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Key Points:

- According to three separate metrics, large-scale convective aggregation increases with warming in 17 of 19 global climate models (GCMs) examined
- There is substantial spread in large-scale convective aggregation behavior among the GCMs considered
- No statistically significant inter-model relationship between degree of aggregation and tropical-mean precipitation extremes was found

Supporting Information:

Supporting Information may be found in the online version of this article.

Correspondence to:

C. P. O. Bläckberg,
carlphiliposcar@gmail.com

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Author Contributions:

Conceptualization: C. P. O. Bläckberg, M. S. Singh
Data curation: C. P. O. Bläckberg
Formal analysis: C. P. O. Bläckberg
Funding acquisition: M. S. Singh
Investigation: C. P. O. Bläckberg
Methodology: C. P. O. Bläckberg, M. S. Singh
Supervision: M. S. Singh
Validation: C. P. O. Bläckberg
Visualization: C. P. O. Bläckberg
Writing – original draft: C. P. O. Bläckberg

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Increased Large-Scale Convective Aggregation in CMIP5 Projections: Implications for Tropical Precipitation Extremes

C. P. O. Bläckberg[1,2] and M. S. Singh[1,2]

[1]School of Earth, Atmosphere, and Environment, Monash University, Melbourne, VIC, Australia, [2]Centre of Excellence for Climate Extremes, Monash University, Melbourne, VIC, Australia

Abstract Convective aggregation refers to the clustering of convective events and occurs on a wide range of spatial scales. It has been suggested that the behavior of convective aggregation may change under global warming, with potential implications for future changes in precipitation extremes. Here, convective regions of the tropics are defined from a percentile threshold on gridded daily precipitation data and used to quantify large-scale convective aggregation in an ensemble of global climate models. Applying three separate indices for aggregation, it is found that large-scale convective aggregation increases in 17 of the 19 analyzed models under future warming. However, aggregation is found not to be correlated with tropical-mean precipitation extremes, either climatologically or with respect to the sensitivity to warming. The large model spread in aggregation indices across the ensemble suggests the possible utility of large-scale convective aggregation as a target for model evaluation.

Plain Language Summary Rainfall in the tropics is not evenly distributed, rather it occurs in clusters of clouds of various sizes and shapes, from a line of thunderstorms to "superclusters" spanning thousands of km. The size and spatial distribution of these clusters are hypothesized to influence the frequency and intensity of heavy rainfall in the tropics. In this study, we develop a method for quantifying the amount of clustering in the tropics, and we investigate whether it is projected to change in the future in a suite of state-of-the-art climate models. Almost all the models project increases in clustering in the future, but, surprisingly, a model's projection of clustering does not seem to affect its projection of changes to heavy rainfall. The results suggest that effects other than clustering play a dominant role in determining the range of heavy rainfall outcomes projected by climate models.

1. Introduction

Organized convection in the tropics strongly affects radiative feedbacks, the large-scale circulation and moisture distribution, and the hydrological cycle (Hartmann et al., 1984). Understanding how the organization of convection might change under global warming is therefore crucial to understanding the future large-scale climate. Organized deep convection is characterized by multiple deep convective cells combining to form coherent structures such as a squall lines (~100 km; Houze, 1977), mesoscale convective complexes (~100–1000 km; Maddox, 1980), or tropical cyclones (~1,000 km; Chavas & Emanuel, 2010). On even larger scales, organization can include the clumping and clustering of these convective systems and their associated precipitation. Such clustering, which we will refer to as "large-scale convective aggregation", may be associated with long-lived "superclusters" (~10,000 km; Mapes & Houze, 1993), or stationary features such as the intertropical convergence zone.

Recent studies have suggested that changes in the degree of convective organization at various scales may be an important driver of future changes in precipitation extremes (e.g., Bao et al., 2017; Pendergrass et al., 2016; Pendergrass, 2020). In this paper, we investigate this hypothesis by examining the relationship between large-scale convective aggregation and tropical precipitation extremes in historical simulations and future projections using 19 global climate models (GCMs) from Phase 5 of the Coupled Model Intercomparison Project (CMIP5).

