

# pyTCR: A tropical cyclone rainfall model for python

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## Summary

pyTCR is a climatology software package developed in the Python programming language. It implements a horizontally distributed and vertically integrated model (Zhu, Quiring, and Emanuel 2013) for estimating rainfall driven by tropical cyclones (TCs). Along TC tracks, rainfall is estimated by computing the cross-boundary-layer, upward water vapor transport caused by different mechanisms including frictional convergence, vortex stretching, large-scale baroclinic effect (i.e., wind shear), topographic forcing, and radiative cooling (Lu et al. 2018). The package provides essential functionalities for modeling and interpreting spatio-temporal TC rainfall data. pyTCR requires a limited number of model input parameters, making it a convenient and useful tool for analyzing rainfall mechanisms driven by TCs.

To sample rare (most intense) rainfall events that are often of great societal interest, pyTCR leverages outputs from a statistical-dynamical TC downscaling model (Lin et al. 2023) capable of rapidly generating a large number of synthetic TCs given a certain climate. As a result, pyTCR significantly reduces computational effort and improves the efficiency in capturing extreme TC rainfall events at the tail of the distributions from limited datasets. Furthermore, the TC downscaling model is forced entirely by large-scale environmental conditions from reanalysis data or coupled General Circulation Models (GCMs), simplifying the projection of TC-induced rainfall and wind speed under future climate using pyTCR. Finally, pyTCR can be coupled with hydrological and wind models to assess risks associated with independent and compound events (e.g., storm surges and freshwater flooding).

## Statement of need

TCs – that is, hurricanes and tropical storms – are among the most destructive weather events, causing massive economic and human losses worldwide each year (Mendelssohn et al. 2012; Krichene et al. 2023). In the United States, hurricanes

can trigger a surge of deaths long after the storms through complex chains of lasting impacts (Young and Hsiang 2024). Much of the damage caused by TCs is done by water – particularly by torrential rainfall (which is sensitive to a variety of a storm’s structural characteristics, intensity, and movement) and subsequent flooding (Shi et al. 2024; W. Zhang et al. 2018). Accurately capturing TC rainfall characteristics at high spatial (e.g., <10 km) and temporal resolution (e.g, hourly) is therefore of critical importance. Moreover, a growing body of evidence suggests that TC rainfall is becoming more intense under a warming climate due to the Clapeyron–Clausius scaling of water vapor in the atmosphere (Held and Soden 2006), increasing the likelihood of extreme rainfall and flooding (Emanuel 2021; Zhu, Emanuel, and Quiring 2021). Given the societal consequences of TCs, it is crucial to understand not only TC risk in the current climate, but also how the risk might evolve with warming. Advancing tools and models to accurately and efficiently quantify these risks is of great significance.

The ability of GCMs to simulate climate extremes has been substantially improved over the past few decades, primarily those participating in the Coupled Model Intercomparison Project phase 6 or CMIP6 (Eyring et al. 2016; Kim et al. 2020). These climate models have become one of the main tools used for exploring the effect of global warming on precipitation and climate variability (Emanuel 2021; Le et al. 2021, 2023). While high-resolution GCMs (e.g., those in the HighResMIP experiments) have improved the representation of TCs (Haarsma et al. 2016; Li and Srivastava 2018; Q. Zhang et al. 2024), they remain too computationally expensive for risk analysis, which requires robust sampling of extreme rainfall events. pyTCR responds to this need for an easy to use and efficient tool that facilitates TC-driven rainfall analysis across scales. It takes the advantage of a synthetic downscaling approach that can generate large ensembles of synthetic TCs at the basin (ocean) scale based on comprehensive climate conditions from observations and reanalysis data and a large number of GCM simulations (Emanuel, Sundararajan, and Williams 2008; Lin et al. 2023). pyTCR provides a fast and highly efficient tool for risk analysis related to TC rainfall.

## Mathematical Approach

PyTCR implements a TC rainfall model described in Zhu, Quiring, and Emanuel (2013) and Lu et al. (2018) that simulates along-track convective rainfall by relating the precipitation rate to the total upward velocity within the TC vortex. We refer to the study by Lu et al. (2018) for detailed formulation of this model. Here we give a brief overview of the main rainfall mechanisms used in this model and implemented in pyTCR.

Let  $P_{TC}$  be the precipitation rate driven by TCs [ $LT^{-1}$ ], it is calculated as:

$$P_{TC} = \epsilon_p \frac{\rho_{air}}{\rho_{liquid}} q_s \max(w, 0)$$

where  $\epsilon_p$  is precipitation efficiency [-],  $\rho_{air}$  and  $\rho_{liquid}$  are the density of water vapor and liquid water [ $ML^{-3}$ ], respectively (the ratio  $\rho_{air}/\rho_{liquid} \approx 0.0012$ ),  $q_s$  is the saturation specific humidity [-], and  $w$  is the upward vertical wind velocity that brings surface moisture into the upper atmosphere [ $LT^{-1}$ ]. The key assumption used here is that TC rainfall is organized around the storm track and proportional to  $w$ . The core function of pyTCR includes estimating  $w$  as a linear combination of five major components:

