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RESEARCH ARTICLE
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A Global Assessment of Precipitable Water Vapor Derived From GNSS Zenith Tropospheric Delays With ERA5, NCEP FNL, and NCEP GFS Products

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Abstract In precipitable water vapor (PWV) retrievals from Global Navigation Satellite System (GNSS) data, the two essential parameters, namely, surface pressure ($P_s$) and weighted mean temperature ($T_w$), are often not available due to the lack of collocated meteorological sensors or improper data retention. Hence, this study presents a comprehensive assessment of the GNSS PWV retrieval using alternative $P_s$ and $T_w$ data from the European Centre for Medium-Range Weather Forecasts (ECMWF) ReAnalysis 5, National Centers for Environmental Prediction Final (NCEP FNL) Analysis, and NCEP Global Forecast System (GFS) products. The assessment was based on 691 globally distributed GNSS stations over the entire year of 2019. The zenith hydrostatic delay (ZHD) and $T_w$ integrated from the three types of numerical weather prediction (NWP) atmospheric profiles achieve varying accuracies in ranges of 2.4–3.0 mm and 1.1–1.5 K, respectively. PWVs estimated using ZHD and $T_w$ calculated by empirical models with surface pressure and temperature from the NWP datasets. The assessment of PWVs with the global pressure and temperature 2 wet model yields a root mean square (RMS) error of 3.73 mm. The relative RMS decreases from 30%–40% at high latitudes (70–80°S/N) to ~5% around the equator. The monthly variations of relative RMS show that (a) low-latitude regions outperform the high-latitude regions, and (b) winter months have significantly worse performance than other months in both hemispheres.

1. Introduction

As an important constituent of the atmosphere, water vapor exerts significant influences on a range of processes in the ecosystem, such as atmospheric radiation, hydrological cycle, weather pattern, and climate change (Jade & Vijayan, 2008; Trenberth & Smith, 2005; Vey et al., 2009). Accurate knowledge of water vapor distribution and variation is crucial to advance our understanding of the various atmospheric processes. Despite its importance, water vapor remains one of the most poorly quantified components in the atmosphere for two reasons. First, water vapor is highly variable in space and time, including its active responses to global warming and anthropogenic activities (Liu et al., 2013; Ohtani & Naito, 2000). Globally, water vapor content ranges from ~4% of the volume of the air near the equator to a mere fraction of 1% of the atmospheric gases at the poles and large deserts (Chen & Liu, 2016b; Mendes, 1998). Moreover, none of the current techniques, from in situ observations to satellite remote sensing, can provide accurate and continuous measurements of water vapor with high spatial-temporal resolutions (Z. Li et al., 2003; Niell et al., 2001).

Among the various observation techniques, the Global Navigation Satellite System (GNSS) has been extensively proven to be a uniquely powerful tool in retrieving precipitable water vapor (PWV) with advantages of low operational cost, consistently high accuracy, high temporal resolution, and all-weather operability (Bevis et al., 1992; Duan et al., 1996; Niell et al., 2001; Zhang, Zhang et al., 2019). GNSS signals are significantly affected by atmospheric refraction when traveling through the troposphere, and the effect on a GNSS signal coming from the zenith is defined as the zenith total delay (ZTD). The subtraction of the zenith hydrostatic delay (ZHD) from ZTD yields the zenith wet delay (ZWD) from which PWV can be inferred (Bevis et al., 1992; Davis et al., 1985). GNSS-derived PWV has been presently applied in broad fields, including...
The retrieval of PWV from ZTD requires two essential meteorological parameters, namely, the surface pressure \( (sP) \) and the weighted mean temperature \( (mT) \). The former is adopted by the Saastamoinen model to calculate ZHD, and the latter is used to compute the ratio value in the conversion from ZWD to PWV (Chen, Dai, Liu, Wu, Kuang, & Ao, 2018). Surface pressure can be accurately measured using a barometer at each GNSS site. Ideally, the weighted mean temperature should be calculated by numerical integral from the temperature and humidity profiles (Davis et al., 1985). However, atmospheric profiles are hard to obtain. Specifically in the near-real-time mode, \( T_m \) is often alternatively estimated from its linear relationship with the surface temperature \( T_s \) (Bevis et al., 1992; Jiang et al., 2016). Most GNSS stations are initially built for positioning purposes and are not equipped with collocated meteorological sensors (Means & Cayan, 2013). In addition, many GNSS stations with collocated meteorological sensors may suffer from outages or improper data retention, leading to discontinuities in the historical meteorological records. In these cases, \( P_s \) and \( T_m \) could be determined by the following three methods: (1) derived from global atmospheric reanalysis products (Jade & Vijayan, 2008; Means, 2013; Vey et al., 2009; Wang et al., 2007; H. Zhang et al., 2017; Zhang, Zhang, et al., 2019), (2) interpolated using nearby meteorological sensors (Alshawaf et al., 2015; Chen, Dai, Liu, Wu, Kuang, & Ao, 2018; Musa et al., 2011), and (3) predicted by empirical models developed from reanalysis datasets (Böhm et al., 2015; Huang et al., 2019; Sun et al., 2019; Yao et al., 2013). For post-mission applications using historical archived GNSS data, for example, long-term climate change, the first method is often employed due to the advantages of global coverage, long-term availability, good quality, and free accessibility (Chen & Liu, 2016b; Parracho et al., 2018). The second and third methods could be used in near-real-time and real-time applications, such as heavy precipitation monitoring (Chen, Dai, Liu, Wu, Kuang, & Ao, 2018). However, the second method is still limited by the lack of nearby meteorological sensors or data delivery latency. The use of empirical models is not limited by such issues. However, most

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**Figure 1.** Geographic distribution of the 47 selected Global Navigation Satellite System stations in this study.
models (e.g., global pressure and temperature 2 wet [GPT2w]) are developed using multi-year historical reanalysis data, and their performance is greatly degraded when the atmosphere undergoes large diurnal/regional variations. An alternative solution to these issues is to derive $P_s$ and $T_m$ from NWP-forecasted atmospheric profiles.

