Replay to the review of "Opposing trends of cloud coverage over land and ocean under global warming" by Liu et al.

We would like to thank the reviewers for the effort and thoughtful, constructive comments that helped us improve and clarify the manuscript. We have addressed all the comments in a point-by-point manner and have revised the manuscript and Supplemental Information (SI) accordingly. Before presenting our specific responses to all the comments and questions, we will begin with a brief summary of the main changes that were made in the manuscript:

1) The introduction was revised to describe better the background to this work and previous relevant works.
2) Information was added about how cloud cover is calculated in ERA5 and the advantages and limitations of using ERA5 for trend analysis.
3) Comparison between EOF results of cloud coverage using ERA5 and MODIS data, during 2003–2020, was added to validate and justify the use of ERA5 data and EOF analysis.
4) The skin temperature is replaced by the air temperature at 2 meters above the surface as suggested.
5) The description of the relative humidity analysis was improved to provide a clearer explanation.
6) A figure that shows the trend significance of near-surface relative humidity is added to the SI (Fig. S3).
7) A more conclusive discussion about our results and how they compare with previous studies based on long-term cloud observations is given.
8) Subsections that contain technical description of the Oceanic Niño Index and Spearman's Correlation Coefficient were moved to the SI to focus the main text better.

Please find below the specific responses to all comments (marked in blue). Citations from the revised manuscript appear in *italics*.

Response to Reviewer #1

Reviewer #1 (Comments to the Author):

General comments:

This paper analyses long-term trends and decadal scale variability over the globe using ERA5 reanalysis data for the last 40+ years. The authors argue for opposing trends in cloud cover over continents and over the oceans and try to associate this phenomenon with the changes in the relative humidity. Generally the topic is extremely interesting, as the analyses of interannual and longer-scale dynamics of cloud cover are still limited compared to the other meteorological variables. However, I have serious caveats preventing acceptance of this paper in its present state. They are both of conceptual and methodological nature. I suggest that major and mandatory revisions should be performed before the paper is considered for publication I will be available for the inspection of the revised version if the editor decides so.

Answer: We are glad that the reviewer found the topic interesting and is willing to review the revised version. We appreciate the encouragement and have carefully considered your comments and suggestions. Please see our detailed answers below.

Specific comments:

1. Introduction is somewhat very general and does not bring a clear message outlining why this study is important. Generally I would expect from the introduction the justification of the use of ERA5 total cloud cover for quantifying long-term changes. In this respect I would expect here or in the data section explanation of what is total cloud cover in ERA5 (and more generally) in reanalyses. A useful guide on this WRT to ERA5 is https://www.ecmwf.int/sites/default/files/elibrary/2016/17117-part-iv-physical-processes.pdf#section.3.6. Moreover there were several attempts to compare regional and global patterns of the cloud cover over the ocean in visual data and reanalyses (see, e.g. DOI: 10.1002/joc.1490). The major problem of the reanalyses total cloud cover is the fact that it is strongly constrained by parameterizations used (see the link above). Given problems with adequate parameterizations of hydrometeors, especially in free atmosphere, this implies large (and most importantly regionally dependent) uncertainties in reanalysis total cloud cover. Very likely that in ERA5 considerable progress was done in some respects, however in the paper nothing was said about this. Also reference to Norris et al. (2016, Nature) could be considered under this light, as they analyse CMIP5 models where parameterizations in many respects similar to those used in reanalyses. Also I am a bit unhappy with the context under which visual observations are described in the introduction (lines 30+). In fact for the period in which the authors are interested the problems of interpretation of visual data are

mostly sampling problems over the ocean. Real problems with observational practices appear for periods prior 1960s and here references to Warren et al. (2007) and Eastman et al. (2011). Regarding incomplete sampling, cloud cover data from ICOADS do experience problems, which are however quantified and can be also treated using cloud cover PDFs (DOI:10.1175/JCLI4010.1, DOI: 10.1175/JCLI-D-17-0317.1).

Answer: We would like to thank the reviewer for this valuable comment that helped us update our literature survey and improve the description of the background of this work. We have revised the introduction to summarize the relevant literature better and integrate it into our study.

For clarity, we have divided this answer into several subsections: (1.1) changes in the Introduction section to better describe the background and our motivation; (1.2) a revised Materials and Methods section to provide more detailed information on cloud coverage in ERA5; (1.3) an additional analysis in the Results section that validates the EOF results of cloud cover from ERA5 against MODIS observations; and (1.4) a list of additional references.

With regard to the reference of Norris et al. (2016), we agree that part of the reasons for the consistent results may be due to the similarity of the parameterization used. However, please note that in addition to CMIP5 models, they also used satellite observations and obtained consistent results, suggesting that the similar patterns are based on physical reasons as well.

(1.1) Changes in the Introduction section to better describe the background and our motivation:

"*Previous works that examined tendencies in cloud coverage under a warmer climate show substantial discrepancies among them (Gettelman and Sherwood, 2016; Ceppi et al., 2017; Zelinka et al., 2020). Even estimations for the same cloud type vary between studied periods, locations, datasets, and models (e.g., Norris and Evan, 2015; Zhou et al., 2016; Zelinka et al., 2017; Karlsson and Devasthale, 2018). Key factors in these discrepancies are related to data uncertainties due to measurement errors in observational datasets, on one hand (Chepfer et al., 2014), and the unsatisfactory representation of clouds in climate models, on the other (Stevens et al., 2013). For example, long-term surface observations, such as cloud coverage from the International Comprehensive Ocean – Atmosphere Data Set (ICOADS, Freeman et al., 2017) and the Extended Edited Cloud Reports Archive (EECRA, Hahn and Warren, 1999; Hahn et al., 2012), suffer from non-uniform sampling, changes in the synoptic-code format and stations, and limited coverage (e.g., Eastman et al., 2011; Aleksandrova et al., 2018). On the other hand, long-term satellite records, such as cloud coverage from the International Satellite Cloud Climatology Project (ISCCP, Rossow and Schiffer, 1999), the Pathfinder Atmospheres – Extended dataset (PATMOS-X, Heidinger et al., 2014), and the cloud component in the European Space Agency's (ESA) Climate Change Initiative (CCI) programme (Cloud_cci, Stengel et al.,* *2017), suffer from changing view geometries and orbit drifts (e.g., Evan et al., 2007; Norris and Evan, 2015). While attempts are being made to correct some of these issues in satellite observations, those corrections may remove actual cloud tendencies at a global scale (e.g., Norris and Evan, 2015; Norris et al., 2016). In addition, those corrected products show significant discrepancies between linear trends in their cloud coverage (Norris and Evan, 2015). As for climate models, the representation of clouds in a coarse resolution grid is subordinate to the small-scale parameterization schemes employed, accounting in a limited way for the full range of scales involved therein (Zelinka et al., 2016; Zelinka et al., 2020).*"

"*Despite the challenges, recent advancements in assimilation techniques and computing power have led to the production of high-quality reanalysis data. The latest version is the 5th generation of Atmospheric Reanalysis data from the European Centre for Medium-Range Weather Forecasts (ERA5), which offers uniformly sampled, long-term data of the atmosphere (Hersbach et al., 2019). To investigate the dominant processes that affect cloud coverage and examine the details both in the spatial and temporal domains, we analyze modes of variability in global cloud coverage by performing an Empirical Orthogonal Function (EOF) decomposition on 42 years (1979 – 2020) of ERA5 data (Hersbach et al., 2020); see Sect. 2. To evaluate the extent to which ERA5 captures climate variability and set the stage with fields having a well-studied reference, we analyze the global Surface air Temperature (ST, the air temperature at 2 meters above the surface) together with the Total Cloud Cover (TCC, the part of a grid box covered by clouds).*"

(1.2) A revised Materials and Methods section to provide more detailed information on cloud coverage in ERA5:

