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ABSTRACT

Water vapor is a vital basis of water and energy cycles and varies with space and time. When researching the variations of moisture in the atmosphere, it is intuitive to think about the total water vapor of the atmosphere column, precipitable water. It is an element that needs high-altitude observations. A surface quantity, surface water vapor pressure, has a close relationship to precipitable water because of the internal physical linkage between them. The stability of their linkage at climatic scales is verified in this work, while studies before mainly concentrated on daily and annual cycles. The consistency of their variations is checked with three reanalysis datasets from three angles, including the interannual variations, the long-term trends, and the first EOF modes. Results show that the interannual correlation of surface water vapor pressure and precipitable water can reach a quite high level in most areas, and the weak correlation regions mainly exist in low-latitude areas. The long-term trends, as well as the first EOF modes of these two quantities also show that their variations are well consistent, but specific differences appear in some regions, and there are discrepancies among different datasets. With the correspondence of precipitable water and surface water vapor pressure, the variations of total column water vapor can be indicated by the surface quantity, surface water vapor pressure. The correspondence is also meaningful for the analysis of the co-variation of total column vapor and temperature. For example, we could research the relations between surface vapor pressure and air temperature, and it can reflect the co-variance of total column

vapor and near-surface air temperature. Linking the column integrated moisture content to surface temperature directly or integrating the column temperature can be avoided.

1. Introduction

As a component in the global water and energy cycles, atmospheric water vapor is also an important part of climate variability and change (e.g., Stewart et al. 1998; Semmler et al. 2005; Trenberth and Fasullo 2013). Water vapor is the material basis of precipitation, and the latent heat released by precipitation is a part of the energy cycle and can drive atmospheric circulation anomalies (e.g., Mathew and Kumar 2019; Hao and Lu 2021). The circulation may, in turn, transport water vapor, and change the spatiotemporal distribution of the water vapor (e.g., Zhou and Yu 2005). As the highest content greenhouse gas in the atmosphere, water vapor can also affect the radiation transfer in the atmosphere (e.g., Radcliff et al. 2015).

Precipitable water (PW), a conventional quantity of humidity, is the column-integrated water vapor amount in the atmosphere. In a regional column, the water vapor evaporated from the earth's surface, along with the water vapor converged from the surroundings, is used to increase the PW. When the air saturates, at least at certain levels, precipitation may be produced.

In the early stage, the acquirement of PW data nearly all relied on the radiosonde observations (e.g., Cady-Pereira et al. 2008; Durre et al. 2009). Because of the high costs of radiosonde and the sparsity of observation stations, studies about empirical equations between PW and surface elements appeared. A surface quantity, the surface vapor pressure (SVP), has been stressed that it has a close statistical linkage to PW (e.g., Wang and Gaffen 2001; Dai 2006; Willett et al. 2008; Isaac and Wijngaarden 2012). This linkage can also be explained from physical respect. Surface vapor pressure can be regarded as the force exerted by the total moisture in the air column (e.g., Wallace and Hobbs 2006), in analogy with the surface pressure to the total mass of the air column. With the normal profile, water vapor content is maximal at the near-surface level and decreases with altitude because of the existence of gravity. Hence, the surface vapor pressure can well represent the column total water vapor content (e.g., Lu and Zeng 2005; Lu 2007). Because of the lack of upper-air detections, the

empirical relations between PW and SVP were utilized to estimate the PW with surface observations, especially during the early stage when there were just a few sounding observations (e.g., Reber and Swope 1972; Viswanadham 1981; Liu 1986; Hsu and Blanchard 1989).

The studies before mainly concentrated on the relation of PW with SVP at daily and hourly scales. In the present study, we focus on the consistency of interannual variations and the long-term trends of the monthly mean PW and SVP. Because of the warming and enhanced evaporation, atmospheric moisture is often linked to tropospheric temperature or surface air temperature (e.g., Gaffen et al. 1992; Sun and Held 1996; Bauer et al. 2002; Mears et al. 2007; L et al. 2014). Some advanced methods can be used to obtain the data of PW on the current, including the remote sensings such as the radar observations and satellite retrievals (e.g., Dostalek and Schmit 2001; Deeter 2007), the GPS observations (e.g., Radhakrishna et al. 2015; Torri et al. 2019), the model outputs, and the reanalysis (e.g., Zveryaev and Chu 2003; Ssenyunzi et al. 2020).

