Response to the reviewers: Sensitivities of cloud radiative effects to large-scale meteorology and aerosols from global observations

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We thank the two anoymous reviewers for their careful reviews of the manuscript, their constructive criticism and overall positive evaluation. We have added the sentence: “We thank two anonymous reviewers for their valuable comments.” in the acknowledgements. In the following, comments by the reviewers are colored in black, our replies or comments are colored in blue.

Reviewer 1

General comments

This paper examines the sensitivity of cloud radiative effects (CREs) to a wide range of cloud-controlling factors and aerosol proxies using ridge regression models. The trained models are skillful in predicting both shortwave and longwave CREs, enabling further sensitivity analysis of CREs to different cloud-controlling factors, such as main low-cloud controls, three-dimensional wind fields, and various aerosol proxies.

Overall, I find this paper to be well-written and to present interesting results. The use of ridge regression and aerosol proxies expands the traditional framework of cloud-controlling factor analysis. Please see specific comments and technical corrections below.

Specific comments

Page 2, Introduction: Since this paper focuses on both the shortwave and longwave cloud radiative effect, it is recommended that the authors provide more background on the high-cloud feedback in addition to the low-cloud feedback.

We agree and have added the following sentence to the introduction:“The longwave or high-cloud feedback is also positive, where high clouds rise with warming temperatures, leading to a larger temperature differences between cloud top and the warming surface (Zelinka et al. 2010, Gettelman et al. 2016).”

Page 4, Line 15-20: To improve the paragraph's flow, please consider moving the sentence "Satellite observations from the polar-orbiting platform Terra are used" to line 20, before "Two commonly used proxies for CCNs ..."

Thanks for this suggestion, done.

Page 4, Line 29: What is meant by "single-layer reanalysis"? Does it refer to data at a single level? Please provide clarification.

With single-layer reanalysis we referred to the data set "ERA5 monthly data on single levels from 1940 to present". We now refer to this as "surface layer of the reanalysis" in the updated version of the manuscript.

Page 4, Line 30: Please consider adding references for ERA5 reanalysis and Merra-2 reanalysis. For example:

Hersbach, H., Bell, B., Berrisford, P., Hirahara, S., Horányi, A., Muñoz-Sabater, J., et al. (2020). The ERA5 global reanalysis. Quarterly Journal of the Royal Meteorological Society, 146(730), 1999–2049. https://doi.org/10.1002/qj.3803

Randles, C. A., Silva, A. M. da, Buchard, V., Colarco, P. R., Darmenov, A., Govindaraju, R., et al. (2017). The MERRA-2 Aerosol Reanalysis, 1980 Onward. Part I: System Description and Data Assimilation Evaluation. Journal of Climate, 30(17), 6823–6850. https://doi.org/10.1175/JCLI-D-16-0609.1

Thanks for pointing us to the QJRMS paper from Hersbach et al., this is a better reference than the one we used in the manuscript, and we now cite this in the updated version of the manuscript. We actually do cite Randles et al. (2017), though in the paragraph on the MERRA-2 reanalysis on page 6.

Page 5, Section 2.2: A few suggestions for this subsection:

The equation at line 10 is missing prime symbols in the parentheses?

No, this is the equation from Scott et al. (2020), ($\frac{\delta CRE}{\delta X_i}$) is the sensitivity.

To help the readers to appreciate the connection and difference between ordinary least square(OLS) regression and ridge regression, the authors might consider rewriting the first equation in terms of coefficient β (and also including the loss function). This way, when λ=0, it reduces to OLS.

We have decided to keep the equations as they are currently, but agree that it is helpful to more clearly point out the connections between OLS and ridge regression. We have thus made the following changes: added the case-specific sensitivity from equation 1 ("Ridge regression makes use of the L2 penalty: the squared magnitude of the coefficient (β, here: $\frac{\delta CRE}{\delta X_i}$)"), and added a sentence below equation 2: "When λ is set to 0, the penalty is 0 as well so that the ridge regression is essentially an ordinary least squares regression Hastie et al. (2021)."

The authors emphasized in the introduction that a benefit of ridge regression is providing robust estimation in the case of collinear predictors. It would be worthwhile to briefly explain why ridge regression can help with collinearity here.

