and predicted rainfall-runoff during TC events by combining physically-based models and ANNs. Then, Humphrey et al. (2016) explored a hybrid approach using simulated soil moisture from a conceptual rainfall-runoff model and a Bayesian ANN statistical model for monthly streamflow forecasting.

In addition, considering the close relationship between TC-induced rainfall and flood hazards, Lin et al. (2013b) established an SVM-based model to forecast the rainfall and runoff at the leading time of 1–6 h, and it significantly improved the flood forecasting at the leading time of 4–6 h (Lin et al., 2013b). On this basis (Lin and Jhong, 2015), a new type of inundation forecasting model (Figure 6) with effective TC characteristics was constructed by Jhong et al. (2016). They compared the model with existing models based on BPN and the SVM-based model without TC characteristics to highlight the important role of TC characteristics on the improvement in inundation forecasting performance. Accurate prediction of suspended sediment concentration to reduce reservoir deposition for maintaining the reservoir storage capacity also plays an important role in reservoir management and flood disaster prevention (Halbe et al., 2013). The reservoir sedimentation issue is regarded as the urgent subject in the forecasting of TC-induced rainfall (Wisser et al., 2013). Observing the operation of most reservoirs for decades, the deposition rate was confirmed to be higher than the original estimation because climate change caused the yielded sediment to increase during TC periods (Huang et al., 2019). As attractive method for integrating various sources of information (Babovic, 2000), neural networks have been widely used in real-time forecasting of suspended sediment concentration in the past few years (Zounemat-Kermani et al., 2016; Alizadeh et al., 2017; Malik et al., 2017), e.g., ANN-based or neuro-fuzzy models (Lohani et al., 2007; Cobaner et al., 2009; Liu et al., 2013; Kumar et al., 2016; Ghose and Samantaray, 2018). Huang et al. (2019) proposed a two-stage forecasting approach integrating numerical and ML-based models (Figure 7) to provide accurate real-time forecasting of half-hourly suspended sediment concentration during TC periods.

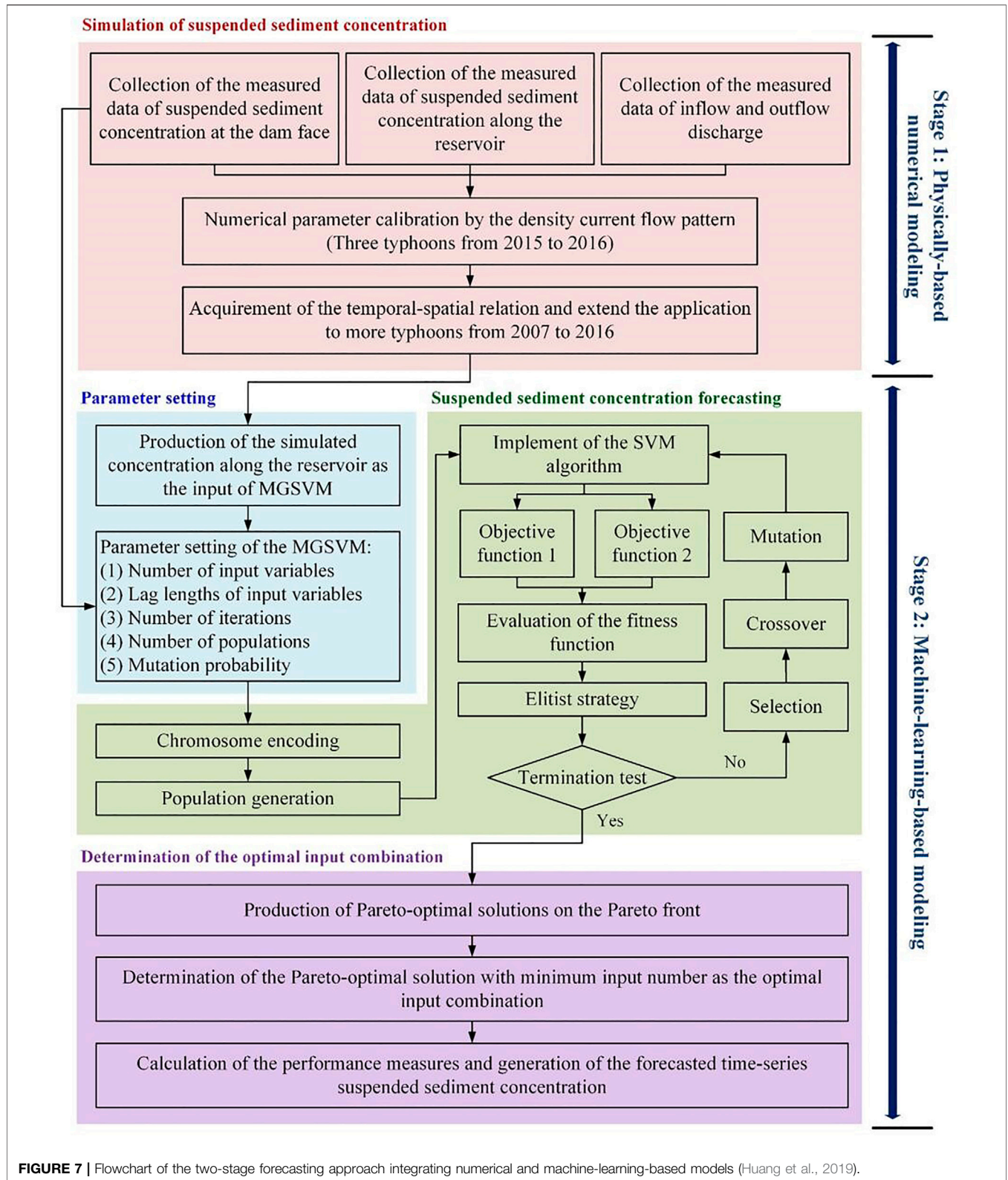


FIGURE 7 | Flowchart of the two-stage forecasting approach integrating numerical and machine-learning-based models (Huang et al., 2019).

Disaster Impact Assessment

Recently, ML classification algorithms have also been applied to the impact assessment of TC disasters. Most studies used historical TC

information and the disaster information in the early stages of TC to train models and reasonably estimate the grade of current disaster. Chen and Liu (2011) and Lou et al. (2012) established

the prediction model of TC disaster grade based on the Hopfield neural network and SVM algorithms, respectively. In addition, Pham et al. (2016) constructed an assessment model of landslide vulnerability based on the SVM and DT classification algorithms. In this model, the geographic location, slope gradient and aspect, curvature and other landslide factors were taken into account, and the assessment accuracy was more than 80%.

