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WMO Typhoon Landfall Forecast Demonstration Project (2010–22): A Decade of Transition from Track Forecasts to Impact Forecasts

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ABSTRACT: The Typhoon Landfall Forecast Demonstration Project (TLFDP) (2010–22) was an international cooperative scientific project conducted under the framework of the WMO. The primary objectives of the TLFDP were to enhance the capability of tropical cyclone (TC) forecasters and support related decision-makers in effective utilization of the most advanced forecasting techniques for the ultimate purpose of reducing and preventing disasters associated with TC landfall. Forty agencies/organizations/projects globally participated in the activities of the TLFDP following its inception in 2010, although the primary focus was on landfalling TCs in the western North Pacific. The TLFDP facilitated collaborations and workshops that realized notable achievements in four key areas: 1) the collection, production, and sharing of TC data; 2) the development and application of TC forecast verification metrics; 3) research on TC forecast skill; and 4) development of new techniques for TC forecasting. An obvious outcome was the shift from prediction of TC features, including track and intensity, toward prediction of TC impacts with more probabilistic conception. The final years of the project also promoted increasing application of artificial intelligence and machine learning techniques in various techniques for analysis and forecasting of TCs. Although the TLFDP ended in 2022, its core activities have continued to be extended through new WMO projects and regional cooperative initiatives.

SIGNIFICANCE STATEMENT: The WMO Typhoon Landfall Forecast Demonstration Project was an international scientific cooperation project that continued for over a decade, and it was the first-ever project of this duration to have tropical cyclone (TC) forecasting as a research theme. Forty agencies/organizations/projects globally participated in its activities, and the landmark achievements included notable expansion of TC datasets, development and application of TC forecast verification metrics, and development of new TC forecasting techniques. Key research findings on TC forecast skill also informed the direction of future developments in TC forecasting technology.

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1. Introduction

Tropical cyclones (TCs), commonly known as typhoons by residents in the western North Pacific (WNP) region, are among the primary causes of catastrophic natural disasters globally, posing a severe threat to human life and property (Yu and Chen 2019). The Typhoon Landfall Forecast Demonstration Project (TLFDP) was an international cooperative scientific project under the framework of the WMO, a specialized agency of the United Nations dedicated to international cooperation and coordination on weather, climate, and the water cycle. The primary objectives of the TLFDP were to enhance the capability of weather forecasters and support related decision-makers in effective utilization of the most advanced TC forecasting techniques for the ultimate purpose of preventing and reducing disasters associated with TC landfall. The TLFDP was launched in May 2010 as a component of the Shanghai Multi-Hazard Early Warning System project to support weather forecast services for the Expo 2010 Shanghai China (Tang et al. 2012), and it concluded at the end of 2022. Initially, the TLFDP focused on the WNP region; however, toward its concluding phase, it progressively expanded to encompass other basins affected by TCs.

Over its 13-yr lifetime, a range of activities were conducted through four consecutive phases of the TLFDP (Table 1), each focusing on a primary theme associated with TCs: track (Phase I), genesis (Phase II), intensity and precipitation predictions (Phase III), and probabilistic forecasting (Phase IV). Forty agencies/organizations/projects participated in the activities of the TLFDP (appendix A). These agencies/organizations/projects, with considerable broad regional and/or disciplinary coverage, contributed to the TLFDP through various means, including

Table 1. Four phases of the TLFDP. See appendix A for the full names of the listed agencies/organizations/projects.

	TLFDP-I (2010–12)	TLFDP-II (2013–15)	TLFDP-III (2016–18)	TLFDP-IV (2019–22)
Main theme(s)	Track	Genesis	Intensity and precipitation	Probabilistic forecast
Leading agency(s)	STI		STI, HKO	
Chair(s) of the International Scientific Steering Committee/Affiliation	Lianshou Chen/CAMS Xu Tang/ECRMC		Ajit Tyagi/IMD	
Administrating WMO Programmes	WWRP, TCP, PWS		WWRP, TCP	WWRP, TCP, GDPFS
Major references	Tang et al. (2012), Lei and Yu (2015), Lei et al. (2016b)		Yu et al. (2018, 2022a)	

data provision, support for training activities, and the development of forecasting or verification techniques and tools.

This paper reviews the major achievements of the TLFDP, and it is organized according to the major implementation tasks of the project. Section 2 describes the efforts to expand TC data collection and sharing. Section 3 discusses the development of TC forecast verification metrics. Section 4 covers the research on TC forecast skill. Section 5 presents details of the development of new techniques for TC forecasting. Section 6 presents an overview of the surveying, workshop, and training activities. Finally, section 7 provides a summary.

2. Collection, production, and sharing of TC data

Observational and forecast data of TCs are indispensable for activities related to operational warnings, research with the objective of improving the fundamental understanding of TC physical processes, and development of applications in support of research-to-operation processes. To support these important activities, the TLFDP dedicated substantial effort to identifying gaps between user needs and available data resources, primarily through discussions in a series of workshops and training courses. This process identified several major gaps, which included the following: 1) lack of recognition or awareness by researchers and forecasters of many existing TC datasets; 2) lack of available datasets supporting research or operations on TC structure and impacts; 3) fragile and ephemeral nature of the capability of the current system for operational and forecast data sharing, being maintained primarily on an as-needed basis and with limited funding; and 4) wide variety of formats of disseminated observational and forecast data, which often resulted in difficulties regarding efficient storage and transfer of data and hindered easy use of data in research and operations.

Following the identification of these gaps, action has been taken as part of the TLFDP to expand the collection, production, and sharing of three types of TC data: 1) routine observations and derived products, 2) field experiment data, and 3) operational forecast data (as listed in appendix B).

a. Routine observations and derived products. The TLFDP collected TC best track datasets for the WNP region from the official websites of four agencies, including the China Meteorological Administration (CMA), Hong Kong Observatory (HKO), JTWC, and WMO Regional Specialized Meteorological Center (RSMC) Tokyo–Typhoon Center. The project also continuously collected and shared routine TC observations and derived data for TCs affecting China, which included the position, maximum wind speed, minimum central pressure, wind radii, time and location of landfalling TCs (LTCs), and TC-induced wind and precipitation as observed by surface weather stations. The start year of this data record was 1949.

Additionally, the TLFDP actively supported the development of five datasets [see sections 2a(1)–2a(5)] to facilitate the application of operational TC products and meet the increasing demand for impact-oriented products, including TC size, potential risk index, and high-resolution wind fields of TCs. Some datasets were developed by individual TLFDP team members as part of their other research and/or projects through funding mechanisms outside of the TLFDP. However, the development of these datasets benefited from TLFDP activities such as in-person visits and workshops, which promoted greater appreciation for the data gaps that could be filled and provided considerable exposure of the datasets to potential users.

1) NCAR TCGP tropical cyclone real-time data stream of operational estimates. Operational estimates of the analyzed vital parameters of a TC, including position, maximum wind speed, minimum central pressure, and significant wind radii, represent a blended analysis of all available in situ and remote sensing observations. Such operational estimates were found inconsistent between basins owing to differences in operational practices among different forecast centers and variation in wind speed averaging periods. The NHC and JTWC use largely similar operational practices, i.e., a consistent 1-min wind speed averaging period, and their combined analyses cover all global TC basins. The NCAR Tropical Cyclone Guidance Project (TCGP) has been collecting, collating, and sharing these real-time data from the NHC and JTWC since 2011. For the convenience of users, TCGP converts the operational estimates into Automated Tropical Cyclone Forecasting system-formatted files (Miller et al. 1990) and reformats the information in the files that hold the summarized forecasts for track, intensity, and other parameters from TC forecasting aids. These data are made available on the TCGP website specifically for real-time users (https://hurricanes.ral.ucar.edu/repository/data/), and they should not be used for applications or studies requiring postseason best track information.

2) STI/CMA satellite-retrieved tropical cyclone size dataset. The Shanghai Typhoon Institute (STI) of the CMA provided a TC size dataset built from estimations based on geostationary satellite infrared images of TCs with intensity at tropical storm level and above (maximum wind speed: $\geq 17.2\,\mathrm{m\,s^{-1}}$) during 1980–2016 in the WNP region. It included 6-hourly estimates of TC size defined by the azimuthal mean radius of 34-kt ($1\,\mathrm{kt} \approx 0.51\,\mathrm{m\,s^{-1}}$) surface winds and corresponding satellite imagery information. The position and intensity of the TCs, obtained from the IBTrACS dataset, were also provided because they were used in the algorithm for the estimation of TC size. This dataset was unique in terms of providing a consistent estimation of TC size during the satellite era since 1980 (see https://tcdata.typhoon.org.cn/en/tcsize.html and Lu et al. (2017) for further details). An updated dataset for TCs that occurred during 1981–2020 was constructed using machine learning models (Lu et al. 2022a). This new dataset expanded the parameters of TC size to include the radius of maximum wind and the radii of the 34-, 50-, and 64-kt winds in four quadrants [northeast (NE), southeast (SE), southwest (SW), and northwest (NW)].

3) STI/CMA potential risk indices for landfalling tropical cyclones in mainland China. The Potential Risk Indices for Landfalling Tropical Cyclones in Mainland China (PRITC) Dataset V1.0 was developed and released to the public by the STI in 2021 (P. Y. Chen et al. 2021). It included an index of the wind induced by each LTC (IWT), an index of precipitation induced by each TC (IPT), an index combining IWT and IPT (IPWT), and the corresponding TC category level (CAT_IPWT) determined by the relationship between IPWT and the losses of property and life (P. Y. Chen et al. 2019). These indices and CAT_IPWT were valuable supplements to the widely used TC intensity-based categories, serving as indicators of the severity and extent of TC impact. The latest version of the dataset covered TCs that made landfall in China during 1949–2021 (see https://tcdata.typhoon.org.cn/en/qzfxzs.html and P. Y. Chen et al. (2019, 2021) for further details).

4) STI/CMA Engineering Typhoon Model Dataset. The STI Engineering Typhoon Model (STI-ETYM), which is a parametric TC wind field model, was developed by the STI to provide guidance for prompt assessment of the risks and impacts arising from the high-speed winds associated with TCs. The core component of the STI-ETYM was a planetary boundary layer model, which incorporated findings on the reduction in drag coefficient with high wind speeds (Fang et al. 2015, 2018), the boundary layer height (Vickery et al. 2009), and the ratio between the mean wind speed in the TC boundary layer and that at the surface (10-m height) (Fang et al. 2020). The STI-ETYM Dataset V1.0 consists of gridded surface wind fields for historical TCs that occurred during 1949–2021, with the highest horizontal grid increment of 2 km. The horizontal coverage of each wind field extends 240 km from the TC center. The reliability of the data was evaluated against the best track data for 46 historical randomly selected TCs that occurred in the WNP and meteorological observations obtained in coastal areas of China (Fang et al. 2020; Ye et al. 2018).

