



Mechanisms for Extreme Precipitation Changes in a Tropical Archipelago

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ABSTRACT: The Maritime Continent is one of the most challenging regions for atmospheric models. Processes that modulate deep convection are poorly represented in models, which affects their ability to simulate precipitation features accurately. Thus, future projections of precipitation over the region are prone to large uncertainties. One of the key players in modeling tropical precipitation is the convective representation, and hence convection-permitting experiments have contributed to improve aspects of precipitation in models. This improvement creates opportunities to explore the physical processes that govern rainfall in the Maritime Continent, as well as their role in a warming climate. Here, we examine the response to climate change of models with explicit and parameterized convection and how that reflects in precipitation changes. We focus on the intensification of spatial contrasts as precursors of changes in mean and extreme precipitation in the tropical archipelago. Our results show that the broad picture is similar in both model setups, where islands will undergo an increase in mean and extreme precipitation in a warmer climate and the ocean will see less rain. However, the magnitude and spatial structure of such changes, as well as the projection of rainfall percentiles, are different across model experiments. We suggest that while the primary effect of climate change is thermodynamical and it is similarly reproduced by both model configurations, dynamical effects are represented quite differently in explicit and parameterized convection experiments. In this study, we link such differences to horizontal and vertical spatial contrasts and how convective representations translate them into precipitation changes.

KEYWORDS: Maritime Continent; Precipitation; Climate change; Convective parameterization; Extreme events; Mesoscale processes; Climate models; Mesoscale models; Convective-scale processes; Deep convection

1. Introduction

The Maritime Continent (Fig. 1) is the largest archipelago on Earth and one of the most active centers of deep moist convection on the planet. This tropical archipelago comprises thousands of islands of varied sizes and steep topography surrounded by the Indo-Pacific warm pool, a region with very high sea surface temperatures. Intense convective processes in the Maritime Continent (MC) shape its precipitation regimes and thus have direct implications locally. However, the scale and magnitude of the convection are such that it helps transport large amounts of energy and moisture, modulating global circulation patterns (Neale and Slingo 2003; Yamanaka et al. 2018). Their intrinsic relationship with phenomena such as the Madden–Julian oscillation (MJO) (Birch et al. 2016) and the Walker circulation/ENSO (Qian et al. 2010) are key examples of the interaction across scales that occurs in the Maritime Continent.

The region has proven very challenging in terms of understanding and modeling precipitation characteristics and the associated physical processes. Despite the importance of the region at multiple scales, global climate models fail to capture key features of the Maritime Continent such as the MJO propagation (Peatman et al. 2014; Ling et al. 2019) and the diurnal cycle of rainfall (Baranowski et al. 2019), largely due to their coarse resolution. In fact, even the most recent generation of GCMs (CMIP6) still show substantial biases in tropical precipitation (Fiedler et al. 2020). As a result, even though the CMIP multimodel means suggest increases in rainfall over the region [for CMIP5, see Fig. S1 in our online supplemental material and also Jourdain et al. (2013); for CMIP6, see Wang et al. (2020)], individual GCMs strongly disagree in the sign of rainfall changes (Jourdain et al. 2013; Narsey et al. 2020).

Regional climate models (RCMs), which operate at higher spatial resolution, have contributed to improve our understanding and simulation of the mechanisms underlying rainfall in the Maritime Continent (Vincent and Lane 2018; Ruppert and Zhang 2019; Li et al. 2020) through better representation of fine-scale processes (i.e., sea breeze, gravity waves, interaction across scales, air–ocean fine-scale interactions). However, RCMs are still prone to substantial errors, partly originating from the interaction between the convective representation and the land–sea contrasts (Birch et al. 2015; Vincent and

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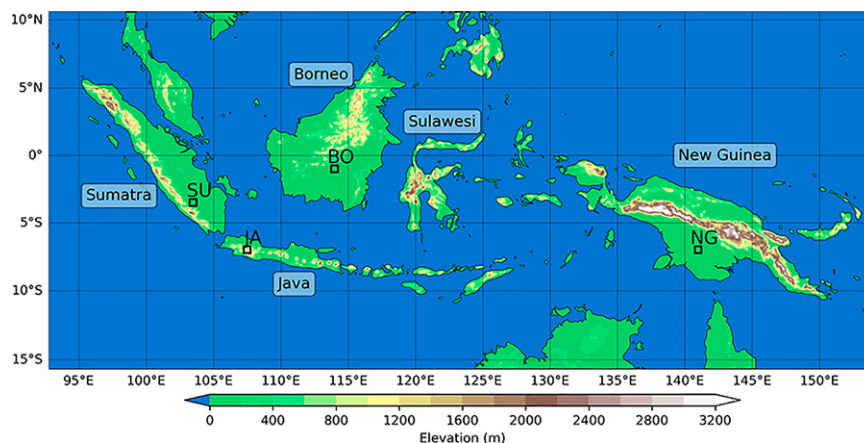


FIG. 1. The Maritime Continent archipelago. The region shown corresponds to the model domain and the black squares are sampling areas.

Lane 2017; Im and Elthair 2018). Models that explicitly represent convection bring improvements in the simulation of the precipitation diurnal cycle but produce unrealistic precipitation over steep topography (Argüeso et al. 2016, 2020), misrepresent the amplitude of the diurnal cycle (Hassim et al. 2016; Argüeso et al. 2020), or introduce errors in the rainfall modulation by the MJO phase (Vincent and Lane 2017; Wei et al. 2020). The challenges posed to models by convective processes in the MC have attracted much attention in the recent years because of their central role in the climate at multiple scales. A perfect example of this interest is the international initiative “Years of the Maritime Continent” (YMC Phase 1 2017–20; Yoneyama and Zhang 2020), aimed at coordinating international modeling and observational efforts to advance our understanding of the MC weather and climate systems, and to improve the representation of convective processes and precipitation in models.

Precipitation in the Maritime Continent tends to concentrate over the islands (Qian 2008), where rainfall is characterized by a strong diurnal cycle that most models struggle to capture. As described by Ruppert and Chen (2020), the “island rainfall enhancement” effect and the land precipitation diurnal cycle are ultimately linked to differences between land and ocean in surface heat capacity and surface energy fluxes. They also show that the diurnal cycle of solar radiation governs mesoscale circulations (i.e., land–sea and mountain–valley breezes), which in turn fuel the convective development, help organize deep convection into mesoscale convective systems, and recharge the convective instability required for intense rainfall rates. Local steep topography further contributes to organize convection by exciting and coupling with gravity waves and, in certain situations, to reinforce it by inducing orographic lifting. These convective systems then propagate offshore, assisted by gravity waves, reversed breezes (land breeze), and cold pools (Ruppert and Zhang 2019; Yang et al. 2020), which together produce a diurnal cycle over water that peaks between night and early morning, although it is generally weaker the cycle than over land. Therefore, rainfall features in the MC strongly depend on local factors such as

land–ocean contrasts, mesoscale circulations, moisture convergence, intense convective instability, and topography.

In the context of climate change, we expect horizontal and vertical warming contrasts that may induce changes in the intensity and spatial distribution of precipitation. For example, differences in warming rates between continents and ocean can alter mesoscale circulations (Joshi et al. 2007) and vertical warming contrasts can modify atmospheric stability (Wang et al. 2020), which will likely affect rainfall in the Maritime Continent. At the ocean basin scale, thermal contrasts will also play a key role in defining future changes of the Walker circulation (Yim et al. 2017), and hence in El Niño–Southern Oscillation, determining which ascending branch is anchored to the Maritime Continent, and likely modulated by the island rainfall enhancement effect (Ruppert and Chen 2020). At continental and seasonal scales, monsoons will be also intensified due to enhanced thermal contrasts (Seth et al. 2019), which may redistribute precipitation.

In the Maritime Continent, Lambert et al. (2017) did not find a consistent shift of rainfall from ocean to land due to warming, as opposed to other tropical regions (i.e., Amazonia). Bony et al. (2013) also identified land–sea thermal contrasts as having an important role in modifying tropical rainfall patterns over land, although they deemed the dominant factor in tropical overturning circulation to be the higher CO₂ concentrations and the resulting radiative imbalance in the atmosphere. However, all these changes were established using global climate models (GCMs), which have serious difficulties in representing crucial features of the Maritime Continent rainfall (Jourdain et al. 2013; Schiemann et al. 2013; Baranowski et al. 2019; Yang et al. 2020). Recent studies have generated future climate projections using RCMs (Supari et al. 2020; Tangang et al. 2020) and found that both increases and decreases in land precipitation over areas of the MC were plausible, depending on the region and the season examined. Yet, the physical mechanisms driving such changes have not been explored.

Therefore, the use of higher-resolution models to better understand the mechanisms driving future changes in precipitation over the region is still necessary. Despite some errors that persist

in high-resolution models, experiments that explicitly resolve convection are especially beneficial in coastal areas, regions of complex topography, and locations with frequent and intense deep convection (Prein et al. 2015; Lucas-Picher et al. 2021), all of which apply to the Maritime Continent. In this study, we use a model at convection-permitting scales to investigate the response of rainfall to a warming climate. For the first time, we examine future climate information at convection-permitting scales in the entire Maritime Continent and determine the different response of rainfall extremes to climate change in parameterized and explicit convection experiments. We also conducted a novel analysis of the role of warming spatial contrasts, land–sea breeze circulations, and modified atmospheric stability in modulating this response. We expect that land–sea thermal contrast changes will affect breeze circulations, and vertical differences in the response to global warming will modify vertical profiles and stability. In combination, they will have implications for future climate precipitation regimes in the region. Since the interactions between convection and the environment are represented differently in explicit and parameterized convection models, precipitation responses to climate change will likely differ between these models too. In view of this possibility and the expectations around convection-permitting models for future projections (Fosser et al. 2020; Prein et al. 2020; Lucas-Picher et al. 2021), we explore the rainfall response to increased temperature in both explicit and parameterized convection experiments at very high resolution.

