Environmental Research Communications

LETTER

Changes of precipitation and moisture extremes in ERA-interim reanalysis viewed from a new space

Banglin Zhang*, Renhe Zhang, Lin Wu and Changchun Nie

1. Guangzhou Institute of Tropical and Marine Meteorology/Guangdong Provincial Key Laboratory of Regional Numerical Weather Prediction, CMA, Guangzhou 510641, People’s Republic of China
2. Department of Atmospheric and Oceanic Science, Fudan University, Shanghai 200433, People’s Republic of China
3. State Key Laboratory of Atmospheric Boundary Layer Physics and Atmospheric Chemistry, Institute of Atmospheric Physics, Chinese Academy of Sciences, Beijing, People’s Republic of China
4. Shantou Meteorological Service, Shantou 515000, People’s Republic of China

E-mail: Banglin.Zhang@yahoo.com

Keywords: total column water vapor, total precipitation, trends, global warming, variable space.

Abstract

We investigate changes of total column water vapor (TCWV) and total precipitation (TP) from the reanalysis ERA-Interim monthly data (1979–2016) in a new space spanned by their ascending values and show that TP extremes increase much more than TCWV extremes do. The trend of the maximum TCWV is 0.47 kg m⁻²/decade, which is equivalent to approximately 0.76%/decade. The trend of the maximum TP is 3.78 mm day⁻¹/decade, which is approximately 8 times the TCWV trend. The trends of extreme TP, defined as the 90th, 95th, 99th, 99.9th, 99.99th percentiles and the maximum of the monthly precipitation values, are 0.63, 1.05, 1.26, 3.29, 10.4, and 12.0%/decade, respectively. These values are larger than the trends of extreme TCWV, ranging from 0.41% to 0.76%/decade.

There are indications that wet regions become wetter at the expense of dry regions (Allan and Soden 2007; Chou et al 2007) and that extreme precipitation increases by more than the increase in atmospheric moisture under global warming (Allan et al 2010, Sugiyama et al 2010, Trenberth 2011 and Trenberth et al 2015). The record-breaking rainfall due to Hurricane Harvey 2017 is a strong evidence supporting this argument (Risser and Wehner 2017, van Oldenborgh et al 2017, Wang et al 2018). This result is quite different from the conventional wisdom (Trenberth 1999a, 1999b, Allan and Ingram 2002) that the intensity of the most extreme rainfall rises at the rate of atmospheric moisture increase, i.e. 6 to 7% per degree of warming based on the Clausius-Clapeyron (CC) relation (Palí et al 2007). Miao et al (2016) also reported that precipitation extremes over China is more sensitive to atmospheric temperature than the Clausius-Clapeyron (C–C) relation of 7% per degree Celsius. Dong et al (2019) further showed that atmospheric temperature’s influence of precipitation intensity and rainfall extremes over are predominantly contributed through increasing water vapor, instead of destabilizing the atmosphere.