$$w = w_f + w_h + w_t + w_s + w_r \quad (1)$$

First,  $w_f$  represents the velocity [ $LT^{-1}$ ] induced by surface frictional convergence that depends on the boundary layer formulation. This process is critical for maintaining deep convection and sustaining the TC's core rainfall. It is the dominant factor of  $w$ , estimated as:

$$w_f = \frac{-1}{r} \frac{\partial}{\partial r} \left( r^2 \frac{\tau_{\theta s}}{\partial M / \partial r} \right) \quad (2)$$

in which  $r$  is the radius from the storm center [ $L$ ],  $f$  is the Coriolis force [ $T^{-1}$ ],  $\tau_{\theta s}$  is the azimuthal turbulent stress [ $L^2 T^{-2}$ ], and  $M = rV + \frac{1}{2}fr^2$  is the absolute angular momentum per unit mass [ $L^2 T^{-1}$ ]. Second,  $w_h$  is the surface vertical velocity [ $LT^{-1}$ ] driven by topographic forcing, representing the upward motion of air as it ascends over elevated terrain:

$$w_h = \mathbf{V} \cdot \nabla h \quad (3)$$

where  $h$  is the topographic height [ $L$ ] and  $\mathbf{V}$  is the total horizontal wind velocity [ $LT^{-1}$ ] given as the vector sum of the storm gradient wind (excluding the radial component) and environmental background wind. Third,  $w_t$  denotes the vertical wind velocity component [ $LT^{-1}$ ] arising from time dependence of the storm's vorticity (vortex stretching):

$$w_t = \int_b^H \frac{1}{r} \frac{\partial}{\partial r} \left( r \frac{\partial M / \partial t}{\partial M / \partial r} \right) dz \simeq H_b \frac{1}{r} \frac{\partial}{\partial r} \left( r \frac{\partial M / \partial t}{\partial M / \partial r} \right) \quad (4)$$

in which  $b$  is the height of the boundary layer [ $L$ ],  $H$  is the mid-level of the troposphere [ $L$ ], and  $H_b = H - b$  is a representative depth scale of the lower troposphere [ $L$ ]. Fourth,  $w_s$  denotes the baroclinic/shear component velocity [ $LT^{-1}$ ] approximated as:

$$w_s \simeq \frac{g}{c_p(T_s - T_t)(1 - \epsilon_p)N^2} V \left( f + \frac{V}{r} + \frac{\partial V}{\partial r} \right) (\Delta \mathbf{V}_e \cdot \mathbf{j}) \quad (5)$$

where  $c_p$  is the heat capacity of dry air [ $L^2 T^{-2} K^{-1}$ ],  $g$  is the acceleration of gravity [ $LT^{-2}$ ],  $N$  is the buoyancy frequency for dry air [ $T^{-1}$ ],  $T_s$  is the surface temperature [ $K$ ],  $T_t$  is the tropopause temperature [ $K$ ],  $\mathbf{j}$  is the unit vector pointing radially outward from the storm center, and  $\mathbf{V}_e$  is the vector wind shear across the troposphere [ $LT^{-1}$ ]. Finally,  $w_r$  represents wind velocity related to radiative cooling mechanism [ $LT^{-1}$ ], a process in which heat is lost from the storm system due to infrared radiation emitted by clouds, the storm core, and surrounding environment. For the sake of simplicity, it is set as a constant parameter (-0.005 m/s) in pyTCR .

The inputs to pyTCR are the gradient and total wind, wind shear, topography, and saturation specific humidity along the storm track. The TC downscaling model (Lin et al. 2023) provides pyTCR with 3-hourly information on TCs such as track, intensity, and size to calculate these inputs. The gradient wind is estimated from analytical wind profile models (Chavas, Lin, and Emanuel 2015) based on TC intensity and size. The total wind are approximated as the sum of the gradient wind and storm translation. The storm-centered specific humidity  $q_s$  is calculated from the 600 hPa atmospheric temperature and TC intensity at each time step following Emanuel (2017).

## Examples

pyTCR generates and provides access to a large set of synthetic rainfall events based on TC tracks. To demonstrate its use, the repository includes downscaled TC datasets for the North Atlantic Ocean, derived from 26 CMIP6 models and ERA5 reanalysis data (Hersbach et al. 2020). These datasets are stored in the Texas Advanced Computing Center (TACC) Corral storage (“Corral - TACC HPC Documentation” n.d.). They provide TC track and intensity information required as inputs for pyTCR. For downscaling TCs in other ocean basins, users are referred to Lin et al. (2023) for further details.

To help users get started, we provide six example Jupyter notebooks. These hands-on tutorials are designed for training purpose, guiding users through the key concepts and functions of pyTCR. The notebooks include:

- Downloading and preprocessing TCs data
- Visualizing and analyzing TC tracks and densities
- Generating TC rainfall timeseries
- Generating TC wind speed
- Generating single rainfall event within polygons
- Generating multiple rainfall events within polygons

We briefly present two notebooks in this paper. Users are encouraged to check out other notebooks for learning pyTCR.

