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# Objective satellite methods including AI algorithms reviewed for the tenth International workshop on tropical cyclones (IWTC-10)

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**Abstract**

Here we explore the latest four years (2019–2022) of using satellite data to objectively analyze tropical cyclones (TC) and issue recommendations for improved analysis. We first discuss new methods of direct retrieval from SAR and geostationary imagers. Next, we survey some of the most prominent new techniques in AI and discuss their major capabilities (especially accuracy in nonlinear TC behavior, characterization of model uncertainty and creation of synthetic satellite imagery) and limitations (especially lack of transparency and limited amount of training data). We also identify concerns with biases and unlabeled uncertainties in the Best Track records as being a first-order limitation for further progress in objective methods. The article concludes with recommendations to improve future objective methods, especially in the area of more accurate and reliable training data sets.


*Keywords:* AI; Tropical cyclone; Deep learning; Satellite imagery analysis

## 1. Introduction

Objective satellite methods are essential to help forecasters characterize tropical cyclones in terms of position, intensity and structure from a steadily increasing number of satellite observations and issue reliable warnings. In the past four years, sensors with higher spatiotemporal resolution have been made more widely available. The use of AI techniques for processing TC satellite imagery has been explored and led to some operational tools. Section 2 describes major sensors and conventional methods that improve TC analyses, notably in the inner-core. Section 3 specifically focuses on the development of AI methods for TC analysis and short-term forecasting, discussing their characteristics, the challenges that arise with them and the opportunities for emerging application. Section 4 highlights a drift in TC characteristics archived in the historical Best Track dataset due to evolving observing systems, which is a major

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concern for the development of accurate objective satellite methods. The report ends with a summary and conclusions in Section 5.

## 2. Major advancements in objective TC analysis methods in the past 4 years

Objective TC analysis involves the post processing of satellite and in situ observations and can be classified into three main types, each with increasing levels of complexity:

1. Meteorological product derivation: this type of analysis involves deriving meteorological products such as wind fields or cloud cover observations through post-processing of each sensor's raw data. This process includes calibration, bias removal, and denoising, which refers to reducing noise or artifacts in the images. The spatiotemporal resolution depends on the type of sensor used. Geostationary satellites provide high spatiotemporal resolutions but are limited to visible and infrared imaging observations. Low-earth-orbit satellites offer various observations, including precipitation and surface wind measurements, but their temporal resolutions are limited.
2. Fix extraction: this type of analysis focuses on extracting fixes related to a tropical cyclone, such as its center position, maximum sustained wind (MSW), mean sea-level pressure (MSLP), radius of maximum winds (RMW), and wind radii at different speeds (34-, 50-, and 64-kt) for each quadrant. These fixes are then archived in the Best Track dataset, providing a global view of the TC at the surface level.
3. TC analyses/reanalyses with NWP/data assimilation: this type of analysis goes beyond TC-specific tasks and involves data assimilation and numerical weather prediction (NWP). Data assimilation aims to combine the latest observations with a short-range forecast to obtain the best possible estimate of the current state of the atmosphere. It provides a comprehensive, gridded description of model variables at multiple vertical levels within the TC and its large-scale environment. This type of analysis is primarily used as initial conditions for TC forecasting with NWP.

Major advancements over the last four years (2019–2022) in objective TC analysis have relied on both the emergence of new satellite sensors and calibration/validation methods for higher quality observations with better spatiotemporal resolution, and on the development of methods for extracting the useful information from all types of satellite sensors.

### *2.1. Availability of new observations*

#### *2.1.1. Development of SAR*

Since IWTC-9, the number of TC observations using C-band co-polarized and cross-polarized Synthetic Aperture Radar (SAR) has dramatically increased. With their high resolution (~1 km) and capability to retrieve high speeds (covering up to at least 70 m/s), SAR images bring an unprecedented means to estimate TC surface wind speed field in the near and inner core region, that was previously poorly estimated by L-band radiometers (that fail to capture high wind speed gradients because of their low spatial resolution) or scatterometers (that have a better spatial resolution but suffer from signal saturation at high wind speeds and rain effects). In 4 years, many papers have been published, reporting validation, tuning, and application (e.g Mouche et al., 2019; Vinour et al., 2021).

