International Journal of Climatology
RMetS Royal Meteorological Society

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Journal:	*International Journal of Climatology*
Manuscript ID	JOC-21-0997.R2
Wiley - Manuscript type:	Research Article
Date Submitted by the Author:	05-Apr-2022
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Keywords:	Tropical Cyclone, Seasonal prediction < 6. Application/context, PCR Model, CFSv2
Country Keywords:	India
Note: The following files were submitted by the author for peer review, but cannot be converted to PDF. You must view these files (e.g. movies) online.	
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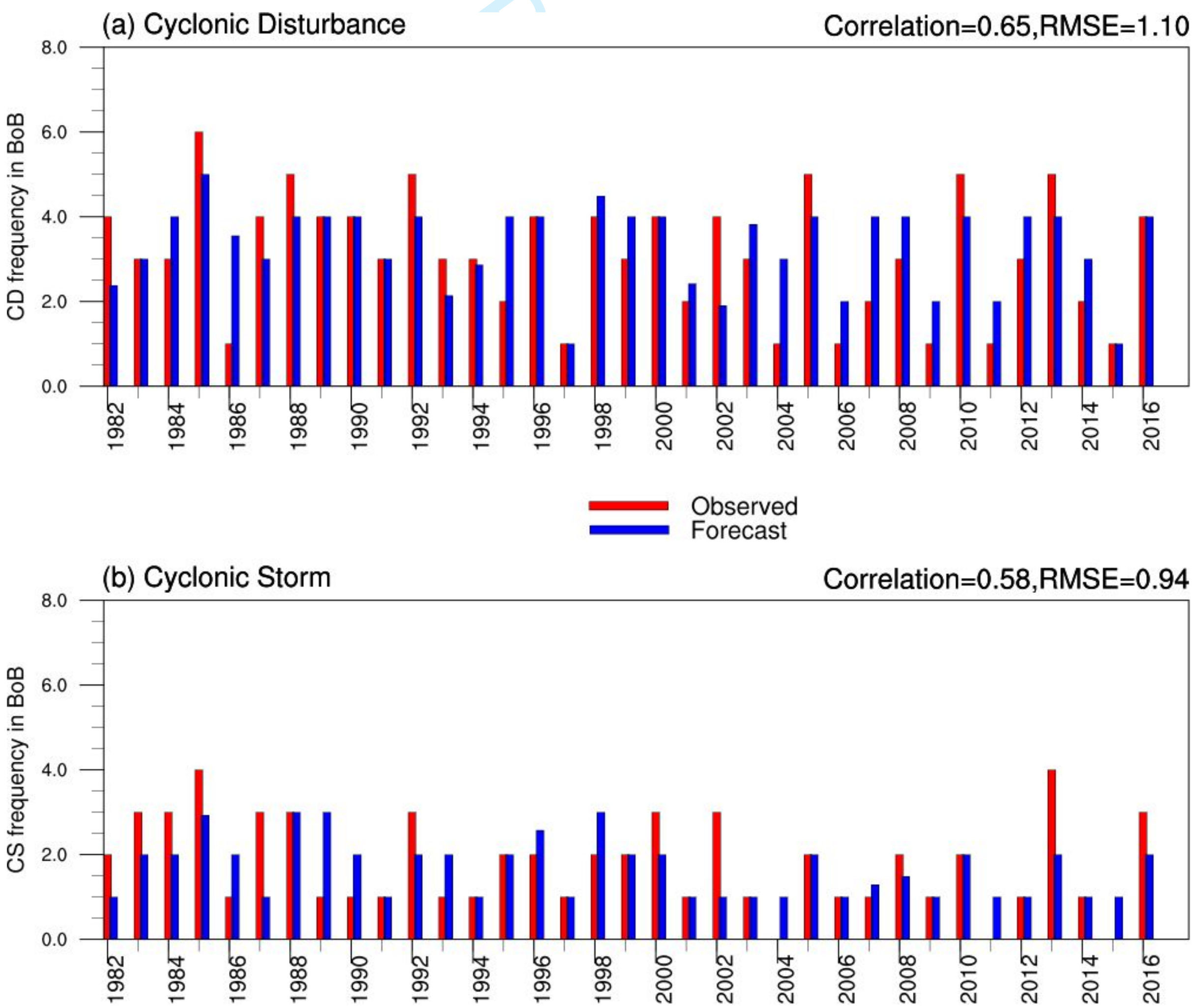

(a) Verification of forecasted cyclonic disturbance frequency over the Bay of Bengal during post-monsoon season by the hybrid model (blue bars) along with corresponding observed cyclonic disturbance frequency over the Bay of Bengal (red bars) for the training period (1982-2016). (b) same as (a) but for cyclonic storm frequencies. The hybrid model achieved a significant skill for seasonal cyclone forecast over the Bay of Bengal.

RESEARCH ARTICLE

Seasonal Forecasting of Tropical Cyclones over the Bay of Bengal using a Hybrid Statistical/Dynamical Model

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Funding information

The post-monsoon (Oct-Nov-Dec) tropical cyclone over the Bay of Bengal is one of the most devastating natural disasters causing economic and human losses over India and its neighboring countries. This study discusses a hybrid statistical/dynamical model developed to forecast the post-monsoon cyclone activities over the Bay of Bengal, where 80% of the tropical cyclones of the north Indian Ocean are originated. In the hybrid model, the coupled model CFSv2 predicts the large-scale climate indices, and the Principal Component Regression (PCR) model is used to relate these indices with the tropical cyclone frequency. A solid concurrent relation between the cyclonic disturbance frequencies and various large-scale variables is noted. The dynamical variable, for example, the zonal wind, acts as a precursor variable. We identified three concurrent predictors (ocean heat content over the Bay of Bengal, SST over the Indian Ocean, and SST over the tropical central Pacific regions) and two precursor predictors (low-level wind at equatorial Indian ocean and strength of upper-level easterly jet over African coast) influencing the cyclonic disturbance frequencies over the Bay of Bengal. The concurrent predictors are calculated from the CFSv2 hindcast/forecast output and the precursor predictors are calculated from the reanalysis data. The predictors influencing the cyclonic disturbance over the Bay of Bengal are also influencing the cyclonic storms. Hence, the same predictors are used for developing a hybrid model for cyclonic disturbance and storm frequencies. A significant inter-correlation among different predictors is observed and the PCR model avoids these inter-correlations and, in this method, PCs are estimated on the predictors to make them orthogonal to each other. The hybrid model achieved a significant skill for seasonal cyclone forecast over the Bay of Bengal. Results suggest the potential for using the hybrid model for the operational seasonal forecasting of post-monsoon cyclone activity over the Bay of Bengal.

KEYWORDS
Tropical Cyclone, Seasonal Prediction, PCR Model, CFSv2

1 | INTRODUCTION

Tropical Cyclones (TCs) are one of the most devastating natural disasters on the planet, causing significant socio-economic impacts. India's coastal belt and adjoining south Asian nations are vulnerable to the strong wind, heavy rainfall, and storm surges associated with these storms (Fakhruddin et al., 2022). The India Meteorological Department (IMD) defined the criteria for the classification of cyclonic disturbances (from low-pressure area to super cyclonic storm) over the north Indian Ocean (Table 1). Over the south Asian domain, although there are two major seasons for the TCs which are pre-monsoon season (March through May) and post-monsoon season (October to December), the peak TCs storm activities observe in the post-monsoon season (Mohapatra et al., 2012).

The genesis locations of cyclonic storms over the North Indian Ocean during the post-monsoon season (October-December) for the period 1891-2020 are given in Figure 1. The Bay of Bengal is a more active basin than the Arabian Sea for brewing cyclonic storms (Maximum Sustainable Wind (MSW) $\geq 34knots$) during the post-monsoon season. More details on the tropical cyclone genesis over the North Indian Ocean are provided in previous studies (Wahiduzzaman et al., 2019; Wahiduzzaman and Yeasmin, 2019; Wahiduzzaman et al., 2020). The monthly distribution of TCs over the Bay of Bengal showed that the cyclonic disturbance ($MSW \geq 17knots$) frequencies increase gradually from April onwards, and it peaks in August and October and then decreases towards the end of the year (Figure 2). At the same time, the cyclonic storm (named storms) frequencies over the Bay of Bengal peaks in the post-monsoon season, followed by the pre-monsoon season (Figure 2).

Every year, the government spends considerable money to reduce the potential damage to life and property TC could cause. The considerable reduction in loss of lives because of tropical cyclones is achieved because of timely, accurate early warnings issued by National Meteorological and Hydrological Services in the region. Currently, IMD has a well-established short-range to medium-range forecast for TCs activates but those forecasts may not be useful for longer planning for disaster management. Therefore, the seasonal outlook of tropical cyclone activities could help the coastal population and government agencies to prepare in advance for the upcoming tropical cyclone season. This will be helpful for the disaster managers and decision-makers to take adequate measures based on the seasonal outlook of tropical cyclone activities and hence reduce the economic and human losses. Insurance companies also make use of this seasonal forecast of tropical storms for their policy decisions. Hence, the seasonal forecasting of tropical cyclone activities over the Bay of Bengal is very much demanded by many south Asian countries for advanced preparedness.

Several methodologies have been developed for the seasonal forecast of tropical cyclone activities in different parts of the world (Elsner and Schmertmann, 1993; Chan et al., 1998; Camargo and Barnston, 2009; Kim et al., 2010; Vecchi et al., 2014; Balachandran and Geetha, 2012; Camp et al., 2015; Nath et al., 2015, 2016; Sen et al., 2021; Wahiduzzaman et al., 2019) since its first attempts made by Nicholls (1979) and Gray (1984a,b) for the Australian and North Atlantic regions, respectively. Currently, many institutions are issuing seasonal outlooks of tropical cyclone activities for various regions (for example, north Atlantic, eastern North Pacific, northwestern Pacific, South Pacific, or Australian region). Most of these forecasts are based on empirical/statistical models. The statistical relationship between different climate indices and tropical cyclone frequency is used to predict cyclone frequency. The major drawback of the statistical model is the assumption of the relationship between the observed tropical cyclone activities and precursor large-scale climate indices derived from the historical data persist in the future, which is not always the case (Klotzbach, 2007; Chan, 2008). Many studies explored the use of the dynamical model for the seasonal forecasting of tropical cyclones (Bengtsson et al., 1982; Vitart and Stockdale, 2001; Camargo and Barnston, 2009)). The performance of the seasonal forecast of tropical cyclone activities using a dynamical model depends on many factors, such as the model resolution (Bengtsson et al., 1995) and the model used (Camargo et al., 2005). The high-resolution models can better simulate tropical cyclone storms' characteristics than low-resolution models (Shaevitz et al., 2014). Over the north Indian Ocean, the skill of the seasonal forecasting of cyclone frequency is very poor in dynamical models (Camargo et al., 2005; Pattanaik and Mohapatra, 2016). It is still not clear whether this poor skill is due to model errors or lack of predictability. The hybrid statistical/dynamical method has become more prevalent in recent times for the seasonal forecast of tropical cyclones, where a dynamical model forecasts the large-scale climate indices and the statistical model used to relate these indices with the tropical cyclone frequency (Vecchi et al., 2011; Villarini and Vecchi, 2013).

