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ScienceDirect

Tropical Cyclone Research and Review 12 (2023) 136–150

Tropical Cyclone Research and Review

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Advances in tropical cyclone prediction on subseasonal time scales during 2019–2022

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Available online 4 June 2023

Abstract

This review describes advances in understanding and forecasting tropical cyclone (TC) subseasonal variability during the past four years. A large effort by the scientific community has been in understanding the sources of predictability at subseasonal timescales beyond the well-known modulation of TC activity by the Madden-Julian Oscillation (MJO). In particular, the strong modulation of TC activity over the western North Pacific by the Boreal Summer Intra-Seasonal Oscillation (BSISO) has been documented. Progress has also been realized in understanding the role of tropical-extratropical interactions in improving subseasonal forecasts. In addition, several recent publications have shown that extratropical wave breaking may have a role in the genesis and development of TCs. Analyses of multi-model ensemble data sets such as the Subseasonal to Seasonal (S2S) and Subseasonal Experiment (SubX) have shown that the skill of S2S models in predicting the genesis of TCs varies strongly among models and regions but is often tied to their ability to simulate the MJO and its impacts. The skill in select models has led to an increase over the past four years in the number of forecasting centers issuing subseasonal TC forecasts using various techniques (statistical, statistical-

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Peer review under responsibility of Shanghai Typhoon Institute of China Meteorological Administration.

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https://doi.org/10.1016/j.tcrr.2023.06.004

dynamical and dynamical). More extensive verification studies have been published over the last four years, but often only for the North Atlantic and eastern North Pacific.

Keywords: Tropical cyclones; Subseasonal; Forecasts; Hurricanes; MJO

1. Introduction

Camargo et al. (2019) reviewed the significant progress in our understanding and prediction of subseasonal tropical cyclone (TC) activity during 2015–2018. The current review provides a similar summary for the subsequent four years. A great advance in predicting subseasonal TC activity in the last four years has been the maturation of the Subseasonal Experiment (SubX; Pegion et al., 2019) and the World Meteorological Organization (WMO) Subseasonal-to-Seasonal (S2S; Vitart et al., 2017) model intercomparison projects. These models have produced increasingly skillful Madden–Julian Oscillation (MJO) forecasts beyond three weeks. Hybrid statistical–dynamical models have been created to leverage these MJO forecasts and the known relationships between the MJO and TC activity (e.g., Hansen et al., 2022). Some dynamical models can even produce skillful forecasts of subseasonal TC activity with minimal post-processing (Camp et al., 2018). The increasing skill of these models has empowered several operational forecast centers to produce experimental and even operational TC forecasts for week 3 (see section 4).

2. Modulation of TC activity by subseasonal modes of variability

2.1. Impact of tropical waves on tropical cyclone activity

In the four years since Camargo et al. (2019), many studies have focused on the sub-basin scale and elucidating how the MJO/Boreal Summer Intraseasonal Oscillation (BSISO) modulates TC activity in tandem with other shorter period phenomena (e.g., tropical waves). Fowler and Pritchard (2020) showed that the South China Sea (100°E–120°E) is the most sensitive region in the western North Pacific (WNP) to the MJO/BSISO. In this region, the favorable decrease in vertical wind shear coincides with an increase in mid-level moisture. On the other hand, the eastern WNP (160°E−180°) is less sensitive to the MJO/BSISO because these factors are out of phase with one another: the increase in moisture precedes the decrease in vertical wind shear (Fig. 1). Along with the MJO/BSISO and the quasi-biweekly oscillation (QBWO), other modes of variability such as equatorial Rossby waves (ERW), Kelvin waves (KW), and the combination of Mixed Rossby-gravity waves (MRG) and tropical depression-type disturbances (collectively MRGTD) also contribute to TC genesis in the Bay of Bengal (BoB; Landu et al., 2020) and the WNP (Zhao et al., 2019). Landu et al. (2020) showed that during simultaneous ERW and MJO events, more TCs formed in the BoB than during any other combination of waves. ERW increased low-level vorticity, and the MJO increased moisture. On the other hand, simultaneous MRGTD and KW were associated with fewer BoB TCs than any other combination of waves. The MRGTD reduced vertical shear and contributed to drying at mid-levels, and KW decreased low-level vorticity, which results in fewer TCs in the BoB.

Understanding how TC tracks and thus landfall risk are modulated by the MJO/BSISO could potentially lead to better TC risk decision-making. In the WNP, TCs tend to move northwestward during the enhanced convective phases of the MJO/BSISO and QBWO, but during the suppressed convective phases recurving storms are more common (Wang et al., 2019; Ling et al., 2020; Nakano et al., 2021). A westward extension of the WNP subtropical high (Ling et al., 2020) or eastward extension of the monsoon trough (Wang et al., 2019) lead to more northwestward-moving TCs during the convective phases.

In addition to these sub-basin studies, significant progress has been made in examining nonlinear interactions between the MJO and the El Niño Southern Oscillation (ENSO). For example, Atlantic TC activity generally increases during La Niña episodes. However, Hansen et al. (2020) found that the most favorable MJO phase for Atlantic TC activity also shifts with the ENSO state. During neutral ENSO states, MJO phases 1 and 2 were associated with the highest level of TC activity in the Atlantic. During strong La Niña states, MJO phases 4 and 5 were most likely to have above-average accumulated cyclone energy (ACE; Bell et al., 2000). To investigate other potential factors that influence subseasonal TC activity, Hansen et al. (2020) developed a compositing technique that isolated subseasonal signals of environmental conditions in association with TC activity, which were referred to as ACE By Year (ABY). The most important predictors of enhanced TC activity were negative vertical wind shear anomalies in the North Atlantic Main Development Region (MDR), and positive vertical shear anomalies in the subtropical North Atlantic (Fig. 2). The vertical shear pattern associated with MJO phases 1 and 2 was similar to, but distinct from, the shear pattern in the ABY composite. Both nonlinear MJO/ENSO interactions and the subseasonal vertical shear signals appear to be linked to potential vorticity streamers, which suggests mid-latitude interactions may contribute to a significant portion of the subseasonal variability of North Atlantic TC activity (Hansen et al., 2020).

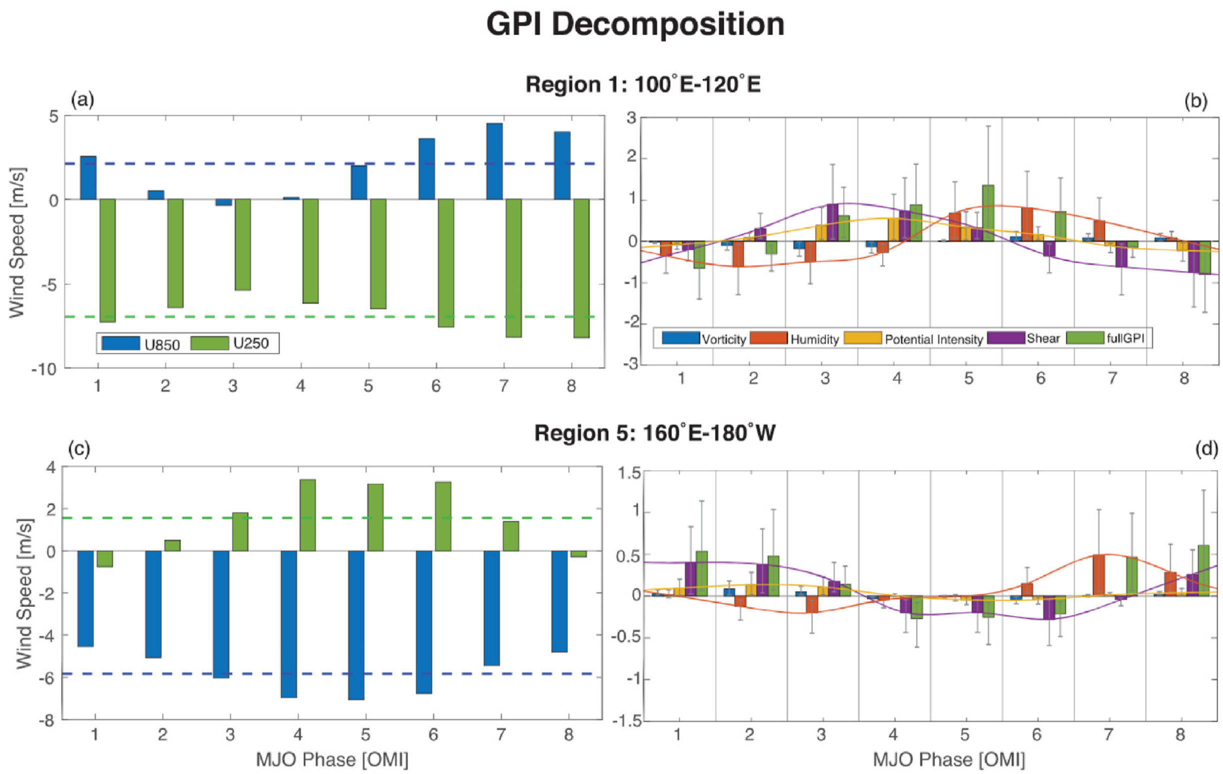

Fig. 1. (a, c) Average 850-hPa (blue) and 250-hPa (green) winds for each MJO phase; dashed lines represent the Phase 1–8 mean. (b, d) Genesis Potential Index (GPI) decomposition for each MJO phase, defined using the OLR-only MJO Index (OMI, Kiladis et al., 2014). (from Fowler and Pritchard 2020).