The rate at which precipitation responds to surface temperature changes is known as precipitation scaling (Trenberth 1999; Held and Soden 2006) and has two main components: dynamical and thermodynamical [see Box 11.1 in Seneviratne et al. (2021)]. In the past, the covariational term was also explored (Bony et al. 2004). The thermodynamical component is linked to the Clausius–Clapeyron relationship—increased atmospheric water-holding capacity with temperature—and is a primary mechanism for climate-scale precipitation changes. Under climate change conditions, this should contribute to more intense precipitation rates, particularly for extremes (Drobinski et al. 2018). The dynamical component includes changes in large-scale circulation patterns that determine the supply of moisture and in local circulations that contribute to vertical motions. The intensification of sea breeze, atmospheric instability, and convective processes is framed in the latter group (i.e., local circulations). Here, we focus on the role of local circulations to explain the spatial patterns of precipitation changes, which are related to the dynamical part. However, we also explore the contribution of thermodynamical changes to provide a comprehensive picture. We examine the separate contribution of thermodynamical and dynamical mechanisms to intense precipitation changes in the region and we identify differences between parameterized and explicit convection models in this context.

2. Methods

a. Model and present-climate experiments

In this study, we use the Weather Research and Forecasting (WRF) Model v3.9.1 (Skamarock et al. 2008) to simulate

the atmosphere over the Maritime Continent and investigate rainfall patterns under climate change conditions. The model was run at 4-km spatial resolution over a domain covering 5916 km $\times$ 2556 km (1479 $\times$ 639 grid points) in the Maritime Continent and resolving the vertical with 50 hybrid coordinate levels. The experiments span three consecutive austral summers (1 November–1 March in 2013/14, 2014/15, and 2015/16), each preceded by a 10-day spinup period (22–31 October) that was discarded in the analysis. The analysis period covers the wet season for most of the Maritime Continent and the selected years span both positive and negative phases of El Niño–Southern Oscillation.

The physical parameterization schemes are among the most widely used options and were chosen according to previous studies over the region (Li et al. 2017; Argüeso et al. 2016; Vincent and Lane 2017). The setup consists in the WRF single-moment six-class microphysics scheme (WSM6; Hong and Lim 2006), the Yonsei University (YSU) scheme for planetary boundary layer turbulence, the Rapid Radiative Transfer Model (RRTM) scheme for longwave radiation, the Goddard scheme for shortwave radiation, the Noah land surface model, and the MM5 similarity scheme for the surface layer. In the parameterized convection experiment, the Betts–Miller–Janjic (BMJ; Betts and Miller 1986, 1993; Janjic 1994) scheme was chosen to represent both deep and shallow convection, while it was turned off for the explicit convection experiment [see Argüeso et al. (2020) for additional details on the model configuration]. In this framework, clouds are driven by the microphysics parameterization regardless of the convective representation. However, the environmental conditions in the model will depend on the convective representation and thus the microphysics scheme will likely generate different clouds. In the explicit simulations, it is the model equations (dynamical core) that represent convection and its effects on the atmosphere vertical profile. In the parameterized runs, the BMJ scheme does not directly inhibit explicit convection, but it reduces the potential for explicit convection because it removes energy from the atmosphere through the adjustment toward a stable vertical profile. Explicit convection at scales resolved by the model grid is still possible though, especially in environments that favor strong convective processes.

Present climate experiments are directly initialized and driven by ERA5 reanalysis (Hersbach et al. 2020) at $\sim 0.3^\circ$ spatial resolution and updated every 6 h. Argüeso et al. (2020) already analyzed these simulations and compared them against satellite-derived products to examine the role of different convective representations and the spatial resolution in representing realistic rainfall features. They concluded that, as opposed to higher-resolution experiments, 4 km provides the best estimates of precipitation while maintaining computational and storage costs affordable. This is the upper boundary of the convective gray zone (Prein et al. 2015), a range of spatial resolutions (~ 4 –10 km) where explicit and parameterized convection may compete. It is yet unclear whether convection should be parameterized in this range. Thus, it further justifies the analysis of both parameterized and explicit convection setups.

b. Pseudo global warming experiments

This study expands the existing set of runs in [Argüeso et al. \(2020\)](#) by incorporating pseudo global warming (PGW; [Schär et al. 1996](#)) experiments to examine the response of rainfall to a particular climate change signal. These experiments were built adding the climate change signal obtained from a global climate multimodel ensemble from phase 5 of the Coupled Intercomparison Model Project (CMIP5). We calculated the seasonal cycle of all variables ingested by the model (i.e., wind components, humidity, geopotential height, and temperature at pressure levels; as well as 2-m dewpoint temperature, 2-m temperature, 10-m wind components, surface pressure, mean sea level pressure, and sea surface temperature) for historical (1989–2009) and future (2080–2100) climate experiments from 33 GCMs (see the online supplemental material). We computed the climate change signal for each calendar month, each variable, and each model, and interpolate them to a common 0.72° grid to calculate a multimodel mean climate change signal. These monthly changes are linearly interpolated in time to 6-hourly intervals and nearest-neighbor interpolated to the ERA5 grid. Then they are added to ERA5 to create the initial and boundary conditions to drive WRF under a synthetic future climate scenario. The PGW method has been previously evaluated in a “perfect model approach” with satisfactory results ([Yoshikane et al. 2012](#); [Donat-Magnin et al. 2021](#)) and was applied in a wide range of studies from tropical cyclones ([Chen et al. 2020](#)) to ice sheets ([Donat-Magnin et al. 2021](#)).

The future climate change signal is here represented by the representative concentration pathway 8.5 (RCP8.5 scenario). We chose this high-emission scenario to examine the impact of a marked climate change signal on the Maritime Continent, but this choice does not imply any assumptions on its likelihood.

Even though this experiment setup does not constitute a rigorous future climate projection and thus has limitations, it offers numerous advantages. While runs are not long enough to be completely representative of the climate, their duration is a very good reason to force future climate runs with climatological anomalies from the GCMs’ multimodel ensemble (MMM). This way, our results are less dependent on the interannual variability produced by individual models for specific years. Furthermore, it is often argued that changes projected by the MMM are in general more credible than projections produced by individual models ([Knutti et al. 2010](#)). In addition, CMIP5 model biases are stationary even under strong climate changes ([Krinner and Flanner 2018](#)) and hence this method partly overcomes the biases in the climate states produced by individual models. The MMM estimates are still subjected to biases such as the sea surface temperature warming patterns that require complex bias-correction methods ([Dutheil et al. 2020](#)), but the same applies to direct downscaling of individual highly biased GCMs. The PGW method includes the thermodynamical effects produced by a given climate change signal and some dynamical features. For example, it considers the mean change in the large-scale dynamics because the geostrophic balance is linear. However, it misses changes in the structure and variability of circulation patterns, as well as some

nonlinear large-scale dynamics and variability. These include phenomena such as MJO or ENSO, some of which may undergo frequency changes in the future ([Cai et al. 2018](#)). Another potential limitation is that nonstationary biases that may be shared by CMIP5 models are not removed with the multimodel mean. It is important to note that these features can affect the spatial patterns of precipitation changes in our experiments.

Overall, the method constitutes an interesting, efficient, and solid approach to quantify the response of the climate change system to plausible future conditions. It also brings the analysis down to the physical-process level at feasible computational costs, especially considering the demands of convection-permitting experiments at continental scales. In this study, we refer to the PGW simulations as “future” experiments for reasons of clarity. Changes projected by the selected multimodel ensemble over the Maritime Continent are shown in the online supplemental material (see Fig. S1) for temperature, wind, precipitation, and integrated water vapor.

c. Scaling calculation

We first calculate the scaling of extreme precipitation with temperature directly from the model outputs. To further understand the underlying mechanisms, we also calculate changes in precipitation extremes using the physical scaling diagnostic described in [O’Gorman and Schneider \(2009b\)](#), which estimates precipitation rates from vertical profiles of vertical pressure velocity, temperature, and pressure. This methodology is usually applied to high-percentile precipitation events by selecting times when they occur. It expresses the precipitation rate during an extreme event at each grid point as

$$P_e \sim - \left\{ \omega_e \frac{dq_s}{dp} \right\}_{\theta^*, T_e}, \quad (1)$$

where P_e is the precipitation amount during an extreme event, ω_e is the corresponding vertical pressure velocity, $\{\cdot\}$ is a mass-weighted integral over the troposphere, and the remainder is the vertical derivative of the saturation specific humidity q_s at constant saturation equivalent potential temperature θ^* (i.e., moist adiabatic) and evaluated at the mean temperature T_e during the intense rainfall event [see [O’Gorman and Schneider \(2009b\)](#) for additional details]. By comparing estimates from present- and future-climate experiments, it is possible to approximate the full precipitation scaling for extremes, which aggregates the effects of thermodynamic and dynamic processes.

