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Tropical Cyclones Across Global Basins: Dynamics, Tracking Algorithms, Forecasting, and Emerging Scientometric Research Trends

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ABSTRACT

Tropical cyclones (TCs) pose significant threats to life and property across global ocean basins, and forecasting their structural evolution, track, and intensity remains a major scientific challenge. This review synthesizes the current understanding of TCs across major basins, that is, the Pacific, Atlantic, and North Indian Oceans, with a focus on the key environmental factors influencing TC behavior, such as sea surface temperature (SST), vertical wind shear (VWS), mid-tropospheric moisture, and land surface conditions. A special emphasis is further placed on the comparative skill of operational numerical weather prediction (NWP) models employed globally for TC forecasting. The review also discusses TC tracking algorithms, structural diagnostics, and the evolution of forecasting frameworks, along with emerging research trends revealed through scientometric mapping. The 51 peer-reviewed studies were selected and analyzed, and scientometric analysis was conducted on these 51 studies. Out of these selected studies, 37.25% focused on the Pacific, 23.52% on the Atlantic, and 17.64% on the North Indian Ocean (NIO, that is, the Bay of Bengal (BoB) and Arabian Sea). Out of these 51 studies, it has been found that while most studies utilized satellite-based methods, data assimilation (DA) techniques were emerging during 2006–2013, gaining momentum with machine learning (ML) applications post-2019. Notably, research since 2019 highlights a shift toward machine-based algorithms aimed at improving intensity predictions. While these AI/ML-based TC prediction models show promise, challenges remain in scalability, interpretability, and integration into forecasting workflows. The review emphasizes the need for assimilating next-generation satellite datasets (e.g., CYGNSS, TROPICS, rapid-scan AMVs, LIDAR), improved storm surge modeling, and real-time ensemble forecasting with high spatiotemporal resolution. Ultimately, advancing TC forecasting requires a collaborative, interdisciplinary approach involving model developers, operational centers, and observational programs. Bridging short-term forecasting with climate-informed strategies will be pivotal in enhancing global resilience to cyclonic hazards in a warming world.

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1 | Introduction

TC forecasting entails the prediction of several interconnected elements, such as the cyclone's track, intensity, induced storm surges, associated rainfall, and the identification of impacted coastal regions (Willoughby et al. 2007; Elsberry 2014; Woodruff et al. 2013; Leroux et al. 2018; Hoque, Phinn, Roelfsema, and Childs 2017; Hoque, Phinn, and Roelfsema 2017). Among these elements, knowing where a cyclone will travel is the most critical, as it enables early warnings for potentially affected populations, thereby reducing damages and saving human lives.

Various approaches have been developed to improve track and intensity prediction of cyclones in both the North Indian Ocean (NIO) and other global ocean basins. For instance, Osuri et al. (2013) demonstrated that using higher resolutions (18 km and 9 km) in the Advanced Research Weather Research and Forecasting (WRF-ARW) model led to notable reductions in mean track errors compared to the 27-km resolution, based on 100 simulations for 17 TCs during 2007–2011 over the Indian region. Similarly, Nadimpalli et al. (2023) demonstrated that using SST from the Regional Ocean Modeling System (ROMS) as a lower boundary condition in the ARW model improved the simulation of TCs Phailin and Hudhud over the BoB. For TC Phailin, the ROMS experiment captured the peak intensity with an underestimation of ~20 knots, compared to ~40 knots in the control run, while the maximum intensity error reduced from –45 knots in CNTL to –35 knots in ROMS. Though improvements for TC Hudhud were modest, the ROMS run better captured the wind structure and rainfall distribution than the control run, which used low-resolution Reynolds SST. Bhasi et al. (2023) demonstrated that assimilating scatterometer winds using the 3DVAR technique in the WRF model improved forecasts of 36 BoB cyclones (2010–2020), reducing mean sea level pressure (MSLP) root mean square error (RMSE) by 12%, 17%, and 21% at 24, 36, and 48 h, respectively. Further, maximum sustained wind (MSW) forecast accuracy improved by 53%, 37%, and 25% over the same timeframes, highlighting the importance of improved initial conditions (ICs) in TC track and intensity prediction over the Indian region. Munsi et al. (2021) generated high-resolution (6 km × 6 km) reanalysis data using WRF-ARW and a three-dimensional variational-Ensemble Kalman Filter (3DVarKF) system with six-hourly cyclic downscaling to simulate the full life cycle of three rapidly intensifying TCs, that is, Fani, Ockhi, and Luban, over the NIO region. They further found that assimilating multi-source data, including scatterometer/radiometer winds, surface and upper-air observations, and radiances, the modeling system represented improved simulation of surface wind variation and drop of MSLP. Further, wind distributions at 850 hPa matched well with the 5th Generation European Centre for Medium-Range Weather Forecasts Reanalysis (ERA5), and rainfall patterns showed strong agreement with Global Precipitation Measurement (GPM), effectively capturing rapid intensification (RI) phases.

Over other ocean basins, Zhong et al. (2024) introduced TC-SINDy, a physics-based yet data-driven framework that derives governing equations for TC track and intensity from historical data using the Sparse Identification of Nonlinear Dynamics (SINDy) method. Their models outperform traditional deterministic models in capturing intensity evolution and track

behavior over the Western North Pacific (WNP) and North Atlantic (NA) basins, and when coupled with a parametric wind field, reproduce realistic surface wind distributions, offering a robust, climate-adaptive TC simulation tool. Baker et al. (2024) demonstrated that fully coupled global storm-resolving models with atmospheric resolutions of 28–2.8 km and oceanic resolutions of 28–5 km better capture TC intensity, structure, and RI processes. Notably, simulations at ~5 km resolution produced more realistic peak intensity and inner-core dynamics, which were absent in coarser models. The study highlights the critical role of storm-resolving resolutions in improving cyclone risk assessment and climate representation. Emerton et al. (2024) evaluated ensemble and high-resolution deterministic forecasts from ECMWF and the UK Met Office (UKMO) for TCs in the Southwest Indian Ocean (SWIO) over 2010–2020. While both models show comparable skill, ECMWF outperforms UKMO in predicting TC tracks beyond 1.5 days and intensity (MSLP and maximum wind speed). Both systems consistently underestimate cyclone intensity and translation speed, impacting hazard planning and response. Notably, high-resolution deterministic runs outperform ensemble forecasts for intensity, supporting their combined use for capturing both accuracy and uncertainty. They further reported that forecast skill for tracks clearly improved, with UKMO gaining ~1.5 days and ECMWF ~1 day in lead time over the decade. These gains were attributed to model upgrades and increased resolution, increasing the ability to resolve cyclone features. The assimilation of radar radial velocity, Doppler Weather Radar (DWR) observation data into NWP models has also significantly improved track and intensity forecasts of TCs (Xu et al. 2025; Chakraborty et al. 2024; Lin et al. 2022).

Another crucial advancement is vortex initialization, which involves accurately initializing the cyclone's core using atmospheric data such as wind fields, SST, and MSLP to simulate the cyclone's genesis and further evolution (Magnusson et al. 2025; Nadimpalli et al. 2021b). The number of TCs (or hurricanes) with wind speeds ≥ 35 knots has shown an increasing trend during 1940–2010 (Figure 1). Singh, Panda, Sahoo, and Mohapatra (2019) confirmed this intensification trend through a detailed study of TC climatology over the NIO region during 1891–2015. As a result, meteorological centers globally rank cyclone track forecasting among their top three operational priorities (Titley et al. 2020; Landsea and Franklin 2013). Given the variations in cyclone behavior across basins, meteorological agencies often use different forecasting methodologies tailored to the basin of origin to optimize accuracy in predicting track and intensity. Singh, Panda, and Rath (2019) emphasized the need for such tailored approaches by highlighting landfalling trends of cyclonic disturbances in the NIO during different climatic phases.

Forecasting TCs that undergo rapid intensification (RI) remains particularly challenging and often leads to the greatest forecast errors (Rappaport et al. 2009). Over the NIO, the India Meteorological Department (IMD) defines RI as an increase in maximum sustained surface wind speed of ≥ 30 knots (≈ 15.5 m/s) within 24 h (Tiwari and Kumar 2023). Kumar et al. (2023, 2025) analyzed the influence of environmental factors on the radial structure of NIO TCs, revealing key variables that govern intensification processes. RI events

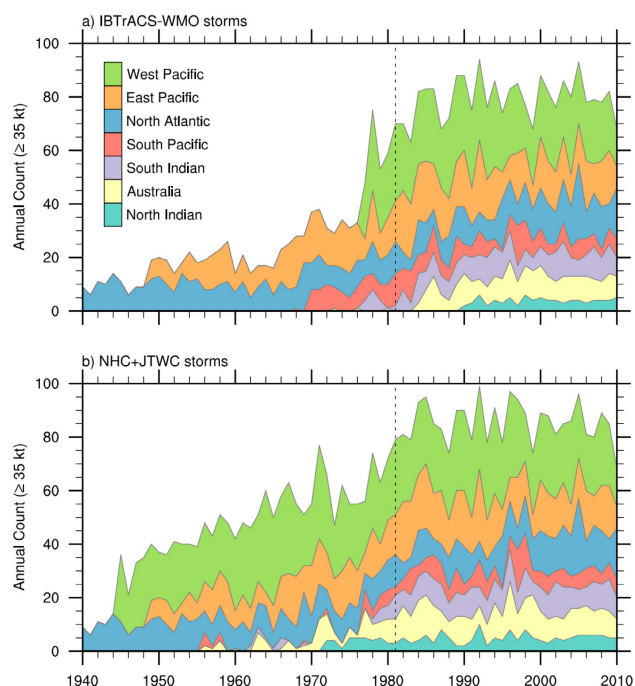


FIGURE 1 | Annual count of the total number of cyclones having maximum sustained wind speed intensity ≥ 35 knots for the world's seven cyclone-forming basins using (a) International Best Track Archive for Climate Stewardship (IBTrACS)-World Meteorological Organization (WMO) and (b) National Hurricane Centre (NHC)+Joint typhoon warning centre (JTWC) observations respectively (Used with permission from Schreck III et al. (2014) American Meteorological Society).

are typically supported by high precipitable water (~ 55 mm), surface flux (~ 500 W/m²), and tropical cyclone heat potential ($50\text{--}60$ kJ/cm²) under moderate vertical wind shear ($6\text{--}8$ m/s), as noted by Vinodhkumar et al. (2022). RI in strong TCs poses a significant threat when communities lack adequate time to prepare or evacuate. Panda, Paul, and Kumar (2023) discussed unique TC characteristics over the NIO, focusing on intensity and movement, and highlighted the influence of atmospheric and oceanic drivers such as moisture, ocean eddies, low-level VWS, SST, and climate variability (e.g., monsoons, cold air intrusion, and El-Nino Southern Oscillation (ENSO)). They also highlighted the potential of ensemble prediction and DA for improving forecasts. Paul et al. (2024) compared the intensification of two pre-monsoon TCs, Amphan and Fani, over the BoB, revealing differences in VWS, mid-tropospheric humidity, sea surface cooling, aerosol loading, and ocean productivity. Their study demonstrated the superior performance of the Model for Prediction across Scales-Atmosphere (MPAS-A) over WRF-ARW in simulating radial TC structures. Paul et al. (2022) further examined the genesis and RI of super cyclonic storms in the NIO (1982–2020), emphasizing the dominant role of oceanic factors, including high SST, heat potential, and warm-core eddies, as well as the influence of convectively coupled equatorial waves and moderate shear environments.

Although the overall number of TCs has remained relatively stable in recent decades, increasing evidence suggests that the proportion of storms intensifying into major cyclones or hurricanes has grown substantially (Klemas 2009; Bhatia et al. 2022;

Willoughby et al. 2007; Atlas et al. 2015). Delivering accurate TC forecasts is essential for minimizing human and economic losses. However, the geographical and climatological diversity of cyclone formation basins implies that a one-size-fits-all forecasting strategy is insufficient. Therefore, the integration of global forecasting techniques with basin-specific models is crucial to improve forecasting accuracy. Despite substantial progress, major challenges persist in accurately forecasting TC track, intensity, and structural evolution, especially under the growing influence of climate change. Basin-specific variability in forecasting model performance and data quality further complicates prediction efforts. While many studies have explored isolated aspects of TC behavior, there has been a lack of an integrative review that simultaneously discusses dynamics, tracking algorithms, model skill, and emerging approaches such as ML and advanced DA techniques across global basins. Further, given the accelerating pace of research, a scientometric analysis further provides valuable insights into evolving priorities and underexplored areas. This review addresses a critical gap by synthesizing current knowledge of environmental influences, forecasting methodologies, and scientometric trends across global basins. It serves as a comprehensive resource to guide future interdisciplinary research in TC prediction, with the overarching goal of enhancing climate resilience.

The review paper is further structured as follows to provide a comprehensive and multidisciplinary understanding of TCs forming across the world's major basins. Section 2 focuses on the dynamics of TCs, highlighting the key environmental and oceanic variables that influence their structure, intensity, and track variability across global basins. Section 3 discusses the evolution of automated TC tracking systems and major forecasting models, along with various approaches used for TC prediction, including dynamical, statistical, and emerging hybrid techniques. This section further outlines how real-time operational TC forecasting is carried out across global basins by discussing the TC forecast and risk mitigation cycle, and summarizes the advantages, limitations, and potential solutions associated with various forecasting methodologies, data assimilation techniques, and NWP models. Section 4 explores the current scientometric research trends in the TC domain, beginning with a three-field plot analysis and keyword co-occurrence networks to identify evolving research themes. It further synthesizes selected 51 studies categorized into major focus areas, including advancements in modeling TC characteristics, cyclone-induced rainfall prediction, ML-based forecasting (e.g., artificial neural networks (ANNs)), the impact of DA systems, influence of physical parameterization schemes, and developments in cyclone disaster management. Section 5 deals with conclusions and challenges ahead.

