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Predicting Indian Ocean Cyclone Parameters Using an Artificial Intelligence Technique

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Abstract: Precise prediction of a cyclone track with wind speed, pressure, landfall point, and the time of crossing the land are essential for disaster management and mitigation, including evacuation processes. In this paper, we use an artificial neural network (ANN) approach to estimate the cyclone parameters. For this purpose, these parameters are obtained from the International Best Track Archive for Climate Stewardship (IBTrACS), from the National Oceanic and Atmospheric Administration (NOAA). Since ANN benefits from a large number of data points, each cyclone track is divided into different segments. We use past information to predict the geophysical parameters of a cyclone. The predicted values are compared with the observations.

Keywords: cyclone prediction; artifical neural networks; land crossing point; mean distance error; scatter index

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1. Introduction

A tropical cyclone (TC) is one of the deadliest and most damaging natural disasters affecting people, livestock, agriculture, and the economics of coastal areas. Reductions in uncertainty are of great benefit for disaster-management authorities to plan for evacuation and mitigation processes [1,2]. The major components of cyclone warnings are forecasts of the track, winds, and pressure, in addition to a precise landfall point with the time of crossing the land. Predicting the track of a cyclone helps in knowing the direction in which it is moving and the area it is likely to affect. The intensity is primarily estimated from the maximum sustained wind speed, which provides a measure for the severity of a cyclone. The wind is one of the major hazards associated with a TC, as it creates damage to houses, bridges, electrical poles, mangroves, and the ecosystem. While the damage in the coastal region is typically quite high, inland damage cannot be ruled out. Strong winds are present at the eyewall of a cyclone. The intensity of a cyclone together with the wind speed and the pressure aids in predicting the storm surge, although the spatial extent of the storm and the direction of travel are also important in the prediction process [3,4]. A storm surge is the most devastating component of cyclones, particularly along coastlines that have a highly varying bathymetry, which are plentiful in India. Since bathymetry is one of the most critical components in estimating a storm surge, even a slight error in predicting the landfall point can lead to different storm-surge heights. The time of crossing the land is used to include the impacts of tides and to help in arranging the evacuation process. Thus, location, winds, and the pressure of a cyclone, as well as the landfall point and the time of land crossing, are the critical components in predicting the storm surge.

Several dynamiccal, statistical, and statistical–dynamic models have been developed to predict cyclone parameters. Mohanty and Gupta [5] and Gupta [6] summarised different track-prediction techniques. Bell [7] described the operational forecasting models. Ali et al. [8] summarised the different approaches used in predicting cyclones. They used the Artificial Neural Network (ANN) technique to predict the position of a cyclone alone, in terms of the latitude and longitude using the previous 12 h of observations. In this paper, we attempt to use the same technique to predict winds, pressure, and landfall, in addition to the storm location in terms of latitude and longitude.

ANN is a powerful data-mining tool for computing input–output relationships. It is an information-processing paradigm that works somewhat like a hypothesized biological system in the human brain. ANN consists of an interconnected assembly of models, with functionality that is based on a neuron [9]. The analysis can be used as a standalone application or as a complement to statistical analysis. This non-dynamic numerical model has been used in many oceanographic [10–15] (and meteorological studies [16–18]. The ANN technique is also useful for satellite-parameter retrievals [19–22]. Multiple linear regression (MLR) is a method dealing with linear dependencies, whereas neural networks deal with nonlinearities. If data has some nonlinear dependencies, neural networks outperform the MLR approach. In addition, many studies have used statistical and machine-learning techniques for cyclone studies because those techniques require less computing time. For example, Swain et al. [9] concluded that the ANN approach gave a better result compared to multiple linear-regression techniques (MLR) in the estimation of mixed-layer depth. Sharma et al. [21] also demonstrated the benefits of the ANN technique over MLR. Hence, we used the ANN approach in this study. ANN requires three sets of data: one for training, another for verification, and a third for validation. The first dataset is used to train the model, the second dataset is used to test the model for any shortcomings, and finally, the validation dataset is used in statistical-parameter estimation. The validation dataset is independent: it is not considered in developing the model. In an ANN model, both the input and output variables are normalized to vary between 0 and 1. Popular ANN models include radial-basis functions (RBF) and multilayer perceptions (MLP).

