Response to the comments from Anonymous Referee #1 for the manuscript:
"Uncertainties in climate change projections covered by the ISIMIP and CORDEX model subsets from CMIP5" by Ito et al.

We would like to appreciate your careful review and constructive comments and suggestions for improving our manuscript. We almost agree with them. We have made modifications through our manuscript according to the responses. Please check our detailed responses below. The numbers of page and line are corresponding to the number in the original file (https://www.geosci-model-dev-discuss.net/gmd-2019-143/gmd-2019-143.pdf). Revised sentences according to your and the other reviewer's comments are colored by orange and blue in the following revised manuscript, respectively. Green-colored sentences represent the revised sentences by ourselves.

In this modification, we added a CMIP5 model of CSIRO-Mk3L-1-2, to the original 49 models for the historical run we analyzed. It is because there is no member of r1i1p1 by CSIRO-Mk3L-1-2, but there is r1i2p1 as well as CESM1-WACCM which was already used. The results did not change from the original manuscript by this modification. I apologize for the change.

In this revision, McSweeney and Jones (2016) have referred to as MJ2016 except for the first reference.

Thank you once again for your review.
We would be glad to respond to any further comments you may have.

**--- Summary and General comments**

The paper by Ito et al. investigates the uncertainty ranges in projections from the ISIMIP and CORDEX projects. Both of these projects selected a sub-sample from CMIP5 Global Climate Models (GCMs) to bias correct and then drive impact models (ISIMIP) or to downscale the GCM's (CORDEX). ISIMIP and CORDEX have different goals and also the number of models selected and the approach to sub-select the GCMs were different. The authors look into how well these two projects cover the uncertainty ranges provided by the original CMIP5 model set. They show that the ISIMIP and CORDEX uncertainty ranges are smaller than the original range but still larger than from a subset only selecting well performing models, even though the number of models selected in ISIMIP and CORDEX was smaller than the number of well performing models they were compared to. The authors also conclude that better subsets with smaller biases and/or higher scores would be possible than the current ISIMIP and CORDEX selections.

While it is interesting to see how different the uncertainty ranges of different model selections are, I am not necessarily sure if the comparison is fair, given that as far as I know neither ISIMIP nor CORDEX selected their GCMs based on these criteria. Among other points explained below, I am also missing a clear recommendation that would help the next rounds of ISIMIP and CORDEX to sub-select their GCMs.

We glad to hear your interests in our study. We have made our response to the comments about the unfair comparison between the subsets from ISIMIP and CORDEX and about the recommendations towards the next rounds, as the responses to specific comment #1 and #4 respectively. Please find below.

**--- Specific comments**

1. For ISIMIP the main constraint in choosing GCMs was data availability, and they needed many more variables than the ones the authors consider in this study. Hence, even if "better" subsets in terms of performance based on precipitation and temperature would be possible, that does not necessary mean these subsets would have been an option for the ISIMIP project. For CORDEX data availability was also a major constraint, so again, even if better subsets based on temperature and precipitation would have been possible, if the data to drive the RCMs was not available that would not have helped the CORDEX project. These aspects should at least be discussed in the manuscript.

We appreciate your accurate comments. Our explanation was not sufficient. The "better subset" is based only on the model bias and Taylor's skill score in our analysis. From an additional analysis in this revision, it is found that such a subset can be obtained under the condition without considering the data

availability and with focusing on one variable of temperature or precipitation. We have described the following sentence to the section of discussion which made in this revision.

(P8 L23) "… a much better model subset, regarding to biases and skill scores, can be selected with making use of the advantage of the small number of models. However, such a selection can be conducted when there are no constraints of data availability which was the main constraint to select the current subsets in ISIMIP and CORDEX and when we use one variable of either temperature or precipitation."

As you noted, ISIMIP and CORDEX select their subset under the different constraints at the present. We have also added the followings in the section of discussion:

(P8 L23) "In this study, we assessed the current ISIMIP and CORDEX subsets to investigate whether the subset indicates small biases in the historical climatology and covers the uncertainty in the future projections widely using temperature and precipitation. Both variables are most frequently used in future projections and also weather forecasts. The evaluation for such a principal variable is important for the studies of ISIMIP and CORDEX. It should be noted, however, that ISIMIP needs the dataset with reasonable for multiple variables used in their impact assessment and with enable to discuss the uncertainty in the projections. CORDEX requires the dataset with based on a plausible mechanism of the climatology as the input data for RCMs. Thus, there is a possibility that a good subset which we presented based on the model performance for temperature and precipitation will be an option of their future subsets."

2. I was also missing the link from the performance in the historical projections to the projected uncertainty ranges. Do the sub-sampling based on lower bias/higher score cover larger, smaller or similar uncertainty ranges in the projections? The data is all there in the figures, but it is not discussed in the text.

We had mentioned the uncertainty range for the temperature change obtained from the subsets on P6, L24-26 and on the other hand, for the precipitation change on P6, L30. Especially for precipitation, there was less explanation. We have added the description below to P6, L29. With the addition, we have modified a whole of the paragraph more understandably.

"The subsets of $\Delta$P(CMIP′$_{\mathrm{lowB}}$) and $\Delta$P(CMIP′$_{\mathrm{highS}}$) cover 70% and 60% of the full range of uncertainty from CMIP$_{\mathrm{Full_Future}}$ as the average over 14 regions, respectively, with totally covering the full range in Australasia. The largest difference between the coverages from $\Delta$P(CMIP′$_{\mathrm{lowB}}$) and $\Delta$P(CMIP′$_{\mathrm{highS}}$) appears in East Asia. Therefore, we need to pay attention that, when the model performance is the condition to select subsets, the uncertainty changes depending on which evaluation index are used, like at least the bias or the skill score."

3. I also find it hard to believe that neither the ISIMIP nor the different CORDEX regions did any analysis similar to what the authors provide here? At least for ISIMIP McSweeney and Jones (2016) seem to already have done this in a very comprehensive way. What is this study adding on top of that?

McSweeney and Jones (2016) (hereafter MJ2016) have discussed the uncertainty in the projections but not mentioned the ability to represent the present-day climate and the projections itself which we have investigated. Also, as the update from MJ2016, we have analysed four GCMs used in the newer round of ISIMIP, instead of the GCMs analysed in MJ2016. On the other hand, as you pointed out, there are some CORDEX regions where their GCM subsets have been assessed but the assessments are limited.

Uniform assessment over the regions permits to discuss the difference of performance among the regions. In addition, Gutowski et al. (2016) have mentioned there is a possibility of the heterogeneity on climate information among the regions as one of the main problems in CORDEX. This study has indicated that the subsets can widely capture the uncertainty in both projections of temperature and precipitation in the regions with a large ensemble. Thus, it is found the heterogeneity exists in the current dataset when focusing on the uncertainty. Furthermore, from the added results in this revision, we suggest that nine model members are needed to solve the heterogeneity of the uncertainty.

From the assessment of the subsets selected in each program in the same method, we understand how different the climate information from a global consistent subset is from the original one by using the

ISIMIP subset in the CORDEX framework, with assuming CORDEX CORE.

We have added the above contents to P4 L3.

"The ability for the ISIMIP subset was not mentioned by MJ2016 and thus we investigated that in region-by-region. We analysed four GCMs selected in ISIMIP2b (unless specified otherwise, hereafter refers to as ISIMIP) here. Thus, discussion about the projections is also updated from MJ2016. The GCMs used in CORDEX have been assessed by region in previous studies, but are limited (e.g., Haensler et al. 2013 for Africa; Bartók et al. 2017 for Europe; Karmalkar 2018 for North America). Even simple assessment conducted is needed for the present CORDEX. Furthermore, uniform assessment across regions permits to discuss the difference of characteristics among the regions and the possibility of heterogeneous scenario as mentioned above. By using the subsets from the two programs, we can explore the difference between the original subset in CORDEX and the subset selected with assuming CORDEX CORE, which is helpful information for the model selection in CORDEX CORE."

4. On page 8, lines 19-22, the authors mention results what would happen if a larger number of models would have been used in the Central Asia region. This result, I imagine something similar to Figure 3 in McSweeney and Jones (2016) but for the CORDEX regions, would have been very interesting. I think it would allow to show how many models would need to be selected to cover a certain uncertainty range, which would help to make a recommendation for the next round of CORDEX. I would also be curious to see if these numbers differ between different regions.

We appreciate your constructive suggestion to gain more insight into our results. We added the results about the change of coverage depending on the number of models in each region to Section 3.3. We have referred the idea by McSweeney and Jones (2016). They have changed the number of models to explore how the coverage changes with the number of models when a subset covers the uncertainty in each grid most widely over the globe or regions. On the other hand, in this study, to consider making better use of the current subsets, we have changed the number of models from the current model members and explored how the coverage changes. The details are as what followings:

(P8 L19) "From Fig. 4, the subsets with nine models or more can capture the uncertainty of projections in both temperature and precipitation widely, implying that there is a heterogeneity on the dataset by a different number of models (Gutowski et al. 2016). We explored whether a similar tendency can be obtained in the other regions when the number of models changed. The same approach was performed by MJ2016. They focused on a subset covering the uncertainty in each grid most widely over the globe or regions and investigated how the coverage changes with the number of models. On the other hand, in this study, to consider making better use of the current subsets, we investigated how the coverage changes with changing the number of models from the current model members.

Figure 5 shows the change of coverage performance with the number of models changing in each region. When the number of models is larger than the current number, we added models randomly selected to the current members. By contrast, when the number of models is less, we removed models randomly selected from the current members. Here we focused on the median of the FRA values obtained from the possible 10,000 random samples, meaning the FRA value obtained with a possibility of 50% when selected subsets randomly. For the temperature change, the median exceeds 60% in all regions when changing the number of models from the current four ISIMIP members to seven members which are less than nine members (Fig. 5a). The median above 60% is also obtained in 13 regions (except for Antarctica) when changing the number from the current CORDEX members to nine members. For the precipitation change, the coverage in nine members is above 50% in 10 regions and in 12 regions by changing the number of models from the current members in ISIMIP and CORDEX, respectively (Fig. 5b). Even when using nine members, the median is less than 50% in Four regions of MENA, Africa, and South and East Asia for the change of number from the ISIMIP subset and in two regions of MENA and North America for that from the CORDEX subset.

The IQR for $\Delta T$ shifts to a high FRA smoothly with the number of models in all regions. By contrast, the IQR for $\Delta P$ sometimes gets large suddenly and/or shifts sharply, for instance, MENA and Africa. The discontinuous change is caused by a large variance of $\Delta P$ from each model member. That is to say, when there are model members indicating a large change ratio relative to the other members, the coverage largely differs depending on the inclusion of the member with the large ratio or not. The change

amounts, ΔT are similar among the model members and the variance is small. Thus, the FRA increases with the number of models and the IQR also increases smoothly. To prevent selecting the subset with a large change of the coverage depending on a model with extremely large or small change amount, investigating the variance of the projections in each region is needed when the number of models is decided."

(P9 L18) "The current CORDEX subsets can capture both uncertainties for temperature and precipitation in the regions with a relatively large ensemble. However, it is found that changing the number of models from the current CORDEX members to nine members can capture more than half of the full uncertainty in both projections of temperature and precipitation in more than 85% of all regions, with a possibility of 50%. Furthermore, the same is also shown as for the ISIMIP subset, but for 70% of all regions. Focusing on the uncertainty in the future projections, this result proposes that the current number of models need to be changed to discuss a similar uncertainty range among the regions."

**--- Technical corrections**

1. Figures: While I kind of like the illustration of the graphs on the map it takes up quite a lot of space while the graphs itself are rather small. I wonder if the graphs could be increased but would take up less space in a more classical arrangement?

We appreciate your suggestion. We can understand a lot of space, especially in Supplement 4 and 5. We deeply considered the modification but the graphs on the map is good from the point of seeing the property corresponding to the region at a glance. We have redrawn the figures with reducing the space as much as possible.

2. Supplement 1: I find this table not very informative, I would be more interested to know in which regions which models were used than in how many regions each model was used.

The table has been changed to a table presenting the models used in each CORDEX regions. Please check the modified manuscript.

3. Supplement 4 and 5: I think the Obs are missing in these Figures.

Differed with the precipitation, one observation dataset, CRU, is used as the temperature reference data as indicated on P4, L26-27. Thus, there is no plot for the observation.

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We have revised our manuscript to address comments from Anonymous Reviewer #1.

Response to the comments from Anonymous Referee #2 for the manuscript:
"Uncertainties in climate change projections covered by the ISIMIP and CORDEX model subsets from CMIP5" by Ito et al.

We would like to appreciate your careful review and constructive comments and suggestions for improving our manuscript. We almost agree with them. We have made modifications through our manuscript according to the responses. Please check our detailed responses below. The numbers of page and line are corresponding to the number in the original file (https://www.geosci-model-dev-discuss.net/gmd-2019-143/gmd-2019-143.pdf). Revised sentences according to your and the other reviewer's comments are colored by blue and orange in the following revised manuscript, respectively. Green-colored sentences represent the revised sentences by ourselves.

In this modification, we added a CMIP5 model of CSIRO-Mk3L-1-2, to the original 49 models for the historical run we analyzed. It is because there is no member of r1i1p1 by CSIRO-Mk3L-1-2, but there is r1i2p1 as well as CESM1-WACCM which was already used. The results did not change from the original manuscript by this modification. I apologize for the change.

In this revision, McSweeney and Jones (2016) have referred to as MJ2016 except for the first reference.

Thank you once again for your review.
We would be glad to respond to any further comments you may have.

**--- General comments**

This manuscript aims to quantify the spread of CMIP5 projections and biases covered by the subsets of models used in the ISIMIP and CORDEX experiments. The first section of the results examines the spread of model performance in reproducing the temperature and precipitation over the historical period (1986-2005), relative to a range of observational and reanalysis products. The rest of the results examines the spread in projected end-of-21st-century changes in annual mean temperature and precipitation, and how it compares to the spread covered by randomly selected subsets. The main findings are that (i) the small ensembles used in ISIMIP and CORDEX generally perform well over the historical period but are not optimal in minimizing historical biases, and (ii) the ISIMIP ensemble outperforms the CORDEX and randomly selected ensembles in covering the full CMIP5 range of projected temperature changes, but both ISIMIP and CORDEX cover a smaller spread of precipitation changes than randomly selected subsets.

This manuscript presents a valuable study to put the CORDEX and ISIMIP subsets in the context of the full CMIP5 ensemble. At this stage, it is mostly descriptive and would greatly benefit from a more comprehensive discussion, including the benefits/limitations of the metrics used, and the implications of its findings. Please clarify how this specific study sets itself apart from existing studies such as McSweeney & Jones (2016), and how your results fit into the context of the existing literature. Minor adjustments to language and sentence structure are needed to improve the readability of the manuscript.

We appreciate your useful comments to improve our manuscript. We have made our response to the general comments as the response to the following specific comments:
- the benefits/limitations of the metrics used and the implications of its findings (#11, #15)
- how this specific study sets itself apart from existing studies such as McSweeney & Jones (2016) and how your results fit into the context of the existing literature (#2, #14).

Also, we have added a section to discuss the results and provide our considerations.
Please find below.

**--- Specific comments**

☐ Section 1 Introduction

1. P2 L. 19: Please specify what these previous studies have found, and why we have yet to reach a consensus on the method to select small ensembles. Also, revisiting these papers in a discussion section would provide the necessary context to interpret the results and whether the methodology used in this study is distinct from, or improves upon, the ones used in these studies.

In the previous study, the condition for selecting subsets depends on their purpose. For example, whether

the model performance is considered, which climatological or extreme variables are used and which region is interested. Thus, we have yet to reach a consensus. Our purpose in this study, however, is to indicate the property of ISIMIP and CORDEX subsets for the ability to reproduce the present-day temperature and precipitation and for their future change, and is not suggestions of model selection methodology (P3 L23-25). In P2 L19-21, we have described that, although there are various methods, it is most desirable for the methods to select subsets of GCMs that have smaller biases in the historical climate simulations and cover the widest possible uncertainty range of future projections. We have discussed whether the current subsets in ISIMIP and CORDEX are such a subset.
We have just modified the related sentence as the response to "why we have yet to reach a consensus on the method to select small ensembles";

(P2, L19) "... Gobiet 2016). The optimum method, however, remains to be determined because the interests depend on the studies, for instance, how the model performance is considered, which climatological or extreme variables are used and which region is interested."