The seasonal forecasting of TCs over the Indian Ocean basin is still a challenging task due to less number of systems formed over the Indian Ocean basin and the forecast skill tends to be poor in many statistical models. Balachandran and Geetha (2012) attempted to forecast the cyclonic disturbance days over the north Indian ocean using multiple regression techniques. Using the correlation analysis, they identified four potential predictors influencing the cyclonic disturbance days over the north Indian ocean. The following four predictors viz., 1) upper-level meridional wind (v200 hPa) averaged over 5S-2N, 95-105E during August (2) upper-level zonal wind (u200 hPa) averaged over 7S-5N, 30-42E during August (3) July through August mean SST averaged over 38-34S, 46-56E (4) 700 hPa zonal wind averaged over 5S-Equator, 73-80E, during August are used in their study. The performance of their multiple regression model in predicting cyclonic disturbance days over the north Indian ocean is reasonable. The RMSE and bias error between the predicted and observed cyclonic disturbance days over the north Indian ocean is 5 days and 0.36 days, respectively. Recent studies explored the artificial neural network models to forecast seasonal cyclone activities over the north Indian Ocean (Nath et al., 2016; Sen et al., 2021). The nonlinear artificial models offers a reasonable skill in forecasting the seasonal cyclone activities over the north Indian Ocean in terms of various statistical metrics (Nath et al., 2016; Sen et al., 2021). Using a statistical model, Wahiduzzaman et al. (2019) has shown that the state of the quasi-biennial oscillation (QBO) has the potential to improve the seasonal forecast skill of TCs over the north Indian Ocean. Further, Pattanaik and Mohapatra (2016) explained that an empirical six-parameter principal component regression (PCR) model can be used for the seasonal forecasting of tropical disturbance frequency over the Bay of Bengal. In their study the following six thermodynamical/dynamical predictors (parameters) viz., (1) the mean SST over the NINO4 region (2) the mean SST over the northwest Pacific ocean (3) the mean low-level meridional wind (v850 hPa) over the southeast equatorial Indian ocean (4) the strength of the low-level monsoon westerly wind (u850 hPa) over the north Indian ocean (5) the strength of the upper-level easterly wind over the African coast (6) the sea level pressure over the southeastern equatorial Indian Ocean act as a precursor to the Bay of Bengal cyclonic activities. A significant correlation (r=0.77) between the predicted and observed cyclonic disturbance frequencies is noted in their PCR model. However, the PCR model performance in forecasting the cyclonic storm (named storms) is not addressed in their study. In recent years, in their empirical PCR model, many predictors/environmental parameters do not maintain a significant predictor-predictands relationship (figure not shown). In this contest, we believe that the influence of concurrent/simultaneous predictors is more important and accurate than the precursor predictors. Hence, the present study uses a hybrid statistical-dynamical method to provide a seasonal forecasting system for cyclonic disturbance and cyclonic storm activities over the Bay of Bengal.

Section 2 describes the data used for the seasonal forecast of tropical cyclone activities and validation methodologies used to measure the deterministic skill of the forecast. Section 3 illustrates the hybrid statistical/dynamical model construction. Section 4 and 5 discuss the performance of the hybrid model for the deterministic forecast of cyclonic disturbance and cyclonic storm frequencies. Section 6 provides conclusions and a summary.

2 | DATASETS AND VALIDATION METHODS

2.1 | Observational data

This study uses the tropical disturbance frequency and tropical storm frequency data over the Bay of Bengal from 1982 to 2020. These datasets are available from storm e-atlas published by IMD (`https://rsmcnewdelhi.imd.gov.in/frequency-of-formation-of-cyclone.php`). The large-scale atmospheric fields (low level (850 hPa) and upper level (200 hPa) zonal wind) are obtained from NCEP/NCAR reanalysis (Kalnay et al., 1996). Sea surface temperature (SST) data are obtained from ERSSRv5 (Huang et al., 2017). The observed ocean heat content is estimated using the bias-corrected (g10) ocean temperature data from the 4.2.2 version of the EN4 database (Good et al., 2013). In this dataset, the mechanical bathythermograph (MBT) biases are corrected using the scheme described by (Gouretski and Cheng, 2020) and the expendable bathythermograph (XBT) biases are corrected using the scheme described by Gouretski and Reseghetti (2010). The EN.4.2.2 data were obtained from the Met Office website (`https://www.metoffice.gov.uk/hadobs/en4/`).

2.2 | Model Data

In the hybrid statistical/dynamical model, the concurrent climate indices/predictors (for example, the SST over the Indian Ocean, the SST over the central equatorial Pacific ocean, and ocean heat content over the Bay of Bengal) influence the cyclonic activities over the Bay of Bengal are derived from the NCEP Climate Forecast System version 2 (CFSv2) model (Saha et al., 2014) hindcast/forecast output. The details of these concurrent predictors are given in Table 2. The CFSv2 is a fully coupled atmosphere-ocean-land model, where the atmosphere component is Global Forecast System (GFS; Moorthi et al. (2001)) and the ocean component is Geophysical Fluid Dynamics Laboratory (GFDL) Modular Ocean Model (MOM) version 4p0d (Griffies et al., 2004). More details of the model are given in Saha et al. (2014). The CFSv2 hindcast/forecast outputs are downloaded from the NOAA website (https://www.ncei.noaa.gov/thredds/model/model.html). Using CFS reanalysis, the hindcast runs are initialized at 5 days intervals starting from 01 January and each hindcast run is integrated for a 9 month lead time. In the present study, we have used the ensemble mean of hindcast runs initialized from the days in September month for the period 1982-2020. We have used the October through December mean SST and ocean temperature data from the hindcast/forecast output of the CFSv2 coupled model, which covers the period 1982-2020. The ocean heat content (OHC) is derived from the upper ocean temperature data (Chu, 2011).

2.3 | Validation Methods

The performance of the hybrid statistical/dynamical model has been evaluated using popular statistical skill scores such as Spearman rank correlation, Root Mean Square Error (RMSE), Mean Absolute Errors (MAE), Mean biases. We have also used Willmott's refined index of agreement and the Kling-Gupta Efficient (KGE) index for additional verification.

Willmott's refined index of agreement (dr) is a dimensionless index whose values vary from -1 to 1 (Willmott et al., 2012). The values close to one indicate a better agreement. The refined index of agreement (d_r) is defined as follows.

$$d_r = \begin{cases} 1 - \dfrac{\sum_{i=1}^{n} |P_i - O_i|}{c \sum_{i=1}^{n} |O_i - \overline{O}|} & \text{when } \sum_{i=1}^{n} |P_i - O_i| \le c \sum_{i=1}^{n} |O_i - \overline{O}| \\ \\ \dfrac{c \sum_{i=1}^{n} |O_i - \overline{O}|}{\sum_{i=1}^{n} |P_i - O_i|} - 1 & \text{when } \sum_{i=1}^{n} |P_i - O_i| > c \sum_{i=1}^{n} |O_i - \overline{O}| \end{cases} \tag{1}$$

Here, P_i is the predicted time series and O_i is the observed time series. The c takes the value equals two.

The KGE index is an objective statistical index that uses correlation, bias, and similarity in invariance to evaluate the agreement between two-time series (Gupta et al., 2009; Kling et al., 2012). The value of the KGE index varies from -infinity to 1, where the value one indicates a perfect agreement between the time series. The KGE index is expressed as follows.

$$KGE = 1 - \sqrt{(r-1)^2 + (\gamma - 1)^2 + (\beta - 1)^2}, \tag{2}$$

Where r is the Pearson's correlation coefficient between observed and predicted time series. β represents the bias normalized by the observed data standard deviation and γ is a fraction of variation coefficient, defined as $\gamma = U_s/U_0$ where Us represents the mean of the predicted time series and U_o represents the mean of observed time series.

3 | HYBRID STATISTICAL/DYNAMICAL MODEL

The modulation of seasonal tropical cyclone activities by large-scale environmental parameters has been reported by a previous study (Chu and Zhao, 2007). The correlation between the cyclonic disturbance frequencies and various large-scale environmental parameters has been carried out to find a solid physical relationship. We believe that the effect of concurrent parameters on the cyclonic activities is more important than the precursor variables. We first calculate synchronous/concurrent correlation between the observed cyclonic disturbance frequencies and various observed/reanalysis large-scale variables during the October through December (OND) season to understand the potential large-scale variables influencing the tropical cyclonic disturbance frequencies over the Bay of Bengal (Figure 3a-d). The large-scale parameter which shows a statistically significant correlation with the cyclonic disturbance frequencies over the Bay of Bengal is kept as a potential predictor. Figures 3a and 3d display a solid concurrent relation between the cyclonic disturbance frequencies and various large-scale variables (For example, ocean heat content over the Bay of Bengal, SST over the Indian Ocean, and SST over the tropical central Pacific (NINO4) regions). Interestingly, the dynamical parameters, for example, wind act as a precursor to the cyclonic disturbance frequencies over the Bay of Bengal. The concurrent relationship between cyclonic disturbance frequencies and winds during the OND season is weak (figure not shown). However, the July through August average zonal wind at a lower level (U850) and upper level (U200) significantly correlate with cyclonic disturbance/cyclonic storm frequencies (Figures 3b and 3c).

The post-monsoon season SST over the tropical central Pacific and tropical western Indian Ocean are negatively correlated with cyclonic disturbance frequencies over the Bay of Bengal (Figure 3 and Table 2). It is consistent with the previous study of Girishkumar and Ravichandran (2012), where they showed that El Nino Southern Oscillation (ENSO) and Indian Ocean Dipole (IOD) are negatively correlated with post-monsoon season cyclonic activities over the Bay of Bengal. The cyclonic disturbance frequencies over the Bay of Bengal are positively correlated with ocean heat content (OHC; Figures 3 and Table 2). The importance of ocean heat content in the development and intensification of the tropical cyclone is widely studied (Wada and Usui, 2007; Ali et al., 2013; Sharma and Ali, 2014; Yu et al., 2016; Li et al., 2019). The thermal energy required for the development of tropical cyclones comes from the upper layers of the ocean. The low-level wind (850 hPa) anomalies over the equatorial Indian Ocean during July and August are positively contributing to the cyclonic disturbance activities over the Bay of Bengal (Figure 3 and Table 2). An easterly (a westerly) wind anomalies over the equatorial Indian Ocean in July and August of the positive (negative) phase of IOD creates warm (cold) SST anomalies over the western Indian Ocean during October through December. These SST anomalies over the tropical western Indian Ocean finally impact tropical cyclonic disturbance activities over the Bay of Bengal, as seen from Table 2 and Figure 3. The upper-level easterly jet is one of the semi-permanent features of the Indian summer monsoon and extends from the east coast of Vietnam to the west coast of Africa (Koteswaram, 1958). This easterly jet observed in July through August across the western equatorial Indian ocean and Africa negatively correlates with post-monsoon season cyclonic activities over the Bay of Bengal (Table 2 and Figure 3). Pattanaik and Mohapatra (2016) also showed the importance of easterly jets across the western equatorial Indian ocean and Africa in influencing the cyclonic disturbance frequency over the Bay of Bengal.

