

# SPIN (v1.0): A Spontaneous Synthetic Tropical Cyclone Model Empowered by NeuralGCM for Hazard Assessment

Yurong Gao<sup>1</sup>, Dazhi Xi<sup>1</sup>

<sup>1</sup>Department of Earth and Planetary Sciences, The University of Hong Kong, Hong Kong, 0000, China

**Correspondence:** Dazhi Xi (dazhixi@hku.hk)

**Abstract.** A hybrid framework for simulating SPontaneous synthetic tropical cyclones (TCs) with realistic INtensity, hereafter SPIN, is developed for TC risk assessment. ~~A key advantage of SPIN over previous~~Unlike earlier statistical synthetic TC models ~~is that it avoids~~, SPIN retains intra-month variability and provides ~~the assumption of independence between TCs, while enabling two-way interactions between synthetic TCs and their~~ ambient environment, ~~for each storm~~. The SPIN model leverages a Neural General Circulation Model (NeuralGCM) to simulate spontaneously generated TC tracks, and then couples a ~~dynamied~~dynamical TC intensity model to estimate their intensity ~~evolution~~evolution based on the large-scale environment. SPIN~~It~~ reproduces ~~the key features of~~ observed TC climatology ~~of TC activity~~, including interannual variability, seasonal cycle, genesis, ~~tracks~~, and ~~track patterns~~, lifetime ~~maximum intensity distributions~~. It also ~~faithfully reproduces the observed return periods of regional~~ landfall ~~intensity across different regions, enabling its future application to TC risk assessment~~ return periods and inter-genesis intervals. It also improves the representation of interannual TC variability in basins where ENSO-related influences are spatially mixed. Beyond individual TC events, SPIN~~the model~~ demonstrates improved ~~skills~~skill in representing multiple tropical cyclone events (MTCEs), ~~including capturing their interannual~~year-to-year variability, ~~peak concurrent TC count per and~~ cluster, ~~and the spatial relationship between consecutive TCs~~. By circumventing the independent TC assumption and allowing for two-way TC environment interactions, SPIN opens new potential for assessing size. SPIN advances TC risk assessment by enabling compound TC hazards like MTCE, such as MTCEs and beyond, to be assessed as dynamically organized events rather than statistical co-occurrences alone.

## 1—Introduction

Tropical cyclones (TCs) are among the most destructive hazards in coastal regions. On average, about 90 TCs form worldwide each year (Emanuel, 2006; Zhou and Lin, 2024), affecting 20.4 million people annually and causing mean direct economic losses of 51.5 billion USD over the past decade (Krichene et al., 2023). Beyond the impacts of individual storms, back-to-back TCs (Fu et al., 2025; Xi et al., 2023; Xi and Lin, 2021) can lead to especially severe impact, as communities may not recover from one event before the next occurs (Zscheischler et al., 2018). These societal consequences underscore the importance of assessing not only the risks of individual TCs but also those arising from their clustering.

Style Definition: Balloon Text

Style Definition: Footer

Style Definition: Kontakt

Style Definition: Name

Style Definition: Copernicus\_Word\_template

Style Definition: Bibliography: Space After: 0 pt, Line spacing: 1.5 lines

Formatted: English (Hong Kong SAR)

Formatted: English (Hong Kong SAR)

Formatted: English (Hong Kong SAR)

Formatted: English (Hong Kong SAR)

Formatted: English (Hong Kong SAR)

Formatted: English (Hong Kong SAR)

Formatted: English (Hong Kong SAR)

Formatted: English (Hong Kong SAR)

Formatted: English (Hong Kong SAR)

## 1 Introduction

Tropical cyclones (TCs) are among the most destructive hazards in coastal regions. On average, about 90 TCs form worldwide each year (Emanuel, 2006; Zhou and Lin, 2024), affecting 20.4 million people annually and causing mean direct economic losses of 51.5 billion USD over the past decade (Krichene et al., 2023). Beyond the impacts of individual storms, back-to-back TCs (Fu et al., 2025; Xi et al., 2023; Xi and Lin, 2021) can lead to especially severe impact, as communities may not recover from one event before the next occurs (Zscheischler et al., 2018). These societal consequences underscore the importance of assessing not only the risks of individual TCs but also those arising from their clustering.

The high risks associated with TCs lead to the development of TC hazard downscaling frameworks. Over recent decades, two major approaches have been used to downscale TC hazards: statistical and dynamical downscaling. Statistical downscaling models (Bloemendaal et al., 2020; Emanuel et al., 2006; Jing and Lin, 2020; Lee et al., 2018; Lin et al., 2023) provide an efficient way to simulate TCs under given climate conditions. These models are driven by environmental variables and can rapidly generate large numbers of synthetic TCs to estimate the occurrence chances of the extremes, costing minimal computational resources. A common drawback of these models is that the generated TCs do not feedback to the ambient environment. This limitation prevents the representation of two-way interactions between storms and their surroundings. Furthermore, all TCs in these models are assumed to be independent, which is not physically realistic, since storm-storm interactions do occur in nature. One prominent example is multiple TCs have motivated the development of TC hazard downscaling frameworks. Here, “downscaling” denotes approaches that generate event sets large enough for risk assessment, rather than the spatial refinement of gridded meteorological fields. Over recent decades, two major approaches have been used for TC hazard downscaling: statistical and dynamical downscaling. Statistical downscaling models efficiently generate large ensembles of synthetic TCs from large-scale environmental conditions without requiring spatially explicit high-resolution wind fields, enabling estimates of extreme-event likelihoods at low computational cost. Statistical approaches include resampling methods based purely on historical observations (Bloemendaal et al., 2020; Vickery et al., 2000). Although useful for present-day risk assessment, such models are limited in their ability to represent non-stationary climates because they do not explicitly account for changes in the large-scale environment. To address this limitation, environment-dependent synthetic TC models have been developed to allow TC activity to vary with changes in climate conditions. These models differ in how they represent genesis, track and intensity evolution. Examples include statistical-deterministic models incorporating random-seeding frameworks (Emanuel et al., 2008; Lin et al., 2023) and purely statistical frameworks such as CHAZ (Lee et al., 2018) and PepC (Jing and Lin, 2020).

These models have several constraints when applied to compound TC hazard assessment. First, because they are driven by monthly-mean environmental fields, they are not designed to resolve intra-month variability relevant to TC genesis. Second, synthetic TCs are treated as independent events. Third, they do not provide time-evolving ambient environmental fields associated with each storm. These limitations make it difficult for traditional statistical downscaling models to move beyond statistical co-occurrence and represent compound TC hazards as dynamically organized events. Multiple tropical cyclone

events (MTCEs), where two or more TCs occur simultaneously within the same basin (Fu et al., 2023; Schenkel, 2016). ~~with subsequent TCs potentially being preconditioned by synoptic-scale cyclonic disturbances generated by preceding TCs~~ highlight this challenge because they are often controlled by intra-month variability (Gao and Li, 2011; Ito and Yamauchi, 2026) and disturbances from preceding storms (Ritchie and Holland, 1999; Yoshida and Ishikawa, 2013). ~~In addition, for synthetic TC models based on random seeding (Emanuel et al., 2008; Lin et al., 2023), seeds are placed randomly in space and time rather than being diagnosed from evolving circulation fields, which may weaken the representation of interannual variability in TC frequency.~~

By contrast, dynamical downscaling explicitly simulates TCs in numerical models, allowing ~~two-way interactions between the TCs and their storm evolution to be embedded within an evolving~~ environment. However, even the high-resolution models with grid spacing of 4–25 km still have difficulty in representing the most intense TCs (Buonomo et al., 2024; Davis, 2018; Judt et al., 2021). ~~Most~~ More importantly, they ~~are~~ remain prohibitively expensive to run over ~~sufficiently~~ long periods to ~~produce~~ generate the large samples needed for robust TC risk assessment.

~~The recent development of~~ Recent advances in artificial intelligence (AI) weather forecast ~~or~~ and climate models (Bi et al., 2023; Bodnar et al., 2025; Kochkov et al., 2024; Price et al., 2025) (Bi et al., 2023; Bodnar et al., 2025; Kochkov et al., 2024; Price et al., 2025) have made ~~the rapid simulation of it possible to simulate~~ synthetic TCs ~~that can interact with their surrounding environment possibly rapidly within evolving environmental fields~~. Building on this progress, Jing et al. (2024) developed a TC downscaling model based on a data-driven approach that accounts for two-way storm–environment interactions throughout the storm life cycle. Nonetheless, this approach still requires manually seeded vortices rather than permitting spontaneous genesis from environmental fields. In addition, as with numerical models, TCs directly extracted from AI-simulated outputs still tend to underestimate intensity, since the models are trained on ERA5 reanalysis data whose resolution cannot adequately resolve TC structure (Jing et al., 2024). In short, there remains a gap for models that can efficiently generate large ~~storm samples~~ ensembles of synthetic TCs that emerge spontaneously ~~emerging from the environment, co-evolving with it, and environmental fields while~~ achieving realistic ~~maximum~~ intensities and representing intra-month processes.

Rather than functioning like most AI weather forecast models, the Neural General Circulation Model (NeuralGCM) (Kochkov et al., 2024) offers sufficient stability for long-term climate simulations by preserving a GCM-like numerical solver for large-scale dynamics while replacing small-scale parameterization schemes with a neural network. ~~It provides hourly large-scale environmental fields and~~ reproduces key climate diagnostics with considerable skill, including realistic TC frequency and trajectories. Recent studies have further demonstrated ~~its~~ NeuralGCM's ability in predicting seasonal TC activity ~~under simplified boundary conditions (Zhang et al., 2025) (Zhang et al., 2025), long-term heatwave projections (Duan et al., 2025), and (Duan et al., 2025), the spectra of large-scale tropical waves (Baxter et al., 2025), and MJO teleconnections (Peings et al., 2026). Broader evaluations also show its skill in simulating extratropical cyclones, interannual teleconnection responses, and large-scale responses to out-of-distribution uniform-warming forcings, comparable to physics-based Earth system models~~

Formatted: Font: 12 pt, English (United States)

(Chen et al., 2026). These features suggest that NeuralGCM provides a suitable basis for developing a synthetic TC  
95 downscaling framework.

In this study, we propose a hybrid framework that functions as a synthetic TC downscaling model, termed SPIN (a  
SPontaneous synthetic tropical cyclone model with INtensity fidelity). The model employs a two-step process: ~~firstly~~first, it  
leverages NeuralGCM (Kochkov et al., 2024) to simulate ensembles of spontaneously generated TC tracks; then, it couples  
these tracks with the FAST TC intensity simulator (Emanuel, 2017; Lin et al., 2023) to compute realistic intensities based on  
100 the large-scale environment. Compared with traditional statistical synthetic TC models, ~~this model~~SPIN provides a more  
physically consistent representation of synthetic TCs and their ambient environment by generating ~~TCs~~storms that emerge  
from ~~evolving environmental fields~~ and ~~interact with the environment~~by explicitly representing intra-month processes, while  
remaining ~~substantially more~~ computationally ~~more~~-efficient than dynamical downscaling. ~~Thus, this model has proved to~~  
~~be~~This makes SPIN particularly ~~advantageous~~well suited for ~~the study of~~studying compound TC hazards such as MTCEs.

105 This paper is organized as follows. Section 2 describes the data used for model development along with the model  
components and evaluation methods. Section 3 evaluates SPIN simulated climatological characteristics of TCs and MTCEs  
against observations. Section 4 compares observed and simulated return periods at different regions of the globe. Section 5  
provides a summary and discussion.

## 2 Materials and ~~Methods~~methods

### 110 2.1 Observational and ~~Reanalysis Data~~reanalysis data

The ERA5 reanalysis data (Hersbach et al., 2020) from 1979 to 2022 at  $0.25^\circ \times 0.25^\circ$  resolution are used to initialize and force  
the NeuralGCM component of SPIN (see Section 2.2). The initialization fields include wind, geopotential, temperature,  
specific humidity, and specific cloud ice and liquid water content on pressure levels, while the forcing consists of sea surface  
temperature (SST) and sea ice concentration (SIC) at the surface level. The simulated TCs are evaluated at both global and  
115 basin scales. We adopt a similar basin classification as Lin et al. (2023), dividing the global ocean into seven basins where  
TCs are prevalent: the Western Pacific (WP), Eastern Pacific (EP), Northern Atlantic (NA), Northern Indian Ocean (NI),  
Southern Indian Ocean (SI), Southern Pacific (SP), and the Australian Basin (AU). The boundaries of each basin are illustrated  
in Figure S1. For model evaluation, we use the USA archive from the International Best Track Archive for Climate Stewardship  
(IBTrACS) (~~Knapp et al., 2010~~)(Knapp et al., 2010), which provides 3-hourly latitude and longitude positions as well as  
120 maximum sustained wind speeds for each storm.

### 2.2 Model ~~Components~~components

The SPIN model follows a two-step approach: (Figure 1). First, it leverages NeuralGCM (Kochkov et al., 2024) to simulate  
ensembles of spontaneously generated TC tracks. Then, FAST intensity model (Emanuel, 2017; Lin et al., 2023) is coupled to

Formatted: Font: (Asian) SimSun, 10 pt, Not Bold, (Asian)  
Chinese (Simplified, Mainland China)



each track to compute realistic intensities based on the large-scale environment. In this way, SPIN generates large samples of TCs that emerge from and interact with the simulated environment.

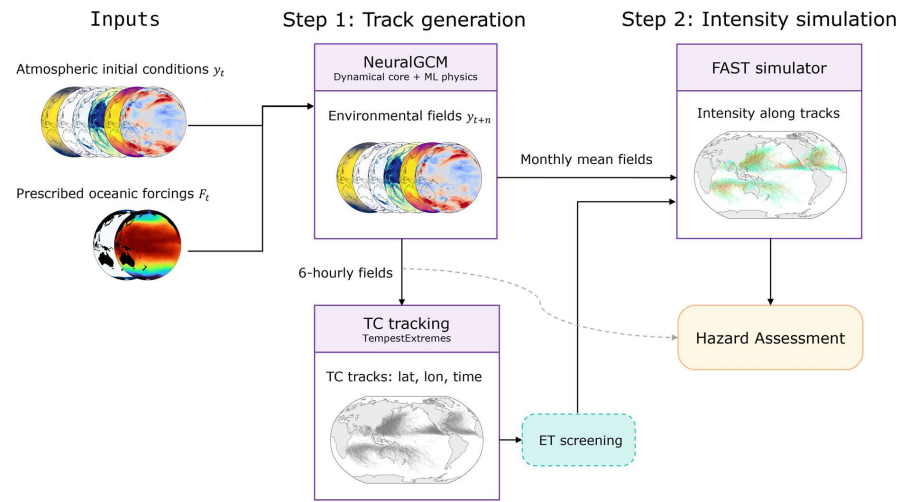


Figure 1.2.2.1. Simulation of Environmental Fields

Workflow of the two-step SPIN modelling framework. In Step 1, atmospheric initial conditions  $y_t$  and prescribed oceanic forcings  $F_t$  are provided to NeuralGCM to generate environmental fields. The simulated 6-hourly environmental fields are used to detect and track TCs with TempestExtremes. Extratropical transition (ET) screening is then applied to the simulated tracks. In Step 2, the generated tracks and simulated monthly-mean environmental fields are passed to the FAST intensity simulator to estimate TC intensity along each track. The synthetic tracks and their ambient environments can then be used for hazard assessment.

2.2.1. Simulation of environmental fields

NeuralGCM is a hybrid physics-machine learning atmospheric model (Kochkov et al., 2024) that preserves a GCM-like numerical solver for large-scale dynamics, while replacing small-scale parameterization schemes with a neural network. It offers orders-of-magnitude computational savings over conventional GCMs and is sufficiently stable for long-term climate simulations. It has been shown to reproduce key climate diagnostics with considerable skill, and demonstrates promising performance in simulating realistic TC activity in tests for the year 2020 (Kochkov et al., 2024).

