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1 **Large climate model ensembles reveal underdispersion in seasonal Atlantic**  
2 **tropical cyclone counts**

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9 ABSTRACT: Seasonal Atlantic tropical cyclone (TC) counts are commonly modeled as a condi-  
10 tional Poisson process, implying that the distribution of possible seasonal outcomes—the range of  
11 TC counts that could plausibly occur in a given year—exhibits equidispersion for a given climate  
12 state, with its variance equal to its mean. This assumption underlies many statistical frameworks  
13 used for seasonal TC prediction and risk assessment, yet to the best of our knowledge has not been  
14 extensively tested directly. Using large ensembles from physics-based climate models (AM2.5-  
15 C360 and HiRAM) and a deep learning-based climate emulator (ACE2; Ai2 Climate Emulator  
16 version 2), we examine the distributional properties of seasonal TC counts in a controlled modeling  
17 framework. Across all models and years, we find that the ensemble distribution of within-season TC  
18 counts is systematically underdispersed, with ensemble variances smaller than their corresponding  
19 means. This behavior violates the equidispersion implied by a Poisson process and is consistent  
20 with a finite opportunity or binomial framework. This interpretation of TC genesis suggests that  
21 storms arise from a limited number of precursor disturbances whose likelihood of development  
22 depends on large-scale environmental conditions. We fit seasonal TC count distributions from  
23 a 1,000-member ACE2 ensemble to the Poisson and binomial distributions and find statistical  
24 evidence that the binomial formulation provides a better fit to TC count distributions. The Poisson  
25 assumption is not supported by current climate model simulations, given that simulated seasonal  
26 TC counts are more constrained than implied by traditional Poisson-based frameworks.

27 SIGNIFICANCE STATEMENT: Seasonal Atlantic tropical cyclone (TC) forecasts are critical  
28 for risk preparedness, energy planning, and insurance decision-making. Many statistical models  
29 used for these forecasts assume that TCs occur randomly, following a Poisson process. Leveraging  
30 unprecedentedly large ensembles from state-of-the-art physics-based and deep-learning climate  
31 models, we show that simulated seasonal TC counts systematically violate this assumption. Instead,  
32 TC counts are more constrained. This behavior is consistent with a physical picture in which TCs  
33 arise from a finite number of precursor disturbances ('seeds') whose likelihood of development  
34 depends on the large-scale environment. These results motivate more physically grounded statistical  
35 models for seasonal TC prediction.

## 36 **1. Introduction**

37 North Atlantic Tropical cyclones (TCs) can cause tens to hundreds of billions of dollars in  
38 damage annually in the United States, Americas, and Caribbean (Klotzbach et al. 2018), as well  
39 as mortality both coincident with the storm and for the years following (Young and Hsiang 2024).  
40 Understanding the controls on seasonal TC activity and developing accurate seasonal forecasts  
41 are an element of risk preparedness, energy planning, and insurance decision-making. Seasonal  
42 outlooks, issued prior to the climatological June through November TC season, predict the number  
43 of storms that will form throughout the season. These forecasts are generated using a range of  
44 modeling approaches, including dynamical climate models (e.g., Chen and Lin 2013; Murakami  
45 et al. 2016b, 2025; Vecchi et al. 2014; Zhao et al. 2010), deep learning (DL)-based weather  
46 prediction models (Zhang et al. 2025), and statistical or statistical-dynamical frameworks (e.g.,  
47 Vecchi et al. 2011; Villarini et al. 2019). Seasonal TC predictions will necessarily be probabilistic  
48 in nature (Vecchi et al. 2014), so understanding both the expected TC activity and the plausible  
49 deviations from it are essential.

50 Statistical and statistical-dynamical approaches relate large-scale environmental conditions, such  
51 as sea surface temperature (SST), vertical wind shear, and atmospheric humidity, to seasonal  
52 Atlantic TC activity. Based on the statistical relationships of large-scale conditions to TCs, these  
53 approaches model the plausible distribution of seasonal TC counts conditioned on the large-scale  
54 environment for the given year. Early statistical studies (e.g., Gray 1984; Gray et al. 1992) used  
55 linear regression to link environmental predictors to TC counts, but such approaches can yield

56 non-integer predictions that are not physically meaningful for discrete storm counts. Subsequent  
57 developments innovatively addressed this limitation by explicitly modeling TC counts using discrete  
58 probability distributions. The canonical choice has been the Poisson distribution (e.g., Davis et al.  
59 2015; Elsner and Jagger 2004, 2006; Jagger and Elsner 2010; Murakami et al. 2016a; Villarini  
60 et al. 2012), which provides a natural framework for count data. Additionally, Li et al. (2023) and  
61 Villarini et al. (2010) went to length to explore whether a Poisson model or Negative Binomial  
62 discrete model was better to fit the distribution of possible seasonal TC counts, and found that the  
63 Poisson model was better suited.

64 In the Poisson formulation, seasonal TC activity is assumed to arise from a Poisson process:  
65 storm occurrences within a season are treated as independent in time, each with a small probability  
66 of occurring within an infinitesimal interval, while their accumulation over the TC season yields a  
67 finite number of events. The process is fully characterized by a single rate parameter, representing  
68 the expected seasonal TC count, conditioned on the large-scale environmental conditions. Statis-  
69 tical and statistical–dynamical studies therefore seek to estimate this conditional rate parameter,  
70 typically via Poisson regression, by relating large-scale environmental conditions to the expected  
71 number of storms in a given season. A key implication of this assumption is equidispersion,  
72 meaning that the variance of the seasonal TC count distribution equals its mean.

73 The Poisson formulation is attractive due to its mathematical simplicity and minimal parameter-  
74 ization with one free parameter (i.e., seasonal rate parameter), and it is often motivated by viewing  
75 TC formation as the outcome of many random independent trials with a low probability of success  
76 at any given time (Blitzstein and Hwang 2014). However, the assumption that seasonal TC counts  
77 are equidispersed is a modeling convenience and statistical fit from several models (Villarini et al.  
78 2010), rather than a physically derived constraint.

79 Several alternative discrete distributions have been proposed to represent seasonal TC counts. For  
80 example, Li et al. (2023) and Villarini et al. (2010) explored a negative binomial distribution, which  
81 allows for overdispersion relative to the Poisson model. In contrast, Vecchi et al. (2019) and Hsieh  
82 et al. (2020) propose that climatological TC activity be viewed through a binomial framework in  
83 which TC formation is viewed as a sequence of Bernoulli trials, with a finite number of precursor  
84 disturbances or seeds providing the number of trials for a given season. In this formulation,  
85 both seed frequency and the probability that a seed develops into a TC depend on the large-scale

86 environment, although the climate dependence of each is different. These alternative approaches  
87 imply fundamentally different dispersion properties of the seasonal TC count distribution. While  
88 the Poisson distribution is equidispersed, the negative binomial distribution is overdispersed (with  
89 the distribution variance larger than its mean), and the binomial distribution is underdispersed (with  
90 the distribution variance smaller than the mean) (Johnson et al. 2005). Dispersion plays a central  
91 role in seasonal TC prediction, as it governs the spread of possible outcomes for a given season.  
92 Differences in dispersion affect the probability of extremely active or inactive seasons, which  
93 correspond to outcomes with substantially different predictability and possibly distinct societal  
94 and economic consequences. Despite its importance, the equidispersion assumption underlying  
95 the Poisson formulation has rarely been tested directly, largely due to limited sample sizes in  
96 observations and traditional modeling frameworks.

97 A rigorous evaluation of the appropriate distribution for seasonal TC counts requires examining  
98 the distribution of simulated or forecasted counts across a large ensemble for a given season.  
99 In such ensembles, each member experiences identical large-scale environmental forcing, such  
100 as SST, but differs slightly in its initial conditions, representing a plausible realization of that  
101 season’s TC activity. Confidence in quantifying dispersion and performing goodness-of-fit tests  
102 for discrete count distributions therefore requires a sufficiently large number of ensemble members,  
103 as these higher moments are less well constrained in typical dynamical model ensembles (order  
104 ten members).

105 Traditional seasonal TC prediction systems from physics-based numerical models are generally  
106 limited in ensemble size because of substantial computational costs. For example, the seasonal  
107 forecasting systems described in Murakami et al. (2025) and Zhang et al. (2025) employ approx-  
108 imately ten to fifteen and 20 ensemble members, respectively, and the AM2.5-C360 and HiRAM  
109 simulations used to examine multidecadal variability in Kortum et al. (2024) and Levin et al.  
110 (2026b) are limited to five to ten ensemble members. Such ensemble sizes are insufficient to  
111 robustly assess the distributional form and dispersion properties of seasonal TC counts.

112 Recent advances in DL-based weather and climate models provide an opportunity to overcome  
113 this limitation. Once trained, these models can be run efficiently at a fraction of the computational  
114 cost required by conventional dynamical models, enabling the generation of very large ensembles  
115 (e.g., Bi et al. 2023; Chen et al. 2023; Lam et al. 2023; Lang et al. 2024; Kochkov et al. 2024; Watt-

116 Meyer et al. 2025). These systems have been shown to realistically reproduce TC characteristics  
117 across subseasonal to interannual timescales (Chien et al. 2025) and recover a well-calibrated  
118 representation of internal variability of seasonal TC activity (Levin et al. 2026a). In this study,  
119 we leverage idealized and historical simulations from two atmosphere-only models developed at  
120 the Geophysical Fluid Dynamics Laboratory (GFDL), AM2.5-C360 and HiRAM, as well as a  
121 state-of-the-art DL-based climate emulator, ACE2, to generate large ensembles of seasonal TC  
122 counts. In particular, we use a 1,000-member ensemble from ACE2 to enable robust distributional  
123 and dispersion diagnostics.

