Answer to RC1:

Review of “Cloud properties and their projected changes in CMIP models with low/medium/high climate sensitivity”

by Lisa Bock and Axel Lauer

This paper presents an intercomparison of the simulation of clouds in the CMIP5 and CMIP6 multi-model ensembles. The models are grouped in three different categories: low, medium and high Effective Climate Sensitivity. In general, high-sensitivity models tend to perform better in the metrics analysed in this study. The paper is well written and the content is adequate for publication in ACP. It provides a valuable intercomparison, making it a useful addition to the scientific literature, and I recommend publication subject to minor revision. Please see my specific comments below.

We thank Reviewer #1 for the constructive comments that helped improving the manuscript. We think we addressed all comments in the revised version and in our point-by-point answers below (given in bold). If not otherwise noted, all line numbers refer to the “track changes” version of the revised manuscript.

GENERAL COMMENTS

I believe the results need to be put in the context of other intercomparisons that use different types of metrics. Studies like Brunner at al. (2020) reach very different conclusions by using a metrics that incorporate information about trends. I think this different approach needs to be critically discussed.

Following the suggestion of the reviewer, we added a paragraph about relevant studies using different approaches and metrics.
Lines 59-64: “The performance of CMIP models has also been investigated in other studies. For example, Kuma et al. (2023) applied an artificial neural network to derive cloud types from radiation fields. They found that results from models with a high ECS agree on average better with observations than from models with a low ECS. Jiang et al. (2021) found that the models’ ECS is positively correlated with the integrated cloud water content and water vapor performance scores for both CMIP6 and CMIP5 models. In contrast, Brunner et al. (2020) showed that some CMIP6 models with high future warming compared to other models receive systematically lower performance weights when using anomaly, variance, and trend of surface air temperature, and anomaly and variance of sea level pressure to assess the models’ performance. ”

A more detailed description of the caveats in the comparisons of the IWP is needed. The model variable used (clivi) includes precipitating frozen hydrometeors only if the precipitating hydrometeor is seen by the model's radiation code. This is model-dependent and can introduce significant biases in the comparisons. Also, I wonder if the observational datasets chosen are representative of the diversity in observational estimates. Both ESACCI and MODIS are based on passive retrievals, and therefore will share similar caveats and biases (Waliser et al., 2009). I'd suggest using an alternative reference dataset based on a different remote sensing technology like CloudSat.

Thanks for pointing that out. We changed the alternative measurement of iwp and lwp in Fig. 3 for the pattern correlation to the CloudSat dataset. We used the same version as Lauer et al. (2023), who excluded precipitating columns to estimate cloud water path values with no precipitating particles.

To highlight the observational uncertainties, we added:
Lines 175-180: "For cloud ice and cloud liquid water path the pattern correlations between ESACCI Cloud (passive instrument) and the alternative measurements of CloudSat (active instrument) show the large uncertainties of these quantities derived from satellite observations (e.g., Lauer et al., 2023). An additional uncertainty in this comparison is introduced, as some CMIP models may provide the sum of cloud ice and falling ice (e.g. snow) in the ice water path values if the falling ice is included in their radiation calculations. The number of models including falling ice radiative effects, however, is rather small and thus not expected to play an important role in the group means. An overview can be found e.g. in Li et al. (2020a), their Table 1."

SPECIFIC COMMENTS

-L41-42: there are other studies that looked into the reasons for the increased in sensitivity in specific models, like Gettelman et al. (2019) and Bodas-Salcedo et al. (2019). It's worth noting that coupled feedbacks (e.g. sea-ice albedo) can play a significant role in some models (Andrews et al., 2019).

As suggested, we added these citations and now mention also connections to other coupled feedbacks.
Lines 47-49: "They also point out that the simulated present-day mean state of cloud properties is correlated with the simulated cloud feedback but could also be connected to other coupled feedbacks (Andrews et al., 2019)."

- Table 2. Please specify which CERES-EBAF version you've used. Also, the reference for ERA5 is missing.

We added the version of CERES-EBAF (Ed4.2) to Table 2 and fixed the citation entry of ERA5.

REFERENCES

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