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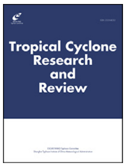

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A review of recent advances (2018–2021) on tropical cyclone intensity change from operational perspectives, part 2: Forecasts by operational centers

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Abstract

This paper summarizes the progress and activities of tropical cyclone (TC) operational forecast centers during the last four years (2018–2021). It is part II of the review on TC intensity change from the operational perspective in the rapporteur report presented to the 10th International Workshop on TCs (IWTC) held in Bali, Indonesia, from Dec. 5–9, 2022. Part I of the review has focused on the progress of dynamical model forecast guidance. This part discusses the performance of TC intensity and rapid intensification forecasts from several operational centers. It is shown that the TC intensity forecast errors have continued to decrease since the 9th IWTC held in 2018. In particular, the improvement of rapid intensification forecasts has accelerated, compared with years before 2018. Consensus models, operational procedures, tools and techniques, as well as recent challenging cases from 2018 to 2021 identified by operational forecast centers are described. Research needs and recommendations are also discussed.

Keywords: Forecast error; Intensity forecast; Operational forecasts; Tropical cyclone

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1. Introduction

Tropical cyclone (TC) forecasts usually rely on observations, numerical weather prediction (NWP) dynamical model forecast guidance, as well as specific techniques and tools used by field forecasters. As discussed in the rapporteur report on TC intensity change from the operational perspective presented to the 10th IWTC[1] held in Bali, Indonesia, from Dec. 5–9, 2022, TC intensity forecasts have continued to improve since the 9th International Workshop on Tropical Cyclones (IWTC) in 2018. Zhang et al. (2023) summarized the improvements made in the intensity forecast guidance from dynamical models since the 9th IWTC, as part I of the review into operational perspectives on TC intensity change during the last four years (2018–2021). This paper is part II of the review, summarizing the progress made in TC intensity forecasts by operational TC forecast centers as well as challenges. Note that TC intensity means the maximum sustained 10-m wind speed unless otherwise specified in the following discussion.

Section 2 presents the annual TC intensity forecast errors from the National Hurricane Center (NHC), Joint Typhoon Warning Center (JTWC), and regional specialized meteorological center (RSMC) Tokyo – Typhoon Center. Section 3 reviews several consensus models used by operational centers. Section 4 is contributed by NHC, JTWC, and other RSMCs, describing current operational procedures in these respective centers. Section 5 presents the performance of rapid intensification (RI) forecasts and challenges. Modeling challenges identified by forecasters are described in Section 6, along with a list of difficult cases. Recommendations for the research and operational communities for the next four years are given in Section 7. For convenience, a list of acronyms used in the paper is provided at the end of the paper.

2. Performance of TC intensity forecasts by operational centers

The performance of TC intensity forecasts has continued to improve. This section presents the inter-annual TC intensity forecast errors contributed by NHC, JTWC, and RSMC Tokyo – Typhoon Center.

2.1. NHC

Fig. 1 shows the yearly trend of the root mean square (RMS) intensity forecast errors at different forecast lead times for North Atlantic (NATL) storms from 1990 to 2021. There is a clear trend that the forecast errors for all lead times have decreased over the years, with the greatest improvement for the 120-h forecast lead time (Cangialosi et al., 2020). Table 1 lists the NHC's RMS intensity errors and the 95th percent confidence intervals calculated by decade for all forecast times. The RMS errors at 72 h decreased from 18.8 kt in 1990–99 to 13.8 kt in 2000–2019. The 120-h forecast errors decreased from 21 kt in 2000–2009 to 15.2 kt in 2010–2019. Table 2 shows the composite intensity skill and the frequency of the NHC's official forecast (OFCL) outperforming Decay-SHIFOR5 (Climatology and Persistence model; DeMaria et al., 2023) averaged over the entire forecast period by decade. Compared with 1990–99, the NHC's official intensity forecast skill averaged from 12- to 120-h lead times increased from 16% in 2000–09 to 24% in 2010–19, compared with Decay-SHIFOR5, with the frequency of outperformance increasing from 59% to 64%. The improvement of official forecasts is partially attributed to the improved NWP dynamical models as summarized in Zhang et al. (2023).

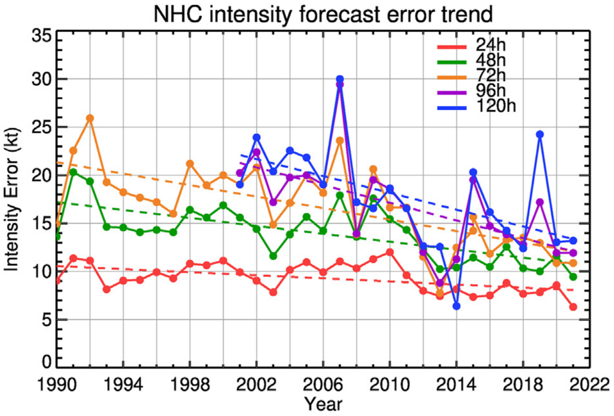

Fig. 1. Trend of RMS intensity forecast errors at different forecast lead times for North Atlantic storms from NHC since 1990. A linear trend line over the years is shown for each lead time (dashed lines).

Table 1
NHC's RMS intensity forecast errors (kt) and 95th percent confidence intervals calculated during 1990–1999, 2000–2009, and 2010–2019 for all forecast times.

Forecast Time (h)	1990–99	2000–09[a]	2010–19
12	6.1 ± 0.3	6.6 ± 0.3	5.7 ± 0.3
24	9.8 ± 0.5	10.1 ± 0.5	8.5 ± 0.5
36	12.7 ± 0.7	12.5 ± 0.7	10.4 ± 0.7
48	15.3 ± 0.9	14.7 ± 0.8	12.0 ± 0.7
72	18.8 ± 1.2	18.3 ± 1.1	13.8 ± 1.0
96	–	19.3 ± 1.4	14.5 ± 0.9
120	–	21.0 ± 1.7	15.2 ± 1.2

[a] 96 h and 120 h forecasts began in 2001.

Table 2
Composite intensity skill and the frequency of NHC's official forecast outperforming Decay-SHIFOR5 averaged over the entire forecast period by decade.

Decades	OFCL Intensity Skill	Frequency of outperformance
1990–1999 (12 h–72 h)	9%	56%
2000–2009 (12 h–120 h)[a]	16%	59%
2010–2019 (12 h–120 h)	24%	64%

[a] 96 h and 120 h forecasts began in 2001.

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[1] https://community.wmo.int/meetings/tenth-international-workshop-tropical-cyclones-iwtc-10.

2.2. JTWC

The RMS intensity forecast errors in the Western North Pacific (WNP) basin from JTWC forecasts have continued to decrease since 2018, consistent with the long-term 20-year trend (Fig. 2). The RMS errors at lead times of 72–120 h set a record low in 2021, and RMS errors at a lead time of 48 h was the second-lowest recorded. The averaged short-term intensity error at 24-h lead time is 10.0 kt during 2018–2021, a 12% improvement relative to the 2000–2017 mean of 11.3 kt, a time period during which the error trend was nearly flat. JTWC forecast skill relative to the Statistical Typhoon Intensity Forecast (ST5D; Knaff et al., 2003) also generally increased in the WNP basin during 2018–2021, with record high skill in 2021 for lead times of 72–120 h (Fig. 3). This is consistent with the general increasing trend in intensity forecast skill observed since around 2010.