The National Environmental Satellite Data and Information Service (NESDIS) produces fix data from the 3-km SAR wind speeds that are now accessible to operational forecast centers. The fix values (MSW, RMW, R34, R50, & R64) are determined from the 95th percentile found in azimuthal/quadrant averages (Jackson et al., 2021, Fig. 1). These are impacting operations positively, along with SMAP/SMOS and AMSR-2, providing a good 2-D estimate of the surface winds at times and intensities (Howell et al., 2022) These offer a limited but very detailed view of the TC wind field used to influence the working and final best tracks (Knaff et al., 2021), and are being used for research studies(e.g. Combot et al., 2020).

#### *2.1.2. Use of high frequency imaging with third generation geostationary satellites*

The use of high-frequency imaging with third generation geostationary satellites (Himawari-8/9, GOES-16/17/18, GEO-KOMPSAT-2A/B) targeting TCs gives access to more detailed TC characteristics. Tsukada and Horinouchi (2020) and Tsujino et al. (2021) showed that the 2.5-min "targeted observation of TCs" with Himawari-8 can be used to estimate low-level tangential winds in clear TC eyes, allowing continuous monitoring of TC intensity changes and indirect estimates of small-scale turbulent processes (Fig. 2). The high-frequency observation was also shown to be useful to detect convective bursts and gravity waves (Horinouchi et al., 2020). A special operation of Himawari-8 to observe TCs every 30 s was tested, and it is becoming evident that this ultra-high frequency sampling allows one to detect transient asymmetric disturbances in the inner core (Horinouchi et al., 2023, Fig. 3).

#### *2.1.3. Recommendations for better satellite coverage to improve products and services*

The near- and inner-core TC structure is still insufficiently sampled. For instance, regarding the surface RMW of intense storms, valuable observations are limited to a few aircraft and SAR samples. Yet, the RMW contraction is in general either concurrent with or preceding intensification, and these changes are not sampled at sufficient frequency (Li et al., 2021; 2022). In addition, inner-core wind distribution also seems important when predicting TC intensification (Vinour et al., 2021). In their review, Knaff et al. (2021) recommended a satellite coverage of at least 1100 km from the TC center with a 2 km spatial resolution and a 6-hr temporal resolution in order to picture the whole TC surface structure and its evolution. To address the need, the efforts should focus on developing the sampling rate of these sensors: scatterometers (dual-polarization C-band), SAR (C or L Band) and L-band radiometers.