5) The extended flight level dataset of tropical cyclones. The Extended Flight Level Dataset of Tropical Cyclones (FLIGHT+ Dataset) (Vigh et al. 2020) represents a high-quality research-grade dataset of flight-level data in TCs obtained by the NOAA Hurricane Hunters and U.S. Air Force Reserve flights. The compilation of the dataset involved extensive value-added processing of the flight-level data, including standardizing the source data from various formats into a single common format, applying automatic and manual quality control processes to remove artifacts when possible, automatic parsing of the radial legs of flight patterns, and translation of the data onto a storm-relative radial grid. The FLIGHT+ Dataset primarily covers TCs that occurred in the Atlantic, eastern Pacific, and central Pacific since 1997. It also includes flight-level data for eight TCs in the WNP, which were obtained during U.S. Air Force Reserve flights in field campaigns in 2008 and 2010. The FLIGHT+ Dataset was updated irregularly depending on the availability of funding, and the most recent major update incorporated data up to 2019 (https://verif.rap.ucar.edu/tcdata/flight/).

b. Field experiment data. The TLFDP collaborated with several projects operated at the WMO or its member level to develop and popularize datasets derived from TC field experiments. These collaborative activities promoted the sharing of experiences in data quality control and data application, especially in relation to three datasets in the WNP region [see sections 2b(1)–2b(3)], which played important roles in improving the understanding of the physical processes modulating TC intensity and structure change, advancing operational model physics and associated improvements to TC forecasts, improving data assimilation systems in operational models, and enhancing development of new technologies. Additionally, experiences from other basins such as the NOAA Hurricane Field Program Dataset (Rogers et al. 2013; Zawislak et al. 2022) were also shared through TLFDP workshops and training activities.

1) HKO tropical cyclone aircraft reconnaissance flights dataset. In 2011, the HKO commenced reconnaissance flights of TCs over the South China Sea in collaboration with the Hong Kong Government Flying Service, representing the only operational TC reconnaissance effort over the region during the TLFDP. Overall, 24 low-level TC reconnaissance missions were conducted during 2011–16 for 19 systems with intensity ranging from low-pressure area to severe typhoon. In September 2016, a dropsonde system (Hock and Franklin 1999; Vaisala 2014) installed onboard a fixed-wing aircraft became operational, and the first-ever dropsonde mission was conducted during the approach of Severe Typhoon Megi (2016). Dropsonde missions continued in the following TC seasons. Figure 1a shows an example of the upper-air measurements taken around Typhoon Kompasu (2021) on 12 October 2021. The data included profiles of wind, temperature, and dewpoint temperature. The dropsonde data collected in each flight mission were sent to WMO members in near–real time as bulletins disseminated via the Global Telecommunication System (GTS) after initial quality checks. An example distribution of dropsonde observations (approximately 300 profiles containing more than 100 000 measurements for flights conducted during 2019–23) is depicted in Fig. 1c. As summarized by Hon and Chan (2022), the data obtained during the reconnaissance flights have been used in

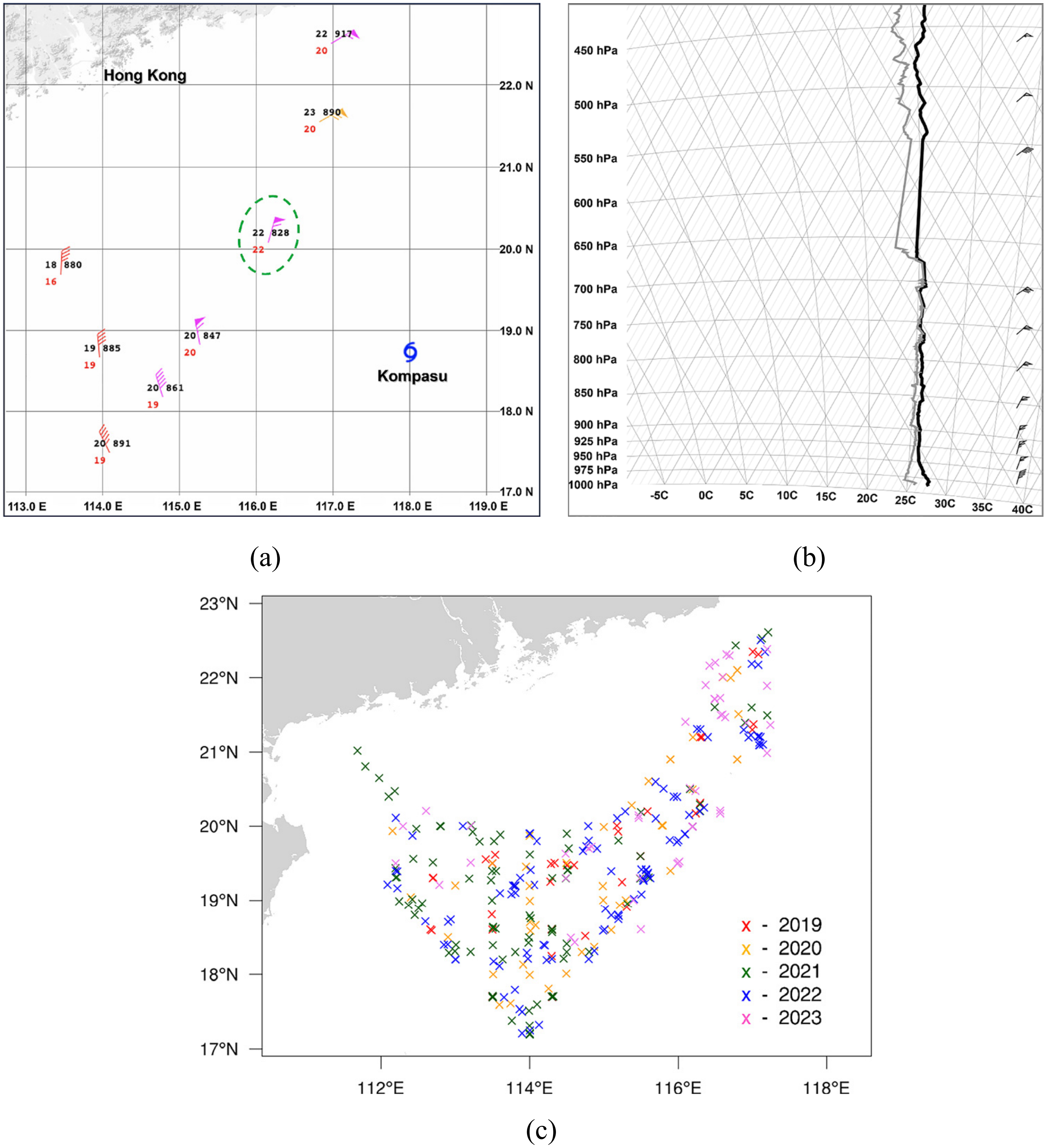

Fig. 1. **(a) Dropsonde wind measurements at the 900-hPa level in Severe Tropical Storm Kompasu (2021) at approximately 0400 UTC 12 Oct 2021. The position of the center of Kompasu, marked by a TC symbol, reflects the HKO best track data, and the green dashed ellipse denotes the position of the dropsonde profile shown in (b). (b) Profiles of horizontal winds, temperature (black line), and dewpoint temperature (gray line) from a dropsonde over the northwest quadrant of the storm. (c) Locations of dropsonde profiles of flight measurements during 2019–23.**

various studies that have contributed to extending scientific understanding of TC structures and underlying physical processes. Archived dropsonde data for flight missions performed from 2016 are available upon request.

2) NJU C-POL and 2-DVD tropical cyclone dataset. The mobile C-band polarimetric (C-POL) radar and 2D video disdrometers (2-DVDs) of Nanjing University (NJU) have been used to obtain observations of LTCs in China since 2014 as a part of the World Weather Research Programme (WWRP) Research and Development Project, namely, "Understanding and Prediction of Rainfall Associated with Landfalling Tropical Cyclones" (UPDRAFT). The data for seven TCs (G. Chen et al. 2019; Wen et al. 2018), i.e., Matmo (2014), Soudelor (2015), Meranti (2016), Megi (2016), Hato (2017), Pakhar (2017), and Ewiniar (2018), have been archived and are available upon request. It should be noted that the UPDRAFT field experiment was stopped by the COVID-19 pandemic during 2020–22.

3) CMA Tropical Cyclone Landfalling Process Field Science Experiments Database. Several field experiments conducted to collect data from targeted TCs affecting China were led by the CMA and supported by several key national scientific projects of China. These projects included the Landfalling Tropical Cyclone Research Project during 2009–19 (Duan et al. 2019) and the Experiment on Coordinated Observation of Offshore Typhoons in China during 2019–21 (Lei et al. 2019b). These field experiment activities were also partly supported by the United Nations Economic and Social Commission for Asia and the Pacific (ESCAP)/WMO Typhoon Committee Cross-cutting Project and the WWRP Research and Development Project "Experiment on Typhoon Intensity Change in Coastal Area" (EXOTICCA) (Lei et al. 2017). More than 30 TCs were targeted during 2007–22, and the TC Landfalling Process Field Science Experiments Database (TCLPFieldSED) was established by the STI to archive the data obtained from various observational platforms, including meteorological satellites, reconnaissance aircraft, meteorological buoys and ships, island-based meteorological towers, and ground-based vehicles equipped with meteorological instruments. The database contains all the raw data following the automatic calibration of the instruments, together with some data products produced after basic quality control. Portions of the data were released to the public through https://tcdata.typhoon.org.cn/en/ywgc.html (Lu et al. 2021), grouped by storm name and instrument type; the remaining data are available upon request.

c. Forecast data. Since the commencement of the TLFDP in 2010, the STI has been collecting and sharing a wide variety of TC forecast data for the WNP region in support of the project (Tang et al. 2012). These data were gathered from various providers (appendix A) and data streams via the GTS, ftp, http, or e-mail. The data include deterministic track and intensity forecasts, ensemble track and intensity forecasts, deterministic wind radius forecasts, wind probability forecasts, two-dimensional gridded wind and precipitation forecasts, and three-dimensional gridded model output. Substantial efforts have been made to convert the data provided in different formats into unified formats. In 2019, the STI began collecting and archiving TC forecast data for the central-eastern and southern Pacific Ocean, Atlantic Ocean, and Indian Ocean Basins from WMO RSMCs and Tropical Cyclone Warning Centers (TCWCs) (also listed in appendix A) as a database for global TC forecast verification (Chen et al. 2020; Yang et al. 2021). These forecast data, archived as the "STI/CMA Tropical Cyclone Forecast Dataset for TLFDP," are freely available to all WMO members upon request.

The TLFDP received strong support from the NCAR's TCGP in collecting and sharing a variety of TC forecasting aids for TC basins globally, including several global deterministic models and their ensemble prediction systems (EPSs), and a regional model. The public can access the track and intensity outputs of these forecasting aids on the TCGP website https://hurricanes.ral.ucar.edu/. In 2021, the TCGP began offering visualizations of the probabilistic wind hazard outputs from the Massachusetts Institute of Technology's Forecasts of Hurricanes using Large-Ensemble Outputs (Lin et al. 2020), which is run in real time at the NCAR. It is a probabilistic framework for predicting TC wind hazards, leveraging the flow-dependent uncertainty simulated by global EPSs to supply real-time pointwise predictions of TC wind hazards.

Implementation of the 10-yr WWRP project "The Observing System Research and Predictability Experiment" (THORPEX) during 2005–14 substantially advanced the capability of EPSs and improved the use of EPSs through the THORPEX Interactive Grand Global Ensemble (TIGGE) archive (Parsons et al. 2017; Swinbank et al. 2016). The TLFDP initiated the use and verification of EPS TC forecasts as a joint effort with the North Western Pacific Tropical Cyclone Ensemble Forecast Project (Yamaguchi et al. 2014). The ensemble prediction products of TCs were collected in real time from two sources. The first source was the WMO's GTS, which was used to collect forecasts from the ECMWF and NOAA's NCEP. The second source was the Research Data Archive of NCAR's Computational and Information Systems Laboratory (https://rda.ucar.edu/datasets/ds330.3/), supplying the TIGGE TC forecast dataset in the Cyclone XML format.