Because of the appearance of these measuring methods, maybe the demands of calculating PW with surface elements are not so imperious as earlier. However, analyzing the relationship between them is still meaningful. Firstly, it is easy to understand that over areas with few instructions such as oceans, the SVP can be calculated with PW retrieved by satellite remote sensings. Some studies researched the linkage between PW and surface air temperature (Smith and Arkin 2015; Wang et al. 2016a) and reestablish the PW at periods that lack high-altitude observations. The surface quantity which can directly reflect the PW is SVP. Because of the physical relation between SVP and temperature, there is also a tight linkage between PW and surface air temperature. The trend of PW was studied in some studies under global greenhouse warming (Trenberth et al. 2005). The long-term trends and interannual variations of total water vapor in the atmosphere can be reflected by SVP if the variations of the two quantities are well consistent. Then SVP is more suitable than PW to be used to analyze the synergetic variations of moisture content with air temperature and other

elements because we could use the quantities that are all at the surface level. It can avoid the problems brought by linking the column integrated moisture with surface-level temperature or integrating the intensive quantity. The linkage between PW and SVP is analyzed from three angles concurrently. The first one is fixing the correlation of their interannual variations. Different from the daily or annual cycles, the interannual variations of these two physical variables may be much smaller. Hence, whether the linkage between them is still stable at interannual variations is the question to which is tried to answer. For similar reasons, the long-term trends of PW and SVP are also compared. To further verify the consistency of their variations, the first empirical orthogonal function (EOF) modes of them including spatial distributions and time series are shown and compared too.

When verifying the interannual relationship between PW and SVP, the simple correlation coefficient is adopted. There are some ways to estimate the trends of hydrological and meteorological elements including parametric and non-parametric methods (Duhan and Pandey, 2013). Analysis of long-term trends includes the confirmation of increasing or decreasing slopes and significance testing (Jain and Kumar, 2012). The non-parametric methods are preferred because of their indeterminacy of the distribution of the variables. Mann-Kendall test was formulated by Mann (1945) as a non-parametric test for trend detection. And the test statistic distribution had been given by Kendall (1970) for testing non-linear trends and the turning points. It is an excellent non-parametric method and is preferred by many researchers (Mondal et al., 2012; Jain and Kumar, 2012). The MK test does not need the variable to follow a normal distribution and show homogeneity of variance. Transformations are not required if the data already follow the normal distribution (Duhan and Pandey, 2013). The MK test also discusses the function of slope in the trend, coefficient of variation, and type of probability distribution. It is used for trend analysis as it eliminates the effect of serial dependence on auto-correlated data which modifies the variance of datasets (Hamed and Rao, 1998). Sen's slope estimation, also a non-parametric method, gives the magnitude of the trend (Sen, 1968). This method assumes that the trend line is a linear function in the time series.

Another advantage of Sen's slope is that it is not affected by outliers and single data errors in the dataset (Pal et al. 2017).

The reanalysis datasets universally own decent accuracy in broad areas, with the support of the accumulations of vast amounts of historical observations, advanced modeling, and data assimilation systems. They have been applied in the studies on the hydrological fields and their effects have been verified (Wang et al 2016b). With the aim of the global-scale study and ensuring the credibility of the results, three reanalysis datasets from different institutions including the European Centre for Medium-Range Weather Forecasts (ECMWF) Reanalysis v5 (ERA5), Japanese 55-year Reanalysis (JRA55), and the National Centers for Environmental Prediction and the Department of Energy (NCEP-DOE) Reanalysis-2 (NCEP2) are used in the paper.

The datasets together with the methods adopted are presented in Section 2. The consistency of interannual variations and long-term trends of PW and SVP are shown in the first half of Section 3. And the EOF modes are compared in the second half. Section 4 shows the summary and discussion.