2 | World's Seven Ocean Basins and Factors Affecting Dynamics of TCs

According to the National Hurricane Center (NHC) under the National Oceanic and Atmospheric Administration (NOAA), the distribution of TCs across the globe reveals a strong hemispheric asymmetry. Approximately 69% of all TCs occur in the Northern Hemisphere, whereas only 31% originate in the Southern Hemisphere. This imbalance is largely attributed to the

greater proportion of oceanic area in the Northern Hemisphere, combined with more favorable environmental conditions for cyclone genesis such as elevated SSTs, pre-existing disturbances, and increased low-level vorticity, especially within the monsoon trough regions.

Further, breaking this down by ocean basins, the Pacific Ocean alone accounts for an overwhelming 57% of global TC activity, making it the most active cyclone-generating basin worldwide. The NIO contributes roughly 31% of the total global TCs, with both the BoB and the AS playing critical roles in regional cyclone formation and intensification. In contrast, the Atlantic Ocean, which receives a disproportionate amount of public and scientific attention, particularly due to its proximity to highly populated and economically vulnerable regions like the south-eastern United States and the Caribbean, accounts for only about 12% of all global tropical cyclones. Despite its smaller share, the Atlantic basin is particularly important due to the intensity and frequency of landfalling hurricanes with high socioeconomic impacts.

Globally, cyclones are most commonly categorized within seven primary basins: the WNP, Eastern North Pacific, North Atlantic, South Pacific, South Indian Ocean, the Australian region, and the NIO. These basins with their detailed geographic expanse are illustrated in Figure 2. Each of these regions is governed by unique meteorological and oceanographic features that significantly influence cyclone behavior. For instance, the WNP basin is the most active in terms of storm frequency and is notable for producing the strongest typhoons due to vast warm waters and low VWS environments (Wang and Zhou 2008; Shu et al. 2012). The NIO basin, while less active in terms of annual storm count, is infamous for some of the deadliest cyclones on record due to high population densities along vulnerable coastlines, complex interactions with monsoonal flows, and limited evacuation infrastructure.

2.1 | Factors that Influence the Structure, and Intensity

The three main factors determining the structure and intensity (S&I) of TCs are: (i) environmental conditions (vertical wind shear (VWS), peripheral circulation systems, and extratropical transition (ET)); (ii) inner-core dynamics (Vortex Rossby Waves (VRWs), the eye-wall, and Mesoscale Convective Systems (MCSs)); and (iii) variations in underlying surface forcing ((SST), Drag coefficient, Sea Spray and Topography; Lian-Shou (2012)) (Figure 3). Among the environmental factors, VWS plays a crucial role in TC development and intensification of TCs (DeMaria 1996; Wong and Chan (2004); Wang and Holland 1996). A critical wind shear threshold of approximately 10 ms^{-1} marks the transition from “intensification” to “dissipation” of TCs. Wind shear below 10 ms^{-1} supports intensification, with values between 2 to 4 ms^{-1} favoring RI, while shear exceeding 10 ms^{-1} is linked to weakening, with values above 12 ms^{-1} promoting rapid weakening (Paterson et al. 2005). Low to Moderate VWS is generally favorable, as it facilitates the maintenance of a vertically aligned vortex, whereas strong shear disrupts the system by inducing “vortex tilt” and displacing deep convection, thereby inhibiting intensification or even leading to storm dissipation. The peripheral circulation system, including monsoon troughs, subtropical ridges, and mid-latitude westerlies, modulates TC movement, with steering flow anomalies often dictating re-curvature and landfall probabilities. Additionally, TCs that migrate into higher latitudes may undergo ET, wherein baroclinic forcing, frontal interactions, and increased wind shear contribute to a shift from a “warm-core” structure to a “cold-core” extratropical cyclone. This process can result in structural reorganization, sometimes leading to secondary intensification due to enhanced baroclinic energy conversion.

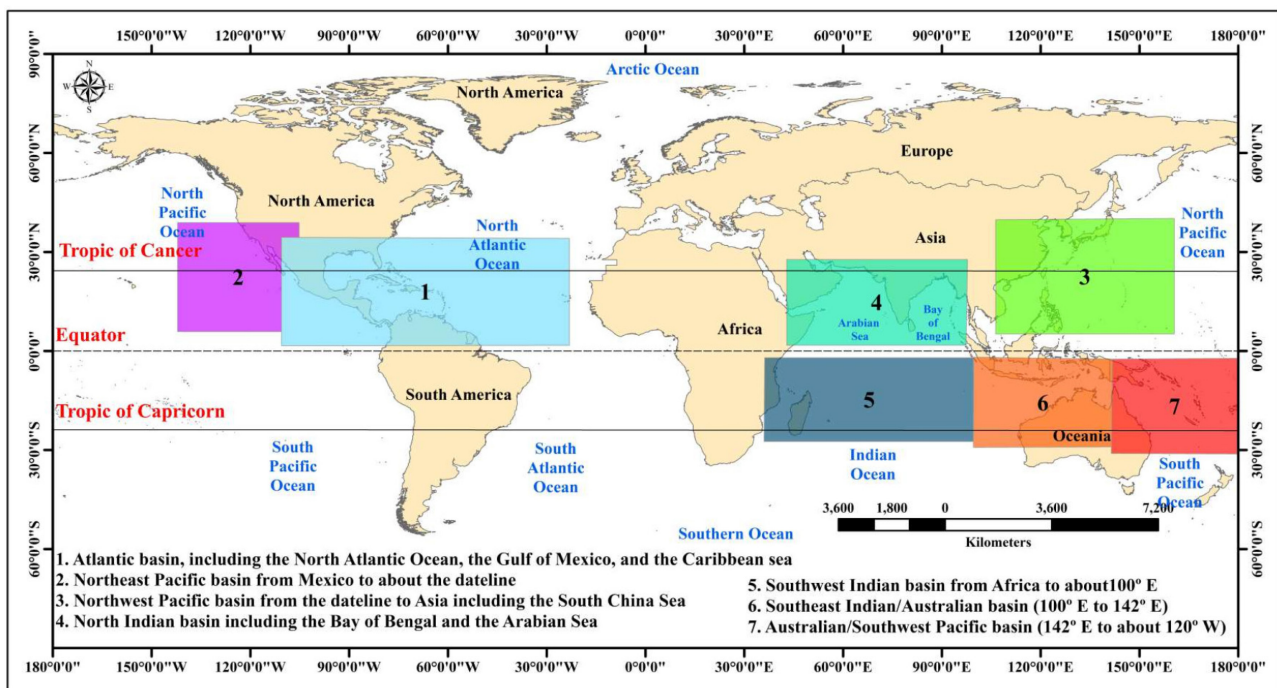


FIGURE 2 | Geographical locations of the world's seven tropical cyclone formation basins.

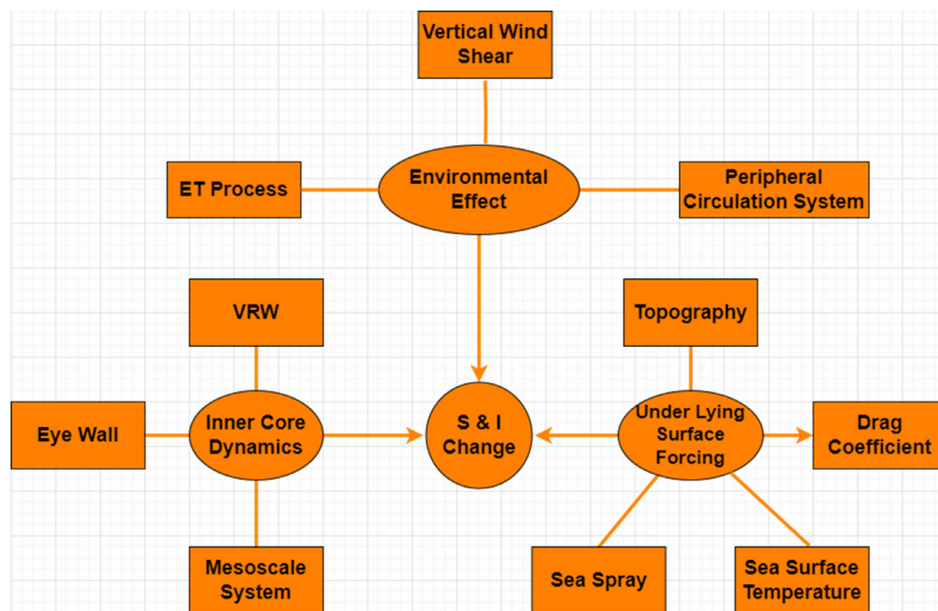


FIGURE 3 | An illustration of the variables that influence the structure and intensity of the tropical cyclone (ET: Extratropical transition, S&I: Structure and Intensity, VRW: Vortex Rossby waves). The figure is regenerated and the concept is adapted from Lian-Shou (2012).

The inner-core dynamics further modulate storm evolution through mesoscale and vortex-scale interactions. VRWs contribute to the redistribution of angular momentum within the eye-wall, influencing storm symmetry and eye-wall replacement cycles (Montgomery and Kallenbach 1997; Nikitina 2013). These eye-wall replacement cycles common in intense TCs involve the formation of an outer eye-wall, which contracts and eventually replaces the inner eye-wall, temporarily weakening the storm before re-intensification occurs. Additionally, mesoscale convective systems (MCSs) embedded within the TC core provide concentrated latent heat release, fueling RI. The organization and persistence of MCSs are closely linked to mid-level moisture availability, vorticity anomalies, and local environmental forcing.

The surface forcing factors are critical in determining the energy available for TC intensification. SST above 25.5°C or 26°C is a fundamental requirement for TC genesis and intensification (Palmen 1948; Dare and McBride 2011), but the depth of the warm oceanic layer is equally important. Ocean Heat Content (OHC), which accounts for the heat stored in the upper ocean, plays a more decisive role than SST alone, particularly in cases where deep warm layers reduce the impact of storm-induced ocean cooling and upwelling (Albert and Bhaskaran 2020). The presence of barrier layers and warm-core eddies further increases TC intensification by insulating the warm surface layer from cold upwelled water, thereby sustaining convective activity. Warm SST anomalies favor more frequent and stronger RI events because of their often association with phenomena like El Niño (Hu et al. 2018). Regions with deep warm layers due to the OHC support strong and sustained RI events as well, particularly in the WNP Ocean basin (Song et al. 2020; Fudeyasu et al. 2018; Lin et al. 2013).

In addition to thermal oceanic properties, TC-ocean interactions are modulated by “drag coefficient” and “sea spray” dynamics. The drag coefficient, which governs surface frictional stress, exhibits a nonlinear relationship with wind speed. At moderate

wind speeds, increased drag enhances surface fluxes of heat and moisture, promoting intensification. However, at extreme wind speeds (> 30 m/s), the drag coefficient tends to level off or even decrease, potentially limiting further intensification by reducing surface energy transfer efficiency (Donelan 2018; Powell et al. 2003). Additionally, sea spray plays a crucial role in moisture flux enhancement, as evaporating spray droplets contribute to latent heat release in the boundary layer, thereby sustaining deep convection and intensification. This process is particularly relevant in major hurricanes and super cyclones, where extreme wind-induced spray generation significantly modifies boundary layer thermodynamics. Furthermore, topographic interactions influence TC structure and intensity, particularly in coastal and mountainous regions. When TCs encounter elevated terrain, enhanced friction leads to asymmetric convection, orographic lifting, and localized extreme precipitation on windward slopes. Conversely, subsidence and downslope drying on the leeward side often result in rapid storm decay. The degree of topographic influence varies depending on storm intensity, forward speed, and the alignment of the prevailing wind flow with terrain features.

2.2 | Factors That Influence the Track of TCs

TCs are governed by multiple atmospheric and oceanic factors that determine their track across global basins. The primary driver of TC motion is the large-scale environmental steering flow, typically represented by the deep-layer mean wind (Carr III and Elsberry 1990; Wang et al. 1999; Ito et al. 2020). This flow is influenced by the subtropical ridge (STR), mid-latitude westerlies, and monsoonal circulations (White 1995; Deng et al. 2010; Riemer and Jones 2014; Lander 1996). The beta effect, arising from the latitudinal variation of the Coriolis parameter, induces a westward and poleward drift known as beta drift, which becomes significant in weak steering flow environments (Holland 1982; Zhang et al. 2018; Chan 2005; Peng et al. 1999). The STR plays a crucial

role in TC track deflection, where its position and strength determine whether a TC moves westward or undergoes re-curvature (Harr and Elsberry 1991; Akter and Tsuboki 2021). As TCs enter mid-latitudes, interactions with upper-level troughs and the jet stream lead to re-curvature and extratropical transition (Knippertz 2007; Dimri et al. 2016; Leroux et al. 2013, 2016). The impact of SST and OHC further modulates TC intensity, influencing convective asymmetries and, subsequently, track deviations (Lin et al. 2008; Shay et al. 2000). Topographic effects, such as those observed near the Philippines and Taiwan, can obstruct or deflect TCs due to orographic lifting and increased surface friction (Tang and Chan 2014; Huang et al. 2020; Hsu et al. 2018). Internal storm dynamics, including eye-wall asymmetries, vortex Rossby waves, and secondary circulations, also contribute to deviations in TC motion, leading to trochoidal tracks (Wang 2002; Oda et al. 2006; Kuo et al. 2009; Muramatsu 1986).