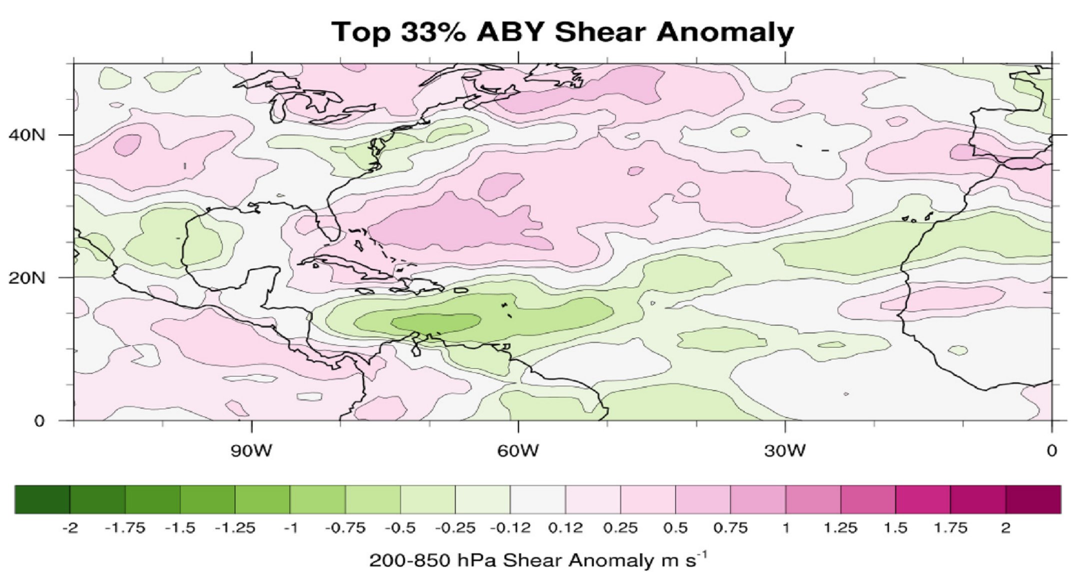

Fig. 2. Vertical wind shear anomalies associated with subseasonal active TC periods in the North Atlantic using the ABY composite technique (from Hansen et al., 2020).

2.2. Impact of extratropical wave breaking on tropical cyclones

Several recent studies (Zhang et al., 2016; 2017; Li et al., 2018; Papin 2017; Papin et al., 2020; Jones et al., 2020) demonstrated that occurrence of extratropical Rossby wave breaking (RWB) events tend to reduce TC activity on subseasonal and longer time scales through larger vertical wind shear and mid-tropospheric dryness. Using semi-idealized numerical model simulations, Chang and Wang (2018) showed that these negative extratropical impacts on Atlantic TC activity may exceed the positive impacts of local sea-surface temperature (SST) anomalies in some years. Jones et al. (2022) showed that the dynamical impacts of RWB on vertical wind shear are predictable through the link between the North Atlantic Oscillation (NAO) and the RWB event. Thus, including such dynamical impacts may improve seasonal TC predictions. Zhang et al. (2021) analyzed a large ensemble of climate simulations forced by observed SSTs and demonstrated that seasonal variations of RWB events are potentially predictable owing to SST forcing in both the tropics and extratropics.

The tropical and extratropical impacts on TC activity can be integrated in the framework of summertime stationary waves. In particular, tropical upper-tropospheric troughs (TUTTs), interpreted here as stationary waves, are the preferred regions of RWB (e.g., Postel and Hitchman 1999), and become the regions of active interaction between the tropics and extratropics. These TUTTs are subject to the modulation by diabatic heating, which leads to variability of the North Pacific TUTT and the North Atlantic TUTT. This variability of large-scale environmental conditions thus contributes to the variability of TC activity (Fig. 3). In addition, the anti-correlation of TUTTs between the North Atlantic and North Pacific leads to the TC activities in the two basins tending to compensate for each other. Thus, Northern Hemisphere TC activity may be less variable than it would be if these two TUTTs were independent.

While most recent studies have focused on RWB and North Atlantic TC activity, Takemura and Mukougawa (2021) investigated tropical cyclogenesis over the WNP triggered by RWB to the east of the Asian coast. A composite observational analysis indicated that approximately 55% of the detected RWB events were accompanied by the genesis and development of TCs to the southwest of the wave breaking center (Fig. 4). A RWB event leads to an intrusion of the upper-level positive potential vorticity toward the southwest and consequently enhanced convection over the subtropical WNP. This enhanced convection is a favorable condition for TC genesis and development. It is noteworthy that Takemura and Mukougawa (2021) showed that no TC genesis occurred after the peak day of a RWB event.

3. Simulation of subseasonal TC activity in S2S and SubX models

3.1. Model description

Research on subseasonal-to-seasonal prediction of TCs has been accelerated by the maturation of multi-model datasets. There have been expansions and updates to the WMO S2S (Vitart et al., 2017) and the SubX (contains only North American models; Pegion et al., 2019) datasets. There are also new global model simulations and improvements in global models that can potentially lead to advances in subseasonal TC predictions. Some examples of these models are the GFDL SPEAR global coupled model (Xiang et al., 2022a), the new version of the NASA GMAO GEOS S2S system (Molod et al., 2020) and the Australia Bureau of Meteorology (BoM) ACCESS-S1 with an ensemble Kalman filter (ACCESS-GE2, Gregory et al., 2020). Additionally, Richter et al. (2022) showed that the CESM2 can be used as a community resource for research on subseasonal predictability (see Table 1 for details).

Lee et al. (2020) evaluated regional TC events (genesis and subsequent track) in 20° longitude and 15° latitude boxes

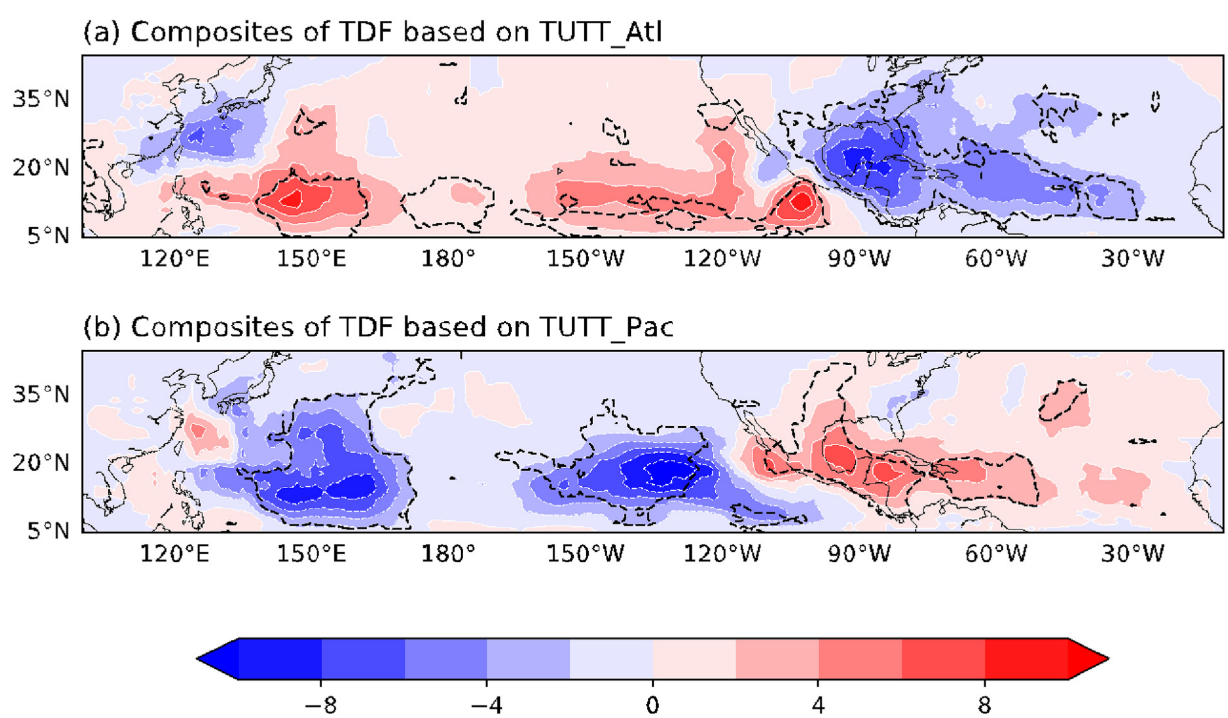

Fig. 3. Composites of tropical cyclone track density function (TDF, number of TCs per month within a 10° × 10° grid box) based on (a) the North Atlantic TUTT index and (b) the North Pacific TUTT index. Dashed contours depict anomalies exceeding the 95% confidence level. The TUTT index is defined based on the equatorward extension of the upper-level westerly flow over a subtropical ocean (adapted from Wang et al., 2020).