CONCLUSION AND DISCUSSIONS

Conclusion

Forecasting the genesis, tracks, intensity and disastrous impact of TCs is a key issue to be addressed in TC early warning and forecasting, and even disaster prevention and mitigation. Traditional statistical methods use a set of interrelated predictors to predict TC through linear statistics. However, the currently used simple statistical relationship cannot handle the complex and nonlinear relationship between the TC-related predictors. Therefore, the actual situation cannot be accurately described. Advanced numerical models based on a physical interpretation have been applied to the operational TC forecast. Although they are the main tools for predicting TC, they have some limitations. Issues such as insufficient description of complex physical processes, inaccurate vortex initialization and coarse resolution degrade the performance of the models. The numerical model combining kinetics and statistics, as one of the current TC prediction techniques, not only retains the basic kinetic mechanism described by the physical equations, but also uses statistical means to deal with the uncertainties in the kinetic process, playing an increasingly important role in TC forecast. The predictors of this model are often extracted subjectively, so the efficiency and objectivity are low, and the accuracy depends on the experience of the forecaster. With the explosive growth of satellite data, surface observation data and reanalysis data, the ML algorithm with high portability and significant advantages in data processing and image recognition, has provided a brand-new method for overcoming the bottleneck in traditional of TC prediction. Its application in TC forecasting was reviewed in this paper, and main conclusions were shown as follows.

- (1) The DT, logistic regression, RF, AdaBoost and SVM algorithms have shown significant advantages in predicting whether tropical disturbances can develop into TCs. And the SVR and multi-layer perceptron algorithms have been widely used in predicting the occurrence frequency of TCs in TC-prone areas in different seasons.
- (2) Using the best track data with temporal information, the neural network, SVM, artificial neural network algorithms, cluster analysis and ensemble learning can be used to predict TC tracks. Using remote sensing image data with spatial information, the neural network and CNN can effectively extract three-dimensional spatial features of TCs and improve TC track forecasting.
- (3) For TC intensity forecasting, the CNN algorithm has a bright application prospect in the judgment of TC grade. By using the regression algorithms such as the back-propagation

neural network algorithm, partial least squares regression, SVM and DT algorithm, and the classification algorithms such as the deep CNN, logistic regression and Bayesian Network, the objective forecast accuracy of TC intensity can be improved. The application of DL models based on infrared images, passive microwave-retrieved precipitation and prior physical knowledge augmentation has also greatly improved the level of TC intensity forecasting.

- (4) More refined forecasting of TC wind field can be realized through correcting the numerical weather forecasting by the algorithms such as RNN, SVM, PCA-RBF, least absolute shrinkage and selection operator regression, RF and DL. In particular, ANN has been widely utilized in simulating the wind field inside TCs. The application of single algorithm (neural network) and hybrid algorithm (such as the hybrid neural network model, MOGA and the SVM hybrid model) has greatly improved the prediction of rainfall and runoff. Furthermore, the fusion of physical conceptual models and ML methods also provides new horizons for improving the level of TC-induced rainfall forecast. The algorithms, such as neural network, SVM and DT, had mature application in the assessment of TC disaster impact.

Discussions

With the rapid development of satellite remote sensing data and numerical weather models, it is still challenging to use the ML for mining efficient, accurate and intelligent meteorological data to achieve TC forecasting. Firstly, ML algorithms tend to solve data science problems of optimizing specific target functions and mining the statistical laws and evolution trends of various factors only in mathematical expressions, but the ML algorithms lack a reasonable explanation for the physical mechanisms of TCs. Secondly, to obtain an excellent prediction model, a large amount of training data and high-performance computing equipment are required. However, the TC observation data are sparse, irregular and uncertain in some areas, and the observations usually cannot be extracted from heterogeneous instruments used to compare with the model data. Thirdly, the parameter optimization of the ML training process has a greater impact on the simulation results, and there are interactions and constraints among parameters in some algorithms. Further research on the ML algorithms, with more complex structure, higher prediction accuracy, stronger generalization ability and wider suitability, is needed. It is imperative to establish a ML method for TC prediction with higher interpretation, intervention and precision.

AUTHOR CONTRIBUTIONS

HH and ZW contributed to conception and design of the review. ZW combed through research findings and wrote the first draft of the manuscript. HH wrote sections of the manuscript. HH, ZW, JZ and XW participated in the revision of the article format. All authors contributed to manuscript revision, read, and approved the submitted version.