3. Development of TC forecast verification metrics and tools

Verification of TC forecast guidance facilitates appropriate use of the guidance and identifies areas for improvement in forecasting systems. Thus, one of the major tasks of the TLFDP since its establishment was to develop TC forecast verification metrics (appendix C) and perform verification on available TC forecast guidance. Since 2013, annual reports on the performance of operational TC forecast guidance in the WNP were issued as a joint effort between the TLFDP and the Working Group of Meteorology under the ESCAP/WMO Typhoon Committee (Lei et al. 2019a). In 2019, the project issued its first annual report on the performance of operational TC forecast guidance in global TC basins, as an action to support the Leading Center of Tropical Cyclone Forecast Verification under the framework of the Global Data-Processing and Forecasting System (GDPFS). The public can access all annual verification reports via the project's website, http://www.tlfdp.net. The annual verification reports for the WNP region are also accessible on the official website of the ESCAP/WMO Typhoon Committee (https://www.typhooncommittee.org).

The TC forecast verification metrics developed by the TLFDP are categorized into two groups. The first group comprises traditional metrics such as the position error (PE), along-track/cross-track (AT/CT) bias, root-mean-square error (RMSE) of intensity, and hit ratio of the probability circle (HRPC). Their definitions are provided in the review paper by Yu et al. (2012b) and are not repeated here. The second group consists of metrics developed by the TLFDP or newly incorporated into TC forecast verification practice by the project, together with software tools that facilitate routine forecast verification activities.

a. TFID and TER for track forecast verification. The Track Forecast Integral Deviation (TFID) was proposed by Yu et al. (2013a) based on the mathematical consideration that a "good" forecast position should consistently be located a small distance from the observed track, not only at zero order but also at higher orders. The TFID index is defined as the average value of two quantities: the first (zero order) is the mean of the forecast position errors during any specified lead time interval (e.g., from 0 to 120 h, 0 to 72 h, and so on), and the other (higher orders) is the average of the absolute deviations of the errors from their mean. A perfect forecast should have a TFID value of zero. Comparison of the TFID with the traditional PE revealed that TFID could be a valuable supplement to the PE in distinguishing good and poor track forecasts, especially in terms of identifying the "fake" good cases with small PE at a specific lead time point but a large TFID for the entire lead time interval.

The track error rose (TER) diagram, developed by Chen et al. (2013), follows the style of the "wind rose" diagram. In a TER diagram, distinct color bars represent the different magnitudes of PEs, and the lengths of the color bars represent the sample sizes as a percentage of the total sample. The azimuthal angle of the color bars represents the forecast error in the direction of TC motion. Taking the results for 72-h forecasts from the CMA official guidance in 2022 as an example (Fig. 2), notable biases were found to exist toward either the southwest quadrant (W, SW, and S) or the northeast quadrant (E and NE). Most errors were below 300 km, with notable westward or southwestward displacements. Large errors over 300 km mainly occurred in the SW, NE, or E directions. The TER diagram intuitively indicates the track error distribution in both magnitude and direction. It has been adopted in the annual verification reports and serves as an informative expansion from the boxplot of PEs.

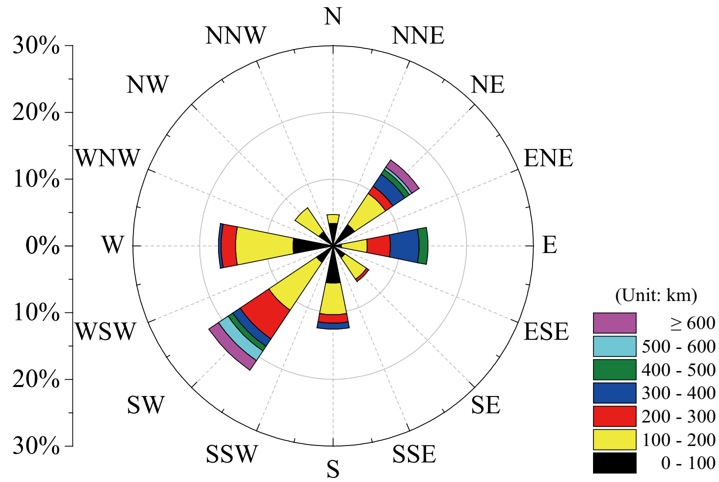

Fig. 2. **TER diagram for 72-h forecasts of the CMA official guidance in 2022. The color bars represent the different magnitudes of PEs, and the lengths of the color bars represent the sample sizes as a percentage of the total sample. The azimuthal angle of the color bars represents the forecast error in the direction of TC motion.**

b. ICCT and Taylor diagrams for intensity forecast verification. The intensity forecast verification contingency table proposed by Aberson (2008) was first introduced to the TLFDP by Chen et al. (2011), wherein all forecasts and observations of maximum wind were categorized into 5-kt intervals and entered into a contingency table composed of forecast–observation pairs. Inspired by those studies, Yu et al. (2013b) developed the Intensity Category Contingency Table (ICCT), which sorted samples by intensity category following the national standard of China ICS 07.060 instead of using 5-kt intervals. The ICCT and its derivative scores proved instrumental in the practice of forecasting the category of a TC.

Since 2015, the annual verification reports of TLFDP included Taylor diagrams (Taylor 2001) for intensity forecast verification (G. M. Chen et al. 2016). The Taylor diagram integrates the standard deviation of the forecasts, the correlation coefficient between forecasts and observations, and the RMSE of the forecasts. It facilitates the simultaneous comparison of these various metrics among different lead times, different forecast guidance, or different years. Taking the results for maximum wind speed forecasts of the CMA official guidance in 2022 as an example (Fig. 3), clear degradation in performance is evident with an increase in the forecast lead time, as evidenced by the reduction in the correlation coefficients and the increase in the RMSE; however, the standard deviation does not show notable difference among different lead times.

c. MODE and CRA for wind and precipitation forecast verification. As was the practice a decade ago, routine verification of TC wind and precipitation forecasts in operational forecast centers was performed in an ad hoc manner and could include a mixture of TCs and other weather systems (Xue et al. 2020; Yu et al. 2012b). However, the TLFDP made considerable progress in incorporating object-based spatial forecast verification techniques into the evaluation of TC rainfall and wind forecasts, in addition to the traditionally used scores derived from contingency tables.

An early case study involved evaluation of the forecasts from numerical weather prediction (NWP) models using the Method for Object-Based Diagnostic Evaluation (MODE)

(Brown et al. 2007; Davis et al. 2006) for the TC-related heavy rain event that occurred in Shanghai during the Expo 2010 Shanghai China [Fig. 4 in Tang et al. (2012)]. Pak and Ri (2016) and T. Xu et al. (2022) evaluated the model forecasts of several other rainfall events caused by LTCs. Both studies demonstrated the advantages of MODE over traditional verification scores in supplying diagnostic information about the attributes of the forecast "rain object" such as the size, centroid displacement distance, and axial angle. Lu et al. (2022b) introduced MODE-based verification for evaluating the TC wind field forecasts from the ECMWF Integrated Forecasting System (ECMWF-IFS) and EPS (ECMWF-EPS). In addition to MODE, Yu et al. (2020) and He et al. (2022) introduced the contiguous rain area (CRA) method (Ebert and McBride 2000) to diagnose the source of systematic errors from the displacement, rotation, volume, and pattern of the forecasted rain fields for TC versions of the Australian Community Climate and Earth System Simulator and the CMA TC model based on the Global and Regional Assimilation Prediction System. The major findings of these object-based verifications are presented in the following section.

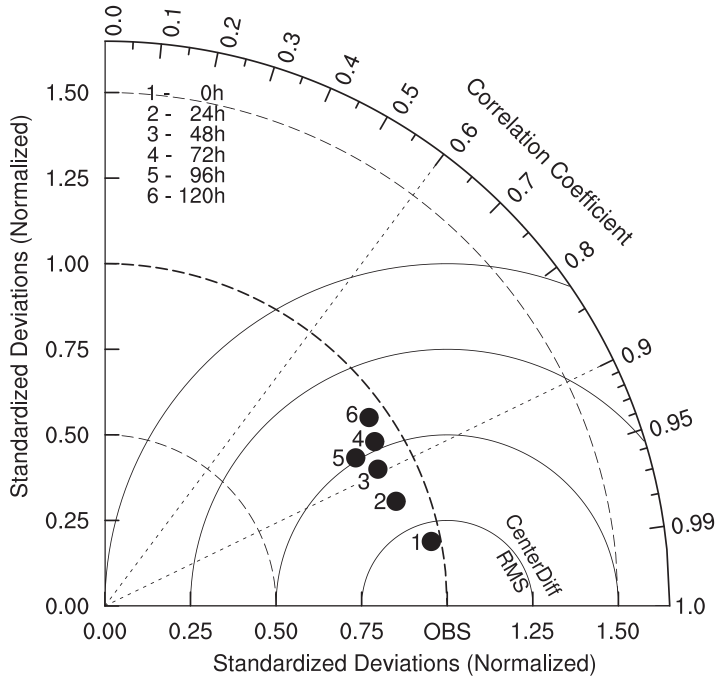

Fig. 3. **Taylor diagram for maximum wind speed forecasts of the CMA official guidance in 2022. This diagram integrates the standard deviations of the forecasts (quarter arcs), the correlation coefficient between forecasts and observations (OBS; radial lines), and the RMSE of the forecasts (semicircles centered on OBS). The numbers 1–6 represent different lead times from 0 to 120 h.**

d. Ensemble forecast verification. THORPEX promoted the development of EPSs, which had driven the increasingly widespread application of ensemble forecast products. A joint plot of ensemble mean position error and ensemble spread (Fig. 4) was designed to evaluate the track forecasts from EPSs in the annual verification reports of the TLFDP (G. M. Chen et al. 2016; Lei et al. 2016a). The ensemble spread was the root-mean-square average of the distances between the ensemble mean position and the ensemble member positions (Whitaker and Loughe 1998). The colored points in the figure are defined by the mean values of the position errors and the ensemble spreads at a specified forecast lead time. A point on the diagonal line means that the EPS forecasts have a mean error matching the mean spread. A point above (below) the diagonal line means that the EPS forecasts have a mean error larger (smaller) than the mean spread, implying that the spread is underestimated (overestimated). The example given in Fig. 4 shows that the ECMWF-EPS tends to overestimate the spread, and the variances in error are consistently larger than those in the spread for different lead times in the 2022 WNP TC season. The Brier score (BS) and the Brier skill score (BSS) are used most frequently in the evaluation of EPS-based probabilistic forecasts of intensity (P. Y. Chen et al. 2016; Xin et al. 2021) and precipitation (Guo et al. 2022; Jiang and Yu 2019). Xin (2021) adopted the relative operating characteristics diagram in a study on the 10-yr progress of EPS forecasts of TC intensity.

e. Forecast verification tools. The Typhoon Forecast Evaluation Tool (TyFET) was developed by the STI to support the routine track and intensity forecast verification activities of the TLFDP. The tool operates in two modes, i.e., real time and postseason. In real-time mode, TyFET references the real-time TC bulletin of the CMA, providing PEs for track forecasts and relative errors for intensity forecasts based on all available real-time forecast guidance. The real-time verification results from TyFET are stored in the "STI/CMA Tropical Cyclone Forecast Dataset For TLFDP," which can be accessed using visualization tools such as the WNP Tropical Cyclone Retrieval System (see section 5d for further information about this system). In postseason mode, TyFET uses the best track data as reference, and its major outcomes were summarized and presented in the annual verification reports released by the TLFDP.