2.3. RSMC Tokyo – Typhoon Center

In 2016, the RSMC Tokyo – Typhoon Center began trialing the Typhoon Intensity Forecast Scheme (TIFS), the JMA's WNP version of Statistical Hurricane Intensity Prediction Scheme (SHIPS) (Yamaguchi et al., 2018). TIFS is developed by Japan Meteorological Agency (JMA) along with the simultaneously produced Logistic Growth Equation Model (LGEM) (DeMaria 2009) and the Rapid Intensification Index (RII) (Kaplan et al., 2010).

Fig. 4a shows that the RMS errors of the official RSMC Tokyo intensity forecasts decreased in 2017, which is partially attributable to the use of TIFS data and the fact that there were fewer RI events during the year. Fig. 4b also shows that official forecasts have been greatly improved since 2016. RSMC Tokyo began using these intensity guidance models on an operational basis in 2019 (Ono et al., 2019).

3. Consensus model guidance

Consensus models are used by forecasters to blend multiple TC intensity and track forecasts including dynamical and statistical models. This section discusses the updates of NHC and JTWC consensus models.

3.1. NHC consensus models

In early years, NHC's forecasters were challenged by having few NWP models available to consider in their efforts to

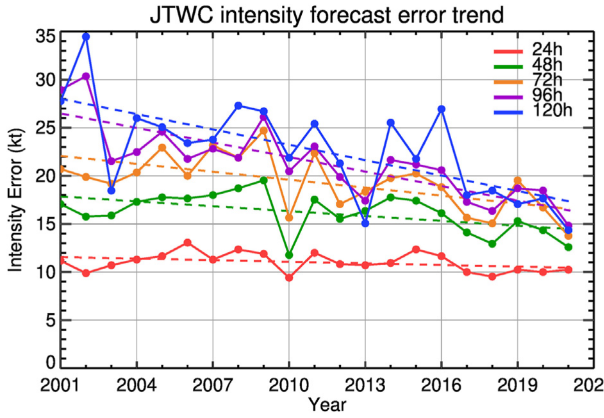


Fig. 2. JTWC annual RMS intensity forecast errors from 2001 to 2021 at lead times of 24, 48, 72, 96, and 120 h for TCs in the WNP basin. A linear trend line over the years is shown for each lead time (dashed lines).

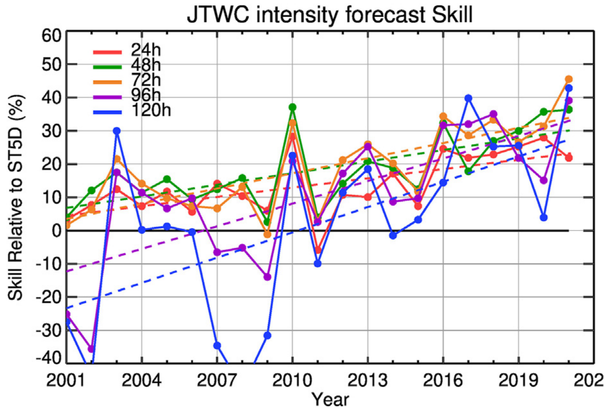


Fig. 3. JTWC annual mean intensity skill relative to the Statistical Typhoon Intensity Forecast (ST5D) from 2001 to 2021 at lead times of 24, 48, 72, 96, and 120 h for TCs in the WNP basin. A linear trend line over the years is shown for each lead time (dashed lines).

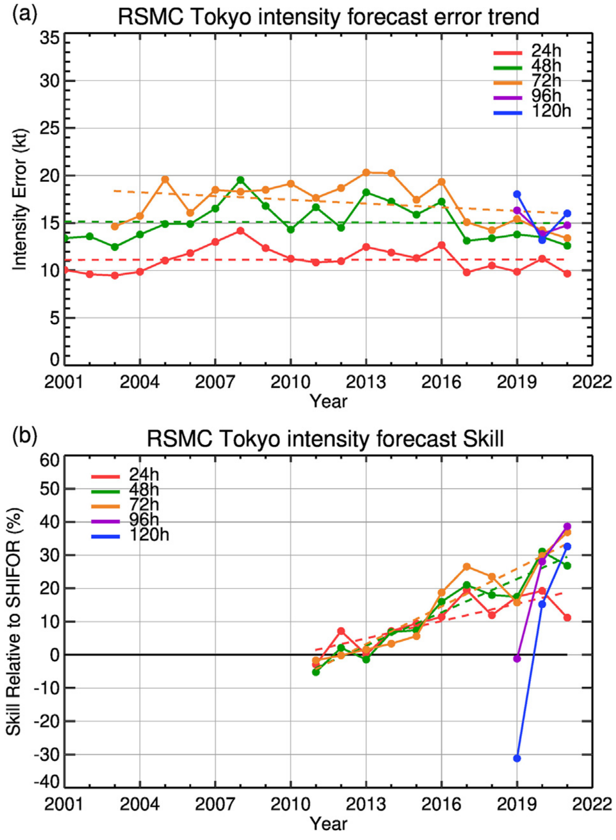


Fig. 4. (a) RMS errors of RSMC Tokyo official intensity forecasts for the WNP basin. (b) RSMC Tokyo official intensity forecast skill relative to SHIFOR (statistical baseline, Jarvinen and Neumann 1979; Knaff et al., 2003). Linear trend lines are shown for the 24 h, 48 h, and 72 h lead times for errors and skills (dashed lines).

produce the best official forecast. As the number of skillful track forecast models increased in the 1970s–1990s, however, they became faced with a new challenge: how to make the best use of multiple models that sometimes provided a wide geographical range of guidance tracks. Lacking *a priori* knowledge of which model outcomes were likely to be the most accurate, NHC usually forecast the track to be within the geographic spread of the typically best-performing models, often not far from the middle as they could determine subjectively. The forecasters came to realize that approach over the long haul led to smaller errors than any of the individual models. Software was then developed to provide arithmetic averages of the typically best-performing computer model forecasts to the forecaster (Sampson and Schrader 2000). These so-called consensus models have led the way in track forecasting accuracy during most of the past 15 years.

Beginning in 2008, NHC had a sufficient number of intensity models to create an intensity consensus. There are today two types of consensus aids. Both are discussed below and each has its advantages. A "simple" consensus model equally weights each member (Sampson et al., 2008). A "corrected" consensus often weights models differently and considers past error characteristics in attempting to correct for member biases (Simon et al., 2018). It is hoped that continued improvement of the equally weighted and corrected consensus aids will allow for further improvements in skill of the NHC intensity forecasts.

3.1.1. Simple consensus models - intensity variable model consensus (IVCN)

The Intensity Variable Consensus model (IVCN) was one of the first simple consensus aids used in NHC operations. In 2008, the makeup of IVCN was a four-member average of SHIPS, LGEM, and the interpolated early versions of the Geophysical Fluid Dynamics Laboratory (GFDL) and Hurricane Weather Research and Forecast (HWRF) models. The IVCN was quite successful in 2008, as it had more skill than any of the individual members and slightly more skill than NHC official forecasts. It should be mentioned that IVCN is a variable consensus model, meaning the composition of the consensus changes based on model availability. For example, sometimes, the 120-h forecast is based on a different set of members than the 12-h forecast. At the conclusion of every hurricane season, NHC evaluates IVCN, looks at the performance of alternatives, and makes adjustments accordingly. As of this writing, IVCN is a five-member model that includes equal weighting of SHIPS (DeMaria et al., 2005), LGEM, and the interpolated early versions of HWRF, Hurricanes in a Multi-Scale Ocean-Coupled Non-hydrostatic model (HMON; Mehra et al., 2018; Wang et al., 2019), and the version of the U.S. Navy's Coupled Ocean/Atmosphere Mesoscale Prediction System for TCs (COAMPS-TC) that uses GFS initial and boundary conditions (CTCX; Doyle et al., 2014). Because of the improvement in the dynamical models, a new consensus aid, called IVDR, was first computed at NHC in 2018. The composition of IVDR includes a double-weight for the interpolated versions of CTCX, HWRF, and HMON, and single weight for the interpolated version of GFS, SHIPS, and LGEM. During the past couple of hurricane seasons, IVDR has generally had slightly more skill than IVCN (not shown) due to the improved performance of regional models (CTCX, HWRF, and HMON).

