Dynamical downscaling of a multimodel ensemble prediction system: Application to tropical cyclones

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Abstract
This study attempts dynamical downscaling to improve north Indian ocean (NIO) tropical cyclone prediction from a global multimodel ensemble prediction system using weather research and forecasting (WRF) model. A total of 16 ensembles are used in the WRF simulations, these ensembles are bias-corrected prior to downscaling for model climatological errors. The ensemble mean constructed from the output of all downscaled ensembles is analyzed for added value to global predictions. This mean is also compared against observation as well as high-resolution (12 km) deterministic forecast from global forecast system (GFS). Two devastating NIO tropical cyclone cases of year 2017 which were not reliably predicted by global systems have been selected for this study. The results show that downscaled predictions well simulate the intensity and spatial distribution of the rainfall and relative vorticity associated with these cyclonic storms. The wind and temperature vertical profiles during cyclone mature stage are also captured more accurately than raw prediction and high-resolution global deterministic forecast. The study affirms the adequacy of dynamical downscaling in predicting the cyclonic storms over global real-time weather forecasting system.

Keywords
bias correction, dynamical downscaling, regional modeling, tropical cyclone

1 | INTRODUCTION
The synoptic scale disturbances over warm tropical oceans often develop into calamitous tropical cyclones under favorable large scale conditions Ramage (1959); Gray (1968, 1998). These cyclones are one of the important modes of heat transfer from the oceans into the atmosphere. At the same time, they are immensely destructive and claim millions of lives every year Emanuel (2001, 2003). The cyclonic systems forming over north Indian ocean are known to be weaker than in the Pacific and the Atlantic ocean but severely impact the densely populated and agriculture-based countries along the shorelines Lee et al. (1989). Therefore the accurate and timely-apt prediction of cyclonic storms is pivotal for disaster management Saranya Ganesh et al. (2018).
Predictions from coarse-resolution global climate models (GCMs) sometimes fail to meet risk-assessment and mitigation demands, due to the under-representation of the processes and circulations occurring at sub-GCM horizontal grid scale, which are important modulators of weather over any region Giorgi et al. (2001). The advances in technology and increased computing power have made it possible to run GCMs at high resolution, but confidence in these simulations is limited due to lack of optimization of GCMs for high resolution Giorgi et al. (2001). Downscaling of GCMs is a common practice and has wide-range of applications for regionalization of climate data from coarse-resolution GCMs. The regional climate models (RCMs) used for dynamical downscaling purposes have better representation of the subgrid scale processes and orographic features, hence are known to bring out relatively resolved-scale information which is otherwise missing from the coarse-resolution global data Giorgi et al. (1990, 1994, 2001); Xue et al. (2014). The driving GCM signals refined with bias-correction techniques for minimizing error growth in regional simulations are proved to increase the RCM efficiency Bruyère et al. (2013); Christensen et al. (2008); Xu and Yang (2012, 2015).

The weather research and forecasting (WRF) model is widely used for regional studies and is known to have good prediction skill for Indian monsoon region Mukhopadhay et al. (2009); Srinivas et al. (2013); Raju et al. (2015); Ratnam et al. (2017). Several studies addressed the impact of physical parameterizations Osuri et al. (2012), monsoon climate change projections Jayasankar et al. (2018), basin scale hydro-meteorological applications and flood forecasting Lin et al. (2015); Srivastava et al. (2015), tropical cyclone cases Mohanty et al. (2010); Singh et al. (2011), simulations of extreme rainfall events Kumar et al. (2008); Routray et al. (2010); Alam (2014) using WRF.