The European Centre for Medium-Range Weather Forecasts (ECMWF) ReAnalysis 5 (ERA5) is the fifth generation of ECMWF atmospheric reanalyzes of the global climate (Hersbach & Dee, 2016). Compared with its predecessor ERA-Interim (Dee et al., 2011), ERA5 reanalysis has been greatly upgraded in the spatiotemporal resolution and assimilation method (Zhang, Cai, et al., 2019). Previous publications have demonstrated the superiority of ERA5 reanalysis for PWV retrieval in China (Sun et al., 2019; Zhang, Zhang, et al., 2019), but few attentions focus on its global performance. The 5-day latency of the ERA5 reanalysis limits its application to post missions. The National Centers for Environmental Prediction Final (NCEP FNL) analysis (∼10 h latency) and NCEP Global Forecast System (GFS) products (no latency)
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have significant potentials for near-real-time and real-time GNSS PWV retrievals. However, very few investigations have been reported regarding their performance in PWV retrieval, specifically on a global scale. To our knowledge, no studies have assessed the performance of GFS forecasts in PWV retrieval from a global scale. In this study, we perform a global assessment of the PWV retrievals from GNSS ZTD data using sP and mT generated by ERA5 reanalysis, NCEP FNL analysis, and NCEP GFS forecast. In addition, the GPT2w model is involved in the assessment. Our study mainly aims to demonstrate whether the ERA5, FNL, and GFS products are accurate enough to provide alternative parameters for high-accuracy GNSS PWV retrieval, which can benefit the climate change research and extreme weather forecasting.

This paper is further structured as follows. Section 2 describes the methodology for PWV retrieval, including the descriptions of data sets from GNSS, radiosonde, ERA5, NCEP FNL, and GFS. Section 3 presents the global assessments of PWV retrievals by radiosonde and ERA5 data. Finally, Section 4 concludes the study and provides the outlook.

### 2. Data and Methodology

#### 2.1. Retrieval of PWV From GNSS-Estimated ZTD

As stated above, the PWV retrieval from GNSS ZTD is normally performed via two steps: (a) subtracting the ZHD from ZTD to obtain the ZWD and (b) converting the ZWD to PWV with a ratio value. For the first step, the Saastamoinen model is often used to calculate the ZHD (Chen & Liu, 2016a; Saastamoinen, 1972):

\[
ZHD = 0.0022793 \cdot \frac{P_s}{f(\phi, H)},
\]

\[
f(\phi, H) = 1 - 0.00266 \cdot \cos(2\phi) - 0.00028 \cdot H,
\]

where \(P_s\) (unit: hPa) is the surface pressure, \(\phi\) (unit: radians) is the station latitude, and \(H\) (unit: meters) denotes the height of the station above mean sea level. Moreover, if the atmospheric profiles are available, then ZHD can be determined by an integration of hydrostatic refractivity with respect to height (Chen & Liu, 2016a):

\[
ZHD = 10^{-6} \sum \left[ \frac{H_i - H_{i+1}}{\ln N_{h_i} - \ln N_{h_{i+1}}} \left( N_{h_{i+1}} - N_{h_i} \right) \right]
\]

\[
N_h = k_1 R_T \left( \frac{P_d}{T \cdot R_T} + \frac{P_w}{T \cdot R_w} \right)
\]

where \(H_i\) (unit: meters) and \(N_{h_i}\) (mm/km) represent the height and hydrostatic refractivity of the \(i\)th layer, respectively; \(P_d\) (unit: hPa) and \(P_w\) (unit: hPa) are the partial pressures for dry air and water vapor, respectively; \(T\) (unit: kelvin) is the temperature; \(k_1 = 77.6890\) (unit: K/hPa) is the refractivity constant; and \(R_T = 287.053\) (unit: J·K\(^{-1}\)·kg\(^{-1}\)) and \(R_w = 461.495\) (unit: J·K\(^{-1}\)·kg\(^{-1}\)) are the gas constants for dry air and water vapor, respectively.

In converting ZWD to PWV, their ratio value \(\Pi\) can be obtained using the following formula (Askne & Nordius, 1987):

\[
\Pi = 10^5 \left( \frac{R_w}{k_2 (T_m + k_2)} \right)
\]

| Schemes          | Bias (mm) | RMS (mm) |
|------------------|-----------|----------|
| ZHD_Era5         | 0.32      | 2.41     |
| ZHD_Era5_model   | −5.91     | 7.10     |
| ZHD_FNL          | 0.82      | 2.74     |
| ZHD_FNL_model    | −5.81     | 7.00     |
| ZHD_GFS          | 0.97      | 3.00     |
| ZHD_GFS_model    | −5.51     | 6.73     |
| ZHD_GPT          | −5.66     | 17.79    |

*Note. The whole year data of 2019 were used in the calculation.*
where $T_m$ (unit: kelvin) is the weighted mean temperature and $k_3 = 3.776 \times 10^5$ (unit: K²/hPa) and $k'_3 = 16.52$ (unit: K/hPa) are refractivity constants (Rüeger, 2002). $T_m$ is defined as follows (Davis et al., 1985):

$$T_m = \frac{\int \frac{P}{T} \, dh}{\int \frac{P_k}{T^2} \, dh}$$

Equation 6 requires complete humidity and temperature profiles, which are often difficult to obtain in practice. An alternative way is to use the linear $T_m - T_s$ relationship to calculate the $T_m$:

$$T_m = a + bT_s$$

Figure 3. Relationship between root mean square error and latitude for the zenith hydrostatic delay comparison between radiosonde and Global Navigation Satellite System.
where \( a \) and \( b \) are coefficients that can be fitted using radiosonde or reanalysis profiles.