3.1.2. "Corrected" consensus models - HFIP Corrected Consensus Approach (HCCA)

Beginning in 2015, the HFIP (Hurricane Forecast Improvement Project) Corrected Consensus Approach (HCCA) was implemented at NHC to provide "in-house" track and intensity forecast guidance (Simon et al., 2018). The consensus is broadly based on the technique used in the proprietary Florida State Superensemble (see Krishnamurti et al., 1999; 2010; 2011; Williford et al., 2003) but specifically tailored to NHC's operational constraints. Since 2015, HCCA has been one of the best performing guidance models for both track and intensity in the Atlantic basin (not shown).

The HCCA intensity forecasts rely on a mix of statistical-dynamical and dynamical model forecasts that are basin-specific. Unequal weighting coefficients are derived from a set of training forecasts and applied to the input model predictions to create the HCCA forecast. To allow for operational flexibility, a forecast-specific training set is created in real-time to match the input model availability of the current forecast. Based on input model sensitivity experiments, the HWRF and CTCX forecasts currently make the largest contribution to the positive skill of the HCCA intensity forecasts in the Atlantic basin.

3.2. JTWC consensus models

The primary TC intensity consensus forecast aid computed and utilized by JTWC is called ICNW, an equal-weighted variable consensus of five core inputs: HWRF, CTCX, GFS, SHIPS using NCEP GFS forecast parameters, and SHIPS using Navy Global Environmental Model (NAVGEM) forecast parameters. A sixth member, the Rapid Intensity Prediction Aid (RIPA) (Knaff et al., 2018; 2020) is added to the consensus when it predicts at least a 40 percent chance of RI defined by any of the following thresholds: 20 kt in 12 h, 25, 30, 35, or 40 kt in 24 h, 45 or 55 kt in 36 h, 55 or 70 kt in 48 h, and 65 kt in 72 h. The RIPA intensity forecast added to the consensus is constructed from a constant rate of intensification matching the RI threshold with the highest probability, terminating at the end of the time interval associated with that threshold. The addition of this short RI-triggered deterministic forecast results in no noticeable shock in the variable ICNW's temporal variation, but rather a subtle nudge to higher intensity forecasts.

Beginning in 2022, JTWC will be evaluating a separate, experimental intensity consensus (ICNE) containing additional guidance on RI, with the goal of reducing negative intensity biases in ICNW during RI cases. Contributing to this new consensus are several new RI intensity aids that have been recently developed utilizing a variety of statistical techniques (Sampson et al., 2022). Among these is the aforementioned RIPA, which uses logistic regression on storm and environmental parameters from SHIPS to produce a probabilistic RI forecast. An alternative Forest-based Rapid Intensification Aid (FRIA, Slocum 2021) was developed using a random forest algorithm on the same parameter set to yield an RI forecast with an independent method. The Rapid Intensification Deterministic Ensemble (RIDE, Knaff et al., 2022) uses logistic regression on existing statistical and dynamical TC intensity aids to determine the likelihood of RI. Two additional RI aids are included based on the Coupled Hurricane Intensity Prediction System (CHIPS; Emanuel et al., 2004) ensemble (CHR4) and the COAMPS-TC ensemble (CTR1; Komaromi et al., 2021). These two ensembles generate forecasts when the RI probability reaches 50 percent and 10 percent, respectively. The ICNE consensus is then formed by taking the members of ICNW other than HWRF and replacing them with one of RIPA, FRIA, CTR1, CHR4, or RIDE if their respective thresholds for generating an RI forecast are triggered (10 percent for CTR1, 40 percent for all others). The result is thus a deterministic intensity forecast based on RI aids when RI is predicted, falling back to the standard members of ICNW when RI is not predicted. Fig. 5 compares the mean absolute error and bias for ICNE and ICNC (ICNW without RIPA) during cases from the years 2020–2021 when at least one of ICNE's members is triggered. The result for ICNE is little change in mean error compared to ICNC, but a reduction in bias at short lead times, by more than 5 kt at a lead time of 36 h relative to ICNC. During its evaluation period, JTWC hopes to see ICNE mimic 2020–2021 statistics, and demonstrate skill in real-time RI scenarios when the consensus of standard forecast aids tends to underpredict TC intensity. Finally, as NWP models improve and more RI aids are developed, JTWC consensus aids will change and likely continue to improve.

4. Operational intensity procedures

Historically, the adoption of novel forecasting tools and applications into operations has typically lagged the basic science. Operational forecasters are presently using many of the forecast concepts and tools either objectively via direct use of the forecast aids themselves or subjectively by applying knowledge that is provided by those forecasting tools to individual forecasts. Encouragingly, intensity forecasts have continued to become more skillful as the forecasting aids, which are numerical weather prediction, statistical or statistical-dynamically based, have improved. The documentation of these overall improvements of guidance and operational forecasts are described in various annual reports (e.g., Cangialosi 2021; Francis and Strahl 2021; JMA 2020; Mohapatra and Sharma 2019). These generally show improvements or a leveling off of improvements in the past four to five years, depending on forecast lead time and seasonal difficulty. The largest improvements are readily seen in intensity forecasts at the 24-h to 72-h forecast lead-times.

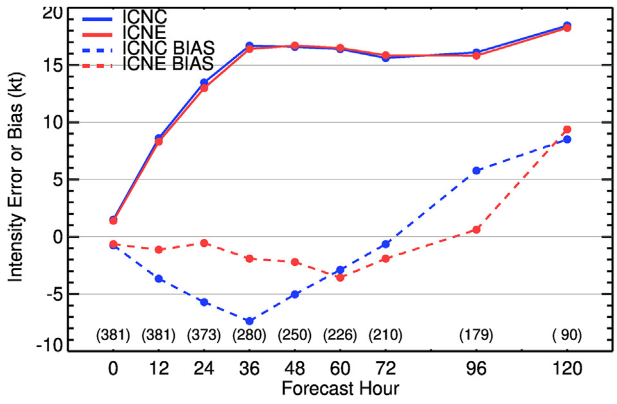


Fig. 5. RMS errors (sloid lines) and biases (dashed lines) of intensity forecast (kt) at different lead times for ICNE (red) vs. the control ICNC (blue) for cases during 2020–2021 during which at least one deterministic RI aid in ICNE is triggered. Sample sizes are shown in parentheses along the abscissa.

TC forecasting centers from around the world among others routinely forecast TC intensities out to day 5. Forecasters analyze the current and future atmospheric and oceanic environmental factors as a baseline to determine how strong the TC is currently and to aid in future projections. Analyzing the current intensity of a TC is often based on a blend of satellite, radar, and aircraft information and although the forecasting centers do not list uncertainty in the initial intensity, the true intensity of a TC is often impossible to fully measure. Therefore, the initial intensity listed in the advisories and post-analyzed best tracks are the forecaster's interpretation of the most accurate data.