Similar to the correlation map of cyclonic disturbance frequencies, we also made a correlation map between cyclonic storm (named storms) frequencies and large-scale environmental parameters to understand the potential predictors influencing cyclonic storm frequencies (Figures 3e-h). The large-scale pattern of correlation is identical to that of cyclonic disturbance frequencies (Figure 3). It implies that the environmental parameters influencing cyclonic disturbance frequencies are also influencing cyclonic storm frequency. Hence, we used the same environmental parameters for developing the hybrid model for the seasonal forecasting of both cyclonic disturbance and cyclonic storm frequency over the Bay of Bengal.

We identified three concurrent predictors and two precursor predictors based on the maximum correlation values in Figure 3. Table 2 displays these five predictors influencing the post-monsoon cyclonic disturbance and storm activities over the Bay of Bengal. From Table 2 it is clear that cyclonic disturbance frequencies are significantly correlated with all these five predictors. However, the correlation values between the cyclonic storm frequencies and five predictors are less compared to that of cyclonic disturbance frequencies. Although the correlation values are less compared to that of cyclonic disturbance frequencies, it is still significant and reasonable (Table 2). It is also clear from Figure 4 that there are inter-correlations among different predictors.

A consistent predictor-predictand relationship is vital for the success of any statistical model. We calculated a 21-year running correlation between each predictor variable with predictand to understand the predictor-predictands relationship during 1982-2020. We find that the five predictors identified in our study maintain a stable predictor-predictands relationship and keep the same correlation throughout 1982-2020 (Figure. 5). However, a slight increase in the predictor-predictand relationship in recent years is noted in four parameters, which may be attributed to the recent increase in the sea surface temperature and associated changes in circulation patterns. However, a detailed study is required to confirm this explanation and it is beyond the scope of this study.

Finally, the performance of a hybrid statistical/dynamical model relies on the skill of predictors obtained from the model. Hence, it is imperative to understand the skill of the three concurrent parameters/predictors from the CFSv2 model before developing a hybrid statistical/dynamical model. The skill of CFSv2 in forecasting the individual concurrent predictors is summarized in Figure 6. The CFSv2 forecast for all the three concurrent predictors correlates significantly with observed values when the model initialized in September (Figure 6). The indices of NINO4 SST and Indian Ocean SST from CFSv2 show a very high correlation with the observed values (correlation value 0.87 and 0.90, respectively). The CFSv2 is also skillful in representing the ocean heat content over the Bay of Bengal. The correlation between the observed and model-predicted ocean heat content indices over the Bay of Bengal is 0.38, which is also statistically significant. The skill in the prediction of these three parameters in CFSv2 with respect to observations justifies the use of these parameters as the predictors of the hybrid model.

Keeping this in mind, we developed a hybrid statistical/dynamical model to forecast both the cyclonic disturbance and cyclonic storm frequencies over the Bay of Bengal. In this model, the large-scale concurrent predictors are forecasted by CFSv2 coupled model, and the precursor wind predictors are calculated from the reanalysis data. Then the statistical PCR model uses these predictors to relate this with the tropical cyclonic disturbance/storm frequency. The PCR model is advantageous when the predictors are highly inter-correlated, as in this method PCs are estimated on the predictors to make them orthogonal to each other. The PCR model avoids the inter-correlations and helps to reduce the degree of freedom by restricting the number of predictors. We considered the years from 1982 to 2016 as the training period and the remaining four years as the independent test period. In the PCR model, we first applied the principle component analysis (PCA) on the predictor data of the training period (1982-2016). The principal components PC1, PC2 ....PCn are sequenced from highest to lowest variance. The first four principle components that explain maximum correlation with predictands time series (Cyclonic disturbance/cyclonic storm frequencies) are chosen. Multiple regression equations are then used to relate these selected principle components and the predictands time series for the same training period. More details about the PCR model are given in the following papers (Pattanaik and Mohapatra, 2016; Pai et al., 2017; Acharya et al., 2013). A general form of the PCR model is represented by the following equation.

$$Y = b_0 + b_1(PC1) + b_2(PC2) + .. + b_n(PCn), \tag{3}$$

Where Y is the dependent variable and the coefficients b_0, b_1, b_2 ...b_n are estimated using the least square methods. PC1, PC2,..., PCn are the principal component scores obtained from PCA.

Since the CFSv2 model hindcast data is available from 1982, we limited our analysis period to 1982-2020. The distribution for the cyclonic disturbance frequency and cyclonic storm frequency is non-normal. Hence, the predictand variable is transformed to normal distribution before performing the PCR analysis to ensure regression modeling requirement. Normality of the transformed predictand data is assessed by calculating the skewness and kurtosis. In the regression modeling, the predictand variable is assumed to have a normal distribution and that the regression errors are normally distributed with a mean of zero (Saunders et al., 2020).

Cross-validation is essential (Michaelsen, 1987) in a statistical climate forecast system to minimize the artificial skill in the training data. This study used a cross-validation window of length (k) equals three years (k=3). At each cross-validation step k, consecutive years are removed from the training period data. The model is then wholly reconstructed and the middle year of the years removed from the training period data is forecast. For example, if the cross-validation window of length (k) equals three, the first two years are removed together with the last one in the first year's cross-validation forecast. Similarly, when predicting the second year, the first three years are removed. This process repeated for all years during the training period.

4 | PERFORMANCE OF HYBRID STATISTICAL/DYNAMICAL MODEL DURING THE TRAINING PERIOD (1982-2016)

4.1 | Cyclonic Disturbance frequency forecast

To see the performance of the hybrid statistical/dynamical model, above mentioned verification scores of the deterministic forecast of cyclonic disturbance frequency, are calculated for the training period 1982-2016. Table 3 lists different cross-validation scores for the cyclonic disturbance frequency hindcast. The model has a cross-validated Spearman rank correlation skill of r=0.65 for predicting the cyclonic disturbance frequencies over the Bay of Bengal. We use the Spearman rank correlation as our correlation matrix because the forecasted and observed cyclonic disturbance frequency does not follow the Gaussian distribution. Spearman rank correlation explains the skill of the forecast system to identify the relative ordering of years in the observed record correctly.

The root means square error (RMSE) and mean absolute errors (MAE) between the observed and predicted cyclonic disturbance frequency is close to one (1.10 and 0.86 respectively) and its values are less than the standard deviation of observed cyclonic disturbance frequency (1.43). The index of agreement between the observed and predicted cyclonic disturbance frequency also shows a higher value (0.63). Similarly, the KGE score is 0.50, which is reasonably good. The mean bias is negligible, implying that model climatology and observed climatology is very close. It is also shown that the mean and the standard deviation of predicted cyclonic disturbance are very close to the observed values (Table 3).

The cross-validated hindcast of the hybrid statistical/dynamical model for the seasonal cyclonic disturbance frequencies over the Bay of Bengal is compared to its observed counterpart in Figure 7a. It is found that the forecasted cyclonic disturbance frequency and observed cyclonic disturbance frequencies match very well in most years, except few years. In some years the actual cyclonic disturbance frequency and predicted cyclonic disturbance frequencies are almost coinciding. However, in a few years, the predicted cyclonic disturbance frequencies do not coincide with the observed cyclonic disturbance frequencies. Overall, the hindcast forecast the general fluctuations of cyclonic disturbance frequencies in accordance with the observed number of cyclonic disturbances over the Bay of Bengal (Figure 7a).

4.2 | Cyclonic storm frequency forecast

It is challenging to forecast the cyclonic storm frequency over the Bay of Bengal due to fewer storms forming over the Bay of Bengal than other ocean basins. However, for disaster managers, even a forecast with reasonable skill is highly useful for advanced preparedness. We calculated the above-mentioned verification scores of the deterministic forecast of cyclonic storm frequency for the training period of 1982-2020. Table 4 lists different cross-validation scores for the cyclonic storm frequency forecast. The cross-validated result from the hybrid statistical/dynamical model display a significant prediction skill for cyclonic storm frequencies over the Bay of Bengal, with a Spearman rank correlation of 0.58 between the hindcast and observation for 1982-2016. The index of agreement between observed and predicted cyclonic storm frequencies is 0.64. The mean bias close to zero indicates that model climatology and observed climatology of cyclonic storm frequency over the Bay of Bengal are very close. The RMSE and MAE between the observed and predicted cyclonic storm frequency is minimal (0.94 and 0.67 respectively) and less than the standard deviation of observed cyclonic storm frequency (1.09). It also shows a reasonable KGE score of 0.41. The mean and standard deviation of the predicted cyclonic storm frequency are in line with the observed values.

The deterministic forecast of cyclonic disturbance frequencies from the hybrid model compares against its observed counterpart in Figure 7b. In most years, the forecasted cyclonic storm frequencies matched very well with observed cyclonic storm frequencies (Figure 7b). In some years, the observed and forecasted cyclonic storms exactly coincide. However, in a few years, there is a difference in the forecasted cyclonic storm frequency from the actual cyclonic storm frequencies, as in cyclonic disturbance frequencies. Overall, the hybrid statistical model faithfully forecasts the cyclonic storm frequencies over the Bay of Bengal (Figure 7b).

5 | PERFORMANCE OF HYBRID STATISTICAL/DYNAMICAL MODEL DURING THE INDEPENDENT TESTING PERIOD (2017-2020)

The deterministic forecast of cyclonic disturbance frequencies for the independent testing period 2017-2020 is given in Figure 8a. The deterministic forecast of cyclonic disturbance frequencies for the period 2017-2020 is 4,3,3,5 respectively, which is very close to the observed cyclonic disturbance frequency of 5,3,1,4 for the period 2017-2020. Except for the year 2019, the difference between the observed and predicted cyclonic disturbance frequencies is less than or equal to one.

