

Water Vapour Climate Change Initiative (WV_cci) - CCI+ Phase 1



Climate Assessment Report (CAR)

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1. INTRODUCTION

1.1 Purpose

This Climate Assessment Report (CAR) complements the detailed Level-2/Level-3 validation and comparisons described in the ESA WV_cci Product Validation and Intercomparison Report (PVIR) (D5.1). The climate assessment efforts within the ESA WV_cci project focus on the analysis of the clear-sky bias, trend estimations, variability analysis across various temporal and spatial scales, covariance with other Essential Climate Variables (ECVs), atmospheric moisture transport and comparison with CMIP6 data.

Results related to atmospheric moisture transport and comparisons to CMIP6 are extended summaries from submitted publications.

1.2 Scope

This document describes the climate assessment of the water vapour products by the ESA WV_cci project. The activities are an integral part of the international research on atmospheric water vapour.

Specific tasks include:

- Trend estimation applied to long-term data records
- Analysis of the compliance with theoretical expectation
- Analysis of atmospheric moisture transport
- Climate studies using data from CMIP6 and ERA5.

The overall scope of this document is to assess strengths and weaknesses in the ESA WV_cci climate data records, and their value to the climate users.

1.3 The ESA Water_Vapour_cci project

Water vapour is the single most important natural greenhouse gas in the atmosphere, thereby constraining the Earth's energy balance, and it is also a key component of the water cycle. Due to its importance, the WMO's Global Climate Observing System (GCOS) program has highlighted water vapour as an ECV in the GCOS 2016 Implementation Plan (GCOS, 2016). There is consequently the need to consolidate our knowledge of natural variability and past changes in water

vapour and to establish climate data records of both total column and vertically resolved water vapour for use in climate research. These climate data records need to be homogeneous in space and time, which bears great challenges due to changing instrument characteristics and performances. Well-characterised uncertainties are a key attribute of such climate data records in order to reduce the uncertainty in estimates of climate change and global radiative forcing.

The Climate Change Initiative (CCI) is a program of the European Space Agency (ESA), established to tackle the challenges encountered in merging climate data records of ECVs and has the goal to provide climate modellers and researchers with long-term satellite records from current and past European (and other space agencies') missions. The ESA CCI Water Vapour project generates stratospheric and tropospheric water vapour by developing novel methods to determine, merge and estimate such water vapour data and associated uncertainties.

1.4 The WV_cci datasets

The WV_cci datasets comprise four CDRs:

- CDR-1: gridded monthly and daily time series of TCWV in units of kg/m^2 that cover the global land areas with a spatial and temporal resolution of 0.05° and daily, respectively. It covers the period July 2002 to December 2017.
- CDR-2: gridded monthly and daily time series of TCWV in units of kg/m^2 that cover the global land and ocean areas with a spatial and temporal resolution of $0.05^\circ / 0.5^\circ$ and daily, respectively. It covers the period July 2002 to December 2017.
- CDR-3 contains the vertically resolved water vapour ECV in units of ppmv (volume mixing ratio; VMR) and will be provided as zonal monthly means on the SPARC Data Initiative latitude/pressure level grid (SPARC, 2017; Hegglin et al., 2014). It covers the vertical range between 250 hPa and 1 hPa, and the time period 1985 to the end of 2019.
- CDR-4 consists of three-dimensional vertically resolved monthly mean water vapour data (in ppmv) with spatial resolution of 100 km, covering the troposphere and lower stratosphere.

2. ANALYSIS OF THE CLEAR-SKY BIAS

Ulrike Falk (DWD), Marc Schröder (DWD), Rene Preusker (SE)

Total column water vapour can be retrieved from satellite observations on a global scale since the late 1970s. Measurements are obtained over land and ocean in different parts of the electromagnetic spectrum: among others, the ultraviolet/visible (UV/vis), infrared (IR), the microwave, and with high spatial resolution over land the near infrared (NIR) frequencies. Except for microwave observations, all related retrievals are predominantly applied under clear-sky conditions. Though instantaneous water vapour products show high quality and low uncertainty, this is not necessarily true for the gridded and temporally averaged products: Conditions in clouds are typically more humid than the surrounding clear-sky areas, and are not taken into account by the satellite's clear-sky observations. This effect is called clear-sky bias (CSB) and is in the order of 10% (Sohn and Bennartz, 2008). In order to provide a reliable uncertainty estimate for gridded and temporally averaged clear-sky products, the contribution of this source of uncertainty to the total uncertainty needs to be characterised.

2.1 Characterisation of the clear-sky bias using ERA5 data

Within the framework of the EU-funded Copernicus Climate Change Service (C3S), ECMWF produced the ERA5, i.e. the fifth generation of ERA reanalysis of the global weather and climate (Hersbach et al., 2020). The main objective of the ERA5 project is to give a detailed record of the global atmosphere, land surface and ocean waves from 1950 onwards. The ERA5 data is being used to look into the differences between full (all-sky) TCWV data and TCWV data filtered by the obstruction by cloud occurrence. Data records and access are described in full detail in the DARD (2021).

All metrics are described in the PVP (2021), but for the sake of completeness, the detailed formulas are given here. One major main difference between the ERA5 data output and the satellite observations is the time stamp of the single data- and grid points. The L3 globally gridded satellite datasets consist of daily and monthly averages where each grid point contains satellite observations from a specific overpass time. Each satellite observation is strictly speaking a function of local time (LT). However, the NIR sensors taken into account in the WV_cci are on platforms that are in sun-synchronous orbit, meaning that the satellites are crossing the equator and any point on the Earth's surface at approximately the

same local time. Deviations may occur from eccentricity. However, this approximation is valid at near-nadir pixels in view of the considered hourly time window (see below). The ERA5 data, on the other hand, are datasets of model output for each time step of the model run in UTC. Here, the globally gridded data fields have the same time stamp in UTC for each time step of the model output. In order to compare observations with model data, it is, thus, imperative to convert the data fields into the same temporal systems. This is done here by slicing the ERA5 data into longitudinal fields according to local time of the respective satellite overpasses and patch them back into data fields with the same local time stamp (e.g. MERIS overpass local time ≈ 10 am) with a temporal resolution of 1 hour translating into 15° spatial resolution. The temporal collocation window is then set to ± 0.5 hours. Note that the fixed swath width in km covers increasingly larger longitude regions with increasing latitude. In consequence, the swath can cover more than one hourly bin. This effect is ignored in our analysis, i.e. ERA5 are not exactly sampled as a single, specific satellite would have seen it. Instead, the results are meant to allow for a general analysis of and potential application to various satellites. Also, the CSB can be analysed at e.g. 10 and 11 local time to see an impact of differences in temporal sampling.

The cloud mask is simulated by filtering total column cloud liquid water (TCLW) and total cloud cover (TCC) of ERA5. The filters were set to $TCC > 0.95$ and $TCLW > 0.005 \text{ kg m}^{-2}$ following the work of Sohn and Bennartz (2008). The filter criteria were responsible for the exclusion of 75% of the data points per month on average, with an annual cycle of average amplitude of approximately 7.5% and very little year-to-year variability. Of the filtered data, the TCC criterion filtered $66.3\% \pm 0.3\%$, and the TCLW criterion $87.1\% \pm 0.2\%$ of all filtered data. It is noted that Stubenrauch et al. (2012) observe 62 and 69% of average global cover in two different MODIS products.

2.1.1 Tools

The clear-sky bias (CSB) is estimated here as the difference of the sampled data to the climatology (see PVP, 2021), applied to each grid point:

$$CSB_{i,j}(t) = x_{i,j}(t) - \overline{C_{i,j}}^{(2002-2012)}$$

where i is latitude, and j is the longitude, $\overline{C_{i,j}}^{(2002-2012)}$ the all-sky and all times climatology computed over the whole time period (here 2002–2012) for each grid point, and t is the time step (e.g. equator crossing time of 10 am local time).

We dissect the *csb* into its local time scale, monthly and spatial components, i.e. $CSB = function(\text{local time, month, longitude, latitude})$:

$$\overline{CSB_{t,j}}^T = \left(x_{t,j}(t) - \overline{C_{t,j}}^{(2002-2012)} \right)^T$$

where T indicates an average at each equator crossing time (here all full hours), at each month over all years. The respective standard deviation is given as uncertainty measure for each time scale. The results are plotted spatially and assessed qualitatively (see Section 2.1.2).

2.1.2 Results of ERA5 analysis

The climatology of the CSB calculated from the hourly ERA5 climate data records is displayed in Figure 2-1. It shows a coincidence of maximum clear-sky biases with cloud occurrence, i.e. over the ITCZ and extratropical storm tracks, and of minimum and even positive clear-sky bias over deserts and stratocumulus regions. As mentioned in the introduction of Section 2 it is expected that the clear-sky bias is generally negative as observed for most regions and as seen in an average CSB of -0.85 kg/m^2 . However, also positive values are observed with a similar spatial structure as in Sohn and Bennartz (2008). Over ocean such regions mainly occur in the presence of stratocumulus clouds. In the presence of such clouds, mostly dry atmospheres are observed, while in clear sky the atmosphere likely exhibits more mixing and is thus more humid (Fetzer et al., 2006; Sohn and Bennartz, 2008).

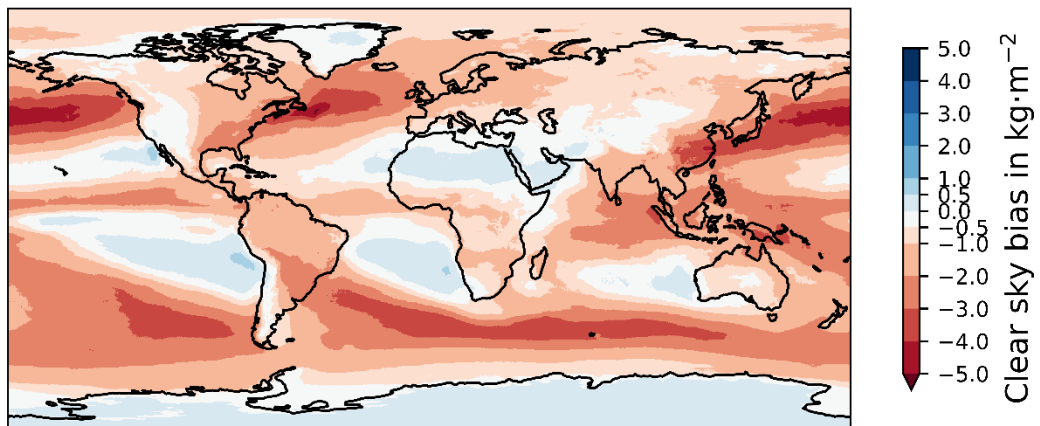


Figure 2-1: 11-year climatology of the clear-sky bias assessed for ERA5 data records on hourly basis (time period 2002–2011), resulting in an area-weighted global $CSB_{\text{mean}} = -0.85 \text{ kg m}^{-2}$.

According to the spatial location, the filters of the CSB assessment lead to a reduction in data points used for averaging over the 11-year time period.

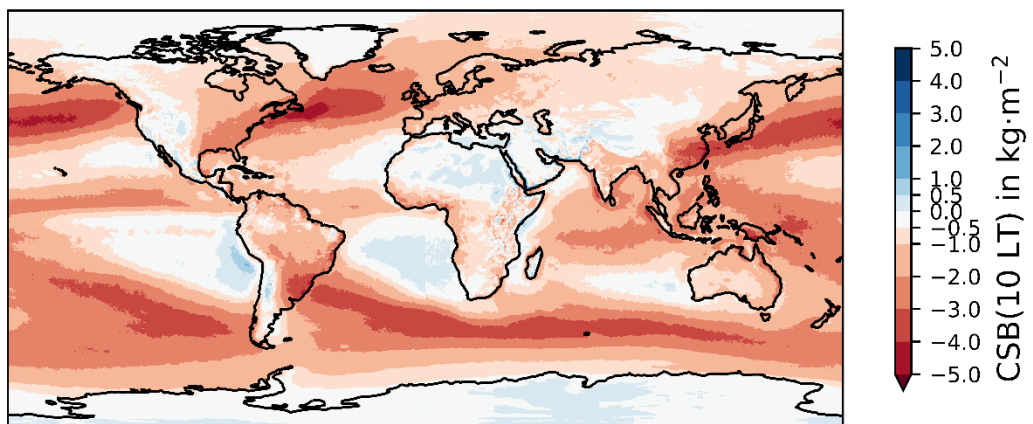


Figure 2-2: 11-year climatology of the clear-sky bias for local time, LT=10; the assessment is based on hourly ERA5 data records for local overpass time of MERIS (time period 2002–2011). The area-weighted global average computes to $CSB_{\text{mean}} = -0.87 \text{ kg m}^{-2}$.

Figure 2-2 shows the climatological clear-sky bias for 10:00 local time. Overall the two climatologies (Figure 2-1 and Figure 2-2) exhibit similar features, except that the latter seems to be damped somewhat and more noisy. Theoretically, the differences between the two climatologies (Figure 2-1 and Figure 2-2) illustrate the effect of the temporal sampling bias in the clear-sky bias, which is related to the overpass time of the satellite. It seemingly results in a more noisy pattern

especially over tropical and subtropical land surfaces over South America and Africa. Also visible in the comparison is the less intense wet bias in the northern mid to high latitudes over sea surfaces. The reduction of the dry bias for the Antarctic continent is only in the order of 0.5 kg m^{-2} . Since observations for this region are scarce, and modelling efforts still carry high uncertainties, this might also be considered artificial.

The monthly climatologies of the CSB are displayed in Figure 2-3. It illustrates the impact of the large-scale circulation pattern like the movement of the ITCZ and an intensification of the wet bias for ocean surfaces in mid to high latitudes during the summer months of the respective hemisphere.

Figure 2-4 shows an example of the hourly CSB assessment for the month of January for the Amazon region to demonstrate the diurnal scale of the CSB for tropical regions. Here, the diurnal course in, especially, cloud coverage is dominating the seasonal course. White spots signify areas with no data due to the cloud mask filter in the CSB assessment. The Amazon basin shows a regular development of (convective) cloud coverage that is associated with the diurnal course of solar incidental radiation. Over the year, this region shifts slightly south and north according to the position of the ITCZ.

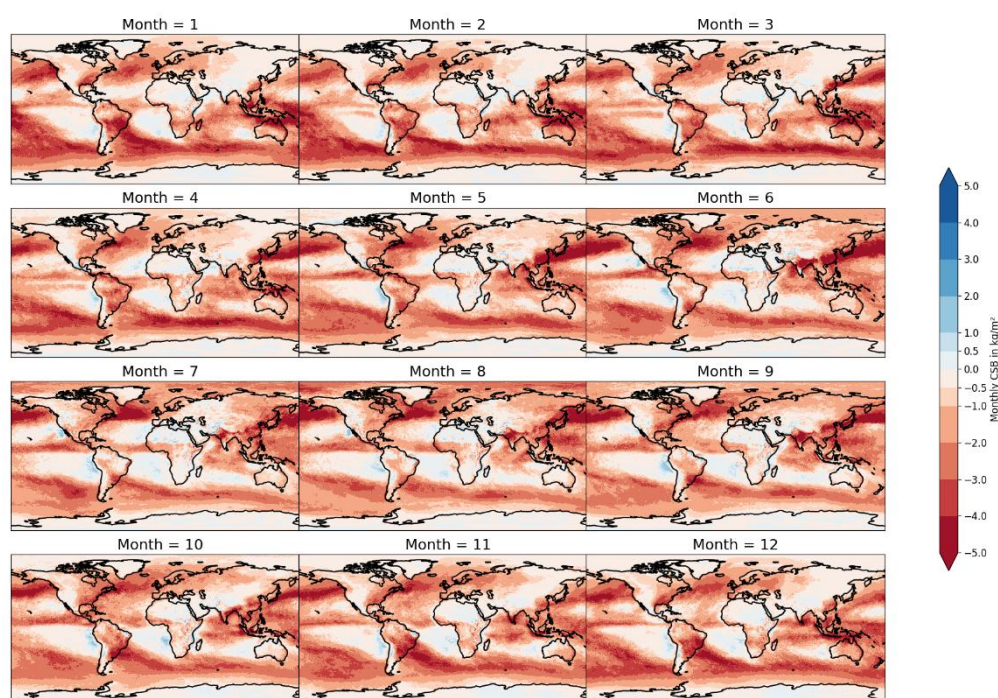


Figure 2-3: Monthly assessment of the clear-sky bias assessment for ERA5 data records for the time period 2002–2011.

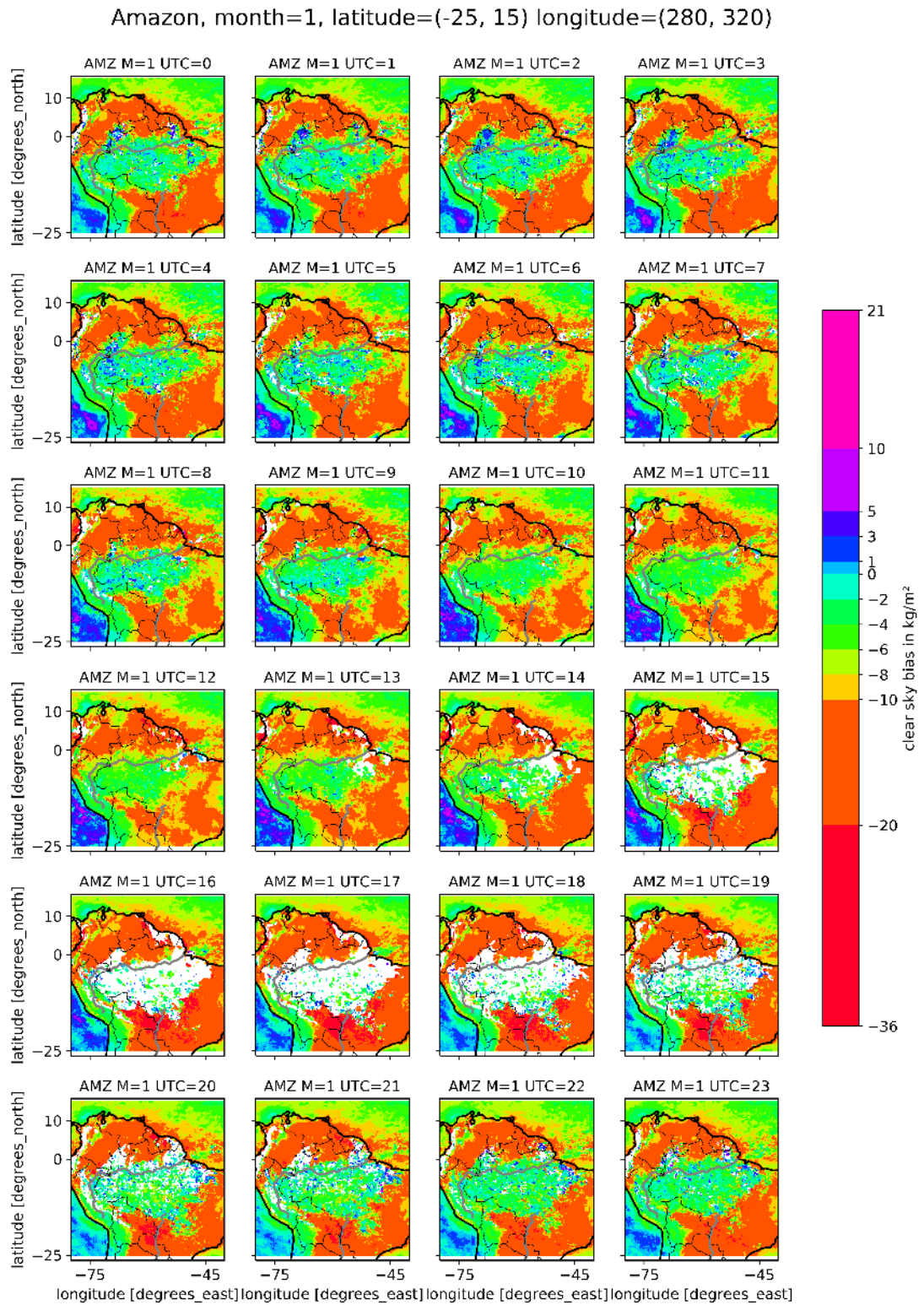


Figure 2-4: Example of hourly assessment of the clear-sky bias assessment for the Amazon region based on ERA5 data records for January (month = 1) and the time period 2002–2011. White areas mean no data is available.

2.2 Validation of clear-sky bias assessment

For the validation of the CSB assessment on the basis of ERA5 data records, two different cloud masks were used to filter GPS data from the SuomiNet global observation network. Data records and access are described in full detail in the DARD (2021).

The validation of the CSB analysis was carried out for two time periods: 2005–2011 (MERIS cloud mask) and 2016–2018 (OLCI cloud mask). The restraining element of the time periods is the existence of a valid cloud mask. The calculated statistics for the two assessments both show a significant correlation between the ERA5-based estimation of the CSB, and a mean non-zero bias of the CSB. The data has been filtered for GPS stations and ERA5 data at the same point showing a normal distribution, in other words, if the data time series can be considered representative for that specific location. We attribute failure to comply with the restrictive condition of normal distribution to, firstly, non-representativeness of the GPS observations (a possible error source is also the assumption of a tropospheric temperature within the signal-processing). Secondly, the cloud mask is associated with a lot of problems in, especially, coastal areas, and, thirdly, the regional circulation and climatologies might show systematic bias towards non-normal distributed observations.

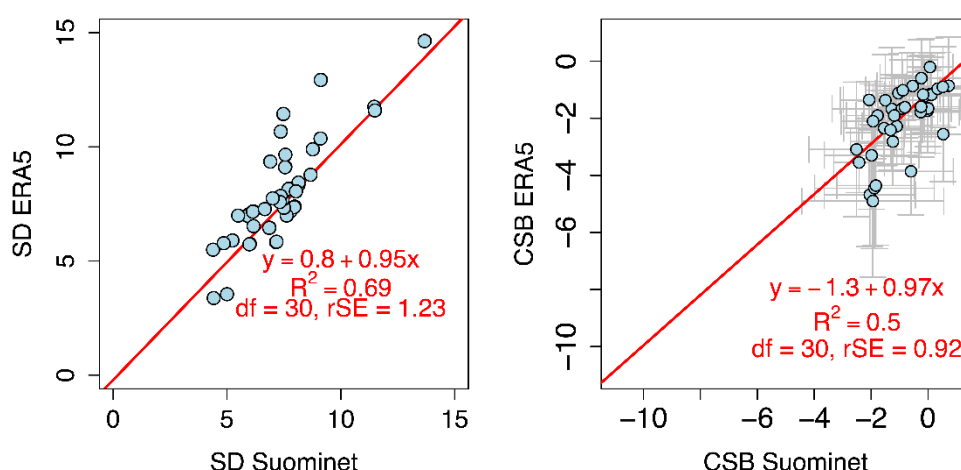


Figure 2-5: Validation of the clear-sky bias assessment: standard deviation (SD) and CSB in kg m^{-2} calculated from ERA5 data records against SD and CSB in kg m^{-2} derived from analysis of GNSS (Suomi Net) data records using the MERIS cloud mask for the time period 2005–2011. Error bars are derived from uncertainties attached to the observations.

The statistics using the MERIS cloud mask (time period 2005–2011) yield a rather good correlation with an $R^2 = 0.5$ for a sample size of $N = 30$, whereas the statistics for the OLCI cloud mask result in a much higher $R^2 = 0.82$, but for a smaller sample size of $N = 12$. The mean difference in CSB between ERA5 and SuomiNet is 3.65 kg m^{-2} when using the MERIS cloud mask for the time period 2005–2011, and is -1.13 kg m^{-2} when using the OLCI cloud mask for the time period 2016–2018. The larger sample size of the CSB assessment ($df=30$) for the time period 2005–2011 using the MERIS cloud mask yields a normal distribution of the differences between the clear-sky biases, whereas the sample size for the time period 2016–2018 using OLCI cloud mask amounts to only $df=12$. The error bars (in Figure 2-5 and Figure 2-6) are derived from the error propagation of uncertainties attached to the data records. In both figures it is evident that the ratio of standard deviation to the calculated CSB is for most data points around or greater than one, and at least greater than 0.25. For both validation efforts, a higher sample size would thus be necessary to deduce statistically reliable results.

The extreme values for the CSB assessment do not fall below $CSB_{era5, min} > -6 \text{ kg m}^{-2}$ and $CSB_{suo, min} > -4 \text{ kg m}^{-2}$, whereas in the OLCI CSB assessment, more extreme values, $CSB_{era5, min} < -10 \text{ kg m}^{-2}$ and $CSB_{suo, min} < -7 \text{ kg m}^{-2}$ are visible.

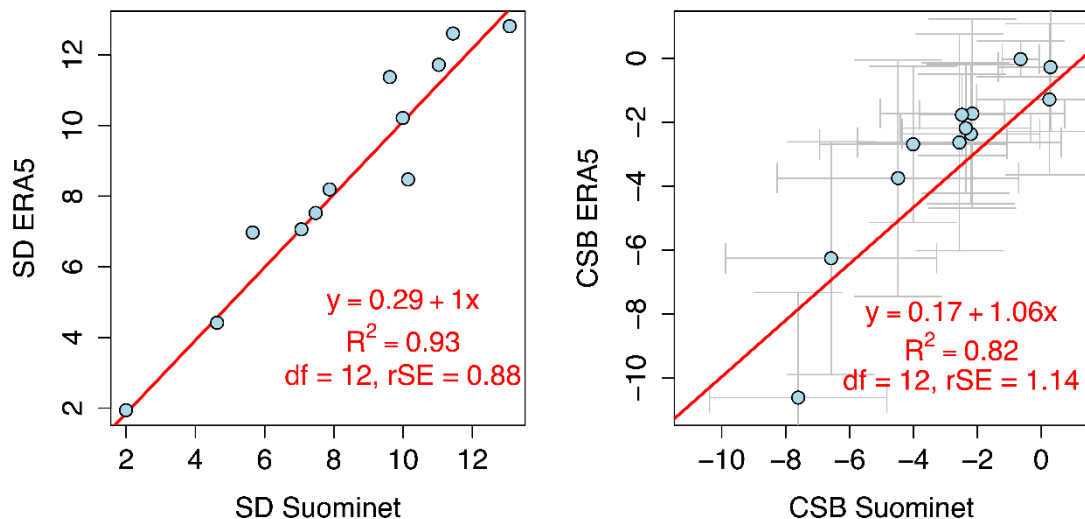


Figure 2-6: Validation of the clear-sky bias assessment: standard deviation (SD) and CSB in kg m^{-2} calculated from ERA5 data records against SD and CSB in kg m^{-2} derived from analysis of GNSS (SuomiNet) data records using the OLCI cloud mask for the time period 2016–2018. Error bars are derived from errors attached to the observations.

2.3 Significance of clear-sky bias assessment

The significance of the CSB assessment is tested by analysing the ratio of the standard deviation of the time series against the value of the CSB. The natural variability on the diurnal and monthly scale leads to high standard deviations of the time series, and thus, a ratio of SD to CSB that can be close to or greater than 1 kg m^{-2} .

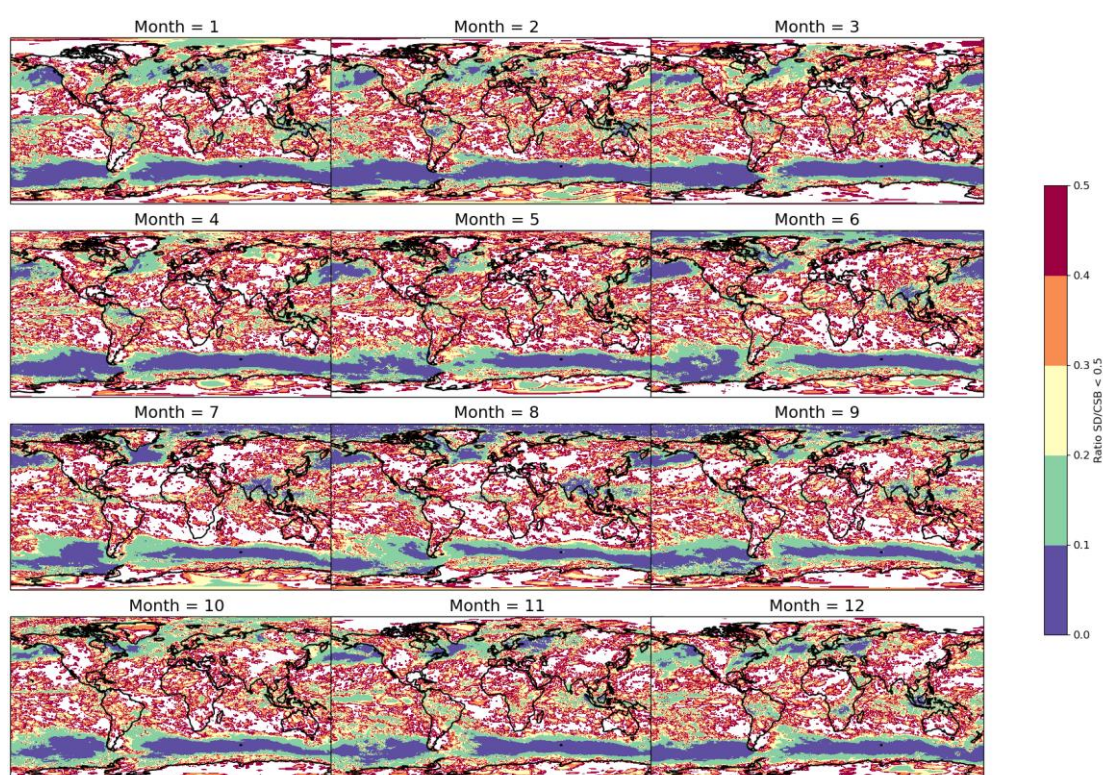


Figure 2-7: Ratio of standard deviation (SD) to clear-sky bias (CSB) with $SD/CSB < 0.5$ based on monthly CSB assessment from ERA5 data records for the time period 2002–2012. In white are points with a ratio $SD/CSB \geq 0.5$.

Shown in Figure 2-7 is the global distribution of the ratio of the monthly climatologies of standard deviation (SD) of the clear sky bias to the monthly climatologies of CSB, filtered for values $SD/CSB < 0.5$. Most regions in the latitudes below $\pm 45^\circ$ exhibit a heterogeneous pattern of mostly red areas, i.e. $SD/CSB \geq 0.4$, and white areas, i.e. values $SD/CSB \geq 0.5$. The CSB assessment for most of these tropical and subtropical latitudes is thus considered as non-significant or just significant. In comparison to the monthly CSB climatologies (see Figure 2-3), it is apparent that regions with higher values for the CSB also coincide

with higher values of SD. For areas above 45° South and North, the calculated clear-sky bias leaves mostly sub-polar and polar regions marked in green and blue, meaning a significant CSB assessment. This is caused by the lower standard deviation of the grid-point time series that can be attributed to the low sample sizes due to the cloud filter in the CSB assessment, though. The distribution for the northern summer months shows a slightly better adherence to this restriction. Due to the high natural variability in the time series of CSB assessment, longer time series are necessary.

The CSB is either non-significant or hardly significant and elsewhere affected by a low number of valid points. Thus, it is proposed not to include the clear-sky bias in the CDR-1 and CDR-2 NIR data, but to make the user aware of the existence and magnitude of the CSB effect in the Product User Guide (PUG, 2021).

2.4 Conclusions

The CSB assessment based on the analysis of ERA5 data records shows the high natural variability in the time series of CSB and indirectly cloud coverage (cloud fraction). Climatologies of CSB on annual and monthly scale show a distinct spatial distribution of wet and dry biases that are dominated by large-scale circulations for the mid to high latitudes and by the diurnal course of cloud coverage and the position of the ITCZ in tropical and subtropical regions.

The area-weighted global average of the CSB is calculated to $CSB_{\text{mean}} = -0.85 \text{ kg m}^{-2}$ for the full-day assessment, and to a slightly lower $CSB_{\text{mean}} = -0.87 \text{ kg m}^{-2}$ for the assessment based on local time LT=10.

For latitudes within the range of approximately $\pm 45^\circ$, the CSB assessment can be considered not significant or just about significant. For the higher latitudes the CSB assessment can be considered significant according to the criterion of $SD/CSB < 0.5$, but sample sizes are rather low. It is therefore recommended to carry out the CSB assessment and validation on longer time series.

Thus, and in order to further assess its usefulness, it is recommended to include the CSB in the analysis of consistency of the CDRs as a sanity check and not to include the CSB in the CDRs themselves.

3. ANALYSIS OF VARIABILITY, TRENDS AND COMPLIANCE WITH THEORETICAL EXPECTATION USING WV_CCI TCWV DATASETS (CDR-1, CDR-2)

Ulrike Falk (DWD), Marc Schröder (DWD), Tim Trent (U Leicester, NCEO)

A focus of this section is on the analysis of global trends in TCWV using WV_cci CDR datasets. This analysis not only provides these estimates for comparison but the trend analysis needs to be understood as a tool to potentially identify issues in the datasets, very similar to approaches in the GEWEX Water Vapor Assessment (G-VAP, see, e.g. Schröder et al., 2017, 2018, 2019). TCWV trends are assessed on a global scale, i.e. by providing estimates on grid basis as spatial maps and by analysing near global averages. During trend estimation the Niño 3.4 El Niño Southern Oscillation (ENSO) Index and four frequencies in order to address the annual cycle are fitted as well. The variability is shown as spatial maps of associated weights.

Furthermore, the compliance of variability in TCWV with theoretical expectation using ESA SST_cci and ESA LST_cci data records is assessed. In view of increasing temperatures it can be expected that TCWV will increase at a rate of approximately 6 – 7.5 %/K according to the Clausius–Clapeyron law.

Associated results are put into the perspective of G-VAP results and results available from the literature.