This section briefly describes how operational centers use available products and tools to produce TC intensity forecasts, depending on their experience and geographic locations.

4.1. NHC

The operational procedure of forecasting TC intensity is to analyze a combination of statistical-dynamical guidance (e.g., SHIPS, LGEM) and TC-specific dynamical regional models (e.g., HWRF, HMON, COAMPS-TC). Forecasters are quite skilled at assessing the models' performance and using combinations of projections to come up with their own forecast. There is no specific rule on how to make a TC intensity forecast, however. It needs to be emphasized that producing a TC intensity forecast is subjective and a blend of science, art, and consistency. The consistency factor is quite important, as forecasting centers are focused on the service they provide and try very hard to make changes gradually. The NHC official forecasts (i.e. OFCL) have been consistently performing quite well, and had skill values close to the best aids IVCN and HCCA (Fig. 6).

Forecasters are well aware that vertical wind shear affects the predictability of intensity change and subjectively apply that information to their forecasts. Complex interactions between upper-level storm outflow and environmental upper-level wind shear have been documented in Ryglicki et al. (2018a, 2018b, 2019). These interactions that can be modulated by convective storm outflow (Ryglicki et al., 2020) are currently trying to be addressed by improved use and analysis of satellite-based atmospheric motion vectors (DeMaria et al., 2022), and will be tested soon in operations. In a similar

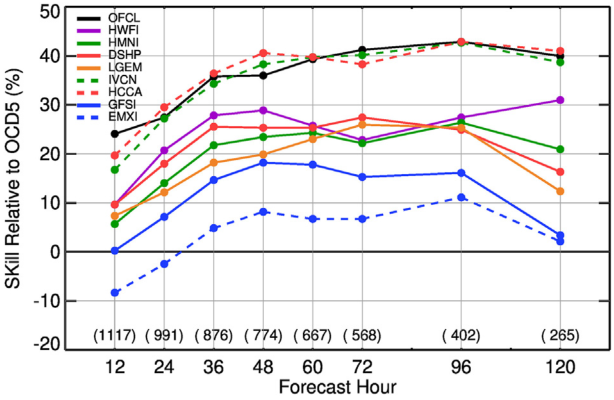


Fig. 6. Homogenous comparison for selected Atlantic basin early intensity guidance models for 2019–2021. OFCL is the NHC official forecast. The number of sample at each lead time is shown in parentheses.

vein, the response of a TC to the formation of a secondary eyewall is often mentioned in the TC discussions. The Microwave-based Probability of Eyewall Replacement Cycle tool that predicts the probability of secondary eyewall formation in the future (no specific time) is sometimes used for making decisions regarding future intensification, and a comparison with RMSC, Miami's analyses is presented in Pulmano and Joykutty (2021). Additionally, forecasters routinely monitor microwave imagery that reveals the convective (85–91 GHz) and microphysical structures (37 GHz) for evidence of improved organization in both the emissions (e.g., increased warm/stratiform rain, increased symmetry) and scatter (circular bands, eyewall formation, secondary eyewall formation) signatures.

Globally there has been a push to use artificial intelligence and machine learning techniques to advance predictive capabilities. Some new methods have been developed (Griffin et al., 2022; Su et al., 2020; Wei and Yang 2021), but as is the case with basic research there is a time lag between the development of new forecast aids and their operational implementation. Studies by Cloud et al. (2019) and Su et al. (2020) showed that neural network methods can provide more accurate predictions of TC intensity change, including RI, than current operational guidance. If those results prove to be robust in an operational setting, that will lead to further improvements in operational RI prediction. Time will tell if continued improvement in methods and models will produce better forecasts of intensity as we are running into barriers caused by NWP predictability and uncertainty in our basic measurements of intensity operationally (see Torn and Snyder 2012; Combot et al., 2020). Nonetheless it is obvious that improved guidance has led to improvements to this point and there is little doubt that will continue at least for a while.

4.2. RSMC New-Delhi (IMD)

TC forecasts in RSMC at New Delhi rely on dynamical and statistical models. Since 2018, RSMC New Delhi (IMD) issues track and intensity forecast of TCs from the stage of depression, where the maximum sustained wind (MSW) is 17–27 kts, onwards with a lead time of 72 h (Mohapatra and Sharma, 2019) and disseminates 5 times a day (i.e. based on observations at 00, 03, 06, 12 and 18 UTC). The lead period of forecast extends up to 120 h and frequency of bulletins increases to 8 times per day (i.e., 3-hourly observations at 00, 03, 06, 12, 18 & 21 UTC) from the stage of cyclonic storm (MSW ≥34 knots). Recently from March 2022, IMD has also introduced the pre-genesis of track and intensity forecast up to next 72 h from the stage of low-pressure area (shown in Fig. 7).

The forecast generation process of RSMC at New Delhi utilizes the TC forecasts from three different categories of NWP systems: individual deterministic models, single model ensemble prediction system (EPS), and multi-model ensemble (MME). The deterministic models include (i) NCEP-GFS, a 12-km and 10-day global model (i.e., horizontal resolution ~12 km and forecast duration of 10 days), (ii) NCMRWF (National Center for Medium Range Weather Forecasting) Unified Model (NCUM), a 12-km and 10-day global model, (iii) NCEP-Global Ensemble Forecasting System (GEFS), global probabilistic model (resolution and forecast duration are similar to NCEP-GFS), (iv) NCMRWF Ensemble Prediction System (NEPS), (resolution and forecast duration are similar to NCUM), (v) 3-km and 3-day mesoscale Weather Research Forecast (WRF) model, (vi) 4-km and 5-day NCUM-Regional model, and (vii) 2-km and 5-day HWRF model for cyclone prediction. IMD also makes use of NWP products prepared by other operational NWP centers like NCEP-GFS, USA, JMA, UK Met Office (UKMO), Global Tropical model, Meteo-France etc. Statistical cyclone intensity prediction (SCIP) model (Kotal et al., 2008), RI model (Kotal et al., 2008) are developed and operated using various NWP model outputs described above. The MME for cyclone track forecast (Kotal and Bhowmik, 2011) is based on a statistical linear regression approach using five operational NWP models (ECMWF, IMD-GFS NCEP-GFS, UKMO, and JMA). The single model-based ensemble forecast products over Northern India Ocean from ECMWF (50 + 1 Members), NCEP (20 + 1 Members),