We improved the text by being more specific by now stating: "In classical statistical techniques (e.g. OLS), collinearity frequently leads to high variance in the regression parameters (i.e. overfitting).", and "Ridge regression is a specific regularized linear model that has been shown to perform particularly well in the case of collinearity among the predictors (Dormann et al. 2013). ", and "A λ greater than 0 helps deal with collinearity by reducing model variance and in the case of many predictors thus provides more robust sensitivity estimates. "

Page 6, line 27: the authors state that the differences in predictive skill between the locally optimized and λ = 12 settings are negligible. And, it would be interesting to compare the predictive skill of the λ = 12 setting and that of the λ = 0.001 (-3 in log scale) setting. One way to demonstrate the superiority of ridge regression over OLS is to use a small penalty, such as λ = 0.001, and show that ridge regression is more skillful than OLS.

While the skill of the ridge regression models to predict CRE in the test data is only marginally worse when setting λ to 0.001 or to 0 (about 1% lower skill), the models that are regularized less or not at all tend to overfit by making use of large coefficients that cancel each other out. These coefficients are not physically plausible and do not agree with previous literature. Below this can be seen in the sensitivity of CRE_{SW} to SST (left) and EIS (right) when λ = 12 (paper, top), 0.0001 (middle) and 0 (bottom). In the case of $lambda$ = 0.0001 or 0, the EIS sensitivity is larger by a factor of $\approx$ 10, which is balanced by a physically implausible (and very noisy) SST sensitivity. We have added the following sentence to the manuscript: " While the skill to predict CRE in the test is only marginally improved when using ridge regression instead of an ordinary least squares regression (OLS), the OLS tends to fit very large, spatially noisy coefficients that are physically inconsistent (see supplementary Fig. A1). "

Page 8, line 1-5: what's the average skill over the Sc regime? How does it compare with the previous studies?

We have added the following sentence to the manuscript: "In the Sc regime the average prediction skill of CRE_{SW} is 0.55, which seems to be markedly higher than in Scott et al. (2020) and Wall et al. (2022), even though the exact regime-specific skill is not reported in their studies."

Page 8, lines 5-9: The authors attribute the low skills in simulating the Southern Ocean (SO) to the low quality of reanalysis data. However, are there other possible explanations? Is it possible that the factors controlling SO clouds are not well represented by this set of CCFs?

Yes, indeed - thanks for the valuable comment. We have added the following sentence to the manuscript: "A second possible reason for the low skill in this region maybe that the CCFs may not adequately capture the influence of the large day-to-day variability of synoptic-scale dynamics on clouds of this region Kelleher et al. (2019) at the monthly time scale. This is supported by findings from Jia et al. (2023), who use a machine learning framework to predict marine low cloud cover with a similar set of predictors at a daily time scale and achieve a notably high skill over the Southern Ocean." We have also included this in the discussion of CRE_{LW}: "Over the Southern Ocean, the assumed lower quality of the reanalysis data and the large influence of transient weather systems not being captured adequately at the monthly time scale may also contribute to the lower skill. "

Page 17, Line 9-10: It would be helpful to add references to discuss where sulfate would dominate CCN and where it would not.

We have added two sentences to address this, the text now reads: "Findings from McCoy et al. (2017) indicate that the variable spatial emissions of diffuse natural sources of sulfate (e.g. marine biogenic dimethylsulfide) are not as well captured by MERRA-2 as emissions from anthropogenic source regions, leading to a spatial variability in the quality of the MERRA-2 sulfate data. While sulfate aerosols dominate the aerosol optical depth signal in many regions of anthropogenic emissions, continental outflow regions and natural sources, it is not the main contributor in other regions (e.g. Southern Ocean, Li et al.