3.1 Datasets

The CM SAF / WV_cci TCWV product consists of microwave-based observations over the ice-free ocean from the Hamburg Ocean Atmosphere Parameters and Fluxes from Satellite data (HOAPS) and of near-infrared based observations over land, sea-ice and coasts. The combined global TCWV dataset covers the period August 2002 until December 2017 and is provided as monthly and daily means with a spatial resolution of 0.05° and 0.5°. It is noted here that CDR-2 is released by European Organisation for the Exploitation of Meteorological Satellites (EUMETSAT) Satellite Application Facility on Climate Monitoring (CM SAF) (https://doi.org/10.5676/EUM_SAF_CM/COMBI/V001). As CDR-1, the WV_cci TCWV dataset over land, is fully included in CDR-2 without changes by any means, we analyse CDR-2 “only”. Subsequently we speak of CDR-1 if land only

TCWV values are meant; else we use the term CDR-2. Further details on CDR-1 and CDR-2 are given in the PSD v3.2.

Validation results carried out within WV_cci show that bias and cRMSD exhibit a different level when OLCI data is included into the CDRs (PVIR v2.1). Although this is still within user requirements, it would create a break point and thus impact any trend analysis in a non-physical way. The MERIS and MODIS period is stable when analysing clear-sky and 10 am local time averages over global land surfaces. Thus, we use the MERIS and MODIS time series only, i.e. the period until March 2016.

The trend, compliance and variability analysis is also carried out for AIRS+AMSU v6 and ERA5. Both data records exhibit global coverage. AIRS contains monthly means only and is provided at $1^\circ \times 1^\circ$ spatial resolution while ERA5 is also available at higher resolutions (see DARD v3.2 for more details).

In order to assess compliance with theoretical expectations following Clausius–Clapeyron, surface temperature data records from ESA SST_cci and from ESA LST_cci are used (see DARD v3.2 for more details). Both datasets characterise the surface while strictly speaking the air temperature at surface (TAS) should be used. Such a product was generated and provided by the EU-funded project EUSTACE (EU Surface Temperature for All Corners of Earth). Here, the dataset is called EUSTACE for simplicity and further details are given in the DARD v3.2. Note that the coverage of EUSTACE over ocean contains hardly any valid values after 2012. When analysing the anomaly time series of TAS and TCWV over land and ocean, the expected overall synchronisation in temporal variability is hardly visible after approximately 2014, maybe earlier over ocean. A clear identification of the exact date is hampered by low frequency variability (not shown). Thus, it was concluded, that the EUSTACE dataset is not used in this analysis. While an analysis over ocean using surface temperature is in most cases acceptable, an analysis over land is fairly strongly hampered by large differences between surface temperature and TAS, depending on region and time of day. Thus, the compliance over land is only analysed for CDR-1 and LST_cci data record. Further discussions are provided in Section 3.3.

3.2 Methodology

For a straightforward intercomparison of the results from trend analysis of between CDR-2, ERA5 and AIRS+AMSU, the analysis is carried out on the lowest common spatial resolution (here $1^\circ \times 1^\circ$) using monthly data, and over the common time

period from 2002 to 2016. As a further requirement, commonly defined values are analysed only, i.e., where there are, for all time steps and in all data records, defined TCWV values. As a consequence from WV_cci internal analysis it was recommended to apply a **common, conservative cloud mask** prior to the estimation of near global averages and subsequent trend estimation. The reason is that the cloud masks between MERIS/OLCI and MODIS exhibit differences, such that in the case of MODIS significantly more valid values remain in the extra-tropics in monthly means which would lead to smaller global mean TCWV values relative to a global mean based on less contributions from the extra-tropics (see PVIR v2.1). The above approach indirectly ensures that this is not impacting the results related to analysis of (near) global averages.

Trend estimates are computed for TCWV averages over global, global land and global ice-free ocean surfaces and on grid-basis. In each case the trend estimation and estimation of associated uncertainties and their significance follows methodologies described in Weatherhead et al. (1998), Mieruch et al. (2014) and Schröder et al. (2016, 2019), similar to approaches applied in G-VAP. A linear regression is fitted to the time series simultaneously with the Niño 3.4 ENSO Index and four frequencies that allow for an analysis of annual cycles. The weights associated with ENSO and the annual cycle are discussed in the assessment of variability. The estimation of uncertainties also considers auto-correlation.

Finally, it is assessed whether or not changes in TCWV agree with change in surface temperature, i.e. as expected from Clausius–Clapeyron. Again, the methodology follows approaches used within G-VAP (Dessler and Davis, 2010; Mears et al., 2007; Schröder et al., 2016, 2019). Deseasonalised anomalies of TCWV and surface temperature are filtered with a 12-month low-pass filter to smooth the time series. Subsequently the linear regression between deseasonalised and smoothed anomalies of TCWV and surface temperature is computed.

3.3 Results

3.3.1 Variability

The variability in TCWV associated with ENSO and annual cycles is described and inter-compared by showing global maps of weights which are output from trend estimation (see Section 3.2) and by considering CDR-2, ERA5 and AIRS+AMSU.

Spatial maps of the annual cycle contribution to variability in TCWV for the three data records are shown in Figure 3-1. Large (small) absolute weights indicate the presence of a strong (small) annual cycle. Weights in the Southern Hemisphere are actually negative which reflects the shift by half a year between boreal and austral summer in presence of a symmetric annual cycle. Generally, the strength of the annual cycle is stronger in the Northern Hemisphere than in the Southern Hemisphere and small annual cycles are present in the ITCZ, i.e. where the maximum northern and southern position of the ITCZ overlap, over parts of ocean deserts and the Southern Ocean. Peak values are usually associated with the movement of the ITCZ, here, its northern- and southern-most branches, monsoon activity, e.g. over India (see, e.g. <https://www.clivar.org/clivar-panels/monsoons> for a map of monsoon regions) and with low-level jet activity in boreal/austral summer (Gimeno et al., 2016), partly associated with Hurricane seasons (Yang et al., 2021). Interesting to see is the overlap of winter monsoon regions with minima in annual cycle weights. A local maximum in the weight of the annual cycle is observed off the coast of California in ERA5, CDR-2 and, less pronounced, in AIRS. Annual cycles in TCWV are observed over stratocumulus regions including the stratocumulus region off the coast of California (Millán et al., 2019). However, such annual cycles are also observed over the other stratocumulus regions (Millán et al., 2019) which do not exhibit peak values in the annual cycle weight.

Fairly good agreement between the three data records is observed. Differences in the annual cycle strength between ERA5 and CDR-2 are very small and most evident over the North of Australia and Brazil. Larger, but still small differences occur between AIRS and ERA5/CDR-2, with the strength of the annual cycle being generally weaker in AIRS.

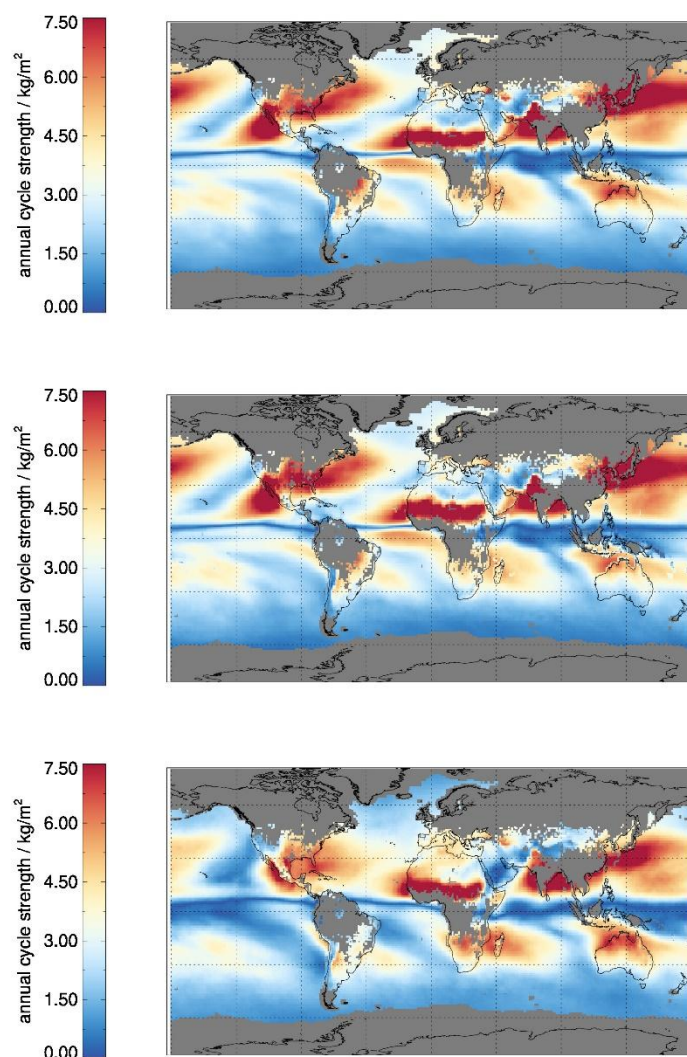


Figure 3-1: Maps of the annual cycle contribution to variability in TCWV for (top) ERA5, (middle) CDR-2 and (bottom) AIRS+AMSU. In order to increase readability the absolute values of the weight are plotted, i.e. weights in the Southern Hemisphere are actually negative.

Spatial maps of the ENSO contribution to variability in TCWV for the three data records are shown in Figure 3-2. Absolute large (small) weights indicate a strong (small) impact on variability by ENSO. Large positive weights would indicate an increase in TCWV with El Niño (or a decrease with La Niña) while large negative weights indicate an increase in TCWV with La Niña (or a decrease with El Niño). The observed spatial pattern is similar to features in similar analysis (e.g., Trenberth et al., 2005) and exhibits overlap with structures observed in changes in precipitation and SST with ENSO. Maximum values are observed in the central Pacific and minima are observed over the Western Pacific warm pool and the Southern Pacific Convergence Zone (SPCZ). A side maximum occurs over central

West Africa and the Eastern Indian Ocean. A few smaller positive weights can be observed which are likely linked to ENSO teleconnections (e.g. Yeh et al., 2018).

Hardly any differences between CDR-2, AIRS+AMSU and ERA5 can be observed in the ENSO contribution to variability in TCWV.

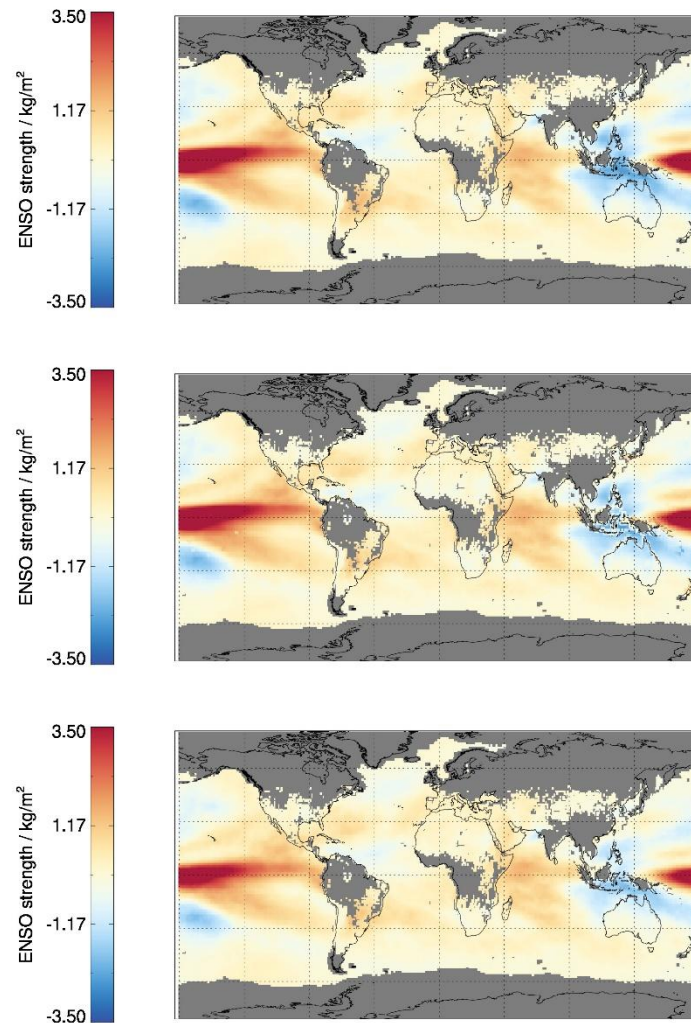


Figure 3-2: Maps of the ENSO contribution to variability in TCWV for (top) ERA5, (middle) CDR-2 and (bottom) AIRS+AMSU.

3.3.2 Trends

In this subsection the trend estimates of TCWV are analysed using CDR-1, CDR-2, AIRS+AMSU and ERA5 data. Trends and their uncertainty are estimated as described in Section 3.2. An analysis of large-scale averages is followed by a presentation of spatial maps.

Figure 3-3 shows the anomaly time series of TCWV over global, global land and global ice-free ocean surfaces for all three data records. Results from linear regression are plotted as straight lines and the associated slope, i.e. the trend estimate together with the associated uncertainty is given in the legend. The La Niña and El Niño events are visible as minima (2008) and maxima (2010, 2016) in all the time series, with the maximum value in 2016 being the absolute strongest anomaly in all time series.

The time series are very similar between the three data records. Maximum (but small) differences in anomalies are associated with ENSO over global ice-free ocean. It is noted that the combined results from global land and global ocean are not necessarily matching results shown in the global time series because the latter also includes sea-ice and coastal regions as well as large inland water bodies. These regions exhibited reduced quality during validation (see PVIR v2.1). While AIRS+AMSU and ERA5 exhibit fairly similar trend estimates, the CDR-1 and CDR-2 trends are larger in the three considered cases. Over ocean this difference is smallest but still significant given the associated uncertainties.

The observed trend estimates should not be considered as an analysis of climate change, mainly because the considered temporal coverage is fairly short but also because the trend estimates are strongly affected by the El Niño event at the end of the time series. When looking at Figure 3-3 it is obvious that trend estimates would be significantly smaller when the period until 2015 would be considered only. The presence of an El Niño event in temporal vicinity of the start of the considered period was analysed in Mieruch et al. (2014) and a change in trend estimates by a factor of approximately 2 was observed when changing the start data from 1991 to 1997. The importance of such an impact can obviously be generalised to the presence of an ENSO event relative to the start and/or stop of the considered period. Other trend estimates are given in, e.g. Sherwood et al. (2010), Mieruch et al. (2014), and Schröder et al. (2016, 2017). However, due to differences in considered periods but also due to differences in the considered spatial extend the results can hardly be compared. Nonetheless, we note that, not surprisingly, the trends given here are usually larger than trends given in the literature.

It is mentioned above that variability caused by ENSO is evident in the time series shown in Figure 3-3. The ENSO variability has a strong impact on trend estimates, even when the ENSO signal is fitted during trend estimation (this report; Mieruch et al., 2014). Certainly such a fit is not perfect but it should also be kept in mind

there is a lag of approximately 2–3 months between the ENSO index (defined via SST) and the global mean response in air temperature and water vapour (Wentz and Schabel, 2000; Shi et al., 2018). Shi et al. (2018) also analysed this lag as a function of ocean basin and observed lags ranging from 0 months (Pacific) to 5–6 months (Indian Ocean). A global or regional lag is not considered during trend estimation and thus, given the lag, ENSO variability is not fully removed.

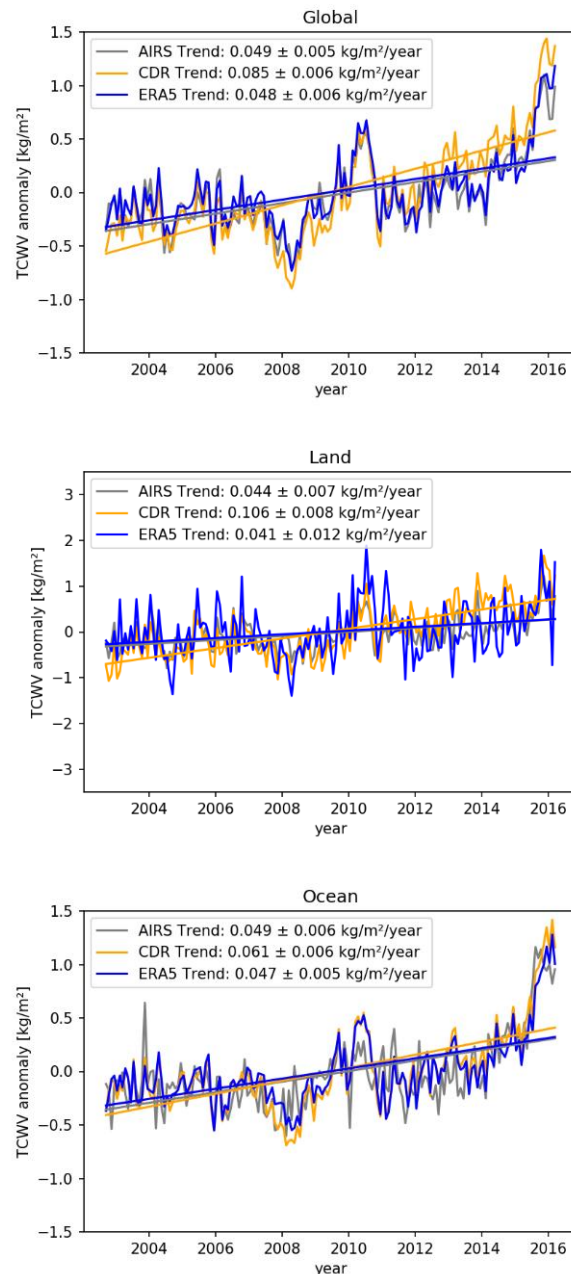
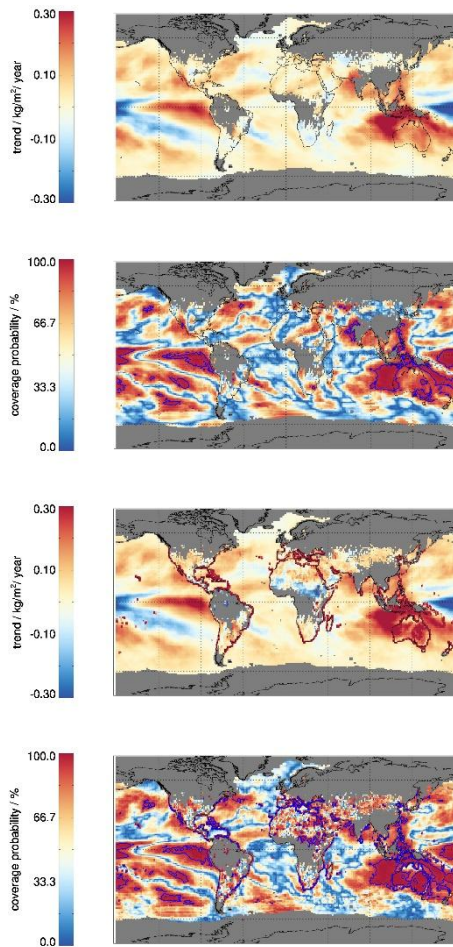


Figure 3-3: Time series of TCWV anomalies of (top) global, (middle) land, and (bottom) ice-free ocean data from CDR-1 (land), CDR-2 (else), AIRS+AMSU and ERA5 data. The plot covers the time period September 2002 – March 2016.

Global maps of trend estimates in $\text{kg}/(\text{m}^2 \text{ decade})$ for ERA5, CDR-2 and AIRS+AMSU are shown in Figure 3-4. The uncertainty related to the trend estimates is shown in Figure 3-5. Figure 3-4 also shows the 95% confidence level. This level depends on uncertainty and trend strength, and trend estimates values associated with coverage probabilities larger than the 95% confidence level contours are considered to be significantly different from $0 \text{ kg}/(\text{m}^2 \text{ yr})$. The trend estimates display a heterogeneous pattern of positive and negative trends. The largest positive trends are observed over southern regions of the Pacific tropical warm pool and regions south of it and the central Eastern Pacific. Largest negative trends are seen over the central Western Pacific and the SPCZ. Some smaller positive trend estimates seem to occur in regions with frequent cloud and rain presence. Regions with significant trend estimates are fairly small and mainly occur in regions with large absolute trend estimates, i.e. in the central Eastern Pacific and south of the Pacific tropical warm pool. The main exceptions are trend estimates in the Southeastern Pacific. This occurs in regions where the uncertainty estimates are fairly small while trend estimates are not maximal but still large. Trend estimates over land are hardly significant, despite the usually fairly small uncertainties. Thus, this relates to the presence of generally small trend estimates. It needs to be kept in mind that the significance level also depends on the number of valid observations, and the considered time period covers less than 14 years. The number of years required to allow climate change detection is discussed in Weatherhead et al. (1998) and Whiteman et al. (2011) and depends on the trend, the noise level and autocorrelation. Our results indicate that the estimation of significant trends on global scale would require longer time series.

The trend estimates, the coverage probability and the uncertainties are very similar between all three data records in terms of spatial structure and absolute strength. Largest and smallest, in a relative sense, absolute trends and uncertainties are observed for HOAPS and AIRS+AMSU, respectively, with a corresponding consistent picture in the coverage probability. However, it is recalled that CDR-2 exhibits reduced quality over coastal and sea-ice regions as well as over large inland water bodies (PVIR v2.1). This becomes evident here as well: large trends and large uncertainties are observed over coastal areas in CDR-2 and trend estimates appear different in CDR-1 over Lake Victoria and the Caspian Sea relative to ERA5 and AIRS+AMSU.

Again, a direct comparison to results published in the literature is hardly possible, given mainly the differences in considered periods. Nonetheless, it is noted that the spatial structure of observed trends exhibits differences relative to results shown in Schröder et al. (2016) and, to a lesser extent, to results shown in Trenberth et al. (2005). For completeness the considered periods are recalled here: 2002–2016 (this study), 1988–2008 (Schröder et al., 2016), and 1988–2001 (Trenberth et al., 2005).



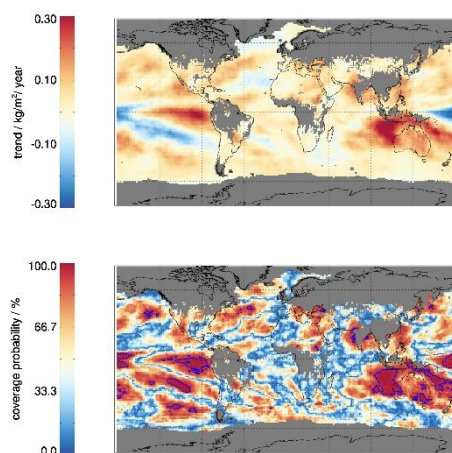


Figure 3-4: The left column shows the spatial distribution of trend estimates in TCWV for (top) ERA5, (middle) CDR-2 and (bottom) AIRS+AMSU. The right column shows the coverage probability with values above the 95% confidence level marked in blue. The map indirectly also shows the global common mask applied to all datasets (grey areas).

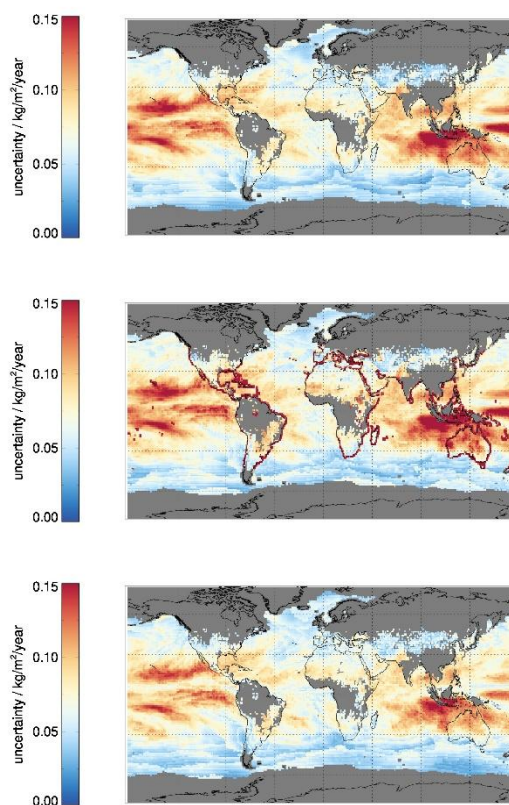


Figure 3-5: Spatial distribution of trend uncertainty estimates in TCWV for (top) ERA5, (middle) CDR-2 and (bottom) AIRS+AMSU v6. Associated trends are shown in Figure 3-4.

3.3.3 Compliance with theoretical expectation

Changes in TCWV are strongly related to changes in surface temperature. This change is expected to follow Clausius–Clapeyron scaling of approximately. 6–7.5 %/K (e.g. Wentz and Schabel, 2000; O’Gorman and Muller, 2010). The assessment of compliance with theoretical expectation largely follows approaches applied within G-VAP (Schröder et al., 2016, 2019). Preparations of CDR-1 and CDR-2 and intercomparison and reference data records were already described in Sections 3.1 and 3.2.

Table 3-1 summarises the results from regression analysis. It includes the regression and correlation for CDR-1, CDR-2, ERA5 and AIRS+AMSU with SST data from ESA CCI and the regression and correlation for CDR-1 with LST data from ESA CCI. Over ocean the values range from 8.22 %/K (ERA5) to 11.92 %/K (CDR-2). In all ocean cases the values are larger than the theoretically expected values. Nonetheless, the associated correlation is fairly large with values around 0.8. In contrast, the regression over land is only 0.53 %/K and thus smaller than the expectation. The uncertainty assigned to the regression values is purely based on the quality of the regression and does not account for uncertainties in TCWV, SST and LST data. We refer to the PVIR v2.1 and to the Group for High Resolution SST (GHRSSST, see <http://www.ghrsst.org>) and PVIRs from ESA SST_cci and ESA LST_cci (see <https://climate.esa.int/en/projects/sea-surface-temperature/> and <https://climate.esa.int/en/projects/land-surface-temperature/>).

The observed values over ocean are different from values published by, e.g. Wentz and Schabel (2000), Mears et al. (2007) and Schröder et al. (2016, 2019). Again, the differences in considered time periods impact results. Impacts can also be expected from differences in utilised methods and time scales (see, e.g. Wentz and Schabel, 2000; Mears et al., 2007; Dessler and Davies, 2010). This is also an indication that the considered temporal coverage and the covered ENSO variability can have an impact on results. The imprint of ENSO on TCWV is not identical between ENSO events (see, e.g. missing lag for the El Niño event in 1987/1988 between SST and air temperature, Wentz and Schabel, 2000). The observed time lag between SST and TCWV and its dependence on ocean basin further impacts the results (Shi et al., 2018). However, results shown in Wentz and Schabel (2000) indicate that this lag can also be a function of event and with that time. Even more so, the local response to ENSO will likely also exhibit variability, as observed by Stephens et al. (2018) for precipitation. The presence of time lags between SST and TCWV during El Niño events, at least occasionally, and the number of observed events impacts the correlation, regression and associated

uncertainty and consequently, a comparison to results from the literature is hardly possible when considered periods are different. We further note that different TCWV and SST data records were used in the cited references.

Table 3-1: Results from regression analysis for TCWV from CDR-1, CDR-2, AIRS+AMSU-B and ERA5

Data record	Global ice-free ocean		Global land surfaces	
	regression $\pm$ uncertainty / %/K	correlation (R^2)	regression $\pm$ uncertainty / %/K	correlation (R^2)
CDR-2/CDR-1	11.92 $\pm$ 0.51	0.78	0.53 $\pm$ 0.44	0.01
ERA5	8.22 $\pm$ 0.32	0.82	-	-
AIRS+AMSU	9.79 $\pm$ 0.45	0.76	-	-

In order to discuss potential reasons for the regression being larger (ocean) / smaller (land) than the expectation, a brief discussion of dependencies and assumptions and limitations behind the regression is given. This is largely based on Mieruch et al. (2014) and was slightly adapted and extended: Following Hyland and Wexler (1983) saturation vapour pressure is a function of air temperature and change in air temperature. Saturation vapour pressure can be transferred into a change in mixing ratio assuming constant relative humidity and pressure. For a temperature change of 1 K the expected change in mixing ratio is between 6% at 300 K and 7.5% at 275 K. The relationship between TCWV and surface temperature is affected by advection, precipitation, and other small-scale and regional events, which impact equilibrium between surface and atmosphere. Also, surface temperature and TCWV instead of near-surface air temperature and mixing ratio are considered here. This might lead to an amplification of the regression over ocean (Trenberth et al., 2005). Over land, the relation between air temperature and surface temperature is complex and locally the difference between air and surface temperature reaches a few Kelvin. This depends on various factors, such as local time, cloudiness and surface type (e.g. Good, 2016 and Rayner et al., 2020). It is thus difficult to estimate its impact on regression. In contrast to ocean, the potential flux of water vapour into the atmosphere can be

limited over land and is fairly complex (Byrne and O’Gorman, 2016). Such an input flux depends on various processes and parameters, among others, advection from ocean to land, presence of surface water (lakes, rivers, swamps, etc.), soil moisture, and vegetation density, type and physical stress. It is noted that temperature increases more rapidly over land than over ocean (e.g. Byrne and O’Gorman, 2013) and this itself will also impact differences in regression over land and ocean. Nonetheless, Byrne and O’Gorman (2016) conclude that the moisture transport from the ocean is the dominating process for changes in specific humidity over land while evapotranspiration processes play an important role for changes in relative humidity over land. Finally, the presence of increased SST and TCWV over ocean during El Niño events might lead to larger transport of moisture from ocean to land. At the same time increased LST might not be present and can thus further contribute to a reduced correlation between LST and TCWV.

3.4 Conclusions

In this section the following analysis was carried out using TCWV from the CDR-1, CDR-2, ERA5 and AIRS+AMSU data records:

- Contribution of the annual cycle and ENSO to variability
- Trend estimation on grid-basis and for large scale regional averages
- Compliance analysis with theoretical expectation following Clausius–Clapeyron using regression.

Based on the presented results it can be concluded that the spatial representation of variability, trends and associated uncertainties are very similar between the considered data records. However, trend estimates and regression values using near global data differ between AIRS+AMSU, ERA5 and CDR-1, CDR-2, with CDR-1 and CDR-2 exhibiting the largest values. A regression analysis over land is pursued for CDR-1 only because the changes in TCWV over land are driven by advection from oceans and not by LST or surface air temperature.

A comparison to published trend estimates and regression results is hardly possible, mainly given the differences in temporal coverage and ENSO coverage but also due to differences in spatial coverage, utilised data records and applied methods.

Given the fairly short temporal coverage and the presence of an El Niño event at the end of the considered time series, the presented trend estimates cannot be considered as long-term climate trends.

4. ANALYSIS OF TIME SERIES, TRENDS AND VARIABILITY OF VERTICALLY RESOLVED WV PRODUCTS (CDR-3)

Daan Hubert (BIRA-IASB), Jean-Christopher Lambert (BIRA-IASB)

The vertically resolved water vapour data products developed by ESA's WV_cci project are compared to similar Climate Data Records produced by NASA (GOZCARDS, <https://gozcards.jpl.nasa.gov>) and NOAA (SWOOSH, <http://www.esrl.noaa.gov/csd/swoosh>). The objective is to assess the value of the CCI data products for climate studies, through a comparative analysis of known spatial and temporal patterns, variability and trends. Past studies concluded to different long-term trends in water vapour, depending on the analysis methods and data records being used (e.g. Hegglin et al., 2014 and Hurst et al., 2011). Here, we reassess the (dis)agreement between current satellite-based monthly-zonal-mean CDRs by comparing the parameter estimates for different (geophysical) patterns inferred by Multiple Linear Regression analyses.

4.1 Monthly zonal mean H₂O Climate Data Records

This assessment includes four CDRs: CCI CDR-3 v0 (ATBD, 2020), SWOOSH v2.6 (Davis et al., 2016), GOZCARDS v1.01/1.02 (Froidevaux et al., 2015) and GOZCARDS v1.10. They all report monthly mean H₂O VMR on a fixed pressure and latitude grid. These CDRs are constructed using different sets of satellite sensors, different Level-2 data versions and different merging algorithms. Each of these choices can have an important impact on the short-term and long-term temporal stability of the CDR. The four H₂O CDRs are not independent as they all include HALOE H₂O retrievals in the 1991–2005 period and Aura MLS data since 2005. The number of sensors included is largest for the CCI data record (11), hereby distinguishing itself clearly from SWOOSH (6) and GOZCARDS (3–4).

Recent trends (since 2005) are fairly sensitive to the Aura MLS data version used. The latest Aura MLS data processor (v5) includes corrections which reduce the positive drift in H₂O retrievals noticed in earlier data versions v3/v4 (Hurst et al., 2016; Livesey et al., 2021). Hence, it is expected that CCI CDR-3 v0 and GOZCARDS v1.10 exhibit smaller positive recent trends (both using Aura MLS v5) than GOZCARDS v1.01/1.02 and SWOOSH v2.6 (both using Aura MLS v3/v4). The latest GOZCARDS incarnation uses the same merging algorithm as

its predecessor, but does not include UARS MLS data which may lead to differences in the early 1990s.

4.2 Baseline regression model

Let $\{Y_t\}$ denote the set of monthly H₂O VMR measurements, for a given pressure level and latitude band. Changes in stratospheric water vapour have been attributed to or are co-variant with a number of processes (e.g., Hurst et al., 2011, Dessler et al., 2014; Hegglin et al., 2014; Lossow et al., 2017a, 2017b, 2018; Schieferdecker et al., 2015; Diallo et al., 2018; Randel et al., 2019). Here, we assume a linear response of H₂O VMR to each of the following processes

$$Y_t = \mu + A_t + QBO_t + X_t + N_t.$$

In this model, μ represents the mean H₂O VMR over the Jan 2005 – Dec 2015 period. Seasonal changes are modelled as a sum of two Fourier components (12 and 6 month period, AO and SAO): $A_t = \sum_{j=1}^2 \alpha_{j,1} \cos(2\pi jt/12) + \alpha_{j,2} \sin(2\pi jt/12)$. The Quasi-Biennial Oscillation (QBO) is parameterised using two (orthogonal) principal components of Singapore winds at 30 hPa and 50 hPa¹: $QBO_t = \beta_1 QBO_{PC1,t} + \beta_2 QBO_{PC2,t}$. Long-term changes are parameterised as a continuous series of three linear trends X_t inflecting in January 1998 and in January 2004. Left-over noise N_t is modelled as a first-order autoregressive process : $N_t = \phi N_{t-1} + \epsilon_t$.