Following [Pfahl et al. \(2017\)](#), we can decompose changes in heavy rainfall into thermodynamic and dynamic contributions. To calculate the separate effect of thermodynamic processes, we ignore changes in the vertical profile of ω_e and we use instead the time average from present climate experiments calculated only for extreme precipitation hours ($\overline{\omega_{e,\text{present}}}$). The new heavy rainfall estimates [$P_{e,\text{thermo}}$; Eq. (2)] will be due to changes in the vertical derivative of q_s only. The dynamic contribution [$P_{e,\text{dyn}}$; Eq. (3)] is calculated by subtracting the thermodynamic scaling [Eq. (2)] from the full scaling [Eq. (1)]:

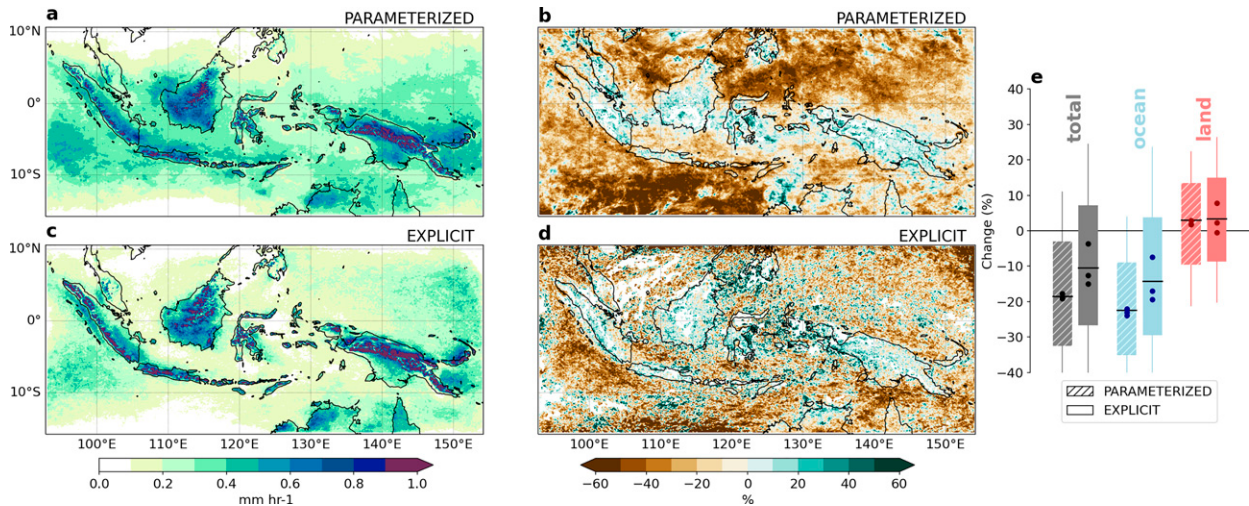


FIG. 2. Present mean precipitation rates in the (a) parameterized and (c) explicit convection runs, and relative mean precipitation changes using the PGW approach (future minus present) for (b) parameterized and (d) explicit convection runs. Areas with no statistically significant changes according to a Mann–Whitney U test at the 99% confidence level are masked out in (b) and (d). These areas are 7.9% and 14.7% of the domain, respectively. (e) Boxplots show changes for all (gray), ocean-only (blue), and land-only (red) grid cells for parameterized (hatched) and explicit (solid) experiments. The boxes represent the interquartile range, whiskers are the 10th–90th percentile range, horizontal lines are the median changes over all grid points in each category, and markers show the median for each of the 4-month periods individually.

$$P_{e_thermo} \sim - \left\{ \overline{\omega_{e_present}} \frac{dq_s}{dp} \right|_{\theta^*, T_e} \right\}, \quad (2)$$

$$P_{e_dyn} = P_e - P_{e_thermo}. \quad (3)$$

In this study, we apply for the first time this diagnostic to convection-permitting experiments and hourly model outputs to disentangle the contribution of thermodynamic and dynamic processes and explain possible deviations from the Clausius–Clapeyron relationship at very high spatiotemporal scales. Prior to applying the scaling, we horizontally smoothed the vertical pressure velocity (ω_e)—not the vertical derivative of q_s —using a Gaussian filter with a standard deviation of 20 km. Reasons for this include 1) to reduce the effect of downdrafts produced by intense rainfall within the convective cell and characterize the environment producing the extreme episode, 2) to filter out the influence of single-cell storms that models may generate at these scales (Murata et al. 2017), and 3) to better match the scales previously used with this method (~ 100 km) (Pfahl et al. 2017). Scaling was also calculated without any prior spatial smoothing.

3. Results

a. Precipitation changes in explicit and parameterized convection models

In this section, we analyze changes in mean precipitation as simulated by the parameterized (PA) and explicit (EX) convection experiments. We compare present and future experiments over three consecutive austral summers [November–February (NDJF)] and calculate changes relative

to present-climate values $[(\text{future} - \text{present}) \times 100/\text{present}]$. Mean precipitation changes show a prominent contrast between a net increase over land and a decrease over the ocean (Fig. 2). Both model configurations simulate a domain-average decrease in mean precipitation (-13.3% for PA and -6.2% for EX), probably because they are driven by the same boundary conditions, which exert control over the large-scale dynamics. The MMM of the CMIP5 ensemble used here to create the PGW scenario project a slight increase in the domain-average rainfall (4.9%), but precipitation is a model prognostic variable and is not used to generate the boundary conditions. While this difference in the sign of changes may seem contradictory, the link between the large-scale conditions and precipitation in models is complex. Factors that contribute to this disparity include differences in the spatial scale (grid-averaging effects), in the efficiency of convective schemes, in the response of convective schemes to environmental changes, and in surface evapotranspiration. Furthermore, the CMIP5 ensemble projects a wide range of possible changes over the domain (between -16.6% and 19.8%). Despite these differences and the divergence across CMIP5 models (IPCC 2013; see also Fig. S1), the ensemble consistently projects larger increases over land than over the ocean, which is coherent with our results (Fig. 2).

Both our experiments produce an increase in rainfall over land (4.3% PA; 5.0% EX) and a decrease over the ocean (-20.2% PA; -12.7% EX). Narrow waters in between islands and coastal areas are notable exceptions to this general response. Thus, according to our experiments, a warmer atmosphere would generate more rainfall over land in the Maritime Continent, although the spatial variability is large over both land and ocean (Fig. 2e). Changes are similar across all three austral summers in the PA runs and results from one

year deviate from the other two in the EX run (Fig. 2e and Fig. S2). Altogether, this provides confidence on the robustness of the results.

The spatial pattern of precipitation changes is broadly similar in both experiments, but there are features in the response that differ between the two. First, the magnitude of changes: PA produces larger decreases of rainfall over the ocean. Second, EX experiments are spatially noisier and so is the response to warming. This is partly explained by the length of the simulations, but PA is spatially much smoother, which suggests that the noise is inherent to how convective processes are represented. In fact, changes in EX shows a larger year-to-year variability than PA under the same large-scale conditions (Fig. 2e). This contrast is relevant because the next generation of climate projections will shift toward convection-permitting models (Prein et al. 2015, 2020), which may produce less spatially homogeneous projections if they behave like our model. None of the two model projections can be deemed more likely than the other because their relative performance varies depending on the metric analyzed (Argüeso et al. 2020). However, explicit convection brings increased realism of precipitation features often misrepresented in models, such as the diurnal cycle and its coupling with the land–sea breeze (Birch et al. 2015; Argüeso et al. 2020).

In addition to mean precipitation, we analyze the model extreme precipitation response to a climate change signal and quantify the role of convective representation in that response (Fig. 3). We characterize changes in precipitation events through a range of percentiles (50th–99.9th) and focus on the upper tail of the distribution (95th, 98th, 99th, and 99.9th percentiles). The statistical significance of changes was tested at the 90% confidence level using a bootstrapping approach based on resampling with replacement following Contractor et al. (2018, 2021). For each grid point, we concatenated present and future, and resampled the resulting time series with replacement under the null hypothesis that there is no change. The same permutation is used for all grid points to preserve spatial dependence in the resampled data. The resampling was done using 12-h blocks to preserve temporal dependence of events. This assumes independence of rainfall from one 12-h period to the next, which is supported by the distinct diurnal cycle of rainfall in the region. The diurnal cycle was considered when defining the blocks (0600–1800 and 1800–0600 UTC) so that the rainfall peak at around 1700 local standard time (LST) is not split across two blocks. This approach neglects correlation in rainfall on daily or longer time scales, which could lead to some overestimation in the number of independent samples.

We split the resampled time series in two equal parts and calculate the change in the percentiles between the two. The process was repeated 1000 times to build a distribution of quantile change ratios between the two, which is normally distributed around 0, and estimate the p values of the original quantile change ratios. Percentiles were calculated for each grid point and each period (present and future) separately. Percentiles can be calculated using all hourly values (Schär et al. 2016) or wet-only values (Chan et al. 2016) depending

on the purpose of the analyses. While both may have advantages, we chose the all-hourly values approach because having a fixed population of events ensures that 1) changes in each percentile univocally mean that events exceeding that percentile (extreme) must change, 2) upper percentiles are not affected by changes in light rain frequency, and 3) percentiles represent a fixed number of events at all locations, runs, and periods. For instance, the upper percentiles we focus on represent approximately 433, 173, 87, and 9 hourly events in all grid cells and all experiments. These advantages make our results easier to interpret in the context of this study. Present climate values of these percentiles are provided in the online supplemental material (Fig. S3). Changes in percentiles using wet-only values ($>0.1 \text{ mm h}^{-1}$) are shown in Fig. S4 for comparison with the all-hourly values approach. Changes in wet-only percentiles are comparable to higher percentile changes using all-hourly values. This is because wet-only percentiles characterize a higher section of the rainfall distribution tail. Although changes in wet-only percentiles are affected by changes in the entire distribution of rainfall, the spatial patterns between the two approaches are very similar for very intense precipitation events. They both show a land–sea contrast. Differences between PA and EX are also similar using one approach or another.

Domain-average changes of precipitation percentiles are summarized in Table 1 along with separate changes over land and ocean. These changes were computed using the mean of percentiles each region (domain, land, and ocean) for both present and future runs, and then the relative changes with respect to present climate were calculated. PA suggests a decrease in all selected percentiles when aggregating over the entire domain and ocean grid points. It also suggests an increase in all but the 95th percentile over land. EX projects a similar behavior, except for the highest one (99.9th), which increases both over land and ocean. On average, EX produces larger decreases for the 95th and 98th percentiles compared to PA. This difference is strongly dominated by decreases over water in EX, since changes over land are very similar between the two experiments. As we move to more intense precipitation events (99th), the contrast between land and ocean is further enhanced, especially for PA, which suggests substantial changes both over land and ocean but with opposite signs (9.6% and -32.6% , respectively). Indeed, some large islands such as New Guinea show a strong and statistically significant response of the upper tail to warming in the PA experiment (Fig. 3i).