We use the pre-trained 1.4° deterministic version of NeuralGCM to simulate the environmental fields from which TC tracks are extracted. The 1.4° version is about ten times faster in inference than the 0.7° version while still producing reliable TC

Formatted: Font: Times New Roman  
Formatted: Font: Times New Roman, Not Italic  
Formatted: Font: Times New Roman

activity, and was also adopted in Kochkov et al. (2024). Following Kochkov et al. (2024), we initialize a 14-member ensemble at 6-hour intervals in mid-October of each year from 1979 to 2021. Each ensemble member is integrated from its initialization date through December of the following year, with outputs saved every 6 hours. Simulations are then evaluated for the January–December periods from 1980 to 2022. Monthly SST and SIC fields are linearly interpolated to 12-hourly resolution and updated accordingly to force the model throughout the simulation. The 1.4° version is about ten times faster in inference than the 0.7° version and has been shown in previous studies to reasonably reproduce trajectories and counts of TCs (Kochkov et al., 2024; Zhang et al., 2025). For each target year from 1980 to 2022, we initialize a 14-member NeuralGCM ensemble simulation. The ensemble is generated using lagged initial conditions, with members initialized at 6-hour intervals in mid-October of the preceding year and integrated continuously through December of the target year. For example, the simulations used for the 1980 analysis are initialized in mid-October 1979 and integrated through December 1980. The preceding October–December period is treated as spin-up, and the January–December period of the target year is used for TC tracking and subsequent analysis. All initial and lower-boundary fields are derived from ERA5 (see Section 2.1). The initial atmospheric states include wind, geopotential, temperature, specific humidity, and specific cloud ice and liquid water content on pressure levels. Monthly mean SST and SIC fields are linearly interpolated to 12-hourly resolution and prescribed as lower-boundary conditions throughout the simulations.

Following the NeuralGCM documentation ([https://neuralgcm.readthedocs.io/en/latest/checkpoint\\_modifications.html](https://neuralgcm.readthedocs.io/en/latest/checkpoint_modifications.html)), we fix the global-mean log surface pressure to reduce long-term model drift and enhance numerical stability. Although this adjustment substantially improved the stability of the rollouts, numerical instability still occurs in approximately 1.75% of simulated member months, defined by non-meteorological outliers followed by missing values across the domain at later output steps. To maintain a consistent ensemble size across target years, we generate three additional backup members using the same mid-October initialization protocol but independent initialization times. For each target year, unstable original members are removed before TC detection and replaced by full-year simulations from backup members for the same target year. Backup members are considered in a fixed order. For each target year, the first backup member-year that is both stable and not previously assigned within that target year is used for replacement. Backup member-years that have already been used within the same target year, or are themselves unstable, are skipped.

### 2.2.2. Tracking of TCs

We apply the ~~TempestExtreme~~TempestExtremes method (Ullrich et al., 2021)(Ullrich et al., 2021) to track TCs from the simulated environmental fields, using geopotential and vorticity as primary criteria, and without imposing any minimum wind speed thresholds. In this study, most parameter settings in ~~TempestExtreme~~TempestExtremes are similar with those in Kochkov et al. (2024), who ensures that the global frequency of identified TCs matches the counts obtained from the  $0.25^\circ \times 0.25^\circ$  ERA5 reanalysis data. We further fine-tune parameters separately for each basin, aiming to align the simulated historical annual average number of tracks and storm lifetimes with those reported in the IBTrACS. After track extraction, tracks whose

Formatted: Font: Times New Roman, English (United Kingdom)

[points are located entirely over land are removed](#). A total of 14 ensemble members, each simulated for 43 years, produces approximately 52,000 tracks globally. The ensemble mean number of extracted TCs in each basin agrees well with the observations, without any additional bias correction (Figure S2).

### 2.2.3. Intensity model

TC intensities along the modeled tracks are simulated with the FAST intensity model, originally proposed by Emanuel (2017) and Emanuel and Zhang (2017)(2017), and later extended to the global scale by Lin et al. (2023). FAST is a physically based and computationally efficient model that simulates the maximum sustained wind speed by solving two coupled ordinary differential equations. This model has been successfully used in probabilistic TC forecasting (Lin et al., 2020)(Lin et al., 2020) and in physics-based statistical downscaling frameworks (Lin et al., 2023).

In the Lin et al. (2023; hereafter JL23) framework, only tracks that reach the intensity threshold of  $18 \text{ m s}^{-1}$  within 48 hours are retained, while others are discarded. In our approach, we retain all extracted tracks to maintain consistency with the observed track count. For tracks that do not reach  $18 \text{ m s}^{-1}$  within 48 hours, we apply a bias correction at the 48-hour point and all subsequent times by adding a random constant offset, so that the intensity of 48-hour is at or slightly above  $18 \text{ m s}^{-1}$ , following the protocol of Lin et al. (2023). All model parameters are adopted from Lin et al. (2023), except for the surface enthalpy coefficient ( $C_k$ ), ~~which is regionally-tuned~~. We use  $C_k = 1.05$  as the default setting for the assessment of lifetime maximumall SPIN results presented in this manuscript. This value is slightly smaller than the  $C_k = 1.2$  used in JL23 default settings, as larger values produced an overly heavy upper tail in the simulated LMI distribution under the 6-hourly forced SPIN configuration. No basin- or region-specific tuning is applied. However, this value is not intended to be an optimal calibration for every basin or regional intensity (LMI) and landfall intensity distribution. As noted in the JL23 documentation, model parameters are provided through the namelist for tuning. Users may therefore explore parameter space for application-specific regional hazard assessments. Because the FAST equations require initialization of a random draw to initialize the maximum azimuthal wind speed using a random seeding approach, we, the intensity simulation is not deterministic for a given track and environmental forcing. We therefore perform 10 simulations per track with different random seedsdraws, resulting in 10 intensity realizations for each ensemble member (equivalent to 6020-year of simulation in total). In our analysis, we define TC genesis as the first time the storm reaches  $18 \text{ m s}^{-1}$ , and dissipation as the last time it exceeds this threshold.

### 2.2.4. Extratropical transition screening module

For storms extending into the mid-latitudes, the FAST intensity model may continue to estimate intensity under a TC framework even after the storm has entered environments favourable for extratropical transition (ET) (Jones et al., 2003). This may lead to overestimated intensities and a positive bias in MTCE counts. We therefore implemented an optional ET-screening module that masks storm records after the onset of ET-like environmental conditions in analyses that depend on TC intensity.

Formatted: Font: Not Bold, English (United States)

Formatted: English (United Kingdom)

ET involves structural changes in the storm core and would ideally be diagnosed using three-dimensional thermodynamic metrics such as cyclone phase space (CPS) diagnostics (Hart, 2003). However, applying CPS-based metrics to NeuralGCM-1.4° would require dedicated validation of the model’s three-dimensional thermal phase of the storm. In particular, these metrics are sensitive to the resolution of the input data and lack universal thresholds for determining when ET occurs (Wood et al., 2023). Here, our objective is not to classify ET explicitly, but to limit retaining TC intensity after storms enter ET-favourable environments. We therefore use SST and latitude as simple environmental indicators. This choice is consistent with the physical understanding that ET is often associated with poleward motion into cooler SSTs (Evans et al., 2017), and with the statistical results of Bieli et al. (2020), which identified SST and latitude as important predictors of ET occurrence. Specifically, when both conditions are satisfied for two consecutive time steps, we truncate the storm starting from the first of those two time steps: (1) the area-averaged SST within a 2° radius of the storm center is  $\leq 25.5^{\circ}\text{C}$ , and (2) the storm’s latitude exceeds the basin-specific median ET latitude derived from IBTrACS. Sensitivity tests using SST thresholds of 25.0 and 26.0 °C and latitude thresholds shifted by  $\pm 2^{\circ}$  show little influence on the reported results.

The screening is intended to limit the inclusion of records that are likely affected by extratropical transition, although the conclusions of this study are not sensitive to its application.

2.3. Model Evaluationevaluation and Benchmarksbenchmarks

2.3.1. Benchmark models

To assess the intensity component of SPIN, we benchmark against the physics-based statistical downscaling framework developed by JL23, which applies the FAST model to statistical synthetic tracks. The JL23 model is driven by monthly statistics of daily environmental winds at 250 and 850 hPa, together with monthly-mean temperature, relative humidity, and sea surface temperature.

For comparison of SPIN-simulated MTCE (see Section 2.5 for definition) metrics with statistical downscaling methods, we use two benchmarks: (1) the JL23 statistical-downscaling-frameworkmodel, and (2) a monthly-uniform-sampled version of IBTrACS. Like most statistical downscaling models, the archived track output from JL23 model-reports-tracks-on-a-monthly-seale-rather-than-giving-preciseprovides storm year and month, together with the number of time steps since genesis-and-dissipation-dates-, but not the specific calendar genesis date. We therefore assign genesis dates to JL23 tracks by uniformly sampling within each month-for-the-tracks-produced-by-the-JL23-model, following previous studies (Xi et al., 2023), and perform 1000 Monte Carlo simulations of the daily-scale genesis dates to quantify uncertainty-(Xi et al., 2023), and use 1,000 Monte Carlo simulations to quantify the associated uncertainty. The number of sampled tracks per basin in JL23 follows its own TC frequency. This uniform-sampling strategy assumes independent TC genesis and neglects storm-storm interactions. To circumvent the bias in TC genesis frequency in JL23, we also apply the same sampling approach to observed TCs from IBTrACS dataset. Comparing SPIN with these benchmarks, we test whether SPIN can more faithfully reproduce observed MTCE characteristics than a month-level uniform-sampling framework (both benchmarks).

Formatted: Normal, Left, Line spacing: single

Formatted: Font color: Accent 4

### 2.3.2. Statistical Metrics

To quantify SPIN performance compared to the benchmarks in simulating observed probability distributions of various TC-related metrics (e.g. LMI, TC inter-genesis [dates](#)[intervals](#)), we use two statistical measures: the Kullback-Leibler (KL) divergence and the area between the cumulative distribution functions (ACDFs) of the model and observations.

The KL divergence  $D_{KL}(O \parallel M)$  measures the difference between the probability distributions of model ( $M$ ) and observations ( $O$ ) for a given metric, reflecting the information loss when the model distribution is used to approximate the observations. It is particularly sensitive to regions where the model assigns low probability to events that are frequent in observations, and is therefore especially useful for evaluating differences in the tails of distributions. It is defined as:

$$D_{KL}(M \parallel O) = - \sum_i P_M(i) \log \left( \frac{P_M(i)}{P_O(i)} \right) \quad (1)$$

$$D_{KL}(O \parallel M) = \sum_i P_O(i)$$

where  $P_M(i)$  and  $P_O(i)$  denote the probability of the  $i$ -th bin for the model and observations, respectively. The value of  $D_{KL}(O \parallel M) = 0$  indicates perfect agreement between the two distributions. Higher values indicate greater divergence.

The area between the cumulative distribution functions (ACDFs) of the model and observations quantifies the direction and magnitude of the distributional shift between the model and observations. It is calculated as:

$$\text{ACDFs} = \int_{-\infty}^{+\infty} [F_{\text{model}}(x) - F_{\text{obs}}(x)] dx \quad (2)$$

where  $F_{\text{model}}$  and  $F_{\text{obs}}$  are the CDFs of the model and observations, respectively. A positive (negative) value indicates that the model systematically underestimates (overestimates) the metric relative to observations.

### 2.4. Landfall Locations

We discretize global coastline into evenly spaced milepost points using the 1:110m Natural Earth shapefile ([www.naturalearthdata.com](http://www.naturalearthdata.com)). Mileposts are equally spaced along the coastline at approximately 1.4° arc-length intervals. For each storm track, the location that the TC first transits from ocean to land is identified as the landfall location. This point is then assigned to the nearest milepost based on geographic distance. The method is applied consistently to both observational and modelled tracks, enabling direct spatial comparison of landfall frequencies.

### 2.5. MTCE Identification

MTCEs are defined as two or more TCs that simultaneously coexist within the same basin (Fu et al., 2023; Schenkel, 2016). In this study, the algorithm for identifying MTCE clusters is implemented as follows: (1) The genesis and dissipation times of each individual TC track are merged into a single timeline and sorted chronologically. (2) An MTCE cluster is defined to

Formatted: Text, Space After: 6 pt

commence when the active TC count reaches or exceeds two, persists for as long as this condition is maintained, and terminates once the count falls below two.

For each identified MTCE cluster, the maximum value of the active TC count during its duration is defined as the peak concurrent TC count for that cluster.

## 2.6.—Return-Period Calculation

MTCEs are defined as two or more TCs that simultaneously coexist within the same basin (Fu et al., 2023; Schenkel, 2016). In this study, the algorithm for identifying MTCE clusters is implemented as follows: (1) The genesis and dissipation times of each individual TC track are merged into a single timeline and sorted chronologically. (2) An MTCE cluster is defined to commence when the active TC count reaches or exceeds two, persists for as long as this condition is maintained, and terminates once the count falls below two.

For each identified MTCE cluster, the maximum value of the active TC count during its duration is defined as the peak concurrent TC count for that cluster.

## 2.6. Return period calculation

The return period  $RP(x)$  is defined as the average time interval between events (e.g., landfall intensity, inter-genesis time between MTCEs) whose magnitude exceeds inverse of the occurrence rate of a specified threshold event:

$$RP(x) = \frac{1}{[\lambda(1 - F(x))]} \quad (3)$$

$$RP(x) = \frac{1}{r_x} \quad (3)$$

where  $F(x)$  is the cumulative distribution function threshold applied to the metric of interest, and  $r_x$  is the occurrence rate per unit time. In this study, for events satisfying that threshold. For landfall intensity  $I$ , the threshold event is  $I \geq x$ . For MTCE intervals, the threshold event is  $\Delta t_{MTCE} \leq x$ , where  $\Delta t_{MTCE}$  is the interval between successive MTCE onset times.

For discrete observational or model data,  $RP(x)$  the return period is computed empirically as:

$$RP(x) = \frac{T_{total}}{N(x)} \quad (4)$$

where  $T_{total}$  is the total sampling period (i.e., the total observation period or the sum of the total simulation period across all model realizations), and  $N(x)$  is the number of events exceeding satisfying the threshold  $x$ -condition.

Formatted: English (United Kingdom)

Formatted: English (United Kingdom)

Formatted: English (United Kingdom)

Formatted: English (United Kingdom)

Formatted: English (United Kingdom)

Formatted: English (United Kingdom)

Formatted: English (United Kingdom)

Formatted: English (United Kingdom)

Formatted: English (United Kingdom)

Formatted: English (United Kingdom)

Formatted: English (United Kingdom)

285 **3 Model Evaluation**

This section evaluates the performance of SPIN in reproducing key TC characteristics. Specifically, we assess annual frequency and seasonal cycle, patterns of TC genesis and track, and intensity statistics at the global scale. Special attention are paid on MTCEs metrics in the WP and NA basins, where such events are most frequent (Fu et al., 2025). For MTCE evaluation, model simulations are compared with observations and benchmarks introduced in section 2.3.

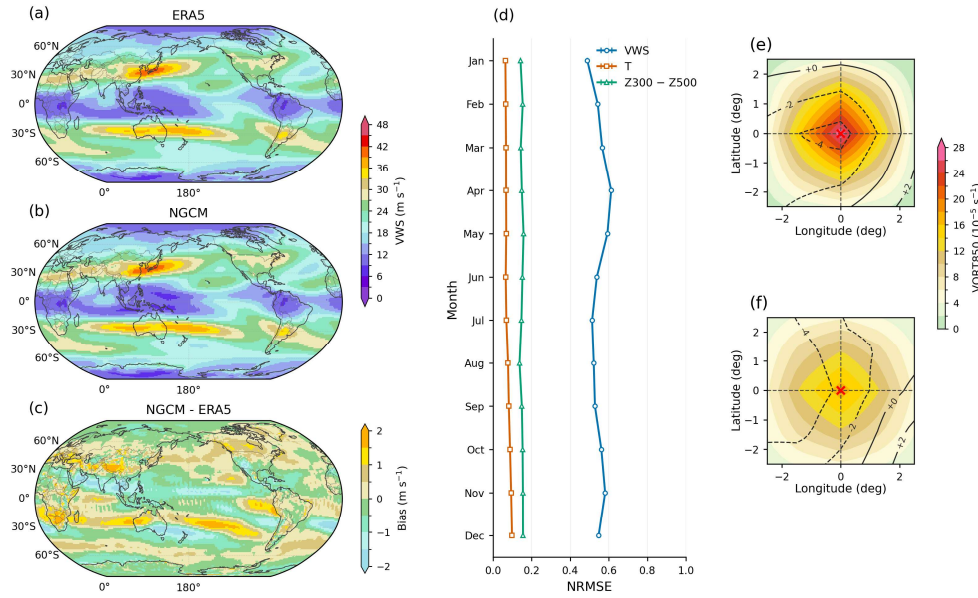
290 **3.1 Inter-annual Variability and Seasonal Cycle** This section evaluates the performance of SPIN in reproducing key TC characteristics. We first assess the large-scale environmental fields simulated by NeuralGCM, followed by annual frequency, seasonal cycle, patterns of TC genesis and track, and intensity statistics at the global scale. We then focus on MTCEs metrics in the WP and NA basins, where such events are most frequent (Fu et al., 2025).