Each ocean basin exhibits unique track characteristics: in both the west and east Atlantic regions, the Miller Type-B cyclones, characterized by a 300-hPa jet streak or upper-level trough and robust lower-level baroclinicity, dominate (Dacre and Gray 2009); in the western Pacific, the STR's variability determines track behavior (Lander 1996); and in the NIO region, SST, monsoonal circulations, and Indian Ocean dipole (IOD) mode significantly influence TC tracks (Wang et al. 2024; Yuan and Cao 2013). Despite improvements, uncertainties in steering flow, ocean-atmosphere coupling, and mesoscale processes continue to challenge forecast accuracy. Improved observational capabilities from satellites and aircraft reconnaissance missions will play a critical role in refining TC track predictions in the coming years.

A key yet often underrepresented factor in cyclone prediction is soil moisture, which plays a crucial role in modulating land-atmosphere coupling, especially during the landfall and post-landfall evolution of TCs. While primary atmospheric and oceanic parameters such as sea SST, vertical wind shear, and mid-tropospheric humidity are widely recognized as critical in governing cyclone track and intensity, land-surface conditions, particularly soil moisture anomalies, have gained growing scientific attention for their influence on TC behavior across global ocean basins (Martius et al. 2021; Kellner et al. 2012; Routray et al. 2023; Navale and Karthikeyan 2023; Nellipudi et al. 2022). Soil moisture directly affects the partitioning of surface energy fluxes into latent and sensible heat, modifying the boundary layer structure, near-surface thermal gradients, and moisture availability (Lodh et al. 2022). Dry soils increase sensible heat flux, thereby increasing boundary layer instability and potentially aiding in secondary convection that can steer or deform a cyclone's low-level vortex. In contrast, wet soils increase latent heat flux and moisten the lower troposphere, which may sustain convective activity while also dampening surface thermal gradients, affecting cyclone weakening rates and post-landfall rainfall patterns.

Across different global basins, soil moisture has been shown to influence cyclone behavior in region-specific ways. Kishtawal et al. (2012) found that soil bulk density, as a proxy for soil heat capacity, significantly influences the inland decay of TCs over the United States, with stronger cyclones showing a greater sensitivity to soil properties, emphasizing the need for soil heat flux feedback in improving intensity decay predictions. Further, Rao et al. (2019) analyzed the water budget of 12 BoB TCs of varying

intensities and found that rainfall is not directly proportional to the intensity of TCs. Moisture flux convergence accounted for 61% of rainfall before landfall, while evaporation contributed 39%. After landfall, the contribution reversed, with evaporation accounting for nearly 63% and moisture flux convergence for 37%. In 7 out of 12 cases, a secondary peak in precipitation or sustained high rainfall occurred over land. Both observations and WRF simulations highlighted the role of soil moisture in maintaining post-landfall rainfall. Song et al. (2021) found that increased soil moisture significantly contributes to the prolonged decay timescale (τ) of WNP TCs after landfall over the Asian continent, particularly enhancing cyclone persistence in south-eastern and southern China through its association with dynamic factors like low-level vorticity and upper-level divergence. Fearon et al. (2023) found that land surface soil moisture significantly influences the intensification of Arctic cyclones. Further, using the Coupled Ocean-Atmosphere Mesoscale Prediction System (COAMPS) model experiments for an August 2016 cyclone case, they showed that soil moisture accounts for approximately 30% of the moist-air intrusion. When regional soil moisture was reduced, there was a noticeable decrease in cloud cover and a corresponding increase in surface solar radiation by more than 90 W m^{-2} . Kolassa et al. (2024) showed that assimilating Soil Moisture Active Passive (SMAP) observations into the Goddard Earth Observing System (GEOS) model quantitatively improved forecasts of Cyclone Idai (2019) over the Southwest Indian Ocean, yielding better storm structure, more accurate storm size, and reduced intensity and track errors, particularly at 36–72-h lead times. The increased soil moisture initialization led to greater latent heat flux, increased column-integrated moisture, and a more realistic cyclone structure and size. Further, forecast errors in both intensity and track were notably reduced, particularly at 36–72 h lead times. These regional examples illustrate the broader principle that soil moisture is a dynamic factor capable of influencing cyclone structure, rainfall patterns, decay rates, and in some cases, track deviations. The growing integration of high-resolution soil moisture observations into Land Data Assimilation Systems (LDAS) has significantly improved our capacity to capture these interactions (Routray et al. 2023; Christophersen et al. 2022). As cyclone forecast systems continue to evolve toward fully coupled earth system models, accurate representation of land-atmosphere feedbacks, especially through soil moisture, will be crucial. The sensitivity of TCs to even modest variations in land-surface conditions suggests that ignoring soil moisture dynamics may limit the accuracy of both intensity and rainfall forecasts.

3 | Tracking and Forecasting of TCs

3.1 | Evolution of Automated TC Trackers and Major Cyclone Forecasting Models

During the early 1990s, at first, Murray and Simmonds (1991) developed an automated algorithm for locating the position of the centre of southern hemispheric cyclones, based on numerical analysis. Using global analyses from the European Centre for Medium-Range Weather Forecasting (ECMWF) and ensemble model data, Trenberth (1992) devised an objective procedure to detect and track TCs in model fields. Vitart et al. (1997) included TC tracking schemes developed by Murray and

Simmonds (1991) and Trenberth (1992) and further developed a TC tracker for the ensemble general circulation model. At the United Kingdom Met Office (UKMO), the project to develop a fully automated cyclone tracking tool was initiated during the early 1990s. Heming (1994, 2017) presented an outline of a TC tracker to be used for UKMO operational TC forecasting. The Met Office TC tracker, which is currently also operational at India's National Centre for Medium-Range Weather Forecasting (NCMRWF), Ministry of Earth Sciences (MoES), uses seven meteorological fields, namely, orography, surface temperature, u-component of wind at 10 m, v-component of wind at 10 m, u-component of wind at 850 hPa, v-component of wind at 850 hPa, and MSLP. Orography and surface temperature are generally utilized solely for identifying the system in the model's analysis field. In contrast, for other forecast lead times, the remaining five parameters are employed.

Another method of identifying TCs in forecast data, as outlined by Hodges and Klingaman (2019) and Hodges and Emerton (2015), involves tracking vorticity maxima. Forecast relative vorticity (6-hourly, out to 7 days ahead) is vertically averaged between 850 and 600 hPa and spatially filtered to T63 resolution, with wavenumbers ≤ 5 removed to eliminate large-scale background flow. Vorticity centers exceeding $5 \times 10^{-6} \text{ s}^{-1}$ and lasting ≥ 2 days are tracked as TCs. The maximum 10-m wind (within 6° radius) and MSLP (within 5°) near each center are extracted to assess storm intensity.

At the National Centre for Environmental Prediction (NCEP), the first of its kind, a new tracking algorithm was adopted to produce global TC forecasts (Marchok 2002). The tracker described by Hewson and Titley (2010) is mainly used for tracking extratropical cyclones. However, it is also capable of identifying barotropic lows, which makes it suitable for tracking cyclonic storms too. Several more tracking software packages are known to exist. All TC trackers face difficulties in real-time operations, which stem partly from the difficulty of adequately representing TCs and their vital information in a model (Tsai and Elsberry 2013; Tort and Dubos 2014) and partly from the complexity of TC structures in nature.

Empirical forecasting methods rely on the forecaster's ability to recognize and interpret recurring patterns in cyclone movement based on historical data and observational experience. It can help to minimize big errors like missed re-curling and storm acceleration toward mid-latitude storms (Frazier et al. 2010; Gao et al. 2014; and Fang et al. 2016). The fundamental flaw with these methods is the amount of time it takes for the person forecasting to develop the requisite amount of skill (Titley et al. 2020; Leroux et al. 2018; Landsea and Franklin 2013). Estimates for the duration of wind acceleration, upper limits of the wind, and the cyclone's likely track are among the results of this technique (Moura et al. 2016; Kim et al. 2019).

In India, operational models for TC track and intensity forecasting are primarily managed by the India Meteorological Department (IMD) and the NCMRWF, MoES India. The IMD employs high-resolution coupled model "HWRF-POM-TC", such as the WRF with a horizontal grid resolution of 3 km, along with a Multi-Model Ensemble (MME) approach for predicting TC track and intensity over NIO region (Das et al. 2021; Srivastava

et al. 2021; Mishra et al. 2021). NCMRWF, on the other hand, utilizes its global model (NCUM-G) with a horizontal resolution of approximately 12 km, the regional Unified Model (NCUM-R) with a resolution of 4 km (Ashrit et al. 2021), as well as ensemble prediction systems, namely the Global (NEPS-G) and Regional (NEPS-R) NCMRWF Ensemble Prediction Systems, for medium-range forecasts (Dube et al. 2020; Sarkar et al. 2022).

A few of operational TC forecasting models along with their details are listed in Table 1.

3.2 | Various Approaches for the TC Prediction

TC forecasting has undergone significant evolution, encompassing a range of methodologies that leverage various aspects of meteorological data and modeling techniques. Figure 4 categorizes these methodologies into several key approaches: (i) averaging across occurrences, (ii) statistical, (iii) dynamical and numerical, (iv) statistical-dynamical, (v) hybrid, and (vi) other forecasting techniques (Roy and Kovordányi 2012). Each of these methods offers unique strengths and limitations, and their selection often depends on specific forecasting requirements, data availability, and computational resources. It should be noted that averaging across occurrences, also known as "extrapolation" techniques, represents one of the most straightforward approaches to TC forecasting. This method relies on the assumption that a cyclone will continue to move in the same direction and at a similar speed as it has in the recent past. By averaging the direction and speed of the current and previous positions of a cyclone, forecasters can generate short-term predictions of its future track. Holland (2009) described these as among the simplest techniques for cyclone track forecasting. The accuracy of this method, however, hinges heavily on the precise selection of time-tagged positions of the cyclone, especially its most recent location and movement vectors (Roy and Kovordányi 2012). When implemented properly, extrapolation can provide reasonable short-range forecasts, typically up to 12–24 h ahead (Jeffries and Miller 1993). However, this approach does not consider environmental factors such as atmospheric steering flows, SST gradients, or pressure anomalies, which are crucial for longer-range and intensity forecasts. Consequently, while averaging across occurrences can be valuable for rapid and early-stage predictions, it is generally inadequate for medium to long-term forecasts and is often supplemented or replaced by more advanced statistical or dynamical techniques in modern operational forecasting systems. Statistical forecasting of TCs utilizes historical data to identify correlations among variables like SST, atmospheric pressure, and wind shear. These models, primarily based on regression analysis, are computationally efficient and applicable for both short-term (24 h) and long-term (up to 72 h) forecasts (Miller and Chase 1966). Techniques include statistical-synoptic methods, climatology-persistence models, and steering airflow determination (Roy and Kovordányi 2012; Jeffries and Miller 1993; Neumann 1979). Predictor datasets may be derived from previous storms, numerical simulations, or synoptic analysis (Lee and Liu 2004; Neumann 1985). While these methods perform well under climatological norms, their reliability diminishes during anomalous synoptic conditions or in data-sparse regions (Jeffries and Miller 1993; Keenan 1985).

TABLE 1 | Details of major NWP cyclone prediction models currently operational in various countries.

S. No.	NWP models	Horizontal resolution	Vertical levels and coordinates	DA system	Convective scheme	References for further details of models
1	Météo-France Operational Prévision d'Ensemble ARPEGE (PEARP) model	Spectral (resolutions 7 and 5 km over France, and 36 km over New Zealand)	47; standard pressure levels and height levels	Météo-France ensemble data assimilation system	Mass flux scheme based on Kain and Fritsch (1993)	Descamps et al. (2015)
2	NOAA's Global Forecast System (FV3-GFS)	Finite Volume Cubed Sphere (~13 km)	91, Hybrid sigma pressure	Hybrid 4D-EnVar/GSI	Simplified Arakawa and Schubert (1974) and Grell (1993)	Chen, Lin, et al. (2019)
3	ECMWF-Integrated forecast system (IFS)	Spectral (~9 km)	137, Hybrid Sigma-pressure	4D-VAR	Tiedtke (1989) mass-flux convective parameterization	Johnson et al. (2019)
4	U.K. Met Office Deterministic Global Model	Grid point (~10 km)	70, Hybrid sigma pressure (lid ~80 km)	4D-VAR	Mass flux convection scheme based on Gregory and Rowntree (1990)	Walters et al. (2017)
5	Canada's regional Deterministic reforecast system	Grid point (~10 km)	80, Hybrid Sigma-pressure	4D-EnVar system	Kain and Fritsch (1993)	Gasset et al. (2021)
6	Japan Meteorological Agency (JMA) global ensemble prediction system	Spectral (~27 km)	128, stretched sigma pressure hybrid levels (0.01 hPa)	Global analysis with ensemble perturbations	Prognostic Arakawa-Schubert cumulus parameterization	Tokuhiro (2018)
7	Australian Community Climate and Earth-System Simulator (ACCESS) tropical cyclone (TC) model	Grid point (~12 km)	50, Hybrid Sigma-pressure	Four Dimensional Variational (4D-VAR)	Modified mass flux scheme based on Gregory and Rowntree (1990)	Davidson et al. (2014)
8	Hurricane Multi-scale Ocean-coupled non-hydrostatic mesoscale model	Nested Grid point (18–6–2 km)	61, Hybrid Sigma-pressure	GFS Initial condition/Boundary conditions + GSI	Simplified Arakawa Schubert	Tallapragada et al. (2014)
9	India Meteorological Department's operational HWRF ocean coupled model	Nested Grid point, (18–6–2 Km)	61, Hybrid levels (Sigma to pressure at 150 hPa)	HDAS (GSI + 3DVAR)	Scale-aware Simplified Arakawa-Schubert scheme	Das et al. (2021)
10	Chinese Global/Regional Assimilation and Prediction System (GRAPES)_ GFS	0.25° × 0.25° horizontal resolution	60, Sigma vertical levels	Three Dimensional Variational (3DVAR)	New Simplified Arakawa-Schubert (NSAS) shallow and deep convection scheme	Ma et al. (2018)
11	National Centre for Medium Range Weather Forecasting (NCMRWF), global unified model (NCUM-G), NOIDA, INDIA	~12 km	70, Hybrid sigma pressure (lid ~80 km)	Hybrid incremental 4D-Var	Mass flux convection scheme based on Gregory and Rowntree (1990)	Mohandas et al. (2022); Kumar et al. 2022