The International GNSS Service (IGS) currently operates a worldwide GNSS network with more than 500 permanent tracking stations. The daily ZTD products are regularly released by IGS on its official website (http://www.igs.org/). The IGS released ZTD products are shown to have a mean uncertainty of about 4 mm (W. Li et al., 2012). For the study period over the whole year of 2019, ZTD data from 691 GNSS stations are available. In the assessments by radiosonde, a total of 47 globally distributed IGS stations (Figure 1) are adopted to examine the performance of ERA5, NCEP FNL, and NCEP GFS Products in PWV retrieval. The validation station is selected based on two criteria: (a) its distance to the nearest radiosonde site is less than 30 km and (b) the height difference between the validation station and the radiosonde site is less than 50 m. Given that water vapor is highly concentrated near the surface, PWV error caused by the height difference should not be neglected. For example, as a typical monsoon-influenced subtropical metropolis, Hong Kong experiences a humid summer with high frequencies of heavy showers. A height difference of 50 m could cause a discrepancy of \( \sim 1 \) mm in PWV. Therefore, we first interpolate/extrapolate radiosonde profiles to the height of the GNSS station by spline function and then calculate the PWV using the following formula (Ross & Elliott, 1996):

\[
PWV = \frac{1}{g} \int_0 \frac{0.622 P_w}{P - 0.378 P_w} dp
\]

where \( g \) (unit: m/s\(^2\)) is the acceleration of gravity and \( P \) (unit: hPa) is the total atmospheric pressure. Radiosonde can measure the PWV with an accuracy of better than 1 mm, which is thus usually adopted as a reference to assess water vapor estimates from other techniques (Chen & Liu, 2016a).

### 2.2. ECMWF ERA5 Reanalysis Data

As the latest generation of ECMWF reanalysis data, compared with its former ERA-Interim, ERA5 reanalysis has substantial upgrades in many features including spatial grid (79–31 km), temporal resolution (6–1 h), and vertical layers (60–137 levels) (Albergel et al., 2018). At present, ERA5 reanalysis covers the period from January 1, 1979 onward and continuously extends forward in time with a data latency of 5 days. The ERA5 data set is expected to be eventually extended back to 1950. Moreover, this data set is generated using the most advanced Earth system model and data assimilation methods of ECMWF. Hence, the ERA5 data set has richer climate information and more accurate products compared with the predecessor ERA-Interim. The hourly ERA5 reanalysis has great potential in PWV retrieval, particularly for GNSS stations without meteorological sensors. In this study, the geopotential height, temperature, and relative humidity data at 37 pressure levels from 1,000 to 1 hPa with a horizontal resolution of 0.25\(^\circ\) \( \times \) 0.25\(^\circ\) are used. For atmospheric profiles at a certain GNSS station, they are derived from bilinear interpolation of the ERA5 data at four neighboring grid points. Finally, ZHD and \( m_T \) can be calculated using Equations 3 and 6, respectively.

### 2.3. NCEP FNL and GFS Data

NCEP FNL operational global analysis data, also known as NCEP final, are produced from the Global Data Assimilation System (GDAS). It uses the same data assimilation and forecast system as the NCEP GFS. The forecast system runs earlier to support the time-critical forecast needs and adopts the FNL from the previous 6-h cycle as the background field for the current data assimilation. Compared with GFS, the FNL analysis is delayed by \( \sim 60–90 \) min because it needs to wait for additional observations to be assimilated (Jiang et al., 2016). Typically, the FNL ingests \( \sim 10\% \) more observational data into the initial condition than GFS. The FNL analysis data are published every 6 h on a 1\(^\circ\) \( \times \) 1\(^\circ\) global latitude–longitude grid, whereas the GFS data are available every 6 h with a higher resolution of 0.25\(^\circ\) \( \times \) 0.25\(^\circ\). The NCEP GFS can provide forecasts with a time step of 3 h from 0 to 240, which are very promising for real-time GNSS PWV retrieval. To examine its performance in real-time applications, GFS forecasts with time steps of 6 and 9 h are used. Since the accessibility to forecasts usually has a latency of \( \sim 3 \) h, forecasts with a time step of 3 h are not included in this work to fully simulate the real cases. FNL and GFS provide the geopotential, temperature, relative humidity, and other parameters at 26 mandatory (and a few other pressure) levels from 1,000 to 10 hPa. We apply the same methods of ERA5 on FNL and GFS data to interpolate the ZHD and \( m_T \) at a generic site.

