On the seasonal predictability of the 2020 North Atlantic tropical cyclone season

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ABSTRACT: The 2020 Atlantic tropical cyclone (TC) season was unprecedented, producing a record storm count that exceeded the seasonal forecasted ranges, despite their anticipation of high activity. Here we assess the likelihood of the extreme 2020 season given the observed sea surface temperature (SST) forcing by examining a hierarchy of statistical, dynamical, and deep learning (DL) modeling frameworks, all constrained by observed SSTs. Although physics-based models anticipated a moderately active season, the observed outcome lay beyond their ensemble ranges. To investigate this result, we first test if the 2020 large-scale environment was conducive to a hyperactive season. Although the 2020 conditions were relatively favorable for TCs, they were not indicative of potentially record-breaking TC activity. We also generate 1,000 samples of plausible 2020 Atlantic TC season outcomes given the observed SSTs by leveraging a DL model. From this large ensemble, the observed season emerges as a 0.5% event, which is highly unlikely, but not implausible. These results suggest that SST forcing provided a limited seasonal signal, and that internal atmospheric variability could have driven the observed hyperactivity on top of the moderately favorable large-scale conditions. The inability of physics-based model ensembles to encompass the observed outcome does not indicate a model failure, but reflects both limited predictability from SST forcing and the inability of relatively small ensembles (N=O(10)) to sample and estimate extreme tail risk like the 2020 season, seasons which are extremely unlikely any given year but have a substantial probability of occurring some year across decades.

SIGNIFICANCE STATEMENT: The 2020 Atlantic tropical cyclone (TC) season was the most active on record by number of named storms. Although forecasts anticipated above-normal activity, they did not encompass the observed hyperactivity. Even state-of-the-art physics-based, statistical, and deep learning (DL) models, when given "perfect" observed sea surface temperature (SST) inputs, did not capture the observed outcome within their simulated ranges. We assess how predictable this extreme season was from the observed SSTs. We show that while the large-scale conditions in 2020 were generally favorable for TCs, they were not exceptionally conducive to a record-breaking season. Using a 1,000-member DL ensemble forced with observed SSTs, we find that the 2020 season was a rare outcome that a small ensemble could not have represented.

1. Introduction

Tropical cyclones (TCs) that form in the North Atlantic Ocean pose severe hazards to communities across the United States and the Caribbean (Pielke et al. 2008; Weinkle et al. 2018; Klotzbach et al. 2018; Young and Hsiang 2024). Accurate forecasts are therefore essential for preparedness and risk mitigation. Short-term weather forecasts, issued several days in advance, provide critical guidance for evacuation decisions and emergency response. In contrast, seasonal forecasts, issued before the onset of the TC season, aim to anticipate the overall characteristics of the upcoming season, particularly the range in possible storms that will form throughout the course of the season.

Many seasonal modeling and prediction systems rely on sea surface temperatures (SSTs) as a primary source of predictability. Atmosphere-only dynamical models, including both physics-based and deep learning (DL) approaches, can generate seasonal TC forecasts using predicted SSTs or extensions of pre-season SST anomalies as their boundary conditions (e.g., Zhao et al. 2010; Chen and Lin 2011, 2013; Gao et al. 2019; Zhang et al. 2025a). Similarly, hindcast and attribution analyses prescribe these models with historically observed SST boundary conditions to understand the relationship between SST forcing and historical Atlantic TC seasons (e.g., Zhao et al. 2009; Chan et al. 2021; Kortum et al. 2024; Levin et al. 2026; Chien et al. 2025). Statistical and statistical-dynamical frameworks likewise use SSTs as predictors of seasonal TC activity (e.g., Villarini et al. 2010; Vecchi et al. 2011; Eusebi et al. 2025). Although these approaches do not aim to reproduce the exact storms that occurred, they provide physically plausible realizations of seasons consistent with the specified SST forcing.

The 2020 Atlantic TC season presents a striking test of this SST-based predictability framework. By multiple measures, it was the most active Atlantic TC season on record, producing the greatest number of named storms (systems attaining maximum sustained winds exceeding 17 m s^{-1} at least once), the greatest number of long-duration TCs (systems maintaining winds exceeding 17 m s^{-1} for at least 48 hours), and tying the record for major hurricanes (MHs) while ranking second in hurricane count (Fig. 1). Although seasonal forecasts correctly anticipated above-normal activity, they substantially underestimated the magnitude of the hyperactivity. For example, NOAA's May 2020 outlook (`https://www.cpc.ncep.noaa.gov/products/outlooks/hurricane2020/May/hurricane.shtml`) projected 13–19 named storms, 6–10 hurricanes, and 3–6 MHs, compared with the observed 30, 14, and 7, respectively.

Atmosphere-only dynamical models forced with observed monthly SSTs also failed to encompass the observed hyperactivity across their ensemble ranges. Two state-of-the-art models developed at the Geophysical Fluid Dynamics Laboratory (GFDL), HiRAM and AM2.5-C360, have demonstrated skill in simulating historical interannual and multidecadal Atlantic TC variability under observed SST forcing (Levin et al. 2026). Yet for 2020, despite simulating a moderately active season relative to the historical record, neither model's ensemble range (ten members for AM2.5-C360, and five members for HiRAM), captured the observed storm counts across any intensity category (Fig. 1). While observations occasionally fall outside ensemble spread in individual years (e.g., 1982 and 2013), as expected from internal variability (Vecchi and Villarini 2014), the 2020 season represents the most extreme discrepancy from the ensemble range in the historical record for long-duration TCs, and it was the only year where the observed count lay outside the ensemble range across all intensity bins. Although the 2020 season's activity was remarkable, such hyperactivity is not without precedent. Even the similarly hyperactive 2005 season fell within the simulated range of AM2.5-C360, with both models indicating strongly enhanced activity.

The inability of these dynamical models' ensemble range to capture the 2020 TC season when forced with observed SSTs raises a central question: to what extent was the hyperactive 2020 season predictable from the observed SST forcing? The failure of SST-forced models to capture the observed outcome across their ensemble spread could indicate deficiencies in the models or observational inputs, or it could instead reflect the intrinsic limits of predictability from SST boundary conditions, with 2020 representing a rare but dynamically plausible realization that a

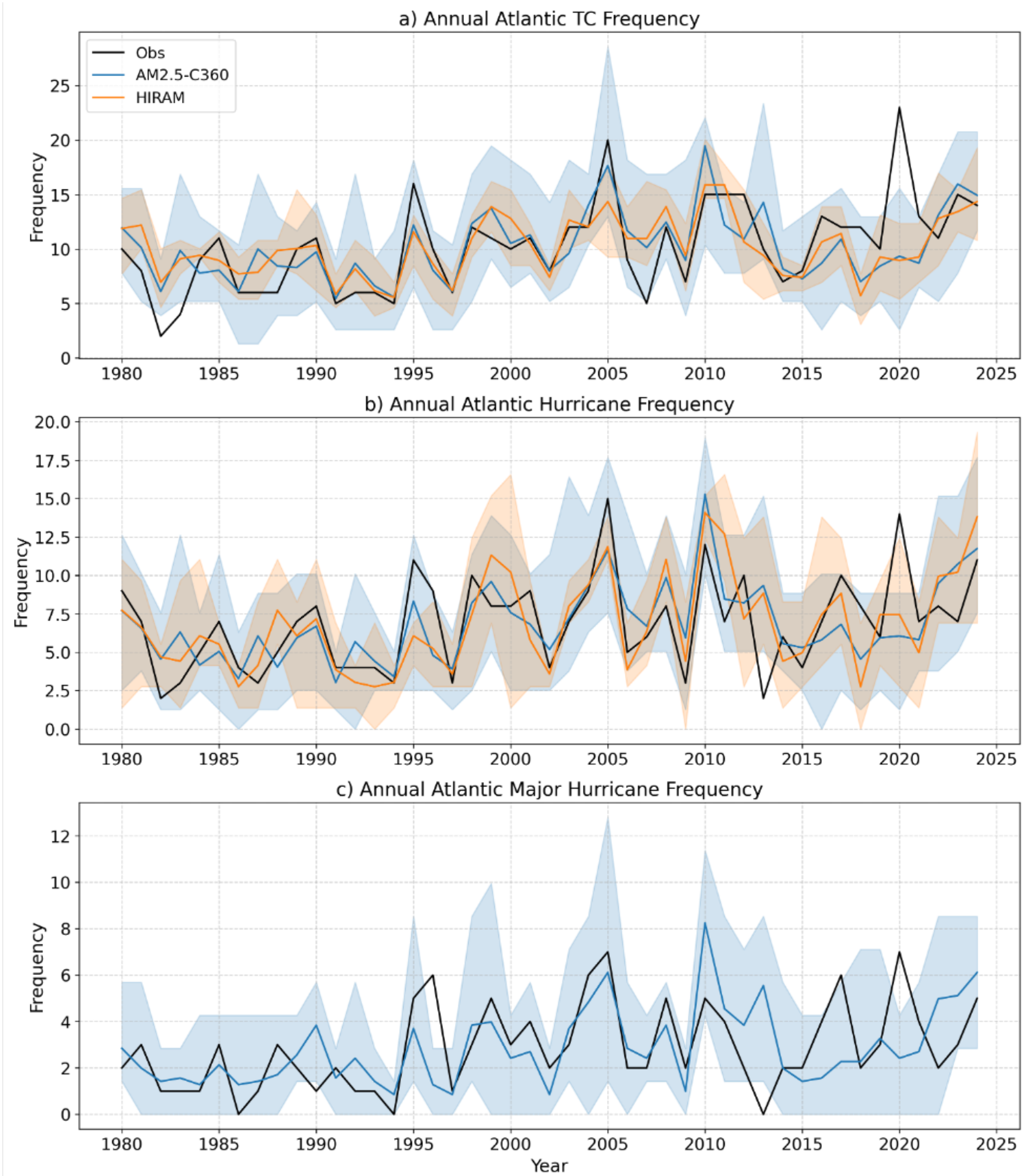

FIG. 1. Annual frequency of (a) long-duration TCs, (b) hurricanes, and (c) MHs from 1980–2024. The observational storm counts are shown in black, obtained from datasets described in Section 2a. Model simulations include AM2.5-C360 forced with observed and bias-corrected SSTs from Chan et al. (2021) (blue) and HiRAM forced with the same SSTs (orange). Shading denotes the full ensemble range (minimum–maximum) for each model (ten members for AM2.5-C360; five members for HiRAM), and solid lines indicate ensemble means. Panel (c) shows only AM2.5-C360 results, as HiRAM does not produce storms of sufficient intensity to be classified as MHs.

small ensemble size failed to sample. We evaluate these competing explanations through two broad hypothesis families:

The first family of hypotheses considers whether deficiencies in models or observational datasets contributed to the poor simulation of 2020 Atlantic TC counts. Within this framework, we assess the following possibilities:

1. Atmosphere-only models may exhibit structural limitations in their representation of TC formation, reducing their reliability in simulating interannual Atlantic TC variability.