2. Date and Methodology

2.1. Data

Cyclone parameters available over the north Indian Ocean from IBTrACS (International Best Track Archive for Climate Stewardship, https://www.ncei.noaa.gov/data/international-best-track-archive-for-climate-stewardship-ibtracs/v04r00/access/csv/) (accessed on 29 January 2021) during 1971–2019 are used in this analysis. IBTrACS provides information on cyclones from different sources. Here, we use JTWC (Joint Typhoon Warning Center) data alone. These data contain latitude, longitude, surface central pressure, and maximum wind speed of cyclones. Although these data are available both at 3- and 6-h intervals, we use only 6-h interval data in this study because the number of cases with 3-h intervals is much smaller. Based on availability, also used in this study are wind field data from 1973 to 2019, pressure field data from 2001 to 2019, and position (latitude and longitude) data from 1971 to 2019. It is better to have a large number of observations for ANN analysis. If we consider only the period for which pressure fields are available, the dataset would become smaller, so the errors would be larger. Hence, we consider the periods as they are available. However, a segmentation procedure (described later) is used to increase the number of points for ANN analysis. After eliminating those cyclone positions at irregular intervals, 323 cyclones are studied for position, 239 cyclones for wind speed, and 104 cyclones for pressure. An ANN approach is used to forecast future position using past cyclone observations. The tracks are segmented to provide the number of records required by ANN. The selection of training, verification, and validation is described in the next section.

2.2. Segmentation of the Tracks

ANN requires a large number of data records (i.e., sets of conditions for a specific time) to develop the model. Since we do not have enough points if we consider the actual cyclone points rather than just landfall points, each cyclone track has been divided into different segments. A schematic representation of the procedure adopted for segmentation into a 24-h forecast with 6-h interval data is given in Figure 1. For example, for a 24-h forecast if the present position (in terms of latitude and longitude) is at point 3 in Figure 1, that position as well as the previous two six-hour positions (at 2 and 1) are considered as the predictors, and the position at 7 after 24 h from the present position is taken as the predictand. Thus, the positions for the predictors for this first segment are 1, 2, and 3, and the predictand is 7 (pink line). For example, if the present position is at 18 h, locations of 6, 12, and 18 h are the predictors (current and past positions), and the location at 18 h (the next day) is the predictand (forecast position). Then, the second segment is moved to position 2 after 6 h and, for the second segment, positions at 2, 3, and 4 are the predictors, and position at 8 is the predictand (magenta line). Similarly, for segment 12, positions at 10, 11, and 12 are the predictors, and position at 16 is the predictand.

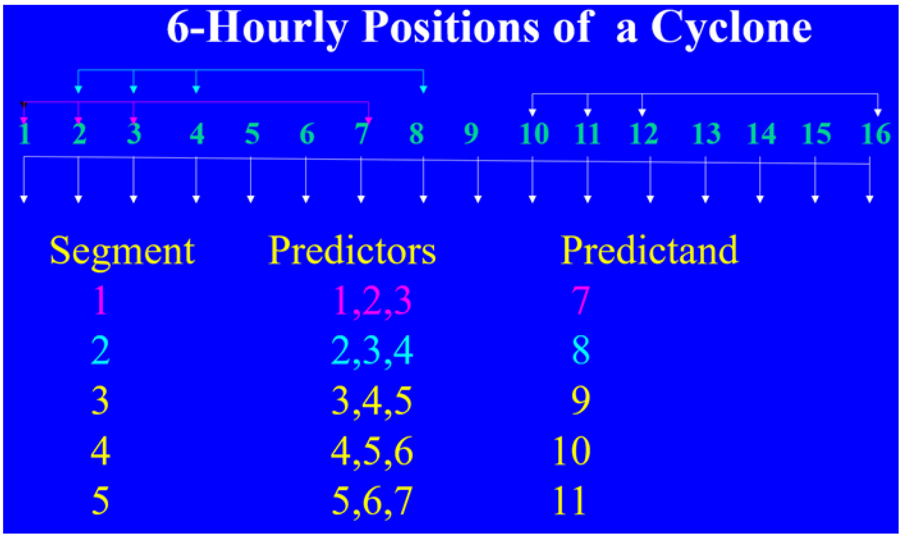

Figure 1. Division of cyclone tracks to various segments.

Since ANN requires three sets of data (one for training, another for verification, and a third for validation), out of the total of 49 years of data on latitude and longitude from 1971 to 2019, 20 years from 1971 to 1990 are used for training, 17 years from 1991 to 2007 for verification, and 12 years from 2008 to 2019 for validation. The same analysis is repeated for cyclone wind speed and pressure. Since these three parameters have different periods, the periods used for training, verification, and validation are also different, as reported in Table 1. In this analysis, the Multi-Layer Perceptron (MLP) approach is used. The period of study, the number of past hours used as predictors, and the hour of forecast as predictand, as well as the total number of segments used for training, verification, and validation for cyclone position, wind speed, and pressure, are given in Table 1. The first column in the table indicates the past number of hours used as the predictors, and the second column indicates the hours in advance for which the forecast is given as the predictand. Thus, a forecasted time of 6 h using the past 6 h has the two past six hourly positions in addition to the current position as predictors and the future 6 positions as predictands. As explained earlier, the total number of points in each dataset depends on the type of segmentation and the period of the data availability. Thus, the number of records decreases as the forecasted time increases from 6 h to 24 h, besides the past number of hours used as predictors.