2. Data and Method

a. Data

The three reanalysis datasets from three different institutions, the ERA5, JRA55, and NCEP2 are used in the paper. The ERA5 (Hersbach et al. 2020), provided from the ECMWF, is the fifth generation ECMWF atmospheric reanalysis of the global climate covering the period from January 1950 to the present. ERA5 is produced by the Copernicus Climate Change Service (C3S) at ECMWF. The data covers the Earth on a 30km grid and resolves the atmosphere using 137 levels from the surface up to a height of 80km. Different horizontal resolutions can be chosen, and a version with the horizontal resolution of $1^{\circ} \times 1^{\circ}$ in latitude and longitude is adopted. The pressure level elements that are shown in vertical profiles are at 11 isobaric levels (from 1000hPa to 100hPa). The NCEP-DOE Reanalysis-2 project performs data assimilation using past data from 1979 through the previous year

(Kanamitsu et al. 2002). The data with the $2.5^{\circ} \times 2.5^{\circ}$ horizontal resolution in latitude and longitude is used and there are 12 isobaric levels in vertical. Spanning 1958-present, JRA-55 is the longest third-generation reanalysis that uses the full observing system. Compared to the previous generation Japanese Meteorological Agency (JMA) reanalysis (JRA-25), JRA-55 uses a more advanced data assimilation scheme, increased model resolution, a new variational bias correction for satellite data, and several additional observational data sources (Kobayashi et al. 2015). Its horizontal resolution is $1.0^{\circ} \times 1.0^{\circ}$ and there are also 12 layers used in the vertical direction.

The elements used include the monthly mean precipitable water (W), the 2-m temperature (T), and dewpoint temperature (T_d) of 42 years from 1979 to 2020. The near-surface water vapor pressure and saturation water vapor pressure are calculated using the raw data, T and T_d , through the modified-tetens formula (Alduchov and Eskridge 1996), then the relative humidity can be calculated. As for the quantities at pressure levels, the moisture-related quantity given by ERA5 and JRA55 is specific humidity and that given by NCEP2 is relative humidity. Utilizing one of them with temperature, the other one can be figured out. In the contents of interannual variations and EOF analysis, calculations and plots are performed for all 12 months, and results of four representative months, including January, April, July, and October, are presented. As for the analysis of long-term trends, the results of four seasons are shown, but not the representative months.

b. Method

1) Mann-Kendall Test

The MK test statistic S is given by

$$S = \sum_{i=1}^{n-1} \sum_{j=i+1}^n \text{sgn}(x_j - x_i), \quad (1)$$

in which x_i and x_j are time sequences of the variable and n denotes the length of the sequence. The series x_i is ranked from $i = 1, 2, \dots, n-1$ and x_j is ranked from $j = i+1, i+2, \dots, n$. The function sgn is denoted as

$$sgn(t) = \begin{cases} 1, & \text{for } t > 0 \\ 0, & \text{for } t = 0 \\ -1, & \text{for } t < 0 \end{cases} .$$

(2)

Each of the data point x_i is taken as a reference point which is compared with the rest of the data points x_j . The sign of S represents the direction of the trend, while a positive value means increasing and a negative means decreasing. When the length of the sequence, n , is over eight, the statistic S follows normal distribution approximately and satisfies

$$E(S) = 0 \quad (3)$$

and

$$Var(S) = \frac{n(n-1)(2n+5) - \sum_{i=1}^m t_i(t_i-1)(2t_i+5)}{18} ,$$

(4)

where E and Var are the mathematical expectation and the variance respectively. The quantity t_i is the number of ties up to the sample i and m is the number of tied groups (the group that includes samples with the same values). Then the normalized test statistic is calculated as

$$Z = \begin{cases} \frac{S-1}{\sqrt{Var(S)}}, & \text{for } S > 0 \\ 0, & \text{for } S = 0 \\ \frac{S+1}{\sqrt{Var(S)}}, & \text{for } S < 0 \end{cases} .$$

(5)

It follows the standard normal distribution. The trend is considered to pass the α significance level (non-zero) if $|Z_{MK}| \geq Z_{\alpha/2}$.

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2) Sen's Slope Estimator

The values of the long-term trends are calculated with the Theil-Sen slope estimator and it is also a non-parameter method (Sen, 1968). In this model, the slope values reflect the increasing and decreasing magnitudes of variables. The slopes between two points are given as

$$T_i = \frac{x_j - x_k}{j - k}, \text{ for } i = 1, 2, 3, 4, \dots, N ,$$

(6)

in which x_j and x_k are the data values for j and k times of a period where $j > k$. A single slope value is achieved with each pair of values and the total number of slope values is

$$N = \frac{n(n-1)}{2}.$$

Then the median of N slopes is Sen's Slope.

