Reply RC2

RC2: 'Comment on esd-2021-43', Anonymous Referee #2, 25 Jul 2021
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Climate change in the High Mountain Asia in CMIP6

Mickaël Lalande et al. (https://esd.copernicus.org/preprints/esd-2021-43/#discussion)

Review Comments

We thank referee #2 for having accepted to review this paper and for his constructive comments.

Specific comments

Comments of reviewers are displayed in *italic,* replies are in normal text and when additional text is added within a paragraph (between quotation marks), it is shown in **bold**.

1. *Introduction, L35: "As a large mid-tropospheric heat source…" The role of the Tibetan Plateau as a heat source for monsoon is a debated topic. Authors may refer to Boos and Kuang (2010; Dominant control of the South Asian monsoon by orographic insulation versus plateau heating. Nature 463, 218–222 (2010). https://doi.org/10.1038/nature08707)*

L35: "**The Asian summer monsoon provides almost 80~\% of the annual precipitation in the central and eastern parts of the Himalayas during the monsoon season (June-September) \citep{Bookhagen2010, Palazzi2013, Sabin2020}. Several studies suggested that the geographical configuration of the TP was enhancing the triggering of the Asian monsoon, this dry area acting as a heat source transferred to the mid-troposphere directly enhancing the vertical uplift typically found at the start of the summer monsoon** \citep{Li1996, Wu1998, Yihui2005, Wu2012}**. This finding has been partly questioned in other studies suggesting that the Himalayan chain is insulating the warm and moist air found over the Indian subcontinent from the cold areas found in TP \citep{Boos2010}. Therefore, the Himalaya itself and not the TP seems to be an essential geographical feature that favors vertical uplifts of warm and moist air masses, mainly on its southern flank.**"

2. *Taylor diagram is a useful tool in multi-model inter-comparison, especially when the models are compared with respect to the observations. I suggest that the authors use Taylor diagrams to compare temperature, precipitation, snow cover, etc. simulated by the models.*

The following Fig. X will be added in Section 3.5 (Metrics).