The land-crossing position of the cyclone track at the coastline has been computed using ArcGIS software.

Table 1. Number of sectors used to compute cyclone position, pressure, and wind speed.

Past Hours Used for Prediction	Forecasted Hour	Total No. of Sectors	No. of Train Sectors	No. of Verification Sectors	No. of Validation Sectors
Latitude/Longitude (Degrees)					
6	6	6245	2747	2165	1333
6	12	5923	2587	2072	1264
6	18	5602	2428	1979	1195
6	24	5283	2271	1886	1126
12	6	5923	2587	2072	1264
12	12	5602	2428	1979	1195
12	18	5283	2271	1886	1126
12	24	4967	2117	1793	1057
	Years considered:		1971–1990	1991–2007	2008–2019
Wind Speed (Knots)					
Past Hours Used for Prediction	**Forecasted Hour**	**Total No. of Sectors**	**No. of Train Sectors**	**No. of Verification Sectors**	**No. of Validation Sectors**
6	6	4757	1268	2165	1324
6	12	4519	1191	2072	1256
6	18	4282	1115	1979	1188
6	24	4045	1039	1886	1120
12	6	4519	1191	2072	1256
12	12	4282	1115	1979	1188
12	18	4045	1039	1886	1120
12	24	3809	964	1793	1054
	Years considered:		1973–1990	1991–2007	2008–2019
Pressure (hPa)					
Past Hours Used for Prediction	**Forecasted Hour**	**Total No. of Sectors**	**No. of Train Sectors**	**No. of Verification Sectors**	**No. of Validation Sectors**
6	6	2066	742	632	692
6	12	1962	706	599	657
6	18	1858	670	566	622
6	24	1754	634	533	587
12	6	1962	706	599	657
12	12	1858	670	566	622
12	18	1754	634	533	587
12	24	1650	598	500	552
	Years considered:		2001–2007	2008–2013	2014–2019

3. Results and Discussion

The cyclone position in terms of latitude and longitude, pressure, and wind speed are estimated from an ANN approach and compared with the observations in the following sections.

3.1. Comparison of the Position

Forecast of the cyclone position in terms of the latitude and longitude are predicted for 6, 12, 18, and 24 h in advance using the current position and 6- and 12-h past positions. The skill in prediction dropped if the forecast period is increased beyond 24 h. Thus, there are two forecasts (latitude and longitude) for 6, 12, 18, and 24 h using 6- and 12-h past positions. Thus, altogether there are eight forecasts. The forecast statistics are given separately for the latitude and longitude in Table 2. Statistics for longitude are indicated in parenthesis. The Pearson Correlation Coefficient (CC) for all forecasts for each of the three datasets (training, testing, and validation) is greater than 0.97, which shows that the patterns of change in the estimations are well-captured. Comparable values among the three datasets for all statistical parameters indicate that they share similar characteristics. Further, the Absolute Residual Mean (ARM) and Root Mean Square Error (RMSE) for longitude are greater than those for latitude in all three dataset forecasts. This is because the longitude values (ranging from 50 to 100 degrees) are greater than the latitude values (ranging from 0 to 25 degrees), because the correlation does not indicate goodness of fit but indicates goodness of patterns of change (i.e., the change in the predicted variable is proportional to the change in the comparison data). That proportionality could be way off and not impact the correlation. Hence, emergency managers will probably find the RMSE value more useful than the correlation.

The Mean Distance Error (MDE) between the observed and predicted positions are computed using 6- and 12-h past positions for the lead hours of 6, 12, 18, and 24. Thus, altogether eight forecasts are given, as shown in Figure 2. This error, for all the cyclones together, varies from 30.7 km (06P06F) to 151.7 km (12P24F). For example, the mean distance error for the 6-h past positions (as input) and 24-h lead position (as the output) is 139.14 km (06P24F in Figure 2). Ali et al. [8] reported an MDE of 137.5 km using ANN and 182.5 km using the CLIPER approach [23,24] for the same 6-h past positions (as input) and 24-h lead position (as the output). Hence, we do not repeat the comparison of the track errors from the ANN approach and CLIPER in this paper. The MDE between the best track and predicted tracks are almost the same for 6-h ANN forecasts, based on a 6-h lead time and a 12-h lead time.

