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 integrates the capabilities of several legacy physical models (Emanuel, Sundararajan, and Williams 2008; Langousis and Veneziano 2009) into a reduced-complexity framework, enabling rapid estimation of tropical cyclone (TC) rainfall consistent with the large-scale environment. Specifically, `pyTCR` implements a horizontally distributed and vertically integrated model (Zhu, Quiring, and Emanuel 2013) for simulating rainfall driven by TCs. Along storm 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` adapts and 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` provides a tractable approach for 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 Earth System Models (ESMs), 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

Tropical cyclones (TCs)—that is, hurricanes and tropical storms—are among the most destructive weather events, causing massive economic and human losses worldwide each year (Krichene et al. 2023). In the United States, hurricanes can trigger a surge of deaths long after a storm 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 and subsequent flooding (Shi et al. 2024; Zhang et al. 2018). Accurately capturing TC rainfall characteristics at high spatial (e.g. <10 km) and temporal (e.g. hourly) resolution 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 Clausius–Clapeyron scaling of water vapor in the atmosphere (Held and Soden 2006), increasing the likelihood of extreme rainfall and flooding (Zhu, Emanuel, and Quiring 2021). Given the societal consequences of TCs, it is crucial to understand not only TC rainfall 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 ESMs to simulate climate extremes has substantially improved over the past few decades. These models have become key tools used for exploring the effect of global warming on precipitation and climate variability (Emanuel 2021; Le et al. 2021, 2023). While high-resolution ESMs have enhanced the representation of TCs (Haarsma et al. 2016; Li and Sriver 2018) they remain computationally intensive such that often only a limited number of simulations are performed. This constrains their application in TC rainfall risk analysis which requires extensive sampling of extreme events (Emanuel, Sundararajan, and Williams 2008). `pyTCR` addresses this need with an easy-to-use and fast tool that facilitates TC-driven rainfall analysis across scales. Specifically, it leverages a synthetic downscaling approach that combines statistical track generation with simple deterministic intensity modeling. This approach uses thermodynamic and kinematic statistics, derived from ESM outputs or reanalysis data, to generate large numbers (~10^3–10^4) of synthetic TCs (Emanuel et al. 2006; Lin et al. 2023). As a result, `pyTCR` produces statistically robust estimates of the probability distributions of storms for risk assessment.

Mathematical approach

`PyTCR` implements a TC rainfall model described in Lu et al. (2018) that simulates along-track convective rainfall by relating the precipitation rate to the total upward velocity within the TC vortex. Let P_{TC} be the precipitation rate driven by TCs, calculated as:

$$P_{TC} = \epsilon_p \frac{\rho_{air}}{\rho_{liquid}} q_s \max(w, 0) \tag{1}$$

where ϵ_p is precipitation efficiency, ρ_{air} and ρ_{liquid} are the density of water vapor and liquid water, respectively, q_s is the saturation specific humidity, and w is the upward-positive vertical wind velocity that brings surface moisture into the upper atmosphere. The key assumption here is that time-evolving TC rainfall is organized around the storm track and is proportional to w. The core function of `pyTCR` includes estimating w as a linear combination of five major components:

$$w = w_f + w_h + w_t + w_s + w_r \tag{2}$$

where w_f represents the velocity induced by surface frictional convergence, w_h is the velocity driven by topographic forcing, w_t denotes the velocity component arising from time dependence of the storm's vorticity, w_s denotes the baroclinic/shear component of velocity, and w_r represents the velocity related to radiative cooling. We refer to Lu et al. (2018) for detailed formulations of these components.

Examples

To help users learn key concepts and functionalities of `pyTCR`, we provide `Jupyter` notebooks designed for training purposes. For example, Figure 1 compares the tracks and mean power dissipation index (PDI) of TCs downscaled from the outputs of the E3SM-1-0 model and ERA5 reanalysis data using the TC downscaling model (Lin et al. 2023) with those obtained from the IBTrACS observations (Knapp et al. 2010) in the North Atlantic Ocean during the historical period (1964-2014). Along each TC track, `pyTCR` can generate time series and spatial patterns of rainfall events. Figure 2 illustrates the spatial distribution of total rainfall along a TC track.

