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Recent advances in seasonal and multi-annual tropical cyclone forecasting

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Abstract

Seasonal tropical cyclone (TC) forecasting has evolved substantially since its commencement in the early 1980s. However, present operational seasonal TC forecasting services still do not meet the requirements of society and stakeholders: current operational products are mainly basin-scale information, while more detailed sub-basin scale information such as potential risks of TC landfall is anticipated for decision making. To fill this gap and make the TC science and services move forward, this paper reviews recent research and development in seasonal tropical cyclone (TC)

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forecasting. In particular, this paper features new research topics on seasonal TC predictability in neutral conditions of El Niño–Southern Oscillation (ENSO), emerging forecasting techniques of seasonal TC activity including Machine Learning/Artificial Intelligence, and multi-annual TC predictions. We also review the skill of forecast systems at predicting landfalling statistics for certain regions of the North Atlantic, Western North Pacific and South Indian oceans and discuss the gap that remains between current products and potential user's expectations. New knowledge and advanced forecasting techniques are expected to further enhance the capability of seasonal TC forecasting and lead to more actionable and fit-for-purpose products.

Keywords: Tropical cyclones; Seasonal forecasting; Climate services

1. Introduction

Seasonal forecasts of tropical cyclones (TCs) developed in parallel for the Australian (Nicholls, 1979; 1984) and the North Atlantic (Gray 1984a; 1984b) regions due in large part to a newly-discovered relationship between the El Niño–Southern Oscillation (ENSO) and TCs in these two basins. The first hurricane outlook for the Atlantic basin relied on a statistical model based upon three predictors (ENSO, the phase of the Quasi-Biennial Oscillation, and sea-level pressure over the Caribbean Sea). Both the predictors and the statistical model evolved over time, as new statistical relationships were discovered and prior predictors started to fail. While this forecast product was the only hurricane outlook produced annually until the late 1990s, the increased availability of newer, longer and more complete datasets combined with increased computing power and a better understanding of hurricane variability provided an opportunity for motivated groups or individuals to start producing these outlooks on a regular basis using an ever-growing number of innovative techniques. Nowadays, TC outlooks are realised as operational seasonal TC forecasts at major modelling centres, through various research groups and some private companies for all basins supporting TC genesis (Camargo et al. 2007; Klotzbach et al. 2019). While ENSO remains an important climate factor modulating TC activity, and skillful prediction of the ENSO state is still an integral part of TC forecasting at the seasonal time scale for some basins, new climate factors have started to emerge as potentially providing additional skill, in particular during ENSO-neutral years. Forecast products covering multiple TC seasons are also now developed.

This paper aims to highlight recent advances in the field of seasonal TC forecasting. Section 2 presents various sources of seasonal TC predictability other than ENSO that have been identified, thus providing predictability in ENSO-neutral conditions for some basins. Section 3 provides an overview of emerging advances in Machine Learning (ML), which have the potential to improve upon existing forecasting techniques. Section 4 presents an integrated and collaborative operational activity for seasonal TC forecasts that has been running for several years. Section 5 presents an overview of the ability of current seasonal outlooks to forecast TC landfall, and Section 6 discusses the application of seasonal outlooks (or lack thereof). Section 7 showcases a prototype of climate services for multi-annual TC forecasts developed in the context of the Copernicus Climate Change Service (C3S) and discusses the origin of Atlantic Multidecadal Variability (AMV), which has strong implications for the ability of initialised climate models to forecast TC activity at this timescale. We conclude with a summary and offer some ideas for future initiatives in Section 8. For recent developments in operational forecast systems related to TC activity, we refer the readers to the 10th International Workshop on Tropical Cyclone report on seasonal forecasting (Takaya et al. 2022).

2. Predictability in ENSO-neutral conditions

Traditionally, the prediction capability for seasonal TC activity has predominantly relied on ENSO (Feng et al. 2020; Gray 1984a; 1984b; Zhan et al. 2012 for review), which is the dominant mode of tropical variability with widespread global influences. More recent studies pointed out that ENSO flavour (Central-Pacific type ENSO and East-Pacific type ENSO) and transition are also important properties modulating the influence of ENSO on WNP TC activity (e.g., Choi et al. 2019). In addition, recent studies have revealed new influences on seasonal TC activity in various basins in ENSO-neutral conditions, and thus new potential sources of predictability. This section reviews recent findings of seasonal TC predictability in ENSO-neutral conditions in the western North Pacific (WNP), North Atlantic (NA) and southern Indian Ocean (SIO). It is important to note that an ENSO neutral phase does not necessarily mean that the large-scale circulation is completely devoid of ENSO's influence, but rather that the influence of the ENSO transition and non-ENSO climate phenomena become more predominant (e.g., Hansen et al. 2022).

2.1. Predictability of TC activity over the WNP in ENSO-neutral conditions

Several recent studies have shown a significant impact of the Pacific Meridional Mode (PMM; Chiang and Vimont 2004) on the interannual variability of WNP TC activity (Zhang et al. 2016c; Gao et al. 2020a; Liu et al. 2019; Takaya 2019). PMM is an atmosphere–ocean coupled variability mode in the subtropical North Pacific. These results were further confirmed by Wu et al. (2021), who showed a robust influence of the PMM on both TC genesis and tracks after accounting for the influence of decadal variability and ENSO. Positive phases of the PMM increase TC activity by inducing anomalous cyclonic winds and positive vorticity anomalies over the WNP.

The tropical North Atlantic (TNA; 0°–20°N, 80°–10°W; Gao et al. 2020b) is another important driver of WNP TC activity, which is somewhat independent of ENSO. Many studies have documented significant correlations between TNA sea surface temperature (SST) anomalies and both WNP cyclogenesis and landfalling events (Huo et al., 2015; Yu et al., 2016; Gao et al., 2018). Gao et al. (2020b) also found a significant positive correlation between spring TNA SST and the autumn frequency of intense TCs landfalling over mainland China in neutral ENSO conditions.

SSTs in the Indian Ocean (IO) and the western Pacific are other contributors to seasonal TC activity in the WNP. Zhan et al. (2019) quantified the contributions of SST anomalies in the Indo-Pacific Oceans to the interannual variability of WNP TC genesis frequency. They found that the spring SST gradient between the southwestern Pacific and the western Pacific warm pool and summer SST anomalies over the eastern IO predominantly contribute to the interannual variability of TC genesis frequency compared to ENSO.

Takaya et al. (2021) also investigated seasonal TC activity in the WNP in relation to IO basin (IOB; 20°N–20°S, 40°E−100°E) and Niño3.4 SSTs (Fig. 1). They suggested that the IO mediates the delayed influence of preceding El Niño due to IO warming following El Niño (Indo-western Pacific Capacitor mode; Xie et al. 2016), and also modulates WNP TC activity in summers that follow El Niño events. In addition, they found that the combined effect of the IOB and Niño3.4 SSTs can explain WNP TC activity (TC days, Fig. 1a), even in ENSO-neutral phases. They further demonstrated that the Japan Meteorological Agency/Meteorological Research Institute-Coupled Prediction System version 2 has the ability to replicate the IOB and equatorial Pacific influence in ENSO-neutral summer (June–August) forecasts starting from the end of April (one month lead, Fig. 1a). A composite analysis also supported this result (right column in Fig. 1b), indicating that there is moderate predictability of seasonal TC activity in ENSO-neutral years.

2.2. Predictability of TC activity over the North Atlantic in ENSO-neutral conditions

Over the North Atlantic, phenomena shown to recently impact ENSO-neutral hurricane seasons include Rossby wave breaking (RWB; Zhang et al. 2016a, 2017; Wang et al. 2020; Papin et al. 2020; Jones et al. 2022) and the Indian Ocean Dipole (IOD; Wood et al. 2020).