"*ERA5 is a state-of-the-art reanalysis dataset and has been validated as the most reliable one for climate trend assessment (Gulev et al., 2021). In ERA5, The cloud fields are calculated using prognostic equations based on assimilated meteorological (thermodynamic and dynamic) variables that are optimally constrained by observations (Hersbach et al., 2019). The TCC is then calculated as a diagnostic parameter based on the prognostic cloud cover field using a generalized cloud overlap assumption based on a stochastic cloud generator. This assumption means that the degree of overlap between two cloudy layers becomes more random as the vertical distance between the layers increases; see more details in Barker (2008). The calculated TCC has been shown to essentially capture the spatiotemporal characteristics of measured cloud coverage on climatic (Yao et al., 2020) and weather scales (Binder et al., 2020).*"

(1.3) An additional analysis in the Results section to compare EOF results of cloud coverage from ERA5 with MODIS:

"*First to set the stage and to explore modes and sensitivities in the ERA5 TCC data as compared to direct measurements we conducted an area-weighted EOF* *analysis on annual TCC anomalies and compared it with the observed CF from MODIS; see Fig. 1. To mimic the MODIS CF observations, we resampled ERA5 TCC data to a grid with a horizontal resolution of 1 ° and considered only a subset of data between 60 °S to 60 °N during 2003 – 2020. Figure 1 shows the three dominant EOF modes and PCs of the annual ERA5 TCC and MODIS CF anomalies. The very similar explained variance, spatial patterns in EOFs, and time evolution in PCs suggest that although ERA5 TCC is a simulated parameter, the model and assimilation techniques are able to reproduce essential variations of observed cloud coverage."*

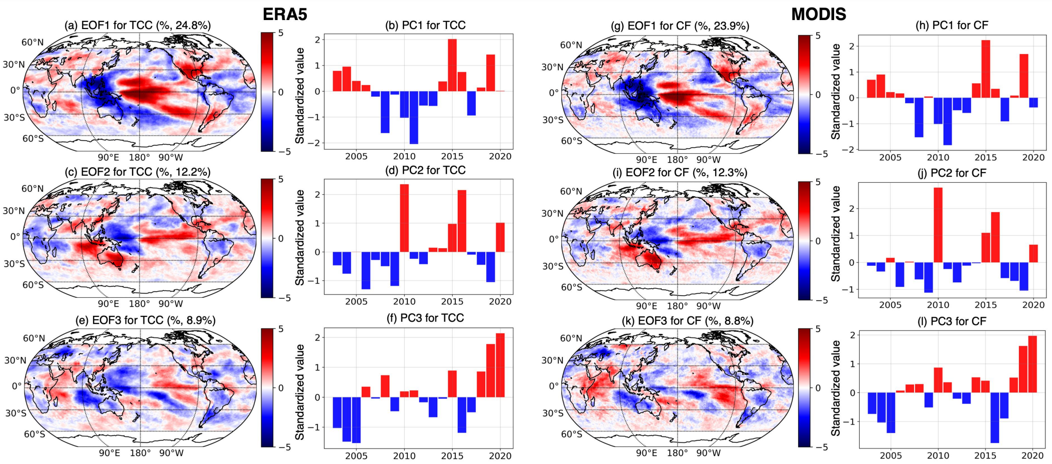

Figure 1: The three dominant EOF modes and their corresponding PCs of the annual cloud coverage anomaly (unit: %) from ERA5 (a–f) and MODIS (g–l) during 2003–2020. (a, g) The scaled leading EOF mode (EOF1, amplified by the standard deviation of its PC). (b, h) The standardized leading PC (PC1, divided by its standard deviation). (c, i) The scaled second EOF mode (EOF2). (d, j) The standardized second PC (PC2). (e, k) The scaled third EOF mode (EOF3). (f, l) The standardized third PC (PC3). The values given in the parenthesis of the title of panels a, c, e, g, i and k are the explained variances. The red and blue bars in panels b, d, f, h, j and l highlight the positive and negative PC values, respectively.

(1.4) A list of additional references:

1. Binder, H., Boettcher, M., Joos, H., Sprenger, M., and Wernli, H.: Vertical cloud structure of warm conveyor belts–a comparison and evaluation of ERA5 reanalysis, CloudSat and CALIPSO data. Weather and Climate Dynamics, 1, 577–595, doi.org/10.5194/wcd-1-577-2020, 2020.

2. Barker, H.W.: Representing cloud overlap with an effective decorrelation length: An assessment using CloudSat and CALIPSO data. Journal of Geophysical Research: Atmospheres, 113, doi.org/10.1029/2008JD010391, 2008.

3. Platnick, S., King, M.D., Ackerman, S.A., Menzel, W.P., Baum, B.A., Riédi,

J.C., and Frey, R.A.: The MODIS cloud products: algorithms and examples from Terra, IEEE Transactions on geoscience and Remote Sensing, 41, 459-473, doi.org/10.1109/TGRS.2002.808301, 2003.

4. Aleksandrova, M., Gulev, S.K. and Belyaev, K.: Probability distribution for the visually observed fractional cloud cover over the ocean. Journal of Climate, 31, 3207–3232, doi.org/10.1175/JCLI-D-17-0317.1, 2018
5. Freeman, E., Woodruff, S.D., Worley, S.J., Lubker, S.J., Kent, E.C., Angel, W.E., Berry, D.I., Brohan, P., Eastman, R., Gates, L., and Gloeden, W.: ICOADS Release 3.0: a major update to the historical marine climate record. International Journal of Climatology, 37, 2211–2232, doi.org/10.1002/joc.4775, 2017.
6. Hahn, C.J., and Warren, S.G.: Extended edited synoptic cloud reports from ships and land stations over the globe, 1952–1996, United States, doi.org/10.2172/12532, 1999.
7. Hahn, C.J., Warren, S.G., and Eastman, R.: Cloud Climatology for Land Stations Worldwide, 1971-2009 (NDP-026D) (No. NPD-026D), United States, doi: 10.3334/CDIAC/cli.ndp026d, 2012.
8. Heidinger, A.K., Foster, M.J., Walther, A., and Zhao, X.T.: The pathfinder atmospheres–extended AVHRR climate dataset. Bulletin of the American Meteorological Society, 95, 909–922, doi.org/10.1175/BAMS-D-12-00246.1, 2014.
9. Rossow, W.B., and Schiffer, R.A.: Advances in understanding clouds from ISCCP. Bulletin of the American Meteorological Society, 80, 2261–2287, doi:10.1175/1520-0477(1999)080,2261:AIUCFI.2.0.CO;2, 1999.
10. Stengel, M., Stapelberg, S., Sus, O., Schlundt, C., Poulsen, C., Thomas, G., Christensen, M., Carbajal Henken, C., Preusker, R., Fischer, J., and Devasthale, A.: Cloud property datasets retrieved from AVHRR, MODIS, AATSR and MERIS in the framework of the Cloud_cci project, Earth System Science Data, 9, 881–904, doi.org/10.5194/essd-9-881-2017, 2017.

2. Selection of variables. Here I am concerned about the use of Tskin as a proxy for global climate warming (my understanding). Indeed, in ERA5 Tskin is different to that in e.g. NCEP DOE and other early reanalyses. However, the extent to that this variable is relevant to represent long-term climate variability is unclear, at least from the text. Why no to use simply surface air temperature? In any case changes in Tskin should be compared to Tair-surf. Figures show that the revealed patterns are similar (by my inspection) to what we expect for surface temperature. My other concern is the use of RH. From section 1.2 I could not get what was done in fact. Looks that a kind of column–integrated RH was retrieved. This step requires

justification. Given that RH is non-linear function of temperature and specific humidity and strongly varies over vertical coordinate, this metric (vertically integrated RH) looks for me being hardly interpretable. I might be wrong, but in any case a clear explanation should be provided here.

Answer: We thank the reviewer for this comment.