**3.1 Large-scale atmospheric environment**

295 NeuralGCM captures the main climatological structures of the large-scale environments relevant to tropical cyclone activity. The ensemble mean reproduces the observed VWS pattern, including the subtropical maxima evident in ERA5, although regional biases remain (Figure 2a–c). It also captures the broad vertical temperature structure, with warmer conditions in the lower troposphere and colder conditions aloft (Figure S3), and reproduces the expected meridional contrast in Z300–Z500, an upper-level warm-core proxy used in TempestExtremes, with larger values in the tropics and smaller values toward higher latitudes (Figure S4).

300 Upper-tropospheric temperature biases increase with rollout time (Figure S3). Biases in Z300–Z500 and VWS vary seasonally, with Z300–Z500 tending to be higher than ERA5 during the early-to-peak TC season and lower during the late season, whereas VWS tends to be lower than ERA5 during the early-to-peak season and higher during the late season (Figure S4 and S5). Monthly normalized root-mean-square errors (NRMSEs), normalized by the spatial standard deviation of the ERA5 reference fields, also generally increase with rollout time, indicating gradual bias growth during the simulations (Figure 2d). Despite these biases, the broad agreement with ERA5 supports the use of NeuralGCM to simulate large-scale environmental fields relevant to TC hazards.

305 We next assess whether the FAST-derived intensity ranking is dynamically consistent with the corresponding NeuralGCM atmospheric fields. Using the NA basin as an example, the top 10% of storms ranked by lifetime maximum intensity show stronger 850-hPa relative vorticity and surface pressure anomalies than the lowest 10% (Figure 2e,f). This correspondence indicates that the FAST-derived intensity ranking is qualitatively reflected in the NeuralGCM atmospheric fields.



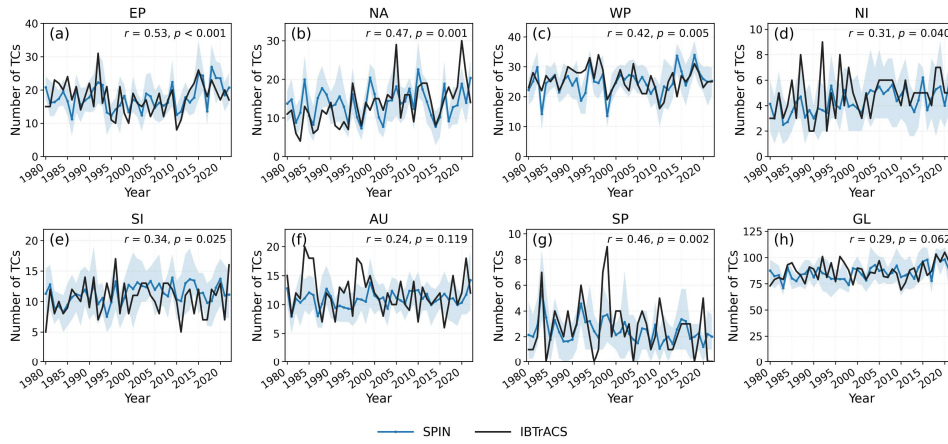
**Figure 2** Evaluation of simulated atmospheric environmental fields. Panels show the 1980–2022 mean 200–850-hPa vertical wind shear (VWS;  $\text{m s}^{-1}$ ) from (a) ERA5, (b) the NeuralGCM ensemble mean, and (c) their difference. Panel (d) shows monthly normalized root-mean-square errors (NRMSEs) between NeuralGCM and ERA5 for VWS, the meridional temperature profile (T;  $\text{K}$ ), and the 300–500-hPa geopotential height difference (Z300-Z500;  $\text{m}^2 \text{s}^{-2}$ ), averaged over 1980–2022, with error bars indicating the 10th–90th percentile range across ensemble members. Panels (e,f) show storm-centred composites of the surrounding environment for FAST-simulated extreme TCs in the North Atlantic basin during 1980–2022. Composites are shown for the (e) top 10% and (f) lowest 10% of storms ranked by lifetime maximum intensity, evaluated at the time of lifetime maximum intensity. Shading shows 850-hPa relative vorticity ( $\text{s}^{-1}$ ), and contours show surface pressure anomalies (hPa) relative to the mean pressure within a storm-centred 500–800-km annulus.

### 3.2 Interannual variability and seasonal cycle

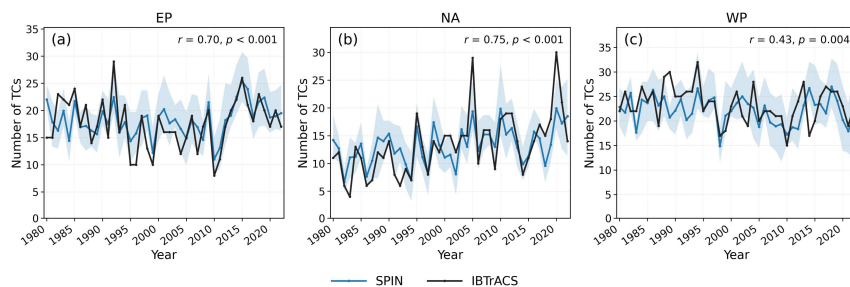
To evaluate the model’s ability to represent interannual variability in TC activity, we calculated the correlation coefficients between basin-scale TC frequency in SPIN and observations over 1980–2022. As shown in Figure 1, correlation coefficients of all basins are statistically significant at the 0.05 level. (Figure 3). Consistent with previous statistical downscaling models (Lee et al., 2018; Lin et al., 2023), SPIN performs best in the EP and NA basins ( $r = 0.62$  and  $r = 0.42$ , respectively). The correlations may be further increased if the NeuralGCM simulations are initialized in April (instead of October in the previous year) and restricted evaluation to the TC season (June to December for Northern Hemisphere) (Figure S3). Moreover, SPIN



demonstrates noticeably higher skills over previous statistical downscaling models in the WP and Southern Hemisphere basins (Lin et al., 2023). A possible explanation of this improvement is that in statistical downscaling frameworks (e.g., JL23), the interannual genesis signals can be smoothed in regions where ENSO variability has mixed-signed influences (53 and  $r = 0.47$ , respectively). We use January–December simulations here to maintain comparability with previous hazard-model evaluations (Lee et al., 2018; Lin et al., 2023). For application-oriented experiments, however, initializing closer to the target TC season can shorten the forecast lead time and reduces the accumulation of model drift. Consistent with this interpretation, April initialization simulations followed by evaluation over the Northern Hemisphere hurricane season yields higher basin-scale TC-frequency correlations (Figure 4).



**Figure 3.** Interannual variability of TC frequency during 1980–2022. Panels show the (a) EP, (b) NA, (c) WP, (d) NI, (e) SI, (f) AU, (g) SP, and (h) GL basins. The blue line shows the ensemble mean of 14-member SPIN simulations initialized in mid-October at 6-hour intervals, with shading indicating the 10th–90th percentile range, and observations are shown in black. Pearson correlation coefficients ( $r$ ) with significance levels ( $p$ ) are reported in the upper-right of each panel.



**Figure 4.** Interannual variability of TC frequency during May–December from 1980 to 2022 for the EP, NA, and WP basins. The blue line shows the ensemble mean of 14-member SPIN simulations initialized in early April at 6-hour intervals, with shading indicating the 10th–90th percentile range. Observations are shown in black. Pearson correlation coefficients ( $r$ ) with significance levels ( $p$ ) are reported in the upper-right of each panel. Global-mean log surface pressure was not fixed in these simulations, as model drift is negligible over their integration timescale.

SPIN also shows markedly improved agreement with observations relative to JL23 in the WP, SP, and SI basins. Lin et al. (2023) suggested that lower predictability in these basins may reflect the mixed-sign influence of El Niño–Southern Oscillation (ENSO) on TC genesis across subregions (Camargo et al., 2007; Lin et al., 2023). Specifically, the spatially-random seeding approach used in their genesis component (Figure S6, Camargo et al., 2007; Lin et al., 2023), which can cause the basin-integrated interannual genesis signal to be averaged out. In contrast, SPIN better retains ENSO modulation in these basins, with ENSO conditioned TC frequency anomalies closer to IBTrACS than JL23 (Figure S7). A possible reason is the difference in the treatment of seed disturbances. Previous diagnostic frameworks express TC genesis rates as the product of seed frequency and a transition probability controlled by the large-scale environment (Emanuel, 2022; Hsieh et al., 2020). JL23 uses random seeding (Emanuel et al., 2008; Lin et al., 2023), in which seeds are placed randomly in space and time and then allowed to evolve within the large-scale environment. Because this seed supply is not dynamically coupled to ENSO related circulation changes, it may artificially increase genesis probability in low-activity regions while decreasing it in high-activity regions, such that positive and negative biases across the basin may offset when summed, especially in mixed-signed ENSO signal regions. In contrast, SPIN extracts TCs directly diagnoses candidate storms from the environmental-evolving circulation fields simulated generated by NeuralGCM. This allows SPIN to retain year-to-year changes in both environmental favorability and precursor disturbance supply. We regard this as a plausible mechanism rather than relying on random seeding, thereby improving performance in regions with mixed ENSO signals a definitive attribution. Overall, these results highlight the potential of SPIN to capture interannual variability in TC activities across most basins.

Formatted: English (United Kingdom)

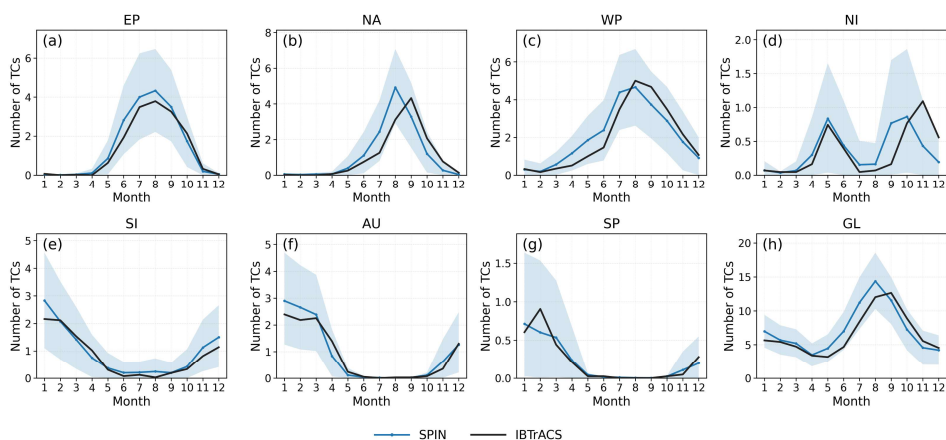
Formatted: English (United Kingdom)

Formatted: English (United Kingdom)

Formatted: English (United Kingdom)

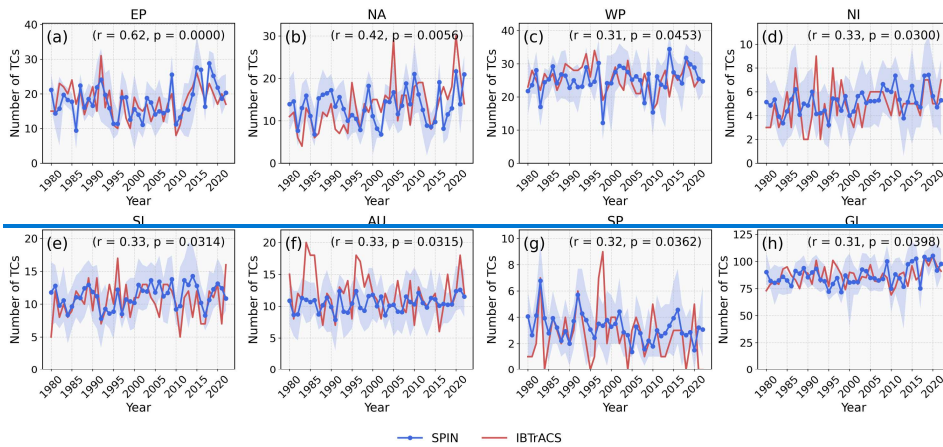
Formatted: English (United Kingdom)

Formatted: English (United Kingdom)



**Figure 5.** Seasonal cycle of TCs genesis averaged over 1980–2022. Panels show (a) EP, (b) NA, (c) WP, (d) NI, (e) SI, (f) AU, (g) SP, and (h) GL basins. The blue line shows the SPIN ensemble mean, with shading denoting the 10th–90th percentile range. Observations are shown in black. Only storms with lifetime maximum intensity exceeding  $18 \text{ m s}^{-1}$  are included.

For the seasonal cycles of TC genesis (Figure 2), SPIN reproduces the bimodal distribution in the NI basin and the unimodal patterns in other basins, with a slight tendency to overestimate TC counts from the early to peak season and underestimate them from the peak to late season. A similar bias was noted by Zhang et al. (2025, supplementary) that evaluates the performance of NeuralGCM.

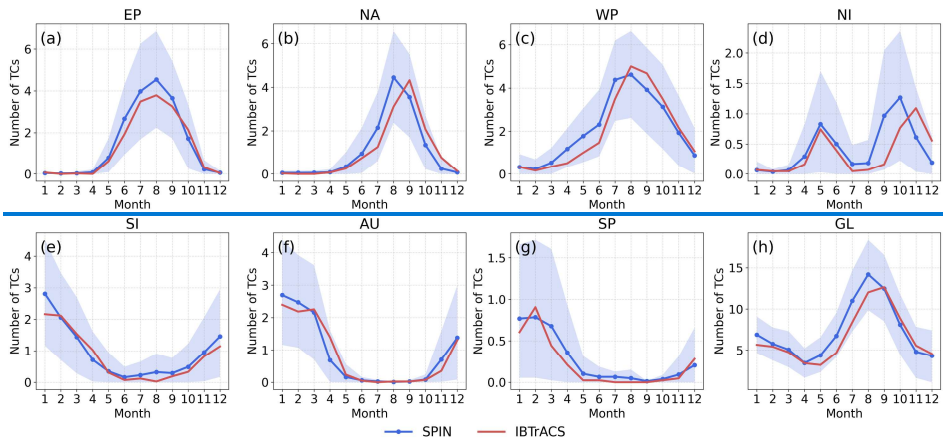


**Figure 1.** Interannual variability of TC frequency during 1980–2022. Panels show (a) EP, (b) NA, (c) WP, (d) NI, (e) SI, (f) AU, (g) SP, and (h) GL basins. The blue line shows the ensemble mean of 14-member SPIN simulations initialized in mid-October at 6-hour intervals, with shading indicating the 10th–90th percentile range, and observations are shown in red. Pearson correlation coefficients with significance levels are reported in the upper-right of each panel.

