Improved skill of NCMRWF Unified Model (NCUM-G) in forecasting tropical cyclones over NIO during 2015–2019

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Operational forecasting of tropical cyclone (TC) track and intensity in the India Meteorological Department (IMD) relies more and more on the numerical weather prediction (NWP) model guidance from national and international agencies particularly, on the medium range (24–120 h). Any improvement in TC forecasts by the NWP models enhances the operational forecaster's confidence and capability. The real-time information from the National Centre for Medium Range Weather Forecasting (NCMRWF) global NWP model (NCUM-G) is routinely used by operational forecasters at IMD as model guidance. The present study documents the improved skill of NCUM-G in forecasting the North Indian Ocean (NIO) TCs during 2015–2019, based on a collection of 1810 forecasts involving 22 TC cases. The study highlights three significant changes in the modelling system during the recent five years, namely (i) increased grid resolution from 17 to 12 km, (ii) use of hybrid 4D-Var data assimilation (DA), and (iii) increased volume of assimilated data. The study results indicate a consistent improvement in the NCUM-G model forecasts during the premonsoon (April–May, AM) and post-monsoon (October–December, OND) TC seasons. In addition to a 44% reduction in the initial position error, the study also reports a statistically significant decrease in the direct position error (DPE) and error in the intensity forecast, resulting in a forecast gain of 24 hrs. Comparing NWP models with IMDs official track error shows that NCUM-G and ECMWF model forecasts feature lower DPE than IMD in 2019, particularly at higher (96, 108, and 120 h) lead times.

Keywords. Tropical cyclone forecast; unified model; NCUM; model verification; track error; intensity prediction; landfall prediction.

1. Introduction

Tropical cyclones (TCs) are among the strongest and the most destructive natural disasters worldwide. In particular, over the North Indian Ocean (NIO), which consists of two basins, i.e., the Bay of Bengal (BoB) and the Arabian Sea (AS), their effect is very devastating due to the frequency and intensity of the TCs along the long coastlines with dense population. In terms of frequency of

occurrence, NIO witnesses 5–7% of cyclones that form worldwide (Neumann 1993). The BoB cyclones alone have accounted for 75% of global deaths caused by TCs in the last 300 years (Dube *et al.* 2014), with more frequent systems developing over this basin in recent years (Singh *et al.* 2000). There are two main cyclone seasons over the NIO, i.e., the pre-monsoon season, which is April–May, and the post-monsoon season is from October to December. In recent years, the number of intense cyclones has increased (Knutson *et al.* 2010; Deo and Ganer 2013), resulting in increased destruction (Emanuel 2005). For these reasons, the accurate and timely forecasting of TCs is of extreme importance in this region.

There are many studies based on NWP model forecasts of TC generation and propagation in the NIO (Mohapatra 2014; Mohanty *et al.* 2014, 2019; Mohapatra and Sharma 2019). Mohapatra and Sharma (2019) discussed various models and methods used by IMD in cyclone warning services in the NIO. They emphasized NWP models' importance, including NCMRWF Unified Model (NCUM-G) and Global Forecast System (GFS), for predicting track and intensity for 24–120 h forecasts. Mohapatra (2014) presented a detailed description of methodologies used to verify track forecasts. It highlights that the DPE of track forecasts is higher in the AS than the BoB, and also, this error is higher in the pre-monsoon season than post-monsoon. Kotal *et al.* (2014) presented the cyclone prediction system (CPS) developed at IMD for operational cyclone forecasting over NIO. The forecasts of TCs from CPS were verified, and it was observed that this model has good skill in predicting genesis, track, intensification, and decay of a TC. Mohanty *et al.* (2019) showed that although the TC track prediction has improved in recent years, the intensity prediction is still a challenge for forecasters. However, with the development of high-resolution NWP models, the forecasts of the TC intensity have shown considerable improvement (Bender *et al.* 2007; Gopalakrishnan *et al.* 2012).

Many studies relate the effect of data assimilation (DA) on the forecasts of TCs (Rakesh and Goswami 2011; Mohanty *et al.* 2014; Kutty *et al.* 2018, 2020). Rakesh and Goswami (2011) studied the effect of background error statistics (BES) on TC forecasts over the NIO. They used a 3D-Var DA method with different BES in the Weather Research and Forecasting (WRF) model and concluded that regional BES provides better TC track forecasts than a global BES. Mohanty *et al.* (2014)

showed that a reliable TC forecast could be obtained from the WRF by assimilating good quality observations from several sources. Kutty *et al.* (2020) demonstrated the superiority of the hybrid ensemble transform Kalman filter (ETKF) over the 3D-Var system in the WRF model.

Although NCUM-G has been operational at NCMRWF since 2012, the operational TC forecast started in 2015. NCUM-G is based on the United Kingdom's Unified Modeling (UKMO) framework adopted under 'UM partnership'. It uses an advanced Hybrid 4D-Var DA method. In June 2018, NCUM-G was upgraded to NCUM-G: V5 and one of the major changes was the increase in the model's horizontal resolution. Details about the modelling, DA systems, and upgrade timelines are presented in section 2.

IMD briefly reports the performance of NWP model data used in TC prediction for all the tropical cyclones over NIO as part of its routine activity (http://rsmcnewdelhi.imd.gov.in/report.php?internal_menu=MjY=). Routray *et al.* (2017) and Singh *et al.* (2021) evaluated TC prediction skills of NCUM-G, but their studies are limited to only case studies. In the present study, we have compared the skill of operational global model forecasts (NCUM-G: V5) with its predecessor (NCUM-G: V4) in predicting the tracks, intensity, and landfall for 22 NIO TC cases from 2015 to 2019. All the verification is carried out against the best track (BT) data obtained from IMD. More details about these cyclones are presented in section 3.

