Reviewer's comments:

Reviewer #2:

This paper studies the dominant modes of variability in total cloud cover. The Principal Component Analysis (PCA) is used to decompose the observed total cloud cover into dominant modes and the Canonical Correlation Analysis (CCA) is used to identify the physical linkage with known atmospheric-ocean variabilities. The authors show that the dominant modes are the Central Pacific ENSO and the ENSO modoki in the tropical Pacific region.The PCA and CCA analyses used in this study are well established in the scientific community and have been commonly used in climate studies. However, I am concerned about the physical interpretation of the results.

We thank the reviewer for comments and suggestions. Please find below a detailed response to all the comments/suggestions made by the reviewer.

As the authors discussed in Section 1, cloud is a highly uncertain variable in climate prediction because of its spatial variability in both vertical and horizontal and because of the fact that cloud at different altitudes induces very different and sometimes opposite climate forcings. Therefore, I am a little hesitant to study the total cloud variability instead of studying high and low clouds separately. The authors should explain more clearly why studying the total cloud cover is important.

Both most widely used lengthy satellite cloud records, ISCCP and the PATMOS-x, are not perfect and some issues were raised by more authors using these datasets. For ISCCP there is systematic relationship between changes in cloud fraction and changes in geostationary satellite zenith angle (Evan et al. 2007). For PATMOS there are relationships between changes in reported cloud fraction and equatorial crossing time PATMOS-x (Heidinger et al. 2014). Particularly, uncertainties were found for low cloud observations: artificially induced trends due to satellite changes (Evan et al. 2007) or the possible masking of lower clouds by higher cloud structures (Palle 2005). For regional studies such artefacts are not important, however for global studies one should consider these. Therefore the confidence in the results obtained using observed low cloud cover data would be reduced.

The ISPCC and PATMOS-x data, corrected from the specific measurement induced artefacts (Norris and Evan 2015) are provided only for total cloud cover suggesting that the methodology used in the correction of the data in not as straightforward when applied to low and high cloud separately. This exact corrected version of total cloud cover (and not low and high clouds in separate fields) was used in a study published in Nature magazine in order to identify the anthropogenic impact on clouds on a global scale (Norris et al. 2016).

The principal modes in the total cloud cover, the CP ENSO and ENSO Modoki, have already been known in a previous study which studies high cloud fraction [Li et al. (2016), An Analysis of High Cloud Variability: Imprints from the El Niño-Southern Oscillation, Climate Dynamics, 10.1007/s00382-016-3086-7]. Therefore, the principal modes found in this study are not new and are primarily due to the high clouds instead of the total cloud cover, as is also explained by the authors in their Section 3.5. It also goes back to my comment above that why should we study the total cloud cover?

The variability of cloud cover is not totally due to high clouds and studying the coupled sea surface temperature – total cloud cover patterns allowed us to identify specific areas where a changes are due to a certain type of cloud, which is not always high cloud. Indeed, in the tropical Pacific, the positive SST-TTC correlation suggest that the high clouds are predominant in the TCC patterns, but over the SE and NE pacific, the observed anticorelation between the SST and TCC suggest that low level marine stratiform clouds are predominant in the TCC patters. If only high or only low clouds are considered, part of the cloud response to changes in SST would be masked or simply would not show.

We further emphasize two feedbacks, related mainly to high, respectively low clouds, with impact on the global radiative balance. Therefore the use of total cloud cover provides a much comprehensive picture, considering also the superior quality of the data used compared to an investigation using the low cloud ISPCC and PATMOS-x data.

A critical issue with the authors' interpretation of the principal modes is that they ignore the second mode of ERA5R total cloud cover because "[t]he second EOF derived using the ERA5R TCC data (Supp. Fig. 1) is not of interest for our study due to its temporal characteristics." The PCA is a pure mathematical decomposition of any given matrix, random or not, where the principal modes are forced to be mutually orthogonal singular vectors and no physical constraints are applied in the construction of the singular vectors. Therefore, one must be extremely careful when trying to attribute physical meanings to the principal modes. The fact that the phenomenon of the authors' interests has shifted from the second mode to the third in ERA5R TCC means that the second and third modes are likely degenerated because the eigenvalues of these modes are statistically indistinguishable. A serious problem associated with degenerated modes is mode-mixing, which makes the physical interpretation of the degnerated modes difficult. As the authors are trying to compare ERA5R modes with those obtained from ISCCP and PATMOS-x, simply ignoring the second mode without considering possible mode-mixing in ERA5R TTC could potentially lead to inaccurate conclusion about the quality of the ERA5R assimilations. The authors may check whether there are also mode-mixing in the second and third modes in ISCCP and PATMOS-x TCC. For more details on mode-mixing, see Quadrelli et al. (2005), On Sampling Errors in Empirical Orthogonal Functions, Journal of Climate, 10.1175/JCLI3500.1.

Cloud trends were eliminated from the corrected version of the observed data, and their origin is still not clear (e.g. Usoskin et al. 2006; Norris and Slingo 2009; Laken and Čalogović 2011). Since there is no similar pattern, with a corresponded trend in the corrected observational data, we did not interpret the spatial pattern of the second EOF from ERA5R but consider the third EOF from that dataset, based on its spatial and temporal similarities with the second EOF identified in observational data. Therefore one can say that the ERA5R capture with accuracy the interanuual cloud variability but is unable to assess the quality of the simulated trend.

