We thank reviewer Richard Allan for taking the time to review our manuscript, engaging in collegial discussion, and providing constructive comments and suggestions. These have been helpful in improving the manuscript. The manuscript is revised as described below. For clarity, reviewer's original comments are included in black, our responses are written in blue, and the revision in the updated manuscript is marked with green.

Author response to Reviewer # 1, Richard Allan

An assessment of four satellite upper tropospheric humidity (UTH) data sets are made with a focus on interannual variability and the effect of El Nino Southern Oscillation (ENSO) on spatial anomalies. Although the spatial anomalies associated with ENSO variability are well known, the strength of this article is in comparing 4 contrasting datasets. In general, users of these or similar datasets will probably wish to know the best dataset for their application so any statements on the relative quality of the datasets and any issues such as inhomogeneities or artificial drifts will add value to the paper. In particular, are there any spurious jumps or trends such as HIRS before and after 2000 or jumps in the CMSAF record? It would also be useful to comment on whether there are systematic biases for any particular meteorological regimes (e.g. convective, anvil, descent, etc).

Thank you for the comments. To assist users of similar datasets, additional statements on the relative strength and weakness of infrared and microwave (MW) UTH datasets are added to the conclusions. Regarding HIRS data, we noted that after 2000 the magnitudes of anomalies during El Nino events appear slightly smaller than those before 2000, but such pattern is also inferred by the FIDUCEO MW UTH dataset (albeit with a short data length before 2000). The Multivariate El Niño/Southern Oscillation Index (MEI), which incorporates surface air temperature, sea-level pressure, zonal and meridional components of the surface wind, and total cloudiness fraction of the sky together with the SST field, also shows noticeable stronger El Nino events in the 1980s and 1990s compared to those after 2000, indicating a possibility of decadal or multi-decadal change of some meteorological variables. The jumps between satellites in the CMSAF UTH dataset were discussed in the Lang et al. (2020) paper, and these were described but the analysis was not repeated in the current article. The UTH datasets have been mostly used in large-scale interannual variability studies, and thus the current consistency assessment is focused on large-scale interannual regimes such as ENSO, rather than on mesoscale meteorological regimes.

Specific comments:

Abstract: some more quantitative statements would be useful in assessing the magnitude of differences.

Some quantitative statements are added to the abstract in the revision:

During a major El Niño event, UTH had higher correlations with the coincident precipitation (0.60 – 0.75) and with 200 hPa velocity potential (-0.42 - -0.64) than with SST (0.37 - 0.49). Due to differences in retrieval definitions and gridding procedures, there can be a difference of 3-5% UTH between datasets on average, and more significant anomaly values are usually observed in the microwave UTH data. Nevertheless, the tropical-averaged anomalies of the datasets are close to each other with their differences being mostly less than 0.5% over tropical domain average, and more importantly the phases of the time series are generally consistent for variability studies.

L45 - application for model evaluation and processes understanding studies could be highlighted

Some references are added in the Introduction to cite studies that use UTH measurements to evaluate climate models for large-scale atmospheric process studies:

The UTH datasets facilitated the evaluation of climate models and contributed to a better understanding of large-scale atmospheric processes (Allan et al., 2003; Soden et al., 2005; Chung et al., 2016; Allan et al., 2022; John et al., 2021).

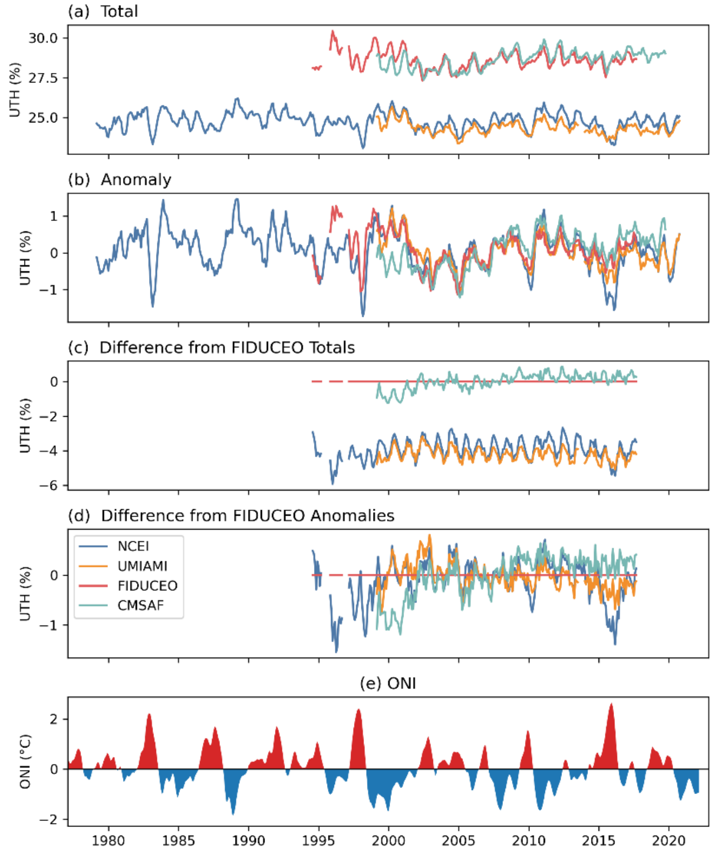
L131 - presumably non-linearities in the UTH calculation affect the computation of UMIAMI UTH from gridded data and this will affect the absolute magnitude but probably not the anomalies