**Formatted:** Font: Times New Roman

**Formatted:** Font: Times New Roman, Not Italic

**Formatted:** Font: Times New Roman

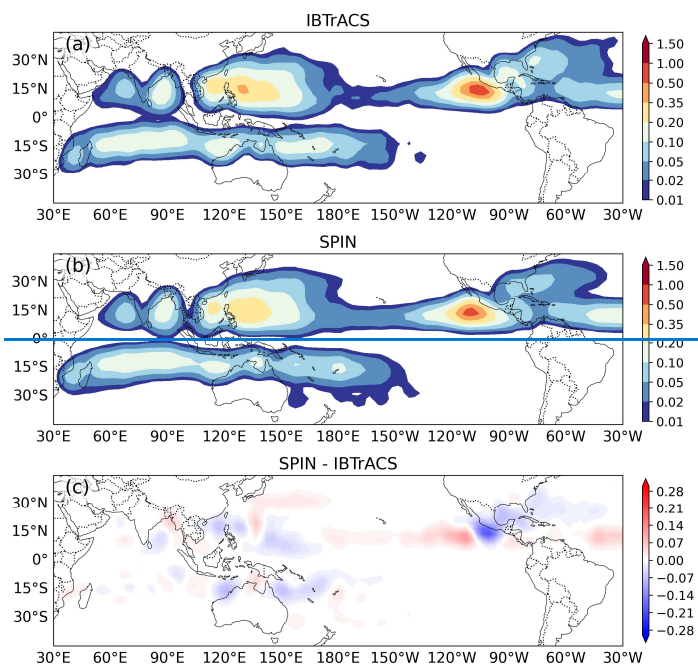


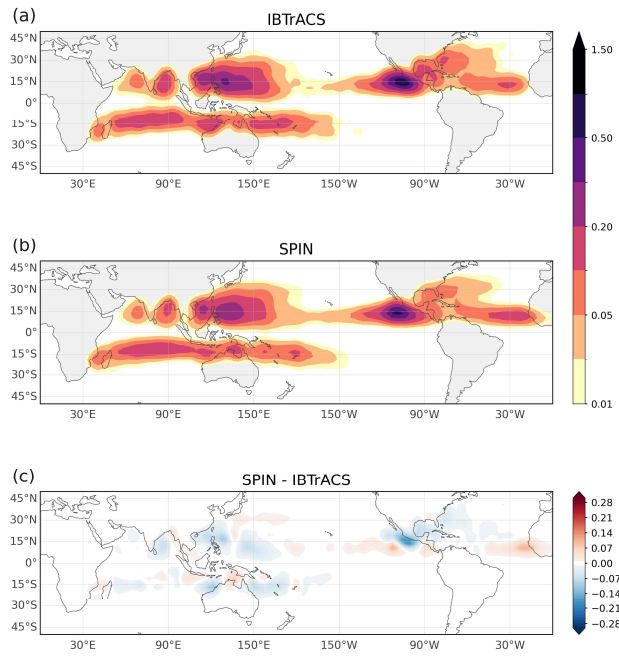
~~Figure 2. Basin-wide seasonal cycle of TCs genesis averaged over 1980–2022. Panels show (a) EP, (b) NA, (c) WP, (d) NI, (e) SI, (f) AU, (g) SP, and (h) GL basins. For the seasonal cycles of TC genesis (Figure 5), SPIN reproduces the bimodal distribution in the NI basin and the unimodal patterns in other basins, with a slight tendency to overestimate TC counts from the early to peak season and underestimate them from the peak to late season. A similar bias was noted by Zhang et al. The ensemble mean of SPIN simulations is shown in blue with shaded bands indicating the 10th–90th percentile range, and observations are shown in red. (2025, supplementary) that evaluates the performance of NeuralGCM. This seasonal bias is likely linked to the large-scale environmental biases in NeuralGCM. As shown in Section 3.1, NeuralGCM tends to predict lower VWS than ERA5 during the early-to-peak TC season, but higher VWS during the late season (Figure S5). These biases favour TC genesis earlier in the season but suppress it later, consistent with the simulated seasonal genesis bias.~~

~~3.3 Only storms with lifetime maximum intensity exceeding  $18 \text{ m s}^{-1}$  are included.~~

### **3.2 Genesis and Track Statistics**

We first compare the spatial pattern of SPIN-simulated TC genesis patterns with observations from 1980–2022.  $3^\circ \times 3^\circ$  grid boxes are used to calculate the genesis density (Figure 6). Overall, the spatial pattern of simulated genesis events aligns well with historical observations, though some regional biases remain. For example, SPIN tends to underestimate genesis frequency in the Bay of Bengal, the South China Sea, the Philippine Sea, the northern part of the AU basin, the eastern part of the EP basin, the Gulf of Mexico, and the western part of the NA basin. In contrast, it tends to overestimate genesis in the southern parts of the Eastern Pacific and NA basins, as well as in the northern part of the WP basin. Several reasons may contribute to this bias. First, TC numbers are sensitive to the detection scheme; although we have fine-tuned the detection method to allow TC numbers to align with observations at the basin scale, subregional differences remain. Second, in SPIN, NeuralGCM is forced with monthly SST and SIC fields linearly interpolated to 12-hour resolution. The interpolated forcing fields lack sub-monthly scale variability, which may also introduce bias. In addition, because genesis is defined as the first time the simulated surface wind of a TC exceeds  $18 \text{ m s}^{-1}$ , the bias in the intensity model may also influence the location of genesis events. Nevertheless, despite these biases, SPIN demonstrates skillful performance in reproducing the observed spatial distribution of TC genesis.





**Figure 6.** Tropical cyclones (TCs) genesis density per year on a  $3^\circ \times 3^\circ$  grid with Gaussian smoothing averaged over 1980–2022. (a) IBTrACS, (b) ensemble-mean simulations from SPIN, and (c) their difference (b – a). Genesis is defined as the first occurrence time that a TC's maximum wind speed  $\geq 18 \text{ m s}^{-1}$ .

To validate SPIN's performance in reproducing how well SPIN captures TC translation characteristics of TC movements, a comparison of Figure 7 compares the 6-hourly zonal and meridional and zonal displacements of simulated and observed tracks is shown in Figure 4 with those from observations. SPIN tends to underestimate the magnitude of the meridional displacement, suggesting that simulated biases in the steering flow (e.g., the subtropical high and trough structures) may appear overly smoothed (Duan et al., 2025)(Duan et al., 2025). Such biases can in turn affect the recurvature latitude.

Nevertheless, the overall simulation results show good agreement with observations.

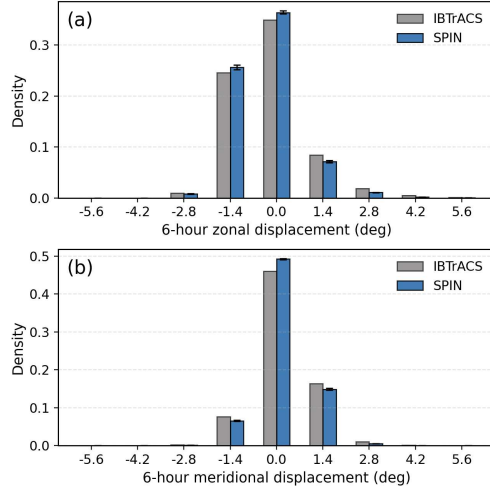
Formatted: English (United Kingdom)

Formatted: English (United Kingdom)

Formatted: English (United Kingdom)

Formatted: English (United Kingdom)

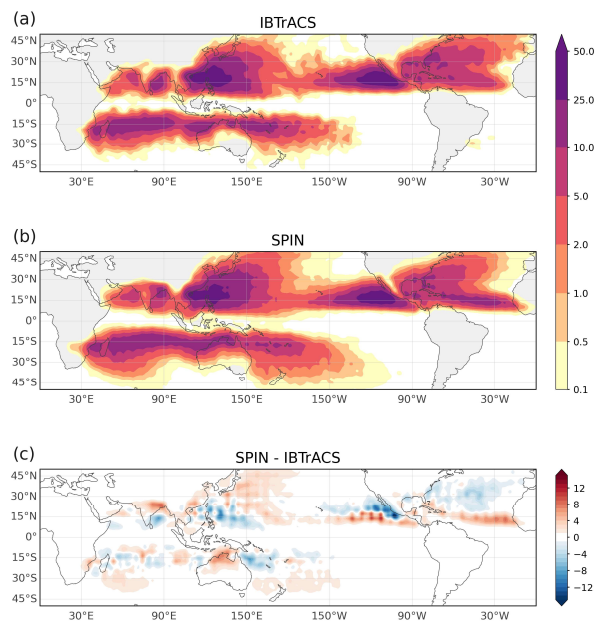
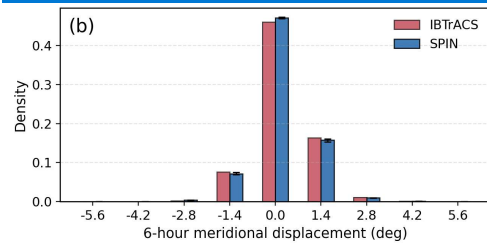
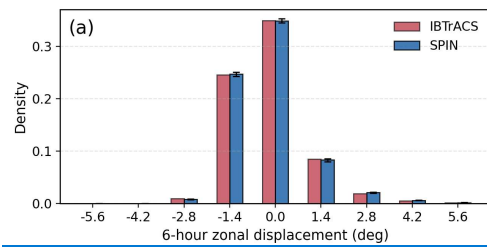
Formatted: English (United Kingdom)



**Figure 7.** Comparison of six-hour TC displacement statistics between observations and the SPIN ensemble. (a) Zonal and (b) meridional displacements of TCs in IBTrACS (grey) and SPIN (ensemble mean, blue). Error bars indicate the 10–90% ensemble spread for SPIN. Bins are defined at 1.4° intervals.

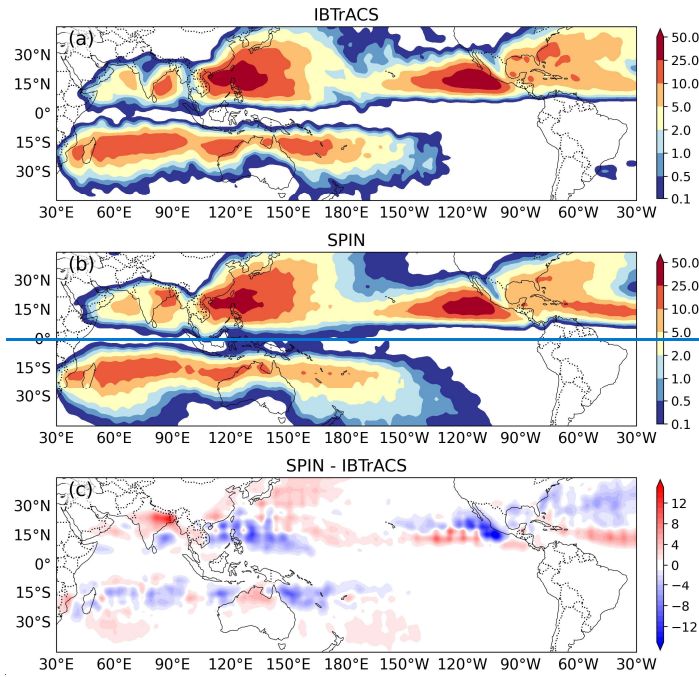
Next, we validate the annual track density simulated by SPIN. Next, we validate the annual track density simulated by SPIN. We calculate the track density using  $1^\circ \times 1^\circ$  grid boxes (Figure 8). The spatial pattern of the bias of track density resembles that of genesis density, with SPIN underestimating density in the Bay of Bengal, southern part of WP basin, the northern part of the AU basin, and the northern part of the EP and NA basin. These biases in track density are therefore largely attributable to bias in simulated genesis locations. Differences in TC duration may also contribute to the bias in track density, with SPIN producing a mean global TC duration of 5.474 days versus 4.785 days in the observation.





**Figure 8.** Comparison of six-hour TC displacement statistics between observations and the SPIN ensemble. (a) Zonal and (b) meridional displacements of TCs in IBTrACS (red) and SPIN (ensemble mean, blue). Error bars indicate the 10–90% ensemble spread for SPIN. Bins are defined at  $1.4^\circ$  intervals.

Next, we validate the annual track density simulated by SPIN. We calculate the track density using  $1^\circ \times 1^\circ$  grid boxes (Figure 5). The spatial pattern of the bias of track density resembles that of genesis density, with SPIN underestimating density in the Bay of Bengal, southern part of WP basin, the northern part of the AU basin, the northern part of the EP and NA basin. These biases in track density are therefore largely attributable to bias in simulated genesis locations. Differences in TC duration may also contribute to the bias in track density, with SPIN producing a mean global TC duration of 5.4 days versus 4.7 days in the observation.

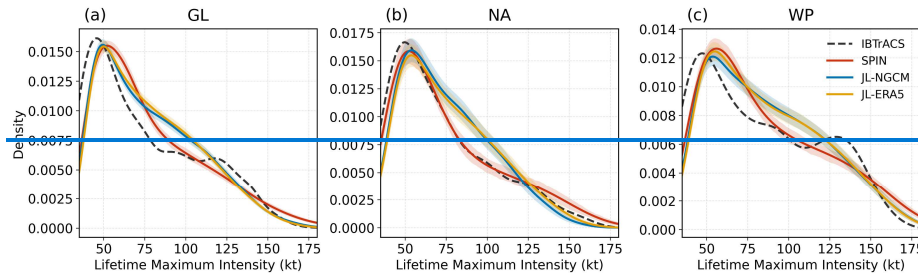


**Figure 5.** Annual 6-hourly TCs track density on a  $1^\circ \times 1^\circ$  grid with Gaussian smoothing for 1980–2022. (a) IBTrACS, (b) ensemble-mean simulations from SPIN, and (c) their difference (b – a). Only storms reaching maximum wind  $\geq 18 \text{ m s}^{-1}$  are included, with tracks evaluated from the first occurrence of that threshold.

### 3.34 Lifetime Maximum Intensity

We compare the SPIN-simulated lifetime maximum intensity (LMI) of TCs with observations at the global scale and in the basins with most TC-related economic losses, i.e., the NA and WP basins (Krichene et al., 2023) (Krichene et al., 2023) (Figure 9). In addition, the LMI derived from the JL23-model is included for comparison, which also adopts the FAST intensity model. This comparison allows us to determine whether the bias in SPIN simulated LMI originates from the FAST model or not. For comparison, we include the JL23-downscaled ERA5 experiment, hereafter JL-ERA5, which also uses the FAST intensity model (Emanuel, 2017). We further include a JL23-downscaled NeuralGCM experiment, hereafter JL-NGCM, to assess how biases in the NeuralGCM large-scale environment affect the simulated LMI distribution.

SPIN generally well-reproduces the observed distribution of LMI, showing a peak followed by an exponential decay. This behavior is also captured by the JL23-downscaled ERA5 (hereafter JL-ERA5) and the JL23-downscaled NeuralGCM-simulated environments (hereafter JL-NGCM, representing the bias inherited from the large-scale environment simulated by NeuralGCM). The close agreement with observed distributions is supported by low  $D_{KL}(M \parallel O)$  values across basins (0.009–0.029 in SPIN, 0.029–0.034 in JL-ERA5, 0.026–0.035 in JL-NGCM; Table S1). Both models exhibit a rightward shift of the peak, as indicated by consistently negative ACDF values (−0.853 to −3.353 in SPIN, −1.009 to −3.133 in JL-ERA5, −1.07 to −1.414 in JL-NGCM; Table S1), reflecting a modest overestimation of high intensity events. In addition, both models underestimate the frequency of rapid intensification events (15.5–28.4% in SPIN, 14.5–26.6% in JL-ERA5, 16.9–28.1% in JL-NGCM, and 23.3–33.2% in observations across basins; Figure S4). These biases are therefore inherited from the FAST intensity model (Emanuel 2017). We also compared the LMI distributions from JL-ERA5 and JL-NGCM. The results show that JL-NGCM yields an LMI distribution similar to that derived from JL-ERA5, indicating that NeuralGCM-simulated environmental fields carry negligible bias for TC intensity simulation.

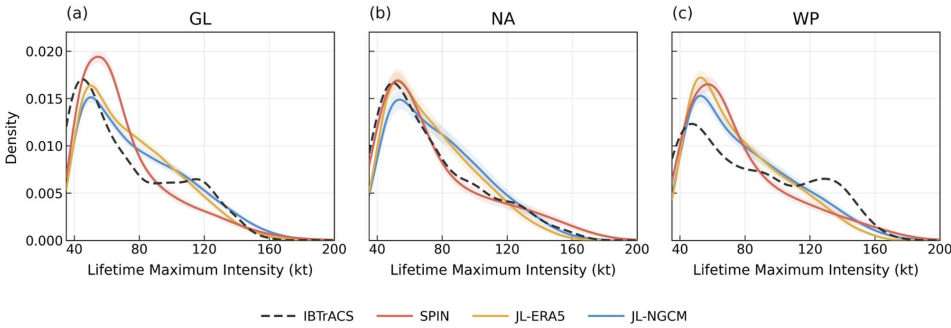


Both SPIN and JL23-downscaled models capture the main features of the observed LMI distributions, with most storms reaching weak-to-moderate intensities and progressively fewer storms reaching the highest intensities. This agreement is reflected in relatively small  $D_{KL}(O \parallel M)$  values, which range from 0.015 to 0.085 for SPIN, compared with 0.030 to 0.101 for JL-ERA5 and 0.029 to 0.048 for JL-NGCM (Table S1). Nevertheless, the agreement varies across basins. SPIN performs best

Formatted: Font: Times New Roman, English (United Kingdom)

in the NA basin, where the simulated distribution closely follows IBTrACS. In the GL and WP domains, the simulated distributions show a modest shift toward weaker-to-moderate intensities and a reduced frequency of some higher-intensity storms. A similar tendency is also evident in the JL23-based experiments, particularly in the WP basin.