Similarly, the deterministic forecast of cyclonic storm frequencies for the independent testing period 2017-2020 is given in Figure 8b. Except for the 2018 year, the predicted and observed cyclonic storm frequencies are very close to each other. For example, the observed and predicted cyclonic storm counts are the same in the year 2019 and 2020, whereas in the year 2017 the difference between the observed and predicted cyclonic storm counts is one. These results suggest that the hybrid statistical/dynamical model can be used for the seasonal forecasting of cyclonic disturbance and cyclonic storm frequencies over the Bay of Bengal.

6 | CONCLUSIONS

The cyclonic storms over the Bay of Bengal are one of the most devastating natural disasters causing threats to the lives of people living across the coastal areas of India and other South Asian nations. Seasonal forecasting of cyclonic activities over the Bay of Bengal is highly useful for advanced preparedness for coastal people and disaster managers. The monthly distribution of Bay of Bengal cyclonic storm activities shows a peak in the post-monsoon season, followed by the pre-monsoon season. This study developed a hybrid statistical/dynamical model for the seasonal forecasting of cyclonic disturbance and cyclonic storm activities over the Bay of Bengal.

This study first identified the large-scale climatic indices that influence cyclonic activities over the Bay of Bengal. For this purpose, we have correlated the cyclonic disturbance and storm frequency with different large-scale variables obtained from reanalysis/observations. We used different large-scale environmental parameters such as sea surface temperature (SST), ocean heat content (OHC), zonal wind at 200 hPa and 850 hPa, meridional wind at 850 hPa, and surface salinity to correlate with cyclonic disturbance and storm frequency. The parameters that show a significant and consistent correlation with cyclonic disturbance and storm frequency are retained. We found a solid concurrent correlation between cyclonic activities over the Bay of Bengal and few large-scale environmental parameters such as SST and OHC. The ocean heat content over the Bay of Bengal during the OND season is positively correlated with the Bay of Bengal cyclonic activities. Similarly, during the OND season, the SST over the central Pacific and the western Indian Ocean have negatively correlated with the post-monsoon season Bay of Bengal cyclonic activities. However, the low-level zonal wind over the equatorial Indian Ocean and upper-level easterly jet over the African coast are precursor variables for the Bay of Bengal cyclonic activities. The July-August mean low-level zonal wind over the equatorial Indian Ocean is positively correlated with Bay of Bengal cyclonic activities. However, the July-August mean upper-level zonal wind over the south African coast negatively correlated with the Bay of Bengal cyclonic activities. Based on these correlation values, we defined three concurrent and two precursor predictors by averaging the corresponding large-scale variable over the regions of maximum correlation values. The two precursor predictors are taken from observations and three concurrent/simultaneous predictors obtained from the operational hindcast/forecast outputs of the CFSv2 coupled model. The empirical PCR model relates these indices with the tropical cyclone activities over the Bay of Bengal.

We found that the predictors that influence the cyclonic disturbance frequency over the Bay of Bengal also influence the cyclonic storm frequency. Hence, using the same predictors, we tried to forecast the cyclonic disturbance frequency and cyclonic storm frequency over the Bay of Bengal. Various verification scores are used to understand the performance of the hybrid statistical/dynamical models in forecasting both cyclonic disturbance and cyclonic storm frequencies. The cross-validation statistics showed that the forecast of cyclonic disturbance frequency is highly skillful. The performance of the cyclonic disturbance activities outperforms cyclonic storm activities. Although the cyclonic storm frequency is not as skillful as the cyclonic disturbance frequency over the Bay of Bengal, it is still significant and reasonable. Hence, this hybrid statistical/dynamical model can be used for the operational forecasting of Bay of Bengal cyclonic activities in the India Meteorological Department.

acknowledgements

We express our sincere thanks and gratitude to Dr. M. Mohapatra, DGM, IMD. We are also thankful to all the Climate Monitoring and Prediction Group officers and staff, IMD Pune, for their support. We acknowledge the UK Met Office for providing the EN.4.2.2 datasets. The EN.4.2.2 data were obtained from https://www.metoffice.gov.uk/hadobs/en4/ and are © British Crown Copyright, Met Office, [2013], provided under a Non-Commercial Government Licence http://www.nationalarchives.gov.uk/doc/non-commercial-government-licence/version/2/. We acknowledge NOAA ERSST V5 data provided by the NOAA/OAR/ESRL PSL, Boulder, Colorado, USA, from their Web site at https://psl.noaa.gov/data/gridded/data.noaa.ersst.v5.html. We thank the Editor and two anonymous reviewers for their valuable time and constructive comments.

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TABLE 1 Criteria for classification of cyclonic disturbances over the North Indian Ocean.

No.	Type of Disturbance	Associated maximum sustained wind
1	Low-Pressure Area	Not exceeding 17 knots (<31 kmph)
2	Depression	17 to 27 knots (31-49 kmph)
3	Deep Depression	28 to 33 Knots (50-61 kmph)
4	Cyclonic Storm	34 to 47 Knots (62-88 kmph)
5	Severe Cyclonic Storm	48 to 63 Knots (89-117 kmph)
6	Very Severe Cyclonic Storm	64 to 90 Knots (118-167 kmph)
7	Extremely Severe Cyclonic Storm	91 to119 Knots (168-221 kmph)
8	Super Cyclonic Storm	120 knots and above ($\geq 222 kmph$)

TABLE 2 Five predictors identified for the hybrid statistical/dynamical model. The correlation of each parameter with the cyclonic disturbance frequency and cyclonic storm frequency is provided in the right two columns (1982-2020). The same predictors are used for the forecast of cyclonic disturbance and cyclonic storm frequencies.

Predictor No.	Predictors	Averaging area	Correlation with cyclonic disturbance frequency (1982-2020)	Correlation with cyclonic storm frequency (1982-2020)
1	Sea surface temperature during OND over the NINO4 region	5S-5N, 160E-210E	-0.41	-0.35
2	Sea surface temperature during OND over the Indian ocean	10S-10N, 50E-80E	-0.51	-0.37
3	Ocean heat content during OND season over the Bay of Bengal	15N-21N,87E-94E	0.58	0.41
4	Low-level zonal wind (July-August mean) at equatorial Indian ocean (U850)	5S-2N, 73E-98E	0.49	0.41
5	Strength of upper-level easterly jet (July-August mean) over African coast (U200)	12S-2S, 25E-45E	-0.44	-0.26

TABLE 3 Verification scores for the cross-validated hindcast of cyclonic disturbance frequency by hybrid model for the training period 1982-2016.

Cross-validation statistics	Scores for the training period 1982-2016
Pearson's Correlation	0.64
Spearman rank Correlation	0.65
Mean Bias	0.19
Root mean square error (RMSE)	1.10
Mean absolute error (MAE)	0.86
Index of Agreement	0.63
KGE index	0.50
Standard deviation observed CD frequency	1.43
Standard deviation of predicted CD frequency	1.0
Mean of observed CD frequency	3.11
Mean of predicted CD frequency	3.30

TABLE 4 Verification scores for the cross-validated hindcast of cyclonic storm frequency by hybrid model for the training period 1982-2016.

Cross-validation statistics	Scores for the training period 1982-2016
Pearson's Correlation	0.51
Spearman rank Correlation	0.58
Mean Bias	-0.11
Root mean square error (RMSE)	0.94
Mean absolute error (MAE)	0.67
Index of agreement	0.64
KGE index	0.41
Standard deviation of observed CS frequency	1.09
Standard deviation of predicted CS frequency	0.67
Mean of observed CS frequency	1.77
Mean of predicted CS frequency	1.66

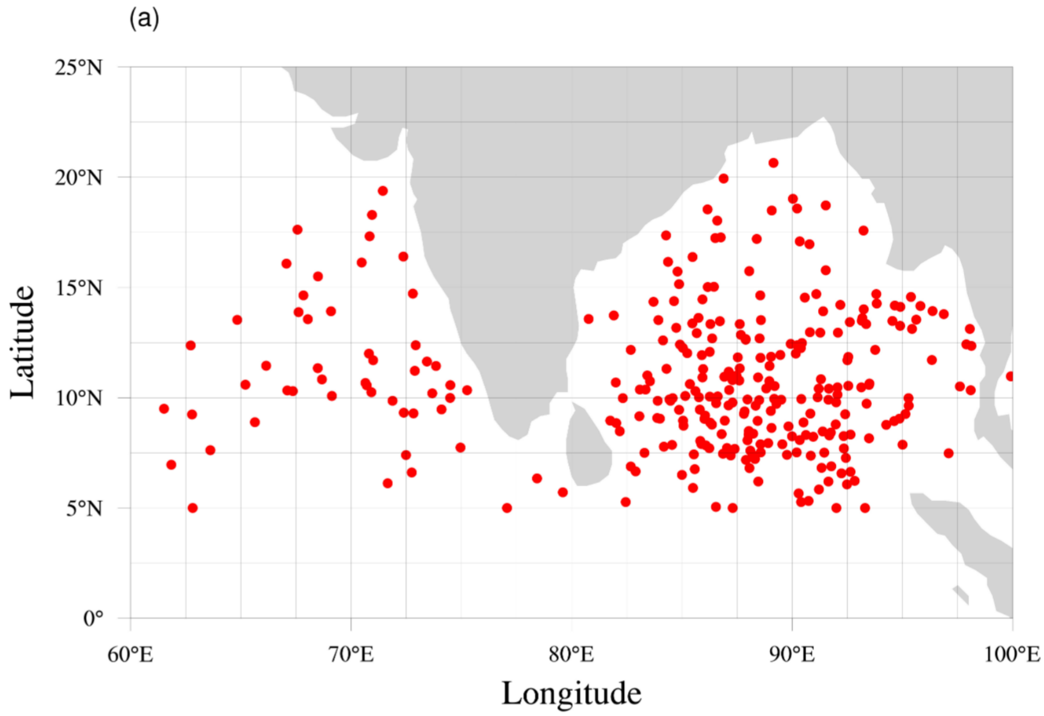


FIGURE 1 Genesis location of cyclonic storms (Maximum Sustainable Wind (MSW) $\geq 34knots$) over the North Indian Ocean during post-monsoon season (October-December) for the period 1891 to 2020.