2. P3 L. 23-36 Please clarify what is specific to this study: is some aspect of the methodology new? Is this performing an existing analysis to a new set of data? Is the added value of the manuscript to specifically address whether region-specific subsets (CORDEX) outperform a globally consistent sub-set (ISIMIP)? Stating this explicitly would improve the value and readability of the manuscript.

The methodology is not new. The analysed subset has been changed from the subset analysed in McSweeney and Jones (2016) by following the updated selection in ISIMIP. The added value of our manuscript is following, which have been added to P4 L2:

(P4 L2) "The ability for the ISIMIP subset was not mentioned by MJ2016 and thus we investigated that in region-by-region. We analysed four GCMs selected in ISIMIP2b (unless specified otherwise, hereafter refers to as ISIMIP) here. Thus, discussion about the projections is also updated from MJ2016. The GCMs used in CORDEX have been assessed by region in previous studies, but are limited (e.g., Haensler et al. 2013 for Africa; Bartók et al. 2017 for Europe; Karmalkar 2018 for North America). Even simple assessment conducted is needed for the present CORDEX. Furthermore, uniform assessment across regions permits to discuss the difference of characteristics among the regions and the possibility of heterogeneous scenario as mentioned above. By using the subsets from the two programs, we can explore the difference between the original subset in CORDEX and the subset selected with assuming CORDEX CORE, which is helpful information for the model selection in CORDEX CORE."

From an additional analysis in this revision, we suggest that nine models are needed to solve the heterogeneity of the uncertainty. This result can provide suggestions to the next generations of model selections.

(P9 L18) "The current CORDEX subsets can capture both uncertainties for temperature and precipitation in the regions with a relatively large ensemble. However, it is found that changing the number of models from the current CORDEX members to nine members can capture more than half of the full uncertainty in both projections of temperature and precipitation in more than 85% of all regions, with a possibility of 50%. Furthermore, the same is also shown as for the ISIMIP subset, but for 70% of all regions. Focusing on the uncertainty in the future projections, this result proposes that the current number of models need to be changed to discuss a similar uncertainty range among the regions."

☐ Section 2.1

3. P4 L. 18 Why focus on land area only? Regional precipitation, including over the seas/ocean, is relevant for impact studies. Please clearly state the scope (and the application) of this study.

The impacts of climate change appear over the land and ocean as you mentioned. The reason why focusing on land is that the assessment sectors in ISIMIP are mainly over land, and it is important for both programs because of the relevance to human activities. We have added the sentence below:
(P4, L18) "… we focused on the global land area, considering the importance for both programs because of the relevance to human activities."

4. P4 L. 22 Can you justify why you excluded low-precipitation models from the precipitation analysis? I understand these models significantly bias your ensemble but this undermines the stated aim of the study (i.e. to quantify the spread of the full CMIP5 ensemble covered by the ISIMIP and CORDEX subsets). You arbitrarily reduced the model spread covered in this study. Please at least provide more information as to how many models were excluded (and thus the size of your remaining ensemble), why 0.1mm/day was chosen as a threshold, and the reasoning to exclude these models from the precipitation study but to keep them for temperature (if the argument is that the climate they produce is too unrealistic to be a plausible representation of today's climate).

We have expressed the future change of precipitation as a change ratio of the future precipitation to the present-day precipitation. The expression, which has been often used, is highly sensitive in dry grids. Even if the change amount is quantitatively small, the ratio is extremely large. Such a large ratio leads to a large regional average. The large ratio by a small change in dry grids is difficult to explain the validity, and thus we took the dry grids out of consideration. The threshold can be permitted the exclusion of grids with the ratio of 100% over around the Sahara, and be suppressed the exclusion under 5% of all analyzed grids. We added the following sentence to explain the exclusion:

(P4, L22) "The future change of precipitation expressed in a ratio here. That is the change ratio tend to be large at too dry grid even when the change is quantitatively extreme small. Such a large ratio is difficult to explain its meanings physically. By applying the threshold, the grid indicating an extremely large ratio, for instance, 100% were excluded. The total number of the excluded grids is approximately 5% of all target grids as an average over the used members."

5. P4 L. 32 Please include a definition of the skill score used here, or a reference to a published paper using the exact same skill score. In Taylor (2001), two examples of skill scores are used, to illustrate that the skill score can be adjusted depending on whether you value high correlation or matching the variability most. In addition, it is explicitly stated that the value of Ro should be reported every time a skill score is used.

We appreciate your pointing out. The definition below has been added to P4, L32,

(P4, L32) "… we used the skill score proposed by Taylor (2001) (hereafter referred to as skill score) as follows:

$$S=4(1+R)/\{(\sigma+\sigma^{-1})^2(1+R_0)\}, \quad (1)$$

where R is the spatial correlation coefficient between referred observation and simulation, σ is the standard deviation of simulation normalized by the reference spatial pattern and $R_0$ is the maximum correlation attainable. The value of $R_0$ was assumed to 1 here."

6. P5 L5 Is R the min-max range of a given subset? Please clarify. Using 'uncertainty range' is misleading; it sounds like you are sampling your ensemble. If I understand correctly, you generate 10,000 values of RSub, then look at ensemble spread (in Fig 4).

The value, Rsub which we used here, is the max.-min. ranges of the uncertainty estimated from the ISIMIP subset, the CORDEX subset, or the 10,000 random subset samples from $CMIP_{Full\_Future}$. The corresponding parts have been modified as follows:

(P5 L4) "The FRC from the regional averages (FRA) was defined as the fraction of the maximum-minimum range of the uncertainty in the regional averaged projections from a subset of $CMIP_{Full\_Future}$ ($R_{Sub}$) to the range from $CMIP_{Full\_Future}$ ($R_{Full}$), as follows:
(Equation 2)
The range of $R_{Sub}$ was computed from the ISIMIP and CORDEX subsets and also arbitrary subset samples we generated. From the comparison with the arbitrary samples, we can investigate how well the ISIMIP and CORDEX subsets captured the uncertainty range of projections. McSweeney and Jones (2016) presented the comparison using their 500 samples as 'representation'. Our arbitrary samples were generated by randomly selected $n$ models without repetition from $CMIP_{Full\_Future}$ 10,000 times, where $n$ is the sample size of subsets in ISIMIP ($n$ = 4) or CORDEX ($n$ depends on the regions; see Table 1). Then, the variance of the FRA was estimated from the 10,000 random samples of the subset of $CMIP_{Full\_Future}$ and compared with the FRA from the ISIMIP and CORDEX subsets."

☐ Section 3

7. This section is entitled 'Results and Discussion' but mostly contains the description of the results. Regardless of whether it is included in this section or a separate section, the manuscript needs a more comprehensive discussion (see other comments below).

We have made an additional section in this revision for the discussions. Please check the responses below.

☐ Section 3.1

8. P.5, L. 28-29 Please include the top 50% ensembles in the supplementary material, so that future model selection can rely on your analysis to select less biased models.

We appreciate your constructive suggestion. We have added the high performance subsets as an supplementary material. The material has been refereed in P5, L19 ("The models included in the high performance subset is shown in Supplement 3.").

10. P5 L29-30 Can you suggest why the spread is different between the two ensembles over the Northern Hemisphere? In Fig.1, the spread for ISIMIP is sometimes significantly larger, sometimes significantly smaller than CORDEX. Could this be due to the number of models in CORDEX? Do some of the regions have models that overlap across ISIMIP and CORDEX? Simply stating that they are different in some regions is not very informative.

We appreciate your accurate indication. As you pointed out, we have found that part of the characteristics of the difference in the spread has a relationship to the overlapping of model members used. The sentence has been modified and added more explanation:

(P5 L29-30) "The difference in the spread between the ISIMIP and CORDEX subsets has a characteristic in region-by-region and part of them relates to the overlapping of model members used across ISIMIP and CORDEX. For example, in five regions of Central and South America, Europe, Africa and South Asia, the CORDEX subsets include more than three of four ISIMIP models and the ensemble is large in CORDEX than in ISIMIP (Supplement 1). As the result, the variance of biases estimated from the CORDEX subset covers that from the ISIMIP subset. Especially in Europe, the difference of the variance between the CORDEX and ISIMIP subsets is large and it is found that the models used in the CORDEX subset but not included in the ISIMIP subset make the variance increase. Focusing on the regions where the CORDEX subsets include only two models in the ISIMIP subset, the variance from the CORDEX subset tends to be larger than that from the ISIMIP subset, especially in the regions with large ensemble of the CORDEX subsets, like North America, SEA and Australasia. By contrast, the variance from the CORDEX subsets is relatively small in the regions with small ensemble of the CORDEX subsets, like MENA and Central Asia. In East Asia, the variance is small in CORDEX despite using seven models in contrast to four models in ISIMIP. Thus the biases from the seven models are almost same."

Also, we have modified the sentence about the spread of the temperature bias:

(P6 L9-11) "The spread of B(T(ISIMIP)) is covered by that of B(T(CORDEX)) in the same four regions as the bias in the precipitation except for Europe, because of the overlapping of model members used. The spreads of B(T(ISIMIP)) and B(T(CORDEX)), however, resemble each other compared with the precipitation bias, indicating that CORDEX used models with a quantitatively similar performance to ISIMIP, despite using more models than ISIMIP except for Central Asia."

11. P6 L1-3 This paragraph would benefit from an earlier explanation about how the skill and bias metrics are different and the insight gained by using both. Include some interpretation of why the model ensembles that perform relatively well in a bias metric perform less well in the skill metric. (same comment for P6 L11)

Thank you for your suggestion. The skill score quantifies the similarity of the spatial pattern by a correlation coefficient and a standard deviation. The bias evaluates the quantity itself by the regional average of the difference from the observation. Thus there is a case with large positive and negative biases in each grid even when the spatial average is small, that is to say, the spatial pattern is different

from the observation. The ensemble showing a small bias and a low score represents the quantity closed to the observation as the spatial average but a low similarity of the pattern. Therefore both metrics are needed to assess how well the ensemble represents the reality. We have added the following sentences in each part:

(P4, L32) "In addition to the skill score, we use the model bias to evaluate the quantity itself. The usage of the two metrics enables the assessment of both the spatial pattern and the quantity."
(P6, L2) "That is to say, ISIMIP and CORDEX subsets include the member showing a low similarity of the spatial pattern to the observation."
(P6, L11) "Therefore, relative to $CMIP_{highS}$, the subsets can quantitatively represent the observed temperature as a regional average well but the spatial pattern represented by some members in the subsets has not much resembled the observation."

12. P6, L. 15-16 Please include the top 50% ensembles in the supplementary material. In addition, please include in the discussion whether the 'best performing models' perform well both in temperature and precipitation, and whether selecting according to high skill or low bias makes a difference. As you state that a better ensemble can be selected, please give the evidence from your results that this can be done robustly.

We appreciate your constructive suggestion. We have added the top 50% models as Supplement 3 (Response #8). The comparison between the top 50% ensembles for the bias and skill score is interesting. From Supplement 3, when we focus on one variable of either temperature or precipitation, 13 models in 25 all high-performance models are included in both subsets of high-performance models for the bias and skill score. Thus, the model with a small bias indicates a high score with 50% of the possibility. We have described this explanation to Section of discussion which we have added in this revision:

(P8 L23) "Focusing on one variable of either temperature or precipitation, 13 models in 25 all high-performance models are included in both subsets of high-performance models for the bias and skill score (Supplement 3). In addition to the two indices of bias and skill score for one variable, the number of models indicating the high performance for both two variables of temperature and precipitation is 0 at the minimum in Southeast Asia and the Arctic and 9 at the maximum in Africa. The averaged number over the regions is approximately 4. Therefore, although the model with a small bias indicates a high score with 50% of the possibility, it is difficult to select models with a high performance for both variables of temperature and precipitation."

In addition, explanation and discussion were not enough for the description of selecting a better ensemble. We have added the limitation.

(P8 L23) " … a much better model subset, regarding to biases and skill scores, can be selected with making use of the advantage of the small number of models. However, such a selection can be conducted when there are no constraints of data availability which was the main constraint to select the current subsets in ISIMIP and CORDEX and when we use one variable of either temperature or precipitation."

☐ Section 3.2

13. P6, L.25 Please place this into context by mentioning other studies that have looked at emergent constraints, even if it's only in specific regions (e.g. Bracegirdle et al, 2018 for Southern Ocean winds; Bracegirdle and Stephenson 2013 for Arctic warming).

As you noted, we have added related previous studies and modified the sentence,

(P6 L25) "… suggesting that the bias and skill score are not good emergent constraints to reduce the uncertainty of $\Delta T$ in this study though the previous studies have showed the reduction of the uncertainty (e.g. Smith and Chandler 2010; Bracegirdle and Stephenson 2013; Bracegirdle et al., 2013; Simpson et al. 2016)"

☐ Section 3.3

14. In general, this section is confusing. It would benefit from clearly stating what is being compared,

and referring to specific aspects of Fig 4 to support your statements. Specifically: P8 L1-2: Please clarify which metric you use to make that statement (i.e. the total coverage on the y-axis). I got confused because the performance of FRACORDEX remains low compared to FRARandom_C, even as the number of models increases. Please state explicitly where you are comparing it to the full range, or to Random_C (3 sentences later). P8 L16: Please specify which FRA you are talking about: the median of FRARandom_C? Or FRACORDEX? Or both? P8 L19-22: This is an interesting point, but if you make the point that increasing the number of models produces a higher FRA, please show the evidence for it. The latter part of the description is unclear so adding the technical details and a figure would make a stronger point.

We have modified each sentence you pointed out as what follows:

(P8 L1-2) "A relatively high coverage, above ~50%, is shown on $FRA_{CORDEX}$ for both changes of temperature and precipitation in eight regions when using nine models or more, except for temperature in Antarctica (Fig. 4a, b): that is to say, the CORDEX subset captures more than half of the range from $CMIP_{Full\_Future}$."
(P8 L16) "…and thus the large model ensemble results in an increase in $FRA_{CORDEX}$ and $FRA_{Random\_C}$."
(P8 L19-22) We have added the figure for the change of FRA with the number of models not only in Central Asia but also in the other regions. Please check Figures 5 and 6.

☐ Summary and Conclusions

15. This section provides a general summary of the findings, but would benefit from providing context as to how these results compared to other studies (e.g. those cited in the introduction), and how the findings advance the general understanding of the field. In addition, statements in P9 L4-5 and P9 L 15-16 seems to indicate CORDEX performance to be bad relative to randomly selected ensembles, while P9 L8-9 states 'relatively wide coverage of both uncertainties'. Please clarify so that the message is not ambiguous. For example, it is ok to state that CORDEX is not performing well compared to the randomly selected ensembles, but is marginally better than ISIMIP at sampling uncertainties in projected change in precipitation.

Regarding the comparison with other studies, as mentioned in P7 L9, "... global consistent four models used in ISIMIP2b, which are taken into consideration of the ability of reproduction, still remains difficult to capture the uncertainties in regional precipitation change, as in McSweeney and Jones (2016) which analysed for five models in the fast track." The result of assessing the CORDEX subset was not able to compare with other studies because of the difference in the variables, part of the regions and seasons. For results from an additional analysis conducted in this revision, we referred to the approach in McSweeney and Jones (2016) but the results couldn't compare each other. It is because "They focused on a subset covering the uncertainty in each grid most widely over the globe or regions and investigated how the coverage changes with the number of models. On the other hand, in this study, to consider making better use of the current subsets, we investigated how the coverage changes with changing the number of models from the current model members." (Added to Section 3.3)

Thanks for your suggestion on the ambiguous statement. We have added the following statement to P9 L14 and have modified the statement on P9 L15-16.
(P9 L14) "The CORDEX subset is not performing well compared to the randomly selected samples but is marginally better than ISIMIP at covering uncertainties in the projected change in precipitation when a large model ensemble used."
(P9 L15-16) "The region-specific model subset, like CORDEX, captures coverage of both uncertainties well compared to the global common subset, but large ensemble is needed."

