Assessing Tropical Cyclones' Contribution to Precipitation over the Eastern United States and Sensitivity to the Variable-Resolution Domain Extent

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ABSTRACT

Tropical cyclones (TCs) can subject an area to heavy precipitation for many hours, or even days, worsening the risk of flooding, which creates dangerous conditions for residents of the U.S. East and Gulf Coasts. To study the representation of TC-related precipitation over the eastern United States in current-generation global climate models, a novel analysis methodology is developed to track TCs and extract their associated precipitation using an estimate of their dynamical outer size. This methodology is applied to three variable-resolution (VR) configurations of the Community Atmosphere Model, version 5 (CAM5), with high-resolution domains over the North Atlantic and one low-resolution conventional configuration, as well as to a combination of reanalysis and observational precipitation data. Metrics and diagnostics such as TC counts, intensities, outer storm sizes, and annual mean total and extreme precipitation are compared between the CAM5 simulations and reanalysis/observations. The high-resolution VR configurations outperform the global low-resolution configuration for all variables in the North Atlantic. Realistic TC intensities are produced by the VR configurations. The total North Atlantic TC counts are lower than observations but better than reanalysis.

1. Introduction

While the sign of the annual mean precipitation trend over the past century displays a regional dependence, an increase in the frequency and intensity of heavy precipitation events has been consistent across the continental United States (Hayhoe et al. 2018). In coastal regions, tropical cyclones (TCs) are likely contributing

to this observed increase in extreme precipitation. Although the trend in hurricane landfalls over the continental United States from 1900 to 2017 was decreasing, this trend was statistically insignificant at the 95% level (Klotzbach et al. 2018). Nonetheless, multiple studies of recent impactful TCs using different methodologies conclude that the storms produced more precipitation than they would have in the absence of anthropogenic forcing (Van Oldenborgh et al. 2017; Risser and Wehner 2017; Emanuel 2017; Patricola and Wehner 2018; Wang et al. 2018; Trenberth et al. 2018; Reed et al. 2020). These results are highly relevant since precipitation from TCs poses a serious threat to residents of the coastal states; approximately 90% of the TC-related fatalities in the United States from 1963 to

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2012 occurred by drowning or other water-related incidents (Rappaport 2014). Additionally, the economic cost of TC landfalls continues to be a major national issue, with 2017 Hurricanes Harvey, Irma, and Maria alone costing an estimated \$265 billion (Blake and Zelinsky 2018; Cangialosi et al. 2018; Pasch et al. 2019). With growing populations and infrastructure along the coasts (Mendelsohn et al. 2012; Peduzzi et al. 2012) and precipitation from North Atlantic TCs projected to increase by an estimated 10%–30% due to climate change by the end of the century (Knutson et al. 2013; Patricola and Wehner 2018; Gutmann et al. 2018), the socioeconomic damage from future storms will likely worsen. Because the risks and costs associated with TC-related precipitation are so high, it is important to quantify how much of the annual mean total and extreme precipitation comes from TCs in different regions of the United States.

A few recent studies have examined the observed fraction of total precipitation due to TCs in the United States using gauge data (Kunkel et al. 2010, 2012; Villarini et al. 2014b; Khouakhi et al. 2017; Aryal et al. 2018) and satellite products (Shepherd et al. 2007; Jiang and Zipser 2010; Prat and Nelson 2013). While the analysis periods and precipitation metrics varied among these studies, the overall results were generally consistent. Khouakhi et al. (2017) concluded that about 10%–15% of total annual precipitation is TC-induced along the East Coast, Florida Peninsula, and Mexican Gulf Coast, while Prat and Nelson (2013) estimated the percentage as 9%–11%, with maxima over southern Florida and along the coasts. Limiting the analysis to only the North Atlantic hurricane season increased the percentages to 20%–25% for September through November over Florida, coastal Georgia, and the Carolinas (Khouakhi et al. 2017) and 15%–20% along the coasts for June through November (Prat and Nelson 2013). Differences in the definitions of the hurricane season, the time periods examined, and the data sources (i.e., gauge vs satellite) may explain the discrepancies between the studies' percentage ranges.

The fraction of total precipitation due to TCs is generally greater for extreme precipitation than annual or seasonal mean precipitation over the same areas, which reflects the role that TCs play in the upper tail of precipitation distributions (Khouakhi et al. 2017). Looking at metrics of maximum precipitation, TC contribution exceeds 30% at locations along the East Coast and is around 20% for most of the Gulf Coast (Aryal et al. 2018). Kunkel et al. (2010) concluded that TCs are responsible for 13% of heavy precipitation events in the entire United States in June through October and 6% for the calendar year, noting that the South and

Southeast regions experience the most TC-induced heavy precipitation events. Furthermore, Kunkel et al. (2012) estimated that 51% and 71% of extreme precipitation events in the Southeast are TC related throughout the whole year and in the fall, respectively. The Northeast and South also experience significant TC-related events, 36% and 17% annually and 44% and 22% in the fall. The areas that experience the most TC-induced extreme precipitation are also those that see the most TC-induced flooding, specifically Florida, coastal North Carolina, and the Gulf Coast (Aryal et al. 2018). The chance of flooding depends on a variety of factors including soil moisture, basin shape and size, and local land use, but extreme rainfall is a key factor for inducing flooding (Aryal et al. 2018; Hayhoe et al. 2018). While high winds and storm surge are typically concentrated near the landfall location of the storm, extreme precipitation from TCs (or their remnants) can cause inland flooding in states as far northwest as Illinois, Wisconsin, and Michigan (Villarini et al. 2014a).

One underexamined TC characteristic that can worsen hazards such as flooding is storm size. A larger TC can subject an area to a longer duration of precipitation and high wind speeds than a smaller storm. Multiple studies of satellite-observed TC outer size, defined by some measure of the size of the near-surface outer TC circulation, have concluded that this outer circulation remains more constant in time than the size of the inner circulation and is only weakly dependent on intensity (Merrill 1984; Chavas and Emanuel 2010; Lee et al. 2010; Chan and Chan 2012, 2015; Chavas et al. 2015, 2016). Limited work has been done to compare TC outer sizes in climate models to those derived from observations and reanalysis.