Zhang et al. (2016a, 2017) and Papin et al. (2020) showed that while anticyclonic RWB events may be synoptic and transient in nature, they have strong seasonal impacts on the large-scale boreal summer (July–October) environment, particularly on vertical wind shear (VWS). VWS tends to increase along the downstream slope of midlatitude high potential vorticity streamers that penetrate the tropical environment. This leads to an overall increase in VWS across the Atlantic Main Development Region (MDR; 10°N–20°N; Goldenberg and Shapiro, 1996), suppressing hurricane activity. Jones et al. (2020) further showed that RWB accounted for the second leading mode in July–September NA VWS variability following ENSO. These studies suggest that RWB can partially account for low activity Atlantic hurricane seasons, such as the 2013 season. This particular Atlantic hurricane season produced one of the lowest seasonal Accumulated Cyclone Energy (ACE) values on record (36.1×10^4 kt^2). Despite having persistent neutral ENSO conditions throughout the summer, the peak of the season (August–October) was characterised by anomalously high VWS and reduced relative humidity (RH)

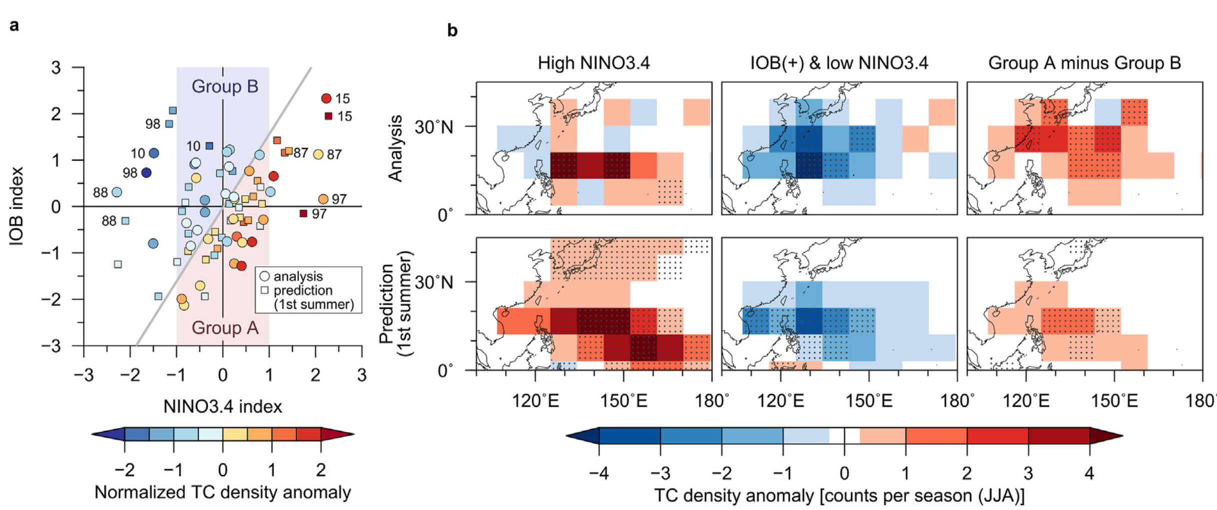

Fig. 1. a) Scatterplot of the analysed (circles) and predicted (squares) TC densities (TC days) with respect to Indian Ocean Basin (IOB) and Niño3.4 SST indices. Colours indicate the TC density accumulated in the western North Pacific (WNP) region normalised by the climatological mean and standard deviation. Two-digit numbers shown alongside circles or squares indicate years. b) Composites of observed and predicted TC density anomalies for summers with (left) a Niño3.4 index >+1.5 std. dev., (middle) an IOB index >0 and Niño3.4 index <−1 std. dev., and (right) Group A minus Group B (groups shown with background colours in Fig. 1a). Stippled regions are statistically significant at the 5% level using a bootstrap method (10,000 resamplings). Material from: Takaya et al. Skilful predictions of the Asian summer monsoon one year ahead, Nature Communications, published 2021, Springer Nature.

over most of the Atlantic MDR. Zhang et al. (2016a) associated this anomalous season with above-normal RWB activity.

The above-mentioned environmental impacts of RWB on NA TC activity are predictable on seasonal timescales (Wang et al. 2020; Zhang et al. 2021; Jones et al. 2022). Zhang et al. (2021) showed that extratropical baroclinic wave activity leading to RWB is predictable throughout the year and can be predicted using current operational climate models. Using an RWB-associated predictor, Jones et al. (2022) showed that RWB can improve the skill of early-April NA TC forecasts as wintertime RWB events can precondition the environment, in association with the North Atlantic Oscillation, to induce more wave breaking in the summer. Colorado State University (CSU) very recently included RWB-related predictors in its early-April outlook in the form of 200-hPa subtropical NA zonal winds (Klotzbach et al. 2021; Klotzbach and Bell 2022).

Wood et al. (2020) suggested that the IOD may be another source of seasonal TC predictability over the NA during neutral ENSO phases. The IOD played a role in suppressing late-season TC activity during the 2019 NA hurricane season with ENSO-neutral conditions during August–October. By modulating the Walker circulation, positive IOD phases (warm western IO and cool eastern IO) suppress NA TC activity by increasing VWS and reducing RH over the NA MDR, while negative IOD phases are associated with more favourable environmental conditions for NA TC activity. The added value of including the IOD as a predictor of seasonal hurricane activity in a statistical model has yet to be evaluated however.

2.3. Seasonal TC activity modulation over the SouthWest Indian Ocean associated with Subtropical Indian Ocean Dipole events

Over the South West Indian Ocean (SWIO) basin, the observed interannual variability of TC activity can only partially be explained by ENSO. Over the last few years, Météo-France in La Réunion has investigated the role played by some regional climate drivers for both basin-wide TC activity as well as the geographical distribution within the basin (Bonnardot et al. 2021). In this context, the Subtropical Indian Ocean Dipole (SIOD) mode was identified as a significant influence on cyclone activity during ENSO-neutral years.

The SIOD appears as the dominant PCA mode of SST variability in the southern IO during the austral summer (December–February, the peak of the cyclonic season in the SWIO basin). The SIOD is an ocean-atmosphere coupled oscillation characterised by a zonal dipole of SST anomalies over the subtropical southern IO (Fig. 2). The coupling with the atmosphere results in atmospheric circulation and sea level pressure (SLP) anomalies over the South IO. While the SIOD may be phased with ENSO, it can operate during neutral ENSO periods with strong positive or negative phases like the IOD.

Positive events are associated with colder-than-normal SST off Australia and a positive SLP anomaly over the tropical and subtropical south central IO. This atmospheric anomaly drives cool and dry air from austral latitudes all the way to the MDR of the SWIO basin (5°S-15°S, 55°E–90°E), reducing basin-wide TC activity by ~20%. Similarly, negative events result in a negative SLP anomaly pattern driving moisture and warm equatorial air over the MDR, while cool and dry air is advected from austral latitudes to the western part of the SWIO (west of 55°E including the Mozambique Channel and Madagascar). Consequently, negative SIOD events tend to facilitate TC development within the MDR, enhancing overall TC activity by ~20%.

The SIOD may also modulate the geographical distribution of TCs by shifting TC genesis regions and TC tracks. Positive SIOD events tend to favour enhanced activity on two opposite sides of the basin (east of 70°E and over the Mozambique Channel) while TC activity is considerably suppressed in the central part of the basin (from Madagascar to Mascarene Islands). Negative SIOD events tend to favour TC developments over the central and eastern part of the basin (east of 50°E), with southeastward oriented TC tracks, thus reducing the risk of impacts for Madagascar and Mozambique but increasing the risk for the Mascarene Islands.

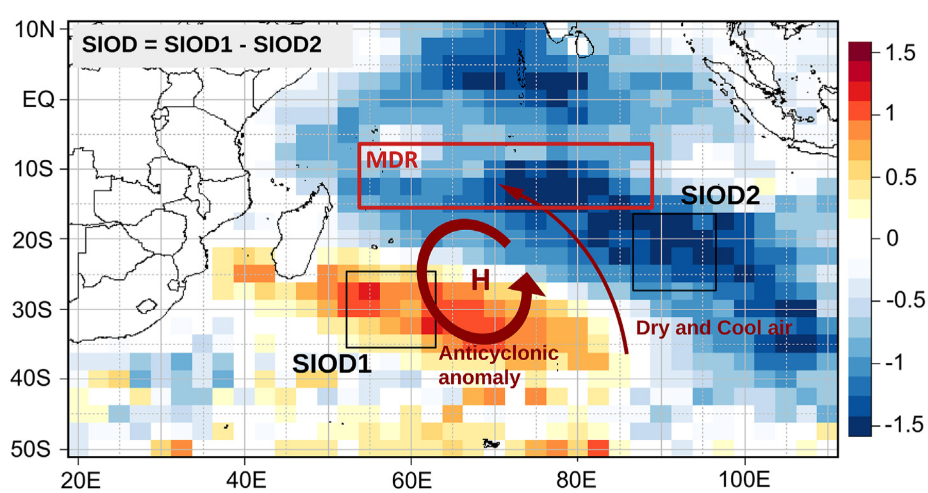

Fig. 2. Representation of the positive phase of the SIOD constructed using composites of standardised SST anomalies. The composite includes SST anomalies for the austral summer seasons (December–February) of 1981–1982, 1992–1993, 1998–1999, 2005–2006, 2010–2011, and 2016–2017.

