Response to Reviewer 1

We thank the reviewer for their positive review of the manuscript. Their specific comments will improve the paper, especially the discussion of precipitation in our two simulation suites.

Replies to specific comments

1. A wet bias over the Maritime Continent is common for atmosphere-ocean coupled models (Roberts et al., 2019), especially in DJF (Liu et al., 2023). This is a long-standing problem in simulations over the Maritime Continent: atmosphere-only models tend to underestimate mean precipitation over the MC (e.g. Neale and Slingo, 2003; Toh et al., 2018), while coupled models tend to overestimate it (e.g. Inness and Slingo, 2003; Liu et al., 2023).

   It is also common for convection-permitting models to exacerbate wet or dry biases compared to the same model run with parametrized convection; this is certainly true for the Met Office Unified Model (e.g. Muetzelfeldt et al., 2021), and in general there is no systematic improvement in mean precipitation bias for convection-permitting models over parametrized models (Prein et al., 2015). That the strongest biases in MC2 are close to the inflow boundaries is also consistent with other regional convection-permitting modelling over the MC (Jones et al., 2023) [note that they only see the strong wet bias close to the eastern boundary, but this is because their analysed period 1-11th Jan 2018 had a consistent strong easterly over that part of the domain, whereas the winds at the western boundary fluctuated much more]. This is likely due to differences in model physics between the parametrized and explicit versions of the model; for instance, if the explicit physics prefers a slightly drier atmosphere (consistent with manuscript Fig. 6b), then excess moisture advected in at the boundaries will be rapidly precipitated out.

   There is certainly an impact of higher resolution on model biases, but this link is complex (e.g. Roberts et al., 2019; Holloway et al., 2013). It is not possible to perform a clean analysis of the effects of model resolution on precipitation bias using this dataset, due to the confounding effects of very different model physics — especially parametrized versus explicit representations of convection.

   We have modified the text in Section 3 in response to this comment (ll. 253–262):

   > Both models exhibit a wet bias compared to the GPM-IMERG climatology averaged over the same period, as indicated by Figure 4. This is consistent with other high resolution coupled models ~~*using the MetUM framework*~~ in the Maritime Continent region (e.g., Roberts et al., 2019), with both parametrised and explicit convection, especially in DJF (Liu et al., 2023). The wet bias over the ocean is stronger in MC12 than MC2 and has a typical magnitude of around 3 mm/day (panels c, e). Both models also have strong wet biases over high orography, and MC12 has a dry bias over lowlands in Sumatra, Borneo and Java. It is common for convection-permitting models to exacerbate wet or dry biases compared to the same model run with parametrised convection; this is certainly true for the Met Office Unified Model (e.g. Muetzelfeldt et al., 2021), and in general there is no systematic improvement in mean precipitation bias for convection-permitting models over -parametrised models (Prein et al., 2015). Strong boundary effects can be seen near the equator in MC2, where localised wet biases are present 3° from the edges of the domain, consistent with other regional convection-permitting modelling over the MC (Jones et al., 2023).

   We also added a sentence to Section 5 on air-sea coupling (ll. 462–464):

   > This is a long-standing problem in simulations over the Maritime Continent: atmosphere-only models tend to underestimate mean precipitation over the MC (e.g. Neale and Slingo, 2003; Toh et al., 2018), while coupled models tend to overestimate it (e.g. Inness and Slingo, 2003; Liu et al., 2023).

2. All analyses of precipitation used GPM-IMERG v06B (clarified in l. 230 of the revised manuscript). We used the "precipitationCal" product, which is satellite observations including correction to rain gauge (clarified in ll. 232–233 of the revised manuscript).

   In response to the reviewer's comment regarding observational uncertainty, we have reproduced Figure 4 of the manuscript using the "past" precipitation product from MSWEP (Beck et al., 2017) (see attached Figure 1). Since the rain gauge network is very sparse over the Maritime Continent, the algorithms used by both GPM-IMERG and MSWEP weight the satellite observations much more highly than in regions with dense rain gauge coverage, so differences in the datasets over the Maritime Continent should largely be due to different satellite retrieval methods. The differences between the two simulation runs, and the differences between the runs and either precipitation dataset, are much larger than the difference between the two individual datasets. In particular, the spatial patterns are very similar for both satellite datasets.

We therefore conclude that the rain gauge-corrected satellite observational uncertainty is less important for the mean precipitation than the difference between the two models, and than the difference between the models and those observations.

For the interannual variability, GPM has a fairly uniformly positive interannual standard deviation anomaly over ocean, and close to zero anomaly over land, relative to MSWEP (see attached Figure 2). This strengthens the conclusion that MC2 overestimates the interannual precipitation variability everywhere. For MC12, the interannual standard deviation of precipitation over ocean is generally weakly overestimated relative to MSWEP, compared to underestimated relative to GPM. For both simulations, the relative spatial uniformity of the GPM minus MSWEP anomaly causes the spatial pattern of the model biases to be broadly similar relative to both reference datasets.

In previous work, differences in diurnal cycle phase have been found to be negligible between different precipitation products over the Maritime Continent, especially at the 3 hour temporal sampling rate of many observational datasets (see e.g. Supplementary Figure 7 of Dong et al., 2023).

It is an excellent point that rain gauge coverage of the Maritime Continent is very poor (see e.g. Figs. 2, 3, B4, B8 of Lewis et al., 2019). This is especially true over areas with high orography, where the MC2 and MC12 biases are worst compared to GPM-IMERG and MSWEP, and of course over the ocean, where there is a general wet bias in both models. Given this fact, we feel that it is beyond the scope of this paper to perform a direct comparison with gauge data.

