Global total precipitable water trends from 1958 to 2021

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ABSTRACT

This study investigates the trend in global total precipitable water (TPW), surface skin temperature ($T_s$) and surface air temperature ($T_{2m}$) from 1958 to 2021 using ERA5 and JRA-55 reanalysis datasets. We found that TPW trends in most regions of the world are moistening. Larger moistening trends were in tropical land areas from 1958 to 2021. Such moistening trends over large tropical lands, the Indian Ocean, high latitudes in the Northern Hemisphere (NH) were confirmed by the Atmospheric Infrared Sounder (AIRS) satellite and the Integrated Global Radiosonde Archive version 2 (IGRA2) observations. The average global TPW trend ranged from 0.16 and 0.21 mm decade$^{-1}$ for ERA5 and JRA-55, respectively. We also found that significant warming of $T_{2m}$ and $T_s$ was found in almost all regions especially the Arctic where the temperature anomaly trend (0.55 K decade$^{-1}$) was three times more than the global average trend (around 0.15 K decade$^{-1}$). In addition, this warming over land was obviously larger than ocean’s warming. The TPW trend was positively correlated with surface warming over oceans while this correlation over land was negative. The TPW change in response to temperature $T_{2m}$ or $T_s$ changes showed larger variations of 5-11% K$^{-1}$ over oceans than over land (below 4% K$^{-1}$ and even negative). In view of global dTPW/dT in the banded-latitudes, two stronger response zones were in the southern high-latitudes and tropical zones, and the dTPW/dT ratios over land were mostly lower than the theoretical ratio of ~7% K$^{-1}$ in tropical zones.

SIGNIFICANCE STATEMENT

The purpose of this study is to better understand to what extent has the total precipitable water and temperature changed from 1958 to 2021, and whether the moistening of the global atmosphere is following the model/theory assumed relationship with surface T ($T_{2m}$ or $T_s$). Our results indicated TPW trends are moistening especially over large tropical lands, the Indian Ocean, high latitudes in the Northern. And significant warming of $T_{2m}$ and $T_s$ was found in the Arctic where the temperature anomaly trend was three times more than the global average trend. The TPW change in response to temperature $T_{2m}$ or $T_s$ changes showed larger variations of 5-11% K$^{-1}$ over oceans than over land.

1. Introduction

As the most critical greenhouse gas in the Earth’s atmosphere accounting for ~75% of the greenhouse effect, water vapor plays a key role in atmospheric processes from the microscale
(including the formation of clouds and precipitation) to the global scale, and is related to the earth’s radiation budget, hydrological cycle, and climate change (Held and Soden 2006; Ruckstuhl et al. 2007; Lacis et al. 2010). Water vapor is mainly present in the low atmosphere below 5 km (Mockler 1995), and the amount of water vapor is primarily controlled by the air temperature when the relative humidity (especially over the ocean) remains unchanged in the low troposphere. The total precipitable water (TPW), also known as the column-integrated amount of water vapor, increases 6-7% with a 1 K increase in air temperature according to the Clausius-Clapeyron (CC) equation and thus enhances the strength of global warming with strong positive feedback due to the greenhouse effect (Held and Soden 2006). Therefore, evaluating the long-term trend of TPW change and its relationship with temperature is important for understanding the role of water vapor in climate change, as well as the water vapor feedback on global warming.

Because of the short residence time of water vapor in the atmosphere, studies in terms of long-term water vapor trends and its variability still face challenges. Observations from various weather station networks, satellites, and reanalysis datasets that combine models with observations are the two main categories of water vapor data. The former has difficulty obtaining long-term trends because of sparsely distributed stations, discontinuous, and inhomogeneous observations (Dee et al. 2011), while in some of the previous reanalysis datasets, biases and errors in observations that are assimilated into the reanalysis system may affect the reanalysis dataset’s quality and therefore cause concerns about their reliability for detecting climate trends (Dai et al. 2011; Trenberth et al. 2011; Schröder et al. 2016). Mostly based on satellite observations and early version reanalysis datasets, many studies have investigated trends and changes in atmospheric water vapor distribution either on global or regional scales for relatively short study periods (e.g., Wang et al. 2016; Parracho et al. 2018; Zhang et al. 2019, 2021; Borger et al. 2022). However, the latest reanalysis datasets provide us with longer and newer TPW and temperature datasets. For example, the Japanese 55 Reanalysis (JRA-55) is the third-generation reanalysis that uses the full observing system. It also uses a more advanced four-dimensional variational analysis and spans the period from 1958 to the present day. The JRA-55 provides a more suitable dataset for studying multidecadal variability and climate change than previous reanalysis datasets (Kobayashi et al. 2015). Comparably, the newest reanalysis dataset is the European Centre for Medium-Range Weather Forecasts reanalysis version 5 (ERA5) spanning from 1950 onwards, and benefits from many improvements compared with ERA-Interim (Hersbach and Dee 2016).
Therefore, both datasets provide us with a robust means of analyzing long-term global TPW changes and their relationship with global temperatures.