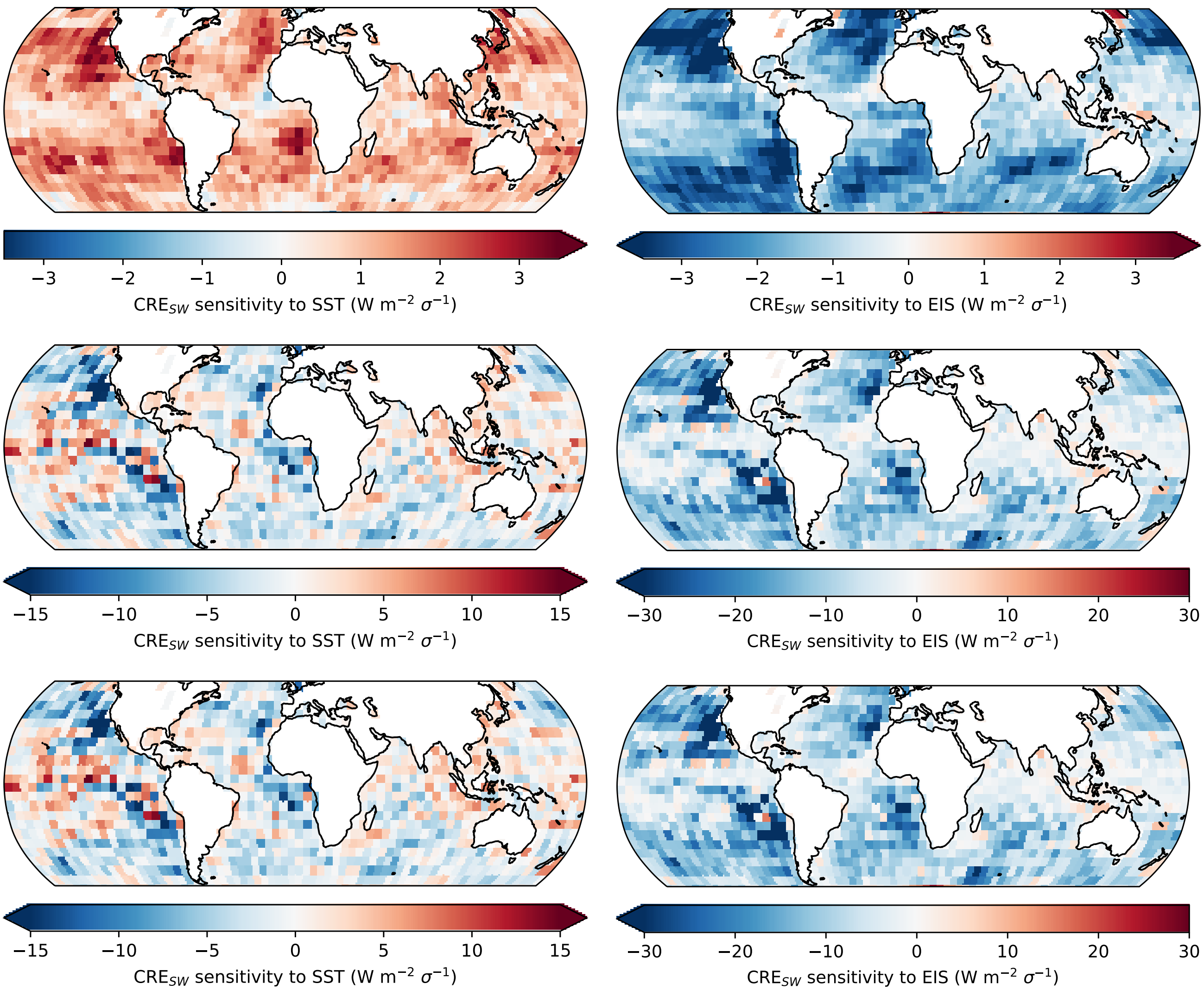

Figure 1. Sensitivity of CRE$_{SW}$ to SST (left) and EIS (right) with λ set to 12 as in the paper (top), to 0.0001 (middle) and 0 (OLS, bottom). Note the difference in the value range represented in the colorbars.

(2022)). In the regions where sulfate does not dominate CCN, $\log_{10}s$ is not expected to be a good proxy for CCN at cloud base."

Technical corrections

Page 1, Line 7: "CRE", please gives full name since this is the first appearance.

Done.

Page 1, Abstract: It would be helpful for the readers to include the time span and latitude range covered in this study.

Done.