16. Please include a more comprehensive discussion of your methods and results, including:
Two metrics for "good performance" are used in parallel throughout the study (low bias and high skill score). Please comment as to how similar/distinct these two metrics are, and on the insights gained by using both (qualitatively or quantitatively). Similarly, how different are the 'top 50%' ensembles? i.e. does using skill or bias for selection of the best performing models significantly affect the ensemble?

We appreciate your comments.
First, how similar/distinct these two metrics are, and on the insights gained by using both?
As described in Response #11, we can evaluate the abilities to represent the spatial pattern and the quantity itself by using the two metrics. How similar these two metrics are can be estimated by how many the models selected by each metric overlap. Because 13 models in 25 all high-performance models are included in both subsets of high-performance models for the bias and skill score, the similarity is not so high, around 50%. The number of overlapped models is described in Section of discussion added in this revision. (P8 L23)

Second, how different are the 'top 50%' ensembles?
How different are the top 50% ensembles have been shown in Response #11. Please check. The model with a small bias indicates a high score with 50% of the possibility. Thus a significant influence appears on the selected ensembles.

17. The results section 3.1 focuses mostly on whether the ISIMIP and CORDEX fall within the observational spread (e.g. L. 2-3 on page 6). It would be helpful to distinguish whether this is mainly due to a large spread in the model ensembles, or whether a systematic bias is seen in certain regions (e.g. Fig 1 shows model ensembles overestimate precipitation in most regions). Also, please include a discussion of the expected variance of model ensembles. In coupled models, the timing of climate variability modes is unlikely to match that of observations, so the variance over a 20-year period is likely to be higher in model ensembles than observations.

Here, the observational spread is the spread of the 20-year averaged precipitation calculated from seven observational datasets, not the variance over a specific period. Therefore we cannot discuss the different variance between the model and observations, resulted from the timing of climate variability.

18. In this study, the performance of CORDEX and ISIMIP are considered independently for the temperature and precipitation changes (with precipitation being scaled by the temperature change). Please discuss whether there is any evidence that a selection on one variable (e.g. precipitation) is sufficient to select good performing models, or whether a combined approach is necessary to select models. In climate impacts, people care about the plausibility and diversity of climate sampled, not a single variable.

We appreciate your important suggestion. In this revision, we confirmed a quite small number of models indicating a high performance for both principal variables of temperature and precipitation. In addition, we considered that the evaluation for the simulated principal variables is needed for the studies of ISIMIP and CORDEX, but not possibly sufficient for model selections. Because the large-scale circulation characterized the regional climate, its performance is also important. When we can obtain the reference data, the method used in this study can be applied to the evaluation of the performance. To select subsets in the next generations with the performance considered, it is necessary to construct a combined approach that can take into account multiple variables. We have described this explanation to Section of discussion which we have added:

(P8 L23) "…Therefore, although the model with a small bias indicates a high score with 50% of the possibility, it is difficult to select models with a high performance at the quantity and the spatial pattern for both variables of temperature and precipitation.
In this study, we assessed the current ISIMIP and CORDEX subsets to investigate whether the subset indicates small biases in the historical climatology and covers the uncertainty in the future projections widely using temperature and precipitation. Both variables are most frequently used in future projections and also weather forecasts. The evaluation for such a principal variable is important for the studies of ISIMIP and CORDEX. It should be noted, however, that ISIMIP needs the dataset with reasonable for multiple variables used in their impact assessment and with enable to discuss the uncertainty in the projections. CORDEX requires the dataset with based on a plausible mechanism of the climatology as the input data for RCMs. Thus, there is a possibility that a good subset which we presented based on the model performance for temperature and precipitation would be an option of their future subsets.
Although ISIMIP and CORDEX have tight constraints for model selection at the present, both programs will select the subset showing a reasonable climate based on a plausible mechanism in the future. In the

case, two variables of temperature and precipitation are not possibly sufficient for model selections. At least for the regional climatological studies and the assessment of its impact, it is important to reproduce large-scale circulations which characterize the regional climate. Especially, the spatial pattern of precipitation depends on the accuracy of the circulation. Indeed, model change in ISIMIP from the fast track to ISIMIP2b has already been performed with a consideration of the ability to reproduce ENSO and monsoon (Frieler et al. 2017). The evaluation method used in this study can be applied to the other variables when we can obtain the reference data. For instance, Taylor's skill score which we used to evaluate the pattern of temperature and precipitation can also apply to the pattern of circulation. However, as more variables and evaluation indices are employed, it is more difficult to obtain the CMIP5 models with high accuracy as described above.
It is preferable to select subsets in the next generations based on a combined approach that can consider not only the ability to reproduce the principal variables of temperature and precipitation but also the other ones which are also important to characterize the regional climate. Construction of such an approach would be one of the important tasks for both programs."

In addition, we described the following sentence to Summary:

(P9 L18) "In this study, we have assessed the subsets using the principal variables of temperature and precipitation. It is not sufficient for selecting subsets in the next generations. We suggest that it is preferable a combined approach that can consider the ability not only for temperature and precipitation but also for the other ones which are also important to characterize the regional climate. Construction of such an approach would be urgently demanded for both programs."

**--- Technical corrections**
P1 L18 (and after) High performed models -> high performance models or high-fidelity models
We have modified them as the referee mentioned. Thanks.

P1 L20-25 Please rework this section to clarify the meaning. As you have not previously introduced the 10,000 sampling strategy, these two sentences are confusing.
I am sorry for the confusing. The section has been rephrased,
"Compared with the randomly selected 10,000 arbitrary subset samples, the CORDEX subset shows low coverage of the uncertainty for the temperature change projections in some regions, and the ISIMIP subset high coverage in all regions. On the other hand, for the precipitation change projections, the CORDEX subsets show lower coverage in half of the regions than the arbitrary subsets, but tend to cover the uncertainty wider than the ISIMIP subset."

P2 L33 Please rephrase this sentence for better readability. For example: "In addition, paper X and Y showed that combining region-specific subsets covers more uncertainty than a single, globally consistent, subset of models."
The sentence has been rephrased as follows:
"They also illuminated that region-specific subsets generally cover more the uncertainty than globally consistent subsets in 26 global regions."

P5, L11 Please rephrase that last sentence for readability.
The sentence has been rephrased as follows:
"Then, the variance of the FRA was estimated from the 10,000 random subset samples of $CMIP_{Full\_Future}$ and compared with the FRA from the ISIMIP and CORDEX subsets."

P7, L9-12 This sentence needs to be reworked for readability.
The sentence has been rephrased as follows:
"Therefore, the subset of four models used in ISIMIP2b shows the difficulty of capturing the uncertainties in regional precipitation change. This result is the same as stated using the subset of five models used in the fast track of ISIMIP discussed by MJ2016, despite two of the five models changed."

P7, L15 "with those of the 10,000" -> remove "the"

We have modified them as the referee mentioned. Thanks.

P7 L16 “randomly sampled subsets” of what?
We have rephrased to “randomly samples subsets of $CMIP_{Full\_Future}$”.

P9 L17 Be more specific: ‘it depends on the number of models used’ is too vague to be informative -> “FRA increases with the number of models used”, or “regions covered by bigger ensembles generally have higher FRA”. . .
We agree with the comments. The sentence has been modified to “large model ensemble is needed”.

P13 L8 “areal mean of the reference data” -> normalized by the regional average of GPCC data.
We appreciate your revised. We have modified the sentence as you mentioned.

P14 Figure 2 Why does Antarctica have no top 50% in temperature? Explain that somewhere (main text or figure caption).
We apologize for missing the explanation. The reference data of temperature does not cover the Antarctica, and thus we cannot indicate the results for the top 50%. We have added the sentence below in the caption of Figure 2 and also Supplement 4.
“The top 50% of the CMIP5 models cannot be plotted over Antarctica because of missing the CRU reference data.”

P16 Figure 4 “uncertainty range” -> range Also, why are red dots missing in some regions in Fig 4a?
We have changed to “range”. Red dots look missing because the dots overlap where the coverage is the same between ISIMIP (blue dot) and CORDEX (red dot). “The ISIMIP and CORDEX coverages in (a) overlaps in MENA, N. America and Africa.” is added to the caption.

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We have revised our manuscript to address comments from Anonymous Reviewer #2.

# Uncertainties in climate change projections covered by the ISIMIP and CORDEX model subsets from CMIP5

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**Abstract.** Two international projects, ISIMIP (Inter-sectoral Impact Model Inter-comparison Project) and CORDEX (Coordinated Regional Climate Downscaling Experiment), have been established to assess the impacts of global climate change and improve our understanding of regional climate, respectively. Model selection from the GCMs (general circulation models) within CMIP5 (fifth phase of the Coupled Model Inter-comparison Project) was conducted by the different approaches for each project: one is a globally consistent model subset used in ISIMIP and another is a region-specific model subset for each region of interest used in CORDEX. We evaluated the ability to reproduce the regional climatological state by comparing the subsets with the full set of CMIP5 multimodel ensemble. We also investigated how well the subsets captured the uncertainty in the climate change projected by the full set, to provide increased credibility for the scientific outcomes from each project. The spreads of the biases and Taylor's skill scores from the ISIMIP and CORDEX subsets are smaller than that from the full set for the regional means of surface air temperature and precipitation. However, the spreads in ISIMIP and CORDEX extend beyond the spreads from high ~~performed~~ performance models from full set, despite using a small number of models. It was shown that better subsets exist that would have smaller biases and/or higher scores than the current subset. The ISIMIP subset captures the uncertainty range of the regional mean of temperature change projections by the full set better than the CORDEX subsets in 10 of 14 terrestrial regions worldwide. Compared with the randomly selected 10,000 arbitrary subset samples, the CORDEX subset shows low coverage of the uncertainty for the temperature change projections in some regions, and the ISIMIP subset high coverage in all regions. On the other hand, for the precipitation change projections, the CORDEX subsets show lower coverage in half of the regions than the arbitrary subsets, but tend to cover the uncertainty wider than the ISIMIP subset. In the regions where CORDEX used nine models or more, good coverage (>50%) is evident for the projections of both temperature and precipitation. The globally consistent model subset used in ISIMIP could have difficulty in capturing uncertainties in the regional precipitation change projections, whereas it widely covers uncertainties in the temperature change projections. The region-specific model subset, like CORDEX, can cover the uncertainties in both temperature and precipitation changes well compared to the global common subset, but a large number of models is needed. By changing the number of models from the current ensemble members to at least nine members, high coverage for both uncertainties can be also obtained in the other regions and this information would help model selections in the next generations.

## 1 Introduction

A global dataset of climate change projections has been generated by the Coupled Model Inter-comparison Projects (CMIP). Using this dataset, numerous climatological studies have been in progress to advance our understanding of the increasingly severe problems associated with climate change. Regarding regional climate change, dynamical and statistical downscaling experiments have been conducted to create high-resolution climate products derived from the global CMIP dataset via a regional climate model. In addition, impact studies and examinations of adaptation planning have progressed in close parallel with the climate studies, using those climate products at both global and regional scales.

When we conduct an impact assessment of climate change and consider possible adaptation or mitigation measures, the information regarding the largest potential change in the climate is required to consider the most severe states of climate change, in addition to information regarding how the climate changes on average. Although the CMIP multiple global climate model (GCM) ensemble is the ensemble of opportunity and do not necessarily represent the full uncertainty in the climate projections (Knutti 2010), they are useful for investigating the uncertainty in the future projections. By using the climate projections from the CMIP ensemble, it is at least possible to examine the maximum−minimum climate change scenarios within the ensemble. Although it is desirable to use GCMs as much as possible, due to limitations in computing resources, relatively small subsets of the models are generally used in regional downscaling studies and impact assessments. The subset is selected under the conditions that the simulation accuracy is better for the climatological state of interest or the data required for the study is readily available. Methods of specifying the best subset, based on the accuracy of the historical climate simulations and/or capturing the possible maximum range in the variation of projections among the models (hereafter uncertainty), have been proposed (Reichler and Kim 2008; Cannon 2015; Mendlik and Gobiet 2016). The optimum method, however, remains to be determined because the interests depend on the studies, for instance, how the model performance is considered, which climatological or extreme variables are used and which region is interested. When the sample size of a subset is limited, appropriate strategies are necessary to select subsets of GCMs that have smaller biases in the historical climate simulations and cover the widest possible uncertainty range of future projections. Without such a strategy, we might erroneously interpret the information regarding climate change and impact assessment obtained from the subsets.

The inter-sectoral impact model inter-comparison project (ISIMIP; https://www.isimip.org) was designed as a framework to assess the impacts of climate change in different sectors and at different scales (Schellnhuber et al. 2014). This project used consistent climate and socio-economic input data to multiple impact models. Five GCMs were selected in the fast track of ISIMIP: HadGEM2-ES, GFDL-ESM2, IPSL-CM5A-LR, MIROC-ESM-CHEM, and NorESM1-M. The main selection condition was that the climate data generated by the models was available at the relevant stage of the project, with the attempt of broadly capturing the global change in surface air temperature (hereafter referred to as 'temperature' for simplicity) and precipitation (Warszawski et al. 2014; ISIMIP protocol 2018). After that, the five GCMs had been changed to four GCMs in the next round simulations (ISIMIP2b; Frieler et al. 2017) because of a lack of wind data for NorESM1-M and a higher horizontal resolution and the better representation of various fields (e.g., El Niño–Southern Oscillation and the monsoon) in

MIROC5 than in MIROC-ESM-CHEM. A feature of the uncertainty range identified from the five GCMs in the fast track was investigated in detail by McSweeney and Jones (2016) (hereafter MJ2016), who indicated that the subset covers the uncertainty in the projected changes in the temperature and precipitation expressed from 36 CMIP5 GCMs wider than the other five-GCM subsets which were randomly sampled. ~~In addition, a higher coverage of the uncertainty range had been shown to appear as an average of 26 global regions, in region-specific subsets than in globally consistent subsets which are consistent with the aim of ISIMIP.~~ They also illuminated that region-specific subsets generally cover more the uncertainty than globally consistent subsets in 26 global regions.

One subset of GCMs was globally used in ISIMIP, but in the coordinated regional climate downscaling experiment (CORDEX; http://www.cordex.org) project, a GCM subset was selected for each defined region to generate a regional climate dataset for climate studies and impact assessments (Giorgi et al. 2009; Giorgi and Gutowski 2015). Fourteen regions of interest were defined and subsets of between 3 and 15 GCMs were used for each region. The conditions required here were that input data to a regional climate model (RCM) were available and easily acquired, and they also tended to select GCMs that were developed at the institute located in the region of interest. The advantage of CORDEX is that it enables a regional climate assessment using a dataset from 'optimal' multi-GCMs and multi-RCMs for the region of interest. ~~Meanwhile,~~ However, Gutowski et al. (2016) pointed out as one of the problems in the first phase of CORDEX that the different models, especially the number of models, among the regions make difficulty to provide the consistent climate scenario among their regions. Therefore, in the next generation of CORDEX to be included in the sixth phase of CMIP, they have an intention to downscale projections from a core set of GCMs as a minimum model set that is common across the regions, similar to the approach in ISIMIP (CORDEX CORE; Gutowski et al. 2016).

A globally consistent GCM subset will facilitate discussion of climate change and its impacts beyond regional divisions. However, it is unclear whether the globally consistent subset adequately represents the phenomena that characterize the climate in the region of interest. In particular, the spatial pattern of a projected change in precipitation is strongly dependent on the GCMs selected (Giorgi and Gutowski 2015; McSweeney et al. 2015). Therefore, the possibility of insufficiently capturing the regional climate change and its valid uncertainty could be increased, as noted by MJ2016. In contrast, a region-specific GCM subset can include GCMs which more precisely reproduce the target regional climate (McSweeney et al. 2015). However, it does not enable discussions about the difference among regions and the interaction of impacts across the regions. Although there are advantages to both approaches to select a subset, it is necessary that we understand the characteristics of the current subsets selected using the approaches of the ongoing projects if we are to improve the process in the next generations of the projects.