Despite enormous research on added local climate information by dynamical downscaling in last three decades Xue et al. (2014), to the best of our knowledge, minimal attempts have been made for exploring bias correction and dynamical downscaling for real-time weather predictions over Indian region. Weather uncertainties and extremes are becoming increasingly challenging with changing hydro-climatic conditions Easterling et al. (2000). In view of challenges imposed by weather hazards for real-time predictions on higher-spatial scale, this study attempts to downscale a multimodel ensemble prediction system that is being used at official Indian weather agency that is, India Meteorological Department (IMD) for extended range prediction (ERP) Pattanaik et al. (2019). The known potential predictability signals in tropics are Madden-Julian Oscillation (MJO), soil-moisture, ocean conditions, and tropical–extratropical interactions Vitart and Robertson (2018). The ERP system downscaled here is a combination of coupled and atmospheric model, and is known to have good skill in capturing these large scale signals Sahai et al. (2016).

This paper is arranged into following sections. The data and methodology used for the study is explained in Section 2. The results from downscaled simulations are collated under Section 3, followed by conclusions from the study in Section 4.

## 2 | MODEL, DATA, AND METHODOLOGY

### 2.1 | Dynamical downscaling

#### 2.1.1 | Lateral boundary conditions

We have downscaled the outputs from a real-time extended range prediction (ERP) system. This ERP is a combination of higher (T382) and lower (T126) resolution of National Center for Environment Prediction (NCEP) Climate Forecast System version 2 (CFSv2) Saha et al. (2014) and its atmospheric component Global Forecast System (GFS) forced with bias-corrected sea-surface temperature (SST) from CFSv2 forecasts Sahai et al. (2013); Abhilash et al. (2014a, 2014b, 2014c). Initial conditions (ICs) used to run these models are obtained from National Center for Medium Range Forecast and Indian National Centre for Ocean Information Services, and these ICs are perturbed to generate four ensembles each Abhilash et al. (2014c). Hence, a total of 16 ensembles are created using four model variations with four ensembles of ICs. This ERP prediction system is operational at IMD and runs once in a week (every Wednesday) for 33 days, hindcast (on the fly) is also being generated for each IC. The initial and lateral boundary conditions for regional model are obtained from ERP which will be termed as raw-ERP hereafter in this paper.

#### 2.1.2 | Bias correction of ERP data

The meteorological variables from each of the 16 ERP ensembles (raw-ERP) are corrected for daily climatological biases for each IC with respect to Climate Forecast System Reanalysis (CFSR) Saha et al. (2010). The model climatology is calculated from available ERP hindcast period (2003–2016), and CFSR climatology is computed for the period (1998–2010). At first, model anomalies are calculated as...
\[ M_{i}^{\text{anom}} = M_{i} - \bar{M} \]  \hfill (1)

where \( i = 1,16 \). The daily model anomaly \( (M_{i}^{\text{anom}}) \) for \( i \)th ensemble member \( (M_{i}) \) with respect to the model climatology \( (\bar{M}) \) is superimposed on the six-hourly observed (here CFSR) climatology \( (\bar{O}) \) to obtain the bias-corrected ensemble member \( (M_{i}^{bc}) \) as following.

\[ M_{i}^{bc} = M_{i}^{\text{anom}} + \bar{O} \]  \hfill (2)

\[ M_{i}^{bc} = (M_{i} - \bar{M}) + \bar{O} \]  \hfill (3)

These corrections are applied to all vertical levels of winds, relative humidity, temperature, and to the surface variables like sea-surface temperature, mean sea level pressure, surface pressure, soil moisture, and soil temperature. All the 16 ERP members are individually downscaled using these six-hourly bias-corrected boundary conditions.

### 2.1.3 Regional model

Weather Research and Forecasting-Advanced Research WRF (WRF-ARW) version 4.0 Skamarock et al. (2019) is used to downscale the datasets mentioned earlier. Here the regional domain (Figure 1) at 9 km resolution having 1001 × 945 points covering 25°S–55°N, 30°E–128°E area, and 37 vertical levels is considered. The mentioned model configuration runs are made with WRF single-moment class 5 microphysics Hong et al. (2004), New-Tiedtke cumulus scheme Zhang and Wang (2017), Yonsei University (YSU) boundary layer scheme Hong et al. (2006), Dudhia shortwave Dudhia (1989), and Rapid-Radiative Transfer Model Mlawer et al. (1997) longwave radiation schemes. Landuse/landcover datasets generated by National Remote Sensing Centre (NRSC) Gharaib et al. (2018) for Indian region along with the United States Geological Survey (USGS) data Loveland et al. (2000) is deployed in the model. WRF outputs are postprocessed for further analysis using Unified Post Processor McKee et al. (2019).