In many data assimilation schemes, near-surface air temperature (2 m air temperature, $T_{2m}$) and surface skin temperature ($T_s$) are two commonly used surface temperatures. The former describes the thermodynamic temperature at a 1.5-2 m height while the latter refers to ‘radiometric surface temperature’ that is governed by the terrestrial radiation balance (Jin et al. 1997; Jin and Dickinson 2010). Recent studies investigated how the TPW responds to changes in surface temperature using modeling estimation, satellite observations, or ground-based observation systems (Held and Soden 2006; O’Gorman and Muller 2010; Wang et al. 2016; Alshawaf et al. 2017; Yuan et al. 2021; Borger et al. 2022). In these studies, however, the temperature used is either from the global surface air temperature over land or from the sea surface temperature. Therefore, in this study both $T_{2m}$ and $T_s$ are used in trend analysis and TPW responses over global land and ocean.

In addition, these two recent reanalysis datasets, ERA5 and JRA-55, are used to analyze the decadal trends of TPW and the changes of two different temperatures ($T_{2m}$ and $T_s$), as well as the relationship between TPW trends and temperature changes. We focus on answering the following questions: (1) To what extent has the TPW changed from 1958 to 2021? (2) What is the difference between the surface air temperature and surface skin temperature variations on a multi-decade scale? (3) What the relationship between trends of TPW change and temperature change stand? And additionally, how does the use of $T_{2m}$ versus $T_s$ affect the results?

Therefore, this paper is organized as follows. In section 2, we introduce the datasets and methods of trend analysis. In section 3, the TPW variations are compared with radiosonde observations and satellite observations over land and ocean. The trends and differences of $T_{2m}$ and $T_s$ are also analyzed and compared with satellite observations. Finally, the conclusion is presented in section 4.

2. Data and method

a. Data

Two reanalysis datasets containing TPW and temperature ($T_{2m}$, $T_s$) from 1958 to 2021 were used in this study, these being ERA5 (Hersbach et al. 2020) and JRA-55 (Kobayashi et al. 2015). In both reanalysis products, the TPW is defined as the amount of water vapor in a
column extending from the surface to the top of the atmosphere, and $T_{2m}$ refers to the air temperature at 2 meters. For ERA5, $T_s$, namely skin temperature, is the temperature estimated from the surface energy balance. For JRA-55, skin temperature is a diagnostic variable computed from surface upward longwave radiation under the assumption that the surface is a black body. We used monthly reanalysis datasets from January 1958 to December 2021. Both variables in these two datasets were resampled into $1^\circ \times 1^\circ$ resolution gridded data by using a spatial-averaging resampling.

| Name   | Spatial resolution | Temporal Coverage | Temporal resolution | Variables      |
|--------|--------------------|-------------------|---------------------|----------------|
| ERA5   | Global 0.25°       | 1958-2021         | monthly             | TPW, $T_s$, $T_{2m}$ |
| JRA-55 | Global 1.25°       | 1958-2021         | monthly             | TPW, $T_s$, $T_{2m}$ |
| AIRS   | Global 1°          | 2003-2021         | daily               | TPW, $T_s$      |
| IGRA2  | Global stations    | 1958-2021         | twice a day         | TPW, $T_a$      |

In addition, the level-3 gridded mean product from the Atmospheric Infrared Sounder (AIRS-only) satellite (Tian et al. 2020) from 2003 to 2021 was used for comparison between the reanalysis and satellite observations. Both daily ascending and descending observations were averaged into the monthly ascending and descending data, which were then arithmetically averaged to the AIRS monthly data products with a $1^\circ \times 1^\circ$ spatial resolution.