Based on this comment we have decided to replace Tskin with surface-air temperature (the temperature at 2 m). Upon inspection, we found that the two variables produce nearly identical results. In the revised Results section, we have re-calculated the correlation coefficient between PC2 for total cloud cover and global mean surface-air temperature, which yielded a Spearman's ρ value of 0.88 and a p-value of 3.28×10^{-14}. We have also updated the figures (Fig. 2a–b, Fig. 3, the black curve in Fig. 4d, and fig. S1a–c) and the accompanying texts in the Introduction section accordingly, which you can see below:

"*To evaluate the extent to which ERA5 captures climate variability and set the stage with fields having a well-studied reference, we analyze the global Surface air Temperature (ST, the air temperature at 2 meters above the surface) together with the Total Cloud Cover (TCC, the part of a grid box covered by clouds).*"

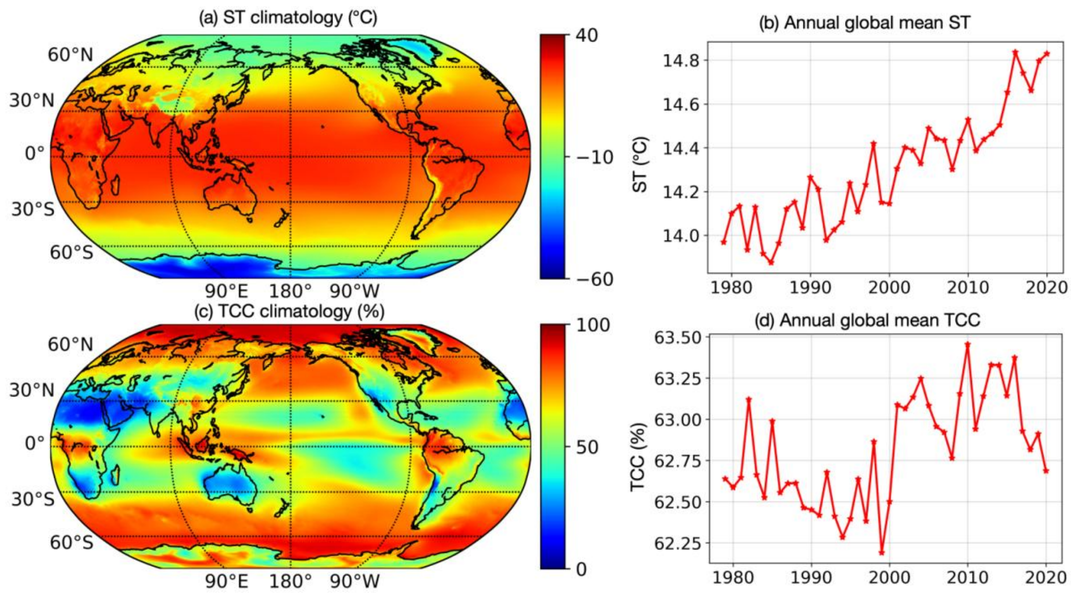

Figure 2: Climatological mean maps and the annual global means (area-weighted) of ST (unit: °C) and TCC (unit: %) during 1979–2020. (a) A global map of the climatological mean of ST. (b) Time series of the annual global mean of ST. (c) A global map of the climatological mean of TCC. (d) Time series of the annual global mean of TCC.

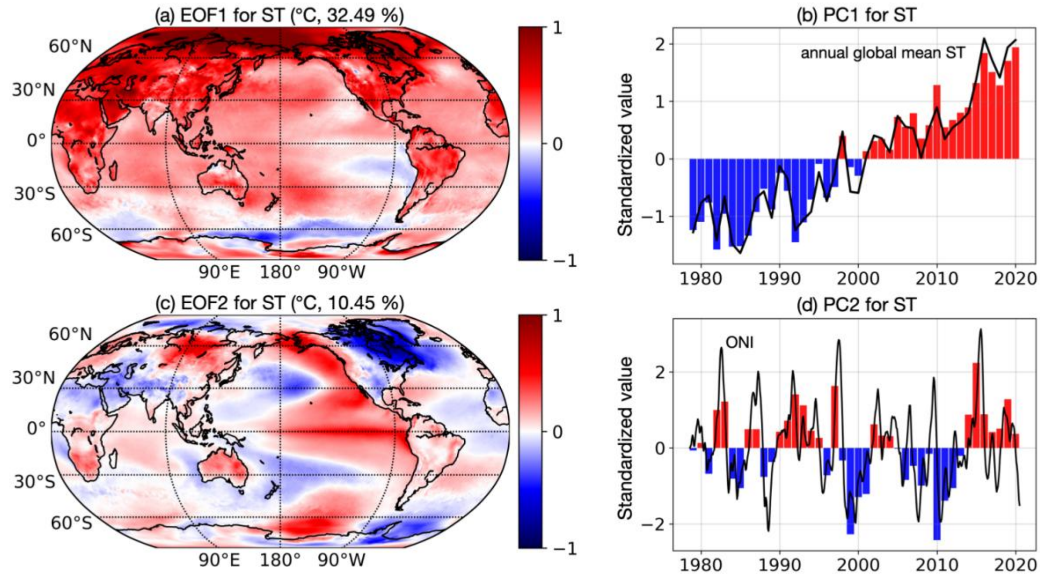

Figure 3: The two dominant EOF modes and their corresponding PCs of the annual ST anomaly (unit: °C) during 1979–2020. (a) The scaled leading EOF mode (EOF1, amplified by the standard deviation of its PC). (b) The standardized leading PC (PC1, divided by its standard deviation). (c) The scaled second EOF mode (EOF2). (d) The standardized second PC (PC2). The values given in the parenthesis of the title of panels a and c are the explained variances. The black curves in panels b and d are standardized annual global mean ST and ONI. The red and blue bars in panels b and d highlight the positive and negative PC-values, respectively.

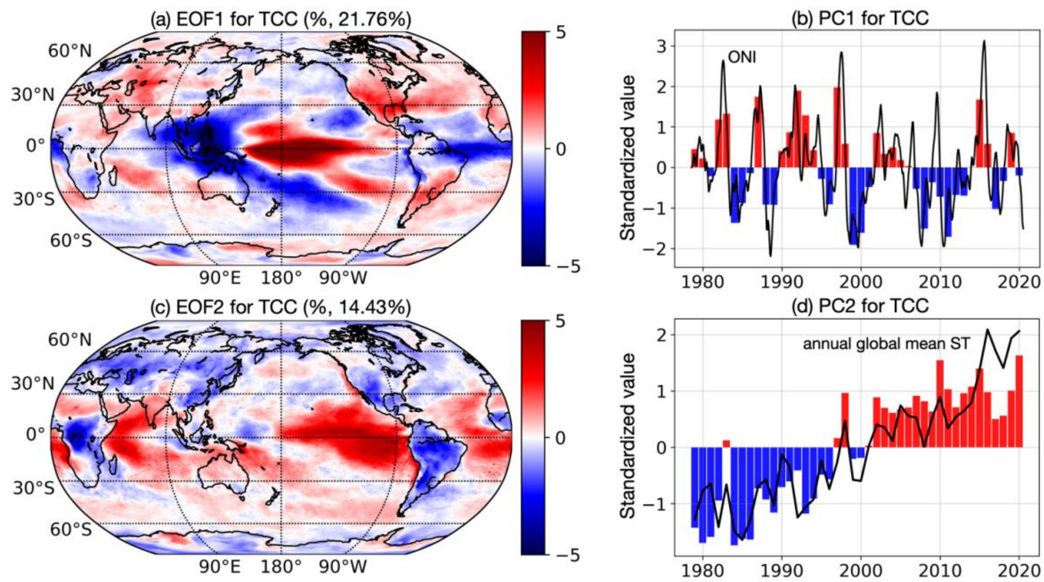

Figure 4: The two dominant EOF modes and their corresponding PCs of the annual TCC anomaly (unit: %) during 1979–2020. (a) The scaled leading EOF mode (EOF1, amplified by the standard deviation of its PC). (b) The standardized leading PC (PC1, divided by its standard deviation). (c) The scaled second EOF mode (EOF2). (d) The standardized second PC (PC2). The values given in the parenthesis of the title of panels a and c are the explained variances. The black

curves in panels b and d are the standardized ONI and annual global mean ST, respectively. The red and blue bars in panels b and d highlight the positive and negative PC values, respectively.