2. Observed storm counts in recent decades, as shown in Fig. 1 (black lines), may be inaccurate.

3. Errors may be present in the observed monthly SST datasets used to force the models in 2020.

4. SST-forced models may not adequately represent the influence of observed aerosol changes on TC activity. Two major events in 2020 likely altered aerosol concentrations over the Atlantic basin. First, International Maritime Organization (IMO) regulations on the sulfur content of shipping fuel took effect on 1 January 2020, reducing maximum sulfur content from 3.5% to 0.5%. Implemented to improve air quality, this policy reduced aerosol loading over the oceans and altered regional radiative fluxes (Diamond 2023; Jordan and Henry 2024; Zhang et al. 2025b). Second, the onset of the COVID-19 pandemic led to substantial reductions in global emissions. Previous work suggests that decreased aerosol concentrations over North America and Europe can be associated with enhanced Atlantic TC activity (Murakami 2022, 2024). Because the SST-forced simulations analyzed here employ prescribed CMIP5 aerosol forcings rather than observed 2020 aerosol fields, the combined radiative and dynamical effects of these aerosol perturbations may not be represented.

The second hypothesis family considers the possibility that the hyperactive 2020 season was a highly unlikely realization of the internal variability of the climate system that could not have been captured by the small ensemble sizes of the GFDL models. The mean signal from the 2020 large-scale environment and observed monthly SST forcing could have been largely indicative of a moderately active season. However, under this hypothesis, internal atmospheric variability could have enhanced the environment's favorability for TC activity beyond the large-scale signal. As a result, the small model ensemble size might have been limited in sampling such an unlikely realization of subseasonal variability beyond the mean signal. This hypothesis suggests that limited ensemble sizes restrict our ability to accurately estimate the tail probabilities of rare, extreme outcomes. To fully address this second family of hypotheses, this paper seeks to answer the following research questions:

1. Was the 2020 season an extreme tail event in the small AM2.5-C360 and HiRAM ensembles whose likelihood could only be quantified by a very large calibrated ensemble?

2. To what extent could the hyperactive 2020 TC season have been predictable from the observed monthly SST forcing?

In the following sections we apply statistical analyses, dynamical diagnostics, DL–based climate simulations, and a theoretical framework to evaluate the two competing hypothesis families and the posed research questions. The evidence presented in this paper suggests that the 2020 season was a low-probability outcome, rather than a structural failure in the models or observational record. Our results suggest that the observed 2020 SST forcing provided limited predictability for the extreme hyperactivity that occurred, with the observed season representing a tail outcome that was not sampled by the relatively small GFDL ensembles. At the same time, we cannot exclude the possibility that additional mechanisms not examined in this paper influenced the 2020 season.

2. Methods and data

a. Observed TC data

For the historical record of Atlantic TC activity from 1980–2024, we use the adjusted long-duration TC dataset developed following the methods of Landsea et al. (2010) and evaluated by Villarini et al. (2011a). In this dataset, a TC is required to maintain maximum sustained winds exceeding 17 m s^{-1} for at least 48 hours. This definition is more stringent than the standard named-storm criterion, which classifies a system as a tropical storm if it attains maximum sustained winds exceeding 17 m s^{-1} at any point during its lifetime. Using the long-duration criteria ensures robustness in TC counts across datasets and model simulations (Villarini et al. 2011a). We use the HURDAT2 dataset for the historical 1980-2024 record of observed Atlantic hurricanes and MHs (Landsea and Franklin 2013). A time series of the different storm intensities from 1980-2024 is shown in Fig. 1.

b. Dynamical Models

To place the 2020 Atlantic TC season in the context of recent historical variability, we generate a multi-ensemble record of long-duration TC, hurricane, and MH activity using two global TC-permitting atmospheric models developed at GFDL: AM2.5-C360 and HiRAM (Zhao et al. 2009). Following the methods of Levin et al. (2026), we conducted multi-ensemble historical experiments with both models. We generated ten (five) ensemble members for AM2.5-C360 (HiRAM), each forced with bias-corrected observed monthly SSTs from the HadISST dataset (Chan et al. 2021) over the period 1980–2024. From these simulations, we compute annual counts of long-duration TCs, hurricanes, and MHs to construct a modeled range of historical Atlantic TC activity.

To evaluate Hypothesis 4 from Section 1, which proposes that the 2020 reduction in atmospheric aerosols was not represented in the SST-forced simulations, we conduct additional experiments. We simulate the 1980-2024 historical Atlantic TC seasons given observed MERRA2 aerosol forcing (Gelaro et al. 2017), in contrast to the aforementioned historical experiments which prescribe the models with CMIP5 aerosol projections. To do so we use the lower resolution version of AM2.5-C360 with 50 km grid cells, AM2.5-C180, to create a five-member ensemble. This experiment isolates the effect of realistic interannual aerosol variability on modeled TC counts.

As a second approach, we perform an idealized modeling experiment to obtain additional samples to the five ensemble members obtained from the observed aerosol experiment described above and better quantify the relationship between sulfate and black carbon aerosols and Atlantic TC activity. Using the HiRAM model, we perform four simulations to isolate the effects of sulfate aerosols, which declined markedly in 2020 following the implementation of the IMO shipping regulation, and black carbon, which also decreased in 2020 due to reduced industrial activity and travel during the COVID-19 pandemic.

We perform a control experiment (cntl) in which the model is forced by the annual cycle of SSTs averaged over the period 1986–2005, following the methodology of Vecchi et al. (2019). This climatological SST cycle is repeated for 200 years following a 10-year spin-up, such that the 200-year mean represents the model's steady-state climatological baseline. We then perform three additional experiments using the same SST forcing as the control. In the first experiment, sulfate aerosols are removed over the North Atlantic (zeroSO4NA), and the model is integrated for 50 years. In the second experiment, sulfate aerosols are removed globally (zeroSO4global), and the model is again integrated for 50 years. In the final experiment black carbon emissions are removed globally (zeroBCglobal), and the model is integrated over 50 years. This serves as an exaggerated analogue to the global reduction in black carbon brought on by the COVID-19 pandemic.

To identify TCs and seed disturbances in both models across all the aforementioned experiments we follow the tracking procedure described in Levin et al. (2026), where we set thresholds for wind speed, minimum sea level pressure, lifetime length, and warm-core characteristics. For seed disturbances, we require candidate points to exceed a vorticity threshold and span a minimum radius. For TCs, to ensure longevity and robustness, we consider long-duration TCs to be storms with at least a 72-hour lifetime, at least 48 hours of a warm core, and at least 36 consecutive hours with both a warm core and maximum 10-m winds exceeding 15 m s^{-1}. We also mandate that the maximum wind speeds exceed 17 m s^{-1} at least once. Hurricanes are defined as long-duration TCs that attain maximum winds exceeding 33 m s^{-1} at least once during their lifetime. MHs are identified in AM2.5-C360 as long-duration TCs whose maximum winds exceed 45 m s^{-1}, a threshold slightly lower than the observed 50 m s^{-1} standard because the model rarely produces storms at the observed MH intensity. HiRAM does not reliably simulate storms of sufficient intensity to meet this MH threshold, and therefore MH statistics are reported only for AM2.5-C360.

c. Statistical-Dynamical Model

To characterize the range of plausible seasonal Atlantic TC counts over the recent historical period (1980–2024), we employ the statistical–dynamical model of Vecchi et al. (2011) that uses monthly SST data as an input and source of seasonal TC predictability. This framework estimates the expected annual Atlantic long-duration TC count, λ, using a Poisson regression in which λ depends solely on SST. λ is modeled as a function of the mean seasonal SST anomaly in the Atlantic main development region (MDR) and the mean seasonal SST anomaly across the tropics, since these two predictors together have been shown to be a robust indicator of Atlantic TC activity in the present climate (Vecchi and Soden 2007; Villarini et al. 2011b; Eusebi et al. 2025). Specifically, the logarithm of λ is modeled as the following linear function:

$$\lambda = \exp\left(1.707 + 1.388 SST_{MDR} - 1.521 SST_{TROP}\right), \quad (1)$$

where SST_{MDR} and SST_{TROP} are defined relative to the 1982–2005 climatology. The coefficients of Equation 1 have not been updated from those of Vecchi et al. (2011). The MDR is defined as 10°–25°N, 80°–20°W, and the tropical mean spans 30°S–30°N.

This statistical-dynamical framework allows us to generate a full conditional probabilistic distribution of seasonal Atlantic TC counts, given SST forcing. Thus, for each year in 1980–2024, the model yields a distribution of possible long-duration TC counts. We use this distribution to quantify the percentile rank of the observed 2020 season relative to SST-forced expectations.