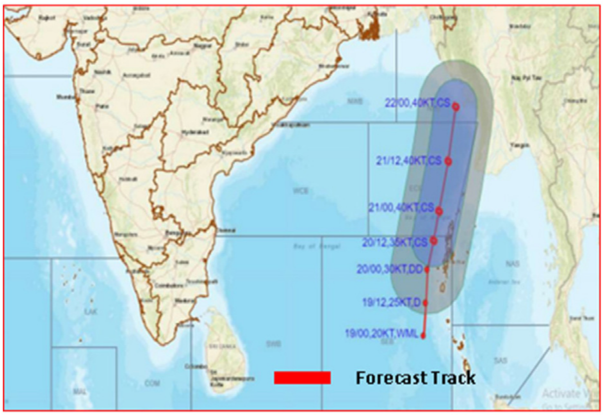


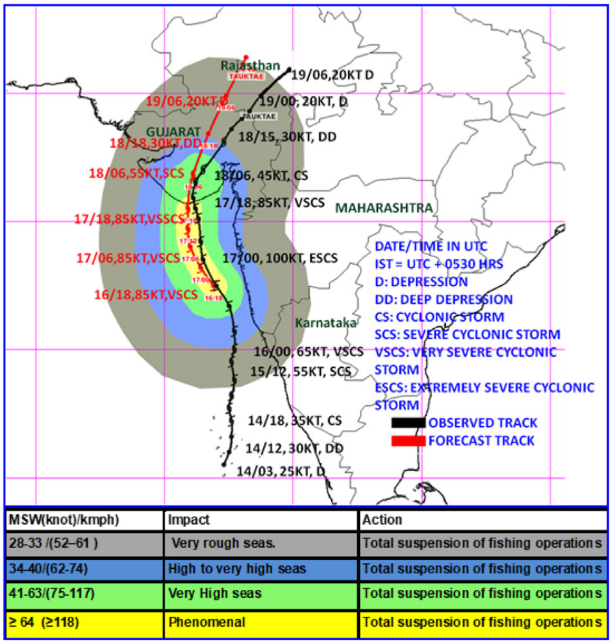
Fig. 7. Pre-genesis forecast issued at the stage of low-pressure area on 17th March (3 days prior to formation of depression over the southeast Bay of Bengal on 20th March and 5 days prior to actual landfall over Myanmar on 22nd March) (Source: Preliminary Report published by RSMC New Delhi, 2022).

UKMO (23 + 1 Members) and Meteorological Services, Canada (MSC) (20 + 1 Members) and JMA (20 + 1 Members) are also available to provide guidance in near real-time. The super-ensemble has also been developed based on the above ensembles. A typical operational intensity forecast during extremely severe cyclonic storm Tauktae is presented in Fig. 8.

4.3. RSMC Tokyo – Typhoon Center

TIFS, LGEM, RII, cyclone phase space (Hart 2003), and intensity forecasts based on deterministic NWP models such as JMA's Global Spectral Model (GSM) and regional mesoscale model, HWRF, NCEP GFS, ECMWF IFS, and MOGM (Met Office Global Model) are used for TC intensity forecasting. Forecasting primarily involves the use of TIFS data as a basis along with analysis of LGEM, RII, cyclone phase space, and NWP model forecasts to develop intensity change scenarios, including rates of change in intensity, peak intensity and related timing, and extratropical transition. This approach clarifies individual model characteristics and related considerations in specific cases, e.g., RII and HWRF forecasts for potential RI occurrence. The JMA regional mesoscale model is mainly used to forecast TCs approaching Japan, since it tends to favorably predict topography-related changes in intensity. JMA's GSM forecasts are particularly reliable for TCs in the extratropical transition stage.

For the TC formation stage, during which TIFS data tend to be overdeveloped (e.g., Shimada et al., 2018), the estimated rate of intensity change in RSMC official forecasts is often smaller than that in TIFS guidance. For the subsequent intensification stage, the TIFS intensity change rate is adjusted on the basis of the latest Dvorak analysis and used for official RSMC forecasting. In addition, water vapor imagery showing dry air intrusion, and microwave imagery showing TC structural changes are also taken into account.



MSW(knot)/kmph)	Impact	Action
28-33 /(52–61)	Very rough seas.	Total suspension of fishing operations
34-40/(62-74)	High to very high seas	Total suspension of fishing operations
41-63/(75-117)	Very High seas	Total suspension of fishing operations
≥ 64 (≥118)	Phenomenal	Total suspension of fishing operations

Fig. 8. Observed and forecast track of extremely severe cyclonic storm Tauktae based on 0600 UTC of 16th May 2020 (42 h prior to landfall) (Source: RSMC New Delhi, 2022).

4.4. The Bureau of Meteorology (BoM)

The intensity forecast process at BoM begins with an assessment of the analysis fix and the current large-scale environment (e.g., upper-level flow, vertical wind shear, ocean heat content, atmospheric moisture, low-level inflow, and any surface friction the system may encounter). Considering the trend of intensity change in the past 24-h in addition to any expected change in the broad scale environment leads to an initial intensity forecast estimate in the Dvorak T-no framework. For example, D for 0–24 h, D+ 24–48 h, D-/S for 48–72 h, W 72–96 h etc. where D represents an increase of 1.0 T-no per day.

Following from this initial estimate a full review of objective NWP intensity estimates is performed, utilizing both deterministic, high-resolution models and ensemble prediction systems. Ensemble guidance is typically used for trends in intensity forecasting rather than absolute intensity values due to poor performance in determining peak intensity values that is confirmed with verification. Other inputs that are considered include JTWC's version of SHIPS and ICNW guidance as well as RII. Consistency between NWP models is an important consideration, with intensity forecasting bias given to the better performing and higher resolution models.

Combining all these factors - the analyzed intensity trend, the assessment of objective guidance and the subjective analysis of the potential change to the environment is what ultimately determines the forecast intensity. Typically, a synoptic assessment and persistence approach is heavily weighted within 0–24 h, after which objective guidance and consistent trends in NWP become more influential. Weight is given towards models that have shown consistency over a series of model runs, though it is noted when any of the guidance makes a significant change to intensity as something to monitor on subsequent model runs. RI can also be forecast in the short-term (0–48 h) when there are enough objective aids and environmental indicators that assess it to be a risk, however it is very seldom forecast at longer lead times due to the difficulty of picking the timing of such a rate of change.

As a final consideration, previous forecast policy is assessed to avoid fluctuation from one forecast to the next. This is more typically applied when considering intensity beyond 48 h and when there is a lack of consistency in NWP intensity and trends in intensity. Significant changes to intensity forecasts are only made when there is overwhelming evidence to do so.

5. Dealing with rapid intensity changes in operational centers

Accurately forecasting the rapid intensity changes of TCs remains a challenge despite recent improvements in the overall performance of TC intensity forecasts. Improving the forecast of rapid intensity changes is a high priority of operational centers. This section briefly describes the progress and/or challenges of dealing with rapid intensity changes contributed by NHC, JTWC, BoM, and JMA.

5.1. NHC

The statistical-dynamical models rarely predict rapid intensity changes. Before 2017, the limited horizontal resolution of the GFDL and early versions of the HWRF model restricted the ability of these two models to predict large intensity changes. Without reliable guidance, the NHC official forecast rarely included large changes in intensity (Blake et al., 2016). To partially address the limitation of the statistical-dynamical models, a new component was added to the SHIPS model (i.e., RII), beginning in 2001 (Kaplan and DeMaria 2003). RI was defined as a 30-kt or greater increase in the maximum wind speed in 24 h, based roughly on the 95th percentile of the observed intensity changes in the Atlantic basin. The RII treats RI forecasting as a classification problem, where a subset of the SHIPS predictors are used to discriminate RI cases from non-RI cases. The output of the RII is a probability of RI, which forecasters subjectively use to supplement deterministic model output. The RII has improved since the initial 2001 version (DeMaria et al., 2021).

DTOPS (Deterministic TO Probabilistic Statistical model) was introduced in 2018. It has been developed for NHC and uses IFS, GFS, HWRF, LGEM, and SHIPS guidance. It applies binomial logistic regression to deterministic model forecasts, along with basic vortex and geographic parameters, to produce a probabilistic forecast of RI. DTOPS is currently the most skillful among NHC's probabilistic RI guidance. The generally good DTOPS performance shows that the deterministic models contain useful RI information even though their probability of detection (POD) values for RI are generally fairly low when used directly to forecast RI (DeMaria et al., 2021). To measure programmatic progress in forecasting RI, HFIP has introduced a new RI metric that calculates the traditional mean absolute error only in those cases where RI occurred in the verifying best track or was forecast. With this metric, NHC RI forecasts have improved by about 20–25% compared with the 2015–2017 baseline (DeMaria et al., 2021).