These results suggest that the SIOD is a promising source of predictability for SWIO TC activity at seasonal time scales, bringing additional information for TC seasonal outlooks to that provided by ENSO. However, predicting oscillations of the SIOD accurately is still challenge and improving the understanding of the mechanisms that may force rapid variations in the SIOD (e.g., the role of ENSO, IOD or other intra-seasonal drivers) will be necessary to capitalise on this new source of predictability.

3. Recent development and application of machine learning to the seasonal TC forecasting problem

In the last decade, the use of ML and Artificial Intelligence (AI) algorithms has shown huge potential for a wide range of applications. These techniques have emerged also in climate, meteorological and oceanographic fields (among others) with convincing results. The key concept behind ML is to provide data to machines and let them infer rules from it. Typically, a user will define the algorithms, a potential target (e.g., the number of TCs in a given basin), and a scoring method (minimising a particular type of error). Then, during the training phase, the machine will automatically adjust the different degrees of freedom in the model and optimise the skill. Then the algorithm can be deployed on new unseen data.

ML algorithms have broad applications, from regression/classification problems to feature selection or clustering. ML can strongly benefit two key aspects of TC seasonal forecasting: (1) constructing statistical models for useful parameters (number of TCs, major TCs (Category 3-4-5 on the Saffir-Simpson scale), ACE, etc.), (2) mining databases to extract physical patterns that can be used in statistical models. These aspects are discussed in more detail below.

3.1. Predictive models of seasonal TC activity

ML can advance and improve statistical forecasting approaches; for example, support vector regression (SVR) was used by Richman et al. (2017) to predict the number of seasonal TCs in the NA, leading to 40% improvement compared to multiple linear regression. Nath et al. (2016) obtained similar promising results using different types of neural networks combined with large-scale climate variables to predict seasonal TC activity over the North IO (NIO).

More recently, by combining an ensemble of statistical models and using ML to select and weight top performing ensemble members, Sun et al. (2021) demonstrated similar skill to standard ensemble averages for basinwide NA activity, but found improved skill for major hurricanes and more granular details (such as sub-basin activity). They pointed out limitations when large systematic biases of the same sign occurred for a majority of the ensemble members.

3.2. Predictors mining and patterns extraction

For extracting key modes of variability driving TC activity, ML can play a key role in mining the large amount of observed data and modelled ensemble data collected and generated over the past decades. These physical climatic patterns can then be directly used in predictive models. Using a causal effect network approach, Pfleiderer et al. (2020) identified skillful spring predictors of seasonal Atlantic hurricane activity that in turn increased the prediction skill of statistical forecast models conditioned to these climate drivers. By combining neural networks for data mining, clustering, and a conditional chain of supervised ML algorithms, Rodney and Loridan (2019) investigated landfalling forecasts along the US coast and showed skill in predicting US landfalling systems originating from the Cape Verde/MDR region. Asthana et al. (2021) developed a Fused Convolutional Neural Network forced by climatic fields (SLP, SST, among others) that achieved a prediction skill similar to that of other statistical models for ACE in the NA, but at longer lead times. However, they highlighted limitations in finding convincing explanations for the physical patterns emerging from their Singular Value Decomposition analysis. Similarly, Ham et al. (2019) showed that a convolutional neural network could not only improve on current state-of-the-art dynamical forecast systems in predicting ENSO, but also provide skilful forecasts for lead times of up to one and a half years. While no study has yet investigated the impact of integrating these models into TC outlooks, their results suggest ML techniques could be used to increase the skill of TC forecasts for longer lead times, possibly past the traditional spring barrier, for basins strongly impacted by ENSO.

Machine learning offers a new way to extract potential climate patterns driving TC activity around the world and could be particularly useful for basins that have been previously less studied. ML could also help in predicting potential correlations between basins. Recent reviews by Chen et al. (2020) and Wang et al. (2022) further illustrate this growth in the use of ML for short- to long-term TC forecasting.

Despite its great potential, there are some general limitations to applying ML for TC forecasting. ML methods require a large amount of training data. While a broad range of observed and simulated data are available, a limited number of years of data on TC activity exist (e.g., the number of cyclones for a season for the past few decades). Some ML algorithms might suffer from this limited data, and particular care needs to be given when training models (e.g., preventing overfitting). Pitfalls in developing and evaluating statistical models are elaborated in the next subsection.

3.3. Common problems associated with building statistical forecast models

A common issue in constructing statistical models is the selection of model predictors, which is usually done by choosing parameters based on correlation scores. Often correlations between ENSO and climate predictors are no more significant than those produced with time series of pairs of Gaussian noise. The shortness of the instrumental record can suggest swings in model predictands may be correlated with low-pass-filtered modes of climate variability, but they may just reflect the typical stochastic nature of random processes (Gershunov et al. 2001).

Any models using predictors selected based on correlation must be tested further against models using additional predictors, which is often called a 'double' or 'external' cross-validation, to account for selection bias, and to avoid problems due to autocorrelation in the predictors. Autocorrelation (or serial correlation) removes degrees of freedom and can generate spurious correlations among variables, suggesting spurious physical relationships. It can also invalidate significance tests. See Legendre and Trousselleir (1988) and Fang and Koreisha (2004) for further discussion.

Selection bias is a common issue when building predictive statistical models across all areas of science. Failure to account for sample bias will create an over-fitted model, usually identified by a model which demonstrates large differences between 'in-sample' and 'out-of-sample' forecast skill. Older methods of predictor selection (e.g. stepwise selection) have been used in recent literature, despite being prone to selecting biassed model predictors and being prone to overfitting. Hastie et al. (2017) and Ambroise and McLachlan (2002) show how it is essential that cross-validation, or the bootstrap method, be used external to the selection process to remove selection bias.

For seasonal TC prediction models, the recent history of ENSO events can also influence model behaviour. Often, model skill is derived mainly from a few large ENSO events from the late 20th century, which can lead to poorer model forecasts for 21st century ENSO mechanisms due to the non-stationary behaviour and influence of ENSO. For example, Dowdy (2014) showed large reductions in correlation between Australian TC activity and ENSO indices (SOI and Niño 3.4) between 1982 and 1997, and 1998 and 2013. Results displayed in Fig. 3 from Greenslade and Gregory (2023) suggest that this issue applies to sub-basins and other indices as well.

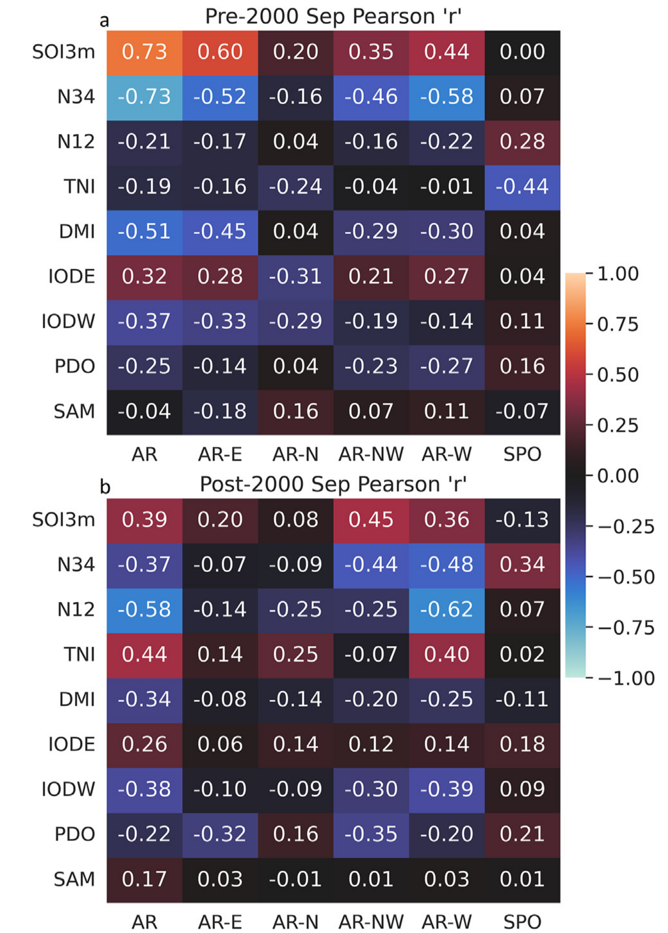

Fig. 3. Correlations for climatic indices (y-axis) against TC counts for the subsequent season (October–April) in the Australian and South Pacific regions (x-axis) for the period 1970–2000 (a) and 2000–2021 (b). Climate indices from top to bottom (September means unless indicated otherwise): Southern Oscillation Index (JAS), Niño3.4 (JAS), Niño1+2 (JAS), Trans-Niño Index, Dipole Mode Index, Indian Ocean (East Pole) SST, Indian Ocean (West Pole) SST, Pacific Decadal Oscillation, Southern Annular Mode. Regions from Left to Right: Australian Region (90°E – 160°E), Australian Eastern Region (142.5°E – 160°E), Australian Western Region (90°E – 125°E), Australian Northern Region (125°E – 142.5°E), South Pacific Region (142.5°E – 120°W). All regions span 5°S - 40°S latitude except AR-NW, which is restricted to 5°S - 25°S.