We also used in-situ observations from the Integrated Global Radiosonde Archive version 2 (IGRA2) (Durre et al. 2018). It is a collection of historical and near-real-time global radiosonde observations archived by the National Centers for Environmental Information and can be accessed at ftp://ftp.ncdc.noaa.gov/pub/data/igra. In the radiosonde observations, sounding-derived variables are recorded daily at different levels from 1000 hPa to 100 hPa. We estimated the radiosonde TPW from the surface to 500 hPa by using barometric pressure, air temperature, and air dew point depression. The $T_{2m}$ used in the study from the radiosonde observations was taken from temperature observed at the lowest layer. A total of 510 radiosonde stations were collected from IGRA2 (Ferreira et al. 2018). The datasets used in this study are summarized in Table 1.

b. Methods

Monthly TPW and temperature anomalies were first calculated from 1958-2021 for reanalysis datasets. We divided the globe into the tropical (23.5°S–23.5°N), temperate
(23.5°S–66.5°S and 23.5°N–66.5°N), and polar regions (66.5°S–90°S and 66.5°N–90°N). The regional average values, presented by different latitude bins, were calculated with a cosine (latitude) weighting factor to account for the convergence of grid points for each region. For the global distribution, all datasets were resampled into 1° x 1° resolution using spatial-averaging resampling, then the area-weighted average of anomalies was computed to formulate a global time series.

The radiosonde IGRA2 data used include TPW (from the surface to 500 hPa) and surface temperature taken at the lowest layer (i.e., around 1000 hPa). Due to daily data missing in radiosonde observations, valid monthly data required at least 15 days of data available within a month. At least 50% of the months were available (i.e., at least 384 months for 1958–2021) for this time series study. We selected at least 30 years of data available for trend analysis using linear regression following the method of Chen and Liu (2016). Thereby, a set of 510 radiosonde stations met these criteria and were selected for this study.

For the seasonal linear correlation between the TPW and temperature, the climatology in December, January, and February (DJF), and June, July, and August (JJA), were determined the seasonal anomaly of DJF and JJA. Finally, simple Pearson correction coefficients (r) were estimated after removing seasonal anomaly trends in the time series. In addition, to obtain the percent change of TPW with respect to surface temperature, the relative TPW anomaly change was calculated as the TPW anomaly divided by the 64-year averaged TPW. After that, we fitted a linear regression of relative TPW anomaly change with temperature anomaly, in which the regression slope was selected as the TPW change in response to the temperature change (O’Gorman and Muller 2010; Wang et al. 2016). For all trend analyses using continued time series reanalysis datasets in this study, considering the seasonality in TPW and temperature (T_s, T_{2m}) series, we selected the Seasonal Kendall (SK) test (Hirsch et al. 1982) using the Theil-Sen slopes (Sen 1968; Theil 1992) to calculate the trends of TPW and temperature (T_s, T_{2m}). The statistical significance of all linear correlation and trends used was at the 5% level for all analyses in this study.

To evaluate the agreement of two reanalyses datasets, the Data Concurrence Index (DCI) was calculated from Eq.1 (Anabalón and Sharma 2017; Kim et al. 2022).

\[
DCI = \frac{1}{N} \sum_{i=1}^{N} \frac{h_i T_i}{|T_i|}
\]  

(1)
Where $N$ is the total number of datasets used for trend analysis and $T_i$ is the trend. $h_i$ is the index for p-value. When the trend is statistically significant at a 95% level ($\alpha = 0.05$), $h_i = 1$, otherwise $h_i = 0$ for the $i^{th}$ dataset. Therefore, if the DCI equals 1 (or -1), the two datasets would show a significant upward (or downward) trend. A DCI of zero means the trend of both datasets is not significant while an absolute DCI of 0.5 indicates no consistency between the two datasets.

