Convective Aggregation and the Amplification of Tropical Precipitation Extremes

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**Abstract** It is widely believed that precipitation extremes will increase in response to a warming climate, as inferred from both observations and numerical simulations. In the absence of changes in atmospheric circulations, extreme precipitation is expected to increase in already-moist regions along a thermodynamical Clausius-Clapeyron scaling. However, within the tropics, the sensitivities inferred from observations of interannual variability are roughly twice as large, implying an unknown contribution from atmospheric dynamics. In this paper, we use satellite observations and climate model simulations to investigate the relationship between convective aggregation and precipitation and the role that convective aggregation plays in amplifying the response of tropical precipitation extremes to interannual surface warming. We find that the occurrence of heavier precipitation coincides with a higher degree of convective aggregation. Extreme precipitation events and convective aggregation tend to increase during warm, El Niño events compared to colder, La Niña events. Although both the frequency and intensity of heavy to extreme precipitation can increase with increased aggregation during El Niño, the changes in frequency are more consistent among the observations and models than changes in intensity. In both the observations and models, increases in large-scale convective aggregation contribute to roughly one third of the increase in extreme precipitation frequency due to interannual warming by shifting moderate-to-heavy precipitation events to more extreme precipitation intensities. The linkages between convective aggregation and precipitation extremes considered here offer insights into their potential response to anthropogenic warming.

**Plain Language Summary** As climate warms, one of the most prominent changes in the global water cycle is more common extreme rainfall events in the tropics. A mechanism that enhances the convection process and its related precipitation could increase the rate of occurrence and strength of these events rising with the temperature. Here, we investigate how a phenomenon known as convective aggregation contributes to more common tropical extreme rainfall events on a year-to-year basis. We find that heavier rainfall is closely tied to a more aggregated state of atmospheric water vapor. Both observations and models show that more extreme rainfall events and the aggregation of moisture occur during warm, El Niño events relative to colder, La Niña events. The enhanced aggregation process creates extra moisture in the already-moist regions leading to more common heavier precipitation events and less common lighter precipitation ones. As a result, the increase in convective aggregation amplifies the increase in extreme rainfall events related to year-to-year surface warming by roughly one third. Our findings provide new insight on projections of future rainfall extremes, which have strong implications for disaster risk management.

1. Introduction

Improving the accuracy of model projections of precipitation extremes is crucial to society. Extreme precipitation is expected to increase substantially as the climate warms (Allan & Soden, 2008; Kharin et al., 2013; O’Gorman, 2012, 2015; Pendergrass & Hartmann, 2014b)—with intensification in the moist equatorial and extratropical regions and little change or decrease in the dry subtropics (Pfahl et al., 2017). The most prominent changes can be found in the deep tropics (O’Gorman, 2015; Pfahl et al., 2017), where the rates of intensification in observations and climate model projections of future warming (O’Gorman, 2012, 2015; Pfahl et al., 2017) are roughly twice as large as a thermodynamical Clausius-Clapeyron (C–C) scaling (6–7% K\textsuperscript{−1}) (Allen & Ingram, 2002; Held & Soden, 2006; Trenberth, 1999). This amplified sensitivity in the tropics is thought to arise from either a dynamical or microphysical mechanism (O’Gorman, 2015;...
Recent observations confirm that CA increases during warm, El Niño relative to cold, La Niña (Sullivan et al., 2019). Given that the frequency of extreme precipitation also increases during an El Niño (Allan & Soden, 2008), it is reasonable to seek an observational connection between CA and the response of tropical extreme precipitation (Pfahl et al., 2017).

Insights from idealized numerical simulations suggest that self-organized CA could amplify the sensitivity of precipitation extremes to warming. Muller (2013) showed that the amplification of precipitation extremes without shear (unorganized) and with critical shear is close to the C-C scaling, whereas supercritical shear strengthens the response of precipitation extremes to warming. Though Cronin and Wing et al. (2017) use cloud-resolving models (CRMs) and found that the changes of extreme precipitation with warming are similar between disorganized and self-organized simulations, Pendergrass et al. (2016) highlighted that the sensitivity of extreme precipitation to warming rapidly increases at the transition from disorganized to organized convection in general circulation model (GCM) simulations. Bao et al. (2017) found that the sensitivity of extreme precipitation to mean surface water vapor is closely associated with the convective-organization-related changes in domain-mean relative humidity and vertical velocity. Validation of this theory that CA amplifies precipitation extremes against observations is vital. In addition, diverse CA processes have been found in very different models from high-resolution CRMs to global climate models with parameterized moist convection (e.g., Coppin & Bony, 2015; Held & Hemler, 1993; Muller & Held, 2012; Pendergrass et al., 2016; Wing & Emanuel, 2014). Although aggregated states are generally characterized by a stronger contrast in humidity between deep convective and non-convective regions (Tobin et al., 2012), there is no universal definition for the spatial scale of CA nor the scale over which extreme precipitation might be expected to increase with aggregation. In reality, tropical convection exhibits complex aggregated behavior from the mesoscale to large scale. It is essential to investigate how the amplification of precipitation extremes depends on degree of aggregation on different spatial scales.