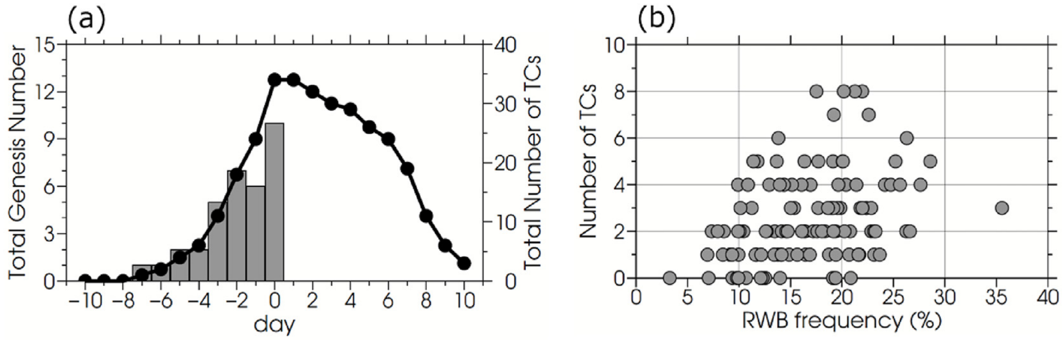

Fig. 4. (a) Daily time series for the total numbers of TCs (black line; right axis) and TC genesis (gray bars; left axis) detected in 24 RWB cases during a period from 10 days before (day −10) to 10 days after (day +10) the peaks of RWB. (b) Scatter diagram between area-averaged monthly RWB frequency over 25°N–45°N, 140°E–180° and the monthly numbers of TCs detected from 15°N to 45°N and from 120°E to 180°E in July and August during the period from 1958 to 2018. (from Takemura and Mukougawa 2021).

Table 1
List of available subseasonal TC reforecast datasets. V01 refers to the tracker from Vitart and Stockdale (2001). Other than S2S TCs, data availability requires further confirmation from each research group. (Table prepared by Dr. Jorge Garcia-Franco).

Model	Native resolution	Coverage period (most updated)	Ensemble size	frequency	TC tracker	data availability
BoM	2°, L17	1981–2013	33	6/month	V01	S2S
CNRM	1.4°, L91	1993–2014	15	4/month	V01	S2S
CNR-ISAC	0.75°, L54	1981–2010	5	5 days	V01	S2S
CMA	0.5°, L56	2006–2020	4	2/week	V01	S2S
ECCC	0.35°, L45	1998–2017	4	weekly	V01	S2S
ECMWF	0.15°; 0.3° L137	2000–2020	11	2/week	V01	S2S
HMCR	1.2°, L28	1985–2010	10	weekly	V01	S2S
JMA	0.5°, L60	1981–2012	5	3/month	V01	S2S
KMA	0.75°, L85	1991–2016	3	4/month	V01	S2S
NCEP	1°, L64	1999–2010	4	daily	V01	S2S
UKMO	0.75°, L85	1993–2016	7	4/month	V01	S2S
CESM2 (CAM6)	1°, L32	1999–2020	11	weekly	Tempest Extremes	Climate Data Gateway
CESM2 (WACCM6)	1°, L70	1999–2020	5	weekly	N/A	N/A
GEOS-S2S-2	0.5°, L72	1999–2020	4	5 days	Tempest Extremes	Unk
SPEAR	0.5°, L33	2000–2019	10	5 days	Unk	Unk

in the WMO S2S database models' reforecasts and found that the European Center for Medium-range Weather Forecasts (ECMWF) model had one of the best performances in simulating the TC climatology as well as having higher prediction skill. Lee et al. (2020) found that a key limitation in prediction skill of regional TC activity is genesis prediction, and the ECMWF model had the smallest errors in genesis climatology when compared to other WMO S2S models (Lee et al., 2018).

Camargo et al. (2021) reported that North Atlantic TC tracks in the ECMWF subseasonal reforecasts had clusters with similar characteristics to the observed. However, the ECMWF model had an additional cluster of recurving North Atlantic hurricane tracks near the coast of Africa with characteristics that do not correspond to the observed track clusters in that region, which may be due to some systematic biases in low-level winds and geopotential heights in the ECMWF model. When evaluating the climatology of TC intensity, model resolution was found to play an important role (Camargo et al., 2021; Gao et al., 2019). Gregory et al. (2020) compared subseasonal forecasts for the Southern Hemisphere among the ACCESS-S1, ACCESS-GE2, and ECMWF models and concluded that the superior performance of the ECMWF system was due to a larger ensemble size, higher spatial resolution, and an improved data assimilation scheme.

The MJO modulation of TC activity in these subseasonal forecast models has also been examined (Lee et al., 2020; Camargo et al., 2021). With the improvement of the MJO representation in models (Vitart 2017), the MJO–TC relationship is also simulated more realistically. Recently, Xiang et al. (2022b) suggested that landfalling TCs near the U.S. coast can be influenced by three localized atmospheric circulation modes with significant subseasonal (10–30 day) variability that is distinct from the MJO: (1) an anomalous low pressure center in the eastern U.S.; (2) a zonal dipole pattern with a low pressure centered in the western U.S. and a trough extending southeastward to the Gulf of Mexico; and (3) a meridional dipole pattern with a low centered over the Caribbean Sea and a high over central-eastern North America. There are more U.S. landfall TCs during the positive phases of these modes. The GFDL SPEAR model can simulate these landfall track modulations.

3.2. Model verification

Whereas the ECMWF model has the highest prediction skill among the WMO S2S models (Lee et al., 2020, Fig. 5a), the skill analysis is sensitive to what validation metrics are used as well as how the forecast is defined. Results from Lee et al. (2020) are based on the verification of probabilistic predictions of regional TC activity measured by the Brier Skill Score (BSS). When verified against a total seasonal climatological forecast (BSS_c), reforecasts from ECMWF and Météo-France/Center National de Recherche Météorologiques models are skillful for most TC basins with lead times up to week 3 or longer. The BoM model is skillful for Southern Hemisphere TC basins. However, when validated versus weekly climatology activity (BSS_m), only the ECMWF model shows skill in predicting TC occurrence anomalies beyond one week. In the Southern Hemisphere, Gregory et al. (2020) showed that ACCESS-S1 is skillful in predicting TC occurrence (not TC anomalies) at up to 3 week lead times. Regional BSS is not always consistent with basin-wide mean BSS values. The week 2 BSS for the ECMWF system is shown in Fig. 5b.

In terms of TC ACE, the WMO S2S models have low prediction skill when measured by the Ranked Probability Skill Score (RPSS), which may be attributed to insufficient horizontal grid resolution to simulate either the TC's core structure or the occurrence of the most intense TCs (Lee et al., 2020; Camargo et al., 2021). Using the Heidke Skill Score (HSS) in reference to a random forecast, Gao et al. (2019) showed that the HiRAM model with a 8-km inner nested domain was skillful in predicting basin-wide (not regional) ACE associated with hurricanes and major hurricanes in the North Atlantic.

Prediction skill of regional TC occurrence predictions can be improved via post-processing calibrations such as removing model mean biases (Camp et al., 2018; Gregory et al., 2020). Lee et al. (2020) showed that while removing mean biases works in some cases, it does not guarantee a positive impact globally. To improve a probabilistic forecast skill (often measured by BSS), one needs to increase the correlation between forecasts and observations and/or reduce the conditional and unconditional biases. Removing the mean TC occurrence biases reduces the unconditional bias to zero, but does not always guarantee a smaller conditional bias even in the training data. Thus, Lee et al. (2020) suggested a linear regression method (van den Dool et al., 2017) that removes the unconditional biases and minimizes the conditional biases. In addition, Gregory et al. (2020) showed that improved forecast skill could be obtained by using multi-model ensemble prediction, and including lag-averaged forecasts at t-12 h, t-24 h, etc. to increase the number of ensemble members.