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REFERENCES

- Ahijevych, D., Pinto, J. O., Williams, J. K., and Steiner, M. (2016). Probabilistic Forecasts of Mesoscale Convective System Initiation Using the Random Forest Data Mining Technique. *Wea. Forecast.* 31 (2), 581–599. doi:10.1175/WAF-D-15-0113.1
- Aleman, S., Beltran, J., Perez, A., and Ganzfried, S. (2018). Predicting Hurricane Trajectories Using a Recurrent Neural Network. *Proc. AAAI Conf. Artif. Intell.* 33, 468–475. doi:10.1609/aaai.v33i01.3301468
- Alizadeh, M. J., Jafari Nodoushan, E., Kalarestaghi, N., and Chau, K. W. (2017). Toward Multi-Day-Ahead Forecasting of Suspended Sediment Concentration Using Ensemble Models. *Environ. Sci. Pollut. Res.* 24 (36), 28017–28025. doi:10.1007/s11356-017-0405-4
- Babovic, V. (2000). Data Mining and Knowledge Discovery in Sediment Transport. *Comp-aided Civ. Eng.* 15 (5), 383–389. doi:10.1111/0885-9507.00202
- Baik, J.-J., and Paek, J.-S. (2000). A Neural Network Model for Predicting Typhoon Intensity. *J. Meteorological Soc. Jpn.* 78 (6), 857–869. doi:10.2151/jmsj1965.78.6_857
- Camargo, S. J., Robertson, A. W., Gaffney, S. J., Smyth, P., and Ghil, M. (2007). Cluster Analysis of Typhoon Tracks. Part I: General Properties. *J. Clim.* 20 (14), 3635–3653. doi:10.1175/JCLI4188.1
- Chandra, R., and Dayal, K. S. (2015). Coevolutionary Recurrent Neural Networks for Prediction of Rapid Intensification in Wind Intensity of Tropical Cyclones in the South Pacific Region. *Lect. Notes Comput. Sci.* 9491, 43–52. doi:10.1007/978-3-319-26555-1_6
- Chaudhuri, S., Basu, D., Das, D., Goswami, S., and Varshney, S. (2017). Swarm Intelligence and Neural Nets in Forecasting the Maximum Sustained Wind Speed along the Track of Tropical Cyclones over Bay of Bengal. *Nat. Hazards* 87 (3), 1413–1433. doi:10.1007/s11069-017-2824-4
- Chen, B.-F., Chen, B., Lin, H.-T., and Elsberry, R. L. (2019a). Estimating Tropical Cyclone Intensity by Satellite Imagery Utilizing Convolutional Neural Networks. *Wea. Forecast.* 34 (2), 447–465. doi:10.1175/WAF-D-18-0136.1
- Chen, J.-M., Elsberry, R. L., Boothe, M. A., and Carr, L. E. (1999). A Simple Statistical-Synoptic Track Prediction Technique for Western North Pacific Tropical Cyclones. *Mon. Wea. Rev.* 127 (1), 89–102. doi:10.1175/1520-0493(1999)127<0089:assstp>2.0.co;2
- Chen, R. (2018). *Research on the Key Technology of Typhoon Prediction Based on Deep Learning*. dissertation/master's thesis (Hunan: National University of Defense Technology). (in Chinese).
- Chen, R., Wang, X., Zhang, W., Zhu, X., Li, A., and Yang, C. (2019b). A Hybrid CNN-LSTM Model for Typhoon Formation Forecasting. *GeoInformatica* 23 (3), 375–396. doi:10.1007/s10707-019-00355-0
- Chen, R., Zhang, W., and Wang, X. (2020b). Machine Learning in Tropical Cyclone Forecast Modeling: A Review. *Atmosphere* 11 (676), 676. doi:10.3390/atmos11070676
- Chen, S. H., and Liu, X. Q. (2011). Typhoon Disaster Evaluation Model Based on Discrete Hopfield Neural Network. *J. Nat. Dis.* 20 (5), 47–52. (in Chinese). doi:10.13577/j.jnd.2011.0507
- Chen, X. P., Chen, Y. W., and Shi, J. (2020a). Rainfall Modeling and Prediction by Radar Echo Data Based on Machine Learning. *J. Nanjing Univ. Inf. Sci. Technol. Nat. Sci. Ed.* 12 (4), 483–494. (in Chinese). doi:10.13878/j.cnki.jnuist.2020.04009
- Chen, Z., Yu, X., Chen, G., and Zhou, J. (2018). “Cyclone Intensity Estimation Using Multispectral Imagery from the FY-4 Satellite,” in 2018 International Conference on Audio, Language and Image Processing (ICALIP) (IEEE), 46–51. doi:10.1109/icalip.2018.8455603
- Cobaner, M., Unal, B., and Kisi, O. (2009). Suspended Sediment Concentration Estimation by an Adaptive Neuro-Fuzzy and Neural Network Approaches Using Hydro-Meteorological Data. *J. Hydrology* 367 (1-2), 52–61. doi:10.1016/j.jhydrol.2008.12.024
- Cui, L. L., Chen, Z., and Yu, X. X. (2020). Deep Learning Estimation of Tropical Cyclone Intensity along the Southeast Coast of China Using FY-4A Satellite. *J. Remote Sens.* 24 (7), 842–851. (in Chinese). doi:10.11834/jrs.20209124
- Cui, Y. H., Shang, C., and Chen, S. Q. (2019). Overview of AI: Developments of AI Techniques. *Radio Commun. Technol.* 45 (3), 225–231. (in Chinese). doi:10.3969/j.issn.1003-3114.2019.03.01
- Czajkowski, J., Simmons, K., and Sutter, D. (2011). An Analysis of Coastal and Inland Fatalities in Landfalling US Hurricanes. *Nat. Hazards* 59 (3), 1513–1531. doi:10.1007/s11069-011-9849-x
- Deb, K., Pratap, A., Agarwal, S., and Meyarivan, T. (2002). A Fast and Elitist Multiobjective Genetic Algorithm: NSGA-II. *IEEE Trans. Evol. Comput.* 6 (2), 182–197. doi:10.1109/4235.996017
- Demuth, J. L., DeMaria, M., and Knaff, J. A. (2006). Improvement of Advanced Microwave Sounding Unit Tropical Cyclone Intensity and Size Estimation Algorithms. *J. Appl. Meteor. Climatol.* 45 (11), 1573–1581. doi:10.1175/JAM2429.1
- Demuth, J. L., DeMaria, M., Knaff, J. A., and Vonder Haar, T. H. (2004). Evaluation of Advanced Microwave Sounding Unit Tropical-Cyclone Intensity and Size Estimation Algorithms. *J. Appl. Meteor.* 43 (2), 282–296. doi:10.1175/1520-0450(2004)043<0282:eoamsu>2.0.co;2
- Deng, H., Zhang, Y. C., and Gu, R. (2018). Correction Method of Short-Term Wind Speed in Wind Farm Research Based on PCA and RBF Neural Network. *Meteor. Sci. Technol.* 46 (1), 10–15. (in Chinese). doi:10.19517/j.1671-6345.20170014
- Dong, L., and Zhang, F. (2016). OBEST: An Observation-Based Ensemble Subsetting Technique for Tropical Cyclone Track Prediction. *Wea. Forecast.* 31 (1), 57–70. doi:10.1175/WAF-D-15-0056.1
- Dong, P. P. (2021). *Research on Tropical Cyclone Track Prediction Method Based on Multi-Modal Data*. dissertation/master's thesis (Shanghai: Shanghai Normal University). (in Chinese).
- Dorffner, G. (1996). Neural Networks for Time Series Processing. *Neural Netw. world* 6 (4), 447–468
- Dvorak, V. F. (1975). Tropical Cyclone Intensity Analysis and Forecasting from Satellite Imagery. *Mon. Wea. Rev.* 103 (5), 420–430. doi:10.1175/1520-0493(1975)103<0420:tciaaf>2.0.co;2
- Emanuel, K. (2018). 100 Years of Progress in Tropical Cyclone Research. *Meteor. Monogr.* 59 (11-68), 1–15. doi:10.1175/AMSMONOGRAPHIS-D-18-0016.1
- Emanuel, K., and Nolan, D. S. (2004). “Tropical Cyclone Activity and the Global Climate System,” in Proceedings of the 26th Conference on Hurricanes and Tropical Meteorology.
- Fetnat, G., Homaifar, A., and Knapp, K. R. (2013). Objective Tropical Cyclone Intensity Estimation Using Analogs of Spatial Features in Satellite Data. *Wea. Forecast.* 28 (6), 1446–1459. doi:10.1175/WAF-D-13-00006.1
- Fu, B., Peng, M. S., Li, T., and Stevens, D. E. (2012). Developing versus Nondeveloping Disturbances for Tropical Cyclone Formation. Part II: Western North Pacific. *Mon. Wea. Rev.* 140 (4), 1067–1080. doi:10.1175/2011MWR3618.1
- Gao, S., Zhang, W., Liu, J., Lin, I.-I., Chiu, L. S., and Cao, K. (2016). Improvements in Typhoon Intensity Change Classification by Incorporating an Ocean Coupling Potential Intensity Index into Decision Trees*. *Wea. Forecast.* 31 (1), 95–106. doi:10.1175/WAF-D-15-0062.1
- Gao, S., Zhao, P., Pan, B., Li, Y., Zhou, M., Xu, J., et al. (2018). A Nowcasting Model for the Prediction of Typhoon Tracks Based on a Long Short Term Memory Neural Network. *Acta Oceanol. Sin.* 37 (5), 8–12. doi:10.1007/s13131-018-1219-z
- Geng, H., Shi, D., Zhang, W., and Huang, C. (2016). A Prediction Scheme for the Frequency of Summer Tropical Cyclone Landfalling over China Based on Data Mining Methods. *Metall. Apps* 23 (4), 587–593. doi:10.1002/met.1580
- Geng, H., Sun, J., Zhang, W., and Huang, C. (2015). “Study on Index Model of Tropical Cyclone Intensity Change Based on Projection Pursuit and Evolution