These biases likely originated from the following model limitations. One common limitation is the underestimation of rapid intensification in the FAST intensity framework. The observed RI ratio ranges from 23.3% to 33.2% across the GL, NA and WP domains, whereas the simulated values are 6.0–11.1% in SPIN, 8.1–11.6% in JL-NGCM and 10.5–14.0% in JL-ERA5 (Figure S8). For SPIN, track-distribution biases may also contribute. In particular, excessive track occurrence at higher latitudes in the GL and WP domains may place more storms in environments less favourable for reaching high LMI (Figure 8 and Figure 9). The broad similarity between JL-ERA5 and JL-NGCM suggests that biases in the NeuralGCM large-scale environment are not the dominant source of the LMI bias, although they may still contribute. Overall, the remaining LMI biases appear to arise from a combination of limitations in the intensity model, biases in the track detection algorithm and residual environmental fields errors.

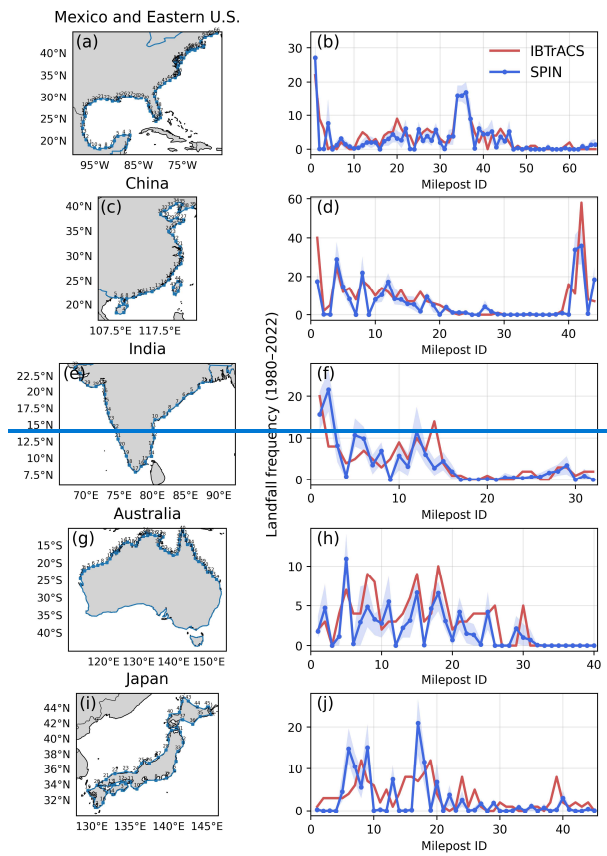


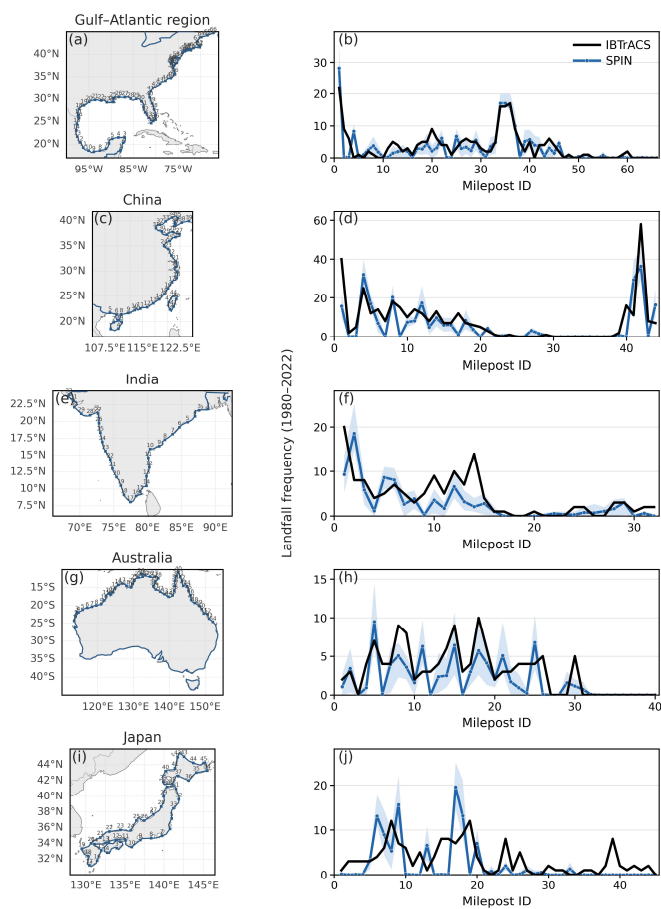
**Figure 9.** Distribution of LMI of TCs during 1980–2022. (a) shows the global distribution, (b) the NA basin, and (c) the WP basin distributions. Distributions are estimated using Gaussian kernel density fitting. Results of IBTrACS are shown as black dashed lines, SPIN simulations in red, JL-downscaled-NeuralGCM (using a single ensemble member) in blue, and JL-downscaled-ERA5 in yellow. For both JL-downscaled-NeuralGCM and JL-ERA5, the number of TCs is obtained by sub-sampling the downscaled events are randomly subsampled to match the number of observed events. For SPIN, shading denotes the 10th–90th percentile ranges are indicated by shading range across ensemble members; for the JL-downscaled results, shading denotes the 10th–90th percentile range from repeated subsampling to the observed sample size.

### 3.4.5 Landfall frequency

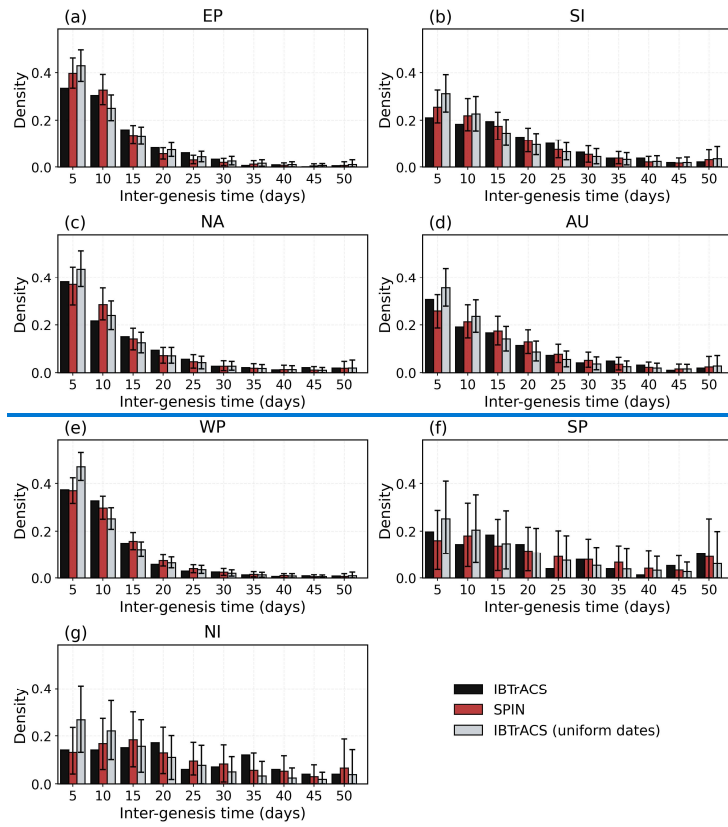
To investigate the model's performance in We next assess SPIN's ability to reproduce landfalling TC characteristics, we evaluated the activity by comparing simulated landfall frequency across the main major TC-impacted affected

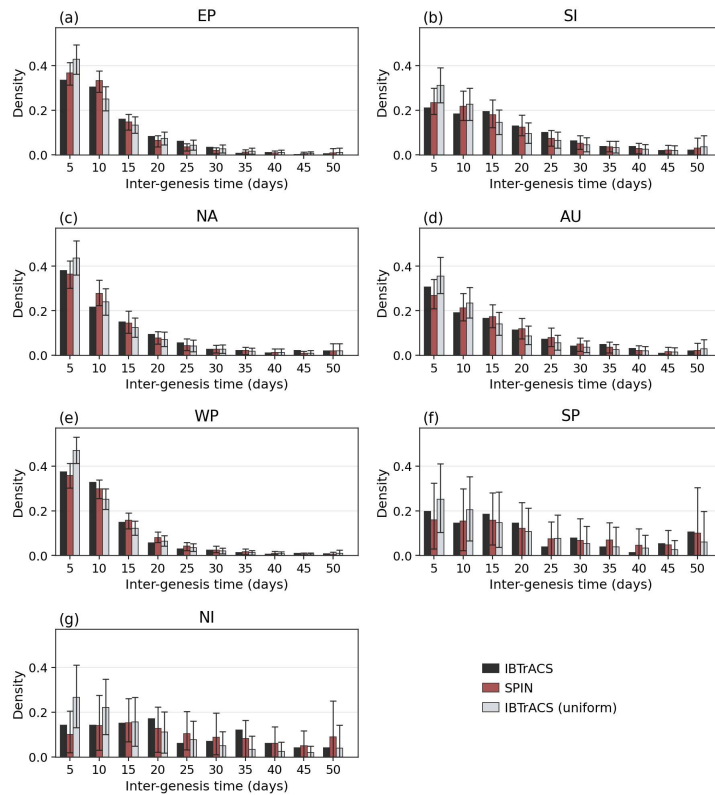
regions (Figure 10). The comparison shows SPIN has negligible bias relative to observations, particularly for Mexico, the eastern United States, Gulf-Atlantic Region, and China. In India, Australia, and Japan, spatial patterns of the bias in landfall frequency largely mirror those in track density. Also, due to the complex geometry of the coastline and the coarser spatial resolution of the modeled tracks, the first ocean-to-land crossing of a modeled track may not correspond to the actual landfall location, thereby leading to incorrect milepost assignments. Despite these biases, SPIN successfully reproduces the spatial pattern of landfall hotspots.





**Figure 10.** Landfall frequency of TCs along coastline mileposts during 1980-2022. Mileposts are equally spaced along the coastline at approximately 1.4° arc-length intervals for (a) [Mexico and the eastern United States](#), (c) [Eastern Gulf-Atlantic Region](#), (e) [China](#), (g) [India](#), (i) [Australia](#), and (j) [Japan](#). The SPIN ensemble-mean landfall frequencies are shown in (b), (d), (f), (h), and (j) in blue, with shaded bands indicating the 10th-90th percentile range across ensemble members. Observations are shown in [redblack](#).





**Figure 11.** Histogram of TC inter-gensis [dates intervals](#) from 1980-2022. Calculations are limited to the TC season in each year, defined as April–November for Northern Hemisphere basins (EP, NA, WP, NI; panels a, c, e, g) and from November to the following April for Southern Hemisphere basins (SI, AU, SP; panels b, d, f). Results from IBTrACS (black), IBTrACS with uniformly sampled dates (grey), the ensemble mean of SPIN simulations (red) are shown for comparison. [The 10th–90th percentile ranges are indicated in error bars](#)Error bars denote the 10th–90th percentile range across ensemble members for SPIN and across 1,000 Monte Carlo realizations for the uniform experiments.

Formatted: Font: Not Bold

Formatted: Font: Times New Roman



### 3.56 Inter-genesis ~~dates~~intervals

We assess whether SPIN realistically reproduces TC inter-genesis ~~times~~intervals in each basin (Figure 11). ~~Because traditional statistical downscaling models (e.g., JL23) provide only monthly information on TC genesis, previous studies on back-to-back TCs derived event onset times by sampling from a Poisson–Gaussian model parameterized by seasonal variability (Xi et al., 2023; Xi and Lin, 2021). This procedure assumes that individual TCs are independent and thus lacks physical realism. Such challenge also extends to MTCEs, as pre-existing TCs may influence the genesis of subsequent ones (Ritchie and Holland, 1999; Yoshida and Ishikawa, 2013), violating the assumption of independence.~~

We include IBTrACS with uniformly sampled genesis dates (hereafter IBTrACS-uniform) for comparison, providing a ~~clean reference of TC inter-genesis time~~. Traditional statistical downscaling models, such as JL23, provide the month of TC genesis ~~and the corresponding storm lifetime, but do not resolve intra-month variability needed to determine daily genesis time. As a result, previous studies of back-to-back TCs have derived event onset times by statistically sampling dates (Xi et al., 2023; Xi and Lin, 2021). This procedure assumes that individual TCs occur independently within the month and ignores intra-month processes that organize TC genesis.~~

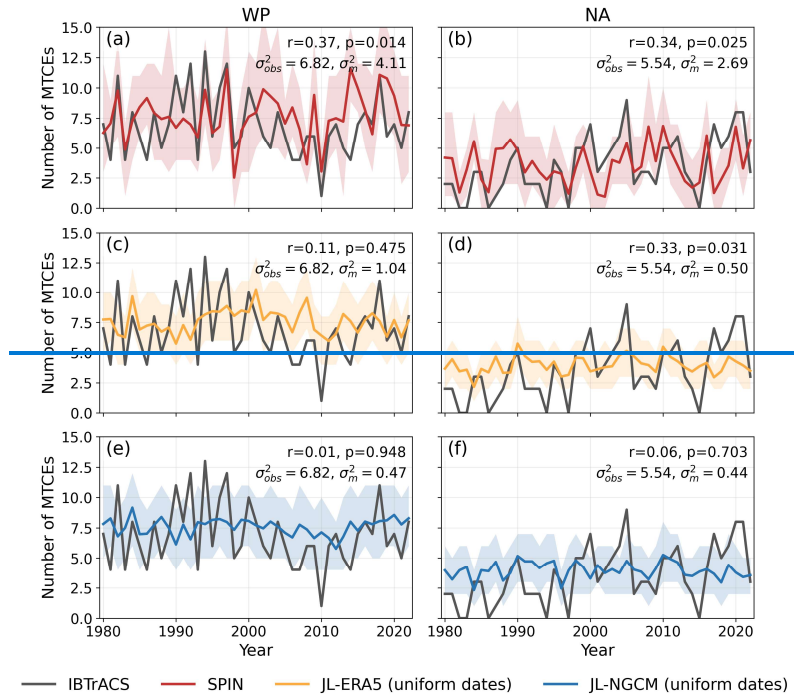
We include IBTrACS with uniformly sampled genesis dates (hereafter IBTrACS-uniform) for comparison, providing a ~~clean reference of TC inter-genesis interval~~ distribution without the influence of biases from statistical downscaling models. SPIN exhibits lower  $D_{KL}(O \parallel M \# \theta)$  values than IBTrACS-uniform in most basins, indicating a closer match to observations (0.007–0.012–0.062069 for SPIN versus 0.019–0.168182 for IBTrACS-uniform; Table S2). Additionally, IBTrACS-uniform tends to show a stronger left skew in its distribution, particularly within the 0–5 day bin, with ACDF values ranging from 0.25 to 0.63, compared ~~to~~with –0.2420 to 0.3417 for SPIN (Table S2). Given that the global average TC lifetime is around 5 days, overestimation of IBTrACS-uniform in 0–5 ~~daydays~~ may lead to an overestimation of MTCE hazards. ~~Overall, these results highlight SPIN’s improved capability in capturing the TCs inter-genesis dates, suggesting its potential to provide a more reliable basis for MTCE estimates.~~

### 3.6 — Evaluation of MTCEs

In addition to evaluating individual TC events, this study also assesses MTCEs, a dimension rarely explored in earlier synthetic TC model evaluations. Specifically, we evaluate the performance of SPIN in simulating MTCEs in the WP and NA basins by examining MTCE inter-annual variability, the peak number of concurrent TCs per cluster, and the spatial relationship between pre-existing and subsequent TCs. For comparison, the JL23 model is also used to downscale both ERA5 and NeuralGCM-simulated large-scale environments. Like most statistical downscaling models, the JL23 model reports tracks on a monthly basis rather than giving precise genesis and dissipation dates. We therefore assign dates by uniformly sampling within each month for the tracks produced by the JL23 model, following previous studies (Xi et al., 2023; Xi and Lin, 2021).