Fig. 1 Maps of correlation coefficients of PW and SVP (The dataset used is ERA5). The correlation coefficients in shaded areas cannot pass the 0.01 significance level. Blue squares are areas selected to show the vertical profiles.

3. Results

a. The theoretical linkage between PW and SVP

PW is the total vapor amount in the atmosphere column and can be expressed as

$$W = \int_0^{\infty} q \rho dz,$$

(7)

in which q is specific humidity and ρ is air density. In equations, the precipitable water is denoted as W . Under the condition of hydrostatic equilibrium, the equation can be transferred to the isobaric-coordinate form

$$W = \int_0^{p_s} q / g dp.$$

(8)

214 Employ the σ -coordinate $\sigma \equiv p/p_s$ and express specific humidity with water vapor pressure
 215 as $q = \varepsilon(e/p)$ where e is water vapor pressure and ε is the ratio of dry and wet gas
 216 constant. As shown by Lu (2007), the PW can be written as

$$217 \quad W = \left(\frac{\varepsilon}{g}\right) \int_0^1 e \cdot d\ln\sigma. \quad (9)$$

218 The vapor pressure e normally reaches its maximum at surface level, then decreases with the
 219 altitude (Peixoto and Oort 1992). Vapor pressure can be seen as a function of σ
 220 approximately and expressed as $e = E\sigma^m$. In the formula, SVP is denoted as E and m is a
 221 constant in a specific area. Then, the relationship between PW and SVP can be expressed as

$$222 \quad W = k \cdot E, \quad (10)$$

223 and $k = \varepsilon/(gm)$ in the formula. As a result, W has a close linkage with surface vapor
 224 pressure E .

225 In another point of view, SVP is produced by the total water vapor in the air column and
 226 their linkage is the same as the relationship between surface pressure and the total quality of
 227 the columnar air mass. The atmosphere is not motionless, so the stratification stability is an
 228 important precondition of the stability of this linkage. Numerous studies before have proved
 229 the relationship of SVP and PW from the statistical aspect, and there are empirical equations
 230 of them (Reber and Swope 1972; Viswanadham 1981; Hsu and Blanchard 1989). Due to the
 231 appearance of progressive observation methods such as satellite remote sensing, the PW data
 232 can be used to estimate values of SVP in reverse in the areas where are hard to establish
 233 observation stations (Liu 1986). Studies before mainly focused on daily or annual cycles. In
 234 daily or seasonal variations, the radiation processes vary dramatically, so following the
 235 temperature, PW and SVP both have obvious variations and are easy to be consistent. When
 236 analyzing the interannual variations or long-term trends, the fluctuation may be much smaller.
 237 The question researched here is whether the consistency is reliable at climatical scales. And
 238 the relationships are verified from three angels.

Fig. 2 Similar to Fig. 1, but the dataset used is JRA55.

Fig. 3 Similar to Fig. 2, but the dataset used is NCEP2.

b. The Consistency of Interannual Variations

Fig. 1 to Fig. 3 shows the maps of interannual correlation coefficients of monthly mean PW and SVP calculated with three reanalysis datasets respectively. Correlation coefficients in four representative months including January, April, July, and October are exhibited. The coefficients in most of the world are positive and can pass the 0.01 significance level. Just a few areas do not pass the significance test and they are almost all in low-latitude regions. As has been said before, the stratification of the tropical atmosphere is less stable and the more

251 convections there probably break the strong linear relation. The linear relation is especially
252 strong in some areas, such as the Antarctic, Australia, Eurasian Continents, North America in
253 January, and Eurasian Continents, North America in July. With temporal variations,
254 insignificant correlation areas in January are smaller than those in July. Values of coefficient
255 at high latitudes in January, April, and October are large and can reach the 0.01 significance
256 level. Differently, there exist some weak correlation areas at mid-to-high latitudes in the
257 Northern Hemisphere in July. It is plausible that this pattern is also relevant to stronger
258 convections in these areas in Boreal Summer. Comparing the results got with different
259 datasets, the weak correlations in the Tropical Western Pacific, the coast of South Asia,
260 Indo-China Peninsula, small parts of Tropical Atlantic in all four months, and the coast of
261 North America in July are uniform. The strong correlations in a large number of areas are
262 similar among the results calculated with the three datasets. There also exist differences
263 among different datasets. Overall, insignificant correlation areas of NCEP2 are larger than
264 those of ERA5 and JRA55. Results of the three datasets uniformly show that PW and SVP are
265 strongly correlated in most regions and prove the linear relation at the monthly scale when
266 analyzing their interannual variations. The spatial patterns of correlation coefficients are also
267 concurrent among the three datasets.