Interest in convective aggregation has recently grown out of studies using cloud-permitting models in the idealized setting of radiative-convective equilibrium (RCE; Bretherton et al., 2005; Held et al., 1993; Tompkins & Craig, 1998). Simulations of RCE in a homogeneous domain with no imposed shear or lateral energy transport were found to spontaneously develop organization in a process termed "self-aggregation". In regional-scale domains, the aggregated state is characterized by a single region of convective activity surrounded by a dry, quiescent atmosphere, and its development is driven by feedbacks between convection, surface fluxes, and

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radiation, with longwave radiation being particularly important (Wing & Emanuel, 2014). Simulations of RCE in both global or quasi-global convection-permitting models (Wing & Cronin, 2016; Wing et al., 2018) and in GCMs (Popke et al., 2013; Reed et al., 2015) show evidence of self-aggregation on planetary scales, producing multiple convective regions spanning thousands of km across. While GCMs do not resolve the convective-scale processes that lead to mesoscale organization, their tendency to produce large-scale convective aggregation has been argued to be a result of similar feedbacks to those operating in cloud-permitting models (Wing et al., 2017). These feedbacks are also thought to play an important role in driving observed convective systems such as tropical cyclones (Carstens & Wing, 2020) and the Madden-Julian Oscillation (Arnold & Randall, 2015).

While self-aggregation in both cloud-permitting models and GCMs is known to be sensitive to details of the model configuration such as the dynamical core, parameterizations, domain size, and geometry, the tendency for the simulated atmosphere to aggregate is often found to increase with temperature (Bony et al., 2016; Wing & Emanuel, 2014; Wing et al., 2017). Furthermore, researchers suggest that changes in the degree of aggregation of convection may be related to changes in the intensity of precipitation extremes under global warming (Pendergrass, 2020). Increasing trends in precipitation extremes are observed (Westra et al., 2013) and projected by GCMs (Bador et al., 2018), but the sensitivity of precipitation extremes to warming varies across models, particularly in the tropics (O'Gorman, 2012, 2015). While it is known that this model spread is related to the dynamics of precipitation extreme events (O'Gorman & Schneider, 2009), the precise mechanisms that drive it, and the possible role played by convective organization, remains unclear. Studies have highlighted the importance of the degree of aggregation in determining precipitation extremes (Bao & Sherwood, 2019) and their sensitivity to warming (Bao et al., 2017) at various scales in idealized models. In particular, a number of global RCE or near global RCE studies have found that precipitation extremes, defined at a gridpoint level, appear to be sensitive to measures of convective aggregation, defined on large scales (Pendergrass et al., 2016). This motivates us to examine whether differences in large-scale convective aggregation might be related to precipitation extremes in more realistic simulations as part of CMIP5.

Observations also point to a role for convective aggregation in influencing the large-scale atmospheric state. For example, Tobin et al. (2013) found using satellite observations that regions with a higher degree of convective aggregation are accompanied by a drying of the mean state atmosphere (see also Holloway et al., 2017). However, observing trends in convective aggregation remains challenging due to the limited extent and quality of historical records and the large variability and low frequency of events most relevant for aggregation (Jones & Carvalho, 2006; Knutson et al., 2010). Nevertheless, Tselioudis et al. (2010) used satellite observations to identify trends toward an increased frequency of organized convection with warming, while Zelinka and Hartmann (2010) showed that the fractional anvil cloud area decreases as a response to increases in tropical mean temperature, which is another feature commonly associated with self-aggregation in simulations of RCE (Bony et al., 2016; Emanuel et al., 2014). Finally, Tan et al. (2015) found that a large fraction of the observed trends in regional precipitation in the tropics could be associated with the change in frequency of organized convection. However, trends in precipitation extremes have not yet been associated with changes in the organization of convection based on observations.

In this study, we seek to bridge the gap between idealized studies relating convective aggregation to precipitation extremes in RCE and the observational work described above by investigating large-scale convective aggregation in simulations with comprehensive GCMs. Specifically, we use a precipitation rate percentile to define convectively active regions (Bao et al., 2017; Pendergrass et al., 2016) in the tropics and apply it to quantify large-scale convective aggregation in an ensemble of CMIP5 models and in observations from the Global Precipitation Climatology Project (GPCP). Based on this quantification, we investigate how large-scale convective aggregation is projected to change in the future, and what implications such changes may have for precipitation extremes.

2. Simulations and Precipitation Extremes

Our analysis is based on 19 GCMs participating in CMIP5 (Table S1 in Supporting Information S1; Taylor et al., 2012), chosen by selecting one model from each modeling center for which the desired data was available. We used 30-year periods from the historical (1970–2000) and representative concentration pathway 8.5 (RCP8.5; 2070–2100) scenarios to represent historical and future climates, respectively. Precipitation extremes and large-scale convective aggregation were quantified based on daily precipitation accumulations in the tropical region (30°S–30°N). To ensure comparability across models, we applied a first-order conservative interpolation following Jones (1999) to a common 2.8 × 2.8° grid prior to the analysis. Differences between the historical and RCP8.5 scenarios may be expressed per kelvin warming by dividing by the change in tropical- and time-mean surface air temperature between the relevant periods. Finally, as an observed reference point for the results from the historical climate, satellite-based estimates of daily precipitation from the GPCP (v1.3; Huffman et al., 2001) for the years 2007–2017 were regridded to the same 2.8 × 2.8° grid and analyzed using the same methodology.