Field Code Changed

Formatted: Font: Calibri, 11.5 pt, Not Italic, Font color: Text 1

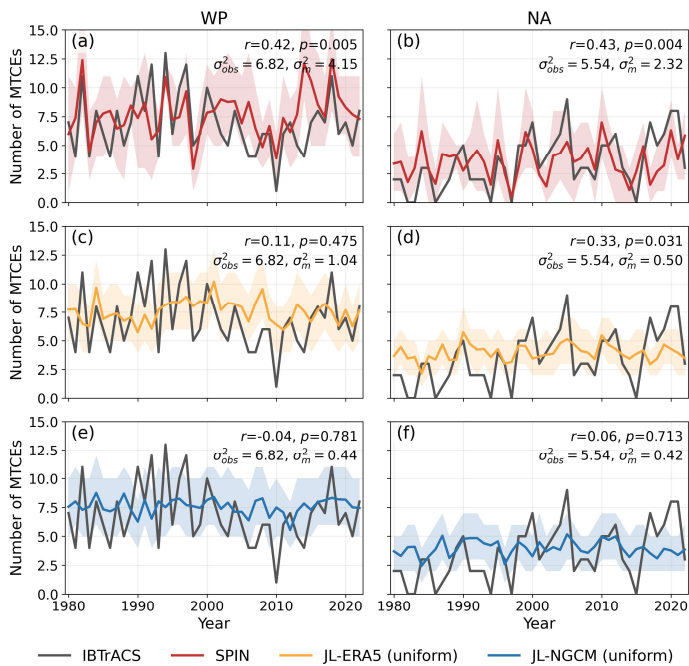


545 Although SPIN uses monthly SST and sea-ice boundary forcing, it resolves submonthly atmospheric variability. Its improved representation of inter-genesis intervals may therefore reflect the ability of the NeuralGCM component to capture intramonth environmental evolution, including MJO-related teleconnections (Peings et al., 2026). By allowing TC to emerge from the evolving atmospheric state, rather than imposing independence among storms, SPIN provides a more physically consistent basis for MTCE estimates.

### 550 3.7 Evaluation of MTCEs

In addition to evaluating individual TC events, this study also assesses MTCEs, a dimension rarely explored in earlier synthetic TC model evaluations. Specifically, we evaluate the performance of SPIN in simulating MTCEs in the WP and NA basins by examining MTCE interannual variability, cluster size, and the spatial relationship between pre-existing and subsequent TCs. For comparison, we also include TCs downscaled with the JL23 model using large-scale environments from ERA5 and

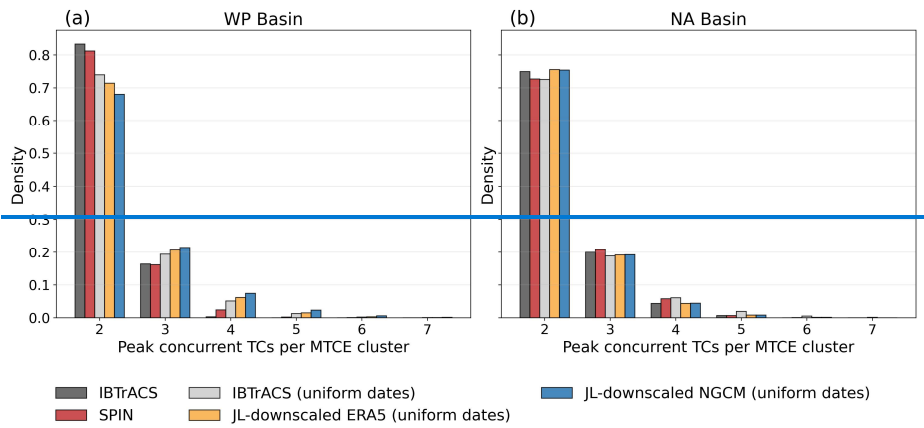
555 [NeuralGCM](#). Because JL23 provides storm occurrence information at monthly resolution, we assign genesis dates within each month by uniform sampling, following previous studies (Xi et al., 2023; Xi and Lin, 2021).



560 **Figure 12.** Interannual variability of multiple tropical cyclone events (MTCEs) in the WP and NA basins during 1980–2022. Results for IBTrACS are shown in black. The ensemble mean of SPIN simulations is shown in red (a-b), the JL23 model downscaling with uniformly sampled [genesis](#) dates is shown in yellow for ERA5 (c-d) and in blue for NeuralGCM (e-f, [with shaded](#)). [Shaded](#) bands [indicating](#) denote the 10th-90th percentile range. For SPIN, it represents the spread across ensemble members. For the “uniform” experiments, the range is [estimated across 1000 Monte Carlo realizations](#). Pearson correlation coefficients [with \(r\)](#), associated significance levels [between the observations and the model are shown in the upper-right corner of each panel, along with \(p\), and](#) the variances of the modelled  $\sigma_m^2$  and observed  $\sigma_{obs}^2$  annual frequencies. ( $\sigma_m^2$  and  $\sigma_{obs}^2$ ) are reported in the upper-right corner of each panel.

Formatted: Font: Not Bold

Here, we begin by evaluating the interannual variability of MTCEs, which is inherently influenced by the interannual variability of the TC frequency. As shown in (Figure 12), which is inherently influenced by the interannual variability of the TC frequency, SPIN successfully reproduces the observed year-to-year fluctuations of MTCEs MTCE variability in both the WP and NA basins, with statistically significant correlations with observations. In contrast, JL23 performs poorly. JL23-uniform, however, shows limited skill in the WP basin, where, consistent with its simulated TC annual frequency shows little weak correlation with observations for annual TC frequency in this basin (Lin et al., 2023), leading to insufficient interannual variability of MTCEs. Moreover, SPIN simulated MTCEs better capture the observed variance, while JL23 downsampled results exhibit markedly lower variance, likely because the model synthesizes TCs from monthly mean environmental fields, which smooths out environmental conditions favoring MTCEs.



SPIN-simulated MTCEs also better capture the observed variance, whereas the JL23-uniform downsampled results show markedly weaker variability. This may partly reflect the fact that JL23 is driven by monthly mean environmental fields, which smooth high-frequency variability important for TC genesis and MTCE occurrence. The poorer performance of JL23-uniform when driven by NeuralGCM (Figure 12 e,f), relative to ERA5 (Figure 12 c,d), may arise for two reasons. First, environmental anomalies may be weaker in NeuralGCM than in ERA5 (Duan et al., 2025), and monthly averaging may further damp the signals relevant to TC genesis. Second, because the parameters in JL23 are tuned based on ERA5, applying it to NeuralGCM output introduces differences in the input environmental fields, including grid resolution and systematic biases, which may further reduce its performance.

Formatted: English (United Kingdom)

Formatted: English (United Kingdom)

Formatted: Font: Times New Roman, English (United Kingdom)

Formatted: English (United Kingdom)

Formatted: English (United Kingdom)

Formatted: English (United Kingdom)

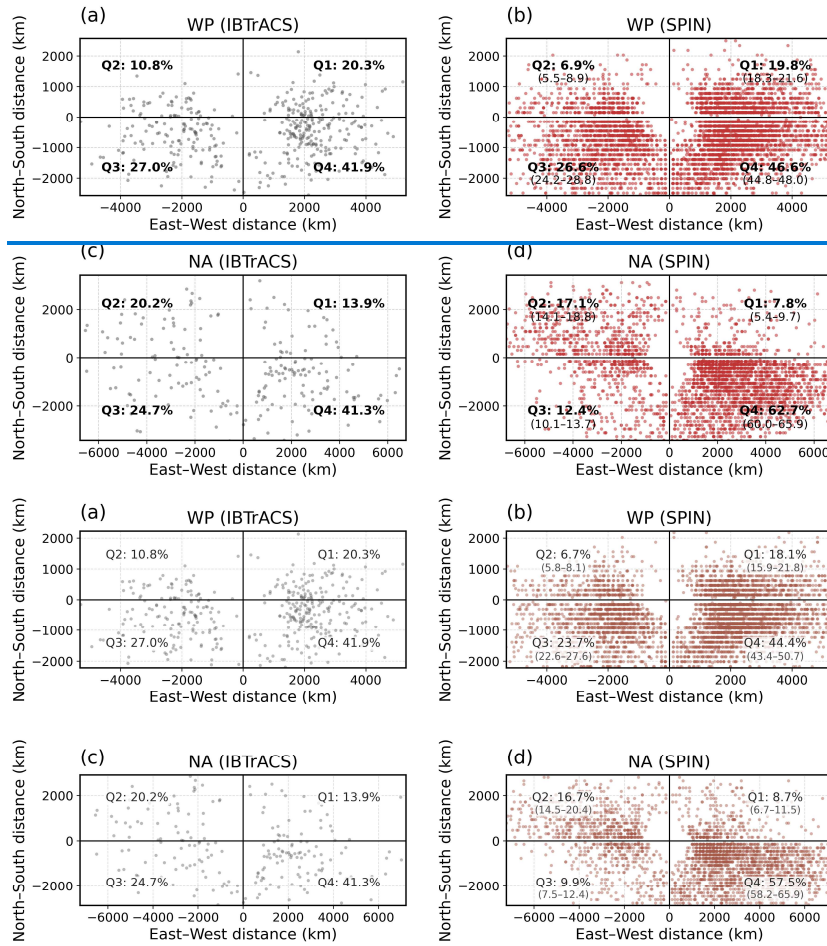
Formatted: English (United Kingdom)

Formatted: English (United Kingdom)

Formatted: English (United Kingdom)

Formatted: English (United Kingdom)

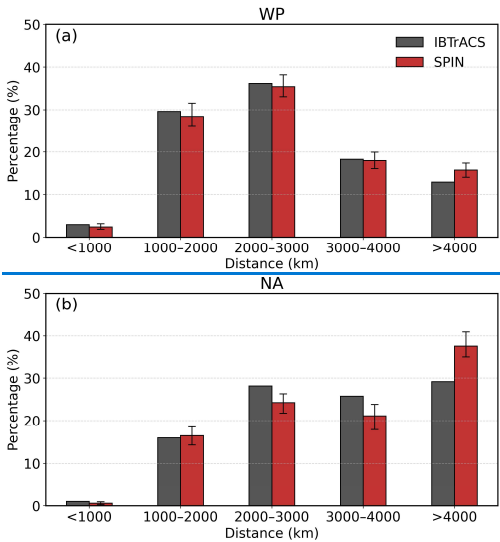


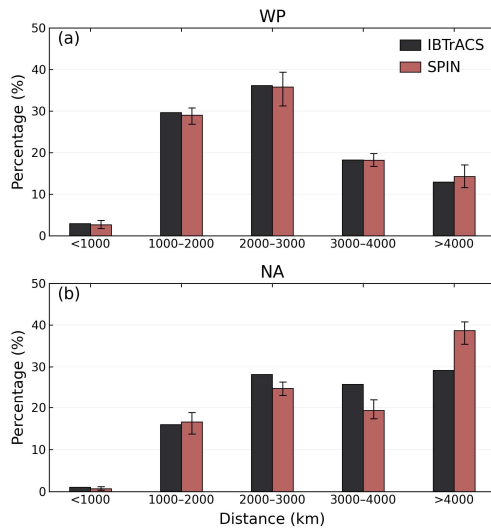


**Figure 14.** Relative locations between pre-existing and subsequent TCs in MTCEs from 1980 to 2022 for the WP (a–b) and NA (c–d) basins. The crosshair center marks the pre-existing TC. Points in the four quadrants show the relative positions of subsequent TCs for IBTrACS

615 (first column) and for SPIN (second column; all ensemble members with a single velocity initialization run). Percentages for each quadrant are reported. SPIN results include the 10th-90th percentile range.

SPIN also well-captures the spatial pattern of MTCE compared to observation (Figure 14). ~~SPIN reproduces the observed preference for subsequent TC genesis in the southeastern quadrant relative to the pre-existing TC (Krouse and Sobel, 2010; Yoshida and Ishikawa, 2013), with the fewest events occurring in the northwestern quadrant in the WP basin and in the northeastern quadrant in the NA basin. However, the percentage of events in each quadrant simulated by SPIN does not fully match the values observed. For example, SPIN overestimates the share of subsequent genesis events in southeastern quadrant in NA basin (Figure 3). For inter-storm distances (~~~~).~~ ~~It reproduces the observed preference for subsequent TC genesis in the southeastern quadrant relative to the pre-existing TC (Krouse and Sobel, 2010; Yoshida and Ishikawa, 2013), with the fewest events occurring in the northwestern quadrant in the WP basin and in the northeastern quadrant in the NA basin. The agreement is particularly close in the WP basin, whereas in the NA basin SPIN shows a larger discrepancy, overestimating events in the southeastern quadrant and underestimating those in the southwestern quadrant (Figure 14). For inter-storm distances (Figure 15), SPIN reproduces the observed distribution in both basins, with fewest events at <1000 km, a peak at 2000–3000 km in the WP, and a peak at >4000 km in the NA. SPIN slightly overestimates~~~~The overestimation of the >4000 km bin in both basins, which the NA basin may be related to the overestimation of lifetime in thereflect excess TC genesis near West Africa (Figure 6), slightly longer simulated TCs~~~~TC lifetimes (Figure S9), or a combination of both.~~





**Figure 15.** Histogram of distances between pre-existing and subsequent TCs within MTCEs from 1980 to 2022. Panel (a) shows the global distribution, panel (b) the NA basin, and panel (c) the WP basin distributions. Results are binned into fixed 1000-km intervals. IBTrACS are shown in black bar, and the SPIN ensemble mean is shown in red with 10th-90th percentile ranges.

#### 4 Return Periods

In this section, we evaluate SPIN's skill in estimating return periods of metrics of interest at both global and regional scales. In particular, we investigated return periods of landfall intensity and the inter-event time between MTCEs.

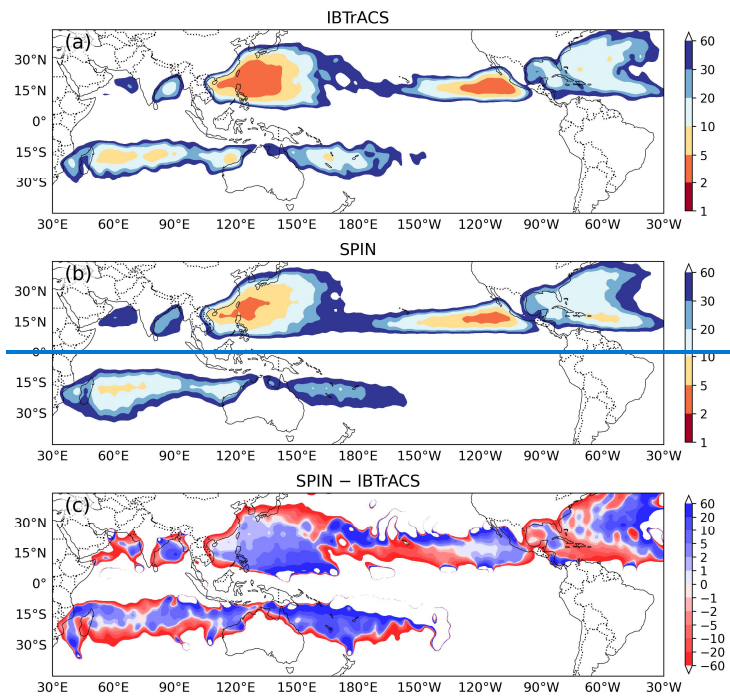
##### 4.1 Return period of landfall intensity

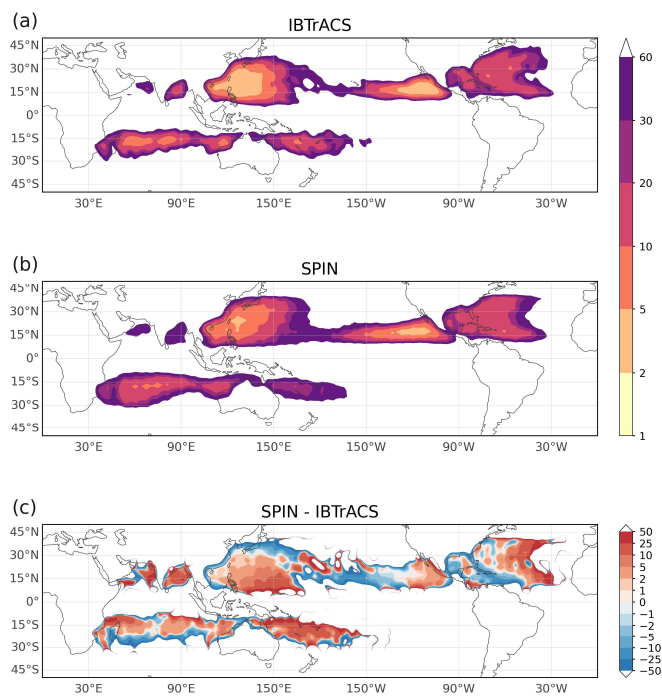
Figure 16 presents global maps of the return period for Category 1 and above TCs based on observations and SPIN downscaled results. SPIN successfully captures the main hazard hotspots, including the southwestern part of the western North Pacific, which covers southeastern China, southern Japan, and the Philippines, as well as the southeastern part of the eastern North Pacific. In these regions, return periods are generally less than 10 years and, in some areas, less than 5 years. Compared to observations, SPIN tends to overestimate hazard, indicated by shorter return periods, along the coasts of China, India, Australia, Japan, and the eastern United States, as indicated by shorter return periods, while it underestimates underestimating hazard, indicated by longer return periods, along in some other regions, including India and the west coast of the United States, where return periods are longer than observed. These regional differences are generally broadly consistent with the