~~In this study, we assessed the current subsets of CMIP5 multi-GCM ensemble being used in ISIMIP and CORDEX by clarifying the climatological characteristics expressed by each subset, which is an important aspect for increasing the credibility of the scientific outcomes from each project. By comparing the simulations of the subsets and also the full set of the multi-GCM ensemble with observed data, we evaluated their ability to reproduce the historical climate (i.e., model performance). We also compared the projected change of climate between the subsets and the full set, and clarified how extent the uncertainty~~

~~in the projections obtained from the subsets covers the uncertainty from the full set. In addition, with reference to McSweeney and Jones (2016), we also explored whether the subset used was able to capture the uncertainty from the full set more widely than the other model subsets when using the same sample size. Although the five GCMs analysed by McSweeney and Jones (2016) were selected in the fast track of ISIMIP, this has been changed to four GCMs in the next round of the ISIMIP simulations (ISIMIP2b; Frieler et al. 2017). Frieler et al. (2017) explained that NorESM1-M was removed from the five GCMs because of a lack of near-surface wind data, and MIROC-ESM-CHEM was changed to MIROC5 because of the horizontal resolution and improvements in the representation of various fields (e.g., El Niño–Southern Oscillation and the monsoon) in the historical experiments. Therefore, we used the four GCMs from ISIMIP2b here, and ISIMIP refers to ISIMIP2b hereafter unless specified otherwise.~~

In this study, we assessed the current subsets of CMIP5 multi-GCM ensemble being used in ISIMIP and CORDEX by clarifying the climatological characteristics expressed by each subset from two points of view: how high the ability to reproduce the historical climate is (i.e., model performance) and how extent the uncertainty in the projections obtained from the subsets covers the uncertainty from the full set. We examined temperature and precipitation climatologies in a simple method, but the clarification of characteristics is important for understanding the basic nature of dataset and increasing the credibility of the scientific outcomes from each project. In addition, with reference to MJ2016, we also explored whether the subset used was able to capture the uncertainty from the full set more widely than the other model subsets when using the same sample size.

The ability for the ISIMIP subset was not mentioned by MJ2016 and thus we investigated that in region-by-region. We analysed four GCMs selected in ISIMIP2b (unless specified otherwise, hereafter refers to as ISIMIP) here. Thus, discussion about the projections is also updated from MJ2016. The GCMs used in CORDEX have been assessed by region in previous studies, but are limited (e.g., Haensler et al. 2013 for Africa; Bartók et al. 2017 for Europe; Karmalkar 2018 for North America). Even simple assessment conducted is needed for the present CORDEX. Furthermore, uniform assessment across regions permits to discuss the difference of characteristics among the regions and the possibility of heterogeneous scenario as mentioned above. By using the subsets from the two programs, we can explore the difference between the original subset in CORDEX and the subset selected with assuming CORDEX CORE, which is helpful information for the model selection in CORDEX CORE.

## 2 Data and Methods

### 2.1 Dataset

We analysed the historical runs of 50 atmosphere–ocean GCMs (AOGCMs) and the Representative Concentration Pathways (RCP) 8.5 scenario runs of 42 AOGCMs participating in CMIP5 (Taylor et al. 2012). A single ensemble member, r1i1p1, was selected for each model, except for CESM1-WACCM (r2i1p1), CSIRO-Mk3L-1-2 (r1i2p1) and EC-EARTH (r8i1p1). It is because the member, r1i1p1, of CESM1-WACCM and CSIRO-Mk3L-1-2 were not available and temperature change from

r1i1p1 of EC-EARTH was over two-standard deviation of the changes from the 42 models in more than 60% of our target regions. In the followings, the full set of the multi-GCM ensemble indicates the 50 historical runs when we assessed the ability to reproduce the historical climate ($CMIP_{Full\_Hist}$), while does the 42 future projections which are estimated from both historical and rcp85 runs when we discussed the future projections ($CMIP_{Full\_Future}$).

We compared the simulations of the subsets of GCMs used in ISIMIP and CORDEX with the full ensemble. ISIMIP used four GCMs for their various impact assessments: GFDL-ESM2M, HadGEM2-ES, IPSL-CM5A-LR and MIROC5 (Frieler et al. 2017). On the other hand, CORDEX used the subset in which the combination of GCMs were altered for each defined region. The number of GCMs used in each of the defined regions is listed in Table 1, and each GCM is listed in Supplement 1. The regional classification used to investigate the regional performance and the projection was based on the classification in CORDEX shown in Supplement 2. In this study, we focused on global land area ~~only~~, considering the importance for both programs because of the relevance to human activities.

The analysis periods were the year 1986–2005 (but 1985–2004 for HadGEM2-CC and HadGEM2-ES) for the historical runs and the year 2081–2100 (but 2080–2099 for MRI-AGCM60 and CESM1-WACCM) for the RCP8.5 runs. Monthly mean temperature and precipitation data over these periods were interpolated onto a 2.5° × 2.5° grid for each model. 'Too dry' grids (then mean precipitation are < 0.1 mm/day in each member) were excluded from the analyses using precipitation. The future change of precipitation expressed in a ratio here. That is the change ratio tends to be large at too dry grid even when the change is quantitatively extreme small. Such a large ratio is difficult to explain its meanings physically. By applying the threshold, the grid indicating an extremely large ratio, for instance, 100% were excluded. The total number of the excluded grids is approximately 5% of all target grids as an average over the used members.

To validate the model representations, we compared the simulated estimates with the observed datasets. With respect to precipitation, Sun et al. (2018) highlighted differences among the observational datasets. Consequently, to avoid a misreading of the model performance due to such discrepancies, we used multi-precipitation products that covered the global land area over the period of interest. The observation products were the Climatic Research Unit Timeseries (CRU) v.4.01 (Harris et al. 2014) for temperature and precipitation, and the following for precipitation only: the global unified gauge-based analysis by NOAA Climate Prediction Center (CPC) v.1.0 (Xie et al. 2010), the Global Precipitation Climatology Centre (GPCC) full data reanalysis v.7.0 (Schneider et al. 2016), NOAA's Precipitation reconstruction over Land (PRECL) v.1.0 (Chen et al. 2002), the CPC Merged Analysis of Precipitation (CMAP; Xie and Arkin, 1997), the Global Precipitation Climatology Project (GPCP) v.2.2 (Huffman et al. 2015), and the Multi-Source Weighted-Ensemble Precipitation (MSWEP) v2.1 (Beck et al. 2019).

To quantify the ability to reproduce spatial patterns of the observations, we used the skill score proposed by Taylor (2001) (hereafter referred to as skill score) as follows:

$$S=4(1+R)/\{(\sigma+\sigma^{-1})^2(1+R_0)\}, \quad (1)$$

where $R$ is the spatial correlation coefficient between referred observation and simulation, $\sigma$ is the standard deviation of simulation normalized by the reference spatial pattern and $R_0$ is the maximum correlation attainable. The value of $R_0$ was

assumed to 1 here. In addition to the skill score, we use the model bias to evaluate the quantity itself. The usage of the two metrics enables the assessment of both the spatial pattern and the quantity.

### 2.2 Coverage of uncertainty and random selection

Coverage was estimated from a comparison between the full uncertainty range of the projections made by two model sets, which was defined by McSweeney et al. (2015) as a fractional range coverage, FRC. In this study, we computed the regionally averaged projections for each model, and then the FRC were estimated using the regional averages ~~for each model~~. ~~The FRC from the regional averages (FRA) was defined as the fraction of the uncertainty range of the regionally averaged projections obtained from each model subset (RSub) to the range from CMIPFull_Future (RFull), as follows:~~ The FRC from the regional averages (FRA) was defined as the fraction of the maximum−minimum range of the uncertainty in the regional averaged projections from a subset of $CMIP_{Full\_Future}$ ($R_{Sub}$) to the range from $CMIP_{Full\_Future}$ ($R_{Full}$), as follows:

$$FRA = \frac{R_{Sub}}{R_{Full}}. \quad (2)$$

~~To investigate how well the model subsets used in ISIMIP and CORDEX captured the uncertainty range of projections compared with the other arbitrary subsets, which McSweeney and Jones (2016) presented as 'representation', we randomly selected n models without repetition from CMIPFull_Future 10,000 times, where n is the sample size of subsets in ISIMIP (n = 4) or CORDEX (n depends on the regions; see Table 1). Then, the 10,000 of RSub values and the spread from the 10,000 of the FRA were estimated from the samples.~~ The range of $R_{Sub}$ was computed from the ISIMIP and CORDEX subsets and also arbitrary subset samples we generated. From the comparison with the arbitrary samples, we can investigate how well the ISIMIP and CORDEX subsets captured the uncertainty range of projections. MJ2016 presented the comparison using their 500 samples as 'representation'. Our arbitrary samples were generated by randomly selected $n$ models without repetition from $CMIP_{Full\_Future}$ 10,000 times, where $n$ is the sample size of subsets in ISIMIP ($n$ = 4) or CORDEX ($n$ depends on the regions; see Table 1). Then, the variance of the FRA was estimated from the 10,000 random subset samples of $CMIP_{Full\_Future}$ and compared with the FRA from the ISIMIP and CORDEX subsets.

## 3 Results ~~and discussion~~

### 3.1 Performance in reproducing historical climate

Using model biases and skill scores, we evaluated the historical climate reproduced by the GCM subsets used in ISIMIP and CORDEX. The GCM subsets used in ISIMIP and CORDEX are hereafter referred to as the ISIMIP subsets and CORDEX subsets, respectively. For the evaluations, we also used two high ~~performed~~ performance subsets: one is composed of models with lower bias than the 50th percentile (median) of the $CMIP_{Full\_Hist}$ biases: the other is models with higher skill score than the median of the $CMIP_{Full\_Hist}$ scores (referred to $CMIP_{lowB}$ and $CMIP_{highS}$, respectively). The models included in the high

performance subset is shown in Supplement 3. B($v(E)$) and S($v(E)$) indicate the regional mean biases and skill scores for variable $v$ and ensemble subset $E$, respectively.

Figure 1 shows the model bias associated with the annual mean precipitation in the 14 CORDEX regions over a 20-year period. Compared with the maximum values of B(P($CMIP_{Full\_Hist}$)) for the precipitation ($v$=P), the maximum values of B(P(ISIMIP)) and B(P(CORDEX)) are clearly small, especially in the Mediterranean (MED), Southeast Asia (SEA), and the polar regions. The spreads of B(P(ISIMIP)) and B(P(CORDEX)) in MED are within the spread of the discrepancy among the observations, which suggests that the model selection works effectively to select models with high ability to reproduce the observed regional mean precipitation quantitatively. However, compared with the high ~~performed~~ performance subsets, some models in the ISIMIP and CORDEX subsets have a bias exceeding the maximum values of B(P($CMIP_{lowB}$)), or B(P($CMIP_{highS}$)) in some regions, despite the small number of models used in ISIMIP and CORDEX. Therefore, our results indicate that less bias models could be selected than those currently being used. ~~The difference in the spread between the ISIMIP and CORDEX subsets is large in the high- and mid- latitude Northern Hemisphere regions, regardless of the number of models.~~ The difference in the spread between the ISIMIP and CORDEX subsets has a characteristic in region-by-region and part of them relates to the overlapping of model members used across ISIMIP and CORDEX. For example, in five regions of Central and South America, Europe, Africa and South Asia, the CORDEX subsets include more than three of four ISIMIP models and the ensemble is large in CORDEX than in ISIMIP (Supplement 1). As the result, the variance of biases estimated from the CORDEX subset covers that from the ISIMIP subset. Especially in Europe, the difference of the variance between the CORDEX and ISIMIP subsets is large and it is found that the models used in the CORDEX subset but not included in the ISIMIP subset make the variance increase. Focusing on the regions where the CORDEX subsets include only two models in the ISIMIP subset, the variance from the CORDEX subset tends to be larger than that from the ISIMIP subset, especially in the regions with large ensemble of the CORDEX subsets, like North America, SEA and Australasia. By contrast, the variance from the CORDEX subsets is relatively small in the regions with small ensemble of the CORDEX subsets, like MENA and Central Asia. In East Asia, the variance is small in CORDEX despite using seven models in contrast to four models in ISIMIP. Thus the biases from the seven models are almost same.

With respect to the spatial pattern of the annual mean precipitation, ISIMIP and CORDEX incorporate some models with a worse score than the minimum value of S(P($CMIP_{highS}$)) (Supplement 3). That is to say, ISIMIP and CORDEX subsets include the member showing a low similarity of the spatial pattern to the observation. S(P(ISIMIP)) and S(P(CORDEX)) fall within the observational spread only in the Arctic.

We also assessed model performance for the annual mean temperature ($v$=T). The spread of B(T($CMIP_{Full\_Hist}$)) is greater in the high- and mid-latitude Northern Hemisphere regions than in the low-latitude Northern and Southern hemisphere regions, which would be related to the magnitude of seasonal variability (Supplement 4). The same spatial pattern of spread is also evident in B(T(ISIMIP)) and B(T(CORDEX)). The maximum values of B(T(ISIMIP)) and B(T(CORDEX)) are smaller, or equal to the maximum value of B(T($CMIP_{highS}$)) (except for the CORDEX subsets in East Asia and North America), but are larger than the maximum value of B(T($CMIP_{lowB}$)). ~~The spreads of B(T(ISIMIP)) and B(T(CORDEX)) are similar, indicating~~

~~that CORDEX used models with a similar performance to ISIMIP, despite using more models than ISIMIP (except for Central Asia).~~ The spread of B(T(ISIMIP)) is covered by that of B(T(CORDEX)) in the same four regions as the bias in the precipitation except for Europe, because of the overlapping of model members used. The spreads of B(T(ISIMIP)) and B(T(CORDEX)), however, resemble each other compared with the precipitation bias, indicating that CORDEX used models with a quantitatively similar performance to ISIMIP, despite using more models than ISIMIP except for Central Asia. Both subsets included models with a worse score than the minimum value of $S(T(CMIP_{highS}))$ in 85% of the regions (Supplement 5). Therefore, relative to $CMIP_{highS}$, the subsets can quantitatively represent the observed temperature as a regional average well but the spatial pattern represented by some members in the subsets has not much resembled the observation.

Even though the model selections conducted in ISIMIP and CORDEX narrow the spreads of model bias and the score from $CMIP_{Full\_Hist}$, the largest bias and the worst score from the ISIMIP and CORDEX subsets distribute beyond the biases and the scores from high ~~performed~~ performance models in the full set. ~~Therefore, a much better model subset, regarding to biases and skill scores, can be selected with making use of the advantage of the small number of models.~~

### 3.2 Uncertainty range of the projected changes in annual mean temperature and precipitation

Future projections obtained from the ISIMIP and CORDEX subsets were compared with those from the full set, and also from high ~~performed~~ performance models, as with the evaluations in Section 3.1. Because the small biases or high skill scores models used in this section are composed of the models included in $CMIP_{Full\_Future}$, we refer as $CMIP'_{lowB}$ and $CMIP'_{highS}$ instead of $CMIP_{lowB}$ and $CMIP_{highS}$. Projected change of annual mean temperature and precipitation are designated by $\Delta T(E)$ and $\Delta P(E)$, respectively.

Figure 2 shows the uncertainty range of the projected increments of the temperature for each GCM subset. Although ISIMIP used fewer models than CORDEX, the uncertainty range of $\Delta T(ISIMIP)$ exceeds that of $\Delta T(CORDEX)$ except for South Asia, Australasia, South America, and Central America. The uncertainty ranges of $\Delta T(CMIP'_{lowB})$ and $\Delta T(CMIP'_{highS})$ broadly cover the range of $\Delta T(CMIP_{Full\_Future})$, suggesting that the bias and skill score are not good emergent constraints to reduce the uncertainty of $\Delta T$ in this study though the previous studies have showed the reduction of the uncertainty (e.g. Smith and Chandler 2010; Bracegirdle and Stephenson 2013; Bracegirdle et al. 2013; Simpson et al. 2016).