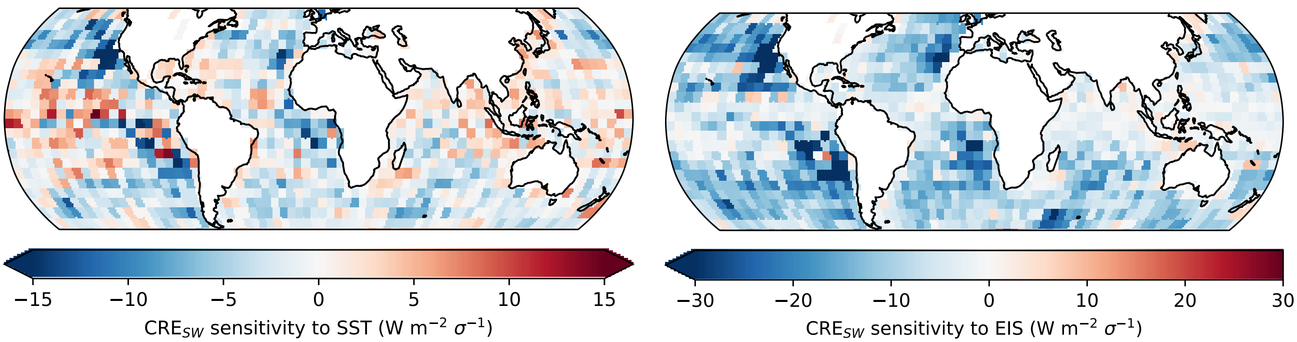

Figure 2. [New supplementary Fig. A1:] Sensitivity of CRE$_{SW}$ (left) and CRE$_{LW}$ (right) to SST (top) and EIS (bottom) with λ set to 0 (OLS) The regression models are overfitting to the training data resulting in much larger, noisy and (in the case of SST) physically inconsistent sensitivity patterns.

Page 2, Line 9: Please check the double quotation marks.

Thanks, the double quotation marks are now correctly formatted.

Page 4, Line 14: Please remove the s after CRE_{LW}.

Done.

Figure 1 (and other Figures): I noticed that some color bars in the figures have pointy ends while others are rectangular. If they indicate different meanings (e.g. some values have been clipped), please add a description in the figure caption (at least for Figure 1).

We have included the sentence “Pointy ends of the colorbars indicate that not the entire value range is shown in the figure to improve its clarity.” in the caption of Fig. 1.

Figure 2: In the figure caption, please specify that λ=12 was chosen.

We have included the following sentence in the caption: “To achieve comparable sensitivity estimates across different regions, the median λ value of 12 is chosen for the following analysis.”

Figure 3 & Table 1: In Figure 3, “ML” can be changed to “Ml” to be consistent with the table and the texts. It might help to give the full name in addition to the abbreviation.

Thanks for spotting, done.

Page 8, Line 1-10: Please mention Fig.4, where the results are from. The same is also true for Fig.5 in section 3.2.

Thanks, we have added a sentence for both figures: “Fig. 4 shows the skill of the ridge regression models to predict CRE$_{SW}$ (left) and CRE$_{LW}$ (right) in the independent test data (2016–2020).” and “Fig. 5 shows the spatial patterns of the sensitivity of CRE$_{SW}$ (left) and CRE$_{LW}$ (right) to SST (top) and EIS (bottom).”

Page 8, Line 4: “ACI”, please gives full name since this is the first appearance.

We have decided to write out aerosol-cloud interactions instead, as “ACI” was only used twice in the text.

Reviewer 2

General

This study performed the sensitivity analyses with added cloud controlling factors with different aerosol proxies using a regularized linear regression (Ridge regression). Based on the high prediction skill of model, the authors have explained the dominant predictor (or proxy) for the CRE sensitivity.

The subject of this work is important to capture processes relevant to grasp CRE variability and cloud feedbacks. However, the manuscript needs some more explanations on the concepts for the variables and notable findings shown in the figures. Please see the details in the comments and questions below.

