Weighted Mean Temperature Modelling Using Regional Radiosonde Observations for the Yangtze River Delta Region in China

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Abstract: Precipitable water vapor can be estimated from the Global Navigation Satellite System (GNSS) signal’s zenith wet delay (ZWD) by multiplying a conversion factor, which is a function of weighted mean temperature \( T_m \) over the GNSS station. Obtaining \( T_m \) is an important step in GNSS precipitable water vapor (PWV) conversion. In this study, aiming at the problem that \( T_m \) is affected by space and time, observations from seven radiosonde stations in the Yangtze River Delta region of China during 2015–2016 were used to establish both linear and nonlinear multifactor regional \( T_m \) model (RTM). Compared with the Bevis model, the results showed that the bias of yearly one-factor RTM, two-factor RTM and three-factor RTM was reduced by 0.55 K, 0.68 K and 0.69 K, respectively. Meanwhile, the RMSE of yearly one-factor, two-factor and three-factor RTM was reduced by 0.56 K, 0.80 K and 0.83 K, respectively. Compared with the yearly three-factor linear RTM, the mean bias and RMSE of the linear seasonal three-factor RTMs decreased by 0.06 K and 0.10 K, respectively. The precision of nonlinear seasonal three-factor RTMs is comparable to linear seasonal three-factor RTMs, but the expressions of the linear RTMs are easier to use. Therefore, linear seasonal three-factor RTMs are more suitable for calculating \( T_m \) and are recommended to use for PWV conversion in the Yangtze River Delta region.

Keywords: weighted mean temperature \( (T_m) \); multifactor; regional \( T_m \) model; precipitable water vapor (PWV); ground-based GNSS meteorology; Yangtze River Delta

1. Introduction

Atmospheric water vapor is one of the significant driving forces to atmospheric circulation and climate changes [1]. The dynamical variation of water vapor is a significant factor in forecasting thunderstorms and other weather disasters [2]. However, the traditional sensors (e.g., radiosondes and water vapor radiometers) are not practical to monitor atmospheric vapor at a higher spatio-temporal resolution, predominantly due to their higher operational expense [3].

Contemporarily, the Global Navigation Satellite System (GNSS) has been a new technology to retrieve the atmospheric precipitable water vapor (PWV), due to its lower cost, higher precision, higher spatio-temporal resolution, 24 h availability and global coverage [4–7]. Zenith tropospheric delay (ZTD) could be readily determined from GNSS observations. ZTD is composed of zenith hydrostatic delay (ZHD) and zenith wet delay (ZWD). GNSS-PWV is derived from the ZWD and has the potential to predict severe weather [8–10] and studying climate [11,12]. Previous studies [9,13–16] have shown that serious rainstorms occur in the descending trends of GNSS-PWV after ascending.
Benevides et al. [17] suggested that the reliability and precision of weather forecast could be improved after analyzing 3D distribution variations of PWV [17–22].

GNSS-PWV can be obtained by multiplying a conversion factor, which is a function of weighted mean temperature \( T_m \) [4,23]. Therefore, the precision of GNSS-PWV relates to the precision of \( T_m \) [23,24]. The most precise method for obtaining \( T_m \) is to use radiosondes [4,25]. However, GNSS stations seldom have co-located radiosondes due to their higher expense. The global \( T_m \) model, established using the ground surface temperature \( T_s \) by Bevis in 1992 \( (T_m = 0.72T_s + 70.2) \), was commonly used for real-time applications. The Bevis model was derived from the profiles of vapor partial pressure and dewpoint temperature of North American radiosondes over a 2-year period. However, the relationship of \( T_m - T_s \) varies at different locations and seasons, due to the rapid atmospheric variations. It is found that the global performance of the Bevis model is uneven. For example, the systematic deviations of the Bevis model are mostly above 4 K, even exceeding 8 K in some regions [26,27]. Under severe weather conditions, the bias of the Bevis model can cause a significant deviation in GNSS PWV [23,24].