3. Results

a. Trends in total precipitable water

Figure 1 shows the decadal trends in TPW calculated from ERA5 and JRA-55 monthly data between 1958 and 2021. In general, the two reanalysis datasets provided similar trend patterns of global TPW distribution. TPW trends in most regions of the world indicated an increasing TPW except for some small regions over the southern tropical ocean areas (Fig. 1). The strongest increased trends were located across equatorial regions and these trends in JRA-55 were slightly stronger than trends in ERA5. Both reanalysis datasets show that TPW trends are largely positive with statistical significance over the eastern Americas, as well as the tropical land surface including the Amazon rainforest, north of Australia, the Southeast Asia Archipelago, and at the middle latitude in the Northern Hemisphere and the Arctic in both hemispheres. On the other hand, TPW trends are statistically significant decreasing in both reanalysis datasets over south tropical eastern Pacific regions and the south Atlantic Ocean. The decreasing trend in southwest Australia was not statistically significant. The drying areas over the Pacific Ocean were also observed by previous studies (Trenberth et al. 2005; Chen and Liu 2016; Wang et al. 2016; Borger et al. 2022), one of which explained that these negative TPW trends were influenced by the change of the ENSO phase (Trenberth et al. 2005). In contrast, these two reanalysis datasets show opposite trends over eastern Africa including the Sudan and Ethiopia where ERA5 trends are positive, but JRA-55 trends are negative. The reason for opposite trends can be due to the different representations of large-scale moisture transport, surface-atmosphere processes, and their data assimilation (Parracho et al. 2018). Chen and Liu (2016) and Parracho et al. (2018) also showed decreasing trends in North Africa using ERA-Interim reanalysis for 1979-2014 and 1980-2016.
FIG. 1. Monthly total precipitable water trend (mm decade\(^{-1}\)) from 1958 to 2021 from (a) ERA5 and (b) JRA-55. The stippled areas represent trends that are not significant at the 95% confidence level.

After observing global TPW trend patterns, Figures 2a-e show the time series of monthly TPW anomalies over tropical, temperate, and polar regions. Overall, these trends and variations in ERA5 and JRA-55 are in good agreement. Specifically, the TPW trends are significantly positive with a rate of 0.23 mm decade\(^{-1}\) for ERA5, and 0.36 mm decade\(^{-1}\) for JRA-55 over the tropical regions, ranging from 0.1 to 0.14 mm decade\(^{-1}\) over Northern Hemisphere temperate and polar regions, and less than 0.1 mm decade\(^{-1}\) over Southern Hemisphere temperate and polar regions for both reanalysis datasets. The TPW trends were the largest although with strong month-to-month variability (coefficient of variation, CV, is 0.7 on average) in the tropical region and smaller over middle and high latitudes which are consistent with the global distribution viewed in Figure 1.

The global climate system can also be viewed through the lens of examining land and ocean areas separately. Figures 2f-h depict these trends of TPW estimated over the ocean, land, and the globe. It is noticeable that monthly TPW anomalies were consistently and statistically significantly increased, yielding a rate of 0.15 mm decade\(^{-1}\), 0.17 mm decade\(^{-1}\) and 0.16 mm decade\(^{-1}\) for ERA5 and 0.22 mm decade\(^{-1}\), 0.19 mm decade\(^{-1}\), and 0.21 mm decade\(^{-1}\) for JRA-55 over ocean, land, and the globe, respectively. The monthly TPW anomalies showed a similar variability over ocean, land, and globe (CVs, around 0.4) and only had large differences in some years, which had been dominated by ENSO evolution (Trenberth et al. 2005; Wang et al. 2016). The distinct turning points may be attributed to the intensity of ENSO events, for example, one of the most powerful ENSO events -1997/1998 El Niña led to a significant tropical TPW increase (Wagner et al. 2005), and 2015/2016 El Nino caused a moistening TPW trend over tropical regions (Garfinkel et al. 2018).
FIG. 2. Timeseries of mean monthly TPW anomaly (°C) over (a) the Northern Hemisphere (NH) polar, (b) NH temperate, (c) Tropical, (d) Southern Hemisphere (SH) temperate, (e) SH polar, (f) ocean, (g) land, and (h) the globe from the ERA5 (green curves) and JRA-55 (orange curves) reanalysis datasets during the period 1958–2021. A 12-month running smoother was applied to the time series, and all trends are significant at a 95% confidence level.