Fig. 4 The vertical profiles of temperature, vapor pressure, and relative humidity in Strong and weak correlation areas. The dashed lines are those with strong correlations. The columns from left to right corresponds to three datasets respectively. The upper row is oceanic areas and the bottom row is continental areas.

In Fig. 4, the vertical profiles of temperature, vapor pressure, and relative humidity in weak and strong correlation regions are shown to fix the distinctions between strong and weak correlation situations. The regions chosen are squared in Fig. 1-Fig. 3 correspondingly, and the subgraphs in the upper row correspond to oceanic areas. It can be seen that the relative humidity in Tropical Southeast Pacific (the strong correlation area) decreases fast below the mid-troposphere and the slopes are steeper in weak correlation areas that means it decreases more slowly. The profiles of vapor pressure have similar features to those of relative humidity, and the distinctions of vapor pressure between weak and strong correlation areas are smaller. As for the oceanic areas with abundant moisture sources, the lower relative humidity at middle levels indicates the weaker convections there. Meanwhile, the vapor concentrates at lower levels, so PW and SVP have concurrent variations, as expected before.

Subgraphs in the bottom row exhibit profiles in continental areas. The weak correlation area is near North Africa and it is nearly the sole continental area with insignificant correlations. The vapor pressure decreases fast with altitude in the weak correlation area and

is nearly exhausted at 600hPa. The profiles of temperature in weak and strong correlation areas are similar, and the relative difference between low and middle levels is larger in strong correlation areas. The relative humidity has the most obvious distinctions between weak and strong correlation areas in the results of all three datasets. The relative humidity in strong correlation areas reaches its maximum at middle levels, while the condition is almost reversed in weak correlation areas. The extremely dry situation in some parts of North Africa corresponds to the unstable relationship between PW and SVP. The internal reasons are dubious here and just a plausible explanation can be given. The drought in these areas is brought by the strong subsidence of the atmosphere. Not only upward motion, but downward movement may also affect the relationship between PW and SVP. In an environment with poor moisture contents, the effects of vertical movement may be relatively larger. Even little fluctuation may double the SVP and the PW just has little variations. The more specific physical processes still need further study combing the details of circulations.

Fig. 5 The long-term trends of PW (the left column, unit: $kg \cdot m^{-2}/yr$) and SVP (the right

column, unit: hPa/yr) in four seasons calculated with the ERA5 dataset. The subgraphs from top to bottom respond to Spring to Winter respectively. The trends in shaded areas reach the 0.05 significance level.

Fig. 6 Similar to Fig. 5, but the dataset used is JRA55.

Fig. 7 Similar to Fig. 6, but the dataset used is NCEP2.

c. Consistency of long-term trend

Fig. 5-7 shows the maps of long-term trends of PW and SVP in four seasons during 1979-2020 calculated with three datasets separately. Some similar features can be seen from the results of the three datasets. The large slope areas mainly concentrate on the Tropics. The accordant variations of the two quantities include the positive trends in Southeast Asia, Tropical Northwest Pacific, Tropical Southwest Pacific, Equatorial North Atlantic, Northwest of South America, India Peninsula, and Arabian Peninsula in Spring, together with negative trends in Tropical Southeast Pacific and Equatorial Indian Ocean all around the year. The specific positions of these regions with significant trends may have some differences among different datasets, but the differences are not large. There are also some areas with biggish discrepancies among different datasets, such as some parts of Africa. The values of the slope got with NCEP2 in these areas are generally larger and the significant trends cover more regions. There appears a positive-negative-positive pattern in the meridional direction. The