The representation of TC structure in high-resolution global climate models (GCMs), such as the Community Atmosphere Model (CAM), is comparable to observations, including spatial mean composites and radial profiles of precipitation (Villarini et al. 2014b) and radial profiles of wind (Reed and Chavas 2015; Chavas et al. 2017). CAM, version 5 (CAM5), run with global 28 km grid spacing, can also produce reasonable simulations of North Atlantic TC climatology (Bacmeister et al. 2014; Wehner et al. 2014; Reed et al. 2015; Wehner et al. 2015; Bacmeister et al. 2018). CAM5 has been used to understand fundamental controls on TC genesis and size on Earth as well (Chavas and Reed 2019). Variable-resolution (VR) grid support in CAM allows for high-resolution grid spacing over an area of interest, in this case the North Atlantic basin, and does not require nearly as much computational resources as traditional global models run at high resolutions since the high resolution is not required over the entire globe

(Zarzycki et al. 2014, 2015). Since TCs are localized to certain ocean basins and their representation in models is dependent on grid spacing, they are ideal phenomena to study with VR. In CAM-VR, TC structure, counts, and spatial distribution were shown to match well with observations (Zarzycki and Jablonowski 2014). Further, the computational savings from the use of VR enables savings to be spent on an ensemble of runs (Zarzycki and Jablonowski 2014), which is in turn useful for extreme event analysis because uncertainties can cause highly divergent behavior in the extreme feature (Sillmann et al. 2017; Bacmeister et al. 2018).

To facilitate the analysis of TC precipitation and size in climate model output, a novel systematic methodology is developed that tracks TCs and automatically extracts TC-related precipitation based on an estimated size of the outer storm circulation. This methodology can be utilized to efficiently study TC track, count, precipitation, and size climatologies globally or in specific basins and compare results between different models or different model setups. This study details this methodology and demonstrates its usefulness in assessing the representation of North Atlantic TC climatology in three VR model configurations. Although several studies have been performed examining VR modeling of TCs, work remains to understand how extensive a high-resolution region must be to capture TC behavior with the same fidelity as a global high-resolution model. To this end, this work investigates the impacts of three CAM-VR grids with high-resolution domains extending over different areas of the North Atlantic basin on TC precipitation over the eastern United States as well as landfalling TC track and size climatologies. The goals of this work are to explain and demonstrate our novel methodology and to evaluate which VR grid configuration provides the best combination of skill and computational cost so that it can be used for ensemble simulations of future climate. Section 2 describes the model setup and analysis methodology for quantifying TC-related precipitation in the models and observations. Section 3 analyzes the results of the experiments, and section 4 provides a discussion of the results and concluding thoughts.

2. Data and methods

a. Tropical cyclone tracking and storm-related precipitation extraction

Objective detection and tracking of TCs within the model output are performed using the TempestExtremes package (Ullrich and Zarzycki 2017). Candidate cyclones are detected in the model output on the native model grid using the following procedure (step 1 in Fig. 1):

- 1) Identify candidates by searching for local minima in the sea level pressure (SLP) field. Remove candidates if a more intense SLP minimum exists within 6° great-circle distance (GCD).
- 2) Check for closed SLP contours around the minimum by requiring an increase in SLP of at least 2 hPa within 5.5° GCD of the candidate using a graph search.
- 3) Check for a warm-core by requiring that the 300–500-hPa geopotential thickness decreases by at least 6 m within 6.5° GCD of the grid point within 1° GCD of the candidate with maximum 300–500-hPa thickness.

The TempestExtremes command line corresponding to this procedure is given in appendix A. These candidates, which are identified at each 6-hourly model time step, are stitched together to create TC tracks after candidates within 8° GCD of each other are connected (step 2 in Fig. 1). For a track to be recorded, the following thresholds must be satisfied for at least ten 6-hourly time steps (not necessarily sequential): maximum near-surface wind greater than or equal to 10 m s^{-1} , maximum surface geopotential less than or equal to $150 \text{ m}^2 \text{ s}^{-2}$, and center latitude less than or equal to 50°N . The wind speed criterion is lenient by the standards of Walsh et al. (2007), which suggested a TC tracking wind speed threshold of 14.5 m s^{-1} for a 125-km resolution model. Within one track, there can only be three consecutive time steps where no candidate is identified; otherwise, two separate trajectories are recorded. These criteria are based off of results from Zarzycki and Ullrich (2017) in which a sensitivity analysis was performed on the TempestExtremes tracking settings that compared the accuracy of the TC tracking against observed TC tracks to determine which tracking criteria, when applied to reanalysis data, maximize hit rate minus false alarm rate. The same tracking thresholds were applied for all model configurations and the reanalysis, regardless of resolution, to allow for the assessment of the value added from increased horizontal resolution to discretely simulated TCs as well as the impact of varying refinement extents on TC genesis and tracks that ultimately impact the eastern United States.

After storm trajectories are identified, radial profiles of the azimuthal wind speed are produced for each TC at each time step in its life cycle. Radial wind profiles are calculated from the zonal and meridional wind components at the lowest model level (approximately 64 m above the surface) following the process described in Chavas et al. (2015) and at 10 m in reanalysis as described in section 2c (step 3 in Fig. 1). First the wind field is

FIG. 1. Schematic of the TempestExtremes algorithm that identifies TCs, tracks them, estimates their outer sizes, and extracts TC-related precipitation. The profile on the bottom left is an idealized radial profile of the azimuthal wind of a TC, and r_8 is notated by the red star. The colored contours in the bottom right are precipitation, and the black dotted line is the TC's track. The precipitation within the red circle is that within r_8 and is recorded as the TC-related precipitation.

split into radial and azimuthal components based on the storm center location calculated by TempestExtremes. Next nearby grid centers are assigned into approximately 28 km (0.25°) bins, and the azimuthal wind speeds are averaged azimuthally around the storm center to create the radial profile of the azimuthal wind. The largest radius outside of the eyewall where the azimuthally averaged azimuthal wind speed exceeds 8 m s^{-1} (r_8) is identified from this radial profile, and this is the radius used to define the outer size of the TC. In Fig. 1, the red star in the wind profile represents r_8 , which was chosen because Schenkel et al. (2017) concluded that r_6 – r_8 are the best outer size metrics to use

for North Atlantic TCs in reanalysis data, and this metric has been used to investigate the TC wind–pressure relationship (Chavas et al. 2017) in CAM5. Six-hourly averaged precipitation within r_8 (within the red circle in Fig. 1) is extracted at each time step and recorded as the precipitation associated with the TC (step 4 in Fig. 1). Since the recording and impact of TC-related precipitation is not dependent on the TC making landfall, precipitation from TCs that come close to shore but do not actually make landfall is included in all precipitation analyses in this study. While TCs decrease in size after they begin interacting with land due to friction, r_8 is sufficiently far enough from the TC

FIG. 2. Depictions of the (left) EXT, (center) REF, and (right) WAT variable-resolution grids in CAM5.

centers to capture TC precipitation, as discussed further in [appendix B](#).

b. Model description

The model used for this study is the Community Earth System Model (CESM), a fully coupled global climate model with atmosphere, ocean, land, and sea ice components. CAM is the atmospheric component of CESM, and specifically CAM5 ([Neale et al. 2012](#)) with the spectral element (SE) dynamical core ([Taylor et al. 1997](#); [Taylor 2011](#); [Dennis et al. 2012](#)) is utilized. CAM5 is a comprehensive atmospheric GCM that includes parameterizations of shallow convection ([Park and Bretherton 2009](#)), deep convection ([Zhang and McFarlane 1995](#)), cloud microphysics ([Morrison and Gettelman 2008](#)), cloud macrophysics ([Park et al. 2014](#)), and radiative transfer ([Mlawer et al. 1997](#); [Iacono et al. 2008](#)). CESM is a contributing model to the Climate Model Intercomparison Project (CMIP).