This paper is organized into seven sections. Section 2 gives a detailed description of NCUM-G (V4 and V5) modelling and DA systems. A brief description of the NIO TC cases during 2015–2019 is presented in section 3. In section 4, the TC tracker and verification methodology are discussed. A detailed discussion of results is presented in section 5. Additionally, a comparison of IMD official track errors with NCUM-G and NWP models from other international operational centers for 2019 is shown in section 6. Finally, conclusions based on this study are summarized in section 7.

2. Description of NCMRWF unified modelling system

2.1 *Model description*

In recent years, there has been an increasing demand for location-specific forecasts for high

impact or extreme weather events, leading to a need to increase the NWP model's resolution. The NCUM-G model was upgraded from NCUM-G: V4 to NCUM-G: V5 in May 2018 (Kumar *et al.* 2018). One of the major changes was the increase in the horizontal resolution from 17 km in V4 to 12 km in V5, reducing the model time step from 7.5 to 5 min. The model's vertical resolution was retained from V4 to V5, i.e., with 70 vertical levels reaching a height of 80 km. NCUM-G model uses a semi-implicit semi-Lagrangian formulation to solve the non-hydrostatic, fully compressible deep-atmosphere equations of motion (Wood *et al.* 2014). The science setting components of the model for the atmosphere and land remain the same for both the versions (Kumar *et al.* 2018) which are the Global Atmosphere Science version 6 (GA6) and Global Land version 6 (GL6) (Walters *et al.* 2017). The dynamic core for the NCUM-G model is the ENDGame (Even Newer Dynamics for General atmospheric modeling of environment, Wood *et al.* 2014), introduced in November 2015. This dynamic core exhibits improved stability, accuracy, and reduced damping, resulting in increased variability in the tropics with improved representation of tropical systems like cyclones and reduced surface biases (Walters *et al.* 2017; Kumar *et al.* 2018). Comparison between the two versions of NCUM-G have been tabulated and presented in table 1.

2.2 *Data assimilation*

For creating 6-hourly atmospheric analyses, NCUM-G has adapted the 4-Dimensional Variational (4D-Var) DA method based on Rawlins *et al.* (2007) since its operational implementation at NCMRWF in 2012. 4D-Var allows more effective use of observations through the consistent use of observation-operators in the model equations (Rabier *et al.* 1998, 2007). The NCUM-G DA has undergone many modifications during the study period. In the early part of 2015 and before it, 4D-Var assimilation was carried out at 60 km resolution with the baseline observations shown in table 2, while the forecast model resolution was $\sim$25 km (Rajagopal *et al.* 2012). The DA resolution was increased to 40 km in late 2015, while the model forecast resolution was increased to 17 km (George *et al.* 2016). A weakness of the primary 4D-Var method is that it uses a fixed 'climatological' model of the error covariance in the background forecast, which lacks the flow-dependent

error of the day (Lorenc 2003). To address this issue, the NCUM-G 4D-Var DA system was upgraded to Hybrid 4D-Var following Clayton *et al.* (2013) and implemented operationally in October 2016 (Kumar *et al.* 2018). NCMRWF runs an ensemble prediction system based on NCUM-G, i.e., the NCMRWF Ensemble Prediction System (NEPS; Sarkar *et al.* 2016; Mamgain *et al.* 2018). The NCUM-G Hybrid 4D-Var assimilation system combines the flow-dependent errors calculated from the Ensemble Transform Kalman Filter (ETKF) based NEPS forecasts with the climatological background errors. The hybrid approach is scientifically attractive as it elegantly combines the benefits of an EPS and 4D-Var in a single DA system (Barker and Clayton 2011).

The bias correction method applied to the satellite radiances at NCMRWF has changed during the study period. Until October 2016, a static bias correction scheme based on Harris and Kelly (2001) was operational. Later, it was upgraded to an adaptive bias correction scheme following Cameron and Bell (2018). Biases in the satellite radiances are corrected using an adaptive bias correction algorithm known as the Variational Bias Correction (VarBC), closely following the incremental formulation described in Auligne *et al.* (2007).

In addition to the above changes in DA technique and bias correction, many new observations in the DA were introduced, particularly after 2017. These include: (i) the radiances and atmospheric motion vectors from Spinning Enhanced Visible and InfraRed Imager (SEVIRI) onboard Meteosat-8 relocated to the Indian Ocean Data Coverage (IODC) in February 2017, (ii) scatterometer sea surface winds from Scatsat-1 operated by Indian Space Research Organization (ISRO) since November 2017, (iii) Advanced Himawari Imager (AHI) radiances from Himawari-8 satellite, (iv) sea surface winds from Windsat since May 2018, and (iv) Global Precipitation Mission (GPM) Microwave Imager (GMI) radiances and INSAT-3D imager radiances (Rani *et al.* 2019) since August 2018. For accurate prediction of the track and intensity of TCs, the location and the magnitude of the low pressure in the model analysis should be as realistic as possible. In NCUM-G, the location and the minimum low pressure associated with the TCs are adjusted by assimilating the estimated surface pressure information from the TC Vital (TC Vital) reports since October 2018 (Heming 2016). Figure 1 shows the timeline of the changes in the DA

Table 1. *Comparison of model configuration of NCUM-G: V4 and V5.*

Parameters	NCUM-G: V4	NCUM-G: V5
Implementation	November 2015	May 2018
UM version	UM 10.2	UM 10.8
Dynamics	ENDGame	ENDGame
Resolution	N768L79 ($\sim$17 km)	N1024L70 ($\sim$12 km)
Numerical scheme	Semi-implicit	Semi-implicit
	Semi-Lagrangian	Semi-Lagrangian
Vertical levels	70	70
Time step	7.5 min	5 min
Model top height	80 km	80 km
Atmosphere science version	GA6	GA6
Land science version	GL6	GL6
Microphysics scheme	Wilson and Ballard (1999)	Wilson and Ballard (1999)
Radiative transfer scheme	Edwards and Slingo (1996)	Edwards and Slingo (1996)
Boundary layer scheme	Lock *et al* (2000)	Lock *et al* (2000)