result got with ERA5 exhibits a nearly reverse distribution in these areas in Spring, but the trends in Summer and Autumn are similar to those of NCEP2. The negative trends in Tropical Southeast Pacific calculated using JRA55 are distinctly weaker than the trends got with the other two datasets. On the whole, NCEP2 has the largest absolute slope values and the negative slopes of JRA55 are the weakest. Larger areas of trends in the Antarctic pass the significance test in the result of JRA55. The holistic distributions of the slope of ERA5 are moderate among the three datasets. The distributions of trends also have temporal variations. In Australia, for example, the trends there in Summer and other seasons are disparate. In some regions with the same signs of the slopes all around the year, the absolute values are larger in Summer and weaker in Winter. The absolute values of the slopes in polar areas are not large, but trends in most parts of these places can reach the 0.01 significance level, due to the climate of low air temperature and little vapor there.

Maps of SVP trends are shown in the right columns of Fig. 5-7. The trends of SVP and PW of each set of data are compared separately. In JRA55, focusing on the regions with significant trends, SVP and PW have concurrent distributions to some extent, such as the negative trends in Central Europe. However, the negative trends of SVP over oceans are weaker than those of PW, including the shallow areas in Tropical Pacific in Spring, Tropical South Atlantic in Summer, and Tropical South Pacific in Autumn. Over Eurasia, the areas with significant trends of SVP are larger than those of PW, while the situation is inverse in Northwest Pacific.

Fig. 8 The time series of global areal weighted averaged 2m-temperature, PW, and SVP of three datasets. The three numbers at the top-right of subgraphs are Sen's value of three elements separately (the units are the same as those in Fig. 5).

In the result calculated with ERA5, the trends of SVP and PW are a little more consistent than those in the result of JRA55, although the problem that the trends of SVP are weaker than those of PW still exists. The phenomenon in Eurasia is similar, SVP having more significant trends in larger areas, but the differences of SVP and PW are smaller than those of JRA55. The long-term trends of SVP and PW in some places, such as the West Pacific, Africa, Atlantic, North and South America are well consistent all around the year. Similar to the distributions of PW, trends of SVP got with NCEP2 are also generally stronger than those calculated with the other two datasets. The values of slopes and the areas with significant trends are both larger, and the trends of SVP still weaker than those of PW in the result of NCEP2. The trends of SVP are weaker than those of PW in the Pacific and the trends of two quantities are even reversed in the Indian Ocean. In the North of Eurasia and Arctic, the trends

of SVP are stronger. Trends of the two quantities in North Atlantic and North America are relatively consistent, but the decreasing of SVP on the east coast of South America is not so obvious as that of PW.

Fig. 9 EOF1 of PW (left) and SVP (right) calculated with ERA5. The percentages at the top-right of subgraphs are fractional mode variances corresponding to PW and SVP.

Fig. 10 Similar to Fig. 9, but the dataset used is JRA55.

Fig. 11 Similar to Fig. 10, but the dataset used is NCEP2.

The curves of global areal weighted average PW, SVP, and surface air temperature are shown in Fig. 8. The trends of all three quantities can pass the 0.01 significance level with the MK test in four months. Under greenhouse warming, the global average of SVP and PW both have significant increasing trends. From this point, results calculated with three sets of data can reach an agreement, and the trends of SVP and PW both amplify in July and October. However, when comparing the slope values of SVP and PW, there are still some differences among different datasets. Their trends are not so consistent as temperature. From the curves, it can be seen that the normalized PW and SVP overlap in quite a few parts of 42 years. Even in the rest periods, the two curves are almost parallel and the only relatively large difference exists in October in the result of NCEP2. Hence, the global averages of PW and SVP have consistent long-term trends and interannual variations, that is to say, the interannual variations and trend of global mean SVP can reflect those of PW to a large extent.