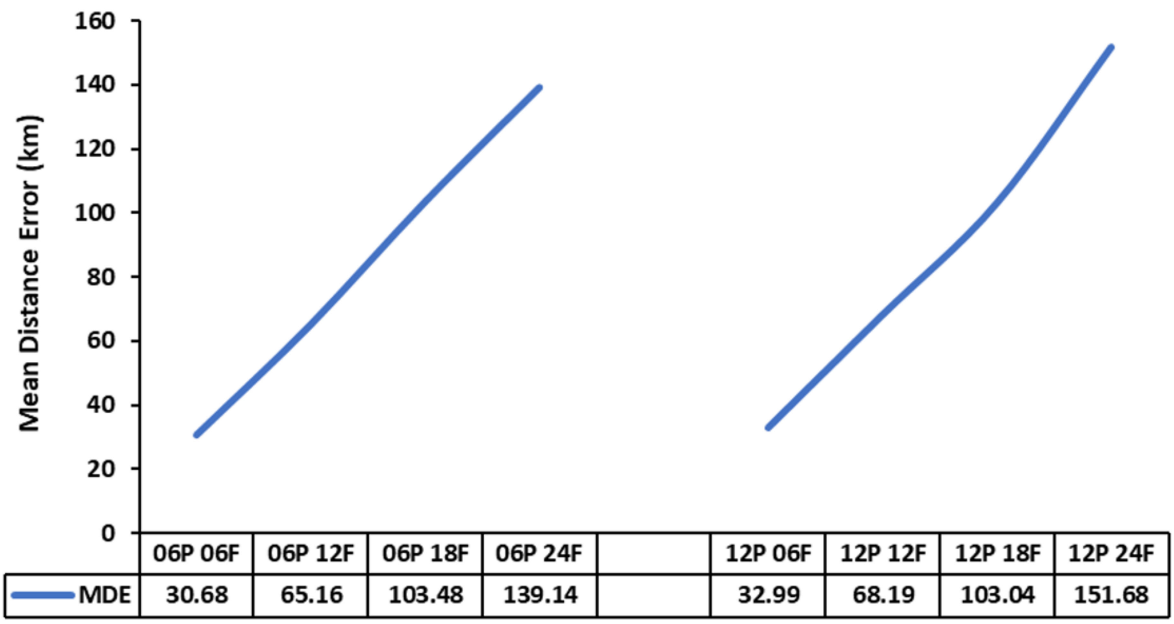

Figure 2. Mean Distance Error (MDE) for the different time periods with 6-h and 12-h past positions with 6-h interval data.

Table 2. The statistical parameters for Absolute Residual Mean (ARM), Root Mean Square Error (RMSE), Correlation Coefficient (CC) for Latitude (Longitude), and Scatter Index (SI), as well as wind speed and pressure.

Latitude (Longitude)									
Forecast Time	Training			Verification			Validation		
	ARM	RMSE	CC	ARM	RMSE	CC	ARM	RMSE	CC
06P 06F	0.1266 (0.1629)	0.1777 (0.2539)	0.9994 (0.9997)	0.1384 (0.1533)	0.1991 (0.2175)	0.9993 (0.9998)	0.1671 (0.1902)	0.2393 (0.275)	0.9983 (0.9998)
06P 12F	0.2918 (0.4009)	0.3999 (0.5954)	0.9971 (0.9983)	0.3228 (0.3699)	0.4450 (0.5056)	0.9967 (0.9991)	0.3395 (0.4144)	0.4676 (0.579)	0.9938 (0.9991)
06P 18F	0.4771 (0.666)	0.6397 (0.9475)	0.9926 (0.9959)	0.528 (0.6086)	0.7085 (0.823)	0.9913 (0.9975)	0.5275 (0.672)	0.7027 (0.9164)	0.9859 (0.9979)
06P 24F	0.6583 (0.9402)	0.8664 (1.2806)	0.9864 (0.9925)	0.7226 (0.8784)	0.9641 (1.1591)	0.9838 (0.9953)	0.7261 (0.8954)	0.9595 (1.1786)	0.9737 (0.9965)
12P 06F	0.1288 (0.1677)	0.1790 (0.2503)	0.9994 (0.9997)	0.1431 (0.1699)	0.2047 (0.2443)	0.9992 (0.9997)	0.1694 (0.2132)	0.2413 (0.3113)	0.9983 (0.9997)
12P 12F	0.3009 (0.4389)	0.4078 (0.6262)	0.997 (0.9982)	0.3596 (0.4167)	0.4901 (0.5747)	0.9962 (0.9988)	0.3448 (0.4465)	0.4739 (0.601)	0.9938 (0.9991)
12P 18F	0.475 (0.6524)	0.6269 (0.9026)	0.9929 (0.9963)	0.5376 (0.6428)	0.7203 (0.8551)	0.9913 (0.9975)	0.535 (0.6629)	0.7107 (0.8856)	0.9858 (0.998)
12P 24F	0.6718 (1.0006)	0.8799 (1.3312)	0.9861 (0.9921)	0.7994 (0.9636)	1.0478 (1.2746)	0.9818 (0.9945)	0.7411 (1.0243)	0.9716 (1.3324)	0.9742 (0.996)