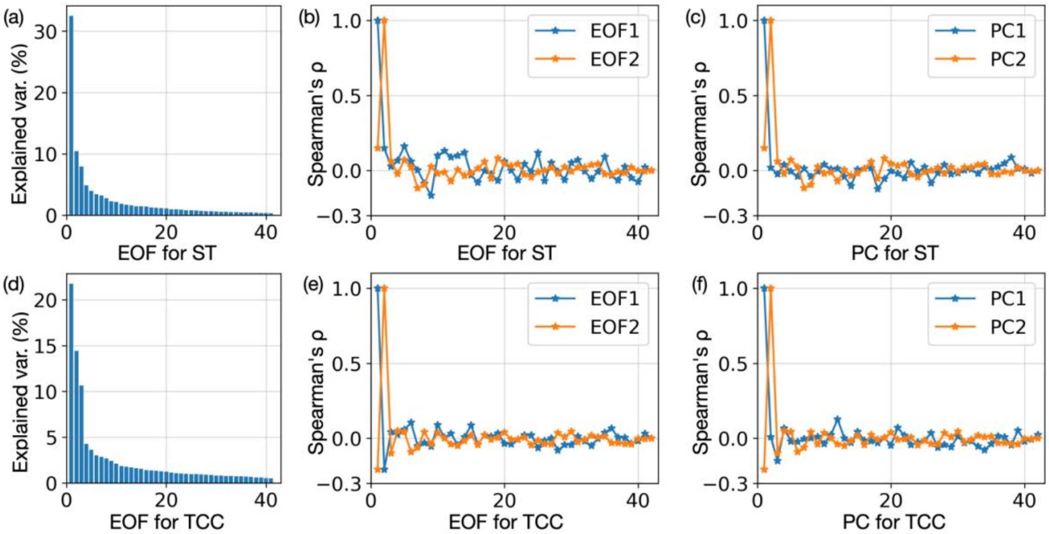

Figure S1: A signal leakage test for the top two EOF modes and PCs for ST and TCC. (a) Explained variance (unit: %) of all EOF modes for ST. (b) Correlations between the top two EOF modes and all EOF modes for ST. (c) Correlations between the top two PCs and all PCs for ST. (d–f) Same results as shown in (a–c), but for TCC.

As for the RH analysis, following this comment we realized that the description of this part was not clear enough. We did not retrieve an integrated RH. Instead, we analyzed the TCC correlations with RH (as well as with all other key variables) separately per 23 standard pressure levels as shown in Fig. 4 (Fig. 5 in the revised version). Later based on these results, we introduced the interpolated near-surface RH (RH_{NS}) as shown in Fig. 5 (Fig. 6 in the revised version). In the revised manuscript, we have updated the Materials and Method section to provide a clearer explanation and included an equation for calculating RH_{NS}. Please refer to the details below:

"*The study uses three datasets: (1) 42 years (1979 – 2020) of monthly atmospheric data from ERA5 (https://www.ecmwf.int/en/forecasts/datasets/reanalysis-datasets/era5, Hersbach et al., 2020), which include ST, TCC, Land-Sea Mask (LSM) and Surface Pressure (SP) at single levels, as well as Relative Humidity (RH), Specific Humidity (SH), Temperature (T), vertical velocity (ω), U-wind component (U), V-wind component (V), wind Divergence (Div), Potential Vorticity (PV), and Relative Vorticity (RV) at 23 standard pressure levels (1000, 975, 950, 925, 900, 875, 850, 825, 800, 775, 750, 700, 650, 600, 550, 500, 450, 400, 350, 300, 250, 225 and 200 hPa). The original horizontal resolution of all ERA5 data is 0.25 °; (2) 18 years (2003 – 2020) of daily Cloud Fraction (CF) data observed by the MODerate* *resolution Imaging Spectroradiometer (MODIS) onboard the Aqua satellite (https://search.earthdata.nasa.gov/search?q=MYD08_D3, Platnick et al., 2003), with a horizontal resolution of 1 °; and (3) 44 years (1978 – 2021) monthly Niño-3.4 index from the National Oceanic and Atmospheric Administration center for Weather and Climate Prediction (https://origin.cpc.ncep.noaa.gov/products/analysis_monitoring/ensostuff/ONI_change.shtml)*"

"*Near-Surface Relative Humidity (RH_{NS}) is calculated here as RH at 950 hPa over the ocean and at 50 hPa above surface over land. Ocean is identified as grid boxes with a LSM-value no larger than 0.2 and land is identified as grid boxes with a LSM-value larger than 0.2. For each land grid box, its RH_{NS}-value is estimated based on a pressure-difference weighted linear interpolation given by the following equation:*

$$\mathrm{RH}_{\mathrm{NS-land}} = \frac{|\mathrm{P}_1 - \mathrm{SP}| \times \mathrm{RH}_{\mathrm{P}_2} + |\mathrm{P}_2 - \mathrm{SP}| \times \mathrm{RH}_{\mathrm{P}_1}}{|\mathrm{p}_1 - \mathrm{p}_2|}$$

where P_1 and P_2 are the adjacent standard pressure levels that contain the pressure level of 50 hPa smaller than the local SP."

3. Conceptual and the main one. With no regard whether Tskin or Tsurf is used for me it is unclear the context of the analysis of temperature using the same methodology as for clouds (EOFs). Figures2 and 3 (EOF and normalized PCs) for TS and TCC are not informative in the context of the paper title and focus. Further use of the correlations (be it Spearman or Pierson) (fig 4) reveals vague results which can be hardly interpreted. Given the focus of contrasting / opposing trends over the continents and oceans, I would expect first of all a picture(s) showing time series of cloud cover over oceans and continents (also for different regions). Figure 5 (top panel) is not showing trend significance and in this respect is hardly interoretable. But even if all trends are significant (unlikely), the pattern does not imply unconditionally the message on opposing trends. It is also unclear which units are used, whether these are percentages of cloud cover or percentages of changes per decade. In the latter case you should note that mean values are different over ocean and land. For me the most novel picture is the mid panel in Fig 5 (correlations with RH), however it is unclear whether these are correlations before or after de-trending.

   Answer: We thank the reviewer for the detailed feedback on our work and the suggestions for improvement. We clarified the context of the temperature analysis and re-examined the results presented in Fig. 4 (Fig. 5 in the revised manuscript) to ensure that they are adequately explained. In fig. 5 (Fig. 6 in the revised manuscript), panel a shows the map of linear trends in RH_{NS} during 1979–2020, with a unit of percentage of RH per decade (% decade^{-1}); panel b shows the map of correlations between annual RH_{NS} and annual TCC (no de-trending is performed).

For clarity, we have divided this answer into several subsections : (3.1) time series of cloud coverage over land and ocean; (3.2) the context of using the same methodology for temperature and clouds; (3.3) explanation of correlations presented in Fig. 4 (Fig. 5 in the revised manuscript); (3.4) revised caption of Fig. 5 (Fig. 6 in the revised manuscript); and (3.5) an additional figure in the SI to give significance for trends in RH_{NS}.

(3.1) time series of cloud cover over land and ocean:

We appreciate the suggestion of giving the time series of cloud cover over oceans and continents to focus on their contrasting/opposing trends. However, as we mentioned in the manuscript (Fig. 2d in the revised manuscript), the climate perturbations actually prevent us from having a consistent trend in global mean cloud coverage. Instead, the time series gives us significant inter-annual and short-term cloud amount variations. Therefore, we conducted the EOF analysis in the manuscript to reveal the variability modes to overcome this obstacle (Fig. 4 in the revised manuscript). There, we see a consistent trend-like mode (Fig. 4c – d in the revised manuscript) that shows a decreasing trend over most of the land and an increasing trend over most oceans, especially over the tropical and eastern subtropical oceans. For proving our claim, we show below the time series of cloud cover over land and ocean (Fig. R1). The figure shows an overall decreasing trend over land, but no consistent trend over ocean.

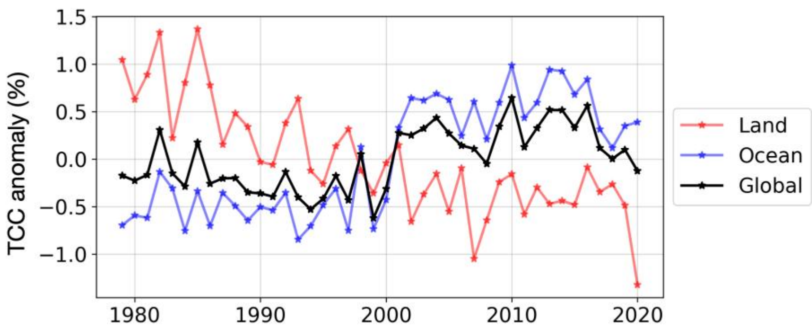

Figure R1: Time series of the anomaly of annual mean TCC over the 3 different domains (land, ocean and global), compared to the 1979–2020 average.