4. Multi-model tropical cyclone forecasting and intercomparison

The current seasonal TC forecasting landscape is fragmented among many research and operational groups. Thus, the coordination of a seasonal prediction website that hosts multiple contributors has significant benefits, such as simplifying the search for information for interested users. Currently, the NA is the only basin for which there exists an aggregator of seasonal hurricane forecasts. This is due in part to the large number of groups producing forecasts for that region compared to other basins where there might not be such a need at present. There are currently nearly 30 different groups producing seasonal forecasts for the NA. Nearly half of these groups are private vendors, while the other half consists of government agencies and universities. In general, the forecasters tend to rely on a combination of statistical and dynamical forecasts, although some groups do produce purely statistical or dynamical forecasts. This so-called hybrid approach is one that relies conjointly on large-scale predictors from dynamical models (though not the simulated TCs themselves) and observed statistical relationships. In recent years, forecasts relying on machine learning have also been included (Pfleiderer et al. 2020; Rodney and Loridan 2019). For many organisations, the final outlook is often a combination of one or multiple models along with expert judgments (Klotzbach et al. 2017).

Established in 2016, the platform[1] aggregating the NA outlooks displays the forecasted seasonal numbers of named storms, hurricanes and major hurricanes as well as forecasted seasonal ACE. While all participating groups produce an initial forecast between the end of March and the beginning of June, many groups update their forecast up until early August, just ahead of the peak of hurricane season. Some groups will keep a regular schedule from year to year (e.g. the National Oceanic and Atmospheric Administration (NOAA) releases a first forecast in May and produces an update in early August), while other groups

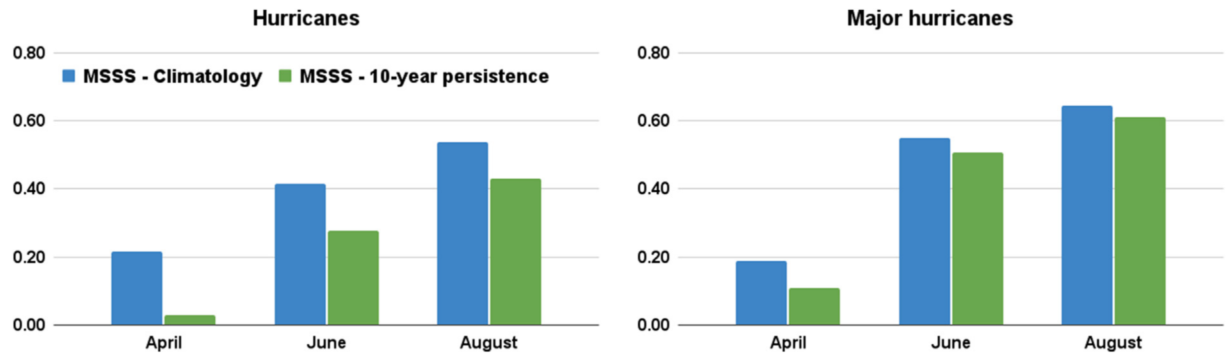

Fig. 4. MSSS of the ensemble mean forecast for the number of hurricanes (left) and major hurricanes (right) for the period 2016–2021. The MSSS is defined as $MSSS = 1 - \frac{MSE_{forecast}}{MSE_{benchmark}}$, where $MSE_{forecast}$ and $MSE_{benchmark}$ are, respectively, the mean-square error of the forecast and of a benchmark. Skill with respect to the 1981–2010 climatology (10-year persistence) is in blue (green). MSSS = 1 shows a perfect forecast and MSSS≤0 is a forecast with no improvement over the benchmark. We note that 10-year persistence is a more difficult benchmark to improve upon than climatology.

will issue a new forecast only if they need to adjust a prior forecast. Fig. 4 shows the skill, defined as the mean-square skill score (MSSS), of the ensemble mean forecast for the number of hurricanes and major hurricanes for the period 2016–2021. The ensemble mean is constructed by 2-month periods (March–April, May–June, July–August) using a subset of organisations that have consistently submitted a forecast since the platform began operating. Note that the organisations included in each 2-month subset vary from each other. Information on the members included in the ensemble is provided in Appendix A. While the sample is small, it is interesting to note the steady increase in skill from March–April to July–August. There is low but positive skill for forecasts issued in March–April. Skill reported this early in the year is typically minimal (Klotzbach et al. 2017; 2019). Whether this is an artefact of the small sample size or emerges due to the combination of multiple forecast systems (Hagedorn, 2005) is not yet known. Continuing operations of the platform will allow a more robust evaluation of these multi-model ensembles.

5. Seasonal TC landfall prediction

Potentially the most valuable and actionable information of seasonal TC forecasting is the quantification of the risk of landfalling TCs for various coastal regions. In this section we present recent advances on this topic for three different basins.

5.1. Seasonal forecasting of TC landfalls in the NA

There are only a limited number of peer-reviewed studies on the skill of seasonal forecasts at predicting landfall over the NA and most of the available literature on the topic is derived from analysis of landfalling TCs in dynamical forecasts. Vecchi et al. (2014) showed that the Geophysical Fluid Dynamics Laboratory (GFDL) model initialised on April 1st and July 1st showed significant skill in predicting TC activity over the Caribbean Sea. The skill of that particular forecast system over the Caribbean Sea was later confirmed by Murakami et al. (2016), who showed statistically significant skill at predicting the number of named storms, hurricanes and even major hurricanes over that region for forecasts initialised in July. Murakami et al. (2016) showed that their system could even forecast the number of landfalling storms over the Caribbean islands with some skill using April to July start dates. However, only the June and July start dates offered a significant improvement over a climatological forecast. That same study also investigated the skill at forecasting landfalling storms over the continental United States, and while some level of skill was detected, only marginal improvement over climatology was detected for the June and July start dates.

Predictability of TC activity over the Caribbean region was also found in the UK Met Office GloSea5 system (MacLachlan et al. 2015; Williams et al. 2015; Camp et al. 2015). Statistically significant skill was found over that region with their June forecasts. This skill was linked to the good model response to the ENSO signal (Camp and Caron, 2017). Investigating the 2017 hurricane season more specifically, Camp et al. (2018) detected positive anomalies in TC tracks across the northeast Caribbean in September 2017 — a signal which was consistent with the observed tracks of major hurricanes Irma, Maria and Jose observed that year. A study looking at landfalling storms was also performed using ECMWF System 4 (Bergman et al. 2019), and some skill was found for the number of landfalling named storms over the North American continent as a whole, but not for the continental U.S. alone.

Skill for the Caribbean region was also detected for at least one statistical model. Klotzbach (2011) developed a statistical model, which showed skill at predicting hurricane activity during the months of October–November. Klotzbach et al. (2022) showed that the hyperactive end to the 2020 hurricane season, for which the October–November period was particularly active with 6 hurricanes and 5 major hurricanes, could have been anticipated using this simple two-predictor model. Colorado State University now issues October–November Caribbean TC activity forecasts operationally.

These results suggest that the Caribbean region is a particularly predictable area of the NA and, given its proximity to land, might offer the best potential for the development of reliable predictions for landfalling storms in the NA for the near future.

5.2. Seasonal forecasting of TC landfall in the WNP

Attempts have also been made to develop skillful landfall forecasts over the WNP. For these studies, the coastline is often divided into three regions, which may vary across studies but broadly correspond to: i) Japan and the Korean peninsula, ii) East China, and iii) South China, Vietnam and the Philippines (Fig. 5a). For example, Zhang et al. (2016b, 2017a) applied a hybrid approach to forecast landfalling TCs over East Asia. In this case, the statistical model uses Poisson regression, and the dynamical model is the GFDL FLOR with flux adjustment (FLOR-FA) coupled system (Vecchi et al. 2014). For predicting the WNP landfalling TC frequency, the simulated PMM, Atlantic Meridional Mode (AMM), North Atlantic SSTA and the Niño-3 SST index were used as predictors based on previous studies showing substantial effects of the SSTs over the tropical and subtropical Pacific and Atlantic on the WNP TCs (e.g. Zhang et al. 2016c; 2017b). The hybrid model dramatically outperforms FLOR-FA in predicting landfalling TCs over South East Asia (SEA) for all of the initial month predictions as well as Middle East Asia (MEA) and North East Asia (NEA) for most initial months (Fig. 4b).The study highlights that the remote effects of the PMM and North Atlantic SST can be used to improve forecast skills for East Asia landfalling TCs.