Many researchers have tried to use the linear relationship between \( T_m \) and \( T_s \) to establish regional \( T_m \) models (RTM) based on local radiosondes [27–31]. This one-factor model is easy to use and has only one independent variable \( T_s \). Several RTMs using a one-factor (\( T_s \)) have been established in China [32–36]. The RTM used in Hong Kong outperformed the Bevis model [32], which controls the bias within 4 K. Li and Mao [33] studied monthly coefficients of the RTM in eastern China. Yu and Liu [34] found that the \( T_m \) was correlated with altitude as well. Chen et al. [37] established a global \( T_m \) model based on the NCEP reanalysis data of 650 radiosondes from 2007 to 2011. Guo et al. [38] established a better yearly one-factor \( T_m \) model based on the profiles from seven radiosonde stations in the Yangtze River Delta region.

Different from the abovementioned one-factor (\( T_s \)) RTM, some researchers established multifactor RTMs by adding pressure (\( P_s \)) and vapor pressure (\( e_s \)) into the RTM [36,39,40]. Gong [39] analyzed the relationships between \( T_m \) and its factors over the 123 radiosonde stations during 2008–2011, and the linear multifactor RTMs were established for different climate regions in China. He found that the multifactor RTMs were slightly better than the one-factor RTM. However, Wang et al. [40] claimed no significant differences between one-factor and multifactor RTMs results in Hong Kong.

In addition, some researchers believe that traditional linear regression models cannot well express the relationships between \( T_m \) and meteorological factors. Yao et al. [41] suggested a nonlinear relationship between \( T_m \) and \( T_s \), and the precision of the established nonlinear RTM is slightly better than linear unary RTM. Zou et al. [42] proposed a nonlinear \( T_m \) model suitable for Jilin province, and its precision is better than the commonly used one-factor linear regression model in Jilin province.

This paper aims to utilize the data profiles from seven radiosondes in the Yangtze River Delta region, during 2015–2016, to develop yearly and seasonal multifactor RTMs based on the least square principle. The correlation between RTMs and meteorological factors is analyzed. In addition, the collinearity of the meteorological factors is also presented. Their precisions were evaluated using 2016–2017 radiosonde-derived \( T_m \) as the reference value.

The outline of this paper is as follows. The methodology for the evaluation of \( T_m \) and PWV from radiosonde and GNSS data will be shown in the second section. The data sources and their relationships between \( T_m \) and other factors will be given in the third section. The establishment of yearly and seasonal linear/nonlinear multifactor RTMs and their performance are shown in the fourth section. Discussions and conclusions are given in the fifth and sixth section.
2. Materials and Methods

2.1. Obtaining PWV

The relationship between GNSS-PWV and ZWD is

\[ \pi = \frac{10^6 \rho_w R_v \left( k_3 T_m + k'_2 \right)}{k_2} \]  

(1)

\[ \text{PWV} = \pi \cdot \text{ZWD} \]  

(2)

where \( \pi \) is the conversion factor, \( R_v \) is the specific gas constant for water vapor, satisfying \( R_v = 461 \text{ (J·kg}^{-1}·\text{K}^{-1}) \) and \( \rho_w \) is the density of liquid water. \( k'_2 \) is given by the following expression:

\[ k'_2 = k_2 - m k_1, \]

in which \( m \) is the ratio of molar masses of water vapor and dry air \( \left( \frac{m_v}{m_d} = 0.622 \right) \), \( k_1 = 77.6 \text{ (K·hPa}^{-1}) \) and \( k_2 = 71.98 \text{ (K·hPa}^{-1}) \). \( k_3 = 3.754 \times 10^5 \text{ (K}^2\cdot\text{hPa}^{-1}) \).

\[ \text{ZWD} = \text{ZTD} - \text{ZHD}. \]

ZTD can usually be estimated by using undifferenced precise point positioning. ZHD can be calculated with Saastamoinen model \([43,44]\), and this can be taken as

\[ \text{ZHD} = 0.0022768 \times \frac{P_c}{1 - 0.00266 \cos 2 \phi_c - 0.00028 H_c} \]  

(3)

where \( P_c \) is the air pressure (in hPa) measured at the station, \( \phi_c \) is the geographic latitude (in radian), and \( H_c \) is the altitude of the stations (in km). When calculating \( \pi \), the values of parameters other than \( T_m \) are already known. Since \( \pi \) is an important step in calculating PWV, it results that \( T_m \) is an important parameter that affects the precision of \( \pi \) and PWV.