Table 2. *List of baseline observations.*

Observation type	Observation description
AHIClear	Advanced Himawari imager radiances from Himawari-8
Aircraft	Upper-air wind and temperature from aircraft
AIRS	Atmospheric infrared sounder of AQUA
AMSR	Radiances from AMSR-2 onboard GCOM satellite
ATOVS	AMSU-A, AMSU-B/MHS, HIRS from NOAA-18 & 19, MetOp-A&B
ATMS	Advanced technology microwave sounder in NPP satellite
CrIS	Cross-track infrared sensor observations in NPP satellite
GOESClear	Cloud clear imager radiances from GOES
GPSRO	Global positioning system radio occultation observations from various satellites
GroundGPS	Ground based GPS observations from various locations
IASI	Infrared atmospheric sounding interferometer from MetOp-A&B
SAPHIR	SAPHIR microwave radiances from Megha-Tropiques
Satwind	Atmospheric motion vectors from various geostationary and polar orbiting satellites
Scatwind	Advanced Scatterometer in MetOp-A&B
SEVIRIClear	Cloud clear observations from SEVIRI of METEOSAT 11
Sonde	Radiosonde observations, upper-air wind profile from pilot balloons, wind profiles, VAD wind observation from Indian DWR
Surface	Surface observations from land and ocean
SSMIS	SSMIS radiances

system, including the new observations during the period from January 2015 to December 2019.

3. Tropical cyclone cases during 2015–2019

For robust and reliable statistical results, a relatively large number of data samples are preferred. This study has considered 22 TCs formed over NIO during 2015–2019, resulting in 1810 forecasts (forecasts based on 00 and 12 UTC at 6-hr interval and all lead times from 0 to 120 h). There are ten TCs, out of which three cyclones formed over AS and seven cyclones formed over BoB from 2015 to May 2018. Based on maximum sustained surface wind speed (MSW), IMD classifies the cyclonic disturbances over NIO. This classification is presented in table 3. Out of these ten TCs, three were extremely severe cyclonic storms (ESCS), two were very severe cyclonic storms (VSCS), one was a

severe cyclonic storm (SCS), and four were in the category of cyclonic storms (CS). Twelve TCs formed during June 2018–2019, out of which six TCs formed over AS and the rest over BoB. These TCs are also of mixed intensity, with one having the intensity of a super cyclonic storm (SuCS). Figure 2 shows each system's observed tracks obtained from the IMD BT data. The details like name, the basin of formation, dates/duration, category, MSW, minimum mean sea level pressure (MSLP), and life (number of days) of all the TCs are presented in table 4. The sample size of cyclones used to compare forecasts from the two versions of the model, NCUM-G: V4 and NCUM-G: V5, are very similar in number and distribution over the BoB and AS.

4. TC Tracker and verification methodology

4.1 *Tracking algorithm*

To get the information of a TC from NCUM-G forecasts, an objective TC-tracker is operationally run at NCMRWF. This TC-tracker uses a bivariate approach for tracking a storm. In this

Figure 1. Change in data assimilation (DA) system during 2015–2019.

algorithm, firstly, the maximum value of relative vorticity at 850 hPa (850RV) is used to provide the approximate position of a cyclonic system. This approximate position is then relocated to the location of local minimum MSLP which provides the center of the storm. The threshold for 850RV and MSLP for the formation of a TC is set to 1.5×10^{-4} s^{-1} and 1000 hPa, respectively. However, these thresholds are tunable for different resolutions of the model. The TC-tracker algorithm uses seven model parameters: orography, surface temperature, u and v components of winds at 10 m and 850 hPa, and MSLP. Orography and surface temperature are used only for identifying the system in the model's analysis field. For other forecast lead times, the remaining five parameters are used. Details of the TC tracking algorithm are available in Heming (2017). The tracker output provides the position and intensity of a cyclone at every 6-h interval up to 120 h.

4.2 *Verification methodology*

To convey the skill of an NWP model to a forecaster, regular forecast verification and model evaluation statistics related to it are essential. At NCMRWF, model track and intensity for all the TCs over NIO are verified, and the model performance report is shared with IMD. The verification of a TC track is carried out using standard verification scores like direct position error, the along and cross-track errors. Errors in model predicted MSW and MSLP provide the intensity verification scores (Heming 2009; Mohaptra *et al.* 2013a, b; Heming 2017). Further, the landfall location and time error are also calculated. Errors related to landfall are crucial for disaster management and planning to minimize the loss of life and property. This verification is done against IMD BT data. BT data are a post-cyclone estimation of TC position, which gives the latitude, longitude, and intensity in terms of MSW and MSLP. IMD provides the BT data of a TC post the event. The details of BT data
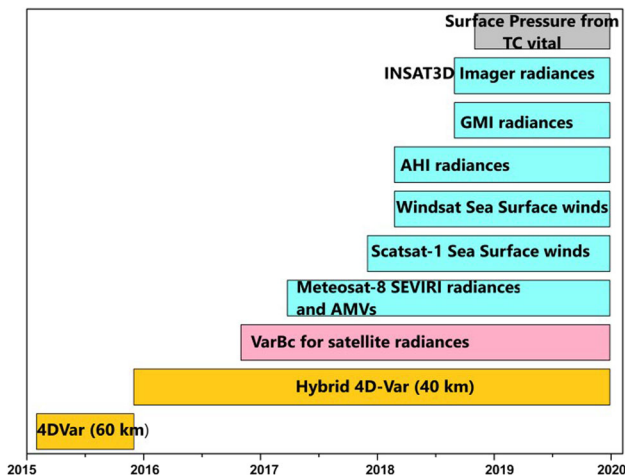
Table 3. *Classification of cyclonic disturbances over the NIO by IMD 2015.*