It is worth noting that Zhang et al. (2017b) made use of all available dynamical forecasts for and prior to the initialization month to build their hybrid models. That is, they included the predictors from the dynamical forecasts prior to the initialization month of interest if they were found to improve the hybrid model compared to the results obtained using only the predictions for the initialization month of interest. They found that this helped alleviate some of the issues they had forecasting of WNP TC activity with FLOR-FA as the lead time decreases. These issues might have been related to initialization shock that sometimes occurs in dynamical models.

A hybrid forecast system for the WNP was also developed with GloSea5. This system has been shown to exhibit significant skill for predictions of TC landfall in East Asia for the June–August (JJA) period when using the Western Pacific subtropical high (WPSH) as a predictor (Camp et al. 2019). Following these results, a trial climate service providing a TC landfall forecast for East China, was issued in 2019, and provided good guidance of the near-average TC activity observed in East China in JJA 2019 (Camp et al. 2020). Forecasts were issued monthly from March–May during subsequent typhoon seasons following improvements to the forecast method (Mitchell and Camp 2021).

It is worth noting that for that particular region (East China coastline), the landfall count does not appear to be correlated to cyclone frequency or genesis location of WNP TCs, but is more closely tied to the steering flow over the East China Sea (Sparks and Toumi, 2021). As such, dynamical forecasts systems which can successfully forecast this flow, or large-scale features associated with it, have the potential to be integrated into a hybrid forecast system such as those developed with FLOR-FA, GloSea5 and PNU CGCM (Kim et al., 2021).

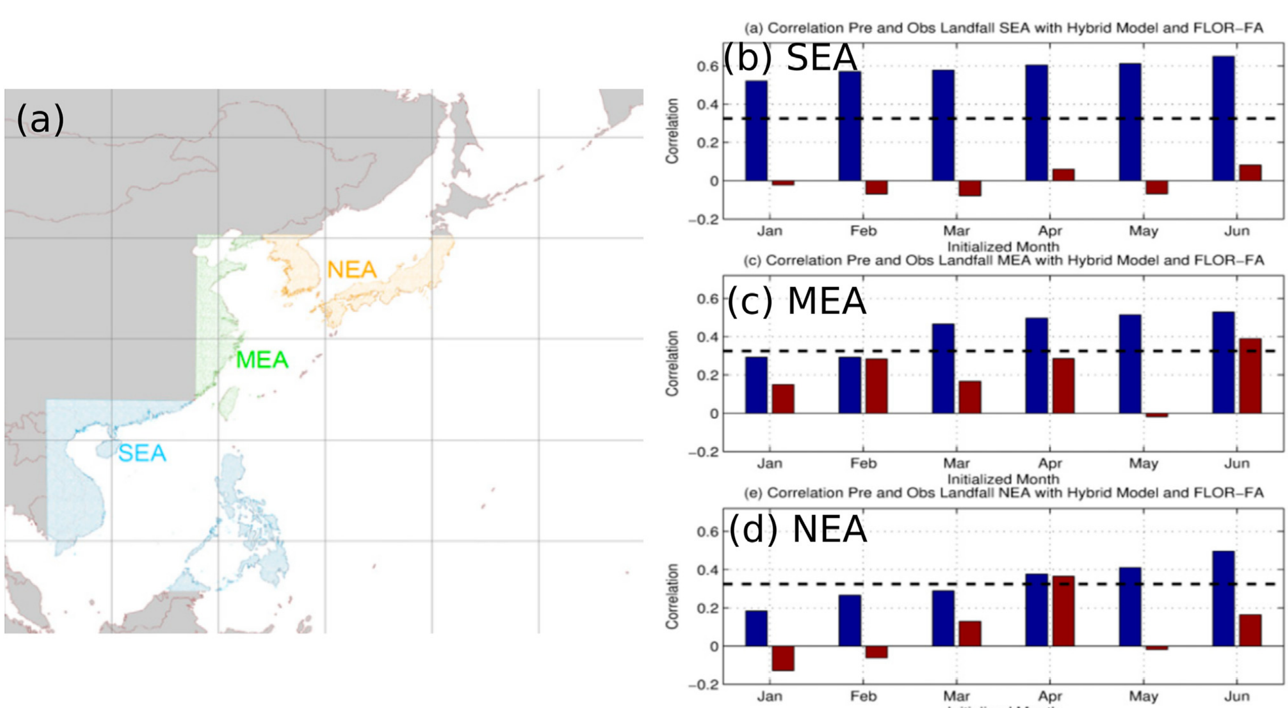

Fig. 5. Statistical-dynamical prediction of landfalling TCs over East Asia by Zhang et al. (2017a). (a) Targeted domains of South East Asia (SEA), Middle East Asia (MEA), and North East Asia (NEA). (b) Correlation coefficients between observed June–November landfalling TC frequency and corresponding predicted landfalling TC frequency by the hybrid model (blue bar) and FLOR-FA (red bar) over (b) SEA, (c) MEA, and (d) NEA over the period 1980–2015 for each initial month. Adapted from Zhang et al. (2017a). © American Meteorological Society. Used with permission.

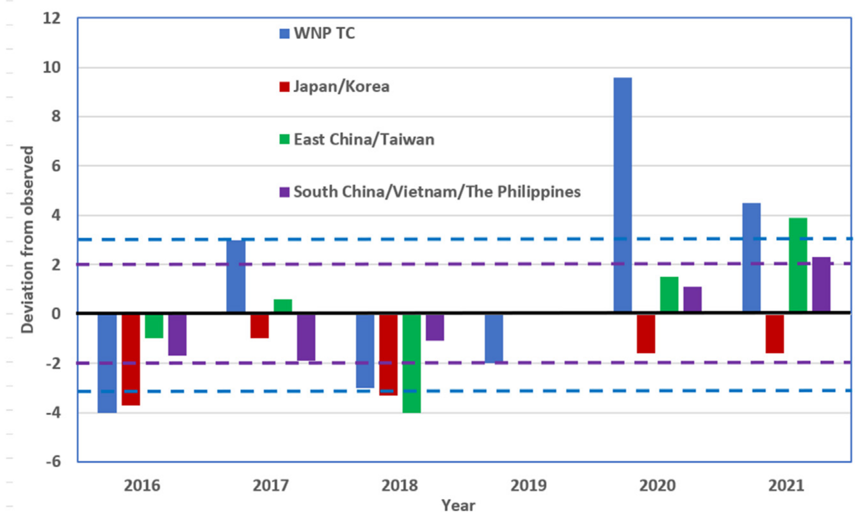

Fig. 6. Verification of real-time seasonal (May–October) TC frequency forecasts for the entire WNP (blue bar) and for landfall in different regions along the East Asia coast (red: Japan/Korea, green: East China/Taiwan, purple: South China/Vietnam/Philippines) for 2016–2021. Zero means a perfect forecast, and positive and negative values indicate an over-forecast and under-forecast, respectively. The blue and purple dashed lines indicate the approximate value of one standard deviation from the climatological mean of the number of TCs over the entire WNP and those making landfall in the southern region respectively. Note that there was no landfall forecast in 2019.

While dynamical seasonal forecasts of TC activity are becoming more common thanks to increases in horizontal model resolution and forecast capability, attempts have been made to produce more skillful seasonal TC forecasts using dynamical downscaling. Huang and Chan (2014) developed a dynamical forecast model of seasonal TC activity for various regions along the East Asia coast using the ICTP Regional Climate Model Version 3 (RegCM3; Pal et al. 2007) in combination with NCEP Climate Forecast System (CFS) forecasts (Saha et al. 2010) as both initial and lateral boundary conditions. Using this setup, the Guy Carpenter Asia-Pacific Climate Impact Centre has been issuing real-time 6-month forecasts for the May–October period. Fig. 6 shows the verification of these forecasts for 2016–2021. The RegCM3 forecasts of the total number of WNP TCs are correct within one standard deviation in four out of six years. For landfall forecasts, the best skill is for the southern region (South China/Vietnam/Philippines), in which the predicted numbers for all five years are within ±2 TCs of the observed number. While the sample is small, these results suggest that it might be possible to use a dynamical model to produce reasonable seasonal TC frequency forecasts for landfall frequency for the southern region.