The highest end of the distribution (99.9th percentile) represents events above 10 mm h^{-1} in most cases and well above 25 mm h^{-1} in many land grid points (Fig. S3). In EX, the 99.9th increases over land (14.9%) under climate change conditions, but there is no clear signal over the ocean. In fact, significant changes are mostly located over land. PA shows an increase in extreme precipitation (99.9th) over land (22.4%) too, but it produces significant decreases over the ocean (-10.9%). As a result, PA exhibits a domain-average decrease of high-end extremes (-3.2%), while EX produces an increase (4.0%).

Figure 3 provides a more detailed and visual description of the precipitation response to warming. As opposed to the

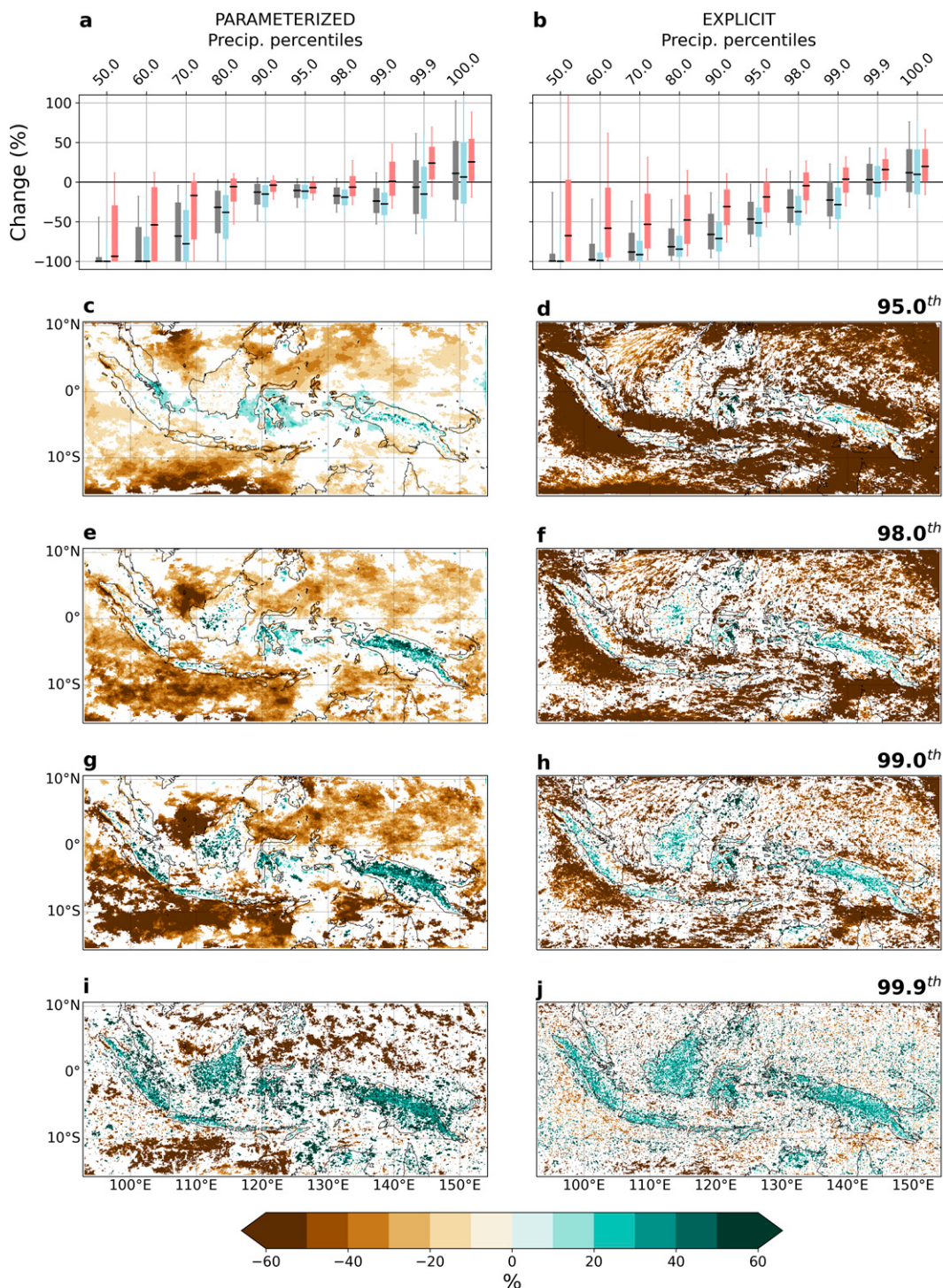


FIG. 3. Changes in rainfall percentiles. Statistics of changes over the entire domain (gray), ocean-only (blue), and land-only (red) grid points for (a) the parameterized case and (b) the explicit case. Boxes represent the interquartile range; whiskers are the 10th–90th percentile range, and horizontal lines are the medians. Spatial patterns of relative changes in rainfall for the (c),(d) 95th, (e),(f) 98th, (g),(h) 99th, and (i),(j) 99.9th percentiles for the (left) parameterized and (right) explicit model setups. Statistical significance was tested using a bootstrap approach based on 12-h blocks resampling with replacement repeated 1000 times. According to the test, 43.2%, 46.7%, 42.1% and 19.5% of all the grid points show significant changes for the corresponding percentiles in the parameterized runs, and 52.2%, 35.3%, 25.8%, and 13.1% for the explicit case. Nonsignificant changes were masked out.

TABLE 1. Domain-average changes in mean precipitation and the upper percentiles of hourly rainfall for the parameterized (PA) and explicit (EX) convection experiments. Changes are shown for all grid points, land-only grid points, and ocean-only grid points. Changes are in percentage with respect to present climate, and positive changes are in bold typeface.

	Mean	95th	98th	99th	99.9th
PA					
Total	−13.3	−9.8	−14.4	−19.2	−3.2
Ocean	−20.2	−11.8	−22.0	−32.6	−10.9
Land	4.3	−5.3	1.5	9.6	22.4
EX					
Total	−6.2	−18.9	−17.3	−12.8	4.0
Ocean	−12.7	−47.1	−33.4	−23.7	0.6
Land	5.0	−5.3	0.6	5.4	14.9

summary discussed above (Table 1), Fig. 3 includes aggregated information on other percentiles (50th–100th) and shows the spatial variability of changes. Rates below the 90th percentiles are usually light rainfall events ($<0.1 \text{ mm h}^{-1}$) in EX (Fig. S3), and their contribution to total precipitation is limited. The contribution of events below the 90th percentile to total precipitation may be larger in PA, because the 0.1 mm h^{-1} rate is reached at a much lower percentile (70th). This is likely due to the drizzle effect that typically affect models with convective schemes (Gutowski et al. 2003; Sun et al. 2006; Dai 2006; Stephens et al. 2010; Pendergrass and Hartmann 2014).

Moderate rainfall events (95th percentile) decrease with warming in most locations according to both experiments (Figs. 3c,d). Very few grid points show an increase of moderate precipitation, and they are mostly located over or near the islands. The land–sea contrast becomes increasingly clear in the upper percentiles for both experiments (Figs. 3c–j). However, EX already concentrates rainfall over land much more than PA under present climate conditions, so the contrast will become even sharper in EX under warming. Therefore, the spatial pattern of mean precipitation changes (Fig. 2) is largely explained by changes in the high end of the distribution, according to Fig. 3.

Overall, explicit and parameterized convection produce different precipitation distributions and different precipitation changes under the same large-scale climate change signal, especially in the upper tail of the distribution. Although the spatial pattern of changes is broadly similar (land–sea contrast), their fine spatial detail, their magnitude, and the response of each percentile to climate change is different between the two convective representations.

b. Thermodynamical and dynamical contributions to precipitation changes

Our experiments suggest that the islands of the Maritime Continent will undergo higher precipitation rates and more intense rainfall extremes in a warmer climate. Mechanisms that produce rainfall changes are often interlaced and their contributions may act in opposite directions.

We quantified their combined effect by calculating changes in high percentiles of precipitation and express them as a ratio with respect to the domain-average near-surface warming (the *direct* method). Using near-surface temperature to estimate rainfall scaling imposes important limitations because it does not consider changes in moisture availability, which often play a primary role in defining precipitation extremes (Lenderink et al. 2017). Also, it assumes homogeneous warming in the vertical and thus does not allow for different changes in the atmospheric water-holding capacity at different vertical levels. However, it is a standard way of measuring the precipitation scaling (Westra et al. 2014; Bao et al. 2017; Lenderink et al. 2017; Drobinski et al. 2018; Allan et al. 2020) because it relies on widely available observations and model outputs. We also estimated the aggregated contribution of the thermodynamical and dynamical terms of rainfall scaling with temperature using the theoretical approach described in section 2c (O’Gorman and Schneider 2009a), and we refer to this method as *full* scaling. The precipitation scaling was decomposed into thermodynamical and dynamical terms following Pfahl et al. (2017). The *direct* method serves as a backdrop to test the adequacy of the theoretical approach (*full* scaling).

We focus on the scaling of the 99th percentile. For all methods we quantified the scaling by calculating the mean of all events above the percentile for each period and each grid point, and compute the change relative to present climate values, as we have done with other precipitation changes. Then, we divide it by the domain-average near-surface temperature change and estimate the scaling of intense rainfall with temperature for both experiments (Figs. 4a–d). The *direct* scaling calculation shows a strong land–sea contrast of the scaling in PA. Most islands undergo increases in the range 10%–20% K^{-1} , while much of the ocean experience decreases, sometimes as large as $-20\% \text{ K}^{-1}$. The spatial pattern of scaling is similar in EX, but the rates are not as pronounced.