The POD for intensification rates of 20 kt or greater over the 24-h forecast period of 12–36 h is shown in Fig. 9 for the NHC's OFCL, SHIPS, and HWRF from 1990 to 2019 (SHIPS and HWRF forecasts began in 1991 and 2007, respectively). The sample size is dramatically increased using a 20 kt or greater threshold (compared to the strict definition 30 kt over a 24-h forecast period for RI). Despite the large amount of year-to-year variability, OFCL and HWRF exhibited a positive trend of increasing POD for these events. For HWRF, increasing horizontal grid resolution (e.g., the horizontal grid spacing of the innermost nest of HWRF decreased from 3 km to 2 km in 2015, and then to 1.5 km in 2018) and improvements to the physical parameterizations and data assimilation techniques have helped the model resolve these intensification rates while limiting false alarms. These improvements in model guidance and the introduction of RI probability guidance (e.g., RII) has provided NHC forecasters with the ability to better discriminate between real and false intensification events in model predictions, helping to improve the POD. Despite the improvements in POD over recent years, Fig. 10 shows that there has been no notable improvement in the false alarm rates (FAR) for the same short-term intensification rates of 20 kt or greater in the NHC forecasts or SHIPS and HWRF models. Reducing FAR should be a priority to be addressed in the near future.

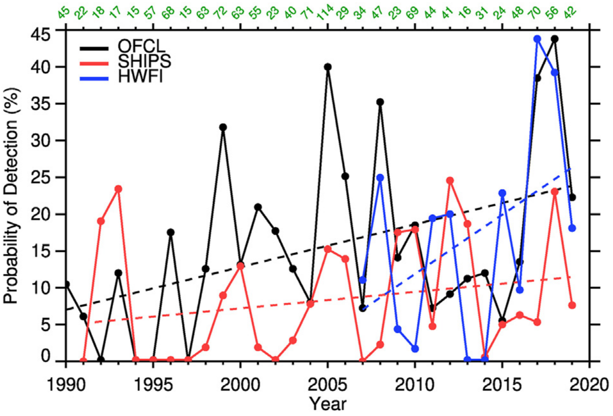


Fig. 9. POD for intensification rates of 20 kt or greater over the 24 h forecast period of 12–36 h for North Atlantic storms. Trend lines are shown for OFCL (black), SHIPS (red), and HWFI (blue). HWFI is the early interpolated forecasts by HWRF. The number of verifying events for each year is shown in green.

5.2. JTWC

Since 2018, some advances have been made toward improving intensity forecast skill during RI events. RIPA, described in Section 3.2, has been in operational use at JTWC since 2018, and remains the best-performing aid for RI as measured by Peirce score (Manzato 2007), even against the set of new experimental RI aids (FRIA, RIDE, CHR4, CTR1) also described in section 3.2. Fig. 11 shows the Peirce score of all of these aids for different RI thresholds for cases during the 2020–2021 TC seasons. NWP models HWRF (HWFI) and COAMPS-TC (CTCI) demonstrate high skill at RI of 65kt/

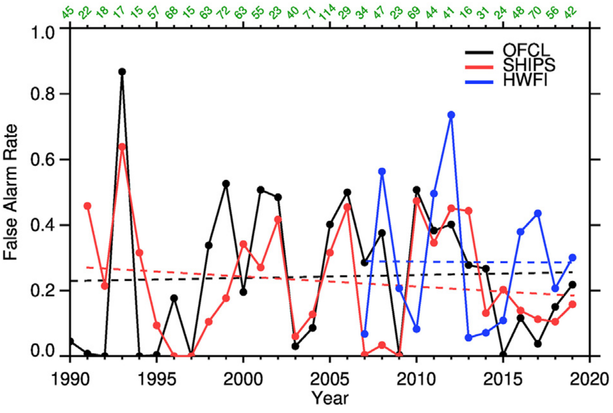


Fig. 10. Same as Fig, 9 except for false alarm rate.

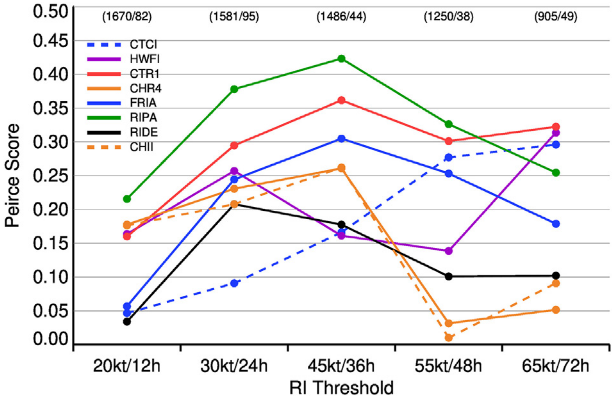


Fig. 11. Peirce skill scores for RI thresholds of 20 kt/12 h, 30 kt/24 h, 45kt/36 h, 55 kt/48 h, and 65 kt/72 h for JTWC RI aids, along with the HWRF (HWFI) and COAMPS-TC (CTCI). Evaluation includes JTWC 2020–2021 TC seasons. Sample sizes (all cases/RI cases) are annotated along the top of the figure.

72 h, while RIPA, FRIA, RIDE and CHR4 peak in skill at RI of 45 kt/36 h. As discussed in Section 3.2, an experimental consensus formed from these RI aids and HWRF is currently being evaluated in JTWC operations, with preliminary statistics suggesting that it can outperform the standard intensity consensus aid (ICNW) in cases when RI is predicted by one or more deterministic RI aids.

A growing challenge to skillful RI forecasting is the declining frequency of microwave satellite passes over TCs. The number of currently operational sensors has fallen from 16 to 10 since 2014, and gaps between images of TCs are growing (Howell 2022). A similar challenge exists for estimates of the two-dimensional TC surface wind field through scatterometer or synthetic aperture radar measurements, which are currently at an inadequate cadence for TC monitoring. Accurate knowledge of current tropical cyclone core structure is important to predicting TC intensity, and primarily comes from low earth orbiting satellites in basins where aircraft reconnaissance is not conducted.

5.3. BoM

In BoM, rapid intensity change continues to be the most challenging aspect of operational intensity forecasting due to only a small number of objective aids to rely upon. From the perspective of rapidly increasing intensity, the RII is a useful probabilistic tool indicating risk of occurrence, with some high-resolution NWP yielding potential upper-bound forecast limits if RI were to occur. Difficulties arise for systems which do not have either the RII or high-resolution modeling running until after identification and development, which is particularly a risk for small systems that can develop very quickly.

Rapid weakening (RW) of a system also represents a challenge in forecasting intensity. Typically seen during eyewall replacement cycles (ERC) these phases of intensity changes pose challenges in a range of ways. From a short-term forecasting or nowcasting perspective, a lack of instantaneous, and consistently available microwave imagery makes it difficult to properly assess the eyewall structure to confirm that an ERC is occurring and what phase it is currently in to effectively assess the short-term intensity change trend. From the perspective of longer lead time forecasting, due to the difficulty of picking the timing of an ERC occurring, there is no guidance to support weakening and subsequent strengthening of a system for this phenomenon.