The model simulations completed for this work are historically forced using Atmospheric Model Intercomparison Project (AMIP) protocols ([Gates 1992](#)) and run from 1984 to 2014 (with 1984 discarded for spinup), resulting in 30 years of data. Since the model simulations do not include coupling to an ocean model, SST boundary conditions are set using the merged Hadley–NOAA/optimum interpolation (OI) dataset as described in [Hurrell et al. \(2008\)](#). A disadvantage of using prescribed SSTs is the lack of TC-generated cold wakes, which could result in

positive TC intensity biases ([Schade and Emanuel 1999](#)). Simulations were performed with three different variable-resolution grids as shown in [Fig. 2](#). Each grid has 28-km grid spacing in the high-resolution focus region and 1° (111 km) grid spacing throughout the rest of the globe, which is a typical grid spacing for conventional global climate models. In [Zarzycki et al. \(2014\)](#) TCs were advected through the transition regions (boundaries of the high-resolution areas) in similar CAM-VR configurations, and the study found no evidence of wave reflection or other numerical noise. The western Atlantic (WAT) grid has the smallest high-resolution domain, only covering the western North Atlantic and eastern United States. The reference (REF) grid has the high-resolution domain covering the whole North Atlantic and eastern United States, and the extended (EXT) grid is the same as the REF grid except the high-resolution domain extends over most of northern Africa. The possible advantage of extending the domain over northern Africa is a better representation of African easterly waves (AEWs), synoptic-scale disturbances that form over sub-Saharan Africa in June–October and often instigate TC genesis. Since it has been estimated that 61% of TCs originate directly from AEWs ([Russell et al. 2017](#)), the representation of AEWs in models would seem to be important to accurately capture North Atlantic TC climatology. However, previous work has shown that AEWs are not essential to get realistic North Atlantic TC counts in model simulations ([Caron and Jones 2012](#)), although the absence of AEWs does affect the spatial climatology of

North Atlantic TCs (Patricola et al. 2018). The high-resolution domains in this study roughly resemble the three regional climate models used to study the links between AEWs and North Atlantic TCs in Caron and Jones (2012). Three ensemble members are created for each grid by varying the initial state, and all model results are presented as ensemble means. A global uniform 1° model configuration (GLOB) with three ensemble members is also performed to compare the VR grids with a grid comparable to conventional CAM5 AMIP simulations. TCs in climate model simulations are affected by the resolution of the model (e.g., Wehner et al. 2014; Roberts et al. 2015; Camargo and Wing 2016; Wehner et al. 2017), and while convection-permitting horizontal grid spacings are ideal for simulating the complex processes within TCs (Gentry and Lackmann 2010), running multidecadal simulations at these high resolutions is currently too computationally expensive for climate models. Multiple studies have shown that climate models with approximately 25-km grid spacing, while not perfect, are useful for exploring TC climatology (e.g., Bacmeister et al. 2014; Zarzycki and Jablonowski 2014; Reed et al. 2015; Bacmeister et al. 2018; Reed et al. 2019). VR configurations are an attempt to find a balance between resolution and computational expense, as there is relatively high resolution over a region of interest with low resolution over the rest of the globe, cutting down the computational costs. For TCs specifically, Davis (2018) found that models with 0.25° (approximately 28 km) or coarser grid spacing should severely underestimate the number of category 4 and 5 TCs compared to observations if the TCs' wind fields are simulated realistically.

c. Observational and reanalysis data

The International Best Track Archive for Climate Stewardship (IBTrACS; Knapp et al. 2010) provides the 6-hourly observed TC track data for the same time period as the model simulations, 1985–2014 (Fig. 3, top). Additionally, 6-hourly 10-m wind, sea level pressure, and geopotential height data from the fifth major global reanalysis produced by the European Centre for Medium-Range Weather Forecasts (ERA5; Copernicus Climate Change Service 2017) with 31-km horizontal grid spacing for 1985–2014 are used for TC track (Fig. 3, bottom), size, and precipitation analyses. Since reanalysis is an observationally constrained version of a GCM simulation, one could anticipate there to be better agreement between the CAM5 simulations and ERA5 than the model simulations and IBTrACS. An additional consideration regarding TC observations is the lack of a consistent, long-term observational spatial wind field dataset from within TCs, so r_8 cannot be used to calculate TC-related precipitation using IBTrACS. Although it is typical that a 500-km radius is

FIG. 3. Continental U.S. landfalling TC tracks from (top) IBTrACS and (bottom) ERA5 for 1985–2014 to match the model time period. The colors of the lines represent the intensity of the storm as measured by the Saffir–Simpson scale.

used as an estimate of TCs' radii throughout their whole lifetime (e.g., Jiang and Zipser 2010; Barlow 2011; Prat and Nelson 2013; Villarini et al. 2014b; Khouakhi et al. 2017), it is known that TCs' outer sizes can fluctuate throughout their lifetime and this can cause an overestimation of TC-related precipitation when the storm is over land (see appendix B). To avoid the use of an arbitrary distance when estimating outer storm size, this study will use ERA5 track data in combination with an observational precipitation dataset for the precipitation analysis as the TempestExtremes software is straightforwardly applied to ERA5 and an outer size can be estimated from ERA5 winds.