For extreme precipitation and water vapor, which can be defined in many ways, the choice of definition affects how they respond to warming (Pendergrass 2018). The most common definitions of extreme events are locally defined with respect to local climates during their base periods (Zhang et al 2011). In this research, we sort monthly precipitation and moisture values over equal area cells (Zhang et al 2004) in ascending order. This sorting is performed over a spatial domain, instead of a temporal period, and provides continuous spectrum aligning the spatial distribution of precipitation and moisture content. This is a new space, which we called the variable space. The extreme values are defined as the nth percentile portion of the spectrum. Following this definition, we obtain a continuous time series of extreme precipitation and moisture in the variable spaces and study their changes under global warming over recent decades. The definition will help us get a big picture of global warming on extreme precipitation and water vapor without getting into the details of spatial and local impacts.
The reanalysis ERA-Interim (ERAi) total precipitation (TP) and total column water vapor (TCWV) data are used for climate and trend analysis because of their long term record and global coverage (Dee and Uppala (2011)); however, uncertainties exist especially relating to large regional and seasonal differences (Cui et al 2017), which could be reduced by transforming into variable spaces. We remap the 1° × 1° latitude-longitude grid monthly data over the whole globe from January 1979 to December 2016 into 41,252 equal area cells with size of about 110 km × 110 km (Zhang et al 2004) and then sort them, spatially, in an ascending order for each month. For latitude-longitude grid of 1° × 1°, the grid size varies greatly with latitude, with a size of approximately 111 km × 111 km near the equator, 57 km × 111 km at 59° NS−1, and only 2 km × 111 km at 89° NS−1. To obtain cell sizes that are approximately the same size for each data point, we tessellate the globe into a set of equal area grid with size equal to the grid at the Equator. Thus, there are 41,252 cells in total over the whole globe, with the number of cells in each latitude zone varying from 360 at the Equator to only 3 at the poles. The use of equal area grid cells has its place in scientific use. For example, calculating global or zonal averages is simplified. This is especially useful for sorting climate data. The monthly TP and TCWV extremes are defined with different thresholds to the sorted data: the maximum value (top 1st), 99.99th (top 4th), 99.9th (top 41st), 99th (top 412nd), 95th (top 2062nd), and 90th (top 4125th) percentile values. As shown in figure 1(a), the big increasing of the maximum and 99.99th percentile time series of TP in 1979–2016 seems mainly due to the big jump around 2004. Before 2004 smaller positive trends are observed. Even decreasing appears after 2004. Such abrupt change may not be directly related to global warming and could be resulted from a model deficiency or inadequacy in the observation system. For the time series of TP at 90th, 95th, 99th, 99.9th percentiles the changes increase gradually, and are more likely the result of an extreme precipitation mode related to global warming, which could be a part of mode extracted by Empirical Orthogonal Function (EOF) analyses of the sorted TP anomalies.

On the other hand, the variation of extreme TCWV does not reflect that of extreme TP. The changes in the of maximum and 99.99th percentile TCWV do not show the large jumps near 2004 while TCWV at 90th, 95th, 99th, 99.9th percentiles have similarly linear changes to those of TP (figure 1(b)). This result implies that that the moistening atmosphere is not the only factor increasing extreme TP. The linear trend of the maximum TCWV is 0.47 kg m−2/decade (equivalent to 0.47 mm/decade) and its normalized trend by the climatic mean is 0.76%/decade. The maximum TP increases at a rate of 3.78 mm day−1/decade (12%/decade), which is approximately 8 times that of the TP trend. This increase is another evidence showing extreme precipitation increases at or above the rate of moisture (Pendergrass and Gerber 2016, O’Gorman et al 2018). Such a large increase in extreme precipitation could be related to extreme modes (Pendergrass and Hartmann 2014) or multiple evaporation and precipitation cycles (Trenberth 1999b). Table 1 summarizes the linear trends, climatic means, normalized linear trends and student-t test values of extreme TP and TCWV based on different percentiles. The normalized trends

Figure 1. Time series of sorted TP and TCWV showing different increasing rates. A, B, Time series of the maxima (black), 99.99th (red), 99.9th (blue), 99th (green), 95th (cyan), 90th (magenta) percentiles of TP (a) and TCWV (b).
of extreme precipitation events defined as the 90th, 95th, 99th, 99.9th, 99.99th percentiles and the maximum TP are respectively 0.63, 1.05, 1.26, 3.29, 10.4, and 12.0%/decade. The more extreme the TP is, the more rapid it increases. The same also holds for extreme TCWV, whose normalized trends are 0.41, 0.55, 0.61, 0.70, 0.75 and 0.76%/decade for its 90th, 95th, 99th, 99.9th percentiles and the maximum value, but its increasing rates are obviously slower than that of TP. All these trends are at least 99% statistically significant.

The geographical locations of the mean cell indices of TP and TCWV in variable space indicate that TP extremes (figure 2(a)) are most likely along the equator with some wetter regions over the land, while TCWV extremes (figure 2(b)) are also along the equator but with wider north-south span. As an example, figures 2(c) and (d) give the spatial distribution of TP and TCWV extremes in September 2016. In order to understand the relationship between the atmospheric moisture and precipitation response to climate change, it is important to learn more about the statistical distributions in their variable spaces. Figure 3 plots the statistical characteristics of sorted TP and TCWV during 1979–2016. The climatic means of the sorted TCWV and TP are plotted in figures 3(a) and (b). The climatic values of sorted TCWV increases approximately linearly along the ascending equal area cell order (figure 3(a)) while that of TP increase exponentially (figure 3(b)). The major difference between the climatic mean distribution of sorted TCWV and TP is a very interesting characteristic and could be