Wind Speed (Knots)												
Forecast Time	Training				Verification				Validation			
	ARM	RMSE	S I	CC	ARM	RMSE	S I	CC	ARM	RMSE	S I	CC
06P 06F	3.085	4.2322	0.0996	0.9772	3.2571	4.8692	0.1287	0.9735	3.5398	5.0605	0.11	0.9795
06P 12F	5.0849	7.0811	0.164	0.9365	5.6212	8.2533	0.2143	0.9233	6.4378	9.1879	0.1959	0.9327
06P 18F	7.0698	9.7056	0.2218	0.8801	7.6532	11.174	0.2854	0.8578	9.03	12.903	0.2702	0.8653
06P 24F	8.8106	11.931	0.2694	0.8174	9.5734	13.864	0.3488	0.7762	11.591	16.175	0.333	0.7849
12P 06F	3.0419	4.2051	0.0974	0.978	3.2997	4.8726	0.1265	0.9739	3.5699	5.1055	0.1088	0.9797
12P 12F	5.0169	7.0494	0.1611	0.9387	5.6424	8.2383	0.2104	0.9252	6.3792	9.1725	0.1921	0.9349
12P 18F	6.9808	9.7024	0.2191	0.8835	7.6686	11.218	0.2822	0.8598	9.1124	13.035	0.2684	0.8668
12P 24F	8.7629	11.952	0.2669	0.8224	9.5918	13.858	0.3438	0.7826	11.78	16.425	0.3329	0.7862

Table 2. *Cont.*

Pressure (hPa)												
Forecast Time	Training				Verification				Validation			
	ARM	RMSE	S I	CC	ARM	RMSE	S I	CC	ARM	RMSE	S I	CC
06P 06F	2.2318	3.8428	0.0038	0.9717	2.6246	4.161	0.0041	0.9674	3.4215	4.946	0.005	0.9665
06P 12F	3.7496	5.9774	0.006	0.9326	4.7196	7.1908	0.0072	0.9018	6.0367	8.4201	0.0085	0.9024
06P 18F	5.4029	8.5577	0.0086	0.8612	6.3798	9.7563	0.0098	0.8168	8.1882	11.266	0.0114	0.8221
06P 24F	6.6066	10.307	0.0103	0.7993	8.0948	12.076	0.0122	0.7242	9.9595	13.661	0.0138	0.7426
12P 06F	2.2772	3.7356	0.0037	0.9741	2.6854	4.2219	0.0042	0.9671	3.5482	5.0836	0.0051	0.9654
12P 12F	3.8243	6.1372	0.0061	0.9314	4.56	7.2014	0.0072	0.9034	6.0451	8.4673	0.0085	0.9034
12P 18F	5.4258	8.5138	0.0085	0.8683	6.285	9.6772	0.0097	0.8299	8.136	11.327	0.0114	0.8297
12P 24F	6.6914	10.437	0.0105	0.8047	8.0294	11.953	0.012	0.7341	9.8206	13.467	0.0136	0.7548