- On the aerosol proxy, before introducing the usage of aerosol proxy for CCF frameworks in the previous studies, specific explanation on its definition or concept could be more helpful for readers to understand that role and further results in this study.
  We agree that this was not optimally communicated and have modified the text to state: "In recent studies, boundary layer sulfate aerosol concentrations from an aerosol reanalysis have been shown to be a promising alternative to satellite-retrieved columnar aerosol proxies to study aerosol-cloud interactions (McCoy et al. 2017, 2018, Wall et al. 2022). Wall et al. (2022) used sulfate aerosol concentrations in a low-cloud controlling factor framework to quantify the forcing from aerosol-cloud interactions, thereby controlling for the variability in the meteorological CCFs in their forcing estimate of -1.11 W m^{-2}."

- In Fig. 1, the resource of label bars is different. Please double-check.
  We are not sure if the reviewer refers to the lacking explanation of the pointy ends of the colorbars in some of the panels, but as this was recommended by the other reviewer, we have added the following sentence to the caption: "Pointy ends of the colorbars indicate that not the entire value range is shown in the figure to improve its clarity."

- Please correct the 'Res' in the line 11 of page 6 section 2.2 (Ridge regression) as the Italic.
  Done.

- What is the specific reason for the selection of four regions of clouds?
  We have added a sentence here to better explain our intention of using these regimes: "This is done to summarize sensitivities in climate regimes with similar cloud types, which are expected to be driven by different mechanisms and related to different cloud feedbacks (e.g. low–cloud feedback mainly in Sc vs. high–cloud feedback in Ta). "

- What is 'ACI' in the line 4 of page 8?
  We have decided to write out aerosol-cloud interactions instead, as "ACI" was only used twice in the text

- Lines 15-17 of page 8 is important interpretation on the role of regularization strength for ability of predictors to explain the CRE variability. They seemed to have more explanations.
  We have modified the sentence to more clearly explain this aspect: "This is an indication that in these regions where

the predictors do not explain the CRE variability well, the regression coefficients are less certain and model variance is higher, and that the increase in the model bias when the coefficients are nudged towards 0 (thereby predicting less CRE variability) is relatively small."

– It would be better to describe what the positive/negative sensitivity of each CRE for certain variable indicates, such as explanations of SW reflectance or LW emission/trapping, before breaking down the explanations.
We agree that this is a good idea and have added this the following sentences in the last paragraph of section 2.2: "In general, positive CRE$_{SW}$ sensitivities mean that an increase in a CCF is connected to a reduction in the shortwave cooling effect of clouds from reflected solar radiation (e.g. by reducing of cloud amount or reflectivity), whereas positive CRE$_{LW}$ sensitivities relate the increase in a CCF to a stronger longwave warming effect of clouds (more clouds or higher/colder clouds that effectively trap more LW radiation from surfaces below than they emit). As such, one can expect that CRE$_{SW}$ and CRE$_{LW}$ sensitivity patterns are generally anticorrelated. "

– A band of moderate positive CRE_{LW}-SST sensitivity shown in Fig. 5 seemed to be related to the tropical ascending (Ta) regimes. That is, in the mechanism of convection, vertical ascending in the convection may comparatively more relevant to the CRE_{LW}. Also, negative CRE_{LW} sensitivity to SST showed notable over trade cumulus (Tc) regimes. Is there any further interpretation or implication on this?
Good point to further discuss the implications of the CRE$_{LW}$-SST sensitivities. We have added the following sentences to the text [on the negative CRE_{LW} sensitivity to SST in the Tc regime]: "Still, a negative CRE$_{LW}$-SST sensitivity in the Tc regime suggests that the overall (weak) low cloud feedback in the Tc regime might be further reduced by the longwave effect partly balancing the shortwave effect.", and [on the positive CRE_{LW}-SST sensitivity in the Ta regime:] "As the CRE$_{SW}$ sensitivity is only slightly negative in some of these regions, the results suggest that most of this positive CRE$_{LW}$ sensitivity is driven by cloud altitude/temperature and not high cloud cover. "

– 'The sensitivity patterns of CRE_{SW} and CRE_{LW} (Fig. 7)' in lines 6-8 should be corrected as 'The sensitivity of CRE_{SW} and CRE_{LW} to ω_{300}'.
Thanks for catching this, done.