The set of parameter coefficients θ is inferred using a generalised least-squares regression technique that accounts for data gaps. This regression is applied to all pressure levels and latitude bands independently, on the native grid of the CDR. Reported H₂O VMR errors are not considered by the regression since the contribution of actual measurement uncertainty and geophysical variability varies between CDRs. The MLR implementation utilised here can be downloaded from https://arg.usask.ca/docs/LOTUS_regression/index.html

Figure 4-1 illustrates the parameters estimated for the CCI CDR-3 data record.

¹ From <http://www.geo.fu-berlin.de/met/ag/strat/produkte/qbo/qbo.dat>

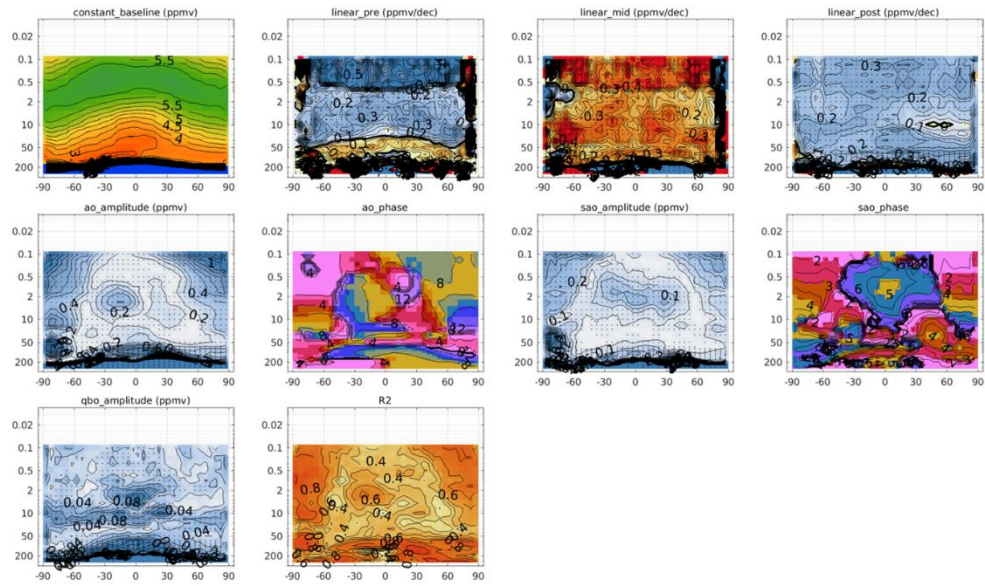


Figure 4-1: Pressure–latitude cross-section of regression parameters estimated from CCI CDR-3: the 2005–2015 mean (top left), three linear trend terms (top row; pre: 1984–1997, mid: 1998–2003, post: 2004–2018), followed by amplitude and phase of the annual (ao), semi-annual (sao) and quasi-biennial (qbo) oscillations. The last panel shows the coefficient of determination R^2 . Stippled cells show statistically significant parameters (2σ). The unit is displayed at the top of each panel.

4.3 Comparison of parameter estimates

Parameter coefficient estimates $\hat{\theta}$ are expressed as *ppmv* or as *ppmv/decade*. Relative parameter coefficient estimates $\hat{\theta}_r$ (in % or %/decade) are obtained by dividing by the estimate of the multi-annual mean: $\hat{\theta}_r = 100 \times \hat{\theta} / \hat{\mu}$. Difference statistics use the CCI CDR-3 as a reference: $\hat{\delta} = \hat{\theta} - \hat{\theta}_{CCI}$ (ppmv or ppmv/decade) and $\hat{\delta}_r = \hat{\theta}_r - \hat{\theta}_{r,CCI}$ (% or %/decade)². The uncertainty of the differences is obtained by assuming uncorrelated, Gaussian coefficient errors: $\hat{\sigma}_{\delta} = \sqrt{\hat{\sigma}_{\theta}^2 + \hat{\sigma}_{\theta_{CCI}}^2}$. Parameter (difference) estimates are considered statistically significant when their significance exceeds the 5% level: $|\hat{\theta}| > 2\hat{\sigma}_{\theta}$ or $|\hat{\delta}| > 2\hat{\sigma}_{\delta}$.

² To avoid any confusion, quoted percentage differences of the relative parameters are not defined as $100 \times \frac{\theta}{\theta_{CCI}}$.

4.4 Multi-annual mean (Jan. 2005 – Dec. 2015)

Figure 4-2 (top row) displays the multi-annual mean distribution of H₂O for each of the four CDRs. The general spatial structure is in agreement between all CDRs: very high H₂O VMRs below the tropopause, a dry lower stratosphere, especially in the tropics, and gradually increasing VMRs at higher altitudes and latitudes. Differences in the multi-annual mean (Figure 4-2, bottom) between the CDRs exhibit a weak spatial structure.

CCI CDR-3 is drier than the other CDRs across almost the entire stratosphere and mesosphere. In the stratosphere, the negative bias of CCI is about 0.5–0.8 ppmv or 10–14% (GOZCARDS v1.10), 0.6–1.0 ppmv or 14–18% (GOZCARDS v1.01/1.02) and 0.7–1.5 ppmv or 20–25% (SWOOSH v2.6). In the mesosphere, the negative bias of CCI amounts to 0.7–1.2 ppmv or 13–24% (GOZCARDS v1.10) and 1.0–1.5 ppmv or 16–28% (GOZCARDS v1.01/1.02). In other parts of the atmosphere, the CCI CDR-3 multi-annual mean is wetter than other CDRs. Below the 150–170 hPa level CCI data exhibit a clear positive bias w.r.t. SWOOSH of 20–45% in the tropics and 20–70% in the polar regions. In the Antarctic lower stratosphere (~100 hPa) the CCI multi-annual mean is 4% (SWOOSH) to 10–12% (w.r.t. GOZCARDS) larger.

Multi-annual mean H₂O of CCI differs clearly from GOZCARDS and SWOOSH, while the latter are in better mutual agreement. The use of (many) more sensors and the different merging approach (e.g. the transfer standard) may lead to this difference.

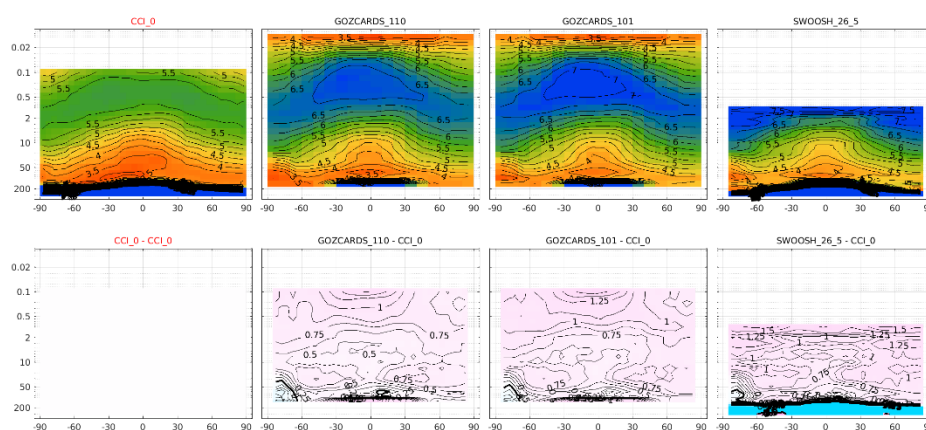


Figure 4-2: Top: pressure–latitude cross-section of the mean H₂O VMR between January 2005 and December 2015 for four CDRs (left to right: CCI CDR-3 v0, GOZCARDS v1.10, GOZCARDS v1.01/1.02 and SWOOSH v2.6). Bottom: absolute difference of each CDR w.r.t. CCI CDR-3 (positive values indicate that CCI is drier). All units are ppmv.

4.5 Annual cycle

The strongest periodic variation in the CDRs is a 12-month (annual) oscillation (AO). This cycle is clearly detected across the entire stratosphere and mesosphere (Figure 4-3). Its amplitude (i.e., half of the peak-to-peak range) is especially large in the lower stratosphere (>0.6 - 0.8 ppmv, >8 - 20%), in the upper stratopause around 20°S (0.4 - 0.5 ppmv, 8 - 10%) and in the polar regions (>0.6 ppmv, $>8\%$). Lossow et al. (2017a, 2017b) discuss in detail the processes underlying the annual cycle, leading to the observed spatial structure in amplitude (Figure 4-3) and phase (Figure 4-4).

The agreement between CDRs of the magnitude and spatial structure of annual cycle properties is overall fairly good. CCI CDR-3 amplitudes are smaller than other CDRs in the tropical lower stratosphere (by 0.1 ppmv, 2%) and the polar middle stratosphere and mesosphere (by >0.2 ppmv, 2%). GOZCARDS exhibits a weaker cycle (not more than 0.05 ppmv) than CCI, in large parts of the upper stratosphere. Across the entire upper stratosphere percentage amplitudes CCI are (~ 0.5 – 1%) larger than all other CDRs. Sign changes between the difference in absolute and relative parameter estimates are a result of differences in the multi-annual mean H_2O VMR for CCI and other CDRs (discussed in Section 4.4).

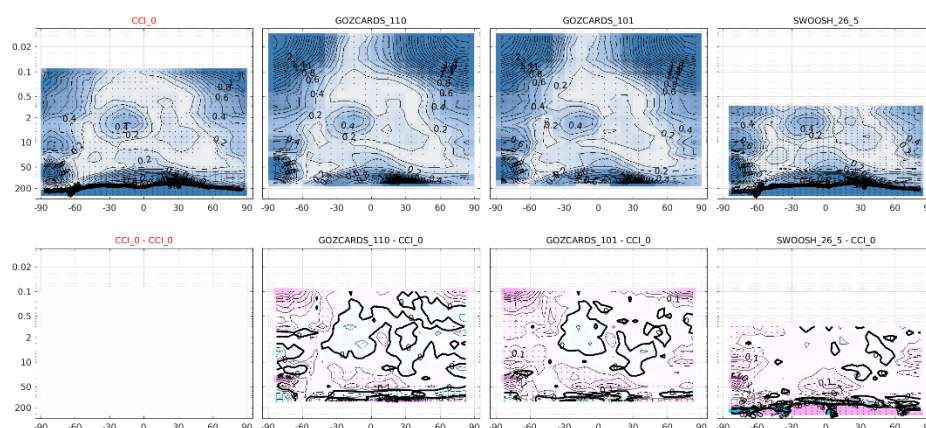


Figure 4-3: Top: pressure–latitude cross-section of the amplitude of the annual cycle for four CDRs. Bottom: absolute difference CDR minus CCI CDR-3 (pink: positive, cyan: negative). The zero level is indicated as a thick black contour. All units are ppmv. Stippled cells indicate statistically significant estimates (2σ).

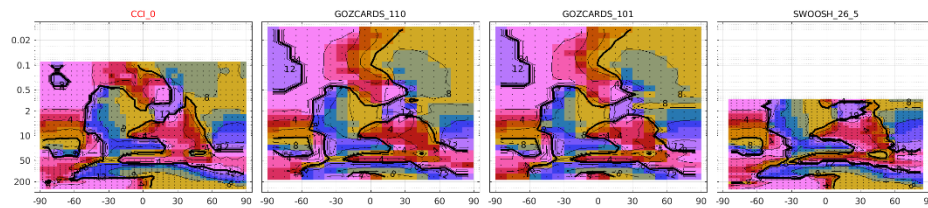


Figure 4-4: As Figure 4-3, but for the phase of the annual cycle. The thick contour line indicates July. Unit is month number.

4.6 Semi-annual cycle

Clear signs of a six-month oscillation (SAO) are detected across the entire atmosphere, except in the middle stratosphere at low and middle latitudes. The amplitudes are largest (0.2 ppmv, 4%) in the lowermost stratosphere, the tropical upper stratosphere (0.2 ppmv, 3–4%) and across the polar stratosphere and mesosphere. Spatial structure of amplitude (Figure 4-5) and phase (Figure 4-6) agree with earlier reports (e.g. Lossow et al., 2017a).

Differences between the CDRs are small and exhibit little spatial structure, except for a region with larger differences in the Antarctic. Amplitudes agree mostly within 0.02 ppmv or 0.5%. Patterns in SAO phase are very similar between CDRs.

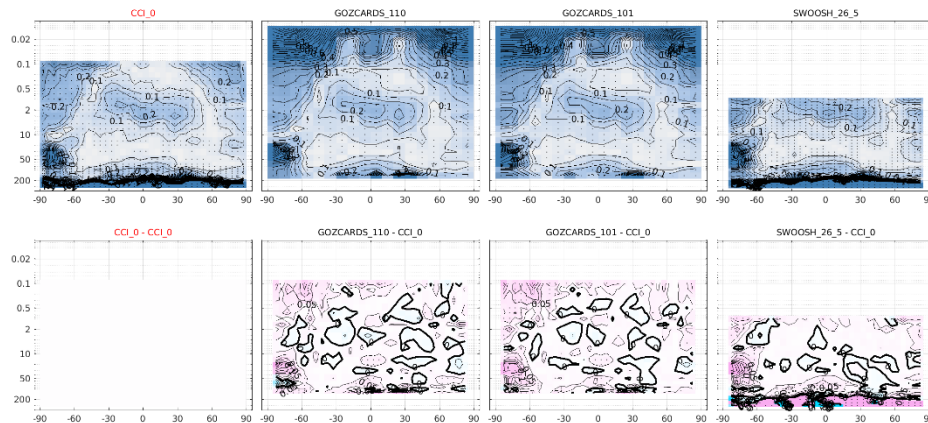


Figure 4-5: As Figure 4-3, but for the amplitude of the semi-annual cycle. All units are ppmv.

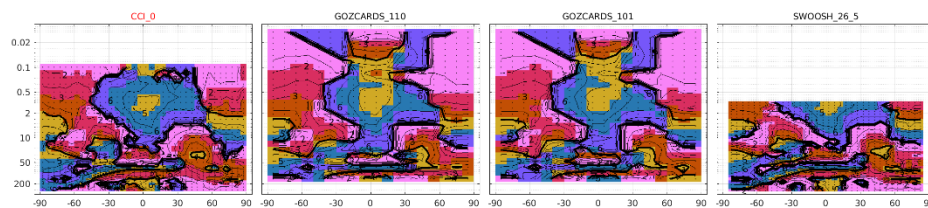


Figure 4-6: As Figure 4-4, but for the phase of the semi-annual cycle. The thick contour indicates April. Unit is month number.

4.7 Quasi-Biennial Oscillation

The response of H₂O to QBO is particularly strong around 3–5 hPa in the tropics (0.08–0.12 ppmv, 1.5–2.5%), between 10 and 20 hPa (0.06–0.10 ppmv, 1.5–2.5%) in the tropics and mid-latitudes, and across the entire upper troposphere (>0.10 ppmv, >3%).

As for the other periodic cycles, the spatial structure of QBO properties is very similar for the different CDRs. Regions where the QBO is statistically significant coincide for all data records. Generally the difference in amplitude is less than 0.01 ppmv or ~0.2% and exhibits no clear systematic structure in the sign of the bias.

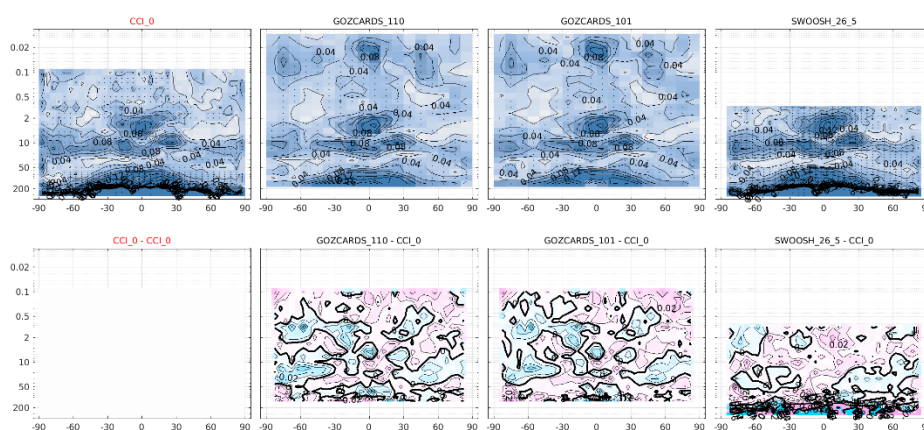


Figure 4-7: As Figure 4-3, but for the amplitude of the QBO. All units are ppmv.

4.8 Trends

Figure 4-8 displays the long-term evolution in CCI CDR-3 H₂O data for several latitude bands and pressure levels. The residuals are obtained by subtracting the regressed AO, SAO and QBO cycles from the observations, then smoothing using a 10-year moving mean window (black). Also shown is the regressed trend model (red) consisting of three piecewise continuous linear trends inflecting at January 1998 and January 2004. Such a model is a reasonable description in large parts of the atmosphere. However, in some regions and for some periods there are signs of overfitting. This is mostly the case for the trend estimates prior to 2004 in the mesosphere and at high latitudes. These estimates should therefore be interpreted with care. Trends since 2004, on the other hand, are well modelled across the entire probed atmosphere.

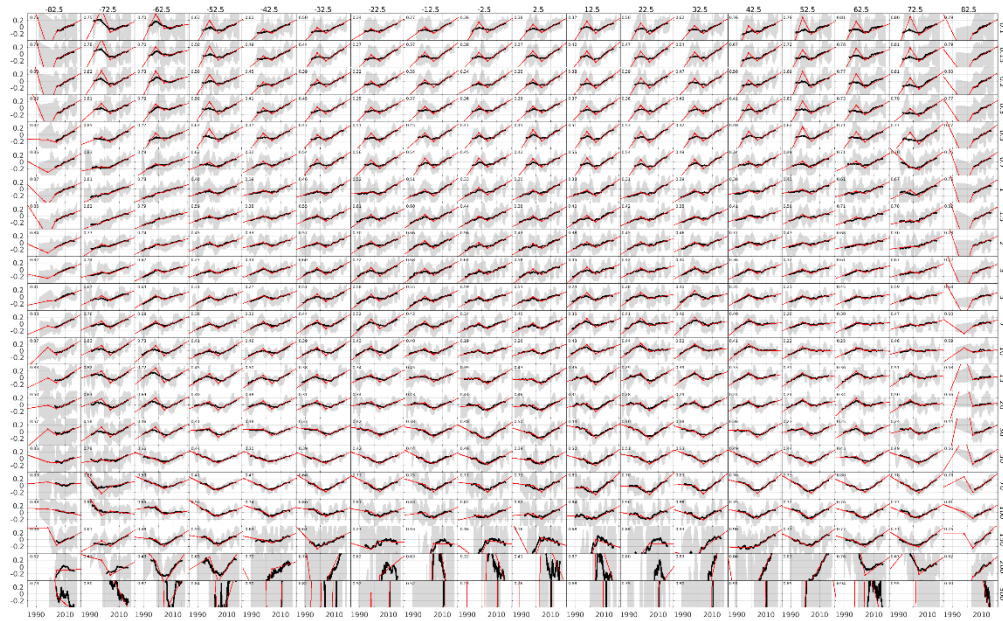


Figure 4-8: Time series of CCI CDR-3 residuals after subtraction of the regressed AO, SAO and QBO cycles, then smoothed over 10 years to highlight long-term changes (black). Grey shades indicate shorter-term changes: 2-year smoothed residuals and their standard deviation. The trend component of the MLR fit is shown in red. Each panel represent a latitude bin (columns) and pressure level (rows). Units are ppmv.

The spatial structure of each of the three trends for all CDRs, and their difference w.r.t. CCI, is shown in Figure 4-9 to Figure 4-11. The long-term behaviour differs considerably between the CDRs.

4.8.1 Prior to 1998

GOZCARDS trends prior to 1998 are not comparable to CCI or SWOOSH results due to a much later start of the CDR (1991 versus mid 1980s). These are therefore not further discussed here. Also not discussed are the CCI trend results above the 0.7 hPa level since affected by a considerable positive bias due to overfitting.

Figure 4-9 (top) shows that, during this early period, both CCI and SWOOSH exhibit highly significant ($>3-4\sigma$) positive trends in the middle and upper stratosphere (up to 0.35 ppmv/decade or 8%/decade) and significant negative trends in the lower stratosphere (up to -0.2 ppmv/decade or -6%/decade). Trends in the tropical upper troposphere vary in sign in magnitude but are not significant.

While CCI and SWOOSH trends are statistically significant, the difference in trend between these CDRs is not. Percentage trends (%/decade) for CCI are mostly more positive (or less negative) than for SWOOSH (Figure 4-9, bottom). However, absolute trends (ppmv/decade) for CCI are more negative (or less positive) than

for SWOOSH (not shown). The sign change between percentage and absolute trends is a result of the difference in multi-annual mean between these CDRs. But, again, CCI and SWOOSH trends are consistent when errors are considered.

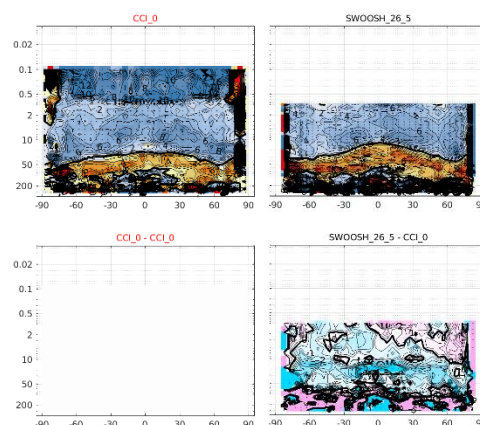


Figure 4-9: As Figure 4-3, but for the trend between start of CDR and December 1997 (%/decade). GOZCARDS trends prior to 1998 are not shown since they are incomparable to CCI or SWOOSH results (see text).

4.8.2 Between 1998 and 2003

A highly coherent picture of significantly decreasing H_2O VMRs is seen during this period across the lower and middle stratosphere for all CDRs, including the smaller scale spatial structure. However, trend magnitudes do differ between CDRs in large parts of the stratosphere.

GOZCARDS trends are generally more than 5%/decade more negative than the other CDRs. At this point, it is unclear how reliable the GOZCARDS estimates are. Additional work will be needed to verify whether this bias is related to overfitting by the MLR (due to the shorter data record?) or results from actual different temporal behaviour in the GOZCARDS time series.

SWOOSH trends are 4-5%/decade larger (and positive) than CCI or GOZCARDS (which are negative) across the upper stratosphere (above the 5 hPa level). The difference is statistically significant in this region. At lower altitudes, SWOOSH trends remain larger (i.e. less negative) than other CDRs but the difference is less pronounced. At 20 hPa, the SWOOSH trend is about -8%/decade compared to -10%/decade for CCI and -15%/decade for GOZCARDS.

A discontinuity appears in the vertical domain for CCI trends around 0.7 hPa. This is likely a result of the overfitting issue reported earlier. Hence, additional work will

be needed to consolidate CCI trend estimates in the mesosphere. At this point the negative mesospheric trends may be overestimated.

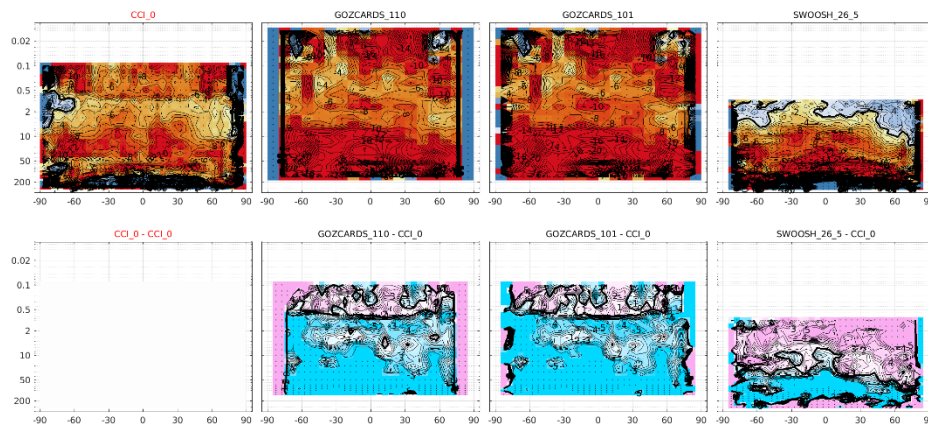


Figure 4-10: As Figure 4-3, but for the trend between January 1998 and December 2003 (%/decade).

4.8.3 Since 2004

Since early 2004, all CDRs exhibit very significant ($>3-4\sigma$) increases in H_2O across most of the atmosphere. Some regions with insignificant, negative trends lie in the tropical UTLS ($-2\%/decade$), the polar UTLS ($-4\%/decade$) and between 5 and 20 hPa at Northern mid- and high-latitudes ($1-2\%/decade$). Elsewhere, positive trends are found of up to $8-10\%/decade$ in the lowermost stratosphere, and $4-6\%/decade$ in the middle and upper stratosphere and mesosphere.

Directly comparing both GOZCARDS versions, we find that v1.10 trends are $2-3\%/decade$ smaller (less positive) than v1.01/1.02 trends across the entire atmosphere. This difference is in line with expectations from the drift correction applied to the recent Aura MLS H_2O data version (Livesey et al., 2021). Hence, these findings can be explained by the different Aura MLS data version.

Differences between SWOOSH v2.6 and GOZCARDS v1.01/1.02 are small ($<1\%/decade$) and insignificant, both largely rely on Aura MLS for data from recent decades.

While CCI trends are mostly larger (often $>1\%/decade$) than those inferred from GOZCARDS or SWOOSH, these differences are statistically insignificant in large parts of the atmosphere. One notable exception is that CCI trends are $3-4\%/decade$ more positive than GOZCARDS v1.10 below the 10 hPa level, a difference that is significant. Differences of $2-3\%/decade$ between these records are significant in the tropical upper stratosphere as well. Hence, it seems that the

inclusion by CCI of additional sensors and not just Aura MLS in the past 15 years leads to significantly different long-term trends in CCI when compared to GOZCARDS or SWOOSH.

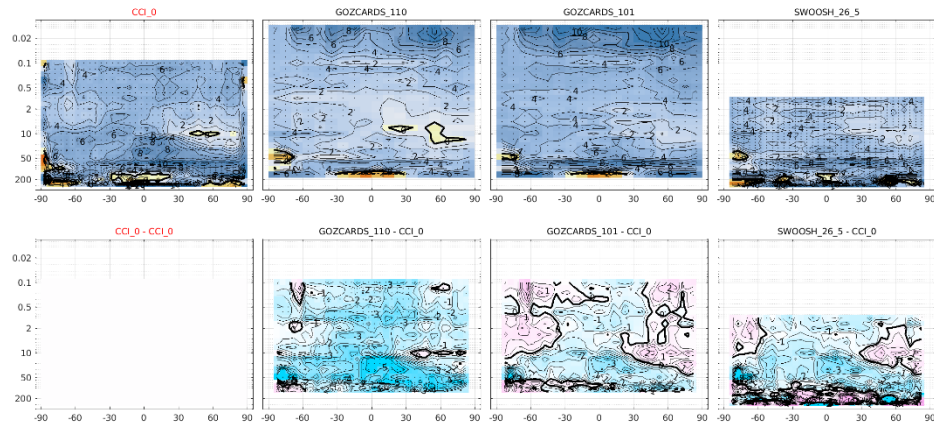


Figure 4-11: As Figure 4-3, but for the trend between January 2004 and end of CDR (%/decade).

4.9 Conclusions

The CCI CDR-3 data record is constructed from a different, considerably larger set of limb sensors than GOZCARDS and SWOOSH, while the latter are based on a similar set of input data. The challenge of the CCI approach is then to obtain accurate offsets for more sensors but with the potential benefit of obtaining a data record less sensitive to errors in one of the input data sets (e.g. sampling bias, drift).

CCI CDR-3 complements the GOZCARDS and SWOOSH data records in terms of spatio-temporal coverage and sampling. Compared to GOZCARDS, the CCI time series start up to seven years earlier (depending on latitude/pressure), has a higher vertical and latitudinal sampling resolution, extends into the troposphere but does not cover the upper mesosphere. Compared to SWOOSH, the CCI record starts up to two years earlier and covers the mesosphere, but offers less spatio-temporal sampling resolution.

Differences in the multi-annual mean (Jan. 2005 to Dec. 2015) inferred from the CDRs are generally statistically significant. The CCI multi-annual mean is clearly smaller than the other CDRs in the stratosphere and mesosphere, by 0.5–1.5 ppmv (or ~10–25%). In contrast, at altitudes below the 150 hPa level (by up to 20–70%) and in the Antarctic lower stratosphere (by 4–12%), the CCI multi-annual mean is biased high relative to the other CDRs.

The dominant patterns of geophysical cycles in CCI CDR-3 are well represented across different temporal and spatial scales. Amplitude and phase of (quasi-)periodic cycles (annual, semi-annual, QBO) generally agree very well with those obtained for GOZCARDS or SWOOSH.

A fairly coherent picture of the longer-term evolution in H₂O emerges from the CDRs. Trends prior to 1998 are mostly positive (and negative in the lower stratosphere), between 1998 and 2003 they are mostly negative and since 2004 again mostly positive. While the inferred trend values differ, often by several %/decade, these differences are generally statistically insignificant. GOZCARDS trends prior to 1998 are incomparable to the other CDRs due to the much later start of the record. Poor agreement is found over the (fairly short) 1998–2003 period during which significant differences are noted in the upper stratosphere (SWOOSH biased high by 4–5%/decade) and below the UTLS. Significant differences in trends since 2004 are noted between CCI and GOZCARDS v1.10, the latter being 2–4%/decade smaller. Both records include Aura MLS v5 data for this time period. Hence, the additional sensors in the CCI record seem to lead to a larger change in the long-term behaviour than the presence of a residual drift in Aura MLS v4 data (used by SWOOSH and GOZCARDS v1.01/1.02).

5. ATMOSPHERIC MOISTURE TRANSPORT

Jorge Eiras-Barca (U. Vigo), Luis Gimeno (U. Vigo)

In this section it is analysed how well do ERA5 and ERAIn solve integrated water vapour (IWV) in regions of particular interest for atmospheric moisture transport processes, particularly atmospheric rivers (ARs; e.g. Gimeno et al., 2014) and nocturnal low-level jets (LLJs; e.g. Algarra et al., 2019a). ERA5 and ERAIn are the most frequently used reanalyses in Lagrangian particle dispersion models and also in moisture tracer simulation both within Eulerian and Lagrangian perspectives (e.g. Eiras-Barca et al., 2017; Algarra et al., 2019b). The cited tools are mostly used to analyse the large moisture transport phenomena, as well as the source and sink regions of the atmosphere–ocean and atmosphere–lithosphere interactions.

CDR-2 is used here as a set of reliable and comprehensive observations that are used to test the goodness of both ERAIn and ERA5 in strategic source regions for the two most important moisture transport processes: ARs and LLJs.

Particularly, the resemblance between the reanalysis and the CDR-2 datasets is tested in strategic regions for moisture transport processes in three different ways:

1. Plots of mean monthly BIAS (ERA5 vs CDR-2 and ERAIn vs CDR-2) using CDR-2 monthly data with a resolution of $0.5^\circ \times 0.5^\circ$.
2. Plots of mean daily temporal correlation (ERA5 vs CDR-2 and ERAIn vs CDR-2) using CDR-2 daily data with a resolution of $0.5^\circ \times 0.5^\circ$. The results are presented annually, which also allows a comparison between the different years of the period under consideration (2003–2017).
3. Considering more than 30×10^3 AR events and more than 8×10^3 LLJs events detected worldwide from 2003 to 2017 (Algarra et al., 2019a, 2020); the probability density functions (pdf) of IWV (ERA5 vs CDR-2 and ERAIn vs CDR-2) are included in the analysis, first having divided the global domain into a set of independent regions of interest.

The full results are available in Eiras-Barca et al. (2022). Here, the mean monthly BIAS (Reanalysis–CDR-2) throughout the period 2003–2017 is shown as example result. Regions of interest for moisture transport processes are highlighted with

dotted polygons. Also, the two most important tropical rainforests are highlighted in red (Figure 5-1 and Figure 5-2). Regions of interest for relevant moisture transport processes (particularly atmospheric rivers, black dotted polygons) are located offshore in regions where the reanalysis and the CDR-2 observations show an overall good agreement. These regions are characterised by low biases both in the Northern and Southern Hemispheres. The latter is true both for ERA5 and ERAIn, which show a good agreement.

In general Eiras-Barca et al. (2022) conclude that the regions of high interest for moisture transport phenomena show a high degree of agreement between both reanalyses and CDR-2. The BIAS are, in general, lower than 2 mm —with low standard deviations in their errors— and the temporal correlations —calculated on a daily time scale— are higher than 0.8.

Discrepancies are accentuated with ERAIn compared to ERA5, as well as in period P5; corresponding to the year 2017. Similarly, relatively high discrepancies are observed in the regions corresponding to tropical forests. Although these regions are rich in moisture content, they do not play any role as source regions for ARs and LLJs. Therefore, it can be concluded that the reanalyses that have been used in recent times have been providing and will provide reliable TCWV information to moisture transport models that analyse sources, sinks and moisture transport phenomena.