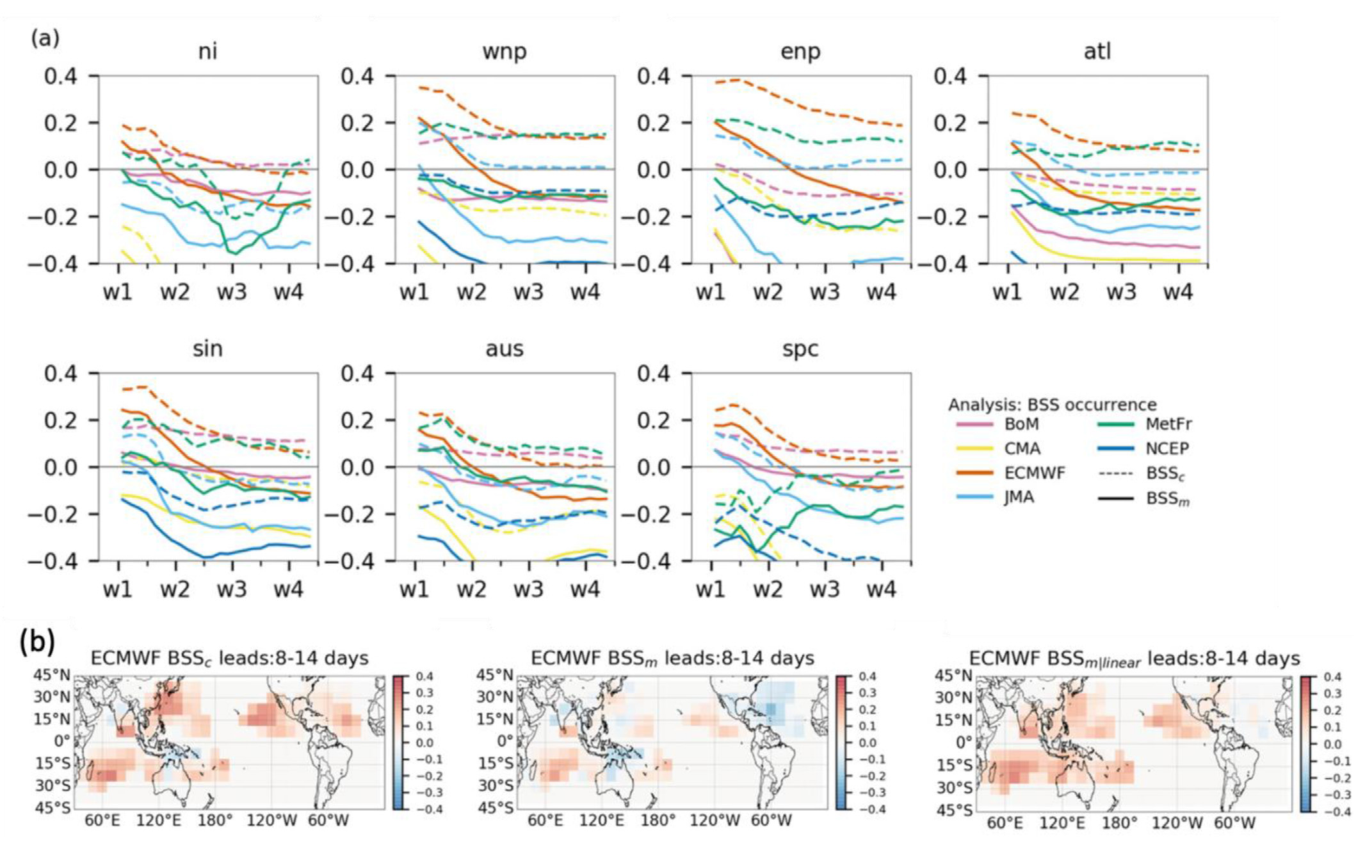

Fig. 5. Brier Skill Score (BSS) of (a) regional TC occurrence predictions from six WMO S2S models, listed in the middle-row right and (b) global map of TC occurrence from the ECMWF model. BSS_c and BSS_m indicate seasonal-total and weekly-varying climatology references. $BSS_{m|linear}$ is the BSS_m for a bias-corrected forecast with a linear-regression bias-correction scheme. The TC basins are as follows: Atlantic (ATL), northern Indian Ocean (NI), western North Pacific (WNP), eastern North Pacific (ENP), southern Indian Ocean (SIN, 0°–90°E), Australia (AUS, 90°–160°E), and southern Pacific (SPC, east of 160°E) (from Lee et al., 2020).

Several recent case studies with deterministic or ensemble models have extended TC forecasts into the subseasonal TC range. For example, the landfall of Cyclone Hilda (2017) in northwestern Australia was predicted 2–3 weeks in advance by the ACCESS-S1 model, and the multi-model ensemble with the ACCESS-S1 and the ECMWF predicted cyclones Gebile and Gita (2018) two weeks in advance (Gregory et al., 2020). Domeisen et al. (2022) showed successful ECMWF ensemble week 3 or 4 forecasts for TCs Belna (2019, southern Indian Ocean), Claudia (2020, Australia), and Chan-Hom (2015, western North Pacific), which Domeisen et al. (2022) attributed to the occurrence of a strong MJO coinciding with the occurrence of these storms. This is consistent with findings from Lee et al., which demonstrated that the WMO S2S models were more skillful when the convectively-enhanced phase of the MJO was active in that basin.

In addition to using direct TC forecasts from dynamic models, Kolstad (2021) suggested the inclusion of large-scale variables as predictors in a hybrid statistical–dynamical forecasting system could potentially extend the prediction time of potential precursor, and thus allow early detection of possible tropical cyclones. The hybrid model from Qian et al. (2020) indeed had superior forecast skill for predicting basin-wide tropical cyclone genesis count over the western-north Pacific, compared to the dynamical model that provided input to the hybrid model. Similarly, Maier-Gerber et al. (2021) demonstrated that their hybrid model for subseasonal tropical cyclone activity in the North Atlantic Main Development Region and Gulf of Mexico had comparable skill to numerical weather prediction systems.

Lee et al. (2020) had earlier demonstrated that the WMO S2S models were more skillful when the convectively-enhanced phase of the MJO was active in that basin. However, the impact of the MJO on TC prediction skill varies by basin and by model. Kolstad (2021) recently suggested the inclusion of large-scale variables as predictors in a hybrid statistical–dynamical forecasting system could potentially extend the MJO subseasonal prediction time, and thus allow early detection of possible tropical cyclones. To that end, Maier-Gerber et al. (2021) showed that a hybrid model for subseasonal TC activity in the North Atlantic Main Development Region and Gulf of Mexico had comparable skill to numerical weather prediction systems.

4. Operational subseasonal forecasts of tropical cyclones

4.1. NOAA products

The NOAA Climate Prediction Center (CPC) provides the once-a-week Global Tropics Hazards (GTH) Outlook. An important component of informing the operational CPC GTH outlook is global TC identification and tracking utilizing S2S model data for the Weeks 1–4 target forecast period. The CFS, ECMWF, ECCC, and GEFSv12 operational ensemble model systems are utilized as forecast guidance for the GTH, and the TC activity is identified and tracked using the methods outlined in Camargo and Zebiak (2002). The forecasts are bias-corrected using a false alarm climatology based on model reforecasts and the National Hurricane Center (NHC) and the Joint Typhoon Warning Center (JTWC) best track datasets (Long et al., 2020). In addition to this model guidance, the GTH TC outlook includes (i) the state of ENSO and the MJO; (ii) coherent subseasonal tropical variability such as atmospheric KW, ERW, and African easterly waves (AEW); and (iii) interactions with the extratropical circulation (i.e., low-latitude fronts, wave breaking).

The Symmetric Extreme Dependency Score (SEDS)—a metric that focuses on relatively rare events—for TC tracks at Weeks 1–3 is shown in Fig. 6 for the CFS and ECMWF deterministic models, and for the GEFSv12 and the ECCC ensemble prediction systems for their respective reforecast periods. The contingency table for the SEDS calculations defines a hit when a forecast TC track point comes within a 3° box of a verifying TC track point within the same weekly interval. For clarity and to show better results, only the North Atlantic (ATL) and the eastern North Pacific (ENP) basins are shown. Note that the ENP has better skill than the ATL for both Week 2 and Week 3, and the ECMWF has the best scores among the four models shown. Although forecast skill in Week 3 is lower than in Week 2, it is noteworthy that substantial areas of skill have been found for Week 3, and especially with all four models in the ENP basin.