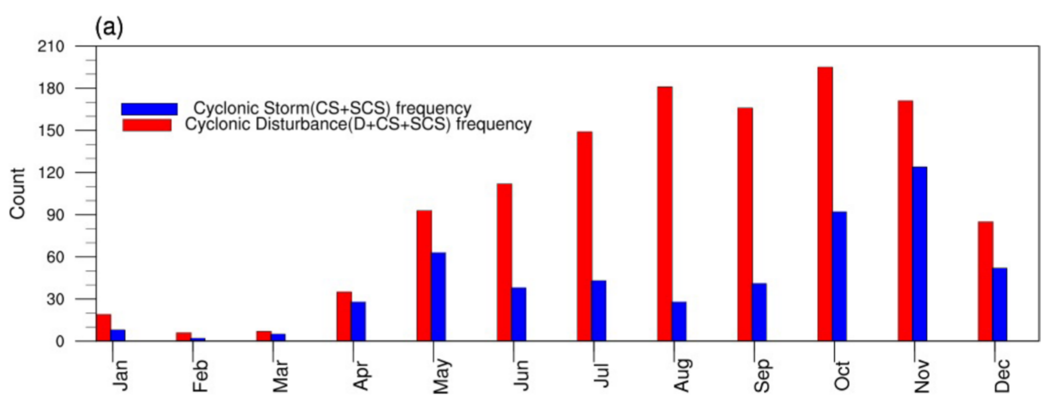


FIGURE 2 Monthly distribution of the total number of cyclonic disturbances (Maximum Sustainable Wind (MSW) $\geq 17knots$) and cyclonic storms ($MSW \geq 34knots$) during 1891-2020 over the Bay of Bengal.

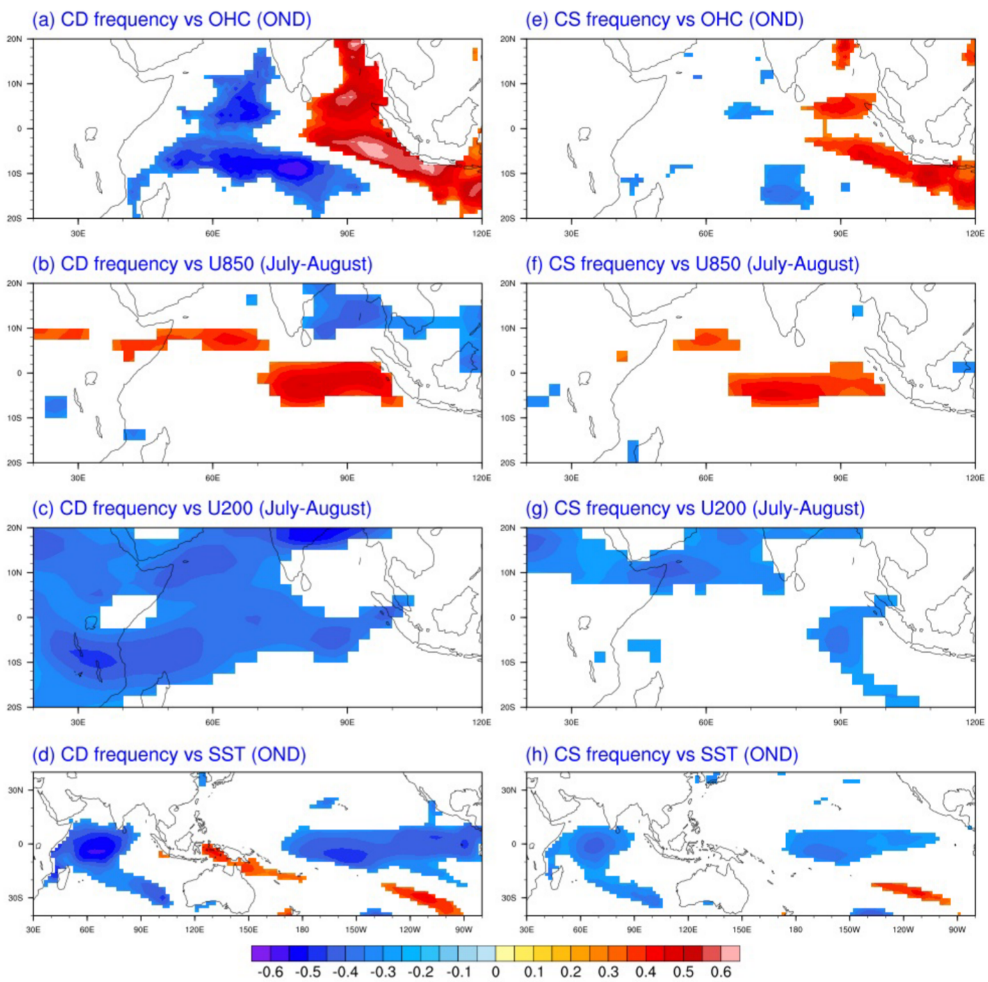


FIGURE 3 Spatial correlation between the observed Cyclonic Disturbance (CD) frequencies over the Bay of Bengal and observed (a) October through December (OND) mean ocean heat content (OHC) (b) July through August mean low-level zonal wind (U850) (c) July through August mean upper-level zonal wind (U200) (d) October through December mean sea surface temperature (SST). (e-h) is same as (a-d) but correlated with cyclonic storm frequency. The statistically significant correlation values are shaded (significant at 95% confidence interval)

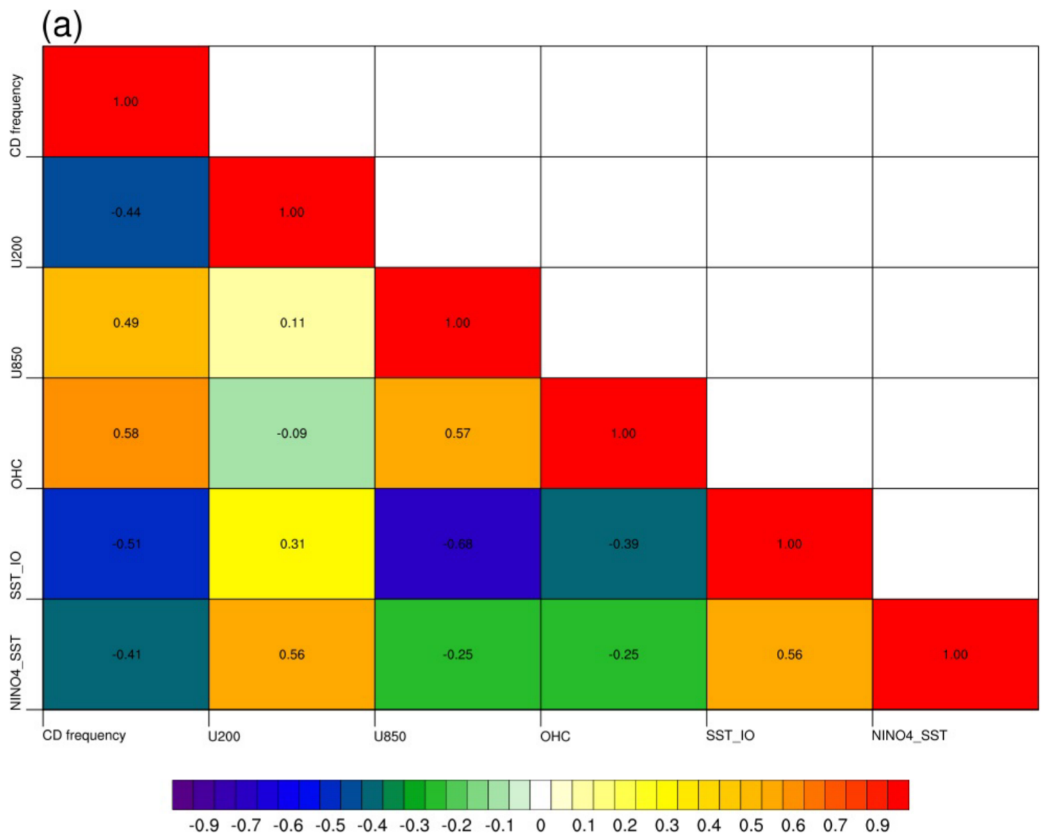


FIGURE 4 The correlation matrix represents Pearson's correlation between different combinations of predictand and predictors variables. The diagonal value of the correlation matrix is always one that represents the correlation between the variable and itself. The predictand and predictors are listed from left to right in the x-axis and top to bottom in the y-axis.

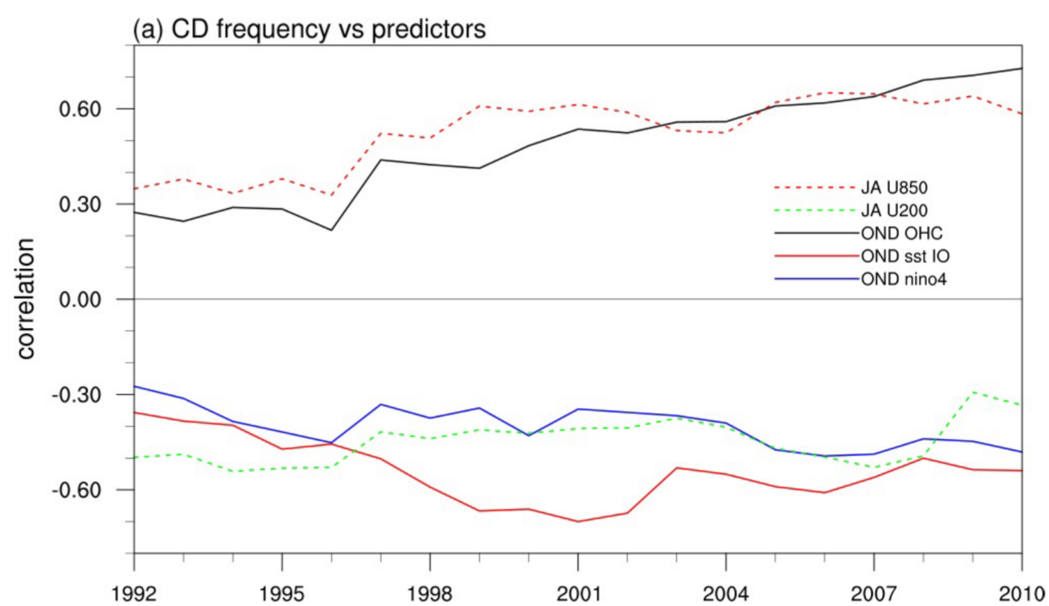


FIGURE 5 21-year running correlation between the cyclonic disturbance (CD) frequencies over the Bay of Bengal and five parameters listed in Table 1.