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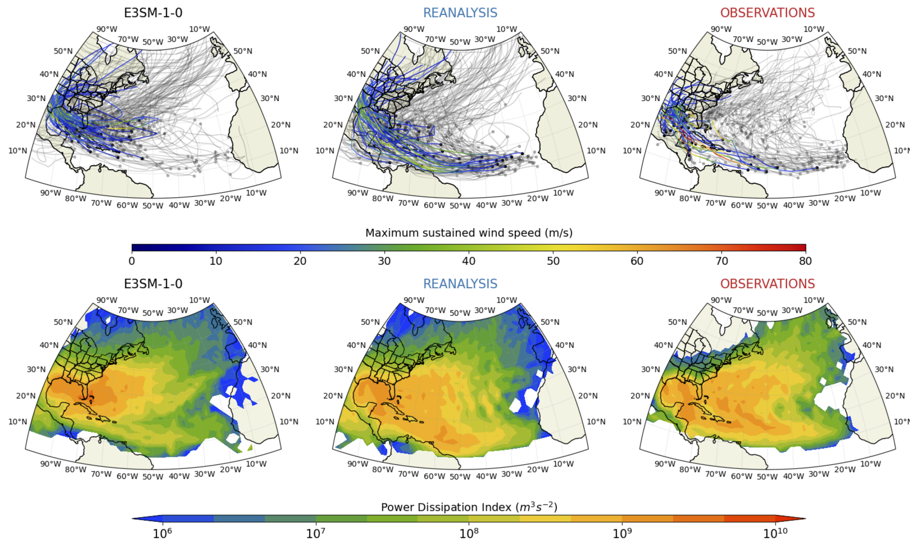

Figure 1: (Top) Tracks of 200 example TCs in the North Atlantic. Color lines indicates wind speed and TC tracks that landfall in Texas.(Bottom) Mean power dissipation index (PDI) per $2° \times 2°$ box per year. Plot was generated using the notebook `ex1_tropical_cyclone_tracks.ipynb` in the repository.

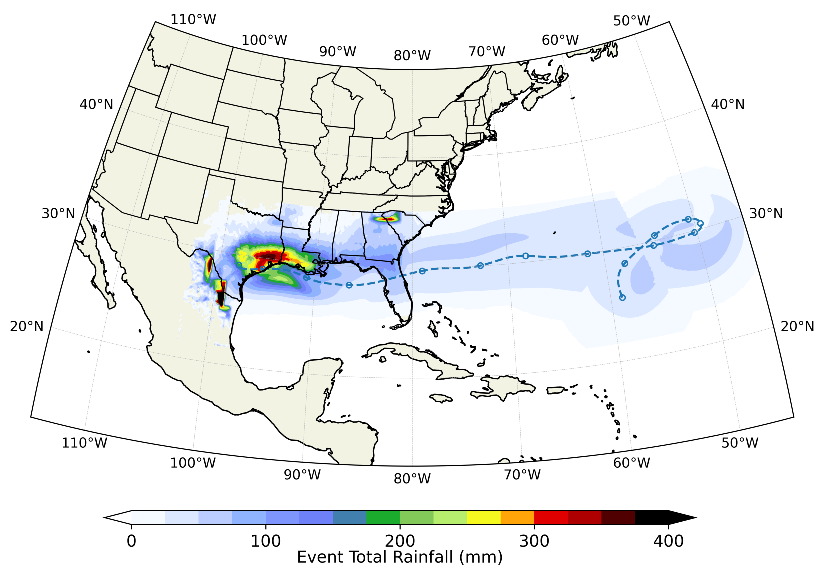

Figure 2: Spatial distribution of total rainfall generated for a particular TC track that makes landfall on Texas, USA. Plot was generated using the notebook `ex2_rainfall_generation.ipynb` in the repository

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