4.2. ECMWF forecasts

ECMWF has issued week 1–4 forecasts of TC activity for each TC region since 2010 (Vitart et al., 2010). The TC forecast products include: (1) the predicted number of tropical storms/hurricanes or ACE over a TC basin for a weekly period (calendar week 1–4); and (2) a TC strike probability map: the probability of a tropical depression/storm/intense storm (hurricane intensity) passing within 300 km (see example in Fig. 7). Maps of TC strike probability anomaly relative to model climatology are also available. These forecasts produced with the ECMWF TC tracker (Vitart and Stockdale, 2001) are issued twice a week and are now publicly available. Tropical cyclone tracks predicted by the ECMWF ensemble model during the 46-day integrations are available from the S2S database, but with a 3-week delay (more information at www.s2sprediction.net). The forecast skill of these forecasts has been evaluated in Camargo et al. (2021) for the North Atlantic and by Lee et al. (2020) for the entire globe. It is planned in mid 2023 to increase the frequency of these forecasts from twice weekly to daily and to increase the ensemble size from 51 to 101 ensemble members. The objective is to provide more frequent updates and more accurate probabilistic distribution functions of TC activity.

The Elsberry et al. (2022) TC high-wind lifecycle guidance product based on the ECMWF ensemble (ECEPS) could improve decision-making related to ENP TCs compared to presently available probabilistic genesis or TC activity products. This technique provides time-to-formation (T2F) and time-to-hurricane (T2H) to the nearest 6-h synoptic time and at a position along generally highly accurate ECEPS track

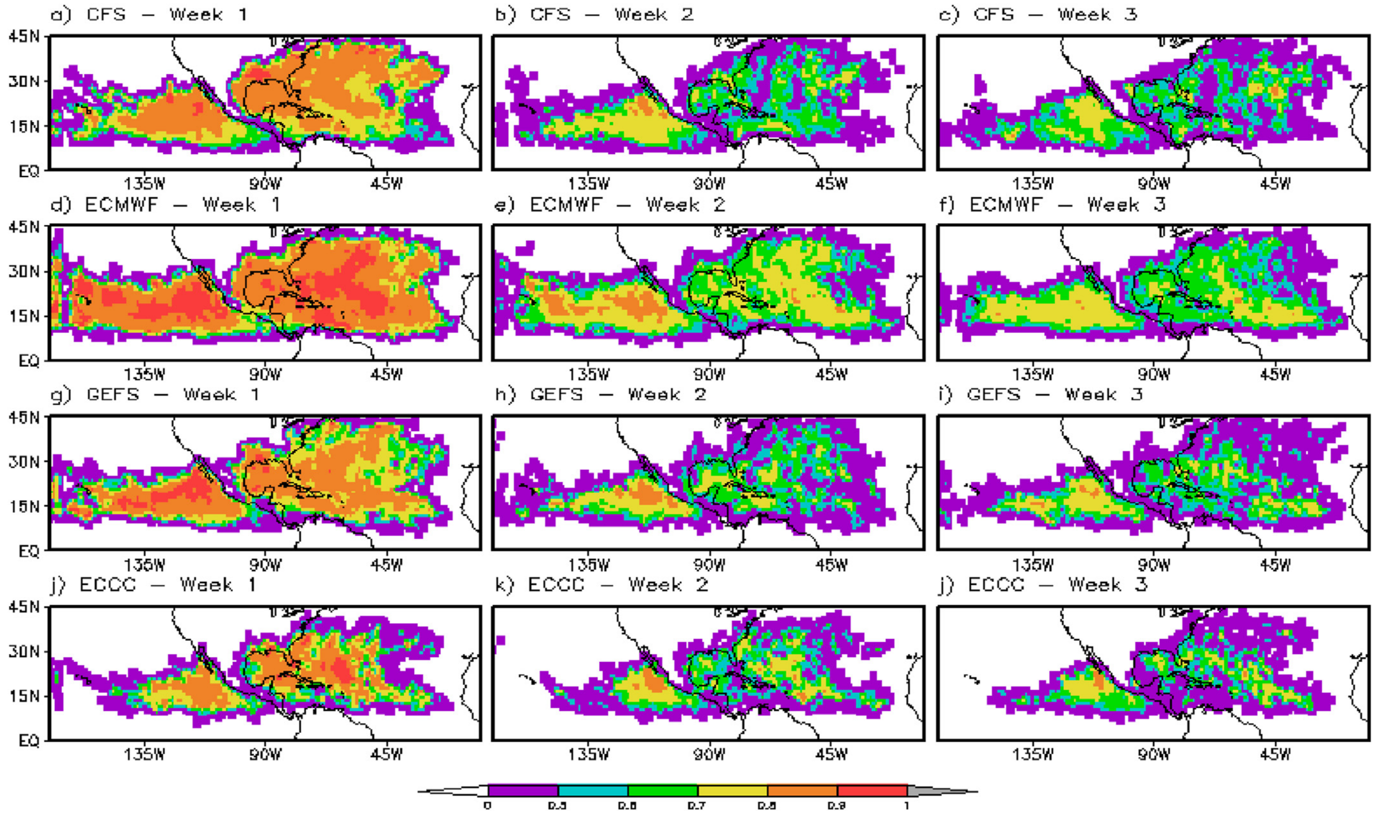

Fig. 6. Spatial maps of SEDS for TC tracks during Weeks 1–3 in the left, middle, and right columns for the (a–c) CFS, (d–f) ECMWF, (g–i) GEFSv12 and (j–l) ECCC for the ATL and ENP basins.

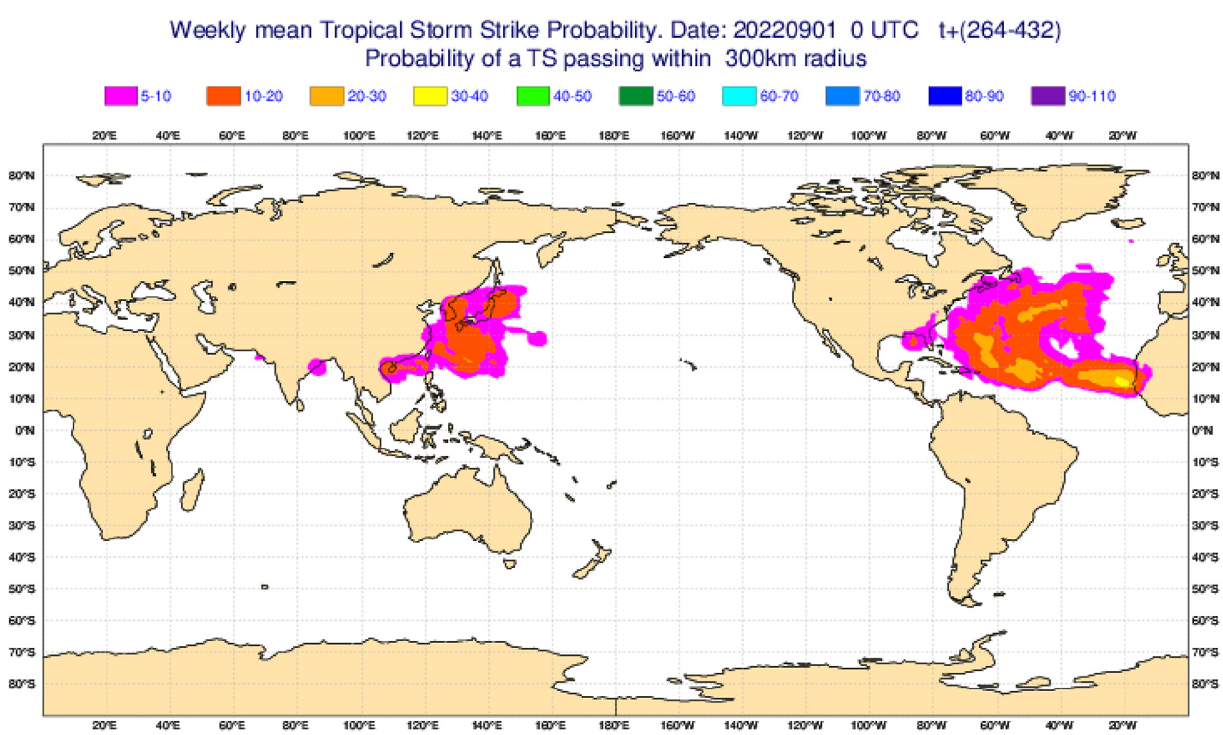

Fig. 7. Probability of a tropical storm strike within 300 km for the period 12 to September 19, 2022 from the ECMWF subseasonal forecast issued on 1 September (lead time is day 12–18).

forecasts of up to 15 days in length. In addition, the technique provides the ending time as a hurricane (TEHU) and ending time as a tropical storm (TETS) along that up to the 15-day ECEPS track forecast. For the first six hurricanes of the 2021 ENP season, the first detections in the ECEPS were 8–12 days in advance of the T2F, and 9–13 days in advance of the T2H.