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2.4. GPT2w Model

The global pressure and temperature 2 (GPT2) model developed by Lagler et al. (2013) can provide pressure and temperature data at any location in the vicinity of the Earth’s surface. Böhm et al. (2015) further improved the GPT2 model in terms of its ability to determine ZWD in blind mode and named this new version as GPT2w. The successive GPT2w model can also provide parameters including water vapor pressure and weighted mean temperature. The GPT2w model codes with the gridded input file are freely accessed at https://vmf.geo.tuwien.ac.at/codes/. In this study, GNSS PWVs calculated from GPT2w outputs $P_i$ and $T_m$ are also included for a direct comparison with those derived using the NWP models.

2.5. Validation Method

In this study, PWV estimates retrieved from ZTD measurements of 47 global GNSS stations using ERA5, NCEP FNL, and NCEP GFS products were evaluated against radiosonde data over the whole year period of 2019. Moreover, ZHD and $T_m$ derived from the three NWP models were also compared with those from the radiosonde. Neither the NWP model nor the radiosonde is able to provide meteorological parameters at the height where air pressure is essentially zero. For instance, if the radiosonde balloon fails to reach the height of 50 hPa, then an error of $\sim 11$ cm in the calculation of ZHD may occur. Therefore, only radiosonde observations containing complete atmospheric profiles up to the height where air pressure is $\leq 30$ hPa are adopted to ensure the quality of radiosonde-derived ZHDs (Hopfield, 1971). In addition, we apply a small correction calculated by Equation 1 to the ZHD derived using Equation 3 to mitigate the error caused by the lack of data at pressure levels less than 30 hPa (or <30 hPa) for radiosonde (or 10 hPa for NCEP products and 1 hPa for ERA data). Furthermore, the PWVs derived from atmospheric profiles and retrieved with only the surface pressure and temperature interpolated from the NWP products are also included in the comparison. The surface pressure $P_s$ and temperature $T_s$ are determined via two procedures, namely, a vertical adjustment and a horizontal interpolation. First, the pressure and temperature data at the height of a generic station for its four nearby grid points are determined as follows:

$$P_j^i = P_j^i \exp \left( \frac{H_j^i - H_j^{i+1}}{H_j^{i+1} - H_j^i} \cdot \ln \frac{P_j^{i+1}}{P_j^i} \right), \quad (9)$$

$$T_j^i = T_j^i + \frac{H_j - H_j^i}{H_j^{i+1} - H_j^i} \cdot (T_j^{i+1} - T_j^i), \quad (10)$$

where $P_j^i$ and $T_j^i$ represent the adjusted pressure and temperature of the $i$th grid point; $P_j^i$ and $P_j^{i+1}$ represent the pressure values at the nearest two mandatory levels to the station; $T_j^i$ and $T_j^{i+1}$ represent the temperature values at the nearest two levels; $H_j^i$ and $H_j^{i+1}$ represent the geopotential heights at the nearest two levels. Once the adjusted pressure and temperature data of the four nearby grid points are obtained, a bilinear interpolation is performed to determine the surface pressure and temperature at the station.

Prior to the evaluation, outliers possibly caused by instrumental, processing, or other errors are excluded from the datasets. An outlier is identified if the absolute difference between its value and the mean is greater than the triple standard deviation. For each station, the bias and root mean square (RMS) errors of the differences between radiosonde and GNSS are calculated to assess the PWV accuracy. The bias and RMS errors are calculated as follows:

$$\text{bias} = \frac{1}{n} \sum_{i=1}^{n} \text{PWV}^R_i - \text{PWV}^G_i, \quad (11)$$

$$\text{RMS} = \left( \frac{1}{n} \sum_{i=1}^{n} \left( \text{PWV}^R_i - \text{PWV}^G_i \right)^2 \right)^{1/2}, \quad (12)$$

where \( \text{PWV}^R \) and \( \text{PWV}^G \) represent the PWV derived by radiosonde and GNSS at time epoch $i$, respectively.
3. Results and Discussion

3.1. Evaluation of ZHD by Radiosonde

As stated above, two approaches are applied to derive ZHD from NWP products. One is to calculate ZHD using NWP atmospheric profiles according to Equation 3 plus a small correction from Equation 1 with the top pressure (ZHD\_ERA5, ZHD\_FNl, and ZHD\_GFS signify the ZHDs calculated using this approach from ERA5, NCEP FNL, and GFS products, respectively). Another one is to use empirical model (1) to compute the ZHD with surface pressure determined from Equation 9. Here, ZHD\_ERA5\_model, ZHD\_FNl\_model, and ZHD\_GFS\_model signify the ZHDs calculated using the Saastamoinen model with ERA5, NCEP FNL, and GFS products, respectively. In addition, ZHDs calculated using the Saastamoinen model with surface pressure provided by GPT2w (ZHD\_GPT) are included in the comparison. ZHDs derived from the various approaches are then evaluated by those from the radiosonde. The time span covers the entire year of 2019.

Figure 4. Bias (indicated by the color of the circle) and root mean square (indicated by the size of the circle) values of \(T_m\) at the 47 Global Navigation Satellite System stations for the seven different schemes.
Biases and RMS errors between the ZHDs calculated at the GNSS sites and observed by nearby radiosonde stations are derived using the whole year data. Figure 2 displays the derived bias and RMS values at all the selected 47 GNSS stations. ZHDs derived from NWP atmospheric profiles (Figures 2a, 2c and 2e) are more accurate than those calculated using the Saastamoinen model (Figures 2b, 2d and 2f). RMS errors of schemes ZHD_ERAS, ZHD_FNL, and ZHD_GFS are comparable and vary in the range of 0.85–7.07 mm depending upon the location. On the contrary, those errors for ZHD_ERAS, ZHD_FNL, and ZHD_GFS have a larger range of 1.11–15.05 mm. ZHD_GPT performs worst with RMS errors varying from 4.24 to 30.74 mm.