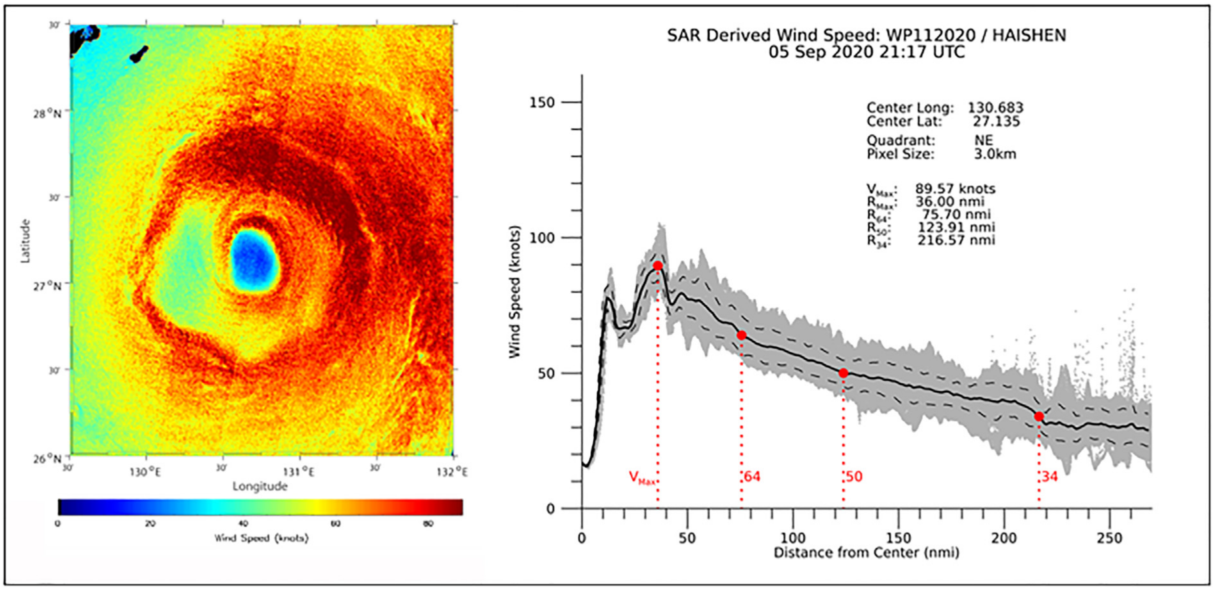


Fig. 1. This SAR-derived wind speed map (left) shows the eye region of Typhoon Haishen on September 5, 2020 at 21:17 UTC based on data from RADARSAT-2. Two-dimensional wind speed maps like this produce very accurate estimates of eye location and extent and clearly resolve steep wind speed gradients (shown by strong variations in the color scale). These maps are also used to create wind speed profiles (right) that help determine maximum wind speed, the radius of maximum winds, and the extent of winds at the critical speed thresholds that forecasters use to characterize a storm as a tropical depression, tropical storm, or hurricane. Gray dots represent SAR-derived wind speeds at each 3 × 3-km pixel in the northeastern quadrant of the map at left, and the solid black curve represents the average wind speed at each distance from the storm's center (in nautical miles, nmi). The two peaks in the wind speed profile near 15 and 36 nautical miles (28 and 67 km) from the center indicate that Haishen had a double eyewall. [Fig. 2 of Jackson et al., 2021); the figure caption is also taken from the paper].

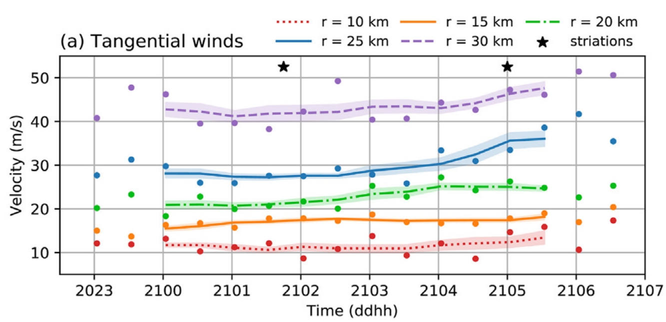


Fig. 2. Radial distribution of tangential winds obtained from the 2.5-min target observation, which is operationally conducted with the Himawari-8 satellite whenever a typhoon is present over the Western Pacific. Visible-light images of the clouds in the eye of Typhoon Lan (2017) are combined, and two-dimensional spectra with respect to time and azimuth are used to estimate the rotation speed of low-levels flow at radii from 10 to 30 km. The star marks indicate independent estimates of the motion of the cloud features called "striations" (or "finger-like features") where the tangential winds are discontinuously faster in the eye. These features are present in a limited portion of the eye adjacent to the inner edge of the eyewall clouds, which were at around 30 km and the features are considered an outcrop of the main secondary circulation. [Fig. 4a of Tsukada and Horinouchi, 2020].

Currently, SAR images are acquired sporadically with only a few observations per TC life cycle, which is insufficient in terms of temporal resolution. In general, the series of satellite within the same orbit should ideally respect a 6-hr time gap for developing 6-hr TC structure products.

Geostationary satellites are the only platforms that observe the whole life cycle of TCs without interruption, so the development of their conventional imaging remains important. Geostationary IR hyper-spectral sounders would be very useful for more detailed depiction of the near and inner-core TC structure through moisture and wind (AMVs). Efforts should also be put on increasing spatial and temporal resolution of microwave sounders. Some areas such as the Arabian Sea are at the edge of third generation geostationary satellite coverage and are in need of higher temporal, spatial and spectral resolution measurement.