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- Strategy," in 2015 IEEE Symposium Series on Computational Intelligence (IEEESSCI), 145–150. doi:10.1109/SSCI.2015.31
- Ghose, D. K., and Samantaray, S. (2018). Modelling Sediment Concentration Using Back Propagation Neural Network and Regression Coupled with Genetic Algorithm. *Procedia Comput. Sci.* 125, 85–92. doi:10.1016/j.procs.2017.12.013
- Giffard-Roisin, S., Yang, M., Charpiat, G., Kumler Bonfanti, C., Kégl, B., and Monteleoni, C. (2020). Tropical Cyclone Track Forecasting Using Fused Deep Learning from Aligned Reanalysis Data. *Front. Big data* 3, 1. doi:10.3389/fdata.2020.00001
- Girshick, R., Donahue, J., Darrell, T., and Malik, J. (2014/2014). Rich Feature Hierarchies for Accurate Object Detection and Semantic Segmentation. *IEEE Conf. Comput. Vis. Pattern Recognit.*, 580–587. doi:10.1109/CVPR.2014.81
- Gray, W. M. (1968). Global View of the Origin of Tropical Disturbances and Storms. *Mon. Wea. Rev.* 96 (10), 669–700. doi:10.1175/1520-0493(1968)096<0669:gvotoo>2.0.co;2
- Gray, W. M. (1998). The Formation of Tropical Cyclones. *Meteorol. Atmos. Phys.* 67 (1–4), 37–69. doi:10.1007/BF01277501
- Gu, J. R., Liu, H., Liu, X., and Lv, Q. (2011). Application of Genetic Algorithm-Support Vector Machine Model in Tropical Cyclone Intensity Forecast. *Mar. Forecasts* 28 (3), 8–14. (in Chinese).
- Halbe, J., Pahl-Wostl, C., Sendzimir, J., and Adamowski, J. (2013). Towards Adaptive and Integrated Management Paradigms to Meet the Challenges of Water Governance. *Water Sci. Technol.* 67 (11), 2651–2660. doi:10.2166/wst.2013.146
- Halperin, D. J., Fuelberg, H. E., Hart, R. E., Cossuth, J. H., Sura, P., and Pasch, R. J. (2013). An Evaluation of Tropical Cyclone Genesis Forecasts from Global Numerical Models. *Wea. Forecast.* 28 (6), 1423–1445. doi:10.1175/WAF-D-13-00008.1
- Ham, Y.-G., Kim, J.-H., and Luo, J.-J. (2019). Deep Learning for Multi-Year ENSO Forecasts. *Nature* 573 (7775), 568–572. doi:10.1038/s41586-019-1559-7
- Hennon, C. C., Helms, C. N., Knapp, K. R., and Bowen, A. R. (2011). An Objective Algorithm for Detecting and Tracking Tropical Cloud Clusters: Implications for Tropical Cyclogenesis Prediction. *J. Atmos. Ocean. Tech.* 28 (8), 1007–1018. doi:10.1175/2010JTECHA1522.1
- Hennon, C. C., and Hobgood, J. S. (2003). Forecasting Tropical Cyclogenesis over the Atlantic Basin Using Large-Scale Data. *Mon. Wea. Rev.* 131 (12), 2927–2940. doi:10.1175/1520-0493(2003)131<2927:ftcota>2.0.co;2
- Hochreiter, S., Technische, U. M., Fakultät, F. I., Munich, G., and Schmidhuber, J. (1997). Long Short-Term Memory. *Neural Comput.* 9 (8), 1735–1780. doi:10.1162/neco.1997.9.8.1735
- Hornik, K., Stinchcombe, M., and White, H. (1989). Multilayer Feedforward Networks Are Universal Approximators. *Neural Netw.* 2 (5), 359–366. doi:10.1016/0893-6080(89)90020-8
- Hu, K., Yan, H., and Xia, M. (2017). Satellite Imagery Cloud Classification Based on Transfer Learning. *Trans. Atmos. Sci.* 40 (6), 856–863. (in Chinese). doi:10.13878/j.cnki.dqkxb.201710106002
- Huang, C.-C., Fang, H.-T., Ho, H.-C., and Jhong, B.-C. (2019). Interdisciplinary Application of Numerical and Machine-Learning-Based Models to Predict Half-Hourly Suspended Sediment Concentrations during Typhoons. *J. Hydrology* 573, 661–675. doi:10.1016/j.jhydrol.2019.04.001
- Huang, J. W., Duan, Y., and Yang, K. (2021). Relationship Analysis of Radar Echo and Rainfall Based on Machine Learning. *Softw. Eng. Appl.*, 35–43. (in Chinese). doi:10.12677/sea.2021.101006
- Huang, W. F., and Xu, Y. L. (2013). Prediction of Typhoon Design Wind Speed and Profile over Complex Terrain. *Struct. Eng. Mech.* 45 (1), 1–18. doi:10.12989/sem.2013.45.1.001
- Huang, X. Y., and Jin, L. (2013). An Artificial Intelligence Prediction Model Based on Principal Component Analysis for Typhoon Tracks. *Chin. J. Atmos. Sci.* 37 (5), 1154–1164. (in Chinese). doi:10.3878/j.issn.1006-9895.2012.12059
- Huang, Y., Jin, L., Zhao, H.-s., and Huang, X.-y. (2018). Fuzzy Neural Network and LLE Algorithm for Forecasting Precipitation in Tropical Cyclones: Comparisons with Interpolation Method by ECMWF and Stepwise Regression Method. *Nat. Hazards* 91 (1), 201–220. doi:10.1007/s11069-017-3122-x
- Humphrey, G. B., Gibbs, M. S., Dandy, G. C., and Maier, H. R. (2016). A Hybrid Approach to Monthly Streamflow Forecasting: Integrating Hydrological Model Outputs into a Bayesian Artificial Neural Network. *J. Hydrology* 540, 623–640. doi:10.1016/j.jhydrol.2016.06.026