Overall, from the angle of spatial distributions, three datasets all exhibit a feature that the

trends of SVP are weak in the Pacific and strong in Eurasia. The increasing (decreasing) trends of PW may be contributed from two parts. The first one is the increasing evaporation directly caused by greenhouse warming, and the other is the column integrated vapor convergence (divergence). With the comparison of trends of PW and SVP in West Pacific and Southeast Asia, it can be concluded that the contributions of vapor convergences at mid-to-high levels takes a large part in the increased PW there. Similar conditions exist in Tropical Southeast Pacific. And combining the phenomena in these two areas, the weakening trend of the westerly stream may be indicated. The trends of SVP in high-latitude areas of Eurasia are stronger than those of PW. It is plausible that the increasing trends of SVP over there are mainly contributed from the increased water capacity and evaporation, but the vapor transport at higher levels may be weakened with the weakened circulation. Eventually, the trends of PW are not so obvious as SVP in these areas. The global areal average SVP and PW also have consistent increasing trends and the trends calculated with three datasets are all significant.

d. The consistency of the first leading EOF mode

To further confirm the reliability of the relationship between SVP and PW, the first EOF modes of PW and SVP are shown and compared. Fig. 9 to Fig.11 is the spatial patterns of the first EOF modes of PW (left) and SVP (right) get with three datasets respectively. There exist ENSO-like patterns, the inverse deviations in Northwest and Mid-to-East Pacific, in all four seasons. However, what is mostly cared about is the similarity of distribution modes of the two quantities. The result of ERA5 shows that the spatial patterns of the two quantities are quite similar, and just little differences exist in the negative value parts of Tropical Pacific in April and July. The result calculated with JRA55 is similar, while the little divergences between PW and SVP are also over Tropical Pacific in April and July. What needs notice is that the two modes are nearly inverse in April, but the time series of the two quantities are also in contrast. Hence, due to the peculiarity of the EOF method, the entireties of the first leading modes of PW and SVP still correspond well to some extent, but not as well as those in

other months. The differences between spatial patterns of PW and SVP are relatively larger in the results of NCEP2. The distinctions of patterns are obvious in April, July, and October. Especially in October, not only the density of the negative center in the Tropical Pacific is not so coherent, but there are also some apparent differences in the Middle East and Southeast of Africa. However, regions with similar patterns of SVP and PW are still preponderant. The large values are almost all at low latitudes and concentrate in oceanic regions in January and October. As a whole, the spatial patterns of the first EOF modes of PW and SVP got with ERA5 and JRA55 datasets are more coherent than those got with NCEP2. The spatial patterns of the first EOF modes of each element among the three datasets are similar too, but the specific values are a little different, especially the values calculated with NCEP2.

Fig. 12 The principal component time series (PCs) of EOF1 of PW and SVP were calculated with three datasets separately (scaled to unit variance). The percentages at the top-right of subgraphs are fractional mode variances corresponding to PW and SVP.

The time series of the first EOF modes are exhibited in Fig. 12. Corresponding to the

consistency of spatial patterns, the time series of SVP and PW got with ERA5 almost overlap in many parts in all months except April. The problem in April is just the steeper of the curve of SVP in some periods. A similar problem appears in the result of JRA55. Because of the nearly inverse spatial patterns in April, the time series are also inverse in many periods. However, there are also some differences between the amplitudes of the two curves. Compared to those in other months, the coherence of the time series is weaker in April. As for NCEP2, the time series with the largest discrepancies exist in October, and the differences in July are also obvious. In October, the time series of SVP is stable with an increasing trend, while the PW is fluctuating and its trend is not so apparent. Correspondingly, the spatial patterns in October are also more moderate than those in other months, even with inverse patterns in some areas.

Combining the spatial patterns and time series synthetically, the first EOF modes of PW and SVP can correspond better than expected. The consistency of PW and SVP in the result of ERA5 is the best, next JRA55, and NCEP2 is the last. It is just the rank of the coherence of the two quantities but does not mean the quality rank of the three datasets. The consistency of the first EOF modes of PW and SVP in results got with three sets of data further proves the close relationship between them in interannual variations and long-term trends. It is a supplement to the statistical basis of using the variations of SVP to represent those of PW, or reversely.