### *2.2. Development of methods for objective TC analysis in intensity and structure*

The Advanced Dvorak Technique (ADT) (Olander and Velden 2019) has undergone significant updates since ITWC-9. Version 9 of the ADT includes upgrades to the ARCHER algorithm for position centering and microwave inputs (ARCHER-2), inclusion of subtropical intensity analysis and extension of intensity fixes into and including extratropical transition. It can now also provide continuous estimates of outer vortex surface wind radii, and operate with the new generation of higher spatiotemporal geostationary satellite sensors.

As for TC structure, Chavas and Knaff (2021) have developed a simple and objective method to produce estimates using only 3 predictors: the TC intensity (MSW), the outer size (R34) and the latitude (in the form of the Coriolis parameter). With potential limitations for fitting the coefficients of the relationship using best-track data, this enables better methods to systematically estimate RMW using both intensity and outer-core information. Tsukada and Horinouchi (2023) found that, when

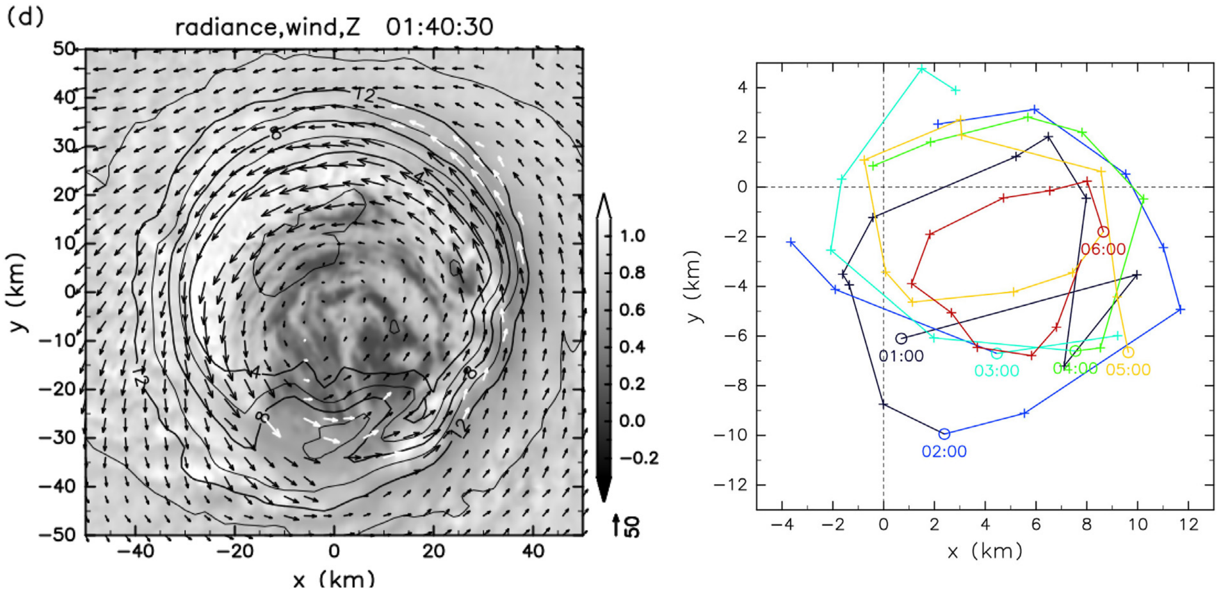


Fig. 3. Left (Fig. 3d of Horinouchi et al., 2023): an example of the high-resolution high-frequency atmospheric motion vectors (AMVs) from a special observation of Typhoon Haishen (2020) conducted on September 4, 2020 every 30 s with the Himawari-8 satellite. Five consecutive images over 2 min are used to derive AMVs on a 2-km grid. The length scale of the arrows is shown on the lower-right margin in m/s. Contours show the cloud-top altitudes estimated from infrared images over the 2 min, while gray-scale shading showsthe reflectivity at a visible wavelength (0.64 μm)at the central time of the 2 min. Right (Fig. 10 of Horinouchi et al., 2023): an example of analyses available with these AMVs. The figure shows the trajectory of the wind minima, which circulates at a period of 1-h. Further analysis indicates that it is an algebraically growing unstable vortex-Rossby wave that redistributes angular momentum in the eye to speed up the rotation near the center.