- Jhong, B.-C., Wang, J.-H., and Lin, G.-F. (2016). Improving the Long Lead-Time Inundation Forecasts Using Effective Typhoon Characteristics. *Water Resour. Manage* 30 (12), 4247–4271. doi:10.1007/s11269-016-1418-3
- Ji, S., Xu, W., Yang, M., and Yu, K. (2013). 3D Convolutional Neural Networks for Human Action Recognition. *IEEE Trans. Pattern Anal. Mach. Intell.* 35 (1), 221–231. doi:10.1109/TPAMI.2012.59
- Jia, P. T., He, C. H., and Liu, L. (2007). Overview of Time Series Data Mining. *Appl. Res. Comput.* 24 (11), 15–18+29. (in Chinese).
- Jiang, G. Q., Xu, J., and Wei, J. (2018). A Deep Learning Algorithm of Neural Network for the Parameterization of Typhoon-Ocean Feedback in Typhoon Forecast Models. *Geophys. Res. Lett.* 45 (8), 3706–3716. doi:10.1002/2018GL077004
- Jiang, H., Tao, C., and Pei, Y. (2019). Estimation of Tropical Cyclone Intensity in the North Atlantic and Northeastern Pacific Basins Using TRMM Satellite Passive Microwave Observations. *J. Appl. Meteor. Climatol.* 58 (2), 185–197. doi:10.1175/JAMC-D-18-0094.1
- Kim, M., Park, M.-S., Im, J., Park, S., and Lee, M.-I. (2019a). Machine Learning Approaches for Detecting Tropical Cyclone Formation Using Satellite Data. *Remote Sens.* 11 (10), 1195. doi:10.3390/rs11101195
- Kim, S., Kim, H., Lee, J., Yoon, S., Ebrahimi Kahou, S., Kashinath, K., et al. (2019b). "Deep-hurricane-tracker: Tracking and Forecasting Extreme Climate Events," in 2019 IEEE Winter Conference on Applications of Computer Vision (WACV), 1761–1769. doi:10.1109/wacv.2019.00192
- Kim, Y.-D., and Choi, S. (2007). Nonnegative Tucker Decomposition. *Proc. IEEE Comput. Soc. Conf. Comput. Vis. Pattern Recognit.*, 1–8. doi:10.1109/CVPR.2007.383405
- Klotz, B. W., and Jiang, H. Y. (2016). Global Composites of Surface Wind Speeds in Tropical Cyclones Based on a 12 Year Scatterometer Database. *Geophys. Res. Lett.* 43 (19), 10480–10488. doi:10.1002/2016gl071066
- Knaff, J. A., and Sampson, C. R. (2015). After a Decade Are Atlantic Tropical Cyclone Gale Force Wind Radii Forecasts Now Skillful? *Wea. Forecast.* 30 (3), 702–709. doi:10.1175/WAF-D-1400149.110.1175/waf-d-14-00149.1
- Knutson, T. R., Sirutis, J. J., Garner, S. T., Held, I. M., and Tuleya, R. E. (2007). Simulation of the Recent Multidecadal Increase of Atlantic Hurricane Activity Using an 18-Km-Grid Regional Model. *Bull. Amer. Meteor. Soc.* 88 (10), 1549–1565. doi:10.1175/BAMS-88-10-1549
- Kordmahalleh, M. M., Sefidmazgi, M. G., and Homaifar, A. (2016/2016). A Sparse Recurrent Neural Network for Trajectory Prediction of Atlantic Hurricanes. *GECCO Proceedings Genet. Evol. Comput. Conf.* 16, 957–964. doi:10.1145/2908812.2908834
- Kossin, J. P., Knaff, J. A., Berger, H. I., Herndon, D. C., Cram, T. A., Velden, C. S., et al. (2007). Estimating Hurricane Wind Structure in the Absence of Aircraft Reconnaissance. *Wea. Forecast.* 22 (1), 89–101. doi:10.1175/WAF985.1
- Kovordányi, R., and Roy, C. (2009). Cyclone Track Forecasting Based on Satellite Images Using Artificial Neural Networks. *ISPRS J. Photogrammetry Remote Sens.* 64 (6), 513–521. doi:10.1016/j.isprsjprs.2009.03.002
- Krishna, K., and Narasimha Murty, M. (1999). Genetic K-Means Algorithm. *IEEE Trans. Syst. Man. Cybern. B* 29, 433–439. doi:10.1109/3477.764879
- Krizhevsky, A., Sutskever, I., and Hinton, G. E. (2017). ImageNet Classification with Deep Convolutional Neural Networks. *Commun. ACM* 60 (6), 84–90. doi:10.1145/3065386
- Kumar, D., Pandey, A., Sharma, N., and Flügel, W.-A. (2016). Daily Suspended Sediment Simulation Using Machine Learning Approach. *Catena* 138, 77–90. doi:10.1016/j.catena.2015.11.013
- Landsea, C. W., and Franklin, J. L. (2013). Atlantic Hurricane Database Uncertainty and Presentation of a New Database Format. *Mon. Wea. Rev.* 141 (10), 3576–3592. doi:10.1175/MWR-D-12-00254.1
- LeCun, Y., Boser, B., Denker, J. S., Henderson, D., Howard, R. E., Hubbard, W., et al. (1989). Backpropagation Applied to Handwritten Zip Code Recognition. *Neural Comput.* 1 (4), 541–551. doi:10.1162/neco.1989.1.4.541
- Lee, R. S. T., and Liu, J. N. K. (2000). Tropical Cyclone Identification and Tracking System Using Integrated Neural Oscillator Elastic Graph Matching and Hybrid RBF Network Track Mining Techniques. *IEEE Trans. Neural Netw.* 11 (3), 680–689. doi:10.1109/72.846739
- Lee, Y.-J., Hall, D., Stewart, J., and Govett, M. (2019). Machine Learning for Targeted Assimilation of Satellite Data. *Mach. Learn. Knowl. Discov. Databases*, 53–68. doi:10.1007/978-3-030-10997-4_4