Formatted: Font: Times New Roman, 9 pt, Bold



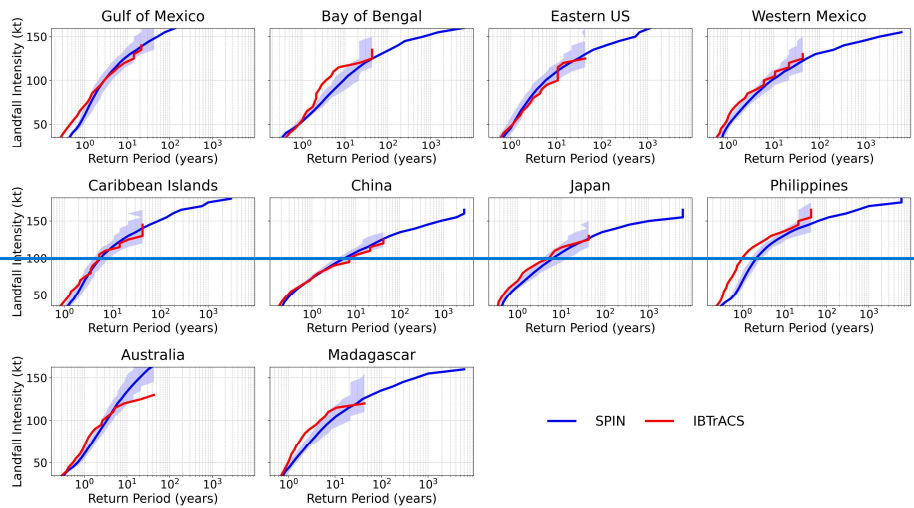
overestimation of biases in simulated storm activity in these regions, as shown in Figure 8, and may also reflect biases in the intensity simulations. It should be noted that, since TCs are rare events and the observational record is limited in duration, the observed hazard may not necessarily reflect the true underlying risk (Lee et al., 2018; Lin et al., 2023).





**Figure 16.** Global return period of TCs reaching  $\geq 33 \text{ m s}^{-1}$  (Category 1): (a) IBTrACS, (b) SPIN ensemble mean, and (c) their difference on a  $1^\circ \times 1^\circ$  grid with Gaussian smoothing. In panel (c), red (blue-red) indicates longer (shorter) return periods in SPIN than in IBTrACS, i.e., hazard underestimation (overestimation) by the model.

Next, we evaluate return period of landfall intensity for various TC-prone regions worldwide (Figure 17), with regional definitions following Lee et al. (2018) and Lin et al. (2022). The curves are presented without bias correction to the observations. Overall, the modelled return periods show good agreement with observations at lower intensities, although some biases remain, such as an overestimation of the return period for weak TCs in Gulf of Mexico, Philippines, and Madagascar. In contrast, the agreement is strong in the Eastern United States, China, and Japan. Biases in the return periods reflect biases in both landfall frequency and intensity. Further improvements may be achieved by tuning the intensity model and TCs tracking parameters.

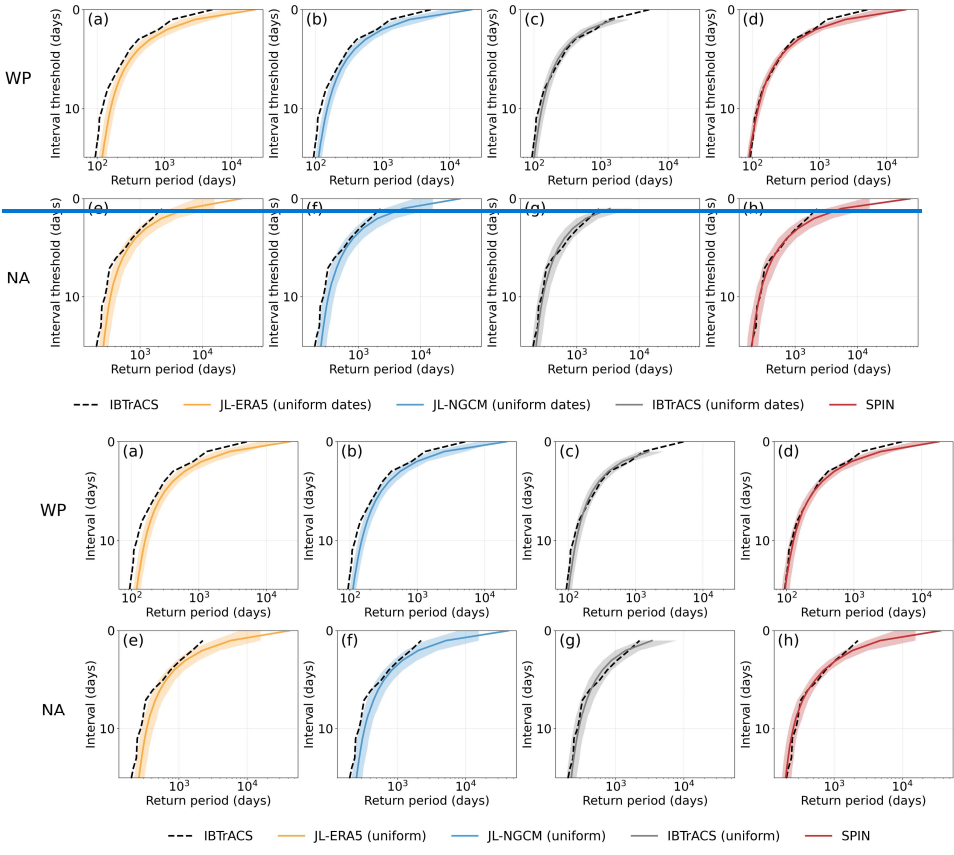


). The curves are shown without regional bias correction. Overall, SPIN captures the observed order of magnitude of landfall return periods in most regions. Regional biases remain, with longer return periods in some regions such as the Bay of Bengal, Philippines, Australia and Madagascar, and shorter return periods in parts of China and the Eastern US. These biases likely reflect a combination of regional landfall-frequency biases and biases in landfall intensity. Because SPIN applies a single set of FAST parameters across regions, this configuration is not necessarily optimal for every region. For application-specific hazard assessments, targeted calibration of the FAST parameters may further improve regional estimates of landfall intensity return periods.



Overall, compared to previous synthetic TC models, SPIN achieves a more comprehensive coupling between environmental fields and TCs. This enables physically consistent MTCE return period estimates even with limited computational resources, providing a novel tool for assessing TC-related compound hazards.

690



**Figure 18.** Return periods of inter-MTCE time. The y-axis shows the MTCE inter-genesis interval (0–15 days), and the x-axis shows the return period (days). Panels (a–d) correspond to the WP basin and panels (e–h) to the NA basin. Shown for comparison are results from IBTrACS (black), IBTrACS with uniformly sampled dates (grey), JL-downscaled-ERA5 with uniformly sampled dates (yellow), and JL-

695

~~downscaled-NeuralGCM~~NGCM (single ensemble member) with uniformly sampled dates (blue), and SPIN (red). The solid line in each panel indicates the return period computed from all Monte Carlo simulations (a, b, c, e, f, g) or all ensemble members (d, h). The shaded region represents the 10th–90th percentile range across individual ensemble members.

700 **5 Summary and ~~Discussion~~discussion**

In this study, we develop a hybrid framework, SPIN, that functions as a spontaneous synthetic TC model with realistic intensity, to downscale TCs for risk analysis. The model leverages NeuralGCM (Kochkov et al., 2024) to simulate ensembles of spontaneously generated TC tracks, and couples the FAST intensity model (Emanuel, 2017; Lin et al., 2023) to compute realistic intensities based on the large-scale environment. ~~In this way, SPIN bridges the gap between statistical and dynamical downscaling models, enabling the generation of large ensembles of physically consistent synthetic TCs at low computational cost. In contrast to traditional and offers two key improvements over earlier statistical downscaling models that assume independent TC methods. First, it generates large ensembles of synthetic TCs together with their ambient environments. Second, it resolves intra-month processes. Therefore, SPIN explicitly simulates advances TC emergence from and interactions with the environment, enabling improved representation of multiple risk assessment by enabling compound TC hazards, such as MTCEs and related events (MTCEs), to be assessed as dynamically organized events rather than statistical co-occurrences alone.~~

SPIN reproduces the observed climatology of TC activity reasonably, including interannual variability of TC frequency, seasonal cycle, patterns of TC genesis and tracks, and the probability distribution of LMI. Compared with previous statistical downscaling models, SPIN better represents interannual variability in regions where ENSO signals (e.g. the WP and Southern Hemisphere basins) are mixed. This advantage of SPIN stems from simulated TCs interacting with the environment, whereas random seeding methods applied in previous synthetic TC models can artificially enhance genesis in low TC activity regions while suppressing it in high TC activity regions (Camargo et al., 2007; Lin et al., 2023). Furthermore, unlike statistical models that provide only monthly information on TC genesis, SPIN explicitly outputs the TC genesis and lysis time, thus can more realistically reproduce the distribution of inter-TC genesis dates in each basin.

Beyond reproducing individual TC events, SPIN shows robust skills in simulating MTCEs. We evaluate SPIN's performance in reproducing MTCE characteristics in the WP and NA basins, where MTCEs occur most frequently (Fu et al., 2025). SPIN reproduces the interannual variability of MTCEs more faithfully than the benchmark models, exhibiting higher correlations with observations and a closer match in interannual variance. SPIN reproduces the peak number of concurrent TCs within MTCE clusters more accurately, benefiting from its improved representation of TC inter-genesis timing. In addition, it captures the spatial distribution and return periods of MTCEs with close agreement with observations.

While SPIN provides a physically consistent and computationally efficient framework for synthetic TC simulation, ~~several~~SPIN reproduces key features of observed TC climatology, including interannual variability of TC frequency, seasonal

Formatted: Normal, Left, Line spacing: single

Formatted: English (Hong Kong SAR)

Formatted: English (Hong Kong SAR)

Formatted: English (Hong Kong SAR)

730 cycle, patterns of TC genesis and tracks, and the probability distribution of LMI. Compared with previous statistical  
downscaling models, SPIN better represents interannual variability in regions where ENSO signals are mixed (e.g. the WP  
and Southern Hemisphere basins). This improvement likely arises because SPIN diagnoses candidate storms from  
NeuralGCM-simulated evolving environmental fields, preserving year-to-year variations in both environmental favourability  
and the supply of precursor disturbances. By contrast, earlier synthetic TC models based on random seeding do not dynamically  
link seed supply to ENSO-related circulation changes. In addition, SPIN explicitly resolves intra-month processes so it can  
more realistically reproduces the distribution of inter-genesis intervals in each basin.

735 Beyond reproducing individual TC events, SPIN shows robust skills in simulating MTCEs. We evaluate SPIN's  
performance in reproducing MTCE characteristics in the WP and NA basins, where MTCEs occur most frequently (Fu et al.,  
2025). Compared with the benchmark models, SPIN better captures observed interannual variability, with higher correlations  
and a closer match to the observed variance. It also more accurately represents MTCE cluster size, consistent with its improved  
simulation of TC inter-genesis intervals. SPIN further captures the observed spatial distribution and return periods of MTCEs  
740 in both basins.

Several aspects can be further-improved in future workwork. For example, although the FAST intensity model-component  
within SPIN-reproduces the overall distribution of LMI reasonably well, it tends to underestimate the occurrence of TC-rapid  
intensification and in turn resulted in fewer is therefore associated with a lower occurrence of extreme-intense TCs compared  
with observation than observed. Moreover, since SPIN is driven by environmental fields simulated by NeuralGCM, biases can  
745 be introduced through the representation of large-scale climate features in TC intensity is diagnosed offline using FAST, and  
NeuralGCM. Leveraging the is an atmosphere only model. Therefore, air-sea interactions related to storm intensity, such as  
storm induced cold-wake cooling, do not feed back onto the simulated environment or influence other TCs.

More broadly, SPIN demonstrates how hybrid AI-physics climate models can be used to build physically informed and  
computationally efficient hazard downscaling frameworks. Its modular design of our model, which allows seamless  
750 integration facilitates future model development. In particular, the framework can be readily integrated with other AI-based  
weather and climate models, SPIN can be further-improved when future AI models generate more realistic and is expected to  
benefit from improvements in the representation of large-scale climate features. In addition, the SPIN framework can variability.  
It could also be extended to explore investigate other types of compound hazards, such as TC-heatwave interactions. It might  
also be associated heatwaves, and coupled with GCM simulations to assess projected changes in TC and MTCE characteristics  
755 under future climate scenarios.

**Code and data availability**

The full code for the SPIN (v1.0) model, together with documentation and sample data is archived on Zenodo at  
<https://doi.org/10.5281/zenodo.17863785> (Gao and Xi, 2025). <https://doi.org/10.5281/zenodo.20796397> (Gao and Xi, 2026).

Formatted: English (United Kingdom)

Formatted: English (United Kingdom)

Formatted: English (United Kingdom)

Formatted: English (United Kingdom)

Formatted: English (United Kingdom)

Formatted: English (United Kingdom)

Formatted: English (United Kingdom)

Formatted: English (United Kingdom)

Formatted: English (United Kingdom)

Formatted: English (United Kingdom)

Formatted: English (United Kingdom)

The SPIN-simulated tracks for all ensembles analyzed in this study are archived on Zenodo under the copyright license CC BY 4.0 at <https://doi.org/10.5281/zenodo.17863932> (Gao, 2025); <https://doi.org/10.5281/zenodo.20795548> (Gao, 2026). The TempestExtremes tool (Ullrich et al., 2021) (Ullrich et al., 2021) for tropical cyclone detection and characterization is available at <https://doi.org/10.5281/zenodo.4385656>. The snapshots of the JL23 benchmark model (Lin et al., 2023) and IBTrACS dataset (Knapp et al., 2010) (Knapp et al., 2010) used in this study are archived on Zenodo at <https://doi.org/10.5281/zenodo.18230393> to ensure reproducibility. All original credit for the benchmark model and dataset belongs to their respective authors.

**Author contributions**

DX conceived the study. YG developed the model and carried out the simulations. Both authors discussed and interpreted the results. YG drafted the manuscript, and DX contributed to its revision.

**Competing interests**

The authors declare there are no conflicts of interest in this manuscript.

**Acknowledgments**

The computations were performed using the research computing facilities provided by the Information Technology Services at the University of Hong Kong. Both authors acknowledge support from the HKU Start-up Fund (000250348.130087.25300.100.01) and the New Staff Seed Fund (103032009.376). We also thank Paul Ullrich for valuable guidance on the use of TempestExtremes package.

**References**

Baxter, I., Pahlavan, H., Hassanzadeh, P., Rucker, K., and Shaw, T.: Benchmarking atmospheric circulation variability in an AI emulator, ACE2, and a hybrid model, NeuralGCM, <https://doi.org/10.48550/arXiv.2510.04466>, 6 October 2025.

Bi, K., Xie, L., Zhang, H., Chen, X., Gu, X., and Tian, Q.: Accurate medium-range global weather forecasting with 3D neural networks, *Nature*, 619, 533–538, <https://doi.org/10.1038/s41586-023-06185-3>, 2023.

Bieli, M., Sobel, A. H., Camargo, S. J., and Tippett, M. K.: A Statistical Model to Predict the Extratropical Transition of Tropical Cyclones, *Weather Forecast.*, 35, 451–466, <https://doi.org/10.1175/WAF-D-19-0045.1>, 2020.

Bloemendaal, N., Haigh, I. D., Moel, H. de, Muis, S., Haarsma, R. J., and Aerts, J. C. J. H.: Generation of a global synthetic tropical cyclone hazard dataset using STORM, *Sci. Data*, 7, 40, <https://doi.org/10.1038/s41597-020-0381-2>, 2020.