The *full* scaling estimates (Figs. 4c,d) yield results that compare very well with the *direct* scaling calculation, including both the pattern and the magnitude of changes. Figures 4a–d support the idea that warming leads to processes favoring more intense precipitation over land, while changes of any sign are plausible over water. Ignoring changes in vertical velocities in Eq. (1) (see details in section 2c), we can estimate the separate contribution of thermodynamic (*thermo*) processes to the scaling (Figs. 4e,f). The thermodynamic contribution to extreme precipitation changes is spatially much more homogeneous than the *full* scaling, although it still presents some land–sea contrast in EX. In both experiments, the thermodynamic processes contribute to increases in the range 4.2%–8.2% K^{-1} over virtually the entire domain (95% of grid points), with slightly higher values for EX (4.3%–8.2% K^{-1}) than for PA (4.2%–7.5% K^{-1}). This is roughly consistent with the Clausius–Clapeyron relationship, which establishes an approximate increase in rainfall rates of 7% per degree of near-surface warming (Trenberth et al. 2003). The scaling methods produce similar results when using different percentiles (95th and 99.9th; see Figs. S5 and S6, respectively).

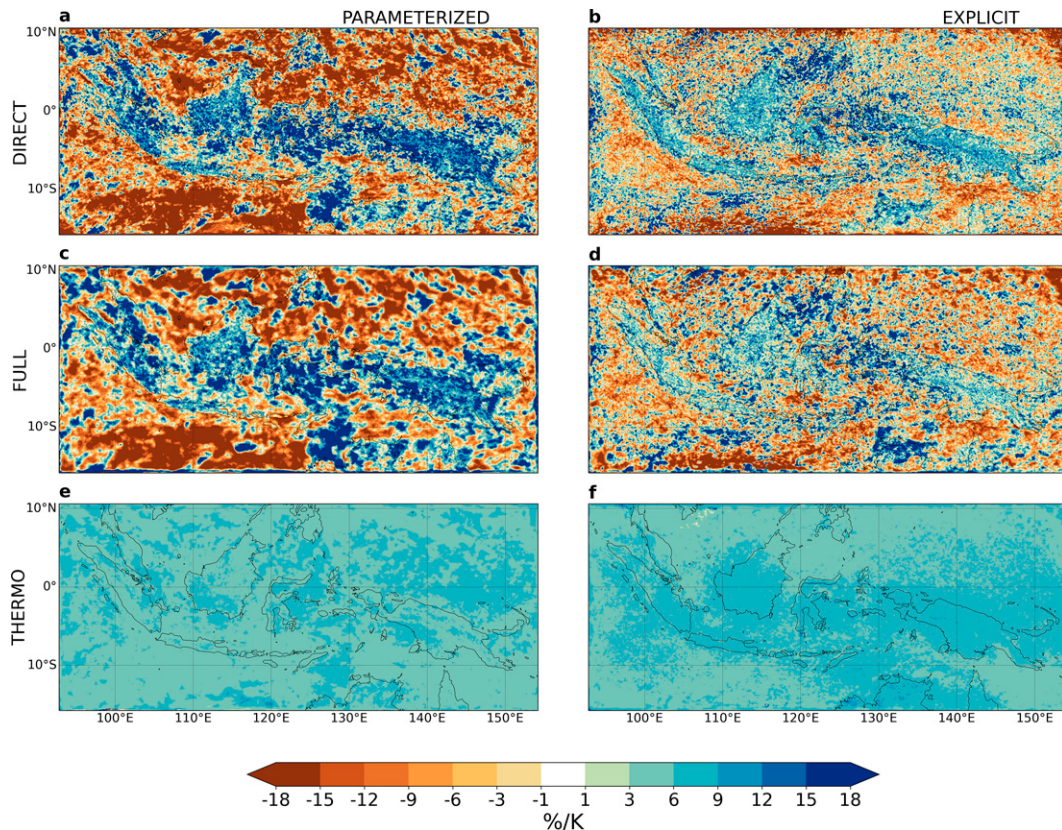


FIG. 4. Scaling of the 99th percentile of precipitation with respect to the domain-average 2-m temperature change using (a),(b) hourly precipitation outputs from the model (*direct* scaling), (c),(d) the full scaling as estimated by the theoretical diagnostic from O’Gorman and Schneider (2009b), and (e),(f) the thermodynamic scaling as approximated by Pfahl et al. (2017), for (left) the parameterized experiment and (right) the explicit simulation.

In the results above, the vertical pressure velocity (ω_c) was smoothed using a 20-km Gaussian filter prior to calculating the scaling. We have also calculated the scaling without the smoothing to determine the impact of this choice (Fig. S7) and found that the smoothing considerably reduces the noise in both model configurations, particularly in EX. While the overall pattern is similar between the two approaches, the spatial details and magnitude of the *full* (theoretical) scaling are closer to the *direct* scaling when smoothing ω_c .

Large spatial variations in *direct* and *full* scaling estimates can only be explained by dynamic processes, because the *thermo* term is spatially homogeneous. The contribution of dynamic processes is calculated as the difference between the *full* scaling and the *thermo* term (Pfahl et al. 2017). The dynamical term enhances or opposes the effect of the thermodynamic mechanisms through changes in vertical motions during extreme precipitation events. Therefore, heterogeneities in vertical motions are responsible for the spatial noise in the dynamical term (Fig. S8), which modulates the homogeneous thermodynamic contribution. This explains the existence of positive and negative values of *direct* and *full* scaling close together. Although this may be alleviated with longer runs and strengthening the Gaussian spatial filter applied to the vertical velocity, differences between

the two experiments suggest that the nature of the convective scheme may also play a role in smoothing out spatial heterogeneities of vertical motions. In fact, explicit convection experiments running at resolutions of a few kilometers are prone to generate single-grid-cell precipitating systems (Murata et al. 2017) that may reflect into this spatial noise.

In general, our results indicate that the dynamic term counteracts the thermodynamic effect over the ocean. Over land, dynamical processes tend to enhance precipitation scaling in PA. In EX, the dynamic contribution also presents a land–sea contrast, but both positive and negative contributions were obtained over land. This land–sea contrast is consistent with results in Pfahl et al. (2017) using GCMs, which suggested that dynamic processes enhanced changes in daily precipitation extremes over large islands in the Maritime Continent. Differences between our two model configurations are further discussed in the next section, where the vertical structure of the atmosphere is analyzed.

c. Land–sea thermal contrasts, stability, and precipitation changes

Our hypothesis is that warming contrasts play a key role in the spatial pattern of the archipelago’s rainfall response to a

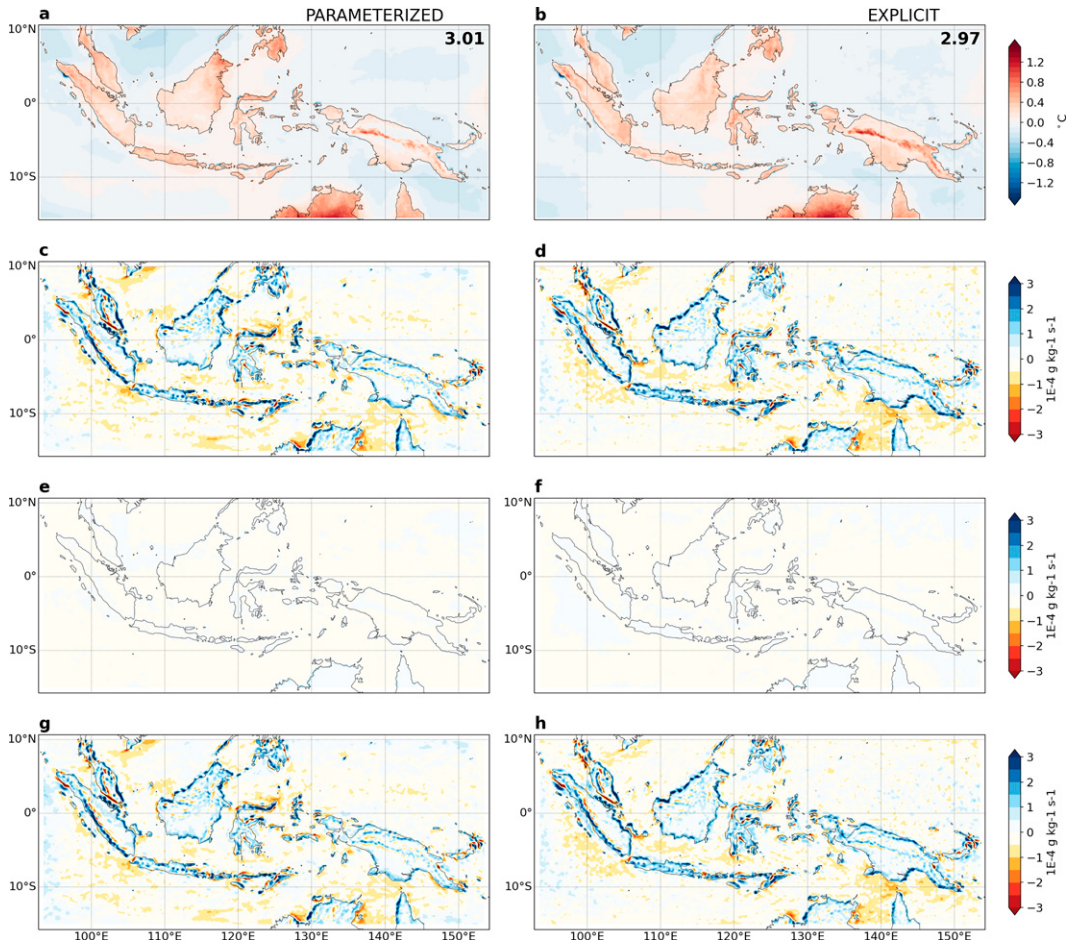


FIG. 5. Near-surface temperature (2 m) changes with respect to the domain average warming [top-left numbers in (a) and (b)] over the entire period (NDJF 2013–16) for (a) parameterized and (b) fully explicit convection runs. Changes in near-surface moisture flux convergence (spatially smoothed using a Gaussian filter with standard deviation of three grid points) for (c) parameterized and (d) fully explicit experiments. Also shown are changes in MFC due to (e),(f) advection changes and (g),(h) convergence changes following decomposition in Banacos and Schultz (2005).

changing climate. Changes in moisture availability due to increased atmospheric water-holding capacity and changes in the large-scale dynamics are spatially too uniform to explain the fine spatial structure of precipitation changes. In the horizontal, land warms faster than the ocean due to their different heat capacity, which intensifies current land–sea thermal contrasts. In the vertical, changes in temperature and humidity profiles may be different at each location, which affects atmospheric stability at different rates. These spatial contrasts create more favorable conditions for mesoscale circulations and increased potential for convective initiation. Whether this potential is realized depends on the convective representation.