124 This study addresses the following research question: Do seasonal Atlantic TC counts produced  
125 by state-of-the-art climate models satisfy the equidispersion implied by a Poisson process, or do  
126 they exhibit systematic departures consistent with alternative generative mechanisms? We further  
127 examine whether these properties are consistent across models with fundamentally different internal  
128 dynamics. In the following sections, we describe the models and experiments used in this analysis  
129 (Section 2), present evidence that seasonal Atlantic TC counts are underdispersed relative to  
130 Poisson expectations (Section 3), and discuss the implications of these findings for statistical TC  
131 prediction models, physical interpretations of TC genesis, and the use of large ensembles from  
132 AI-based climate emulators (Section 4).

## 133 **2. Methods and data**

### 134 *a. Models and experiments*

135 To simulate large ensembles of annual Atlantic TC seasons, we use a combination of global high-  
136 resolution dynamical atmospheric models and an DL-based climate and weather emulator. The  
137 dynamical models used in this study were developed at GFDL and implemented on the Princeton  
138 computing system (Chen and Lin 2013; Chan et al. 2021; Hsieh et al. 2020; Kortum et al. 2024;  
139 Levin et al. 2026b; Yang et al. 2021; Zhao et al. 2009): AM2.5-C360 and HiRAM.

140 We analyze a suite of idealized experiments with the dynamical models forced with distinct  
141 SST patterns. To generate large ensembles of TC activity under identical boundary forcing, each  
142 experiment is integrated for several decades, typically between 30 and 200 years. Each simulated  
143 year represents a plausible realization of TC activity under the prescribed SST pattern, since the  
144 boundary conditions remain fixed and the only source of variability arises from differences in

145 initial conditions. In this way, each experiment produces 30 to 200 ensemble members of seasonal  
146 TC activity. The experiments, summarized in Table 1, largely follow the designs used in previous  
147 studies (e.g., Hsieh et al. 2020, 2022). All experiments use prescribed monthly SST fields that  
148 remain fixed throughout the integration.

149 Each experiment builds on a control simulation in which both models are forced with the annual  
150 cycle of SSTs averaged over 1986 to 2005. This climatological cycle is repeated for 200 years in  
151 HiRAM and 100 years in AM2.5-C360 after a 10-year spin-up. The resulting long-term means  
152 represent the statistically steady-state climatological baselines for each model. TCs are tracked  
153 for every simulated year, and because the boundary conditions do not vary, each year is treated as  
154 an independent ensemble member characterizing TC activity under mean 1986–2005 conditions.  
155 Because the autocorrelation in aggregate of annual TC statistics is effectively zero, differences in  
156 ensemble members represent the result of internal atmospheric variability. Additional experiments  
157 apply perturbations to this baseline, including a uniform  $+2K$  and  $+4K$  SST warming and  $-2K$  and  
158  $-4K$  SST cooling to the 1986-2005 climatology. We also analyze several experiments to represent  
159 isolated perturbations of greenhouse gas radiative forcing, where we double ( $2 \times CO_2$ ) carbon  
160 dioxide concentrations and multiply carbon dioxide concentrations by five ( $5 \times CO_2$ ) relative to  
161 the control experiment. Additionally, we explore an experiment where we both double atmospheric  
162 carbon dioxide concentrations and uniformly warm the climatological 1986-2005 SSTs by  $+2K$   
163 ( $+2K \ 2 \times CO_2$ ). These experiments are also described in Hsieh et al. (2020, 2022); Eusebi et al.  
164 (2025); Kortum et al. (2024); Levin et al. (2026b); Yang et al. (2021).

165 To investigate the influence of El Niño Southern Oscillation on Atlantic TC activity, we also  
166 explore El Niño and La Niña experiments, which are explained in Hsieh et al. (2022). In these  
167 cases, the prescribed SST annual cycles are derived from the strongest events between 1980 and  
168 2015. The El Niño experiment (+Niño) uses the mean SST fields from nine years with Oceanic  
169 Niño Index (ONI) values greater than +1 (1982, 1986, 1987, 1991, 1994, 1997, 2002, 2009, 2015).  
170 The La Niña experiment (+Niña) uses the mean of seven years with ONI values below -1 (1988,  
171 1995, 1998, 1999, 2007, 2010, 2011). Additionally, we analyze two additional experiments to  
172 highlight the contrast between El Niño and La Niña conditions. In the +Nina-Niño (+Nino-Niña)  
173 experiment are forced by subtracting the mean SST fields from the nine most active El Niño (seven  
174 most active La Niña) years between 1980 and 2015 from the seven most active La Niña (nine most

177 TABLE 1. List of idealized experiments used in this study, which are also used in Hsieh et al. (2020, 2022);  
 178 Eusebi et al. (2025); Kortum et al. (2024); Levin et al. (2026b); Yang et al. (2021).

| Experiment              | Years (and models)            | Description   |
|-------------------------|-------------------------------|---|
| CTL                     | 100 (AM2.5-C360), 200 (HiRAM) | 1986-2005 monthly climatological mean SSTs                                      |
| +2K                     | 50 (both)                     | Uniform SST warming   |
| +4K                     | 50 (HiRAM only)               | Uniform SST warming   |
| -2K                     | 30 (HiRAM only)               | Uniform SST cooling   |
| -4K                     | 30 (HiRAM only)               | Uniform SST cooling   |
| 2×CO <sub>2</sub>       | 50 (both)                     | CO <sub>2</sub> doubling  |
| p5×CO <sub>2</sub>      | 40 (HiRAM only)               | ×5 CO <sub>2</sub> increase   |
| +2K & 2×CO <sub>2</sub> | 50 (both)                     | Uniform SST warming and CO <sub>2</sub> doubling                                |
| +Niño                   | 50 (both)                     | SST annual cycles averaged over strong El Niño years                            |
| +Niña                   | 50 (both)                     | SST annual cycles averaged over strong La Niña years                            |
| +Niño-Niña              | 50 (HiRAM only)               | SST annual cycles averaged over strong El Niño years minus strong La Niña years |
| +Niña-Niño              | 50 (HiRAM only)               | SST annual cycles averaged over strong La Niña years minus strong El Niño years |

175 active El Niño) years during that time frame. All aforementioned simulations maintain a constant  
 176 carbon dioxide concentration, with the exception of the 2×CO<sub>2</sub> experiments.

179 We also analyze multi-ensemble experiments with both models to represent historical TC seasons,  
 180 described in detail in Levin et al. (2026b). For AM2.5-C360 we generated ten ensemble members,  
 181 and for HiRAM we generated five ensemble members. Each member was forced with bias-  
 182 corrected observed monthly SSTs (Chan et al. 2021) from the Hadley Centre Sea Ice and Sea  
 183 Surface Temperature (HadISST) dataset for the period 1871–2021, and each was initialized with  
 184 distinct atmospheric conditions while sharing identical SST forcing. Although ensembles of five  
 185 or ten members are not sufficiently large to fit a discrete probability distribution to the outcomes,  
 186 they allow us to evaluate the dispersion of simulated seasonal TC counts by examining the ratio of  
 187 the ensemble variance to the ensemble mean.

188 In this study, we employ the DL-based Ai2 Climate Emulator version 2 (ACE2; Watt-Meyer  
 189 et al. (2025)) trained on ERA5 reanalysis (Hersbach et al. 2020) to perform huge ensemble annual  
 190 simulations of several Atlantic TC seasons. The model is forced by observed HadISST SSTs  
 191 (Schneider et al. 2013) and by annually varying greenhouse gas concentrations. Previous studies  
 192 have demonstrated that ACE2 can reproduce subseasonal and interannual global TC behavior  
 193 (Chien et al. 2025) and recover a well-calibrated representation of internal seasonal Atlantic TC

194 variability (Levin et al. 2026a), motivating our use of the model to generate large ensembles of  
195 Atlantic TC seasons to investigate the range of plausible outcomes. We generate 1,000 ensemble  
196 members for the continuous period 2005-2020 and for the anomalously inactive 1982 Atlantic TC  
197 season following the methods of Levin et al. (2026a).

### 198 *b. Data and storm tracking*

199 For the historical record of observed Atlantic TC counts from 1878 to 2024, we utilize the  
200 adjusted dataset developed using the methods of Landsea et al. (2010) and assessed in Villarini  
201 et al. (2011), where we require that storm maximum wind speeds must exceed  $17 \text{ m s}^{-1}$  for at least  
202 48 hours.

203 We follow the approach described in Levin et al. (2026b) to track TCs and seed disturbances  
204 in both dynamical models. Specifically, we apply the tracking algorithm of Harris et al. (2016),  
205 which identifies candidate storms based on local minima in sea level pressure and applies additional  
206 thresholds on vorticity, warm-core structure, wind speed, and duration. Consistent with Villarini  
207 et al. (2011), we require all identified TCs to have a minimum lifetime of 72 hours. To track TCs  
208 in the ACE2 DL model, we adopt a similar approach following Chien et al. (2025) and Levin et al.  
209 (2026b). In this case, we use the TempestExtremes algorithm (Ullrich and Zarzycki 2017), which  
210 also detects systems based on local minima in sea level pressure and applies additional constraints  
211 on wind speed, duration, location, and warm-core structure.