In order to provide information on the intensity of the landfalling storms, which is too low in RegCM3 due to a relatively coarse resolution, Lok and Chan (2018) nested the Weather Research and Forecasting (WRF) model into the RegCM3 for every TC predicted to make landfall over South China. The WRF model was run for three days up until landfall. The sum of the power dissipation index (PDI) of all landfalling TCs was used as a metric to measure the intensity of the landfalling TCs in a season. Hindcasts show that this setup had skill at predicting variability in PDI near the coast, but the system had difficulty capturing years with either very few or many intense TCs. The skill of the system was linked to its ability at capturing variations in the subtropical high over the East China Sea. Operational forecasts of intensity have not yet been issued.

Finally, Sparks and Toumi (2020) showed the potential of applying subsurface Pacific ocean temperature as a long range (1 year) statistical predictor of landfalling TCs over South China. The source of this predictability is thought to lie in the long-time constant of the ENSO recharge and shows that it may not be necessary to entirely rely on dynamical model forecasts of ENSO.

5.3. Seasonal prediction of TC activity in the South-West IO using a simple track classification developed on historical data

During the last two years, RSMC La Réunion has experimented with a classification technique in order to better describe the spatial distribution of activity within the cyclone season (Bonnardot et al. 2022). The classification method implemented was "impact-oriented" so that the expected predictability of track classes would directly benefit the impact prediction skill. Classes are built with respect to three boxes subdividing the basin in three longitude slices (Fig. 7). For example, class 212 (containing 10.4% of tracks) is extremely impactful for the east coast of Madagascar, while class 333 contains tracks remaining east of 70°E, with no probable impact on inhabited territories.

Climate drivers of influence on seasonal time scales (ENSO, IOD or SIOD; Section 2) show a promising capacity to modulate the frequency of each class for a given season. La Niña conditions favour classes 212 and 313 which historically lead to the main impacts on the east coast of Madagascar

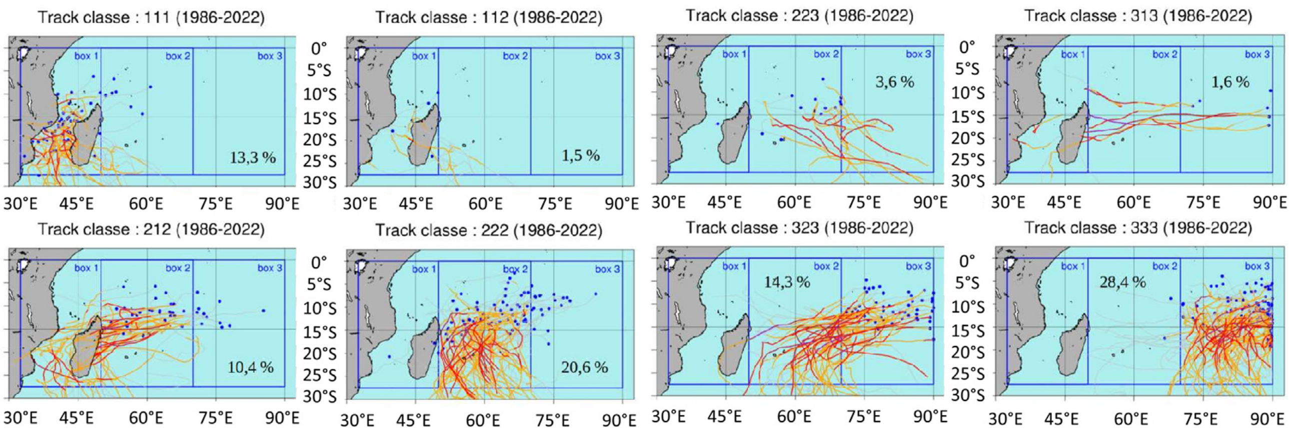

Fig. 7. Different track clusters constructed for the new SIO forecasting system. The proportion of storms in each particular cluster during the period 1986–2022 is also provided. The yellow lines indicate maximum sustained winds from 34 kt to 63 kt while the red lines indicate maximum sustained wind greater than 64 kt.

(Hudah and Eline in 2000; Bingiza in 2011; Batsirai in 2022). El Niño conditions favour class 222 which has the most impact potential for the Mascarene Islands (Mauritius or La Reunion).

Predicting the evolution of the main climate drivers (provided by seasonal forecast modelling systems) can provide useful information on the expected modulations of each class frequency and, consequently, allows for building innovative graphical products showing the anticipated track characteristics for the forthcoming season (Fig. 8). This product is presently implemented using a statistical-dynamical model that performs a canonical correlation analysis between large-scale predictors (like SST or winds at several pressure levels) and the predictand defined by the number of tracks within each class.

Due to La Niña conditions, an increased number of systems with a strong zonal component (westward motion) were predicted for the 2021–2022 season, suggesting an increased risk of impact on the east coast of Madagascar. That first forecast was encouraging, as that season produced three systems associated with class 212 and one system with class 313. These two classes are the two with the most zonal (westward tracks) component, and all four systems (Batsirai, Dumako, Emnati and Gombe) made landfall on the east coast of Madagascar that season.

In the future, RSMC La Reunion plans on exploring the possibility to directly use data issued from the tracking performed within seasonal climate models such as the ECMWF SEAS5 model. This dynamical approach is expected to complement the information already provided by ECMWF through its TC track density anomalies.

6. Seasonal TC prediction: user applications and services

Sub-seasonal to seasonal (S2S) predictions of atmospheric perils have been shown to have a very broad potential user-base that spans sectors as diverse as public health, energy management and disaster preparedness. Users find value when skilful S2S predictions feed coherently into early warning and response management processes (White et al., 2017). Foundational cross-peril and multi-sector S2S research has led to recent efforts to determine the potential for TC-focused S2S applications (Robertson et al., 2020).

It is easy to envisage that, should predictive skill for well-defined applications also exist at the full seasonal timescale, a similar broad user-base would likely find value. Indeed, valuable applications of skilful forecasts for other atmospheric perils have already been employed. As an example, in West

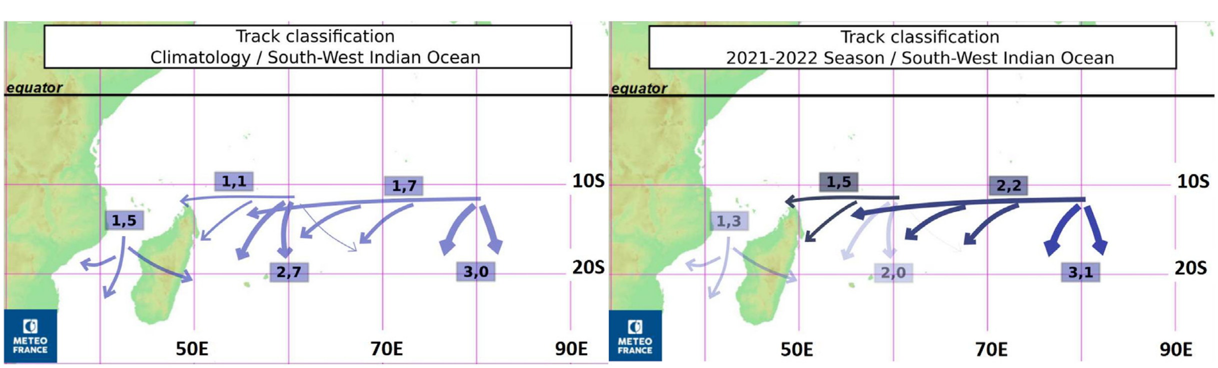

Fig. 8. Example of product produced in October 2021 for the TC outlook mini forum co-organized by WMO, PIROI (Red Cross Intervention Platform for SWIO region) and Météo-France. On the left, the climatological number of named tropical systems during the cyclonic season is listed for each track type. On the right, the predicted numbers for the 2021–2022 season are provided.

Africa in 2008, the International Federation of Red Cross and Red Crescent Societies (IFRC) took multiple advanced risk management actions using seasonal rainfall forecasts, leading to reductions in loss of life and property from floods. The value of this anticipatory action was estimated at a 33% reduction in cost to the eventual aid response (Tall et al., 2012).

In the specific case of TCs though, there are few published applications of seasonal prediction information at present, and no use cases that the authors are aware of in which seasonal information has led to anticipatory action that has been quantified in terms of its value. There are, however, at least some use cases that hint at the potential value of this type of information.