We also investigated the agreement of TPW trends from 2003 to 2021 between two reanalysis datasets and compared them with the AIRS satellite data in Figure 3. The major significant trend patterns in the two reanalysis datasets are similar except for only small areas not consistent with each other (Fig. 3c). The agreements of moistening trends with AIRS observations are shown in Central Africa, the Indian Ocean, Southeast Asia Archipelago, northern South America as well as the eastern coast of the United States (Fig. 3d) but the drying trends are less agreeable over south tropical and eastern Pacific regions. The patterns of Figure 3d are similar to the work of Kim et al. (2022) where AIRS data from 2003-2019 was used. In addition, the regions for significant moistening trends in satellite observation are roughly the same as those from reanalyses but with smaller magnitudes, while the significant drying regions in satellite observations are not provided by reanalysis datasets (Figs. 3a, 3d).
Figures 4a-c present the TPW trends using IGRA2 and reanalysis datasets from 1958 to 2021. Over tropical land regions except for central Africa where the radiosonde observations are sparse, the TPW trends over Southeast Asia Archipelago, northern South America are increased in both IGRA2 observation and reanalysis datasets. The trends over mid-latitude land, however, were decreased in IGRA2 which was inconsistent with reanalysis data (Fig. 3).

FIG. 3. Total precipitable water trends from 2003 to 2021 for (a) ERA5, (b) JRA-55, (c) DCI between ERA5 and JRA-55 trends and (d) AIRS satellite. The stippled areas represent trends that are not significant at the 95% confidence level.

FIG. 4. (a) TPW trends from IGRA2 radiosonde observations, ERA5 (b), and JRA-55 (c) and (d) temperature T_a trends in IGRA2 radiosonde observation, ERA5 (e), and JRA-55 (f).

Overall, TPW trends over large tropical lands, the Indian Ocean, high latitudes in NH, and the eastern coast of the United States are positive either from 1958-2021 or from the
short-term of 2003-2021 in two reanalysis datasets. These moistening trends were confirmed by AIRS satellite observation and IGRA2 radiosondes but not for the eastern coast of the United States. However, the drying regions were less agreeable between TPW trends of reanalysis data and observations in mid-latitude land.

b. Trends in temperature

Overall, the global tendency of temperature ($T_{2m}$ and $T_s$) between 1958-2021 exhibits widespread warming in almost all regions except for some small areas in the Southern Hemisphere in both reanalysis datasets (Fig. 5). The warming over land is larger than over ocean (Fig. 5). The trends of $T_{2m}$ and $T_s$ are in a very similar distribution with an obvious warmer trend in the Northern Hemisphere. The strongest warming occurred in the Arctic and larger warming over mid-latitude than tropical warming in Northern Hemisphere, consistent with Zeng et al. (2021). For the Southern Hemisphere, the south polar also experiences higher warming trends which are consistent with the conclusion of Clem et al. (2020). The difference between $T_s$ and $T_{2m}$ trends ($\Delta T$) show that $\Delta T$ is negative over most regions in ERA5 while the JRA-55 $T_s$ trend is warmer than the $T_{2m}$ trend over the Atlantic and Indian Ocean as well as the south Pacific Ocean. Over Asian and Australia, $\Delta T$ is opposite and is mainly negative (or positive) in JRA-55 (or ERA5). Note that there are also a few negative $\Delta T$ spots located over land areas in JRA-55 but not in ERA5 (Fig. 5f).

![FIG. 5. Trends of air temperature at 2 m ($T_{2m}$) (first column) and surface temperature trend ($T_s$) (second column) from 1958 to 2021 for ERA5 (a, d) and JRA-55 (b, e). The difference of trend between $T_s$ and $T_{2m}$ for ERA5 (c) and JRA-55 (f). The stippled areas represent trends that are not significant at the 95% confidence level. Trend units: (K decade$^{-1}$). The time series of temperature trends ($T_s$ and $T_{2m}$) over different latitude bins in both datasets are consistent with the global distribution (Fig. 6), manifested by much larger warming in the Arctic at a rate of around 0.55 K decade$^{-1}$ which is more than three times the global average (around 0.15 K decade$^{-1}$ in Figs. 6m, 6p). Previous studies show that Arctic
warming seems to be linked to sea ice decline, changes in atmospheric and oceanic heat content as well as moisture transport (Graversen 2006; Zhang et al. 2008; Screen and Simmonds 2010). Antarctic warming is at a rate of 0.2 K decade$^{-1}$ while temperate temperature increases less than 0.1 K decade$^{-1}$. The land experienced larger warming with a rate exceeding 0.2 K decade$^{-1}$ for both $T_s$ and $T_{2m}$ compared to the oceans’ warming (Fig. 6). Joshi et al. (2008) explained that the land-ocean contrast was caused by the strong decrease of lapse rate – a rate of decreasing temperature with height – over ocean than over land under global warming, therefore, a strong decrease in ocean lapse rate caused a small increase in sea surface temperature relative to land.