Despite the assimilation of observational data in ERA5, the TC counts and intensities in the North Atlantic are underestimated compared to IBTrACS. The underestimation of 10-m winds within TCs in ERA5 likely contributes to the lack of tracked TCs, even though the TempestExtremes tracking parameters were optimized using reanalysis data (Zarzycki and Ullrich 2017). ERA5 underestimates total North Atlantic TC counts by about 37% and does not simulate any TCs with 10-m winds higher than a category 2 on the Saffir–Simpson scale. To an extent, this is expected, as multiple previous studies that looked at the representation of TCs in reanalysis datasets, including ERA5's predecessor ERA-Interim, found similar underestimates of TC

intensities (Schenkel and Hart 2012; Murakami 2014; Hodges et al. 2017), and the ERA reanalysis products do not include TC vortex relocation or synthetic dropsondes, which can improve the representation of TCs (Schenkel and Hart 2012). While ERA5 outperforms ERA-Interim, a recent study that used ERA5 data found no wind speeds within TCs that exceeded about 40 m s^{-1} (Dullaart et al. 2020), which is consistent with our results. For TC tracking, making a direct comparison with observations is difficult. Dynamically tracking storms in reanalysis datasets keeps the technique as faithful as possible to the analysis of the model data; however, this method can undercount weak storms by not detecting cyclones that exist in IBTrACS (Murakami 2014; Zarzycki and Ullrich 2017; Hodges et al. 2017). While these studies look at TCs globally, Hodges et al. (2017) specifically show that ERA-Interim underestimates annual average TC counts in the North Atlantic basin (see their Fig. 5). Manually tracking cyclones in reanalysis data (as in Schenkel and Hart 2012) would be the other option, although this means that forecaster expertise is needed to determine observed cyclone trajectories. We have explored both methodologies (see supplemental material for sample analysis with the latter) but chose the first method since it remains most faithful to the analysis technique used for climate models. As reanalysis products increase in complexity and resolution over the coming years, this discrepancy will grow smaller.

The observational precipitation product is the Climate Prediction Center (CPC) Unified Gauge-Based Analysis of Precipitation. This product has 0.25° horizontal grid spacing and is only available over the continental United States. It is available for the full time period of 1985–2014 at daily temporal resolution. To calculate the TC-related precipitation with ERA5 6-hourly center locations and daily precipitation data, the TC center locations for each day, minimum of one center location and maximum of four, were identified and the mean $r8$ from those time steps was calculated. Any precipitation that was within this mean $r8$ from all of the center points from that day was recorded as TC-related precipitation for that day.

d. Description of metrics and diagnostics

To assess similarities and differences between the models, reanalysis, and observations, a set of metrics and diagnostics are defined. As discussed above in section 2a, $r8$ is the radius of the azimuthally averaged 8 m s^{-1} azimuthal wind and approximates the size of a TC's outer circulation. To study TC track climatology beyond landfalling storm counts, landfall and track density diagnostics are used. Landfall density is calculated as the sum of all points within each storm's $r8$ at the time of landfall, multiplied by 6 to convert to hours,

and divided by 30 years. This diagnostic can be interpreted as the number of hours per year that a given point is impacted by TCs at their times of landfall. Track density is similar to landfall density except it is calculated at all times of the TCs' lifetimes, not just the times of landfall, and therefore provides a measure of the number of hours per year a given point is impacted by TCs.

The extreme precipitation diagnostic used in this study is the annual maximum 5-day precipitation total (Rx5day). This diagnostic has been used by Sanderson and Wehner (2017) in the Fourth National Climate Assessment to compare the prediction skill of different CMIP5 models. Rx5day is calculated by summing up precipitation at each grid point for each 5-day window for each year. The maximum 5-day total is then found for each point and that total is recorded as that individual grid point's Rx5day for that year. This is done for each year of data, and the mean Rx5day is calculated by averaging over time for each grid point. Rx5day is more applicable for TC precipitation analysis than a single day precipitation maximum because TCs often produce precipitation over the same areas for multiple days. To calculate the TC-related Rx5day, the same method is applied to the TC-related precipitation data. To calculate the number of Rx5day events that are due to TCs, the full Rx5day dataset is compared to the TC-related Rx5day at each grid point for each year. If the TC-related Rx5day is greater than zero, that Rx5day event is recorded as due to a TC.

For the statistical analysis of the precipitation diagnostic fields, metrics are calculated that are traditionally used in Taylor Diagrams (Taylor 2001). These metrics facilitate the comparison of the precipitation variables across the VR configurations because they summarize the differences between two-dimensional fields using few numbers. To calculate these metrics, the CPC diagnostics are considered the "reference" field while the model diagnostics are the "test" fields that are compared to the "reference." The first metric is the centered pattern correlation [Eq. (1) in Taylor 2001], which reveals how similar the spatial patterns of variation are between the reference and test fields. An optimal pattern correlation is a value of 1, while small positive numbers and negative numbers indicate bad pattern correlation. The second metric is the ratio of the standard deviation of the reference field to the standard deviation of the test field, which is helpful in comparing the amplitude of the variations in the reference and test fields. For this ratio metric, 1 is the optimal value and any divergence from 1 in either direction indicates worse performance. The third metric is the skill score, which takes into account both the pattern correlation and the ratio. The skill score is defined by Eq. (4) in Taylor (2001).

FIG. 4. The U.S. regions defined in the NCA. This study will focus on the Northeast, Southeast, and Southern Plains regions.

It approaches zero as the pattern correlation becomes increasingly negative or as the test field variance approaches zero or infinity. For the skill score, a value of 1 is best while a value of 0 is the worst. This skill score has been used in previous work to compare TC track density from multiple reanalysis products to observations (Murakami 2014).

e. U.S. regions

The U.S. region divisions used in this study and shown in Fig. 4 are the same as used in the National Climate Assessments (NCA; Reidmiller et al. 2018). TC landfalls are counted in each individual coastal region and precipitation variables are area averaged over these regions as well. This method allows the different model grids to be evaluated on how they perform for different regions of the country.

3. Results

a. TC track climatology

First, we analyze TC track patterns and landfall locations in the different CAM5 configurations and compare these diagnostics to observations and reanalysis. To be counted as a TC, the 10-m maximum wind speed of the storm must be at least 17 m s^{-1} , the Saffir–Simpson scale definition of a tropical storm, at any point in the TC's lifetime. The logarithmic model of the boundary layer is used to adjust the model maximum wind at the lowest vertical level to an estimate of the maximum 10-m wind speed. The total North Atlantic TC counts are significantly underestimated in the GLOB and WAT simulations (by 80% and 50% for the ensemble means, respectively) and slightly underestimated in the REF and EXT simulations (by a little over 3% for both ensemble means) compared to IBTrACS (Table 1). These slight underestimates are consistent with global

high-resolution CAM5 simulations (Wehner et al. 2014; Reed et al. 2015, 2019) but outperform other atmospheric general circulation models in representing North Atlantic TC track climatology (Shaevitz et al. 2014). Additionally, the results from all of the REF and EXT ensembles are closer to the IBTrACS count than the ERA5 count, which underestimates IBTrACS by about 37%, likely due to the chronic underestimation of strong low-level winds in reanalysis datasets (Schenkel and Hart 2012; Murakami 2014; Hodges et al. 2017). The ensemble mean REF simulated about the same number of TCs as the ensemble mean EXT, which suggests that the extended high resolution over northern Africa does not impact total TC counts. This result is consistent with Caron and Jones's (2012) analysis of AEW activity and North Atlantic TC activity using three different regional climate models. All three VR grids clearly outperformed the GLOB grid in this category, but the REF and EXT grid configurations perform better than the WAT grid and ERA5.