To relate tropical precipitation extremes to the degree of large-scale convective aggregation, we define an overall metric of precipitation extremes across the tropics. This may be done in a number of ways. Here we take the annual maximum daily precipitation accumulation at each gridpoint (Rx1day; Alexander et al., 2019; Zhang et al., 2011) and then take the time mean over the relevant 30-year period and the spatial mean over the tropical region. We refer to this metric as the tropical-mean Rx1day. Since the tropical-mean Rx1day tends to smear out extremes through spatial averaging, we also test extremes based on a percentile calculated over all tropical gridpoints (99th, 99.9th, or 99.99th). Conclusions about the relationship between precipitation extremes and aggregation are unaffected by using the precipitation percentile approach or taking a longer timescale extreme (Rx5day). We plot results for changes in tropical-mean precipitation extremes as a percentage change per kelvin tropical warming, but once again, our main conclusions remain the same if we use absolute changes in precipitation extremes rather than relative ones.

Figures 1a–1d shows the time-mean value of Rx1day in the historical climate for three models with varying intensity of precipitation extremes and for the GPCP observations. The magnitude of precipitation extremes varies distinctly between models, and this variation is well-captured by the tropical-mean Rx1day metric (Figure 2a). Overall, the model spread in tropical-mean Rx1day in the historical climate is considerable; the interquartile range is ∼33–48 mm day^{-1}, encompassing the GPCP observational estimate. But this range widens to ∼20–82 mm day^{-1} when all 19 models are considered.

As for its climatological value, the fractional change in the tropical-mean Rx1day with warming also varies considerably across models (Figure 2b), with an interquartile range spanning ∼4.2%–7.5%/K, and a maximum range spanning ∼1%–12.5%/K. This is consistent with the recent analysis of Bador et al. (2018) using a larger ensemble of CMIP5 models. Notably, the models that have the largest climatological value of the tropical-mean Rx1day (e.g., bcc-csm1-1) are not necessarily the same models that produce the largest fractional sensitivity per kelvin warming (e.g., IPSL-CM5A-MR). Further, unlike for the climatology, the spatial pattern of changes in Rx1day with warming also varies considerably across models (Figures 1e–1g), demonstrating a limitation in using a single tropics-wide metric for changes in precipitation extremes. Despite this caveat, the large model spread in tropical-mean Rx1day and its changes with warming imply fundamental differences in the representation of precipitation extremes across the ensemble. Our aim is to determine whether this model spread may be explained by differences in large-scale convective aggregation in the simulations.

3. Quantifying Large-Scale Convective Aggregation

In order to quantify the degree of large-scale convective aggregation across the tropics, we first define whether a given gridpoint is "convective". Previous studies have used a range of variables to define regions of active convection such as cloud amount, vertical velocity, outgoing longwave radiation, and precipitation (e.g., Holloway, 2017; Tobin et al., 2012; Tompkins & Semie, 2017). To facilitate comparison with precipitation extremes, here we take gridpoints for which the daily precipitation rate exceeds a threshold value to be convective gridpoints. Since the overall precipitation intensity may vary across models and with climate, we use a separate threshold for each simulation and for the observations to allow for a more robust quantification of large-scale convective aggregation. Specifically, the precipitation threshold is defined as the 97th percentile precipitation rate (including all tropical gridpoints) for each GCM and respective scenario and for the observations. Choosing such a threshold ensures that we identify high precipitation rates in relation to each model's dynamics and that we roughly pick out the same convective area fraction across the tropics each day. Comparing a similar day-to-day area fraction greatly reduces bias in the aggregation assessment (Tobin et al., 2012).

Convective aggregation may loosely be described as the "coming together" or clustering of convective regions; however, it does not currently have a strict quantifiable definition (Retsch et al., 2020; Weger et al., 1992). Nevertheless, it is generally agreed that the degree of convective aggregation increases with the size and proximity of