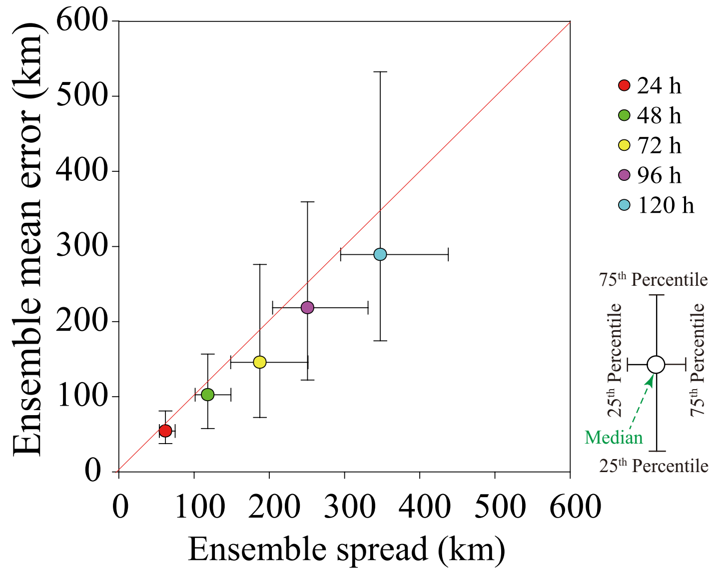

Fig. 4. Joint plot of ensemble mean error and ensemble spread for track forecasts from the ECMWF-EPS in the 2022 WNP TC season. Forecast lead times are shown by different colors of the solid dots defined by the mean values of the position errors and ensemble spreads. The two ends of the two crossing lines denote the 25% and 75% quantiles of the ensemble spread (abscissa) and the ensemble mean error (ordinate), respectively.

Since the beginning of the project, the TLFDP utilized the Model Evaluation Tools (METs), developed by the NCAR–NOAA Developmental Testbed Center, for real-time verification of precipitation forecasts and other model outputs including temperature, wind, and relative humidity. The MET products are available twice daily in real time for both the NCEP GFS and the regional model of the Shanghai Weather and Risk Modeling System. Observational data from automated weather stations are used in the verification of 24-h accumulated precipitation.

4. Research on TC forecast skill

Through the development and application of the aforementioned forecast verification metrics, the TLFDP facilitated a series of studies that deepened and widened our understanding of TC forecast skill. Additionally, the project was the first to address the uncertainty in TC forecast verification that might result from uncertainties in best track analyses.

a. TC track. A representative study on TC track forecast skill was conducted by Yu et al. (2022b), who studied the annual mean PE of TC track forecasts from the CMA, JTWC, and RSMC Tokyo. They identified that the overall track forecast skill has improved by the equivalent of a 48-h (2-day) increase in lead time over the past 30 years, whereby recent 72-h forecast errors are approximately the same as the 24-h forecast errors in the early 1990s. However, noticeable stepwise periods with superposed short-term fluctuations in skill were evident. The stepwise improvements were found to be highly related to the development of objective forecast guidance and application strategies. A further 2-day improvement in TC track forecast lead times might be projected for the coming 15 years up to 2035, at which time the projected 120-h PEs might be comparable with the current 72-h PEs. The study suggested that the reduction in analysis errors is a major contributor to the improvements in TC track forecasts, which is most likely associated with improvements in the initial analyses of

NWP models. The uncertainties in determining the true position of a TC impose limits on the accuracy of the initial analysis for TC track forecasts.

Against this backdrop of substantial progress in improving the overall performance of TC track forecasts over the past 30 years, many forecasts still exhibit extremely large errors. Xu et al. (2016) investigated TCs with abnormal track forecast errors at a lead time of 48 h produced by the ECMWF-IFS during 2010–13. They found that most of those cases were affected either by interaction with land or by interaction with other areas of low pressure. Forecast uncertainty analyses based on EPSs or combinations of several independent models showed that it was possible to alert forecasters to predict such abnormal situations. According to Chen et al. (2022b), the average value of the abnormal track errors for a specified forecast guidance could be 2–3 times that of its annual mean error if the top 10% of errors were used as the definition. These abnormal cases, or forecast busts, should receive more attention to improve TC track forecast skill, and additional case studies should be investigated to identify potential error sources. For example, Chen et al. (2022a) found that the official guidance and NWP models both struggled to correctly predict the propagation speed of Supertyphoon Lekima (2019), although they did predict its direction of motion reasonably well.

b. Intensity and wind structure. In the early years of the TLFDP, Yu et al. (2013b) studied the TC intensity forecasts from six operational models. They found that the models exhibited skill in predicting TC intensity or intensity change. Specifically, all the models had skill in terms of intensity category and trend forecasting at lead times longer than 24 h. Based on this finding, the CMA Expert Team on Typhoon and Marine Meteorology made an official recommendation to the CMA modeling teams to commence issuing real-time TC intensity forecasts in addition to track forecasts.

Xin et al. (2021) evaluated TC intensity forecasts from five global EPSs during the 2015–19 WNP TC seasons. They found that the ensemble mean generally underestimated the TC intensity and that the ensemble probability forecasts were underdispersed. The quality of the EPS forecasts improved consecutively at long lead times (LLTs) during the 5-yr period. However, in comparison with a baseline climatology forecast method, EPSs still had no skill for lead times shorter than 120 h. Furthermore, there were no obvious improvements in forecasts of intensity change, with rapid changes in intensity remaining a notable challenge.

Lu et al. (2022b) studied the forecast skill of the ECMWF-IFS and the ECMWF-EPS in terms of the surface wind fields in the 2020 WNP TC season based on MODE scores. The STI/CMA satellite-retrieved TC size dataset was used as ground truth. Results revealed that both the ECMWF-IFS and the ECMWF-EPS were skillful at predicting the radius of 34-kt winds within 72 h and the radii of 50- and 64-kt winds within 48 h if using a MODE synthetic score of 0.5 as the threshold. Poor model performance found at around the time of landfall or beyond 72 h was highly correlated with the poor track forecasts.

Impacts of the model settings or initial fields on TC forecasts were also studied on a case-by-case basis. M. T. Xu et al. (2022) analyzed the effect of the initial axisymmetric wind structure and moisture on the prediction of the peak intensity of Supertyphoon Lekima (2019) using the Typhoon Ensemble Data Assimilation and Prediction System (Li et al. 2019), which is a 20-member regional EPS developed by the STI. The peak intensity uncertainty was found sensitive to both the initial primary circulation outside the radius of maximum wind and the initial secondary circulation. Initial inner-core moisture was also found to be critical in the development of inner-core convection. Liu et al. (2022) investigated the impact of vertical resolution on the prediction of the structure of the same storm. The results indicated that the vertical grid spacing above 1-km height had a marked influence on the predicted warm-core and eyewall structure of the TC and that a vertical spacing of 200 m might be a critical threshold value, as evaluated by kinetic energy spectra.

Further studies are needed to determine the applicability of the findings derived from this case study to other TCs.

c. Precipitation. As summarized by Yu and Wang (2018) and Cheung et al. (2018), the axisymmetric and asymmetric rainfall distributions, together with their major controlling parameters, such as environmental vertical wind shear, TC intensity and motion, and coastline orientation, play a crucial role in the distribution of rainfall associated with LTCs. However, accurately forecasting rainfall remains a formidable challenge for operational forecasters. Yu et al. (2020) presented results from object-based verification of rainfall forecasts from the Australian Community Climate and Earth System Simulator for LTCs over China during 2012–15. The performance measures for 24-h forecast accumulations were found optimal at 0–24-h forecast lead times, and they deteriorated at longer lead times. Forecast skill also decreased with increase in rainfall amount. The CRA analyses revealed that the errors arose mostly from the rainfall patterns, followed by displacement errors, particularly for very heavy rain. He et al. (2022) used the CRA method to evaluate the rainfall forecast performance of the Global and Regional Assimilation Prediction System TC model through a case study. They revealed that the errors in rainfall pattern and volume gradually increased as the typhoon moved further inland. The interaction between paired TCs or between a TC and its environment also added substantial uncertainty to precipitation forecasts (Bao et al. 2015; Duan et al. 2020; Qi and Cao 2013).

d. Impact of uncertainties in best track datasets on TC forecast skill analyses. It has long been noted that discrepancies often exist among the "best" tracks from different agencies (Lei 2001; Yu et al. 2012a; Bai et al. 2019; Bai et al. 2022a,b). The reasons are mainly attributable to the inherently subjective analysis processes of the determination of best tracks and to differences in the period for averaging wind speed used by different agencies. The forecast verification team of the TLFDP noticed that such uncertainties in the best track had a remarkable impact on the forecast verification results. They were the first to present such findings, which were published in the annual verification report for the 2017 WNP TC season (G. M. Chen et al. 2021). As illustrated in Fig. 5, the largest difference in track errors reached 16% of the mean value at 72 h and 22% at 120 h for the CMA official forecast guidance in 2022, when using different best track datasets as reference. The largest difference in intensity errors

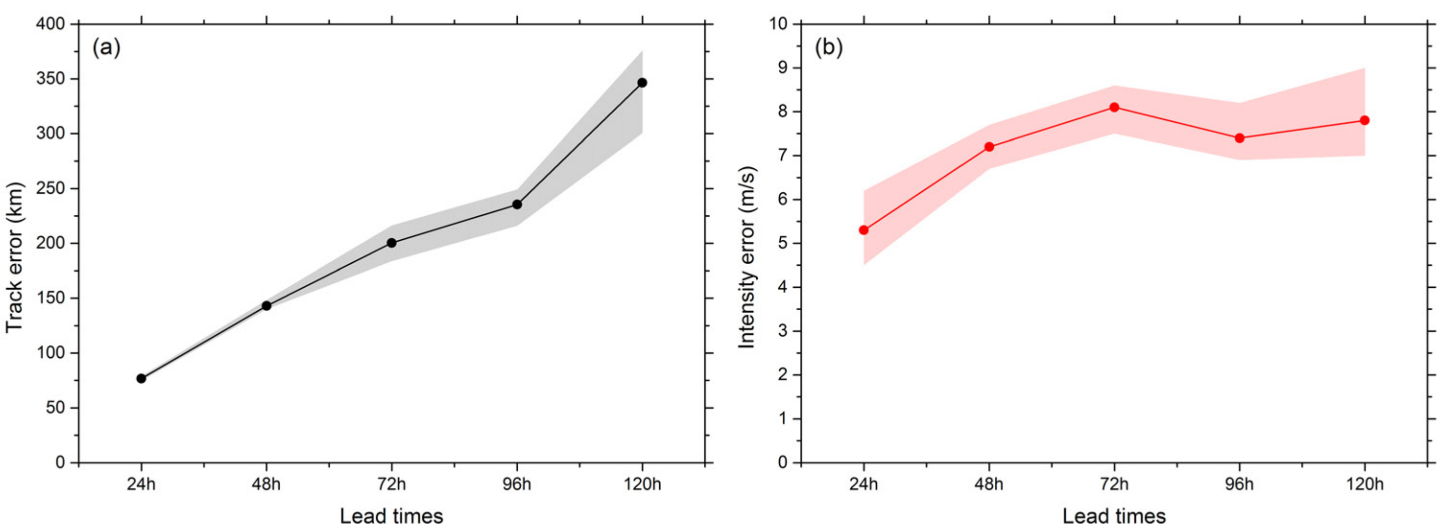

Fig. 5. Annual mean (a) PEs for track and (b) RMSEs for the intensity of the CMA official forecast guidance in 2022. The upper and lower bounds of the shaded area represent the maximum and minimum values, respectively, derived from the results using three different best track datasets as reference; the solid line shows the mean values. The three best track datasets were from the CMA, JTWC, and RSMC Tokyo.

reached 14%–32% of the mean values at 24, 48, 72, 96, and 120 h. It is worth noting that similar uncertainties should also exist in the verification results for wind structure and precipitation owing to the uncertainties in the determination of "true" values.