5.4. RSMC Tokyo – Typhoon Center

RSMC Tokyo shares the challenges of other centers. First, although the RII supports RI forecasting, there is still room for improving RI guidance in terms of the forecasting of timing and magnitude. This is because NWP models do not always provide adequate guidance due to predictability limitations, uncertainties and differences in model characteristics. Second, satellite observation plays an important role in RI forecasts. The current latency and temporal resolution of microwave satellite observation complicate forecasting with no delay for rapid intensity changes associated with the rapid formation of banding structures or eyewall replacement cycles. With existing image analysis, it may also be challenging to evaluate the effects of surrounding dry areas on TC intensity changes (e.g., how much of such areas flow into the inner core and whether this weakens intensity).

6. List of recent difficult cases

Each year, many modelers and forecasters around the world meet in the HFIP annual meeting (https://hfip.org/events/annual-review-meetings) to discuss the success and challenges of TC models and forecasting of the year. Table 3 lists some challenging storms from 2018 to 2021 identified by operational centers (NHC, JTWC, and BoM) for the research community to further investigate. Most of the challenges are associated with intensity and RI guidance of both models and operational forecasts. For example, for Hurricane Dorian (05 L) in 2019, all models (including dynamical and statistical models) and operational forecasts of early cycles (e.g. 2019082718) failed to forecast RI, and totally missed hurricane phase (Fig. 12a). None of the forecasts predicted a near-stationary hurricane over Grand Bahama for a period of time (Fig. 12b).

Unique challenges for Western Australian tropical system intensity forecasts are those systems that threaten to rapidly intensify as they move west off the coast. The significant difficulty in forecasting intensity for these systems is directly related to track position with systems remaining over land not having the potential to develop, and those that move over water threatening intensification, in some cases, RI. An example of this scenario was tropical system 12U during late January and early February 2021. Broad-scale environmental factors were favorable for intensification of a tropical system over waters north of Western Australia. Guidance was not consistent for the steering of the system offshore, however those models that did track 12U offshore had intensity forecasts increasing rapidly to be a severe tropical cyclone ($\geq$ 64 kt 10-min mean winds). The outcome for 12U was for a system that remained inland, and whilst it produced significant rainfall impacts, the

Table 3
List of challenging storms from 2018 to 2021.

Year	Basin	Storm ID	Name	Forecast Challenges
2018	AL	06	Florence	Totally missed first RI and RW; large cross-track errors
	AL	14	Michael	Too low peak intensity, weak intensification,
	AL	13	Leslie	Large track errors
	EP	12	John	Too strong RI, peak intensity timing and magnitude off, large over-forecast errors
	EP	02	Aletta	Biggest RI miss of the year, 70 kt/24 h
	SH	09	Gita	Widespread in model guidance and sharply curved track
	WP	10	Maria	Too weak RI, missed RI from 25 to 130 kt in 54 h
2019	AL	05	Dorian	Failed 24 h RI prediction of early cycles, missed hurricane phase. Move too fast, none predicted stall over Grand Bahama
	AL	13	Lorenzo	Early cycles missed forecast for second intensity peak
	EP	07	Flossie	over forecast peak intensity, high bias
	EP	13	Kiko	Failed RI prediction
	EP	15	Lorena	Poor track forecasts
	WP	10	Lekima	Under-forecast RI
	WP	11	Krosa	Poor track forecasts, quasi-stationary loop
	WP	15	Lingling	Under-forecast RI
	WP	20	Hagibis	Under-forecast extreme RI
	WP	21	Neoguri	Poor track, unanticipated poleward movement
	SH	05	Owen	Failed prediction of eastward movement
	SH	09	Mona	False RI prediction
2020	AL	13	Laura	Incorrect westward shift 2–3 days before landfall
	AL	14	Marco	Interaction between Marco and Laura, huge variability in track guidance
	AL	18	Sally	Track guidance shifted eastward as it approached northern Gulf Coast
	AL	31	Iota	Under-forecast RI, 70 kt/24 h, most guidance 30–40 kt/36 h
	WP	14	Dolphin	Poor track, most guidance too far west, mid-latitude flow interaction
	WP	16	Chan-Hom	Poor track, wider turn
	WP	22	Goni	Under forecast extreme RI, 80kt/24 h
2021	AL	05	Elsa	Over forecast intensity and RI
	AL	06	Fred	False RI, over forecast intensity
	AL	08	Henri	Too strong intensity just before landfall, poor, high variability of curved track guidance
	AL	15	Ida	Under forecast peak intensity
	EP	14	Nora	Incorrect westward track guidance
	EP	15	Olaf	Incorrect westward track guidance of Early cycles
	EP	16	Pamela	False RI, over forecast intensity
	EP	17	Rick	False RI, over forecast intensity
	WP	16	Omais	False RI, over forecast intensity for the longest weak storm (10.5day at ~35 kt)
	SH	18(12U)	Eighteen	False RI, over forecast intensity

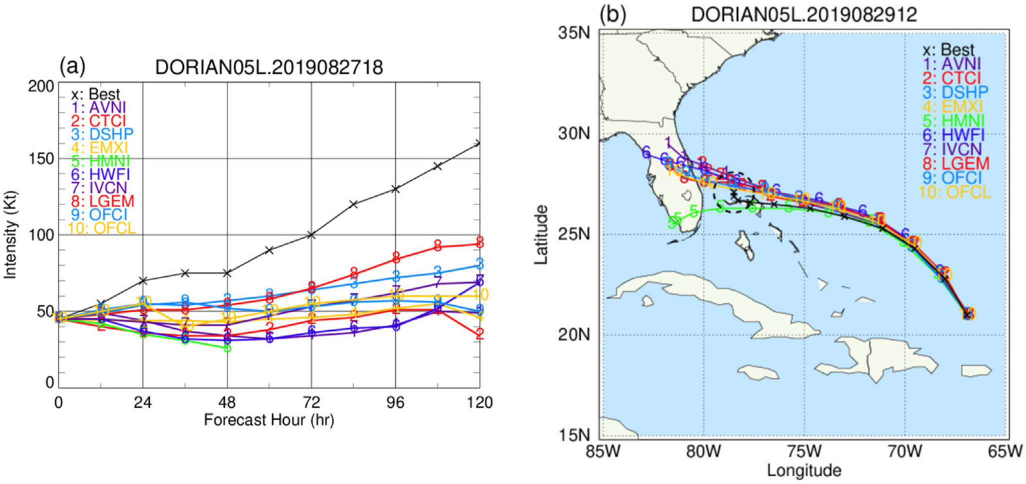


Fig. 12. (a) Hurricane Dorian intensity guidance for the 2019082718 cycle. Intensity of the best-track is shown in black, while results of models and the NHC operational forecast are shown in colors. (b) Hurricane Dorian 120 h track guidance for 2019082912 cycle shown in colors, with the best-track in black. Black dashed circle shows the location of the near-stationary hurricane. (Blake, 2019).

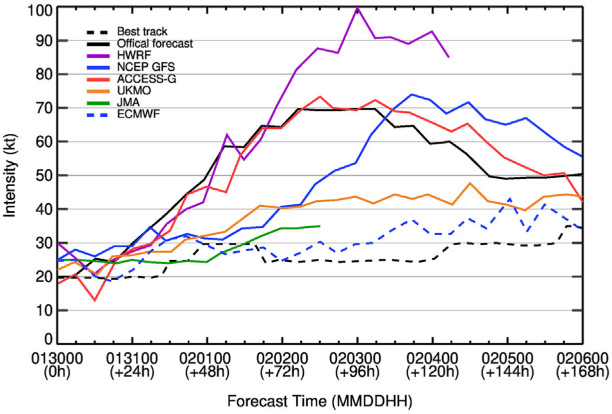


Fig. 13. Intensity guidance comparison for tropical system 12U issued at 00 UTC, 30 January, 2021. See the list of acronyms for model names.

wind intensity did not ever increase to Australian tropical cyclone intensity of 34 kt 10-min mean winds. Fig. 13 shows intensity forecasts from a range of guidance and the official forecast intensity issued at 00 UTC 30 January 2021, with the analyzed post-event best track plotted for comparison.