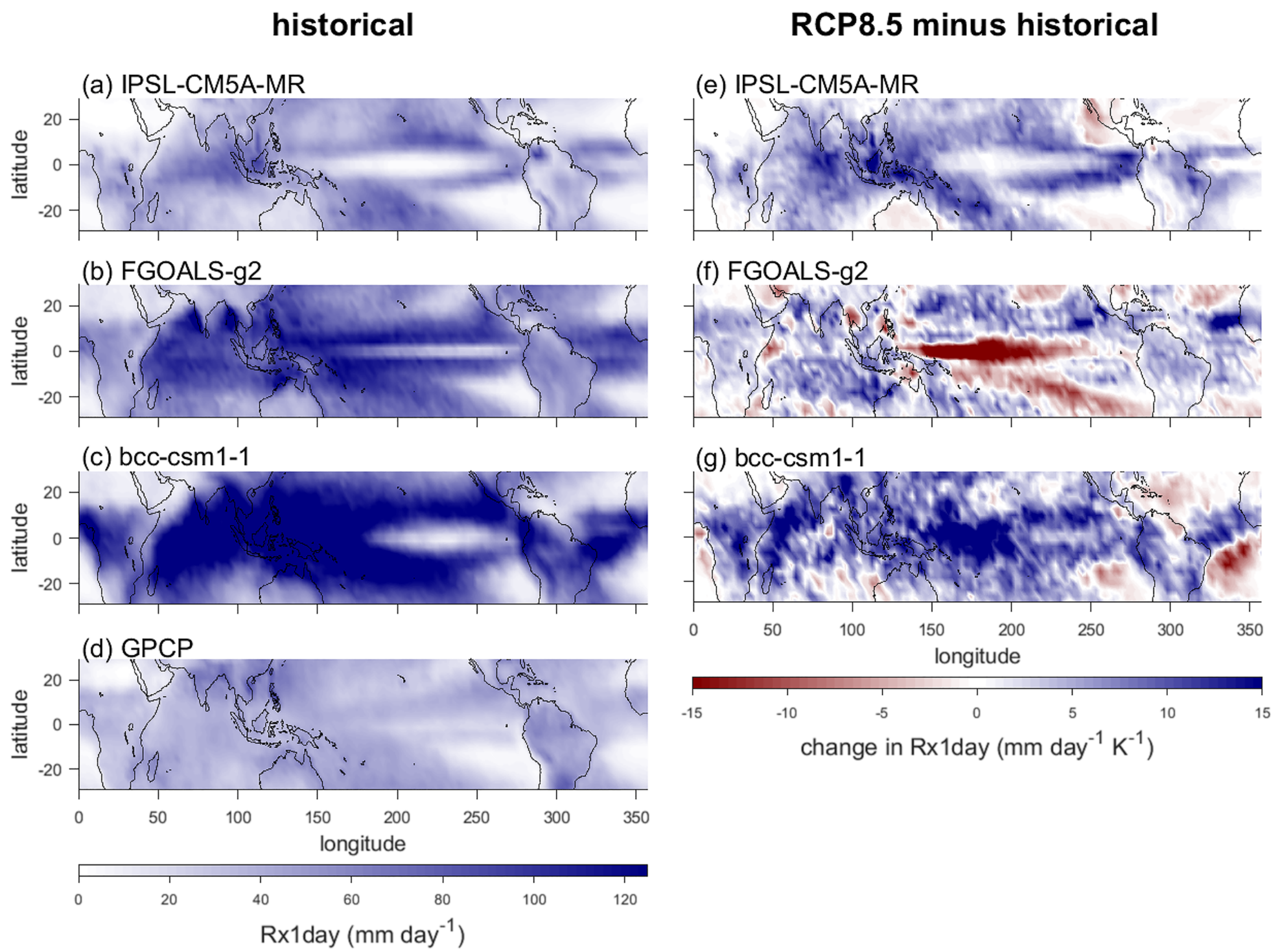

Figure 1. (a–c) Time-mean Rx1day in the historical (1970–2000) scenario and (e–g) change in time-mean Rx1day between the historical and RCP8.5 (2070–2100) scenarios for three models taken from Phase 5 of the Coupled Model Intercomparison Project (CMIP5) as labeled. Panel (d) gives observational estimate of time-mean Rx1day according to Global Precipitation Climatology Project for the years 2007–2017.

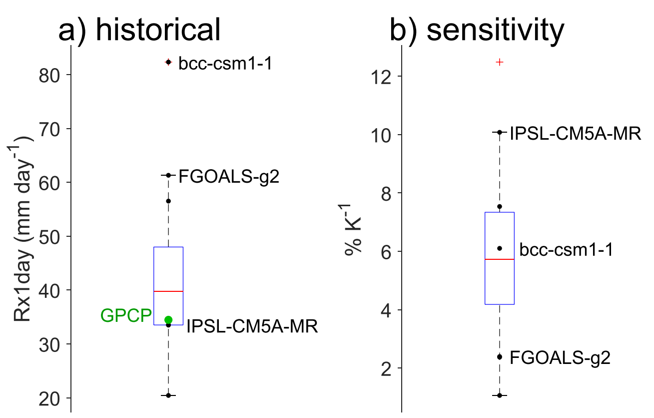

Figure 2. Box-whisker plots of (a) tropical-mean Rx1day in the historical (1970–2000) scenario and (b) fractional increase in tropical-mean Rx1day between the historical and RCP8.5 (2070–2100) scenarios expressed per kelvin of tropical warming for the Coupled Model Intercomparison Project (CMIP5) ensemble. Example models from Figure 1 are shown as labeled, and Global Precipitation Climatology Project observations are shown in panel (a) in green.