The uncertainty range associated with the projected change in annual precipitation is shown in Fig. 3. Compared with $\Delta T$ in Fig. 2, model selection has a large impact on the reduction of the uncertainty in $\Delta P$, as was also found by MJ2016 using five GCMs used in the fast track of ISIMIP. The subsets of $\Delta P(CMIP'_{lowB})$ and $\Delta P(CMIP'_{highS})$ cover 70% and 60% of the full range of uncertainty from $CMIP_{Full\_Future}$ as the average over 14 regions, respectively, with totally covering the full range in Australasia (yellow and orange plots in Fig. 3). The largest difference between the coverages from $\Delta P(CMIP'_{lowB})$ and $\Delta P(CMIP'_{highS})$ appears in East Asia. Therefore, we need to pay attention that, when the model performance is the condition to select subsets, the uncertainty changes depending on which evaluation index are used, like at least the bias or the skill score. The CORDEX subsets capture more than 50% of the full range in eight regions (Europe, MED, Africa, SEA, Australasia,

Central America, South America and the Antarctica). On the other hand, the ISIMIP subsets capture the full range less than 60% in all regions. In 11 regions, the CORDEX subsets capture the wider range than the ISIMIP subsets, differing from broad coverage by the ISIMIP subset for $\Delta$T as seen in Fig. 2. Therefore, the subset of four models used in ISIMIP2b shows the difficulty of capturing the uncertainties in regional precipitation change. This result is the same as stated using the subset of five models used in the fast track of ISIMIP discussed by MJ2016, despite two of the five models changed.

The uncertainty range is narrowed by using the subsets, but the interquartile range of $\Delta$P(CORDEX), IQR($\Delta$P(CORDEX)), shows a high coincidence with the IQR($\Delta$P($CMIP_{Full\_Future}$)), as well as with the IQR($\Delta$P($CMIP'_{lowB}$)) and IQR($\Delta$P($CMIP'_{highS}$)). The maximum−minimum range of $\Delta$P(ISIMIP) also captures the IQR($\Delta$P($CMIP_{Full\_Future}$)). Therefore, the CORDEX and ISIMIP subsets can capture the average tendency of the change projected by the 25th to 75th percentile of $CMIP_{Full\_Future}$. In addition, the median of the uncertainty range is similar between the CORDEX subset and $CMIP_{Full\_Future}$. Only in Central Asia does the maximum−minimum range of $\Delta$P(CORDEX) extend below the 25th percentile of $\Delta$P($CMIP_{Full\_Future}$) and, in contrast, the maximum−minimum range of $\Delta$P(ISIMIP) covers the IQR($\Delta$P($CMIP_{Full\_Future}$)). Thus, three models of the CORDEX subset in Central Asia cannot capture the average tendency of the change projected by $CMIP_{Full\_Future}$, despite being able to select suitable models to discuss the climate change in Central Asia, differing from ISIMIP.

### 3.3 Comparison of uncertainty of the projected changes using randomly sampled models

We investigated whether the ISIMIP or CORDEX subsets were more suitable for capturing the uncertainty range obtained from $CMIP_{Full\_Future}$ by comparing the fractional coverage of uncertainty, FRA, of each subset with those of 10,000 randomly sampled subsets of $CMIP_{Full\_Future}$. As the result, the ISIMIP subset (four models) shows high coverage for the temperature change in all regions compared with the random samples. By contrast, the CORDEX subset yields relatively wide coverage for the temperature and precipitation changes, but this depends on the number of models used.

Figure 4 illustrates FRA of the ISIMIP and CORDEX subsets (referred to $FRA_{ISIMIP}$ and $FRA_{CORDEX}$, respectively) in each region. Along the *x*-axis, the name of regions is arranged in ascending order of the number of models used in CORDEX. The number of models used in CORDEX is indicated in each parenthesis after the name, and by contrast, the number in ISIMIP is four in all regions. The *y*-axis indicates FRA of the uncertainty from each subset relative to that from the full set. The bar presents distribution of the FRA values obtained from the possible 10,000 random samples ($FRA_{Random}$). The blue bar means the distribution using the subsets with four models ($FRA_{Random\_I}$), as large as the ISIMIP subset, and the red bar means that with the same number of models used in CORDEX ($FRA_{Random\_C}$). Both ends of the bar indicate the lowest and highest values of FRA, and both ends of the bar with a dark color and horizontal line in the bar denotes the 25th and 75th percentiles and the median, respectively.

For the temperature change, $\Delta$T, $FRA_{ISIMIP}$ and $FRA_{CORDEX}$ (blue and red dots, respectively) exceed 60% in 13 and 10 regions, respectively (Fig. 4a). However, $FRA_{CORDEX}$ locates around the 25th percentile or less of $FRA_{Random\_C}$ (the bottom of dark red bar) in MED, East Asia, SEA, Europe, and the polar regions where $FRA_{CORDEX}$ is lower than $FRA_{ISIMIP}$. In the region with larger model ensemble in CORDEX, $FRA_{CORDEX}$ tends to be less than the median of $FRA_{Random\_C}$ (horizontal red line). On the

other hand, $FRA_{ISIMIP}$ is typically around the 75th percentile (the top of dark blue bar) or higher than the median (horizontal blue line) of $FRA_{Random\_I}$ for all regions.

A relatively high coverage, above ~50%, is shown on $FRA_{CORDEX}$ for both changes of temperature and precipitation in eight regions when using nine models or more, except for temperature in Antarctica (Fig. 4a, b): that is to say, the CORDEX subset captures more than half of the range from $CMIP_{Full\_Future}$. The value of $FRA_{CORDEX}$ for $\Delta$P is lower than that for $\Delta$T. A high coverage of more than 70%, however, can be gained by the CORDEX subset for $\Delta$P in MED, South America, Europe, Australasia and Africa, which also indicates a high coverage compared with the median of $FRA_{Random\_C}$ (except for Europe) (Fig. 4b). In half of the regions, $FRA_{CORDEX}$ are in the range of the 25th percentile or less of $FRA_{Random\_C}$ (four regions of Asia, MENA, the Arctic, and North America). In Central and East Asia, and North America of these regions, $FRA_{CORDEX}$ is smaller than $FRA_{ISIMIP}$, even though CORDEX has the advantages of selecting suitable models for the region and also more models can be used, especially in East Asia and North America. The ISIMIP subsets in Antarctica and Australasia show a larger coverage than the 75th percentile of $FRA_{Random\_I}$, but the $FRA_{ISIMIP}$ of 60% is less than that for $\Delta$T. In more than 60% of all regions, $FRA_{ISIMIP}$ is less than the median of $FRA_{Random\_I}$; the averaged $FRA_{ISIMIP}$ over all regions is 33%.

From the FRA distributions estimated from the possible random samples regarding to both changes, $\Delta$T and $\Delta$P, the IQR of $FRA_{Random\_C}$ itself rises toward a FRA of 100% as larger model ensemble are used. When random samples are composed of a subset with 15 models as large as subsets in CORDEX-Africa and -South Asia, the 75th percentile of $FRA_{Random\_C}$ is more than 90% in $\Delta$T (Fig. 4a). In addition, the width of the IQR for $\Delta$T is narrowed with increasing the number of models. The relationship between the number of models and FRA is clearly evident in $\Delta$T because there is a small difference in $R_{Full}$ among regions for $\Delta$T compared with $\Delta$P (Fig. 2), and thus the larger model ensemble results in an increase in $FRA_{CORDEX}$ and $FRA_{Random\_C}$. And also, we found that the probability of selecting model subsets with a low coverage was higher for precipitation than for temperature, even if the number of models selected increases.

~~The number of models used in CORDEX are unequal among the regions, especially only three in Central Asia (Gutowski et al. 2016). When we add three, five, or seven randomly selected models to the three current models in Central Asia, the FRA for ΔP increases from 15% to 30%, 50%, and 65%, respectively, at the median of the FRAs from the random samples (not shown).~~

From Fig. 4, the subsets with nine models or more can capture the uncertainty of projections in both temperature and precipitation widely, implying that there is a heterogeneity on the dataset by a different number of models (Gutowski et al. 2016). We explored whether a similar tendency can be obtained in the other regions when the number of models changed. The same approach was performed by MJ2016. They focused on a subset covering the uncertainty in each grid most widely over the globe or regions and investigated how the coverage changes with the number of models. On the other hand, in this study, to consider making better use of the current subsets, we investigated how the coverage changes with changing the number of models from the current model members.

Figure 5 shows the change of coverage performance with the number of models changing in each region. When the number of models is larger than the current number, we added models randomly selected to the current members. By contrast, when the

number of models is less, we removed models randomly selected from the current members. Here we focused on the median of the FRA values obtained from the possible 10,000 random samples, meaning the FRA value obtained with a possibility of 50% when selected subsets randomly. For the temperature change, the median exceeds 60% in all regions when changing the number of models from the current four ISIMIP members to seven members which are less than nine members (Fig. 5a). The median above 60% is also obtained in 13 regions (except for Antarctica) when changing the number from the current CORDEX members to nine members. For the precipitation change, the coverage in nine members is above 50% in 10 regions and in 12 regions by changing the number of models from the current members in ISIMIP and CORDEX, respectively (Fig. 5b). Even when using nine members, the median is less than 50% in Four regions of MENA, Africa, and South and East Asia for the change of number from the ISIMIP subset and in two regions of MENA and North America for that from the CORDEX subset. The IQR for $\Delta$T shifts to a high FRA smoothly with the number of models in all regions. By contrast, the IQR for $\Delta$P sometimes gets large suddenly and/or shifts sharply, for instance, MENA and Africa. The discontinuous change is caused by a large variance of $\Delta$P from each model member. That is to say, when there are model members indicating a large change ratio relative to the other members, the coverage largely differs depending on the inclusion of the member with the large ratio or not. The change amounts, $\Delta$T are similar among the model members and the variance is small. Thus, the FRA increases with the number of models and the IQR also increases smoothly. To prevent selecting the subset with a large change of the coverage depending on a model with extremely large or small change amount, investigating the variance of the projections in each region is needed when the number of models is decided.

## 4 Discussion

From the evaluation of the ability to reproduce the regional temperature and precipitation, it is found that the ISIMIP and CORDEX subsets include the models indicating a larger bias and a worse score than high performed models in the full set. Therefore, a much better model subset, regarding to biases and skill scores, can be selected with making use of the advantage of the small number of models. However, such a selection can be conducted when there are no constraints of data availability which was the main constraint to select the current subsets in ISIMIP and CORDEX and when we use one variable of either temperature or precipitation. Focusing on one variable of either temperature or precipitation, 13 models in 25 all high-performance models are included in both subsets of high-performance models for the bias and skill score (Supplement 3). In addition to the two indices of bias and skill score for one variable, the number of models indicating the high performance for both two variables of temperature and precipitation is 0 at the minimum in Southeast Asia and the Arctic and 9 at the maximum in Africa. The averaged number over the regions is approximately 4. Therefore, although the model with a small bias indicates a high score with 50% of the possibility, it is difficult to select models with a high performance at the quantity and the spatial pattern for both variables of temperature and precipitation.

In this study, we assessed the current ISIMIP and CORDEX subsets to investigate whether the subset indicates small biases in the historical climatology and covers the uncertainty in the future projections widely using temperature and precipitation. Both variables are most frequently used in future projections and also weather forecasts. The evaluation for such a principal variable

is important for the studies of ISIMIP and CORDEX. It should be noted, however, that ISIMIP needs the dataset with reasonable for multiple variables used in their impact assessment and with enable to discuss the uncertainty in the projections. CORDEX requires the dataset with based on a plausible mechanism of the climatology as the input data for RCMs. Thus, there is a possibility that a good subset which we presented based on the model performance for temperature and precipitation will be an option of their future subsets.

Although ISIMIP and CORDEX have tight constraints for model selection at the present, both programs will select the subset showing a reasonable climate based on a plausible mechanism in the future. In the case, two variables of temperature and precipitation are not possibly sufficient for model selections. At least for the regional climatological studies and the assessment of its impact, it is important to reproduce large-scale circulations which characterize the regional climate. Especially, the spatial pattern of precipitation depends on the accuracy of the circulation. Indeed, model change in ISIMIP from the fast track to ISIMIP2b has already been performed with a consideration of the ability to reproduce ENSO and monsoon (Frieler et al. 2017). The evaluation method used in this study can be applied to the other variables when we can obtain the reference data. For instance, Taylor's skill score which we used to evaluate the pattern of temperature and precipitation can also apply to the pattern of circulation. However, as more variables and evaluation indices are employed, it is more difficult to obtain the CMIP5 models with high accuracy as described above.

It is preferable to select subsets in the next generations based on a combined approach that can consider not only the ability to reproduce the principal variables of temperature and precipitation but also the other ones which are also important to characterize the regional climate. Construction of such an approach would be one of the important tasks for both programs.

## 5 Summary and conclusions

We explored the ability for the subsets of CMIP5 multimodel ensemble used in ISIMIP2b and CORDEX to reproduce the observed temperature and precipitation, and how the subsets capture the uncertainty in projected change of temperature and precipitation obtained from the full set of the ensemble. In addition, we discussed whether each subset shows a high coverage of the uncertainty in projected climate change compared with the possible subsets generated using 10,000 random samples.

The spreads of the bias and Taylor's skill score from the subsets used in ISIMIP and CORDEX are smaller than those obtained from the full set of CMIP5 ensemble for the annual mean temperature and precipitation. However, despite of the smaller model ensemble in ISIMIP and CORDEX, the largest bias and the worst skill score distribute beyond the biases and the scores obtained from the half member subsets with less bias or high score of the full set. Therefore, although the ISIMIP and CORDEX approaches were able to select models that acceptably performed to represent the historical state, our results suggest that better subsets can be selected by focusing on smaller biases and/or higher scores for representing the historical climate. Note that such a selection can be performed when there are no constraints for the selection and when we use one variable of either temperature or precipitation as the evaluation index.

For the projected change in annual mean temperature, the subsets capture more than 60% of the uncertainty for the full set in the 13 terrestrial regions in ISIMIP and the 10 regions in CORDEX, from the total of 14 regions. The coverage of the

uncertainty range by the ISIMIP subset is larger and equal to the coverage by the CORDEX subset in 10 regions by using only four models that are common to all regions. The FRA of the current CORDEX subset tends to be lower than the 50th percentile of the FRAs obtained from the possible 10,000 random samples in the regions where a large model ensemble is used. ISIMIP selected the subset of models with relatively high coverage of the uncertainty from the full set in all regions, compared with the 50th percentile from the random samples.

On the other hand, for the projected change in annual mean precipitation, the FRA for the CORDEX subset are around the 25th percentile or less of the FRAs from the random samples with the same number of models in half of all regions. However, CORDEX broadly captures the uncertainty range more than ISIMIP, differing from the temperature change. Additionally, a relatively high coverage (>50%) was obtained for the projections of both temperature and precipitation in eight regions when using nine models or more.

Compared with the random samples, the ISIMIP subset shows high coverage for the temperature change in all regions and, by contrast, low coverage for the precipitation change in more than 60% of the regions. The CORDEX subset is not performing well compared to the randomly selected samples but is marginally better than ISIMIP at covering uncertainties in the projected change in precipitation when a large model ensemble used. Therefore, the global common model set used in ISIMIP could have difficulty in capturing the uncertainty in regional precipitation change projections with capturing most of the uncertainty in the temperature change projections. ~~The region-specific model subset, like CORDEX, yields relatively wide coverage of both uncertainties, but this depends on the number of models used.~~ The region-specific model subset, like CORDEX, captures coverage of both uncertainties compared to the global common subset, but large model ensemble is needed.

The current CORDEX subsets can capture both uncertainties for temperature and precipitation in the regions with a relatively large ensemble. However, it is found that changing the number of models from the current CORDEX members to nine members can capture more than half of the full uncertainty in both projections of temperature and precipitation in more than 85% of all regions, with a possibility of 50%. Furthermore, the same is also shown as for the ISIMIP subset, but for 70% of all regions. Focusing on the uncertainty in the future projections, this result proposes that the current number of models need to be changed to discuss a similar uncertainty range among the regions.