(3.2) The context of using the same methodology for temperature and clouds:

The context of using the same methodology for temperature and clouds is to analyze the spatiotemporal patterns of temperature and their underlying processes in a similar way to how we analyze clouds. Specifically, we aim to clarify that temperature in ERA5 captures both the long-term warming trend and other climate variabilities during the study period, as suggested in comment#2. Additionally, we want to demonstrate that EOF analysis can identify the major processes and separate the warming-related mode from other modes. Along the revised manuscript, we have improved the logical sequence of the text to enhance clarity and facilitate understanding.

(3.3) Explanation of correlations presented in Fig. 4 (Fig. 5 in the revised manuscript):

We agree that a full explanation of the correlations presented in Fig. 4 (Fig. 5 in the revised manuscript) requires further investigation. Nevertheless, our goal in assessing these correlations is to check whether there are dominant meteorological variables that link with the variations in cloud coverage. And indeed, the results highlight RH as the dominant one for continental cloud coverage, while RH, SH, and PV are the major ones for maritime cloud coverage. Hence, we propose changes in RH, especially the low-level RH, as the most plausible explanation for the decreasing trend in continental cloud coverage. To validate this idea, we introduced a hybrid variable, Near-Surface RH (RH_{NS}), to further explore its correlations with cloud coverage and the distribution of its linear trend in Fig. 5 (Fig. 6 in the revised manuscript). Accompanying texts in the Results section has been revised to better describe these findings:

"*By relying on the EOF analysis, we are able to identify an unambiguous signature of the warming climate on global cloud coverage. We explore next the potential thermodynamic drivers that could explain the revealed TCC trend. In that respect, we assess the correlation between each ERA5 meteorological variable (207 in total) and TCC by calculating the corresponding Spearman's* ρ *for the annual data. Meteorological variables that are checked here including RH, SH, T, U, V,* ω*, Div, PV, and RV at 23 standard pressure levels ranging from 1000 to 200 hPa, see Sect. 2.*

Figure 5a presents the average correlations over land (LSM > 0.2) and ocean (LSM $\leqslant$ *0.2); see Sect. 2. These results show that RH, in most pressure levels, exhibits the strongest correlation with continental TCC, while for maritime TCC, RH and SH yield comparably strong correlations. A previous analysis based on satellite observations and other atmospheric reanalysis datasets obtained similar conclusions (Koren et al., 2010). The geographical distribution of the meteorological variables that best correlate with TCC, shown in Fig. 5b, further highlights RH as the strongest component over almost all continents. Moreover, there is no single variable besides RH that correlates strongly with nearly all continental TCC; see Fig. S2 and Supplementary Text 4. As for the maritime TCC, it exhibits a diversity of best correlated variables dominated by RH, SH, and PV. Such correlation differences over land and ocean may link to the different atmospheric conditions over land and ocean, as well as to the different dynamics of continental clouds and maritime clouds.*"

(3.4) Revised caption of Fig. 5 (Fig. 6 in the revised manuscript):

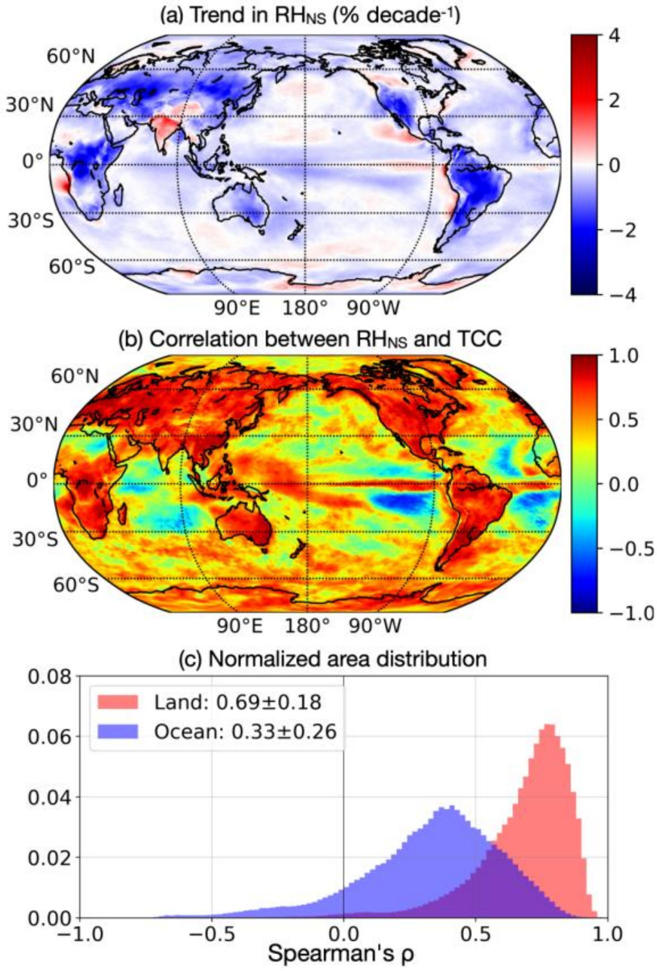

Figure 6: Trends in RH_{NS} and correlations between annual RH_{NS} and annual TCC. (a) A map of the temporal trend in annual RHNS (unit: % decade-1, where % denotes the absolute rather than the fractional percentage change). (b) A map of Spearman's ρ between RH_{NS} and annual TCC. (c) Distribution (area-TCC-weighted) of the correlations presented in panel b over land and ocean. The distribution's mean and standard deviation are displayed in the box.

(3.5) The additional figure in the SI (Fig. S3) for presenting the RH_{NS} trend significance:

Following the suggestion, we added Fig. S3 to the SI to show the RH_{NS} trend significance at the level of 0.05 (p-value < 0.05, two-tailed t-test). As shown, a major part of the continents is statistically significant regarding the decreasing trend in RH_{NS} The main message of this figure is that the RH_{NS} and TCC exhibit similar decreasing patterns over land, but not over oceans. Therefore, we propose that the reduction in RH_{NS} is the most plausible explanation for the decrease in continental cloud coverage, while other variables or mechanisms may be responsible for changes in maritime cloud coverage. Please see the newly added figure (Fig. S3) in the revised SI below:

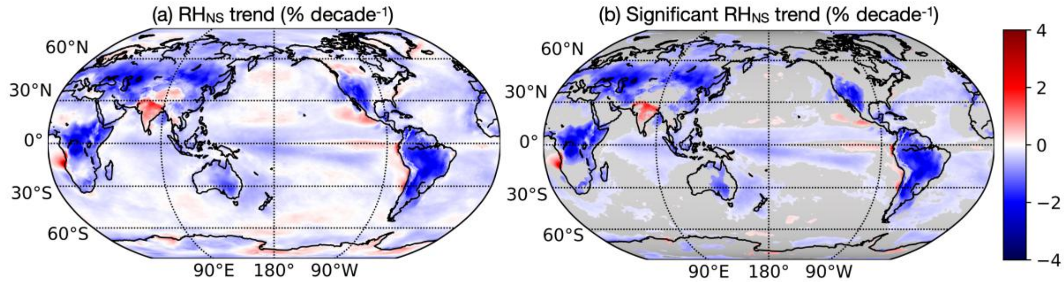

Figure S3: Trends in RH_{NS} during 1979 – 2020. (a) A map of global trend; (b) A map of statistically significant trend values at the level of 0.05 (p-value < 0.05, two-tailed t-test). The insignificant results are coloured in gray in panel b.

4. Links with different parameters (e.g. surface temperature, RH) could be revealed by using e.g. canonical correlation analysis performed on the basis of EOF decompositions. This approach may demonstrate patterns which are mostly correlated with each other. In your case very likely this would distinguish between the first and the second EOFs, as I assume that the first canonical pair may be composed by the first EOF of one variable and the second of the other. However, this is just a hypothesis, needs to be tested.