A summary diagram is provided in Fig. 8 for both the pre-formation and the ending of Hurricane Linda's track forecasts (panel b and panel a, respectively) and the timing errors for these two variables (panels c and d, respectively). Whereas the first NHC advisory forecast of pre-TS Linda was only 12 h before the T2F in panel b, 19 ECEPS forecasts at 12-h intervals

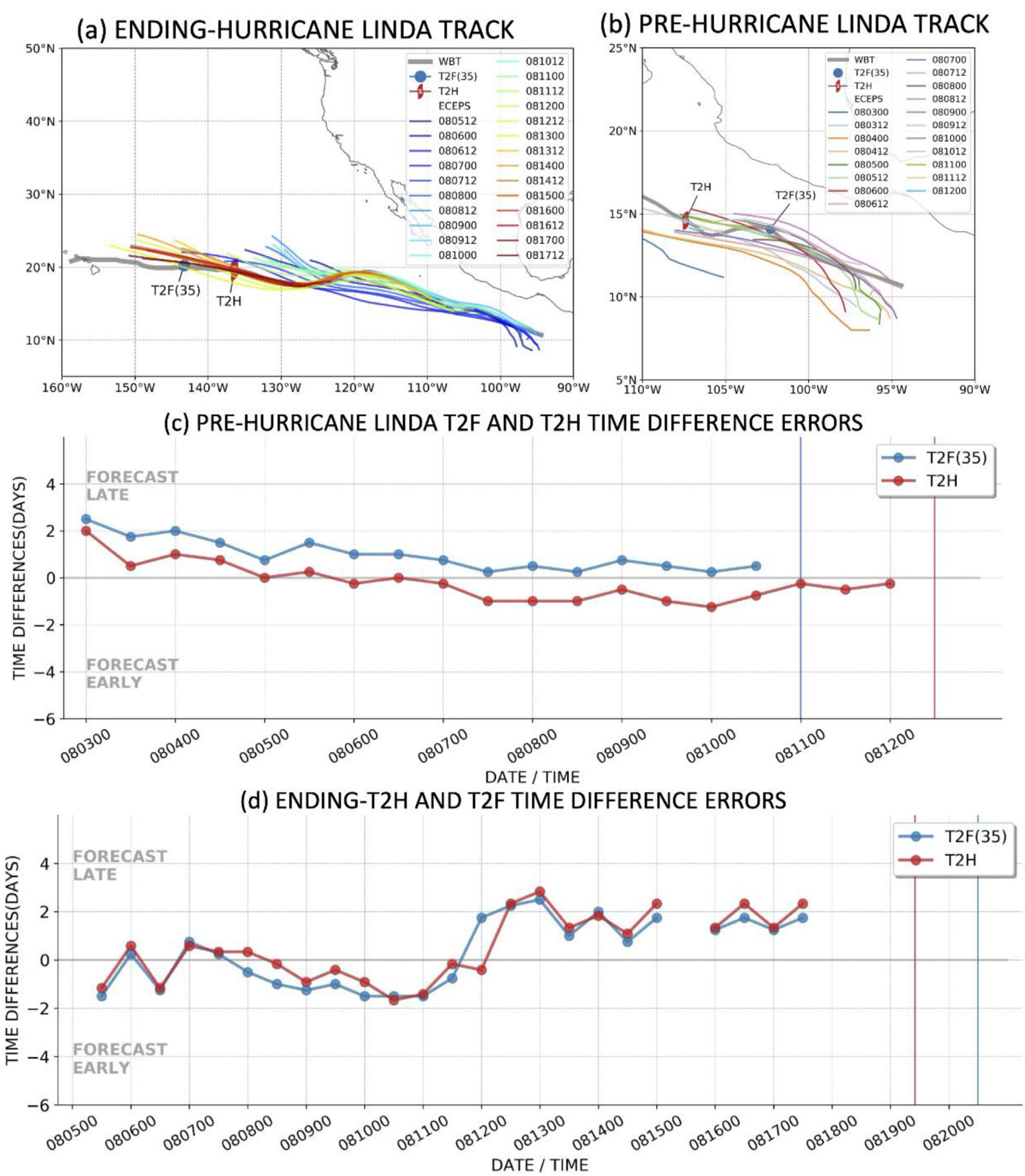

Fig. 8. Summary of the ECEPS pre-formation and ending-stage predictions of the Hurricane Linda (2021) lifecycle. Track forecast initial times (MMDDHH) are indicated in the insets for the (a) ending stage and (b) pre-formation stage, and the T2F and T2H timing errors for the pre-formation and the ending-stage are displayed in panels (c) and (d). (from Elsberry et al., 2022).

were available prior to that T2F. Although there is substantial track spread due to the variations in the initial positions, the cross-track spread among these ECEPS forecasts that included both a TEHU and a TETS, the track spread was reasonable considering that these forecasts started as early as 14 days before the TEHU (panel b). The very small timing errors for the T2F and the T2H along these pre-T2F tracks in panel (b) are presented in panel (c), and the generally small timing errors in TEHU and TETS timing errors are presented in panel (d). This 15-day TC high-wind guidance product in the ENP was in operational testing during the 2022 season and could be extended longer in the subseasonal timeframe in the future if ECEPS forecasts are extended.

4.3. Australian Bureau of meteorology forecasts

The Bureau of Meteorology (BoM) makes available multi-week TC strike probability forecasts for use by National Meteorological Services and the public (see http://www.bom.gov.au/climate/pacific/outlooks/). Operational forecasts are currently available for the South Pacific for weeks 2 and 3, and the WNP for weeks 2, 3 and 4. Forecasts are updated daily during a region's TC season, and a 2-week archive is also made available. Three products are provided: (i) raw model probabilities of TC occurrence; (ii) calibrated probabilities (following Camp et al., 2018) and (iii) calibrated probabilities relative to observed climatology.

Multi-week forecasts are produced using output from the ACCESS-S model, which is based on the UKMO GloSea5 (MacLachlan et al., 2015). Version 1 of this system (ACCESS-S1; Hudson et al., 2017) was operational during the period April 2018–September 2021. This model showed impressive skill for predictions of the MJO out to a lead time of ~30 days. These forecasts also showed skill over climatology for forecasts of TC occurrence over the Southern Hemisphere for lead time weeks 1–5, when a spatial and temporal calibration was applied (Camp et al., 2018). As indicated in section 3.2, ACCESS-S1 provided useful guidance for the development of severe TCs, including Cyclone Gita in the South Pacific and Cyclone Hilda off of the west coast of Australia, at more than two weeks lead time (Gregory et al., 2019). Applying a wind speed threshold to the model TCs also helped to reduce false alarm rates and improve forecast skill early on in the forecast period (Gregory et al., 2019).

In 2020/21 ACCESS-S1 provided good guidance for severe TC Seroja, which became the strongest TC to make landfall in southern Western Australia since 1956 (WMO, 2021). This cyclone presented a major challenge for forecasters due to its Fujiwhara interaction with TC Odette from April 7–9. A tropical low that failed to intensify was also in the region, moving south-east across the Cocos Islands from April 6–11. The uncertainty of the forecast was evident by the large spatial ensemble spread, and the associated low strike probabilities. Forecasts of the probability of TC occurrence for TC Seroja are shown for ACCESS-S1 for lead time weeks 2 and 3 in Fig. 9.

Following the successful trials for the Southern Hemisphere, research was extended to the WNP basin, and skill was found over climatology for calibrated forecasts of TC occurrence out to week 4 (BoM, 2020). Skill of real-time forecasts using a lagged ensemble of 2–3 days was found to provide increased skill for both the WNP and Southern Hemisphere for the trial 2017/18 and 2018/19 TC seasons (BoM, 2020). Finally, combining forecasts from the ECMWF's Medium- and Extended-Range Ensemble Integrated Forecasting System (IFS) and ACCESS-S1 to create a multi-model ensemble showed superior skill to the component models during the 2017/18 and 2018/19 TC seasons (Gregory et al., 2020).

In October 2021 the BoM operational system was upgraded to ACCESS-S2 (Wedd et al., 2022). This system retains the skill of the MJO out to ~30 days and shows skill over climatology for multi-week forecasts of TC frequency over the Southern Hemisphere, western and eastern North Pacific, and North Atlantic out to week 5. However, the skill over climatology in the North Indian Ocean was only to week 2 (Camp et al. 2023a; 2023b).

4.4. Colorado State University forecasts

Colorado State University (CSU) has been operationally issuing two-week Atlantic basin ACE forecasts since 2009. These forecasts are issued six times during August–October. Each forecast is for the probability of above-normal, normal, or below-normal ACE terciles for the North Atlantic. These predictions are based on both statistical and dynamical models and consider several different factors: (1) National Hurricane Center (NHC) current and forecast North Atlantic activity; (2) NHC Tropical Weather Outlooks; (3) Global model forecasts of North Atlantic TC development; (4) Current and projected state of the MJO; (5) Global model forecasts of key atmospheric circulation patterns; and (6) the current TC numbers relative to the CSU Atlantic seasonal hurricane forecast.