5. Development of new TC forecasting techniques

Based on the various TC forecast products it collected and its forecast verification activities, the TLFDP made substantial effort to develop new TC forecasting techniques (refer to appendix D for the list). Specifically, the multi-NWP model ensemble techniques or model output calibration techniques promoted efficient application of NWP models, including EPSs, in operational TC-related forecasting and warning activities.

a. Track forecast. Qi et al. (2014) proposed a selective ensemble-mean technique (SEAV) for producing TC track forecasts from EPSs, which exhibited improved skill of 5%–30% over relevant ensemble means for lead times up to 72 h. At 24 h, the SEAV skill sometimes surpassed that of high-resolution deterministic models. The core of SEAV comprises two components (Fig. 6, left panel): one uses only those EPS members with short lead-time (SLT) errors that meet a given criterion, and the other linearly translates all the selected members according to their observed SLT position. Du et al. (2016) further investigated the impacts of the time-lagged ensemble and the multicenter EPS grand ensemble on the SEAV. They found that the time-lagged ensemble yielded marginal changes to the SEAV, whereas the multicenter EPS grand ensemble could realize notable improvements in forecast accuracy. Based on four global and two regional operational deterministic models, a new multimodel ensemble forecast technique (SHME) was developed by Guo et al. (2019), which combined the ideas of the SEAV with a trend method for lead times longer than 72 h. Verification over a 3-yr sample showed that the SHME outperformed the best individual model, as evidenced by reductions of 5.5%–27% in forecast errors for lead times up to 120 h. Further extending the SEAV approach, Zhang and Yu (2017) developed a grand ensemble probabilistic track forecast technique (SEAV_P), which comprised EPS member selection, mean track shifting, and EPS-based probability ellipses. They achieved a 10% improvement in the mean track forecast errors

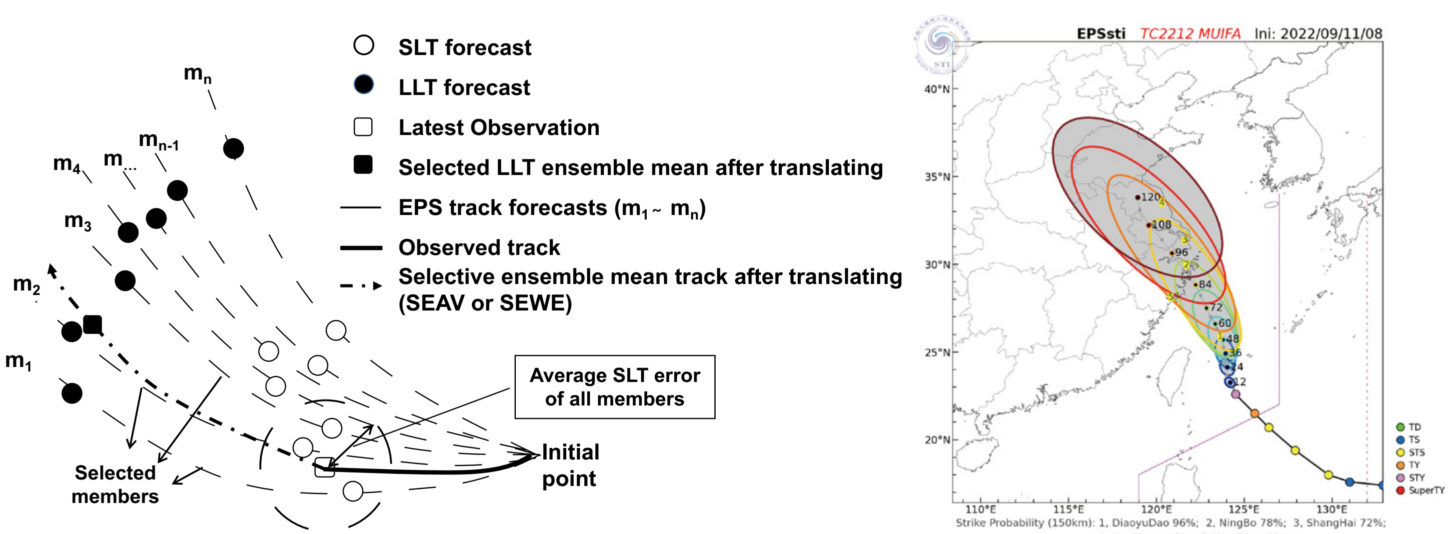

FIG. 6. (left) Schematic of the SEAV. The radius of the dashed circle represents the average SLT errors of all EPS members. The square at the center of the dashed circle represents the most recently observed position of a TC. In this figure, only three members (m_1, m_2, and m_3) that had SLT errors smaller than the average SLT error were selected to determine the LLT ensemble-mean position and track (black square and dashed line with an arrow, respectively), reproduced from Qi et al. (2014). (right) Example of a real-time forecast from the SEAV_P for TC Muifa (2022) initialized at 0000 UTC 11 Sep 2022. The thick black line is the past track and the thin black line labeled with lead times from 12 to 120 h is the forecast track. Colored ellipses show 70% probabilities for forecast TC positions.

over the grand ensemble of the ECMWF-EPS and the NCEP-GEFS, and a 4.5% improvement over the ECMWF-EPS at 24 h for the hit ratio of 70% probability ellipses. The SEAV technique and its derivative SHME were adopted as objective forecast aids into the CMA's operational guidance suite in 2012 and 2017, respectively (Yu et al. 2022b). The SEAV_P technique has also been implemented in the operational guidance suite of the East China Regional Meteorological Center since 2017. Figure 6 (right panel) shows an example of a real-time forecast from the SEAV_P for TC Muifa (2022). The SEAV approach has also been adopted by several groups outside the TLFDP. For example, Nishimura and Yamaguchi (2015) applied the SEAV approach to a set of TC track forecasts produced by 11 operational global deterministic models. Compared with a simple all-member ensemble mean, they obtained reductions of 14.4%, 7.4%, and 4.7% in forecast errors at 24-, 48-, and 72-h lead times.

b. Intensity forecast. Chang et al. (2012) compared several different multimodel ensemble techniques for predicting TC intensity. They found that the equally weighted ensemble technique (EAVI) generally outperformed each of the individual models and other multimodel ensemble techniques, e.g., the weighted ensemble based on initial or SLT forecast errors. Yu et al. (2015, 2013b) revealed that TC intensity forecast errors of operational NWP models could be calibrated because they are highly correlated with TC intensity, size, initial model error in intensity, and environmental circulation features. A multimodel consensus for TC intensity forecasts (CAVI) was then established based on statistically calibrated model forecasts, which showed improvement in skill of 15%–20% over climatology and persistence. Moreover, CAVI was found much more skillful than the consensus of original model outputs.

P. Y. Chen et al. (2016) developed the Probabilistic Climatology-based Intensity Forecast (PCIF) scheme by searching for analogous historical cases that met criteria developed from climatology and persistence predictors. The ensemble size varied between 20 and 51. A verification study of the 2018 and 2019 TC seasons showed that the PCIF scheme outperformed the best EPS at lead times out to 108 h (Xin et al. 2021). This indicated that the PCIF scheme could be used not only as a reference scheme for evaluating other probabilistic intensity forecast guidance, such as EPSs, but also as a provider of skillful guidance.

Xin (2021) proposed a deep neural network calibration model (DNNI) for the mean intensity forecasts of the ECMWF-EPS. Subsequently, a calibrated probabilistic forecast scheme (DNNI_P) was established, based on the assumption that the ensemble spread remained the same as that of the EPS. For a 24-h lead time, DNNI_P achieved an improvement of up to 40% (21%) in forecast skill over the ensemble mean (ensemble probability) forecasts. Meanwhile, Chan et al. (2021) applied a decision-tree-based machine learning algorithm, named XGBoost, to calibrate TC intensity forecasts from both the ECMWF-IFS and the ECMWF-EPS. Their findings indicated that XGBoost reduced negative biases and improved overall accuracy. The technique also showed encouraging potential in capturing the rapid intensification (RI) during the early stage of TC development. Tam et al. (2021) developed TC intensity guidance for RI (TINT-RI) that combined logistic regression and the naïve Bayes classifier using predictors describing physical and environmental conditions extracted from ECMWF model forecasts. The technique provided TC RI forecasts with a lead time of up to 48 h. Verification results showed that TINT-RI generated reliable probabilistic guidance for TCs undergoing RI.

c. Precipitation forecast. To improve TC rainfall nowcasts, the HKO developed a radar echo-tracing scheme that separates the motion of the spiraling rainbands from the overall movement of the associated TC. This scheme has been applied to the Short-range Warning of Intense Rainstorms in Localized Systems nowcasting system of the HKO (Woo et al. 2014). Additionally, the HKO developed a postprocessing technique to calibrate the Extreme

Forecast Index of the ECMWF-EPS (Wong 2019). The actual climatological distribution of daily rainfall is used to construct the Extreme Observed rainfall Index to generate daily rainfall forecasts for subsequent days, and this has been applied in forecasting TC-related heavy precipitation by the HKO. Guo et al. (2022) proposed a deterministic-EPS-combined probabilistic TC (DEPR-TC) rainfall forecast scheme, which combines high-resolution deterministic forecasts from the ECMWF-IFS with relatively low-resolution ensemble forecasts from the ECMWF-EPS. The rainfall forecasts from the ECMWF-IFS are used as reference to calibrate the frequency distribution of the EPS forecasts, with the EPS members selected according to the SLT error of the TC track as in the SEAV. Then, a neighborhood method is used to calculate the probability of precipitation, accounting for the values of all grid points within a predefined spatial range. Experiments on four LTCs demonstrated that DEPR-TC had skill over the climatological scheme.

d. Structure forecast. The consensus approach for TC track or intensity prediction is traditionally based on the TC track or intensity outputs of a vortex tracker run on the fields of the underlying NWP or EPS models, rather than based directly on gridded model outputs. Such an approach relies on the accuracy or representativeness of the vortex tracker, and it is generally unsuitable for predicting TC structure. Zhang et al. (2021) introduced a unified TC ensemble mean forecast (UEMF) based on the feature-oriented mean method, which spatially aligns the TC-related features in each ensemble field to their geographical mean positions before the amplitude of their features is averaged. A test with 219 TC cases showed that the UEMF not only had similar TC track and intensity forecast skill to the traditional consensus approach but also provided forecasts of the 3D structure of the primary circulation of a TC with greater accuracy than that of the arithmetic mean of the unadjusted ensemble fields. The improvements in the RMSEs of 5-day forecasts were approximately 10%–20% for surface wind fields within a radius of 600 km of the TC center.

e. Development of visualization tools aiding TC forecast and warnings. A human–computer interactive platform, known as the WNP Tropical Cyclone Retrieval System (TCRS) (Lu et al. 2021), has been in continuous development by the STI to assist forecasters in viewing and analyzing the rich data collected by the TLFDP. Users of TCRS can query historical TC information, such as track, intensity, wind, precipitation, and corresponding large-scale atmospheric circulation data, together with real-time forecasts and forecast verification results. The historical and real-time information can be combined to assist in TC forecasting and preparing TC impact warnings according to various predesigned rules, such as track similarity, genesis origins, and climatological statistics. Figure 7 shows an example application of the TCRS in supporting the generation of an impact forecast associated with TC Khanun (2023). In this example, TC Saomai (2000) was identified using the rule of track similarity. The winds and precipitation induced by Saomai (2000) were displayed simultaneously to provide hints regarding the potential impact that Khanun (2023) might have on mainland China associated with such a sharply turning track over the ocean. A WeChat applet version of TCRS was developed in 2019 to enable the public to use their mobile phones to query the latest TC forecasts and historical TCs. It should be noted that only a Chinese-language version is currently available for the TCRS.