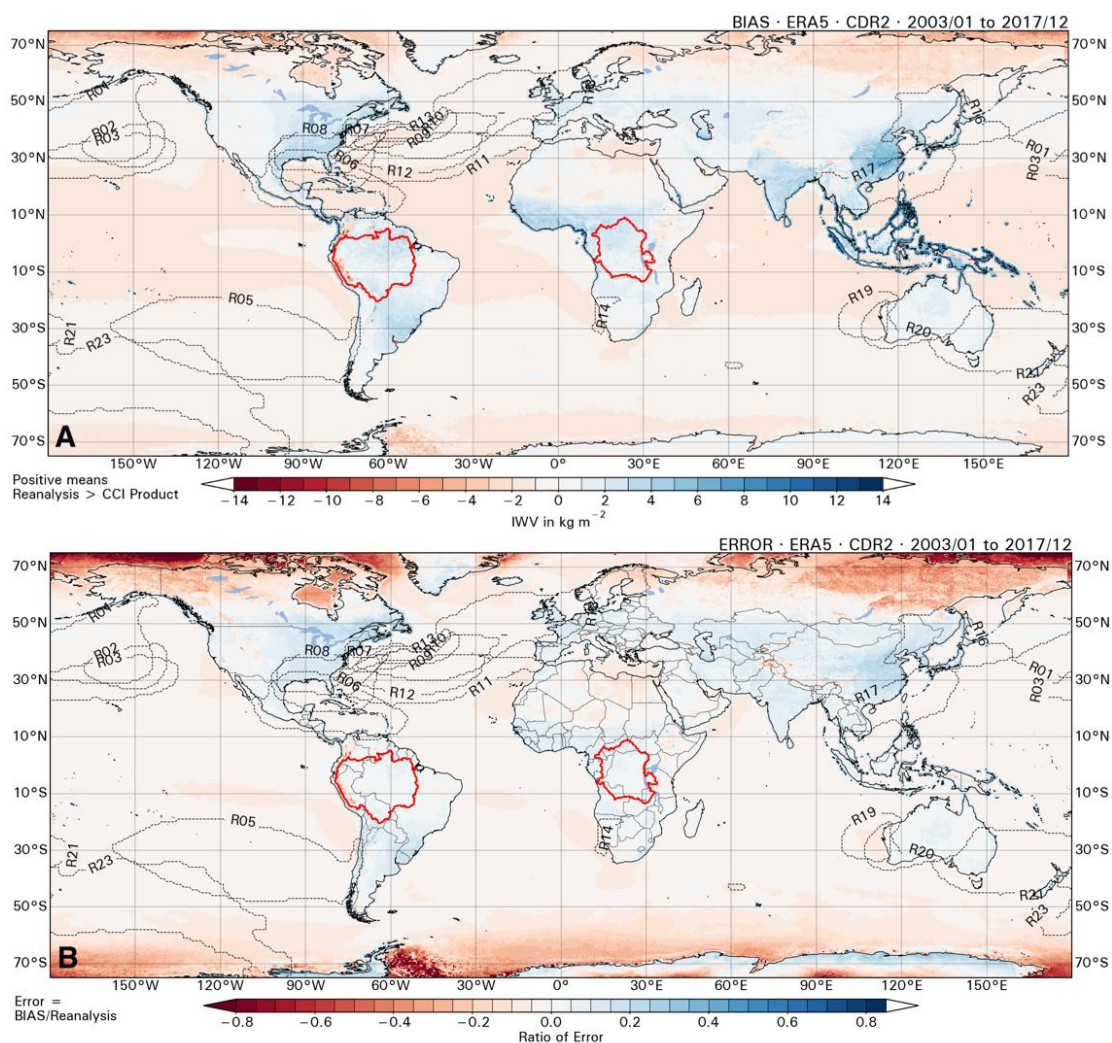


Figure 5-1: (A) The mean monthly BIAS ERA5 – CDR-2 and (B) the ratio of error. Source regions for atmospheric river activity are highlighted with black dotted polygons. The two most relevant tropical rainforests are also highlighted with red polygons.

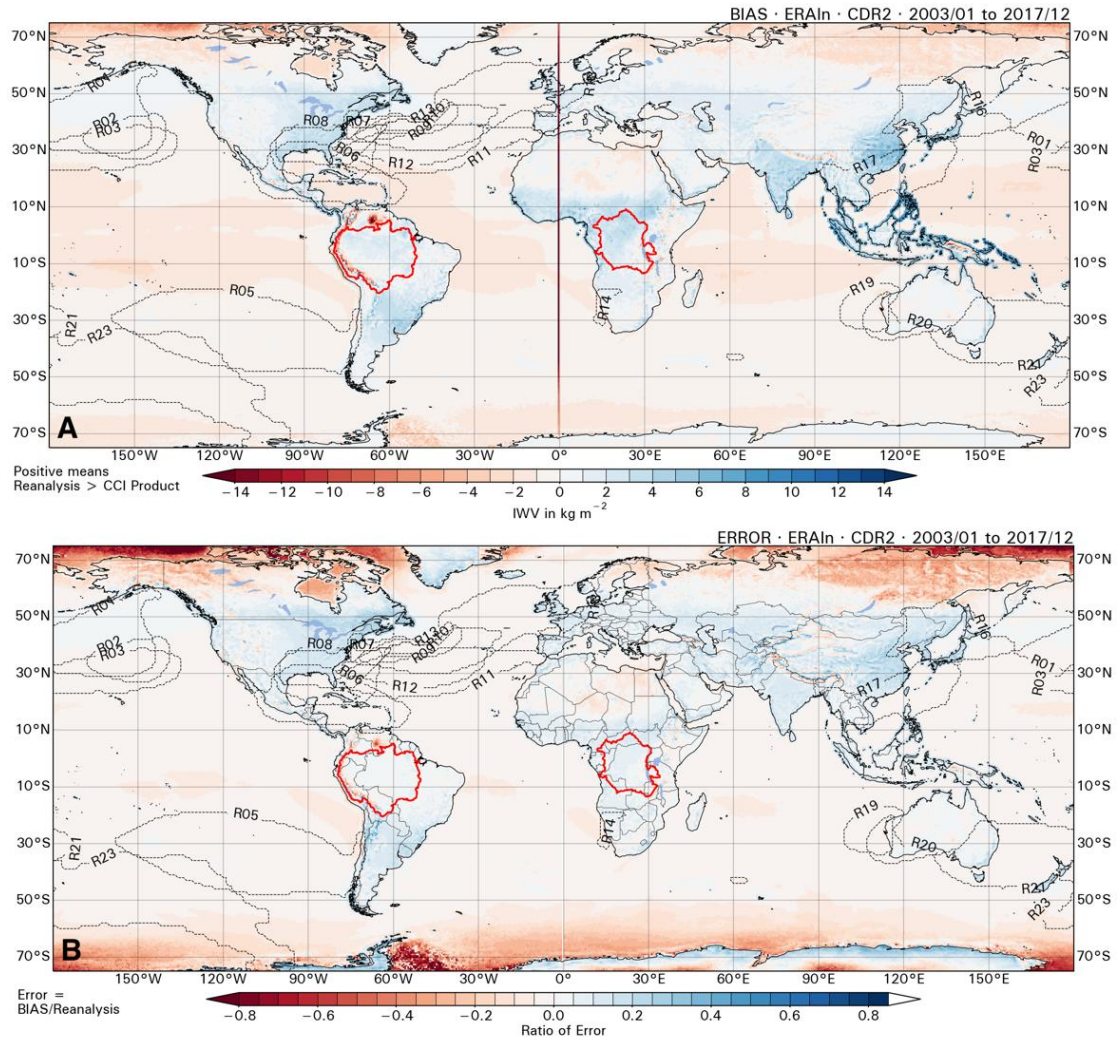


Figure 5-2: (A) The mean monthly BIAS ERA Interim – CDR-2 and (B) the ratio of error. Source regions for atmospheric river activity are highlighted with black dotted polygons. The two most relevant tropical rainforests are also highlighted with red polygons.

6. CLIMATE STUDIES USING CMIP6 AND ERA5

Jia He (UVSQ), H       Brogniez (UVSQ)

Today, how the global atmospheric water cycle will adjust as climate warms is still not fully understood, while the radiative importance of the atmospheric water in maintaining the thermal energy balance of the Earth system is undebated. (The connection between temperature, water vapour and infrared radiation creates a positive feedback that further warms the global climate from an external forcing; cf. IPCC 2013, 2018 and the WCRP strategic plan for the 2019–2029 decade.) However, the representation of the complexity of cloud-moisture–surface interactions remains a central challenge for climate models, and thus restrains our confidence in future climate modifications at all spatial scales.

The increase in surface temperature from anthropogenic forcing yields an observed increase in the atmospheric water vapour (Soden et al., 2005), in accordance with the laws of thermodynamics. This increase in water vapour available in the atmosphere reinforces convergence in tropical regions, with more rainfall in regions particularly sensitive to hydrological changes, and also reinforces divergence in the subtropics (Held and Soden, 2006). This can be summed up as "wetter regions are wetter and drier regions are drier".

Evaluation of the ability of climate models to represent the distribution and variation of tropospheric water vapour according to known patterns of the Hadley–Walker circulation where large-scale subsidence is associated with a dry troposphere and where large-scale ascent is associated with convection and thus a moister troposphere.

6.1 CMIP6 models

Table 6-1 lists the seven CMIP6 models that have been selected for this study. This selection is based on the availability of specific humidity (hus) with sufficient vertical resolution (≥ 19 levels) to calculate total column water vapour, and the corresponding atmospheric vertical velocity (wap), cloud fraction (cl), precipitation (pr) at daily frequency.

The total column water vapour (TCWV) is calculated from all vertical levels available using:

$$TCWV = \int_0^{p_0} q \frac{dp}{g}$$

where g is the gravitational acceleration constant (9.806 m/s), q is the specific humidity, dp is the difference between adjacent pressure levels (hPa).

Since the TCWV CDR-1 and CDR-2 are cloud screened over land, the daily outputs of the CMIP6 TCWV are also screened by cloud thresholds. Here data with cloud fraction less than 50% at all vertical levels over land and precipitation less than 0.001 kg/m²/s² are employed to compare with the CCI water vapour product.

Table 6-1: List of CMIP6 models.

The variables employed are hus: specific humidity; cl: cloud fraction; pr: precipitation; sftlf: land area fraction; wap: atmospheric vertical velocity

Institution	Model ID	Horizontal resolution	Frequency	Start-time	End-time
CCCma	CanESM5	2.81° * 2.81°	daily	1950-01	2014-12
CNRM-CERFACS	CNRM-CM6-1	1.41° * 1.41°	daily	1979-01	2014-12
	CNRM-ESM2-1	1.41° * 1.41°	daily	1979-01	2014-12
IPSL	IPSL-CM6A-LR	1.25° * 2.50°	daily	1979-01	2014-12
MPI-M	MPI-ESM1-2-HR	0.94° * 0.94°	daily	1979-01	2014-12
NCAR	CESM2	0.94° * 1.25°	daily	1950-01	2014-12
	CESM2-WACCM	0.94° * 1.25°	daily	1950-01	2014-12

6.2 ERA5 data

Total column water vapour from ERA5 with hourly frequency are firstly integrated into daily data to be included in this research as reference data. To compare the data under the same conditions, a land–sea mask is employed for land and ocean separation. Similar to CMIP6 data, only data with total cloud cover (tcc) less than 95% and total column cloud liquid water (tclw) less than 0.005 kg/m² over land, and data with total precipitation (tp) less than 0.001 m over ocean are used in this study.

6.3 TCWV and large-scale circulation

6.3.1 Description of the method

Changes in water vapour in the tropical region are important for studies on climate change impacts. However, regional variations are strong and a global look may smooth out all the patterns induced by the large-scale atmospheric circulation. Therefore, in this study, the atmospheric vertical velocity at 500 hPa (w_{500}) is used to decompose the tropical atmosphere into “bins” of dynamic motion, following the method put forth in Bony et al. (2004). In this framework, every dynamical regime is studied in light of its statistical weight within the tropics.

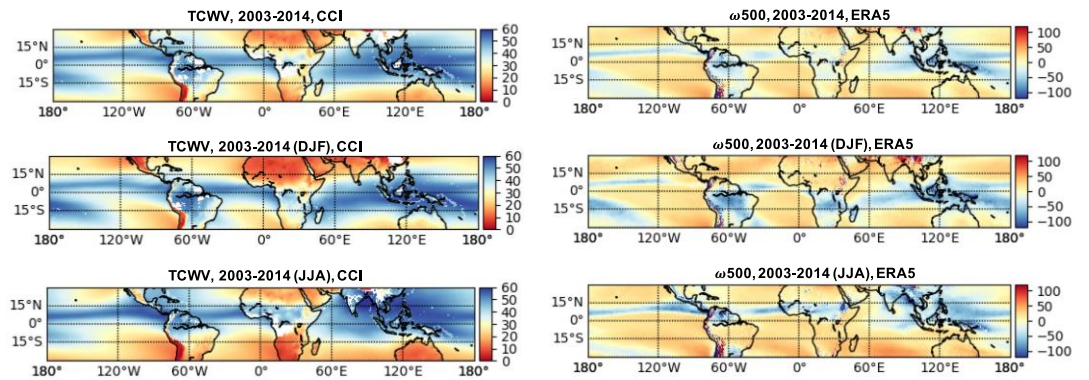


Figure 6-1: Distribution maps of total column water vapour obtained from CCI data record in the tropics (30°S–30°N) during 2003–2014 for the whole period, winter months (December, January, and February), and summer months (June, July, and August) (left panel), and their corresponding vertical velocity of w_{500} observed from ERA5.

Hence, for a given vertical velocity w_{500} (hPa/day) defined at a monthly scale, one can write:

$$\int_{-\infty}^{+\infty} P_{w_{500}} dw_{500} = 1$$

Finite intervals of 10 h Pa are used as a first attempt. The distribution maps of the TCWV from CCI data records and their corresponding vertical velocity of w_{500} from ERA5 are shown in Figure 6-2. The results show that the humid area is related with the ascending motion (negative value in w_{500}) and dry area is related with the subsiding motion (positive value in w_{500}).

As shown in Figure 6-2, the PDFs of the w_{500} from the CMIP6 models agrees well with the ERA5 data. Most of the w_{500} values are around 10–20 hPa/day over both land area and ocean area, which characterises the dominance of the clear-sky radiative cooling of the tropics.

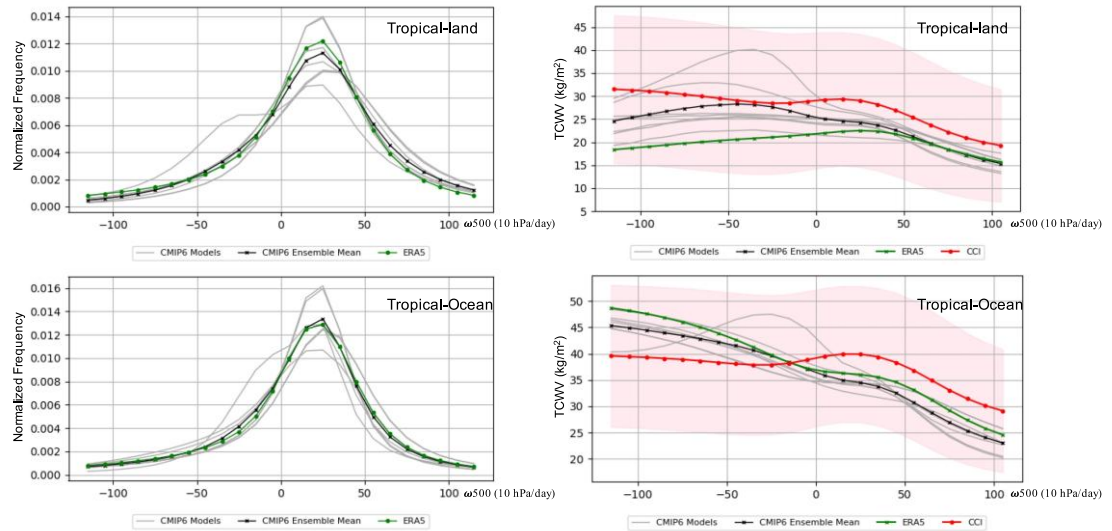


Figure 6-2: PDFs of w_{500} for CMIP6 models (grey lines), the ensemble mean of the models (black line), as well as ERA5 (green line). Here w_{500} from ERA5 is also employed as reference for the CCI data (left panel). Mean total column water vapour observed from the CMIP6 models (grey lines), the ensemble mean of CMIP6 (black line), ERA5 (green line), and CCI (red line) in different circulation regimes of w_{500} . The shaded area in pink represents the $\pm\sigma$ of each bin in CDR-2.

Thanks to this decomposition, the variations of the TCWV can be studied with a dynamical perspective, looking at the behaviour of the TCWV for given bins of w_{500} , rather than with a fixed-box perspective. The CMIP6 models and the reanalysis results all show some differences with the WV_cci variables, but all are within the spread of the observation, indicating that the models could correctly represent the ascending motions and subsiding motions for large-scale circulation.

6.3.2 Analyses of the evolution according to dynamical regimes

We further decomposed the water vapour data into circulation regimes for each year to look into the details of the evolution of the water vapour. The results in Figure 6-3 show the variations of mean value of the total column water vapour for each circulation bins over the common 2004–2014 period in the tropical land region (30°S–30°N). Very different characteristics are observed for different data records. The tcwv from CCI data peak at -120 to -110 hPa/day bins, and it has a second peak in the tcwv value before 2009 at 20–30 hPa/day bins, while for the

tcwv from ERA5, it peaks at 20–30 hPa/day bins. For the CMIP6 models, the high tcwv occurred at around -60 hPa/day bins.

This comparison provides an insight of the variation evolutions of the link between tcwv and the large-scale circulation over land area under clear-sky conditions. Despite the differences observed among the datasets, all the data records agree that the most positive w_{500} bins are associated with the driest troposphere (dark blue) while the most negative w_{500} bins are for the wettest troposphere (dark red).

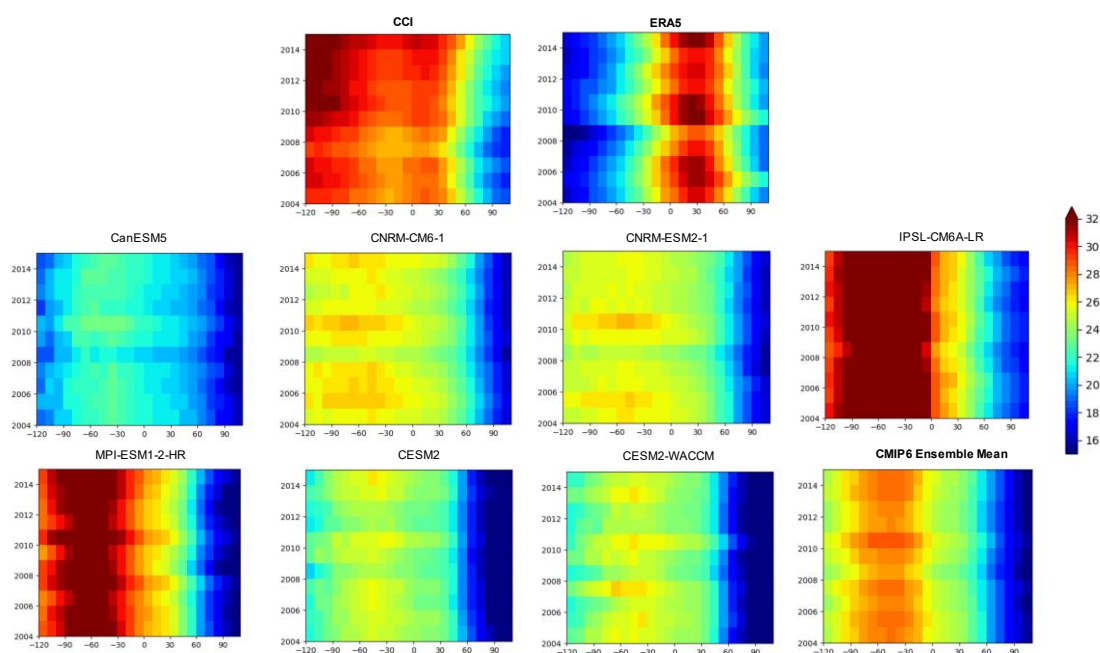


Figure 6-3: Mean water vapour at each 10 hPa/day circulation regime over the land area of the tropics (30°S–30°N) for each year.

To analyse the evolution of circulation regimes, the mean water vapour value for the whole period of each data record at each bin are employed as the reference data to normalize the results. As is shown in Figure 6-4, dry anomalies in 2008 and wet anomalies in 2010 are observed for all data records. This possibly resulted from the La Niña events. In addition, a strong moistening trend is observed after 2009 from CCI data, while no significant moistening or desiccating trend is observed over the years in other data records.

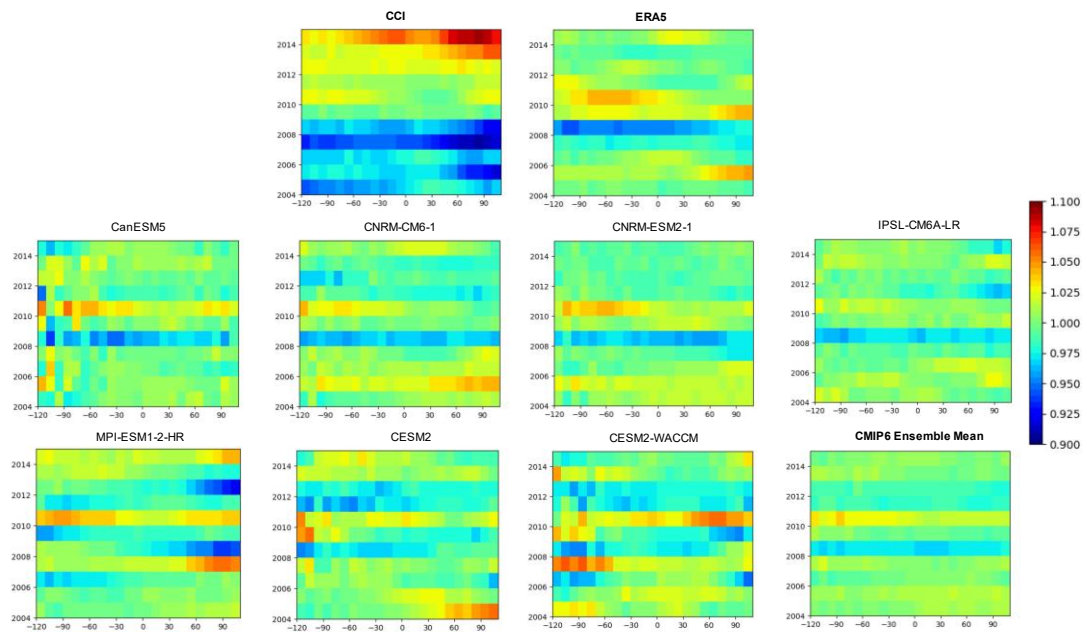


Figure 6-4: Normalised mean water vapour at each 10 hPa/day circulation regime over the land area of the tropics (30°S–30°N) for each year. The mean water vapour observed for the whole period of each data record are employed as the reference data.

The variations of mean value of the total column water vapour for each circulation bins over the common 2004–2014 period in the tropical ocean (30°S–30°N) are shown in Figure 6-5. Similar to the results observed over tropical land, the CCI data peak at -120 to -110 hPa/day bins, and it has a second peak in the tcwv value before 2009 at 20 –30 hPa/day bins, while for the tcwv from ERA5 and most of the CMIP6 models (except for IPSL-CM6A-LR), the most moist value occurred at -120 to -110 hPa/day bins. For the IPSL-CM6A-LR model, the high tcwv occurred at around -30 hPa/day bins. In general, the data records perform more consistently over tropical ocean than over tropical land.

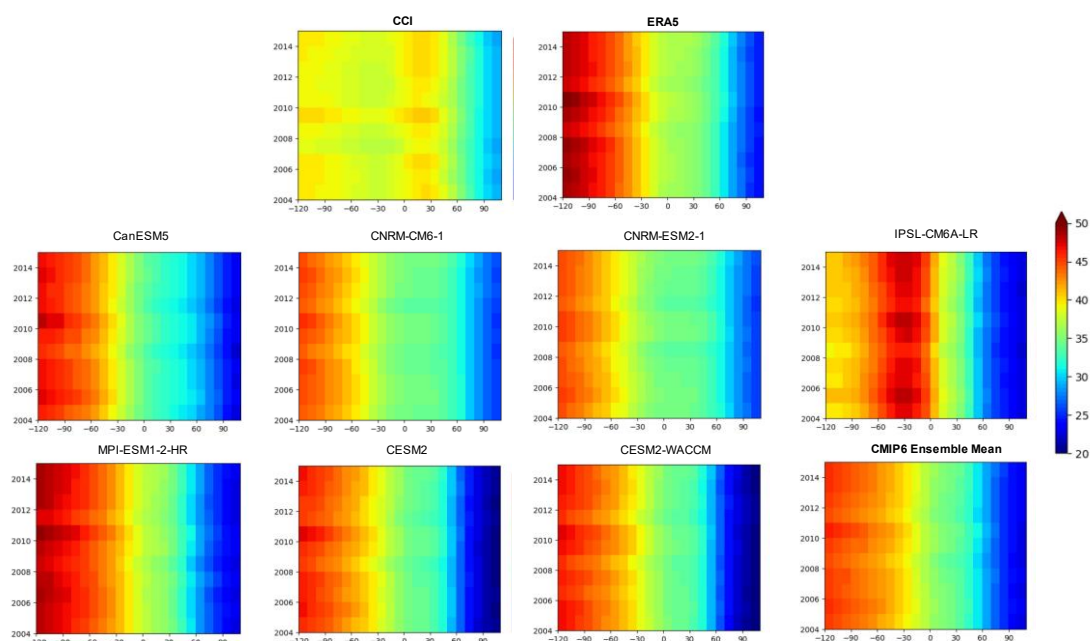


Figure 6-5: Mean water vapour at each 10 hPa/day circulation regime over the ocean area of the tropics (30°S–30°N) for each year.

Moreover, we also normalised the value by employing the mean tcwv observed for each circulation regime over the period 2004–2014 over ocean as the reference, to show the evolution of the water vapour in each circulation bin over the tropical ocean (30°S–30°N) in each year. The results in Figure 6-6 also show the dry anomalies in 2008 and wet anomalies in 2010 for all CMIP6 records and the ERA5 data, while for the CCI data, the dry anomalies are observed in 2007 and wet anomalies are in 2009.

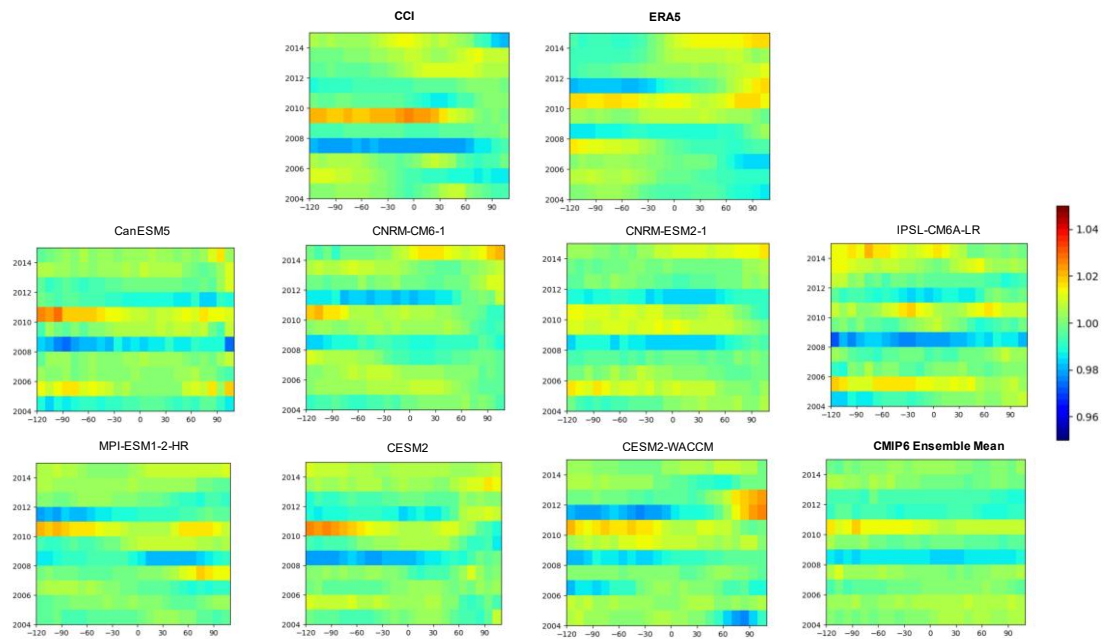


Figure 6-6: Normalised mean water vapour at each 10 hPa/day circulation regime over the ocean area of the tropics (30°S–30°N) for each year. The mean water vapour observed for the whole period of each data record are employed as the reference data.

6.4 Conclusions

The water vapour data obtained from the WV_cci project (CDR-1 and CDR-2), climate models (CMIP6 framework), and ERA5 are evaluated in terms of the representatives of the distribution and variation of tropospheric water vapour with respect to vertical velocity at 500 hPa. The results show that although there are differences observed among the CCI data, CMIP6 models, and the ERA5 data, all are within the spread of the observation, indicating that the models could correctly represent the large-scale circulation, which is that the humid area is related with the ascending motion (negative value in w_{500}) and dry area is related with the subsiding motion (positive value in w_{500}) over both tropical land and tropical ocean area.

7. CYCLES AND TRENDS IN CDR-3/4

Daan Hubert (BIRA-IASB), Jean-Christopher Lambert (BIRA-IASB)

Goal of the study: Estimate parameters of variability & long-term changes from the updates/extensions to CDRs 3 & 4. This study will focus on the coherence of magnitude, spatial structure & uncertainty between, i) CDR-3 vs CDR-4, ii) CDR-3 vs SWOOSH vs GOZCARDS, and iii) CDR-4 vs SWOOSH vs ERA5. Finally, the added-value of CDR-3 & CDR-4 will also be assessed.

8. IMPACTS OF SUB MODEL-GRID TCWV HETEROGENEITY ON REGIONAL PRECIPITATION FORECASTS

Antonio Bruno (UoL) and Tim Trent (UoL)

In a warming climate, the expectation is that most regions will experience an increase in extreme precipitation events under all warming scenarios (Figure 8-1). The latest working group 1 IPCC (AR6) report (IPCC, 2021) finds that since 1950 average precipitation has increased, with this rate growing faster still since 1980. Additionally, they conclude that the frequency and intensity of heavy rainfall events “have likely increased at the global scale over a majority of land regions with good observational coverage”. Therefore, understanding extremes and how they will evolve with future warming and the socio-economic challenges they pose is vital for mitigation and adaptation policy development.

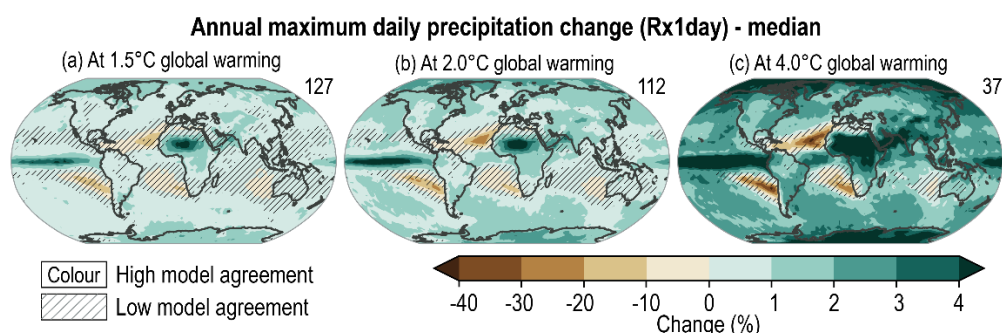


Figure 8-1: Expected annual maximum daily precipitation changes relative to future warming under the CMIP Shared Socioeconomic Pathway scenarios. Number of ensemble members is indicated in the top right of each map. Source: Figure 11.16 in IPCC, 2021: Chapter 11 (Seneviratne et al., 2021).

In regions with sparse or no in situ measurements, this presents a real challenge for long term monitoring, especially if the area is already vulnerable to extreme events. Modern reanalysis products provide sub-daily data coverage globally, covering areas with observational gaps exist. However, reanalysis precipitation products do have limitations in the ability to capture daily total amounts and extreme wet events when compared to rain gauge and satellite measurements (Rhodes et al., 2014, Lei et al., 2022). When we consider mitigating extreme precipitation the ability to accurately forecast levels and distribution of rainfall over an area becomes a key source of information for local decision makers. This is especially true in remote areas where a lack of local infrastructure can make it harder to access HPC computing to provide regular regional forecasts or result in low-to-no availability in ground truth data.

In the absence of ground measurements, satellites provide large volumes of data for assimilation systems. Since 1979, the volume of measurements have increased by around orders of magnitude, with the ERA5 system assimilating ~24 million measurements per day (Hersbach, H., et al. 2020). With the increased capacity to handle more and more data, the opportunity to leverage information from datasets with increasing spatial resolution. The development of the high-resolution TCWV data product within WV_cci project provides such an opportunity for exploitation, where the pixel resolution provides sub-grid information on heterogeneity. An initial study by Saunders, R., (2021) has already shown assimilation experiments of OLCI TCWV consistently showed positive impacts on the forecast scores and some distribution changes of TCWV. Therefore, the goal of the study: Understand how high-resolution TCWV information at reanalysis sub-grid scales (<0.25 degrees) can be exploited to improve precipitation forecasts at regional scales. This study will use the prototype high-resolution CDR-1 product and a new generative emulation NWP model within a data assimilation framework to assess impact precipitation forecast skill for extreme rain events over Pakistan.

For this case study, we will specifically focus on the flooding event caused by the extreme rainfall seen over Pakistan in August 2022 which left over 30 million people homeless, resulted in 1000 deaths and caused significant socioeconomic losses of over 30 billion USD (Hong et al. 2023). (Figure 8-2).