### 212 *c. Theoretical TC proxy*

213 As in Levin et al. (2026b) and Levin et al. (2026a), we employ Hsieh et al. (2020)'s probabilistic  
214 framework, which decomposes annual TC counts into a precursor seed disturbance phase followed  
215 by the phase during which the seed develops into a full TC. Thus, the annual number of Atlantic  
216 TCs is assumed to follow a binomial distribution:

$$N_{TC} \sim \text{binom}(N_s, P), \tag{1}$$

217 where  $N_s$  is the number of seeds and  $P$  is the probability that a seed disturbance transitions into a  
 218 fully developed TC. Consequently, the expected seasonal count of Atlantic TCs  $N_{TC}$ , is given by

$$N_{TC} = N_s \times P. \quad (2)$$

219 In this study, we evaluate the seed–probability framework by using explicitly tracked seed counts  
 220 to estimate  $N_s$ , although the seed proxy developed by Hsieh et al. (2020) has developed a climate-  
 221 conditioned expectation for seed frequency. Additionally, the probability that a seed develops into  
 222 a TC ( $P$ ) is parameterized as a function of the large-scale environmental conditions ( $P(\Lambda)$ ):

$$P \approx P(\Lambda) = \frac{1}{1 + (\Lambda_0/\Lambda)^{1/\gamma}}, \quad (3)$$

223 where  $\Lambda_0 = 0.014$  and  $\gamma = -0.9$  are constant dimensionless fitting parameters, and

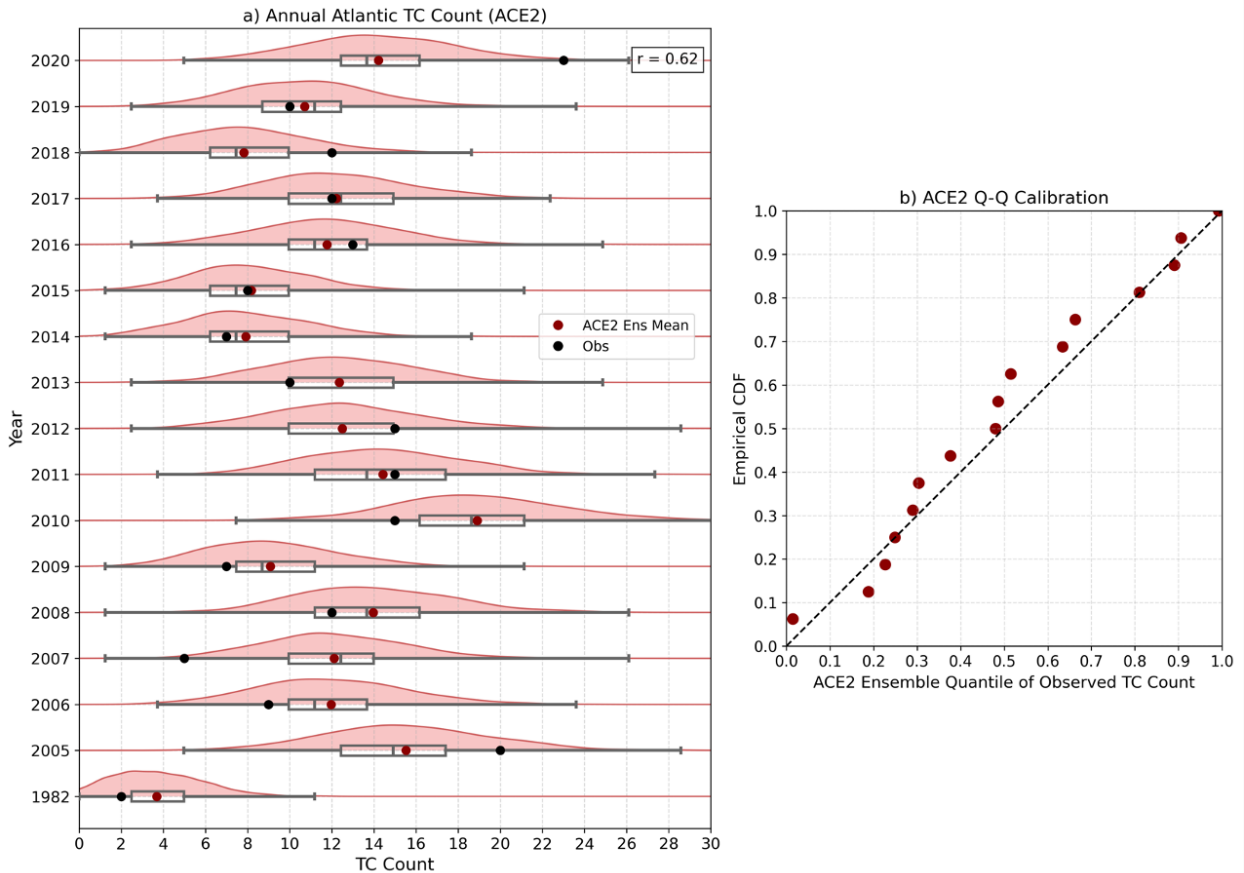
$$\Lambda = \frac{v_s \cdot \chi}{PI}, \quad (4)$$

224 is the ventilation index defined by Tang and Emanuel (2010) and Tang and Emanuel (2012),  
 225 measuring the degree to which entrainment of low entropy air can limit the storm’s intensity.  $v_s$   
 226 is vertical wind shear, PI is potential intensity, and  $\chi$  is moist entropy deficit. As in Levin et al.  
 227 (2026b), We compute the mean Atlantic basin  $P(\Lambda)$  over 10–30°N. Following the methodology  
 228 of Hsieh et al. (2020) and Vecchi et al. (2019), we compute the proxy during the climatologically  
 229 most active portion of the season, June–November.

### 230 3. Results

#### 231 a. *Unprecedentedly large ACE2 historical ensemble*

243 We display the seasonal TC count distributions simulated from the 1,000-member ACE2 his-  
 244 torical ensemble in Figure 1, adapted from Figure 2 of Levin et al. (2026a). Overall, the ACE2  
 245 ensemble exhibits strong calibration to the observed record across multiple metrics. The Q–Q  
 246 calibration diagnostic (Figure 1b) closely follows the 1:1 line, indicating that the observed TC  
 247 counts verify approximately uniformly across the ensemble distributions. This suggests that, in a  
 248 probabilistic sense, the model is well calibrated to the observed record. Consistent with the results



232 FIG. 1. a) The simulated historical observed SST-forced ACE2 1,000-member ensemble distribution of annual  
 233 Atlantic TC counts for 1982 and 2005–2020, shown in red using kernel density estimate (KDE) probability  
 234 density functions, with the corresponding box-and-whisker plots overlaid in gray for each year. The whiskers  
 235 denote the ensemble minimum and maximum values, the box edges represent the 25th and 75th percentiles, and  
 236 the center line indicates the median of the distribution. The red dot represents the ensemble mean, and the black  
 237 dot represents the observed TC count computed using the methods of Landsea et al. (2010). The correlation  
 238 between the annual ensemble-mean TC count and the observed counts is shown in the upper-right corner.  
 239 b) Quantile–quantile (Q–Q) calibration diagnostic of ACE2 over the 17 verification years, where each point  
 240 represents the empirical cumulative distribution of the observed TC count within the corresponding ensemble  
 241 distribution. A well-calibrated ensemble is indicated by alignment with the black dashed 1:1 line. This figure  
 242 has been adapted from Levin et al. (2026a).

249 of the Q–Q plot, the observed TC count lies within the ensemble range for all years considered,  
 250 and falls within the interquartile range (25th–75th percentile) for eight of the seventeen seasons.

251 The correlation between the ensemble-mean and observed TC counts ( $r = 0.62$ ) further indicates  
252 that the model captures a substantial portion of the interannual variability. This retrospective skill  
253 is comparable to that of other dynamical and statistical methods (e.g., Vecchi et al. 2014; Zhao  
254 et al. 2009).

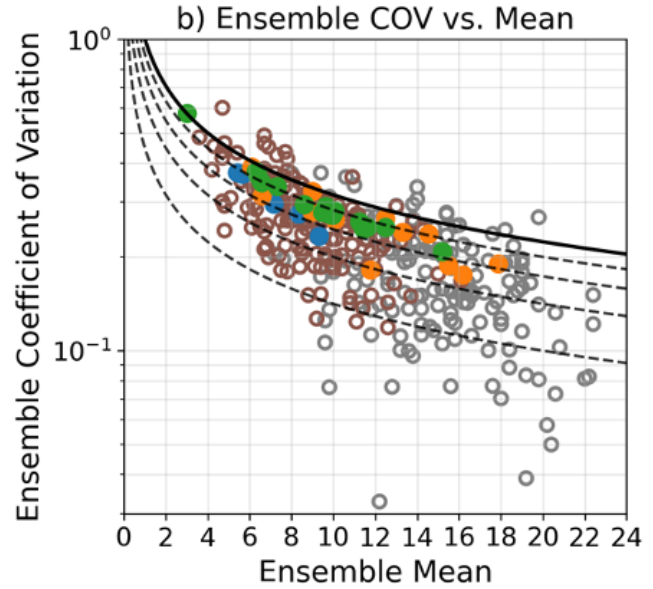
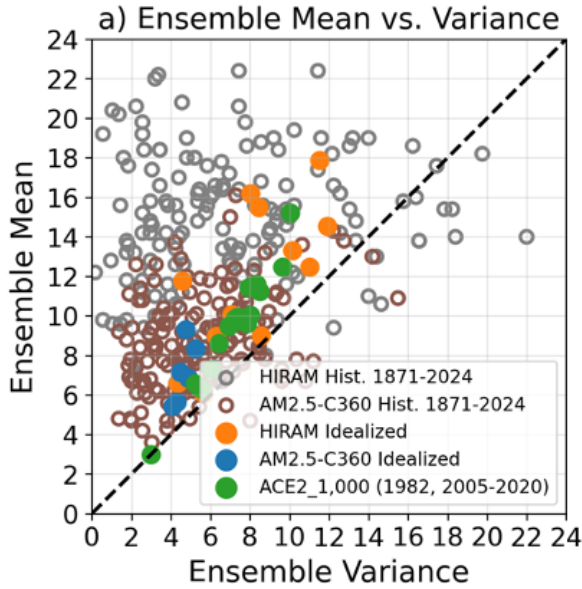
255 The shape and spread of the seasonal distributions also exhibit systematic structure. Most seasons  
256 (eleven out of seventeen) display positive skewness, indicating a tendency toward relatively more  
257 inactive outcomes with a long tail of more active realizations. Fewer seasons are approximately  
258 symmetric (four seasons) or negatively skewed (two seasons). The total ensemble range (maximum  
259 minus minimum count) varies considerably across years, from eleven storms in 1982 to 26 storms  
260 in 2012, highlighting substantial interannual differences in the spread of plausible outcomes.