For the sample of 78 two-week Atlantic TC forecasts since 2009, 64% have verified in the correct tercile, 28% missed by only one tercile, and 8% missed by two terciles. In general, these forecasts have shown improved skill in recent years, with only one two tercile miss (e.g., forecast bust) since 2013.

4.5. Joint Typhoon Warning Center

In 2018, JTWC began providing graphical two-week TC Formation Outlooks that depict geographic areas (boxes), timeframes, and forecaster-designated TC formation probabilities in the Indian, WNP, and South Pacific basins. JTWC will continue to generate and distribute these outlooks at least twice daily while exploring the viability of longer period forecasts. For example, the JTWC and the 14th Weather Squadron (14 WS) Climate Monitoring, Analysis and Prediction teams have conducted weekly collaboration calls to coordinate 14 WS Week 3 TC formation outlooks for the JTWC forecast basins. Although JTWC has no near-term plans to extend its two-week TC formation outlook to the week 3 period, the collaboration has infused new tools and perspectives from 14 WS

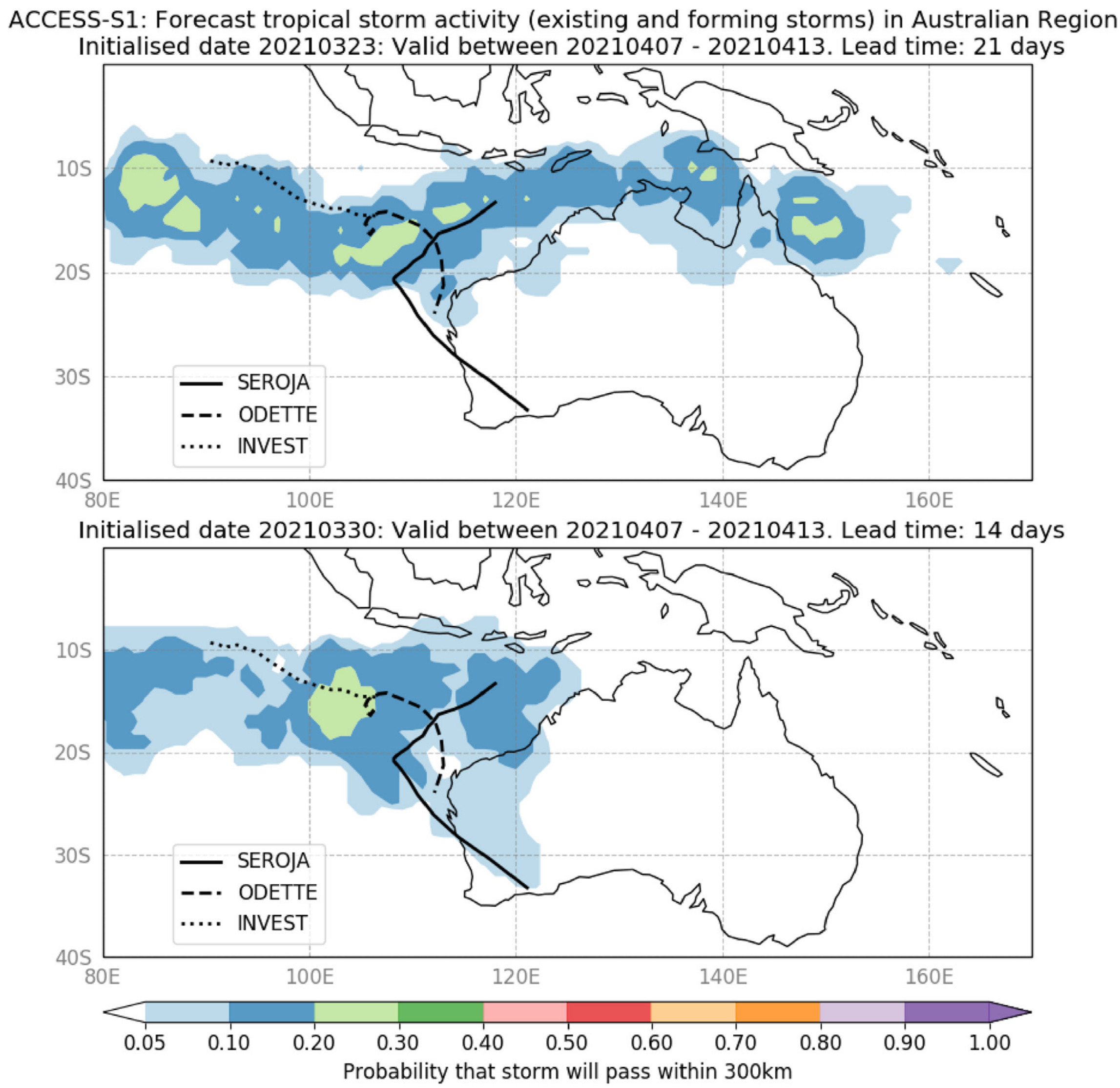

Fig. 9. Probability of a TC passing within a 300 km radius for ACCESS-S1 forecasts valid in a) week 3 (initialized March 23, 2021) and b) week 2 (initialized March 30, 2021) for the period 7–13 April 2021. Corresponding observed tracks for TC Seroja, TC Odette and an invest area are overlain in black. Observed TC tracks are from the US Navy's Joint Typhoon Warning Center (JTWC; Chu et al., 2002). TC Seroja made landfall on April 11, 2021.

climatology experts into the existing JTWC extended-range forecasting process.

The JTWC development efforts also benefit from extensive collaboration with the NOAA CPC and U.S. Department of Defense (DOD) partner organizations. For example, the 16th Weather Squadron (16 WS) numerical modeling team developed a suite of TC prediction guidance for DOD forecasters. Included in the new 16 WS guidance is a multi-model ensemble forecast of large-scale probability of wind speed exceedance that effectively highlights geographic areas and timeframes in which TC formation may occur.

4.6. U.S. Naval Research laboratory

Hansen et al. (2022) examined whether nonlinear MJO/ENSO influences and the subseasonal vertical shear pattern impacts on North Atlantic ACE can be used to improve subseasonal predictions. Hansen et al. (2022) built a statistical-dynamical hybrid model using Navy-Earth System Prediction Capability (ESPC; Barton et al., 2020) reforecasts as part of the SubX project (Pegion et al., 2019). Persistence reforecasts of Niño 3.4 SSTs and MDR SSTs, and Navy-ESPC reforecasts of the first two principal components (PCs) of the MJO, were used as predictors for the basic model. Two shear index predictors evaluated from Navy-ESPC reforecasts were added in one option, and a second option was substituting a nonlinear MJO/ENSO predictor in place of the MJO PCs and Niño 3.4 SST predictors. These predictors were fed into a logistic regression model, which adds and removes predictors to assess the skill contribution from each predictor. North Atlantic SSTs and the MJO were found to be the most important factors contributing to subseasonal North Atlantic TC activity (Fig. 10). The shear pattern improved forecast skill at 5–10 day lead times before forecast shear errors became too large. Nonlinear MJO/ENSO