Table 1 further shows the overall biases and RMS errors computed using all the 47 stations. ZHD_ERAS achieves the best performance with a bias of 0.32 mm and an RMS error of 2.41 mm. ZHD_FNL and ZHD_GFS obtain the second and third highest accuracies of 2.74 and 3.00 mm, respectively. Such results are consistent with the quality superior sequence of the three NWP products as ERA5 reanalysis has the most assimilated data and the longest time latency, followed by the FNL analysis and GFS forecast. ZHDs calculated by the Saastamoinen model have accuracies of 7.10, 7.00, and 6.73 mm for ZHD_ERAS, ZHD_FNL, and ZHD_GFS, respectively. Although their discrepancies are very small, the statistics suggests that ERA5 is unlikely to provide better surface pressure data than FNL and GFS. In addition, ZHD_GPT performs badly with an RMS error of 17.79 mm, which is ~2.5 times of those derived from the Saastamoinen model. Figure 3 exhibits the relationship between the RMS error and latitude. No significant relationships are found for schemes ZHD_ERAS, ZHD_FNL, and ZHD_GFS as shown in Figures 3a, 3c and 3e. The correlations of schemes ZHD_ERAS, ZHD_FNL, and ZHD_GFS model present a clear pyramid-like pattern, indicating that the RMS errors decrease with latitude escalating in both hemispheres. This finding perhaps reveals that the surface pressures derived from the NWP models have worse performance in lower latitudes. Opposite performance is obtained by the ZHD_GPT as its RMS errors increase with latitude escalating. As shown in Figure 3g. RMS errors are less than 16 mm between 40°N and 40°S, but these values are up to 32 mm at higher latitudes.

### 3.2. Evaluation of $T_m$ by Radiosonde

Similar with the ZHD, $T_m$ is also calculated by two approaches from the NWP products. In the first approach, $T_m$ is derived from an integral of temperature and humidity profiles provided by the NWP model. We denote the schemes using ERA5 reanalysis, FNL analysis, and GFS forecast as Tm_ERAS, Tm_FNL, and Tm_GFS, respectively. For the second approach, the time-varying global gridded $T_m$ model developed by Jiang et al. (2019) is adopted to calculate the $T_m$. The authors verified its prominent advantages over other global models, such as Bevis and GPT2w (Jiang et al., 2019). In the present study, Tm_ERAS, Tm_FNL, and Tm_GFS model represent the schemes of calculating $T_m$ from the $T_m$ model using surface temperature data provided by the ERA5, FNL, and GFS, respectively. Moreover, $T_m$ data generated by the GPT2w model are also used in the evaluation (denoted as Tm_GPT).

Figure 4 depicts the biases and RMS errors for $T_m$ comparison calculated using the whole year data of 2019 at the 47 GNSS stations. The first approach outperforms the second one for all the three kinds of NWP products. Specifically, biases and RMS errors of the first approach vary in the ranges of $-1.29$ to $2.08$ K and $0.56$–$2.51$ K, whereas greater ranges of $-1.82$ to $3.98$ K and $0.93$–$4.56$ K are obtained by the second approach. For the Tm_GPT scheme, its biases and RMS errors range from $-5.28$ to $4.19$ K and $0.93$–$4.56$ K, respectively. Our statistics show that RMS errors attained by the first approach are less than 3 K at all the 47 stations. However, RMS errors at 13, 15, and 14 stations exceed 3 K for schemes Tm_ERAS, Tm_FNL, and Tm_GFS, respectively. For Tm_GPT, 68% of the stations (32 stations) have an RMS error exceeding 3 K. In terms of the overall RMS errors, as given by Table 2, Tm_ERAS achieves the best performance with an RMS error of 1.16, whereas the worst is Tm_GPT with an RMS error three times that of Tm_ERAS. In general, RMS errors of the second approach are ~2–2.5 times the first approach. Nevertheless, their biases are
comparable. From a global perspective, except the Tm_GPT, all the schemes can derive the $T_m$ with an accuracy of more than 3 K, corresponding to a relative error of more than 1% in PWV retrieval. Similar with the assessment of ZHD, $T_m$ calculated by empirical models with surface temperature from ERA5 ($T_{m\_ERA5\_model}$) are less accurate than those by FNL ($T_{m\_FNL\_model}$) and GFS ($T_{m\_GFS\_model}$). This is because, as validated by Yang et al. (2020), the surface temperature data provided by NCEP FNL/GFS are more consistent with the radiosonde observations than those of the ERA5. However, ERA5 still performs best in the evaluation by in situ measurements which have not been assimilated into the NWP models (Yang et al., 2020). In addition, as displayed in Figure 5, no obvious correlations between the RMS error and latitude are found for schemes $T_{m\_ERA5}$, $T_{m\_FNL}$, and $T_{m\_GFS}$. While for schemes $T_{m\_ERA5\_model}$, $T_{m\_FNL\_model}$, $T_{m\_GFS\_model}$ and $T_{m\_GPT}$, the RMS errors increase with latitude escalating in both hemispheres.