**FIG. 6.** Timeseries of mean monthly $T_{2m}$ and $T_s$ anomaly over (a, f) Northern Hemisphere (NH) polar, (b, g) NH temperate, (c, h) Tropical, (d, i) Southern Hemisphere (SH) temperate, (e, j) SH polar, (k, n) ocean, (l, o) land, and (m, p) the globe from the ERA5 (green curves) and JRA-55 (orange curves) reanalysis datasets during the period of 1958–2021. A 12-month running smoother was applied to the time series, and all trends are significant at a 95% confidence level.

In order to view the skin temperature difference between AIRS satellite observations and reanalysis datasets, Figure 7 shows the global trends in $T_s$ from 2003 to 2021 and $T_s$ trends are agreeable between ERA5 and JRA-55. When comparing the reanalysis trend (Fig. 7c)
with AIRS satellite observations, the geographical patterns of warming show similar patterns with the largest warming found in the Arctic, and large parts of global areas are warming except for significant cooling in south tropical eastern Pacific regions as well as the high- and low-latitude regions of the North Atlantic. The opposite trends are shown over Asia and north Africa. Compared with the satellite observation, there was a significant increase in temperature occurred over oceans except for the south Pacific Ocean and north Atlantic Ocean (Fig. 7). In addition, the trends of surface air temperature in radiosonde observations are consistent with the trend in reanalysis shown in Figures. 4d-f where most regions show a temperature increase. In general, widespread warming is consistently presented observed in almost all regions from reanalysis, AIRS satellite, and IGRA2 observations.

![Maps showing temperature trends from 2003 to 2021](image)

**FIG. 7.** Surface skin temperature trend from 2003 to 2021 for (a) ERA5, (b) JRA-55, (c) DCI between ERA5 and JRA-55 trends and (d) AIRS satellite. The stippled areas represent trends that are not significant at the 95% confidence level.

c. **TPW change response to temperature**

Previous studies have demonstrated that TPW trends are linked to changes in surface temperature (Wang et al. 2016; Yuan et al. 2021). Here we discuss the relationship between the global TPW and the surface temperature change (T_{2m} and T_s). Figure 8 shows the Pearson’s correlation coefficient between monthly TPW and temperature anomalies for winter (DJF) and summer (JJA). During DJF, we found that both T_s and T_{2m} are significantly and positively correlated with TPW over oceans for both ERA5 and JRA-55 although the magnitude for TPW vs. T_s correlation is lower (Fig. 8). The negative correlation over land mainly occurred in south tropical regions including Australia, South Africa region, and
central South America. For the JJA season, similar positive correlations are noted over oceans except for the eastern Pacific Ocean in TPW vs. $T_{2m}$ and TPW vs. $T_s$ while the negative correlations are shown over tropical regions including India, central Africa, central South America and Mexico (Fig. 8).

![Maps showing correlation coefficients between detrended monthly TPW anomaly and air temperature anomaly at 2 meters ($T_{2m}$) and skin temperature ($T_s$) for DJF and JJA from 1958 to 2021 using ERA5 and JRA-55 datasets. The stippled areas represent correlations that are not statistically significant at the 95% confidence level.](image)

**FIG. 8.** The correlation coefficients between detrended monthly TPW anomaly and air temperature anomaly at 2 meters ($T_{2m}$) and skin temperature ($T_s$) for (a, b, c, d) DJF and (e, f, g, h) JJA from 1958 to 2021 using ERA5 (first column) and JRA-55 (second column) datasets. The stippled areas represent correlations that are not statistically significant at the 95% confidence level.