Agree that the non-linearities in the UTH calculation affect the computation of UMIAMI UTH from gridded data in the absolute magnitude but this process doesn't significantly affect domain-averaged anomaly values. We edited the sentence and now it reads:

Based on a study by John et al. (2006), such different ways of computing UTH can lead to a difference of up to 6% UTH due to the non-linearities in the formula that calculates UTH from brightness temperature values.

Fig.1 - it is expected that HIRS UTH will be lower than microwave estimates since they sample systematically drier, clear-sky scenes. Can the lower UMIAMI values compared to FIDUCEO and CMSAF be explained by the method, in which case why is UMIAMI used as the baseline since it is not computed using swath data?

The lower UMIAMI values can be explained by the gridding method. The purpose of Figures 1c-d and 2c-d is to quantify the relative differences between datasets. UMIAMI UTH has the longest AMSU-B/MHS data, and thus was chosen to be the reference in Figs. 1 and 2. Using a different dataset as a reference would not change the conclusion on relative differences. The following is a plot using FIDUCEO UTH as a reference. The SSM/T-2 UTH in the FIDUCEO time series is not as stable as the AMSU-B/MHS data due to frequent missing data.



To clarify the choice of using UMIAMI UTH as the reference, the following is added to the revision:

To quantify the differences between datasets, the relative differences are calculated. Note that any of the four datasets can be used as a reference for this purpose. Among the MW UTH datasets, the UMIAMI dataset has the lengthiest time period of AMSU-B and MHS to allow for the longest MW comparison with others, and it is used as the relative reference in the calculation. Figure 1d shows that the anomaly values are mostly within ±0.5% UTH of each other, with the exceptions during El Niño events when the anomaly differences can be larger.

L147 and throughout - more quantification of the difference between datasets would be helpful

We think that your comment about L147 refers to the sentence "The values of CMSAF and FIDUCEO UTH are larger than the values of NCEI and UMIAMI UTH." in L146-147. The differences between values of the two groups were discussed and quantified in the following sentence in the same paragraph (L150 of the preprint): "Figure 1c shows that there is a difference of approximately 3-5% UTH between two groups of UTH datasets when a tropical average is taken". Taking your suggestion, we have added quantified difference values between datasets in various places of the revised manuscript.

L153 - please provide quantification of "good agreement"

The “good consistency” in L152 was referred to agreement in interannual variability patterns. The sentence has been edited to clarify the discussion, and one more sentence is added to better describe the patterns:

In spite of this structural discrepancy, the anomaly plot of the UTH in Figure 1b shows consistency in seasonal and interannual variability patterns among the four datasets. All four datasets show major peaks and dips along the time series in the same phases, though there are differences in the magnitudes of the fluctuations.

L155 - how close is "close to each other" in the context of their use?

The closeness of the dataset anomalies was quantified in the sentence that immediately follows (in L155-L156 of the preprint. The sentence is edited to:

Figure 1d shows that the anomaly values are mostly within ±0.5% UTH of each other, with the exceptions during El Niño events when the anomaly differences can be larger.

L157 (and L256) - is the smaller variability in HIRS linked to the fact it is not sampling the full scale of meteorological regimes (e.g. clear-sky only and so sampling less of the tropical deep convective regions)?

We agree. The clear-sky requirement in the HIRS datasets excluded the majority of deep convective regions. We added “as deep convective regions are excluded” to the sentence as:

This indicates that the infrared clear-sky dataset may not fully capture the increase of water vapor during El Niño events due to the exclusion of very humid pixels associated with clouds, and tends to have better sampling of the dry regions.