#### 2.1.4 Model initialization

The bias-corrected ERP forcings are used to drive WRF for two cyclone cases of 2017; severe cyclonic storm (SCS) Mora (28–30, May), and very severe cyclonic storm (VSCS) Ockhi (29 November to 05 December). WRF is initialized using the same initial date as raw-ERP for these cyclones that is, May 24, 2017 (0524) for SCS Mora and 29 November 2017 (1129) for VSCS Ockhi for each ensemble (Table 1). Each run is carried out according to the configuration specified in Section 2.1.3. The bias-corrected downscaled ERP runs are termed as BC-D-ERP hereafter.

#### 2.2 Observational and verification data

IMD gridded rainfall data at 0.25° × 0.25° resolution Pai et al. (2014) is used to assess the spatial and temporal distribution of rainfall from the downscaled forecasts. ERA5 reanalysis is used to compare the meteorological variables other than precipitation. Downscaled outputs are also compared against high-resolution (12 km) deterministic forecast of Global Forecast System version 14 Mukhopadhyay et al. (2019) (hereafter GFS-12km).

| S. No. | Event Description | Duration      | Initial Condition |
|-------|------------------|---------------|-------------------|
| 1     | Severe cyclone Mora | 28–30, May 2017 | 24 May (0524)     |
| 2     | Very severe cyclone Ockhi | 29 November to 05 December, 2017 | 29 November (1129) |

**TABLE 1** Brief description of the cases selected for the study
which is used for short range prediction at IMD. The same initial conditions are used in this study for GFS-12km, raw-ERP and BC-D-ERP (Table 1).

3 | RESULTS AND DISCUSSIONS

The ensemble mean forecasts from raw-ERP and BC-D-ERP, are analyzed for cyclone Mora and Ockhi and are compared against observation and GFS-12km deterministic forecast. All given figures are plotted at common resolution. Observed and predicted characteristics of both cyclonic cases are explained as follow:

3.1 | Spatial characteristics of the selected storms

3.1.1 | Severe cyclonic storm Mora

The cyclonic storm Mora that formed in the Bay of Bengal (BOB) basin on May 28, 2017, intensified into an SCS on 29 May and moved north-northeastward making landfall on the subsequent day IMD (2017b). This cyclonic system caused severe destruction in East and Northeast India, Bangladesh and Myanmar during landfall Sharma (2017).

The daily rainfall spatial distribution associated with SCS Mora is plotted in Figure 2 from 27 May to 31 May, for Observation (a–e), GFS-12km (f–j), raw-ERP (k–o), and BC-D-ERP (p–t). The Figure 2a–e shows observed precipitation pattern associated with daily evolution of the system off the Indian east coast from Southwest to central BOB to head Bay, and finally striking the northeast Indian land mass at Bangladesh and Myanmar border. This distribution pattern is completely missing in GFS-12km forecast (Figure 2f–j) and raw-ERP (Figure 2k–o). However, BC-D-ERP (Figure 2p–t) reasonably simulated the genesis and subsequent movement of the rainfall pattern up to the landfall of the system.

This is well supported by the maximum spatial 850 hPa vorticity values (Figure 4) associated with the evolution of the system from ERA5 reanalysis (Figure 4a), GFS-12km (Figure 4c), raw-ERP (Figure 4e), and BC-D-ERP (Figure 4g). GFS-12km and raw-ERP did
not show any indication of the system but BC-D-ERP clearly predicted the development and advancement of the system close to ERA5.