The error increases from 6-h forecast (30.68 Km) to 24-h forecast (139.14 km) for 6-h interval data by considering the 6-h past positions. Similarly, the error increases from 6-h forecast (32.99 km) to 24-h forecast (151.68 km) by considering the 12-h past positions. From the validation dataset, four cyclones that do not have a straight path (Phet, Madi, Gaja, and Maha) are randomly selected. A comparison of the best track and the predicted track for these four cyclones is shown in Figure 3. First, the very severe cyclonic storm, Phet (31 May to 6 June 2010) (Figure 3a), initially moved northwestward, then curved after passing over the land, and moved northeastward. The ANN's predicted track very nearly followed this best track, with an MDE of 82.5 km. Another very severe cyclonic storm, Madi (5–12 December 2013) (Figure 3b), re-tracked after moving northeastward, and the predicted track is similar to the best track, with an MDE of 53.1 km. This is the least among the four cyclones studied. Gaja, another severe cyclonic storm (11–18 November 2018), began its track by looping almost back to its starting position in the Bay of Bengal, then it crossed the Indian landmass and moved over the Arabian Sea, with an MDE of 75 km. In addition, finally, the extremely severe cyclonic storm, Maha (30 October to 6 November 2019), has the largest MDE of 87.8 km. The errors are large in the beginning but reduce as the storm progresses. The only reason we could find for the sudden changes in direction of the Maha cyclone is that its speed varied significantly during its course. The minimum and maximum distances it traveled in 6 h are 9.97 km and 244.55 km, respectively. Atlantic Ocean storms that change in speed are typically associated with storms undergoing extratropical transition, but that is not normally a consideration for Indian Ocean storms. Other than this extreme (and, hence, hard to train for) change in speed, we could not find any other reason for the large deviations of the predicted track from the best track of the Maha cyclone. We also plotted (figures not shown) the predicted and best tracks for which the MDE is the minimum (33.45 km) and maximum (120.2 km). The difference between the predicted and the best track for the maximum MDE is much less than that for the Maha cyclone.

3.2. Estimation of Wind Speed

Statistical parameters such as ARM, RMSE, SI (Scatter Index), and CC for all eight forecast combinations for training, verification, and validation are given in Table 2. The CC is more than 0.78 for all estimations of the validation dataset. The RMSE varies between 5 and 16 knots depending upon the lead time. The SI, which is one of the best statistical parameters to interpret any estimation, varies between ~0.1 for a 6-h advance prediction to ~0.3 for a 24-h advance prediction for the validation dataset (Table 2 and Figure 4a). The values increase with the lead time, and this increase is the same irrespective of the past number of 6 or 12 h.

3.3. Estimation of Pressure

Estimation of pressure fields of tropical cyclones is a major problem. The statistical parameters in the estimation of pressure for all eight forecast combinations are given in Table 2. The RMSE for the validation dataset varies from 4.9 hPa to 13.7 hPa, with the error increasing with the lead time. The errors are large, as the absolute values themselves are large (on the order of 1000 hPa). Purnachand et al. [25], utilizing the University of Washington Planetary Boundary Layer (UWPBL) model of Patoux et al. [26], estimated the pressure in cyclone Nilam using Ocean Sat-II Scatterometer wind fields. This model has an option providing the background-pressure values. The RMSE from this model is 4.97 hPa if a standard pressure of 1013 hPa was given, however, the error was reduced to 0.67 hPa when the pressure values of all available buoys were utilized. The estimations by Purnachand et al. [25] are a better comparative to ours because they used in situ pressure values as initial conditions. However, our estimations are comparable with theirs, when using a standard pressure value of 1013 hPa.