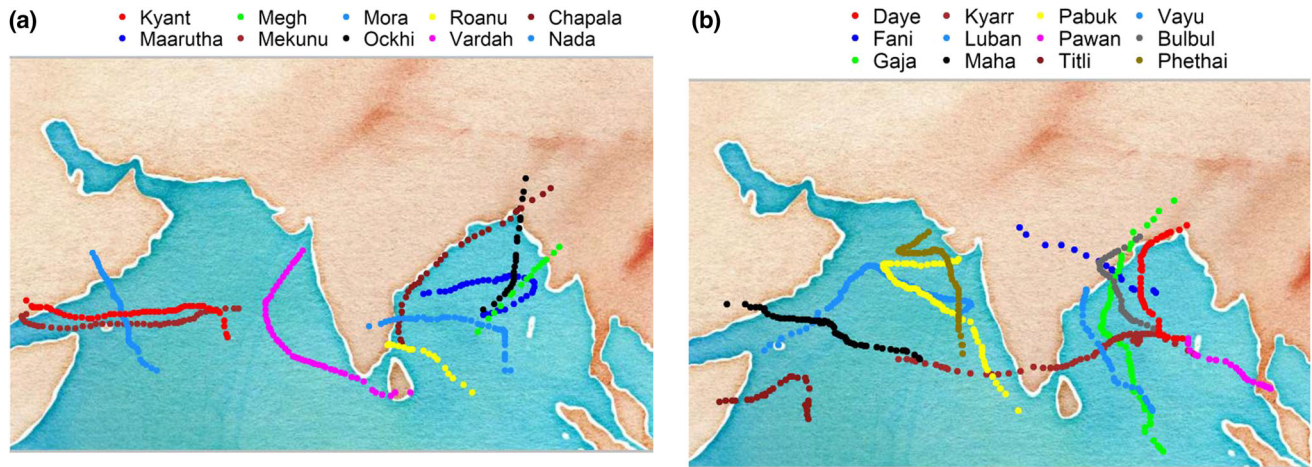| Cyclonic system	Maximum sustained surface winds
Cyclonic storm (CS)	34–47 kts
Severe Cyclonic storm (SCS)	48–63 kts
Very Severe Cyclonic storm (VSCS)	64–89 kts
Extremely Severe Cyclonic storm (ESCS)	90–119 kts
Super Cyclonic storm (SuCS)	≥120 kts

Figure 2. Best track plot of tropical cyclones as obtained from IMD for (**a**) 2015–May 2018 and (**b**) June 2018–2019.

Table 4. *List of tropical cyclones studied and their details.*

Sl. no.	Name	Dates	Basin of formation	Classification	MSW (kt)	MinSLP (hPa)	Life (days)	Landfall
1	Chapala	28 Oct–04 Nov 2015	AS	ESCS	115	940	8	Yes
2	Megh	05–10 Nov 2015	AS	ESCS	95	964	6	Yes
3	Roanu	17–22 May 2016	BoB	CS	45	983	6	Yes
4	Kyant	21–28 Oct 2016	BoB	CS	40	996	8	No
5	Nada	29 Nov–2 Dec 2016	BoB	CS	40	1000	4	Yes
6	Vardah	6–13 Dec 2016	BoB	VSCS	70	975	8	Yes
7	Maarutha	15–17 April 2017	BoB	CS	40	996	3	Yes
8	Mora	28–31 May 2017	BoB	SCS	60	978	4	Yes
9	Ockhi	29 Nov–6 Dec 2017	BoB	VSCS	85	976	8	No
10	Mekunu	21–27 May 2018	AS	ESCS	95	960	7	Yes
11	Daye	19–22 Sep 2018	BoB	CS	35	992	9	Yes
12	Luban	6–15 Oct 2018	AS	VSCS	75	978	10	Yes
13	Titli	8–12 Oct 2018	BoB	VSCS	80	972	5	Yes
14	Gaja	10–19 Nov 2018	BoB	VSCS	70	976	10	Yes
15	Phethai	13–18 Dec 2018	BoB	SCS	55	992	6	No
16	Fani	26 Apr–04 May 2019	BoB	ESCS	115	932	9	Yes
17	Vayu	10–17 Jun 2019	AS	VSCS	80	970	8	No
18	Hikaa	22–25 Sep 2019	AS	VSCS	75	978	4	Yes
19	Kyarr	24 Oct–02 Nov 2019	AS	SuCS	130	922	10	No
20	Maha	30 Oct–07 Nov 2019	AS	ESCS	100	956	9	No
21	Bulbul	05–11 Nov 2019	BoB	VSCS	75	976	7	Yes
22	Pawan	02–07 Dec 2019	AS	CS	40	998	6	Yes

processing methods at IMD are provided in Mohapatra *et al.* (2012b).

5. Discussion of results

5.1 *Improved NCUM-G skill during 2015–2019*

To assess the improvement in forecasting skill of NCUM-G, the Day-3 850 hPa wind forecast is analyzed in terms of Root Mean Square Error (RMSE) during April–May and OND over the Indian region (6.5–38.5°N, 66–98°E) and is shown in figure 3(a). These forecasts have been verified against the radiosonde observations at 39 locations over India, shown in figure 3(b). It is found that the RMSE shows a decreasing trend during both seasons. There is approximately 17% and 23% reduction in the RMSE during AM and OND,

respectively. This reduction in RMSE highlights the consistent and substantial improvement in NCUM-G forecast skill in predicting lower tropospheric circulation during 2015–2019. The impact of improved forecasting skills of the model is also reflected in TC prediction, as discussed in the following subsections.

5.2 *Track and intensity forecast error*

Direct position error (DPE) is the simplest form of track error. It is defined as the great circle distance between the observed and forecast position at any forecast validity time. It is helpful in the estimation of a 'cone of uncertainty', which is generally fixed as some quartile of DPE (Mohapatra *et al.* 2012a). Though DPE is easier to calculate, it does not provide the information related to the system's speed (fast/slow) and directional movement and alone is not sufficient to evaluate the model TC forecasting skill (Heming 2017). Two other error components, Along Track Error (ATE) and Cross Track Error (CTE), provide better information of predicted tracks. If it is assumed that DPE represents the hypotenuse of a hypothetical right-angled triangle, then ATE and CTE are representative of the other two sides. For better illustration, these track errors are diagrammatically represented in figure 4. ATE provides information related to the movement of a system along with the observed position. A positive (negative) value means the model predicted system moves faster (slower) than the observation. CTE tells about the directional

error, and a positive (negative) value indicates the model tracks the system right (left)-wards of the observed position. The sign of CTE will change in the southern hemisphere.