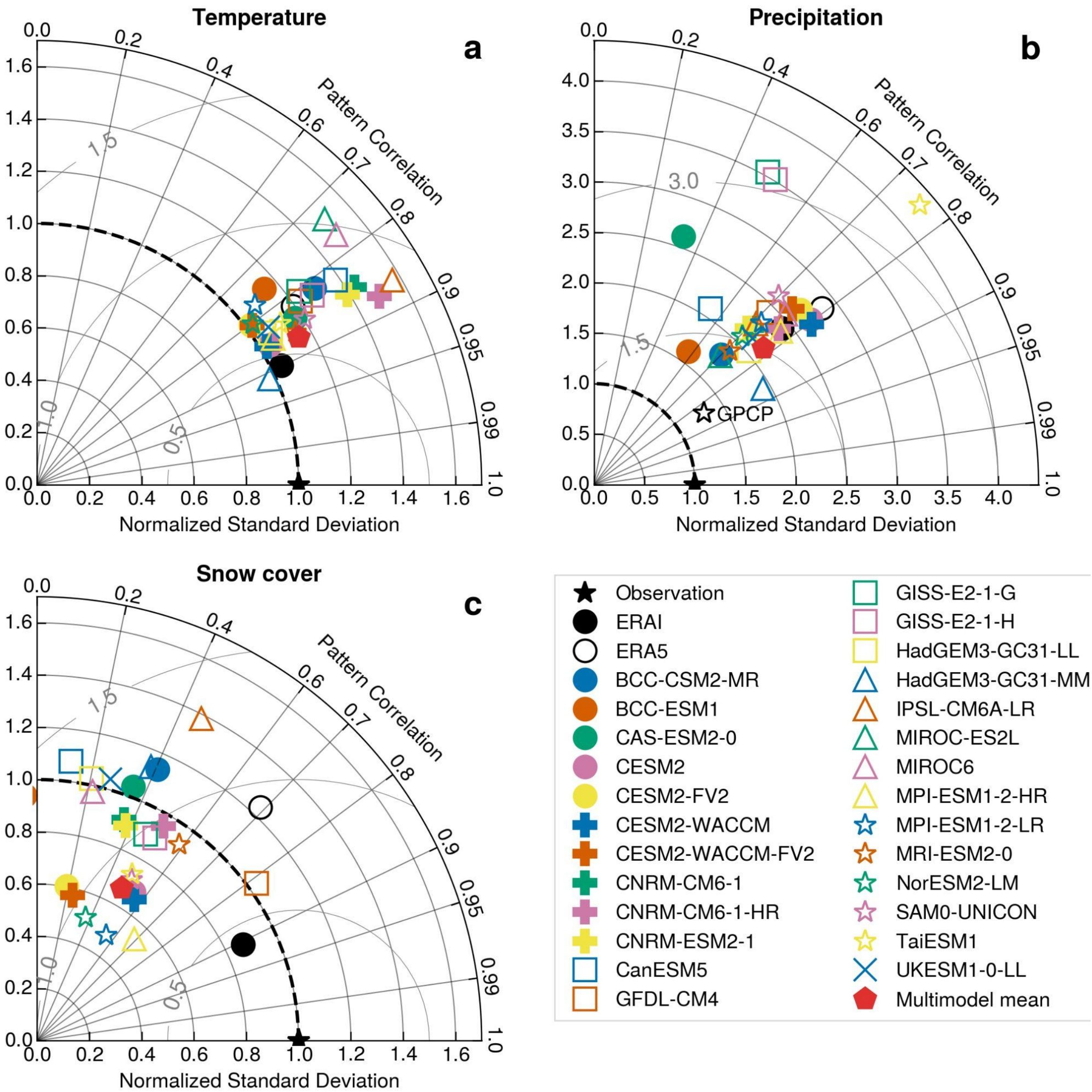

Figure X. Taylor diagram showing for the 26 models over HMA the 1979-2014 mean of the spatial pattern of temperature (a), precipitation (b) and snow cover (c). The observational reference is shown with a black star corresponding to CRU (temperature), APHRODITE (precipitation) and NOAA CDR (snow cover extent). ERA-Interim and ERA5 are shown with the black circles filled and non-filled respectively. The red pentagons correspond to the multimodel mean. The radial distance from the origin is proportional to the area-weighted standard deviation of the spatial pattern (normalized by the observation standard deviation). The area-weighted normalized centered RMSE between the model and the reference is proportional to the distance from the black star (light gray semi-circles). The area-weighted pattern correlation coefficient between the two fields is given by the azimuthal position.

After L360:

"The Taylor diagram (Taylor 2001) shown in Fig. X is used to investigate the realism of the spatial variability simulated in the models as compared to observational references. Overall, the models perform better for temperature than for precipitation, whereas the model skill is even

smaller for snow cover. The pattern correlation (PCC) ranges from 0.7 to 0.9 for temperature, whereas it takes lower values for precipitation varying from 0.6 to 0.8 for most of the models, except for HadGEM3-GC31-MM for which it reaches 0.9 and for 5 other models showing a lower PCC below 0.6. For snow cover, the model PCC is even lower and also heterogeneous among the models, varying from negative values (-0.17 for MIROC-ES2l) to a maximum of 0.8 (GFDL-CM4). Overall, the spatial variance is higher for almost all the models as compared to observations for both the temperature (the normalized standard deviation reaching 1.5 for the worst model) and the precipitation (the normalized standard deviation exceeding 4 for the worst model). This is the contrary for snow cover, a variable for which the models show smaller spatial heterogeneities in comparison to the observational reference, with a normalized standard deviation generally lower than 1, and varying between 0.4 and 1.4 for all the models. The larger temperature standard deviation found for the models is partly explained by the general cold bias over HMA that enhances the temperature contrast between the high elevation areas and the surrounding plains. The excess of precipitation found in the models over the area located under the influence of the Asian monsoons also explains the high standard deviation found in the models for this variable. In contrast, the low standard deviation found in the model for the snow cover is likely related to the too extended and too homogeneous snow cover over TP and its surrounding mountains, while the TP in observations is most often free of snow. Another interesting point is that both ERA-Interim and ERA5 do not perform much better than the CMIP6 models (except ERA-Interim for temperature and snow cover likely due to IMS snow cover assimilation over HMA), suggesting general weaknesses in the models used commonly for climate modeling and for the production of atmospheric reanalysis. While the multimodel mean is having intermediate performances among the models.”