   Answer: This is a very interesting suggestion of the reviewer, and we believe that this idea could benefit from e.g. EOFs that would account for co-variability, i.e. EOFs computed for several variables stacked together. Such an analysis will however take too far the current work which we believe provide sufficiently simple evidences for the main points we want to convey.

5. Misc - There are quite few technical and minor comments, however I assume (again, if the editor decides so) the major reworking of the MS and they can be addressed next. For now, I suggest to drop technical descriptions of the methodologies which are widely used and well known and concentrate on the results and outcomes.

   Answer: We would like to thank the reviewer for this insightful feedback, which has helped us to further refine our focus on the findings. As per their valuable recommendation, we have moved the subsections that contain technical descriptions of the Oceanic Niño Index and Spearman's Correlation Coefficient into the SI (Supplementary Text 2 – 3 in the revised SI).

Response to Reviewer #2

Reviewer #2 (Comments to the Author):

General comments:

Based on the use of a model cloud data set (ERA5) being treated as observations, I recommend a rejection (see detailed comments below). Overall, the authors may find it easy to either spin their paper towards a model only paper, or to substitute in a collection of different long-term observations (a suggested list is provided below).

Answer: We appreciate the thoughtful and constructive feedback. In the revised manuscript and SI, we have taken your comments regarding the description of cloud coverage from ERA5 into account and updated the text accordingly to ensure that the distinction between reanalysis and observations is clear. We agree that using ERA5 provides some limitations. We have updated the motivation for using this data and provided a more conclusive discussion about our results and how they compare with previous studies based on long-term observations. Please see our detailed answers below.

Specific comments:

1. Line 27: Zelinka 2020 doesn't look at trends.

   Answer: We thank the reviewer for this correction. The word "trends" has been revised to "tendencies" in the new manuscript.

   "*Previous works that examined tendencies in cloud coverage under a warmer climate show substantial discrepancies among them (Gettelman and Sherwood, 2016; Ceppi et al., 2017; Zelinka et al., 2020).*"

2. Line 40 (or somewhere similar): you may be interested in (Andrew Manaster et al., 2017).

   Answer: We thank the reviewer for this recommendation. The study by Manaster et al. (2017) provides an in-depth analysis of trends in both observed and simulated cloud liquid water path (LWP). Their discussion of the potential effect of inter-annual variability on forced trends is highly relevant to the points we are making. Therefore, we added it as a reference in the revised manuscript.

   "*Besides the uncertainties tied to observations and modeling, the sensitivity of clouds to temperature patterns (Zhou et al., 2016) and other large-scale climate drivers (Manaster et al., 2017; Gulev et al., 2021) can also lead to discrepancies between estimations of cloud coverage trends over different periods and regions.*"

   Moreover, the trend in observed LWP from the Multisensor Advanced Climatology of Liquid Water Path (MAC-LWP) dataset (1988–2014) suggests consistent results (Fig. 4a and c in Manaster et al., 2017) with our findings (Fig. 4c in our revised manuscript). For example, see the increasing trend in LWP over most tropical and eastern subtropical oceans which is consistent with the increased cloud coverage in our warming-associated mode. Therefore, we have also referenced this work when discussing our results.

"*Additionally, analysis in observed liquid water path from the Multisensor Advanced Climatology of Liquid Water Path (MAC-LWP) dataset yields increasing trends over most oceans (Manaster et al., 2017). These increasing patterns suggest consistent results with our findings as well because the value of liquid water path for cloud-free atmosphere is considered as 0.*"

3. Line 60: Is the cloud cover in this study all based on ERA5? ERA5 is not giving observed cloud properties. ERA5 is just a global circulation model nudged to observations. The relevant properties that are nudged to observations, as state here, thermodynamic properties. These are used with a cloud scheme to generate cloud properties. See for instance https://cds.climate.copernicus.eu/cdsapp#!/dataset/reanalysis-era5-pressure-levels?tab=overview and the discussion of specific rain content. At least according to https://wcd.copernicus.org/preprints/wcd-2020-26/wcd-2020-26-manuscript-version2.pdf the scheme in question is (Tiedtke, 1993) with a few tweaks. If there is not an observed cloud data set, then this study presents an evaluation of the Tiedtke scheme as implemented by ECMWF in response to thermodynamic variability nudged towards observations.

   Answer: We thank the reviewer for raising this major point, which helped us to better justify the use of ERA5 cloud coverage in our study. We have updated the manuscript and added analysis accordingly to provide more detailed information on the advantages and limitations of using ERA5, as well as our specific reasons for selecting this dataset for our analysis. More specifically, information was added about ERA5 calculation of cloud cover. A comparison of cloud coverage EOF analysis using ERA5 and MODIS data sets, for 2003 – 2020, was added to the revised manuscript, to validate and justify the use of ERA5 data and EOF analysis.

   And we thank the reviewer for recommending Binder et al. (2020), which provides a perspective on the weather scales used to evaluate cloud cover estimations from ERA5. Their results emphasize the ability of ERA5 to essentially capture the observed cloud patterns, though some small- and mesoscale structures are missed. Therefore, we have included this work as a reference in the revised manuscript. Once again, we appreciate the helpful feedback provided by the reviewer.

   Below, you will find the revised text in the Materials and Methods section and the newly added analysis (Fig. 1 in the revised manuscript) in the Results section:

   Revised text in the Materials and Methods section: "*ERA5 is a state-of-the-art reanalysis dataset and has been validated as the most reliable one for climate* *trend assessment (Gulev et al., 2021). In ERA5, the cloud fields are calculated using prognostic equations based on assimilated meteorological (thermodynamic and dynamic) variables that are optimally constrained by observations (Hersbach et al., 2019). The TCC is then calculated as a diagnostic parameter based on the prognostic cloud cover field using a generalized cloud overlap assumption based on a stochastic cloud generator. This assumption means that the degree of overlap between two cloudy layers becomes more random as the vertical distance between the layers increases; see more details in Barker (2008). The calculated TCC has been shown to essentially capture the spatiotemporal characteristics of measured cloud coverage on climatic (Yao et al., 2020) and weather scales (Binder et al., 2020).*"

Newly added analysis in the Results section: "*First to set the stage and to explore modes and sensitivities in the ERA5 TCC data as compared to direct measurements we conducted an area-weighted EOF analysis on annual TCC anomalies and compared it with the observed CF from MODIS; see Fig. 1. To mimic the MODIS CF observations, we resampled ERA5 TCC data to a grid with a horizontal resolution of 1 ° and considered only a subset of data between 60 °S to 60 °N during 2003 – 2020. Figure 1 shows the three dominant EOF modes and PCs of the annual ERA5 TCC and MODIS CF anomalies. The very similar explained variance, spatial patterns in EOFs, and time evolution in PCs suggest that although ERA5 TCC is a simulated parameter, the model and assimilation techniques are able to reproduce essential variations of observed cloud coverage.*"

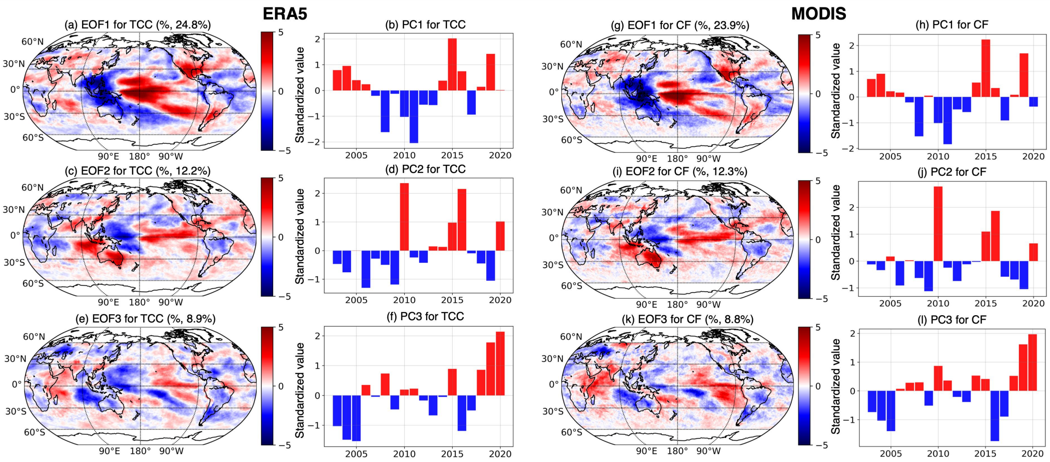

Figure 1: The three dominant EOF modes and their corresponding PCs of the annual cloud coverage anomaly (unit: %) from ERA5 (a–f) and MODIS (g–l) during 2003–2020. (a, g) The scaled leading EOF mode (EOF1, amplified by the standard deviation of its PC). (b, h) The standardized leading PC (PC1, divided by its standard deviation). (c, i) The scaled second EOF mode (EOF2). (d, j) The standardized second PC (PC2). (e, k) The scaled third EOF mode (EOF3). (f, l) The standardized third PC (PC3). The values given in the parenthesis of the title of panels a, c, e, g, i and k are the explained variances. The red and blue bars in

panels b, d, f, h, j and l highlight the positive and negative PC values, respectively.