261 Despite the overall model calibration, there are notable seasons in which the observed TC count  
262 lies in the tails of the ensemble distribution. For example, during the relatively inactive 2007  
263 season (five observed TCs), the ACE2 ensemble distribution is centered around approximately  
264 twelve TCs, placing the observation in the lower tail. Conversely, the 2020 season was extremely  
265 active (23 observed TCs), while the ensemble distribution is centered near fourteen TCs, with the  
266 observed count verifying near the 99.5th percentile (Levin et al. 2026a). This result suggest that  
267 the 2020 season reflected a combination of subseasonal variability and intrinsic unpredictability  
268 that even well-calibrated, state-of-the-art models may fail to capture. Refer to Levin et al. (2026a)  
269 for a well-calibrated distribution of seasonal TC counts for the 2020 season. Finally, while the  
270 kernel density estimates (KDEs) of Figure 1 provide a qualitative visualization of the ensemble  
271 distributions, they are not well suited for quantifying dispersion. In the following section, we  
272 therefore formally assess the dispersion properties of the ACE2 seasonal TC count distributions  
273 and compare them with those from physics-based climate models.

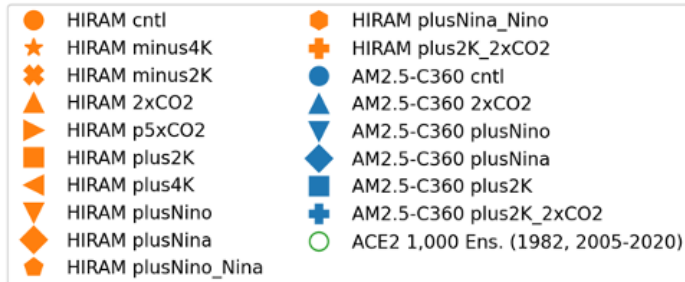
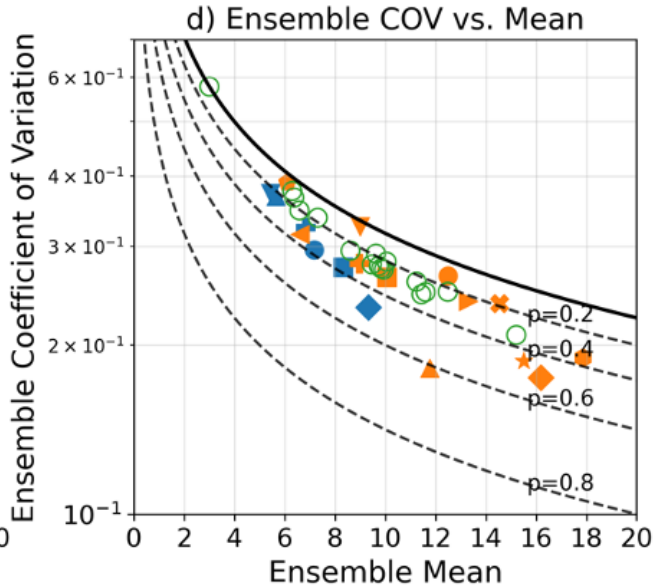
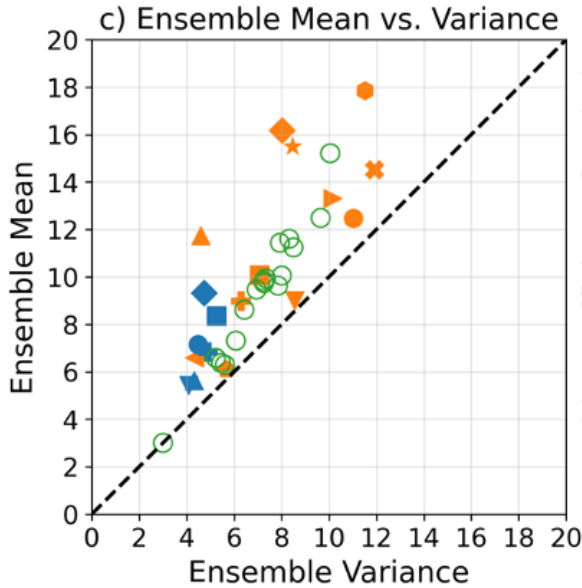
#### 274 *b. Dispersion of simulated conditional TC counts across models*

275 We examine the relationship between the ensemble mean and variance of seasonal Atlantic  
276 TC counts under identical boundary forcing in Figures 2a and 2c across a suite of models and  
277 experiments. For each season, we compute the ensemble mean and ensemble variance of TC  
278 counts subjected to the same prescribed SST forcing, with each point in these figures representing  
279 the mean–variance pair associated with a single season.

### All Experiments



### Experiments with Ensemble Size $n \geq 30$



280 FIG. 2. a) Relationship between the ensemble mean and variance of seasonal Atlantic TC counts under  
 281 identical SST forcing, shown across a suite of models and experiments. Each point corresponds to a single  
 282 season or experiment and represents the variance–mean pair computed from the ensemble distribution of TC  
 283 counts. Brown-outlined (gray-outlined) points denote historical AM2.5-C360 (HiRAM) simulations forced with  
 284 observed SSTs, blue (orange) points indicate idealized experiments from AM2.5-C360 (HiRAM), and green  
 285 points represent the historical 1,000-member ACE2 ensemble. The black dashed line shows the 1:1 relationship,  
 286 corresponding to equidispersion. Points below (above) the line indicate underdispersion (overdispersion). b)  
 287 Relationship between the ensemble mean and the coefficient of variation of seasonal TC counts, using the same  
 288 models, experiments, and color scheme as in panel (a). The solid black curve indicates the Poisson expectation,  
 289  $COV = 1/\sqrt{\mu}$ , while the dashed black curves indicate the Binomial expectation,  $COV = \sqrt{\frac{1-p}{\mu}}$ , where  $p=0.2,$   
 290  $0.4, 0.6,$  and  $0.6,$  labeled in panel d). c,d) Same as panels (a) and (b), respectively, but excluding the smaller-  
 291 ensemble historical AM2.5-C360 and HiRAM simulations. Idealized experiments are distinguished by marker  
 292 shape. Experiments shared across both models (i.e. the 'cntl' experiment) have the same marker shape across  
 293 both models.

294 Across all models and experiments, including both historical and idealized simulations, seasonal  
 295 TC counts are systematically underdispersed. This behavior is evident from the fact that most  
 296 points lie above the 1:1 line, indicating that the ensemble variance is smaller than the ensemble  
 297 mean for most seasons. The only points lying below the 1:1 line are from the smaller ensemble  
 298 sized experiments of HiRAM (five members) and AM2.5-C360 (ten members), where the sample  
 299 variance is less likely to represent the true underlying variance due to the small sample size. Even  
 300 for those historical experiments, the vast majority of points for HiRAM (141/154) and AM2.5-  
 301 C360 (145/154) lie above the 1:1 line. Idealized simulations from AM2.5-C360 and HiRAM  
 302 (Figures 2a and 2c) exhibit this pattern for all experiments. The 1,000-member historical ensemble  
 303 generated using ACE2 (Figures 2a and 2c) also displays pronounced underdispersion, with sixteen  
 304 of the seventeen examined seasons exhibiting variances lower than their corresponding means,  
 305 and none showing overdispersion. The remaining season, 1982, is approximately equidispersed,  
 306 with both the mean and variance near three TCs. This season is exceptionally inactive relative to  
 307 typical TC seasons and represents an outlier within the ensemble. Taken together across several  
 308 state-of-the-art climate models with different underlying dynamics, seasonal Atlantic TC activity

309 violates the equidispersion property of the Poisson distribution and provide clear evidence against  
310 a simple conditional Poisson process description of seasonal TC counts in these models.

311 We further find that the relationship between ensemble mean and variance becomes more tightly  
312 organized as ensemble size increases. For large ensembles with more than 30 members, as in  
313 the ACE2 simulations and AM2.5-C360 and HiRAM idealized experiments shown in Figure 2c,  
314 the mean–variance pairs cluster closely around a well-defined curve and remain within a small  
315 distance of the 1:1 line. In contrast, the AM2.5-C360 and HiRAM historical ensembles, which  
316 contain substantially fewer members (five to ten members), exhibit greater scatter, with some  
317 seasons lying close to the 1:1 line and others deviating more strongly. This behavior is consistent  
318 with sampling variability in the estimation of variance from small ensembles and demonstrates  
319 that larger ensemble sizes yield more robust and stable estimates of the dispersion properties of  
320 seasonal TC counts.

321 In addition to examining the relationship between the ensemble mean and variance, we analyze  
322 how the ensemble coefficient of variation (*COV*) varies with the ensemble mean of seasonal Atlantic  
323 TC counts in Figures 2b and 2d. The *COV* is defined as

$$COV = \frac{\sigma}{\mu}, \quad (5)$$

324 where  $\sigma$  is the ensemble standard deviation and  $\mu$  is the ensemble mean. The *COV* is a dimen-  
325 sionless measure of relative dispersion that quantifies the magnitude of variability normalized by  
326 the mean. Smaller values of *COV* indicate lower relative dispersion, while larger values indicate  
327 greater relative variability. Examining how *COV* varies with  $\mu$  therefore provides insight into how  
328 relative model uncertainty changes for seasons with different levels of simulated TC activity.

329 The expected relationship between *COV* and  $\mu$  differs between common discrete count models.  
330 For a Poisson distribution, the mean and variance are equal, such that  $\mu = \sigma^2 = \lambda$ , where  $\lambda$  is the  
331 rate parameter. In this case,

$$COV_{\text{Poisson}} = \frac{\sigma}{\mu} = \frac{\sqrt{\mu}}{\mu} = \frac{1}{\sqrt{\mu}}, \quad (6)$$

332 implying that the coefficient of variation decreases with increasing mean solely due to counting  
333 statistics. A decreasing *COV* with increasing  $\mu$  is therefore expected under a Poisson process.