TCs have clear eyes, the RWMs diagnosed from C-band SAR observations have a tight correlation with the eye radii diagnosed from IR images from geostationary meteorological satellites. It indicates that short-term RMW changes might be detectable.

Besides conventional methods, major recent advancements have been obtained with the applications of Machine Learning/AI tools in this area which are discussed specifically in the following section.

## 3. AI for TC analysis and short-term forecasting

### 3.1. AI specific characteristics

Certainly, the most active area of development in TC analysis over this last period has been the proliferation of techniques using AI to improve on existing objective methods. The highly data science-driven nature of this line of research has enabled approaches with often greater capability, but this comes from methods that may lie entirely outside the traditional skill set of forecasters and other meteorologists. Several of the most promising aspects of AI include:

- The ability to resolve non-linear relationships between atmospheric variables and the TC system,
- The ability to mine complex spatial and temporal structures in TC datasets,
- The ability to easily combine wide varieties of data comprehensively (imagery, NWP, scalar observations, vector fields),
- The ability to easily characterize model uncertainty with probabilistic output for binary yes/no predictions, and uncertainty spreads for numerical output, and
- Modularity, such that one successful deep learning model can be expanded for new applications.

Olander et al. (2021) serves as a good example for the ability of deep learning to exploit nonlinear relationships with the TC system by reconfiguring the ADTas a two-layer neural network of the ADT state variables, which achieved major improvements in estimating TC intensity.

The convolutional neural network (CNN) is the basis for most AI tools that mine spatial TC structures (e.g. Giffard-Roisin et al., 2020; Higa et al., 2021) through hierarchical image convolution and layered network structures. This can also exploit temporal patterns by using multiple image times as inputs. Alternatively, the recursive neural network (RNN) system applies to sequential data and can resolve temporal patterns, such as using track history to improve landfall locations (Alemany et al., 2019; Bose et al., 2022).

Chen et al. (2019) showed an early example of combined satellite imagery and environmental context (basin, day of year, local time, longitude and latitude) to estimate TC intensity. And finally, probabilistic outputs are used in DeepMultiNet (Fig. 4) and OPEN-AIIR (CIMSS, 2022) for TC intensity estimation as well. Lu et al. (2022) compared several machine-learning algorithms to estimate RMW, R64, R50, and R34 from geostationary-satellite brightness temperature averaged over each quadrant. Even the best algorithm exhibited large variability against Best Track records, indicating the need for further studies.

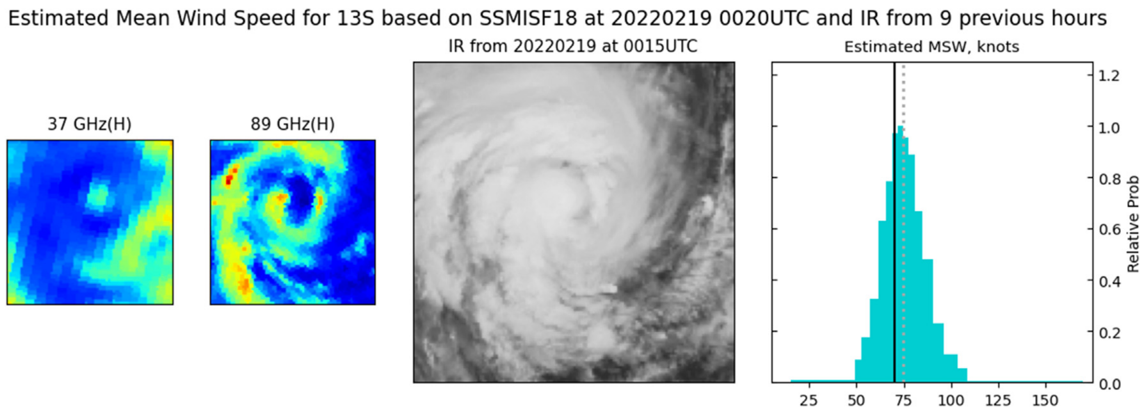


Fig. 4. Example of probabilistic output from DeepMultiNet (DMN) for Cyclone 13S (2022).

However, the advantages listed here also pose challenges in the areas of explainability and generalization, especially in rare events. This is covered in the following section.