We further use this model to evaluate Hypothesis Three from Section 1, which posits that discrepancies between observed and simulated 2020 TC counts may arise from inconsistencies in the observed SST datasets used to force atmosphere-only models. The AM2.5-C360 and HiRAM simulations analyzed here (Section 2b) are forced with a corrected version of the HadISST dataset (Chan et al. 2021). To assess the sensitivity of the inferred TC distribution to the choice of SST product, we apply the statistical–dynamical model separately using three independent SST datasets: the Optimum Interpolation Sea Surface Temperature dataset (OISST; Huang et al. 2021), the Hadley Centre Global Sea Ice and Sea Surface Temperature dataset (HadISST; Schneider et al. 2013), and the Extended Reconstructed Sea Surface Temperature dataset (ERSST; Huang et al. 2017).

d. DL-based Model

Although the multi-ensemble historical integrations with AM2.5-C360 and HiRAM provide a dynamical range of Atlantic TC outcomes and require substantial computational resources, this study questions whether their ensemble sizes of ten and five members, respectively, are too small to fully characterize the probabilistic distribution of plausible 2020 seasonal outcomes.

Recent advances in DL weather models have shown substantial promise for simulating TCs. Once trained, these models can be integrated efficiently with significantly lower computational costs compared to traditional dynamical models like AM2.5-C360 and HiRAM (e.g., Bi et al. 2023; Chen et al. 2023; Lam et al. 2023; Lang et al. 2024; Kochkov et al. 2024). In this study, we employ the Ai2 Climate Emulator version 2 (ACE2; Watt-Meyer et al. 2025) to perform multi-ensemble annual simulations of historical Atlantic TC seasons, including 2020. We use a version of ACE2 trained on the ERA5 reanalysis (Hersbach et al. 2020). Previous studies have demonstrated that

ACE2 is numerically stable over simulations spanning hundreds to thousands of years (Watt-Meyer et al. 2025) and can realistically reproduce TC characteristics across subseasonal to interannual timescales (Chien et al. 2025). These results motivate our use of this model to evaluate the 2020 Atlantic TC season by generating large ensembles.

We generate a 1,000-member SST-forced ensemble for each year during 2005–2020 (including the anomalously active 2005 and 2010 seasons) and for the anomalously inactive 1982 season. Following Chien et al. (2025), ensemble members for a given year are generated by repeatedly integrating the ACE2 model under identically fixed SST boundary forcing. For a given target year (e.g., 2020), observed SSTs from that year are prescribed and repeated cyclically. We then integrate the model autoregressively for 100 years, where at the beginning of each calendar year, the SST forcing is repeated. Therefore, we consider each simulated year to be an ensemble member, where it represents a plausible outcome for the year of interest given this target year's SST forcing.

We parallelize the computation to efficiently generate the 1,000 ensemble members. We complete ten separate rollouts of the 100-year chunks, where each rollout is given different initial atmospheric conditions, although the SST forcing stays constant across all simulations. We generate the ten initial conditions for each separate 100-year rollout by completing several shorter model integrations. For each of these integrations, we initialize the model with the different publicly available ACE2-formatted ERA5 initial conditions. The short integration entails running the ACE2 model for one year under the SST forcing for the year prior to the ensemble target year. For example, to generate the initial conditions for the 2020 ensemble, we initialize the model with the different publicly available initial conditions and run the model for one year under the observed 2019 SST forcing. We then use the outputs of this one year run as the initial conditions for the ten 100-year rollouts to generate the 1,000-member ensemble.

To detect long-duration TCs in ACE2 and maintain consistency with the dynamical simulations and observational dataset used in this study, we follow the methodology of Chien et al. (2025) and Watt-Meyer et al. (2025), using the TempestExtremes TC tracking approach (Ullrich and Zarzycki 2017). Specifically, for ACE2, long-duration TCs are defined as storms with a maximum wind speed exceeding 10 m s^{-1} for at least 60 hours and whose tracks remain within 50°S–50°N for at least 60 hours, thereby excluding extratropical systems. Creating this 1,000-member ensemble allows us to quantify where the observed 2020 23-TC count season verifies against the simulated distribution of possible outcomes.

e. Theoretical Framework

To assess whether the large-scale environmental conditions in 2020 were favorable for a hyperactive Atlantic season, we apply the theoretical framework of Hsieh et al. (2020) to ERA5 reanalysis data (Hersbach et al. 2020) over the period 1980–2024.

The framework conceptualizes TC formation as a two-stage process involving precursor seed disturbances and subsequent development into fully formed TCs. Under this formulation, the annual number of North Atlantic TCs, N_{TC}, is approximated as

$$N_{TC} \approx SPI \times P(\Lambda), \tag{2}$$

where SPI is the seed propensity index, a proxy for the number of precursor seed disturbances, and $P(\Lambda)$ is a proxy for the nondimensional probability that a seed disturbance develops into a TC. The seed propensity index is defined as

$$SPI = (-\omega) \cdot \frac{1}{1 + Z^{-1/\sigma}}, \tag{3}$$

where

$$Z = \frac{f + \zeta}{\sqrt{|\beta + \partial_y \zeta| U}}. \tag{4}$$

The variable ω is the 500 hPa pressure coordinate vertical velocity ($\omega < 0$ for upward motion), $\sigma = 0.69$ is a nondimensional fitting parameter, and Z is nondimensional variable that represents low level vorticity spinup. f is the Coriolis parameter, β is its meridional gradient, ζ is 850 hPa relative vorticity, and U is a constant wind speed of 20 m/s which is empirically fit in Hsieh et al. (2020).

Next, $P(\Lambda)$ is defined as

$$P(\Lambda) = \frac{1}{1 + (\Lambda_0/\Lambda)^{1/\gamma}}, \tag{5}$$

where

$$\Lambda = \frac{v_s \cdot \chi}{PI}. \tag{6}$$

The variables $\Lambda_0 = 0.014$ and $\gamma = -0.9$ are dimensionless fitting parameters, and Λ denotes the ventilation index (Tang and Emanuel 2010, 2012). v_s is vertical wind shear between 250 hPa and 850 hPa, PI is potential intensity, and χ is a dimensionless variable representing entropy deficit.

In this study, we extend the existing framework by incorporating monthly mean data from ERA5, averaged over the tropical Atlantic (10°–30° N) during June through November, to derive a proxy for TC activity. Basin-wide means are calculated over a region extending beyond the MDR (10°–25° N, 80°–20° W) to include the Gulf of Mexico and Caribbean, in order to account for the high concentration of storms that occurred there in 2020 (Fig. S4). Including the Gulf of Mexico and Caribbean ensures that differences in TC track locations among years are appropriately represented in the analysis. We additionally examine several individual components of the seed probability framework, such as PI and vertical wind shear, in this MDR-extended region that encompasses the Gulf of Mexico and Caribbean.

We also construct an alternative proxy for annual Atlantic TC counts that explicitly incorporates tracked precursor seeds. In this formulation, annual TC activity is approximated as

$$N_{TC} \approx N_s \times P(\Lambda), \tag{7}$$

where N_s denotes the observed annual count of explicitly tracked TC seeds. Here, seed frequency is diagnosed directly from reanalysis data, allowing us to more explicitly separate variability in seed frequency from variability in development probability.

3. Results

a. Testing the first hypothesis family

In this section, we present the results to evaluate the first family of hypotheses as to why the GFDL models poorly represented the hyperactive 2020 Atlantic TC season within their ensemble ranges: whether there were fundamental deficiencies in the models or observational datasets.

1) Hypothesis Number One

This hypothesis poses that the dynamical atmosphere-only models used in this study to generate the historical TC record in Fig. 1 (AM2.5-C360 and HiRAM) may be limited in their ability to represent TC genesis, and thus, are unreliable to assess Atlantic TC interannual variability. This analysis appears unlikely, both given past studies examining atmosphere-only models and additional analysis presented in this manuscript. First, several atmosphere-only models with prescribed observed SST boundary conditions, including those used in this study, have skill at capturing the Atlantic TC track locations, storm structure and lengths, seasonal cycle, and interannual variability (LaRow et al. 2008; Zhao et al. 2009), suggesting that given information about the observed SSTs, these models can produce reasonable Atlantic TC seasonal statistics. Additionally, AM2.5-C360 and HiRAM perform well at capturing the long-term historical record of Atlantic TC activity (Levin et al. 2026), the influence of SSTs on TC frequency and intensity (Chan et al. 2021), and the annual TC cycle (Yang et al. 2021).

Moreover, these atmosphere-only models forced with observed or predicted SSTs show deterministic retrospective skill at capturing seasonal Atlantic TC counts, as the model seasonal predictions and historical simulations have high retrospective correlations with their ensemble mean the observed Atlantic TC record (Zhao et al. 2010; Chen and Lin 2011, 2013; Gao et al. 2019). It is notable that the anomalous 2020 season also lies at or beyond the ensemble range in other independent modeling systems. Seasonal forecasts from physics-based coupled models such as GFDL SPEAR and FLOR (Murakami et al. 2025), as well as from DL-based models such as NeuralGCM (Zhang et al. 2025a), similarly place 2020 at the edge or outside their ensemble distributions.