In this study, we have assessed the subsets using the principal variables of temperature and precipitation. It is not sufficient for selecting subsets in the next generations. We suggest that it is preferable a combined approach that can consider the ability not only for temperature and precipitation but also for the other ones which are also important to characterize the regional climate. Construction of such an approach would be urgently demanded for both programs.

**Code and data availability**

CMIP5 multimodel dataset is publicly available via the website of Earth System Grid Federation (http://pcmdi9.llnl.gov/). Observation products are publicly available online via each website: CRU (https://crudata.uea.ac.uk/cru/data/hrg/cru_ts_4.01/), CPC (https://ftp.cpc.ncep.noaa.gov/precip/CPC_UNI_PRCP/), GPCC (https://www.dwd.de/EN/ourservices/gpcc/gpcc.html), PRECL (http://ftp.cpc.ncep.noaa.gov/precip/50yr/gauge/), CMAP (https://ftp-cpc.ncep.noaa.gov/precip/cmap), GPCP

(ftp://meso.gsfc.nasa.gov/pub/gpcp-v2.2/), MSWEP (http://www.gloh2o.org). Code for analysis is available to the editor and reviewers for the purpose of the review. Public access to the code is limited due to the property of TOUGOU program, MEXT, Japan and, however, we can provide the code from the corresponding author upon request under the condition of collaborative research.

## Author contribution

All authors conceptualized the study and participated in the discussion. RI analysed the data and prepared the manuscript and all authors revised the manuscript.

## Competing interests

The authors declare no conflict of interest.

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## Supplement

Supplement 1 is a list of the CMIP5 models used in CORDEX.
Supplement 2 describes the regional classification defined in CORDEX.
Supplement 3 describes the models with the top 50% of the CMIP5 models for the model bias and Taylor's skill score.
Supplement 4 describes the skill score for annual mean model precipitation over land.
Supplement 5 describes the annual mean model temperature bias over land.
Supplement 6 describes the skill score for the annual mean model temperature over land.

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**Table 1: Number of CMIP5 models used in the CORDEX regions.**

| Region | | Region | |
|---|---|---|---|
| Europe | 13 | Southeast Asia | 12 |
| Mediterranean | 5 | Australasia | 13 |
| Middle East and North Africa (MENA) | 5 | North America | 6 |
| Africa | 15 | Central America | 10 |
| Central Asia | 3 | South America | 9 |
| South Asia | 15 | Arctic | 5 |
| East Asia | 7 | Antarctica | 9 |

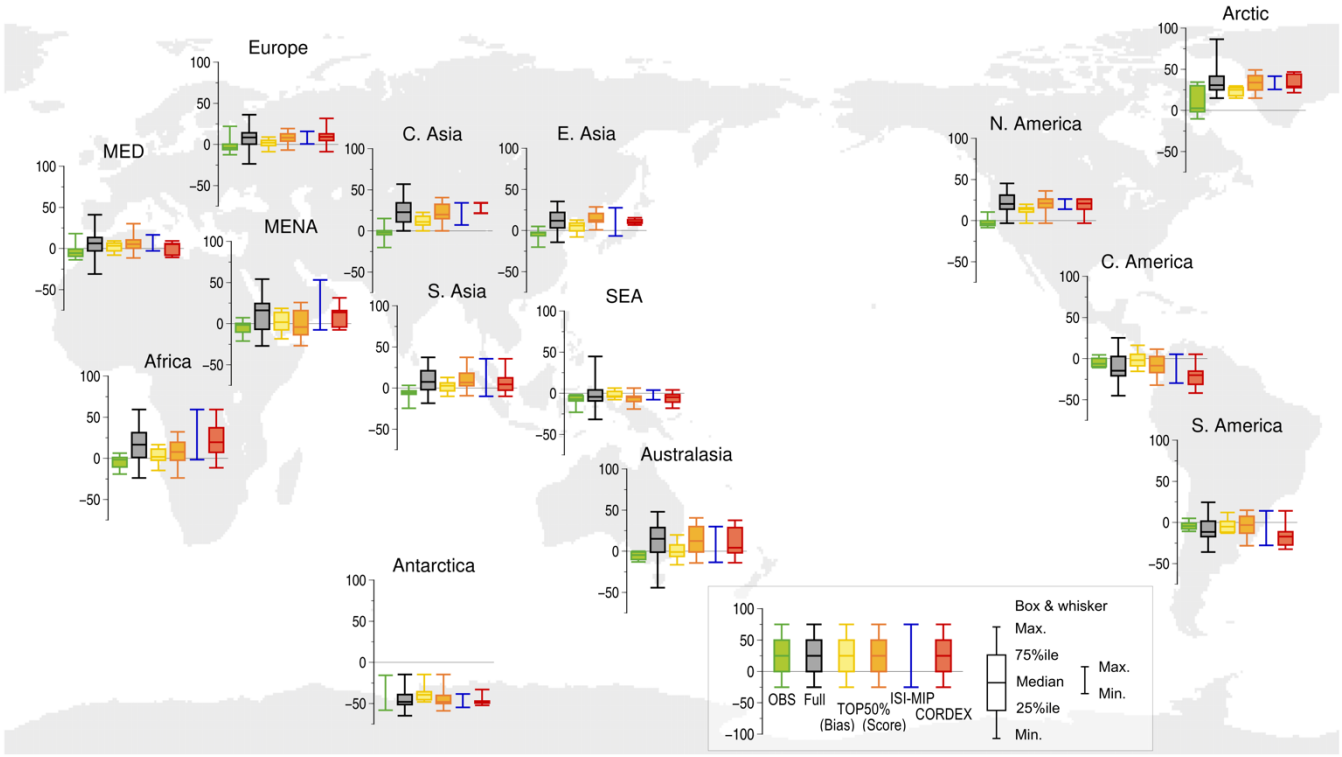



**Figure 1: Normalized annual mean model precipitation bias over land from the GPCC reference data (%). The bias was normalized ~~using the areal mean of the reference data~~ by the regional average of GPCC data. The whiskers of the box plots show the range between the maximum and the minimum biases. The boxes and the lines within the boxes indicate the 25th to 75th percentile range and the median, respectively. Green plots indicate the deviations of six observation data from the reference data. The other plots indicate the model bias in the full set of 50 CMIP5 model set (black), the model sets with a bias with is less than the 50th percentile of biases of the full set (yellow), the model sets with Taylor's skill score with is larger than the 50th percentile of the scores of the full set (orange), and the model sets selected for ISIMIP (blue) and CORDEX (red).**

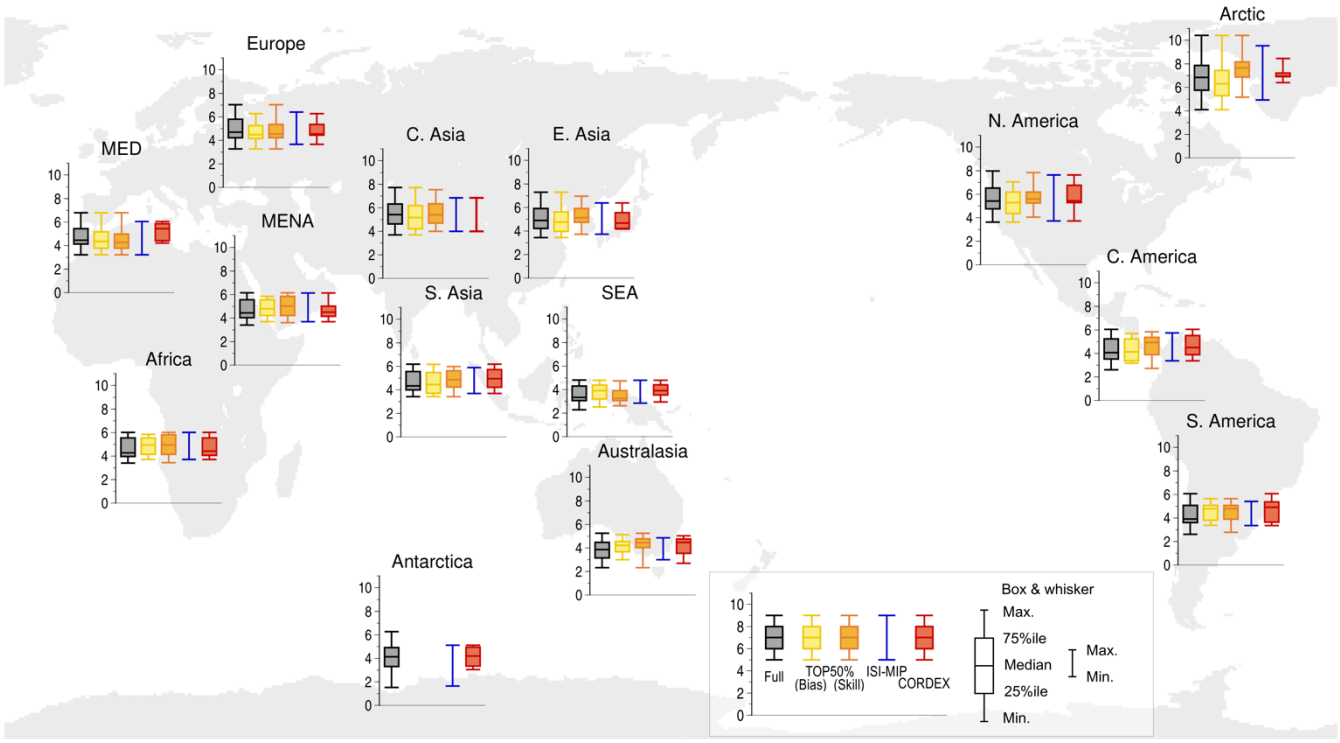



**Figure 2: Annual mean temperature increments in the future climate projection (K). The whiskers of the box plots show the range between the maximum and the minimum biases. The boxes and the lines within the boxes show the 25th to 75th percentile range and the median, respectively. Box plots indicate the model bias in the full set of 42 CMIP5 models (black), the model sets with the top 50% of the CMIP5 models for the bias (yellow) or Taylor's skill score (orange), and the model sets selected for ISIMIP (blue) and CORDEX (red). The top 50% of the CMIP5 models cannot be plotted over Antarctica because of missing the CRU reference data.**

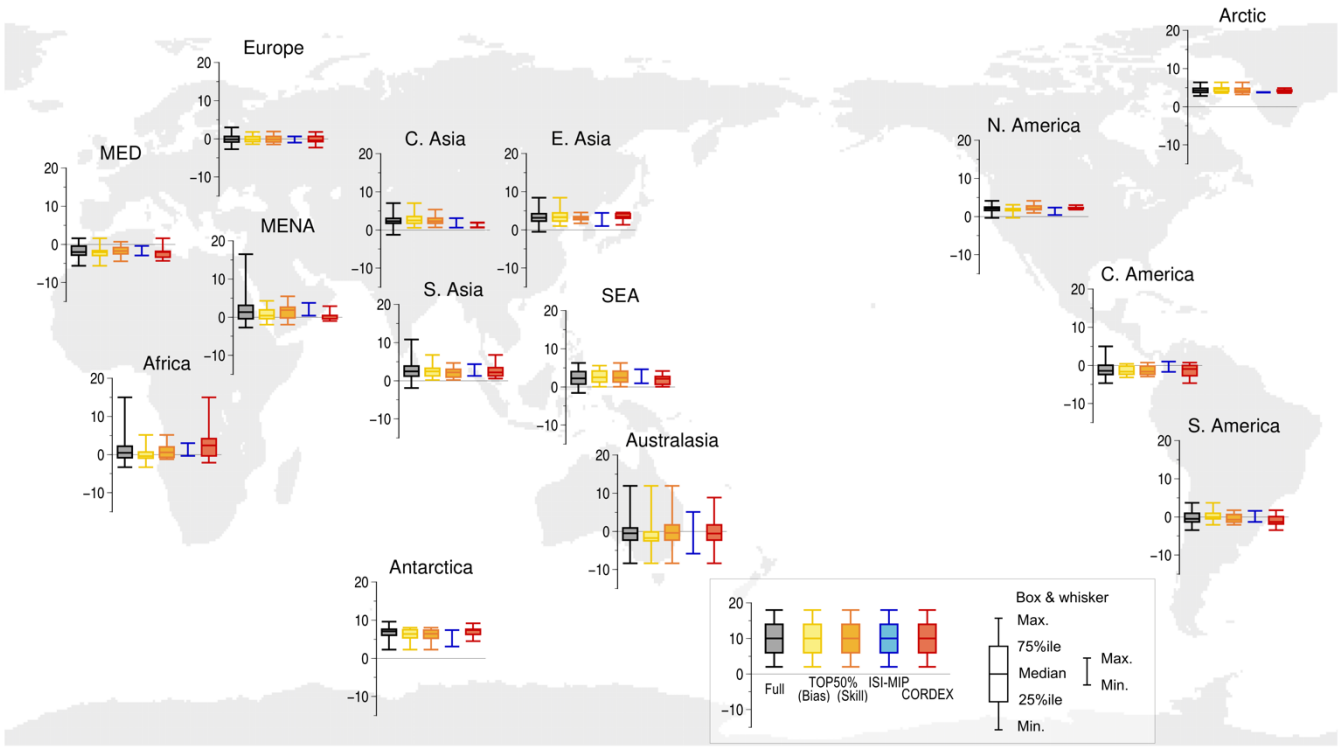



**Figure 3: As for Figure 2, but for the projected change in annual mean precipitation scaled to the regional mean temperature increment over the land (% $K^{-1}$).**