334 For a binomial distribution describing  $n$  independent Bernoulli trials with success probability  $p$ ,  
 335 the mean and variance are given by  $\mu = np$  and  $\sigma^2 = np(1 - p)$ . The corresponding COV is

$$COV_{\text{Binomial}} = \frac{\sigma}{\mu} = \frac{\sqrt{np(1-p)}}{np} = \sqrt{\frac{1-p}{\mu}}. \quad (7)$$

336 Both Poisson and binomial models therefore predict that  $COV$  decreases with increasing  $\mu$  and  
 337 scales as  $1/\sqrt{\mu}$ . However, the binomial distribution includes an additional multiplicative factor  
 338 of  $\sqrt{1-p}$ , which suppresses  $COV$  relative to the Poisson expectation for  $0 < p < 1$ . As a result,  
 339 binomial processes predict systematically smaller coefficients of variation than Poisson processes  
 340 at comparable mean values.

341 We examine the relationship between ensemble  $COV$  and ensemble mean  $\mu$  of seasonal Atlantic  
 342 TC counts under identical boundary forcing across a suite of models and experiments in Figures  
 343 2b and 2d. For each season,  $COV$  and  $\mu$  are computed from the distribution of TC counts across  
 344 ensemble members subjected to the same prescribed SST forcing. Each point therefore represents  
 345 a  $COV$ - $\mu$  pair associated with a single season.

346 Across all models and experiments, including both historical and idealized simulations, the  
 347 ensemble  $COV$  decreases with increasing ensemble mean: the relative model uncertainty is smaller  
 348 in seasons with larger simulated activity. While this decreasing trend alone does not distinguish  
 349 between Poisson and binomial processes, we find that the majority of  $COV$ - $\mu$  pairs lie below the  
 350 Poisson expectation given by  $COV = 1/\sqrt{\mu}$ . Instead, these points fall within the range predicted  
 351 by a binomial framework, as illustrated by the curves corresponding to  $COV = \sqrt{(1-p)/\mu}$  for  
 352 representative values of  $p = 0.2, 0.4, 0.6$ , and  $0.8$ . This behavior is evident in both the physics-based  
 353 AM2.5-C360 and HiRAM simulations and is particularly clear in the 1,000-member historical  
 354 ensemble generated using the ACE2 model, for which all seasons except 1982 fall below the  
 355 Poisson curve.

356 Taken together, the systematically reduced  $COV$  relative to the Poisson expectation provides  
 357 further evidence against a simple Poisson process description of seasonal TC counts. Instead, these  
 358 results are consistent with a finite-opportunity or Bernoulli trial framework, in which TC formation  
 359 is governed by a limited number of precursor disturbances and environment-dependent conversion  
 360 probabilities. Furthermore, the clustering of points from the larger ensemble simulations within

361 the binomial expectation curves for  $p$  between 0.2 and 0.4 in Figure 2d suggests that this range  
362 represents a plausible set of effective seed-to-TC conversion probabilities across the modeled  
363 climate states considered here.

364 *c. Goodness-of-fit tests for 1,000 member ACE2 ensemble*

365 Next, we examine the seasonal Atlantic TC count distributional properties of the 1,000-member  
366 ACE2 historical ensemble. The large ensemble size allows robust statistical inference that is not  
367 possible for conventional seasonal prediction systems, which typically include only a few dozen  
368 members. We analyze ensemble distributions for each season in the continuous period from 2005  
369 to 2020 and 1982, with summary statistics for each season reported in Table 2. Each row in the table  
370 represents properties of the seasonal TC count distribution across the 1,000 ensemble members.

371 As shown in Figure 2, all sixteen seasons in the 2005-2020 period exhibit ensemble variances  
372 that are smaller than their corresponding means, indicating systematic underdispersion. Variance-  
373 to-mean ratios range from 0.69 to 0.84 for these years, while coefficients of variation range from  
374 0.21 to 0.38. The strongest deviation from equidispersion between 2005-2020 occurs in 2010,  
375 which has the lowest variance-to-mean ratio and coefficient of variation, while 2018 is closest  
376 to equidispersed behavior during this period. This consistent underdispersion demonstrates that  
377 the equidispersion property implied by a Poisson process is not supported by the ACE2 ensemble  
378 distributions during the 2005-2020 period.

387 To further assess whether the ACE2 simulated Atlantic seasonal TC count distributions are  
388 consistent with a Poisson process, we conduct Monte Carlo experiments. For each season, we  
389 generate 10,000 synthetic ensembles by drawing 1,000 samples 10,000 times from a Poisson  
390 distribution with rate parameter equal to the ACE2 ensemble-mean TC count for that season. For  
391 each synthetic ensemble, we compute the sample variance, yielding a distribution of variances  
392 expected under Poisson sampling variability at the given mean.

393 We illustrate the results for two representative seasons, 2010 and 2018, which span the range of  
394 dispersion characteristics in the ACE2 ensemble during the 2005–2020 period (Figure 3). Monte  
395 Carlo Poisson simulation results for all seasons are shown in Figure S1. Under the Poisson  
396 assumption, the ACE2 ensemble variance for a given season should fall within the distribution of  
397 variances generated by these Monte Carlo simulations.

379 TABLE 2. Characteristics of the seasonal Atlantic TC count distributions derived from a 1,000-member  
380 ensemble of the ACE2 historical simulation forced with observed seasonal SSTs. For each season, ensemble  
381 mean, variance, variance-to-mean ratio, and COV are shown. Akaike Information Criterion (AIC) scores are  
382 computed by fitting the ensemble TC counts to Poisson and binomial distributions using maximum likelihood  
383 estimation and method of moments. We do not include a Binomial fit for the 1982 season, since the estimate of  
384 the number of trials  $\hat{n}$  in the method of moments estimation is negative, rendering the estimation unphysical. The  
385 quantity  $\Delta$  AIC is defined as the AIC of the binomial fit minus that of the Poisson fit, such that negative values  
386 indicate a preferred binomial formulation.

| Year | Mean | Variance | Variance/Mean | COV  | AIC Poisson | AIC Binomial | $\Delta$ AIC |
|------|------|----------|---------------|------|-------------|--------------|--------------|
| 1982 | 2.96 | 2.97     | 1.00          | 0.58 | 3863.8      | –            | –            |
| 2005 | 12.5 | 9.7      | 0.78          | 0.25 | 5129.7      | 5100.7       | -29.0        |
| 2006 | 9.6  | 7.9      | 0.82          | 0.29 | 4909.9      | 4892.3       | -17.6        |
| 2007 | 9.7  | 7.3      | 0.75          | 0.28 | 4851.3      | 4814.6       | -36.7        |
| 2008 | 11.2 | 8.5      | 0.76          | 0.26 | 5009.4      | 4975.9       | -33.5        |
| 2009 | 7.3  | 6.1      | 0.84          | 0.34 | 4636.1      | 4622.2       | -13.9        |
| 2010 | 15.2 | 10.1     | 0.66          | 0.21 | 5217.1      | 5144.8       | -72.3        |
| 2011 | 11.6 | 8.3      | 0.72          | 0.25 | 4999.1      | 4951.9       | -47.2        |
| 2012 | 10.1 | 8.0      | 0.79          | 0.28 | 4931.1      | 4909.5       | -21.6        |
| 2013 | 9.9  | 7.3      | 0.74          | 0.27 | 4874.9      | 4834.3       | -40.6        |
| 2014 | 6.3  | 5.5      | 0.87          | 0.37 | 4526.5      | 4516.8       | -9.7         |
| 2015 | 6.6  | 5.2      | 0.79          | 0.35 | 4494.1      | 4472.8       | -21.3        |
| 2016 | 9.5  | 7.0      | 0.74          | 0.28 | 4817.0      | 4775.4       | -41.6        |
| 2017 | 9.8  | 7.3      | 0.74          | 0.28 | 4850.7      | 4810.9       | -39.8        |
| 2018 | 6.3  | 5.6      | 0.89          | 0.38 | 4550.3      | 4545.9       | -4.4         |
| 2019 | 8.6  | 6.4      | 0.74          | 0.29 | 4730.0      | 4693.3       | -36.7        |
| 2020 | 11.4 | 7.9      | 0.69          | 0.25 | 4964.2      | 4906.6       | -57.6        |

398 Instead, we find that the ACE2 ensemble variance lies in the extreme left tail of the Monte  
399 Carlo distributions for most seasons, indicating substantially reduced ensemble spread relative to  
400 Poisson expectations. This behavior is summarized in Figure 3c, which shows the percentile rank  
401 of the ACE2 ensemble variance relative to the corresponding Poisson-based variance distribution  
402 for each season. For thirteen of the seventeen seasons analyzed, the ACE2 ensemble variance falls  
403 below the minimum variance produced by the Poisson simulations. With the exception of 1982,  
404 for the remaining three seasons, the ACE2 ensemble variance lies below the 5th percentile of the  
405 Monte Carlo distribution.

406 These results provide strong evidence that the ACE2 seasonal TC count distributions are sys-  
407 tematically underdispersed relative to a Poisson process. In particular, the observed variances are  
408 not merely smaller than the Poisson expectation, but fall outside the range of sampling variability  
409 expected under Poisson statistics for most seasons. This indicates that the discrepancy cannot  
410 be attributed to finite-sample effects, but instead reflects a fundamental deviation from Poisson  
411 behavior in the simulated TC count distributions.