- Li, Y., Kong, N. Q., and Chen, R. Z. (2008). Difference of QBO Structure between East Asia Monsoon Region and South Asia Monsoon Region. *Mar. Forecasts* 25 (3), 81–85. (in Chinese).
- Lin, G.-F., Chen, G.-R., Wu, M.-C., and Chou, Y.-C. (2009). Effective Forecasting of Hourly Typhoon Rainfall Using Support Vector Machines. *Water Resour. Res.* 45 (8), W08440. doi:10.1029/2009WR007911
- Lin, G.-F., and Chen, L.-H. (2005). Application of an Artificial Neural Network to Typhoon Rainfall Forecasting. *Hydrol. Process.* 19 (9), 1825–1837. doi:10.1002/hyp.5638
- Lin, G.-F., Chou, Y.-C., and Wu, M.-C. (2013a). Typhoon Flood Forecasting Using Integrated Two-Stage Support Vector Machine Approach. *J. Hydrology* 486, 334–342. doi:10.1016/j.jhydrol.2013.02.012
- Lin, G.-F., and Jhong, B.-C. (2015). A Real-Time Forecasting Model for the Spatial Distribution of Typhoon Rainfall. *J. Hydrology* 521, 302–313. doi:10.1016/j.jhydrol.2014.12.009
- Lin, G.-F., Jhong, B.-C., and Chang, C.-C. (2013b). Development of an Effective Data-Driven Model for Hourly Typhoon Rainfall Forecasting. *J. Hydrology* 495, 52–63. doi:10.1016/j.jhydrol.2013.04.050
- Lin, G.-F., and Wu, M.-C. (2009). A Hybrid Neural Network Model for Typhoon-Rainfall Forecasting. *J. Hydrology* 375 (3-4), 450–458. doi:10.1016/j.jhydrol.2009.06.047
- Liu, Q.-J., Shi, Z.-H., Fang, N.-F., Zhu, H.-D., and Ai, L. (2013). Modeling the Daily Suspended Sediment Concentration in a Hyperconcentrated River on the Loess Plateau, China, Using the Wavelet-ANN Approach. *Geomorphology* 186, 181–190. doi:10.1016/j.geomorph.2013.01.012
- Liu, Y. (2009). Automatic Calibration of a Rainfall-Runoff Model Using a Fast and Elitist Multi-Objective Particle Swarm Algorithm. *Expert Syst. Appl.* 36 (5), 9533–9538. doi:10.1016/j.eswa.2008.10.086
- Lohani, A. K., Goel, N. K., and Bhatia, K. K. S. (2007). Deriving Stage-Discharge-Sediment Concentration Relationships Using Fuzzy Logic. *Hydrological Sci. J.* 52 (4), 793–807. doi:10.1623/hysj.52.4.793
- Lonfat, M., Rogers, R., Marchok, T., and Marks, F. D. (2007). A Parametric Model for Predicting Hurricane Rainfall. *Mon. Wea. Rev.* 135 (9), 3086–3097. doi:10.1175/MWR3433.1
- Loridan, T., Crompton, R. P., and Dubossarsky, E. (2017). A Machine Learning Approach to Modeling Tropical Cyclone Wind Field Uncertainty. *Mon. Wea. Rev.* 145 (8), 3203–3221. doi:10.1175/MWR-D-16-0429.1
- Lou, W., Chen, H., Shen, X., Sun, K., and Deng, S. (2012). Fine Assessment of Tropical Cyclone Disasters Based on GIS and SVM in Zhejiang Province, China. *Nat. Hazards* 64 (1), 511–529. doi:10.1007/s11069-012-0254-x
- Loukas, A., and Vasilades, L. (2014). Streamflow Simulation Methods for Ungauged and Poorly Gauged Watersheds. *Nat. Hazards Earth Syst. Sci.* 14 (7), 1641–1661. doi:10.5194/nhess-14-1641-2014
- Lu, X. Q., Lei, X. T., and Yu, H. (2014). An Objective TC Intensity Estimation Method Based on Satellite Data. *J. Appl. Meteor. Sci.* 25 (1), 52–58. (in Chinese).
- Lv, Q. P., Luo, J., and Zhu, K. (2009). Experiments on Predicting Tracks of Tropical Cyclones with Climatic Persistence Method Based on Support Vector Machine. *Mar. Forecasts* 26 (1), 76–83. (in Chinese).
- Ma, L. M. (2014). Research Progress on China Typhoon Numerical Prediction Models and Associated Major Techniques. *Prog. Geophys.* 29 (3), 1013–1022. (in Chinese). doi:10.6038/pg20140305
- Malik, A., Kumar, A., and Piri, J. (2017). Daily Suspended Sediment Concentration Simulation Using Hydrological Data of Pranhita River Basin, India. *Comput. Electron. Agric.* 138 (C), 20–28. doi:10.1016/j.compag.2017.04.005
- Melnykov, V., Sarkar, S., and Melnykov, Y. (2021). On Finite Mixture Modeling and Model-Based Clustering of Directed Weighted Multilayer Networks. *Pattern Recognit.* 112, 107641. doi:10.1016/j.patcog.2020.107641
- Mercer, A., and Grimes, A. (2015). Diagnosing Tropical Cyclone Rapid Intensification Using Kernel Methods and Reanalysis Datasets. *Procedia Comput. Sci.* 61, 422–427. doi:10.1016/j.procs.2015.09.179
- Nath, S., Kotal, S. D., and Kundu, P. K. (2016). Seasonal Prediction of Tropical Cyclone Activity over the North Indian Ocean Using Three Artificial Neural Networks. *Meteorol. Atmos. Phys.* 128 (6), 751–762. doi:10.1007/s00703-016-0446-0
- Needham, H. F., Keim, B. D., and Sathiaraj, D. (2015). A Review of Tropical Cyclone-Generated Storm Surges: Global Data Sources, Observations, and Impacts. *Rev. Geophys.* 53 (2), 545–591. doi:10.1002/2014RG000477