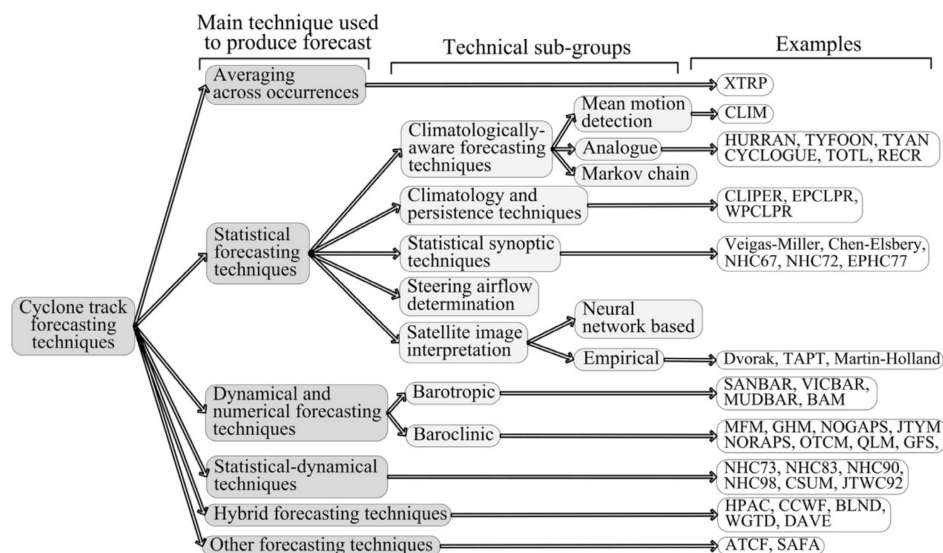


FIGURE 4 | Demonstration of various cyclone track and intensity prediction techniques. The figure is used with permission from Roy and Kovordányi, 2012 *Atmospheric Research Journal*.

Dynamical and numerical forecasting techniques represent the most physically comprehensive and scientifically robust approach to TC prediction. These methods simulate the governing physical processes of the atmosphere by solving the full set of nonlinear, time-dependent primitive equations, comprising conservation of momentum, mass continuity, thermodynamics, and moisture, on a gridded domain. Forecasting is carried out through two primary methodologies. First, the direct prognostic integration of the TC vortex using atmospheric equations, and the identification of steering flow at various tropospheric pressure levels based on wind field prognoses derived from global or regional NWP models (Jeffries and Miller 1993). This approach minimizes dependence on historical climatological baselines by dynamically assimilating real-time observational datasets, including satellite radiances, aircraft reconnaissance data, surface-based measurements, and buoy observations, into high-resolution NWP models (Routray et al. 2016; Krishna and Rao 2009; Osuri et al. 2012). As a result, it enables the generation of accurate forecasts even in data-sparse environments or during atypical synoptic conditions, thereby improving the reliability and adaptability of TC prediction systems (Lee and Liu 2004; Neumann 1985).

Dynamical models such as the Global Forecast System (GFS), Integrated Forecast System (IFS), Hurricane Weather Research and Forecasting (HWRF) model, and the Unified Model (UM) integrate DA systems to initialize atmospheric states with high fidelity, while resolving mesoscale and synoptic-scale interactions critical to TC evolution (Zhang et al. 2023; Ashrit et al. 2021; Routray et al. 2017; Wang, Wan, et al. 2023). These models explicitly represent environmental features such as VWS, mid-level moisture, SST gradients, and atmospheric stability, that is, factors that govern cyclone track, intensity, and structural changes. Due to the high spatial and temporal resolution required to accurately resolve the TC inner-core and surrounding environment, these models are computationally demanding and are typically executed on multi-node high-performance computing (HPC) clusters, rendering them unsuitable for low-resource platforms (Lee and Liu 2004). Despite their complexity, dynamical forecasting

techniques offer a physically consistent and prognostically powerful tool for both operational and research purposes. Their capacity to produce deterministic and ensemble-based probabilistic guidance has made them the cornerstone of modern TC prediction, especially for medium-range forecasts.

The statistical-dynamical forecasting technique represents a mixed approach wherein historical TC data are statistically screened to identify relevant predictors, which are then combined with outputs from dynamical models to yield the final forecast. This methodology effectively integrates the strengths of both statistical and dynamical approaches, using statistical models to interpret and adjust the simulated data generated by numerical models. By doing so, it captures both climatological patterns and real-time atmospheric dynamics, enhancing predictive skill for TC track and intensity forecasts (Maier-Gerber et al. 2021; Kim et al. 2022). Statistical-dynamical models are particularly beneficial for medium-range forecasts and in regions with relatively limited observational data, as they can incorporate large-scale environmental signals along with localized storm-specific characteristics (Sabeerali et al. 2022; Roy and Kovordányi 2012).

Hybrid forecasting techniques for TC prediction represent an integrative modeling approach in which outputs from two or more distinct forecasting methods, typically statistical and dynamical, are combined to utilize the advantages of each system (Jeffries and Miller 1993). These models inherit the strengths of their constituent components, such as the physical realism of dynamical models and the pattern-recognition efficiency of statistical techniques, thereby improving forecast accuracy and expanding the range of usable predictors. However, this synthesis also implies the potential aggregation of methodological weaknesses from the individual components (Jeffries and Miller 1993). A prominent example of this approach is the hybrid dynamical-statistical model developed that combines empirical orthogonal function (EOF)-based TC track patterns with large-scale environmental predictors to forecast WNP TC track density (Zhang and Chen 2023). Their model successfully captured

inter-annual variability and outperforms ENSO-based forecasts, enhancing the model's potential for operational use.

It should be noted that hybrid forecasting differs structurally from statistical-dynamical forecasting. While the latter generally involves a sequential process where dynamical model outputs feed into a statistical model. The hybrid approach allows for deeper integration at multiple stages, including input pre-processing, model execution, and output blending. Hybrid TC modeling systems are increasingly incorporating real-time observations and advanced AI/ML algorithms to assimilate and interpret diverse data sources, capturing complex, non-linear interactions in the atmosphere more adaptively. (Slater et al. 2023, 2022; Arcomano et al. 2022). This makes hybrid forecasting particularly promising for improving forecasting skill in operational TC forecasting systems. The Other Forecasting Techniques has evolved with the development of specialized systems like the “Automated Tropical Cyclone Forecasting System” (ATCF) system and the “Systematic Approach and Forecast Aid (SAFA).”

Recent advancements in AI and ML have further introduced new methodologies for TC forecasting. Deep learning models, such as convolutional neural networks (CNNs) and recurrent neural networks (RNNs), have been applied to predict TC intensity and track by learning complex patterns from large datasets (Wang, Wan, et al. 2023, gsm; Zhang et al. 2022; Xu et al. 2022). These AI-based models offer promising results, particularly in capturing nonlinear relationships and handling high-dimensional data, although they require extensive training data and computational resources.

3.3 | Real-Time Tropical Cyclone Forecasting and Risk Mitigation at Operational Forecasting Centers

At operational TC forecast centers, real-time forecasting and risk mitigation follow a scientifically rigorous, multi-tiered workflow designed to minimize societal and economic impacts from landfalling cyclones. The first step involves the acquisition of real-time observational data from a diverse network of platforms. These include advanced geostationary satellites (e.g., Himawari-8, INSAT-3D/3DR), polar-orbiting satellites (e.g., NOAA-20, MetOp), microwave sounders, ocean-based platforms such as moored and drifting buoys, DWRs, and aircraft reconnaissance missions (e.g., NOAA Hurricane Hunters in the North Atlantic). These datasets provide continuous updates on key atmospheric and oceanic parameters such as SSTs, wind vectors, pressure fields, and water vapor content.

The second step centers on DA and NWP modeling, which forms the scientific backbone of operational cyclone forecasting. The process begins with quality control and pre-processing of observational data obtained from satellites, surface stations, radars, buoys, and aircraft reconnaissance. These observations are then systematically interpolated onto a model grid, followed by DA using advanced techniques such as Three-Dimensional Variational (3DVAR), Four-Dimensional Variational (4DVAR),

or hybrid ensemble-variational (EnVar) schemes. These methods integrate observations with a short-term model forecast (the background state) to produce optimal initial conditions for the NWP system. Once the initial conditions are generated, the NWP model is run, often using high-performance computing systems due to the complexity and resolution required. Models such as the Weather Research and Forecasting (WRF), Hurricane Weather Research and Forecasting (HWRF), and the Unified Model (UM) are typically run at high spatial and temporal resolutions to simulate the atmospheric evolution. The output includes forecasts of key tropical cyclone parameters such as track, intensity, wind structure, mean sea level pressure, and rainfall, etc.

The third phase entails analyzing model outputs to generate forecasts of cyclone track, intensity, precipitation distribution, wind fields, and storm surge. Forecasters interpret dynamically consistent model guidance in conjunction with synoptic diagnostics to derive actionable insights. This involves examining outputs from numerical weather prediction models, including pressure patterns, temperature gradients, humidity profiles, and wind vectors across different atmospheric layers. Synoptic-scale features such as troughs, ridges, and cyclonic circulations are evaluated alongside mesoscale dynamics to assess the cyclone's structure and anticipated evolution. Forecasters validate and refine predictions by comparing multiple model runs with real-time observational data, ensuring consistency and accuracy. This integrated analysis forms the basis for issuing timely and reliable warnings critical for disaster preparedness and risk mitigation.

The fourth and critical step is the communication of forecast information to stakeholders, including national meteorological and hydrological services, emergency management agencies, and the general public. This is facilitated through official bulletins, real-time dashboards, press briefings, and digital dissemination platforms such as mobile alerts and social media, ensuring actionable information reaches at-risk populations promptly.

The fifth component involves the implementation of risk prevention and mitigation strategies. This includes the activation of pre-disaster protocols such as phased evacuations of at-risk populations, reinforcement of vulnerable infrastructure, suspension of transportation and maritime operations, and pre-emptive shutdowns of electricity and utility services in highly exposed areas to minimize damage and ensure public safety. These measures are coordinated by local and national disaster management authorities and are directly informed by forecast inputs to ensure timely and location-specific actions. Effective execution of these strategies is critical to reducing potential loss of life, infrastructure damage, and disruption to essential services.

Finally, disaster response and emergency management protocols are executed post-landfall. These include real-time damage assessments, search and rescue operations, and deployment of humanitarian aid. Forecasting centers continue to provide updates during the dissipation phase, supporting recovery planning and long-term resilience building. This comprehensive operational

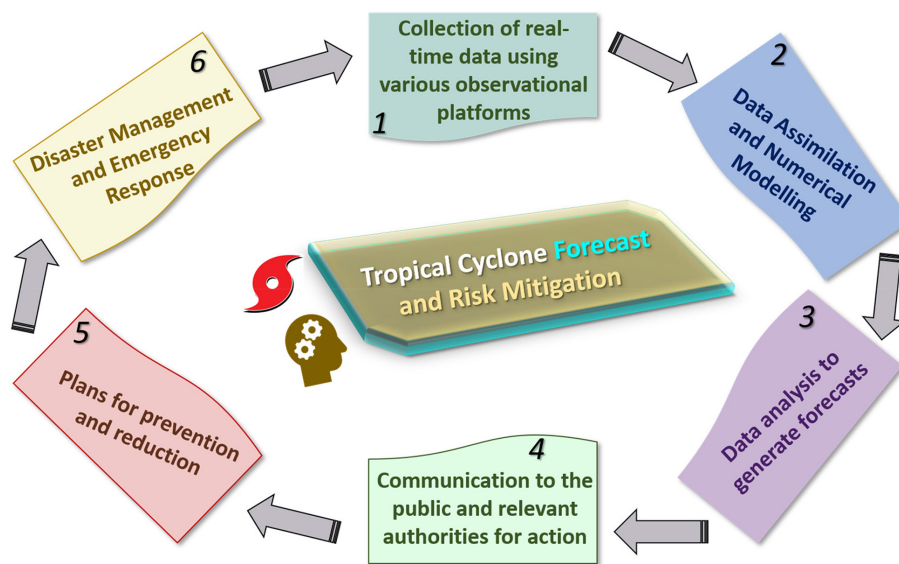


FIGURE 5 | Tropical cyclone prediction disaster preparedness block diagram.

cycle spanning from data acquisition to emergency response is depicted schematically in Figure 5, illustrating how each scientific and logistical component contributes to the integrated framework of TC forecasting and real-time risk mitigation.

As discussed in previous sections, while each cyclone forecasting methodology, DA technique, and NWP model offers unique strengths, ranging from improved track forecasting to better intensity estimation, significant challenges still remain. These include issues such as the coarse resolution of operational global models, limited observational data over oceanic regions, and the difficulty of assimilating high-frequency satellite data in real time. DA techniques often rely on assumptions of linearity and balanced background error covariances, which may not hold in the highly dynamic TC environment. Furthermore, the integration of high-resolution observations and ensemble-based approaches into operational systems remains limited. The following Table 2 provides a detailed overview of the current strengths and weaknesses of various TC forecasting strategies and suggests actionable solutions to enhance their reliability and operational utility. Addressing these challenges is critical for advancing early warning systems and disaster risk reduction efforts.