The possibility of a temperature dependence of CA (Cronin & Wing, 2017; Held & Hemler, 1993; Wing & Emanuel, 2014), together with its substantial impact on large-scale moisture distribution, atmospheric circulations, and energy balance, implies that CA can modulate tropical climate sensitivity (Bony et al., 2015). Interactions between CA and sea surface temperature (SST) exhibit interannual variability in a GCM (Coppin and Bony, 2017). The El Niño-Southern Oscillation (ENSO), originating in the tropical Pacific, is the most significant mode of interannual variability of the ocean-atmosphere system (McPhaden et al., 2006). Recent observations confirmed that CA increases during warm, El Niño relative to cold, La Niña (Sullivan et al., 2019). Given that the frequency of extreme precipitation also increases during an El Niño (Allan & Soden, 2008), it is reasonable to seek an observational connection between CA and the response of tropical extreme precipitation (Bony et al., 2009). Some studies suggest a larger sensitivity of convective precipitation, which mainly occurs in the tropics and dominates extreme precipitation events, than of stratiform precipitation (Berg et al., 2013). A physical scaling diagnostic of global precipitation extremes (O’Gorman & Schneider, 2009) reveals that a dynamic contribution from vertical pressure velocity amplifies the increase of tropical extreme precipitation (Pfahl et al., 2017).
frequency of extreme precipitation to SST changes within this mode of internal climate variability. In this study, we utilize satellite observations and simulations from 23 climate models to analyze the relationship between tropical precipitation and CA on different spatial scales, this relationship on interannual scales, and the role of CA in modulating the response of frequency of tropical precipitation extremes to interannual surface warming.

2. Data

2.1. Special Sensor Microwave Imager (SSM/I)

Instantaneous precipitation rate and column water vapor (CWV) of SSM/I Version 7 of Remote Sensing Systems (RSS) are estimated twice daily (available only over the ocean). The period used in this study is July 1987–December 2018 combining five satellites: F08 (July 1987–December 1991), F11 (December 1991–May 2000), F13 (May 1995–October 2009), F15 (January 2000–July 2006), and F17 (December 2006–December 2018). An average of available data is used for any overlapping periods. The SSM/I data are used at the native resolution of 0.25° × 0.25°. In order to be comparable with the model grids, the SSM/I data are also coarsened to 2.5° × 2.5° via an area-weighted average of each 10 × 10 grid cells.

The unit of instantaneous precipitation rate (mm hr⁻¹) is converted to mm day⁻¹ by multiplying the precipitation rate by 24. This daily precipitation rate can exhibit different absolute values from daily accumulated precipitation rate in the climate models, though the fractional changes of precipitation frequency can be still comparable.

2.2. Coupled Model Intercomparison Project Phase 5 (CMIP5) Models

Twenty-three climate models from the CMIP5 archive (Taylor et al., 2012) are used in this study to examine whether current GCMs with ocean coupling can simulate similar results as observed, even though the convective parameterizations used in GCMs do not typically account for sub-grid convective organization. The 23 CMIP5 models are ACCESS1-0, ACCESS1-3, CanESM2, CMCC-CMS, CNRM-CM5, CSIRO-Mk3-6-0, EC-EARTH, FGOALS-g2, GFDL-CM3, GFDL-ESM 2G, GFDL-ESM 2M, HadGEM2-AO, INMCM4, IPSL-CM5A-MR, MIROC5, MIROC-ESM, MIROC-ESM-CHEM, MPI-ESM-LR, MPI-ESM-MR, MPI-ESM-P, MRI-CGCM3, MRI-ESM 1, and NorESM1-M. Only the first ensemble member of each model is chosen. These CMIP5 models with resolution of 1° × 1°–3° × 3° are analyzed over the period of July 1974–December 2005.