Figure 1 compares the tracks and mean power dissipation index (PDI; [ $L^3 T^{-2}$ ]) of TCs downscaled from the low-resolution outputs of the Exascale Energy Earth

Model (E3SM Project 2018) and ERA5 reanalysis data (Hersbach et al. 2020) using the TC downscaling model (Lin et al. 2023) with those obtained from IBTrACS observations in the North Atlantic ocean during the historical period (1964-2014). The PDI quantifies the total power dissipated annually by all TCs in the ocean basin and is defined as  $PDI = \int_0^\tau V_{max}^3 dt$  (Emanuel 2005). Here,  $V_{max}$  is the maximum sustained wind speed at the conventional measurement altitude of 10 m,  $\tau$  is the lifetime of the storm. The PDI captures not only TC frequency, but also duration and intensity. Overall, the results suggest that pyTCR is able to reproduce the behavior of TCs in North Atlantic ocean over the historical period. However, the PDI maps indicate that TCs downscaled the E3SM tend to underestimate storm activity near the tropical eastern Atlantic region.

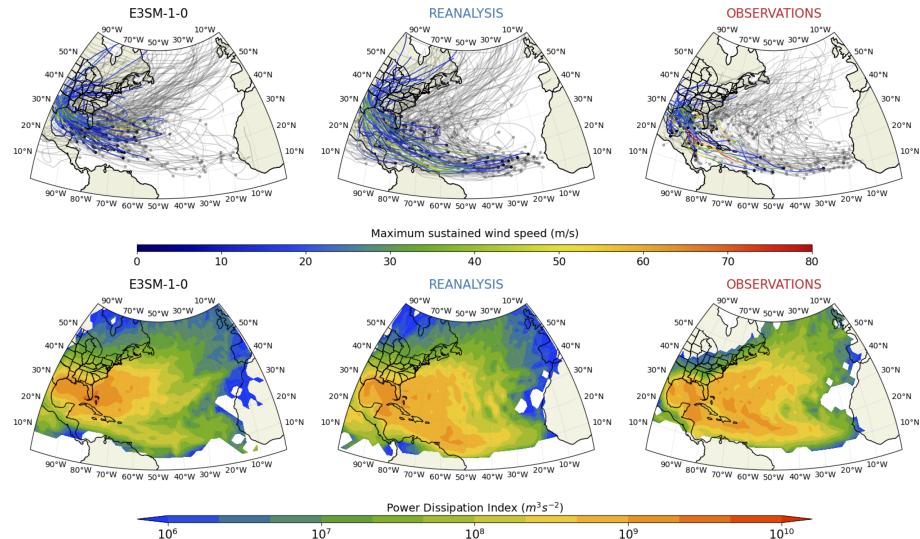


Figure 1: (Top) Tracks of 200 TCs in the North Atlantic. Color lines indicates wind speed and TC tracks that landfall in Texas.(Bottom) Mean power dissipation index (PDI) per  $2^\circ \times 2^\circ$  box per year. Plot was generated using the notebook `ex1_tropical_cyclone_tracks.ipynb` in the repository.

Along each TC track from the downscaling model, pyTCR stochastically generates time series and spatial patterns of rainfall events. Figure 2 illustrates the spatial distribution of total rainfall along a TC track in North Atlantic Ocean. The TC originates in the central Atlantic ( $25^\circ\text{N}, 60^\circ\text{W}$ ) and generally moves westward before making landfall in the United States. Rainfall intensity increases significantly upon landfall in Texas compared to its intensity over the ocean. Time series of rainfall at any domain influenced by the TCs can be easily extracted in pyTCR for other analyses.

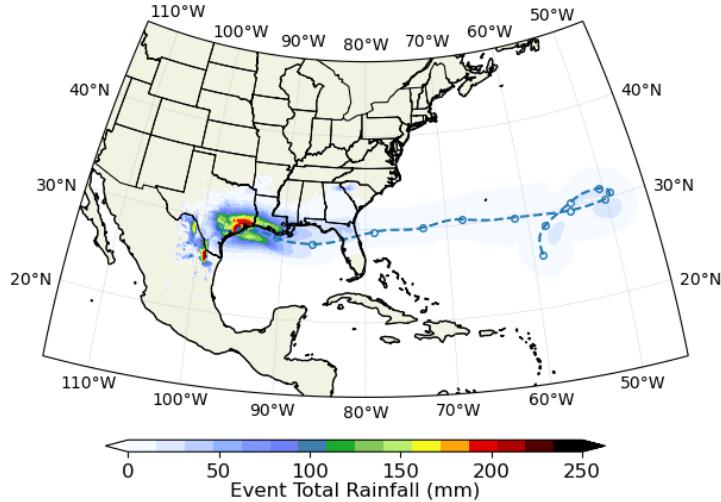


Figure 2: Illustration of the spatial distribution of total rainfall generated for a particular TC track that makes landfall on Texas, USA. Plot was generated using the notebook `ex2_rainfall_generation.ipynb` in the repository

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