Focusing on landfalling TCs only, there is still a low bias in the models in most cases, but the magnitude of the bias is dependent on the model configuration as shown in Fig. 5 and Table 2. Note that the jagged appearance of the trajectories in Fig. 5 is due to the native

TABLE 1. Total North Atlantic TC counts for 1985–2014 in each ensemble member and the ensemble mean. The ERA5 and IBTrACS TC counts for the same time period is also included. Only TCs that reach a lifetime maximum near-surface wind speed of 17 m s^{-1} are counted.

	GLOB	WAT	REF	EXT	ERA5	IBTrACS
Ensemble 1	75	171	382	394	—	—
Ensemble 2	76	201	367	374	—	—
Ensemble 3	93	214	381	358	—	—
Ensemble mean	81.3	195.3	376.7	375.3	244	389

FIG. 5. Continental U.S. landfalling TC tracks for 1985–2014 for all three ensemble members combined (90 total “model years”). The colors of the track lines represent the intensity of the storm as measured by the Saffir–Simpson scale.

grid resolutions. The GLOB grid severely underestimates the total number of landfalling TCs compared to the VR grids, ERA5, and IBTrACS. For the VR grids, the landfalling TC totals are similar to ERA5 but underestimate IBTrACS by 38%–43% (Table 2, top row). For all model configurations, the landfalling percentages in the Southeast are comparable to ERA5 and IBTrACS, although the total number of landfalls in the Southeast are still underestimated compared to

IBTrACS since the total landfalling TC numbers are much lower. For the Southern Plains, ERA5 underestimates IBTrACS’s landfalling percentage by 8.7%, and the GLOB and EXT configurations have similar landfalling percentages to ERA5 while WAT and REF have percentages closer to IBTrACS, although still slightly too low. The underestimation of landfalling TCs in these two regions in the REF and EXT grids is larger than their underestimation of total North Atlantic TCs, suggesting that more of the storms that are simulated in these CAM5 configurations should make landfall than do. For the Northeast, there is an underestimation of landfalls in the WAT simulations while the EXT simulations overestimate landfalls in the Northeast compared to IBTrACS and ERA5. The REF simulations estimate the number of landfalling storms in the Northeast closest to the observations and reanalysis; however, all model configurations have too high of a percentage of their landfalling TCs make landfall in the Northeast compared to IBTrACS (Table 2). The underestimation in the WAT simulations is likely related to a lack of long-track TCs that form in the central-eastern main development region in the North Atlantic and move to the northwest. The WAT grid has 1° grid spacing over the central and eastern North Atlantic, so TCs are less likely to form in this region. This is evident in Fig. 5, with the lack of storm tracks that begin east of 45°W in the WAT compared to the REF and EXT configurations.

Figure 5 also displays the severe lack of intense TCs (categories 3, 4, and 5) in the GLOB simulations compared to the VR simulations. All of the VR grids are capable of simulating intense TCs in regions where they are seen in observations (Fig. 3, top). The capacity of CAM5 to simulate storms of high intensity is dependent on grid resolution (Reed and Jablonowski 2011; Wehner et al. 2014; Zarzycki and Jablonowski 2014; Wehner et al. 2015), and as predicted in Davis (2018) for a model with approximately 0.25° grid spacing, the observed basinwide number of category 4 and 5 TCs is underestimated by 71%, 53%, and 63% in the ensemble mean WAT, REF, and EXT configurations (not shown). ERA5 also underestimates the intensity of landfalling TCs, with no storms exceeding category 2 strength based on maximum wind speed and category 4 strength based on minimum sea level pressure. This underestimation of TC intensity is common among all major reanalysis products, including ERA5’s predecessor ERA-Interim (Murakami 2014; Hodges et al. 2017). Because ERA5’s horizontal resolution is comparable to the high-resolution domains in the VR simulations, the differences in TC intensities between the models and ERA5 must be related to factors other than the resolution, such as the

TABLE 2. Total 1985–2014 continental U.S. landfalling TC counts (top row) and landfalling TC counts for the Southeast (second row), Southern Plains (third row), and Northeast (fourth row). Values in parentheses are the percentages of total landfalls that occur in each region for each configuration or dataset. Model values are ensemble means. Only TCs that reach a lifetime maximum near-surface wind speed of 17 m s^{-1} are counted.

	GLOB	WAT	REF	EXT	ERA5	IBTrACS
Total	15.7	59	59.7	60.6	64	104
Southeast	12.7 (80.9%)	46 (78.0%)	44 (73.7%)	46.3 (76.4%)	52 (81.3%)	78 (75.0%)
Southern Plains	2 (12.7%)	10.3 (17.5%)	10.7 (17.9%)	8 (13.2%)	8 (12.5%)	22 (21.2%)
Northeast	1 (6.4%)	2.7 (4.6%)	4.7 (7.9%)	8 (10.4%)	4 (6.3%)	4 (3.8%)

model physics and the methods of assimilating observational data (Schenkel and Hart 2012).

b. TC size climatology

To analyze the storm size climatologies, distributions of $r8$ are created for all storm times, times when the storm center is over the ocean, and times when the storm center is over land, only including times when the TC's maximum wind speed is at least 17 m s^{-1} (Fig. 6). For the all-storms distributions (Fig. 6, top), the three VR configurations' distributions look almost identical, while the GLOB distribution is skewed toward larger $r8$, as expected since models with lower resolutions tend to produce larger storms (Reed et al. 2012; Reed and Chavas 2015). The three VR distributions peak at comparable $r8$ values, although their distributions are wider than the ERA5 distribution. These differences in the shapes of the distributions could be related to the choices of histogram bins, the sample sizes, or differences in the grid resolutions, but for the purposes of this paper, the focus is on making sure the majority of the $r8$ values are similar among the different model configurations and ERA5. The median values of the distributions (the markers on the x axis) show little variation for the three VR simulations and ERA5, with a maximum difference of 28 km between the four medians. This supports the comparison between the model simulations and ERA5 for the TC precipitation analyses (see section 3d). Since the $r8$ distributions are alike, the precipitation extraction areas are also similar.