We shall add Figures 1 and 2 as supplementary material to the revised manuscript, and summarized the above discussion in Section 3 on the mean state (ll. 268–278):

> Due to the sparsity and incompleteness of rain gauge observations over the MC (e.g. Figs. 2, 3, B4, B8 of Lewis et al., 2019), there is potentially large observational uncertainty in precipitation over our domain of interest. This is especially true over areas with high orography, where the MC2 and MC12 biases are worst compared to GPM-IMERG, and of course over the ocean, where there is a general wet bias in both models. It is therefore beyond the scope of this paper to perform a direct comparison with gauge data. However, to give some insight into how observational uncertainty may impact the model evaluation, we have compared the precipitation climatology of both simulations to the "Past" product from the Multi-Source Weighted-Ensemble Precipitation (MSWEP) v2.8 dataset, which combines satellite and rain gauge observations with reanalysis (Beck et al., 2019). Mean biases relative to MSWEP were similar both in magnitude and spatial pattern to those relative to GPM-IMERG (Supplementary Figure S02). Differences in diurnal cycle phase have been found to be negligible between different precipitation products over the Maritime Continent, especially at the 3 hour temporal sampling rate of many observational datasets (see e.g. Supplementary Figure 7 of Dong et al., 2023).

and in Section 4.2 on interannual variability (ll. 377–381):

> Given the uncertainty in precipitation observations, we again compared the model interannual standard deviations of precipitation to MSWEP (Supplementary Figure S7). GPM-IMERG has notably more interannual variability over ocean than MSWEP, but the variability over land is comparable, likely due to the rain-gauge correction of both datasets. This strengthens the conclusion that MC2 overestimates the interannual variability of precipitation, but weakens confidence in the sign of the bias over ocean for MC12.

3. All of our simulations were run for Boreal winter seasons (NDJF); analyses were conducted for DJF, with November discarded for spin-up. The reasoning for this is that DJF is the most active period for intraseasonal variability over the Maritime Continent (explained in line 87 of the manuscript). Therefore, while it would be an interesting research avenue, it is beyond the scope of this paper to re-run the two simulation suites for MJJASO. We have acknowledged this limitation explicitly in the "Discussion and conclusions" section of the revised manuscript (ll 409–412):

> It must be stressed that this analysis was conducted only for the developing phase of each ENSO year, corresponding to the simulation period (DJF). This matters because ENSO-induced rainfall anomalies over the MC vary greatly both seasonally and regionally. This is a general limitation of this dataset for analysis of seasonal and longer-timescale variability, and their associated teleconnections.

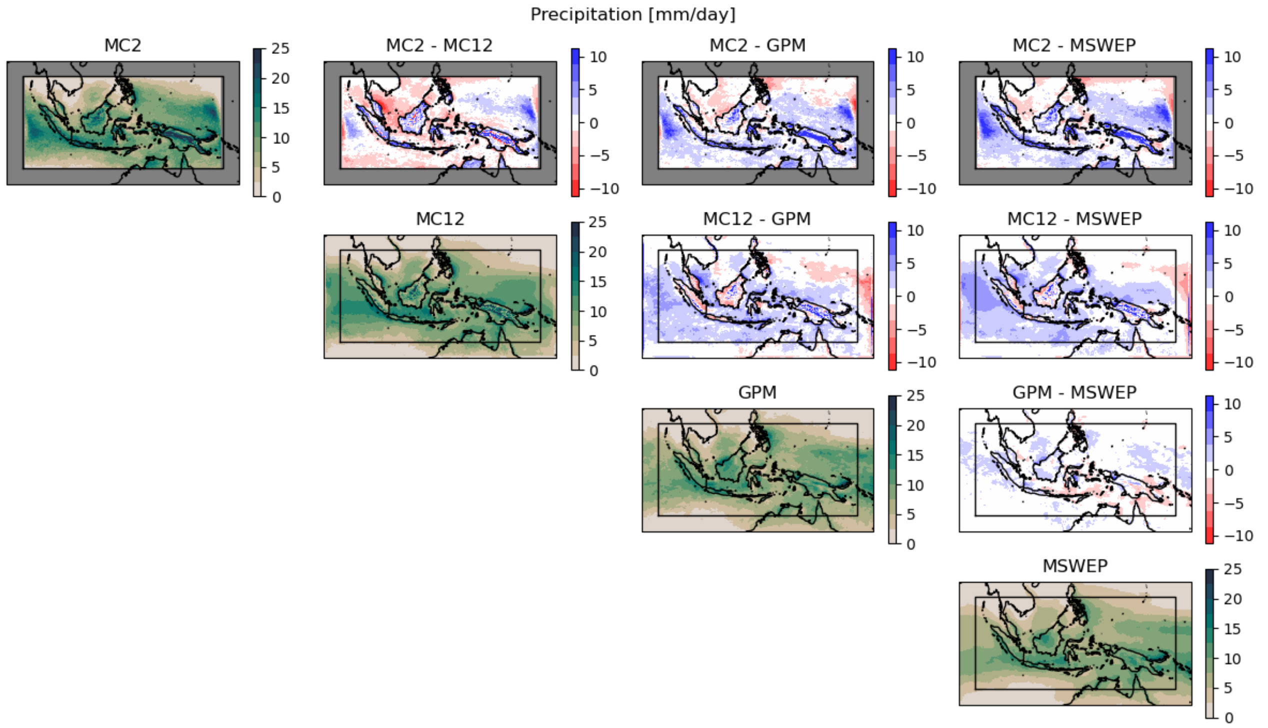

Figure 1: Mean precipitation and biases (mm day^{-1}). Subplots along the diagonal indicate MC2, MC12, GPM-IMERG, and MSWEP respectively. Upper off diagonal subplots show difference plots between each of the datasets. This figure appears as Supplementary Figure S2 in the revised manuscript.