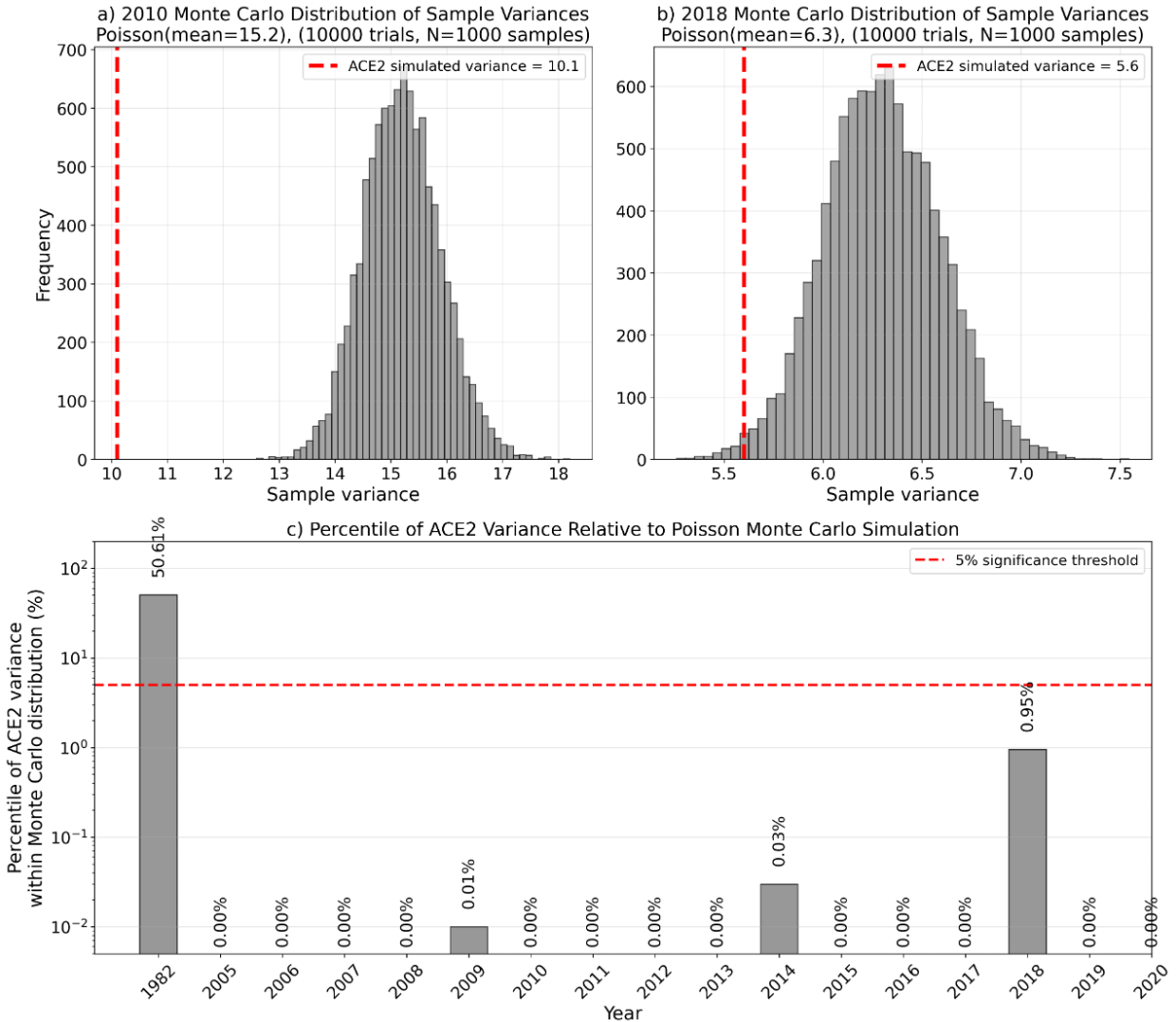
424 Finally, the large ensemble size allows direct likelihood-based comparison of Poisson and bi-  
425 nomial models using the Akaike Information Criterion (AIC). For the historical simulated ACE2  
426 seasons, we fit the 1,000 ensemble TC counts to both distributions. The Poisson model is fit by  
427 setting the rate parameter equal to the sample mean, corresponding to the maximum likelihood and  
428 method of moments estimate. For the binomial model, parameters are estimated using the method  
429 of moments, with the conversion probability given by  $\hat{p} = 1 - s^2/\bar{x}$  and the number of trials given  
430 by  $\hat{n} = \bar{x}/\hat{p}$ , where  $s$  is the sample standard deviation and  $\bar{x}$  is the sample mean. For each fitted  
431 distribution, we compute the AIC,

$$AIC = 2k - 2\ln(\hat{L}), \quad (8)$$

432 where  $k$  is the number of free parameters in the model (one for Poisson, two for Binomial), and  $\hat{L}$   
433 is the maximum likelihood of the model. Thus, the AIC quantifies the trade-off between goodness  
434 of fit and model complexity, allowing objective comparison of competing distributional models  
435 for ensemble TC counts. Lower AIC values indicate a closer approximation to the underlying  
436 data-generating process. AIC values for the ACE2 simulated seasons are listed in Table 2.

437 Across all ACE2 simulated seasons between 2005 and 2020, the binomial model yields a lower  
438 AIC than the Poisson one, indicating superior explanatory power for the ensemble TC count  
439 distributions using a binomial distribution. While this does not rule out other underdispersed count  
440 models for seasonal Atlantic TC count distributions, such as the COM-Poisson or Poisson-binomial  
441 distributions, it demonstrates that the Poisson assumption is not supported by the 2005-2020 ACE2  
442 ensemble data, whereas a Bernoulli-trials framework provides a substantially better description of  
443 the simulated seasonal Atlantic TC counts.

444 Although all seasons from 2005–2020 in the ACE2 historical ensemble exhibit clear underdisper-  
445 sion, characterized by ensemble variances below the 5th percentile of Poisson expectations (Fig. 3)



412 FIG. 3. Monte Carlo assessment of seasonal TC counts Poisson assumption using the 1,000-member ACE2  
 413 ensemble. Panels (a) and (b): For each year (2010 and 2018, respectively), 10,000 Monte Carlo realizations are  
 414 generated by drawing 1,000 samples from a Poisson distribution with mean equal to the ACE2 ensemble mean  
 415 for that season, thereby simulating the ensemble variance that would be expected if seasonal TC counts followed  
 416 a Poisson process. Gray histograms show the resulting distribution of sample variances; the vertical red dashed  
 417 line marks ACE2 ensemble variance. Monte Carlo distributions for all remaining years (1982, 2005–2020) are  
 418 provided in Figure S1. Panel (c): Percentile of the ACE2 ensemble variance within its corresponding Monte  
 419 Carlo variance distribution, indicating how frequently a Poisson process would produce a variance as low as or  
 420 lower than that observed, shown for all available years on a logarithmic scale. The red dashed horizontal line  
 421 marks the 5% significance threshold. With the exception of 1982, the ACE2 ensemble variance falls below the  
 422 5th percentile in every year, confirming that under-dispersion relative to Poisson is a consistent feature of the  
 423 ensemble across the full record.

446 and superior goodness-of-fit to a binomial distribution relative to a Poisson distribution based on  
447 AIC (Table 2), the 1982 season represents a notable exception. As shown in Table 2, the simulated  
448 TC count distribution for 1982 is approximately equidispersed, with its mean and variance nearly  
449 equal. Consistent with this finding, the ensemble variance lies near the 51st percentile of the  
450 Monte Carlo Poisson variance distribution, indicating no clear deviation from Poisson variability  
451 for this particular season. Furthermore, because the ensemble variance slightly exceeds the mean,  
452 the binomial distribution cannot be meaningfully fit: the implied estimate of the number of trials  
453  $\hat{n}$  becomes negative, rendering the parameterization unphysical. Correspondingly, the Poisson  
454 distribution yields the lowest AIC score for 1982 among all candidate models across all years  
455 considered, further supporting the interpretation that this season is consistent with equidispersion.

456 We interpret 1982 as an outlier within both the observational record and the modeled ensemble.  
457 According to the observational dataset of Landsea et al. (2010), 1982 is the least active Atlantic  
458 TC season in the satellite era, with only two observed storms. Such an anomalously inactive  
459 environment likely limits the ability to robustly characterize the underlying distribution of TC  
460 counts, as the small number of events constrains the range of possible variability. Additionally,  
461 because the minimum possible seasonal TC count is zero, when the distribution mean of the  
462 simulated distribution is very low, the distribution variance approaches zero as well, making  
463 dispersion properties difficult to diagnose. In this regime, the distinction between different discrete  
464 distributions becomes less pronounced, and equidispersion can arise naturally due to the low count.

465 Importantly, the presence of other relatively inactive seasons within the ACE2 analysis period,  
466 such as 2007, which also exhibits low observed activity of five storms, does not lead to similar  
467 behavior. These seasons continue to display underdispersion and favor a binomial representation  
468 over a Poisson distribution. This indicates that low activity alone does not imply consistency  
469 with Poisson statistics. Taken together, these results suggest that the near-equidispersed behavior  
470 in 1982 reflects the uniquely extreme and unfavorable environmental conditions of that season,  
471 rather than a breakdown of the broader conclusions. Across all other seasons analyzed, the ACE2  
472 1,000-member ensembles consistently support the conclusion that seasonal TC counts are not well  
473 described by a Poisson process, but are more appropriately represented by a binomial distribution.