The physical meanings of the patterns associated with the EP and the CP ENSO is deducted from the Canonical Correlation Analysis (CCA), through association with known SST patterns and further supported by the regression analysis obtained with the associated PCs. As the referee rightfully observed, the CCA and PCA are standard analysis widely used for separating modes of variability of various fields. CCA is applied to two fields in order to identified pairs of patterns whose associated time series are maximum correlated. Therefore, whereas EOF is based on the distinction between patterns (they are orthogonal), CCA is based on the distinction between time evolutions of patterns (time series of consecutive pairs are uncorrelated). If one assumes that distinct forcing factors (natural or anthropogenic) are characterized by different temporal evolutions, which is a reasonable hypothesis, then CCA appears as a method which could be used to separate the footprint of forcing factors on a given field. However, the similarities between the patterns associated with the EP and the CP ENSO through CCA and the first 2 observed modes of total cloud cover variability identified through EOF indicate that the last also have physical relevance.

All the analyzed EOFs past the rule M for separation ("significance") (North 1982) because the spacing between the eigenvalues is significantly larger than the sampling error for all analyzed EOFs. This aspect will be clearly mentioned in the improvements added to the manuscript and the exact values for each EOFs will be included in the supplementary material. Generally, total cloud cover data do not have any memory (as compared to sea ice and to sea surface temperature to some extent) and the wide (relatively global) area of selection decreases the likelihood of a mixing between modes (Levine and Wilks 2000). Nonetheless, in order to determine the exact degrees of freedom for each PC we used the methodology from Bretherton et al. (1999).

A minor comment is that the authors mentioned in abstract and in the text a few times the ISCCP and PATMOS-x "each corrected for specific errors". I first thought that the authors corrected these data themselves but the authors actually downloaded the corrected data directly from the web. The discussion about the correction by Norris et al. in Section 2.1 is reasonable, but can the authors elaborate more on why they want to emphasize the correction in various places?

The uncertainties in the observed cloud cover data makes their use for studying relatively long term natural or anthropogenic variability debatable (e.g. Norris 2000; Free and Sun 2013; Marvel et al. 2015). Because of the uncertainties regarding cloud data, we preferred to use an established corrected data set, already used in several studies.

The correction of different errors is emphasized more than once because, when a similar signal of cloud variability is found in multiple independent satellite datasets, the confidence increases that the cloud changes and corrections made to the initial data are accurate.

References

Bretherton CS, Widmann M, Dymnikov VP, et al (1999) The effective number of spatial degrees of freedom of a time-varying field. J Clim 12:. https://doi.org/10.1175/1520-0442(1999)012<1990:TENOSD>2.0.CO;2

Evan AT, Heidinger AK, Vimont DJ (2007) Arguments against a physical long-term trend in global ISCCP cloud amounts. Geophys Res Lett 34:. https://doi.org/10.1029/2006GL028083

Free M, Sun B (2013) Time-varying biases in U.S. total cloud cover data. J Atmos Ocean Technol 30:. https://doi.org/10.1175/JTECH-D-13-00026.1

Heidinger AK, Foster MJ, Walther A, Zhao X (2014) The pathfinder atmospheres-extended avhrr climate dataset. Bull Am Meteorol Soc. https://doi.org/10.1175/BAMS-D-12-00246.1

Laken BA, Čalogović J (2011) Solar irradiance, cosmic rays and cloudiness over daily timescales. Geophys Res Lett 38:. https://doi.org/10.1029/2011GL049764

Levine RA, Wilks DS (2000) Statistical Methods in the Atmospheric Sciences. J Am Stat Assoc. https://doi.org/10.2307/2669579

Marvel K, Zelinka M, Klein SA, et al (2015) External influences on modeled and observed cloud trends. J Clim 28:. https://doi.org/10.1175/JCLI-D-14-00734.1

Norris JR (2000) What can cloud observations tell us about climate variability? Space Sci. Rev. 94

Norris JR, Allen RJ, Evan AT, et al (2016) Evidence for climate change in the satellite cloud record. Nature. https://doi.org/10.1038/nature18273

Norris JR, Evan AT (2015) Empirical removal of artifacts from the ISCCP and PATMOS-x satellite cloud records. J Atmos Ocean Technol. https://doi.org/10.1175/JTECH-D-14-00058.1

Norris JR, Slingo A (2009) Trends in Observed Cloudiness and Earth's Radiation Budget: What Do We Not Know and What Do We Need to Know? Clouds Perturbed Clim Syst

Quadrelli R, Bretherton CS, Wallace JM (2005) On sampling errors in empirical orthogonal functions. J Clim 18:. https://doi.org/10.1175/JCLI3500.1

Usoskin IG, Voiculescu M, Kovaltsov GA, Mursula K (2006) Correlation between clouds at different altitudes and solar activity: Fact or Artifact? J Atmos Solar-Terrestrial Phys 68:. https://doi.org/10.1016/j.jastp.2006.08.005