contiguous convective regions (Tobin et al., 2012; White et al., 2018). More generally, convective organization may also depend on other considerations such as the shape, pattern, timing, and general spatial distribution of convective regions (Pendergrass et al., 2016; Retsch et al., 2020).

In this study, we consider contiguous regions of convection as 8-connected convective gridpoints, or single gridpoints of convection if there are no neighboring connections, and we use three simple metrics of varying approaches to quantify the large-scale aggregation of convection in the tropics as a whole. For a fixed area fraction of convection, we expect aggregation to increase with the size and decrease with the number of contiguous convective regions. Therefore, as the first measure of aggregation, we analyze the Precipitation Weighted Area Distribution (PWAD). The PWAD describes the fraction of tropical precipitation that falls in contiguous convective regions of a given size. Here size is quantified by the effective radius $r_{\mathrm{eff}} = \sqrt{a/\pi}$, of a contiguous convective region of area a. A shift in the PWAD from smaller to larger values of effective radius corresponds to an increase in aggregation.

A second, more quantitative, measure of large-scale convective aggregation is given by the average number of contiguous convective regions in a daily

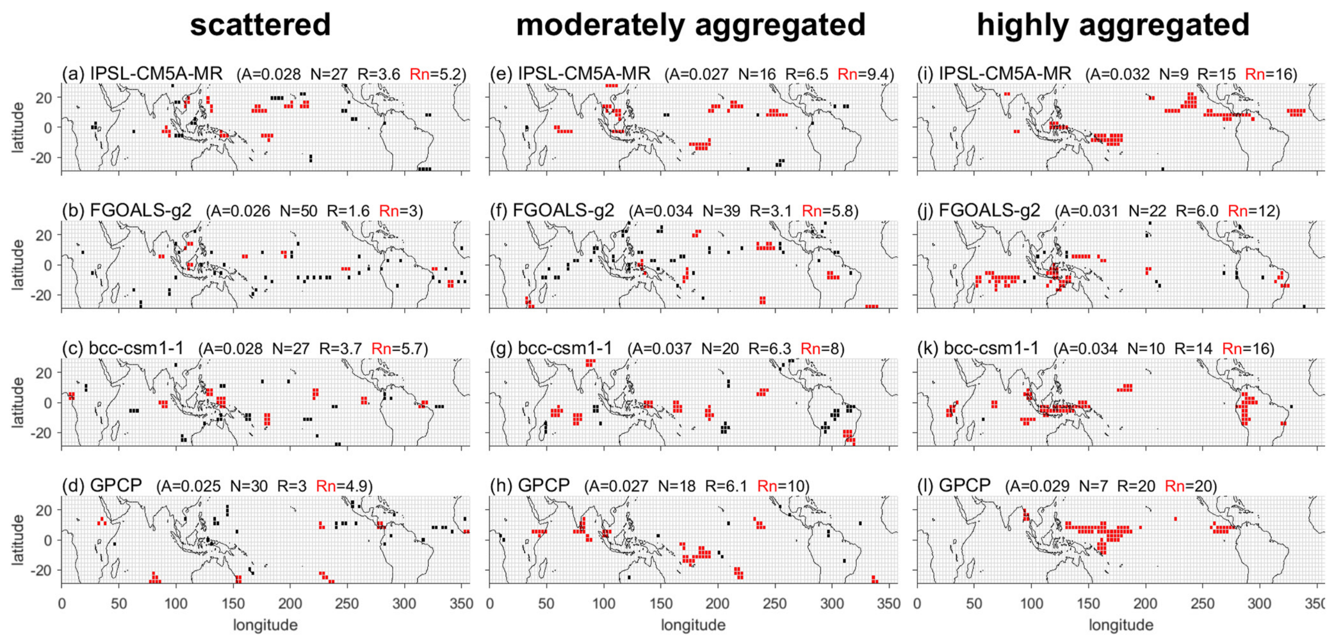

Figure 3. Spatial distribution of convective regions for the (a–d) minimum, (e–h) median, and (i–l) maximum value of Radar Organisation MEtric (ROME) from daily scenes in the historical scenario for the same models as in Figure 1 and for the Global Precipitation Climatology Project observations as labeled. Each panel includes value of area fraction of convective regions in the scene (A), Number Index (N), ROME (R), and ROME based on the eight largest contiguous convective regions (Rn; in red). ROME is given in units of 10^5 km^2.

tropical scene, which we refer to as the Number Index. Considering that our definition identifies convection as occupying roughly the same area fraction of the tropics each day, a decrease in the number of contiguous convective regions is likely to correspond to an increase in the average size of these regions and an increase in the degree of aggregation.