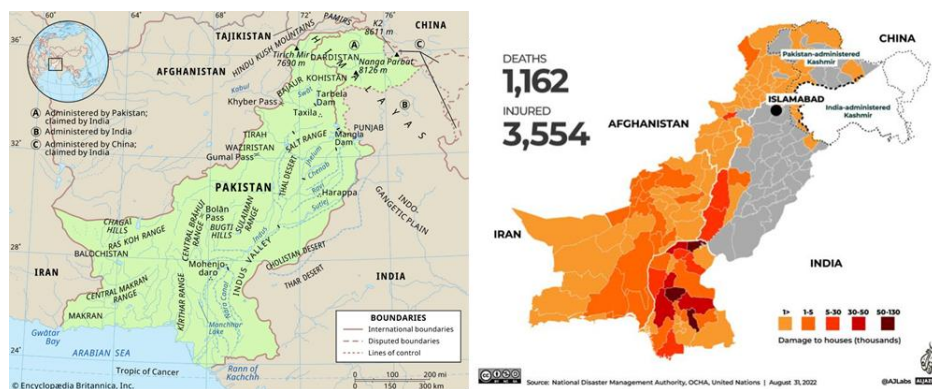


Figure 8-2: United Nations Office for the Coordination of Humanitarian Affairs (OCHA) information on the number of dead and injured resulting from the extreme rainfall during July-August 2022 along with damage. Source for graphic <https://www.aljazeera.com/news/2022/9/1/pakistans-floods-what-caused-the-floods>. Map showing the physical features of Pakistan taken from <https://www.britannica.com/place/Sulaiman-Range>.

8.1 High-resolution TCWV Coverage over Pakistan during the Monsoon Season

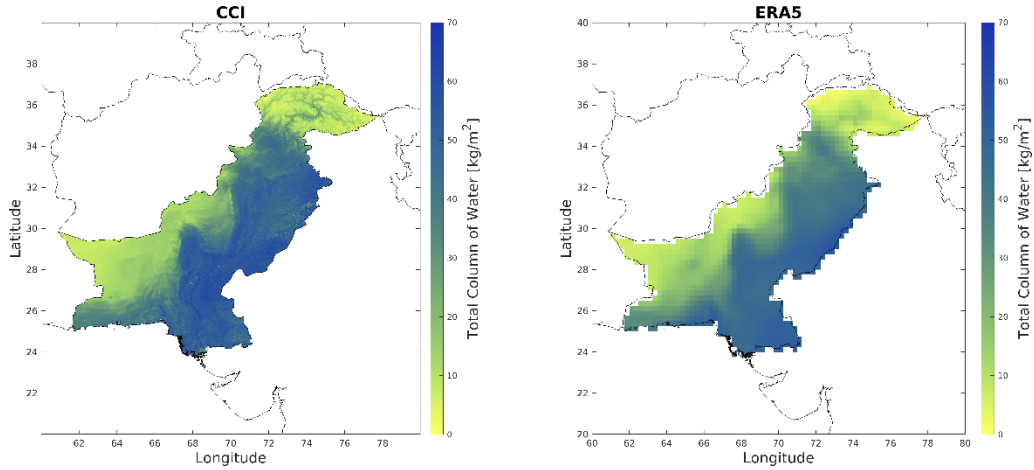


Figure 8-3: Average summer (JJA) TCWV for Pakistan for the prototype high-resolution WV_cci CDR1 product (left) and ERA5 reanalysis sampled at 10:00 hrs UTC (right).

Before building a data assimilation (DA) framework, it is important to first understand the data coverage from high-resolution CDR1 (HR-CDR1) product for periods when we have high levels of cloud coverage over the region. Here we have three key objectives:

- 1) Identify differences in spatial distributions in TCWV of HR-CDR1 relative to ERA5 reanalysis.
- 2) Understand how the representation of HR-CDR1 TCWV varies under different temporal averaging.
- 3) Evaluate the clear-sky sampling of TCWV over Pakistan during the 2022 flooding event.

To support these objectives we also have created a complementary ERA5 TCWV dataset, which has been temporally interpolated to 10:00 hrs UTC and over sampled onto HR-CDR1 0.01x0.01 degree from its native 0.25x0.25 degree grid. To understand how the information differs between the satellite and reanalysis TCWV, PDFs are first calculated over different temporal periods (N days) and then compared to one another using the Total Absolute Probability Difference (TAPD):

$$TAPD_{12} = \sum_{i=1}^N |PDF_2(i) - PDF_1(i)|$$

Where PDF1 and PDF2 are the distributions for HR-CDR1 & ERA5 TCWV respectively, and the i subscript is the specific PDF bin. The concept is illustrated by Figure 8-4, and is interpreted as a dimensionless scale of distance between both PDFs, ranging between 0 to 2, where if both PDFs were identical would result in a TAPD of 0, and for maximum disagreement a value of 2.

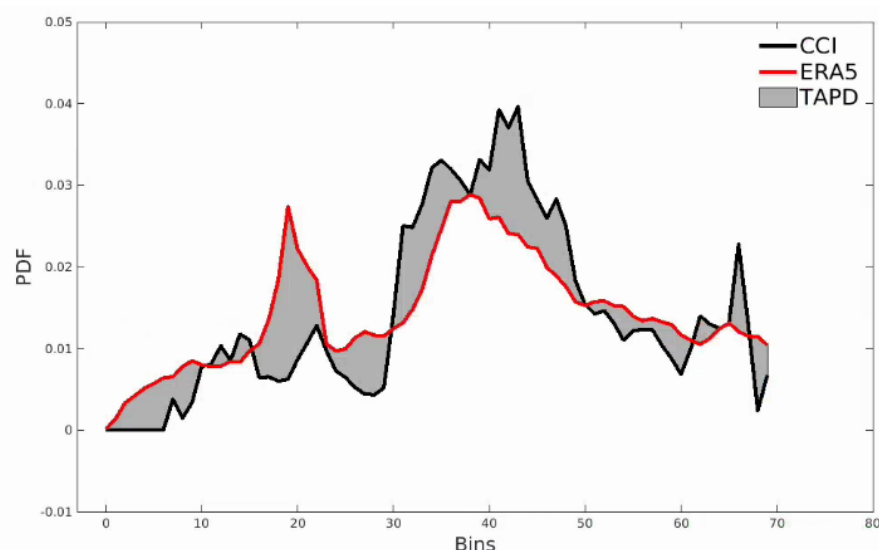


Figure 8-4: Illustration of Total Absolute Probability Difference (TAPD) represented as the the grey shaded area.

For this analysis TCWV fields were sorted into 2, 3, 5, 7, 10 and 15 day periods before, during and after the flooding event in 2022. The 5 year average TCWV for the June, July, August (Clim) was also calculated for both data sets. Examples of the spatial averages for the 7 day period can be seen Figure 8-5, with ERA5 exhibiting wetter atmospheres over higher elevation after the event, where before and during this is confined to the south-west of the country. For the duration of the event, the north-west of the country is generally wetter than the long-term satellite average for both HR-CDR1 and ERA5 with consistent spatial patterns. After the event ERA5 shows dryer atmospheres over the impacted region in the south east. Therefore, within ERA5 this would then suggest there is a slight deficiency in the atmospheric moisture post flooding which potentially contributes towards the source for subsequent precipitation events as the air mass moves from east to west across the country. However, we cannot attribute any difference of TCWV in this area to biases in precipitation at this stage. These results are fairly consistent for 7+ day means, the challenge arises from when the window over which TCWV is averaged decreases, we increase the amount of missing grid cells due to cloud contamination capturing only the western edge of the country.

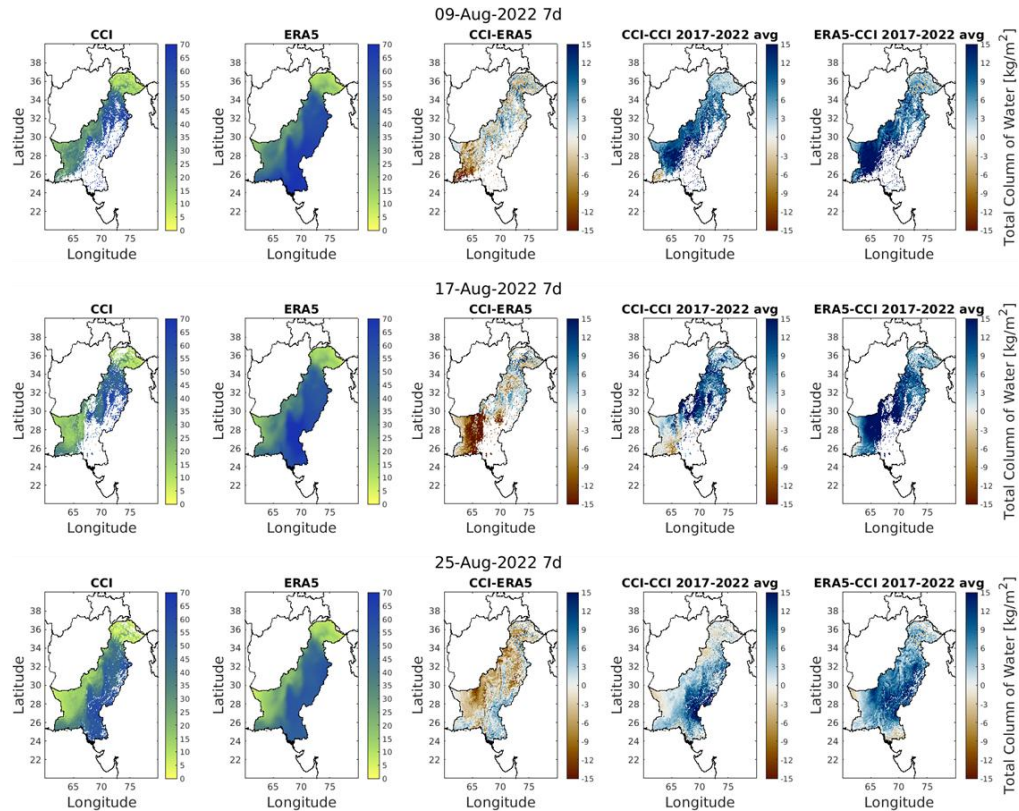


Figure 8-5: 7 day average TCWV fields for before (top row), during (middle row) and after (bottom row) the August 2022 flooding event in Pakistan. The first two map in each row show the 7 day average TCWV, the next the difference between the two, fourth and fifth map show the difference of the 7 day average to HR-CDR1 (CCI) 5 year seasonal average.

The next stage uses the TAPD between PDFs you investigate the common spatial information between HR-CDR1 and ERA5 for each N day period. In each case the daily cloud mask from HR-CDR1 is applied to the ERA5, HR-CDR1 Clim and ERA5 Clim data and PDFs calculated. This approach effectively cuts off the higher end of TCWV distribution within the region of heavy precipitation in order to give a like-for-like comparison. The results from this analysis are presented in Table 8-1 for each N day period before, during and after the flooding event on the 17th of August 2022. The three main take aways from this analysis are:

- HR-CDR1 and ERA5 TCWV are generally more in agreement before the event.
- The TAPD between ERA and ERA5 climatology before and during the event fluctuates around 0.75, indicating a high disagreement between the PDFs (indicating a extreme event). After the flooding occurs the TAPD values are still high but there is a clear decreasing trend until the minimum value of 0.55, i.e. a return to the usual conditions as more data post event is included.

Table 8-1: Total Absolute Probability Differences (TAPDs) calculated between the PDFs of the water vapour total columns from CCI and ERA5 databases and the climatology of CCI. The data have been regridded and masked on the CCI spatial resolution. The TAPD is defined as $TAPD_{12} = \sum_{i=1}^N |PDF_2(i) - PDF_1(i)|$, PDF_1 refers to the column and PDF_2 to the row. The PDFs are calculated averaging the data on multiple days reported on the rows and calculated before, during and after the flood events in Pakistan during August 2022

		Before			During			After		
		CCI	ERA5	clim	CCI	ERA5	clim	CCI	ERA5	clim
2d	CCI	0	0.43	0.76	0	0.32	0.63	0	0.42	0.67
	ERA5	0.43	0	0.86	0.32	0	0.72	0.42	0	0.88
	clim	0.76	0.87	0	0.63	0.72	0	0.67	0.88	0
3d	CCI	0	0.41	0.69	0	0.38	0.60	0	0.49	0.85
	ERA5	0.41	0	0.78	0.38	0	0.61	0.49	0	0.95
	clim	0.70	0.78	0	0.60	0.61	0	0.85	0.95	0
5d	CCI	0	0.34	0.77	0	0.44	0.61	0	0.57	0.56
	ERA5	0.34	0	0.85	0.44	0	0.66	0.57	0	0.82
	clim	0.77	0.85	0	0.61	0.66	0	0.56	0.82	0
7d	CCI	0	0.24	0.72	0	0.49	0.54	0	0.54	0.51
	ERA5	0.24	0	0.74	0.48	0	0.75	0.54	0	0.76
	clim	0.72	0.74	0	0.54	0.75	0	0.51	0.76	0
10	CCI	0	0.26	0.69	0	0.50	0.59	0	0.81	0.44
	ERA5	0.26	0	0.62	0.50	0	0.83	0.81	0	0.71
	clim	0.69	0.62	0	0.59	0.83	0	0.44	0.71	0
15	CCI	0	0.38	0.65	0	0.48	0.64	0	0.52	0.33
	ERA5	0.38	0	0.74	0.49	0	0.85	0.52	0	0.55
	clim	0.65	0.74	0	0.64	0.85	0	0.33	0.55	0

- Between the HR-CDR1 and the HR-CDR1 climatology the behaviour is similar to ERA5. The TAPDs fluctuate around 0.7 before the event and 0.6 during the event. The decreasing trend is also present and it is more rapid, reaching the minimum value of about 0.33. This suggests that ERA5 could be missing information on the broader regional moisture transport.

To better understand the missing representiveness of TCWV within cloudy and precipitating areas the TAPDs are recalculated between ERA5 with and without the HR-CDR1 mask applied to the TCWV fields. The 5 year average for summer time TCWV for ERA5 is also calculated, though this time no mask is applied. Results for this comparison is shown in Table 8-2 again for the 2, 3, 5, 7, 10 and 15 day periods before, during and after the 2022 flooding event. The three key points of this analysis are:

- The TAPD between the masked and unmasked ERA5 is in general always higher than 0.5 across all N day periods. This highlights that

there is large uncertainty around the higher end of TCWV distributions, effecting the overall water mass in the atmosphere above the country.

- The masked ERA5 TCWV is closest to the unmasked 5 year average with TAPD values of ~0.4 when PDFs are clauated for periods ranging between 3 and 10 days.
- Using larger temporal windows after the flooding event yields the TAPD values close to 1, which are the highest levels of disagreement seen between both sets of analysis. This again shows how uncertainty of TCWV distributions increases as wetter air masses moving into the region, and potentially including other precipitation events.

Table 8-2 Total Absolute Probability Differences (TAPDs) calculated between the PDFs of the water vapour total columns from ERA5 masked on HR-CDR1 data ERA5 databases and the ERA5 Climatology

		Before			During			After		
		ERA5 _{mask}	ERA5	Clim	ERA5 _{mask}	ERA5	Clim	ERA5 _{mask}	ERA5	Clim
2d	ERA5 _{mask}	0	0.61	0.72	0	0.69	0.88	0	0.64	0.86
	ERA5	0.61	0	0.77	0.69	0	0.54	0.64	0	0.63
	Clim	0.72	0.77	0	0.88	0.54	0	0.86	0.63	0
3d	ERA5 _{mask}	0	0.77	0.75	0	0.58	0.76	0	0.59	0.88
	ERA5	0.77	0	0.78	0.58	0	0.43	0.59	0	0.56
	Clim	0.75	0.78	0	0.76	0.43	0	0.88	0.56	0
5d	ERA5 _{mask}	0	0.82	0.83	0	0.57	0.83	0	0.63	0.74
	ERA5	0.82	0	0.82	0.57	0	0.43	0.63	0	0.51
	Clim	0.83	0.82	0	0.83	0.43	0	0.74	0.51	0
7d	ERA5 _{mask}	0	0.77	0.82	0	0.58	0.79	0	0.65	0.73
	ERA5	0.77	0	0.68	0.58	0	0.40	0.65	0	0.49
	Clim	0.82	0.68	0	0.79	0.40	0	0.73	0.49	0
10	ERA5 _{mask}	0	0.75	0.77	0	0.54	0.82	0	0.66	0.98
	ERA5	0.75	0	0.63	0.54	0	0.42	0.66	0	0.53
	Clim	0.77	0.63	0	0.82	0.42	0	0.98	0.53	0
15	ERA5 _{mask}	0	0.67	0.69	0	0.65	0.85	0	0.72	0.97
	ERA5	0.67	0	0.62	0.65	0	0.60	0.72	0	0.47
	Clim	0.69	0.62	0	0.85	0.60	0	0.97	0.47	0

8.2 Monsoon Precipitation Biases Over Pakistan

The 2022 floods in Pakistan were the worst the country had seen in a decade, beginning in June and peaking August. A key challenge when studying such extreme events can be the lack of ground station data, either due i) not being public records or ii) local infrastructure doesn't exist. Therefore, in the absence of such records we can use satellite estimates of precipitation, which tend to be a blend of different measurements from different platforms at different wavelengths. In this study, we have chosen to use the Integrated Multi-satellitE Retrievals for GPM (IMERG) product from NASA (Huffman et al., 2015), which combines information from the Tropical Rainfall Measuring Mission (TRMM) satellite (1998 - 2015) and the Global Precipitation Measurement (GPM) satellite constellation (2014-present) to estimate precipitation over the majority of the Earth's surface.

The first step is to understand the performance of ERA5 precipitation over Pakistan during this extreme flooding event. Figure 8-6a-c shows the seven-day total accumulated precipitation during this period, with quite apparent biases in the ERA5 relative to IMERG in the areas of the heaviest rainfall. From Figure 8-6d-e

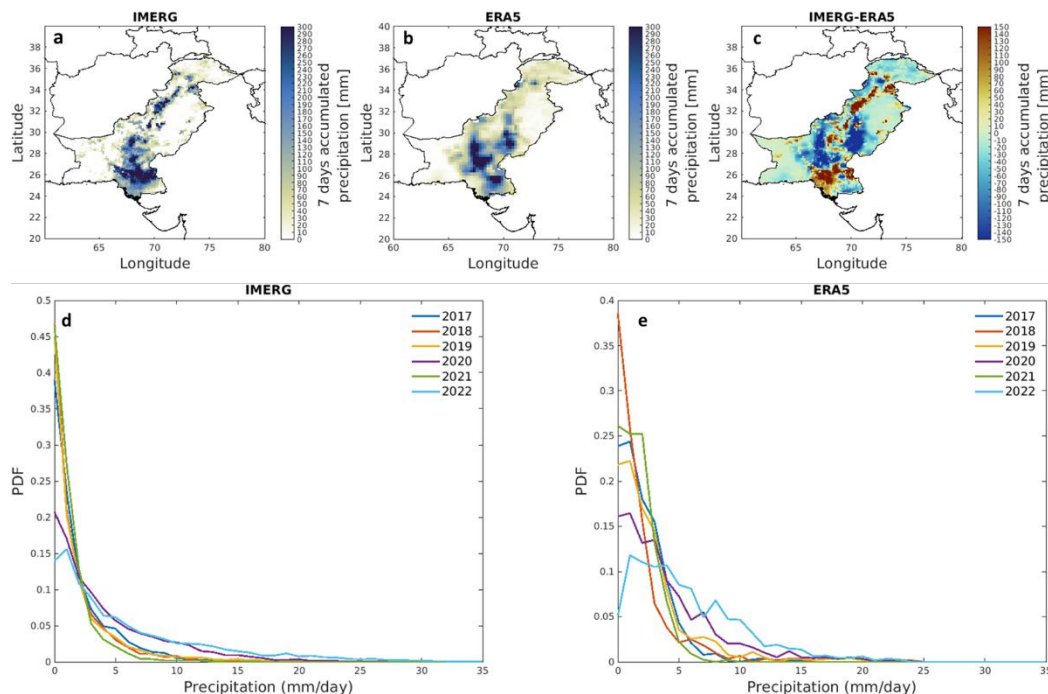


Figure 8-6 Seven-day total accumulated precipitation from on the 14th of August 2022 for the IMERG and ERA5 datasets (a,b). The right-hand frame (c) shows the difference between the two, with brown and blue regions indicating an underestimation and overestimation of rainfall in ERA5, respectively. Finally, PDF distributions of precipitation (mm/day) for each year between 2017-2022 are shown in d & e for IMERG and ERA5 respectively.

which show PDF distributions from 2017-2022 of rain rate for the same seven-day period in August, we observe that ERA5 tends to over estimate the number of grid cells with fluxes above 5 mm/day. This is especially true for 2020 and 2022, where in August 2020 Karachi saw its worst flooding in almost a century, killing at least 41 people. Therefore, we can conclude that precipitation estimates over the region are under constrained within the reanalysis system.

With the previous results highlighting that the HR-CDR1 TCWV data contains clear-sky information that is not present in ERA5, there is an opportunity to constrain the atmospheric source function in the assimilation framework. However, doing this with the ERA5 system is not feasible and outside the scope of this short study. Therefore, we will look to the new generation of Numerical Weather Prediction Emulators (NWPEs) as a mechanism to test the sensitivity of precipitation to perturbations in the background water vapour field.

8.2.1 GraphCast

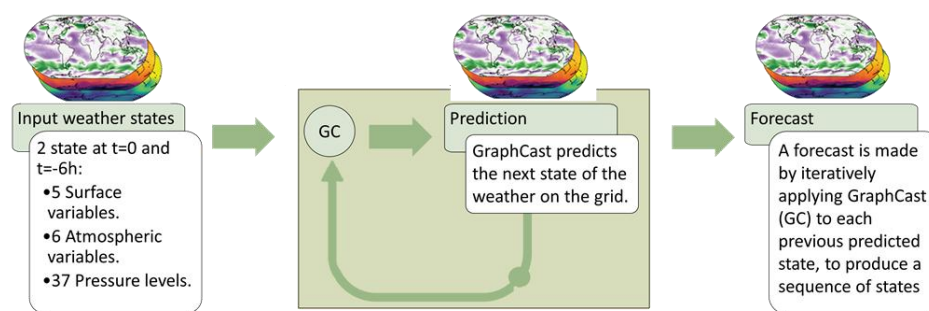


Figure 8-7: Schematic of data pipeline within the GraphCast system.

Developed by Google DeepMind, GraphCast is a machine-learning-based weather forecasting system based on Graph Neural Networks (GNNs) to represent Earth's atmosphere on a $0.25^\circ \times 0.25^\circ$ grid with 37 vertical levels (Lam et al., 2023). GraphCast was trained directly on approximately 40 years of ERA5 reanalysis data and predicts five surface variables (2-m temperature, 10-m u wind component, 10-m v wind component, mean sea level pressure, & total precipitation) and six atmospheric variables (temperature, U component of wind, V component of wind, geopotential, specific humidity, & vertical wind speed) up to 10 days ahead, and in under one minute per forecast from two consecutive states (Figure 8-7). GraphCast, unlike the majority of NWPE models has a precipitation field in its output, making it the ideal starting candidate for this type of study.

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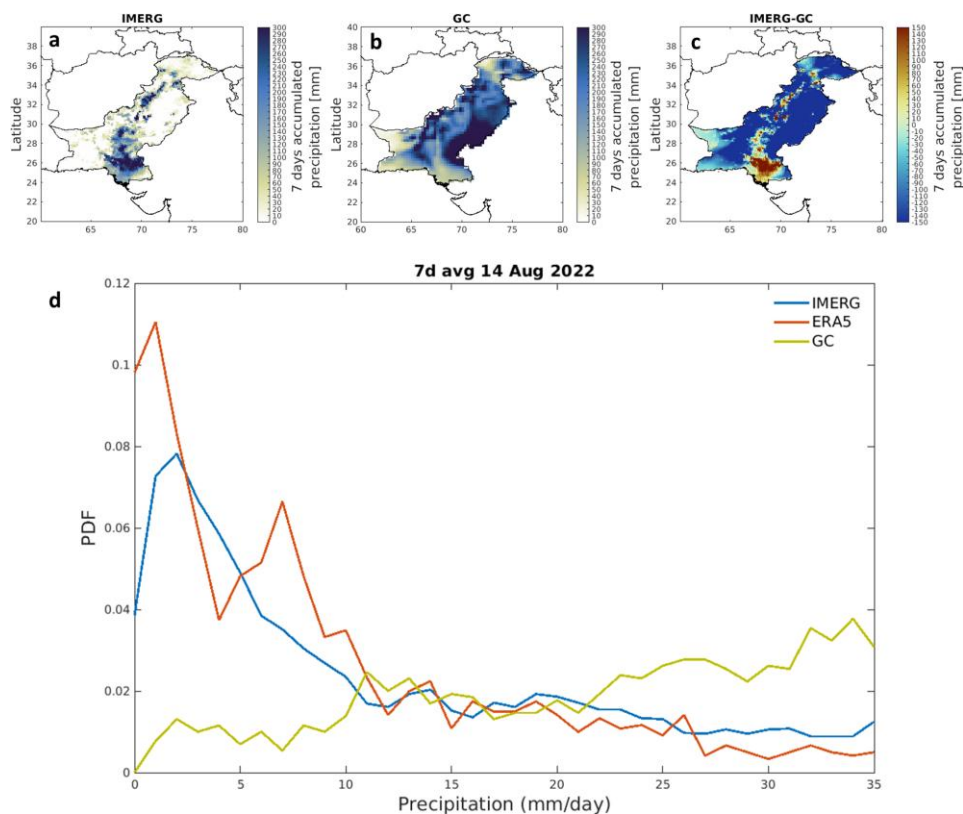


Figure 8-8: As Figure 8-6, seven-day accumulated precipitation from the 14th August 2022 from GraphCast (GC) forecasts (a,b). The right-hand frame (c) shows the difference between the two, with brown and blue regions indicating an underestimation and overestimation of rainfall from GraphCast. PDF distributions from IMERG, ERA5 and GraphCast are shown in d, highlighting the inability of GraphCast to capture low rain rates over the region.

The accumulated precipitation analysis was repeated for GraphCast for the seven-days from the 14th of August, with the results shown in Figure 8-8. What I apparent is that Graphcast cannot capture precipitation with the same level of skill as ERA5, completely over estimating rain rates above 20 mm/day and underestimating rain rates below 11 mm/day. While this is not the best initial result, it does indicate positive potential impact from assimilating clear-sky TCWV. The next step is to determine the sensitivity of GraphCast to background perturbations of the water vapour fields.

8.2.2 GraphCast Sensitivity Tests

To understand the background sensitivity to changes in water vapour, a series of tests were performed using GraphCast. Initially specific humidity profiles in clear-sky grid cells within the ROI were perturbed by $\pm 30\%$, then repeated again for all grid cells within the ROI. This first attempt did not yield any significant change in precipitation. Therefore, the test were adapted to perturb global specific humidity fields instead, between $\pm 30\%$, and for one scenario where the original background values were increased by 30 times. The results for this are shown in Figure 8-9, where the scaled value of the TCWV is shown above the regional map (e.g. $-30\% = 70\%$ TCWV).

What we observe from these tests is that GraphCast precipitation forecasts are not really sensitive to perturbations in the background changes to water vapour. This is evidenced by the fact that a 30 times increase yield similar results to a 30-50% change. At this level of increase we would expect the atmosphere to dump the excess moisture fairly quickly and dramatically. Infact, the only test which yielded significant changes in precipitation were the ones where precipitation itself was perturbed in the previous step.

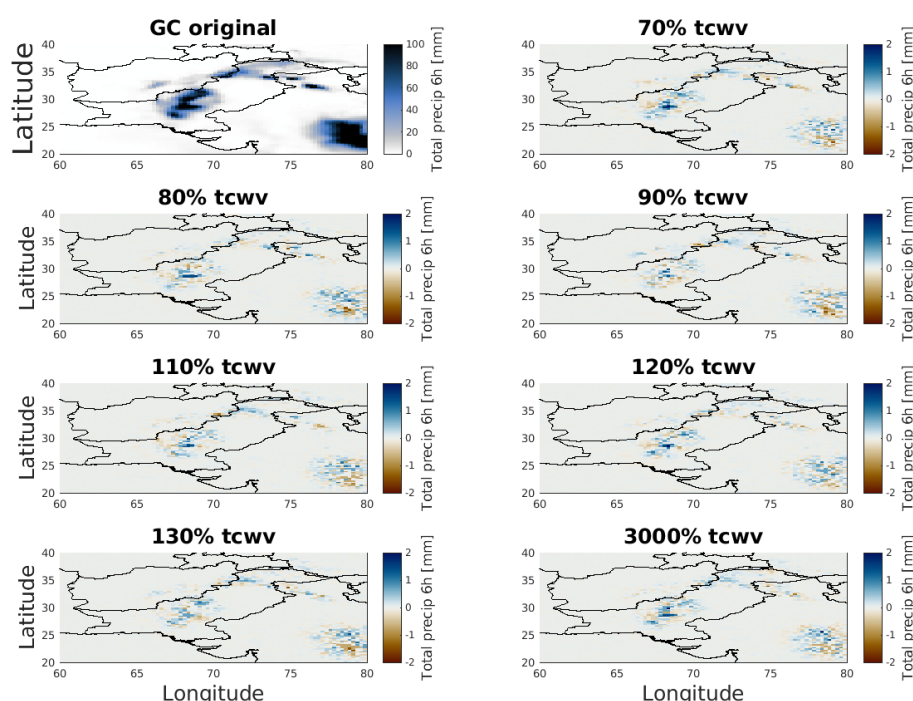


Figure 8-9: Sensitivity testing of 6 hourly accumulated precipitation from a single timestep in a forecast from GraphCast (GC). Top left hand corner shows the original forecast with other plots showing the difference in total precipitation after the background water vapour field has been perturbed by a % of the original TCWV.

8.2.3 The Artificial Intelligence Forecasting System (AIFS)

The Artificial Intelligence Forecasting System (AIFS), is a newer model that has been in operational since 25 February 2025. Developed by the European Centre for Medium-Range Weather Forecasts (ECMWF), AIFS introduces a state-of-the-art data-driven framework for medium-range numerical weather prediction. Leveraging a hybrid architecture of GNN encoders/decoders coupled with a sliding-window transformer processor. Like GraphCast, AIFS is trained on multi-decadal ERA5 reanalysis (1979–2018) but also uses operational IFS analyses (2019–2020), achieving high parallelism and modularity suited for large-scale, high-resolution inputs (Lang et al., 2024a).

The sensitivity test were run again using AIFS, this time perturbing the background water vapour fields by $\pm 50\%$. Results from these tests are shown in Figure 8-9, where we observe significant changes to accumulated precipitation within the 6hr window. Unlike GraphCast which saw changes within ± 2 mm, AIFS shows changes upto 40 times larger (± 40 mm) within the region.

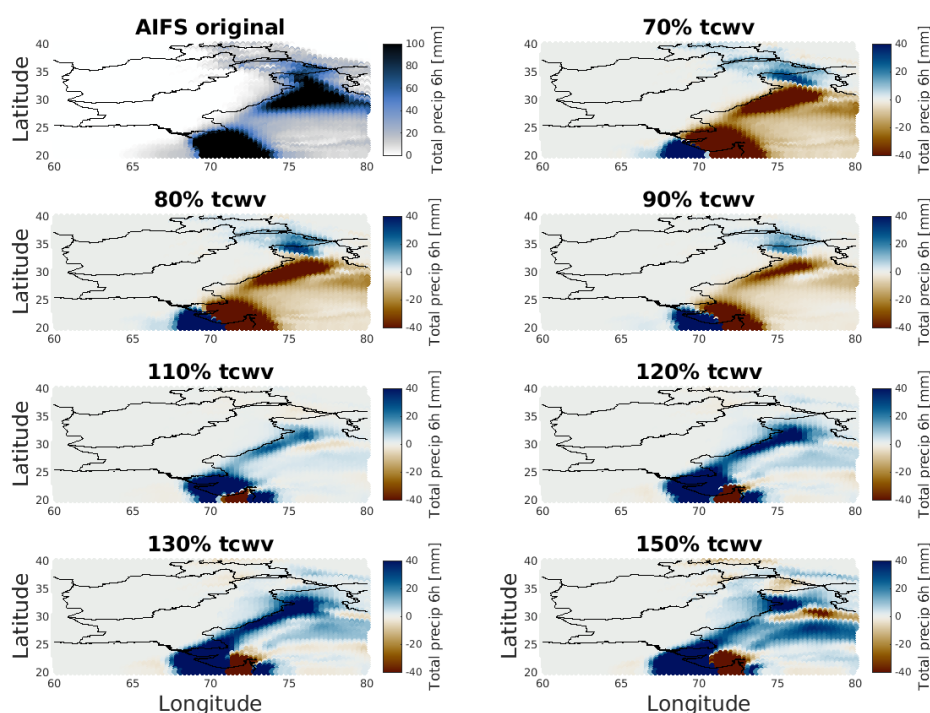


Figure 8-10: As Figure 8-9, sensitivity testing of 6 hourly accumulated precipitation from a single timestep in a forecast from AIFS. Top left hand corner shows the original forecast with other plots showing the difference in total precipitation after the background water vapour field has been perturbed by a % of the original TCWV.

To investigate these differences further we have performed a TAPD analysis on these sensitivity experiments, with the results shown in Table 8-3. What is confirmed is that the PDF distributions of GraphCast accumulated precipitation are very very similar, regardless of the scale of perturbation introduced to the background water vapour. However, for AIFS we do see the PDFs begin to diverge more as the magnitude of the perturbation increases. Interestingly, we see stronger responses in precipitation distributions when the background is reduced compared to the equivalent positive increase in water vapour. Therefore, AIFS is the suitable choice for data assimilation experiments using HR-CDR1 TCWV.

Table 8-3: TAPD results for NWPE precipitation sensitivity tests to perturbations in background water vapour. Grey shaded areas represent tests that were not performed on that specific NWPE.

		Perturbation to background water vapour field (%)								
		-50	-30	-20	-10	10	20	30	50	3000
GC			0.013	0.01	0.013	0.01	0.012	0.011		0.01
AIFS		0.083	0.052	0.04	0.022	0.019	0.024	0.025	0.039	

8.3 Clear-sky TCWV Assimilation Experiment

The final objective of this study is to investigate the value of assimilating high-resolution clear-sky TCWV into NWP systems. Saunders, R., (2021) demonstrated the value of assimilating OLCI TCWV into the UKMO system, for positive impacts on forecast scores for water vapour distribution in the model. Here, we build on this idea by analysing the potential effects on precipitation from assimilating clear-sky TCWV from HR-CDR1. From previous sensitivity tests, we have shown that AIFS has the potential to serve as a forward model in Observation System Simulation Experiments (OSSEs), as it can respond to perturbations in the background water vapour field within one model time step. For this study, we have combined the AIFS model inside a framework utilising a Local Ensemble Transform Kalman Filter (LETKF) to assess the impact of assimilating the HR-CDR1 TCWV fields over Pakistan on the predicted accumulated precipitation during the 2022 flooding event (Figure 8-11).