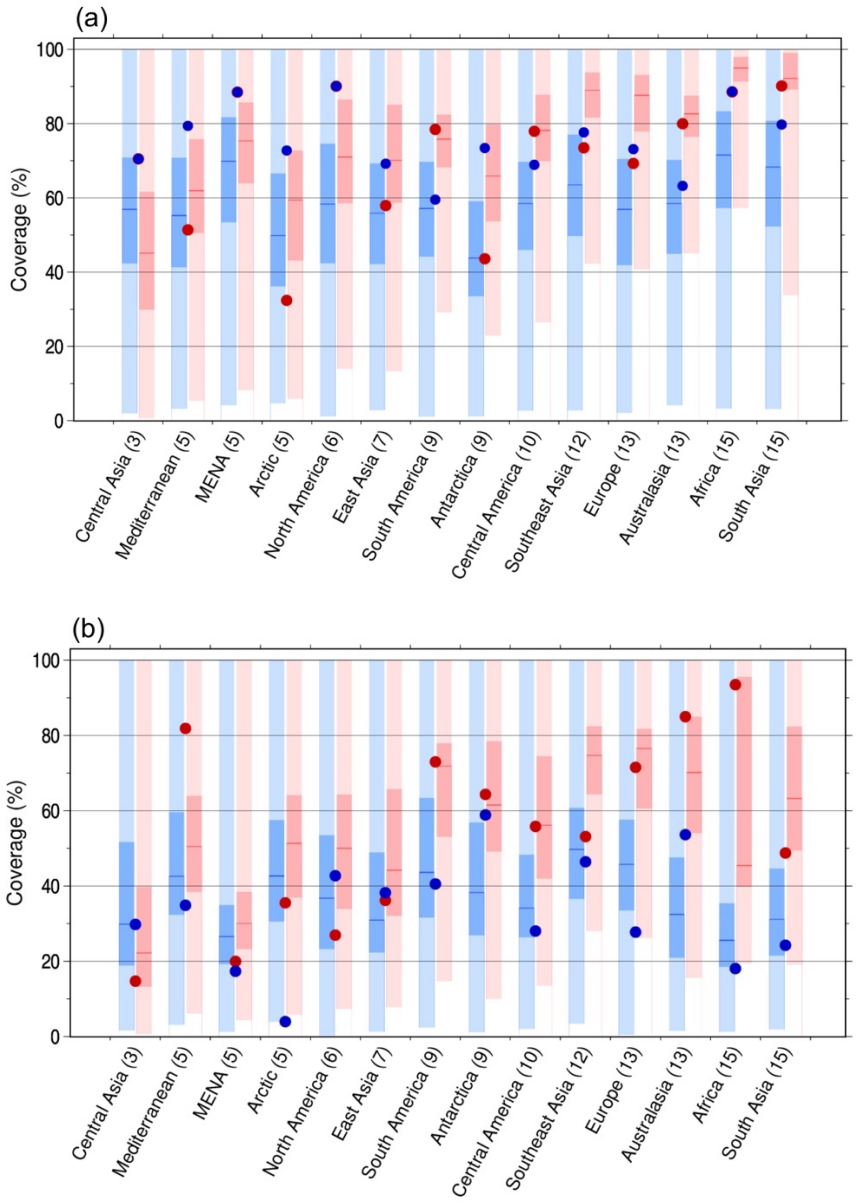
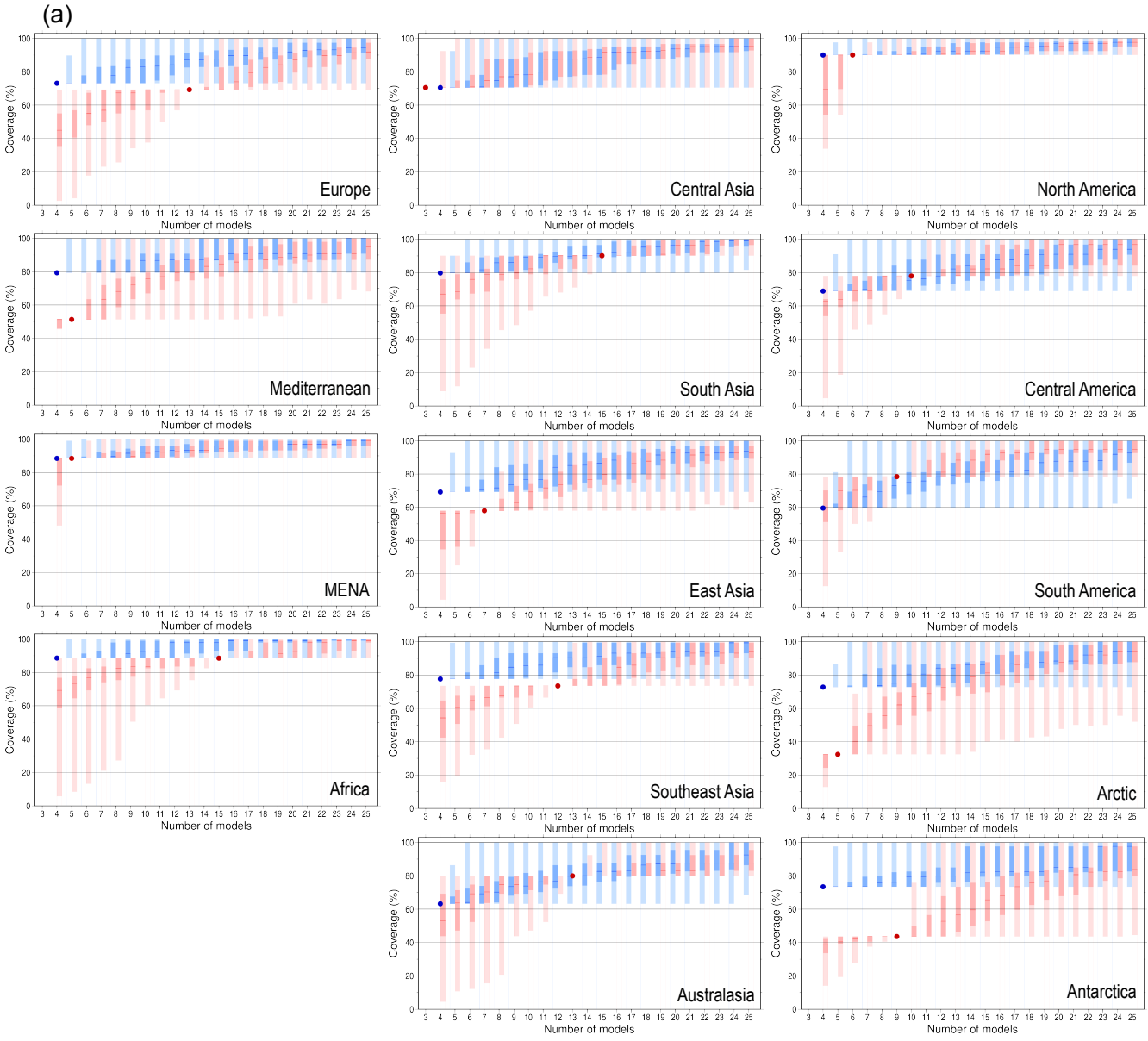



**Figure 4: Coverage performance of the ISIMIP and CORDEX subsets compared with the range of the full set of CMIP5 models for (a) annual mean temperature increment and (b) precipitation change scaled to the regional mean temperature increment. Blue and red dots indicate the coverage in ISIMIP and CORDEX, respectively for each region. Blue bars indicate the spread of coverage (FRA) when four models, as in ISIMIP, are selected randomly in 10,000 times. Red bars indicate the spread when randomly selecting the same number of models as in CORDEX; e.g., 10 models in Central America. The full range of the coloured bars indicates the minimum to maximum coverage. Dark blue and red bars indicate the 25th to 75th percentile range of the FRA spread. Horizontal lines in the dark blue and red regions indicate the median. Numbers in parentheses are the number of models used in CORDEX. The ISIMIP and CORDEX coverages in (a) overlaps in MENA, N. America and Africa.**


(a)
Europe
Central Asia
North America
Mediterranean
South Asia
Central America
MENA
East Asia
South America
Africa
Southeast Asia
Arctic
Australasia
Antarctica
Coverage (%)
Number of models

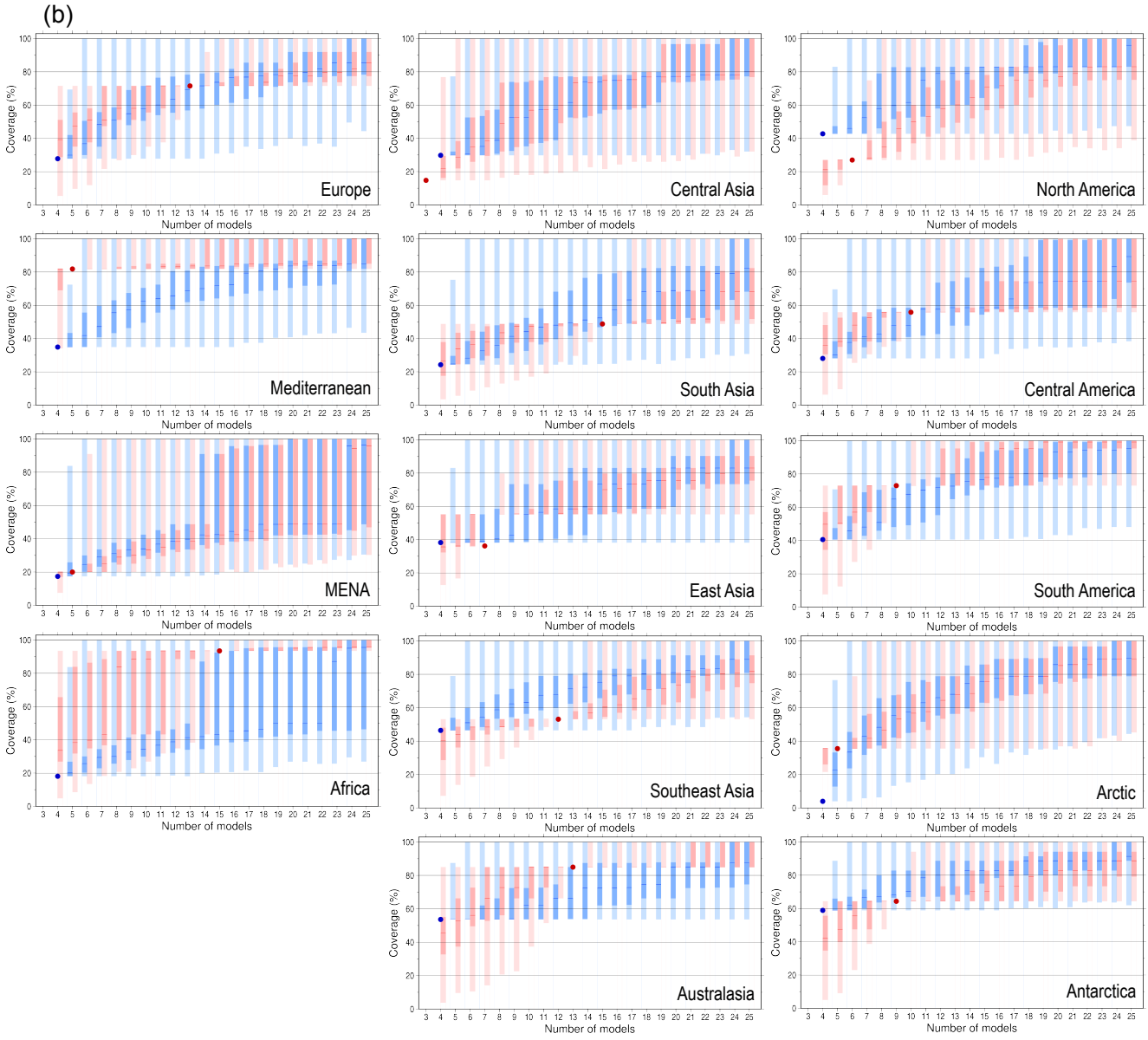
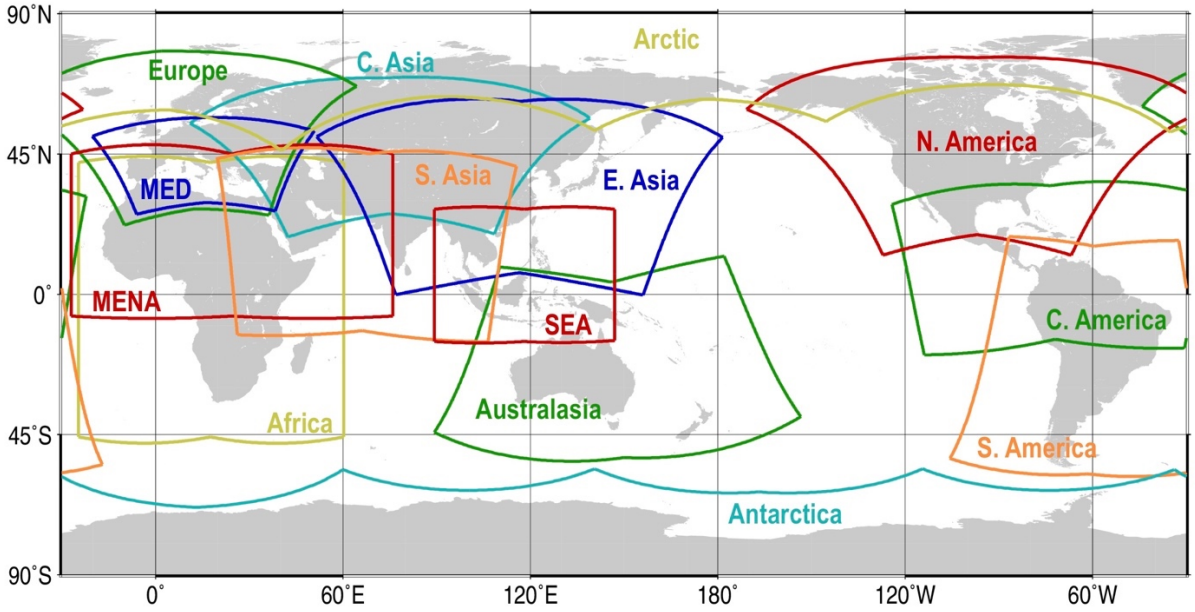



**Figure 5: Change of coverage performance of the ISIMIP and CORDEX subsets depending on the numbers of selected models in each region for (a) annual mean temperature increment and (b) precipitation change scaled to the regional mean temperature increment. As in Fig. 4 but the *x*-axis denotes the number of selected models.**

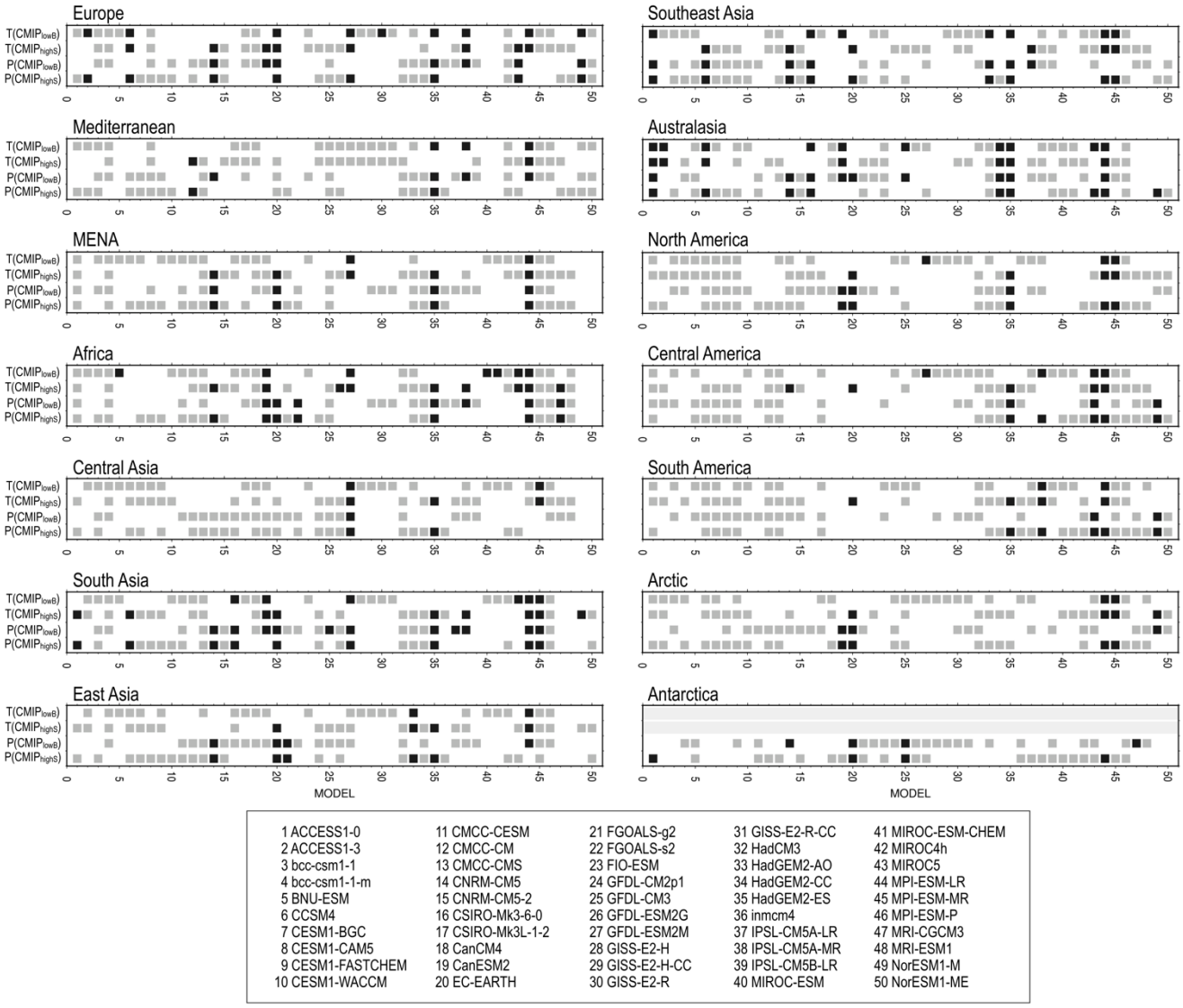
**Supplement 1: List of CMIP5 GCMs used in CORDEX.**