Finally, as a third measure of large-scale convective aggregation, we use a slightly more sophisticated aggregation index, the Radar Organisation MEtric (ROME), which considers the average size, proximity, and size distribution of contiguous convective regions (Retsch et al., 2020). As its name suggests, ROME was originally designed for analysis of radar observations, but we find that it works well for our purposes. ROME assesses organisation by defining "connections" between pairs of continuous convective regions and assigning a weight to each pair that increases with their respective areas and decreases with their separation distance. Specifically, the weight is equal to the area of the larger contiguous convective region plus a contribution from the smaller contiguous convective region that depends on the separation distance. For a given scene, ROME is then taken as the average value of the weights for all pairs of contiguous convective regions in the tropics. ROME is measured in units of area, and its value may be decomposed into a contribution from the mean area of contiguous convective regions and a contribution that depends on the distribution of sizes of and interaction between different contiguous convective regions (Retsch et al., 2020). An increasing value of ROME corresponds to a higher degree of aggregation.

Analysis of daily precipitation distributions in different models reveals that the aggregation assessment from the Number Index and ROME can sometimes be skewed by a large number of isolated single gridpoints of convection. Such "gridpoint storms" are known non-physical features of GCM-simulated precipitation distributions (Pendergrass & Hartmann, 2014). To account for the potential bias introduced by such effects, ROME was also calculated based on the eight largest contiguous convective regions in each daily scene (shown in red in Figure 3).

Examples of daily scenes from different GCMs under the historical scenario and from the GPCP observations reveal that the various aggregation indices correspond well to a subjective visual assessment of large-scale convective aggregation (Figure 3). As aggregation according to ROME and the Number Index increase, the size of contiguous convective regions becomes larger, and their distribution more clustered. Both the observations and GCMs exhibit a wide range of ROME values, demonstrating substantial temporal variability in large-scale convective aggregation across the tropics.

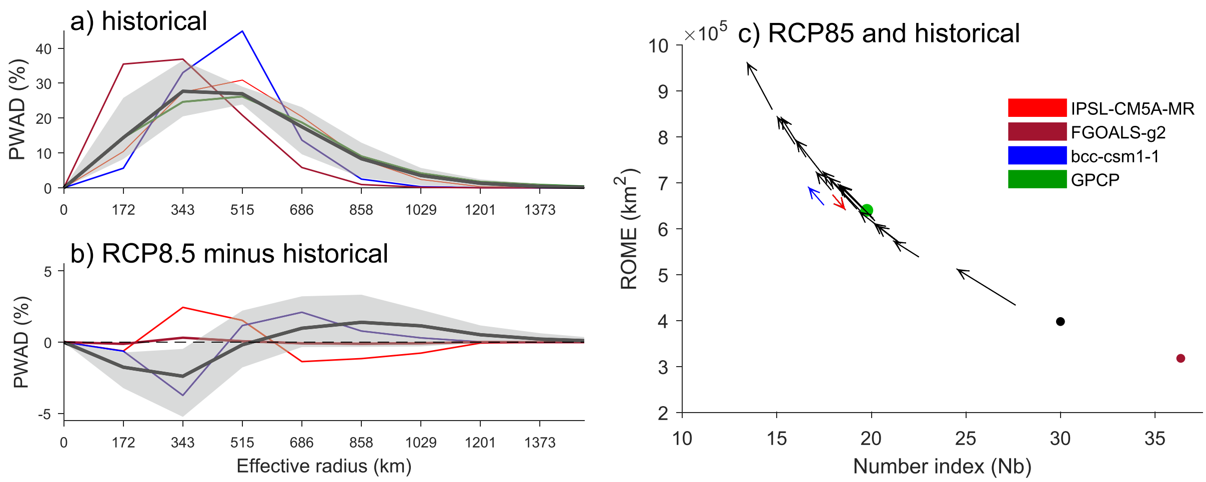

Figure 4. (a) Precipitation-weighted area distribution (PWAD) in the historical scenario and for the Global Precipitation Climatology Project (GPCP) observations (green) and (b) difference in PWAD between the RCP8.5 and historical scenarios. Black line gives ensemble mean and gray shading shows range of 90% of global climate models (GCMs). Colored lines show example models as labeled in (c). PWAD is calculated using bins with width equal to the mean effective radius of tropical gridboxes. (c) Mean Number index plotted against mean Radar Organisation MEtric (ROME) for historical (base of the arrow) and RCP8.5 (tip of the arrow) scenario for each GCM in the ensemble. Dots are used for the GPCP observations and for GCMs with little change in aggregation.