Daily precipitation rate and specific humidity from the “historical” experiment are used. Daily column integrated water vapor (CWV) is calculated from this equation below:

$$CWV = \frac{1}{\bar{\rho}_w} \int_p^{P_s} q(p) \cdot dp$$

(1)

$$\rho_w$$ is the water density, g the gravitational constant, q(p) the specific humidity at pressure p, and $$P_s$$ the surface air pressure. Since most models lack daily surface pressure, we use 1,000 hPa instead.

3. Methods

3.1. Degree of CA

Vertically integrated MSE has been previously used to quantify the degree of CA (Wing et al., 2017). Here, we use CWV instead since the spatial variations of MSE in the tropics are mostly contributed from variations of CWV due to weaker temperature gradients there. The degree of CA is defined as below (Lebsock et al., 2017):

$$\alpha = \frac{\sigma_{CWV}}{CWV}$$

(2)

$$\sigma$$ is the spatial standard deviation of all CWV pixels in the domain (e.g., 3 × 3 grid cells or 30°S–30°N). The overbar stands for the spatial mean of that domain. CWV here can be either daily or instantaneous.

Two CA indices are created based on the degree of CA. One is the monthly percentage anomalies of degree of aggregation of the entire tropical ocean (30°S–30°N), defined as:
\[ \alpha = 100 \times \frac{\alpha_m - \bar{\alpha}}{\bar{\alpha}} \]  

(3)

where \( \alpha_m \) is average of daily/instantaneous degree of aggregation (\( \alpha \)) of 30°S–30°N for a certain month; \( \bar{\alpha} \) is the climatology for that month over the entire period, and \( \bar{\alpha} \) is the average of \( \alpha_m \) of all months.

The other is the monthly percentage anomalies of mean degree of aggregation of all domains with a certain size (e.g., 3 \( \times \) 3 or 7 \( \times \) 7 grid cells), calculated by replacing the \( \alpha \) in equation 3 with \( \alpha_N \), where.

\[ \alpha_N = \frac{\sum_{i=1}^{N} \omega_i \alpha_i}{\sum_{i=1}^{N} \omega_i} \]  

(4)

\( N \) stands for the \( N \) number of domains within the tropical ocean (30°S–30°N), which equals to the total number of grid cells of the tropical ocean. \( \omega \) stands for the area weight.

3.2. Algorithm for Precipitation Rate, Percentile, and Relative Frequency of Raining Pixels as Function of CWV and Degree of CA

For each nonzero 0.25° SSM/I raining pixel over the tropical ocean (30°S–30°N), a domain of 3 \( \times \) 3 or 7 \( \times \) 7 grid cells is chosen with this raining pixel being as the center (supporting information Figure S1). The scale of 3 \( \times \) 3 or 7 \( \times \) 7 grid cells is therefore 0.75° \( \times \) 0.75° or 1.75° \( \times \) 1.75°. For a coarsened 2.5° SSM/I raining pixel, the scale of a 3 \( \times \) 3 domain is 7.5° \( \times \) 7.5°. Degree of CA and area-averaged CWV of this domain are calculated for the domain centered around the raining pixel, with values tagged to that pixel. A precipitation percentile calculated over all grid boxes in the tropics is determined for the centered pixel using the central value of a preselected percentile bin (e.g., 5% for 0–10%). With the set of precipitation rate, percentile, and the corresponding degree of aggregation and CWV being available for each nonzero raining pixel, we sort precipitation rates and percentiles of daily tropical raining pixels during a selected time period or certain months into bin boxes with a certain size of CWV and degree of aggregation (e.g., every 7.5 mm of CWV and 5% of degree of aggregation). Precipitation rates and percentiles are averaged within each bin box. Relative frequency of raining pixels is calculated from the number of raining pixels that fall into each bin box divided by the total number of tropical raining pixels during the entire period.