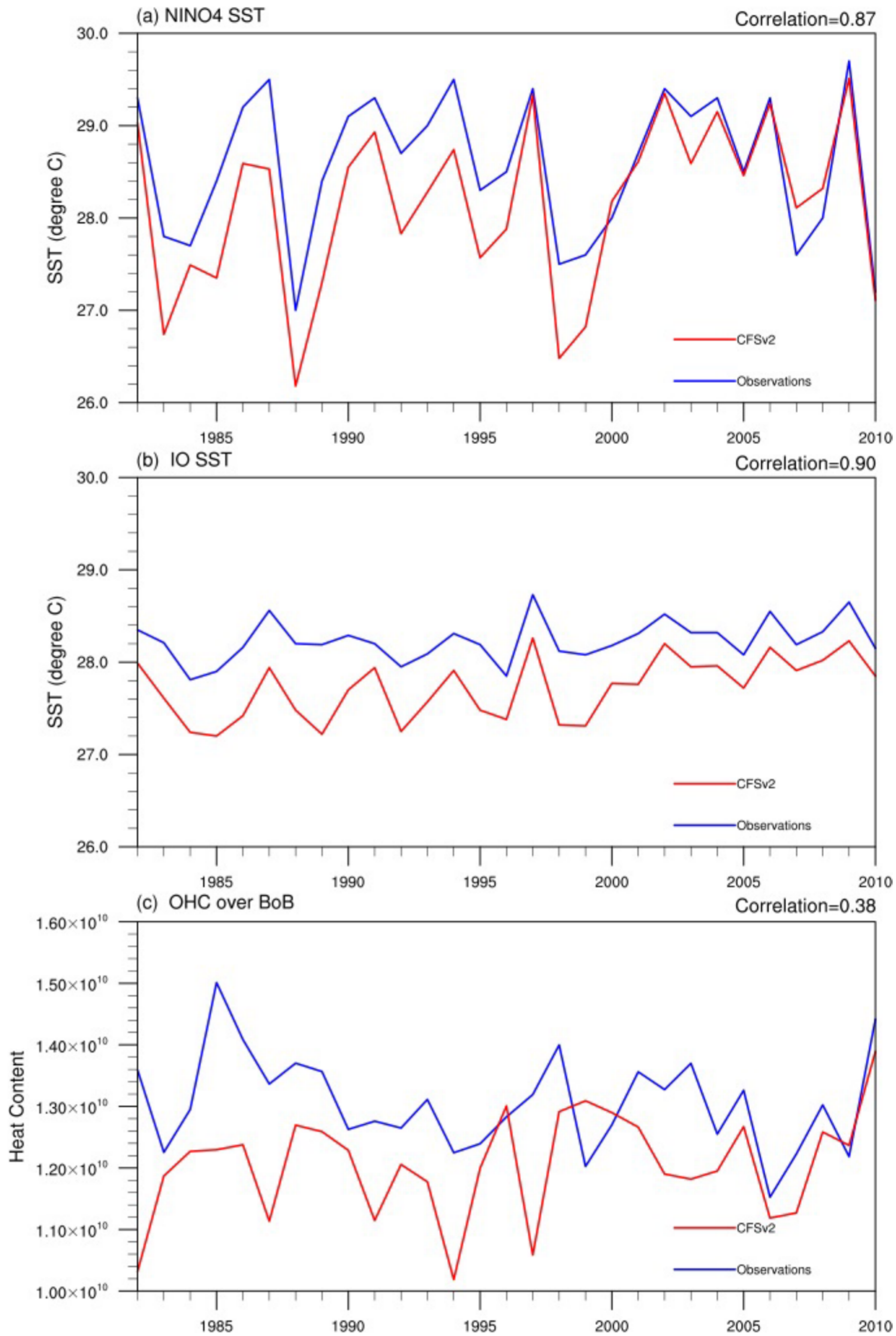


FIGURE 6 The interannual variations of (a) SST averaged over NINO4 area (5S-5N, 160E-210E) (b) SST averaged over Indian Ocean domain (10S-10N, 50E-80E) (c) ocean heat content averaged over the head Bay of Bengal (15N-21N,87E-94E) in CFSv2 (red line) and observations (blue line). The correlation between the model predicted time series and observed time series is given at the top right corners of each panel.

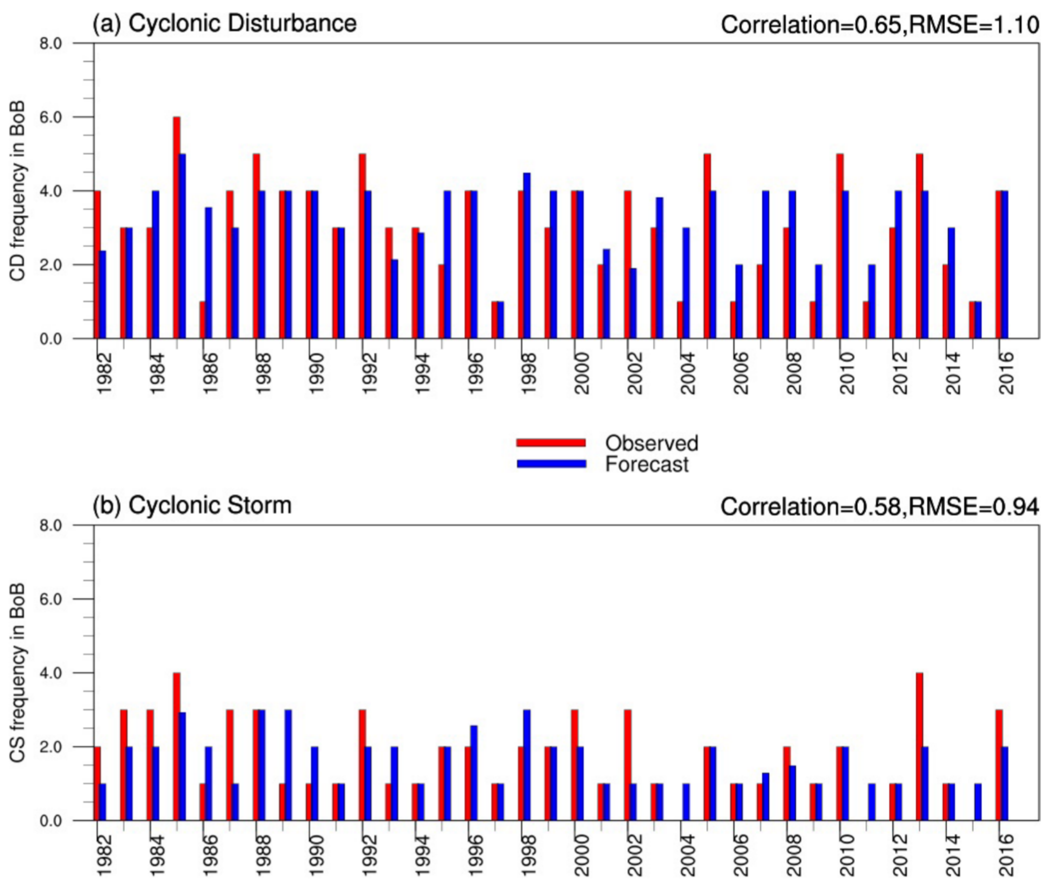


FIGURE 7 (a) Verification of forecasted cyclonic disturbance frequency over the Bay of Bengal during post-monsoon season by the hybrid statistical/dynamical model (blue bars) along with corresponding observed cyclonic disturbance frequency over the Bay of Bengal (red bars) for the training period (1982-2016). (b) same as (a) but for cyclonic storm frequencies.

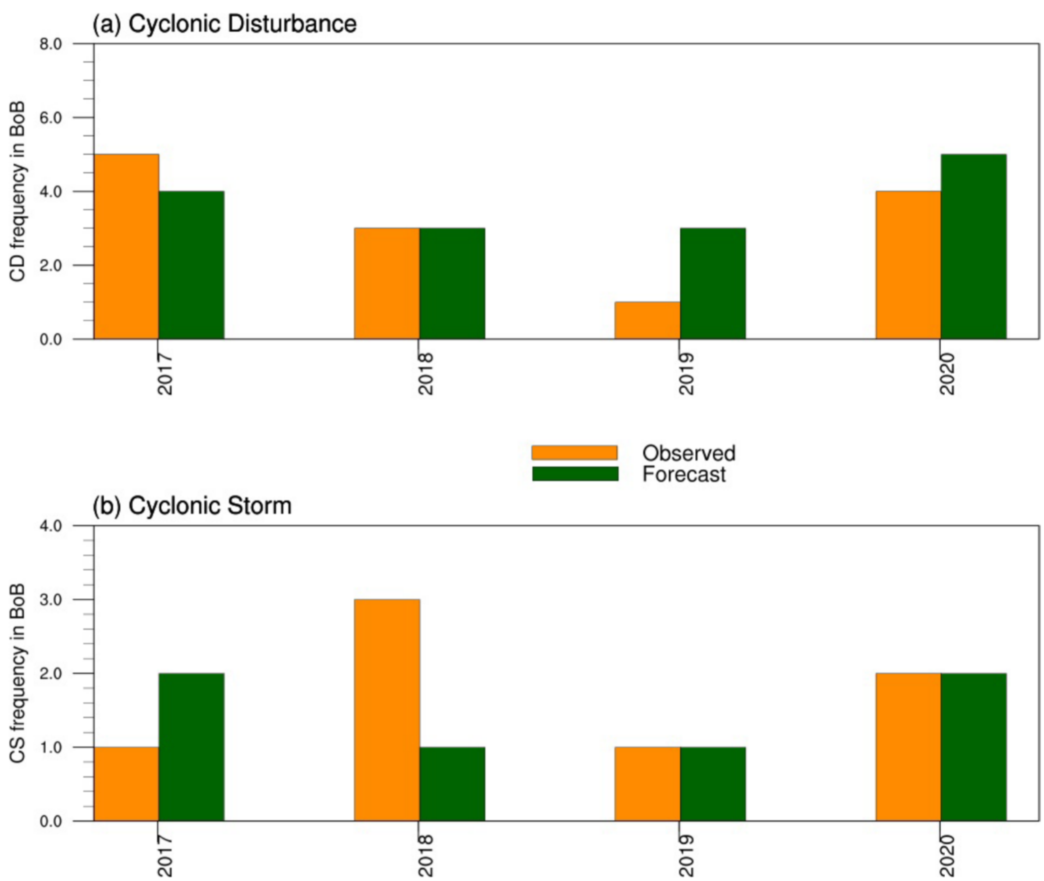
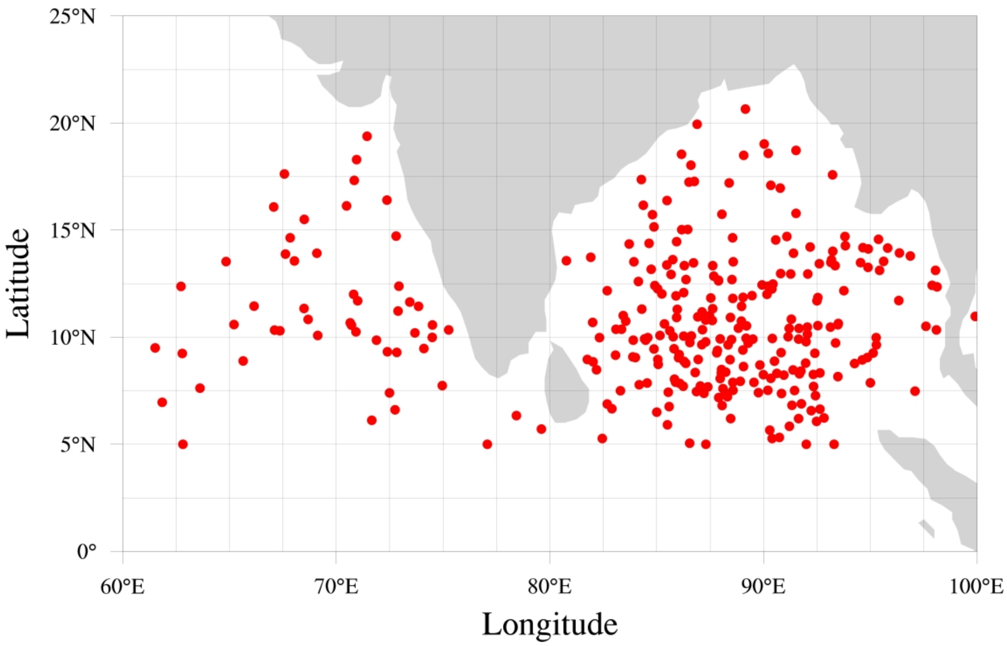