- Neumann, C. J., and Hope, J. R. (1972). Performance Analysis of the HURRAN Tropical Cyclone Forecast System. *Mon. Wea. Rev.* 100 (4), 245–255. doi:10.1175/1520-0493(1972)100<0245:paotht>2.3.co;2
- Olander, T. L., and Velden, C. S. (2019). The Advanced Dvorak Technique (ADT) for Estimating Tropical Cyclone Intensity: Update and New Capabilities. *Wea. Forecast.* 34 (4), 905–922. doi:10.1175/WAF-D-19-0007.1
- Olander, T. L., and Velden, C. S. (2007). The Advanced Dvorak Technique: Continued Development of an Objective Scheme to Estimate Tropical Cyclone Intensity Using Geostationary Infrared Satellite Imagery. *Wea. Forecast.* 22 (2), 287–298. doi:10.1175/WAF975.1
- Park, M.-S., Kim, M., Lee, M.-L., Im, J., and Park, S. (2016). Detection of Tropical Cyclone Genesis via Quantitative Satellite Ocean Surface Wind Pattern and Intensity Analyses Using Decision Trees. *Remote Sens. Environ.* 183, 205–214. doi:10.1016/j.rse.2016.06.006
- Peng, M. S., Fu, B., Li, T., and Stevens, D. E. (2012). Developing versus Nondeveloping Disturbances for Tropical Cyclone Formation. Part I: North Atlantic. *Mon. Wea. Rev.* 140 (4), 1047–1066. doi:10.1175/2011MWR3617.1
- Pham, B. T., Tien Bui, D., Dholakia, M. B., Prakash, I., and Pham, H. V. (2016). A Comparative Study of Least Square Support Vector Machines and Multiclass Alternating Decision Trees for Spatial Prediction of Rainfall-Induced Landslides in a Tropical Cyclones Area. *Geotech. Geol. Eng.* 34 (6), 1807–1824. doi:10.1007/s10706-016-9990-0
- Pradhan, R., Ayygun, R. S., Maskey, M., Ramachandran, R., and Cecil, D. J. (2018). Tropical Cyclone Intensity Estimation Using a Deep Convolutional Neural Network. *IEEE Trans. Image Process.* 27 (2), 692–702. doi:10.1109/TIP.2017.2766358
- Qian, Q. F., Wang, C., and Xu, J. Y. (2021). A Deep Learning Technique of Typhoon Intensity Estimation. *Meteor. Mon.* 47 (5), 601–608. (in Chinese). doi:10.7519/j.issn.1000-0526.2021.05.008
- Rappaport, E. N. (2014). Fatalities in the United States from Atlantic Tropical Cyclones: New Data and Interpretation. *Bull. Am. Meteorol. Soc.* 95 (3), 341–346. doi:10.1175/BAMS-D-12-00074.1
- Rasp, S., Pritchard, M. S., and Gentine, P. (2018). Deep Learning to Represent Subgrid Processes in Climate Models. *Proc. Natl. Acad. Sci. U.S.A.* 115 (39), 9684–9689. doi:10.1073/pnas.1810286115
- Reichstein, M., Camps-Valls, G., Stevens, B., Jung, M., Denzler, J., Carvalhais, N., et al. (2019). Deep Learning and Process Understanding for Data-Driven Earth System Science. *Nature* 566 (7743), 195–204. doi:10.1038/s41586-019-0912-1
- Richardson, K. A., Turk, F. J., Bankert, R. L., Hadjimichael, M., Kuciauskas, A. P., and Hawkins, J. D. (2003). Automating the Estimation of Various Meteorological Parameters Using Satellite Data and Machine Learning Techniques. *Front. Remote Sens. Inf. Process.*, 227–252. doi:10.1142/9789812796752_0010
- Richman, M. B., and Leslie, L. M. (2012). Adaptive Machine Learning Approaches to Seasonal Prediction of Tropical Cyclones. *Procedia Comput. Sci.* 12, 276–281. doi:10.1016/j.procs.2012.09.069
- Richman, M. B., Leslie, L. M., Ramsay, H. A., and Klotzbach, P. J. (2017). Reducing Tropical Cyclone Prediction Errors Using Machine Learning Approaches. *Procedia Comput. Sci.* 114, 314–323. doi:10.1016/j.procs.2017.09.048
- Ritchie, E. A., Valliere-Kelley, G., Piñeros, M. F., and Tyo, J. S. (2012). Tropical Cyclone Intensity Estimation in the North Atlantic Basin Using an Improved Deviation Angle Variance Technique. *Wea. Forecast.* 27 (5), 1264–1277. doi:10.1175/WAF-D-11-00156.1
- Rozoff, C. M., and Kossin, J. P. (2011). New Probabilistic Forecast Models for the Prediction of Tropical Cyclone Rapid Intensification. *Wea. Forecast.* 26 (5), 677–689. doi:10.1175/WAF-D-10-05059.1
- Safavian, S. R., and Landgrebe, D. (1991). A Survey of Decision Tree Classifier Methodology. *IEEE Trans. Syst. Man. Cybern.* 21 (3), 660–674. doi:10.1109/21.97458
- Shao, L. M., Fu, G., and Cao, X. C. (2009). Application of BP Neural Network to Forecasting Typhoon Tracks. *J. Nat. Dis.* 6, 106–113. (in Chinese). doi:10.13577/j.jnd.2009.0618
- Shi, X. J., Chen, Z. R., and Wang, H. (2015). “Convolutional LSTM Networks: A Machine Learning Approach for Precipitation Nowcasting,” in 29th Annual Conference on Neural Information Processing Systems (NIPS).
- Snaiki, R., and Wu, T. (2019). Knowledge-enhanced Deep Learning for Simulation of Tropical Cyclone Boundary-Layer Winds. *J. Wind Eng. Industrial Aerodynamics* 194, 103983. doi:10.1016/j.jweia.2019.103983