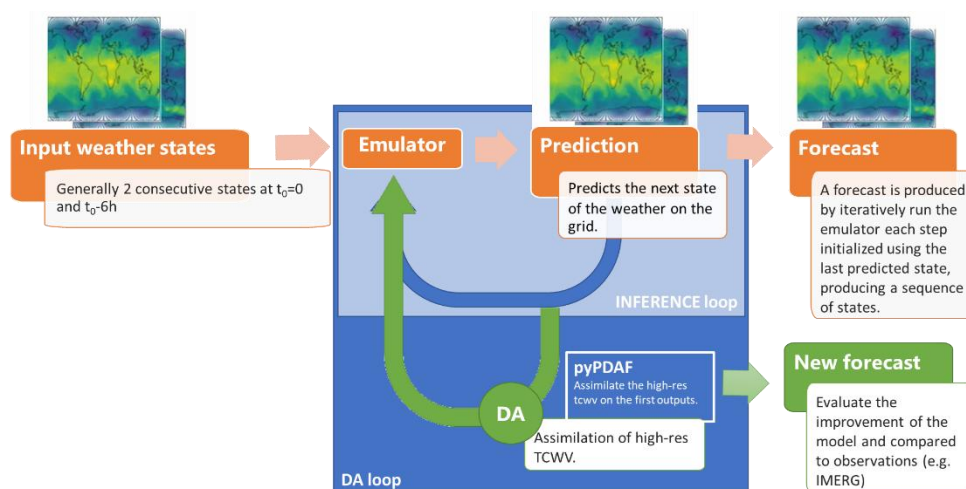


Figure 8-11: Overview of workflow for future Observation System Simulation Experiments (OSSE) for assessing the impacts of sub-model-grid TCWV heterogeneity on regional precipitation forecasts using AIFS and WV_cci HR-CDR1 TCWV.

8.3.1 Study methodology

The AIFS model was initialised from ERA5 reanalysis for the 13th of August and run globally from the 14th to the 24th of August 2022. Smooth additive Gaussian noise is then added to the TCWV fields of the 13th, to create an ensemble of 20 members. Next, the assimilation is performed offline using the LETKF to produce a new initial state and the 10-day forecast is then rerun. It is important to note that, within this method, we have not used an iterative step in which assimilation updates the inputs for the next forecast. Instead, we are testing the precipitation field's sensitivity to the new TCWV information in this scenario to see i) whether we get a positive impact on the following 24 hours accumulated rainfall, and ii) if the updated forecast converges back to the original or continues to deviate.

8.3.2 Study results

The first key result this study focuses on is the impact of the OSSE experiment in the 24 hours following assimilation of the HR-CDR1 TCWV. Figure 8-12 shows the distribution of the 24-hour accumulated rainfall (14th-15th August) over Pakistan as PDF distributions and a difference map. From the PDFs, we observe that the AIFS_{DA} run increases the amount of rainfall at the lower end of the distribution, although loses the few 'hot spots' around 5 mm. The increases seen in the AIFS_{DA} run shifts the precipitation pattern to a more central location within the country. .

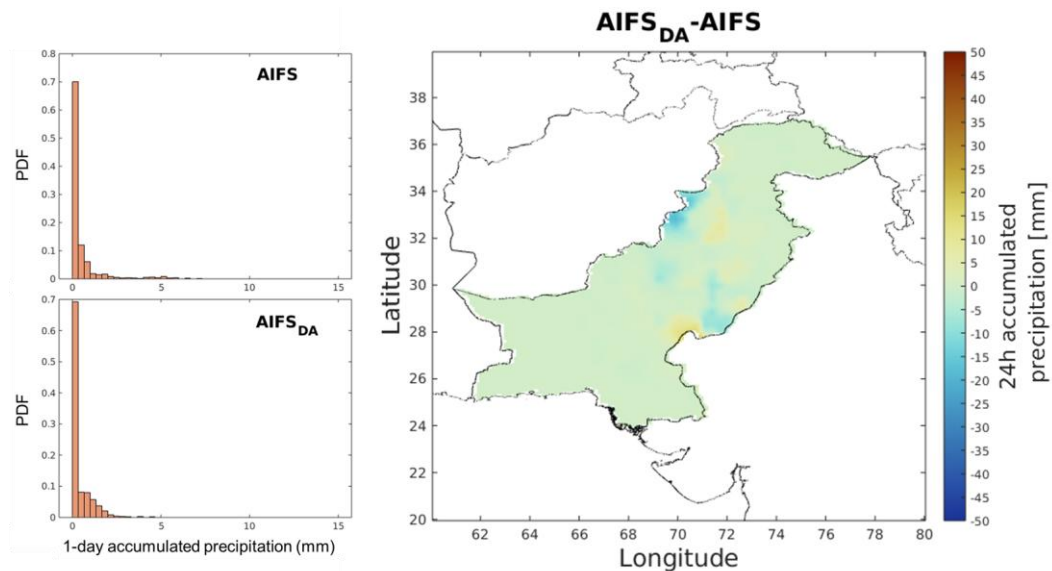


Figure 8-12: PDF plots of AIFS and AIFS_{DA} 24-hour accumulated precipitation after assimilation of HR-CDR1 TCWV. Spatial differences are shown in the map plot on the right-hand side.

The TAPD analysis yields results of ~ 0.4 from both runs, which is due to the very different pattern observed by IMERG (Figure 8-13). The likely cause is the representation of terrain relative to the model grid's 0.25×0.25 degree resolution. From IMERG, we observe heavy rain (>60 mm) over the Central Brahui Range in the central-western region of the country during the 24-hour period, which is absent in both AIFS runs. Assimilation of the HR-CDR1 does have an impact in the region north of these, in the Sulaiman range and the Thal Desert, where we see precipitation align more with the wind corridor that picks up over the Thal Desert (Khatri et al., 2022). The region of heavier rainfall in the IMERG data corresponds to an area of higher wind speed/density, suggesting that the model does not sufficiently capture this transport of moisture over the mountain range from the west, and is not sufficiently constrained by the TCWV, as it lies in the heart of the cloudier region. Regardless, this result is promising as it points to the clear-sky TCWV potentially having a positive impact on the following 24 hours. However, for the full effect to be observed, experiments with a higher resolution regional model that could better exploit the spatial information of the HR-CDR1 product should be investigated.

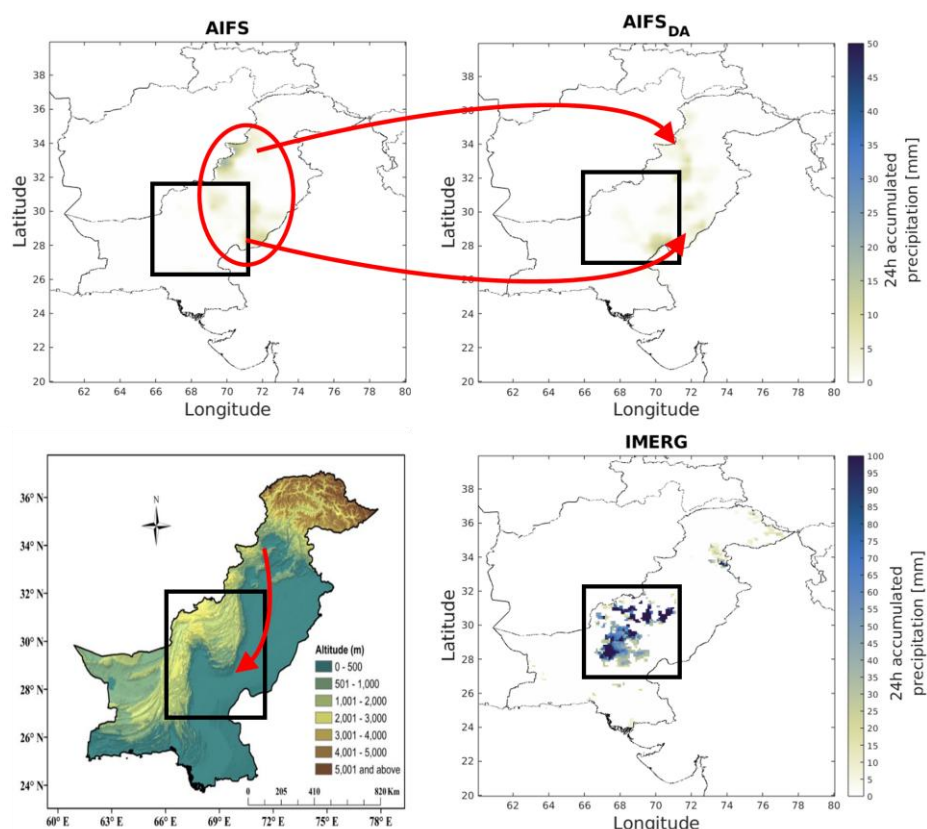


Figure 8-13: Maps of total 24-hour accumulated precipitation from AIFS (top left), AIFS_{DA} (top right), and IMERG (bottom right). A digital elevation model (DEM) of Pakistan, from Karim et al. (2021), is shown in the bottom-left panel. The red ellipse on the AIFS map encompasses the region where the model predicts rainfall, and the arrows indicate where it has diverged in the AIFS_{DA} run and the transport flow on the DEM. Finally, the black square highlights the region over elevated terrain where the models fail to predict the heavier rain observed by IMERG.

The second result of interest in this study is how the model continues after the initial assimilation at the beginning of the run. For this part of the study we switch back to analysing the 7-day accumulated rainfall. If the two runs converge then the 7-day differences will almost identical as the first 24-hour period does not include the most intense period of the flooding event.

From the initial first look of both forecasts, the original AIFS and HR-CDR1 assimilated version (AIFS and AIFS_{DA}, respectively), we observe that both miss i) the corridor of heavy precipitation that runs from north to south, as well as ii) the heavily affected area in the south-east of the country (Figure 8-14). However, we observe an improvement in the AIFS_{DA} total accumulated rainfall relative to the original forecast when compared to the satellite observations (IMERG).

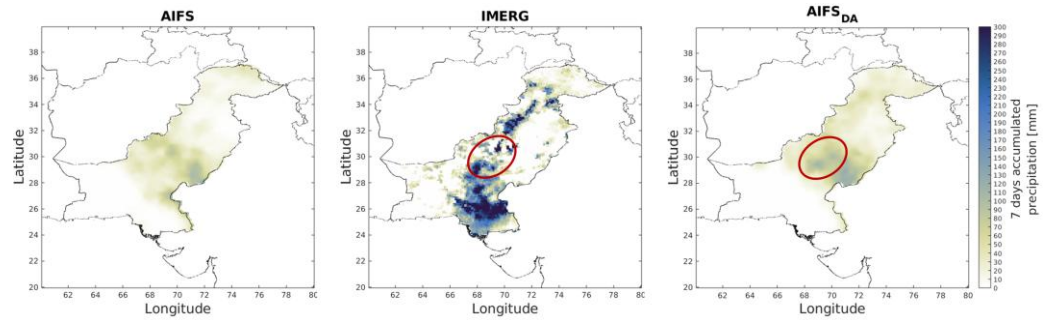


Figure 8-14: Accumulated precipitation over Pakistan during the major flooding event between the 14th and the 21st of August 2022, from left to right, for AIFS (original forecast), IMERG (reference observations), and AIFS_{DA} (OSSE updated forecast). Circled in red highlights improved skill in one region for AIFS_{DA} relative to AIFS total precipitation.

Examining this further, from Figure 8-15 we can directly see that AIFS_{DA} predominantly produces higher amounts of rainfall in the north of the country over the original AIFS run, whilst in the south, we observe less rainfall. However, the increase seen in the north is much greater than the reduction in rainfall seen in the south. Therefore, this confirms that the two runs evolve differently, which is also confirmed from the PDF distributions of total accumulated precipitation in Figure 8-16, which shows a spike in areas which it predicted 25-35 mm of rain.

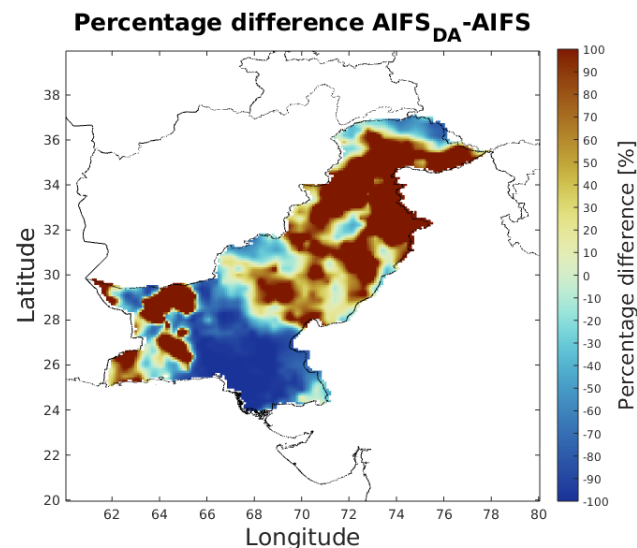


Figure 8-15: Percentage difference in total accumulated rainfall between the updated and original forecasts (AIFS_{DA} and AIFS, respectively). The previously reported central area is more apparent, as is the north of the country, where AIFS_{DA} reports total precipitation exceeding 100% of the original AIFS forecast.

A notable feature for both the 1-day and 7-day accumulated rainfall from the AIFS_{DA} run is that it produces more precipitation in the north of the country, which again suggests that the model's transport could have significant biases, as the initial assimilation at the beginning of the run placed more moisture in the region (source function), which increased precipitation in the first 24 hours. However, from the resulting time steps, we observe that either i) this moisture has not been transported out of the region correctly, or ii) the correlations in the model that trigger precipitation are too sensitive.

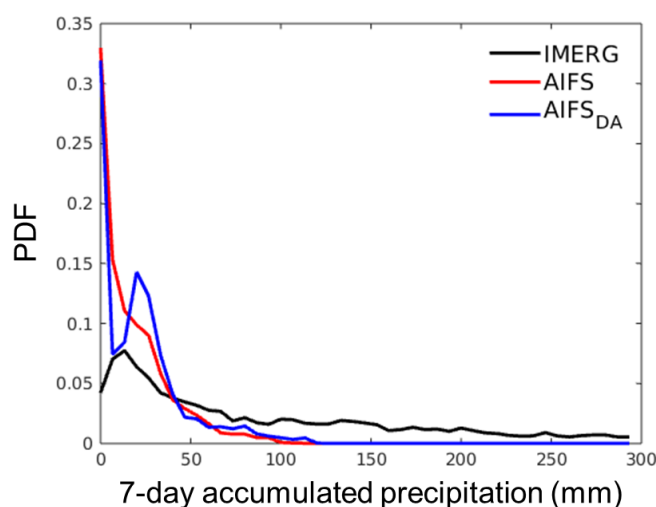


Figure 8-16: PDF distribution of total accumulated rainfall over Pakistan between the 14th and 21st of August 2022 from IMERG, AIFS, and AIFS_{DA}.

8.4 Summary and Outlook

From this short analysis of TCWV PDFs using the TAPD metric, it is evident that there are distinct differences in clear-sky TCWV values between the reanalysis and satellite observations during the 2022 monsoon, which led to catastrophic flooding in Pakistan. A significant uncertainty in these distributions arises from moist atmospheres in cloudy or precipitating areas, where errors in water vapour concentrations would affect daily precipitation fluxes in the reanalysis system. A key benefit of the HR-CDR1 data is that it can provide accurate gradients in clear-sky TCWV to the edges of cloud cover, unlike traditional IR atmospheric sounders used in NWP, which have an instrument footprint of ~10 km at nadir.

An examination of precipitation over Pakistan for this period from ERA5 reanalysis and modern NWPE models shows an overestimation of accumulated rainfall outside the main areas of flooding and a significant underestimation across the

middle of the country, where the heaviest precipitation and flooding occurred. Therefore, it can be asserted that constraints on these data during the production phase would yield more skilful precipitation estimates, which is especially important when considering mitigation planning on seasonal timescales. In this study, we have examined two state-of-the-art NWPEs, GraphCast from DeepMind and AIFS from ECMWF. These two models were chosen because they included precipitation as a diagnostic field in their outputs. In contrast, many models at the time of this study did not include any rainfall information. After sensitivity tests, we observed that GraphCast precipitation was not sensitive to any perturbations in the water vapour field, unlike AIFS, which was chosen as the forward model component of the final part of this study.

A data assimilation system using AIFS and an LETKF was constructed within an OSSE framework, yielding two 10-day forecasts. The first (baseline) run was initialised with ERA5 reanalysis, with the second assimilating clear-sky TCWV from HR-CDR1 at the beginning of the run. The accumulated precipitation was analysed after the first 24 hours and 7 days from the 14th of August 2022. Results suggest that clear-sky TCWV may positively affect episodes of heavy rainfall. However, there are still a few challenges to overcome. The first is to understand better moisture transport biases in AI NWP models, which are likely impacted by model resolution and topography (e.g. AIFS does not use sigma pressure levels as IFS does). The second is to investigate model resolution effects by switching to a high-resolution regional model that can better exploit high-resolution satellite data, as AIFS runs at 0.25x0.25 degrees, for which the HR-CDR1 data needs to be averaged onto, thereby losing finer detail. The final challenge would be to update the DA method to a 4DVar or 4DVar-ENKF system so that the model and observation errors can be used to constrain the assimilation problem better. Finally, it should be noted that AI NWP systems fail to capture extreme events, and lower-intensity events should also be tested, as observations may never provide the forecast of opportunity that leads to the prediction of a grey swan event.

9. LINKING WATER VAPOR, CLOUDS AND SURFACE TEMPERATURE

Cédric G. Ngoungue Langue(UVSQ)/LATMOS), Hélène Brogniez (UVSQ/LSCE-LATMOS), Philippe Naveau (CEA/LSCE)

In the continuation of previous work carried out as part of the project (He et al., 2022), in this section we focus on the assessment of co-variations in water vapour, cloud and surface temperature parameters in the tropical band at different time scales using ESA-cci data (WV_CCI and CLOUD_CCI) and global climate models (GCMs). In order to achieve this goal, we firstly evaluate the representation of water vapour and clouds properties (total cloud coverage and cloud water path) in GCMs using ESA satellite data as reference at different frequencies over the period 2003-2014. Afterwards, we study the co-variations in water vapour and total cloud coverage. We use the same subset of CMIP6 models simulations as in He et al (2022).

9.1 METHODOLOGY

9.1.1 Multi-Resolution Analysis (MRA)

Real world signals consist of a mixture of different components. Quite often, you are interested only in a subset of these components. MRA allows to restrict the analyses by extracting the signal components at the specific resolution. MRA is mathematical tool which consists of decomposing a signal into its subcomponents at different resolution (Oh et al., 2002; He et al., 2013; Lin et al., 2015; Gomez et al., 2016). MRA is mainly used in signal processing to separate signal components in time and can thus be used to represent the temporal evolution of the data at a given frequency. Then a signal $S(t)$ can be broken in two parts namely, the wavelet detail vectors ($D_j(t)$) and the wavelet smooth vector ($S_N(t)$) (see eq.1). In climate analysis, the wavelet detail vectors represent the variability of the signal from high (first values of j) to low frequencies (highest values of j), while the wavelet smooth vector represents the trend:

$$S(t) = \sum_{j=1}^N D_j(t) + S_N(t) \quad (\text{eq.1})$$

N is the maximum scale of decomposition, determined by the number of data in the original signal $S(t)$. To apply the MRA on a signal, its length must be dyadic

(multiple of 2^N). Therefore, the maximum level of decomposition for the MRA operation on a signal is given by :

$$N = \log(\text{length of signal}, 2)$$

Figure 1 shows the MRA decomposition technique of the original signal $S(t)$ into 9 levels.

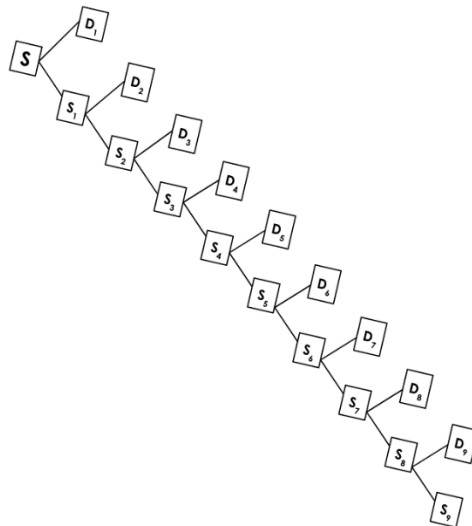


Figure 9-1: MRA decomposition technique until level 9 for a given signal S

This is an iterative procedure : the original signal S is broken down at the first level of decomposition into a wavelet detail vector D_1 and a wavelet smooth vector S_1 . For the second level of decomposition, the wavelet smooth vector S_1 , is now broken down into into a wavelet detail vector D_1 and a wavelet smooth vector S_2 . This process is replicated for all the decomposition levels until level N ($N=9$ in Figure 9-1)

9.1.2 Evaluation of the variability at different frequencies

The scope is to evaluate the times series of water vapor and clouds for a subset of CMIP6 models at all frequencies starting at the daily scale, with respect to ESA-cci data. To do so, we have implemented the following method, illustrated by Figure 9-2:

- (i) The ESA time serie is decomposed by the MRA wich gives 12 detail vectors D_j^{ESA} and one smooth vector S^{ESA} for the trend

- (ii) Similarly, a given GCM_i is decomposed with the MRA into 12 detail vectors $D_j^{GCM_i}$ and one smooth vector S^{GCM_i} for the trend
- (iii) A proxy of the ESA time series, called “ESA_proxy_raw_lev j ” is reconstructed by replacing, at the level j , the detail vector D_j^{ESA} by the corresponding $D_j^{GCM_i}$, all other components coming from the ESA decomposition. This is also done for the smooth vector S .
- (iv) The “ESA_proxy_raw_lev j ” is then compared to the original ESA signal by computing the root mean square (RMSE) and correlation coefficient.

All these steps are followed for all the CMIP6 models, for both the water vapor and the cloud variables.

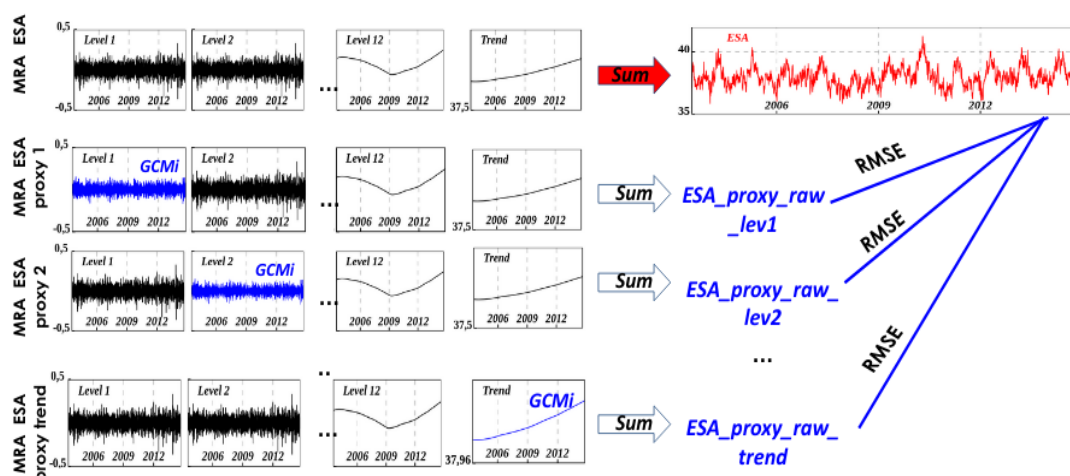


Figure 9-2: Schematic illustration of the evaluation of observed variability in the CMIP6 models at different frequencies of decomposition.

9.2 Results

9.2.1 Evolution of water vapour and cloud coverage at different time scales

The first assessment of this work is on the total column water vapor (TCWV, from WV_CCI) and the total cloud cover (TCC, from CLOUD_CCI). Both are considered at daily frequencies over the tropical regions. The analyses were carried out separately for the tropical ocean and tropical lands. Only AMIP SSST-

forced simulations) are currently analyzed but two periods are considered : the observed period (2003-2014) during which ESA_CCI provides datasets, and a “historical” period (1981-2002) where no ESA record is available, but during which we have ERA5 data. MRA approach permits to assess the temporal evolution of TCWV and TCC at four major time scales of great importance for climate and weather: daily, subseasonal, seasonal to annual and annual to decadal. Figures 3 and 4 shows the MRA decomposition over tropical oceans respectively for TCWV and TCC. Table 1 summarizes the trends computed for all models, ESA and ERA5.

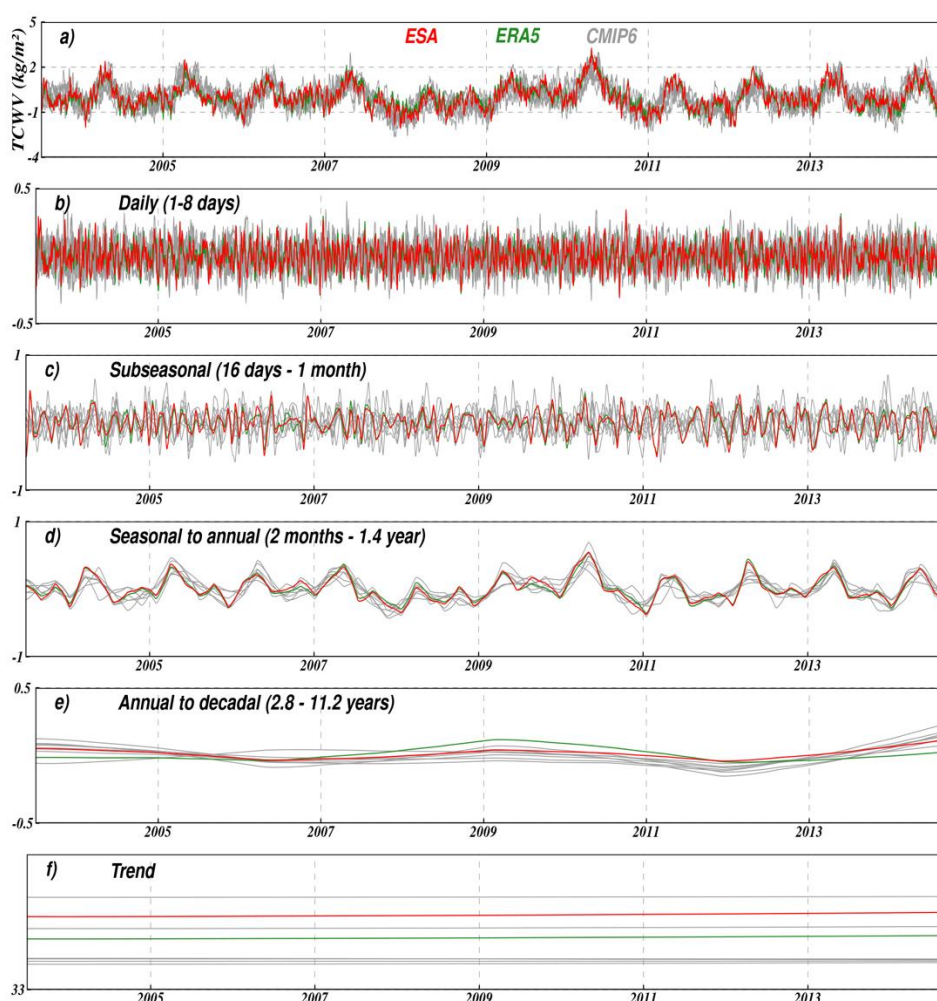


Figure 9-3: Evolution of TCWV (kg/m²) over tropical ocean over the period 2003-2014 using AMIP simulations. The term “Trend” can be confusing, it refers to the climatology of TCWV over the study period. The ‘Y’ axis represents TCWV and the ‘x’ axis the date.

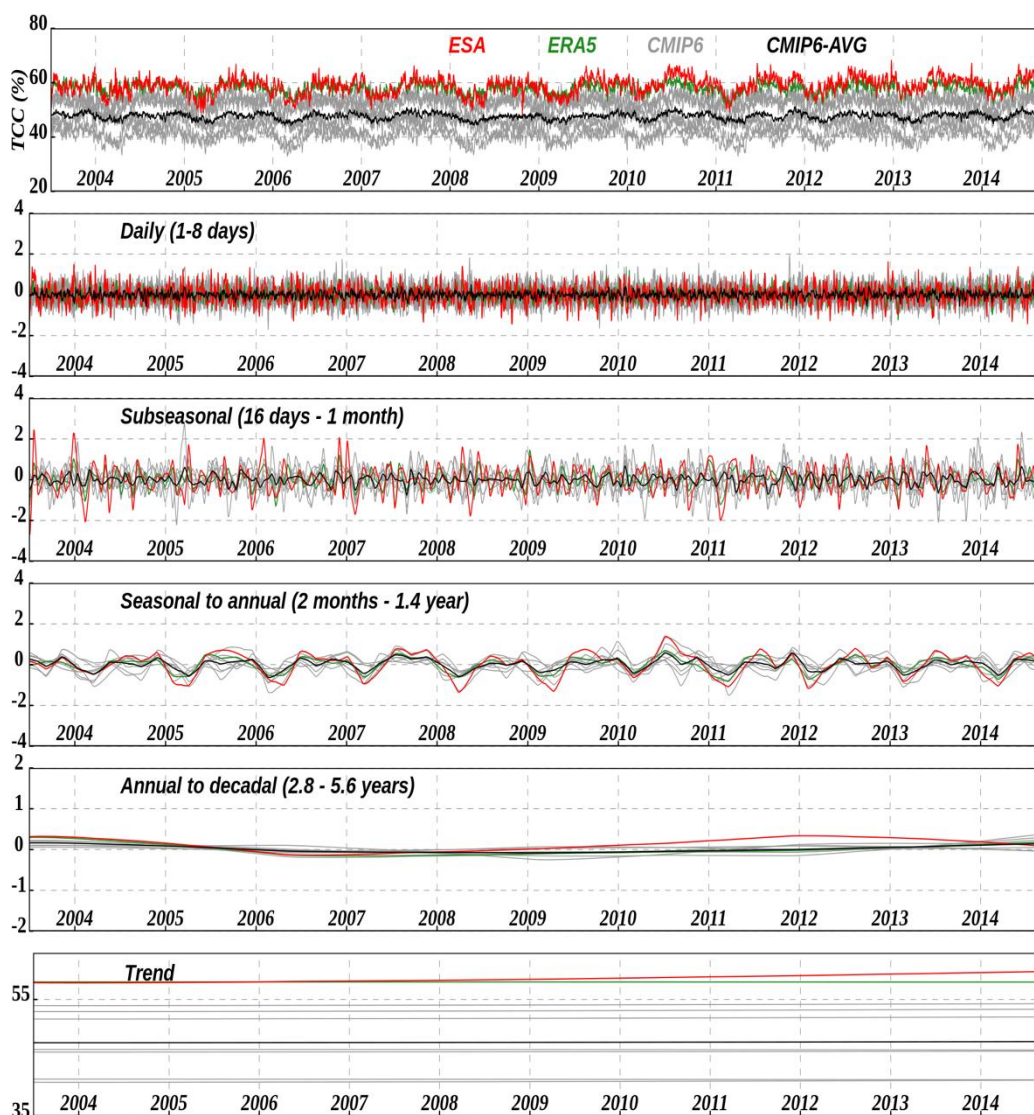


Figure 9-4: As in Figure 9-3 but for TCCC (%).

The evolution of TCWV and TCC over tropical oceans (Figure 9-3 & Figure 9-4) shows a high frequency variability and large differences between CMIP6 models and ESA data at daily scale. At subseasonal scale, the frequency of variability of TCWV and TCC is considerably reduced, but the CMIP6 models fail in reproducing properly the amplitude of the signals with respect to ESA. At seasonal to interannual scales, CMIP6 models produce coherent evolution of TCWV and TCC signals with respect to ESA. When focusing on individual CMIP6 models, we found that all the models underestimate the climatological state of TCWV and TCC except for the IPSL model, which shows an overestimation of TCWV signal. The MPI model produces the closest climatology of TCWV to that of ESA. We found similar results for the evolution of TCWV and TCC over tropical land (not shown).

Most of the CMIP6 models do not capture the trend in the evolution of TCWV over the tropical ocean, except for the MPI model (Table 1). Over tropical land, we notice an increase of about 1.95kg/m²/dec in ESA TCWV already noticed in He et al (2022). The CMIP6 models overestimate the trend in the evolution of TCC with respect to ESA over tropical land, while an underestimation is found over the tropical ocean (see Table 9-1).

Table 9-1 Trends per decade the evolution of TCWV and TCC over the period 2003-2014.

	TCWV		TCC	
	Land	Ocean	Land	Ocean
Models	Trend (kg/m ² /dec)	Trend (kg/m ² /dec)	Trend (%/dec)	Trend (%/dec)
ESA	1.95	0.26	0.10	1.92
ERA5	-0.001	0.20	0.28	-0.037
CanESM5	0.19	0.10	0.7	0.22
CNRM-ESM2-1	-0.59	-0.03	-0.72	0.58
CNRM-CM6-1	-0.325	-0.09	-0.09	-0.56
IPSL-CM6A-LR	-0.20	-0.012	0.49	-0.04
MPI-ESM1-2-HR	-0.10	0.177	-0.51	-0.38
CESM2-WACCM	-0.5	-0.07	1.07	-0.06
CESM2	-0.24	-0.02	-0.13	0.24

9.2.2 Evaluation of the representation of the observed variability in CMIP6 at different time scales over the ESA period of reference

Using the methodology described in section 9.1.2, we proceed to the evaluation of CMIP6 models at different frequencies of variability. Figure 5 represents the scores obtained for TCWV and Figure 6 is for TCC.