In the humanitarian sector, there have been attempts to utilise seasonal TC outlooks for early warnings for small island states in the Southern Hemisphere (Kuleshov et al., 2020; Kuleshov, 2016). Communication of early TC warnings through seasonal TC outlooks has potential to assist at-risk communities with preparedness. Pre-season planning and preparation can help avoid dangerous situations, loss of life and excessive damage to property if a TC does strike a region.

In private industry, an idealised experiment suggest potential economic value of seasonal hurricane forecasts (Emanuel et al. 2012) and interest in the information is evidenced in initiatives such as:

1. A re/insurer-sponsored/supported website collating seasonal NA hurricane predictions from centres around the world.[2]
2. An Insurance Linked Securities (ILS) markets report/white paper suggesting that seasonal hurricane landfall information, if provided regionally, would allow for targeted hedging strategies within a given season (Insurance Linked Securities for Institutional Investors, 2019)

These humanitarian and private market applications/initiatives indicate the potential value of the information, if it can be predictive about well-defined intersections of the predicted hazard with vulnerable exposures (in this instance, the targeted intersection of seasonal TC predictions with high human and/or economic exposures).

While it appears that landfalling prediction is possible at seasonal timescales (Section 5), challenges remain due to structural issues with how seasonal forecasting methods have been developed. For example, the lack of ability for statistical-based seasonal prediction models to adequately forecast subtropical TC activity resulted in seasonal predictions of ACE performing relatively poorly during the 2018 NA hurricane season (Saunders et al., 2020). The inability of typical outlooks to distinguish activity at the subbasin scale impedes the ability to attach coherently to real-world decision processes (and the aforementioned intersections with vulnerable exposures), and stakeholders would need to be cognisant of such structural issues in advance of their use of the information.

A related challenge is that the skill of the forecasts is, at present, usually defined by the scientific community. In the case of seasonal TC prediction, skill is most often judged by comparison to mean activity generated from broad background climatologies. This raises a potentially severe communication challenge with stakeholders whose perceptions of skill may be very different. Recent research has begun to investigate and provide guidance to address this (Robbins et al., 2019).

The timeliness of the forecasts is also important for users and is another aspect that needs to be considered. A skilful forecast that becomes available too late to be integrated into a decision process cannot be relied upon by the stakeholder. New forecast products relying on subsurface ocean temperature (Sparks and Toumi, 2020) or ML (Ham et al., 2019) could help address this issue.

Given the myriad of end users, each of which likely require their own formulation of both the forecast and a measure of its skill and working on their own timeline, it would be prohibitively expensive to generate predictions that were optimal for every single decision-maker (Caron et al., 2020). However, prioritising seasonal TC prediction research streams that address very targeted decision/early action processes, in partnership with as many real-stakeholders as possible, may help to bridge the gap between science and application more quickly than a focus on prioritising an idealised idea of predictive skill.

7. Beyond seasonal timescales: multi-annual TC predictions

7.1. Overview of current research and sectorial application of multi-annual forecasts of TC activity in the NA

Klotzbach et al. (2019) reported on skill in forecasting NA hurricane activity on multi-annual timescales, with skill coming from both external forcings (for example, by anthropogenic aerosols; Murakami 2022), and initialization with the current ocean state (Hermanson et al., 2014). In particular, Caron et al. (2018) showed that multi-annual forecasts derived from decadal prediction systems are competitive with, or improve upon, purely statistical products. Since then, a prototype climate service giving forecasts of 5-year-mean NA hurricane activity has been co-developed with the reinsurance brokers Willis Towers Watson, as part of the C3S Sectoral Applications of Decadal Predictions project (Dunstone et al., 2022). The prototype uses a proxy index predicted by a multi-model ensemble of general circulation models initialised with the current state of the ocean and atmosphere (Lockwood et al. 2023). This proxy index, based on the relative difference between MDR SST and the SST over the entire tropics, has been shown to correlate with various measures of Atlantic TC activity (Villarini and Vecchi 2012; Caron et al. 2014). Statistical relationships between past forecasts of the index and (a) observed ACE index and (b) associated US damages, are then used to make predictions of these measures. The predictions for 2021–2025[3] (Fig. 9 for hindcasts over the 1960–2020 period) indicate an increased likelihood of enhanced TC activity during

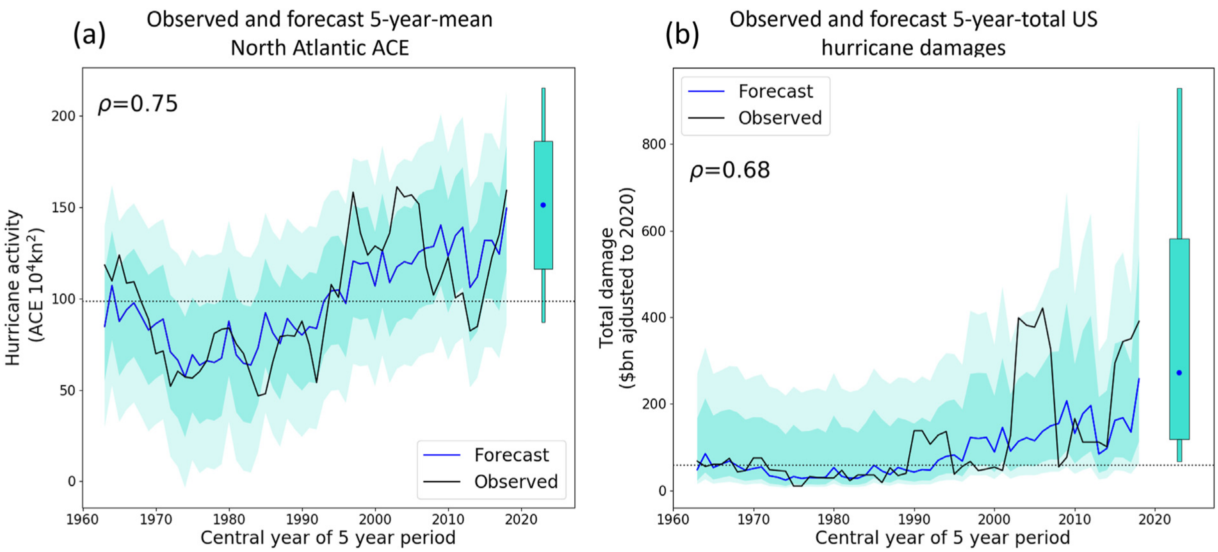

Fig. 9. 2021–2025 NA hurricane forecasts. (a) Observed and forecast 5-year running mean NA ACE forecasts; (b) Observed and forecast 5-year running total US damage forecasts (US damages have been adjusted to 2020 by taking into account changes in wealth, population and inflation, based on the method described in Pielke and Landsea 1998). The blue lines represent past forecasts (hindcasts), and the black lines represent past observations. Shading represents the 75% and 95% hindcast prediction intervals. The box and whisker plots show the 2021–2025 75% and 95% prediction intervals. ρ gives the rank correlation skill score.

this period. However, it was noted that skill in predicting the SST index has declined in the most recent period, so more research is needed to understand under which conditions the forecasts are most skilful.

7.2. Origins of Atlantic Multidecadal Variability and implication for multi-annual TC forecasts

During the 1900–2022 period, NA SST exhibited a long-term warming trend with superimposed multidecadal fluctuations, which has been termed Atlantic Multidecadal Variability (AMV) or the Atlantic Multidecadal Oscillation (Kushnir 1994; Schlesinger and Ramankutty 1994; Kerr 2000; Zhang et al. 2019). It is characterised by a basin-scale anomalous SST pattern that has the same sign over the whole NA, with maximum loading over the subpolar gyre region and the subtropics, including the Atlantic MDR of TCs. Through its tropical SST anomalies, the AMV has been shown to modulate TC activity over the tropical Atlantic (Goldenberg et al. 2001). In addition, the AMV influences the tropical Pacific through an atmospheric bridge (Li et al. 2016; McGregor et al. 2018; Ruprich-Robert et al. 2021), possibly modulating TC activity of this basin at multi-decadal timescale as well (Zhang et al. 2018).

The slow evolution of NA variability is encouraging for the prospect of getting skillful multi-annual predictions of TC activity worldwide through the impacts of the AMV (Dunstone et al. 2011; Hermanson et al. 2014; Gong et al. 2021). In particular, the current decadal forecast systems have skill in predicting NA SST (Smith et al. 2019; Yeager et al. 2018) several years in advance. Yet, the origins of this skill is spatially dependent. The skill originates mostly from the initialization of the ocean in the NA subpolar gyre, and from the predictability of external forcing in the tropical NA.