Added references:

1. Binder, H., Boettcher, M., Joos, H., Sprenger, M., and Wernli, H.: Vertical cloud structure of warm conveyor belts–a comparison and evaluation of ERA5 reanalysis, CloudSat and CALIPSO data. Weather and Climate Dynamics, 1, 577–595, doi.org/10.5194/wcd-1-577-2020, 2020.

2. Barker, H.W.: Representing cloud overlap with an effective decorrelation length: An assessment using CloudSat and CALIPSO data. Journal of Geophysical Research: Atmospheres, 113, doi.org/10.1029/2008JD010391, 2008.

3. Platnick, S., King, M.D., Ackerman, S.A., Menzel, W.P., Baum, B.A., Riédi, J.C., and Frey, R.A.: The MODIS cloud products: algorithms and examples from Terra, IEEE Transactions on geoscience and Remote Sensing, 41, 459-473, doi.org/10.1109/TGRS.2002.808301, 2003.

4. Line 70: Why not just use 2m RH?

   Answer: We thank the reviewer for this comment. ERA5 does not provide this parameter. There is an option to calculate it using the 2m temperature and dew point, and the surface pressure. This calculation is also not free of problems. Moreover, our analysis shows that RH at 925 hPa is the best correlated meteorological parameter with the cloud cover over land (see Fig. 5a in the revised manuscript). We checked it and the RH at 50 hPa above the surface is very close to RH at 925 hPa over major part of the continents. Therefore, we used in our manuscript the RH_{NS}, as RH at a pressure level that is 50 hPa above the surface to further explore the link between RH and cloud amount.

5. Because this study is using reanalysis clouds to try and say something about observed trends, I find it impossible to evaluate the rest of this paper. Their analysis seems of good quality and internally consistent, beyond the basic issue of using model output as observations. I think that the authors have established a nice analysis framework and if they could utilize the many other long term cloud observations (ship observations, PATMOS-X, ISCCP, MAC-LWP, as in (Norris et al., 2016)) they will be able to have some nice, consistent results. As is, I recommend a reject with encouragement to resubmit when observed clouds are used.

   Answer: We appreciate the constructive feedback and encouragement. In response to this comment, we have updated the manuscript and SI to clarify the distinction between reanalysis and observations.

   For clarity, we have divided the following answer into a few subsections: (5.1) changes in the Introduction section that better justify our choice of using ERA5 cloud cover data rather than long-term cloud observations; (5.2) revised discussion in the Results section that better describes our results and how they compare with studies of long-term observations; and (5.3) a list of added references.

(5.1) Changes in the Introduction section that better justify our choice of using ERA5 cloud cover data rather than long-term cloud observations:

We could not use long-term observational datasets for our global trend analysis due to their severe limitations. We need cloud product that is uniformly sampled over the globe for performing EOF analysis, therefore in-situ observations are not suitable for that. With respect to long-term satellite observations, their limitations regard technical issues such as orbit drifting, calibration, replacement of platforms and so on that bias the real physical trend. Until now, we don't have a good method to decouple these artifacts from real signals. A good example for this is the results shown in Norris and Evan (2015) presenting the trend patterns using the two longest satellite observations (ISCCP and PATMOS-X), after an empirical correction of the artifacts. It can be seen in the figure below (Figure. R1) that the two datasets are inconsistent and show completely different trend patterns; adapted from Fig. 6 in Norris and Evan (2015). It means that those datasets can not be trusted regarding trend analysis.

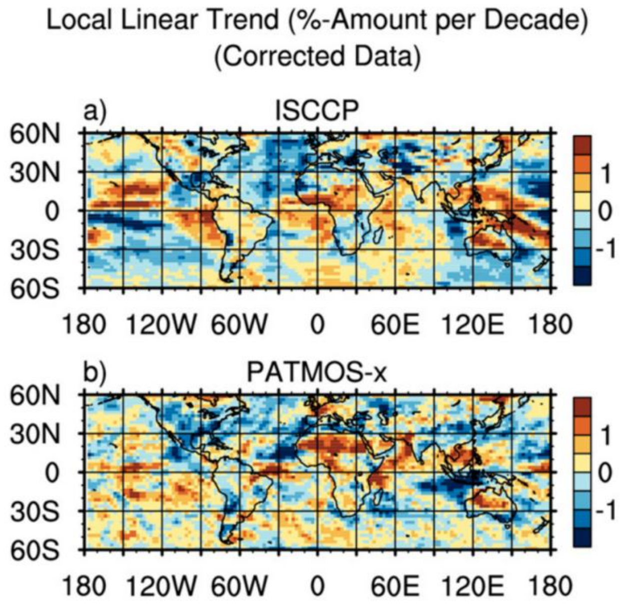

Figure R1: Local linear trend in daytime-only total cloud fraction monthly anomalies for (a) ISCCP after removal of cloud variabilitity associated with satellite zenith angle changes, solar zenith angle changes, and large-scale spatially coherent cloud changes, and (b) PATMOS-x after removal of cloud variabilitity associated with solar zenith angle changes and large-scale spatially coherent cloud changes. The trends are calculated from July 1983 to December 2009. Adapted from Fig. 6 in Norris and Evan (2015).

The revised text in the Introduction section is given below:

"*Previous works that examined tendencies in cloud coverage under a warmer climate show substantial discrepancies among them (Gettelman and Sherwood, 2016; Ceppi et al., 2017; Zelinka et al., 2020). Even estimations for the same cloud type vary between studied periods, locations, datasets, and models (e.g., Norris and Evan, 2015; Zhou et al., 2016; Zelinka et al., 2017; Karlsson and Devasthale, 2018). Key factors in these discrepancies are related to data uncertainties due to measurement errors in observational datasets, on one hand (Chepfer et al., 2014), and the unsatisfactory representation of clouds in climate models, on the other (Stevens et al., 2013). For example, long-term surface observations, such as cloud coverage from the International Comprehensive Ocean – Atmosphere Data Set (ICOADS, Freeman et al., 2017) and the Extended Edited Cloud Reports Archive (EECRA, Hahn and Warren, 1999; Hahn et al., 2012), suffer from non-uniform sampling, changes in the synoptic-code format and stations, and limited coverage (e.g., Eastman et al., 2011; Aleksandrova et al., 2018). On the other hand, long-term satellite records, such as cloud coverage from the International Satellite Cloud Climatology Project (ISCCP, Rossow and Schiffer, 1999), the Pathfinder Atmospheres – Extended dataset (PATMOS-X, Heidinger et al., 2014), and the cloud component in the European Space Agency's (ESA) Climate Change Initiative (CCI) programme (Cloud_cci, Stengel et al., 2017), suffer from changing view geometries and orbit drifts (e.g., Evan et al., 2007; Norris and Evan, 2015). While attempts are being made to correct some of these issues in satellite observations, those corrections may remove actual cloud tendencies at a global scale (e.g., Norris and Evan, 2015; Norris et al., 2016). In addition, those corrected products show significant discrepancies between linear trends in their cloud coverage (Norris and Evan, 2015). As for climate models, the representation of clouds in a coarse resolution grid is subordinate to the small-scale parameterization schemes employed, accounting in a limited way for the full range of scales involved therein (Zelinka et al., 2016; Zelinka et al., 2020).*"

(5.2) Revised discussion in the Results section that better describes our results and how they compare with studies based on long-term observations:

For supporting our claims we conducted an additional analysis to compare our results with linear trends in cloud cover from long-term observations. Figure R2 shows the results. Cloud cover as taken from in-site observations (EECER NDP-026D, Hahn et al., 2012) and corrected satellite observations (PATMOS-X and ISCCP, Norris and Evan, 2015) are considered.