Section 3.1 - Variability in UTH and RH in a range of datasets are shown in Figures 6-8 of Allan et al. (2022) which could be commented on. Can the shifting of wet regions more over land during La Niña and more over the ocean contribute to changes in the biases since the retrieval over land and ocean may differ subtly? Or does it relate more to the changing proportion of "dry" and "humid" regions that are sampled differently by the different instruments (particularly HIRS)? A metric for proportion of the tropics with UTH>X and UTH<X, where X could be 50% or a suitable mid-range value, would be interesting.

A reference to Allan et al. (2022) is added to the revision:

Allan et al. (2022) presented tropical (30°S–30°N) ocean and land averaged anomaly time series of ERA5 relative humidity (RH), AIRS RH, HIRS UTH, and MW UTH (Figures 6 and 7 of their study). The HIRS and MW UTH are the NCEI and UMIAMI UTH datasets analyzed in the present study, and the features of these two datasets are similar to the NCEI and UMIAMI UTH time series in Figure 1b.

Please also see the discussion added for Fig. 3 below that references on Figure 8 of Allan et al. (2022).

Regarding the wet anomalies during La Niña, our figures show that they are primarily the result from the vast moistened Pacific subtropics.

We incorporate your suggestion of plotting the proportion of wet and dry regions (but using anomalies rather than total values), and include it as the new Figure 4 in the revision. The new figure and discussions are copied below:

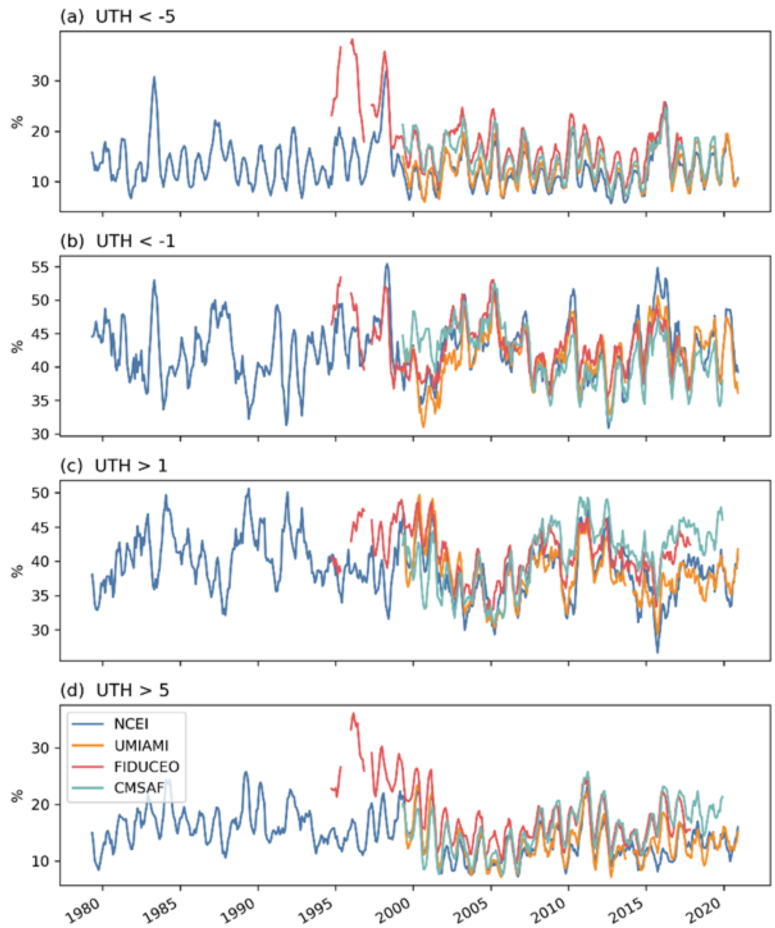


Figure 4: Time series of the ratios of grids over 20°S-20°N with anomaly values less than -5% and -1%, and greater than 1% and 5%.

To quantify the changing proportion of dry and humid regions derived from the different datasets, we calculate the percentage of grids with anomaly values greater or less than a fixed value over 20°S-20°N (Figure 4). Grids with UTH anomaly values > 5% represent very humid anomalies while those < -5% represent very dry anomalies. Among the MW datasets, the SSM/T-2 derived UTH in the FIDUCEO series has the highest proportion of very humid anomalies. For the AMSU-B/MHS series, FIDUCEO dataset generally has 2-4% more very humid anomalies than that of the UMIAMI dataset. The gridding of UTH after the pixel-level brightness temperature values are averaged in the UMIAMI dataset may have smoothed out some of the most humid measurements. The CMSAF UTH has fewer dry anomalies before 2005 than the other datasets, but it has the largest proportion of very humid anomalies in recent years. The infrared dataset has the smallest proportion of humid anomalies compared to the MW datasets at both levels (> 5% and > 1%) due to the exclusion of cloudy pixels.