---

Table 1. Statistics of sorted TCWV and TP extremes during 1979–2016. Climatic means, linear trends and normalized linear trends of extreme TCWV and TP based on different percentiles.

| Cell index | 37126 | 39189 | 40839 | 41210 | 41247 | 41252 |
|------------|-------|-------|-------|-------|-------|-------|
| Percentile | 90.00 | 95.00 | 99.00 | 99.90 | 99.99 | 100.00 |
| TCWV trend (kg m⁻²/decade) | 0.20 | 0.29 | 0.34 | 0.42 | 0.46 | 0.47 |
| TCWV mean (kg m⁻²) | 48.43 | 52.55 | 56.64 | 59.82 | 61.01 | 61.44 |
| Normalized TCWV trend (percentage/decade) | 0.41 | 0.55 | 0.61 | 0.70 | 0.75 | 0.76 |
| t-value | 3.60 | 4.91 | 5.23 | 3.60 | 3.23 | 3.21 |
| TP trend (mm day⁻¹/decade) | 0.05 | 0.10 | 0.17 | 0.61 | 2.58 | 3.78 |
| TP mean (mm day⁻¹) | 7.26 | 9.50 | 13.40 | 18.54 | 25.70 | 31.46 |
| Normalized TP trend (percentage/decade) | 0.63 | 1.05 | 1.26 | 3.29 | 10.43 | 12.00 |
| t-value | 3.19 | 4.45 | 3.86 | 7.54 | 13.13 | 13.15 |
Figure 3. Statistical characteristics of sorted TP and TCWV during 1979–2016. (a), (b), Climatic means of sorted TCWV (a) and TP (b); (c), (d) Long-term trends of sorted TCWV (c) and TP (d); (e), (f), Normalized long-term trends of sorted TCWV (e) and TP (f) at 98% percentile and higher; g, h, t values of sorted TCWV (g) and TP (h).
used for hydrological modeling. One possible explanation of the exponential increase in rate for the mean TP values is the skewness of vertical velocities (O’Gorman et al 2018).

The global temperature rise in recent decades has caused more water vapor stored in the air. However, the trends of sorted TCWV have negative values for the first couple hundred driest cells, then stay constant at approximately 0.02 kg m\(^{-2}\)/decade in the next 25,000 cells (figure 3(c)). In the rest of the wetter areas, the TCWV trends are larger, from approximately 0.02 to 0.34 kg m\(^{-2}\)/decade, with the values almost linearly increasing with respect to the sorted cell index. In the wettest few hundred cells, the increase in trends is even steeper. Although more moisture content has been absorbed by the troposphere, precipitation does not seem to always increase (figure 3(d)). There is a clear partition between the negative trends in the drier areas, comprising approximately 35000 cells out of 41252, and positive trends in the wetter areas, with especially large increases in the areas with the extreme precipitation.

The above results show the water vapor and precipitation have different responses to global warming where a warmer atmosphere has more uniform water vapor increases from the driest to the wettest regions, but moister atmosphere does not necessarily bring more rainfall. In fact, the TP trends derived from the same dataset (so in the same climate system) shows that more precipitation occurs only in the areas with the heaviest rainfall, but less precipitation in drier areas.

Focusing on the normalized trends of the top 2% (98th percentile or higher) of the wettest areas, the TCWV increases by approximately 0.4%–0.7% per decade (figure 3(e)), while the TP increases from approximately 0.63% to 12% per decade (figure 3(f)). The most extreme rainfall TP intensifies far more than does the wettest TCWV.

The significant test of TCWV and TP trends was conducted with the student-t test. The t values are shown in figures 3(g) and (h) for TCWV and TP, respectively. TCWV trends of the cells higher than about 3000 reach 95% confidence level while TP trends of most cells are statistically significant except for first 1800 cells and the 32600th–36200th cells where the trends are near zeros.