The Clausius–Clapeyron (CC) relation expresses the relationship between the change of temperature and the response of the TPW. TPW is expected to increase with air temperature by about 7% K$^{-1}$ if the relative humidity (RH) in the lower troposphere is constant (Trenberth
et al. 2005). When the RH increases with temperature, the ratio should be above 7% K\(^{-1}\), whereas this value is below 7% if the RH decreases with temperature. This relationship is determined by calculating the ratio between changes in TPW and changes in surface temperature (T\(_{2m}\) and T\(_s\)) (Fig. 9) at a global scale for JJA and DJF seasons. Figures 9a-d show that the dTPW/dT\(_{2m}\) is generally larger over ocean than over land during both DJF and JJA. It tends to be greater than or around 7% K\(^{-1}\) over large parts of the oceans for both ERA5 and JRA-55. The ratios over land show different distributions over different latitude regions and tend to be lower over arid to semiarid areas such as the western US, Australia, and South Africa (Fig. 9). The dTPW/dT\(_{2m}\) is around 6 ~ 7% K\(^{-1}\) over high-latitude regions, such as large parts of Canada, Europe, and Russia in DJF (Figs. 9a-b) while dTPW/dT\(_{2m}\) over Russia during JJA is below 7% K\(^{-1}\). Over mid- and low-latitude regions, it is generally lower over western United States and large parts of China with a dTPW/dT\(_{2m}\) rate ranging from 2 to 4% K\(^{-1}\) during DJF. The ratios over South America, Africa, India, and Australia are well below 7% K\(^{-1}\), even significantly negative over central and southern Africa, and Australia during winter and summer seasons. The land-ocean discrepancy and the spatial variability of these ratios could exist because RH changes with temperature (Wang et al. 2016). Denson et al. (2021) found a decreasing trend in RH under the increased temperature using data covering 1955–2020 in Australia, and Vicente-Serrano et al. (2018) also found a strong negative trend in RH between 1979–2014 over southwestern North America and South America. The dTPW/dT\(_s\) patterns shown in Figures 9e-h are similar to the result of dTPW/dT\(_{2m}\) over land but not for the ocean. The ratios are lower in Figures 9e-h, especially in Southern Hemisphere temperate regions where dTPW/dT\(_s\) ranges from 2 to 7% K\(^{-1}\). Overall, the ratios of dTPW/dT are similar over land in the same season regardless of the T\(_s\) or T\(_{2m}\) temperature used. For ocean regions, dTPW/dT are similar over tropical regions for both T\(_s\) and T\(_{2m}\).
FIG. 9. The linear slope of the percentage of TPW change with respect to $T_{2m}$ or $T_s$ anomalies for (a, b, c, d) DJF and (e, f, g, h) JJA from 1958 to 2021 using ERA5 (first column) and JRA-55 (second column) datasets. The stippled areas represent slopes that are not statistical significance at the 95% confidence level. Unit: $\%$ K$^{-1}$.

In addition to the global spatial dTPW/dT ratios, the ratio’s latitude dependency is an interesting subject that was shown in Figure 10, focusing between 60° S and 60° N of latitudes. Although the TPW response values show strong variations across latitudes, the ratios show a similar changing pattern over the globe and ocean, which also vary across the theoretical CC curves of dTPW/dT ratios (Figs. 10a, c, d, f). Over most of the Northern Hemisphere, both dTPW/dT ratios are smaller than the CC response curves but is true only over temperate latitudes (~40 to -20°N) in the Southern Hemisphere for both the globe and ocean. Such strong latitude dependency and discrepancy between land and ocean are
associated with zonal RH changes and possible amplification of surface warming over land relative to the ocean (O’Gorman and Muller 2010) (Figs. 10c, f). There are two stronger response zones, located in the southern high-latitude and the tropics over the globe and ocean (Figs. 10a, c, d, f), which is the same conclusion reached by O’Gorman and Muller (2010).

For land areas, in addition to two stronger response zones similar to the globe and ocean, a local maximum was found in the sub-tropical areas of the Northern Hemisphere (Fig. 10). The ratios for the land region are mainly lower than the theoretical ratio (around 7% K\(^{-1}\)), and they are even negative in tropical latitudes. Comparing the ratios based on \(T_s\) and \(T_{2m}\), their discrepancies are greater over land, which contributes to their discrepancies over the globe.