### *3.2. Advancements*

The last several years has seen the publication of many AI applications for the TC center fixing (e.g., Smith and Toumi 2021), TC intensity and size estimation (e.g., Wimmers et al., 2019 - DeepMicroNet; Zhuo and Tan, 2021 - DeepTCNet; Olander et al., 2021 - AiDT), and TC track and intensity forecasting (e.g., Su et al., 2020; Xu et al., 2021), to name a few. For TC intensity though, this topic is already quite advanced and approaching the limit of precision. This is obviously due to the availability of a labeled dataset in the form of the Best Track (Chu et al., 2002; Landsea et al., 2015). Recent AI model estimates of TC intensity have reached 7–10 kt RMS error, though all share the highest uncertainty in the Category 5 range of intensities. This is due to the natural imbalance of data with TC intensity, which highlights the difficulty in using AI tools to model any comparatively rare event in TC evolution.

Studies have shown that AI models of TC intensity estimation generally reproduce the biases of the Best Track itself (e.g. Wimmers et al., 2019, Fig. 5). This is arguably even more prevalent with AI-based methods than with traditional methods because of AI's more automated process and its power in fitting to the training data. The consequence is that the current direction of research in this area leaves little chance for improving the Best Track itself.

AI techniques are also employed to generate synthetic satellite data of higher spatial and temporal resolution of significant observational interest. Examples include nighttime visible imagery combined with solar zenith angle corrected visible imagery (ProxyVis; Chirokova et al., 2018) and synthetic microwave imagery (Slocum and Knaff 2021; Haynes et al., 2022; Meng et al., 2022).

Another example is applying deep-learning based image target detection methods for identifying TC vortex from satellite imagery (Zhou et al., 2022). Based on this TC identification model combined with two other machine-learning based intensity estimation and prediction models, the China Meteorological Administration (CMA) is building an AI-based typhoon monitoring and forecasting system to achieve automated and objective TC center location determination, intensity determination and intensity trend discrimination of TCs (Zhou et al., 2022).

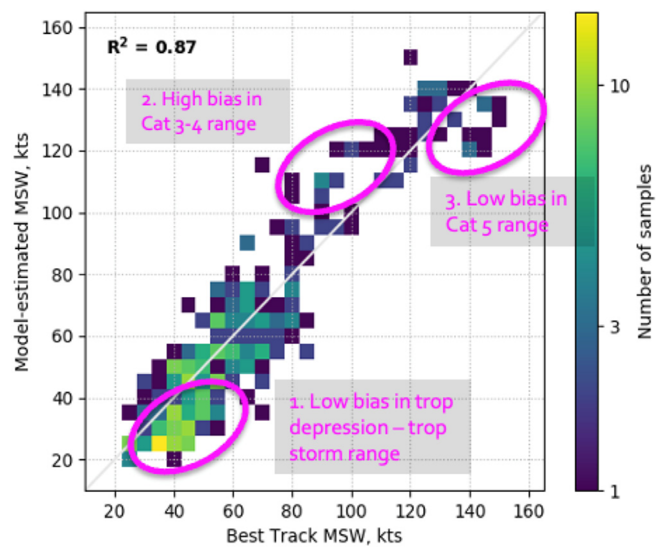


Fig. 5. Example of a best track-trained deep learning model performance compared to reconnaissance-based intensity values only. The deep learning model replicates the bias of the Dvorak Technique in the three most bias-prone intensity ranges. From work based on Wimmers et al. (2019).

### *3.3. Specific challenges*

The advantages of AI listed above come at a high cost, particularly in the integration of new AI-based techniques into the forecasting process. The key difficulty is in reaching a sufficient level of *explainability* in any AI-based technique. Skepticism naturally arises from the attempt of any data science-based technique to reproduce the behavior of a system as complex as the earth's atmosphere, and so the inherent constraints in AI models need to be appropriately identified. However, AI models handle the interactions of potentially millions of variables (each pixel in a geostationary image, for example) and allow for highly nonlinear interactions between each variable. This dynamic can be exceedingly difficult to capture in words or visual patterns, and thus the source of an AI model's power is paradoxically also its weakness. The great challenge posed by AI in the near future is to bring the methods of the most successful models to a level of transparency that they allow the forecaster to actively engage with them.