The results for the distributions when the TC centers are over the ocean (Fig. 6, middle) are similar to those for all storms. All of the VR distributions match up well, and again the GLOB distribution is shifted toward larger storm sizes. The ERA5 distribution peaks at about the same $r8$ as the all-storms distribution, but the medians of the WAT and REF distributions increase by about 14 km while the EXT and ERA5 medians remain the same as for the all-storms distributions. The median of the GLOB distribution also shifts toward larger $r8$ by about 56 km. For the distributions when the TC centers are over land (Fig. 6, bottom), all of the distributions shift toward smaller storm sizes. This is expected, as

when TCs move over land, the increased friction slows down the wind speeds and therefore $r8$ contracts, but the consistency among the VR models and ERA5 still suggests that $r8$ is a good estimation of TC size over land. The GLOB distribution is still shifted toward larger storms compared to the VR and ERA5 distributions. There are slight variations between the VR distributions, but their medians remain very similar, with a maximum difference between the medians of about 42 km. All of the distributions' medians shift toward smaller $r8$ compared to all storms and storms with centers over ocean.

c. TC density over the eastern United States

By utilizing $r8$ for the model simulations and ERA5, we are able to calculate TC landfall and track densities. As shown in Fig. 7, all model simulations show the highest landfall densities along the Gulf Coast, with the maxima over the Florida Peninsula, except GLOB. The GLOB landfall densities are lower than the VR simulations everywhere along the coast, which is expected since the landfalling storm count is much lower (Fig. 5). The EXT grid has the highest landfall density over the Florida Peninsula out of all of the VR grids, with a maximum of 3.3 h per year. The REF and EXT simulations have higher landfall density in the Northeast than the WAT and GLOB, which agrees with Table 2. The landfall density along the Gulf Coast is slightly higher in the WAT grid than the REF and EXT. This is because in the WAT configuration, more TCs form in the western Atlantic where the high-resolution region is, especially south of Cuba and around Puerto Rico (not shown), so therefore these TCs are likely to make landfall along the Gulf Coast because of where they form. Compared to the landfall density from IBTrACS and ERA5, all of the model simulations underestimate the landfall density along the whole coast. While the ERA5 landfall density is comparable to IBTrACS along the East Coast, it is lower over the Gulf Coast (Fig. 7).

The right column of Fig. 7 shows the track densities, which includes all storms even if they do not make landfall. In all model simulations, the track density is larger along the East Coast than the Gulf Coast. It is

FIG. 6. Normalized histograms of $r8$ for (top) all storms, (middle) storms with their centers over the ocean, and (bottom) storms with their centers over land. Bin sizes are 50 km for WAT, REF, EXT, and ERA5 and 100 km for GLOB. The markers on the x axes show the medians of the distributions. Storms are only included at times when their maximum wind speed is over 17 m s^{-1} .

larger in the three VR simulations than the GLOB over the East Coast but about the same over the Gulf Coast. The overland track densities in the model simulations are severely underestimated compared to IBTrACS and slightly underestimated compared to ERA5. This may be related to the steering flow in the models, since the North Atlantic subtropical high pressure is stronger and shifted eastward in the models compared to ERA5 in

June through November (not shown). This shift in the subtropical high pressure may cause many simulated TCs in CAM5 to recurve and not make landfall in the United States. The ERA5 track density pattern is similar to the IBTrACS pattern, but the magnitudes are much smaller in ERA5 over most of the United States, especially the coastal regions, which aligns with the lack of landfalling storms (Table 2) and total storms (Table 1) in ERA5 compared to IBTrACS. The inland penetration of the TC track density in the VR configurations matches that in IBTrACS and ERA5 much better than the GLOB configuration. Since the patterns and magnitudes of the track densities in the models are more comparable to ERA5 than IBTrACS (Fig. 7), it is a more fair comparison for the precipitation analysis to use ERA5 tracks for TC precipitation extraction than IBTrACS tracks.

d. Precipitation over the eastern United States

1) ANNUAL MEAN PRECIPITATION

First, we begin with analyzing the annual mean precipitation, both total and TC related. Note, ERA5 is used for the track data for this analysis and since ERA5 produces fewer TCs than in IBTrACS, the observational plots here are underestimates of reality. However, as noted in section 2c, using ERA5 for the generation of historic trajectories provides a more consistent comparison with climate model data. While the annual mean precipitation over the eastern United States varies little between the VR model simulations (Fig. 8, left column), all CAM5 configurations produce too little annual mean precipitation, especially over the Louisiana and Arkansas area, compared to observations (Table 3, top section). Looking at the skill metrics table (Fig. 9), this poor model performance for annual mean precipitation in the Southeast region is demonstrated further by the negative pattern correlations and mediocre skill scores in all model configurations, although the spatial variability in the model fields are comparable to that in CPC as evidenced by the standard deviation ratios close to 1. The GLOB total annual precipitation is comparable to the VR simulations in the Southeast and Northeast but is too low by over 100 mm yr^{-1} in the Southern Plains (Table 3, top section). In addition, the GLOB configuration underperforms the VR models in the Southern Plains in all metrics in Fig. 9, while the values of the metrics vary little among the VR configurations. Focusing on the Northeast, Fig. 9 shows that the VR configurations predictions of annual mean precipitation are very similar, and the GLOB configuration demonstrates a comparable skill score to the VR models despite its worse pattern correlation due to somewhat better spatial variation magnitudes.

FIG. 7. IBTrACS, ERA5, GLOB, WAT, REF, and EXT 1985–2014 annual mean (left) landfall density and (right) track density. Units are hours of TC impact per year.

FIG. 8. CPC, EXT, REF, WAT, and GLOB (left) total annual mean precipitation (mm yr^{-1}), (center) annual mean precipitation from TCs (mm yr^{-1}), and (right) percentage of the annual mean precipitation that is due to TCs.

When examining the TC-related annual mean precipitation, patterns emerge that relate to the TC tracks and densities. Similar to the total annual mean precipitation, the TC-related annual mean precipitation is also

too low in certain locations in the models (Fig. 8, center column), such as over the Carolinas where CPC has values above 80 mm yr^{-1} while the best VR model, the REF, only has values of up to 60 mm yr^{-1} . This underestimation is

TABLE 3. 1985–2014 mean annual precipitation (mm yr^{-1} ; top section), TC-related annual precipitation (mm yr^{-1} ; middle section), and percentage of Rx5day events due to TCs (%; bottom section) averaged over the NCA regions.