NCAR's TCGP developed an ensemble diagnostic product suite to support forecasters. These products were computed from the two-dimensional fields of global EPSs using a diagnostics package (Alessandrini et al. 2018). Visualizations of these ensemble diagnostics were developed for parameters including storm intensity, radius of maximum wind, minimum sea level pressure, maximum potential intensity, and vertical wind shear. For each diagnostic parameter, the value is plotted along the corresponding track from the ensemble to supply a spatially

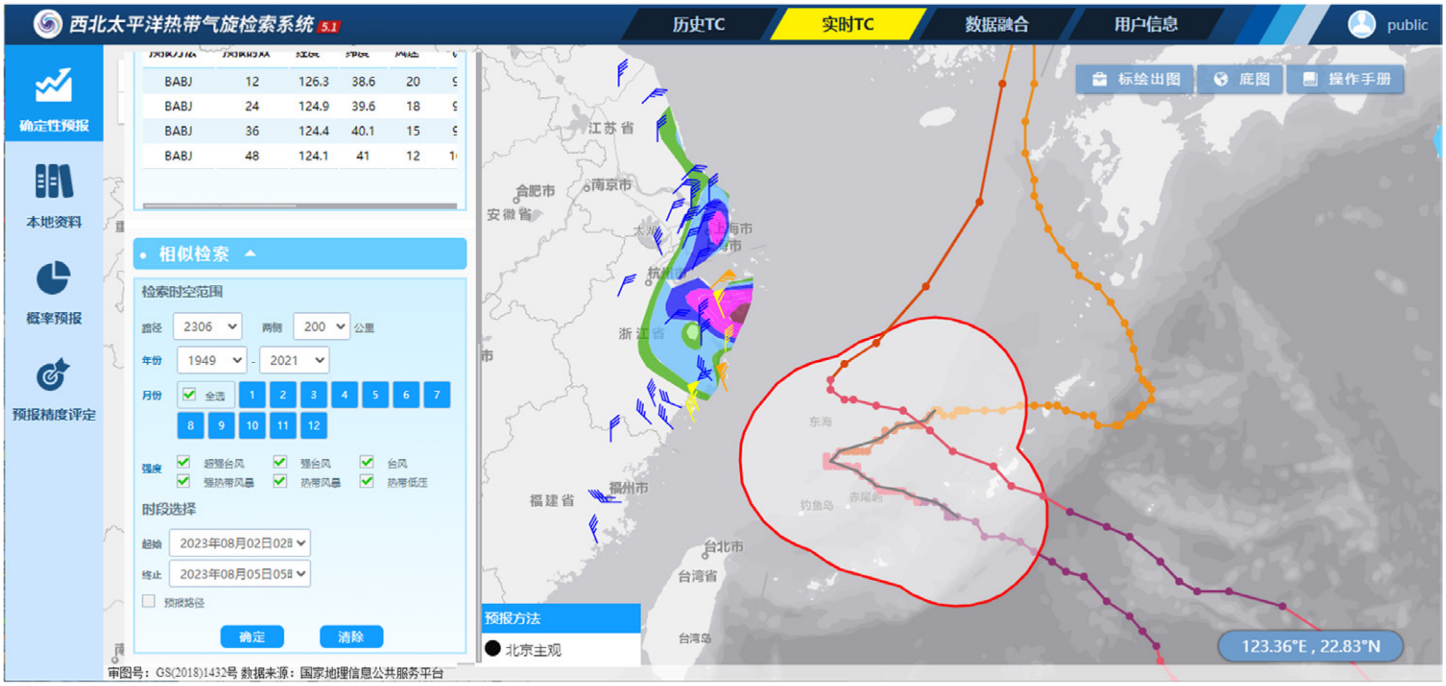

Fig. 7. **Example of obtaining decision-making information for real-time TC forecasting and impact warning with the help of the TCRS. The track with a dark gray segment is that of TC Khanun (2023), and the other track is that of TC Saomai (2000), identified using the rule of track similarity. The wind barbs and color-filled regions on land represent the wind and precipitation, respectively, caused by TC Saomai (2000) in mainland China.**

varying view of the diagnostic along the respective storm-track scenarios. These diagnostics are provided for the 30-member GEFS from NCEP. Figure 8 shows an example diagnostic plot for vertical wind shear along the tracks predicted by the GEFS members for Hurricane Teddy (2020).

One goal of Phase IV of the TLFDP was to provide probabilistic TC model output to support impact assessment and hazard communication. Along these lines, NCAR released the HurricaneRiskCalculator web app (Vigh et al. 2021) in November 2021. Built on serverless cloud-based architecture, this tool supplies location-based wind hazard services to users based on their specified address. The wind hazard information is driven by the probabilistic outputs of the Massachusetts Institute of Technology's Forecasts of Hurricanes using Large-Ensemble Outputs (Lin et al. 2020). The information provided to a user encompasses the probabilities that the wind at the location of the user would exceed various thresholds ranging from tropical storm (34 kt) up to category 5 (>137 kt), the earliest possible arrival time of winds of each threshold, the most likely time that such winds would arrive, the most likely time that such winds would depart, the latest possible time that such winds would depart, and the expected duration of the winds. The web app delivers the information to the user as a comprehensible plain-text narrative as well as an "Advanced View" featuring tables and graphics showing the time-varying cumulative density function.

6. Surveying, workshop, and training activities

A series of surveys, workshops, training activities, and visitor programs have been undertaken under the umbrella of the TLFDP, the most noteworthy of which are listed in appendix E. These activities facilitated better understanding of forecaster needs from diverse perspectives, educated the user community (including weather forecasters and related decision-makers) on the latest TC forecasting techniques and data resources, and promoted active participation of forecasters in the application of new technologies and new datasets.

A survey on the operational practices regarding TC forecast verification in the WNP region collected information from the relevant operational TC forecast centers in 2012, including all members of the ESCAP/WMO Typhoon Committee, the RSMC Tokyo–Typhoon Center,

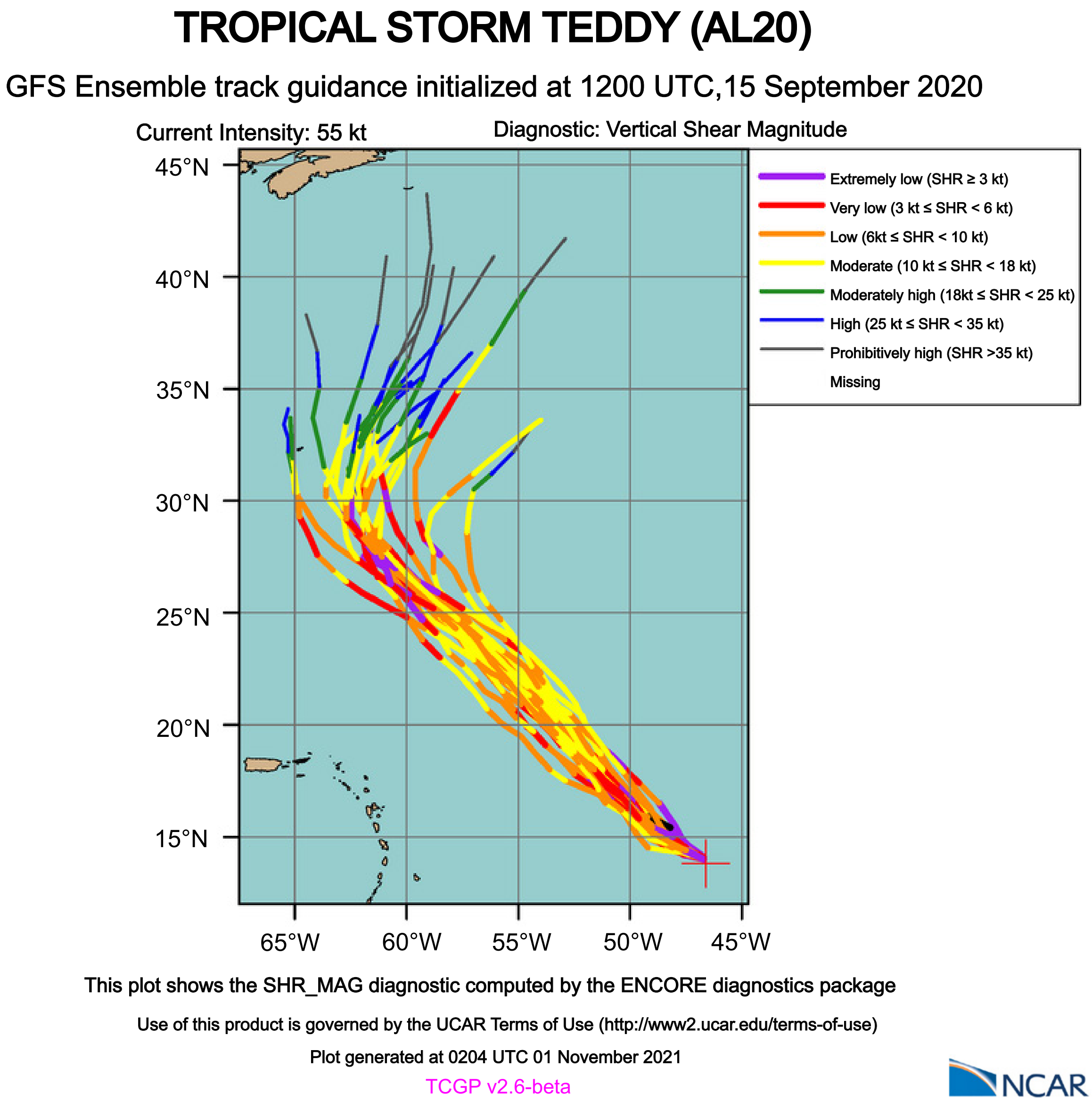

Fig. 8. Plot demonstrating how diagnostics of environmental conditions vary across the 30-member GEFS ensemble for Hurricane Teddy (2020) for the run initialized at 1200 UTC 15 Sep 2020. The colors represent the values of the corresponding diagnostic parameter, in this case, vertical wind shear. The lines represent track forecasts by the ensemble members.

and JTWC. Yu et al. (2012b) summarized the major findings, which identified weaknesses in the verification of probabilistic forecasts, TC-related precipitation forecasts, and high-wind forecasts. The results guided subsequent activities of the TLFDP on TC forecast verification. Another survey was conducted in 2012 (Lei et al. 2016b) to assess the opinions of the public and forecasters regarding typhoon forecasts and warnings in Shanghai. Awareness of the public in Shanghai regarding the availability of weather information and TC warnings was reasonably high, and 70% of the public respondents identified deterministic products as most desirable (compared with probabilistic products). Additionally, the forecasters ranked the landfall position of a TC as the greatest challenge in TC forecasting, followed by intensity change and the rainstorm impact zone.