The intensity of a TC is usually measured in terms of MSW. From an NWP model, these parameters are calculated from standard model outputs, viz., 10 m winds. Prediction of intensity is challenging for global NWP models because they have relatively coarser resolutions. A stronger system is even more challenging to predict in terms of its intensities (Heming 2017). Thus, it would be interesting to assess the performance of a 12-km grid resolution model compared to the 17-km resolution. As highlighted in Heming (2017), the verification of MSW is not that accurate as the model's 10 m winds may not be a true representative of it. Nevertheless, since the same field and same methodology of TC-tracker is applied for all the systems, any improvement in the prediction of the model's 10 m winds around a TC will be anticipated as an improvement in MSW prediction.

5.3 *Verification of model predicted track*

DPE for two different versions of NCUM-G has been compared in figure 5(a) and represented as a box–whisker plot. The plot describes the minimum, first quartile, median, third quartile, and the maximum DPE at each forecast length. The outliers in data are the errors outside the minimum–maximum bound and they have also been represented in the figure. This comparison has been
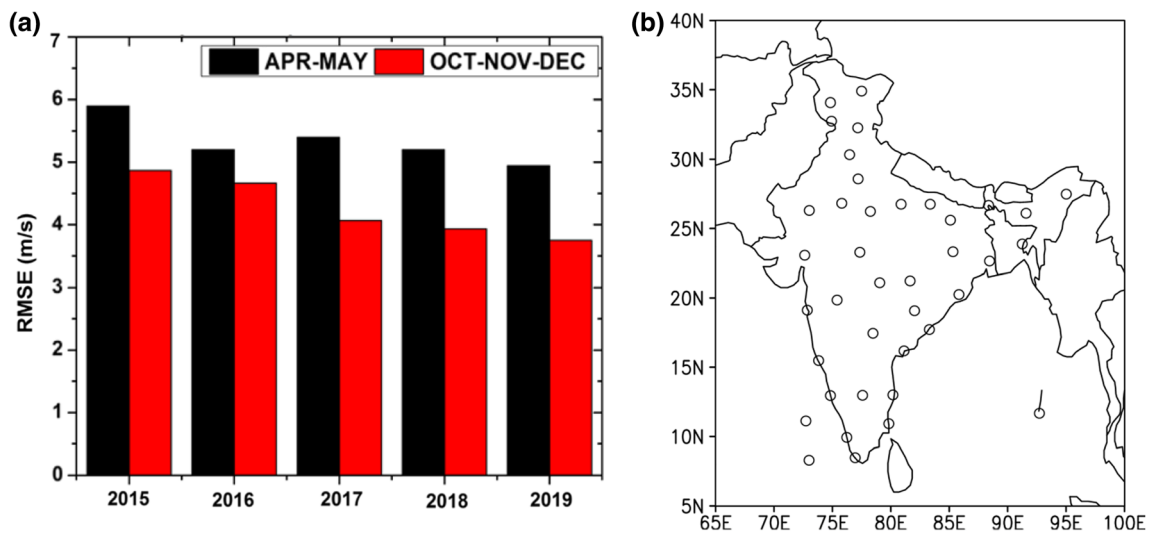

Figure 3. (**a**) Root Mean Square Error in NCUM-G forecast of winds at 850 hPa calculated against radiosonde during 2015–2019 for pre-monsoon (April–May) and post-monsoon (October–November–December) season. (**b**) Location of radiosonde monitoring stations.
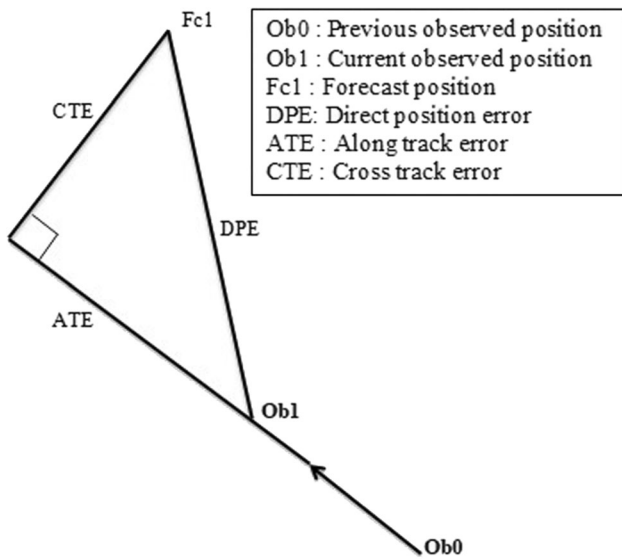
Figure 4. Diagramatical representation of DPE, ATE, and CTE.

made for the initial (model analyzed) position and 6-hrly forecasts up to 120 h. But only initial position and 24, 48, 72, 96, and 120 h forecast errors have been shown for brevity. The model's (V4 and V5) mean initial position error is lower than 100 km. At 120-h forecast lead time, DPE is lower (more) than 300 km in V5 (V4). V5 has a relatively smaller DPE at all the forecast lead times. The mean initial position error in V5 is lower by 44%, whereas the percentage decrease in DPE at 24, 48, 72, 96, and 120 h are 34, 25, 27, 19, and 26%, respectively (table 5). The improvement in model track prediction is statistically significant up to 72 h ($p < 0.05$). Overall, the track prediction skill of V5 against its predecessor has improved by approximately 24 hrs (1-day). These track errors are the mean of DPEs calculated for all the cyclones formed during the study period. The numbers of forecasts verified are shown in figure 5(b). As evident, the forecast points are higher for shorter lead times for both versions of the model. The forecast points are more for the TCs during 2018–2019 as these have relatively longer lives than TCs of the 2015–2018 period, leading to a larger sample of forecast points for V5 than V4.