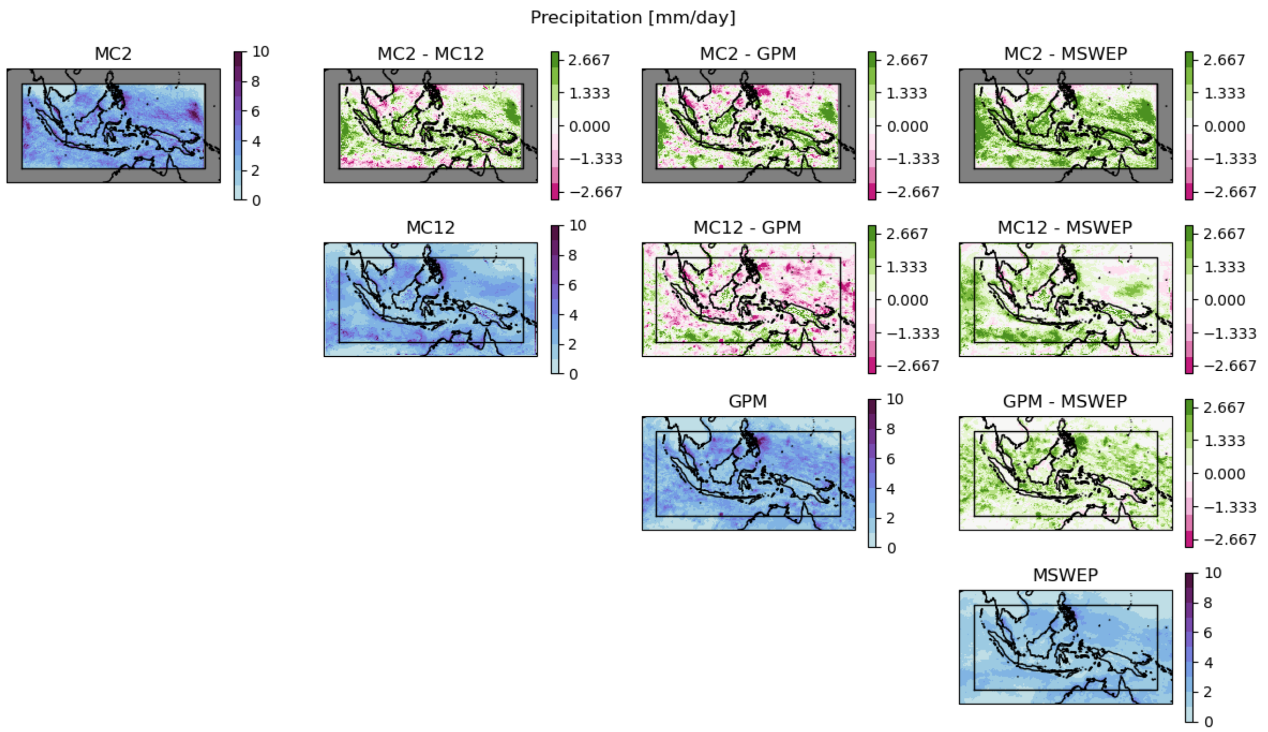

Figure 2: Interannual standard deviation of precipitation and biases (mm day^{-1}). Subplots along the diagonal indicate MC2, MC12, GPM-IMERG, and MSWEP respectively. Upper off diagonal subplots show difference plots between each of the datasets. This figure appears as Supplementary Figure S7 in the revised manuscript.

Response to Reviewer 2

We thank the reviewer for their positive comments on, and constructive criticism of, the manuscript. Their comments will help to improve the quality of the paper, particularly the discussion of air-sea coupling.

Replies to specific comments

1. The purpose of the simulations described in this paper is to provide a framework for investigating the important convective and convectively-coupled processes over the Maritime Continent, and how they are represented in models. It is well-known that important differences arise in the relationship between convection and SST on intraseasonal timescales between coupled and atmosphere-only simulations (see e.g. Figure 7 of Kim et al. (2010)). In atmosphere-only models on intraseasonal timescales convection tends to become in phase with SST as a result of the higher boundary layer moist static energy, whereas in coupled simulations the high SSTs are associated with periods of clear skies and low windstresses which lead to ocean warming. In the MJO this leads to an observed quadrature between convection and the SST in observations and coupled models compared to a more in phase relationship between convection and SST in atmosphere only models. We therefore do not intend to demonstrate that the mean-state and variability produced by the coupled runs are *better* than the same atmospheric model runs with prescribed SSTs when compared to observations; rather, we intend to demonstrate that coupled runs produce realistic mean-state and variability.

   To demonstrate the robust qualitative difference in the phase relationship, we will add a second panel to Figure 13, showing the grid-point lead-lag relationship between precipitation and SST for the 2015-16 season atmosphere-only runs, compared to the same season for the coupled runs (see attached Figure 3). The correlations are weaker at all times in both MC2 and MC12 for the atmosphere-only run. Perhaps more importantly, the shape of the lead-lag relationship is different, with positive correlation at lead/lag 0, compared to approximately zero correlation in the coupled runs. This is in line with other studies in atmosphere-only models (with a fairly symmetric relationship about lag 0 since the SSTs cannot respond to the precipitation) and coupled runs (where higher SSTs promote the development of higher rainfall, but the precipitation and associated increased cloud cover then cool the SSTs). We note that in this configuration with both the boundary conditions and the prescribed SSTs coming from observations the relationship between SST and convection is perhaps more constrained to be close to the observed relationship than in a free running simulation, but even within that constraint the differences between the coupled and atmosphere-only simulations are large.

   We have re-worded and re-structured Section 5 on Air-Sea coupling to clarify these aspects (ll. 414–464):

   > This final section studies aspects of the air-sea coupling between the MetUM atmosphere and the KPP-ocean. The purpose of the simulations described in this paper is to provide a framework for investigating the important convective and convectively-coupled processes over the Maritime Continent, and how they are represented in models. It is well-known that important differences arise in the relationship between convection and SST on intraseasonal timescales between coupled and atmosphere-only simulations (see e.g. Figure 7 of Kim et al., 2010). In atmosphere-only models on intraseasonal timescales convection tends to become in phase with SST as a result of the higher boundary layer moist static energy, whereas in coupled simulations the high SSTs are associated with periods of clear skies and low windstresses which lead to ocean warming. Conversely, SST is negatively correlated with earlier precipitation due to associated cloudiness and the injection of cool fresh rainwater at the surface (Kumar et al., 2013). In the MJO this leads to a quadrature between convection and SST in observations and coupled models compared to a more in-phase relationship between convection and SST in atmosphere only models.
   >
   > Ideally to examine the role of air-sea coupling, a corresponding set of atmosphere-only simulations could be examined as a baseline. However, due to the computational expense of the convection-permitting simulations, this was not feasible. Instead, a single season (2015-16) has been run in atmosphere only model, using 3-day updating OSTIA SSTs as the lower boundary conditions. With a single season we cannot demonstrate robustly whether the mean-state and variability of the coupled runs is more or less realistic than for atmosphere only runs, but the purpose of this paper is to demonstrate that the coupled runs produce a realistic mean state and variability and are thus suitable for process studies where air-sea interaction is important.
   >
   > Figure 13 shows the lead-lag correlations between daily precipitation and sea surface temperatures across the two models and in a combination of observational product (OSTIA SST and