The different sources of predictability of the NA SST echo the debate on the origins of the observed AMV. In fact, the AMV can be driven by ocean processes through heat convergence (e.g. variability in the Meridional Overturning Circulation and its associated heat transport, Yeager and Robson 2017; Swingedow et al. 2015) or by variability in atmospheric dynamics through associated surface heat fluxes (e.g., response to the North Atlantic Oscillation; Clement et al. 2015). It can also be driven by explosive tropical volcanic eruptions and their impacts on radiative forcing (Otterå et al. 2010; Birkel et al. 2018). The variations in the emissions of anthropogenic aerosols are also likely to have contributed to the AMV over the historical period (Bellomo et al. 2018; Watanabe and Tatebe 2019). In addition, it is often stressed that the contributions of those potential drivers are spatially dependent.

In the historical simulations of the Coupled Model Intercomparison Projects (CMIP, Taylor et al. 2012; Eyring et al. 2016), the influence of internal climate variability dominates extratropical NA SST variability, whereas variations in the tropical NA SST are mainly driven by external forcings (Terray 2012). Overall, the heterogeneity between the midlatitudes and low latitudes in the drivers of multidecadal NA SST variability challenged the idea of the AMV being a physically coherent basin-wide mode of variability. An AMV index defined as the SST averaged over the whole NA (Trenberth and Shea 2006; Mann and Emanuel 2006) might thus not be the most adequate TC predictor as such an index might potentially be mixing different signals that do not share the same predictability and link to TC activity. Better disentangling the drivers of the observed AMV is therefore crucial to assessing its predictability and its link to TC activity.

In addition, studies showed that state-of-the-art coupled climate models are missing key processes to correctly propagate anomalies from the extratropical NA to the tropical NA. In fact, SST anomalies generated in the NA subpolar gyre by ocean dynamics are thought to be carried to the tropics by several feedbacks. Warm SST anomalies in the subpolar gyre induce a cyclonic atmospheric circulation in the subtropics, which weaken the trade winds (Klotzbach and Gray 2008). Through the wind-evaporation-SST feedback, this leads to the propagation of the midlatitude warming to the tropics. In addition, the weakening of the trade winds reduces the transport of Saharan dust toward the Atlantic, which leads to the reduction of low cloud cover over the tropical NA (Brown et al. 2016; Yuan et al. 2016; Bellomo et al. 2016). Yet, the current versions of climate models used for seasonal-to-decadal predictions are not able to simulate these feedbacks properly (Martin et al. 2014; Yuan et al. 2016). These shortcomings can explain the limited additional skill coming from the initialization step in the current forecast systems in predicting tropical AMV SSTs and Atlantic TC activity.

7.3. Northern Hemisphere

Other than the AMV, the Inter-decadal Pacific Oscillation (IPO) and Pacific Decadal Oscillation (PDO) are also dominant modes of decadal variability and potentially predictable to some extents (Mochizuki et al. 2010; Meehl et al. 2016). These modes of variability together with the long-term warming trend likely have a multi-year scale interaction and modulate interannual to multi-annual TC variability, potentially providing TC predictability. However, current initialised dynamical forecast system capabilities do not allow us to fully explore this long-term TC predictability.

Recently, Zhao et al. (2022) have attempted to develop a new multi-annual prediction scheme of TC genesis frequency in the Northern Hemisphere by constructing a regression model based on six key climate factors including mean global surface temperature and internal climate variability indices (ENSO, SST anomalies over the eastern Indian Ocean and TNA, AMO and IPO). The predictions for 2020–2030 by combining 100-member simulations by the Max Planck Institute Earth System Model show a significant increase in TC genesis frequency over the ENP while non-significant changes over the NA and the WNP during the same period.

8. Summary and concluding remarks

The community has made further progress in recent years in understanding long-range TC predictability. Recent studies revealed intra-basin and remote influences that can act as sources of seasonal TC predictability in addition to ENSO. These findings promise new capabilities for seasonal TC forecasting in the absence of a strong ENSO influence. New statistical techniques, in particular ML techniques, have shown potential in developing new forecast systems, uncovering new connections between the large scale and TC activity and increasing the skill of longer lead time forecasts while multi-annual forecasts of NA TC activity continue to be investigated through initialised decadal predictions. The skill of these forecasts is linked to the AMV, and although progress has been made on the origin of this climate variability, further research is necessary to disentangle its drivers and thus confidently assess the potential of these forecasts.

The recent developments in forecast systems and numerical modelling (e.g., increased resolution, improved physical representation, and better initialization) have led to skillful forecasts at the subbasin scale. Over the NA in particular, TC activity over the Caribbean region has been identified by multiple studies as being relatively predictable, possibly offering the best opportunity for the development of a reliable landfalling forecast product in that basin. Over the WNP, the East and South China coastal regions also appear as promising areas to focus on for successful landfall forecasts at this timescale. Further improvements in forecast systems might reveal additional regions for which skilful landfalling predictions are possible.

However, while the potential predictability of TC activity near some coastal regions is starting to emerge, seasonal TC outlooks remain detached from any decision-making process as far as we are aware. This does not have to be so, as other seasonal forecast system products have been integrated into early warning systems, and their value has been quantified. This situation does not appear to be due to a lack of interest on the part of stakeholders. Examples of interactions between forecasters and stakeholders from the humanitarian and insurance/financial industries were documented above, but they are by no means the only sectors to have shown interest in TC outlooks. Forecasters have reported providing outlooks for offshore operators, major retailers, utilities, and emergency management. However, the seasonal outlooks, in their current form, are generally viewed by these various stakeholders solely as an awareness-raising tool. Some stakeholders might equate forecasts of an active season with a greater chance that their particular area may be impacted, but such information remains unactionable.

Routinely providing skillful and reliable landfall forecasts, or regional forecasts for some stakeholders, would help bridge the gap between the science and the users. However, in many cases, this might be a necessary but insufficient condition, and sustained interactions with stakeholders is likely to be necessary to develop a product that can link coherently to a real-world decision process. Such a co-development approach is currently underway for the development of a product in the SIO and, perhaps surprisingly, by the decadal forecasting community in the construction of a prototype of multi-annual forecasts of TC activity through the Copernicus Climate Change Service.

To help support the operational implementation of seasonal TC prediction services, more coordinated and formalised efforts of multi-model seasonal TC prediction might be required. One such effort is already underway for the NA. The western North Pacific basin, for which a fair number of organisations are already producing seasonal hurricane outlooks, could also benefit from such effort. In this case, the range of TC metrics, lead times and regions that are considered by various forecast providers would need to be addressed, but this should not represent an insurmountable challenge.

A coordinated effort to make TC tracks derived from multi-model ensemble dynamical forecast systems publicly available would facilitate multi-model intercomparison and could also provide an impetus for the analysis of TC landfall forecast products. Analysing TC tracks of these forecast systems is a technically challenging endeavour which can be a barrier of entry for many research groups as it requires acquiring and storing large amounts of high-frequency climate data. For these reasons, studies on this topic tend to rely on a single forecast system, typically operated locally. More multi-model studies such as Befort et al. (2022) are desirable, but such studies are technically challenging, and the continued increase in horizontal model resolution is likely to exacerbate this problem even further. Moreover, while good options for storm tracking have become available (Ullrich et al. 2021; Biswas et al., 2018; Hodges 1995), these algorithms nonetheless require an investment in time and resources to operate. Ideally, such TC track datasets would be produced using more than one tracking algorithm, thus allowing investigation of the uncertainty linked to the choice of the tracker and increasing the robustness of the results (Roberts et al. 2020; Bourdin et al. 2022).

The future of seasonal forecasting is promising: improvements in forecasting systems, increased computational resources and development of new technologies combined with a deeper understanding of climate variability associated with TC activity offer an opportunity to increase the lead time of skilful predictions and to potentially develop skilful landfalling products for certain regions. Sustained interactions with stakeholders will nonetheless be necessary to develop actionable products, and coordinated activities, such as those highlighted above, could help support this development and bridge the gap between current forecasting product and decision-making.

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Appendix A.

Forecasting systems used in the creation of the multi-system ensemble in Section 4. An asterisk (*) indicates that the organisation only provides a forecast for the number of hurricanes, and not for major hurricanes.

	March–April	May–June	July–August
AccuWeather	X		
Colorado State University	X	X	X
Cuban Institute of Meteorology*		X	X
North Carolina State University	X		
National Oceanic and Atmospheric Administration		X	X
Maxar	X		
StormGeo	X	X	X
Tropical Storm Risk	X	X	X
University of Arizona		X	
UK Met Office*		X	
Weatherbell	X	X	
WeatherTiger	X	X	X
Weather Services International-The Weather Company	X	X	X

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