HIRS UTH also generally has the smallest proportion of the driest anomalies (< -5%), but the ratios are often close to those of the UMIAMI dataset. Interestingly, when the majority of the negative anomalies are examined (UTH anomalies < -1% in Figure 4b), the HIRS dataset frequently has the largest ratios of the dry anomalies. This phenomenon is particularly significant during both major El Niño and La Niña events. For example, during the 2015-16 El Niño, the ratios of UTH anomalies < -1% are approximately 51% for HIRS, 47% for UMIAMI, 46% for FIDUCEO, and 45% for CMSAF dataset. In other words, the HIRS data identifies more dry anomalies than the MW datasets, though the magnitude of the driest HIRS UTH does not usually reach as large values as those of the MW UTH likely due to the definition of the UTH formula used. Overall, the FIDUCEO dataset has the largest amplitude of the ratios for both the most humid and driest measurements.

Fig. 2 - panels c and d do not seem to add much to a and b so could be removed since they are barely referred to

We would keep both panels. We intend to show that while between Figures 1b and 2b the phases of the variations are mostly opposite, the signs (positive and negative) of the difference between infrared and MW UTH datasets remain the same between Figures 1c and 2c and between Figures 1d and 2d. Additional description regarding the moistening trend in the CMSAF UTH dataset shown in the two panels is also added to the paragraph:

Though a moistening trend is shown in the CMSAF UTH time series in Figures 1c and 1d where the tropical average is taken, the moistening trend is not as apparent for the Niño 4 region as displayed in Figures 2c and 2d.

Fig. 3 - there seems to be a change in the anomaly characteristics in NCEI after 2000. Does this relate to the unusual series of La Niña events associated with slower global warming in the 2000-2012 period or are there changes in the instrument? Interestingly the anomaly characteristics of the microwave data after 2000 seem more like the pre-2000 NCEI record than the coincident post-2000 period. A similar change in anomaly characteristics seems present in Figure 8c of Allan et al. (2022) https://doi.org/10.1029/2022JD036728 for zonal means with less positive anomalies after around 2000, though it is rather a subtle change (particularly a decreasing trend in UTH 30-60ºS with positive anomalies before 2000).

The following is added to the revision in the paragraph of the Fig. 3 discussion:

Allan et al. (2022) examined changes in the anomaly characteristics in the zonal mean of AMIP 300–500 hPa RH, ERA5 300–500 hPa RH, and HIRS UTH (their Fig. 8a-c). Both the AMIP and HIRS time series showed a detectable decreasing trend in UTH 30°S-60°S, and all three datasets showed decreasing amplitudes of anomalies after 2000. More specifically, AMIP and HIRS showed smaller positive anomalies while ERA5 exhibits smaller negative anomalies. The FIDUCEO MW UTH in Figure 3c of our study also shows subtly stronger UTH amplitudes before 2000, albeit with only a few years of data available. These changes after 2000 seem to be coincident with the decrease in the strength of El Niño events after 2000 as depicted by the MEI.v2, though such changes are not displayed in SST-only Niño indices such as the ONI.

Fig. 4/5 and 6/7 - a scatter of precipitation anomalies (possibly as % changes) verses UTH anomalies with some quantification of the relationship may be instructive and quite novel. It is not clear what the goal of the El Niño and La Niña comparisons are since these teleconnections are well known. If the goal is to evaluate the differences between datasets it is not so obvious from these plots. La Niña minus El Niño may be another way to present similar information in half the number of plots.