GPM-IMERG precipitation). Correlations are calculated on the MC12 grid, and then spatially averaged across the inner domain. Latitudes north of 3° N are excluded due to low rainrates. As per Kumar et al. (2013), the correlation switches from positive to negative near lag 0 in all three datasets (Figure 13). MC2 shows good performance compared to observations, while MC12 has a higher amplitude than the observational product or MC2. This result suggests that precipitation in MC12 is overly sensitive to SST, and that this issue is resolved in MC2. Both modelled products peak at lead 4. The observational correlation has lower amplitude extrema, peaking near ± 0.1 at lead and lag 6. However, we note that observational uncertainty, any smoothing, and the independent methodologies used in the production of OSTIA and GPM-IMERG may result in reduced correlations for the observational correlation compared to a 'true' atmosphere.

To demonstrate the robust qualitative difference in the phase relationship, the right panel of Figure 13 shows the grid-point lead-lag relationship between precipitation and SST for the 2015-16 season atmosphere-only runs, compared to the same season for the coupled runs. The correlations are weaker at all times in both MC2 and MC12 for the atmosphere-only run. Moreover, the shape of the lead-lag relationship is different: SST and precipitation are approximately in quadrature in the coupled run, whereas the atmosphere-only runs are much more in-phase, with positive correlation at lead/lag 0, compared to approximately zero correlation in the coupled runs. We note that in this configuration, with both the boundary conditions and the prescribed SSTs originating from observations, the relationship between SST and convection is perhaps more constrained to be close to the observed relationship than in a free running simulation, particularly on intraseasonal timescales, but even within that constraint the differences between the coupled and atmosphere-only simulations are large.

Figure 14 shows the precipitation anomalies for this single season in the uncoupled and coupled simulations. The persistent dry biases to the south of New Guinea, Java and Sumatra in the atmosphere-only simulations are resolved in the coupled models. Wet biases to the north of PNG are slightly intensified. In the convection parametrised simulations, a wet bias is present in the South China Sea in both the coupled and atmosphere only model. In general, although the magnitude of the biases is comparable across the simulations, the coupled MC2 simulation shows a greater mix of wet and dry biases, and smaller regions of persistent biases with the same sign. This finding suggests that the coupled MC2 biases are derived to a greater degree by internal variability in this 3-month simulation, which averages out in longer simulations as the signal to noise ratios increase. ~~*The results shown in Figure 4, which shows a consistent 1-3 mm/day oceanic wet bias away from the domain boundaries and compared favourably to previous atmosphere-only convection-permitting simulations, which show 4-7 mm/day oceanic dry biases (e.g. Vincent et al 2016).*~~

The results shown in Figure 4 support this interpretation: averaged over all seasons, the coupled MC2 simulation shows a consistent 1-3 mm/day oceanic wet bias away from the domain boundaries, comparing favourably to previous atmosphere-only convection-permitting simulations, which show 4-7 mm/day oceanic dry biases (e.g. Vincent and Lane, 2017).

This is a long-standing problem in simulations over the Maritime Continent: atmosphere-only models tend to underestimate mean precipitation over the MC (e.g. Neale and Slingo, 2003; Toh et al., 2018), while coupled models tend to overestimate it (e.g. Inness and Slingo, 2003; Liu et al., 2023).

2. We agree that quantifying the overall domain-mean magnitude of the biases is useful. Therefore we have added a table collecting the domain-averaged mean values and interannual standard deviations of variables discussed in sections 3 and 4, as well as their biases and RMS errors relative to reference datasets. We have made a minor addition to the text at the start of Section 3 to introduce the table (ll. 237–239):

    This section considers the mean state of the atmosphere and mixed-layer ocean across the 10 simulation years; Table 3 summarises the domain-mean values, as well as biases and RMS errors relative to reference datasets, of variables considered in this section.

3. We agree that it is important to investigate the representation of clouds when considering convective processes, although cloud fraction itself is not necessarily the most relevant variable for understanding how the variability is represented in models. For example clouds may brighten leading to increases in reflected shortwave radiation or deepen leading to reductions in outgoing longwave radiation without any change in cloud fraction. Furthermore the definition of cloud fraction in models and observations can vary greatly between individual models (or reanalysis products) and depend strongly on the "observation" used

to define them and so a direct comparison between models and observations is not always helpful. We have however compared both the outgoing longwave and reflected shortwave from both model simulations against observations (see attached Figures 4, 5) and find that in both MC2 and MC12 simulations the biases are broadly consistent with typical GCM biases, and that the biases in MC2 tend to be reduced compared to MC12, suggesting a generally better representation of clouds in MC2 (consistent with a higher-resolution convection-permitting simulation). We have added the following text to Section 3 of the revised manuscript to summarize the above (ll. 279–282):

> As proxies for cloud cover, we also compared the outgoing longwave and reflected shortwave from both model simulations against observations (see Supplementary Figures S3 and S4). We find that in both MC2 and MC12 the biases are broadly consistent with typical GCM biases, and that the biases (and RMS errors) in MC2 tend to be reduced compared to MC12, suggesting a generally better representation of clouds in MC2 (consistent with a higher-resolution convection-permitting simulation).

However, as with all other variables considered, the interannual variability is generally too high for both simulations (see attached Figures 6, 7). We have added the following text to Section 4 of the revised manuscript to reflect this (ll. 369–370):

> In each case, standard deviations are comparable but are generally slightly overestimated in both models compared to the observations (this is also true for the top-of-atmosphere shortwave and longwave radiation fluxes; see Supplementary Figures S5 and S6).

We do not agree with the reviewer that biases in the 2m air temperature are particularly important for the kind of process studies for which we expect these simulations to be used. Moreover, over land, surface air-temperature will be particularly sensitive to orographic height and therefore not easy to compare even between the two models where the orography is different. We have therefore not considered this further.

4. We agree that the style of the paper is largely descriptive. We have added a few more explanatory/exploratory comments (in response to both reviewers), but do not wish to present too much speculation without properly digging in to the causes of differences between the model runs, and between the model runs and observations. The purpose of creating this dataset is to explore precisely these questions of why higher resolution/explicit representation of convection changes e.g. the mean state and variability, including for instance coupling with equatorial waves and the MJO.