4. Conclusion and Summary

Because of the deficiency of high-altitude observations and the internal physical relationship of PW and SVP, the linkage between them has been researched for some decades. However, those researched much are the daily and annual cycles. The question answered here is whether the linkage is reliable at climatic scales, including interannual variations and long-term trends of monthly mean variables. With verifications, the monthly mean PW and SVP are strongly correlated in interannual variations. As a whole, correlations in high-latitude areas are stronger than those in low-latitude areas, and correlations in Winter are stronger than

those in Summer. The correlation coefficients in most areas can pass the 0.01 significance level, and the insignificant correlations just exist over tropical oceans and some high-altitude areas in North Hemisphere in boreal summer. Through analyzing and comparing the vertical profiles of humidity-related quantities in weak and strong correlation regions, it is found that the relative humidity is smaller at middle levels in oceanic strong correlation areas. In these areas, the feature of weaker convections is indicated, which matches our hypothesis. The continental areas with weak correlations are quite small, and almost just over a few parts of North Africa. Different from the features of some continental areas with strong correlations, the relative humidity in these regions reaches its minimum at middle-to-low levels, reflecting an extremely dry climatic feature. Associated with the drought, it is probable that the downward motions in these areas break the steady linear relationship. There is a quite small amount of moisture, hence, the effects of vertical movements are relatively more destructive. The first EOF modes of PW and SVP also exhibit decent coherence in all three datasets. The results calculated using ERA5 and JRA55 show better consistencies, but the holistic spatial patterns and time series in the result of NCEP2 can also correspond well. The large value areas of spatial patterns mainly concentrate in low-to-mid latitude areas and there is an ENSO-like pattern in Mid-to-East Pacific.

The long-term trends of SVP and PW are also analyzed. The trends of PW and SVP are coherent in quite large areas of the earth, including the increasing trends in Tropical and North Pacific, North Atlantic, Pole areas, Northwest of South America and Africa, as well as the decreasing trends in Tropical Southeast Pacific and small parts of Africa. However, three datasets exhibit a common characteristic that the trends of SVP in the Pacific are weaker than those of PW, and inverse conditions exist in Eurasia. The increasing trends of PW may be contributed from two parts. One is the increased evaporation following the warming of the troposphere, and the other is the column integrated vapor convergence. The increasing trends of PW in the West Pacific and Southeast Asia are taken a great part by the vapor convergence at high-altitudes, speculated from the comparison of trends of SVP and PW in these regions. The decreasing trends in Tropical Southeast Pacific are contributed by similar components,

and there seems a weakening trend of the westerly streams there. The trends of SVP in high-latitude areas of Eurasia are stronger than those of PW, indicating that the SVP is increased by the attenuated upward movements and enhanced evaporation caused by warming. The vapor transport at high levels may be weaker with the weakening of circulations, corresponding to the trends of PW being weaker than SVP. As a whole, the variations of SVP and PW are consistent in vast areas regardless of the dataset used. Because the specific values of trends, interannual correlation coefficients, and EOF modes differ among different datasets, some areas with large discrepancies need more accurate observations to be verified, such as the Indian Ocean and East South America. In some studies, the relation between PW and surface temperature is established and the surface temperature is used to reestablish the PW at periods of lack of high-altitude observations (Smith and Arkin 2015; Wang et al. 2016a). However, the surface quantity directly related to PW is SVP. With the physical linkage between them and the verification of the consistency of their variations at climatic scales, PW can be established with SVP. Or in other words, the SVP can reflect the variations of column atmosphere vapor content. Then, to comprehend the variation of the total water vapor content and fix its relations to surface elements such as temperature and circulations, analyzing the surface quantity, SVP may be more suitable than PW. The close linkage between SVP and PW is also a foundation for our further studies. First is the study of the contributions of surface temperature and relative humidity to SVP. Secondly, maybe using SVP at several grids to estimate PW (or in reverse order) will archive a better effect. It is also worth trying to do and maybe suitable to combine some neural network methods.

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507 *Data Availability Statement.*

508 Datasets analyzed during the current study include ERA5, JRA55, and NCEP2. The ERA5
509 dataset is available in the [*Copernicus Climate Change Service Climate Data Store*]
510 [<https://cds.climate.copernicus.eu/#!/search?text=ERA5&type=dataset>], provided by
511 ECMWF. The JRA55 dataset is available in the [*Research Data Archive, managed by NCAR*]
512 [<https://rda.ucar.edu/datasets/ds628.1/#!access>], provided by JMA. The NCEP2 dataset is
513 available in the [*Physical Sciences Laboratory (PSL)*]
514 [<https://psl.noaa.gov/data/gridded/data.ncep.reanalysis2.html>], provided by the
515 NOAA/OAR/ESRL PSL.

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