- Song, H.-J., Huh, S.-H., Kim, J.-H., Ho, C.-H., and Park, S.-K. (2005). Typhoon Track Prediction by a Support Vector Machine Using Data Reduction Methods. *Int. Conf. Comput. Intell. Secur.*, 503–511. doi:10.1007/11596448_74
- Staudemeyer, R. C., and Morris, E. R. (2019). Understanding LSTM-A Tutorial into Long Short-Term Memory Recurrent Neural Networks [Preprint]. Available at: <http://specialsci.cn.nudtproxy.yitlink.com/detail/744190dc-1cbe-4617-96d3-12f9883a3e9f?resourceType=0>.
- Su, H., Wu, L., Jiang, J. H., Pai, R., Liu, A., Zhai, A. J., et al. (2020). Applying Satellite Observations of Tropical Cyclone Internal Structures to Rapid Intensification Forecast with Machine Learning. *Geophys. Res. Lett.* 47 (17), 1–10. doi:10.1029/2020GL089102
- Sun, Q., Jiao, R., Xia, J., Haochen, L., Jianhua, S., Lizhi, W., et al. (2019). Adjusting Wind Speed Prediction of Numerical Weather Forecast Model Based on Machine Learning Methods. *Meteor. Mon.* 45 (3), 426–436. (in Chinese). doi:10.7519/j.issn.1000-0526.2019.03.012
- Suykens, J. A. K., and Vandewalle, J. (1999). Least Squares Support Vector Machine Classifiers. *Neural Process. Lett.* 9 (3), 293–300. doi:10.1023/A:1018628609742
- Tan, J., Chen, S., and Wang, J. (2021). Western North Pacific Tropical Cyclone Track Forecasts by a Machine Learning Model. *Stoch. Environ. Res. Risk Assess.* 35 (6), 1113–1126. doi:10.1007/s00477-020-01930-w
- Tian, J., Li, M., Chen, F., and Kou, J. (2012). Coevolutionary Learning of Neural Network Ensemble for Complex Classification Tasks. *Pattern Recognit.* 45 (4), 1373–1385. doi:10.1016/j.patcog.2011.09.012
- Uhlhorn, E. W., Klotz, B. W., Vukicevic, T., Reasor, P. D., and Rogers, R. F. (2014). Observed Hurricane Wind Speed Asymmetries and Relationships to Motion and Environmental Shear. *Mon. Wea. Rev.* 142 (3), 1290–1311. doi:10.1175/MWR-D-13-00249.1
- Ullrich, P. A., and Zarzycki, C. M. (2017). TempestExtremes: a Framework for Scale-Insensitive Pointwise Feature Tracking on Unstructured Grids. *Geosci. Model. Dev.* 10 (3), 1069–1090. doi:10.5194/gmd-10-1069-2017
- Velden, C. S., and Herndon, D. (2020). A Consensus Approach for Estimating Tropical Cyclone Intensity from Meteorological Satellites: SATCON. *Wea. Forecast.* 35 (4), 1645–1662. doi:10.1175/WAF-D-20-0015.1
- Wang, H. (2020). *Research on Multi-Model Algorithm of Typhoon Path Prediction Based on Deep Learning*. dissertation/master's thesis (Sichuan: University of Electronic Science and Technology of China). (in Chinese).
- Wang, M., Xu, X. D., and Li, Y. (2019). The Characteristics of Unusual Turning Tracks of Tropical Cyclone over the Western North Pacific. *J. Trop. Meteor.* 35 (2), 177–186. (in Chinese). doi:10.16032/j.issn.1004-4965.2019.016
- Wang, Y. F., Zhang, W., and Fu, W. (2011). “Back Propagation (BP)-neural Network for Tropical Cyclone Track Forecast,” in International Conference on Geoinformatics. doi:10.1109/geoinformatics.2011.5981095
- Weï, C.-C. (2015). Forecasting Surface Wind Speeds over Offshore Islands Near Taiwan during Tropical Cyclones: Comparisons of Data-Driven Algorithms and Parametric Wind Representations. *J. Geophys. Res. Atmos.* 120 (5), 1826–1847. doi:10.1002/2014JD022568
- Wijnands, J. S., Qian, G., and Kuleshov, Y. (2016). Variable Selection for Tropical Cyclogenesis Predictive Modeling. *Mon. Wea. Rev.* 144 (12), 4605–4619. doi:10.1175/MWR-D-16-0166.1
- Wijnands, J. S., Shelton, K., and Kuleshov, Y. (2014). Improving the Operational Methodology of Tropical Cyclone Seasonal Prediction in the Australian and the South Pacific Ocean Regions. *Adv. Meteorology* 2014 (1), 1–8. doi:10.1155/2014/838746
- Wimmers, A., Velden, C., and Cossuth, J. H. (2019). Using Deep Learning to Estimate Tropical Cyclone Intensity from Satellite Passive Microwave Imagery. *Mon. Wea. Rev.* 147 (6), 2261–2282. doi:10.1175/MWR-D-18-0391.1
- Wisser, D., Frolking, S., Hagen, S., and Bierkens, M. F. P. (2013). Beyond Peak Reservoir Storage? A Global Estimate of Declining Water Storage Capacity in Large Reservoirs. *Water Resour. Res.* 49 (9), 5732–5739. doi:10.1002/wrcr.20452
- Xu, J. M., and Zhang, Q. S. (2006). Overview of Satellite Wind Derivation and Application. *J. Appl. Meteor. Sci.* 17, 574–582. (in Chinese).
- Xu, Y. L., Zhang, L., and Xiang, C. Y. (2015). Typhoon Intensity Estimation Technique and its Operational Application: With Example of Dvorak Technique. *Adv. Meteor. Sci. Technol.* 5 (4), 22–34. (in Chinese). doi:10.3969/j.issn.2095-1973.2015.04.003
- Young, C.-C., and Liu, W.-C. (2015). Prediction and Modelling of Rainfall-Runoff during Typhoon Events Using a Physically-Based and Artificial Neural Network Hybrid Model. *Hydrological Sci. J.* 60 (12), 2102–2116. doi:10.1080/02626667.2014.959446
- Yu, J. H., Zheng, Y. Q., and Wu, Q. S. (2017). K-means Clustering Method for Classification of the Northwestern Pacific Tropical Cyclone Tracks. *J. Trop. Meteor.* 22 (2), 127–135. doi:10.16555/j.1006-8775.2016.02.003
- Zahera, H. M., Sherif, M. A., and Ngomo, A. C. N. (2019). “Jointly Learning from Social Media and Environmental Data for Typhoon Intensity Prediction,” in Proceedings of the 10th International Conference on Knowledge Capture, 231–234. K-CAP. doi:10.1145/3360901.336441319
- Zeiler, M. D., and Fergus, R. (2014). Visualizing and Understanding Convolutional Networks. *Comput. Sci.*, 818–833. doi:10.1007/978-3-319-10590-1_53
- Zhang, M., Qian, D. Y., and Qiu, H. (2017). Estimating Intensity of Tropical Cyclone over the Western North Pacific Based on TY-3C/MWTS-II Data. *Meteor. Mon.* 43 (5), 573–580. (in Chinese).
- Zhang, T., Lin, W., Lin, Y., Zhang, M., Yu, H., Cao, K., et al. (2019). Prediction of Tropical Cyclone Genesis from Mesoscale Convective Systems Using Machine Learning. *Wea. Forecast.* 34 (4), 1035–1049. doi:10.1175/WAF-D-18-0201.1
- Zhang, W., Fu, B., Peng, M. S., and Li, T. (2015). Discriminating Developing versus Nondeveloping Tropical Disturbances in the Western North Pacific through Decision Tree Analysis. *Wea. Forecast.* 30 (2), 446–454. doi:10.1175/WAF-D-14-00023.1
- Zhang, W., Gao, S., Chen, B., and Cao, K. (2013). The Application of Decision Tree to Intensity Change Classification of Tropical Cyclones in Western North Pacific. *Geophys. Res. Lett.* 40 (9), 1883–1887. doi:10.1002/grl.50280
- Zhao, J. P., Wu, L. G., and Zhao, H. K. (2012). Improvement of Tropical Cyclone Genesis Potential Index in the Western North Pacific Basin. *Sci. Meteor. Sin.* 32 (6), 591–599. (in Chinese). doi:10.3969/2012jms.0110
- Zhong, P., Gong, Z., Li, S., and Schonlieb, C.-B. (2017). Learning to Diversify Deep Belief Networks for Hyperspectral Image Classification. *IEEE Trans. Geosci. Remote Sens.* 55 (6), 3516–3530. doi:10.1109/TGRS.2017.2675902
- Zhou, C. (2014). *The Tropical Cyclone Intensity Forecast Model in the Northwest Pacific Based on Partial Least Squares*. dissertation/master's thesis (Shandong: Ocean University of China). in Chinese.
- Zhou, Z. H. (2006). *Machine Learning*. Beijing: Tsinghua university press. (in Chinese).
- Zhuo, J.-Y., and Tan, Z.-M. (2021). Physics-augmented Deep Learning to Improve Tropical Cyclone Intensity and Size Estimation from Satellite Imagery. *Mon. Wea. Rev.* 149 (7), 2097–2113. doi:10.1175/MWR-D-20-0333.1
- Zounemat-Kermani, M., Kişi, Ö., Adamowski, J., and Ramezani-Charmahineh, A. (2016). Evaluation of Data Driven Models for River Suspended Sediment Concentration Modeling. *J. Hydrology* 535, 457–472. doi:10.1016/j.jhydrol.2016.02.012

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