For example, future climate change increases the land–sea thermal contrast (Figs. 5a,b) and the domain-average increase is very similar in both experiments. Air over land warms faster (3.30°C in both cases) than the air above the ocean (2.90°C in EX; 2.94°C in PA). Changes in thermal contrast help explain precipitation changes to some extent, as we described in the previous section, but differences between parameterized

and explicit runs indicate that the convective representation is crucial to define the rainfall response to this thermal forcing.

Here, we investigate the mechanism that links changes in thermal land–sea contrast and rainfall. The primary source of convective potential over the islands is the moisture flux convergence at the lower levels. Moisture flux convergence was calculated using

$$\text{MFC} = -\nabla \cdot (q\mathbf{V}_h), \quad (4)$$

where MFC is the moisture flux convergence, q is water vapor mixing ratio at 2 m, and $\mathbf{V}_h$ is the horizontal wind vector at 10 m. The approach described by Bluestein (1992) was applied to deal with discrete variables.

Because of the enhanced land–sea thermal contrast, the model produces an increase in near-surface MFC along the coastlines (Figs. 5c,d). This agrees with results in Tangang et al. (2020), who also found an increase in low-level moisture flux convergence over the islands using multiple regional climate simulations. This MFC increase on the coastline is accompanied by a decrease far outside over the ocean, where

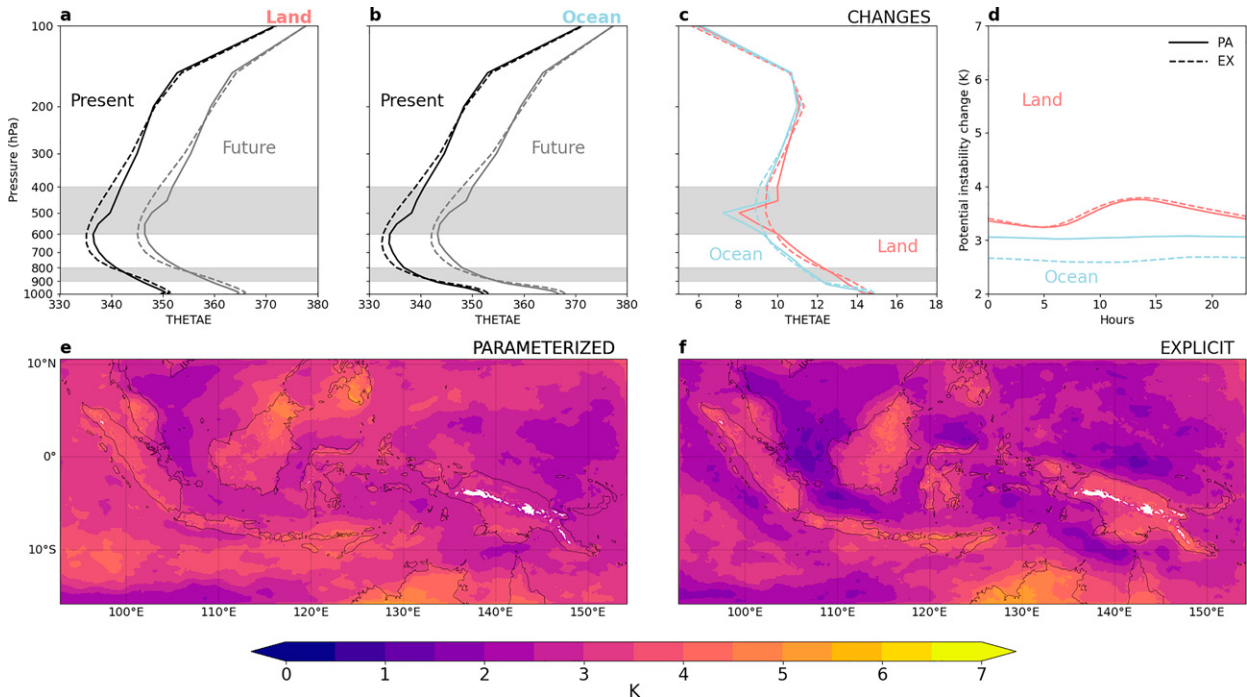


FIG. 6. Atmospheric potential instability changes in parameterized and explicit convection runs. Time-averaged mean vertical profiles of θ_e over (a) land grid points and (b) ocean grid points, and (c) their changes (future minus present). Black is for present climate and gray for future climate. Blue lines are changes over water only and red lines are changes over land only. Solid lines show parameterized convection experiments and dashed lines are for explicit convection runs. (d) Diurnal cycle of potential instability changes ($\theta_e^{850-500\text{hPa}}$) for ocean (blue) and land (red) grid points, and parameterized (solid) and explicit (dashed) convection experiments. Also shown is the spatial distribution of potential instability changes for the (e) parameterized and (f) explicit convection simulations. Changes were statistically significant at the 99% confidence level in all grid points according to a two-sided Mann–Whitney U test.

negative values are observed almost everywhere. MFC was decomposed into two terms [horizontal advection of specific humidity and horizontal mass convergence; Eq. (5)] following Banacos and Schultz (2005),

$$\text{MFC} = -\mathbf{V}_h \cdot \nabla q - q \nabla \cdot \mathbf{V}_h, \quad (5)$$

and then changes were calculated for each of them to estimate their relative contribution to MFC changes. This decomposition reveals that MFC changes were largely driven by horizontal convergence changes, while advection changes play a negligible role on average (Figs. 5e–h).

Therefore, a higher MFC (along the coast and mostly driven by convergence changes) points in the same direction as our hypothesis that mesoscale circulations (sea breeze type) intensify under warmer conditions. This effect is even more marked during the time of the day when sea-breeze usually builds up in the region (1000–1600 LST; Fig. S9). Hence, our results are coherent with the idea that land–sea thermal contrasts and the resulting MFC changes are drivers of rainfall redistribution and more intense precipitation over land.

This mechanism may be partly responsible for the intensification of rainfall over land, but there must be other factors (e.g., stability) causing differences in precipitation changes between the two experiments despite their very similar changes in thermal contrasts and MFC.

Under global warming, the upper troposphere warms faster than the lower troposphere in the tropics, which increases dry static stability (Schneider et al. 2010; Chou et al. 2013). We estimated dry static stability in the lower troposphere from both our experiments using the difference in potential temperature (θ) between the lower (850 hPa) and the middle (500 hPa) troposphere. In both simulations, this difference is reduced in the future, thus indicating increased dry static stability under climate change, especially for the explicit convection run (Fig. S10). However, these changes in temperature are also accompanied by changes in humidity, which directly affect moist adiabatic processes that govern deep convection. To incorporate this factor, we analyzed changes in potential stability (also called moist static stability or convective stability). Herein, we speak in terms of instability to make the interpretation of results more intuitive, but it is conceptually the same. We examined the equivalent potential temperature (θ_e) and its vertical profiles, which accounts for changes in both temperature and humidity. The difference in θ_e between the 900–800- and 600–400-hPa layers provides a measure of potential instability.