	GLOB	WAT	REF	EXT	CPC
Total annual precipitation					
Southeast	1029.6	1084.4	1080.2	1088.8	1281.7
Northeast	1105.2	1108.9	1124.9	1129.8	1105.1
Southern Plains	437.1	554.3	546.8	542.8	678.4
TC-related annual precipitation					
Southeast	13.1	19.2	19.4	20.1	25.3
Northeast	5.0	10.0	10.5	12.6	14.3
Southern Plains	2.0	6.6	7.9	6.6	3.9
Percentage of Rx5day events due to TCs					
Southeast	7.8	10.4	10.2	10.7	11.2
Northeast	3.6	6.8	7.1	8.4	8.5
Southern Plains	1.8	5.1	6.2	5.0	2.1

related to the lack of TC landfalls in this region in the models since the landfall density over the Carolinas in the models is under 1.5 h per year versus above 3 h per year in ERA5 (Fig. 7). When area-averaged over the NCA regions (Table 3, middle section), the TC-related annual precipitation in the VR models is comparable to CPC in the Southeast and Northeast but too large in the Southern Plains by 41%–51%. Focusing on the Southern Plains, the VR models underpredict the total annual mean precipitation yet overpredict the TC-related annual mean precipitation. For the WAT and REF configurations, this could be partially because of the overestimation of TC landfalls compared to ERA5 (Table 1), but since EXT simulates the same number of landfalling TCs in the Southern Plains as ERA5 and still overestimates the TC-related annual mean precipitation (Table 3), this suggests that the models are not simulating other precipitation events that occur over this region such as mesoscale convective systems, which are known to be simulated poorly in CAM (Kooperman et al. 2013).

The percentages of TC-related annual precipitation are of similar magnitude in both the observations and models, with maxima of 6%–7%, although this diagnostic is biased low in the models over the Carolinas and too high in western Florida (Fig. 8, right column). The GLOB simulations underestimate the TC-related annual precipitation diagnostics much more than the VR simulations, which is caused by the lack of TCs impacting the eastern United States in the GLOB, as demonstrated in both the landfall and track densities (Fig. 7). Figure 9 confirms the deficiency of the GLOB configuration compared to the VR models in reproducing observed TC-related annual mean precipitation since all of the metrics for GLOB show worse performances than all the VR models, except for the pattern correlation in the

FIG. 9. Metric scores for total annual precipitation, TC-related annual precipitation, and percentage of Rx5day events due to TCs, separated by NCA region (rows) and model configuration (columns). These scores compare each model configuration to CPC. For all metrics, a value of 1 is optimal. Skill score (Skill) indicates poor performance as it gets closer to 0. Pattern correlation (Corr) indicates worse performance as it approaches and passes 0. Ratio indicates worse performance as it diverges from 1 in either direction.

Southeast where it performs similarly. All of the VR configurations show good performances (i.e., values of 0.79–1.32) in all the NCA regions for TC-related annual mean precipitation (Fig. 9), and the underestimates of TC-related annual mean precipitation and TC-related precipitation percentage in certain areas along the coasts

(Fig. 8) are likely due to the lack of landfalling TCs in the models compared to ERA5 discussed previously (Fig. 7). The slight differences in the TC-related metrics and diagnostics between the VR model configurations are likely due to model variability given the ensemble size. TCs are relatively rare events in the climate system, and TCs that make landfall are even rarer; therefore, it is difficult to interpret differences in these events.

2) EXTREME PRECIPITATION

The model biases in total Rx5day are similar to those for the total annual mean precipitation. The total Rx5days from the model simulations all look similar, but compared to CPC, Rx5day is low in the models along the Gulf Coast and over the Carolinas (Fig. 10, left column). Looking at the observed TC-related Rx5day (Fig. 10, center column), local maxima occur along the coastlines of Louisiana, the Florida Peninsula, and the Carolinas. The VR model simulations capture the general locations of the maxima in TC-related Rx5day, although the exact locations of the maxima differ between all the models and CPC. The GLOB simulations underestimate TC-related Rx5day relative to both the VR model simulations and CPC. These low biases are likely a result of a combination of the underestimation of annual mean precipitation (Fig. 8, left column) and the low bias in landfalling TCs (Fig. 7, left column). The WAT and EXT configurations have local maxima in TC-related Rx5day over Louisiana that are not present in the REF configuration but are more comparable to the observed TC-related Rx5day in this area. The EXT simulation has larger TC-related Rx5day over the Northeast, likely due to the long-track north-westward-moving storms discussed in section 3a, which is comparable to the Rx5day in this area in CPC.

The percentage of Rx5day events that are TC-related averaged over the NCA regions is lower in the models than in CPC, except in the Southern Plains (Table 3, bottom section). The EXT simulation produces the highest area-average percent of TC-related Rx5day events in the Northeast because the EXT simulation produces more TC landfalls there than the REF and WAT grids (Table 2). The EXT grid also shows the highest percentage in the Southeast, although the numbers are close for all VR simulations. In CPC, over 30% of Rx5day events in the 30-yr average are TC-related in locations in Virginia, North Carolina, Florida, and Louisiana (Fig. 10, right column). These observed values are similar to those reported in Aryal et al. (2018) for a different extreme precipitation metric. In the models, all of the VR models overestimate this percentage over Florida and underestimate it over North Carolina. The VR configurations all show good performances in the skill metrics (Fig. 9), particularly in the Southeast. For all the

VR configurations and all the regions, the ratios perform the best, suggesting that the spatial variability in the diagnostic's magnitudes is similar in the models and CPC; meanwhile the pattern correlations tend to perform worse, which is likely related to the patchy, irregular appearance of the percentage of TC-related Rx5day events diagnostic in Fig. 10. Compared to the VR simulations, the GLOB configuration underestimates the TC-related Rx5day and the percentage of Rx5day events that are TC related in all regions of the eastern United States. Again, the GLOB configuration performs worse in all metrics in Fig. 9 in all regions compared to the VR configurations, except for the pattern correlation in the Southern Plains which is comparable.