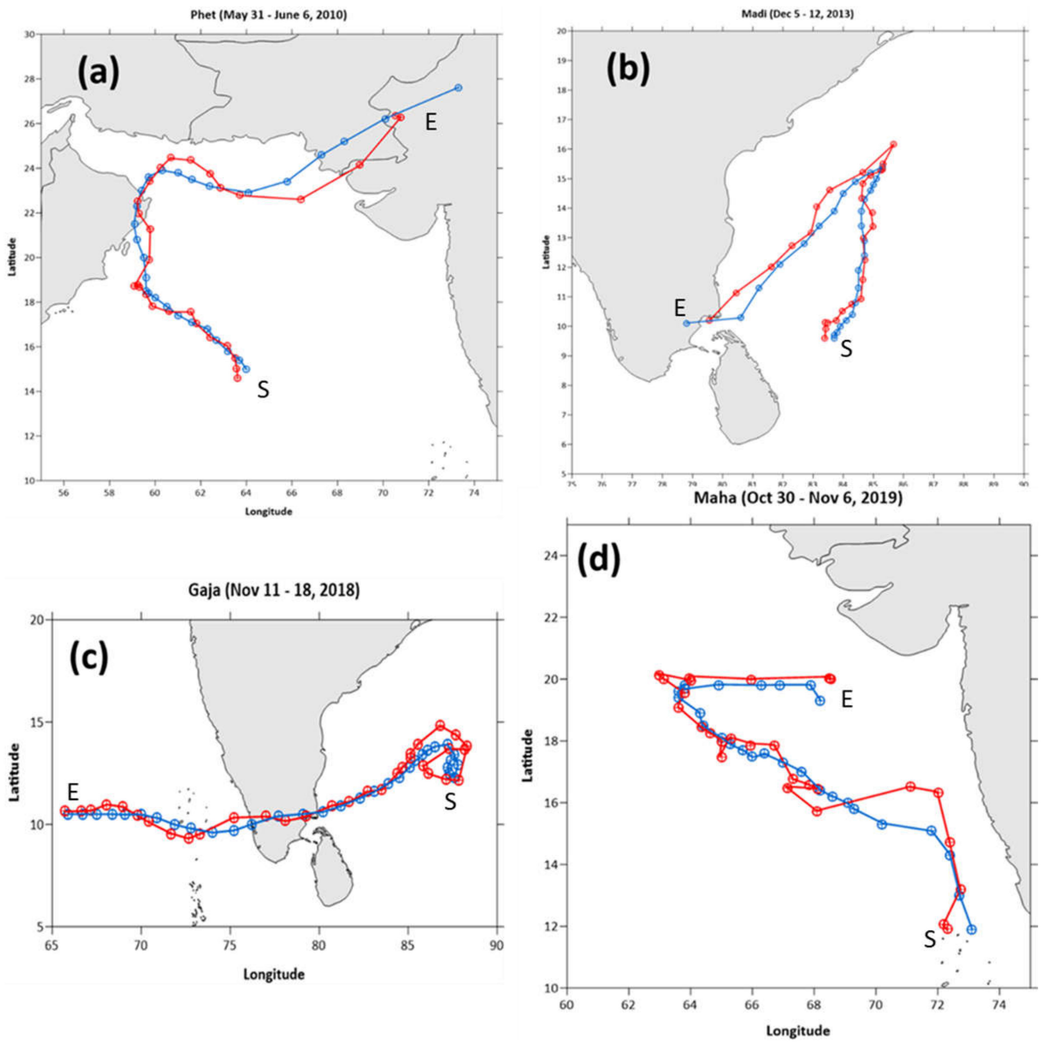

Figure 3. A comparison of the best track from JTWC (blue colour) and the predicted tracks from ANN (red colour) of the cyclones during (**a**) 31 May–6 June 2010 (Very Severe Cyclonic Storm Phet); (**b**) 5–12 December 2013 (Very Severe Cyclonic Storm Madi); (**c**) 11–18 November 2018 (Very Severe Cyclonic Storm Gaja); and (**d**) 30 October–6 November 2019 (Extremely Severe Cyclonic Storm Maha). (Note: S indicates the starting point, and E indicates the ending point).

The SI is very small for all of the eight datasets, varying between 0.0050 and 0.0138 for the validation dataset. The SIs using the 6-h past position and the 12-h past position are shown in Figure 4b. The values increase with the forecast lead time, and this increase is the same irrespective of the past number of 6 or 12 h. In addition to computing the SI, we estimated the skill score (SS) following Murphy [27] (Equation. 3), where the MLR results were considered as the reference. The SS here is 3.9%.

3.4. Land-Crossing-Point Difference

The difference between the land-crossing points indicated by the JTWC's best tracks and the ANN's predicted tracks are given in Table 3, for the 12-h past positions as the predictors and the 12-h and 24-h forecasts' positions as the predictants. For 12-h predictions, the minimum error is 3.8 km, and the maximum error is 124.8 km with a mean value of 38.2 km. In addition, for 24-h forecasts, the minimum error is 0.26 km, and the maximum error is 192.56 km with a mean value of 71.2 km. Mohapatra et al. [28] evaluated the official landfall forecasts by the India Meteorological Department during 2003–2013 for different forecast times ranging from 12 to 72 h. Their average landfall-point-forecast errors are 69 km and 104 km for 12- and 24-h forecasts. During our analysis period of 1971–2019, the average errors are 38 km and 71 km for 12-h and 24-h forecasts, respectively, which are significantly less than those reported by Mohapatra et al. [28].

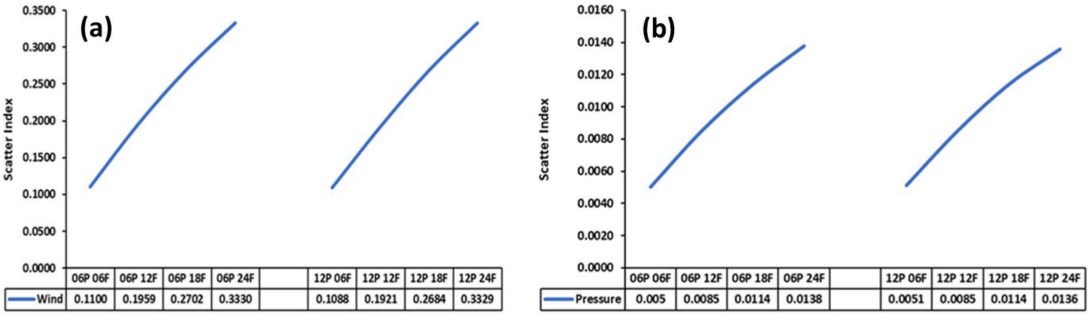

Figure 4. Scatter Index (SI) of (**a**) wind speed and (**b**) pressure for the different lead times of 6 and 12 h and with past 6-h interval data. Note: 'xxP yyF' means xx past hours and yy forecast hour.