In 2021, a pilot project under the WMO Seamless GDPFS framework, called the Tropical Cyclone-Probabilistic Forecast Products (TC-PFP), was initiated under the umbrella of the TLFDP. TC-PFP aimed to coordinate the RSMCs and other forecast centers in identifying best practices for probabilistic TC forecasts under the framework of a value-cycle approach to accelerate the “pull-through” of probabilistic information to impact forecasts (Dunion et al. 2023). As a starting point of the TC-PFP project, the RSMCs and forecast centers were surveyed in 2021 to gain insights into their current efforts and plans to develop probabilistic forecasts. The survey also examined their plans both to support their users, communities, and stakeholders and to address various forecasting challenges. Burton and Vigh (2021) presented the major findings derived from that survey. For example, most forecast centers use cones/circles to express track forecast uncertainties, but the sizes of the cones/circles are determined in several different ways (static based on historical average forecast errors vs dynamic based on ensemble outputs). Another finding was that prediction of TC formation was a more difficult challenge operationally compared with forecasting a TC track. This is partly attributed to the need to track disturbances well before they form, which presents certain logistical and data-related challenges. At the time of the survey, fewer operational centers provided products for TC genesis uncertainty than provided products for TC track prediction, but those that did generally used a graphical approach to convey the probability of a TC forming within a specific region. Outputs were typically color-coded with numerical probabilities and were based on cumulative or time-based representations of when and where TC formation was possible. The TC-PFP survey also helped determine the content for a TC-PFP-hosted workshop held in June 2021 that identified best practices of a value-cycle approach to probabilistic forecasts of TC formation and position. The 2022 Tenth International Workshop on Tropical Cyclones (IWTC-10), held in Bali (Indonesia), highlighted the results of the TC-PFP survey and the outcomes of the workshop.

Another important TLFDP activity involved the postevent survey and assessment of TC impacts. Such assessments were invaluable for supporting research and development of real-time impact assessment tools and for developing public education resources on natural hazards. Supertyphoon Mangkhut impacted Hong Kong on 16 September 2018, bringing the most serious and widespread destruction to the territory experienced in the past 3 decades (Choy et al. 2022a). Following landfall, the HKO conducted a series of postevent field visits and damage surveys that were summarized in Choy et al. (2022b). Mangkhut resulted in direct economic losses in Hong Kong estimated at HKD 4.6 billion (USD 0.49 billion), approximately 3.8 times greater than the estimated losses due to Supertyphoon Hato, another typhoon that wreaked havoc on Hong Kong and the Pearl River Estuary in 2017. On the other hand, the economic losses in the Guangdong–Hong Kong–Macao Greater Bay Area due to Hato were approximately three times greater than those associated with Mangkhut. This could be attributed to several factors including early and effective warning for Mangkhut, increased public awareness and greater preparedness for Mangkhut since the strike of Hato in 2017, and infrastructure enhancements that were introduced in the areas of major impact, as discussed in Choy et al. (2022b). Substantial differences in the translation speed, intensity change, and wind structure between the two events also contributed to the different impacts caused by the two TCs.

Over the life of the TLFDP project, a series of workshops and training courses on TC forecasting technology were held, organized either solely as part of the TLFDP or in collaboration with EXOTICCA and UPDRAFT. Hundreds of forecasters and researchers from numerous agencies and organizations participated in these events. Seventeen research fellowship projects were hosted by the STI or the HKO under the auspices of the ESCAP/WMO Typhoon Committee. The topics of these fellowships dovetailed with the themes and activities of the TLFDP. The research fellows were from Malaysia, the Philippines, Thailand, Vietnam, the DPR Korea, and China. These training and research activities played an important role in involving representatives from typhoon-prone countries as much as possible and facilitated timely exchange of knowledge and transfer of the latest advances in TC forecasting technology among forecasters and researchers.

7. Summary

The TLFDP, assigned by the WMO from 2010 to 2022, contributed to a variety of achievements and technological advances in the observation, analysis, and forecasting of TCs. Throughout the 13 years and four phases of the TLFDP, there was notable promotion of international cooperation in data sharing, development, application, and verification of forecasting techniques, and capacity building. The progress could be attributed to the contributions of the implementation teams and the 40 participating agencies/organizations/projects. Major achievements included the collection and sharing of 17 TC datasets, publication of over 90 research papers, development of 14 new TC forecasting techniques, and the issuance of over 10 forecast verification reports.

The activities of the TLFDP highlighted and promoted the availability of diverse types of TC datasets, ranging from extensive collections of real-time forecasts, retrospective research-grade observations, observation-derived products, and TC-related impact data. The TLFDP workshops and training activities provided opportunities to identify crucial data gaps and areas requiring improvement in existing datasets or the creation of new datasets with feedback from a broad audience. The utilization of existing datasets by international communities was substantially enhanced beyond what would have otherwise occurred. The TLFDP also contributed to "cross-pollination" between dataset producers and to progress toward creation of quality datasets, documentation or publication on their characteristics, and best practices for data dissemination.

The TLFDP realized substantial progress in TC forecasting capability through a series of in-depth analyses on the improvement of forecasting skill over the decades. For example, track forecast lead time was found to have increased by 48 h (2 days) over the past 30 years. Analysis also identified the intrinsic relationship between the progress in TC track forecasting and the development of objective forecast guidance and application strategies. Research also demonstrated the vital importance of track forecast skill in determining the forecast skill of the structure, precipitation, and impact of TCs. Nevertheless, major challenges remain regarding the forecast uncertainties in TC landfalling processes, cases with very large track forecast errors, and prediction of RI and extreme rainfall events. The object-based verification metrics helped identify the sources of errors in TC rainfall forecasts, providing interpretative guidance for further improvement of the models.

Furthermore, prominent new ideas on TC forecast technique developments have been studied, such as the SEAV method in track forecasting, which inspired a series of follow-up studies and expanded the operational application of EPS products. The new techniques developed for forecasting TC intensity, precipitation, and structure engendered new ideas for correcting model biases or efficiently integrating ensembles. The final years of the TLFDP witnessed rapid development in artificial intelligence or machine learning techniques in relation to TC prediction with promising results, as embodied by the consecutive development of DNNI, XGBoost, and TINT-RI. A combination of NWP and artificial intelligence should provide a bright future for further improvement in TC forecasting. Other efforts involved combining Big Data from social, economic, or community infrastructures to develop impact-based forecast systems to foster improved decision-making processes and reduced disaster risk.

The routine release of annual TC forecast verification reports was another noteworthy legacy of the TLFDP. This activity was unique because the reports included many available TC forecast guidance techniques, both objective and subjective, and details of informative new metrics. The reports also considered the uncertainties resulting from best track datasets and included verification of EPS products. Furthermore, the TLFDP succeeded in expanding TC forecast verification metrics beyond those traditionally used to include metrics that provide more detailed or object-based information. The introduction of TyFET and METs provided practical tools for TC forecast verification activities.

A key objective of the TLFDP was to enhance the capability of weather forecasters and related decision-makers to effectively use the most advanced TC forecasting techniques. During the period of TLFDP activity, eight training courses and project workshops, together with five surveys, were organized either independently or jointly with parallel projects. These capacity development activities led to active evaluation and application of new TC data and forecasting techniques and linked the TC research and operational communities in fostering valuable knowledge transfer, collection of feedbacks on TC datasets and forecast products, and personnel training. Forecasters from many TC-prone countries were extensively involved in training courses and workshops, undertaking research fellowship projects, and participating in the development of datasets or forecasting techniques.

Although the ultimate purpose of the TLFDP was to prevent and reduce disasters from LTCs, it should be noted that major TC-related impacts could also occur when TCs are far out to sea away from any coast. Therefore, the activities under the TLFDP were not strictly confined to LTCs. Moreover, while the TLFDP primarily targeted the WNP region, the active involvement of participating scientists from other basins contributed substantially to the overall effort through the lending of their expertise and the broadening of the horizon of the project. The project's activities were further expanded to global basins in the latter years with the launch of TC-PFP and the construction of the Leading Center of Tropical Cyclone Forecast Verification. These activities shared the knowledge and insights gained through the TLFDP with the global TC community. Many publications and activities on similar topics that are not mentioned in this paper also provided valuable reference for TLFDP activities.

As an international cooperative project under the WMO framework, the implementation process of the TLFDP also encountered numerous challenges. These challenges included the multicultural working environment, communication between native and nonnative English speakers, and the differences in conceptual ideas or approaches owing to various levels of economic developments. One major issue was the lack of dedicated funding. The workshops and training activities that formed vital components of the TLFDP were mainly funded by the WMO. They played an indispensable role in many aspects of the project, such as strengthening communication between researchers and forecasters, identifying deficiencies in existing data and technologies in relation to user needs, promulgating new datasets and technologies, and promoting new ideas on the development of datasets and technologies. However, all the concrete research and/or development activities undertaken by participating organizations or institutions were conducted on a voluntary basis with self-funding. Unfortunately, several planned activities were canceled owing to lack of funding. For example, a vision of the TLFDP was to examine how TC data collection in various basins and data sharing could be improved through a multinodal data sharing network. Another vision was to develop a netCDF-based Common Data Model to reduce obstacles to data sharing and research-to-operation processes. However, neither of these visions progressed because of lack of funding. Therefore, it is imperative that dedicated funding mechanisms be established for future projects like the TLFDP. Unforeseen global incidents such as the COVID-19 pandemic also had an adverse impact on the implementation of activities during Phase IV of the TLFDP. Although the rapid development of video conferencing alleviated communication difficulties to some extent, it was far less effective than face-to-face communication. The pandemic also led to suspension of in-person research fellowship attachments such as those coordinated by the Typhoon Committee.

The themes of Phase IV of the TLFDP and the launch of TC-PFP in 2021 clearly embodied the trends and shifts in focus toward probabilistic forecasting and impact forecasting, echoing the recommendations from the Ninth International Workshop on Tropical Cyclones (IWTC-9), held in 2018 in Hawaii (USA). The importance of connecting science with services was reemphasized at IWTC-10. However, the disaster prevention decision-makers were largely involved indirectly in the TLFDP, e.g., through simply listening to briefings from forecasters or reading-related reports. Consequently, it was difficult to quantitatively assess how the behavior of the decision-makers might have been affected by the TLFDP. Although the TLFDP concluded as a Forecast Demonstration Project at the end of 2022, further attention should be directed toward developing TC forecasting technologies with the intention of improving the communication to users of information on forecast uncertainty, as outlined in the implementation plan of not only WWRP but also other related international cooperative mechanisms, e.g., the newly established Asia–Pacific Typhoon Collaborative Research Center (https://www.ap-tcrc.org). Finally, the engagement of social scientists was very limited, although the importance of their potential contribution was recognized at the inception of the project. More action related to social sciences should be encouraged and integrated into future projects.

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Data availability statement. The availability of all datasets associated with the TLFDP is listed in appendix B.

APPENDIX A
Title

Table A1 is a list of agencies, organizations, and projects participating in the TLFDP.

Table A1. List of agencies/organizations/projects participating in the TLFDP (alphabetic order according to abbreviation/acronym). An asterisk (*) indicates a provider of real-time forecast data.