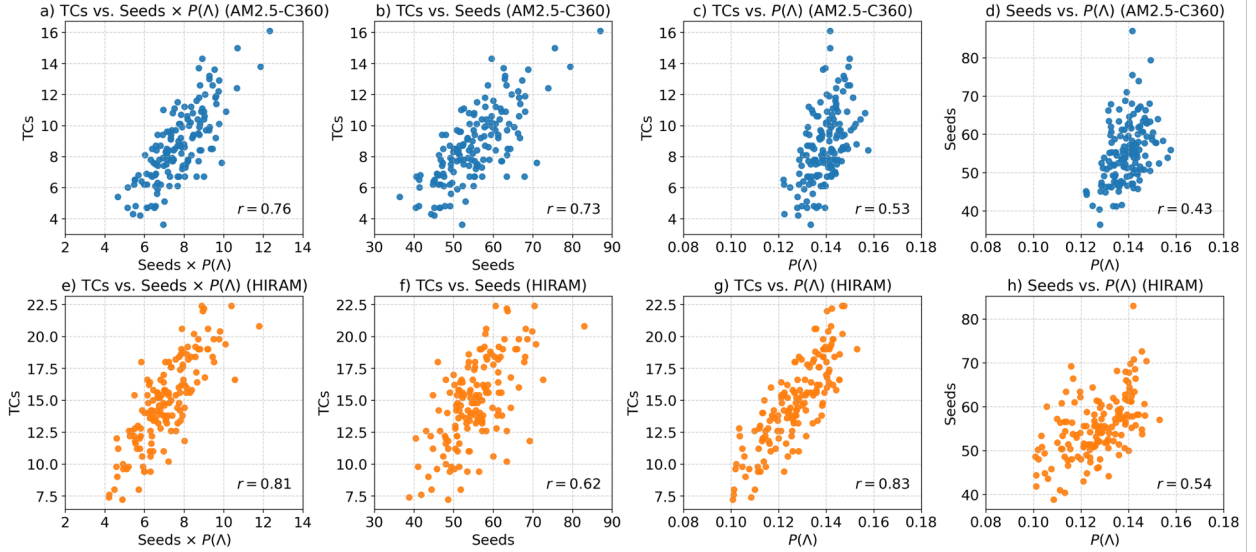
474 *d. Physical basis for the binomial TC framework*

475 The results presented thus far provide strong evidence against describing seasonal TC counts  
476 as a Poisson process. They instead motivate consideration of alternative generative frameworks  
477 in which TC formation is more constrained than implied by purely random arrivals. Here, we  
478 present empirical support for a finite-opportunity or binomial framework for tropical cyclogenesis,  
479 following the conceptual model proposed by Hsieh et al. (2020); in this framework, seasonal  
480 TC counts are interpreted as the number of successes arising from a finite number of precursor  
481 disturbances or seeds, with the probability of each seed developing into a TC governed by large-  
482 scale environmental conditions.

483 Previous studies have demonstrated the utility of binomial-type frameworks for describing TC  
484 variability across a range of timescales, including the annual cycle (Yang et al. 2021) and longer-  
485 term climate variability and idealized experiments (Hsieh et al. 2020, 2022, 2023; Vecchi et al.  
486 2019), especially in the Atlantic basin (Levin et al. 2026b). Building on this work, we explicitly  
487 examine tracked TC seeds and an independent proxy for the environmental conversion probabil-  
488 ity, as described in Section 2, in historical atmosphere-only simulations from AM2.5-C360 and  
489 HiRAM.

490 Figure 4 illustrates the ensemble-mean relationships among simulated seasonal TC counts, the  
491 binomial proxy defined as the product of seed count and conversion probability ( $\text{Seeds} \times P(\Lambda)$ ),  
492 the individual components of this proxy, and the relationship between seed count and conversion  
493 probability. Across both models, we find moderate to strong positive correlations between seasonal  
494 TC counts and each component of the binomial framework. In AM2.5-C360, TC counts are  
495 more strongly correlated with seed count than with conversion probability ( $r = 0.73$  versus  $r =$   
496  $0.53$ ), whereas in HiRAM the opposite is true, with TC counts more strongly correlated with  
497 conversion probability than with seed count ( $r = 0.83$  versus  $r = 0.62$ ). Despite these differences,  
498 the correlation between the full binomial proxy ( $\text{Seeds} \times P(\Lambda)$ ) and simulated TC counts is strongly  
499 positive in both models ( $r = 0.76$  for AM2.5-C360 and  $r = 0.81$  for HiRAM), indicating that the  
500 combined influence of seeds and environmental favorability provides a robust predictor of seasonal  
501 TC activity.

511 We further note that seed count and conversion probability are not independent variables, but  
512 instead exhibit moderate positive covariance in both models ( $r = 0.43$  for AM2.5-C360 and  $r = 0.54$



502 FIG. 4. Scatter plots illustrating relationships between ensemble-mean TC counts, precursor disturbances, and  
 503 conversion probability in historical atmosphere-only simulations forced with observed SSTs during 1871–2021.  
 504 Panels (a,e) show ensemble-mean TC count versus the ensemble-mean approximated TC count, defined as the  
 505 product of seed count and parametrized conversion probability ( $\text{Seeds} \times P(\Lambda)$ ). Panels (b,f) show ensemble-mean  
 506 TC count versus ensemble-mean seed count. Panels (c,g) show ensemble-mean TC count versus ensemble-mean  
 507 parametrized conversion probability  $P(\Lambda)$ . Panels (d,h) show ensemble-mean seed count versus ensemble-mean  
 508 parametrized conversion probability. Top panels correspond to the AM2.5-C360 model (blue), and bottom panels  
 509 correspond to the HiRAM model (orange). Correlation coefficients are reported in the lower-right corner of each  
 510 panel.

513 for HiRAM), consistent with previous findings (Levin et al. 2026b). This covariance suggests  
 514 that environmental conditions conducive to TC formation may simultaneously influence both  
 515 the number of precursor disturbances and their likelihood of development. Taken together, the  
 516 relationships shown in Figure 4 are consistent with a generative picture in which seasonal TC  
 517 counts arise from a finite number of seeds whose conversion probability depends on the large-scale  
 518 environment, rather than from an unbounded Poisson process. However, in spite of this colinearity,  
 519 seeds and genesis probability together provide better explanatory power of seasonal TC frequency,  
 520 as has also been found in other contexts and models (Hsieh et al. 2020; Levin et al. 2026b; Vecchi  
 521 et al. 2019; Yang et al. 2021): seasonal TC frequency arises from the finite probability genesis  
 522 from a finite set of trials (seeds), each of which are climate dependent.

#### 523 **4. Discussion and conclusions**

524 This study provides the first systematic test of the Poisson equidispersion assumption for seasonal  
525 Atlantic TC counts using large state-of-the-art climate model ensembles. By leveraging ensembles  
526 from both physics-based atmosphere-only models (AM2.5-C360 and HiRAM) and a 1,000-member  
527 ensemble generated by a DL-based climate emulator (ACE2), we are able to robustly characterize  
528 the distributional properties of seasonal TC counts under identical boundary forcing across multiple  
529 modeling frameworks. The analysis here indicates that seasonal TC frequency should be best  
530 thought of as a multi-stage process consistent with some recent physically-based arguments (Hsieh  
531 et al. 2020).

532 Several independent lines of evidence consistently support a finite-opportunity interpretation of  
533 TC genesis rather than a Poisson process. First, seasonal TC count distributions are systematically  
534 underdispersed, with ensemble variances smaller than ensemble means across nearly all seasons,  
535 experiments, and models examined. Second, the relationship between the coefficient of variation  
536 and the ensemble mean deviates from the Poisson expectation, with relative uncertainty decreasing  
537 more rapidly in more active simulated seasons than predicted by a Poisson process. Third, Monte  
538 Carlo experiments demonstrate that the observed ensemble variances are inconsistent with those  
539 expected under Poisson randomness. Fourth, likelihood-based comparisons using AIC show that a  
540 binomial distribution provides a superior fit to the seasonal TC count distributions from the 1,000-  
541 member ACE2 ensemble in nearly all seasons examined. Finally, diagnostics based on precursor  
542 disturbances and environmental conversion probability provide physical support for a binomial  
543 framework, consistent with previous studies (Hsieh et al. 2020; Levin et al. 2026b; Sugi et al. 2020;  
544 Vecchi et al. 2019; Yang et al. 2021).

545 These results, implying that simulated TC activity is more constrained than implied by a Poisson  
546 process have important implications:

- 547 • **Statistical modeling of TCs:** Poisson-based formulations may systematically overestimate  
548 uncertainty and misrepresent dispersion structure for seasonal Atlantic TC count distributions,  
549 especially in active seasons. Alternative underdispersed count models, including binomial,  
550 Poisson-binomial, or related formulations, may provide more physically consistent represen-  
551 tations of seasonal TC variability.

552 • **TC forecasting:** The decline in relative ensemble spread during simulated active seasons  
553 (Figures 2b and 2d) implies that models are inherently more confident when environmental  
554 conditions strongly favor TC formation. This behavior has direct relevance for how uncertainty  
555 is communicated in seasonal outlooks, particularly for high-impact seasons. This may arise,  
556 in part, due to the modest colinearity between seed frequency and genesis likelihood (Levin  
557 et al. 2026b).

558 • **Physical interpretability:** The results reinforce the view that TC counts are controlled by  
559 the joint behavior of precursor disturbances (seeds) and environmental conversion probability,  
560 rather than by purely random arrivals. Additionally, the binomial framework offers a physical  
561 mechanism for why the TC count distribution coefficient of variation decreases with the  
562 distribution mean (Figures 2b and 2d), thus the models exhibit less uncertainty for more active  
563 seasons:

564 1. For a binomial distribution, the COV is given by

$$\text{COV} = \sqrt{\frac{1-p}{np}}.$$

565 When the conversion probability  $p$  is held fixed, the COV decreases as  $1/\sqrt{n}$ . Con-  
566 sequently, when a basin experiences a large number of trials or seed disturbances, the  
567 relative spread in total TC counts across the ensemble is reduced. This behavior reflects  
568 a law-of-large-numbers effect: as the number of trials increases, the total number of  
569 successes becomes more tightly constrained and more consistent across realizations.  
570 Thus, in seasons with abundant seeds ( $n$ ), the realized TC counts are intrinsically less  
571 variable.

572 2. A complementary interpretation involves variations in the conversion probability  $p$ .  
573 As shown in Figures 4c and 4g, more active seasons are associated with enhanced  
574 environmental favorability, reflected in higher values of  $P(\Lambda)$ . As  $p$  increases, the  
575 numerator of the COV expression ( $\sqrt{1-p}$ ) decreases, driving the TC count distribution  
576 toward increasingly deterministic outcomes. For example, a conversion probability  
577 of  $p = 0.99$  yields a substantially smaller COV than  $p = 0.5$ . In highly favorable

578 environments, in addition to more seeds being present, nearly every viable seed develops  
579 into a storm, leading to stronger agreement across ensemble members in their simulated  
580 TC activity.