3.1.2 | Very severe cyclone Ockhi

An organized convective system in the south of Sri Lanka developed into cyclonic storm Ockhi by the end of November 2017. Ockhi rapidly intensified into severe cyclone on 01 December and VSCS on the next day moving north-northwestward. The mid-latitude trough in the upper-level westerlies forced cyclone Ockhi to re-curve north-eastward on the following days. It weakened into a depression and moved into the land from south of Gulf of Khambhat IMD (2017a). Another low pressure system formed in BOB near Malay Peninsula on 01 Dec 2017, which later developed into a deep depression on 06 December and moved north-northwestwards. Most of the operational centers forecasted the development of BOB depression over Ockhi, contrary to the observations.

The IMD observed daily rainfall distribution shows the evolution of above mentioned systems from 01 to 05 December (Figure 3a–e). The predicted rainfall for GFS-12km given in the subplots f–j of Figure 3 shows that the advancement of Ockhi cyclone is sluggish while the BOB depression actively approached the coast on 05 Dec, which was not the case in the observations. The rainfall forecasts for raw-ERP also have disagreements with observation (Figure 3k–o). The intensity of Ockhi cyclone is excessively underestimated and the progression of BOB depression is rapid. In BC-D-ERP (Figure 3p–t), the intensity and evolution of the BOB depression is predicted more accurately. Although the intensity of Ockhi cyclone is realistically captured by BC-D-ERP, it could not predict the re-curvature and subsequent landfall of the system on 05 December. Altogether BC-D-ERP represented both systems more precisely than raw-ERP and GFS-12km deterministic forecast.

This becomes even clear in the right column of Figure 4, where BC-D-ERP maximum vorticity

![Figure 3](image-url)
distribution during evolution of these systems (Figure 4h) show improvement over both global predictions that is, raw-ERP (Figure 4f) and GFS-12km (Figure 4d). These vorticity plots comply with the conclusions made from rainfall patterns for both systems.

In terms of the average root mean square error, the BC-D-ERP predicted vortex intensity of Ockhi cyclone is improved by a factor of 1.5 m s$^{-1}$ and 6.4 hPa for maximum wind speed and center sea level pressure, respectively (day-wise values of MWS and CSLP are given in Table 2).

Dynamical downscaling of the global forecasts not only improve the intensity of the predicted fields, but also the spread among the ensembles (Figure S1). It is clear from the figure that the ensemble spread for maximum

**FIGURE 4** Maximum values of 850 hPa vorticity ($\times 10^{-5}$ s$^{-1}$) during the evolution of cyclone Mora (left column) and cyclone Ockhi (right column) for (top to bottom) ERA5 reanalysis (a and b), GFS-12km (c and d), raw-ERP (e and f), and BC-D-ERP (g and h), respectively
wind speed (MWS) (Figure S1a) and center sea level pressure (CSLP) (Figure S1c) for cyclone Ockhi is more among the downscaled members compared to that of raw-ERP ensembles. As the spread between ensembles is known to be a measure of better forecast skill Kalnay and Dalcher (1987), it is asserted that dynamical downscaling

### Table 2

| S. No. | Date       | MWS (m/s) | CSLP (hPa) |
|--------|------------|-----------|------------|
|        |            | OBS       | Raw-ERP    | BC-D-ERP  |
| 1      | 30Nov2017  | 15.43     | 16.21      | 23.29     |
| 2      | 01Dec2017  | 25.72     | 14.82      | 17.46     |
| 3      | 02Dec2017  | 41.15     | 11.91      | 18.50     |
| 4      | 03Dec2017  | 43.72     | 16.70      | 19.78     |
| 5      | 04Dec2017  | 36.01     | 14.90      | 18.39     |
| 6      | 05Dec2017  | 25.72     | 12.86      | 13.33     |

### Figure 5

Vertical profile of horizontal winds (shaded, in m/s) with temperature (contours, °C) and warm core (°C) for mature stage of SCS Mora (first two columns from left) and VSCS Ockhi (last two columns) for (top to bottom) ERA5 reanalysis (a–d), GFS-12km (e–h), raw-ERP (i–l), and BC-D-ERP (m–p).
can provide more confident probabilistic forecasts for extreme weather.