As is shown, the disagreements between long-term cloud observations are clear. For linear trends in cloud coverage from corrected ISCCP, we still see unnatural patterns, such as the discontinuances over Pacific Ocean, Indian ocean and the adjacent Southern Ocean. But generally speaking, wherever the satellite trends agree with the sign, ERA5 show consistent results. Also, the decreasing cloud cover trend over most of the land agrees well with the in-situ observations.

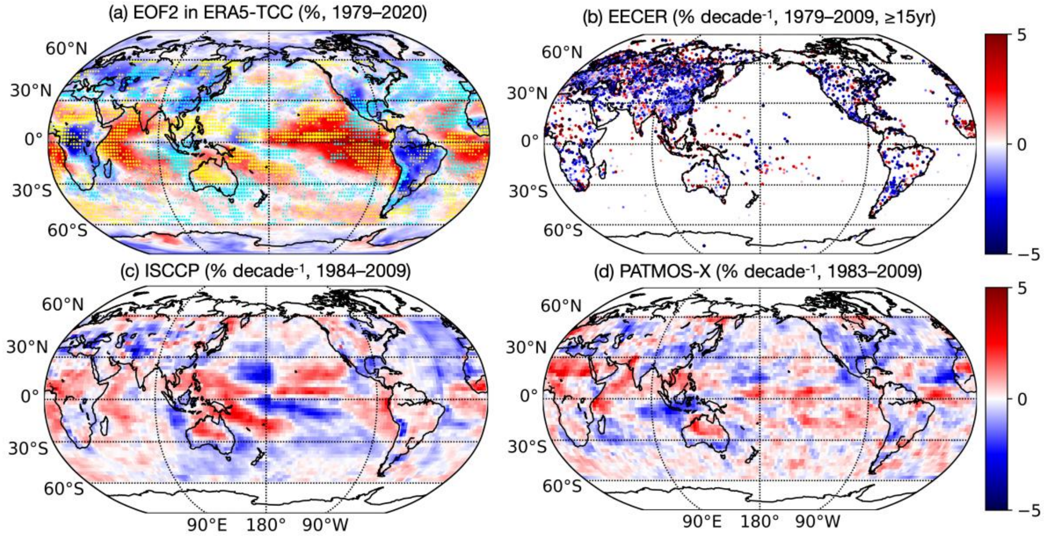

Figure R2: Comparison of trend-mode in cloud coverage from ERA5 and local linear trend in daytime-only total cloud fraction annual anomalies from observations. (a) the scaled second EOF mode (trend-like) for TCC from ERA5 during 1979 – 2020 (same as Fig. 4c in the revised paper); linear trends in cloud coverage from (b) EECER during 1979 – 2009, (c) empirically corrected ISCCP during 1984 – 2009, (b) and empirically corrected PATMOS-X during 1983 – 2009. Note that panel b contains all stations with no less than 15 years of observations. The yellow (cyan) dots in panel a indicate areas with positive (negative) trends in both cloud coverage from both corrected ISCCP and PATMOS-X.

Since previous studies have already provided detailed investigations about these patterns, we didn't add Fig. R2 to our manuscript. Rather, we gave a more comprehensive comparison between our findings and results from previous studies in the Discussion section of the revised manuscript, please see details below:

"*The reported trends are consistent with previously-made estimations based on long-term observations and historical simulations, such as the general decreasing trend over land revealed by surface observations (Warren et al., 2007), and the general increasing trend over tropics and eastern subtropics revealed by satellite observations and historical simulations (Norris and Evan, 2015; Zhou et al., 2016; Norris et al., 2016). Additionally, analysis in observed liquid water path from the Multisensor Advanced Climatology of Liquid Water Path (MAC-LWP) dataset yields increasing trends over most oceans (Manaster et al., 2017). These increasing patterns suggest consistent results with our findings as well because the value of liquid water path for cloud-free atmosphere is considered as 0. However, there are some contradictions with satellite observations, which show decreasing trends over most of the Congo Basin and increasing trends over most* *of the northeast part of tropical Atlantic (Norris and Evan, 2015). Also, some model-based future-climate prediction studies suggested a decrease in marine stratocumulus cloud coverage in warmer climate conditions (Forster et al., 2021; Zelinka et al., 2016).*"

(5.3) The list of added references:

4. Aleksandrova, M., Gulev, S.K. and Belyaev, K.: Probability distribution for the visually observed fractional cloud cover over the ocean. Journal of Climate, 31, 3207 – 3232, doi.org/10.1175/JCLI-D-17-0317.1, 2018

5. Freeman, E., Woodruff, S.D., Worley, S.J., Lubker, S.J., Kent, E.C., Angel, W.E., Berry, D.I., Brohan, P., Eastman, R., Gates, L., and Gloeden, W.: ICOADS Release 3.0: a major update to the historical marine climate record. International Journal of Climatology, 37, 2211 – 2232, doi.org/10.1002/joc.4775, 2017.

6. Hahn, C.J., and Warren, S.G.: Extended edited synoptic cloud reports from ships and land stations over the globe, 1952 – 1996, United States, doi.org/10.2172/12532, 1999.

7. Hahn, C.J., Warren, S.G., and Eastman, R.: Cloud Climatology for Land Stations Worldwide, 1971-2009 (NDP-026D) (No. NPD-026D), United States, doi: 10.3334/CDIAC/cli.ndp026d, 2012.

8. Heidinger, A.K., Foster, M.J., Walther, A., and Zhao, X.T.: The pathfinder atmospheres – extended AVHRR climate dataset. Bulletin of the American Meteorological Society, 95, 909 – 922, doi.org/10.1175/BAMS-D-12-00246.1, 2014.

9. Manaster, A., O' Dell, C.W., and Elsaesser, G.: Evaluation of cloud liquid water path trends using a multidecadal record of passive microwave observations. Journal of Climate, 30, 5871-5884, doi.org/10.1175/JCLI-D-16-0399.1, 2017.

10. Rossow, W.B., and Schiffer, R.A.: Advances in understanding clouds from ISCCP. Bulletin of the American Meteorological Society, 80, 2261 – 2287, doi:10.1175/1520-0477(1999)080,2261:AIUCFI.2.0.CO;2, 1999.

11. Stengel, M., Stapelberg, S., Sus, O., Schlundt, C., Poulsen, C., Thomas, G., Christensen, M., Carbajal Henken, C., Preusker, R., Fischer, J., and Devasthale, A.: Cloud property datasets retrieved from AVHRR, MODIS, AATSR and MERIS in the framework of the Cloud_cci project, Earth System Science Data, 9, 881 – 904, doi.org/10.5194/essd-9-881-2017, 2017.

6. Alternately, the authors can rewrite this as a model-only paper using ECMWF along with GCM output and contrast how GCM EOF patterns differ.

Answer: We believe that following the reviewers comments the revised version of the paper explains better the usage of the ERA5 and gives better, more careful context to the shown results.

References:

1. Andrew Manaster, Christopher W. O'Dell, & Gregory Elsaesser. (2017). Evaluation of Cloud Liquid Water Path Trends Using a Multidecadal Record of Passive Microwave Observations. Journal of Climate, 30(15), 5871–5884. https://doi.org/10.1175/jcli-d-16-0399.1
2. Norris, J. R., Allen, R. J., Evan, A. T., Zelinka, M. D., O'Dell, C. W., & Klein, S. A. (2016). Evidence for climate change in the satellite cloud record. Nature, 536(7614), 72–75. https://doi.org/10.1038/nature18273
3. Tiedtke, M. (1993). Representation of Clouds in Large-Scale Models. Monthly Weather Review, 121(11), 3040–3061. https://doi.org/10.1175/1520-0493(1993)121<3040:ROCILS>2.0.CO;2