- 581 • **Role of AI models:** This study highlights the unique role of AI-based climate models  
582 in enabling statistical diagnostics that were previously infeasible. The ability to generate  
583 ensembles with thousands of members allows robust estimation of dispersion properties and  
584 formal goodness-of-fit testing for discrete count distributions, opening new opportunities  
585 to re-examine long-standing statistical assumptions in climate science. At the same time,  
586 interpreting these AI-driven results relies critically on a strong understanding of the underlying  
587 physical processes governing storms, the large-scale climate, and their interactions. Together,  
588 this highlights the importance of integrating physical insight with advanced statistical and  
589 computational approaches.

590 Several caveats are important to note. Our analysis is conducted within a controlled modeling  
591 framework, whereas the observational record provides only a single realization of each TC season,  
592 precluding direct empirical estimation of observed seasonal count distributions. Furthermore,  
593 interannual variability in observed TC counts reflects not only stochastic variability within a given  
594 climate state, but also systematic changes in the climate forcing across years, such as SSTs. As  
595 such, variability in observed TC counts can be decomposed as

$$\sigma_{\text{total}}^2 = \sigma_{\text{noise}}^2 + \sigma_{\text{climate}}^2, \quad (9)$$

596 where  $\sigma_{\text{total}}^2$  is the total interannual variance in seasonal TC counts,  $\sigma_{\text{noise}}^2$  represents intrinsic  
597 stochastic variability within a fixed climate state for a given season, and  $\sigma_{\text{climate}}^2$  represents vari-  
598 ability due to changes in the large-scale climate (e.g., SST patterns). In our controlled modeling  
599 framework, large ensembles allow direct estimation of  $\sigma_{\text{noise}}^2$  by holding the climate state fixed. In  
600 contrast, the observational record conflates these two components, making it difficult to directly  
601 assess the intrinsic dispersion of seasonal TC counts.

602 To partially address this limitation and quantify a measure of dispersion in the observed TC  
603 record, we estimate the *conditional dispersion* of the observed seasonal TC counts,  $Y_t^{\text{obs}}$ , for year  
604  $t$ , after accounting for the influence of climate and SST, denoted by  $X_t$ . We define the conditional

605 dispersion as

$$\phi_{\text{obs}|X} \approx \frac{\text{Var}(Y^{\text{obs}} | X)}{\text{E}(Y^{\text{obs}} | X)}, \quad (10)$$

606 where  $\phi_{\text{obs}|X}$  quantifies the dispersion of TC counts conditional on the climate state. Values  
607  $\phi_{\text{obs}|X} < 1$  indicate underdispersion,  $\phi_{\text{obs}|X} = 1$  indicates equidispersion, and  $\phi_{\text{obs}|X} > 1$  indicates  
608 overdispersion.

609 Because only a single observed count is available for each year, we approximate this quantity  
610 using historical atmosphere-only simulations forced with observed SSTs. For each year  $t$ , we define  
611 the residual

$$e_t = Y_t^{\text{obs}} - \hat{\mu}_t, \quad (11)$$

612 where  $\hat{\mu}_t$  is the ensemble-mean TC count from the corresponding model simulation for that year.  
613 To account for mean bias between the model and observations, we apply a single multiplicative  
614 scaling factor to the model output, such that  $\hat{\mu}_t$  represents a bias-corrected estimate of the climate-  
615 conditioned mean TC count.

616 We then estimate the conditional variance from the residuals as

$$\widehat{\text{Var}}(Y^{\text{obs}} | X) = \frac{1}{N-b} \sum_{t=1}^N e_t^2, \quad (12)$$

617 where  $N$  is the number of years and  $b = 1$  is the number of fitted mean parameters (the multiplicative  
618 scaling factor). The conditional mean is estimated as the average ensemble mean TC count across  
619 all years of the model simulation:

$$\widehat{\text{E}}(Y^{\text{obs}} | X) = \frac{1}{N} \sum_{t=1}^N \hat{\mu}_t. \quad (13)$$

620 Substituting these estimates into Equation 10 yields an estimate of the conditional dispersion of  
621 the observational record.

622 We apply this methodology using observed TC counts derived following Landsea et al. (2010) for  
623 the period 1878–2024, and historical simulations from ACE2, HiRAM, and AM2.5-C360 forced  
624 by observed SSTs (Section 2). Results are shown in Table 3. We compute dispersion both including

627 TABLE 3. Conditional dispersion (Equation 10) computed by comparing observed TC counts to historical  
 628 model simulations forced with observed SSTs, using all years and all years excluding 2020.

| Model                  | All years | Excluding 2020 |
|------------------------|-----------|----------------|
| ACE2 (1982, 2005–2020) | 1.17      | 0.82           |
| HiRAM (1878–2024)      | 1.25      | 1.09           |
| AM2.5-C360 (1878–2024) | 1.10      | 0.97           |

625 all years and excluding 2020, which has been identified as a high-leverage outlier for TC counts  
 626 (Levin et al. 2026a).

629 When all years are included, the conditional residuals are modestly overdispersed across all three  
 630 models. However, excluding 2020 leads to a systematic reduction in dispersion across all models.  
 631 For ACE2 and AM2.5-C360, the dispersion becomes less than or near unity, suggesting conditional  
 632 underdispersion or near-equidispersion. In contrast, HiRAM remains slightly overdispersed. These  
 633 results highlight the disproportionate influence of the 2020 season. As an extremely active year,  
 634 2020 lies in the far tail of the ACE2 ensemble distribution and outside the spread of the smaller  
 635 dynamical model ensembles. As a result, it contributes strongly to the residual variance and  
 636 inflates the estimated dispersion. The sensitivity of  $\phi_{\text{obs}|X}$  to the inclusion of a single extreme  
 637 season underscores the limited sample size of the observational record and the challenges of  
 638 estimating dispersion from a single realization per year.

639 More broadly, these results suggest that the dispersion characteristics of the observational record  
 640 remain uncertain when conditioned on climate. Differences across models, as well as sensitivity to  
 641 the inclusion of specific years, indicate that estimates of  $\phi_{\text{obs}|X}$  are influenced not only by intrinsic  
 642 variability but also by model-dependent representations of the climate-conditioned mean. In  
 643 particular, residual variance reflects both true stochastic variability and errors in the estimated mean  
 644 state; imperfect representation of the climate-conditioned mean can artificially inflate dispersion  
 645 estimates. In contrast, large ensemble modeling frameworks provide a more direct and robust  
 646 means of quantifying dispersion, as they allow explicit separation of stochastic variability from  
 647 climate-driven changes in the mean. The consistency of underdispersion identified across physics-  
 648 based models, idealized experiments, and the ACE2 DL emulator, independent of observational  
 649 constraints, suggests that underdispersion is a robust feature of the modeled TC genesis process  
 650 across several modeling frameworks. The observational analysis presented here should therefore

651 be interpreted as a complementary, but inherently limited, attempt to assess dispersion in the real  
652 world.

653 As another caveat, this study focuses exclusively on seasonal Atlantic TC counts, a basin for  
654 which Poisson-based statistical models have been widely applied (e.g., Davis et al. 2015; Elsner  
655 and Jagger 2004, 2006; Jagger and Elsner 2010; Murakami et al. 2016a; Villarini et al. 2012).  
656 Preliminary analysis suggests that qualitatively similar underdispersion in the ensemble spread of  
657 modeled seasonal TC activity is also present in the western North Pacific; however, a quantitative  
658 assessment of whether Poisson or binomial frameworks provide an appropriate description of  
659 seasonal TC counts in that basin is beyond the scope of this study. Future work should therefore  
660 examine dispersion properties across additional basins and evaluate the suitability of alternative  
661 discrete count models, particularly given the use of Poisson formulations for TC counts in regions  
662 such as the Pacific (McDonnell and Holbrook 2004).

663 Finally, our results do not assess model accuracy or forecast skill. Several seasons, including  
664 2007 and 2020, lie in the extreme tails of the model-simulated TC count distributions (Figure  
665 1), indicating that accurate prediction of individual seasons remains challenging. As discussed  
666 in Levin et al. (2026a), and expected from the intrinsically probabilistic nature of seasonal TC  
667 information (e.g., Vecchi and Villarini 2014; Vecchi et al. 2014), such discrepancies may arise from  
668 the intrinsic unpredictability of subseasonal atmospheric variability rather than deficiencies in the  
669 model representation of TC genesis itself. Our findings instead clarify how climate models generate  
670 distributions of possible seasonal outcomes and provide a physically grounded interpretation of  
671 their dispersion properties.

672 Overall, this work demonstrates the value of combining physics-based and DL-based climate  
673 models to rigorously test foundational statistical assumptions. By showing that seasonal TC counts  
674 in climate models are underdispersed and more constrained than implied by Poisson randomness,  
675 we motivate the development of more physically grounded statistical frameworks for seasonal TC  
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687 *Data availability statement.* Source code of the HiRAM model is available from [https://](https://www.gfdl.noaa.gov/hiram-quickstart)  
688 [www.gfdl.noaa.gov/hiram-quickstart](https://www.gfdl.noaa.gov/hiram-quickstart), and the source code of the ACE2 model is available  
689 from <https://github.com/ai2cm/ace>. The code to run one year’s 1,000-member ensemble  
690 and process the output, and track TCs is available at [https://github.com/emmalevin/ACE2\\_](https://github.com/emmalevin/ACE2_1000)  
691 [1000](https://github.com/emmalevin/ACE2_1000). TC track data and monthly mean environmental conditions generated from the ACE2 1,000  
692 member ensemble are available at the Zenodo repository: [https://doi.org/10.5281/zenodo.](https://doi.org/10.5281/zenodo.19456833)  
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