| Model / Region | North America | Central America | South America | Europe | MED | MENA | Africa | Central Asia | East Asia | South Asia | SEA | Australasia | Arctic | Antarctica |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| ACCESS1-0 | | | | | | | | | | ○ | ○ | ○ | | ○ |
| ACCESS1-3 | | | | ○ | | | | | | | | ○ | | |
| BNU-ESM | | | | | | | ○ | | | | | | | |
| CCSM4 | | | | ○ | | | | | | ○ | ○ | ○ | | ○ |
| CMCC-CM | | | | | ○ | | | | | | | | | |
| CNRM-CM5 | | ○ | | ○ | ○ | ○ | ○ | | ○ | ○ | ○ | ○ | | ○ |
| CSIRO-Mk3-6-0 | | ○ | ○ | ○ | | | | | | ○ | ○ | ○ | | |
| CanESM2 | ○ | ○ | ○ | ○ | | | ○ | | | ○ | ○ | ○ | ○ | |
| EC-EARTH | ○ | ○ | ○ | ○ | | ○ | ○ | | ○ | ○ | ○ | ○ | ○ | ○ |
| FGOALS-g2 | | | | | | | | | ○ | | | | | |
| FGOALS-s2 | | | | | | | ○ | | | | | | | |
| GFDL-CM3 | | | | | | | | | | ○ | | ○ | | ○ |
| GFDL-ESM2G | | | | | | | ○ | | | | | | | |
| GFDL-ESM2M† | ○ | ○ | ○ | ○ | | ○ | ○ | ○ | | ○ | | | | |
| GISS-E2-R | | | | ○ | | | | | | | | | | |
| HadGEM2-AO | | | | | | | | | ○ | | ○ | | | |
| HadGEM2-CC | | | | | | | | | | | | ○ | | |
| HadGEM2-ES† | ○ | ○ | ○ | ○ | ○ | ○ | ○ | ○ | ○ | ○ | ○ | ○ | | ○ |
| IPSL-CM5A-LR† | | | | | | | | | | ○ | ○ | | | |
| IPSL-CM5A-MR | | ○ | ○ | ○ | ○ | | ○ | | | ○ | | | | |
| MIROC-ESM | | | | | | | ○ | | | | | | | |
| MIROC-ESM-CHEM | | | | | | | ○ | | | | | | | |
| MIROC5† | | ○ | ○ | ○ | | | ○ | | | ○ | | ○ | | |
| MPI-ESM-LR | ○ | ○ | ○ | ○ | ○ | ○ | ○ | | ○ | ○ | ○ | ○ | ○ | ○ |
| MPI-ESM-MR | ○ | | | | | | | ○ | | ○ | ○ | | ○ | |
| MRI-CGCM3 | | | | | | | ○ | | | | | | | ○ |
| MRI-AGCM60 | | | | | | | | | ○ | | ○ | | | |
| NorESM1-M | | ○ | ○ | ○ | | | ○ | | | ○ | | ○ | ○ | ○ |

† denotes the ISIMIP2b model.

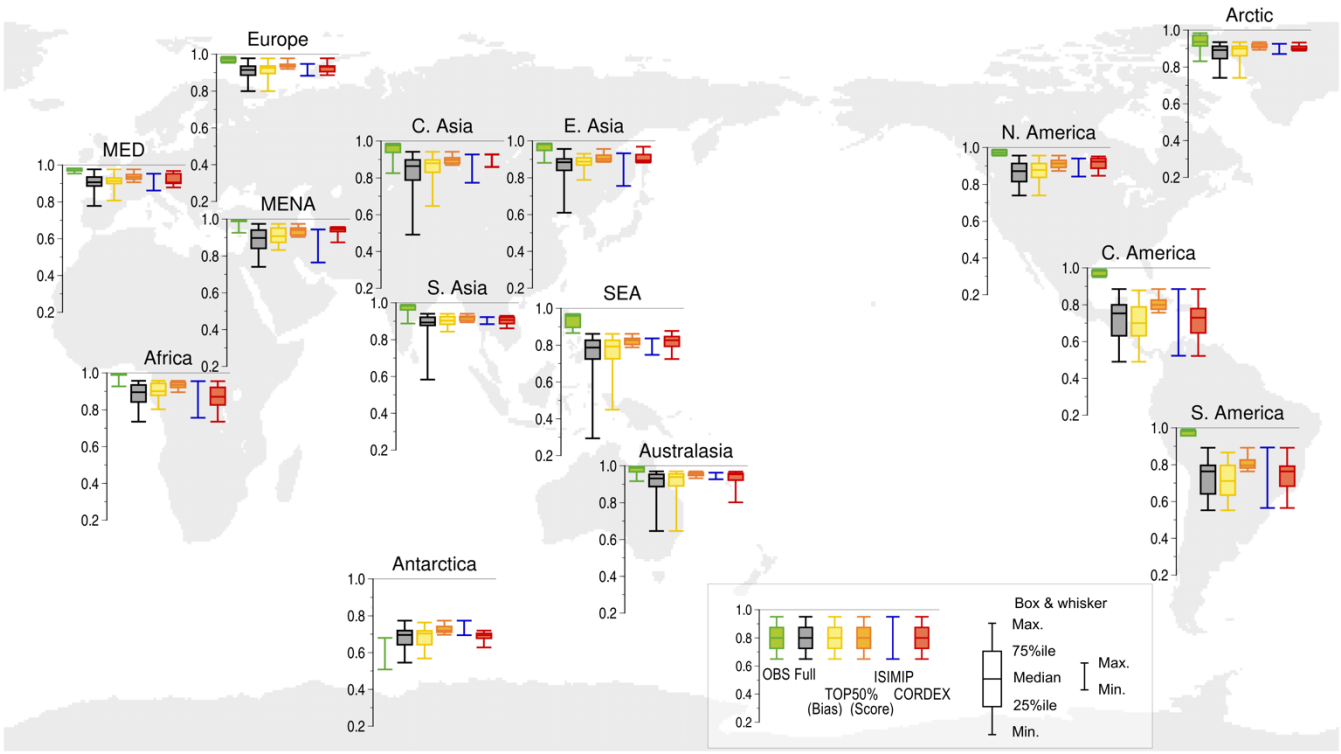



**Supplement 2: Regional classification defined in CORDEX. (Coordinate information is available from: http://www.cordex.org/domains/; last accessed 8 Nov. 2018).**

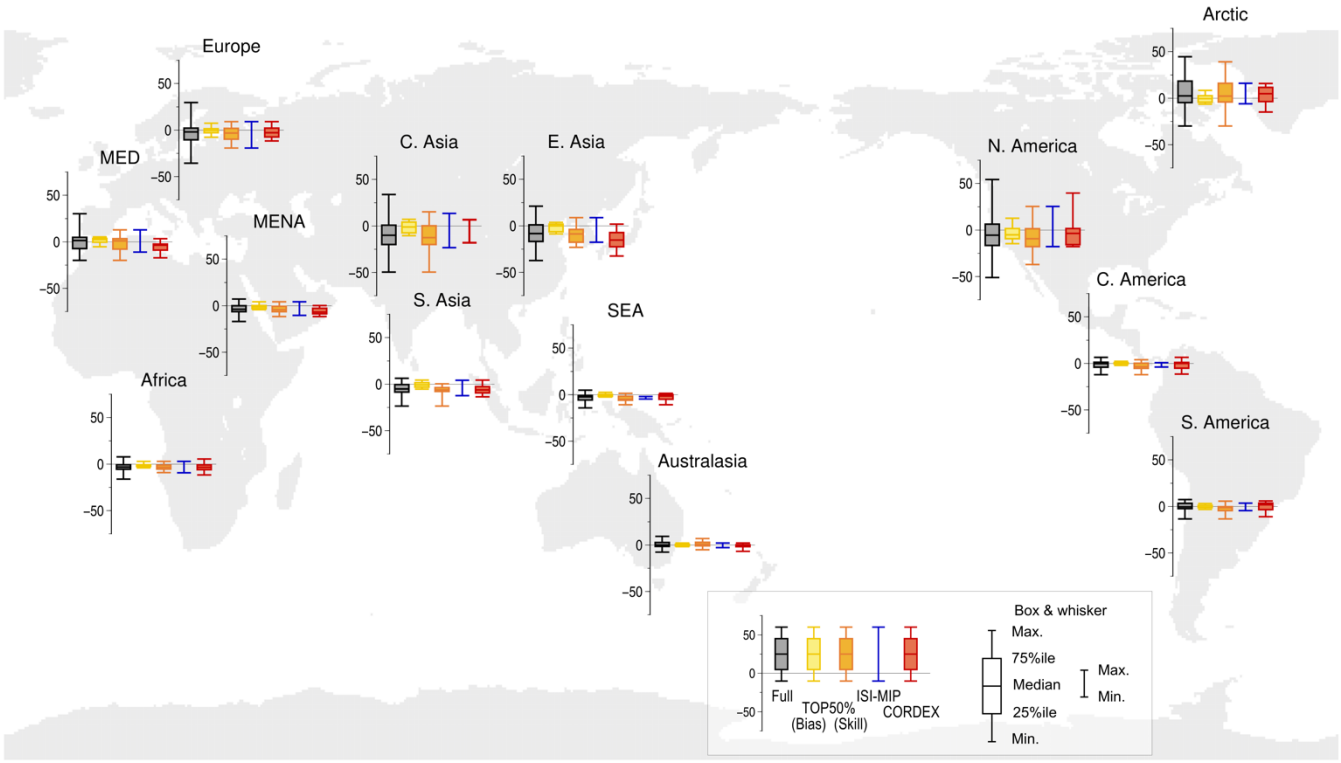



| | | | | |
|---|---|---|---|---|
| 1 ACCESS1-0 | 11 CMCC-CESM | 21 FGOALS-g2 | 31 GISS-E2-R-CC | 41 MIROC-ESM-CHEM |
| 2 ACCESS1-3 | 12 CMCC-CM | 22 FGOALS-s2 | 32 HadCM3 | 42 MIROC4h |
| 3 bcc-csm1-1 | 13 CMCC-CMS | 23 FIO-ESM | 33 HadGEM2-AO | 43 MIROC5 |
| 4 bcc-csm1-1-m | 14 CNRM-CM5 | 24 GFDL-CM2p1 | 34 HadGEM2-CC | 44 MPI-ESM-LR |
| 5 BNU-ESM | 15 CNRM-CM5-2 | 25 GFDL-CM3 | 35 HadGEM2-ES | 45 MPI-ESM-MR |
| 6 CCSM4 | 16 CSIRO-Mk3-6-0 | 26 GFDL-ESM2G | 36 inmcm4 | 46 MPI-ESM-P |
| 7 CESM1-BGC | 17 CSIRO-Mk3L-1-2 | 27 GFDL-ESM2M | 37 IPSL-CM5A-LR | 47 MRI-CGCM3 |
| 8 CESM1-CAM5 | 18 CanCM4 | 28 GISS-E2-H | 38 IPSL-CM5A-MR | 48 MRI-ESM1 |
| 9 CESM1-FASTCHEM | 19 CanESM2 | 29 GISS-E2-H-CC | 39 IPSL-CM5B-LR | 49 NorESM1-M |
| 10 CESM1-WACCM | 20 EC-EARTH | 30 GISS-E2-R | 40 MIROC-ESM | 50 NorESM1-ME |

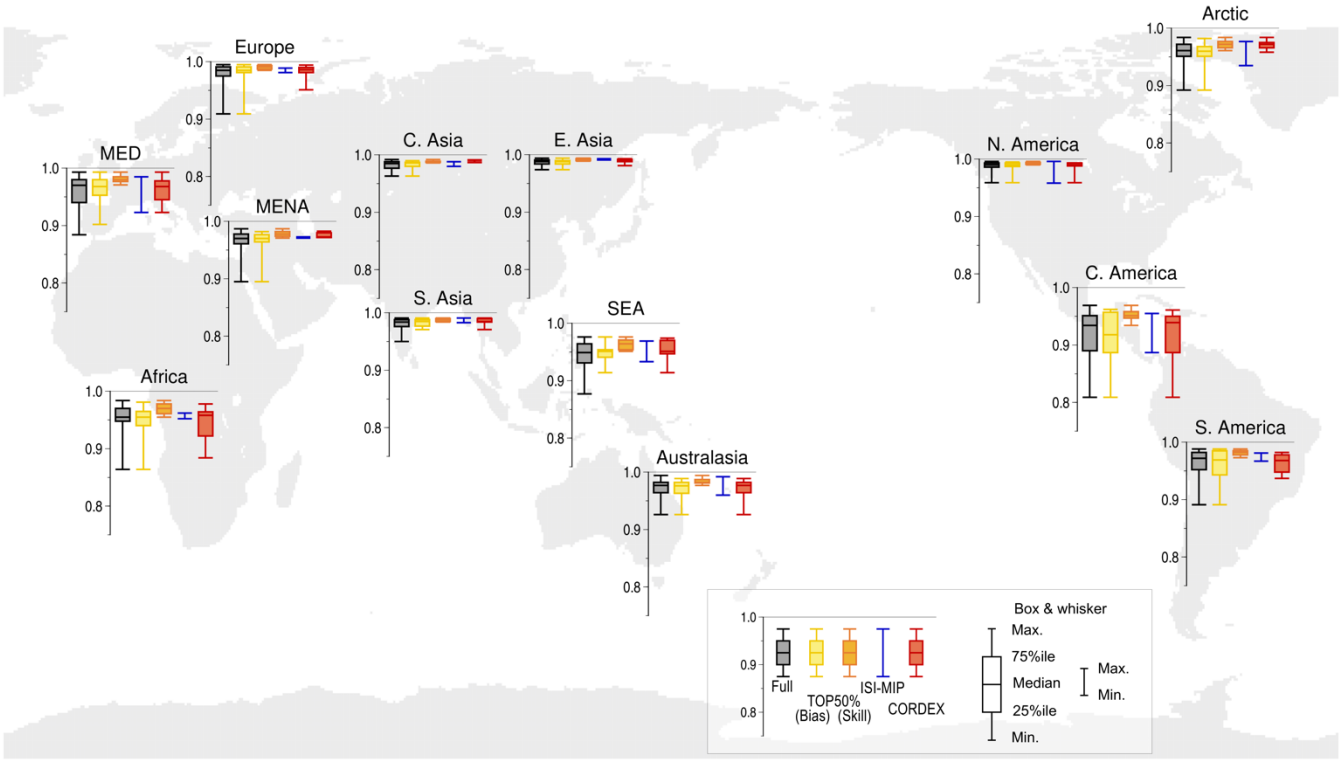
**Supplement 3: Models with the top 50% of the CMIP5 models for the model bias and Taylor's skill score in each CORDEX region. The numbers on the x-axis correspond to the individual model number in the bottom box. The y-axis denotes the models with low bias and with high score for temperature (T(CMIP$_{lowB}$) and T(CMIP$_{highS}$)) and for precipitation (P(CMIP$_{lowB}$) and P(CMIP$_{highS}$)) from the upper to the bottom. Gray square indicates the models fits the condition on the y-axis and black square indicates the inclusion in the CORDEX subset. Light gray bar in Antarctica indicates the missing data because of missing the CRU reference data.**




**Supplement 4: Skill score for annual mean model precipitation over land. Reference data are from GPCC. The whiskers of the box plots show the range between the maximum and the minimum biases. The boxes and the lines within the boxes indicate the 25th to 75th percentile range and the median, respectively. Green plots indicate the spread of the score of six observed data; CRU, CPC, PRECL, CMAP, GPCP 1dd and MSWEP. The other plots indicate the model bias in the full set of 50 CMIP5 model set (black), the model sets with the top 50% of the CMIP5 models for the bias (yellow) or Taylor's skill score (orange) and the model sets selected for ISIMIP (blue) and CORDEX (red).**




**Supplement 5: Annual mean model temperature bias over land (K). Reference data are from CRU TS. The whiskers of the box plots show the range between the maximum and the minimum biases. The boxes and the lines within the boxes show the 25th to 75th percentile range and the median, respectively. The other plots indicate the model bias in the full set of 50 CMIP5 model set (black), the model set with the top 50% of the full set for the bias (yellow) or Taylor's skill score (orange), and the model sets selected for ISIMIP (blue) and CORDEX (red). The top 50% of the CMIP5 models cannot be plotted over Antarctica because of missing the CRU reference data.**




5

**Supplement 6: As for Supplement 4, but for the skill score for the annual mean model temperature over land.**