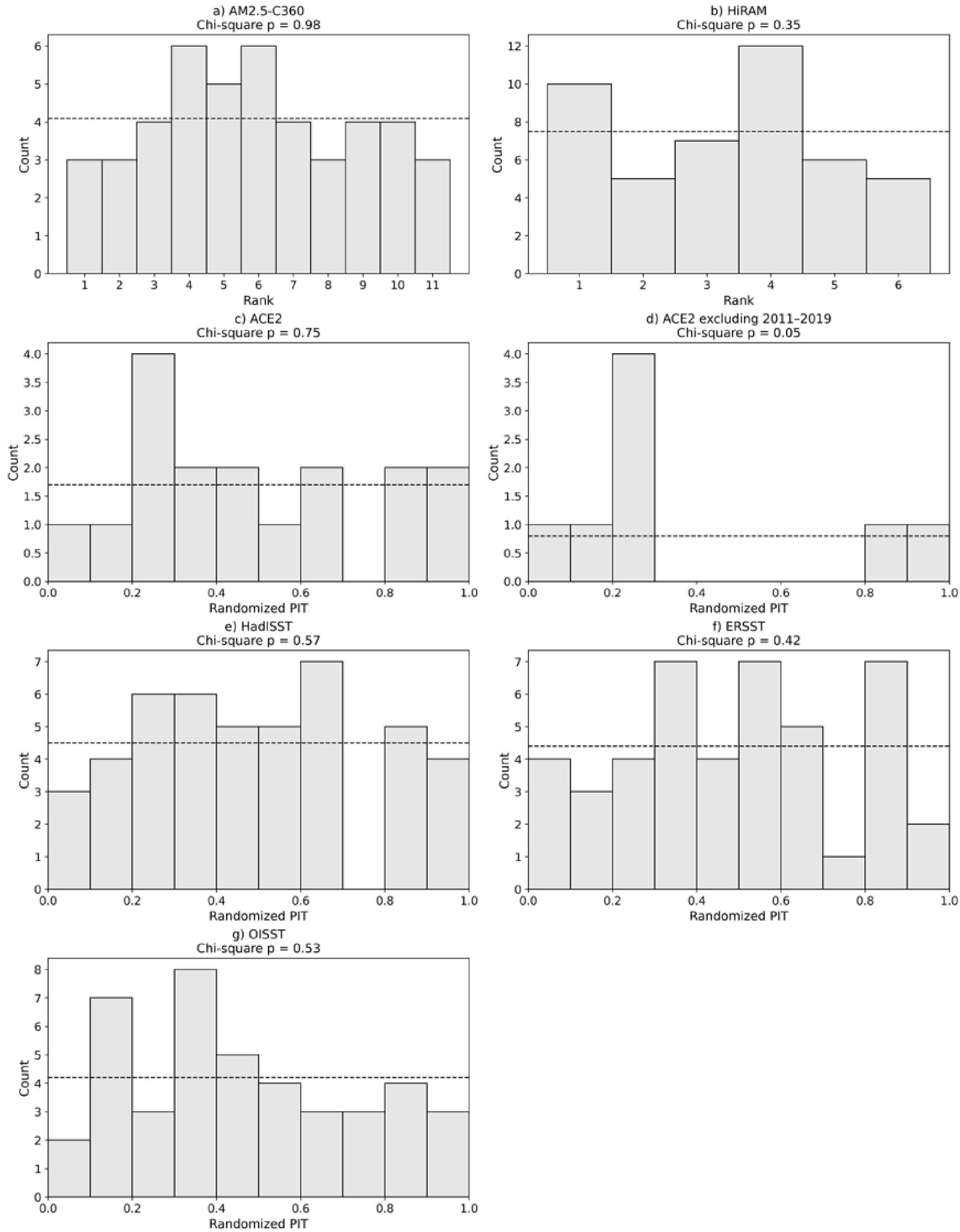
a) AM2.5-C360
Chi-square p = 0.98
b) HiRAM
Chi-square p = 0.35
c) ACE2
Chi-square p = 0.75
d) ACE2 excluding 2011–2019
Chi-square p = 0.05
e) HadISST
Chi-square p = 0.57
f) ERSST
Chi-square p = 0.42
g) OISST
Chi-square p = 0.53
Count
Rank
Randomized PIT

FIG. 2. Reliability diagnostics for the modeling systems used in this study against the observed seasonal long-duration Atlantic TC counts. Panels (a) and (b) show rank histograms for AM2.5-C360 (ten-member ensemble) and HiRAM (five-member ensemble), respectively, forced with observed SSTs over 1980–2024 (n=45 years). Panels (c) and (d) show randomized probability integral transform (PIT) histograms for the 1,000-member ACE2 DL ensemble for 1982 and 2005–2020 (n=17) and for the same years excluding the model training period (2011–2019; n=8), respectively. Panels (e)–(g) show randomized PIT histograms for the statistical-dynamical model of Vecchi et al. (2011) forced with HadISST (1980–2024, n=45), ERSST (1980–2023, n=44), and OISST (1981–2022, n=42), respectively. Chi-square goodness-of-fit tests against the uniform distribution are shown in the subplot titles. The dashed horizontal black line denotes the expected histogram frequency under perfect calibration, for which the ranks or verification quantiles of the observed long-duration TC counts are uniformly distributed. Higher p-values indicate weaker evidence against uniformity.

Although these previous studies demonstrate that atmosphere-only models forced with observed or predicted SSTs possess deterministic skill in simulating seasonal Atlantic TC activity, deterministic skill alone is insufficient to evaluate Hypothesis One. Although the relatively high retrospective correlations between the observed TC counts and the simulated ensemble mean TC counts suggest that the models have reasonable deterministic skill, they do not imply that the ensemble distribution is calibrated probabilistically. A well-calibrated seasonal Atlantic TC ensemble would have the probability of a possible seasonal outcome match the observed likelihood of the event. For example, if the ensemble spread suggests a seasonal TC count will occur with 30% probability, such an outcome should occur 30% of the seasons across the observational record. Assessing the model ensemble calibration is crucial to the analysis of this study, since we utilize a hierarchy of model ensembles to probabilistically quantify the likelihood of the 2020 season.

To evaluate the probabilistic reliability of the historical AM2.5-C360 and HiRAM ensembles, we compare the simulated seasonal Atlantic long-duration TC counts against observations using rank histograms and statistical goodness-of-fit tests (Figs. 2a,b; Hamill 2001; Gneiting et al. 2007). Rank histograms assess whether the observations are statistically exchangeable with the model ensemble members. For each season, the observed TC count is inserted into the ordered ensemble members and its rank is recorded. If the ensemble members and observations are drawn from the same underlying probability distribution, each rank is equally likely and the resulting histogram is uniform. Systematic departures from uniformity indicate ensemble miscalibration arising from model bias or incorrect ensemble spread, such as underdispersion or overdispersion.

Visually, both AM2.5-C360 and HiRAM produce rank histograms that are close to uniform, with only slight concentrations near the center. We quantify the degree of uniformity across these rank histograms using a chi-square goodness-of-fit test, where the null hypothesis suggests the rank histogram is uniform. Under this uniform assumption, the observed storm counts lie within any bin of the histogram with equal probability. With a sufficiently low p-value, we can reject the null hypothesis and assume that the ensemble distribution is not probabilistically calibrated to the observed record. Rejecting the null hypothesis could arise from either a model bias or improper ensemble spread. For both models, the chi-square test yields large p-values ($p = 0.98$ for AM2.5-C360 and $p = 0.35$ for HiRAM), providing no evidence to reject the null hypothesis of uniformity. These results indicate that the historical ensemble distributions are well-calibrated to the observed Atlantic long-duration TC counts.

The significance of this result is that it demonstrates the historical GFDL ensembles are probabilistically well calibrated despite failing to encompass the exceptional 2020 season within their finite ensemble ranges. Consequently, the inability of AM2.5-C360 and HiRAM to simulate a season as active as 2020 is unlikely to reflect a systematic deficiency in their representation of TC genesis or seasonal Atlantic TC variability. Combined with the demonstrated skill of these models in reproducing Atlantic TC climatology, seasonal variability, and deterministic seasonal forecasts, this evidence argues against Hypothesis One.

2) Hypothesis Numbers Two and Three

The second hypothesis regarding the reliability of the TC observations appears unlikely, as the post-1980 Atlantic TC record is considered highly reliable given modern satellite, aircraft reconnaissance, and remote sensing observations, with confidence further enhanced in recent years by newer geostationary satellites. Additionally, this study uses the observed long-duration TC record computed using the methods of Landsea et al. (2010), which excludes short-duration storms that may have been missed in earlier decades due to less advanced observing capabilities, thereby improving temporal homogeneity in the historical record. Moreover, the anomalous 2020 activity extended to hurricanes and MHs, which are even less susceptible to detection ambiguity, making observational error an unlikely explanation for the model–observation discrepancy.

The third hypothesis suggests there are errors in the SST dataset used to force the atmosphere-only models. To test this, we apply the statistical–dynamical model of Vecchi et al. (2011), which predicts seasonal Atlantic long-duration TC activity from SST, using three independent SST products: OISST, HadISST, and ERSST. The PIT histograms for the resulting seasonal TC distributions (Fig. 2) show no statistical evidence of deviation from uniformity based on chi-square tests, indicating that these statistical-dynamical reconstructions are well calibrated. The corresponding time series of the statistical-dynamical models (Fig. S1) capture substantial interannual variability, with correlations of $r = 0.66$–0.70 against observations. Despite known differences among SST datasets in their long-term trends (Menemenlis et al. 2025), the predicted 2020 long-duration TC distributions are nearly identical, with ensemble means ranging from 10.9 to 11.8 storms. This provides no evidence that errors in HadISST, which forces the dynamical simulations, explain the discrepancy.

3) Hypothesis Number Four

Our fourth hypothesis suggests that the failure of the observed 2020 TC count to fall within the AM2.5-C360 and HiRAM ensemble ranges reflects limitations of SST-forced models in representing the impacts of abrupt aerosol perturbations. To test this, we use two approaches. First, we perform a five-member AM2.5-C360 ensemble simulation over 1980–2024 using observed reanalysis-based aerosol concentrations, rather than the prescribed CMIP5 aerosol forcing used in the historical simulations shown in Fig. 1. Even when forced with observed aerosol concentrations, the model simulates 2020 as only a moderately active season (Fig. S2). The absence of a change in simulated Atlantic TC activity when including observed aerosols suggests that any radiative or dynamical effects associated with the 2020 aerosol reduction were either small or already reflected indirectly in the observed SST boundary conditions.

Additionally, we conduct idealized sensitivity experiments in which sulfate and black carbon aerosols are substantially reduced to emulate an exaggerated analogue of the 2020 aerosol decline. The resulting annual Atlantic long-duration TC count distributions are similar to the control, with all experiments producing approximately twelve TCs per year (Fig. S3). Kolmogorov–Smirnov tests show no statistically significant differences from the control in any experiment (p = 0.28–0.99), suggesting that, within this modeling framework, the direct radiative effects of prescribed low-frequency (>monthly) aerosol variations do not exert a robust influence on Atlantic TC activity. This does not preclude aerosol effects operating through SST-mediated pathways or synoptic-scale interactions, which are not represented in these experiments.

b. Testing the second hypothesis family

In this section, we evaluate the second hypothesis family, which considers the possibility that the hyperactive 2020 season was a highly unlikely outcome that could not have been captured by the small ensemble sizes of the AM2.5-C360 and HiRAM models.