Table 3. Land-crossing difference between the best tracks and ANN's predicted tracks.

12 h Past 12-h Forecast			12 h Past 24-h Forecast		
Sl No.	**Year-Cyclone No.**	**Length (km)**	**Sl No.**	**Year-Cyclone No.**	**Length (km)**
1	2008–66	43.72	1	2008–95	18.06
2	2008–90	6.19	2	2009–26	48.47
3	2008–95	24.62	3	2010–24	159.47
4	2009–26	17.61	4	2010–80	50.51
5	2009–64	8.92	5	2011–94	49.77
6	2009–89	61.13	6	2012–81	87.88
7	2010–24	42.4	7	2012–84	62.61
8	2010–80	5.94	8	2013–75	43.31
9	2011–94	33.79	9	2013–93	192.56
10	2012–81	10.61	10	2013–94	38.68
11	2012–84	17.9	11	2014–75	66.58
12	2013–75	14.18	12	2016–91	70.06
13	2013–93	51.31	13	2016–92	66.05
14	2013–94	35.76	14	2018–93	79.98
15	2013–99	79.99	15	2018–102	43.73
16	2014–75	34.29	16	2018–105	129.32
17	2016–91	19.35	17	2019–87	0.26
18	2016–92	14.83			
19	2018–82	89.1		Mean	71.02
20	2018–93	48.78		Max	192.56
21	2018–102	3.8		Min	0.26
22	2018–105	80.42			
23	2019–21	47.56			
24	2019–87	124.8			
	Mean	38.21			
	Max	124.8			
	Min	3.8			

4. Summary and Conclusions

In this study, an ANN approach is used to predict the cyclone parameters, specifically the position in terms of latitude and longitude, wind speed, and pressure. ANN or other machine approaches are less computationally intense than operational numerical weather-predication models. The predicted track is used to estimate the landfall point. After a quality check, 323 cyclones are used for position, 239 cyclones for wind speed, and 104 cyclones for pressure. Since ANN requires a large amount of data, each cyclone has been divided into segments to increase the number of points. Altogether, eight forecast combinations are studied with input from the past 6 and 12 h, each of these past hours having predictions for 6, 12, 18, and 24 h.

The RMSE (which is more relevant to emergency managers) is greater for longitude than for latitude. The MDE increases with the lead time in both 6- and 12-h past positions. A comparison of the best track from JTWC and the ANN's predicted track for the four cyclones randomly selected from the validation dataset match satisfactorily, as described below. The four cyclones selected have different tracks such as looped, curved, and re-tracked. The MDE of these four cyclones varies between 53.1 km and 87.8 km.

The SI of wind speed for the validation dataset varies between 0.11 and 0.33, with a CC of more than 0.7 being quite acceptable. As with the position predictions, the SI for the wind speed increases with lead time. Further, whether using the past 6 h or 12 h, the errors remain close to the same.

The SI for the pressure estimation of the validation dataset is negligible, varying from 0.005 to 0.01, with a correlation of more than 0.7. The high values of RMSE are understandable because the pressure values are in the range of 1000 hPa. As in the case of the previous two parameters, the SI increases with lead time and remains similar for the past 6- and past 12-h predictions.

The difference between the JTWC's best track and ANN's predictions for landfall-crossing points has a mean error of 38.4 km for the 12-h forecast and 71.02 km for the 24-h forecast; both are significantly less than the official Indian weather-forecast errors. We compared the ANN forecasts with seven dynamical model outputs for 21 cyclones during 2017–2019. Our findings show that an ANN approach outperformed all the numerical models. However, during 2019, ANN results were better than three models but worse than four models. Incidentally, cyclone Maha, with the largest track error, occurred during 2019. By analyzing the 33 cyclones in the north Indian Ocean during 2003–2013, Mohapatra et al. [28] obtained an average error of 69 km for 12-h forecasts and 104 km for 24-h forecasts. Compared to these errors, the errors obtained by the ANN's predictions are far better. However, Mohapatra et al. [28] were able to predict 72 h in advance, which could not be done in this paper. Since advance notice is critical, the error of 71.02 km needs to be considered.

In the future, we plan to consider either a multiple numerical-model output or output from the same model with different initial conditions to develop an ANN technique for predicting a cyclone's track.

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