785 Bodnar, C., Bruinsma, W. P., Lucic, A., Stanley, M., Allen, A., Brandstetter, J., Garvan, P., Riechert, M., Weyn, J. A., Dong, H., Gupta, J. K., Thambiratnam, K., Archibald, A. T., Wu, C.-C., Heider, E., Welling, M., Turner, R. E., and Perdikaris, P.: A foundation model for the Earth system, *Nature*, 641, 1180–1187, <https://doi.org/10.1038/s41586-025-09005-y>, 2025.

Buonomo, E., Savage, N., Dong, G., Becker, B., Jones, R. G., Tian, Z., and Sun, L.: Tropical Cyclone Changes in Convection-Permitting Regional Climate Projections: A Study Over the Shanghai Region, *J. Geophys. Res. Atmospheres*, 129, e2023JD038508, <https://doi.org/10.1029/2023JD038508>, 2024.

790 Camargo, S. J., Emanuel, K. A., and Sobel, A. H.: Use of a Genesis Potential Index to Diagnose ENSO Effects on Tropical Cyclone Genesis, <https://doi.org/10.1175/JCLI4282.1>, 2007.

[Chen, Z., Leung, L. R., Zhou, W., Lu, J., Lubis, S. W., Liu, Y., Chang, C.-C., Harrop, B. E., Wang, Y., Yang, M., Zhang, G., and Qian, Y.: Hierarchical Testing of a Hybrid Machine Learning-Physics Global Atmosphere Model, \*AGU Adv.\*, 7, e2025AV002075, <https://doi.org/10.1029/2025AV002075>, 2026.](#)

795 Davis, C. A.: Resolving Tropical Cyclone Intensity in Models, *Geophys. Res. Lett.*, 45, 2082–2087, <https://doi.org/10.1002/2017GL076966>, 2018.

Duan, S., Zhang, J., Bonfils, C., and Pallotta, G.: [Could NeuralGCM-effectivelyTesting NeuralGCM’s capability to simulate future heatwaves? A case study based on the 2021 Pacific Northwest heatwave event](#), *Npj Clim. Atmospheric Sci.*, 8, 251, <https://doi.org/10.48550/arXiv.2410.09120>, 6 April 2025, <https://doi.org/10.1038/s41612-025-01137-2>, 2025.

800 Emanuel, K.: Climate and Tropical Cyclone Activity: A New Model Downscaling Approach, <https://doi.org/10.1175/JCLI3908.1>, 2006.

Emanuel, K.: A fast intensity simulator for tropical cyclone risk analysis, *Nat. Hazards*, 88, 779–796, <https://doi.org/10.1007/s11069-017-2890-7>, 2017.

805 Emanuel, K.: [Tropical Cyclone Seeds, Transition Probabilities, and Genesis](#), <https://doi.org/10.1175/JCLI-D-21-0922.1>, 2022.

[Emanuel, K.](#) and Zhang, F.: The Role of Inner-Core Moisture in Tropical Cyclone Predictability and Practical Forecast Skill, <https://doi.org/10.1175/JAS-D-17-0008.1>, 2017.

[Emanuel, K., Ravela, S., Vivant, E., Sundararajan, R., and Risi, C.: A Statistical Deterministic Approach to Hurricane Risk Assessment](#), [Williams, J.: Hurricanes and Global Warming: Results from Downscaling IPCC AR4 Simulations](#), *Bull. Am. Meteorol. Soc.*, 87, 299–344, <https://doi.org/10.1175/BAMS-8789-3-299-2006347>, 2008.

810 [Evans, C., Wood, K. M., Aberson, S. D., Archambault, H. M., Milrad, S. M., Bosart, L. F., Corbosiero, K. L., Davis, C. A., Pinto, J. R. D., Doyle, J., Fogarty, C., Galarneau, T. J., Grams, C. M., Griffin, K. S., Gyakum, J., Hart, R. E., Kitabatake, N., Lentink, H. S., McTaggart-Cowan, R., Perrie, W., Quinting, J. F. D., Reynolds, C. A., Riemer, M., Ritchie, E. A., Sun, Y., and Zhang, F.: The Extratropical Transition of Tropical Cyclones. Part I: Cyclone Evolution and Direct Impacts, \*Mon. Weather Rev.\*, 145, 4317–4344, <https://doi.org/10.1175/MWR-D-17-0027.1>, 2017.](#)

815 Fu, Z.-H., Zhan, R., Zhao, J., Yamada, Y., and Song, K.: Future Projections of Multiple Tropical Cyclone Events in the Northern Hemisphere in the CMIP6-HighResMIP Models, *Geophys. Res. Lett.*, 50, e2023GL103064, <https://doi.org/10.1029/2023GL103064>, 2023.

- 820 Fu, Z.-H., Xi, D., Xie, S.-P., Zhou, W., Lin, N., Zhao, J., Wang, X., and Chan, J. C. L.: Shifting hotspot of tropical cyclone clusters in a warming climate, *Nat. Clim. Change*, 15, 850–858, <https://doi.org/10.1038/s41558-025-02397-9>, 2025.
- Gao, Y.: SPIN (v1.0) outputs for the study “A Spontaneous Synthetic Tropical Cyclone Model Empowered by NeuralGCM for Hazard Assessment,” Zenodo [dataset], Events in the Western North Pacific\*, *Mon. Weather Rev.*, 139, 885–894, <https://doi.org/10.5281/zenodo.17863932>, 2025 [1175/2010MWR3340.1](https://doi.org/10.1175/2010MWR3340.1), 2011.
- 825 Gao, Y. and Xi, D.: A hybrid framework for simulating spontaneous synthetic tropical cyclones (TCs) with realistic intensity, Gao, Y.: Simulation Outputs from SPIN (v1.0), for Tropical Cyclone Risk Assessment, Zenodo [dataset], <https://doi.org/https://doi.org/10.5281/zenodo.17863785>, 2025 [20795548](https://doi.org/10.5281/zenodo.20795548), 2026.
- Gao, Y. and Xi, D.: SPIN (v1.0): A Spontaneous Synthetic Tropical Cyclone Model Empowered by NeuralGCM for Hazard Assessment, Zenodo [dataset], <https://doi.org/https://doi.org/10.5281/zenodo.20796397>, 2026.
- Hart, R. E.: A Cyclone Phase Space Derived from Thermal Wind and Thermal Asymmetry, *Mon. Weather Rev.*, 131, 585–616, [https://doi.org/10.1175/1520-0493\(2003\)131%3C0585:ACPSDF%3E2.0.CO;2](https://doi.org/10.1175/1520-0493(2003)131%3C0585:ACPSDF%3E2.0.CO;2), 2003.
- 830 Hersbach, H., Bell, B., Berrisford, P., Hirahara, S., Horányi, A., Muñoz-Sabater, J., Nicolas, J., Peubey, C., Radu, R., Schepers, D., Simmons, A., Soci, C., Abdalla, S., Abellan, X., Balsamo, G., Bechtold, P., Biavati, G., Bidlot, J., Bonavita, M., De Chiara, G., Dahlgren, P., Dee, D., Diamantakis, M., Dragani, R., Flemming, J., Forbes, R., Fuentes, M., Geer, A., Haimberger, L., Healy, S., Hogan, R. J., Hólm, E., Janisková, M., Keeley, S., Laloyaux, P., Lopez, P., Lupu, C., Radnoti, G., de Rosnay, P., Rozum, I., Vamborg, F., Villaume, S., and Thépaut, J.-N.: The ERA5 global reanalysis, *Q. J. R. Meteorol. Soc.*, 146, 1999–2049, <https://doi.org/10.1002/qj.3803>, 2020.
- Hsieh, T.-L., Vecchi, G. A., Yang, W., Held, I. M., and Garner, S. T.: Large-scale control on the frequency of tropical cyclones and seeds: a consistent relationship across a hierarchy of global atmospheric models, *Clim. Dyn.*, 55, 3177–3196, <https://doi.org/10.1007/s00382-020-05446-5>, 2020.
- 840 Ito, K. and Yamauchi, K.: Limited Influence of Pre-Existing Tropical Cyclones on Subsequent Cyclogenesis in the Western North Pacific, *J. Geophys. Res. Atmospheres*, 131, e2025JD044793, <https://doi.org/10.1029/2025JD044793>, 2026.
- Jing, R. and Lin, N.: An Environment-Dependent Probabilistic Tropical Cyclone Model, *J. Adv. Model. Earth Syst.*, 12, e2019MS001975, <https://doi.org/10.1029/2019MS001975>, 2020.
- Jing, R., Gao, J., Cai, Y., Xi, D., Zhang, Y., Fu, Y., Emanuel, K., Diffenbaugh, N. S., and Bendavid, E.: TC-GEN: Data-Driven Tropical Cyclone Downscaling Using Machine Learning-Based High-Resolution Weather Model, *J. Adv. Model. Earth Syst.*, 16, e2023MS004203, <https://doi.org/10.1029/2023MS004203>, 2024.
- 845 Jones, S. C., Harr, P. A., Abraham, J., Bosart, L. F., Bowyer, P. J., Evans, J. L., Hanley, D. E., Hanstrum, B. N., Hart, R. E., Lalaurette, F., Sinclair, M. R., Smith, R. K., and Thorncroft, C.: The Extratropical Transition of Tropical Cyclones: Forecast Challenges, Current Understanding, and Future Directions, *Weather Forecast.*, 18, 1052–1092, [https://doi.org/10.1175/1520-0434\(2003\)018%3C1052:TETOTC%3E2.0.CO;2](https://doi.org/10.1175/1520-0434(2003)018%3C1052:TETOTC%3E2.0.CO;2), 2003.
- 850 Judt, F., Klocke, D., Rios-Berrios, R., Vanniere, B., Ziemann, F., Auger, L., Biercamp, J., Bretherton, C., Chen, X., Düben, P., Hohenegger, C., Khairoutdinov, M., Kodama, C., Kornblüch, L., Lin, S.-J., Nakano, M., Neumann, P., Putman, W., Röber,

- N., Roberts, M., Satoh, M., Shibuya, R., Stevens, B., Vidale, P. L., Wedi, N., and Zhou, L.: Tropical Cyclones in Global Storm-Resolving Models, *J. Meteorol. Soc. Jpn. Ser II*, 99, 579–602, <https://doi.org/10.2151/jmsj.2021-029>, 2021.
- 855 Knapp, K. R., Kruk, M. C., Levinson, D. H., Diamond, H. J., and Neumann, C. J.: The International Best Track Archive for Climate Stewardship (IBTrACS), <https://doi.org/10.1175/2009BAMS2755.1>, 2010.
- Kochkov, D., Yuval, J., Langmore, I., Norgaard, P., Smith, J., Mooers, G., Klöwer, M., Lottes, J., Rasp, S., Düben, P., Hatfield, S., Battaglia, P., Sanchez-Gonzalez, A., Willson, M., Brenner, M. P., and Hoyer, S.: Neural General Circulation Models for Weather and Climate, *Nature*, 632, 1060–1066, <https://doi.org/10.1038/s41586-024-07744-y>, 2024.
- 860 Krichene, H., Vogt, T., Piontek, F., Geiger, T., Schötz, C., and Otto, C.: The social costs of tropical cyclones, *Nat. Commun.*, 14, 7294, <https://doi.org/10.1038/s41467-023-43114-4>, 2023.
- Krouse, K. D. and Sobel, A. H.: An observational study of multiple tropical cyclone events in the western north Pacific, *Tellus Dyn. Meteorol. Oceanogr.*, 62, 256–265, <https://doi.org/10.1111/j.1600-0870.2009.00435.x>, 2010.
- Lee, C., Tippett, M. K., Sobel, A. H., and Camargo, S. J.: An Environmentally Forced Tropical Cyclone Hazard Model, *J. Adv. Model. Earth Syst.*, 10, 223–241, <https://doi.org/10.1002/2017MS001186>, 2018.
- 865 Lin, J., Emanuel, K., and Vigh, J. L.: Forecasts of Hurricanes Using Large-Ensemble Outputs, <https://doi.org/10.1175/WAF-D-19-0255.1>, 2020.
- Lin, J., Rousseau-Rizzi, R., Lee, C.-Y., and Sobel, A.: An Open-Source, Physics-Based, Tropical Cyclone Downscaling Model With Intensity-Dependent Steering, *J. Adv. Model. Earth Syst.*, 15, e2023MS003686, <https://doi.org/10.1029/2023MS003686>, 2023.
- 870 [Peings, Y., Dong, C., Mahesh, A., Pritchard, M., Collins, W., and Magnusdottir, G.: Subseasonal Forecasting and MJO Teleconnections in Machine Learning Weather Prediction Models, \*J. Geophys. Res. Atmospheres\*, 131, e2025JD044910, <https://doi.org/10.1029/2025JD044910>, 2026.](https://doi.org/10.1029/2025JD044910)
- Price, I., Sanchez-Gonzalez, A., Alet, F., Andersson, T. R., El-Kadi, A., Masters, D., Ewalds, T., Stott, J., Mohamed, S., Battaglia, P., Lam, R., and Willson, M.: Probabilistic weather forecasting with machine learning, *Nature*, 637, 84–90, <https://doi.org/10.1038/s41586-024-08252-9>, 2025.
- 875 Ritchie, E. A. and Holland, G. J.: Large-Scale Patterns Associated with Tropical Cyclogenesis in the Western Pacific, 1999.
- Schenkel, B. A.: A Climatology of Multiple Tropical Cyclone Events, <https://doi.org/10.1175/JCLI-D-15-0048.1>, 2016.
- Ullrich, P. A., Zarzycki, C. M., McClenny, E. E., Pinheiro, M. C., Stansfield, A. M., and Reed, K. A.: TempestExtremes v2.1: a community framework for feature detection, tracking, and analysis in large datasets, *Geosci. Model Dev.*, 14, 5023–5048, <https://doi.org/10.5194/gmd-14-5023-2021>, 2021.
- 880 [Vickery, P. J., Skerlj, P. F., and Twisdale, L. A.: Simulation of Hurricane Risk in the U.S. Using Empirical Track Model, \*J. Struct. Eng.\*, 126, 1222–1237, \[https://doi.org/10.1061/\\(ASCE\\)0733-9445\\(2000\\)126:10\\(1222\\)\]\(https://doi.org/10.1061/\(ASCE\)0733-9445\(2000\)126:10\(1222\)\), 2000.](https://doi.org/10.1061/(ASCE)0733-9445(2000)126:10(1222))
- [Wood, K., Yanase, W., Beven, J., Camargo, S. J., Courtney, J. B., Fogarty, C., Fukuda, J., Kitabatake, N., Kucas, M., McTaggart-Cowan, R., Reboita, M. S., and Riboldi, J.: Phase transitions between tropical, subtropical, and extratropical cyclones: A review from IWTC-10, \*Trop. Cyclone Res. Rev.\*, 12, 294–308, <https://doi.org/10.1016/j.tcr.2023.11.002>, 2023.](https://doi.org/10.1016/j.tcr.2023.11.002)

Xi, D. and Lin, N.: Sequential Landfall of Tropical Cyclones in the United States: From Historical Records to Climate Projections, *Geophys. Res. Lett.*, 48, e2021GL094826, <https://doi.org/10.1029/2021GL094826>, 2021.

Xi, D., Lin, N., and Gori, A.: Increasing sequential tropical cyclone hazards along the US East and Gulf coasts, *Nat. Clim. Change*, 13, 258–265, <https://doi.org/10.1038/s41558-023-01595-7>, 2023.

Yoshida, R. and Ishikawa, H.: Environmental Factors Contributing to Tropical Cyclone Genesis over the Western North Pacific, <https://doi.org/10.1175/MWR-D-11-00309.1>, 2013.

Zhang, G., Rao, M., Yuval, J., and Zhao, M.: Advancing seasonal prediction of tropical cyclone activity with a hybrid AI-physics climate model, *Environ. Res. Lett.*, 20, 094031, <https://doi.org/10.1088/1748-9326/adf864>, 2025.

Zhou, Y. and Lin, Y.: A Toy Model for the Global Annual Number of Tropical Cyclones, *Earths Future*, 12, e2024EF004839, <https://doi.org/10.1029/2024EF004839>, 2024.

Zscheischler, J., Westra, S., van den Hurk, B. J. J. M., Seneviratne, S. I., Ward, P. J., Pitman, A., AghaKouchak, A., Bresch, D. N., Leonard, M., Wahl, T., and Zhang, X.: Future climate risk from compound events, *Nat. Clim. Change*, 8, 469–477, <https://doi.org/10.1038/s41558-018-0156-3>, 2018.

900