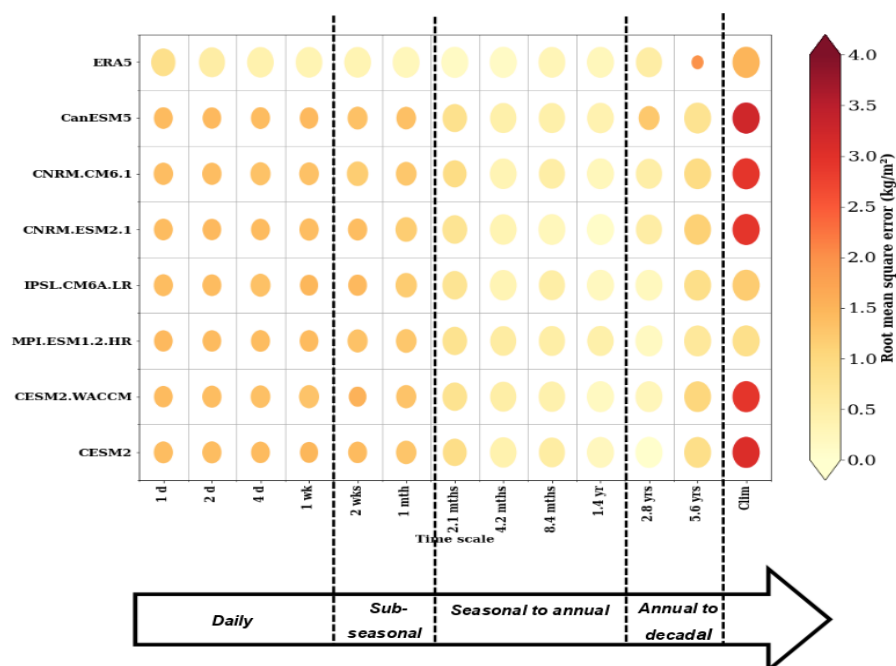


Figure 9-5: Evaluation of CMIP6 and ERA5 with respect to ESA at different frequency for TCWV over the study period. The 'Y' axis represents the different models and the 'x' axis the level of decomposition. The size of the circles indicates the linear correlation, while the color gives the RMSE

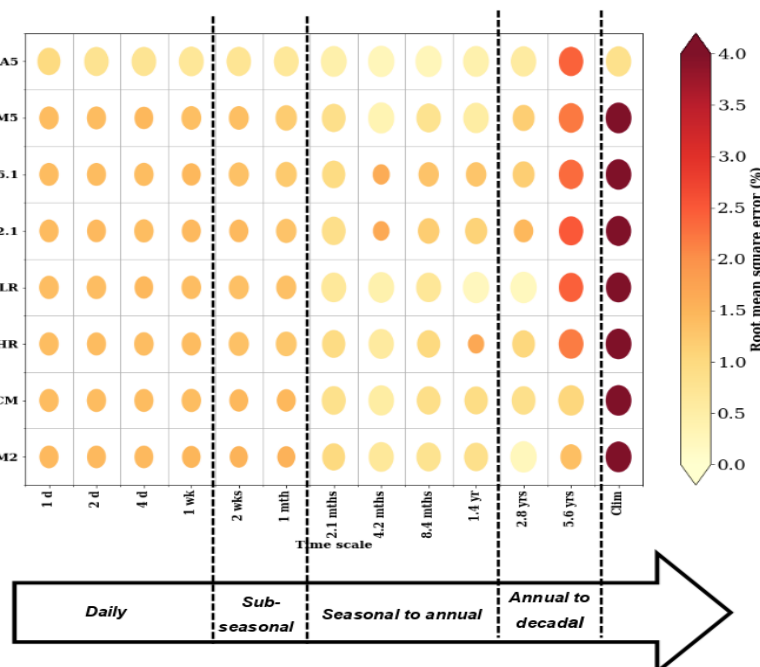


Figure 9-6: Same as Figure 9-5 but for TCC.

We found persistent errors and lowest correlation in the representation of the variability of TCWV and TCC at daily time scale over tropical oceans (see Fig.5 and Fig.6). This could result from a misrepresentation of synoptic processes in CMIP6 models. The lowest errors are observed at seasonal and annual scales, except for the TCC time series with the CNRM and MPI models around 1.5 years (see Figure 9-5 & Figure 9-6). This suggests that CMIP6 models produce reliable evolution of tcwv and tcc at seasonal and annual time scales. However the representation of the climatology of TCWV and TCC remains challenging for the CMIP6 models. Once more, similar results are obtained over land (not shown).

Based on the following results showing the errors between the CMIP6-ESA-proxy and ESA, we will build a “best CMIP6” model which consists of the sum of the best CMIP6 model at each frequency of decomposition. This best CMIP6 model at a given frequency is the one with the lowest error with respect to ESA. We see a slight improvement in the correlation when using the best CMIP6 model for TCWV and TCC signals both over tropical land and ocean. The best CMIP6 model using TCWV or TCC shows higher correlation with respect to ESA over tropical ocean (**0.7 / 0.55**) than land (**0.63 / 0.28**) (see Table 9-2). This can be explained by the use of AMIP simulations which are forced by the Sea Surface Temperatures (SST) leading to good correlation over ocean.

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Table 9-2: Correlation between CMIP6 and ESA TCWV and TCC, including the “best” CMIP6

	TCWV		TCC	
	Land	Ocean	Land	Ocean
Models	Correlation	Correlation	Correlation	Correlation
Best CMIP6	0.63	0.7	0.28	0.55
CanESM5	0.56	0.58	0.21	0.49
CNRM-ESM2-1	0.52	0.67	0.19	0.07
CNRM-CM6-1	0.54	0.65	0.21	0.04
IPSL-CM6A-LR	0.51	0.67	0.09	0.53
MPI-ESM1-2-HR	0.63	0.56	0.2	0.34
CESM2-WACCM	0.57	0.51	0.1	0.22

CESM2	0.56	0.54	0.19	0.15
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9.2.3 Evaluation over pre-ESA historical period

The previous set of analyses was carried during the period 2003-2014 that could be called “calibration period” where the ESA data is available. Using this type of reconstruction technique, one can evaluate the models over historical and future periods based on the evaluation done on the calibration period. In this perspective, we evaluated the CMIP6 models over the historical period (1981-2002) where ESA data are not available. This is illustrated with Figure 9-7.

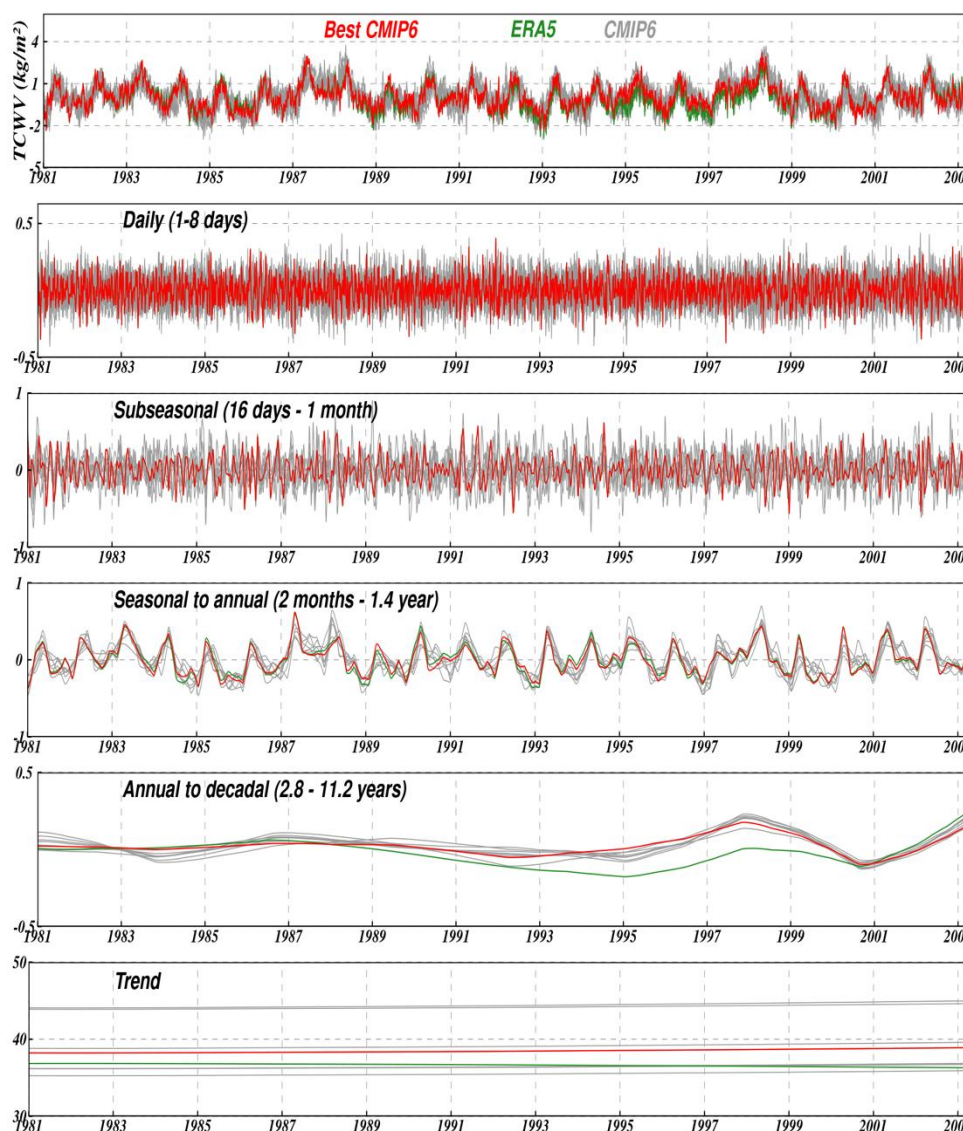


Figure 9-7: Same as Figure 9-3, for TCWV over tropical oceans, but for the historical period 1981-2002.

The best CMIP6 model for TCWV reproduces the closest evolution to ERA5. This is quite interesting knowing that ERA5 and ESA water vapour signal are very close over tropical ocean. CMIP6 models reproduce similar evolution over historical and calibration periods.

9.2.4 Co-variations between TCWV and TCC over the study period

After assessing the evolution of tcwv and tcc signals, we are interested now on their co-variations: how do they vary together? Our region of study, the tropical band is very large and characterized by a strong convective activity. Investigating the co-variations of tcwv and tcc in this region is very difficult because of large- and local- scales processes coming into play. Therefore, we have reduced especially for this analysis, the region of the study to the Nino3.4 region, located at [5N-5S; 170W-120W]. The co-variations between TCWV and TCC is done by computing the co-variance matrix.

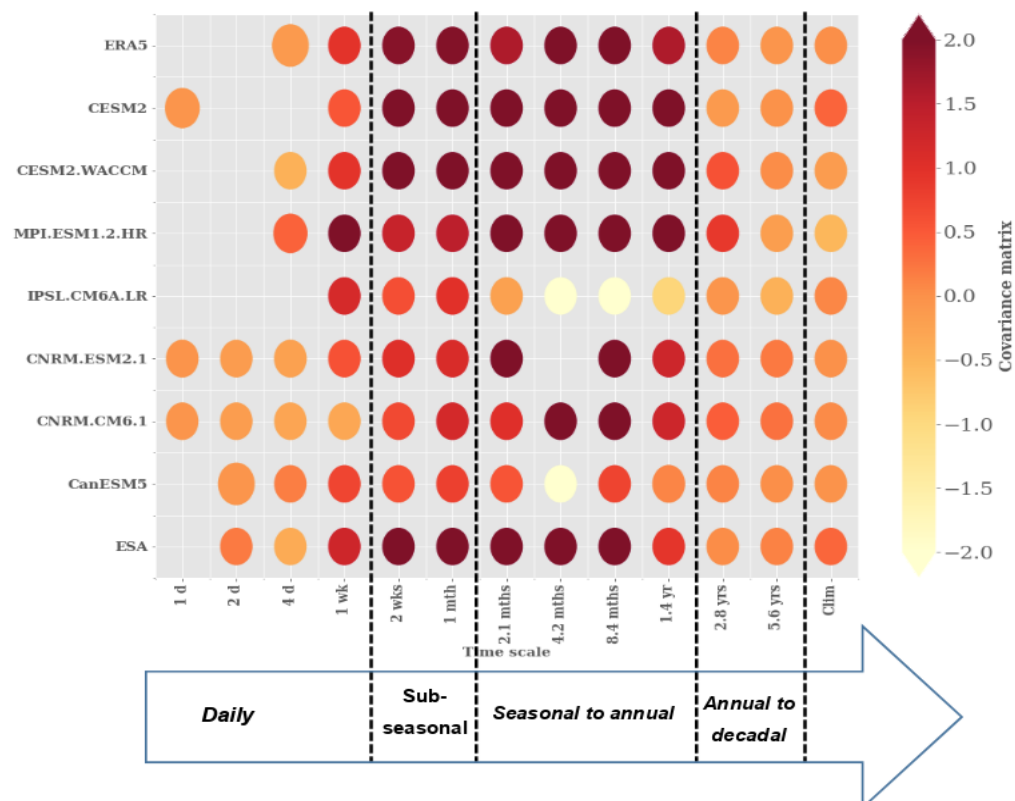


Figure 9-8: Co-variations between TCWV and TCC signals over the Nino3.4 region. The 'Y' axis represents the models and the 'x' axis the date. The blanks rows indicate non-significant values of correlation.

We found at subseasonal time scale a strong correlation and an increase in water vapour and cloud cover signals (Figure 9-8). At seasonal to annual time scales, CMIP6 models show an increase in water vapour and cloud cover, with the exception of the IPSL model, which highlights an opposite evolution between the two variables. At daily and annual time scales, water vapour and cloud cover presents opposite evolution over the study period.

9.3 Conclusions

This work represents an evaluation of CMIP6 models at different time scale using ESA satellite water vapour and cloud cover. We found that CMIP6 models produce reliable evolution of water vapour and cloud cover at seasonal (2 - 8 months) and interannual (1 - 1.4 year) time scales. However CMIP6 models underestimate the climatological state of $tcwv$ and tcc except for the IPSL model, which shows an overestimation of $tcwv$ signal. Most of the CMIP6 models do not capture the trend in the evolution of $tcwv$ over the tropical ocean, except for the MPI model. Over tropical land, we noticed an increase of about $1.95\text{kg/m}^2/\text{dec}$ in ESA water vapour evolution which is very high and probably due to the instrumentation used. We also noticed an overestimation of the trend in the evolution of tcc in CMIP6 over tropical land, while an underestimation is found over the tropical ocean. The analysis of the co-variations between $tcwv$ and tcc shows at subseasonal to annual time scales a strong correlation and an increase in water vapour and cloud cover signals.

10. WATER VAPOUR TRENDS, DRIVERS, AND RADIATIVE FORCING

Daan Hubert (BIRA-IASB), Michaela Hegglin (UoR/FZJ), Hao Ye (UoR)

Goal of study: Currently, there is low confidence in estimates of stratospheric water vapour change due to ongoing discrepancies in satellite and in situ records. Therefore this study will ESA CCI CDRs to revisit trends, drivers of interannual & decadal changes in lower stratospheric H₂O, and impacts on radiative forcing.

11. WATER VAPOUR IN EXTRATROPICAL CYCLONES

Giuseppe Zappa (CNR-ISAC) and Elenio Avolio (CNR-ISAC)

Extreme precipitation events in the mid-latitudes are often associated with extra-tropical cyclones (ETCs). These events result from the combined action of intense cyclone-associated surface winds and high atmospheric moisture, with the latter expected to increase close to Clausius-Clapeyron under climate change. However, climate models and reanalyses still show some biases in the simulation of the precipitation associated to ETCs and an assessment of how well the moisture environment is represented is currently lacking. This section describes the methodology to analyse ETC-associated total column water vapour (TCWV), and the ability of the ESA-CCI Water Vapour CDR2 product to provide valuable information to characterise water vapour in extra-tropical cyclones. In particular, we analyse TCWV in the ERA5 reanalysis and compare it to CDR2 data in order to a) understand the impact of TCWV sampling from CDR2 on the estimation of cyclone-associated TCWV statistics, and b) analyse the differences between the ERA5 reanalysis and CDR2 once sampling has been taken into account. The analyses serve as a basis to provide a methodology for the assessment of TCWV in ETCs between different modelling datasets.

11.1 Methodology

We apply a tracking algorithm to identify extra-tropical cyclones in the ERA5 reanalysis, and then evaluate the TCWV from both ERA5 and the CDR2 dataset along the identified cyclone tracks. This approach enables us to analyse the representation of TCWV conditional on the presence of a cyclone, either spatially as a function of the grid point, or on storm-centered reference frames. The goal is to assess the level of agreement between ERA5 and CDR2 TCWV, and to evaluate whether any discrepancies are mainly attributable to the differences in spatial and temporal sampling, or if they reflect actual biases in the TCWV field. Since ETCs are relatively fast moving, we not only evaluate the sampling impact of data-masking from CDR2, but also evaluate the benefit of the higher 6 hourly temporal resolution available in ERA5.

11.1.1 Datasets

The ERA5 reanalyses (Hersbach et al., 2020) is the latest atmospheric reanalysis product from the European Center for Medium Range Weather

forecasts. The analyses are produced via a 4D-Var data assimilation scheme at a 0.25x0.25 deg spatial resolution (approximately 30 km) and hourly temporal frequency. The TCWV from the ERA5 reanalysis is here compared to the daily TCWV data from the ESA-CCI Climate Data Record 2 (CDR2) at 0.5x0.5 degree spatial resolution. CDR2 combines Near-Infrared (NIR) based retrieval of water vapour over land and sea ice from the MERIS, MODIS and OLCI satellites, and microwave based retrievals over the ocean from the Hamburg Ocean Atmosphere Parameters and Fluxes from Satellite (HOAPS) data record (Andersson et al. 2010). The NIR retrievals over land and sea ice provide sun synchronous TCWV snapshots, while the microwave retrievals over the ocean provide an estimate of daily-mean TCWV resulting from multiple satellites sampling TCWV more than once per day. In the mid-latitudes, missing values in the CDR2 daily data result from both the swaths from satellite overpasses, and from cloudy conditions inhibiting the NIR-based retrieval over land. Intense precipitation may also affect the estimation of TCWV precipitation over the ocean, though this is deemed a minor effect outside the tropics (He et al 2022). In this study, only timesteps flagged with a valid TCWV in CDR2 have been retained for analysis.

In order to both isolate the impact of CDR2 spatial and temporal sampling in the estimation of TCWV in ETCs, and to provide a clean comparison between CDR2 and ERA5 data, ERA5 hourly TCWV data has been degraded to the sampling of CDR2. In particular, the following degraded versions of ERA5 have been produced:

- *ERA5-50km*, consisting in ERA5 hourly data spatially interpolated to the 0.5x0.5 degree resolution from CDR2 using a conservative interpolation scheme.
- *ERA5-50km-day*, as ERA5-50km, but also temporally sub-sampled to approximate CDR2 time frequency, i.e. consisting of TCWV at 12:00 noon solar time over land, ice and coasts, and of daily-mean TCWV over the oceans.
- *ERA5-50km-day-masked*: as ERA5-50km-day, but also masking all grid points in which the quality flag from CDR2 is greater than zero, implying either lower confidence estimations or missing TCWV retrievals, e.g. cloudy sky over land or intense precipitation over the ocean.

We define the contribution of *sampling* to the differences between ERA5 and CDR2 as the difference between ERA5 and ERA5-50km-day-masked. Furthermore, taking CDR2 as the reference, we define the *bias* contribution to the differences between ERA5 and CDR2 as the difference between ERA5-

50km-day-masked and CDR2 data. This provides a like-for-like comparison between the two datasets, since ERA5 data is degraded to the same spatial and temporal resolution and data availability of CDR2. By construction the sum of the *sampling* and *bias* terms is equal to the full difference between ERA5 and CDR2. Furthermore, for comparison with previous studies, in section 1.2.2 we also define the ESA bias due to masking only, as ERA5-50km-day-masked minus ERA5-50km-day statistics.

All data is analysed over a common 15-year period, going from December 2002 to November 2017.

11.1.2 Cyclone tracking

Northern Hemisphere ETCs are tracked in the ERA5 reanalysis 6 hourly sea level pressure field using the feature tracking algorithm TRACK (Hodges 1995, Hoskins and Hodges 2002, Zappa et al. 2013). Mean sea level pressure is first smoothed by removing the spherical harmonics with total wave number smaller than 5 and greater than 63, in order to obtain SLP synoptic-scale anomalies relative to the large-scale SLP field, and filter smaller mesoscale features. Feature points for cyclone tracking are then identified as minima below -1 hPa in the resulting sea level pressure anomaly field. Cyclone tracks are then constructed by linking the feature points in time by minimising a cost function on track smoothness and speed. The resulting tracks lasting at least 2 days and covering a minimum distance of 1000 km are retained. Cyclone tracking is separately performed for each meteorological season, DJF, MAM, JJA and SON. Although higher frequency hourly data are available in ERA5, we chose to perform the tracking using 6-hourly data only, in order to ensure the methodology is applicable to other modelling datasets that do not provide hourly data.

The ETC-associated water vapour is evaluated as the area-mean TCWV within a 5 degree radius around the cyclone centers. This provides an estimate of the moisture content in the most intensely precipitating part of the cyclones (Hawcroft et al. 2012). In ERA5, 6-hourly TCWV snapshots are associated with the cyclone tracks every 6 hours, while for daily datasets, such as CDR2, we associate TCWV to the location of the cyclones detected at 12:00 UTC only. We note that this implies a random offset of up to 12 hours between the time of the cyclone transit and the associated TCWV field over land. Since the component is random, we expect it to cancel out and have only a marginal impact on mean

statistics. Spatial maps of the mean ETC-associated TCWV as a function of latitude and longitude, are produced using spherical kernels (Hodges 1996).

In order to more specifically analyse air streams in ETCs, such as dry intrusions and moist conveyor belts, the spatial distribution of moisture around storms is also quantified in terms of storm-centered composites of TCWV (Field and Wood 2007, McErlich et al, 2023). For each track, the storm-centered map of TCWV is evaluated at the along-track time step of maximum SLP intensity. Storm-centered composites are then produced by averaging the TCWV field within a 10 deg radial cap around the storm centers for all storms with a dynamical intensity, i.e. SLP anomaly, greater than 10 hPa.

11.2 Results

11.2.1 Spatial statistics

Fig. 11-1 compares the spatial distribution of the mean ETC-associated TCWV within a 5 degree radius of cyclone centers in the ERA5 reanalysis and in CDR2 for DJF and JJA. The map is to be interpreted as the mean TCWV conditional on the presence of ETCs. Here, no degradation has been applied to the ERA5 data, which thus consists of snapshots of TCWV every 6 hours, as opposed to the daily information from CDR2. Despite these differences, the two maps show overall remarkable similarities in the large scale patterns, confirming the previously reported good correspondence between the two datasets (He et al. 2022, Eiras-Barca et al. 2022). A closer examination of the ERA5 minus CDR2 difference map (Fig. 11-2 a,b) shows values of up to a few kg/m² and with distinct seasonally-dependent patterns. In winter, ERA5 shows slightly (1 to 2 kg/m²) drier ETCs over the oceans, particularly in the North Atlantic, and slightly wetter ETCs over land regions, particularly in the eastern United States, compared to CDR2. In contrast, in summer, ETCs in ERA5 are typically wetter than in CDR2, with differences locally exceeding 4 kg/m², particularly over north-east North America and Eurasia.

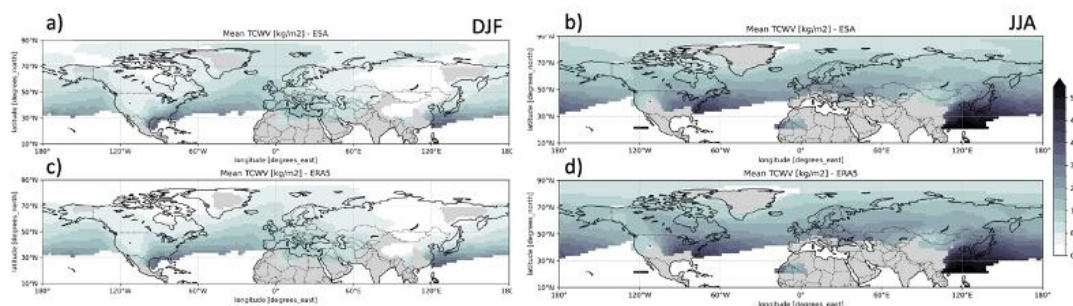


Figure 11-1: Mean ETC-associated TCWV (kg/m^2) averaged within a 5 degree radius of ETCs in CDR2 (a,b) and ERA5 (c,d) for 2003-2017. The results are separately shown for DJF (a,c) and JJA (b,d). Mean ETC-associated TCWV is only shown in storm track regions north of 20N and where cyclone track density is larger than 1 cyclone per month per 10^5 km^2 .

The difference in the ETC-associated TCWV between the two datasets is decomposed in the contribution due to *sampling* and *bias* (see methods) in Fig. 11-2c,d,e,f. In DJF, most of the differences between ERA5 and CDR2 arise from the bias term (Fig. 11-2c). This is evident for the drier ETCs over the oceans, particularly in the North Atlantic, in ERA5 compared to CDR2. Interestingly, the dry bias over the North Atlantic extends into western Europe, presumably via advection of oceanic moisture following the North Atlantic stormtrack. Instead, the difference between ERA5 and CDR2 over the eastern United States appears to result almost entirely from sampling (Fig. 11-2e). This is potentially consistent with the impact of the clear-sky bias over land of CDR2, implying that the moist and cloudy regions of ETCs are undersampled. The clear sky-bias does not appear as prominently in regions other than the eastern United States, which is likely to be a consequence of the overall dry nature of winter storms over Eurasia (TCWV smaller than 10 kg/m^2 in Fig. 11-1a).

The impact of the CDR2 clear-sky bias on sampling tends to become more prominent in JJA. In particular, the much moister representation of ETCs in ERA5 compared to CDR2 over most of North America and Canada is attributed to sampling (Fig. 11-2f). In Eurasia, both the sampling and the bias term contribute to larger ETC-associated TCWV in ERA5 compared to CDR2, while over the oceans the two datasets are in better agreement.

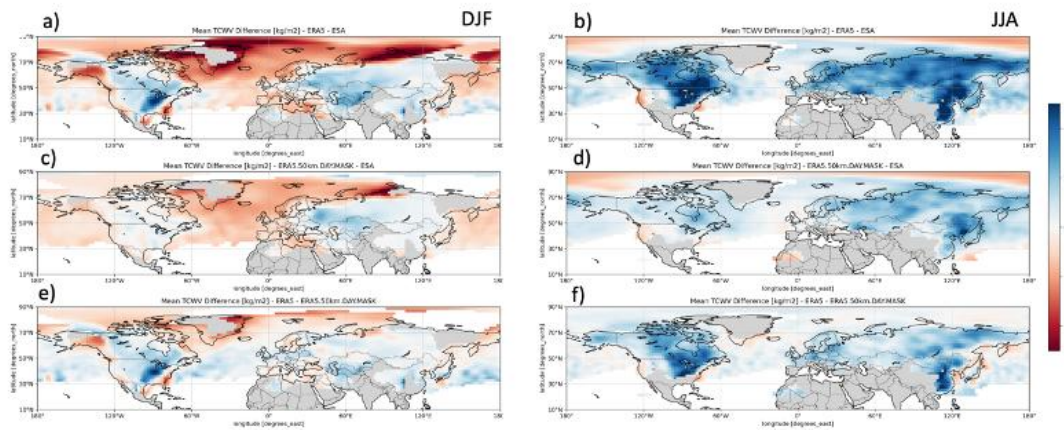


Figure 11-2: Difference in the ETC-associated TCWV between ERA5 full resolution data and CDR2 (a,b), and decomposition in the contribution arising from the bias (c,d), and sampling (e,f) terms. Panels a,c,e) refer to DJF, and b,d,f) to JJA. Units are kg/m².

The full decomposition of the difference of ETC-associated TCWV between ERA5 and CDR2 is summarised in Fig. 11-3, separately for land and ocean grid points, and for each individual season. The summary highlights the seasonal evolution in the difference between ERA5 and CDR2. Over land, the ERA5 minus CDR2 difference evolves from near zero in DJF, to about +1 kg/m² in SON and MAM, to more than +2kg/m² in JJA. The wetter nature of ETCs over land outside DJF in ERA5 is mainly a consequence of sampling, and particularly of masking (ERA5-50km-day minus ERA5-50km-day-masked), with a further contribution coming from the bias term. Over the ocean, Fig 11-3 shows that there is excellent agreement in the transition seasons, while ETCs are slightly drier in ERA5 compared to CDR2 in DJF, and slightly wetter in JJA, mainly as a result of the bias term.

Overall, the sampling and bias terms are generally of comparable magnitude. The largest bias and sampling contributions are both found over land in JJA, where both terms contribute to wetter ETCs in ERA5 compared to CDR2. The decomposition of the sampling term, reveals no impact from finer ERA5 spatial resolution, a small but robust positive impact from the availability 6 hourly data, and a small or positive impact from masking, particularly over land in JJA.

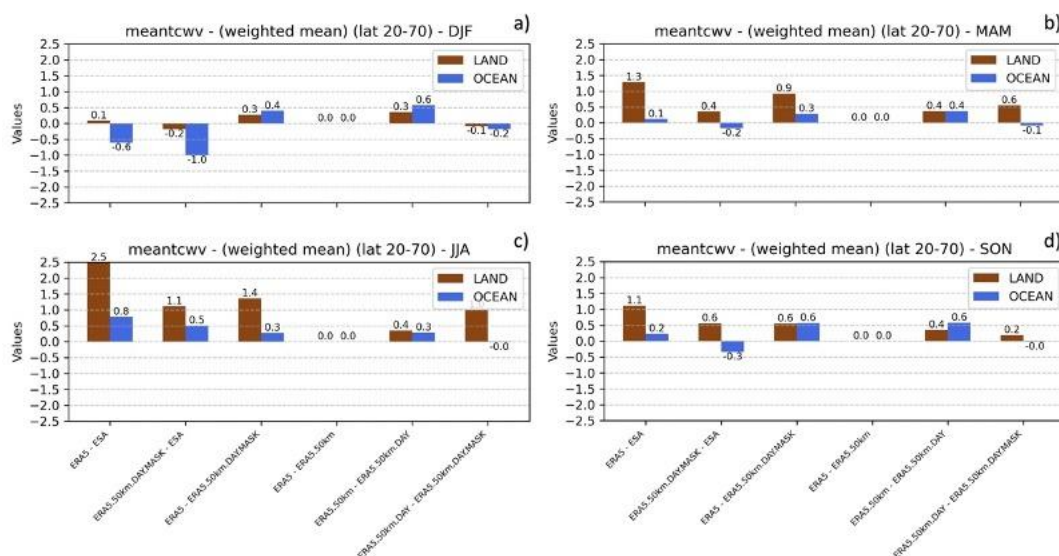


Figure 11-3: Area-averaged summary of the differences in ETC-associated TCWV between ERA5 and CDR2 shown in Fig. 11-2, separately for land and ocean grid points. Each panel shows: the difference between original ERA5 and CDR2, the contribution to the difference from the *bias* (ERA5.50km.DAY.MASK-ESA) and from the *sampling* terms (ERA5-ERA5.50km.DAY.MASK), as well as a decomposition of the sampling term in the contributions from spatial resolution (ERA5-ERA5.50km), temporal resolution (ERA5.50km-ERA5.50km.DAY) and masking (ERA5.50km.DAY-ERA5.50km.DAY.MASK). The four panels refer to DJF (a), MAM (b), JJA (c) and SON (d).

11.2.2 Storm-centered composites

Storm-centered composites of TCWV are now analysed to better interpret the signals identified in section 1.2.1. Storm-centered composites offer the advantage of separating the moisture content in the different sectors of cyclones, so that it is possible to compare the representation of moisture content between ERA5 and CDR2 in different air streams. Furthermore, the approach of composing, on the same storm-centered reference frame, a number of storms at their maximum dynamical intensity, further enables us to focus on robust features, while reducing variations associated to single events.

Given the results from Fig. 11-3, and since CDR2 retrieval of TCWV works differently over land and ocean, we here present the storm-centered composites separately for land and oceanic TCWV. We note that the center of the storms entering into each composite may themselves be either over land or the ocean. However, TCWV over oceanic grid points is masked, i.e. not considered, when producing the land composite. Likewise, land grid points are masked in the oceanic composite.

The storm-centered composite of TCWV over the ocean in DJF is presented in Fig. 11-4 (top row). Both the composites made with the ERA5-50km-day and ESA data display the expected cyclonic rotation of dry air on the eastern side of the cyclone (red, dry intrusion) and moist air transported northward on the western side (blue, warm conveyor belt). A comparison of Fig. 11-4a and Fig. 11-4b shows that the ESA composite is generally moister than ERA5. The impact of cloud masking (Fig. 11-4c) on the estimation of oceanic winter TCWV is minimal, so that most of the difference can be attributed to a dry bias of ERA5 compared to CDR2. The bias is larger over the dry sector of the cyclone, where it reaches 2 kg/m^2 , equal to approximately a 10% to 20% relative difference. This seems to be in line with other studies that found a tendency of a dry bias of ERA5 dry regions compared to observational datasets over the ocean using either different techniques or different reference datasets (McErlich et al. 2022, He et al. 2022). Furthermore, a similar dry bias (not shown) is also found in MAM and SON.