In figure 5(c), a comparison between V4 and V5 predicted mean ATE shows that V5 has reduced error at all forecast lead times, and the maximum gain noticed was at 78 h forecast (not shown in the figure). ATE in V5 is lower than 100 km up to 72 h forecast. Similarly, in figure 5(d), mean absolute CTEs for V4 and V5 have been plotted for

comparison. Both the model versions have CTEs less than 100 km up to 72-h forecast. It is also worth noting that CTEs are relatively lesser than ATEs at shorter forecast lead times. The V5 model has improved skills at all the forecast lead times except for 120 h, where the mean CTE is relatively higher (4%). Overall, the improvement in track prediction by V5 in terms of DPE is majorly attributed to the reduction in ATE.

5.4 *Verification of model predicted intensity*

To evaluate the model's skill in intensity prediction, the error in NCUM-G predicted MSW for both the versions at different forecast lead times has been compared and displayed as a box–whisker plot in figure 6. The plot represents minimum, first quartile, second quartile (median), third quartile, and maximum error at each forecast lead-time. The outliers have been highlighted as open circles. Interestingly, the intensity errors are not consistently increasing with forecast lead time like the mean track errors (DPE, ATE, and CTE). The improvement in model intensity prediction at different forecast lead times is in the range of 9–32% (statistically significant up to 24 h forecast, $p < 0.05$), with more improvement in model analysis and shorter forecast lengths. These errors are calculated for all forecast lead times but are presented only at 24 h intervals for brevity. The minimum reduction in error (9%) in MSW prediction is noticed at 108 h (not shown in the figure). Thus, the NCUM-G: V5 model shows improved intensity prediction skills attributed to the model's improved initial conditions and higher resolution.

5.5 *Verification of model predicted landfall*

The mean errors in landfall position and time have been computed for all the TCs. Out of 22 TCs studied (table 3), six TCs dissipated over the sea. It is to be noted that for two cyclones, namely Megh (November 2015) and Maarutha (April 2017), V4 was not able to predict the landfall. These errors are calculated as the great circle distance between model-predicted landfall and actual position (BT) at the time of landfall reported by IMD. As the model provides forecasts at 6-h intervals, landfall position from the forecasts is obtained by linear interpolation between two successive forecasts (before and after landfall). A similar methodology has been adopted for the calculation of landfall
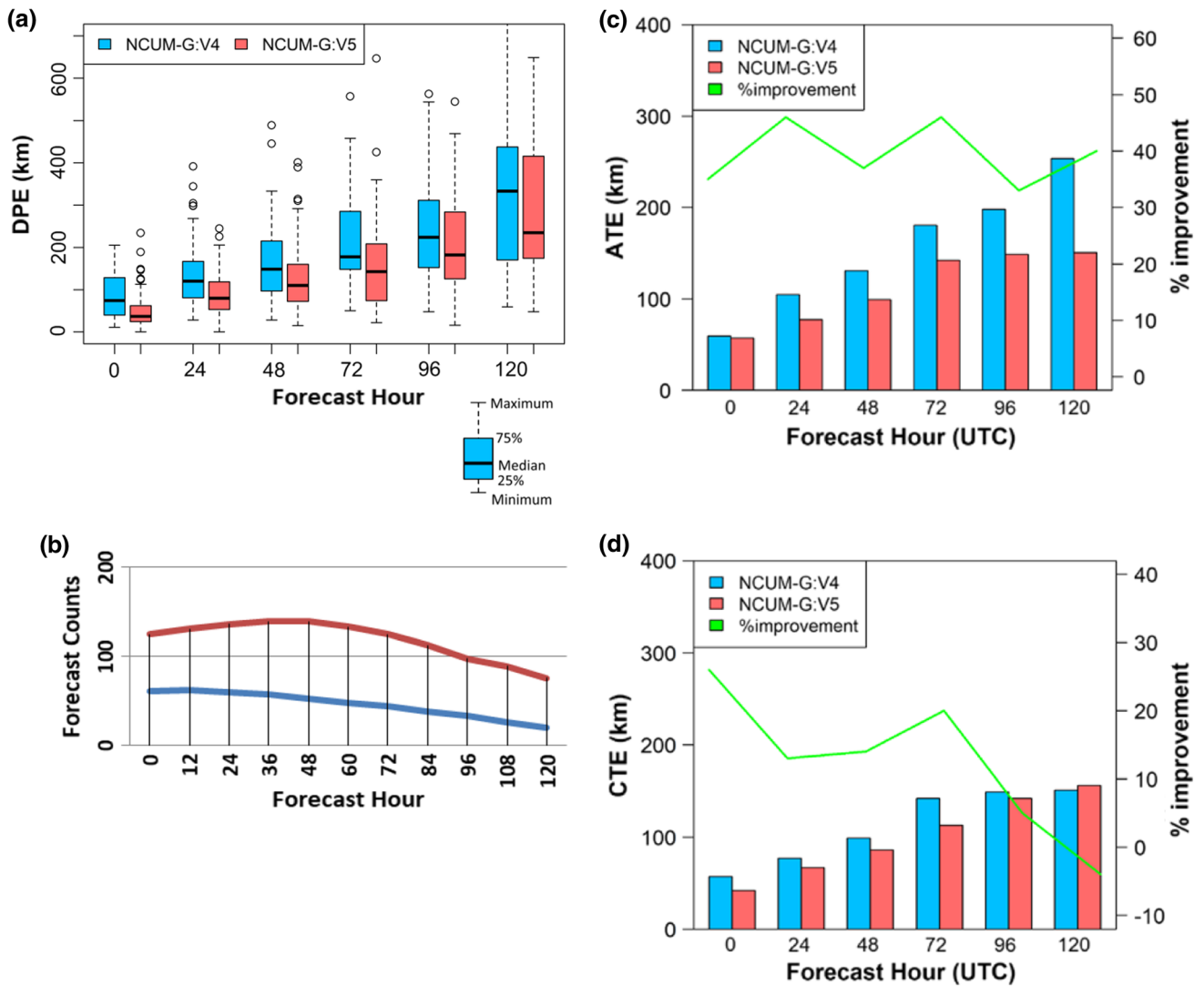
(a)

(b)

(c)

(d)

Figure 5. Comparison of track errors from two versions of model NCUM-G: V4 and NCUM-G: V5. (**a**) Direct position error, (**b**) number of forecast points verified, (**c**) average along track error, and (**d**) average cross track error at different forecast lead times.