Keeping both El Niño and La Niña figures helps readers visualize why there are negative UTH anomalies during El Niño when the tropical domain average is taken and positive UTH anomalies during La Niña. Having both El Niño and La Niña figures also helps the inter-comparison of the four UTH datasets during these major events specifically. Scatter plots (with histograms) of precipitation anomalies verses UTH anomalies, plus plots of SST and 200 hPa velocity potential verses UTH anomalies are added to the revision as new Figures 7-9:

To further assess the consistency of UTH datasets with several environmental variables, histograms of UTH anomalies vs. anomalies of GPCP precipitation, ERSSTv5 SST, and CFSR 200-hPa velocity potential during the peak six months of the 2015-16 El Niño are presented in Figures 7-9. The correlations between the anomalies of UTH and those of the three variables are also calculated and the correlation values are labelled at the top of each panel. Among the three variables, precipitation has the highest correlations with UTH (Figure 7), while SST has the lowest (Figure 8). both precipitation and velocity potential are proxies for vertical motion, so they are more directly tied to wet/dry UTH than the SST surface forcing. The increases of SST during El Niño events usually occur in the eastern-central Pacific, while the increases of both UTH and precipitation are more confined over the central Pacific. The UTH and precipitation fields both have a more balanced dipole between the central and western equatorial Pacific during a major El Niño, while the decrease of SST in the western equatorial Pacific does not match the strength of positive anomalies in the central-eastern equatorial Pacific. These patterns lead to overall higher correlations between UTH and precipitation than those between UTH and SST. The correlation values also illustrate that an SST-only ENSO index may not be as good of an indicator for the strength of UTH compared to an index that includes other environmental variables such as the MEI.

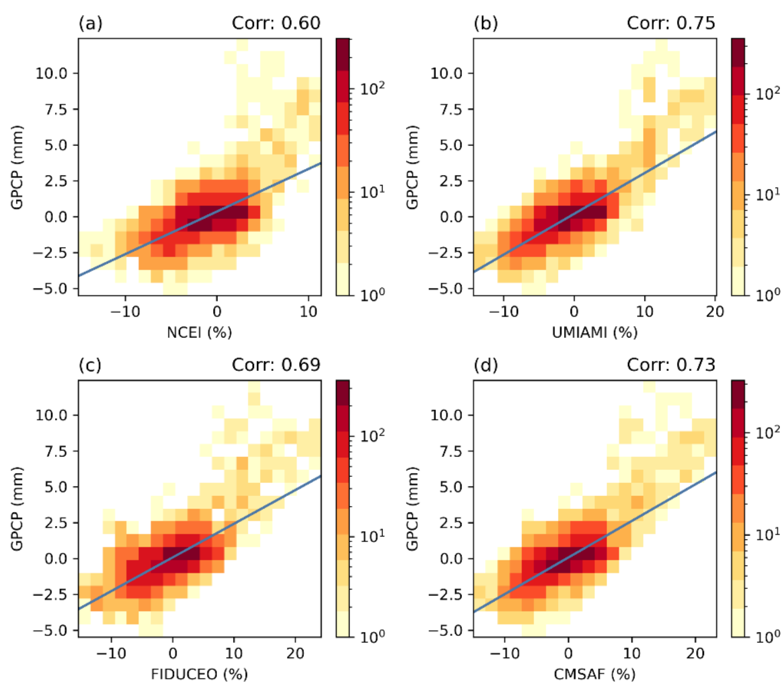


Figure 7: Histograms of UTH anomalies of the four datasets vs. anomalies of GPCP precipitation during the peak six months of the 2015-16 El Niño. The blue line represents the linear regression line. The correlations between UTH anomalies and GPCP precipitation anomalies are labelled at the top of the panels.

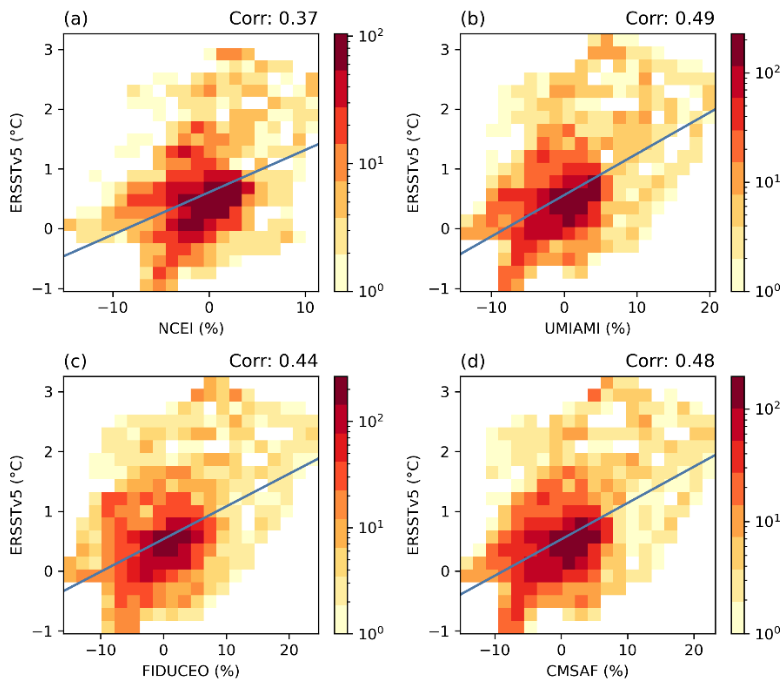


Figure 8: Similar to Figure 7 except for UTH anomalies vs. ERSSTv5 anomalies.