All three approaches analyzed reveal considerable model spread in the simulated large-scale convective aggregation in the historical scenario. The ensemble-mean PWAD peaks at r_{eff} in the range 343–515 km and is very similar to that observed by GPCP, but certain models exhibit substantially different behavior (Figure 4a). For example, FGOALS-g2 generates much greater numbers of small contiguous convective regions, while bcc-csm1-1 tends to predominantly generate contiguous convective regions of medium size. Additionally, the mean values of ROME and Number Index in the historical scenario vary from roughly half to almost double that of the GPCP observational estimate (Figure 4c). This large model spread points to the possible utility of such metrics of large-scale convective aggregation for model evaluation.

We now consider how aggregation changes under warming. All metrics agree that the same 17 of the 19 considered GCMs exhibit an increase in the degree of large-scale convective aggregation in the RCP8.5 scenario. In these GCMs, The PWAD tends to shift from smaller to larger contiguous convective regions (Figure 4b), the average number of objects in each daily scene decreases (Figure 4c), and the average ROME value increases with warming (Figure 4c). In the remaining two models, IPSL-CM5A-MR shows a decrease in aggregation according to all metrics, while FGOALS-g2 shows small changes in aggregation whose sign depends on the choice of metric. We also repeated these calculations with precipitation thresholds for convective regions based on different percentiles (95th, 97th, and 99th percentile) and for ROME calculated using only the largest 8 contiguous convective regions, and while the absolute value of the aggregation metrics is altered, the trend with warming is consistent with the results shown here. An important limitation of the aggregation indices is that they do not distinguish between different forms of aggregation, for example, clustering of individual convective gridpoints versus changes to typical large scale features such as the ITCZ, squall lines, or large storms. From analyzing daily scenes of convection (not shown here), most models appear to experience a mix of aggregation features on various spatial scales. However, a few models seem to predominantly favor one type of aggregation, often in conjunction with exhibiting distinctly different climatological convection features.

4. Relationship Between Large-Scale Convective Aggregation and Precipitation Extremes

Previous researchers have found changes in convective aggregation to be an important determinant of changes in precipitation extremes in idealized simulations of RCE (e.g., Bao et al., 2017). However, our analysis reveals no statistically significant relationship between the degree of large-scale convective aggregation, as measured by ROME, and precipitation extremes, as measured by tropical-mean Rx1day, for either their climatological values (Figure 5a) or their changes with warming (Figure 5b) across the 19 GCMs considered. This result holds for

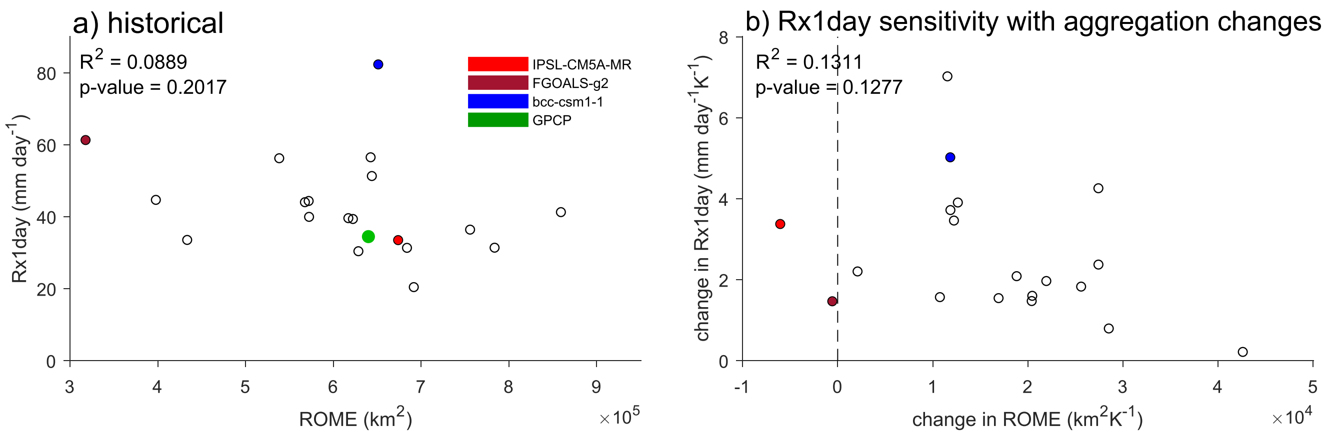

Figure 5. Scatter plot of (a) tropical-mean Rx1day versus Radar Organisation MEtric (ROME) for global climate models under the historical scenario and in Global Precipitation Climatology Project observations (green) and (b) difference in tropical-mean Rx1day and ROME from historical to RCP8.5 scenario per kelvin of tropical warming.