**Figure 5.** Relationship between root mean square error and latitude for the $T_m$ comparison between radiosonde and Global Navigation Satellite System.
3.3. Evaluation of PWV by Radiosonde

Once the ZHD and $T_m$ are determined, PWV can be extracted from the ZTD. PWVs retrieved using ZHD and $T_m$ integrated from ERA5, FNL, and GFS atmospheric profiles are denoted as PWV\_ERA5, PWV\_FNL, and PWV\_GFS, respectively. Moreover, PWV\_ERA5\_model, PWV\_FNL\_model, and PWV\_GFS\_model represent the PWV retrievals using ZHD and $T_m$ calculated from empirical models with surface pressure and temperature data provided by ERA5, FNL, and GFS, respectively. In addition, PWV derived using the GPT2w model is denoted as PWV\_GPT. The accuracy of PWV retrieval is affected by the uncertainties of ZTD, ZHD, and $T_m$. The mean uncertainty of the IGS-produced ZTD product is $\sim$4 mm (W. Li et al., 2012). Applying the error propagation law to the GNSS-PWV retrieval with uncertainties of ZHD and $T_m$ given in Tables 1 and 2.

Figure 6. Bias (indicated by the color of the circle) and root mean square (indicated by the size of the circle) values of precipitable water vapor at the 47 Global Navigation Satellite System stations for the seven different schemes.
we infer that PWV estimates using NWP profiles, empirical models with NWP surface data, and the GPT2w model can achieve accuracies of ∼1.2, 2.0, and 3.8 mm, respectively.

Figure 6 shows the biases and RMS errors of PWV at the 47 GNSS stations. PWVs retrieved from PWV_ERA5, PWV_FNL, PWV_GFS, PWV_ERA5_model, PWV_FNL_model, and PWV_GFS_model are very consistent with RMS errors ranging from 0.5 to 4.7 mm. The worst performance was attained by PWV_GPT at most of the stations with RMS errors varying from 1.4 to 5.3 mm. Table 3 shows the number of stations with RMS error populated at four value domains. For the six schemes using NWP products, most of the stations (>30) have an accuracy of more than 2 mm, whereas only four to six stations obtain RMS errors greater than 3 mm. For PWV_GPT, 47% of the stations have RMS errors larger than 3 mm. In terms of relative RMS, as shown in Figure 7, its values increase greatly with latitude escalating. For the six schemes using NWP products, the relative RMS values range from ∼4% near the equator to more than 50% near the 80°S, which are around half of those of PWV_GPT.

Table 4 further provides the biases and RMS errors derived from the PWV comparison between radiosonde and GNSS at all the 47 selected stations. Consistent with the error analysis above, PWVs retrieved using NWP profiles yield the highest accuracy of ∼2 mm, whereas discrepancies among the three NWP products are negligible. Comparable performances are achieved for PWV_ERA5_model, PWV_FNL_model, and PWV_GFS_model with almost identical RMS errors of 2.26, 2.28, and 2.29 mm, respectively. The quality of PWVs is evidently degraded by PWV_GPT as a much greater RMS error of 3.32 is achieved. Notably, the improvements in PWV retrieval achieved by NWP profiles over that by empirical models are not as significant as the theoretical analysis results. This result is likely because radiosonde-measured PWVs are not error-free and have been shown a mean uncertainty of ∼0.7 mm (Chen & Liu, 2016a).

3.4. Comparison of GNSS PWV With ERA5-Derived PWV

Although the radiosonde is regarded as an accurate means to measure the PWV, this method is usually launched twice a day and often suffers data invalidation. For instance, only 33 validated radiosonde PWV values can be used in the evaluation at the SBOK station, which is very likely to cause a statistically insignificant result. The ERA5 reanalysis data have advantages of global coverage, hourly availability, and homogeneous record, including a high accuracy of 1.8 mm as reported by Zhang, Zhang, et al. (2019). Thus, we further conduct the comparison between GNSS-retrieved PWVs and ERA5-derived PWVs over the whole year of 2019. ZTD products retrieved from a total of 691 GNSS stations provided by the German Research Centre for Geosciences are adopted in this comparison. The same expression as radiosonde shown in Equation 8 is adopted to calculate the PWVs from ERA5 atmospheric profiles.

First, four typical GNSS stations of LHAZ (91.104°E, 29.657°N, 3,622 m), SALU (44.212°W, 2.593°S, 18.9 m), GAMB (134.965°W, 23.130°S, 80.7 m), and SCTB (166.758°E, 77.849°S, −18.9 m) are selected to display the PWV time series derived from various schemes. LHAZ, SALU, and SCTB are selected because they have the highest altitude, the nearest to the equator, and the highest latitude among the 691 GNSS sites, respectively. In addition, GAMB is chosen as a representative station over the vast Pacific Ocean. Figure 8 displays the hourly variations of PWVs at LHAZ, SALU, GAMB, and SCTB stations. The PWVs estimated from these different schemes (except for the PWV_GPT at SCTB station) have a very good agreement with ERA5-derived PWVs. PWVs exhibit evident seasonal variations in which their peaks are dependent on the local climate of the station. Notably, invalid negative PWV values occur at the LHAZ and SCTB stations. This event is caused by two factors: (a) the water vapor content in the atmosphere is very low with PWV values less than 3 mm and (b) the obtained P is not accurate enough leading to a larger ZHD than ZTD. We persist those negative values in the figure to fully demonstrate the performance of the various schemes. Figure 9 shows the discrepancies of PWVs retrieved from the seven schemes with respect to the ERA5-derived PWVs.
of the discrepancies are concentrated within ±5 mm. The time series of PWV discrepancies of PWV_GPT at SCTB station exhibits drastic seasonal variation, whereas consistent variations are shown by other models. In terms of the bias and RMS error at each station, as shown in Figure 10, their values vary within ranges of −8 to 6 mm and 0–14 mm, respectively. RMS errors of PWV for the six schemes PWV_ERA5, PWV_ERA5_model, PWV_FNL, PWV_FNL_model, PWV_GFS, and PWV_GFS_model look similar. PWV_GPT shows worse performance than the other schemes at most stations. The overall statistics given in Table 5 confirm the similar performance between the six schemes as the discrepancies in their RMS errors are less than 0.4 mm. No evident differences in RMS error are found for PWVs derived using ERA5, FNL, and GFS products. PWV_ERA5, PWV_FNL, and PWV_GFS yield RMS errors of ~1.6 mm, whereas those of PWV_ERA5_model,
Table 4
Statistical Results of the Differences Between PWVs Derived From Radiosonde Observations and Calculated at 47 GNSS Sites