1) Analysis of ensemble size

We determine if the small GFDL model historical ensembles (Fig. 1, five and ten members, respectively) can reasonably sample potential extreme tail outcomes, like the 2020 season, across their spread. We contextualize 2020 across the entire 1980-2024 historical record and count how many times the observed storm count falls outside the model ensemble spread.

Because the dynamical ensembles appear well calibrated (Fig. 2), the observed record can be interpreted as an additional equally likely realization drawn from the same distribution as the model ensemble members. Under this assumption, AM2.5-C360 (HiRAM) contains eleven (six) realizations per year, comprising ten (five) model members plus the observational record. The probability that the observation lies outside the modeled ensemble range, is either the minimum or maximum of the combined set, is therefore

$$P(\text{outside ensemble range}) = \frac{2}{n}.$$

Therefore, the resulting annual exceedance probabilitiesare $2/11 \approx 0.18$ for AM2.5-C360 and $2/6 = 0.33$ for HiRAM, corresponding to expected exceedance counts over 45 years of approximately eight and fifteen, respectively.

In Fig. 1, the observed record lies outside the AM2.5-C360 ensemble spread six times for total long-duration TCs, three times for hurricanes, and five times for MHs. These outcomes are well within sampling variability and are therefore consistent with a calibrated system. Similarly, for

HiRAM, the observed record lies outside the ensemble spread fifteen times for long-duration TCs and twelve times for hurricanes, both close or equal to the expectation of fifteen exceedances.

Thus, even in a well calibrated system with only five to ten ensemble members, it is expected that the observation will fall outside the ensemble range multiple times over a 45-year period. Accordingly, the fact that the hyperactive 2020 season exceeded the ensemble ranges of the small dynamical-model ensembles is not surprising. Although 2020 stands out visually because it lies outside the ensemble spread simultaneously for long-duration TCs, hurricanes, and MHs, similar exceedances occur elsewhere in the historical record (e.g., 2013 and 1996). Therefore, this analysis supports the conclusion that the small ensemble sizes of AM2.5-C360 and HiRAM could have been inadequate to capture the extremely hyperactive 2020 season.

At the same time, the limited ensemble sizes of AM2.5-C360 and HiRAM constrain our ability to precisely estimate tail probabilities of extreme events like the 2020 season. This limitation motivates the use of the 1,000 member ACE2 DL–based model ensemble and the statistical-dynamical model from Vecchi et al. (2011) to generate a full distribution of seasonal long-duration TC counts and more robustly characterize the distribution's tail behavior. The ACE2 1,000 member ensemble spans 1982 and 2005-2020, encompassing both active and inactive seasons that are captured within the ensemble spread of dynamical models, including 1982, 2005, 2009, and 2010 (Fig. 1). Our comparison across years in the recent record allows us to assess whether the behavior of the DL–based model diverges substantially from that of physics-based atmosphere-only models.

The observed annual long-duration TC counts and the distribution of simulated TC counts from the 1,000-member historical ACE2 ensemble are shown in Fig. 3. ACE2 exhibits a moderate positive correlation between the observed long-duration TC counts and the ensemble-mean simulated counts (r = 0.62), indicating skill in distinguishing between relatively active and inactive seasons due to SST and carbon dioxide external forcing alone. The ensemble mean peaks during active seasons such as 2005 and 2010, and shows local minima during inactive seasons such as 2009 and 2014, consistent with the observed variability.

Beyond reproducing the observed mean-state variability, the ensemble exhibits substantial interannual spread. For each of the seventeen seasons shown, the simulated range of long-duration TC counts (the difference between the ensemble minimum and maximum) spans roughly ten to 26 storms. For instance, in 2005 the ensemble indicates that between approximately five and 28

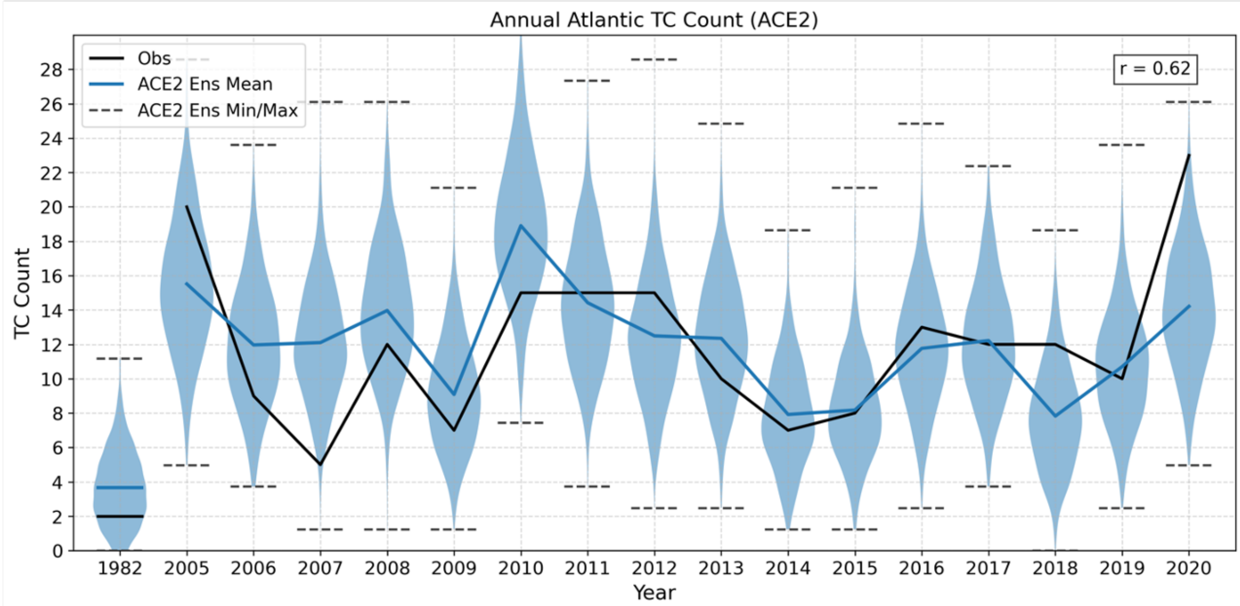

FIG. 3. Annual Atlantic long-duration TC counts for 1982 and 2005–2020. The observational record is shown in black. Blue violin plots depict the distribution of simulated long-duration TC counts from the 1,000-member ACE2 ensemble forced with observed SSTs, with the ensemble mean indicated by the solid blue line, and ensemble minimum and maximum indicated by the dashed dark gray lines. The correlation between the ensemble-mean TC frequency and the observed counts is shown in the upper-right corner.

TCs were plausible, whereas in the relatively inactive 2014 season the simulated range extends from one to nineteen TCs. Despite this considerable variability, the observed TC count falls within the ensemble distribution for most seasons in the historical record. Furthermore, the randomized PIT histogram for the full ACE2 record (Fig. 2c) is not statistically distinguishable from uniform according to the chi-square test (Fig. 2h), indicating that the ensemble dispersion provides a realistic representation of seasonal uncertainty. In other words, the verifying observational quantile is approximately uniformly distributed across years, suggesting that the ensemble dispersion realistically represents seasonal uncertainty.

ACE2's performance is not uniform across all years, however. Visual inspection of Fig. 3 suggests that discrepancies between the ensemble mean and observations are largest prior to 2010 and in 2020, while agreement improves during 2010–2019. Additionally, the randomized PIT histogram for the subset of out-of-sample years (Fig. 2d,h) appears U-shaped, with a chi-square test p-value of 0.05, suggestive of reduced calibration. However, this subset contains only eight years, providing a limited sample size for assessing the reliability during years outside the DL training period. These years with the weaker reliability span the out-of-sample validation period, since the model's training includes 2011–2019 (Watt-Meyer et al. 2025). These results suggest stronger performance during in-sample years than in true out-of-sample evaluation.

There are several years in which the observed long-duration TC count falls near the extreme tails of the ACE2 ensemble distribution. One such case is 2007, an anomalously inactive season with only five observed TCs. The 1,000-member ACE2 ensemble, forced with observed 2007 SSTs, simulated a range of approximately one to 26 storms, with an ensemble mean of twelve. Only fifteen of the 1,000 members produced five or fewer TCs, indicating that the realized season verifies at the 1.5th percentile of the simulated ACE2 distribution. Although the ACE2 ensemble mean represented 2020 as a relatively active season, with the ensemble mean being third highest across the years in Fig. 3, below only 2005 and 2010, the observed 2020 hyperactivity verified at the extreme tail of the ACE2 ensemble distribution. The ensemble simulates a mean of approximately fourteen long-duration TCs (Table 1), compared to the 23 storms observed. Only 37 ensemble members produce at least 20 storms (3.7%), and just five members simulate 23 or more storms (0.5%). Therefore, 23-TC count 2020 season verifies at the 99.5th percentile of the ACE2 ensemble distribution. This quantification suggests that under the observed SST conditions, the hyperactive season was an unlikely outcome.

Table 1 compares the estimated likelihood of the 2020 hyperactive season from the 1,000-member ACE2 ensemble distribution with that derived from the statistical–dynamical Poisson model described in Eq. 1, forced separately with HadISST, ERSST, and OISST SST datasets. The statistical–dynamical model is shown to be well calibrated in Fig. 2, with PIT histograms that are statistically indistinguishable from uniformity. The hierarchy of modeling frameworks used in this study quantify the observed hyperactive 2020 TC season as a 0.1–0.5% event given the observed SSTs, suggesting the SST signal was not particularly favorable for a record-breaking seasonal TC outcome.