any combination of the analyzed large-scale convective aggregation metrics and precipitation extremes metrics described above. Thus while the intensity of precipitation extremes increases with warming for all models and the degree of convective aggregation increases with warming in most models, our results do not support a role for changes in large-scale convective aggregation in modulating precipitation extremes, at least at a tropics-wide level.

5. Conclusions

We have examined projected changes to large-scale convective aggregation and precipitation extremes as simulated by 19 GCMs under the RCP8.5 scenario. We have used a method to identify convective regions based on a percentile precipitation threshold that ensures a roughly fixed fraction of the tropics is identified as convective. This method allows for a robust quantification of the degree of large-scale convective aggregation in the tropics as a whole that is consistent across a range of metrics. Broadly consistent with previous RCE studies (Bony et al., 2016; Wing et al., 2018), we find that, in most models, large-scale convective aggregation increases with warming. However, we find no evidence that changes in aggregation are linked to changes in precipitation extremes across the GCM ensemble, at least for our tropics-wide measures of aggregation and precipitation extremes. This contrasts with previous studies of RCE, for which changes to convective aggregation appear to be an important driver of changes in precipitation extremes under warming, at least in the context of experiments with a single model (Bao et al., 2017; Pendergrass et al., 2016).

An important caveat to our work is that we examine convective aggregation in models that face challenges in realistically representing convection. As convection is parameterized in the models, they do not resolve the processes that lead to organization of convection on mesoscales, and this may affect how they simulate large-scale convective aggregation. Indeed, we show that there is considerable model spread in the degree of large-scale convective aggregation in the GCM ensemble, with some models displaying distinctly different aggregation behavior from the bulk of the models and from the observations. In previous idealized studies, the choice of convection parameterization has been shown to have a large effect on large-scale convective aggregation (Bao et al., 2017), and this provides one explanation for the anomalous behavior seen in some of the CMIP5 models. The representation of large scale convective aggregation is also likely significantly impacted by how the models treat the interaction of aggregation processes and convectively-coupled equatorial waves (Arnold & Randall, 2015). Further investigation into the specific parameterizations and model configurations relevant for large-scale convective aggregation is needed to understand which model features promote or suppress aggregation (Moncrieff, 2019).

The large model spread in large-scale convective aggregation also suggests that it may provide a useful target for model evaluation. While we provide a preliminary assessment of observed large-scale convective aggregation using GPCP data, further work in quantifying the observed uncertainties are required before this could be used for more formal model evaluation.

While our results do not show a relationship between simulated tropical precipitation extremes and large-scale convective aggregation for the tropics as a whole, the extent to which such relationships may exist at a regional level, or for more specific measures of convective organization and precipitation extremes remains an open question. Possible future work to address this question could include analysis of specific geographical areas with distinct climatologies, and development of metrics that look at specific convective shapes (e.g., convergence lines; Weller et al., 2017). Alternatively, the reasons for the lack of a tropics-wide relationship between precipitation extremes and large-scale convective aggregation might be ascertained by tracking precipitation extremes in individual storms or events that are impacted by convective aggregation (Pendergrass et al., 2016). Importantly, preliminary analysis shows that 17 of the 19 models have statistically significant relationships between precipitation extremes and aggregation index on interannual timescales, with R^2 values for these relationships in the range 0.4–0.7 (Figure S2 in Supporting Information S1). These intramodel relationships confirm that large-scale aggregation is relevant to precipitation extremes in the CMIP5 ensemble, despite the absence of relationship across models.

Other considerations for further investigation include analysis of the tropospheric humidity distribution. In RCE, aggregation is characterized by an increased variance of humidity (Wing & Emanuel, 2014), and from both simulations and observations, aggregation is accompanied by a drying of the mean state atmosphere (Holloway et al., 2017). This suggests that simulated changes in large-scale convective aggregation may affect future projections of tropospheric humidity.

Data Availability Statement

Model output used in this paper is available through the U.S. Department of Energy's Program for Climate Model Diagnosis and Intercomparison at https://pcmdi.llnl.gov/mips/cmip5/data-portal.html. The GPCP precipitation data set is available at https://doi.org/10.5065/ZGJD-9B02.

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