Abbreviation/acronym	Full name
AP-TCRC	Asia–Pacific Typhoon Collaborative Research Center
BOM*	Australian Bureau of Meteorology
CAMS	Chinese Academy of Meteorological Sciences
ECMWF*	European Centre for Medium-Range Weather Forecasts
ECRMC*	CMA East China Regional Meteorological Centre
EXOTICCA	ESCAP/WMO Typhoon Committee Cross-cutting Project and WWRP Research and Development Project 'Experiment on Typhoon Intensity Change in Coastal Area'
HRD	NOAA/AOML Hurricane Research Division
IMD	India Meteorological Department
ITMM*	CMA Institute of Tropical and Marine Meteorology
JMA*	Japan Meteorological Agency
JTWC*	Joint Typhoon Warning Center
JXMS	CMA Jiangxi Meteorological Service
KMA*	Korea Meteorological Administration
MacUni	Macquarie University
NBMO	CMA Ningbo Meteorological Observatory
MMD	Malaysian Meteorological Department
MSC*	Meteorological Service of Canada
NCEP*	NOAA National Centers for Environmental Prediction
NHMSV	National Hydro-Meteorological Service of Vietnam
NHC*	NOAA National Hurricane Center
NJU	Nanjing University
NMC*	CMA National Meteorological Center
NWP-TCEFP*	North Western Pacific Tropical Cyclone Ensemble Forecast Project
PAGASA	Philippine Atmospheric, Geophysical, and Astronomical Services Administration
RSMC La Réunion*	WMO Regional Specialized Meteorological Center La Réunion
RSMC Nadi*	WMO Regional Specialized Meteorological Center Nadi
RSMC New Delhi*	WMO Regional Specialized Meteorological Center New Delhi
RSMC Tokyo*	WMO Regional Specialized Meteorological Center Tokyo
TCWC Brisbane*	WMO Tropical Cyclone Warning Center Brisbane
TCWC Perth*	WMO Tropical Cyclone Warning Center Perth
TCWC Wellington*	WMO Tropical Cyclone Warning Center Wellington
TMD	Thai Meteorological Department
UKMO*	United Kingdom Meteorological Office
UniMiami	University of Miami
UPDRAFT	WWRP Research and Development Project "Understanding and Prediction of Rainfall Associated with Landfalling Tropical Cyclones"
WGM	ESCAP/WMO Typhoon Committee Working Group of Meteorology

APPENDIX B

Title

Table B1 is a list of the datasets participating in the TLFDP.

Table B1. List of the datasets participating in the TLFDP (alphabetic order for each type).

Type	Title	Owner	Temporal duration of the data	Accessibility	Reference(s)
Routine observations and derived products	NCAR TCGP Tropical Cyclone Real-time Data Stream of Operational Estimates	NCAR	2011–	https://hurricanes.ral.ucar.edu/repository/data/	
	Routine Observations and Derived Data for Tropical Cyclones Affecting China	CMA	1949–	https://tcdata.typhoon.org.cn/en/index.html	Lu et al. (2021), Ying et al. (2014)
	STI/CMA Satellite Retrieved Tropical Cyclone Size Dataset	CMA	1980– (Updated irregularly with the most recent major update incorporated data up to 2020)	https://tcdata.typhoon.org.cn/en/tcsize.html	Lu et al. (2017, 2022a)
	STI/CMA Potential Risk Indices for landfalling Tropical Cyclones in Mainland China (PRITC Dataset V1.0)	CMA	1949– (Updated irregularly with the most recent major update incorporated data up to 2021)	https://tcdata.typhoon.org.cn/en/qzfxzs.html	P. Y. Chen et al. (2019, 2021)
	STI/CMA Engineering Typhoon Model Dataset (STI-ETYM Dataset V1.0)	CMA	1949– (Updated irregularly with the most recent major update incorporated data up to 2021)	Available upon request (https://tcdata.typhoon.org.cn/en/product_metas.html)	Fang et al. (2020), Ye et al. (2018)
	The Extended Flight Level Dataset of Tropical Cyclones (FLIGHT+ Dataset)	NCAR	1997– (Updated irregularly with the most recent major update incorporated data up to 2019)	https://verif.rap.ucar.edu/tcdata/flight/	Vigh et al. (2020)
	Tropical Cyclone Best Track Datasets for the Western North Pacific Region	CMA, HKO, JTWC, RSMC Tokyo	1949– 1968– 1945– 1951–	http://tcdata.typhoon.org.cn/en/index.html https://www.hko.gov.hk/en/publica/pubtc.htm https://www.metoc.navy.mil/jtwc/jtwc.html https://www.jma.go.jp/jma/jma-eng/jma-center/rsmc-hp-pub-eg/besttrack.html	Lee et al. (2012)
Field experiment data	HKO Tropical Cyclone Aircraft Reconnaissance Flights Dataset	HKO	2011–	Dropsonde data are disseminated via GTS in real time; archived data available upon request (e-mail: a2@hko.gov.hk)	Hon and Chan (2022)
	NJU C-POL and 2-DVD Tropical Cyclone Dataset	NJU	2014–18	Available upon request (https://tcdata.typhoon.org.cn/en/product_metas.html)	G. M. Chen et al. (2019), Wen et al. (2018)
	NOAA Hurricane Field Program Dataset	NOAA	2005–	https://www.aoml.noaa.gov/hrd/data_sub/hurr.html	Rogers et al. (2013), Zawislak et al. (2022)
	Tropical Cyclone Landfalling Process Field Science Experiments Database (TCLPFieldSED)	CMA	2007–	Part of the data are disseminated to the public by https://tcdata.typhoon.org.cn/en/ywgc.html; The remaining are available upon request (https://tcdata.typhoon.org.cn/en/contacts.html)	Duan et al. (2019), Lei et al. (2017, 2019b), Lu et al. (2021)

(*Continued*)

Table B1. (*Continued*).

Type	Title	Owner	Temporal duration of the data	Accessibility	Reference(s)
Forecast data	NCAR TCGP Real-time Forecast Data	NCAR	2011–	https://hurricanes.ral.ucar.edu/repository/	
	STI/CMA Tropical Cyclone Forecast Dataset for TLFDP	CMA	2010–22	Freely open to TLFDP participants; available to the public upon request (https://www.tlfdp.net)	Chen et al. (2020), Tang et al. (2012), Yang et al. (2021)
	TIGGE Tropical Cyclone Ensemble Forecast Dataset	TIGGE data providers	2006–	https://rda.ucar.edu/datasets/ds330.3/	Yamaguchi et al. (2014)

APPENDIX C
Title

Table C1 lists TC forecast verification metrics used in the TLFDP.

Table C1. TC forecast verification metrics used in the TLFDP. An asterisk (*) indicates metrics used routinely in annual verification reports.

		Verification metric	Abbreviation	Reference(s)
Track	Deterministic	1. Position error*	PE	Yu et al. (2012b)
		2. Along-track/cross-track bias*	AT/CT	
		3. Skill score relative to a specified baseline*	SK	
		4. Track error rose diagram*	TER	Chen et al. (2013)
		5. Storm-centered scatterplot for position forecast bias*	PFB	
		6. Track forecast integral deviation	TFID	Yu et al. (2013a)
	Probabilistic	1. Hit ratio of the probability circle	HRPC	G. M. Chen et al. (2016)
		2. Joint plot of ensemble mean position error and ensemble spread of the position*	Error–Spread–Plot	
Intensity	Deterministic	1. Root-mean-square error	RMSE	Yu et al. (2012b)
		2. Mean absolute error*	MAE	
		3. Relative error/bias	RE/Bias	
		4. Percentage of forecasts with correct intensity change tendency	PCT	
		5. Skill score relative to a specified baseline*	SK	
		6. Taylor diagram*		G. M. Chen et al. (2016), Taylor (2001)
		7. Intensity category contingency table	ICCT	Aberson (2008), Chen et al. (2011), Yu et al. (2013b)
	Probabilistic	1. Brier score*	BS	P. Y. Chen et al. (2016)
		2. Brier skill score*	BSS	
		3. Reliability diagram		
		4. Threat skill score of rapid intensification	Tss	
		5. Joint plot of ensemble mean error and observation*		Lei et al. (2016a)
		6. Relative operating characteristics diagram	ROC	Xin (2021, 2021)
Genesis	Deterministic	1. Contingency table and retrieved scores		Lei et al. (2016a)

(*Continued*)

Table C1. (*Continued*).

		Verification metric	Abbreviation	Reference(s)
Precipitation	Deterministic	1. Contingency table and retrieved scores		
		2. Method for object-based diagnostic evaluation	MODE	Davis et al. (2006), Pak and Ri (2016), T. Xu et al. (2022)
		3. Contiguous rain area method	CRA	Ebert and McBride (2000), He et al. (2022), Yu et al. (2020)
	Probabilistic	1. Brier score	BS	Guo et al. (2022), Jiang and Yu (2019)
Surface winds	Deterministic	1. Root-mean-square error	RMSE	Xue et al. (2020)
		2. Bias	Bias	
		3. Frequency distribution of relative error	FDRE	
		4. Method for object-based diagnostic evaluation	MODE	Lu et al. (2022b)

APPENDIX D
Title

Table D1 lists TC forecast techniques developed by the TLFDP.

Table D1. TC forecast techniques developed by the TLFDP.

		Title	Abbreviation	Reference(s)
Track	Deterministic	Selective ensemble-mean technique for tropical cyclone track forecast by using ensemble prediction systems	SEAV	Du et al. (2016), Qi et al. (2014)
		Multimodel ensemble forecast technique for tropical cyclone track	SHME	Guo et al. (2019)
	Probabilistic	Probabilistic tropical cyclone track forecast scheme based on the selective consensus of ensemble prediction systems	SEAV_P	Zhang and Yu (2017)
Intensity	Deterministic	Equally weighted multimodel ensemble technique for tropical cyclone intensity forecast	EAVI	Chang et al. (2012)
		Calibrated multimodel consensus forecast technique for tropical cyclone intensity	CAVI	Yu et al. (2015, 2013b)
		Deep neural network calibration model for the ensemble mean intensity forecast	DNNI	Xin (2021)
		Machine learning in calibrating tropical cyclone intensity forecast of ECMWF EPS	MLIF	Chan et al. (2021)
	Probabilistic	Probabilistic climatology-based analog intensity forecast scheme for tropical cyclones	PCIF	P. Y. Chen et al. (2016)
		Calibrated probability intensity forecast based on DNNI	DNNI_P	Xin (2021)
		Objective forecast guidance on tropical cyclone rapid intensity change	TINT-RI	Tam et al. (2021)
Precipitation	Deterministic	Short-range Warning of Intense Rainstorms in Localized Systems for tropical cyclone	SWIRLS-TC	Woo et al. (2014)
	Probabilistic	Deterministic-EPS-combined probabilistic tropical cyclone rainfall forecast scheme using frequency matching method	DEPR-TC	Guo et al. (2022)
		Calibrated precipitation forecast based on the Extreme Forecast Index of ECMWF EPS	EFI-CAL	Wong (2019)
Structure	Deterministic	Unified ensemble mean forecasting of tropical cyclones based on the feature-oriented mean method	UEMF	Zhang et al. (2021)

APPENDIX E
Title

Table E1 lists noteworthy surveys, workshops, training activities, and visitor programs.

Table E1. Noteworthy surveys, workshops, training activities, and visitor programs.

Theme	Year	Reference(s)
Survey on the operational status of tropical cyclone forecast verification in the western North Pacific region	2012	Yu et al. (2012b)
Survey on public and forecasters' opinions on typhoon warnings in Shanghai, China	2012	Lei et al. (2016b)
Survey on the current probabilistic forecast products and treatment of uncertainty for tropical cyclone formation and track	2021	Burton and Vigh (2021)
Postevent survey and assessment of tropical cyclone impacts	2018, 2019	Choy et al. (2022a,b), Zhou et al. (2022)
Training courses on tropical cyclone forecast technology and project workshops	2010, 2012, 2016, 2018–22	
Visitor programs supported by the ESCAP/WMO Typhoon Committee Research Fellowship projects hosted by HKO and STI on tropical cyclone forecast technique development related to TLFDP	2011–22	

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