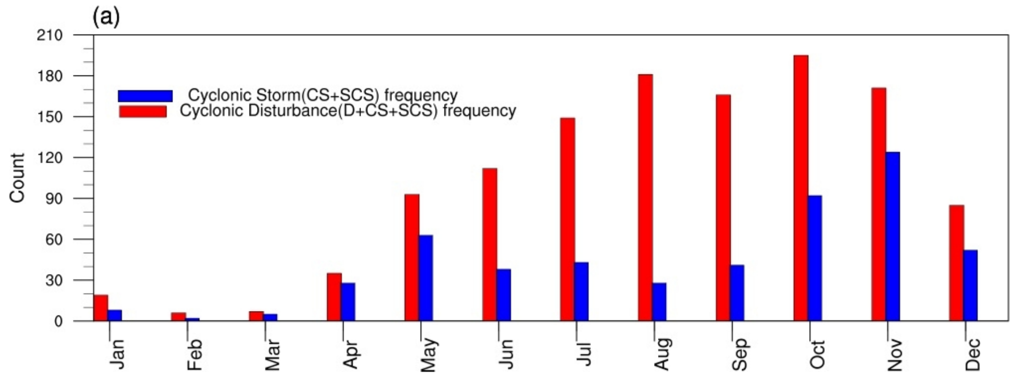
FIGURE 8 a) Forecasted cyclonic disturbance frequency over the Bay of Bengal during the post-monsoon season by the hybrid statistical/dynamical model (green bars) along with corresponding observed cyclonic disturbance frequency over the Bay of Bengal (orange bars) for the testing period (2017-2020). (b) same as (a) but for cyclonic storm frequencies.

(a)



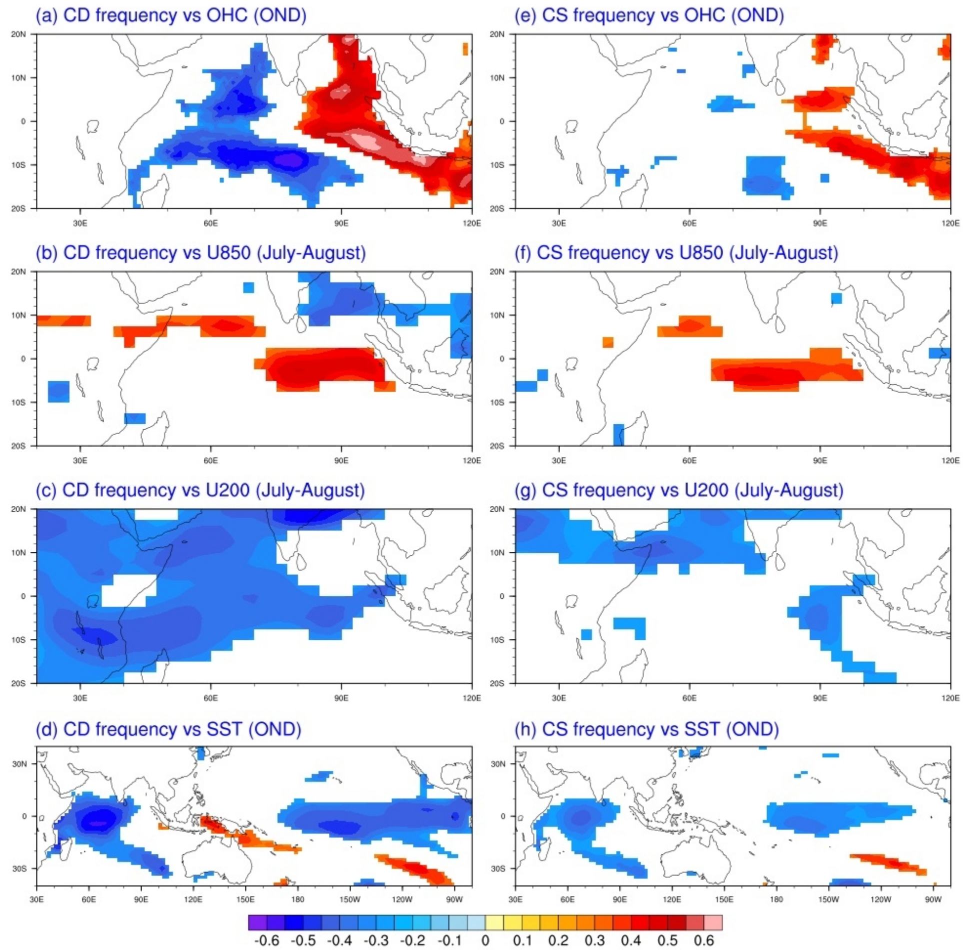
Genesis location of cyclonic storms (Maximum Sustainable Wind (MSW) ≥ 34knots) over the North Indian Ocean during post-monsoon

468x320mm (288 x 288 DPI)



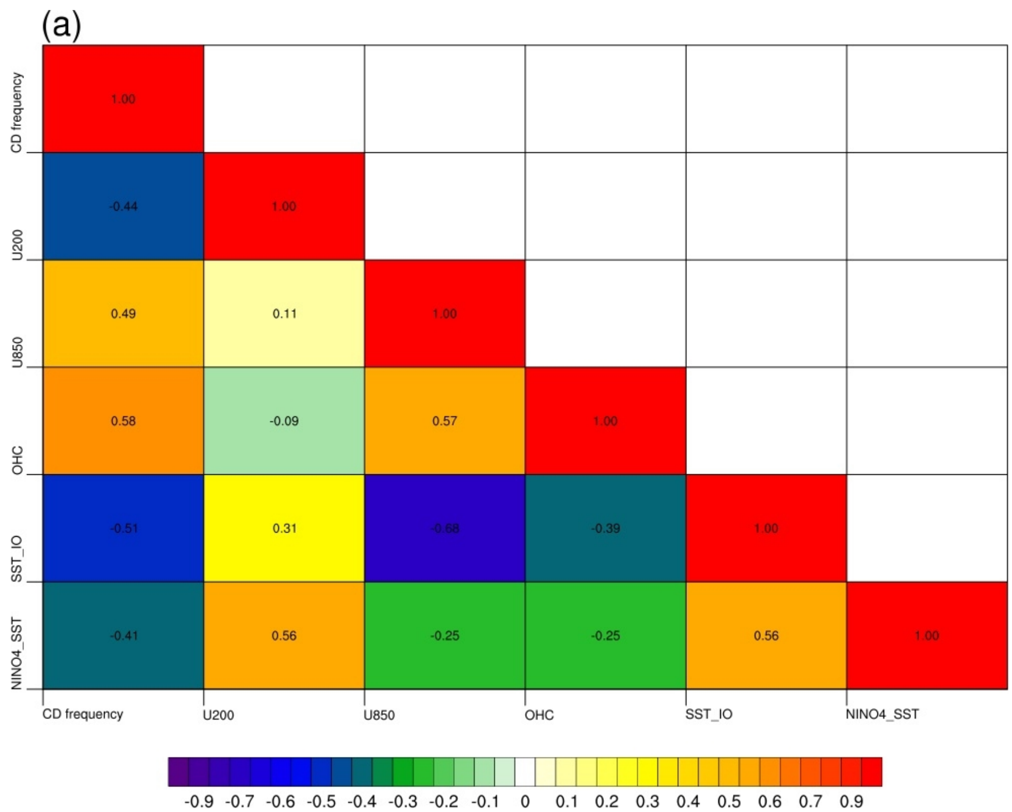
Monthly distribution of the total number of cyclonic disturbances (Maximum Sustainable Wind (MSW) ≥ 17knots) and cyclonic storms (MSW ≥ 34knots) during 1891-2020 over the Bay of Bengal.

212x77mm (120 x 120 DPI)



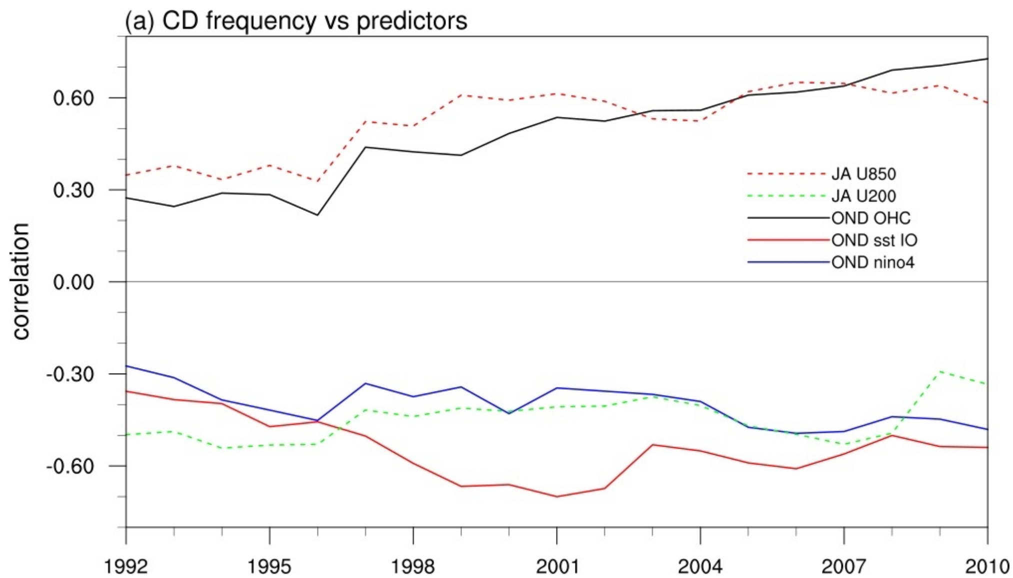
Spatial correlation between the observed Cyclonic Disturbance (CD) frequencies over the Bay of Bengal and observed (a) October through December (OND) mean ocean heat content (OHC) (b) July through August mean low-level zonal wind (U850) (c) July through August mean upper-level zonal wind (U200) (d) October through December mean sea surface temperature (SST). (e-h) is same as (a-d) but correlated with cyclonic storm frequency. The statistically significant correlation values are shaded (significant at 95% confidence interval)