The other significant challenge is in dealing with small and unbalanced training datasets. As stated in Section 3.2, AI-based TC intensity models show a major weakness in estimating TC intensity in the Category 5 range because of the relatively low case number. A similar challenge is to be expected from other rare TC structures such as small but intense storms. More generally, detailed and high standard labeled datasets data are paramount for research on valuable scientific or user-oriented matters and beneficial for the quality of objective models. Some progress, however, has been made on labeled datasets and TC-centric microwave imagery and homogeneous large scale diagnostics (Razin et al., 2023; Slocum et al., 2022).

### 3.4. Valuable scientific/user-oriented tasks

The following areas are the most desirable for future AI efforts to aid analysis operations:

- Predicting cyclogenesis or tropical waves,
- Estimating overland wind,
- Reconstructing 2D/3D wind from remotely sensed observations,
- Estimating/forecasting precipitation,
- Denoising and superresolution (process of enhancing the resolution and level of detail in an image using AI techniques),
- Gap filling for missing observations,
- Improving subgrid parameterizations within NWP and hazard impact models,

Note also that TC intensity forecasting has natural ties to AI application, but forecasting is discussed in a separate chapter of the IWTC-10 report.

A separate but related area of interest is the potential use of AI to better integrate the wealth of TC data in real time for decision making and emergency management. There is general agreement that the constantly growing information environment for TC analysis is becoming overwhelming to its end-users. Here we see the possibility of helping forecasters and emergency managers improve their time management and direct their limited attention to the proper sources. To our knowledge, this idea remains mainly speculative and has not been committed to practice. Nevertheless, the opportunities are numerous and far-reaching. For example,

- Searching through and organizing the most forecast- and impact-relevant data tailored to the event in order to reduce the manual efforts of the forecaster,
- Highlighting key features and environmental context that offer the most guidance for an objective analysis,
- Identifying the most relevant members of ensemble forecasts,
- Using explainable AI (XAI) within the fundamental AI forecasting tools that presents the proper user guidance, including error bounds and uncertainty,
- Improving NWP models and enhancing their usability for forecasting and hazard impacts,
- Translation of a weather image into nowcasting or alert texts.

## 4. Drifts in TC characteristics in the historical record

An ongoing concern with using objective methods to analyze TC characteristics is the lack of standardization in historical data records. Normally this leads to a drift in relative bias with time; other times, the problem is with uncertain error bounds. The importance of this problem is made even more acute because of TC responses to the changing background climate. This was noted as a special concern in characterizing the active 2018–2021 period in the Arabian Sea (Fig. 6).

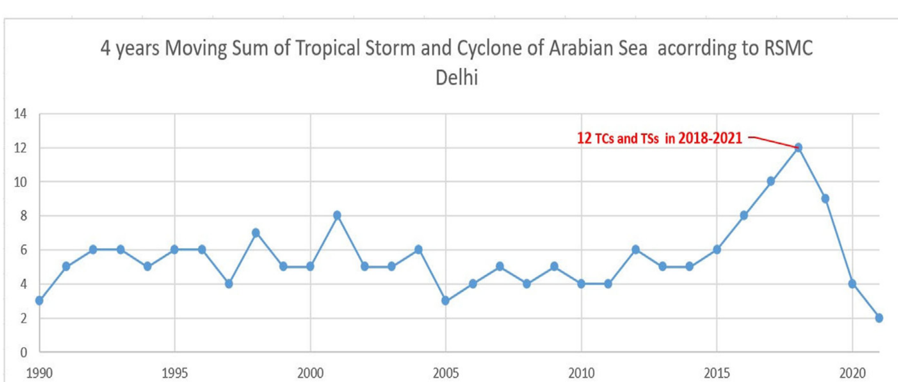


Fig. 6. Moving sum of tropical cyclone and cyclone events in the Arabian Sea, 1990–2021. The last three points are the moving sums for the periods 2019–2021, 2020–2021 and 2021 respectively.