   In response to the reviewer's specific queries:

   - On the wet bias being stronger in MC2 than MC12: this was not unexpected, as it is fairly common in convection-permitting simulations (see response to Reviewer 1, Specific Comment 1).
   - On the SST biases being weaker in MC2 than MC12: this was unexpected, as the relaxation runs to determine the KPP flux corrections were only performed for the parametrized convection model at N1280 grid spacing. It would have been entirely reasonable to expect that the SST biases would therefore be worse in MC2.

     A full exploration of the mechanisms behind this difference is beyond the scope of this paper, but a preliminary analysis of the bias in both simulations suggests that the change in SST bias between MC2 and MC12 are broadly consistent with changes in the surface heat flux and these changes are also consistent with changes in the mixed-layer depth. This is especially clear around the islands of the Maritime Continent, with cooler SST and deeper mixed layers associated with lower heat fluxes into the ocean.

     However, the pattern of surface fluxes is complicated. The changes in surface radiation budget are broadly consistent with changes in the corresponding top-of-atmosphere fluxes, with some cancellation between the shortwave and longwave fluxes. The changes in the latent-heat (LH) flux are more complex, noting that the LH flux is defined as positive downwards and as such a positive change indicates decreased evaporation. The sign of the LH flux change is not consistent with it being driven directly by the SST, as the evaporation is generally higher in regions of colder SST. Similarly over large regions away from the islands evaporation is lower, but the surface wind stress is increased. The relative contributions of each component of the surface fluxes varies from region to region.

     To properly understand the differences in the SSTs would require a detailed analysis of the time evolution of the biases and would be regionally sensitive. It would be particularly interesting to look at these processes around the coastlines where it is clear there is a significant change in the representation of the diurnal cycle of convection, which is known to be associated with strong onshore/offshore circulations. This would make a good focus for a future study. We have therefore only added a brief discussion of this in Section 3 of the revised manuscript (ll. 246–252):

That the SST biases are smaller in MC2 was unexpected, as the relaxation runs to determine the KPP flux corrections were only performed for MC12. A full exploration of the mechanisms behind this difference is beyond the scope of this paper, but a preliminary analysis suggests that the changes in SST biases between MC2 and MC12 are broadly consistent with changes in the surface heat flux and these changes are also consistent with changes in the mixed-layer depth (not shown). This is especially clear around the islands of the Maritime Continent, with cooler SST and deeper mixed layers associated with lower heat fluxes into the ocean. To properly understand the differences in the SST biases would however require a detailed analysis of the time evolution of the biases and would be regionally sensitive.

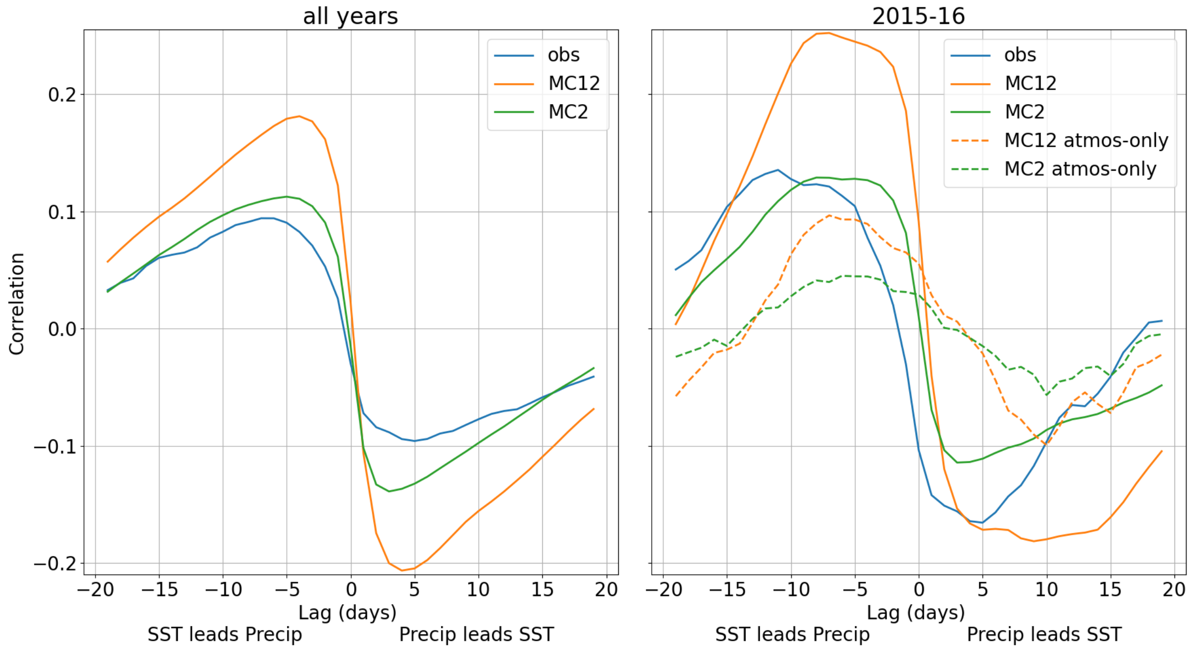

Figure 3: Grid-point lead-lag relationship between precipitation and SST averaged across ocean grid-cells between 15° S and 3 ° N. Each season was linearly detrended before computation to remove seasonal and interannual variability. Coloured lines indicate observations in blue (OSTIA compared to GPM-IMERG), MC12 in orange and MC2 in green. Panel a) shows the lead-lag relationship for both coupled simulations suites and observations for all simulation years; panel b) shows the lead-lag relationship for the coupled (solid lines) versus atmosphere-only (dashed lines) simulations for the 2015-16 season only. This figure appears as Figure 13 in the revised manuscript.