### 3.2 Vertical structure of the selected storms

Vertical cross-section of the cyclones Mora and Ockhi during their mature stage in terms of wind and temperature can be seen in Figure 5. ERA5 reanalysis vertical profile for horizontal wind speed for cyclone Mora (Figure 5a) shows the presence of eye at about 91°E. The warm core of the system (Figure 5b) shows maxima at about 400 hPa. These features are absent in GFS-12km (Figure 5e,f) and raw-ERP (Figure 5i,j) concurrent with Figures 2 and 4. However, BC-D-ERP could realistically predict the vertical structure of wind speed and warm core of the system (Figure 5m,n), with eye of storm clearly visible at 91°E.

For VSCS Ockhi mature stage, observed eye and intense warm core of the system is present at around 71°E (seen in Figure 5c,d). Although GFS-12km (Figure 5g,h) could predict the presence of the system to some extent, it is very weak and displaced by 2° toward east, compared to the observations. The raw-ERP failed to reproduce this structure (Figure 5k,l). The intensity of vertical structure of wind speed is not well predicted by BC-D-ERP (Figure 5o). Despite less intensity, BC-D-ERP captured the warm core of Ockhi (Figure 5p) at same location as in ERA5.

The above analysis indicates that BC-D-ERP potentially improve the raw-ERP predictions and give more reliable cyclone prediction at a higher-spatial resolution.

### 4 CONCLUSIONS

This study undertook dynamical downscaling of a global multimodel ensemble prediction system for two tropical cyclone cases of 2017 using WRF. Downscaled output (BC-D-ERP) is analyzed against observation/reanalysis, raw-ERP, and high-resolution deterministic global forecast (GFS-12km).

It is found that besides having good skill for large scale weather patterns, raw-ERP predictions has spatial, temporal, and intensity biases for the cyclonic storms selected for the study. However, dynamical downscaling of this system surpassed these biases and showed significant improvement in terms of rainfall spatial distribution, maximum vorticity evolution, wind, and temperature profiles for cyclonic mature stage. The betterment seen in BC-D-ERP is probably because downscaling could resolve the regional features, processes, and circulations that are pivotal for the genesis and progression of the storms. For cyclone cases considered in this study BC-D-ERP not only performs better than raw-ERP, but also outperforms GFS-12km global forecast. As indicated from analysis BC-D-ERP could capture the possible dynamical and thermodynamical structure of cyclonic systems, which is favorable for lessening the probabilities for false alarms.

The spatial skillful scale for which global models are optimized is of many grid lengths and the model physics is designed for coarse-resolution. Hence running these models at high resolution have limitations to reproduce regional characteristics Giorgi et al. (2001); Sahai et al. (2015). The results from the study affirm that dynamical downscaling can be an alternative tool for better high-resolution regional weather prediction for extremes like tropical cyclones. The skill for this downscaling framework is subjected to its performance on large sample of such events. The future scope includes improvement in predictions in terms of lead time as well as spatial distribution.

### ACKNOWLEDGEMENTS

This study is a part of Ph.D. dissertation of Manpreet Kaur. The research carried out at IITM is fully funded by Ministry of Earth Sciences, Government of India. We thank Dr. D. R. Pattanaik (IMD) for ERP runs. WRF runs are performed on high performance computing system, Pratyush at IITM. Authors are grateful to the two anonymous reviewers for their valuable suggestions.

### CONFLICT OF INTEREST

The authors declare no potential conflict of interests.

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SUPPORTING INFORMATION  
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How to cite this article: Kaur M, Krishna RPM, Joseph S, et al. Dynamical downscaling of a multimodel ensemble prediction system: Application to tropical cyclones. Atmos Sci Lett. 2020;21:e971. https://doi.org/10.1002/asl.971