4. Discussion and conclusions

This work evaluates North Atlantic TC climatologies in three variable-resolution CAM5 configurations with different high-resolution domains (WAT, REF, and EXT) and one global low-resolution configuration (GLOB). A comparison of TC tracks, counts, outer sizes, and TC-related precipitation over the eastern United States was performed between model simulations and also to observations and reanalysis using IBTrACS, ERA5, and CPC gauge data. These were the main results:

- The CAM5-VR simulations with high-resolution (approximately 28 km) domains over different extents of the North Atlantic greatly outperformed the uniform low-resolution GLOB simulation in total TC counts and landfalling TC counts, although they still underestimate landfalling TCs over the eastern United States compared to observations.
- The REF and EXT configurations, which both have high-resolution domains over the entire North Atlantic Ocean, outperformed ERA5 in TC counts, and all VR configurations outperformed ERA5 in representing TC intensity.
- The distributions of TC outer sizes, defined as the radii of the azimuthally averaged 8 m s^{-1} azimuthal wind, are similar for the VR simulations and ERA5, even when the TCs are over land. The largest differences are seen for the distributions of small storms.
- Total and TC-related annual precipitation are similar between the VR models and comparable to CPC data using ERA5 r8 to extract TC-related precipitation, but the models underproduce precipitation in certain areas. These are underestimates compared to reality since ERA5 also underestimates TC counts, although this is a more fair comparison for the CAM5 models. All of the VR configurations again outperform the GLOB configuration in annual precipitation diagnostics.
- Extreme precipitation, using Rx5day as the diagnostic, is also underestimated in the models compared to

FIG. 10. CPC, EXT, REF, WAT, and GLOB (left) Rx5day (annual maximum 5-day accumulated precipitation) (mm yr^{-1}), (center) TC-related Rx5day (mm yr^{-1}), and (right) percentage of Rx5day events due to TCs.

observations, especially in the southern United States. However, increased model resolution again improves results. The percentage of TC-related Rx5day events is comparable to CPC.

Using the highly customizable and automated TempestExtremes software, TCs are not only identified and tracked, but after using their wind fields to estimate the sizes of their outer circulations, precipitation only

associated with the TCs is extracted from the overall precipitation field. This output is useful to evaluate the contribution of TCs to annual mean and extreme precipitation in model simulations and observations. This standardized methodology could also be used to compare entirely different models or model runs using different future warming scenarios, such as those run as part of CMIP6 (Eyring et al. 2016) and High-Resolution Model Intercomparison Project (HighResMIP; Haarsma et al. 2016).

Another takeaway from this work is the potential of variable-resolution configurations in studying many aspects of TC climatology. When studying precipitation climatologies with the models, TC counts can greatly impact the results. For example, the GLOB configuration greatly underestimates TC-related extreme precipitation compared to the VR models in part because it simulates very few TCs. This is less obvious when looking at the TC-related annual precipitation because TCs in observations contribute more to extreme precipitation than to the annual mean. Because the VR configurations simulate improved landfalling TC counts and intensity climatologies compared to the GLOB configuration, their annual mean and extreme precipitation climatologies over the eastern United States are closer to reality. Using a VR configuration with high-resolution over the North Atlantic is superior in studying North Atlantic TC climatology to using a conventional low-resolution global configuration. Overall, in comparing the three VR setups it is concluded that the REF configuration provides better skill than WAT at simulating TC characteristics, such as annual mean TC landfalls in the Northeast and TC-related annual mean precipitation, and it provides similar skill at reduced computational cost compared to EXT.

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APPENDIX A

TempestExtremes Commands

The command line used to detect TCs and extract TC-related precipitation is provided below:

```
./DetectCyclonesUnstructured --in_data_list
"$infiles" --timestride 2
--in_connect $connectivityf --out $outfile
--closedcontourcmd "PSL,200.0,5.5,0;_
DIFF(Z300,Z500),-6.0,6.5,1.0"
--mergedist 6.0 --searchbymin PSL
--outputcmd "PSL,min,0;_VECMAG(UBOT,VBOT),
max,2;PHIS,max,0"

./StitchNodes --format "ncol,lon,lat,
slp,wind,phis" --range 8.0
--minlength 10 --maxgap 3 --in $outfile
--out trajectories.txt
--threshold "wind,>=,10.0,10;lat,<=,
50.0,10;
lat,>=,-50.0,10;phis,<=,150.0,10"

./NodeFileEditor --in_connect $connectivityf
--in_data_list "$infiles"
--in_file trajectories.txt --out_file rad-
prof.txt
--in_fmt "lon,lat,slp,wind,phis"
--calculate "rprof=radial_wind_profile
(UBOT,VBOT,159,0.125)
;rsizelastwhere(rprof,>,8)" --out\_fmt
"lon,lat,rsizelrprof"

./NodeFileFilter --in_nodefile radprof.txt
--in_fmt "lon,lat,rsizelrprof" --in_con-
nect $connectivityf
--in_data_list "$infiles" --out_data_list
"node_output_files.txt"
--bydist "PRECT,rsizel"
```

For more details about TempestExtremes and the commands shown here, see Ullrich and Zarzycki (2017).

APPENDIX B

Advantages of Using r_8 as Outer Size Metric

TCs in nature exhibit a wide range of sizes and therefore their wind and precipitation fields cover different extents, dependent on the individual storm. Using a static estimation of TC size, such as 500 km, for TC-related precipitation extraction risks missing some of the TC's precipitation field for large storms or including non-TC-related precipitation for small storms. The estimation of TC size based on the outer wind circulation that changes as the TC moves through its life cycle can help avoid these issues. Figure B1 shows the difference in TC-related annual mean precipitation when using r_8 and 500 km as the precipitation extraction radius. Using a static 500-km radius results in higher precipitation totals, especially over Florida and

FIG. B1. CPC TC-related annual mean precipitation (mm yr^{-1}) using (left) r8 and (right) 500 km as the precipitation extraction radius and ERA5 for the tracks.

in noncoastal states, because a set radius likely captures non-TC-related convective precipitation before and after the core of the TC travels through the impacted area.

To get an estimate for the effectiveness of r8 as a TC size metric in containing all of the TC-related precipitation, precipitation radial profiles were calculated for the four CAM configurations using TempestExtremes. The precipitation radial profiles were created using the same process used to create the wind radial profiles described in section 2a. At each time step for each storm, the radius of the 1 mm day^{-1} precipitation rate (r1mm/day) (outside the eyewall) was estimated from the precipitation radial profile, in the same way that r8 was estimated from the wind radial profiles. If r1mm/day is within r8, it is a reasonable assumption that most, if not all, the precipitation associated with the TC is being recorded as TC related using our methodology. Looking at GLOB, WAT, REF, and EXT for only TCs that attain lifetime maximum wind speeds of at least 17 m s^{-1} , r1mm/day is within r8 92.2%, 74.2%, 78.7%, and 79.2% of the time, respectively.

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