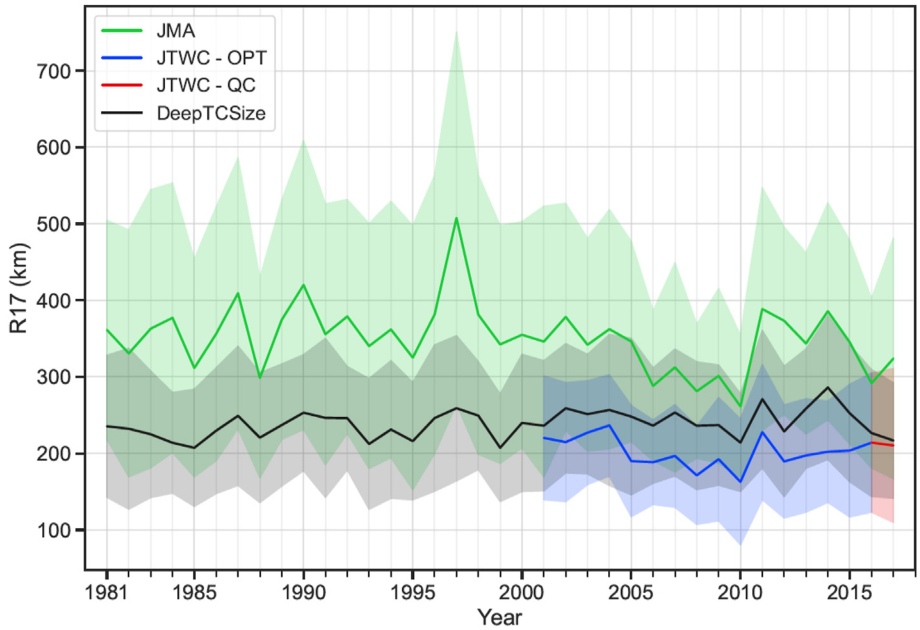


Fig. 7. Time series of the 17-kt wind radius (R17) from JMA best track (green; 1981–2017), JTWC best track with (red; 2016–2017) and without rigorous postseason re-analysis (blue; 2001–2015), and DeepTCSize (black; 1981–2017). The lines and shades denote the mean and standard deviation, respectively. From work based on Zhuo and Tan (2023).

The most recognized problem with all Best Track records is the bias toward higher intensities over the years, due in part to newer satellites' more frequent viewing, higher spatial resolution and lower noise. These factors lead to higher observed eye temperatures over time, which in turn leads to higher Dvorak estimates. However, these factors also result in more observed breaks in the TC cold ring, which complicate the trend analysis.

The other important symptom of drift is in Best Track and Extended Best Track wind radii. We recognize a major improvement in wind radii uncertainty since approximately 2016 because of the influence of improved microwave retrievals from SMAP, SMOS, AMSR2, ASCAT and SAR. Some have also noted an improvement in wind radii estimates in the JTWC Best Track around 2004, due to the institutional change in quality-checking this data at that time.

These two issues could be partially addressed with cross-platform validation. Specifically, this means comparing legacy instruments and methods to the newer instruments/methods most likely in use at the time. There is also an opportunity to use transfer learning from AI models to backfill less reliable histories with estimates trained on more recent and high-quality records. This is used in a recent study to reconstruct TC wind radii history (Zhuo and Tan 2023, Fig. 7).

## 5. Summary and conclusions

In the past four years, the development of new sensors such as SAR and high-frequency imaging with third generation geostationary satellites gave access to a better monitoring of the wind structure in the TC inner-core. Remarkably, numerous methods using AI for objective TC analysis have emerged, competing in terms of performance with traditional ones such as the ADT. AI also opens doors to new applications such as synthetic satellite images or TC vortex identification. This rapid growth is both exciting and challenging, and it is difficult to imagine what the state-of-the-art will be for the next IWTC. It would be desirable that AI helps objective TC analysis move from estimation of simple aggregate point intensity values such as MSW and MSLP to more complete TC 3D wind structure estimates with higher fidelity with the expectation of improved vortex initialization in NWP models. The forecaster community needs to gain confidence in new objective methods to use them. It is essential that future models are trained/calibrated with high quality data and evaluated under standard procedures.

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