3.3. Definition of El Niño and La Niña

The ENSO variability is defined as the time series of the first empirical orthogonal function (EOF) mode of deseasonalized monthly SST anomalies (125°E–115°W and 15°S–15°N). HadISST 1.1 (Rayner et al., 2003) is used for SSM/I and historical SST simulations for the CMIP5 models. We apply a 10-year linear Butterworth high-pass filter to the SST anomalies before the EOF calculation. The ENSO time series of HadISST 1.1 is highly correlated with the detrended Niño 3.4 index (r ~ 0.88). The El Niño (La Niña) months are defined as the top (bottom) 20% months of this ENSO time series. Only the nonzero raining pixels over the tropical ocean of each day during the El Niño (La Niña) months are collected for calculating El Niño (La Niña)-related precipitation rate, percentile, and relative frequency of raining pixels as function of CWV and degree of CA.

3.4. Contribution of CA

The sensitivity of precipitation frequency or intensity to changes in SST (\( dP/dSST \), unit in % K\(^{-1} \)) is obtained from ordinary-least-squares regression of precipitation frequency or intensity against SST. With a multiple linear regression model, the changes in precipitation frequency or intensity (\( \delta P \)) can be decomposed into partial changes from several predictor variables, for example, CA, domain-mean CWV, and SST:

\[ \delta P = \frac{\delta P}{\delta CA} \delta CA + \frac{\delta P}{\delta CWV} \delta CWV + \frac{\delta P}{\delta SST} \delta SST + \text{Constant} \]  

(5)

The contribution from each variable \( X \) to \( dP/dSST \) can then be written as: \( \lambda_X = \frac{\delta P}{\delta X} \frac{\delta X}{\delta SST} \) (unit in % K\(^{-1} \)), which is independent from the contribution from the other variables. Here, \( \lambda_X \) is obtained from ordinary-least-squares regression of variable \( X \) against SST. Therefore, the contribution of CA to the
amplification of extreme precipitation is \( \delta \text{CAPE} \delta \text{CA} \delta \text{SST} \). In this study, \( \delta \text{CAPE} \) has a unit of \( \% \text{ }^{-1} \) and \( \delta \text{CA} \delta \text{SST} \) of \( \% \text{ } \text{K}^{-1} \). Each response or sensitivity is calculated from either simple or multiple linear regression on time series based on averages over the tropics.

4. Relationship Between Tropical Precipitation and CA

Figure 1 displays precipitation rate and percentile as a function of mean water vapor and degree of convective aggregation over the tropical oceans. (a) Mean precipitation rates and percentiles of 0.25° SSM/I raining pixels that fall into each bin box of every 7.5 mm of CWV and 5% of degree of convective aggregation during July 1987–December 2018. Each raining pixel is considered as a center on a domain of 3 × 3 grid cells. Degree of aggregation and area-averaged CWV on the entire domain are computed for the centered raining pixel. Considering the sample size of raining pixels within each bin box, only bin boxes with a relative frequency (number of rain events within the bin box divided by the total number of rain events) larger than 1 × 10^{-6} between 5% and 90% of degree of aggregation as well as 7.5 and 75 mm of CWV are shown. (b–d) Same as in (a), but for 0.25° SSM/I raining pixels on domains of 7 × 7 grid cells (b), coarsened 2.5° SSM/I raining pixels on 3 × 3 domains (c), and the multi-model mean of the 23 CMIP5 models on their 3 × 3 domains (d). The period of July 1974–December 2005 is chosen for the models.
CMIP5 models (Figure 1d) in general do not show any relationship between degree of aggregation and precipitation but do show a similar relationship between degree of aggregation and mean CWV as in the coarsened SSM/I results.

Since the interannual variability of both CA and the frequency of tropical precipitation extremes is strongly associated with ENSO (Allan & Soden, 2008; Sullivan et al., 2019), changes in frequency of precipitation extremes that are associated with CA are likely to be different between El Niño and La Niña. Figure 2 presents composite results of El Niño minus La Niña for 0.25° SSM/I raining pixels on domains of 3 × 3 grid cells (a), 0.25° SSM/I raining pixels on 7 × 7 domains (b), coarsened 2.5° SSM/I raining pixels on 3 × 3 domains (c), and the multi-model mean of the 23 CMIP5 models on their 3 × 3 domains (d). Green means that rain events within the bin box are more frequent during El Niño than La Niña, and purple means the reversal. Only bin boxes with a relative frequency larger than 1 × 10⁻⁶ between 5% and 90% of degree of aggregation as well as 7.5 and 75 mm of CWV are shown. Time period of SSM/I (CMIP5) is July 1987–December 2018 (July 1974–December 2005).