Table 5. *DPE comparison.*

	DPE (km) comparison			
Forecast hour	NCUM-G: V4	NCUM-G: V5	% decrease	*p* value
0	86	48	44	2.76E-06
24	137	91	34	0.0001464
48	164	122.5	25	0.0048
72	210	154	27	0.003
96	259	209	19	0.1595
120	380	282	26	0.1356

time errors as well. In figure 7(a), the mean landfall position error from V4 and V5 has been shown. The errors are seen to be increasing with forecast lead time with a minimum error of 74 and 79 km before 24–48 h of the landfall in V4 and V5, respectively. The reduction in landfall position error has also

been highlighted in the same figure. The maximum reduction of 43% is seen at 72–96 h. The skill of NCUM-G in the prediction of landfall time has been evaluated in terms of landfall time error, and it has been shown in figure 7(b). Interestingly, landfall time error does not increase with forecast

lead time, and it was highest for the forecasts issued before 48–72 h in both versions of the model. The mean landfall time error in V5 is substantially lower at all forecast lead times. V5 has the best prediction skill for landfall time in 24–48 h with the lowest error of 4:00 h compared to 11:00 h in V4.

6. Comparison of NWP models with IMD official forecast in 2019

IMD is an operational agency and the WMO-designated Regional Specialized Meteorological Centre (RSMC). It is responsible for issuing official TC forecasts over NIO and the necessary warnings for India and all the neighbouring countries lying across its coasts by following a standard operation procedure (SOP) described in the IMD manual (Mohapatra and Sharma 2019). A continuous effort
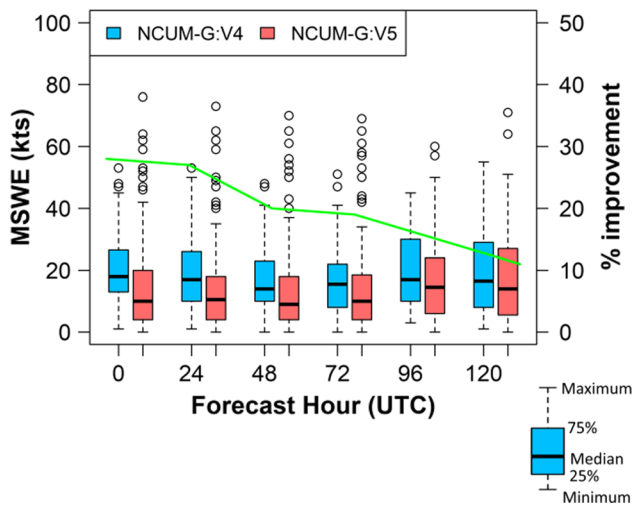

Figure 6. Comparison of errors in model (NCUM-G: V4 and V5) predicted intensity in terms of maximum sustained wind speed (MSWE) and percentage improvement at different forecast lead time.