EOF analyses are applied to decompose and identify the structures of the statistical distributions of the sorted TP. The two leading modes (EOF1 and EOF2) in their variable space and the corresponding temporal changes in the principal components (PC1 and PC2) are shown in figure 4. EOF1, the most dominant mode (57.85% of total variance), has negative values in up to approximately 32000 cells, then positive values in the remaining cells, with greatest values towards the precipitation extremes (figure 4(a)). This mode shows a statistically 99% significant long term trend under global warming and an interannual variability related to El Niño–Southern Oscillation (ENSO) interannual variabilities (figure 4(c)). The second leading mode, EOF2, explaining approximately 19.07% of the total variance, has large positive values near the precipitation extremes as shown in figure 4(b). The temporal evolution of this mode (figure 4(d)) displays an interannual variability with a slightly smaller trend, which is also statistically significant at 99%, and related to ENSO signal. The relationship between ENSO and interannual variability of sorted TP is illustrated in the lag-correlation plot of Nino3.4 index versus PC1 and PC2 of sorted TP (figures 6(c) and (d)). The most significant correlation of the PC1 with Nino3.4 index

![Figure 4](image.png) Dominant variation patterns of sorted TP. a-d, The first (a) and second (b) leading EOF modes of sorted TP, and the corresponding PC1 (c) and PC2 (d).
is lagged at about 2–3 months, while PC2 has most significant correlation with Nino3.4 index lagged at less than 1 month.

Figure 5 displays the two leading EOF modes of the sorted TCWV anomalies. EOF1 represents a globally wet mode, with slowly increasing values in the first ~25000 dry cells, and then faster increases beyond that point (figure 5(a)). EOF2 mode is a dipole mode, with positive TCWV value increasing from the driest cell to its maximum value at ~28000th cell and then drops to negative at ~37000th cell to the end (figure 5(b)). The PC1 mode has a statistically significant long-term increasing trend superimposed with interannual variability, while the PC2 mode has a higher frequency interannual variability without statistically significant trend. Their relationship with ENSO is shown by the lag-correlation in figures 6(a) and (b). The significant correlations of the PC1 with Nino3.4 index peak after about 3–4 months, while PC2 is about 2 months.

The relationship of TP and TCWV in their variable spaces could be investigated by calculating the correlation coefficients of PC1s and PC2s of sorted TP and TCWV. Although the correlation coefficient for PC1 is 0.71, statistically significant, that for PC2s the correlation coefficient is 0.0.

In summary, sorting the monthly ERAi TCWV and TP from their spatial minima to maxima provides continuous statistical spectrum, helps us investigate the extreme TP and TCWV values from a different
 prospective. Our result shows that extreme TP has or occupies much greater trends than extreme TCWV. The trends of TP have large variations at different percentiles when compared with that of TCWV. Thus, it is true that the choice of the definition of an extreme affects the trends observed under global warming (Pendergrass 2018).

The sorted data are the same size as the original one, but the results would have different statistical distributions in their variable spaces and related meanings if using suitable methods. For example, by conducting mean, linear trend and EOF analysis, clearer distribution structures could be identified and the impacts of global warming and El Niño–Southern Oscillation interannual variabilities could be extracted.

**Data and method summary**

Monthly ERA-interim data were provided by ECMWF and downloaded from [https://software.ecmwf.int/wiki/display/CKB/ERA-Interim%3A+monthly+means](https://software.ecmwf.int/wiki/display/CKB/ERA-Interim%3A+monthly+means). The data plotted on a latitudinal-longitudinal grid was remapped to equal area cells and was then sorted in ascending order. Mean, linear trend and EOF analysis were performed on the sorted data to identify the structures of TCWV and TP distribution in their variable spaces. Nino3.4 index was retrieved from [https://climatedataguide.ucar.edu/climate-data/nino-sst-indices-nino-12-3-34-oni-and-tni](https://climatedataguide.ucar.edu/climate-data/nino-sst-indices-nino-12-3-34-oni-and-tni) (Trenberth, Kevin & National Center for Atmospheric Research Staff. Last modified 11 Jan 2019). Simple time series linear regression is used to estimate the linear trend of time series $x_t$ of TP, TCWV and their PCs by

$$y_t = \beta_0 + \beta_1 t + e_t,$$

here $t$ is the monthly index, and Student-$t$ test is used to estimate the statistical significance

$$t - \text{value} = r\sqrt{(n - 2) / (1 - r^2)}.$$

here $r$ is the correlation of $y_t$ and $x_t$.