4 | Recent Scientometric Research Trend in the Field of Tropical Cyclones

In the previous sections, we comprehensively discussed the dynamics, tracking algorithms, and forecasting techniques of tropical cyclones (TCs), along with the detailed steps involved in real-time forecasting and risk mitigation at operational centers across global basins. Incorporating a scientometric analysis in the present section provides a quantitative overview of global research trends, collaborative networks, and existing knowledge gaps in TC-related studies. It also helps prioritize future research directions by mapping the evolution of scientific focus in cyclone-related forecasting and dynamics.

4.1 | Selection of the Studies for Three-Field Plot Analysis

Relevant research literature, with a focus on strategies associated with mitigating the challenges in predicting the track and intensity of cyclones across the world basins, was chosen from the scholarly electronic database, Web of Science. The data inputs were searched between 2006 and 2022. Due differentiation was carried out concerning the discoveries and innovative and scientific inventions for upgradation based on the latest scientific challenges. The keywords used for the search were “tropical cyclones”, “rapid intensification”, NIO Basin and also a combination of words like “numerical weather prediction”, tropical cyclones and forecasting techniques, intensity, structure, and landfall. A total of “17384” articles were identified and 8027 web pages were removed according to specific variables, relevant to the present review article. Out of the remaining 9357 studies, a total of 8084 blogs, books and online article-related matter were removed and the total research articles identified were narrowed down to 1273. To be at par with the recent developments, 321 research articles before 2006 were discarded and 952 research studies were screened dating from 2006 till 2022. Out of these 952 research studies, 612 studies were further eliminated and the eligible number of studies now stood at 340. Out of 340, 289 were eliminated based on the relevance of the topic and the final number of studies was consolidated at “51” which was taken forward for this study and research. The detailed flowchart adopted in the present review article is presented in Figure 6. These 51 peer-reviewed studies published in academic journals from 2006 to 2022, that described the outcomes of original research on challenges related to TC track and intensity prediction across the world basins, are examined and discussed in detail in the present work.

Research articles on cyclone tracking and forecasting using empirical approaches and neural networks are also included in these 51 studies. While selecting the criteria, book chapters and proceedings of various conferences and summits were

TABLE 2 | Summary of the advantages, limitations, and potential solutions associated with various TC forecasting methodologies, DA techniques, and NWP models.

Forecast technique	Advantages	Challenges	Possible solutions
ANN and ML	- ANN ML models have adequate ability to learn complex patterns - They can handle non-linear and complex relationships among weather parameters	- Large datasets are required for training - Models are prone to overfitting	Use of the regularization techniques and data augmentation to enrich datasets could be used to avoid the possible challenges
DA system	- Various DA frameworks improve the forecast accuracy by assimilating real-time observations - Provides better initialization for NWP models	- DA systems are computationally expensive - Data quality is a major issue with this technique	- Use of the more efficient algorithms - Advancement in the observational network and data quality
NWP modeling system	- The NWP models can simulate long-term forecasts - The simulations provide physical insights into the phenomena	- The NWP models also require high computational resources - Models are highly sensitive to initial conditions	- The technically correct application of ensemble forecasting is useful for quantifying the uncertainties - Advanced parallel computing techniques are useful to handle the challenges
Large member ensemble forecasting	The large member ensemble method quantifies forecast uncertainty and provides a probabilistic forecast	- The design of ensemble member generation is a complex task - Requires more computational resources	- By optimizing the ensemble size and selection process the computational resources can be managed - Model downscaling techniques can be a fruitful approach when generating the large member ensembles

Note: This table highlights key operational challenges and outlines strategies to improve forecast accuracy and reliability.

excluded. The articles were primarily classified according to their main focus on the systematic strategy, for example, origin, works done so far, response, shortcomings, and current scientific challenges, pivoting our study and analysis to the main topic of research. Careful insights were offered not to intermix any overlapping topics, like risk disaster management, and so on. From each article, the following data was then captured and analyzed categorically, that is, authors, year of publication, place of study, name of the publishing journal, data type, forecasting methods, aim of the study, verification and authentication of results, whether climate change aspects were inclusive, or whether it presented a further scope for research, and finally what scientific challenges were presented in the studies. The details of 51 selected studies, along with their categories, are presented in Table 3.

Further, we found that a total of 11 journals accounted for the highest number of core article publications (Figure 7). The left column in Figure 7 represents the publication sources (SO), that is, the journals where the papers were published. The middle column shows the authors (AU), that is, the researchers who contributed

to these studies. The right column displays the most popular keywords (DE) used by authors to describe their work. The gray edges (strings) connects these three elements, illustrating their interrelation. The thick gray strings indicate a stronger association between two elements representing a higher frequency of co-occurrence. On the other hand thin gray strings indicate a weaker association, meaning a lower frequency of connection between the elements. From the Figure 7, it is evident that *Monthly Weather Review*, *Atmosphere*, and *Weather and Forecasting* were the top three leading journals among these 51 studies. Additionally, *Forecasting*, *Tropical Cyclones*, and *Numerical Weather Prediction* emerged as the three most frequently used keywords (DE) in these studies. Moreover, Zhang X and Marks F were the authors most strongly associated with the descriptors *Forecasting* and *Tropical Cyclones*. Furthermore, *Zhang F* had the strongest association with the journal *Monthly Weather Review*.

The relationship between keywords produced by hierarchical clustering is depicted by the dendrogram of words (Figure 8). According to Andrews (2003), a dendrogram not only indicates an exact relationship between clusters generated, but it also

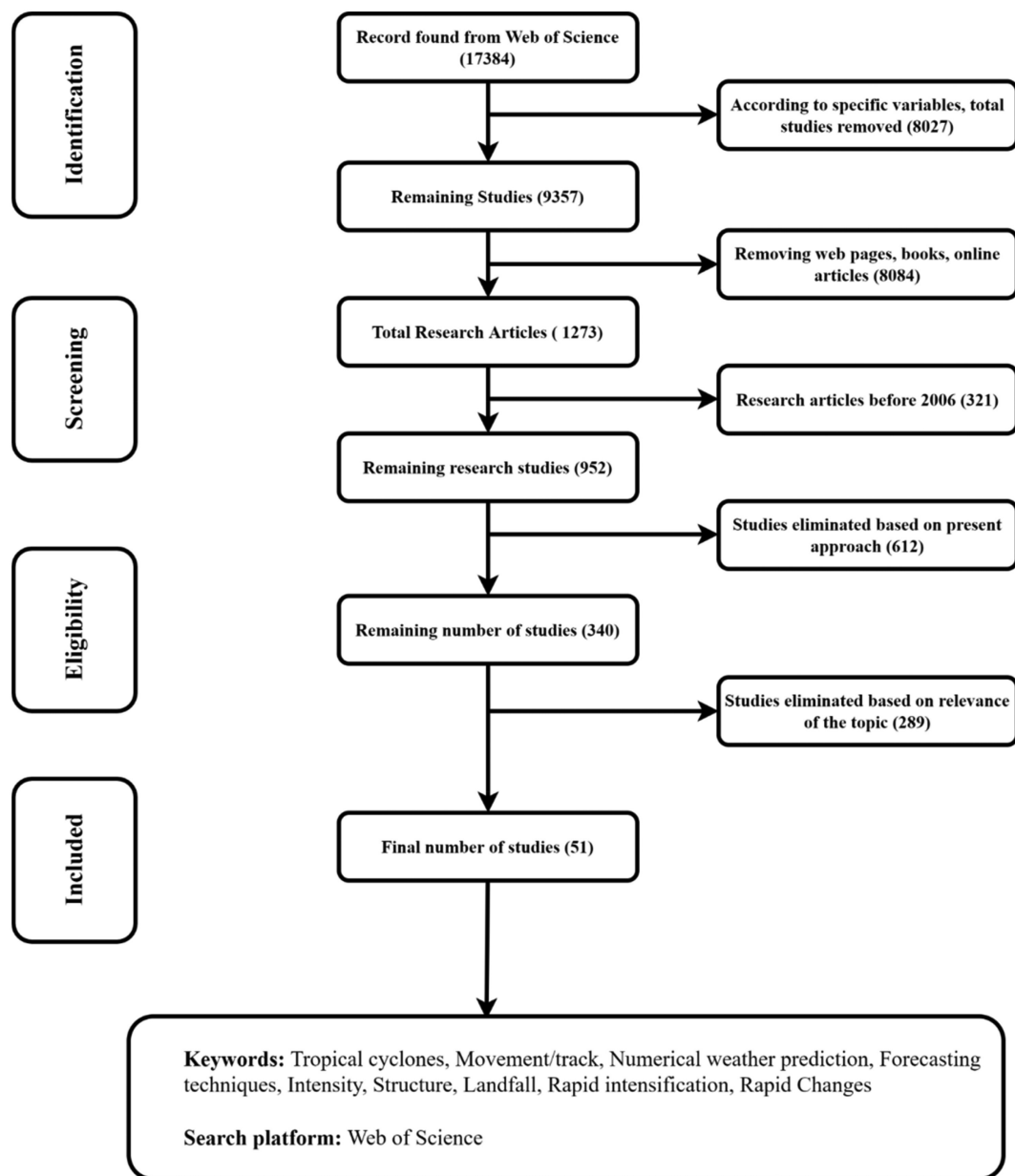


FIGURE 6 | Detailed flow diagram showing the detailed methodology of literature selection.

aims to assess the number of clusters for experts to specify the key drivers across different studies by different authors. The most commonly used keywords, their relationships to other keywords, and the classification of these keywords are shown in different colors in a dendrogram tree diagram. This dendrogram represents two types of keyword classifications: red and blue. It shows that the keywords in the blue classification have little in common with those in the red classification. Each red one is subdivided into several clusters, each of which is subdivided into several sub-clusters. So, Figure 8 shows how different keywords or topics from the cyclone studies are grouped based on their relationships or co-occurrences in the selected 51 research articles. The branches and nodes of the dendrogram indicate the degree of association between the topics, helping to identify major themes and connections between different research areas.

4.2 | Analyses of Authors' Keywords Co-Occurrence Network

Analyzing an authors' keywords co-occurrence network involves exploring the relationships between keywords across multiple authors' works. This can reveal broader trends, common themes, and areas of interconnection in a particular field or across different fields. Based on the frequency of occurrences, associations, and co-occurrences of each keyword in published tropical cyclone documents from 2006 to 2022, the title word co-occurrence network was established. It is shown in Figure 9 that 28 of the most commonly used words in published research articles on tropical cyclone studies include co-occurring, associated, and noded. To represent the number of times a keyword appears alongside other keywords in published texts on tropical cyclones, we used a node-line graph. For each keyword in the published

TABLE 3 | Distribution of 51 articles selected for the scientometric analysis of review articles.

Attributes	Authors (year)	Journal	Lead author country
Expansion of TC characteristic modeling and impact of advanced techniques	Kuroda et al. 2010	<i>Journal of the Meteorological Society of Japan</i>	Japan
	Rhome and Raman (2006)	<i>Indian Journal of Geo-Marine Sciences (IJMS)</i>	USA
	Ashrit et al. 2021	<i>MAUSAM</i>	India
	Chen et al. 2022	<i>Frontiers of Earth Science</i>	China
	Dong et al. 2020	<i>Atmosphere</i>	USA
	Hazelton et al. 2021	<i>Weather and Forecasting</i>	USA
	Leroux et al. 2013	<i>Journal of the Atmospheric Sciences</i>	France
	Leroux et al. 2016	<i>Monthly Weather Review</i>	France
	Lian-Shou (2012)	<i>Journal of Tropical Meteorology</i>	China
	Liu et al. 2017	<i>Advances in Atmospheric Sciences</i>	USA
	Miller et al. 2015	<i>Journal of the Atmospheric Sciences</i>	USA
	Rappin et al. 2011	<i>Journal of the Atmospheric Sciences</i>	USA
	Rios-Berrios (2020)	<i>Journal of the Atmospheric Sciences</i>	USA
	Shieh et al. (2013)	<i>Weather and forecasting</i>	USA
	Short and Petch (2018)	<i>Weather and Forecasting</i>	UK
	Singh et al. (2021)	<i>Atmospheric Research</i>	India
	Subrahamanyam et al. (2019)	<i>Natural Hazards</i>	India
	Torn and DeMaria (2021)	<i>Atmosphere</i>	USA
	Zhu et al. (2019)	<i>Frontiers of Earth Science</i>	China
	Knaff et al. (2020)	<i>Weather and Forecasting</i>	USA
	Tam et al. (2021)	<i>Meteorological Applications</i>	Hong Kong
	Hazelton et al. (2020)	<i>Monthly Weather Review</i>	USA
	Nystrom et al. (2021)	<i>Monthly Weather Review</i>	USA
Techniques utilizing ANN	Chan et al. (2021)	<i>Meteorological Applications</i>	China
	Chen et al. (2020)	<i>Atmosphere</i>	China
	Cloud et al. (2019)	<i>Weather and Forecasting</i>	USA
	Schaffer et al. (2020)	<i>Monthly Weather Review</i>	USA
	Xu et al. (2021)	<i>Weather and Forecasting</i>	USA
Impact of DA system	Chang et al. (2020)	<i>Journal of the Atmospheric Sciences</i>	Taiwan
	Feng and Wang (2019)	<i>Monthly Weather Review</i>	Japan
	Fox and Judt (2018)	<i>Weather and Forecasting</i>	USA
	Lu and Wang (2019)	<i>Monthly Weather Review</i>	USA
	Minamide et al. (2020)	<i>Journal of the Atmospheric Sciences</i>	USA
	Mueller et al. (2021)	<i>Monthly Weather Review</i>	USA
	Nystrom and Zhang (2019)	<i>Monthly Weather Review</i>	USA
	Sawada et al. (2019)	<i>Monthly Weather Review</i>	Japan

(Continues)

TABLE 3 | (Continued)

Attributes	Authors (year)	Journal	Lead author country
Cyclone-induced rainfall prediction	Taylor et al. (2021)	<i>Journal of Advances in Modeling Earth Systems</i>	Japan
	Wu et al. (2014)	<i>Monthly Weather Review</i>	USA
	Ray et al. (2022)	<i>Meteorology and Atmospheric Physics</i>	India
	Kaplan et al. (2015)	<i>Weather and Forecasting</i>	USA
	Kotal and Bhattacharya (2021)	<i>MAUSAM</i>	India
Impact of parameterization schemes	Ren et al. (2018)	<i>Weather and Forecasting</i>	China
	Shimada et al. (2018)	<i>Weather and Forecasting</i>	Japan
	Chen, Lin, et al. (2019)	<i>Geophysical Research Letters</i>	USA
	Hristova-Veleva et al. (2021)	<i>Atmosphere</i>	USA
	Jin et al. (2014)	<i>Monthly Weather Review</i>	USA
Cyclone disaster management	Kalina et al. (2021)	<i>Atmosphere</i>	USA
	Singh and Bhaskaran (2017)	<i>Journal of Atmospheric and Solar-Terrestrial Physics</i>	India
	Zhang and Rogers (2019)	<i>Monthly Weather Review</i>	USA
	Hoque, Phinn, and Roelfsema (2017)	<i>Ocean & Coastal Management</i>	Australia
	Hoque, Phinn, Roelfsema, and Childs (2017)	<i>International Journal of Disaster Risk Reduction</i>	Australia

paper on TC investigations, its width or node size indicates the frequency of recurrence. By examining the node-line graph, we identified that “numerical weather prediction” and “tropical cyclones” and “forecasting” are the most prevalent and central topics in selected 51 studies.