216x216mm (120 x 120 DPI)



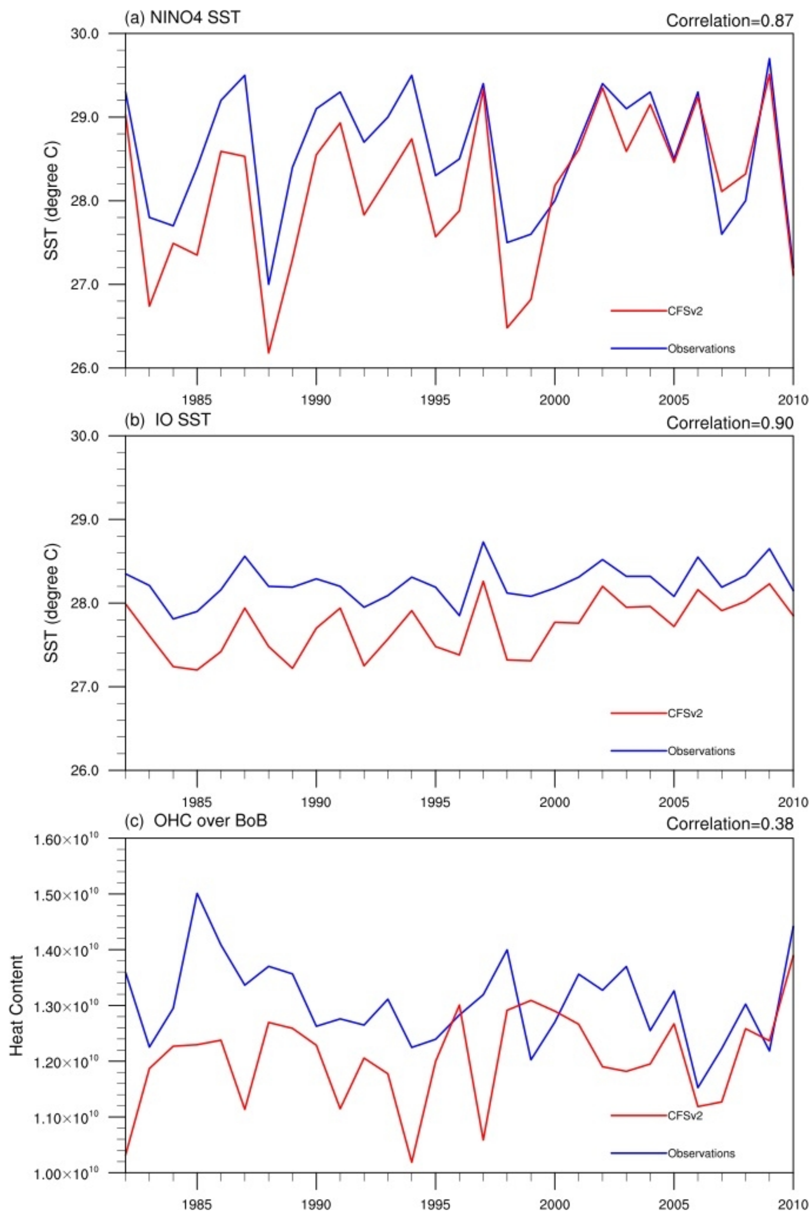
The correlation matrix represents Pearson's correlation between different combinations of predictand and predictors variables. The diagonal value of the correlation matrix is always one that represents the correlation between the variable and itself. The predictand and predictors are listed from left to right in the x-axis and top to bottom in the y-axis.

208x166mm (120 x 120 DPI)



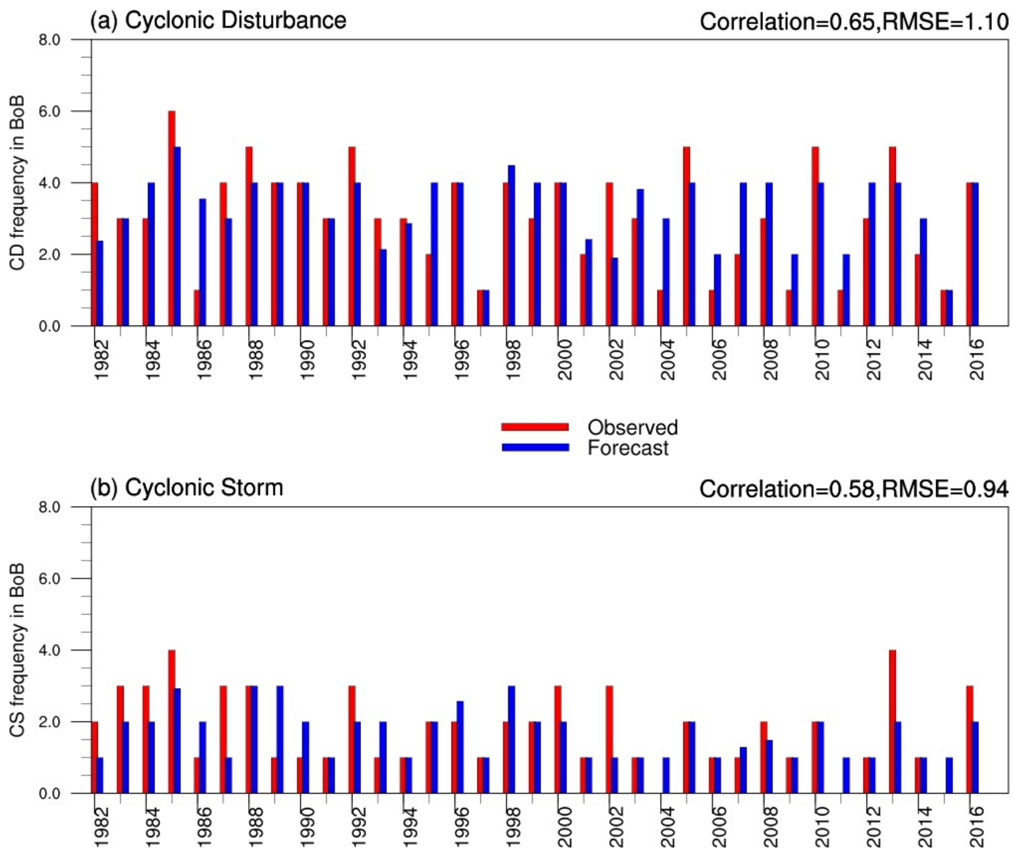
21-year running correlation between the cyclonic disturbance (CD) frequencies over the Bay of Bengal and five parameters listed in Table 1.

212x120mm (120 x 120 DPI)



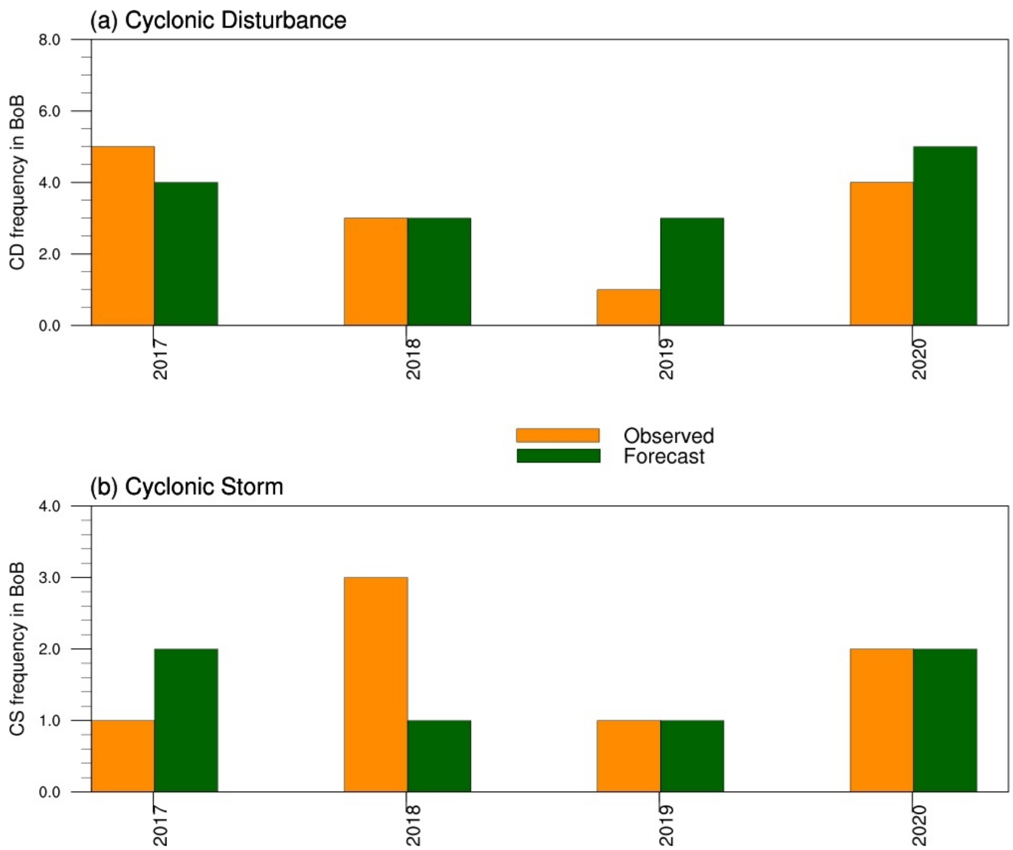
The interannual variations of (a) SST averaged over NINO4 area (5S-5N, 160E-210E) (b) SST averaged over Indian Ocean domain (10S-10N, 50E-80E) (c) ocean heat content averaged over the head Bay of Bengal (15N-21N,87E-94E) in CFSv2 (red line) and observations (blue line). The correlation between the model predicted time series and observed time series is given at the top right corners of each panel.

143x215mm (120 x 120 DPI)



(a) Verification of forecasted cyclonic disturbance frequency over the Bay of Bengal during post-monsoon season by the hybrid statistical/dynamical model (blue bars) along with corresponding observed cyclonic disturbance frequency over the Bay of Bengal (red bars) for the training period (1982-2016). (b) same as (a) but for cyclonic storm frequencies.

212x178mm (120 x 120 DPI)



a) Forecasted cyclonic disturbance frequency over the Bay of Bengal during the post-monsoon season by the hybrid statistical/dynamical model (green bars) along with corresponding observed cyclonic disturbance frequency over the Bay of Bengal (orange bars) for the testing period (2017-2020). (b) same as (a) but for cyclonic storm frequencies.

212x178mm (120 x 120 DPI)