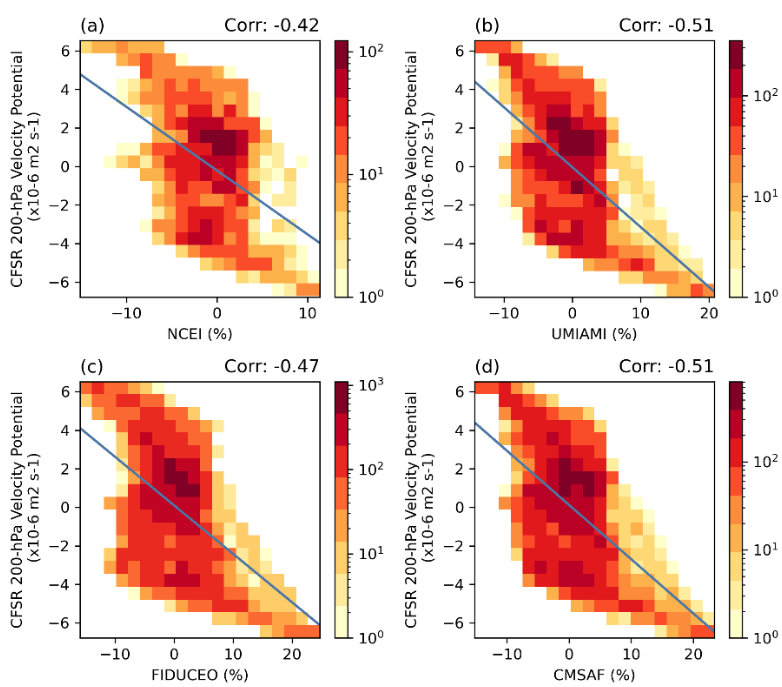


Figure 9: Similar to Figure 7 except for UTH anomalies vs. anomalies of CFSR 200-hPa velocity potential.

Among the UTH datasets, the MW data have higher correlations with the three environmental variables. The HIRS UTH correlation values are about 0.1 lower, primarily due to the lack of very humid anomalies in the infrared dataset. The histograms show that for all UTH datasets, the highest densities of anomalies are consistently centered around zero. The density of HIRS positive anomalies decreases rapidly beyond 5%, in line with the lowest ratio of large HIRS UTH shown in Figure 4d.

Fig. 8 suggests that CMSAF trends are inconsistent with the other datasets with increases in UTH over the whole region. Can this be quantified for the whole tropics and is this understood as the change in satellite offsets as implied. Was there no attempt to intercalibrate the satellite records by CMSAF?

The CMSAF UTH is based on a microwave humidity sounder FCDR generated by EUMETSAT. However, remaining inter-satellite discontinuities are noticed. The discontinuities in CMSAF UTH between satellites were documented in Lang et al. (2020).

Conclusions - some statements on the strengths and weaknesses of the datasets and possible issues identified would be welcome.

In addition to the strengths and weakness of the datasets discussed in the conclusion section (in terms of consistency and differences), a short paragraph is added at the end of the manuscript:

The infrared and MW UTH datasets have their own strengths and weakness. The HIRS dataset has the longest, over 43 years of observations so far, for long-term studies, and its variability, temporal phases, and spatial patterns are generally consistent with MW observations. However, being a clear-sky dataset, it does not capture the most humid regions. The MW datasets have a shorter time series, but they retain almost all-sky data, removing only the precipitating pixels, thus have a better sampling for a full spectrum of UTH especially for very humid data.

L324 - state that this is the CMSAF dataset which exhibits moistening trends relative to the other datasets

It is stated in the revision:

Wider spread of UTH moistening is observed in the CMSAF datasets.

Will future work make comparisons with reanalyses and CMIP6 models?

This would depend on the direction of the next phase of the GEWEX Water Vapor Assessment, and on whether there are sufficient changes in the UTH dataset versions. Current versions of two of the satellite UTH datasets have been compared with reanalyses and CMIP6 models in a few studies.