4.3 | Detailed Discussion of Selected 51 Studies Under Different Categories

4.3.1 | Expansion of TC Characteristic Modeling and Impact of Advanced Techniques

Kuroda et al. (2010) numerically simulated the extremely severe cyclonic storm Nargis (2008) over the Myanmar oceanic region, using two numerical models (i.e., Japan Meteorological Agency's Non-hydrostatic model (NHM) and the Princeton Ocean model). The study concluded that the downscaling of the NHM with a horizontal resolution of ~10km produced more realistic features of the TC in comparison to operational global analysis and global spectral model forecasts. The storm surge could not be reproduced in the Princeton Ocean Model (horizontal resolution ~3.5km) experiment using global spectral model forecast data, but the simulation of the ocean model using NHM forecast data predicted a rise in sea level of over 3m. In a similar type of study by Singh et al. (2021), the authors found that India's NCMRWF operational global model NCUM (horizontal resolution ~12km) was highly

skilful in predicting the track and intensity of an extremely severe cyclonic storm “Fani” (2019) over the BoB. However, this study did not analyze the storm surge associated with the TC.

The performance of a non-hydrostatic limited-area atmospheric model, Consortium for Small-scale Modeling (COSMO), was evaluated and found commendable in the detection of the early genesis of a very severe cyclonic storm Ockhi (2017) over the ARB (Subrahmanyam et al. 2019). In line with the study by Ashrit et al. (2021), Chen et al. (2022) also evaluated the skills of operational models of China for super typhoon Lekima (2019) over the east-China sea region. The main difference between these two studies was that while Chen et al. (2022) evaluated the skill of operational probabilistic (ensemble) models along with deterministic models, Ashrit et al. (2021) evaluated the skill of global and regional models only (i.e., deterministic models). Further, the operational forecasts of various leading meteorological agencies were also compared by Chen et al. (2022). The authors further concluded that all the operational deterministic models were efficient enough for predicting the landfall point of super typhoon Lekima, as reported by Ashrit et al. (2021) for Super Cyclone (SuCS) Amphan using NCMRWF's operational model. The nested finite volume solver (FV-3) based Hurricane Analysis and Forecast System (HAFS) of the NOAA is a hurricane modeling system that is in the evolution phase at present (Dong et al. 2020; Hazelton et al. 2024). Utilizing global-nested and

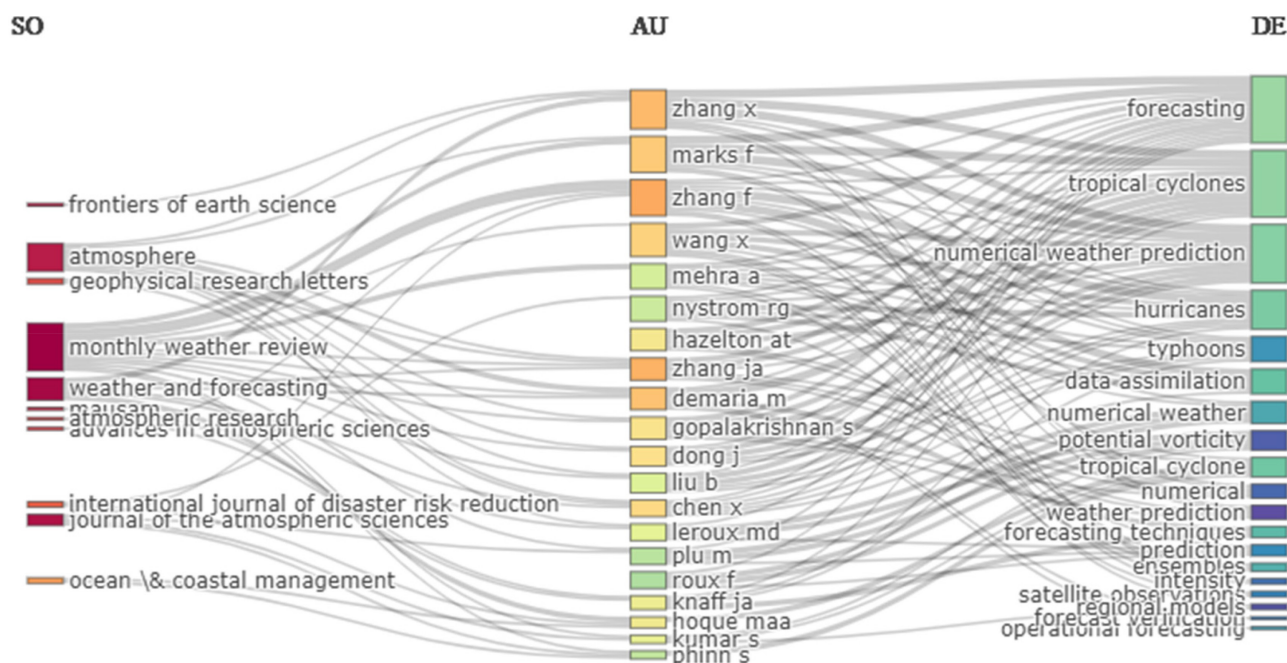


FIGURE 7 | Depiction of three fields plot (i.e., Source (SO), Author (AU) and Author's keywords/Descriptors (DE)) showing an interrelation between them.

regional versions of the HAFS modeling suite, the real-time simulations were conducted in 2019, creating the first baseline for HAFS progressions. Hazelton et al. (2021) showed that even though the ability to predict rapid intensification was slightly inferior to the operational model ability, the global-nested configuration of the modeling suite was more skillful in predicting track, intensity, and structure of hurricanes formed during July–October 2019.

The WRF-ARW model was used to investigate the RI of category-5 Hurricane Katrina (2005) before it made landfall in the southern United States by Liu et al. (2017). The findings of the study suggest accurate hurricane track and intensity prediction require a better representation of vertical mixing and surface fluxes in the planetary boundary layer. Zhu et al. (2019) found an improvement in the prediction skills of the WRF-ARW model for two typhoon rainfall cases (Typhoon Meranti (2016) and Typhoon Fitow (2013)) over the WNP Ocean, when the Kain-Fritsch convection parametrization scheme of the model was optimized using a micro-genetic algorithm. Here, it is worth discussing that in place of the convection parametrization scheme, Liu et al. (2017) compared two popular planetary boundary layer (PBL) schemes (i.e., the Mellor-Yamada-Janjic (MYJ) and the Yonsei University (YSU) schemes). As a result, the MYJ scheme performed better, simulating a more accurate track and intensity evolution, as well as a more accurate vortex structure and landfall time and location of Hurricane Katrina.

In recent times, though significant progress has been made in TC track prediction across the basins, the prediction of intensity still has not improved adequately in the NWP models. The reason behind the sluggish improvement in TC intensity prediction is that numerical models are unable to resolve complex

internal dynamics occurring in the core of TCs (Rhome and Raman 2006; Lian-Shou 2012). In this regard, the task of improving intensity forecasts in numerical models mandates the researchers to look into plausible causes on which the intensity of TCs depends. In the TCs' secondary circulation, the weaker "inertial stability" in the outflow layer is found to reduce the energy sink, resulting in a faster intensification to the maximum potential intensity of TC (Rappin et al. 2011). Convective bursts (CBs) occurring inside the upper-level radius of maximum wind, have the potential to influence hurricane intensification by causing compensatory subsidence of lower-stratospheric air (Miller et al. 2015). The decrement in the tilt of the cyclonic vortex and symmetric convection leads to the intensification of weak TCs (Rios-Berrios 2020). Shieh et al. (2013) proposed that features of upper tropospheric troughs must be considered while forecasting the intensity of TCs. Short and Petch (2018) delineated the superiority of the convection-permitting regional unified model (UM: horizontal resolution ~4.4 km) over its global counterpart for the prediction of intensities of strong TCs formed in the WNP Ocean basin. The TC 'Dora' was formed over the southwest Indian Ocean in the year 2007. The causes of TC's RI under its interaction with upper-level trough forcing were investigated by Leroux et al. (2013) utilizing a limited area operational NWP model. The NWP model with 8-km horizontal resolution was capable of reproducing the main characteristics of the eye-wall replacement cycle observed for the TC. Potential Vorticity (PV) superposition in conjunction with secondary eye-wall formation induced by eddy momentum flux convergence and trough's vertical velocity forcings were identified as the main mechanisms of the TC vortex intensification. Further, it was found that for stronger cyclonic vortices, intensification of the TC was greater under upper-level forcing Leroux et al. (2016).

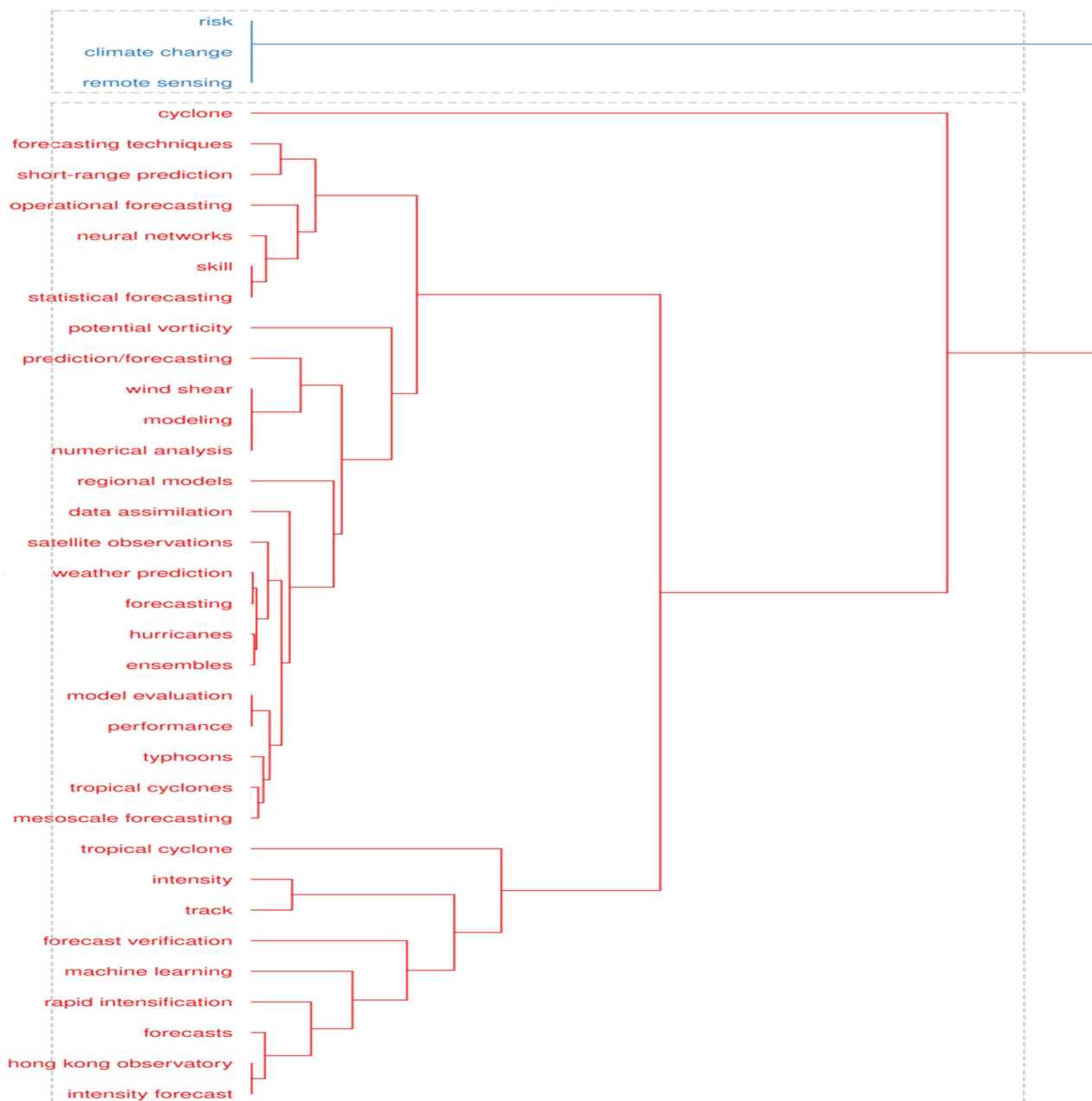


FIGURE 8 | Authors' keyword dendrogram throughout the 51 retrieved articles.