| Schemes            | Bias (mm) | RMS (mm) |
|--------------------|-----------|----------|
| PWV_ERA5           | 0.03      | 2.02     |
| PWV_ERA5mod       | 0.57      | 2.26     |
| PWV_FNL           | −0.04     | 2.04     |
| PWV_FNLmod       | 0.55      | 2.28     |
| PWV_GFS          | −0.05     | 2.07     |
| PWV_GFSmod       | 0.50      | 2.29     |
| PWV_GPT          | 0.52      | 3.32     |

Note. The whole year data of 2019 were used in the calculation.

PWV_FNLmod and PWV_GFSmod are ∼2.0 mm. A much greater RMS error of 3.73 mm is obtained by PWV_GPT.

The probability density functions (PDFs) shown in left panels of Figure 11 indicate that there is a higher probability of positive PWV difference occurrence for all schemes. Especially for PWV_ERA5mod, PWV_FNLmod, PWV_GFSmod and PWV_GPT, significant positive biases can be observed. PWV differences are within the range of −5–5 mm for the 6 schemes using NWP products, while differences of PWV_GPT vary from −10 to 10 mm. Figure 11(right panels) further display the fractional errors as percent by ERA5 5 mm PWV bins. Fractional errors of PWV_ERA5, PWV_FNL, and PWV_GFS vary in the range of −2%–6%, showing a decrease-increase pattern with ERA5 PWV increasing. PWV_ERA5mod, PWV_FNLmod, and PWV_GFSmod all yield positive fractional errors in the range of 0%–24%. When PWV values less than 10 mm, PWVs from the three schemes have an obvious dry bias relative to the ERA5. This dry bias is caused by the overestimation of ZHD by the empirical model shown in Table 1. For the scheme PWV_GPT, as displayed in Figure 11n, wet bias relative to the ERA5 can be observed when PWV values are less than 5 mm. For PWVs within the range of 10–20 mm and greater than 75 mm, significant dry biases relative to the ERA5 occur.

Figure 8. Precipitable water vapor (PWV) time series derived from ERA5 reanalysis, PWV_ERA5, PWV_ERA5mod, PWV_FNL, PWV_FNLmod, PWV_GFS, PWV_GFSmod and PWV_GPT at LHAZ, SALU, GAMB, and SCTB Global Navigation Satellite System stations in 2019.
Figures 12 and 13 exhibit the changes of RMS error and relative RMS with latitude. Figures 12a–12f show that the RMS errors increase from ∼0.5 mm at the 80°S/N to ∼4 mm around the equator for PWV_ERA5, PWV_FNL, PWV_GFS, and PWV_GPT. For PWV_GPT (Figure 12g), its RMS errors basically vary in the range of 1–4 mm between 40°S and 40°N but fluctuate between 4-6 mm below 40°S and above 40°N. The changes of relative RMS with latitude look similar for the seven schemes, all showing a concave curve pattern. The relative RMS decreases from ∼40% at high latitudes to ∼5% around the equator for the six schemes using NWP products. The opposite change patterns between the RMS error and relative RMS is attributed to the fact that tropical atmosphere contains more water vapor than temperate zones, followed by the polar regions. The relative RMS of PWV_GPT decreases from 120% at 80°N/S to 5% at the equator. The GPT2w model performs badly at high latitudes; thus, the RMS error and relative RMS show a similar pattern.

Figure 14 further displays the monthly variations of relative RMS with latitude. Figures 14a–14g show that the Southern Hemisphere achieves comparable performance with the Northern Hemisphere. In both hemispheres, relative RMS increases with latitude ascending in general. Winter months have significantly higher relative RMS than other months in Northern (winter: December, January, and February) and Southern (winter: June, July, and August) Hemispheres. For the overall relative RMS at each month calculated from all the 691 stations (Figure 14h), PWV_ERA5, PWV_FNL and PWV_GFS obtain values of ∼11% with a maximum of ∼12% in February. PWV_ERA5model, PWV_FNLmodel, and PWV_GFSmodel perform slightly worse with relative RMS of about 12%. The relative RMS of PWV_GPT varies from 13% to 38% within the year, which is approximately double the other schemes.
Figure 10. Bias (indicated by the color of the circle) and root mean square (indicated by the size of the circle) values of precipitable water vapors by the seven different schemes with respect to ERA5 at the 691 Global Navigation Satellite System stations.