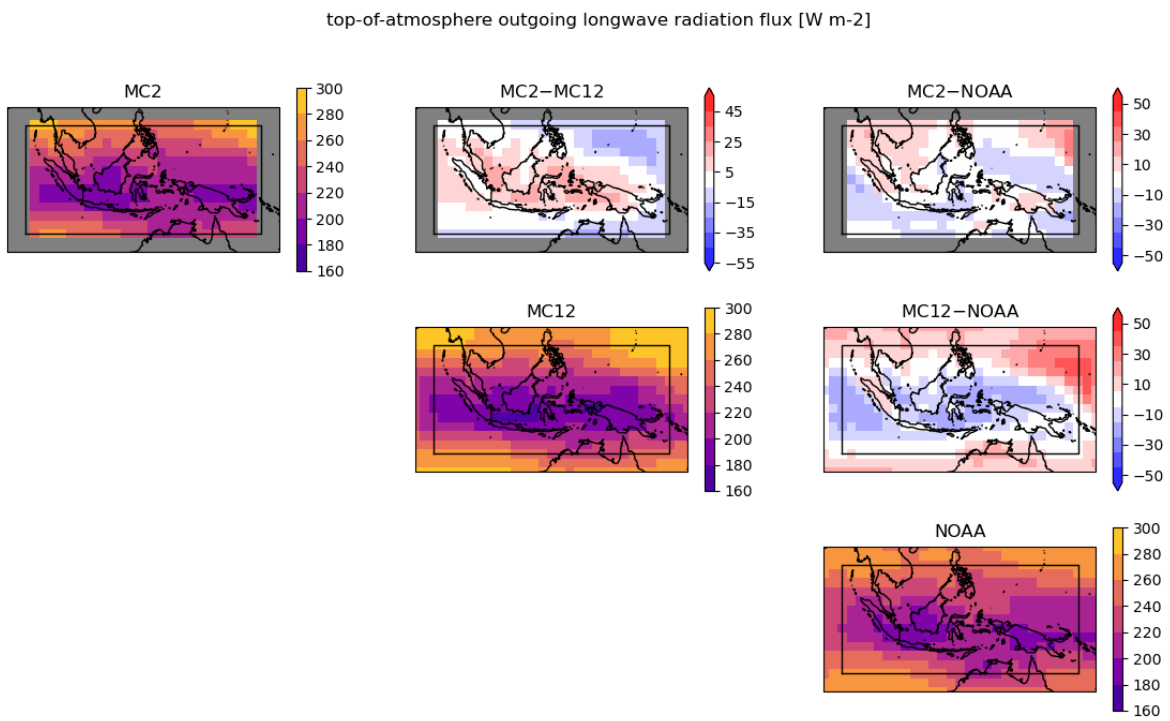

Figure 4: Mean outgoing longwave radiation and biases (W m^{-2}). Subplots along the diagonal indicate MC2, MC12, and NOAA daily OLR respectively. Upper off diagonal subplots show difference plots between each of the datasets. This figure appears as Supplementary Figure S3 in the revised manuscript.

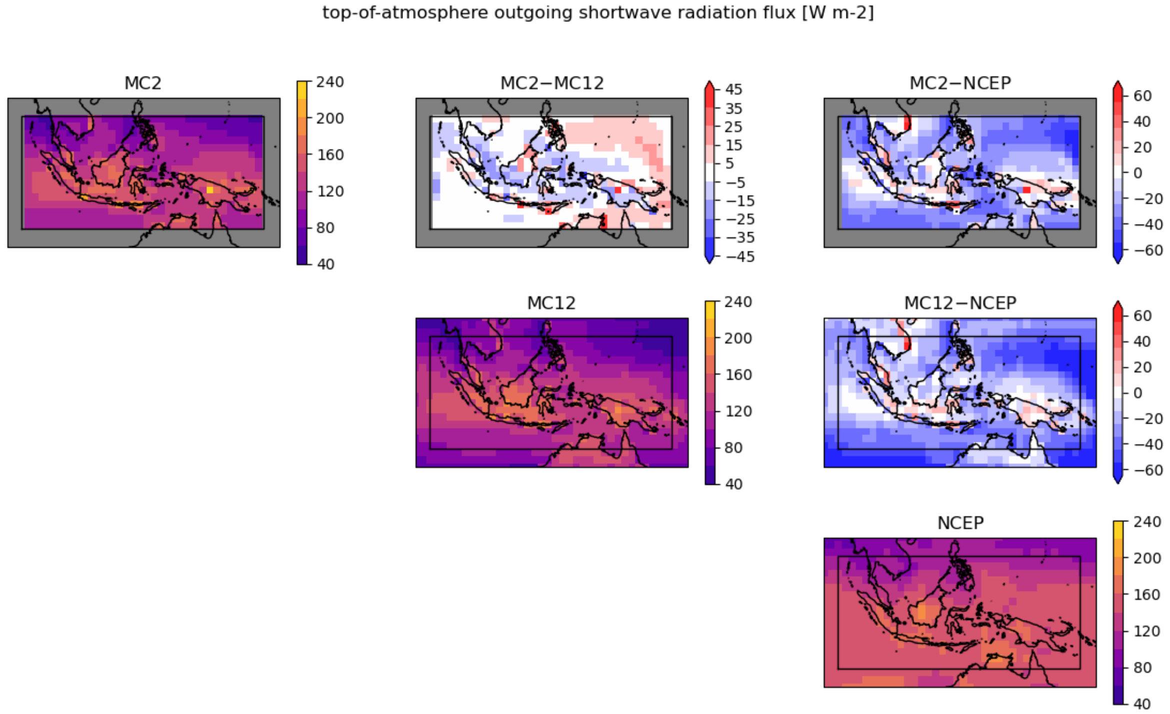

Figure 5: Mean outgoing shortwave radiation and biases (W m^{-2}). Subplots along the diagonal indicate MC2, MC12, and NCEP-NCAR reanalysis respectively. Upper off diagonal subplots show difference plots between each of the datasets. This figure appears as Supplementary Figure S4 in the revised manuscript.