Figure 2. Differences of relative frequency of rain pixels as function of CWV and degree of convective aggregation between El Niño and La Niña. Each bin box exhibits difference of relative frequency (number of raining pixels within the bin box divided by the total number of raining pixels) between El Niño and La Niña (El Niño minus La Niña) for 0.25° SSM/I raining pixels on domains of 3 × 3 grid cells (a), 0.25° SSM/I raining pixels on 7 × 7 domains (b), coarsened 2.5° SSM/I raining pixels on 3 × 3 domains (c), and the multi-model mean of the 23 CMIP5 models on their 3 × 3 domains (d). Green means that rain events within the bin box are more frequent during El Niño than La Niña, and purple means the reversal. Only bin boxes with a relative frequency larger than 1 × 10⁻⁶ between 5% and 90% of degree of aggregation as well as 7.5 and 75 mm of CWV are shown. Time period of SSM/I (CMIP5) is July 1987–December 2018 (July 1974–December 2005).
differences. Overall, the ENSO-related changes of frequency of heavy to extreme precipitation with regard to degree of CA in Figure 2 is more strikingly consistent among the observations and models than the changes of heavy to extreme precipitation intensities in Figure S2, and thus, we further investigate the relationship between CA and the frequency of extreme precipitation on an interannual time scale in the following section.

5. Contribution of CA to the Amplification of Tropical Precipitation Extremes

To understand how change in the degree of CA contributes to change in frequency of tropical precipitation extremes in response to interannual tropical SST variations, indices of CA are created for a range of spatial scales (Figure S3). The interannual percentage anomalies of large-scale aggregation (30°S–30°N) in SSM/I correlate the highest with deseasonalized SST anomalies (Figures 3 and S3 and Table S1). The time series of synoptic-scale aggregation (mean degree of aggregation calculated from coarsened 2.5° SSM/I 3 × 3 domains) is also correlated with the large-scale aggregation. The peaks of these two time-series correspond with moderate to very strong El Niño events, for example, 1987–1988, 1997–1998, 2009–2010, and 2015–2016 El Niño years, suggesting an increase of larger-scale aggregation during warm events. The anomalies of smaller-scale aggregation computed from 0.25° data exhibit weaker interannual variations and are less correlated with both the SST and large-scale aggregation anomalies (Figure S3). This suggests a possible scale dependence of the sensitivity of aggregation to warming. Similarly, in the CMIP5 models, the anomalies of large-scale aggregation are more strongly correlated with the corresponding SST anomalies than are those at smaller scales (Table S2).

Next we analyze the contribution of changes in large-scale aggregation over the tropics (30°N–30°S) to the amplification of precipitation extremes. Figure 3b presents monthly anomalies of frequency of SSM/I precipitation (coarsened to 2.5° × 2.5° to be comparable with the model simulated precipitation) in 13 bins ranging from the lightest 0–10% to the heaviest 99.9–100% following Allan and Soden (2008) (see Methods in supporting information). Higher frequency of extreme precipitation (>99%) corresponds with warmer SST anomalies and keeps pace with the higher degree of large-scale aggregation. The correlation between the time series of CA and extreme precipitation (99–99.9%) frequency anomalies is roughly 0.59 in SSM/I and 0.45 in the models with a 99% confidence level (Table S1).

Since both CA and frequency of extreme precipitation could increase with SST, we first examine how precipitation frequency is dependent on CA for given SST of 27°C, 28°C, 29°C, and 30°C (see Methods in supporting information). Figure S4 shows that, for any SST between 28°C and 30°C, the frequency of SSM/I
precipitation decreases with increased aggregation for lighter precipitation to very heavy precipitation (10–90%) and drastically increases for extreme precipitation (>99%), though the dependence of precipitation frequency on aggregation could change with different SSTs. This further indicates that the frequency of extreme precipitation can increase with CA, at least at 28–30°C of SST. Comparing with the sensitivity to changes in domain-mean CWV, the sensitivity of frequency of precipitation extremes to changes in CA is smaller at 28°C and 29°C but larger at 30°C. At 27°C, the frequency of precipitation extremes tends to decrease or not change much with both CA and domain-mean CWV. These results suggest a possible SST dependence of the response of frequency of extreme precipitation to the changes in both CA and domain-mean CWV.