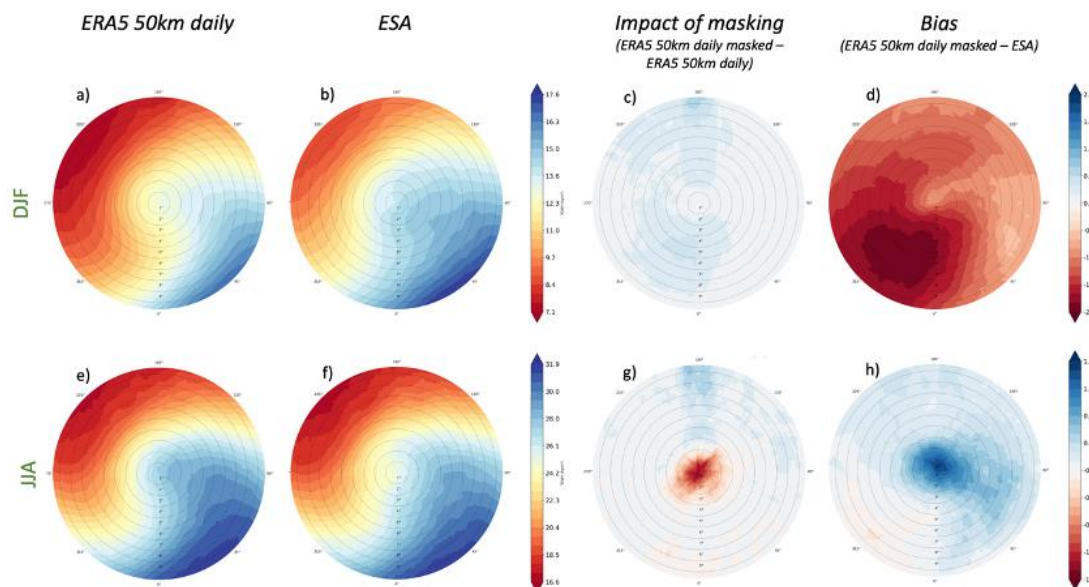


Figure 11-4: Storm-centered composites of TCWV over the oceans. Each plot shows a 10 degree radial cap centered on the storm's MSLP minimum. North is upward. The panels compare: ERA5 data (a,e), CDR2 data (b,f), the impact of CDR2 masking according to ERA5 (c,g), and the residual bias between ERA5 and CDR2 (d,f). The results are presented for DJF (a-d) and JJA (e-h).

The picture found in DJF changes considerably when moving to JJA (Fig. 11-4e-h). First, we find a small ($\sim 1 \text{ kg/m}^2$) dry bias due to masking at the very center of the cyclones (Fig. 11-4g). To interpret this signal, we note that a similar impact from masking is also found in

SON, but not in MAM (not shown). This may suggest that the microwave-based sounding from CDR2 is unable to fully retrieve pockets of moist air during intense, possibly convective, precipitation events at cyclone centers taking place over the relatively warmer summer and autumn sea. Second, even once masking is taken into account, we find a residual wet, rather than dry, bias of ERA5 compared to CDR2 (compare Fig. 11-4h and 11-4d). The wet bias peaks again at the storm centers, but it also further extends, though more weakly, towards the moist sector. The reason why the dry bias in the dry sector is confined to the SON, DJF and MAM seasons, and the wet bias in the wet sector is only found in JJA is currently unclear.

The same analysis, but for the land composite, is presented in Fig. 11-5. Compared to the oceanic composites (Fig. 11-4), it is immediately clear that the differences in TCWV between ERA5 and CDR2 are more pronounced, and that the CDR2 composites struggle to capture the cyclonic rotation of the storms.

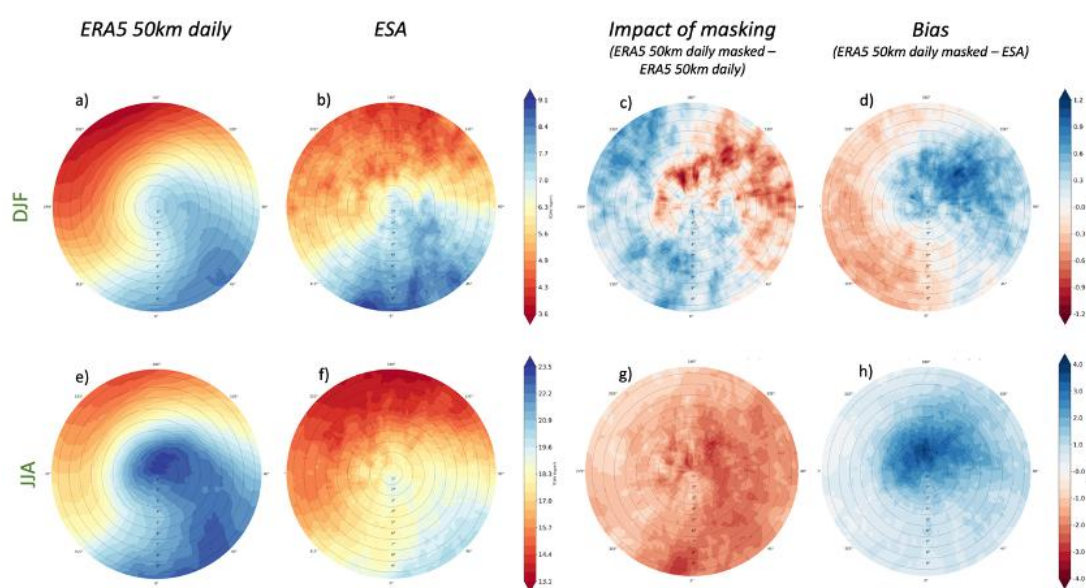


Figure 11-5: as in Fig. 11-4 but for land grid points.

In DJF, the impact of masking is a dipolar, but noisy, pattern implying that CDR2 will on average see drier air on the eastern flank of storms and moister air on the western flank. This impact of masking is however unable to fully explain the difference between CDR2 and ERA5. Instead, a very similar pattern, but with opposite sign, is found in the bias term (ERA5-50km-masked minus CDR2 difference). Given the similarity between the two, we suggest caution in interpreting such difference as a bias of the ERA5 reanalysis. Instead, we

suggest as a possible explanation that the impact of partial cloudiness is not fully controlled by the applied masking in the CDR2 daily data at 0.5 degree resolution. If this hypothesis were correct it would imply that some data flagged as valid in CDR2 would be either under- or over-estimating TCWV in the proximity of ETCs over land in DJF.

The drier nature of ETCs in CDR2 compared to ERA5 is particularly evident in JJA, when ERA5 shows a maximum in TCWV at the cyclone center (Fig. 11-5e) which is entirely missing in the substantially drier CDR2 composite (Fig. 11-5f). This difference is in a large part attributable to masking, presumably as a result of missing TCWV retrievals of moist air under cloudy conditions (Fig. 11-5g). However, we also identify a residual difference (bias) indicating that the masked ERA5 data is still moister than CDR2, particularly at the center of the storm. A residual difference similar to that shown for JJA, is also found in SON and MAM (not shown). Given the amplitude of the difference, and the likely presence of cloudy conditions along the warm front of ETCs in summer, we hypothesize that the difference shown in Fig. 11-5 h may also be the result of undersampling of moist air under partially cloudy conditions by CDR2.

11.3 Conclusions and Discussion

These analyses have shown that there is overall good agreement in the spatial distribution of TCWV associated to ETCs in the NH between the CDR2 product from the ESA-CCI water vapour programme and the ERA5 reanalysis, though some differences have been identified and attributed either to CDR2 sampling and/or to biases between the two datasets. As a result of its more limited sampling, we suggest that CDR2 tends to undersample moist air at the core of intense precipitating ETCs over the ocean in JJA, and at the warm front of ETCs over land in all seasons, and particularly in JJA. While the impact over the ocean is relatively small and limited to the core of ETCs, the impact over land is more tangible, particularly in eastern North America and eastern China. Nonetheless, the impact of sampling is typically of the same order of magnitude as the residual bias between the masked ERA5 data and CDR2. If the residual bias could be attributed to ERA5, this would imply that CDR2 is valuable to study ETCs over both land and ocean. However, the fact that the impact of masking and the residual bias tend to be colocated and feature opposite signs in the storm-centered composites, particularly over land, raise some doubts on whether the assumption is justified. Over the ocean, the bias between ERA5-masked and CDR2 shows a drier dry intrusion in ERA5 compared to CDR2. This result

seems consistent with some previous literature (McErlich et al. 2022, He et al. 2022) supporting a dry bias of the ERA5 reanalysis.

Overall, storm-centered composites appear as a useful approach to contrast reanalyses and satellite datasets in the mid-latitudes, and to examine the impact of cloudy conditions on TCWV retrievals over land. Comparison with other reanalyses and modelling datasets will help to better understand how systematic these differences are.

12. SUMMARY OF THE FIRST WV_CCI USER WORKSHOP

The WV_cci User Workshop was successfully held in the afternoons of 14–16 June 2021, via zoom webinar (hosted by University of Reading) and with 100 registered participants and around 60 attendees each day. The workshop webpage (<https://events.spacepole.be/event/122/timetable/#20210614.detailed>), designed and hosted by BIRA), provides an overview of the agenda, participants, and presentations given at the workshop. A few specific comments are given in Appendix 2: Additional notes from Breakout Group sheets.

The aim of the workshop was to bring together the broader water vapour community, including those interested in the generation of water vapour CDRs and data users (such as climate modellers and NWP researchers) in order to discuss the most recent scientific applications and challenges in processing and using water vapour climate data records (CDRs). More specifically topics of the workshop included:

- Discuss challenges related to the generation of water vapour CDRs
- Show-case climate user applications of water vapour CDRs (with focus on WV_cci CDRs)
- Collect and update user requirements for atmospheric water vapour
- Present and discuss results from climate analysis, climate applications, and process studies using water vapour CDRs.

The three days were (roughly) dedicated to the following themes:

- **Day 1** – WV_cci data products and user requirements
- **Day 2** – Vertically resolved Water Vapour (VRWV) products and climate analysis
- **Day 3** – Total Column WV (TCWV) products and climate analysis.

WV_cci presentations on **Day 1** included an overview of the CCI programme (Simon Pinnock) and introduction to the WV_cci (Michaela Hegglin), followed by two presentations on the TCWV products (Marc Schröder, Ulrike Falk) and VRWV products (Michaela Hegglin, Hao Ye). The session feedback provided helpful insights into the information data users would request when using the WV_cci datasets, including the clear-sky bias over land in the TCWV products (which was

highlighted to be larger than potential long-term trends in the dataset) and the difficulty of the use of satellite measurement in the UTLS (the considered MIPAS observations, for example, only measure in cloud-free scenes, potentially leading to a sampling bias).

The presentations were followed by breakout groups which served the discussion of the user requirements in order to complete the user needs already collected at the start of the project (in the URD). Participants were able to choose the breakout group to join according to their interest in a particular CDR product (TCWV, VRWV-UTLS, and VRWV-stratosphere) WV_cci offers. The following seed questions for the discussion were given:

- How is your community currently defining user requirements for EO products? (surveys, experience, ...)
- How should user requirements ideally be established? (e.g., OSSEs for different requirements,...)
- What science questions should such a CDR be able to respond?
- Discuss the currently identified requirements for your climate data record (see <https://climate.esa.int/en/projects/water-vapour/key-documents/>), suggest updates, and provide evidence where requirements are not sufficient.

One key recommendation concerned the description of the TCWV CDR: the TCWV CDR is a daily product that combines data records over land and ocean. In both cases the diurnal cycle is not fully covered globally and not all atmospheric conditions are sampled. This causes an issue when comparing model output and the TCWV CDR since models are all skies and all-time. Therefore, there is a need for guidelines in the User Guide for *Dos and Don'ts* to apply CDRs.

For CDRs in general, more guidance is requested on how to use the uncertainty information when averaging on spatial and temporal scales, e.g. regional or zonal aggregation.

It was noted that a temporal coverage of approximately 15 years might be too short for climate change analysis.

Concerning user requirements, OSSEs could be defined to pin-point specific needs in terms of long-term trends. However, it has also been highlighted that many applications require different requirements that cannot be met with a single CDR.

On **Day 2**, the workshop continued with **Session 3** on available observational data in the UTLS and in the stratosphere:

- Rolf: JULIA: the Jülich airborne in-situ data base

The aircraft-based JULIA data record was introduced. Among others, it includes water vapour measurements up to a height of 21 km. The analysis of trends on basis of this data was not recommended.

- Rohs: IAGOS water vapour and RH_{ice} products

Also IAGOS is an aircraft based data record of among others water vapour and is based on MOZAIC. It covers the period 1994–present and a trend analysis does not exhibit significant trends.

- Ghysels-Dubois: STRATEOLE 2 balloon observations in the tropics

This data record relies on long-term balloon campaigns and measures in the TTL/lower equatorial stratosphere. A bias relative to data from MLS was observed. In early 2022 there will be a hygrometer intercomparison campaign.

- Davis: SWOOSH: a long-term data base for climate studies

SWOOSH combines various satellite-based observations into a stratospheric water vapour profile data record using MLS as reference. It starts in 1984 and is available in v2.6 and v2.7 beta. The product does not contain uncertainty correlations.

- Schneider: Water vapour isotopologue observations from space

The retrieval and analysis of water vapour isotopologues from IASI (MUSICA) and TROPOMI were presented. Such analysis is not possible with water vapour data alone and the combined utilisation allows extracting vertical information as well.

Day 2 moved on with presentations on VRWV H₂O observations. Some take home messages from **Session 4** include:

- Nielsen et al: Retrieval of high VR trop. specific humidity from RO

The tropospheric specific humidity and temperature retrieved from radio occultations using a 1D-Var model, shows good specific humidity accuracy and vertical resolution in the mid-troposphere. Comparisons with GRUAN radiosonde profiles show that the estimated uncertainties in specific humidity and temperature in RO are similar to the uncertainties from GRUAN.

- Gleisner et al.: ROM SAF humidity climate data records based on RO

The ROM SAF CDR data (specific humidity up to 12 km and temperature in both troposphere and stratosphere) includes a special variable in specific humidity as “a priori fraction” to show the estimated impacts from observations. The statistical analysis shows that the specific humidity variability is dominated by ENSO signals. The specific humidity data starting from 2006 is long enough for climatic trend research.

- Willet et al: HadISDH surface humidity

The HadISDH dataset, a global surface humidity product from *in situ* observations from land stations and ships, shows an increasing specific humidity trend and a

decreasing relative humidity trend over both land and ocean, which are similar to reanalyses and TCWV. This dataset is long enough (from 1973 onward) to compare with reanalyses and historical runs from climate models (CMIP5/6).

There are still big gaps and difficulties to get a combined VRWV data. The specific humidity in troposphere could be potentially used to compare with RAL IMS in the mid- and low-troposphere as IMS is used in CDR-4 in the troposphere. Surface humidity data may have some potential connections with CDR-1&2.

Session 5 focussed on WV_cci internal analysis of TCWV CDRs.

- Ebell et al: Systematic assessment of WV products in the Arctic

Various satellite-based and reanalysis data records were intercompared over the Arctic region. Results indicate good quality for IASI TCWV data while GOME products fairly strongly underestimate TCWV. In presence of sea-ice largest differences are observed between the data records.

- Jorge Eiras-Barca et al: Contribution to atmospheric moisture transport (WV_cci)

CDR-2 was compared with reanalysis and both products exhibit reasonable agreement. CDR-2 cannot be used for a full analysis of atmospheric rivers due to the lack of vertically resolved data.

- Ramos et al.: The use of WV products in Atmospheric Rivers Science

This presentation highlighted the need of the use of novel long-term TCWV climatologies or/and water vapour profiles in order to better understand the genesis and dynamics of atmospheric rivers. An interest in utilising CDR-2 was expressed.

Day 2 ended with a discussion on critical observations gaps (e.g. in terms of resolution, coverage, quality, (potential) sensor loss), how these could be addressed, and what process studies would lead to better knowledge of the role of water vapour in the climate system. It was briefly discussed that a critical gap might occur between currently flying microwave imagers which are all beyond expected life-time and newly launched missions with microwave imagers on board (i.e. EPS-SG, GOSAT-GW). Also, a critical gap might occur for limb sounding missions. Again, the currently flying missions are beyond life-time and new missions are not committed yet. Potential missions might come from ESA and Canada. If a gap occurs ground-based observations might be used to fill the gap. It was generally noted that the validation in the UTLS can be considered as gap.

Day 3 was the final day of the workshop. **Session 6** discussed total column water vapour observations and climate analysis with the following presentation summaries:

- Falk et al.: TCWV: trends, variability & theoretical expectation (WV_cci)

Presentation of ongoing results from the ESA water vapour CCI project, examining trends of TCWV from CDR-1 and 2, AIRS, ERA5 and merged microwave products. The analysis is broken down into global ice-free ocean and land regions between $\pm 60^\circ$ (latitude), and examined for the common time period between the records. Regression against surface air temperature from the H2020 EUSTRACE project, as well as land and sea surface temperatures from the ESA CCI program has also performed. The work is still ongoing, with the final results expected in August (2021).

- Borger et al.: Analysis of global trends of TCWV from OMI observations

This study presents analysis of TCWV trends from the Ozone Monitoring Instrument (OMI). TCWV is retrieved from the blue region in the visible spectrum (400 nm) using the Differential Optical Absorption Spectroscopy (DOAS) technique. This algorithm has already been successfully applied to TROPOMI, with potential for future sensors also. Inter-comparisons to SSM/I TCWV (over ocean) showed around 3% wet bias with some inter-annual variability. Similar results were also seen for comparisons to ERA5 over ocean, with a wet bias of 5% observed. However, over land surfaces this increases to an 11% wet bias relative to ERA5, with most overestimation coming from the Amazon basin. Further work was also presented on work with trends, with no detectable Clausius–Clapeyron response.

- Küchler et al.: Comparison of Sentinel-5P TCWV from different algorithms

This work focused on the comparison of three different TROPOMI TCWV products, i) AMC-DOAS, ii) MPIC, and iii) SRON to demonstrate the advantage of multiple products from the same sensor. These products also make use of different parts of the TROPOMI spectra for water vapour information. An overview of the products was presented, with a focus on differences in quality and cloud filtering. Intercomparison of the products is given by scatter plots, time series, and monthly mean difference map plots. Overall, there is a good agreement between the products (within 2 kg/m^2) and with reanalysis. However, complex structures are present in the difference maps.

- Radice et al.: Novel assessment of model relative humidity with satellite probabilistic estimates

This study focuses on using retrievals of relative humidity (RH) from the SAPHIR microwave sounder to assess NWP forecasts from the ARPEGE model, operated by Météo-France. Rather than bulk metrics (e.g. bias, correlation etc), a novel approach is used whereby the model forecast is projected onto PDF information from the RH retrieval. Transforming the PDF to a CDF then allows for the probability that forecast is higher/lower than the true RH to be determined. This new method highlighted regions where the forecast diverge from the satellite RH which were not visible when comparing the differences directly. Overall, ARPEGE was found to overestimate more frequently than underestimate the RH outside of the 0.25-0.75 confidence interval.

- Castelli et al.: AIRWAVE-TCWV from TIR dual view ATSR-like instruments

This final presentation of the session discussed the AIRWAVE algorithm and the application to ATSR-like instruments that operate in the infrared. The AIRWAVE

algorithm has been developed within the ESA long-term preservation of ATSR framework. While these instruments were designed to measure surface temperature, the dual-view aspect which is used for atmospheric correction can be exploited to provide TCWV information. Validation of version 1 of the algorithm showed biases of 2.43 kg/m² relative to island based radiosondes, and 2.11 kg/m² relative to SSM/I. For updates in version 2, these biases reduced to 0.19 kg/m² and 0.02 kg/m² respectively. Examples of applications using the v1 and v2 datasets were also shown (ITCZ displacement trends and lee wave detection respectively). Ongoing work includes the application of the AIRWAVE algorithm to the SLSTR instruments.

The second session of the third day addressed TCWV, focusing on model intercomparisons.

- He et al., from the LATMOS group

Sought to discern between the dynamic and thermodynamic components of TCWV variations, making more explicit the link between the TCWV and large-scale circulation. They addressed this issue by jointly analysing CDR-2 from WV_cci with ERA5 and CMIP6 outputs. Among other interesting results, they found a moistening trend observed in CCI data, a dry bias in ERA5 over land, and that all CMIP6 models vary within the standard deviation of the CDR-2 in each circulation bin of vertical velocity at 500 hPa.

- Richard P. Allan from the UoR evaluated WV changes in CMIP6 simulations

They found that WV changes are broadly captured by CMIP6 models and observing systems and reported suppressed WV trend in the atmospheric model intercomparison project (AMIP) vs historical.

- Lauer et al., from the DLR

Provided an evaluation of the CMIP6 with the CDR-2 using the ESMValTool. Among other results, they reported that, when talking about TCWV, the multi-model mean climatology is quite close to observations. Also, the seasonal cycle amplitude seems to be overestimated in the Tropics and underestimated over North America and Europe.

- William Ingram, from the Met Office Hadley Centre

Analysed the effects of model resolutions in the WV validation in a GCM. He stated that most GCMs have climate sensitivities above the accepted uncertainty ranges.

- Trent et al. from the U. of Leicester

Addressed the issue of the water vapour residence time (WVRT) from observational and AMIP ensembles. They reported differences up to 0.4 days in WVRT between models and observations and some disparities in TCWV over strong convective regions and in NH summer, being the latter more likely linked to meridional transport in models.

Final discussions on climate analysis, applications & process studies raised the following: Process studies leading to a better knowledge of the role of water vapour in the climate system could be pursued, e.g. the role of

entrainment/detrainment on convective scales. Other topics include a close analysis of the homogeneity of the products and interproduct consistency. An improved parameterisation of the clear-sky OLR using satellite data would be beneficial as well.

Finally the organisers thanked all participants for valuable contributions via presentations and discussions.

13. DEDICATED USER FEEDBACK ON WV_CCI CDRS

13.1 Introduction and usage

The WV_cci datasets comprise four CDRs (see also section 1.4):

- CDR-1: gridded monthly and daily means of TCWV in units of kg/m² that cover the global land areas with a spatial resolution of 0.05°. It covers the period July 2002 to December 2017.
- CDR-2: gridded monthly and daily means of TCWV in units of kg/m² with global coverage and a spatial resolution of 0.05° / 0.5°. It covers the period July 2002 to December 2017.
- CDR-3 contains the vertically resolved water vapour ECV in units of ppmv (volume mixing ratio) as zonal monthly means on the SPARC Data Initiative latitude/pressure level grid. It covers the vertical range between 250 hPa and 1 hPa, and the time period 1985 to December 2019.
- CDR-4 consists of three-dimensional vertically resolved monthly mean water vapour data (in ppmv) with a spatial resolution of 100 km, covering the troposphere and lower stratosphere.

The final versions of CDR-1 and CDR-2 are v3.1 and are available to CCI and on request since February 2021. Results from project internal analysis are summarised in this report (Section 2 to Section 6) and in He et al. (2022) and Eiras-Barca et al. (2022). At the time of writing, CDR-3 and CDR-4 were not available in final form. Nonetheless, a pre-final version of CDR-3 was available for project-internal scientific analysis (see Section 4).

Beyond WV_cci project partners the following institutions requested data access to CDR-1 and CDR-2:

- DLR, Germany
- University of Bremen, Germany
- University of New Brunswick, Canada
- University of Lisbon, Portugal
- MPI-C, Germany
- DWD, Germany
- Planetary Visions Limited, UK

The project is aware of the following WV_cci external publication which utilises WV_cci data:

- Lauer et al. (2022): They assessed the improvement of CMIP6 relative CMIP5 model output using CDR-2 from WV_cci and cloud data records from Clouds_cci.

13.2 Feedback

The summary of feedback from users of WV_cci datasets is based on the following:

- Email exchange between project and WV_cci data record users
- Talk at AR3 on CDR-3 analysis
- Presentations at the WV_cci user workshop.

The feedback from emails relies on three users and is summarised as follows:

- In comparisons to other data records a contrast in results over ocean and land was observed.
- The contrast in uncertainty magnitude between land and ocean was noted.
- The data was partly used independent of its sampling characteristics, i.e. it was treated as all-sky data.

The key feedback is the contrast in different characteristics of the product over land and ocean. Such a contrast can be expected given the nature of CDR-2, as documented in PVIR and PUG. However, CDR-2 was provided to users at an early project stage, with the main motivation to allow timely analysis of the data. At that time PVIR and PUG were not available.

Results from the analysis of CDR-3 were presented at the Annual Review Meeting 3 on 26 and 27 August 2021. The presentation concluded with the following statements:

- Insignificant differences in amplitude and phase of (inter)annual cycles
- Significant difference in multi-annual mean
- Structure and sign of trends generally agree well
- Largest disagreement in 1998–2003 period
- Trends since 2004 depend on Aura MLS version and data sets included.

It was concluded that CDR-3 includes more sensors and more information compared with other available CDRs.

The WV_cci User Workshop was held in the afternoons of 14–16 June 2021. A summary and details from discussions are given in Section 10 and in Appendix 2, respectively. Here, we focus on presentations given by users and the user community with explicit feedback in relation to WV_cci data records. The talks given by the following first authors form the basis for the summary given below: Gimeno Presa, Ramos, He, Lauer, Allan, and Ingram.

The feedback is summarised as follows:

General:

- Gaps, in particular in space, require additional efforts in comparison exercises and might impact the conclusions.
- Despite the significant progress in the generation of satellite-based CDRs a comparison to multiple CDRs is still recommended.
- Products with sub-daily resolution are required for process studies.
- Multi-layer tropospheric data records are required for various applications, as for example for the analysis of atmospheric rivers.

TCWV:

- Relative to ERA5 and a subset of CMIP6 models CDR-1 exhibits a fairly strong increase in anomalies over the tropical land.

It can be concluded that higher resolutions would be supportive for additional or more advanced analysis. Even though the high stability of the TCWV product was demonstrated it seems advisable to reassess its stability in the future.

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APPENDIX 2: ADDITIONAL NOTES FROM BREAKOUT GROUP SHEETS

Here little-changed comments from the breakout group sheets are provided for completeness:

TCWV

- Validation of surface values (e.g. specific humidity and relative humidity from stations and ships (2m)
- Understanding some of the processes leading to large scale anomalies - observed world/model world.
- 25% accuracy for 100 km monthly seems very large - 5% more useful?
- Stability requirements of daily 1 km seems very strict
- Model trends of order 1-2%/decade+/-1%/decade at large scales probably require stability of order 0.2% per decade to be useful
- More work needs to be done to help users understand *how* best to compare model - satellite - in situ versions of reality.
- Would like to compare satellite with in-situ humidity (HadISDH) - but not clear if satellites can help with this?
- Applications of the high spatial resolution TCWV data over land might be more NWP than climate.
- Microwave: various sensors, assumption small scale similar observation time: simply average under the assumption of poor correlation. from there: different times, different sensor platforms, we assume no or very small correlation
- Come up with guideline in User Guide or *Dos and Don'ts* to apply CDRs
- Should we change to only clear-sky product for land and ocean surfaces? Theoretical product, since applied cloud masks would be different, a clear request was not formulated by the audience.
- Model output are only all-sky; would need to happen inside models
- Similar problem with sampling time: model are all-sky and all-time; CDR's are retrieval time (here around 10 am) and clear-sky over land

VRWV-UTLS

- Definition based on in-situ measurements: high vertical resolution requirements driven by dynamics (10 K = ~500m at 17km)
- Maximal sampling resolution in different domains (vertical, horizontal, temporal) always preferred (of course).
- "The" user requirements is an ill-defined concept. There are many applications each with their own requirements.
- But the most demanding application should not be the main driver of "the" final user requirements
- Target versus threshold requirements, it is sometimes discouraging for data providers to see ambitious requirements which cannot be met.
- Proposal: set requirements for future data records, not for existing/past sensors which are not designed to meet these requirements..

VRWV-strato

- Definition of user requirements through CCI activities and GCOS initiatives
- OSSEs would be a better idea. Observations need to be able to detect inter-annual variability and long-term trends in VRWV, accounting for stratospheric methane increases

- Long-term trends in VRWV - is there evidence of changes in the BDC that affect tropical coldpoint temperatures and therefore stratospheric water vapor entry values?
- A count and classification of any short term events that are lost in an e.g. monthly dataset (E.g. sudden stratospheric warming, influences of overshooting convection).

APPENDIX 3: GLOSSARY

Term	Definition
ABC(t)	Atmosphere Biosphere Climate (teledetection)
ACE-FTS	Atmospheric Chemistry Experiment Fourier Transform Spectrometer
ACE-MAESTRO	Atmospheric Chemistry Experiment Measurements of Aerosol Extinction in the Stratosphere and Troposphere Retrieved by Occultation
AMSR-E	Advanced Microwave Scanning Radiometer for EOS
AMSU	Advanced Microwave Sounding Unit
ARA	Atmospheric Radiation Analysis
ARSA	Analyzed RadioSoundings Archive
AVHRR	Advanced Very High Resolution Receiver
BC	Brockmann Consult
CARIBIC	Civil Aircraft for the Regular Investigation of the atmosphere Based on an Instrument Container
CCI	Climate Change Initiative
CDO	Climate Data Operators
CDR	Climate Data Record
CDS	Copernicus Climate Data Store
CEDA	Centre for Environmental Data Analysis
CF	conventions for Climate and Forecast
CM SAF	EUMETSAT Satellite Application Facility on Climate Monitoring
CMAM	Canadian Middle Atmosphere Model
CMIP	Coupled Model intercomparison Project
CMUG	Climate Modelling User Group
CRG	Climate Research Group
DLR	Deutschen Zentrums für Luft- und Raumfahrt
DWD	Deutscher Wetterdienst (German MetService)
ECCC	Environment and Climate Change Canada
ECMWF	European Centre for Medium Range Forecast
ECV	Essential Climate Variable
EDA	ERA5 - reduced resolution ten member ensemble
EMiR	ERS/Envisat MWR Recalibration and Water Vapour Thematic Data Record Generation

Term	Definition
Envisat	Environmental Satellite
ERA5	ECMWF Re-Analysis 5
ERA-Interim	ECMWF Re-Analysis Interim
ESA	European Space Agency
ESGF	Earth System Grid Federation
EUMETSAT	European Organisation for the Exploitation of Meteorological Satellites
FOV	Field of View
FPH	Frost Point Hygrometer
GCOS	Global Climate Observing System
GEOS-5	Goddard Earth Observing System Model, Version 5
GMI	Global Precipitation Microwave Imager
GNSS	Global Navigation Satellite System
GOMOS	Global Ozone Monitoring by Occultation of Stars
GOZCARDS	Global OZone Chemistry And Related trace gas Data records for the Stratosphere
GPS	Global Positioning System
GRUAN	GCOS Reference Upper-Air Network
GUM	Guide to the Expression of Uncertainty in Measurement
HARMOZ	HARMonized dataset of Ozone profiles
HALOE	Halogen Occultation Experiment
HIRDLS	High Resolution Dynamics Limb Sounder
HOAPS	Hamburg Ocean Atmosphere Parameters and Fluxes from Satellite Data
IAGOS	In-service Aircraft for a Global Observing System
IASI	Infrared Atmospheric Sounder Interferometer
ILAS-II	Improved Limb Atmospheric Spectrometer-II
IMS	Infrared Microwave Sounding
IPSL-CM	Institut Pierre Simon Laplace - Climate Model
IR	Infrared
LMD	Laboratoire Météorologie Dynamique
LMS	lowermost stratosphere
LST	Land Surface Temperature
LWP	Vertically integrated liquid water
MERIS	Medium Resolution Imaging Spectrometer Instrument

Term	Definition
MERRA-2	Modern-Era Retrospective analysis for Research and Applications, Version 2
MHS	Microwave Humidity Sounder
MIPAS	Michelson Interferometer for Passive Atmospheric Sounding
MLS	Microwave Limb Sounder
MODIS	Moderate Resolution Imaging Spectrometer
MOZAIC	Measurement of OZone by Airbus In-service airCraft
MPI-M	Max-Planck Institute for Meteorology
MUDB	Match-up database
NASA	National Aeronautics and Space Administration
NCAR	National Center for Atmospheric Research
NCEO	National Centre for Earth Observation
NCEP	National Centers for Atmospheric Prediction
NDVI	Normalized Difference Vegetation Index
NIR	Near IR
NOAA	National Oceanic & Atmospheric Administration
NWP	Numerical Weather Prediction
OLCI	Ocean and Land Colour Instrument
PCs	Principle components
POAM	Polar Ozone and Aerosol Measurement
PSD	Product Specification Document
RAL	Rutherford Appleton Laboratory
RMS	Root mean square
RR	Reduced resolution
RTTOV	Radiative Transfer for TOVS
SAGE	Stratospheric Aerosol and Gas Experiment
SASBE	Site Atmospheric State Best Estimate
SCIAMACHY	Scanning Imaging Absorption Spectrometer for Atmospheric Cartography
SCISAT	Scientific Satellite
SE	Spectral Earth
SMILES	Solar wind Magnetosphere Ionosphere Link Explorer
SMR	Software Modification Report
SNR	Signal-to-noise ratio

Term	Definition
SOFIE	Solar Occultation For Ice Experiment
SPARC	Stratosphere-troposphere Processes And their Role in Climate
SPURT	Spurenstofftransport in der Tropopausenregion, trace gas transport in the tropopause region
SSM/I	Special Sensor Microwave Imager
SSMIS	Special Sensor Microwave Imager Sounder
SST	Sea Surface Temperature
SuomiNet	Global ground based GPS network (named after Verner Suomi)
SWOOSH	Stratospheric Water and OzOne Satellite Homogenized data set
TBD	To be determined
TCWV	Total Column Water Vapour
TMI	Tropical Rainfall Measuring Mission's Microwave Imager
TOA	Top Of Atmosphere
UKMO	United Kingdom Meteorological Office
UoL	University of Leicester
UoR	University of Reading
URD	User Requirements Document
UT	Upper Troposphere
UTLS	Upper Troposphere and Lower Stratosphere
UV	Ultraviolet
vis	Visible
VMR	Volume mixing ratio
VRes	Vertically resolved
WACCM	Whole Atmosphere Community Climate Model
WAVAS-I	Water Vapour Assessment
WAVAS-II	Water Vapour Assessment 2
WCRP	World Climate Research Programme
WGS	World Geodetic System 1984
WMO	World Meteorological Organization
WV	Water Vapour
WV_cci	Water Vapour climate change initiative

End of Document