– For the section 3.3 Sensitivity of CRE_{SW} and CRE_{LW} to large-scale circulation, it is well understandable until the paragraph on the impact of 300. On the other hand, for the subtropics, too complicated contents are explained in a bulk. The conclusion is seemed to be that the decrease in low clouds due to the westerly leads the strong positive CRE_{SW} sensitivity to U_{700} and V_{700}. If is correct, what authors intended to with the explanation of boundary layer humidity (RH_{925}) in Fig. 9.
We have conducted two separate composite analyses to explore U_{700} and V_{700} sensitivities. The main result from the U_{700} analysis is that vertical wind shear-induced turbulence is the mechanism that leads to the marked CRE$_{SW}$–U$_{700}$ sensitivities in the Sc regime. The main result from the V_{700} analysis is that warm, moist meridional advection in certain synoptic settings increasing cloudiness is the likely reason for the subtropical sensitivity belt. For both composite analy-

ses, we also investigated possible other influences by looking at their anomaly patterns (e.g. relative humidity in Fig. 9), and quantified their contributions to the predicted CRE anomaly in these situations using the ridge regression. We have carefully looked at the section again and made the following adjustments to improve the clarity of the section:

- Rearranged Fig. 9 (CRE anomalies first - this helps in the text)
- Mention the CRE anomalies in the text first
- Various other smaller text changes to improve readability in the paragraph on the composite analysis
- We also believe that splitting up the results from U_{700} and V_{700} in the conclusions improves the clarity of the text.

- For the lines 19-20 of page 17, the authors well explained the expected differences from the aerosol proxies, especially for the satellite-observed proxies. However, for the results written in the lines of 16-18 on the same page, they need more interpretations, exactly what differences have induced those results.

  It is not clear from the data what could cause the observed differences in the sensitivity estimates here. An educated guess is: sensitivity to AI is smaller than to AOD because of retrieval issues for AOD, and S is smaller as sulfate aerosols may not dominate the CCN budget and are the diffuse natural sources of sulfate in remote oceanic regions are unlikely to be well represented in the aerosol reanalysis. We have added the following sentence to the manuscript: "Another reason for the weaker sensitivity of CRE_{SW} to $\log_{10}s$ in the Ta regime, and especially the tropical Pacific, could be that in this region sulfate aerosols may not dominate the total CCN budget as sea salt particles also make a large contribution (Shinozuka et al. 2004), and that in such remote oceanic regions the diffuse natural sources of sulfate are unlikely to be perfectly represented in the aerosol reanalysis, potentially leading to spatially inaccurate emissions and concentrations (McCoy et al. 2017)."

- Concluding findings on the zonal and meridional winds (4) and three aerosol proxies (5) on the page 19-20 are too comprehensive. Like other paragraphs, please encapsulate them more briefly.

  We agree that the paragraphs should be more balanced. We have decided to split up the concluding remarks on U_{700} and V_{700} into separate paragraphs and shortened the text for each. We have also shortened the text on the aerosol proxies. The manuscript now reads:

  4. Zonal winds in the free troposphere are shown to be important proxies for synoptic variability relevant for subtropical CREs. U_{700} anomalies are shown to be a good proxy for changes in vertical wind shear between the boundary layer and the free troposphere and thus the generation of turbulence at cloud top, leading to the depletion of low-clouds. Vertical wind shear should thus be included and explored in CCF frameworks, in particular in low cloud studies.
  5. CRE is shown to be sensitive to V_{700} in the subtropics, where poleward V_{700} anomalies are linked to increased cooling from clouds. It is unclear though, to what degree the V_{700} sensitivity is related to warm, moist meridional advection that may increase cloudiness or driven by the correlation of V_{700} with large-scale ascent in the region which may lead to nonphysical statistical associations.

6. The CRE sensitivities to the three aerosol proxies ($\log_{10}s$, $\log_{10}$AI, and $\log_{10}$AOD) share the average sign (negative for CRE_{SW} and positive for CRE_{LW}), and have some qualitative similarities (CRE_{SW} sensitivity strongest in the stratocumulus regime). However, CRE are much more sensitive to $\log_{10}$AI and $\log_{10}$AOD in the tropics than to $\log_{10}s$. Differences between the sensitivities of CRE to the three aerosol proxies can be explained by retrieval biases (confounded relationships), and the varying contributions of $\log_{10}s$ to CCN globally.

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