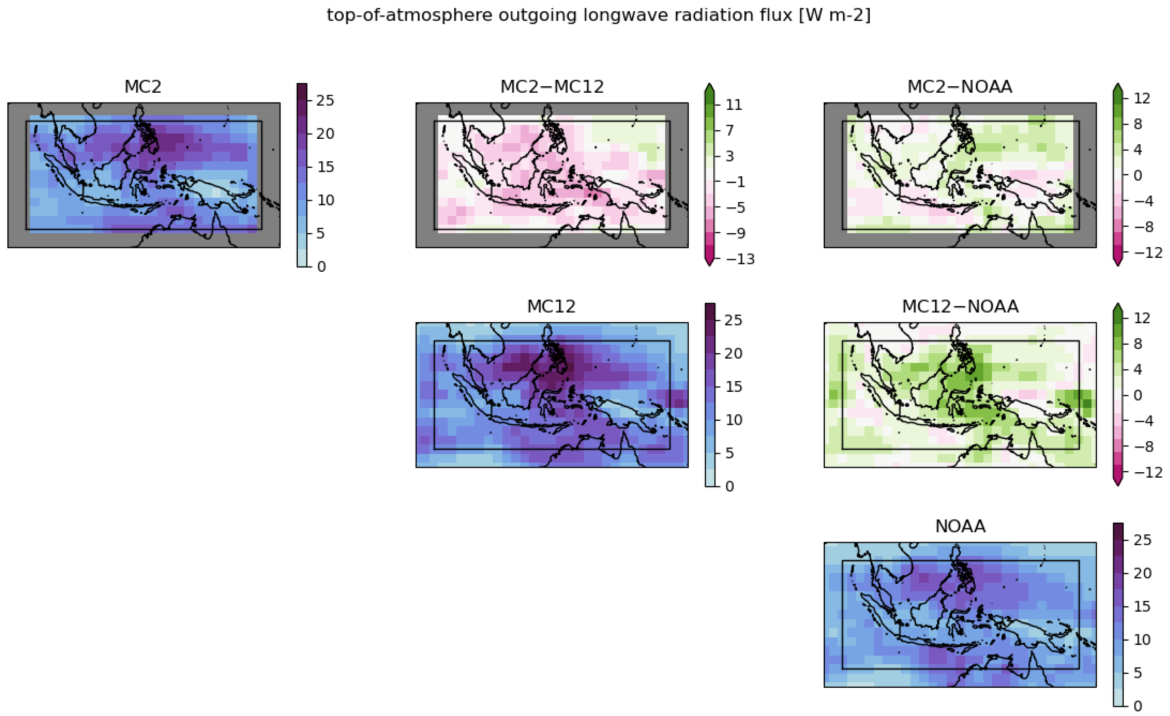

Figure 6: Interannual standard deviation of outgoing shortwave radiation and biases (W m^{-2}). Subplots along the diagonal indicate MC2, MC12, and NOAA daily OLR respectively. Upper off diagonal subplots show difference plots between each of the datasets. This figure appears as Supplementary Figure S5 in the revised manuscript.

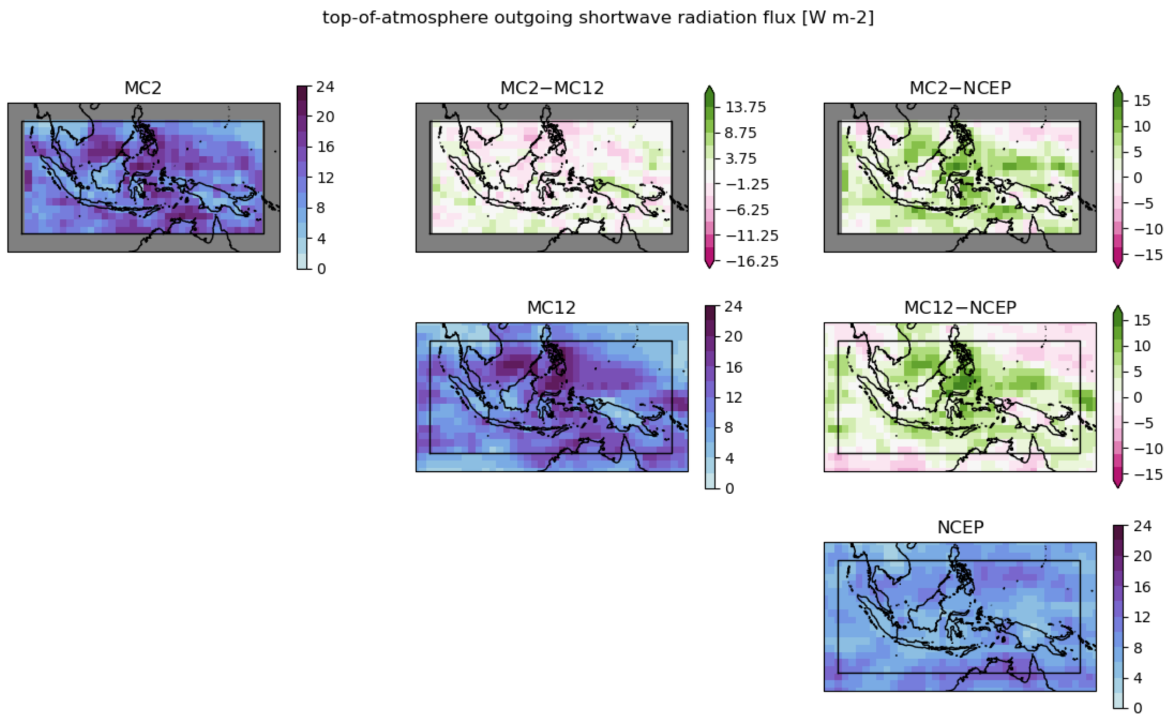

Figure 7: Interannual standard deviation of outgoing shortwave radiation and biases (W m^{-2}). Subplots along the diagonal indicate MC2, MC12, and NCEP-NCAR reanalysis respectively. Upper off diagonal subplots show difference plots between each of the datasets. This figure appears as Supplementary Figure S6 in the revised manuscript.