7. Summary and future direction

This paper is part II of the review on the progress of forecasting intensity changes made in the past 4 years (2018–2021) from the perspective of operational TC forecasts as presented to WMO IWTC-10, focusing on the updates and challenges contributed by operational centers. Part I of the review focuses on dynamical model guidance (Zhang et al., 2023). During the last 4 years since IWTC-9 was held in 2018, the performance of intensity forecasting from operational centers such as NHC, JTWC, and RMSC-Toyko has continued to improve. In particular, the improvement of RI forecasts has accelerated, compared with years before 2018. Based on HFIP's metric, RI forecasts at NHC have improved by about 20–25% since the 2015–2017 baseline period. This may be attributed to the use of DTOPS, a tool introduced in 2018 and currently the most skillful among NHC's probabilistic RI guidance. JTWC also reported that record-breaking improvement in intensity and RI forecasts has been made since 2018, attributed to the implementation of RIPA guidance. The successful applications of DTOPS and RIPA encourage other centers to adapt the existing guidance or develop their specific tools. Nevertheless, rapid intensity changes are still major challenges to operational centers. Several operational centers share the challenge to skillful RI forecasting due to the declining frequency of microwave satellite passes over TCs and inadequate scatterometer or synthetic aperture radar measurements for estimating the two-dimensional TC surface wind field. A list of difficult cases is shown for the research community to investigate, potentially further improving intensity forecasts.

It is worth noting the priority issues or research needs for intensity forecasts identified by forecasters (Brennan 2019; Brennan and Cowan 2021; Cowan 2021; DeMaria and Brennan 2018; Kucas 2020; Zhang et al., 2021), including.

(1) Dynamical and statistical models generally overpredict intensity changes in low-shear environments.
(2) Regional dynamical models often predict convection in the inner core that is too symmetric in environments of vertical wind shear and/or dry air, leading to high-biased intensity forecasts;
(3) Regional dynamical models have difficulty in timing RI onset, and can exhibit large cycle-to-cycle variability in intensity forecasts.
(4) Poor model track forecasts near land negatively affect intensity forecasts.
(5) Model wind structure forecast skill is difficult to verify and evaluate and the forecast of wind gusts is not included.
(6) Probabilistic forecast guidance for TC intensity change, particularly the onset, duration, and magnitude of rapid intensity change events including ERC, over-water RW etc. at 2–3 day lead times should be developed or improved.

Finally, there are two recommendations. Firstly, the research community is encouraged to address the above needs identified by forecasters to further improve intensity, RI and RW forecasts. Secondly, the transition from research to operations should be accelerated through, for example, improving dynamical and statistical models with new findings, exploring new techniques such as machine learning models, and developing new RI/RW analysis tools. We are confident that with the further collaboration of the research and operation communities upgrading models and developing new tools, TC intensity forecasts will continue to improve.

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Acronyms

ACCESS-G	Global version of The Australian Community Climate and Earth-System Simulator

AVNO	ATCF model identifier for NCEP GFS
BoM	The Bureau of Meteorology, Australia
CHIPS	Coupled Hurricane Intensity Prediction System
CHII	Interpolated CHIPS
CHR4	CHIPS ensemble deterministic RI aid
CLP5	5-day Climatology and Persistence Track Forecast
COAMPS-TC	Coupled Ocean-Atmosphere Mesoscale Prediction System for TC
CPHC	Central Pacific Hurricane Center
CTCI	ATCF model identifier for early (interpolated) model forecasts by CTCX
CTCX	ATCF model identifier for GFS-based deterministic COAMPS-TC
CTR1	COAMPS-TC ensemble RI aid
Decay-SHIFOR5	Statistical Hurricane Intensity Forecast Model with inland decay (5-day)
DSHIP	SHIPS with inland decay
DTOPS	Deterministic to Probabilistic Statistical model
ECMWF	European Center for Medium-Range Weather Forecasts
EMXI	ATCF model identifier for early (interpolated) model forecasts by IFS ECMWF
EPS	ensemble prediction system
ERC	Eyewall Replacement Cycle
FAR	False Alarm Rate
FRIA	Forest-based Rapid Intensification Aid
GEFS	Global Ensemble Forecast System
GEPS	Global Ensemble Prediction System
GFDL	NOAA Geophysical Fluid Dynamics Laboratory
GFS	Global Forecast System
GFSI	ATCF model identifier for early (interpolated) model forecasts by AVNO
GSM	Global Spectral Model
HCCA	HFIP Corrected Consensus Approach
HFIP	Hurricane Forecast Improvement Project
HMNI	ATCF model identifier for early (interpolated) model forecasts by HMON
HMON	Hurricanes in a Multi-scale Ocean coupled Non-hydrostatic model
HWFI	ATCF model identifier for early (interpolated) model forecasts by HWRF
HWRF	Hurricane Weather Research and Forecasting System
ICNC	ICNW without RI aids
ICNE	Experimental intensity consensus aid with RI aids
ICNW	Intensity Consensus Aid computed and utilized by JTWC
IFS	Integrated Forecasting System
IMD	Indian Meteorological Department
IVCN	Intensity Variable Consensus model
IVDR	Intensity Consensus of GFSI/DSHIP/LGEM, CTCI/HWFI/HMNI (double weight)
IWTC	international workshop on TC
JMA	Japan Meteorological Agency
JTWC	Joint Typhoon Warning Center
LGEM	Logistic Growth Model
MME	multi-model ensemble
MOGM	Met Office Global Model
MSC	Meteorological Services Canada
MSM	Meso-Scale Model
MSW	Maximum Sustained Wind
NAVGEM	Navy Global Environmental Model
NCEP	US National Centers for Environmental Prediction
NCMRWF	National Center for Medium Range Weather Forecasting
NCUM	NCMRWF Unified Model
NEPS	NCMRWF Ensemble Prediction System
NHC	National Hurricane Center
NOAA	National Oceanic and Atmospheric Administration
NWP	Numerical Weather Prediction
NWS	National Weather Service
OCD5	Operational CLP5 and DSHF Blended Intensity Forecast
OFCL	ATCF model identifier for NHC official forecasts
POD	Probability of Detection
RI	Rapid Intensification
RII	Rapid Intensification Index
RIDE	Rapid Intensification Deterministic Ensemble
RIPA	Rapid Intensification Prediction Aid
RMS	root mean square
RSMC	Regional Specialized Meteorological Center
RW	Rapid Weakening
SCIP	Statistical cyclone intensity prediction
SHIFOR	Statistical Hurricane Intensity Forecast Model (climatology and persistence model)
SHIPS	Statistical Hurricane Intensity Prediction Scheme
ST5D	Statistical Typhoon Intensity Forecast (ST5D)
TC	Tropical Cyclone
TIFS	Typhoon Intensity Forecast Scheme
UKMO	UK Met Office
WRF	Weather Research and Forecasting model
WNP	Western North Pacific

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