Although a 0.5% event is highly unlikely in any single year, its occurrence over a multidecadal record is less implausible. Assuming independence in the unforced atmospheric (weather noise) component between seasons, the probability of observing at least one 0.5% event over a 45-year

TABLE 1. Modeled distribution of 2020 seasonal long-duration TC counts using a statistical-dynamical model with three SST products as inputs and the DL-based ACE2 1,000-member ensemble model. For each modelled TC count distribution we show the distribution's mean, quantile at which the observed 23 TC counts in 2020 verified against the modeled distribution, and the corresponding percent of such an event.

Model	Model Mean Long-Duration TC count	Verified Quantile	Event Percent
Statistical-Dynamical (HadISST)	11.0	0.999	0.1%
Statistical-Dynamical (ERSST)	11.8	0.997	0.3%
Statistical-Dynamical (OISST)	10.9	0.999	0.1%
ACE2 1,000 member ensemble	14.1	0.995	0.5%

period (e.g., 1980–2024) is

$$P(\text{At least one } 0.5\% \text{ event}) = 1 - (0.995)^{45} \approx 0.20. \tag{8}$$

Thus, an event with a 0.5% annual probability has roughly a 20% chance of occurring at least once in a 45-year historical record.

To evaluate how ensemble size influences the ability to capture the full range of plausible 2020 Atlantic long-duration TC outcomes, we conduct a resampling experiment using the 1,000-member ACE2 simulation of the 2020 season. To do so, we randomly sample ten or fifteen of the 1,000 outcomes across the ACE2 ensemble without replacement, since these are the typical ensemble sizes of seasonal TC forecasting models (e.g., Murakami et al. 2025). For each drawn ten-to-fifteen samples, we evaluate several criteria about the TC activity level of the selected outcomes (Table 2). We repeat this process 10,000 times to obtain robust resampling statistics. In particular, we assess the probability that at least one or at least two drawn samples simulate (i) a season with ≥20 long-duration TCs (comparable to other hyperactive years such as 2005) and (ii) a season with ≥23 long-duration TCs, matching the observed 2020 count. We also classify seasons using the drawn sample mean. We define an active season as one with where the drawn sample mean is at least twelve long-duration TCs, which is the climatological mean seasonal long-duration TC activity level from 2005-2020. The $n = 10$ ($n = 15$) drawn samples include at least one occurrence of 23-long-duration TC count season eight percent (twelve percent) of the time, stressing that it is

TABLE 2. The percentage of 10,000 resampled realizations of annual Atlantic TC long-duration counts from the ACE2 model that satisfy specific activity thresholds. We randomly sample ten or fifteen of the 1,000 ACE2 ensembles without replacement and repeat this process 10,000 times.

Criteria across all samples (%)	10 ensembles	15 ensembles
$\geq$1 ens with at least 20 TCs	32.99%	44.96%
$\geq$2 ens with at least 20 TCs	5.86%	12.06%
$\geq$1 ens with at least 23 TCs	8.03%	11.51%
$\geq$2 ens with at least 23 TCs	0.24%	0.56%
mean $\geq$ 12 TCs ('active season')	97.96%	99.62%
mean < 12 TCs ('inactive season')	2.04%	0.38%
mean $\geq$ 17 TCs ('$+1\sigma$ season')	0.65%	0.16%
mean $\leq$ 7 TCs ('-1σ season')	0.00%	0.00%

unlikely for the extreme tail outcome of the 2020 season to be sampled across a small ensemble size.

2) Large-scale environmental conditions in 2020

To evaluate if the hyperactive 2020 season was a highly unlikely realization of the climate system, we examine the large-scale environmental conditions that prevailed during that year. Internal atmospheric variability operating on subseasonal timescales could have amplified activity beyond what would be anticipated from seasonal-mean conditions alone.

To test this idea, we leverage ERA5 reanalysis data in combination with the theoretical TC proxy introduced by Hsieh et al. (2020), defined as $N_{\mathrm{TC}} \approx \mathrm{SPI} \times P(\Lambda)$, which approximates seasonal TC counts as a function of the large-scale environment. We compute the seasonally (June-November) and basin-averaged TC proxy using monthly mean ERA5 inputs for the period 1980–2024 ($\mathrm{SPI} \times P(\Lambda)$, Fig. 4a). The spatial average is calculated over the region spanning 10–30°N in Atlantic, extending beyond the MDR to include the Gulf of Mexico and Caribbean, where many storms during the 2020 season developed (Fig. S4). This framework reproduces a substantial portion of the observed interannual variability in Atlantic long-duration TC activity, yielding a correlation of $r = 0.66$ between observed and both proxy-derived TC counts. Thus, seasonal-mean large-scale environmental conditions explain much of the historical variability in Atlantic TC activity.

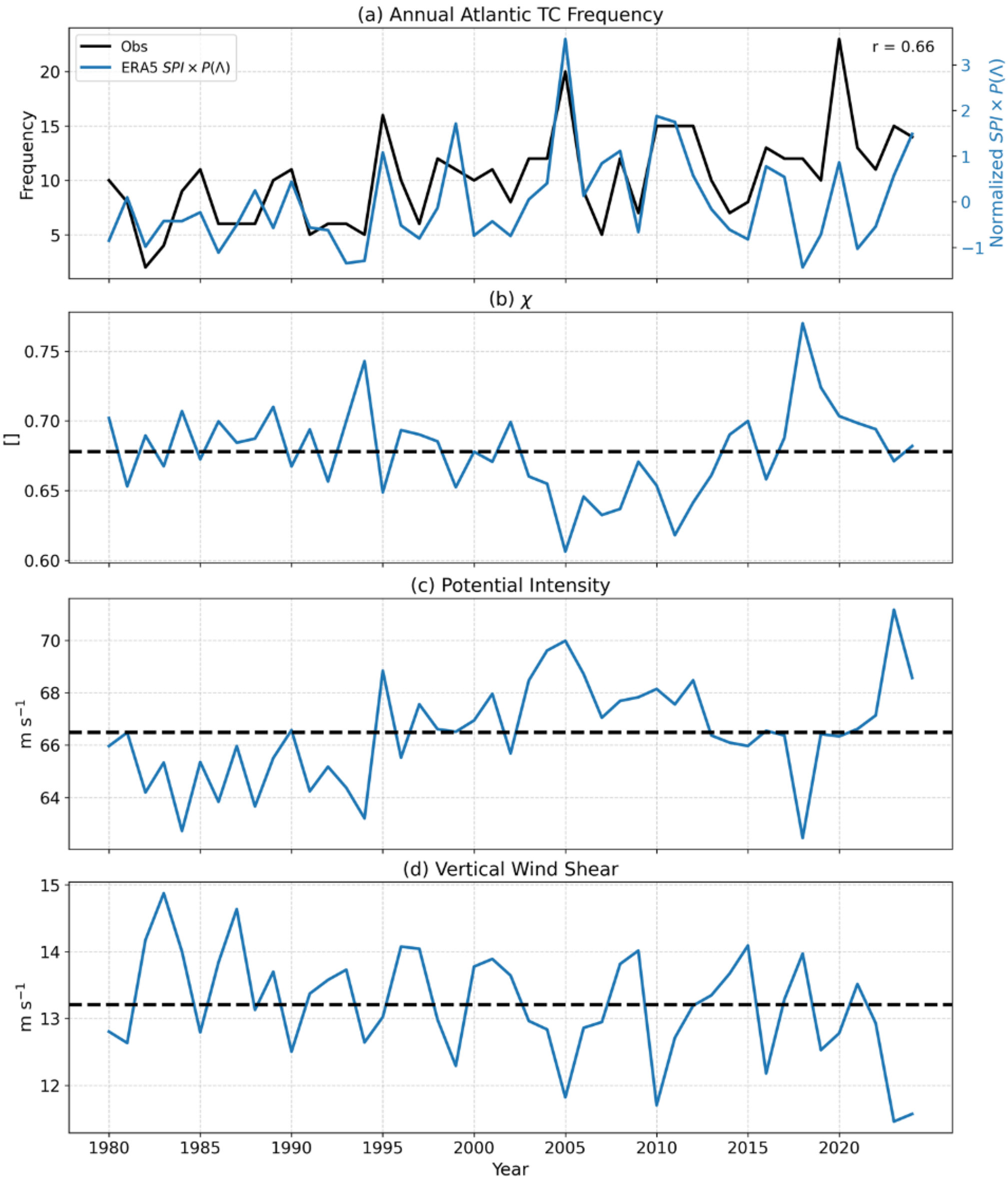

FIG. 4. a) Time series of observed annual Atlantic long-duration TC counts (black; left y-axis), approximated annual TC frequency (SPI$\times P(\Lambda)$; blue; right y-axis) derived from seasonally and basin-averaged monthly ERA5 data for 1980–2024. The parameterized TC frequencies are standardized using Z-score normalization, defined as $Z(x) = (x - \mu_x)/\sigma_x$, where x is the data point, μ_x is the mean over the full record, and σ_x is the standard deviation. The correlation coefficient between observed and approximated TC counts is shown in the upper-right corner of the panel. (b–d) Time series of the seasonal, basin-averaged ERA5 environmental variables that contribute to the ventilation index (Eq. 6), a key control on TC genesis: (b) moist entropy deficit (lower values are more favorable for TC development), (c) PI (higher values are more favorable), and (d) vertical wind shear (lower values are more favorable). Dashed black horizontal lines indicate the 1980–2024 climatological mean of each variable.

Although the TC proxy estimates the 2020 season to be moderately active across the entire historical record of Fig. 4 and a local maximum in favorability in the years surrounding it, the observed long-duration TC count substantially exceeds the proxy estimate of roughly twelve storms. When the 2020 season is excluded, the correlation between the observed counts and the seasonal $\mathrm{SPI} \times P(\Lambda)$ (blue line) increases to $r = 0.70$. Deviations between the proxy and observations are also evident in the surrounding years, particularly from 2018 to 2021. These results indicate that, based on the combination of several key seasonally averaged large-scale conditions alone, 2020 did not appear exceptionally favorable for the record-breaking hyperactivity that occurred.