The response of precipitation frequency to CA \( \frac{\delta \text{Precipitation}}{\delta CA} \) is estimated by the coefficient calculated from a multiple linear regression model in which the precipitation frequency in each bin is regressed against the large-scale aggregation, SST, and mean CWV in the whole tropics in order to remove any inflation on the dependence of precipitation extremes on aggregation caused by the collinearity among the aggregation, SST, and domain-mean CWV. \( \frac{\delta \text{Precipitation}}{\delta CA} \) does not change much when only using aggregation and SST or aggregation and mean CWV as predictor variables in the multiple linear regression. For the coarsened SSM/I and CMIP5 models, the extreme precipitation (>99.9%) exhibits the largest positive responses to aggregation with 1.6% \( \text{K}^{-1} \) in SSM/I and 2.1% \( \text{K}^{-1} \) for the multi-model average (Figure 4a). The precipitation frequency response to synoptic-scale aggregation is in fact very close to the response to large-scale aggregation (Figure S5a), indicating that the majority of increase in frequency of extreme precipitation could be attributed to CA on the synoptic scale. Note that \( \frac{\delta \text{Precipitation}}{\delta CA} \) could be sensitive to the spatial resolution of the precipitation rate. For example, \( \frac{\delta \text{Precipitation}}{\delta CA} \) of extreme precipitation (>99.9%) is higher with uncoarsened SSM/I precipitation (at its native resolution of 0.25° × 0.25°, Figure S5a right column) than at the coarsened resolution (Figure S5a left column) for any scales of CA.

The sensitivities of precipitation frequencies to interannual SST changes (Figure 4b) share a similar distribution shape as in Figure 4a. The observed sensitivity of extreme precipitation is 24.8–30.7% \( \text{K}^{-1} \) (Table S3). A similar behavior is found in the CMIP5 models, although the sensitivities of extreme precipitation among models are very diverse. Figure 4c estimates the contribution of large-scale aggregation to the amplification of extreme precipitation. The sensitivity of large-scale aggregation to SST is 5.4% \( \text{K}^{-1} \) in SSM/I and 4.6% \( \text{K}^{-1} \) for the multi-model mean. The sensitivities of extreme precipitation contributed from the large-scale aggregation are 8.4–8.9% \( \text{K}^{-1} \) in SSM/I and 7.7–10.1% \( \text{K}^{-1} \) in the model average—both are roughly one third of the sensitivity of frequency of extreme precipitation to interannual SST changes. Such contribution can even reach 90% of the sensitivity of frequency of precipitation extremes (>99.9%) to SST with uncoarsened SSM/I precipitation rate (Figure S5c right column), as a result of higher response (2.6% \( \text{K}^{-1} \)) of frequency of extreme precipitation to large-scale CA and lower sensitivity to SST (15.4% \( \text{K}^{-1} \)). Due to a lower dependence on SST changes, the contribution of synoptic-scale aggregation explains one sixth to half of the sensitivity of frequency of extreme precipitation (Figure S5c), depending on the resolution of the precipitation rate. These results imply that CA, especially the aggregation that is strengthened by large-scale atmosphere-ocean coupling, plays a key role in amplifying the sensitivity of frequency of tropical extreme precipitation to SST.

To further understand the mechanism of how CA impacts the amplification of extreme precipitation, we decompose the response of precipitation frequency to large-scale aggregation into two modes, shift and increase, following Pendergrass and Hartmann (2014a) (see Methods in supporting information). The reconstructed rainfall frequency response (shift plus increase) closely fits the original response for precipitation larger than 50% (Figure S6). In all cases, the increase mode shows a maximum response around 50% followed by a slow decrease to 100%. The response of shift mode, on the other hand, increases after 80%, exceeds the increase mode before 99%, and reaches a peak between 99% and 100%. Given a much larger response of the shift mode to SST changes than the increase mode (Table S3), it indicates that CA contributes to the amplification of extreme precipitation by shifting heavy rainfall (70–80%) events to more frequent extreme precipitation.
Figure 4. Response of precipitation frequency to changes in degree of convective aggregation and SST in SSM/I and CMIP5 models over the tropical oceans. (a) Responses \( \frac{\delta \Delta P(\%)}{\delta \text{CA}(\%)} \) of percentage anomalies of precipitation frequencies in 13 percentile bins to percentage changes of degree of aggregation over the entire tropics. The response is a coefficient calculated from multiple linear regression model in which the precipitation frequency in each bin is regressed against convective aggregation, SST, and domain-mean CWV. (b) Sensitivities \( \left( \frac{\delta \Delta P(\%)}{\delta \text{SST}(\text{K})} \right) \) of precipitation frequencies in 13 percentile bins to tropical SST calculated from simple linear regression. (c) Responses \( \frac{\delta \Delta P(\%) \cdot \delta \text{CA}(\%)}{\delta \text{SST}(\text{K})} \) of precipitation frequencies to SST contributed from the responses of precipitation frequencies to degree of aggregation. The responses or sensitivities are calculated using time series filtered with a 3-month running mean. Black lines represent the responses in SSM/I and blue lines for the multi-model mean of 23 CMIP5 models. Black error bars in (a) and (b) denote standard error for the regression coefficients in SSM/I. Blue error bars stand for ±1 standard deviation among the models.
6. Conclusions