This choice is motivated by the fact that atmospheric models (e.g., CMIP5 ensemble; Fig. S11) often show a discontinuity in the vertical derivative of θ_e , which is likely linked to how convective processes are parameterized. The discontinuity is linked to how the schemes work around the freezing

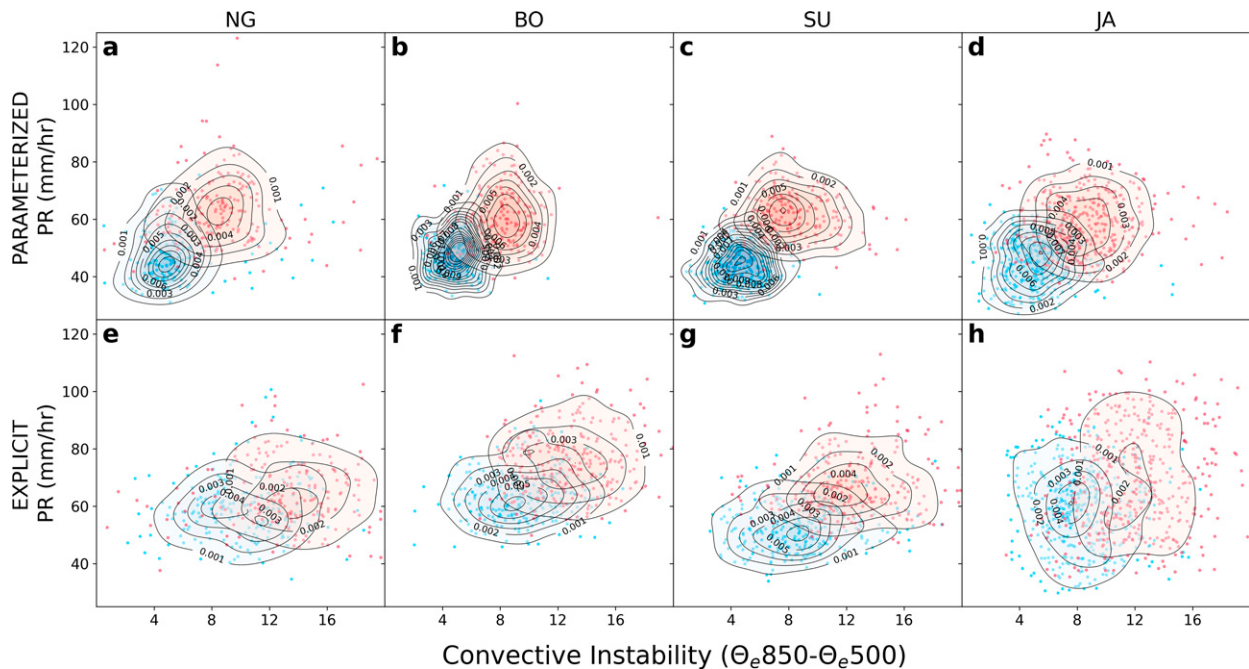


FIG. 7. Extreme precipitation events (>99.9 th percentile) vs convective instability in different locations for present (blue) and future (red) experiments using (top) convective parameterization and (bottom) explicit convection. Convective instability is measured as the difference in equivalent potential temperature between the 900–800- and 600–400-hPa layers and averaged over the 12 h preceding the intense rainfall event. Each dot represents an event in the areas delimited by squares in Fig. 1 and the contours represent the probability estimated using a Gaussian kernel density estimator. All present and future point clouds are statistically different from each other using a Fasano-Franceschini test at the 0.01 significance level.

level, their interaction with microphysics schemes and the quasi-equilibrium profile used in certain parameterizations such as the Betts–Miller–Janjić, which is used in the parameterized simulations here. Indeed, this behavior is also detected in PA around the 500-hPa level. This reflects on changes of the vertical profiles simply because the discontinuity is shifted upward. To reduce the dependence of our results on this issue, which we assume is a model artifact, we computed potential instability using the above reference layers.

Vertical profiles of equivalent potential temperature (θ_e) reveal that time-mean potential instability will increase everywhere under the prescribed climate change signal according to both experiments (Fig. 6c). This is shown by steeper vertical profiles of θ_e under future climate conditions with the largest increases in θ_e near the surface (~ 14 – 15 K). Changes over land are on average very similar between PA and EX, and both show an intensification of instability in the early afternoon (Fig. 6d). On the other hand, changes over the ocean are slightly larger in PA and are flat throughout the day in both model runs. This spatial distribution of potential instability changes is further illustrated in Figs. 6e and 6f, which suggest that instability will increase the most over large landmasses. These changes were tested for statistical significance using a Mann–Whitney U test at the 99% confidence level and they are significant everywhere in the domain. The land–sea contrast of potential instability changes is more pronounced in EX, mostly because EX produces more moderate changes over water. If we select only days when precipitation exceeds the

99.9th percentile in each grid cell and calculate the changes in potential instability, EX produces much stronger changes than PA during such events (Fig. S12). Therefore, despite similar time-mean changes in potential stability and mean precipitation changes, EX suggest more intense extreme precipitation in a warming climate accompanied by higher potential instability.

To understand the link between this increase in potential instability and precipitation extremes, we focus on potential instability preceding events above the 99.9th percentile. To that purpose, we selected $0.5^\circ \times 0.5^\circ$ areas in the four largest islands (squares in Fig. 1) and calculated the area-averaged potential instability ($\theta_e^{850-500\text{hPa}}$) over the 12 h before any grid cell exceeds its 99.9th percentile of hourly precipitation. Figure 7 shows the relationship between the intensity of heavy rainfall events versus the preceding potential instability for present and future simulations, in both model configurations, and over the four selected representative areas. Retaining only dry hours to calculate convective instability as opposed to all preceding hours was tested with no substantial differences (not shown) and we decided to keep the all-hour approach so that all instability values were calculated using the same number of preceding hours. Different accumulation periods (6, 18, 24 h) and area sizes (0.2° , 1.0°) were also tested with very similar results (not shown). Different locations within each island were also examined to ensure our results were robust and the outputs were qualitatively the same (Figs. S14 and S15).

In all cases, the atmosphere reaches a clearly different state where both potential instability and extreme rainfall intensity are higher under a warmer climate. While potential instability alone is not enough to determine the intensity of extreme events for each of the periods separately, this is not surprising since many other factors are involved in the generation of heavy rainfall events, thus the dispersion of the point clouds. However, it indicates that the model responses to climate change in terms of precipitation extremes and potential instability are related to each other.

This relationship also reveals an interesting contrast between model runs. The fully explicit convection is much more dispersed in the rainfall instability space depicted in Fig. 7. Some of the differences between experiments noted before can be interpreted through this feature. For instance, it shows that the convective parameterization restricts the atmospheric conditions to a given range because it continuously adjusts the vertical profile toward an equilibrium state. The explicit run, on the contrary, is more flexible in this sense, and it allows for higher precipitation rates (Figs. S14 and S15). In fact, it also produces situations with substantially larger potential instability when the extremes occur (Fig. 7). As a result, the response to climate change in PA is spatially more homogeneous than in EX, which produces a noisier signal because of the higher degrees of freedom explicit convection provides. Precipitation rates above the 99.9th percentile were also compared to other variables such as potential temperature (θ), convective available potential energy (CAPE), and precipitable water (PW) to illustrate their links in a changing climate (Fig. S16). In agreement with our previous findings, changes in the intensity of extreme rainfall are related to an increase in dry static stability ($p^{850-500\text{hPa}}$) and an increase in latent conditional instability (CAPE). It also shows that this contrast between changes in dry static stability (temperature dependent) and convective stability (temperature and moisture dependent) when extremes occur is mostly due to a higher availability of precipitable water, which significantly increases in the future.

Present and future bivariate distributions of rainfall and the various instability metrics (Fig. 7; see also Figs. S14–S16) were tested statistically to determine if they are significantly different. All present and future bivariate distributions were statistically different to each other at the 0.01 significance level using a multi-dimensional version of the Kolmogorov–Smirnov (KS) test (Fasano and Franceschini 1987). A classical 1D KS test was also applied to present and future precipitation distributions and results were found to be different at the 0.01 significance level too.

Increased instability only produces precipitation changes if convective circulation is intensified. Thus, changes in vertical motions must be considered to explain the spatial contrasts of rainfall changes (see section 3b). Here, we relate changes in vertical pressure velocity (ω_e) that precede precipitation extremes with changes in the extremes themselves (Fig. 8). We binned grid points by changes in extreme rainfall (total accumulated above the 99th percentile). For each bin, we computed the average change in the vertical profile of ω_e over the 6 h preceding each extreme event. We chose a 6-h period because vertical motions due to convection start

approximately 6 h before the peak of the precipitation diurnal cycle in the region (Argüeso et al. 2020).

On average, the atmospheric environment preceding intense rainfall is characterized by ascending motions almost through the entire troposphere in both experiments and climate periods (Figs. S17 and S18). Only the bottom and the top levels show small positive values (descending motions). Thus, positive changes ω_e can be generally interpreted as a weakening of ascending vertical motions. Both experiments concentrate stronger vertical motions and rainfall extremes over land, which is consistent with the picture described in section 3b. The average ω_e preceding rainfall extremes and its changes are spatially more homogeneous in the parameterized case (not shown), which is also consistent with the results above (Fig. 7; see also Figs. S14–S16).

Not only rainfall extremes are collocated with more intense upward motions, but also their changes. Areas where rainfall extremes will increase the most coincide with stronger upward motions, particularly above 800 hPa (red in Fig. 8). Likewise, extreme rainfall decreases are accompanied by weakened ascending winds (blue in Fig. 8). Weakened vertical motions (blue) extend across the zero-change line, hence small increases ($<20\%$) in extreme precipitation occur with decreases in vertical rising motions, especially over land and when convection is explicit (Fig. 8f). It is likely that changes in ω_e partly offset the effect of warming, but the latter still dominates in this range. These results are consistent with the decomposition of scaling in dynamical and thermodynamical terms, where vertical motions help explain spatial contrasts in extreme rainfall changes. Similar results were obtained for other percentiles too (95th and 99.9th; not shown).

Most ocean areas show a decrease in precipitation extremes (99th percentile; Figs. 3g,h and 8c,d) and weakening of vertical motions preceding such intense rainfall events (Figs. 8c,d). On the other hand, upward vertical velocity before extreme events tend to intensify where heavy rainfall increases over the ocean.

This aggregated view reveals some similarities and differences between the two convective representations. Both runs expand the range of possible extremes to higher values, especially EX (Figs. S17 and S18). They also tend to increase the land–sea contrast of ω_e under a warmer climate, particularly PA, as shown the intensification of blue areas in Fig. 8c and red areas in Fig. 8e. As for the differences, PA tends to produce larger changes in vertical motions (Fig. 8), and they are spatially more organized and uniform in the vertical (not shown). In the explicit convection run, most changes of extreme precipitation over land lie around 20% (Fig. 8f, top) and vertical motions are weakened in the lower-to-middle troposphere for this range of precipitation and intensified in the atmosphere above. This feature can be interpreted as a deepening of the convective circulation and expansion of the convective cell upward. Argüeso et al. (2020) also found that EX produces deeper convective circulations than PA under present climate condition, a difference that could be enhanced with warming.