We also examine the individual components of $P(\Lambda)$, the proxy for the likelihood that a TC will develop from a seed disturbance, averaged seasonally (June–November) over the tropical Atlantic spanning 10–30°N, extending beyond the MDR to include the Gulf of Mexico and Caribbean (Figs. 4b–d). In 2020, PI was close to its 1980–2024 climatological mean, while the moist entropy deficit was slightly less favorable than average. These thermodynamic variables exhibited similar behavior when averaged over August–October (ASO), corresponding to the climatological peak of the Atlantic TC season (Fig. S6). Seasonally averaged vertical wind shear in 2020 was more favorable than the climatology, but not exceptional relative to other active seasons. Several years, including 1981, 1990, 1994, 1999, 2005, 2010, 2016, 2019, 2023, and 2024, exhibited more favorable June–November shear conditions. However, when considering ASO only, 2020 ranked fifth in terms of the most favorable vertical wind shear, exceeded only by 1999, 2005, 2010, and 2019 (Fig. S6). This result is consistent with Bell et al. (2021), who reported similarly favorable ASO wind shear over the MDR using the NCEP/NCAR reanalysis. Overall, although the large-scale thermodynamic and dynamic environment in 2020 was moderately conducive to TC activity, the combined seasonal-mean values of PI, moist entropy deficit, and vertical wind shear were not exceptional enough to suggest a record-breaking season. This finding suggests that internal atmospheric variability likely amplified TC activity beyond what would be expected from the seasonal-mean large-scale environment alone.

Finally, in addition to examining the climatologically most active portion of the season (ASO), we investigate the October–November (ON) 2020 period, which exhibited historically extreme intensity-based metrics. Klotzbach et al. (2022) showed that the ON portion of the 2020 season produced a record number of hurricanes and MHs and the second-highest accumulated cyclone energy since 1950. Motivated by these findings, we also evaluate the TC proxy and the environmental components of $P(\Lambda)$ over the MDR-extended region, including the Caribbean Sea and Gulf of Mexico, during ON (Fig. S7). Despite the exceptional storm intensity during this period, basin- and period-averaged values of PI, moist entropy deficit, and vertical wind shear remained close to their climatological means in 2020. Klotzbach et al. (2022) found substantial regional heterogeneity in these environmental conditions during the 2020 ON period using ERA5. For example, during ON 2020, the eastern and western Caribbean experienced some of the most favorable PI values since 1979, whereas the Gulf of Mexico experienced some of the least favorable. Likewise, while vertical wind shear over the eastern Caribbean was near climatological values, the western Caribbean and Gulf of Mexico experienced some of the most favorable shear conditions on record (their Fig. 7). Consistent with these findings, we separately compute ON-mean vertical wind shear over the Gulf of Mexico and Caribbean and over the MDR (Fig. S8). The Gulf of Mexico and Caribbean experienced among the most favorable ON shear conditions in the record, whereas the MDR exhibited less favorable-than-average conditions. Together, these results demonstrate that substantial variability existed on sub-basin spatial scales and subseasonal temporal scales in 2020, even when basin-wide seasonal averages appeared only moderately favorable. This supports the conclusion that localized and shorter-timescale atmospheric variability acted in concert with the large-scale SST-forced environment to produce the unprecedented 2020 season, an outcome that would have been unlikely based on observed SST boundary conditions alone.

Beyond examining monthly mean large-scale environmental conditions relevant for TC development from a seed disturbance, we assess whether the abundance of seeds themselves tracked at six-hourly intervals during the June-November season contributed to the hyperactive 2020 TC season emerging as a rare realization within the ensemble spread of multiple models. To do so, we examine explicitly tracked Atlantic TC seeds from three independent ERA5-based datasets (Vishnu et al. 2020; Ikehata and Satoh 2021; Moon et al. 2025), in addition to our own tracking methodology. Each method tracks storms using six-hourly June-November North Atlantic ERA5 data. The resulting seed counts are shown in Fig. 5. These differing approaches yield different mean seed climatologies, yet they share broad interannual patterns. Notably, none identifies 2020 as a local maximum in seed count (Fig. 5). If the hyperactivity of 2020 were driven by anomalously many seeds, we would expect at least one tracking methodology to identify an extreme seed year.

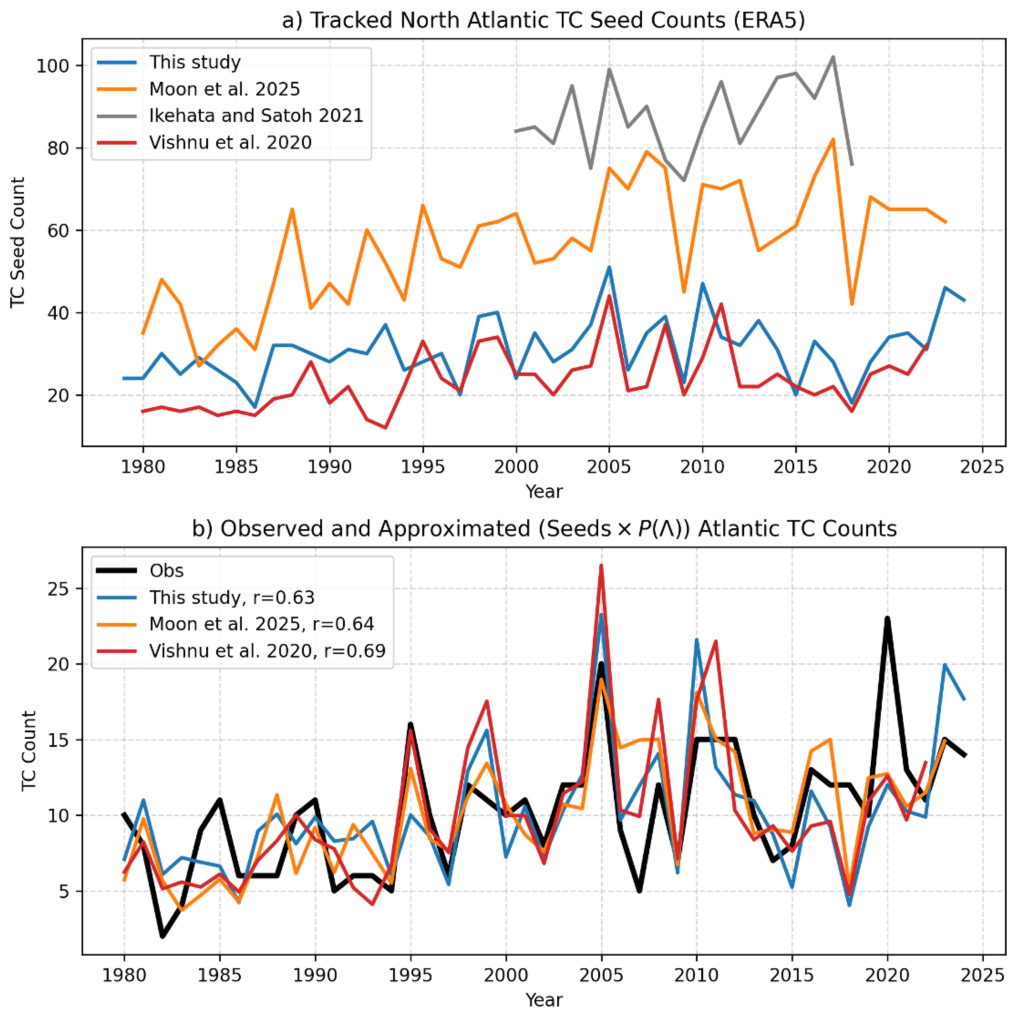

FIG. 5. (a) Tracked Atlantic TC seed counts from the ERA5 dataset using the methods described in Section 2 (blue; 1979–2024), from Moon et al. (2025) (orange; 1980–2023), Ikehata and Satoh (2021) (gray; 2000–2018), and Vishnu et al. (2020) (red; 1980–2022).(b) Observed Atlantic long-duration TC counts (black) and approximated annual TC frequencies derived from seed counts (Seeds $\times P(\Lambda)$), where $P(\Lambda)$ represents the transition probability estimated from seasonally and basin-averaged monthly ERA5 conditions. Seed counts are obtained following the respective tracking methods in Section 2 (blue; 1980–2024), Moon et al. (2025) (orange; 1980–2023), and Vishnu et al. (2020) (red; 1980–2022). Approximated TC counts are scaled by a multiplicative factor so that their mean matches the observed mean. Correlation coefficients between observed and approximated TC counts for each seed dataset are shown in the upper-left corner of panel (b).

We then incorporate explicitly tracked seeds into the TC proxy, replacing SPI with observed seed count to compute $N_{TC} \approx \text{Seeds} \times P(\Lambda)$, where $P(\Lambda)$ is derived from June-November seasonal monthly ERA5 conditions in the MDR-extended region to include the Gulf of Mexico and Caribbean. This modified proxy reproduces a substantial portion of observed interannual variability (correlations $r = 0.63$–0.69) and successfully captures both inactive and active years such as 2005 and 2010. Yet across all three seed-tracking methodologies, the proxy converges on a moderately active 2020 season of roughly twelve storms, below the observed 23. Thus, even when incorporating explicitly tracked seed disturbances at six-hourly resolution, the observed large-scale atmospheric conditions in 2020 do not appear sufficient to explain the record-breaking season.

4. Discussion

This study examines the apparent unlikeliness of the hyperactive 2020 Atlantic TC season given the observed SST boundary conditions, during which activity across all intensity bins exceeded the ensemble spread of state-of-the-art GFDL atmosphere-only climate models forced with observed SSTs (Fig. 1). We considered two broad classes of hypotheses to explain the discrepancy between observations and model simulations. The first posits that model or observational deficiencies prevented the ensembles from reproducing a hyperactive outcome comparable to that observed. The second considers whether the 2020 season represented a low-probability realization under the observed SST forcing that could not have been captured by the limited ensemble sizes of AM2.5-C360 and HiRAM.