**Acknowledgments**

The research is supported by the National Key R&D Program (Grant No. 2018YFC1506900) and the Natural Science Foundation of China (grant No. U1811464).

**ORCID iDs**

Banglin Zhang @ [https://orcid.org/0000-0001-7836-8102](https://orcid.org/0000-0001-7836-8102)

**References**

Allan R P, Soden B J, John V O, Ingram W and Good P 2010 Current changes in tropical precipitation Environ. Res. Lett. 5 025205

Allan R P and Soden B J 2007 Large discrepancy between observed and simulated precipitation trends in the ascending and descending branches of the tropical circulation Geophysical Research Letters 34 L18705

Allen M R and Ingram W J 2002 Constraints on future changes in climate and the hydrologic cycle Nature 419 224–32

Chou C, Tu J-Y and Tan P-H 2007 Asymmetry of tropical precipitation change under global warming Geophys. Res. Lett. 34 L17708

Cui P et al 2017 Natural hazards in Tibetan plateau and key issue for feature research Bull. Chin. Acad. Sci. 32 985–92

Dec D P and Uppala S M 2011 The ERA-Interim reanalysis: configuration and performance of the data assimilation system Q.J.R. Meteorol. Soc. 137 553–97

Dong W, W, Lin Y, Wright J, Xie Y, Yin X and Guo J 2019 Precipitable water and CAPE dependence of rainfall intensities in China Clim. Dyn. 52 3357–3368

Miao C, Sun Q, Borthwick A G and Duan Q 2016 Linkage between hourly precipitation events and atmospheric temperature changes over China during the warm season Sci. Rep. 6 22543

O’Gorman P A, Merlis T M and Singh M S 2018 Increase in the skewness of extratropical vertical velocities with climate warming: fully nonlinear simulations versus moist baroclinic instability Q.J.R. Meteorol. Soc. 144 208–17

Pall P, Allen M R and Stone D A 2007 Testing the Clausius–Clapeyron constraint on changes in extreme precipitation under CO2 warming Clim. Dyn. 28 351

Pendergrass A G 2018 What precipitation is extreme? Science 360 1072–3

Pendergrass A G and Gerber E P 2016 The rain is askew: two idealized models relating vertical velocity and precipitation distributions in a warming world J. Clim. 29 6445–62

Pendergrass A G and Hartmann D L 2014 Changes in the distribution of rain frequency and intensity in response to global warming J. Clim. 27 8372

Risser M D and Wehner M F 2017 Attributable human-induced changes in the likelihood and magnitude of the observed extreme precipitation during Hurricane Harvey Geophys. Res. Lett. 44 457–64

Sugiyama M, Shiogama H and Emori S 2010 Precipitation extreme changes exceeding moisture content increases in MIROC and IPCC climate models Proc. Natl Acad. Sci. USA 107 571–5

Trenberth K E 1999a Conceptual framework for changes of extremes of the hydrological cycle with climate change Clim. Change 42 327
Trenberth K E 1999b Atmospheric moisture recycling: role of advection and local evaporation J. Clim. 12 1368–81
Trenberth K E 2011 Changes in precipitation with climate change Climate Res. 47 123–38
Trenberth K E, Fasullo J T and Shepherd T G 2015 Attribution of climate extreme events Nat. Clim. Change 5 725
van Oldenborgh G J et al 2017 Attribution of extreme rainfall from Hurricane Harvey, August 2017 Environ. Res. Lett. 12 124009
Wang S-Y S, Zhao L, Yoon J-H, Klotzbach P and Gillies R 2018 Quantitative attribution of climate effects on Hurricane Harvey’s extreme rainfall in Texas Environ. Res. Lett. (https://doi.org/10.1088/1748-9326/aabb85)
Zhang Y C, Rossow W B, Lacis A A, Oinas V and Mishchenko M I 2004 Calculation of radiative fluxes from the surface to top of atmosphere based on ISCCP and other global data sets: refinements of the radiative transfer model and the input data J. Geophys. Res. 109 D19105
Zhang X et al 2011 Indices for monitoring changes in extremes based on daily temperature and precipitation data Wiley Interdiscip. Rev. Clim. Chang. 2 851–70