Therefore, the importance of landmasses in the convective development and their role as rainfall attractors in the two model experiments is different. The concentration of rainfall over land seems to strengthen under future climate conditions

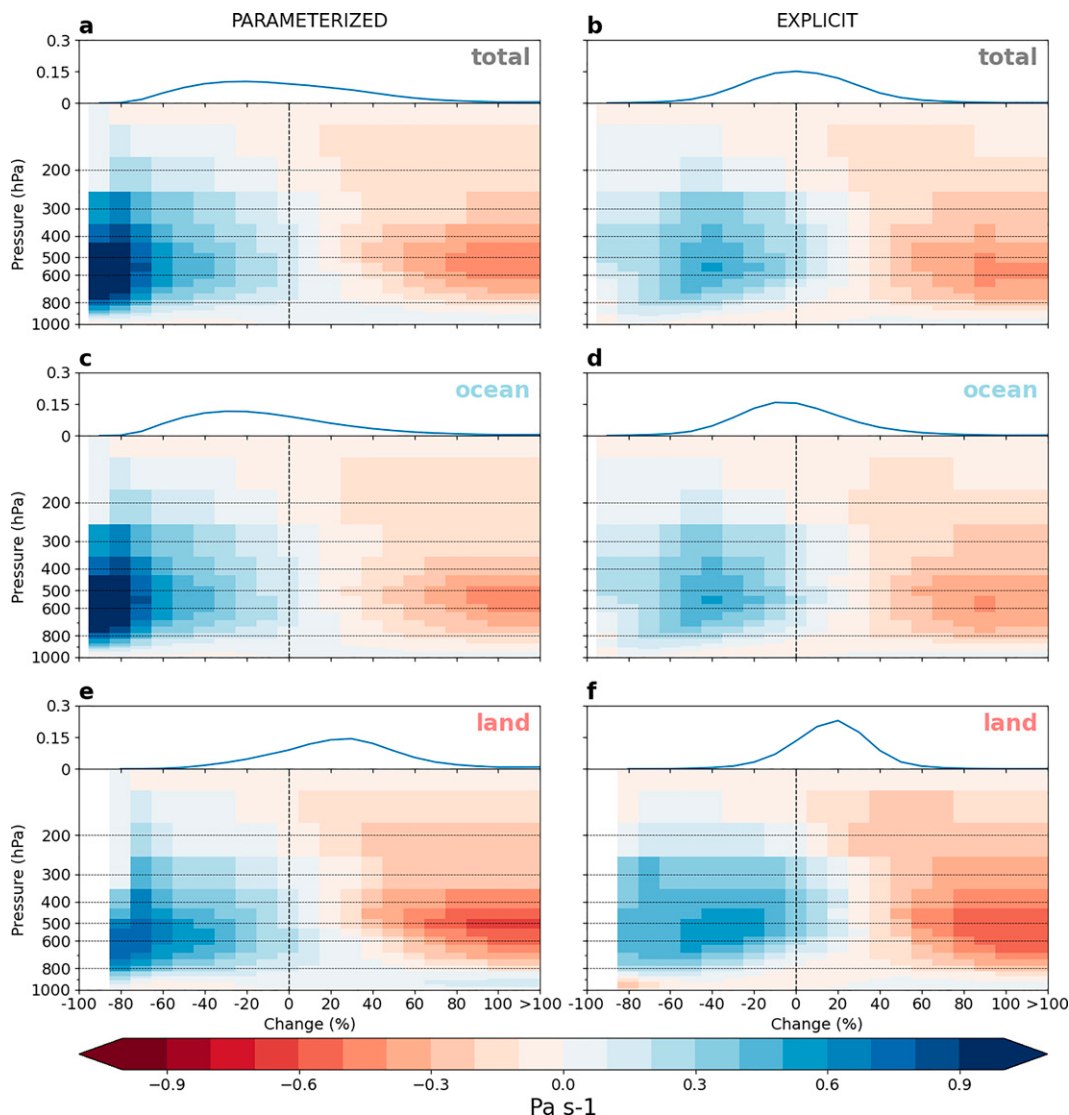


FIG. 8. Changes in vertical pressure velocity (ω_e) vs changes in mean precipitation rates of events above the 99th percentile of hourly rainfall averaged over (a),(b) all, (c),(d) ocean-only, and (e),(f) land-only grid points for the (left) parameterized and (right) explicit convection experiments. Each panel includes a probability distribution of extreme precipitation changes at the top to indicate the most frequent values of changes in the domain.

as the land–sea thermal contrast intensifies and the potential instability increases, because they favor moisture convergence and convective circulations over the islands. However, the model responds differently to these changes depending on how convection is represented, especially in terms of vertical pressure velocity. The need for triggering factors in the explicit case and the constraints imposed by the deep parameterization scheme may help explain these differences in vertical motions and precipitation intensities.

4. Conclusions

We studied the role of horizontal and vertical warming contrasts on precipitation changes in the Maritime Continent for

the late twenty-first century under a RCP8.5 scenario using a pseudo global warming approach. We analyzed results from a regional climate model operating at convection-permitting scales with two different representations of deep convection: parameterized and explicit.

We found that the model produces a domain-averaged decrease of rainfall during the Maritime Continent wet season (NDJF) for both convective representations, although there is a marked land–ocean contrast. Both model configurations tend to produce a decrease over the ocean and an increase over land. Even though GCMs do not agree on the sign of rainfall changes for the region, their spatial pattern of changes is consistent with the land–ocean contrast we obtained (Jourdain et al. 2013; Wang et al. 2020). The ensemble mean of GCMs

selected in this study projects a domain-average increase in rainfall and in the vertically integrated water vapor. Thus, the decline of domain-average precipitation suggested by our model experiments cannot be explained by changes in the large-scale water vapor supply (i.e., advection). Instead, it must be explained by processes that transform the available water vapor into precipitation and how they are represented in models.

Our experiments suggest that the islands of the Maritime Continent will undergo more intense mean and extreme precipitation in a warmer climate. However, the extremes behave differently under the same large-scale climate change signal depending on how convection is represented. This includes their magnitude, spatial pattern, and the relative changes of the various percentiles. The most prominent difference is that the land–sea contrast of changes is more pronounced in the parameterized runs. The upper percentiles of rainfall undergo larger increases relative to present climate extremes when convection is parameterized. However, explicit convection expands the range of possible future extremes to higher values. This is partly because present climate extremes in EX are already more intense than in PA, but also because the convective scheme constrains the response to warming. Therefore, future generations of climate projections at convection-permitting resolutions may project different outlooks for rainfall extremes to those currently available.

We determined the contribution of thermodynamical and dynamical processes to changes in rainfall extremes under a warmer climate. Thermodynamic effects account for changes in precipitation extremes that are consistent with the Clausius–Clapeyron relationship, and their contribution is relatively homogeneous across the domain. Thus, we need to invoke dynamical processes to explain features of extreme rainfall changes, such as their magnitude range (from -20% to $20\% \text{ K}^{-1}$), their spatial contrasts, and the divergences between the two model runs.

According to our simulations, the primary driver of changes in the spatial distribution of rainfall is the land–sea thermal contrast and its enhancement under climate change. Land warms faster than the ocean, which favors local sea-breeze type circulations. These circulations increase low-level moisture flux convergence over land and contribute to create conditions for deep convection development over land. They are also responsible for suppressing rainfall generation over the ocean to some extent.

Deep convection and heavy rainfall require atmospheric instability to occur. Climate change modifies the vertical profile of the atmosphere and thus alters the overall stability. Although dry static stability increases under future climate conditions because the upper half of the troposphere warms faster, the combined effect of temperature and humidity changes in the vertical makes the atmosphere more unstable in terms of moist static stability. While both model experiments show this response to climate change, the convective scheme constrains potential instability and extreme precipitation values within a narrower range. Under future climate conditions, this means the model with explicit convection allows heavier rainfall events to occur. Yet, changes relative to present climate values are higher in the parameterized case. Also, the

convective scheme produces a response to climate change that is spatially more uniform, while explicit convection generates noisier patterns of extreme precipitation changes.

Deep convection entails intense upward vertical motions. Thus, extreme precipitation is linked to high vertical pressure velocity. We found that the model tends to concentrate strong vertical motions and rainfall extremes over land, especially when convection is explicitly resolved. In some land areas, this is enhanced in future climate simulations, which explains departures from the thermodynamic contribution to extreme rainfall changes. Changes in vertical winds also indicate a possible expansion of the convective cell over the islands and a slight weakening of upward motions in the midtroposphere. Even though explicit convection produces more extreme rainfall events over land in the future (due to further concentration of upward motions over large islands and the lack of convective scheme constraints), the parameterized case suggests stronger changes relative to present climate values. In fact, the model produces stronger changes in vertical motions preceding extreme events with climate change when convection is parameterized. This refers not only to the strengthening of vertical winds over land, but also to their weakening over the ocean. In both model configurations, areas of stronger upward vertical pressure velocity are collocated with positive changes in extreme precipitation, and vice versa. This spatial coincidence, together with the scaling decomposition into thermodynamical and dynamical terms, evidences the role of vertical motions in modulating the intensity of future climate rainfall events.

In summary, we showed that the way convection is represented is crucial in defining the model response to warming, because it defines dynamical processes that shape the future distribution of precipitation and the intensity of extremes.

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Data availability statement. The set of data on which this paper is based is too large (~120 TB) to be publicly archived with available resources. The model version used in this study is open source and publicly available (<https://github.com/NCAR/WRFV3/releases>). Sample namelists to reproduce the experiments are archived and available in a public repository (<https://doi.org/10.5281/zenodo.4624353>). All retained data are available upon request addressed to Daniel Argüeso (d.argueso@uib.es).

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