After systematically evaluating four hypotheses within the first category using dynamical and statistical–dynamical models, we find little evidence supporting model or observational failure. Moreover, analysis of the large-scale environmental conditions using the theoretical framework of Hsieh et al. (2020) indicates that 2020 did not exhibit exceptionally favorable environmental conditions for a record-breaking season. These results suggest that the SST-forced atmosphere-only model simulation of 2020 as only moderately active was not a fundamental failure, since the 2020 environment was not highly favorable for hyperactivity. Instead, we hypothesize that an unusually favorable realization of internal atmospheric variability likely enhanced the 2020 TC activity above expected levels from mean conditions alone. This hypothesis is testable through targeted analyses of the 2020 TC season internal atmospheric evolution and its influence on TC genesis and development, but a comprehensive evaluation is beyond the scope of the present study and is left for future work.

Additional features of the 2020 season are consistent with the hypothesis that enhanced internal variability played a key role in the development of the hyperactive season and that there was limited predictability from observed SST boundary conditions for the season's TC activity. The season included a large number of relatively weak storms compared with other hyperactive years such as 2005 and 2010 (Fig. S5). These characteristics are consistent with a scenario in which weather-scale variability amplified seasonal counts beyond what would be anticipated from large-scale environmental forcing alone.

To test whether 2020 could plausibly represent a rare outcome under the observed SST forcing, we generated a 1,000-member ensemble for 2020 using the ACE2 DL model forced with observed SSTs and applied the statistical–dynamical model of Vecchi et al. (2011) to the same SST forcing to estimate the full distribution of possible seasonal outcomes. These distributions indicate that a 23 long-duration TC season corresponds to an event with an approximate probability of 0.1–0.5% under the observed 2020 SST forcing, which is a highly unlikely seasonal outcome. Therefore, we interpret 2020 observed hyperactive 23-long-duration TC season as a low-probability event instead of a failure by the models or observational systems. This result stresses the inability to sample such a low likelihood extreme tail outcome with the small five to ten member GFDL ensembles.

Just as the historical GFDL model ensemble spread failed to capture the observed 2020 outcome, so too did the realized 2020 sesaonal TC count lie outside the ensemble spread in seasonal forecasts generated by both physics and DL-based models (Murakami et al. 2025; Zhang et al. 2025a). Even though these models reasonably predicted the 2020 seasonal accumulated cyclone energy, which reflects the combined effects of storm frequency, intensity, and duration, we specifically analyze the record-breaking storm counts spanning different intensity bins in this study. The analysis of intensity-integrated metrics, such as accumulated cyclone energy therefore lie outside the scope of this manuscript. While seasonal outlooks generally predicted an active season, none anticipated record-breaking levels of activity. For example, NOAA's 2020 seasonal outlook predicted a 60 percent change above-normal TC activity, which is not indicative of a predicted extremely active outcome. Specifically, the observed 2020 TC count lay outside the predicted ranges across all intensity categories, despite the forecasts generally anticipating a moderately active season

(Table S1). However, these seasonal outlooks predict qualitative ranges of TC counts and do not probabilistically quantify the full distribution of outcomes.

To address this limitation, we estimate the likelihood of the observed 2020 long-duration TC count by applying May-initialized North American Multi-Model Ensemble (NMME) forecast SSTs to the statistical–dynamical model of Vecchi et al. (2011), following the methodology of Villarini et al. (2019). Consistent with other seasonal outlooks, these SST forecasts generally predicted a moderately active season relative to their historical forecasts, largely reflecting favorable Atlantic-to-tropical SST gradients. However, none indicated a record-breaking hyperactive outcome. This is consistent with Bell et al. (2021), who also show that although the 2020 Atlantic relative SSTs anomalies were generally high, they were not as high in comparison to other active seasons like 1999, 2005, or 2010. Under the NMME SST forecasts, the observed 23 long-duration TC count corresponds to an event with an estimated probability ranging from less than 0.05% to 4.5%, depending on the forecast model (Fig. S11). However, the models quantifying the realized hyperactive 2020 season outcome with the highest likelihood (1–4.5%) were biased towards artificially inflated TC favorability. Specifically, these models predicted more favorable Atlantic SST anomalies relative to both the observed SSTs and the forecasted SSTs from other models (Figs. S9 and S10). Despite this TC-conducive model bias, these models still assigned a relatively low likelihood to the observed 2020 23-long-duaration TC outcome of less than five percent.

Finally, although Klotzbach et al. (2022) argued that aspects of the elevated ON activity in 2020 may have been anticipated using large-scale predictors, that analysis focused primarily on intensity-related metrics such as accumulated cyclone energy and rapid intensification. To our knowledge, the seasonal predictability of the realized storm frequency itself given observed SST forcing has not previously been examined.

5. Conclusions

The evidence presented here supports the conclusion that the observed 2020 SST boundary conditions did not confer strong predictability for the hyperactive outcome. Instead, the record-breaking season was likely a rare realization of internal atmospheric variability superimposed on a moderately favorable large-scale environmental state. Further, our results support the conclusion that the hyperactive 2020 season can be understood as an unlikely outcomes that even a well-calibrated system, like the modeling systems used in this study, will exhibit. Such rare events may be fundamentally difficult to capture with small ensemble sizes, even when the models themselves are performing appropriately. This interpretation of the 2020 season does not exclude the possibility that additional mechanisms not examined here contributed to the observed activity. Future observations, modeling advances, or reanalysis improvements could alter this assessment. New evidence could emerge to support hypotheses one through four, for which we were not able to find compelling support in the results presented here. Moreover, if similar large discrepancies between observations and model ensembles become more frequent, reassessment of model calibration and structural assumptions would be warranted.

Our findings have several broader implications. First, the 2020 season occurs at the end of the recent historical record and is anomalously hyperactive, which makes it disproportionately influential in linear trend estimates (Fig. S12). Because trend calculations are especially sensitive to extreme values near the endpoints of a time series, the inclusion of 2020 amplifies the estimated 1980–2024 increase in Atlantic long-duration TC, hurricane, and MH activity by approximately six storms per century for long-duration TCs, two storms per century for hurricanes, and one storm per century for MHs. This result suggests that the observed 2020 TC seasonal outcome represents an influential data point to the historically observed TC trend across different storm categories. The sensitivity of the trend to influential data points is important because the projected trends in seasonal TC counts in response to anthropogenic warming are uncertain (e.g., Knutson et al. 2020; Sobel et al. 2021). We hypothesize that subseasonal variability could have amplified the 2020 season's activity above what would be expected from the mean climate signal. Therefore, some component of the 1980-2024 multidecadal TC trend, which is largely influenced by the 2020 season, could be attributed to stochastic weather variability in addition to an externally forced climate signal. These results highlight the need for caution when drawing conclusions about long-term TC trends from relatively short observational records, particularly when extreme endpoint seasons exert substantial leverage on estimated changes. Our findings therefore stress the importance of employing statistical measures more resistant to the influence of outliers, such as the median of pairwise slopes (Lazante 1996).

Next, this study is one of many to highlight the value of very large ensembles (e.g., Mahesh et al. 2025a,b). We found that the five to ten member size from the dynamical models used in this study is not sufficient to study a full distribution of potential outcomes, especially given that the observed record is expected to exceed the ensemble spread across a multidecadal historical record several times. Traditional modeling efforts leverage a relatively small ensemble size. For example, the seasonal forecasting systems in Murakami et al. (2025) and Zhang et al. (2025a) use ensembles of ten to fifteen members, and operational global meteorological agencies generally use no more than a few dozen. In contrast, this study employs 1,000 ensemble members of the ACE2 DL model to assess the full distribution of outcomes for 2020 Atlantic TC season. By leveraging the computational efficiency of DL–based weather and climate emulators, future forecast systems should continue to incorporate much larger ensembles and explicitly consider tail risks, rather than depending primarily on ensemble means, to prepare for low-probability but high-impact events.

In summary, the 2020 Atlantic TC season appears consistent with a rare realization within a probabilistic framework rather than a systemic model failure. Even well-calibrated forecasting systems will occasionally encounter extreme outcomes like the 2020 season. Recognizing and quantifying this possibility is essential for interpreting past extremes and preparing for future risk.

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Data availability statement. Source code of the HiRAM model is available from `https://www.gfdl.noaa.gov/HiRAM-quickstart`, and the source code of the ACE2 model is available from `https://github.com/ai2cm/ace`. The forcing data and initial conditions for the ACE2 model are available from `https://huggingface.co/allenai/ACE2-ERA5/tree/main/initial_conditions`. ERA5 data are available from `https://cds.climate.copernicus.eu/datasets/reanalysis-era5-pressure-levels-monthly-means?tab=overview`, and MERRA2 data are available from `https://gmao.gsfc.nasa.gov/gmao-products/merra-2/data-access_merra-2/`. The OISST data are available from `https://www.ncei.noaa.gov/products/optimum-interpolation-sst`, the HadISST data are available from `https://www.metoffice.gov.uk/hadobs/hadisst/`, and the ERSST data are available from `https://www.ncei.noaa.gov/products/extended-reconstructed-sst`. The code to compute the components of the tropical cyclone activity proxy are available from `https://github.com/tlhsieh/tropical_cyclone_seeds` and `https://github.com/wy2136/wython/tree/main/xtci/shared`. The TC seed dataset of Ikehata and Satoh (2021) is available at `https://doi.org/10.5281/zenodo.5136292`, the low pressure system dataset of Vishnu et al. (2020) is available at `https://portal.nersc.gov/cfs/m3310/VishnuEtAl_TrackDataset/`, and the seed dataset of Moon et al. (2025) is available at `https://doi.org/`

10.5281/zenodo.15227119. The code to run one year's 1,000-member ensemble and process the output, and track TCs is available at https://github.com/emmalevin/ACE2_1000. TC track data and monthly mean environmental conditions generated from the ACE2 1,000 member ensemble are available at the Zenodo repository: https://doi.org/10.5281/zenodo.19456833 (Levin 2026).

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