A thorough examination of high-resolution ensemble predictions of different intensity changes (computed from operational Hurricane WRF (HWRF) and Hurricanes in a Multi-scale Ocean-coupled Non-hydrostatic (HMON) models) thresholds was carried out by Torn and DeMaria (2021) for the select cyclones formed over the Atlantic and eastern Pacific oceans during 2017–2019. After the application of a quantile-based bias correction scheme, both the HWRF and HMON ensemble-based models provided the skillful forecasting of intensity changes for cases without rapid intensification. The inter-comparison of track and intensity forecasts of TCs over the North Atlantic Ocean (NAO) basin revealed that the newly operationalized regional model HAFS Stand-Alone Regional (HAFS-SAR) outperformed the three operational models, that is, Global Forecast System (GFS), HWRF, and HMON in track prediction of TCs (Dong et al. 2020). However, the HAFS-SAR

model was less skillful in intensity prediction as compared to HWRF and HMON. The model showed a little improvement in intensity prediction over the GFS model. The improved convection scheme (i.e., the Finite-Volume cubed sphere (FV3)) may be attributed to the better TC track predicting skill of the HAFS-SAR model.

Though the improvement of RI forecasts has accelerated in comparison to years before 2018 (Wang, Zhu, et al. 2023), numerical models still face challenges in accurately forecasting cyclone intensity. This highlights the need for continued research and development to enhance intensity forecasting capabilities in numerical models. Zhang et al. (2023) highlighted that the accuracy of TC intensity forecasts issued by operational forecast agencies depends on three crucial aspects: the availability of real-time observations, the guidance provided

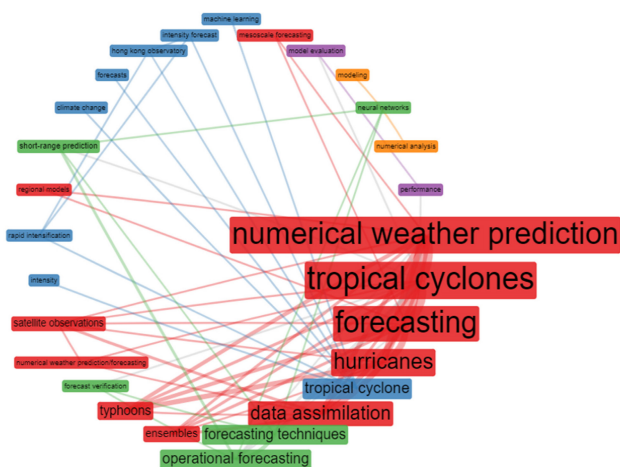


FIGURE 9 | Authors' keywords co-occurrence network on tropical cyclones found in the present study.

by TC dynamical model forecasts, and the methodologies utilized by forecasters. Several factors necessitate consideration to improve the intensity forecasting capabilities of NWP models. Firstly, advancements in model resolution and initialization techniques are crucial. Studies such as Nadimpalli et al. (2020, 2021a) have emphasized the significance of high-resolution modeling and improved initialization methods like vortex initialization that further improve the intensity prediction. Secondly, refining physics parameterizations is essential. Recent research by Chen et al. (2023) highlighted the importance of accurate representation of convective processes, boundary layer interactions, and air-sea interactions in NWP models for simulating cyclone intensification. Further, DA and observational constraints play a pivotal role mainly over the oceanic region. Incorporating high-quality observational data, particularly in critical regions such as the inner core and eyewall, can significantly improve initial condition estimates and constrain model simulations (Leroux et al. (2018)). Additionally, improving the coupling between the atmosphere and underlying ocean, along with precise initialization of SST, is vital for capturing the influence of oceanic conditions on TC intensity, as indicated by Sandery et al. (2010).

4.3.2 | Cyclone-Induced Rainfall Prediction

TCs are characterized by intense and organized rainfall patterns, often concentrated in the cyclone's inner-core region near the radius of maximum wind. These storms exhibit a distinct structure with a central eye, surrounded by eye-walls containing the most intense winds and rainfall, while spiral rainbands extend outward from the centre, contributing to the overall structure and dynamics of the TC. Ankur et al. (2020) delineated that TCs in the BoB region produce extremely heavy rainfall rates of around 9 to 10 mm/h, while TCs in the ARB exhibit very heavy rainfall rates of about 7–8 mm/h within the storm's inner core region, which extends from 0 to 100 km from the centre of the TC. The landfalling TCs are generally associated with various structure and intensity changes, that is, spiral rain bands, mesoscale vortices, remote rain bands, and so on, (Lian-Shou 2012). During the landfall process, the weakening or sudden strengthening of a TC over or near the coast can significantly change rainfall

characteristics associated with a cyclonic storm (Ray et al. 2022). Four predictors associated with TC rainfall and structure features were incorporated in the Japan Meteorological Agency's version of the Statistical Hurricane Intensity Prediction Scheme (SHIPS), which improved the intensity forecasts (both central pressure ($P_{\min}$) and maximum wind speed ($V_{\max}$)) (Shimada et al. 2018). Similarly, incorporating several new predictors in the SHIPS-RII (rapid intensification index) model, the intensity prediction of TCs has been found to improve operationally, for both the Atlantic and eastern North Pacific basins (Kaplan et al. (2015)). The IMD has operationally implemented a state-of-the-art dynamical-statistical cyclone prediction model; Kotal and Bhattacharya (2021) which has been proven highly efficient in the prediction of genesis, structure, track, intensity and the rainfall associated with TCs forming over the NIO region. Ren et al. (2018) developed an objective TC track similarity area index (TSAI) for precipitation forecasting of landfalling TCs over south China by employing a combined dynamical-statistical approach. Based on this index, a landfalling TC precipitation dynamical-statistical ensemble forecast (LTP-DSEF) model was developed, which was found more skilful in comparison to three operational models (i.e., ECMWF, GFS, and T639/China) for higher threshold values of intense precipitation associated with TCs.

4.3.3 | Techniques Utilizing ANN

Neural network-based algorithms can produce forecasts with a reasonable level of accuracy (Wei and Jing 2010). ANNs are one of the new methods for processing data; ANN-based cyclone forecasting algorithms are characterized by robustness, adaptivity, and power/speed relationships. ANN techniques are simple to implement on conventional desktop computers. These methods, although they take a long time to make the network adapt using all of the satellite pictures, only take a few minutes or fractions of a minute to produce TC track and intensity projections after the network is trained. Cloud et al. (2019) developed a feed-forward neural network (FFNN) for TC intensity prediction, which outperformed the operational HWRF model (HWFI) by producing four times more RI hits (RI defined as an intensification of at least 30 kt in 24h). The FFNN showed a mean absolute error (MAE) improvement at forecast lead times from 3 to 57h, and for lead times greater than 24h, the MAEs were similar to the HWFI. In terms of Brier skill scores, the FFNN demonstrated greater skill than the HWFI and the probabilistic Statistical Hurricane Intensity Prediction System RI index in the Atlantic basin. Similarly, a multilayer perceptron (MLP) TC intensity prediction model was found to be more skilful in predicting the RI as compared to the four operational statistical-dynamical TC intensity prediction models (Xu et al. 2021). The MLP model was based on deep learning. Based on evolutionary programming, Schaffer et al. (2020) developed a statistical-dynamical forecast model for intensity prediction. Utilizing a decision-tree-based ML algorithm, XGBoost, increased TC intensity forecast skills have been achieved for ECMWF ensemble prediction system model outputs (Chan et al. 2021). Despite their usefulness in the intensity prediction of TCs, the ML technique provides short lead-time predictions, whose utility is yet to be adopted by disaster managers for real-time operations (Chen et al. 2020).

4.3.4 | Impact of Data Assimilation System

Strong TCs have the highest initial errors and uncertainties (Kieu et al. 2021). The DA technique struggles to mimic the convective-scale and mesoscale processes that are key to intense TC forecasting. Further, Chen et al. (2013) found that position and track forecast errors were notably higher for initially weak TCs compared to initially strong TCs, with better forecasting skill and stability observed for stronger TCs at short lead times. Specifically, the models performed better for large TCs or those with weak vertical wind shear at lead times under 48 h. Additionally, it has been observed that forecasts of westward-moving TCs, particularly weak ones, frequently drift northward abnormally (Magnusson et al. 2021). Generally, non-linear forecast error growth is associated with rapidly intensifying tropical cyclones (Minamide et al. 2020). Furthermore, real observations and axis-symmetric synthetic DA in NWP models are complementary to each other. Parameters such as wind components, relative humidity, sea level pressure, and temperature are commonly included in axis-symmetric synthetic DA. The simultaneous assimilation of these parameters leads to a more realistic representation of the initial cyclonic vortex and results in a stronger TC with an extended period of rapid intensification (Chang et al. 2020). Utilizing the Ensemble Kalman Filter DA technique, the assimilation of the geostationary Multifunctional Transport Satellite (MTSAT) obtained atmospheric motion vectors (AMVs) in the WRF model improved the track, intensity, and structure analyses of Typhoon Sinlaku (2008) over the Pacific Ocean (Wu et al. 2014). On a similar note, the assimilation of these atmospheric vectors obtained from the geostationary satellite Himawari-8 enhanced the efficacy of the operational HWRf model in predicting the track and intensity of three TCs, namely, Nepartak (2016), Meranti (2016), and Megi (2016), formed over the WNP Ocean basin (Sawada et al. 2019). Large improvements in track, MSLP, and maximum wind speed ($V_{\max}$) have been found by assimilating Cyclone Global Navigation Satellite System (CYGNSS) derived winds in the regional HWRf model (Mueller et al. 2021).

Hurricane Patricia (2015) was among the strongest hurricanes of category-5 which formed over the eastern Pacific Ocean. Utilizing a very high-resolution WRF model, the hurricane's intensity evolution was further analyzed by Fox and Judt (2018). The authors attributed vortex initialization and parametrization of dissipative heating to the successful prediction of the intensity of Hurricane Patricia. Nystrom and Zhang (2019) showed that assimilating airborne Doppler radar radial velocity observations into the WRF-EnKF system improved Hurricane Patricia's intensity forecast compared to conventional data. Reducing the model's grid spacing to 1 km and lowering the surface drag coefficient also improved predictions. A 60-member ensemble, initialized with realistic uncertainties, successfully forecasted the peak intensity, though with varying timing and rate of intensification. Sensitivity analysis indicated that initial differences beyond the radius of maximum wind were key to forecast variability. Adopting the methodology of ensemble-variational (EnVar) DA technique in the HWRf model, the assimilation of upper-level wind observations derived from the dropsondes has been found to improve Hurricane Patricia's RI phase (Feng and Wang 2019).

Further, in a relatively more innovative approach, Lu and Wang (2019) did vortex modification and produced more realistic three-dimensional analyses of the same Hurricane by assimilating enhanced atmospheric motion vectors along with inner core observations obtained from different field campaigns. The authors employed the GSI-based, continuously cycled, dual-resolution hybrid ensemble-variational DA system in the HWRf model for the vortex modification. In the cycling EnKF DA scheme, the assimilation of all-sky infrared radiances obtained from the Advanced Baseline Imager on the GOES-16 satellite potentially improved the intensity forecast of TC Harvey (2017) (Minamide et al. 2020). Taylor et al. (2021) performed an observing system simulation experiment (OSSE) on a West Pacific TC to see if geostationary satellite-based Precipitation Radar reflectivity observations can be used for TC prediction. The OSSE proved the utility of assimilating the radar reflectivity observations in the regional cloud-resolving Scalable Computing for Advanced Library and Environment Regional Model (SCALE-RM) model by reducing the intensity errors.

4.3.5 | Impact of Parameterization Schemes

In the context of TCs/Hurricanes, the accurate representation of physical processes within numerical models is essential for improving track and intensity forecasts. Planetary Boundary Layer (PBL) schemes play a crucial role in simulating surface fluxes and turbulent mixing processes, which directly influence the storm's intensification and structure. The momentum and enthalpy fluxes from the earth's surface affect the lower atmosphere (Jaimes et al. 2015). The interaction of these fluxes with the atmosphere is determined by the parametrization of the PBL in NWP models (Stensrud 2007). While the turbulent Prandtl number (Pr) is commonly used to control the relative diffusivity of momentum and heat, several other parameters embedded in PBL schemes have profound impacts on TC track and intensity simulations. Parameters such as the mixing length scale (λ), surface exchange coefficients for momentum (Cd), surface exchange moisture and heat (Ck), eddy diffusivity of moisture and heat (Kh) and eddy diffusivity for momentum (Km) govern the depth of the boundary layer, vertical exchange processes, and the momentum transport into the cyclone core (Hodges and Klingaman 2019; Sateesh et al. 2017). These coefficients are derived based on the exchange of momentum, heat, and moisture fluxes between the land-surface or ocean and the overlying atmosphere. However, considerable uncertainty persists in accurately estimating these parameters due to the complex and dynamic nature of surface-atmosphere interactions.