and modernization of observational and forecasting setup have improved TC forecasting skills (Mohapatra *et al.* 2013a, b; Mohapatra and Sharma 2019). Satellite, radar, and synoptic guidance using statistical methods are given more preference for shorter forecast lead times (up to 12/24 h), whereas, for higher forecast lengths (24–120 h), NWP models are preferred (Mohapatra and Sharma 2019). IMD makes use of NWP products from all the leading global operational NWP centers (European Centre for Medium-Range Weather Forecasts (ECMWF), the National Centers for Environmental Prediction (NCEP), and the United Kingdom's Met Office (UKMO)), including NCMRWF for providing the TC forecasts. In figure 8, mean DPE for NCUM-G: V5 and other NWP models mentioned above have been compared with the official IMD forecast. It is obtained from the IMD's report entitled 'Report on Cyclonic Disturbances over North Indian Ocean during 2019' (https://rsmcnewdelhi.imd.gov.in/uploads/report/27/27_fddc6c_rsmc2020.pdf) for 2019. The NIO in this particular year was relatively more active as it witnessed seven TCs (against the climatology of five, Mohapatra *et al.* 2015). These cyclones had mixed intensities, including one SuCS, two ESCS, three VSCS, and one CS. The forecast DPEs from IMD is available at the 12-h interval going up to 120 h. These forecast errors consistently increase with forecast lead time for both the NWP models and IMD. The forecast DPE from IMD at 0 h (equivalent to model analysis) is not available as the position of a TC at this forecast time is provided by IMD as the best estimate. For the shorter forecast lengths (up to 24 h), IMD's official track information is more accurate than any NWP model. The NWP models from different operational centers have different forecast skills at
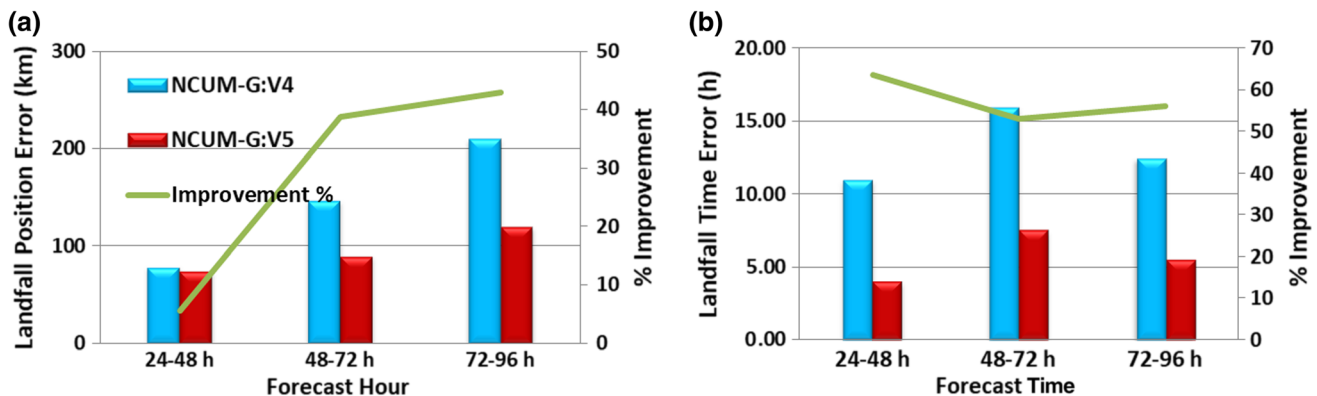
Figure 7. Comparison of mean landfall error from NCUM-G: V4 and NCUM-G: V5 (**a**) in position (km) and percentage improvement and (**b**) same as (**a**) but in time (h).
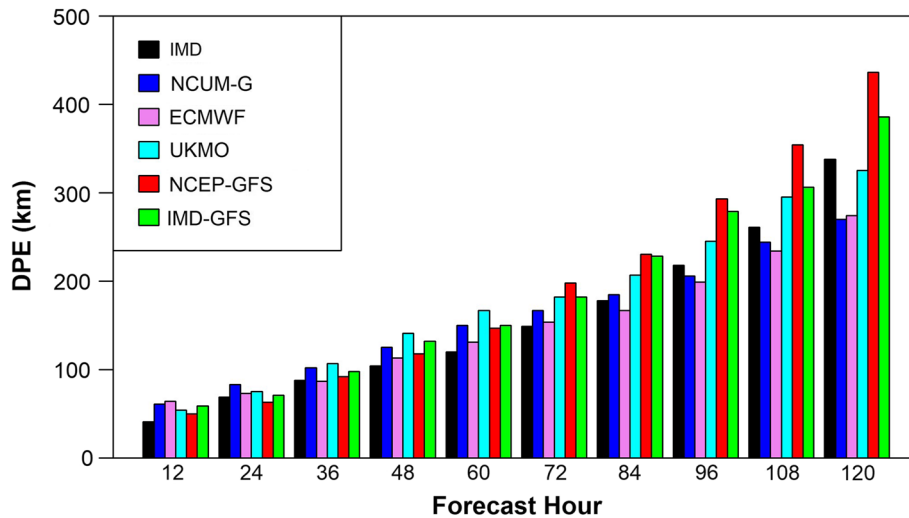
Figure 8. Comparison of DPE from different NWP models with IMD official forecast error.

different forecast lead times. The mean DPE at 12 h from IMD is 22% lower than the best performing model (NCEP-GFS). This margin decreases with an increase in forecast lead time, and at 84 h, the errors from the two forecasts are almost equal. At higher lead times, NCUM-G and ECMWF show an edge over IMD official track forecasts, and the mean DPEs of NCUM-G (ECMWF) at 96, 108, and 120 h is lower than that of IMD by 6 (9)%, 7 (10)%, and 20 (19)%. This intercomparison suggests that NCUM-G and ECMWF show lower DPE than IMD's official DPE, indicating very promising improvements in NWP modelling in recent years. It would be interesting to monitor the performances of NCUM-G in subsequent years for consistent improvement so that improved TC forecasts over NIO based on NCUM-G may form an essential input for the IMD's official TC forecasts.

7. Conclusions

This study documents the improved skill of the NCMRWF Unified Model (NCUM-G) forecast of NIO TC during 2015–2019. The results are based on a collection of 1810 forecasts involving 22 tropical cyclones of NIO during the study period. In this study, the improvement in TC forecasts in terms of intensity, track, landfall location, and time were analyzed from two versions of NCUM-G, i.e., V4 and V5. The major changes in these two model versions included increased model resolution, an improved DA system, and several new observations in DA. Following the June 2018

model upgrade (NCUM-G: V5), there is a consistent improvement in the NCUM-G model during the pre-monsoon and post-monsoon seasons. RMSE in the Day-3 forecast of 850 hPa winds shows a $\sim 17\%$ reduction during pre-monsoon and 23% during post-monsoon season. The model has shown an improved forecast skill of the initial position of TCs, and the decrease in DPE is 44%. The reduction in DPE in V5 is 34, 25, 27, 19, and 26% in 48, 72, 96, and 120 h, respectively. V5 shows gain in skill by approximately 24 h (1-day) over V4. NCUM-G: V5 also shows the reduction in the ATE (33–46%) and CTE, with ATE contributing majorly to the reduction in track forecast errors. V5 shows an improvement in the intensity forecast in terms of MSW in the range of 9–32%. V5 also shows better accuracy in predicting the landfall position, reducing error by 43% in 72–96 h lead time. The landfall time prediction by V5 is more precise than V4, with improvements of more than 50% up to 96 h before the landfall. An intercomparison of the NWP models with IMD's official track forecasts suggests lower DPE in NCUM-G: V5 at higher lead times. The DPE in NCUM-G: V5 (ECMWF) at 96, 108 and 120 h are lower by 6 (9)%, 7 (10)% and 20 (19)%, respectively.

Limitations and future scope: An important outcome of the current study is the impact of enhanced resolution on the TC forecast errors. The results deal with the TC track, intensity, and landfall errors, while the cyclogenesis prediction is out of the scope of the present study. A similar potential future study may be on the possible improvement in the genesis predictions and

reduction in the false alarms. Another essential feature of the current experiment is the great strides in data assimilation and the quality and quantity of the new satellite datasets gone into the improved initial conditions. It is not easy to separate and quantify the effect of resolution and improvements in initial conditions, which caused the improved TC forecasts in the operational environment and warrants a thorough investigation with dedicated resources.

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