![Figure 10](image)

**FIG. 10.** The meridional means of percent change of TPW in response to \(T_{2m}\) (first column) and \(T_s\) (second column) for ERA5 (green line) and JRA-55 (orange line) over (a) globe, (b) land, and (c) ocean. The dashed lines represent the theoretically expected CC-response based on the climatological zonal mean temperature from the trend analysis.
4. Summary and conclusion

Atmospheric reanalysis is widely used in the global climate change assessment and its accuracy has improved in recent years. In this study, we selected ERA5 and JRA-55 reanalysis datasets to estimate global TPW, $T_s$ and $T_{2m}$ trends from 1958 to 2021 and compared them to AIRS satellite and IGRA2 radiosonde observation datasets. In addition, the relationship between trends of TPW and temperature change among seasons is evaluated. General agreement is found in TPW, temperature trends and their spatial variations between the two reanalysis datasets over ocean and land.

TPW moistening trends are shown in most regions of the world except for the regions over the South Pacific Ocean where TPW trends are negative, which are consistent with results from previous studies (Trenberth et al. 2005; Chen and Liu 2016; Wang et al. 2016; Borger et al. 2022). The magnitude of the moistening trends tends to decrease away from the low latitudes from 1958 to 2021. TPW anomalies increase with time and are in good agreement in both reanalysis datasets, yielding a rate of 0.15 mm decade$^{-1}$, 0.17 mm decade$^{-1}$, and 0.16 mm decade$^{-1}$ for ERA5 and 0.22 mm decade$^{-1}$, 0.19 mm decade$^{-1}$, and 0.21 mm decade$^{-1}$ for JRA-55 over ocean, land, and the globe, respectively. Comparing reanalysis with observations, trends in TPW over large tropical lands, the Indian Ocean as well as high latitudes in NH are positive for both longer period of 1958-2021 and the shorter period of 2003-2021 in both reanalysis datasets. These moistening trends are verified by AIRS satellite and IGRA2 radiosonde observations. However, the drying regions were less agreeable between TPW trends of reanalysis data and observations in mid-latitude land.

Besides TPW, significant warming trends of $T_{2m}$ and $T_s$ are noted in almost all regions across the globe except some areas in the Southern Hemisphere in both reanalysis datasets between 1958-2021 and observation datasets. In addition, the warming over land is larger than over ocean. For average temperature time series, warming in the Arctic is the largest (0.55 K decade$^{-1}$) which is three times more than the global average (around 0.15 K decade$^{-1}$). The Antarctic warming is like the warming in NH temperate with a 0.2 K decade$^{-1}$ increasing trend. The land experienced larger warming than the ocean with a rate exceeding 0.2 K decade$^{-1}$ for both $T_s$ and $T_{2m}$.

The TPW monthly anomaly is well correlated with $T_s$ and $T_{2m}$ over ocean and land, and the areas in conjunction with TPW positive trends generally show warming trends in $T_s$ and $T_{2m}$. The ratio of TPW percentage changes with temperature in winter and summer seasons
shows large variations, with larger values over oceans than over land. The ratio ranges from 5-11% K\(^{-1}\) over ocean and below 4% K\(^{-1}\) to even negative over land, which is partially related to the large difference in the land’s RH change (Wang et al. 2016). The ratios of dTPW/dT are similar using temperature \(T_s\) or \(T_{2m}\) over land, while for oceanic regions, dTPW/dT are similar over tropical regions by using \(T_s\) or \(T_{2m}\). For the global mean, the ratios show a similar change over the globe and ocean, and the ratio fluctuates between 6 and 8\% K\(^{-1}\) over 15 - 60°N and increases towards southern high latitudes over oceans. The maximum values in the southern high latitude are found over the globe, land and ocean, which is consistent with the conclusion of O’Gorman and Muller (2010).

**Acknowledgments.**

This study was supported in part by the U.S. Department of Agriculture, National Institute of Food and Agriculture (grant no. 2016-68007-25066). The contribution number of this manuscript is 23-057-J. We thank Dallas Staley for editing and finalizing the paper.

**Data Availability Statement.**

The ERA5 dataset is openly available from ECMWF: https://cds.climate.copernicus.eu/cdsapp#!/dataset/reanalysis-era5-single-levels-monthly-means?tab=overview. The JRA-55 dataset is available from https://rda.ucar.edu/datasets/ds628.0/. The AIRS satellite data is from https://disc.gsfc.nasa.gov/datasets/AIRS3STD_006/summary. IGRA2 data archived by the National Centers for Environmental Information and can be accessed at ftp://ftp.ncdc.noaa.gov/pub/data/igra

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