Table 5
Statistical Results of the Differences Between PWV Derived From ERA5 Reanalysis and Calculated at 691 GNSS Sites

| Schemes      | Bias (mm) | RMS (mm) |
|--------------|-----------|----------|
| PWV_ERA5     | 0.48      | 1.60     |
| PWV_ERA5_model | 1.27      | 1.95     |
| PWV_FNL      | 0.45      | 1.61     |
| PWV_FNL_model | 1.32      | 2.00     |
| PWV_GFS      | 0.41      | 1.59     |
| PWV_GFS_model | 1.27      | 1.96     |
| PWV_GPT      | 1.56      | 3.73     |

Note. The whole year data of 2019 were used in the calculation.
4. Conclusions and Outlook

The surface pressure $P_s$ and weighted mean temperature $T_{\text{w}}$ are two crucial parameters in the extraction of PWV from GNSS ZTD measurements. In many cases, GNSS stations are not equipped with collocated meteorological sensors or suffer from outages or improper data retention, thereby leading to difficulties in PWV retrieval. Atmospheric products provided by ERA5 reanalysis, NCEP FNL analysis, and GFS forecasts have advantages of global coverage, spatial integrity, and homogeneous record. Thus, they are of great value for GNSS meteorology. Owing to their different data latency, ERA5 (∼5 days latency), FNL (∼10 h latency), and GFS (no latency) can be applied for the post, near-real-time, and real-time PWV retrieval, respectively.

This study presents a comprehensive assessment of the performance of ERA5, FNL, and GFS products in PWV retrieval by using 47 global GNSS stations when radiosonde data are adopted as a standard ref-

Figure 11. Probability density functions of precipitable water vapor (PWV) difference between ERA5 and Global Navigation Satellite System (left panels), and fractional errors as percent by ERA5 5 mm PWV bins (right panels).
In the calculation of ZHD, ERA5 achieves the best performance with an RMS error of 2.41 mm, followed by FNL of 2.74 mm, and GFS of 3.00 mm. In the derivation of $T_m$, ERA5, FNL, and GFS obtain RMS errors of 1.16, 1.31, and 1.47 K, respectively. Both results are consistent with the fact that ERA5 has the most assimilated data and the best performance, followed by the FNL and GFS.

In the PWV retrieval, two approaches are applied to calculate ZHD and $T_m$ from NWP products. One is to retrieve PWV using ZHD and $T_m$ integrated from ERA5, FNL, and GFS (denoted as PWV_{ERA5}, PWV_{FNL}, and PWV_{GFS}, respectively) atmospheric profiles. Another one is to use ZHD and $T_m$ calculated from empirical models with surface pressure and temperature derived from the ERA5, FNL, and GFS (denoted as PWV_{ERA5\,model}, PWV_{FNL\,model}, and PWV_{GFS\,model}). PWVs retrieved from the first approach obtain accuracies of $\sim 2$ mm, which are slightly better than those from the second approach with accuracies of

![Figure 12](image-url)
PWVs derived using the GPT2w model (denoted as PWV_GPT) performs worst with an RMS error of 3.32 mm.

In the comparison with ERA5-derived PWV at 691 GNSS sites, globally, the RMS error varies in the range of 0–14 mm for the seven PWV retrieval schemes. The overall RMS errors for schemes PWV_ERA5, PWV_FNL, PWV_GFS, PWV_ERA5_model, PWV_FNL_model, and PWV_GFS_model are ∼1.6–2.0 mm, whereas a value of 3.73 mm is yielded for PWV_GPT. The results show that the relative RMS increases with latitude ascending in Northern and Southern Hemispheres. The GPT2w model was shown to perform specifically bad at high latitudes with relative RMS exceeding 100% at ∼80°N/S. In addition, PWVs retrieved in winter months (December, January, and February for Northern Hemisphere; June, July, and August for Southern Hemisphere) are significantly worse than those of other months in both hemispheres.

Figure 13. Relationship between relative root mean square and latitude for the precipitable water vapor comparison between ERA5 and Global Navigation Satellite System.
The high-accuracy PWV retrievals from the GNSS have great potentials in different applications, such as climate change research, weather forecasting, and numerical assimilation. In this study, the ERA5 reanalysis, FNL analysis, and GFS forecast have been proven to assist the PWV retrieval from the GNSS ZTD measurements with an accuracy of 2–3 mm. The three types of NWP products can satisfy the all-mission GNSS PWV retrieval covering post, near-real-time, and real-time modes. Future work will investigate the performance of GNSS PWV retrieval using NWP products under extreme weather and in regions with highly variable surface topography. The long-term water vapor variability and trend based on PWVs derived from historical GNSS data and ERA5 reanalysis will be analyzed. Real-time PWV retrieval using FNL analysis and GFS forecast, including its benefits to short-term heavy rainfall forecasting, should be examined in the future.

Figure 14. Monthly variations of relative root mean square(%) with latitude for the precipitable water vapor comparison between ERA5 and Global Navigation Satellite System.
Data Availability Statement

The ECMWF ERA5 reanalysis data are freely accessible at the Climate Data Store (https://cds.climate.copernicus.eu/cdsapp#!/dataset/reanalysis-era5-pressure-levels?tab=form). The NCEP FNL analysis and NCEP GFS forecast products can be downloaded for free at websites https://rdac.ucar.edu/datasets/ds083.2/#access and https://rdac.ucar.edu/datasets/ds084.1/, respectively. The IGRA radiosonde data are freely accessible via the link http://www1.ncdc.noaa.gov/pub/data/igra/. The GNSS ZTD products are available online at ftp://cdsiss.gsfc.nasa.gov/gps/products/troposphere/zpd/. The GPT2w programs and coefficients grid file are freely available online (http://gosatm.hg.tuwien.ac.at/Delay/SOURCE/GPT2w/). The PWV data generated in this work can be found in the Supporting Information.

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