Kalina et al. (2021) suggested that the value of Pr significantly affects the intensification and enthalpy fluxes of the rapidly intensifying TC. So, the consideration of the Pr number, while changing the planetary boundary scheme of Global Forecast System-Eddy Diffusivity Mass Flux (GFS-EDMF), may improve the skill of the HWRf model. In the low vertical eddy diffusivity (Km) forecasts of the HWRf model, lowering Km in the PBL increases both inflow and convergence in a TC, resulting in a stronger and more symmetric deep convection (Zhang and Rogers 2019). Similarly, Singh and Bhaskaran (2017) conducted numerical simulations to evaluate the impact of five

PBL and six cumulus convection schemes of the WRF-ARW model on track and intensity predictions of seven landfalling TCs formed over the BoB. The model was the most skilful at TC track and intensity prediction with the Yonsei University (YSU) PBL and the old simplified Arakawa-Schubert cumulus parametrization scheme. The two microphysical parametrization schemes (i.e., the older and newer versions) of the Coupled Ocean-Atmosphere Mesoscale Prediction System-Tropical Cyclone (COAMPS-TC) model were compared for the prediction of 15 Atlantic Ocean cyclonic systems (Jin et al. 2014). The newer version of microphysical parametrization uses a hybrid approach of double moment in cloud, ice, and rain in contrast to the single-moment scheme for the three hydrometeor species employed in the older scheme. The newer scheme significantly reduced rightward cross-track errors and positive intensity bias in control forecasts. A detailed analysis of thermodynamic variables of the vortex core of TC Vicente (2012) using a column-integrated moist static energy budget revealed that before RI, the core of the TC was sufficiently humid (Chen, Zhang, et al. 2019). For 2005's category-5 Hurricane Rita, Hristova-Veleva et al. (2021) showed that different microphysical parameter combinations in the cloud-permitting community WRF model produced significantly different microwave signatures for wind and precipitation.

4.3.6 | Cyclone Disaster Management

Hazards associated with TC landfall pose increasing risks as coastal populations grow, yet accurate forecasts of the timing, location, and impacts of TC landfall remain an ongoing challenge. In recent times, the use of remote sensing and spatial analysis techniques has significantly increased to manage the on-ground impacts of these disasters with rapid advances in a wide range of data availability and processing techniques (Panda, Paul, Routray, et al. 2023). Although TC frequency has stayed approximately constant over recent decades, there is growing evidence that the proportion of TCs that become major hurricanes has increased significantly. Hoque, Phinn, and Roelfsema (2017), Hoque, Phinn, Roelfsema, and Childs (2017) discuss the possible management strategies associated with mitigating the challenges in predicting the track and intensity of cyclones and delineate the application of remote sensing and spatial analysis in the context of response, recovery, prevention/reduction, and preparedness. Substantial coastal mitigation and adaptation strategies will be required soon due to the global incidence of RI of TCs.

5 | Discussion and Current Challenges in Operational NWP

The current review paper discusses the key factors influencing the structure, intensity, and track of cyclones across different ocean basins worldwide. It provides a comprehensive overview of TC tracking algorithms and recent progress in TC modeling and DA. Furthermore, it details various steps involved in operational cyclone forecasting and risk mitigation, an area rarely addressed in recent literature. It also identifies emerging scientometric trends through bibliometric analysis of 51 studies, highlighting a growing research focus on cyclone impacts and

risk assessment, crucial for increasing preparedness, response, and resilience to severe weather events globally.

Global models are capable of capturing the large-scale environmental features that influence tropical cyclones (TCs), such as steering flow and broad-scale moisture patterns. However, the inner core of TCs is governed by convective-scale and mesoscale processes, including eyewall formation, intense updrafts, and sharp pressure and wind gradients. These features occur at spatial and temporal scales that are often at or beyond the resolution limits of current operational global models. As a result, accurate simulation of TC intensity, structure, and rapid changes remains a major challenge in global modeling systems. All the DA strategies have significant TC restrictions; some components (such as tangent linear models) presume linear dynamics and background error covariances that may not reflect the primary dynamic and thermodynamic balances. This is exacerbated by the TC's very low number of observations. More research is needed to see how data from reconnaissance and surveillance aircraft improve analysis and operational model forecasts, and whether new approaches could make greater use of these specialized, high-quality views.

Given that the storm surge is superposed on the astronomical tide, accurate estimates of the timing of TC landfall and the related wind fields are required in storm surge forecasting. The different model components eventually form the basis for inundation models that aim to estimate water levels down to street resolution for flood forecasts based on both storm surge and TC precipitation. This will necessitate not just high-quality TC forecasts, but also ensemble data processing at high spatial and temporal resolutions. Further, it is also crucial to look into the weak teleconnections between ENSO and local SST for seasonal forecasting of TCs. In addition, it is necessary to better comprehend the impact of global warming trends on TCs depicted in the models, when compared to reanalysis data, which is a hot topic in the climate modeling community. All of these issues must be addressed in partnership with model developers and operational TC forecasting centres worldwide.

When a TC is a disorganized depression or weak tropical storm, discrete CBs typically dominate until a coherent vortex forms and begins to symmetrize and intensify within or on the boundaries. These CBs occur on a timescale of a few hours, contributing significantly to RI. The explicit modeling of temporally and spatially smaller-scale convective bursts has not been carried out in the rest of the 50 selected studies, except as conducted by Miller et al. (2015).

A structured evaluation approach for TCs is recommended that goes beyond the current framework to track progress and identify new challenges. An intriguing finding from the review is that among the 51 selected studies, only a small number utilized field campaign data, such as in situ measurements and dropsondes, despite their demonstrated potential to enhance the accuracy of TC intensification forecasts. These limited studies suggest that high-resolution observational data collected during dedicated field campaigns significantly contribute to improving model initialization and capturing RI processes of TCs. However, the sparse representation of such studies highlights the need for further targeted observational efforts and expanded use of field campaign data to strengthen forecast reliability.

One unresolved question in all the selected 51 studies is whether the horizontal scale of DA is still too coarse to fully exploit the fine-scale information in wind regions with strong gradients. Given that the best-track values only represent a small number of features linked to surface pressure and wind, new approaches for evaluating model forecasts are still needed for operational implementations. Because the resolution is believed to be especially essential in the evaluation of both future assimilation techniques and model upgrades, TCs place special limits on the testing approach.

The application of AI, ML, and ANNs in forecasting TC track and intensity is a relatively recent development. Although pioneering efforts were undertaken as early as in the year 2004 using models such as iJADE WeatherMAN and Semo-Mamo, their operational use remained limited due to constraints in data availability, computational power, and model interpretability at that time. Nonlinear neural network-based systems, including Hybrid Radial-Basis-Function networks, iJADE WeatherMAN, and Semo-Mamo demonstrated encouraging results in early studies, notably those by Lee and Liu (2004) and Feng and Liu (2004), highlighting their potential for cyclone intensity prediction. However, despite their initial success, these models have not gained widespread operational use. This limited adoption can be attributed to several challenges: both iJADE WeatherMAN and Semo-Mamo rely on complex architectures that demand extensive computational resources and fine-tuning, which were less feasible during their development period due to limited access to real-time, high-resolution data. Additionally, these models often lack interpretability compared to physically-based dynamical models, making it difficult for forecasters to fully trust and validate their predictions. Their 'black-box' nature, coupled with integration challenges into existing operational forecasting frameworks, has further constrained their utility. Nonetheless, with the advancement of high-performance computing and improved data assimilation techniques, there is renewed potential to revisit and refine such AI-based systems for future applications in TC prediction.

Thus, the use of AI/ML in TC track and intensity prediction presents promising advancements, yet several challenges persist at the global scale. Key limitations include overfitting to limited training datasets, lack of physical interpretability, and sensitivity to regional climatological variability. Nonetheless, the potential of AI/ML techniques to enhance forecasting systems has drawn increasing interest within the scientific community. However, more research and comprehensive reviews are needed to address current scientific gaps and ensure the robust application of these models. Moving forward, integrating pre-trained ML architectures within high-performance computing environments, both for real-time inference in NWP models and in post-processing workflows, offers a viable solution. As neural network-based cyclone tracking matures, it is expected to significantly enhance the skill of forecasts and contribute to overcoming long-standing challenges in global operational cyclone prediction systems.

TC forecasting has seen notable improvements with recent advancements in numerical modeling, particularly through the integration of atmosphere–ocean coupling, which curbs

unrealistically deep intensification, and the implementation of capped surface drag coefficients under extreme wind conditions, enhancing the accuracy of wind–pressure relationships and peak intensity forecasts. However, operational TC forecasting still faces basin-specific challenges in accurately predicting cyclone track, intensity, and landfall, necessitating tailored approaches that integrate regional climatology, ocean–atmosphere interactions, and large-scale modes of variability such as ENSO, IOD, and Madden-Julian Oscillation (MJO). While model fidelity has improved, a critical gap remains; operational systems have yet to systematically incorporate the long-term impacts of climate change on TC behavior. Also, it has been found that out of selected 51 studies, most studies remain retrospective or research-oriented, with limited translation into operational guidance. Moving forward, there is an urgent need to develop and operationalize climate-informed TC forecasting tools that bridge short-term prediction with long-term climate trends, ensuring resilience and preparedness in an era of increasing cyclone risk.

The present study reviewed the evolving role of satellite and radiance assimilation in NWP models aimed at capturing the finer-scale structures associated with TCs. While significant progress has been made, there remains a pressing need to assimilate newer satellite datasets, such as those from the Cyclone Global Navigation Satellite System (CYGNSS; Clarizia and Ruf 2016; Morris and Ruf 2017) mission and small satellite constellations like “Time-Resolved Observations of Precipitation Structure and Storm Intensity with a Constellation of Smallsats” (TROPICS; Zavodsky et al. 2017), into operational forecasting systems.

In the context of operational forecasting, future advancements should focus on the integration of high-resolution and next-generation observational datasets, including data from low-Earth orbit (LEO) satellites, high-temporal-resolution Atmospheric Motion Vectors (AMVs) from rapid-scan geostationary platforms, LIDAR-based wind profiles, ocean surface wind retrievals, and enhanced in situ and remotely sensed ocean observations. Incorporating these observations into DA frameworks can significantly improve the real-time representation of mesoscale and convective-scale features of TCs, leading to more accurate and timely forecasts of cyclone track, intensity, and associated hazards. These improvements are crucial for early warning systems and disaster preparedness in operational settings. Taken together, these efforts are essential for enhancing forecast accuracy and reliability in a changing climate and increasingly data-rich observational environment.

6 | Conclusions

The present study highlighted the critical advancements and persistent challenges in understanding and forecasting TCs across global basins, emphasizing their complex dynamics, the evolution of tracking algorithms, and the growing role of scientometric analyses in this domain. Based on bibliometric selection and scientometric analysis of 51 selected studies, the review found that *Monthly Weather Review*, *Atmosphere*, and *Weather and Forecasting* were the top publishing journals. The

most frequently used descriptors were *Forecasting*, *Tropical Cyclones*, and *Numerical Weather Prediction*. Zhang X and Marks F emerged as the most influential authors strongly linked to forecasting-related research, with Zhang F showing the strongest association with *Monthly Weather Review*. These patterns highlight key contributors, core journals, and dominant research themes in tropical cyclone studies.

The review work further highlighted that high-resolution models such as NHM, NCUM, and COSMO have demonstrated improved skill in simulating realistic features of TCs, including their genesis, movement, and structure. Regional convection-permitting models like HAFS and COSMO offer improved representation of TC inner-core processes and intensification. However, predicting the intensity of TCs, especially cases of RI, remains a major challenge for operational NWP systems due to their limited ability to resolve fine-scale vertical and inner-core dynamics. Research suggests that better representation of processes such as boundary layer fluxes, vortex tilt, CBs, and inertial stability can significantly improve intensity forecasts. The use of ensemble forecasting, model bias correction, and refined physical parameterizations has led to improved forecast accuracy in non-RI cases. Accurate intensity predictions also rely on high-resolution model initialization, particularly with vortex initialization techniques and coupled ocean–atmosphere modeling. Incorporating real-time observations from the TC core and eye-wall regions through advanced DA methods enhances the reliability of forecasts. Ocean surface temperature initialization and the proper representation of air–sea interactions are also critical in capturing TC evolution. Rainfall prediction, strongly tied to storm intensity and structure, particularly near the radius of maximum wind, remains another area of focus. TCs over the BoB tend to produce more intense rainfall than those over the Arabian Sea due to higher convective activity and moisture content. Statistical-dynamical models such as SHIPS and SHIPS-RII, along with hybrid approaches employed by IMD, show promise for improving operational forecasting. Continued advancements in model resolution, physics, observational coverage, and data assimilation techniques are essential for further improving TC intensity and rainfall predictions.

Author Contributions

Vivek Singh: conceptualization, investigation, funding acquisition, writing – original draft, methodology, validation, visualization, writing – review and editing, formal analysis, software, project administration, data curation, supervision, resources. **Gaurav Tiwari:** conceptualization, investigation, funding acquisition, writing – original draft, methodology, data curation. **Amarendra Singh:** conceptualization, methodology, software, formal analysis, validation, investigation. **Rajeeb Samanta:** conceptualization, investigation, writing – original draft, funding acquisition, methodology, validation, visualization, writing – review and editing. **Atul Kumar Srivastava:** conceptualization, investigation, funding acquisition, writing – original draft. **Deewan Singh Bisht:** conceptualization, validation, software, methodology, visualization. **Ashish Routray:** writing – review and editing, supervision, project administration. **Sushil Singh:** supervision, methodology, writing – review and editing. **Shivaji Singh Patel:** software, visualization, data curation, resources. **Abhishek Lodh:** writing – review and editing, methodology, conceptualization, project administration, investigation.

Data Availability Statement

The data that support the findings of this study are available from the corresponding author upon reasonable request.

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