We thank the editor for their helpful comments for improving our manuscript. The editor's comments are shown in **bold**, with responses below in standard font, and lines noted in the latexdiff manuscript where relevant changes have been made in *italics.*

1) The calculation of PM2.5 from models with vastly different size distributions and representations of super coarse dust is quite uncertain. Please caveat your description of this calculation "In cases where the CMIP6 models do not provide PM2.5 directly, we calculate it from speciated mass-mixing ratios at the surface, following Turnock et al. (2020): PM2.5 = BC + SO4 + OA + (0.25 × SS) + (0.1 × DU)" accordingly and discuss potential errors.

Discussion added *(lines 247- 264)*, reflecting:

- Inconsistency between models, i.e. having to calculate PM2.5 for some, some having PM2.5 calculated from size distributions, and others performing postprocessing to calculate PM2.5 using methods similar to above to output PM2.5, makes comparison harder.
    - Models for which PM2.5 could be calculated using equation above were included to improve range of model behaviour discussed.
- Calculation for PM2.5 depends on assumptions about size distribution of individual aerosol species.
- Biases in concentrations for MMRs cause biases in PM2.5.
- Some of Turnock et al (2020)'s evaluation:
    - Areas of strong dust emissions are associated with larger diversity across CMIP6 models, noting the Saharan region as an area of high uncertainty.
    - Outside of these dusty regions CMIP6 models are relatively similar in their simulation of PM2.5 concentrations.
    - Small model bias in PM2.5 concentrations across most regions, excluding oceans where there is higher model diversity,
        - Africa not included for that part of analysis.
    - Generally associated with underestimation of PM2.5 in most regions, likely because the PM2.5 calculation excludes nitrate aerosols.
- Largest source of model diversity for the majority of stations over Africa is differences in dust.
- Another important contributor to model diversity in calculated PM2.5 at coastal locations will be SS.
- No consistent negative or positive bias for models with calculated PM2.5 when compared to observations or models for PM2.5 output available.
    - But outputs from some models for PM2.5 may use similar postprocessing methods to produce PM2.5, so there may not be a clear distinction between models with and without PM2.5 outputs available.

2) Likewise, dust AOD is not directly observationally constrained in CAMS, so it would be good to briefly discuss related uncertainties.

Discussion added *(lines 167-180)*, noting that:

- Necessary to understand that speciated AOD evaluation is done in the context of substantial reanalysis uncertainty and disagreement.
    - Vogel et al (2022) has conducted a review comparing uncertainty in AOD across reanalysis, satellite retrieval, and CMIP model dataset, finding regional AOD from MMMs often fall outside of the range from satellite products, e.g., over North Africa.
    - However North Africa can be seen to be one of the regions of highest uncertainty in Vogel et al (2022).
    - CAMS performs well over Africa in this study, with weaker performance found over east Asia (and localized positive biases associated with volcanic activity Saturno et al (2018)).
- Accurate representation of dust AOD in reanalysis relies on simulation of correct concentration of dust relative to other aerosol species. Aerosol speciation is better represented in locations dominated by dust (e.g. the Sahara), likely to be less well represented in regions where different aerosol species coexist (e.g. northern India, with mixed dust, smoke, and anthropogenic aerosol).
- Dust processes in CAMS and MERRA2 are model-dependent and have associated uncertainties (Xian et al. (2020), Zhao et al. (2022)). Comparisons between models and the reanalyses presented should be interpreted with some caution.
- Dust is distinguished from non-dust aerosols based on fine-mode fraction, Ångström exponent, and single-scattering albedo (Song et al (2021), Inness et al (2019))

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