L361

“**Overall, it is challenging to discard any model from this spatial analysis, as well as RMSE and bias metrics, because of both a large heterogeneity of skill found among the models and a skill that varies also from one variable to another one for the same model.** This finding suggests [...]”

3. *Figure 6.: I suggest that the authors can try showing the agreement among the models in the sign of the trend in this figure. The hatching is often used to show statistically significant trends and not otherwise. Authors may try using contours for not significant trends, shading for significant trends, and hatching for points where > 60 % of the models agree on the sign of the trend.*

Here is the modified version of Fig. 6 taking into account the suggestions of the comment 3. The threshold for the points where the models agree on the sign of the trend is set to 80 % in order to show the robustness of the trends (because 60% showed too many hatched areas including quite a lot of areas where the multimodel mean trends were non-significant).

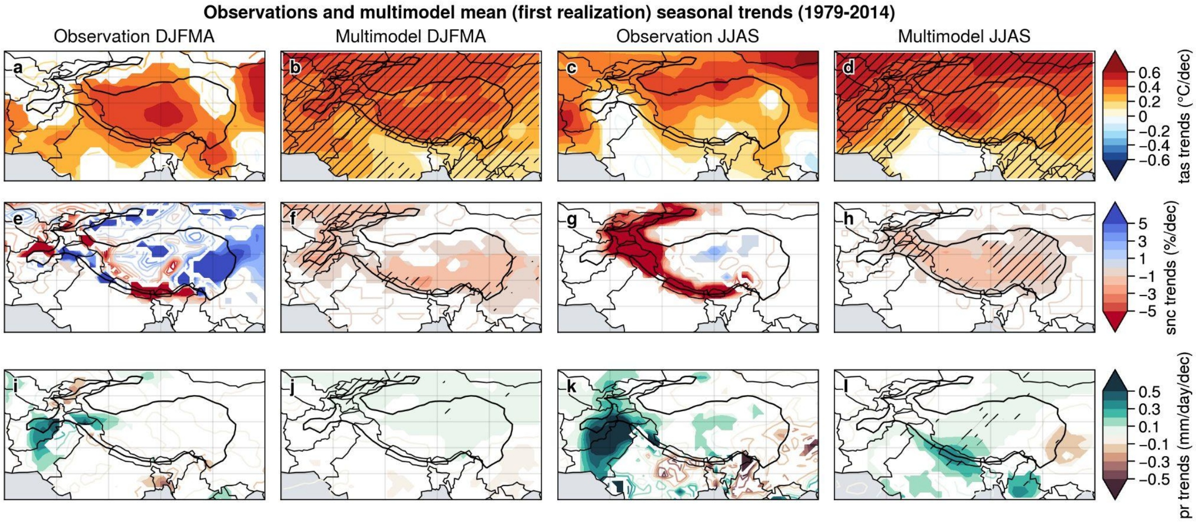

Figure 6. DJFMA (left) and JJAS (right) trends computed over 1979-2014 for temperature (a-d), snow cover (e-h) and precipitation (i-l). CRU temperature, NOAA CDR snow cover and APHRODITE precipitation observations trends (DJFMA: a, e, i and JJAS: c, g, k) are compared to the multimodel mean computed with the first realization for each model (DJFMA: b, f, j and JJAS: d, h, l). **Contours are used for not significant trends, shading for significant trends (p-value < 0.05), and hatching for points where > 80 % of the models agree on the sign of the trend.**

We will similarly modify Figures D3-5 and adapt the text in Sect. 4.1 (Trends) to reflect these changes.

4. *Figure 9: "2081-2010" in the caption should be 2081-2100".*

Thanks for noticing that, we corrected it!