Our work identifies that a major contribution to the interannual amplification of frequency of tropical precipitation extremes comes from changes in the degree of CA, as inferred from both observations and climate models. It strengthens our conviction that CA is indeed important for understanding changes in extreme events. This study shows diverse contributions from different spatial scales of CA to the amplification of extreme precipitation frequency. On smaller spatial scales (e.g., scale less than 200 km), the coincidence of heavy to extreme precipitation occurring with higher degree of CA is more striking than on larger scales, although it does not necessarily mean that smaller-scale CA would amplify the response of extreme precipitation to interannual climate variability (Figure S5c left column). Large-scale CA over the whole tropics is found to be able to explain one third of the amplification of tropical precipitation extremes in both observations and climate model simulations. One caveat is that, although the responses of extreme precipitation to CA used in Figure 4c is independent on SST and the domain-mean moisture content, other dynamical processes could still be entangled with CA and may inflate this estimated dependence on CA. Without idealized numerical simulations, it is difficult to derive a precise estimation by only using observations and simulations of historical climate. This increase in contribution from smaller to larger scale of aggregation could also be attributed the relationship among extreme precipitation, CA, and large-scale environmental conditions. Observations indicate that extreme precipitation comes from more convectively stable and organized systems in a very moist environment (Hamada & Takayabu, 2018), which increase with large-scale SST warming (Sullivan et al., 2019). As inferred from numerical simulations, the interactions among clouds, radiative feedbacks, large-scale circulations, and convective processes can further enhance larger-scale CA behavior (Lau et al., 2020) and thus more extreme precipitation events.

The results of this study on the relationships among interannual variations in SST, CA, and extreme precipitation could be extended to future warming scenarios. To provide an accurate projection of the change of intensity and frequency of extreme precipitation, the models need to well represent the real climate dynamically and thermodynamically. In the CMIP5 models, the simulation of large-scale CA and its link to precipitation extremes on an interannual scale could be constraint by model performance on simulating interannual climate variability, for example, ENSO. Following Dai and Arkin (2017), a subset of “good-ENSO” models in simulating ENSO-related precipitation is chosen (Methods in supporting information). These “good-ENSO” models tend to simulate stronger interannual variations of CA (not shown) and a higher response of frequency of extreme precipitation to aggregation than the underperforming models (Figure S7a), although the “good-ENSO” models also show a much higher sensitivity of extreme precipitation to SST than SSM/I (Figure S7b) and thus may not ideally represent current rainfall distribution. Since uncertainty in the dynamic and potentially microphysical contributions among climate models causes diverse projections of sensitivity of tropical precipitation extremes (Pfahl et al., 2017), improving subgrid cloud, precipitation microphysics, and moist convective parameterizations could also be necessary for reducing intermodel diversity and simulating more realistic CA. These prospective advances, together with reducing large-scale dynamic and thermodynamic biases, will ultimately lead to more robust projections of tropical precipitation in climate models.

Conflict of Interest

The authors declare no conflicts of interest relevant to this study.

Data Availability Statement

SSM/I precipitation rate and column water vapor data are produced by Remote Sensing Systems. Data are available online (www.remss.com/missions/ssmi). CMIP5 are made publicly available by the World Climate Research Programme and are hosted by the U.S. Department of Energy’s Lawrence Livermore National Laboratory at the website (https://esgf-node.llnl.gov/projects/c mip5/). HadISST 1.1 is available from Met Office Hadley Centre (https://www.metoffice.gov.uk/hadobs/hadisst/). OISST is available from National Oceanic and Atmospheric Administration (https://www.ncdc.noaa.gov/oisst).
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