Variable	Reference dataset	Model	Mean	Bias	RMSE	Std. dev.	Bias	RMSE
Precipitation [mm/day]	GPM-IMERG	MC2	8.43	1.1	3.2	3.01	0.466	1.47
		MC12	8.5	1.2	2.97	2.42	-0.112	1.34
	MSWEP	MC2	8.43	1.35	3.41	3.01	1.25	1.77
		MC12	8.5	1.45	3.01	2.42	0.67	1.33
SST [°C]	OSTIA	MC2	28.8	-0.0188	0.144	0.337	0.0296	0.0867
		MC12	28.8	0.0231	0.205	0.349	0.0421	0.0973
TOA outgoing longwave [W/m^2]	NOAA daily OLR	MC2	225	0.19	8.06	11.4	1.14	2.46
		MC12	225	-0.2	14	13.1	3.07	4.03
TOA outgoing shortwave [W/m^2]	NCEP-NCAR reanalysis	MC2	121	-20.8	28.1	11.5	3.43	5.16
		MC12	120	-21.9	29.4	11.7	3.59	5.34
U850 [m/s]	ERA5 reanalysis	MC2	-1.5	-0.69	1.1	1.47	0.226	0.798
		MC12	-1.71	-0.835	1.13	1.28	0.0232	0.235
V850 [m/s]		MC2	-1.14	-0.0659	0.514	0.511	-0.0383	0.328
		MC12	-1.14	-0.0671	0.42	0.652	0.0996	0.199
Zonal mean uplift [Pa/s]		MC2	-0.0309	-0.00397	0.0192	0.00942	0.00122	0.00452
		MC12	-0.0319	-0.00493	0.00841	0.00858	0.000378	0.00183
Zonal mean specific humidity [g/kg]		MC2	5.59	0.0571	0.188	0.184	-0.00709	0.047
		MC12	5.77	0.237	0.331	0.171	-0.02	0.0477
Zonal mean air temperature [K]		MC2	263	0.21	0.441	0.298	0.00569	0.0329
		MC12	264	0.24	0.573	0.293	0.000282	0.038
Zonal mean U [m/s]		MC2	-3.09	0.00449	0.923	1.12	0.00532	0.119
		MC12	-3.07	0.0225	1.2	1.08	-0.0398	0.188
Zonal mean V [m/s]		MC2	0.124	0.0151	0.392	0.321	0.0152	0.0725
		MC12	0.138	0.029	0.576	0.315	0.00896	0.126

Table 1: Summary of domain-averaged time-mean values and interannual standard deviations of variables discussed in the text, as well as their respective biases and RMS errors relative to reference datasets. All values are given to 3 significant figures. All averages are computed over the MC2 domain only. Averages of zonal-mean fields are calculated for pressures less than 100 hPa. This table appears as Table 3 in the revised manuscript.

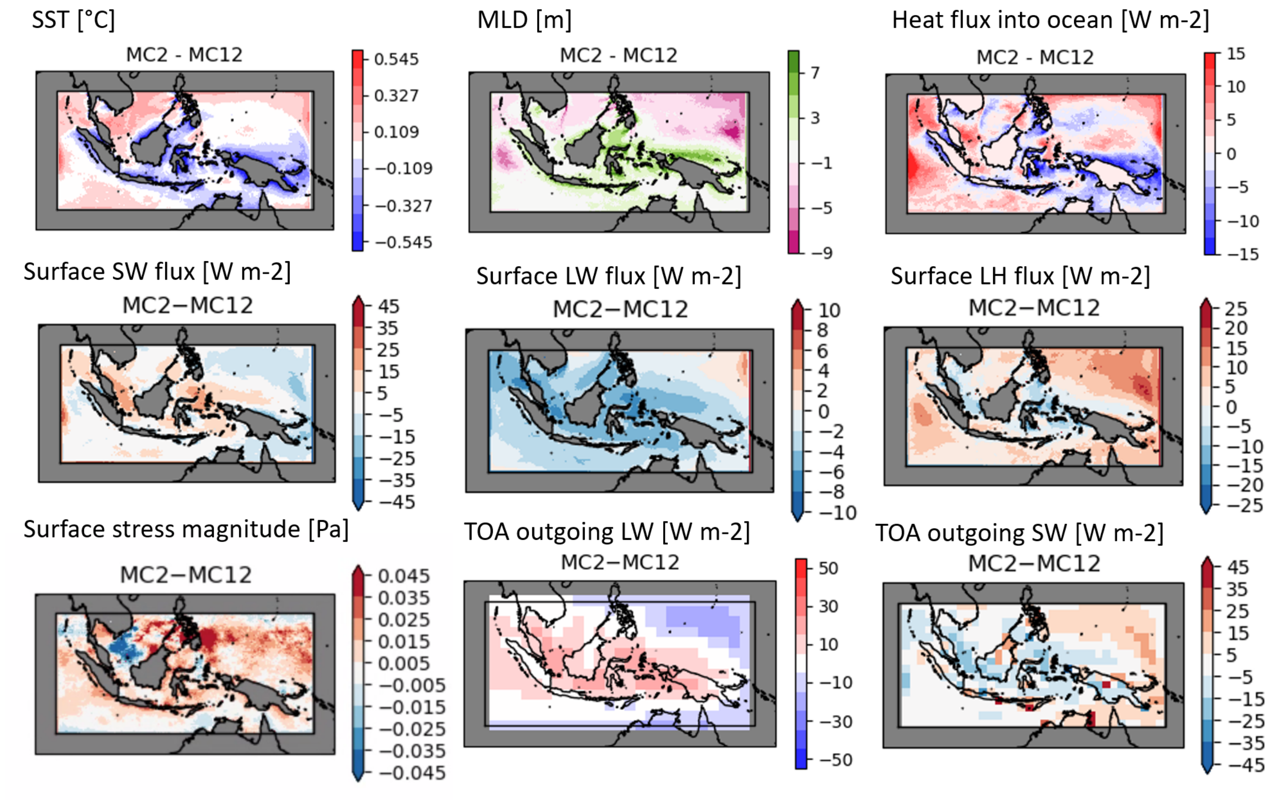

Figure 8: Spatial maps of differences between the all-season means of variables linked to the SST. Top row (L–R): sea surface temperature; mixed-layer depth; heat flux into the ocean. Middle row (L–R): downward surface shortwave flux; downward surface longwave flux; downward surface latent heat flux (a positive change corresponds to reduced evaporation). Bottom row (L–R): magnitude of downward surface wind stress; top-of-atmosphere outgoing longwave radiation flux (as an indication of cloud changes); top-of-atmosphere outgoing shortwave radiation flux (as an indication of cloud changes). Differences in downward surface sensible heat fluxes are not shown; their magnitude is less than ~ 3 W m^{-2} almost everywhere.

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