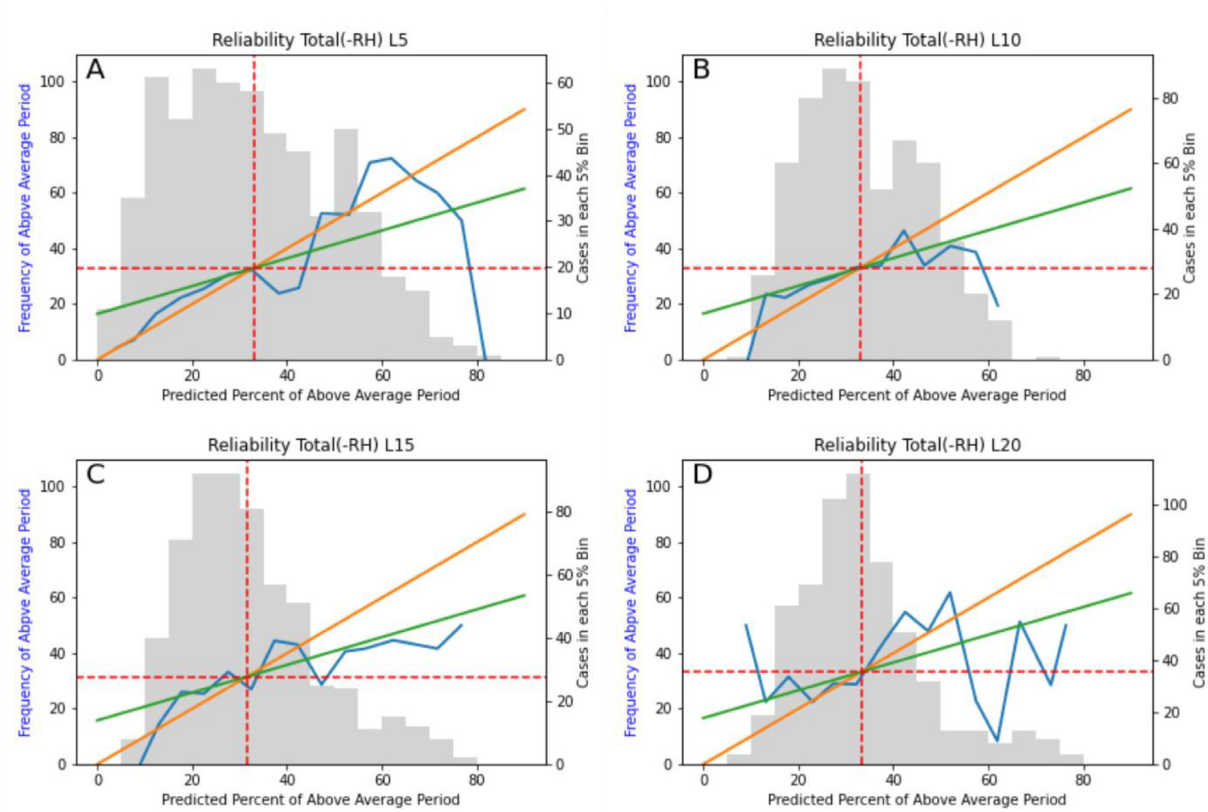

Fig. 10. Reliability diagrams for the "Total (-RH)" scheme, which includes the shear predictors, MJO PCs, Nino 3.4 SSTs and MDR SSTs but not relative humidity (RH) for a) 5-day, b) 10-day, c) 15-day, and d) 20-day forecasts. The blue line indicates the observed frequency of an above-average normalized 5-day ACE period for each 5% forecast bin. The orange line indicates a one-to-one ratio of predicted probability and observed frequency representing a perfect model. The green line indicates climatological skill. Vertical and horizontal dashed red lines indicate the climatological rate of active normalized 5-day ACE periods in the North Atlantic. Gray bars indicate the number of forecasts that fall into each 5% bin. (from Hansen et al., 2022).

interactions did not improve skill compared to separate linear considerations of these factors, but did improve the reliability of predictions for high-probability active TC periods.

4.7. Private sector forecasts

It is well known that a TC strike across an economic point of interest will drive a chain of reactions across the global markets. These market reactions vary depending on the intensity of the TC, the risk of inundation, and even the amount of rainfall. Understanding these risks at longer lead times is always desired, which will require improved numerical weather prediction (NWP) model forecasts of TCs at these long lead times. At subseasonal forecast leads (i.e., forecast weeks 3+), private sector companies often rely on a combination of NWP forecasts and tropical wave-based statistical forecasts of TC activity. While there have been incremental advances in NWP forecasts beyond 10 days, the prediction of TC impacts is still not reliable. This unreliability has resulted in little to no advancements in subseasonal outlooks of TC impacts across the private sector.

In recent years, there has been more desire to utilize the full distribution of an NWP ensemble suite. As the private sector industry gains knowledge about medium-range to subseasonal predictions of TCs, the community is shifting away from deterministic NWP forecasts and toward probabilistic forecasts. Questions often asked by decision makers are, "What is the range of outcomes that could happen?" or "What is the probability of wind speeds greater than 100 mph across this specific location?" As agencies continue to increase the number of ensemble members in their forecast models and improve the forecast skill beyond 7+ days, more private sector groups rely on ensemble probabilistic guidance to hedge risk in whatever TC decision they must make.

5. Summary and conclusions

Progress has been made by the scientific community over the last four years to better understand the sources of predictability and the modulation of TC activity at subseasonal timescales. In particular, several recent publications have evaluated the impact of the BSISO on TC activity over the WNP. There has also been significant progress in the understanding of the impact of extratropical wave breaking on tropical storm development.

The availability of large datasets of subseasonal forecasts (S2S and SubX) has been an opportunity to better understand the capability of S2S models to simulate and predict the subseasonal variability of TCs. Guided by the observational studies, the model diagnostics and comparisons have focused on predicting the MJO and its modulation of TC activity. Most S2S models have difficulties predicting subseasonal TC activity beyond a seasonal varying climatology, although the skill can be improved by post-process calibration.

The improving availability and skill of subseasonal dynamical models has led to a surge in the number of operational subseasonal forecasts of TCs over the past four years. These forecasts are produced by both dynamical models and statistical methods. Given the increasing skill of these forecasts and the ever-present demand for them, we are very optimistic that these improvements will continue in the coming years.

Acknowledgments

Schreck was supported by NOAA through the Cooperative Institute for Satellite Earth System Studies under Cooperative Agreement NA19NES4320002. Janiga acknowledges the support of the Chief of Naval Research through the NRL Base Program PE 62435N. Camargo and Lee acknowledge support from the NASA MAP program (80NSSC21K1495). Camargo also acknowledges support from NOAA (NA22OAR4310610) and the Vetlesen Foundation. Wang was supported by the National Science Foundation under Grant No. 2116804.

Appendix A. Acronyms:

AEW	African Easterly Wave
ABY	ACE by Year
ACCESS-S	Australian Community Climate Earth-System Simulator–Seasonal
ACCESS-GE2	Australian Community Climate Earth-System Simulator–Global Ensemble version 2
ACE	Accumulated Cyclone Energy
ATL	Atlantic
AUS	Australia
BoB	Bay of Bengal
BoM	Australian Bureau of Meteorology
BSISO	Boreal Summer Intraseasonal Oscillation
BSS	Brier Skill Score
CAM6	Community Atmospheric Model version 6
CESM2	Community Earth System Model version 2
CFS	Climate Forecast System
CMA	China Meteorological Agency
CNR-ISAC	Institute for Atmospheric Sciences and Climate, Italy
CNRM	National Center for Meteorological Research, Météo-France
CPC	Climate Prediction Center
CSU	Colorado State University
DOD	Department of Defense
ECCC	Environment and Climate Change Canada
ECEPS	ECMWF Ensemble Prediction System
ECMWF	European Center for Medium-range Weather Forecasts
ENP	Eastern North Pacific
ENSO	El Niño–Southern Oscillation
ERW	Equatorial Rossby Waves
ESPC	Earth System Prediction Capability
GEFSv12	Global Ensemble Forecast System version 12
GEOS-S2S-2	Goddard Earth Observing System Subseasonal-to-Seasonal Prediction System v2
GFDL	Geophysical Fluid Dynamics Laboratory
GloSea5	Global Seasonal forecast system
GMAO	Global Modeling and Assimilation Office
GPI	Genesis Potential Index
GTH	Global Tropical Hazards and Benefits Outlook
HiRAM	High Resolution Atmospheric Model
HMCR	Hydro-Meteorological Center of Russia
HSS	Heidke Skill Score
IFS	Integrated Forecasting System.
JAMSTEC	Japan Agency for Marine-Earth Science and Technology
JMA	Japan Meteorological Agency
JTWC	Joint Typhoon Warning Center
KMA	Korea Meteorological Agency
KW	Kelvin Waves
MDR	Main Development Region
MetFr	Météo-France
MJO	Madden–Julian Oscillation
MRG	Mixed Rossby–Gravity Waves
MRGTD	Mixed Rossby–Gravity Waves and Tropical Depressions
NAO	North Atlantic Oscillation
NCEP	National Centers for Environmental Prediction
NHC	National Hurricane Center
NI	North Indian Ocean
NOAA	National Oceanic and Atmospheric Administration
NWP	Numerical Weather Prediction
OMI	OLR-only MJO Index
PC	Principal Component
QBWO	Quasi Bi-weekly Oscillation
RH	Relative Humidity
RPSS	Ranked Probability Skill Score
RWB	Rossby Wave Breaking
S2S	Subseasonal-to-seasonal
SEDS	Symmetric Extreme Dependency Score
SIN	South Indian Ocean
SPC	Southern Pacific Ocean
SPEAR	Seamless System for Prediction and Earth System Research
SST	Sea Surface Temperature
SubX	Subseasonal Experiment
T2F	Time-to-Formation
T2H	Time-to-Hurricane
TDF	Track Density Function
TC	Tropical Cyclone
TEHU	Time to Ending Hurricane
TETS	Time to Ending Tropical Storm
TS	Tropical Storm
TUTT	Tropical Upper Tropospheric Trough
UKMO	U.K. Met Office

WACCM6	Whole Atmosphere Community Climate Model version 6
WMO	World Meteorological Organization
WNP	Western North Pacific
WS	Weather Squadron

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