2.2. Obtaining \( T_m \)

There are four methods to determine \( T_m \) in GNSS water vapor inversion: constant method, approximate integral method, numerical integral method, and linear regression analysis. The constant method is the simplest method among these, but it has the lowest precision. Linear regression analysis is the method most commonly used for real-time GNSS meteorological applications. Additionally, the Bevis model is derived from this method, but its precision may vary at different locations. The approximate integral method requires the lapse rate of temperature and vapor pressure decline rate, which is hard to calculate and has low precision. Comparatively, since the numerical integration is not easy to calculate, but it can achieve the highest precision among the four methods \([45]\).

In this paper, RTMs are established by curve fitting, and the \( T_m \) calculated by numerical integration is used as the reference value to verify the precision of RTM. Its mathematical expression is

\[ T_m = \frac{\int (e/T) dZ}{\int (e/T^2) dZ} \]  

(4)

where \( e \) is the vapor pressure (in hPa) over the station, \( T \) is the absolute temperature (in K), and \( Z \) is the stratified height (in km) along the zenith.

Since the distribution of \( e \) and \( T \) varies in space at any time, the calculated \( T_m \) should also have time-varying characteristics, which can be obtained by

\[ T_m = \frac{\sum_i \left( \sigma_i / T_i \right) \Delta h_i}{\sum_i \left( \sigma_i / T_i^2 \right) \Delta h_i} \]  

(5)

\[ \frac{\sigma_i}{T_i^2} = \frac{e_i / T_i + e_{i-1} / T_{i-1}}{2} \]  

(6)

\[ \frac{\sigma_i}{T_i} = \frac{e_i / T_i^2 + e_{i-1} / T_{i-1}^2}{2} \]  

(7)
where $e_i$ is the average vapor pressure in $i$th layer (in hPa), $T_i$ is the average temperature (in K), $\Delta h_i$ is the thickness of the $i$th atmosphere (in km), $e_i, e_{i-1}, T_i, T_{i-1}$ are the vapor pressure and temperature at the upper and lower boundary of the atmosphere, respectively. 

The vapor pressure $e$ cannot be directly observed. As recommended by World Meteorological Organization (WMO) [46], it can only be calculated through the saturated vapor pressure formula. When the air is saturated, the air temperature is the same as the dew point temperature ($t_d$), and $e$ is calculated by:

$$e = 6.112 \exp\left[17.62 t_d / (243.12 + t_d)\right]$$

where $t_d$ can be obtained directly from radiosonde data.

2.3. Precision Statistics

The precision of the RTMs established in this paper is measured by the root mean square error (RMSE) and bias. If the precision of the RTMs is higher than that of the commonly used Bevis model, RTMs are worth establishing. The expressions of RMSE and bias are as follows:

$$\text{RMSE} = \sqrt{\frac{\sum_{i=1}^{n} (X_i - X_{ref})^2}{n}}$$  \hspace{1cm} (9)

$$\text{Bias} = X_i - X_{ref}$$  \hspace{1cm} (10)

where $X_{ref}$ represents the reference value and $X_i$ is the predicted value from new RTMs.

3. Materials and Analysis

3.1. Data Sources

Data profiles from radiosonde stations all over the world are available on the website of the University of Wyoming (http://weather.uwyo.edu/upperair/sounding.html, accessed on 2 March 2018). Figure 1 shows the distribution of the 7 radiosonde stations. The locations of the 7 radiosonde stations are shown in Table 1. Radiosondes data collected twice a day from 7 stations in the Yangtze River Delta region of China, during 2015–2017, were selected as the experimental data.

![Figure 1. Distribution map of radiosondes in the Yangtze River Delta region.](image)
Table 1. Location information of 7 radiosondes in the Yangtze River Delta region.

| Station  | ID   | Locations (N, E)            | Elevation (m) |
|----------|------|----------------------------|--------------|
| Anqing   | 58424| (30.53°N, 117.05°E)        | 20           |
| Fuyang   | 58203| (32.86°N, 115.73°E)        | 33           |
| Hangzhou | 58457| (30.23°N, 120.16°E)        | 43           |
| Quzhou   | 58633| (28.96°N, 118.86°E)        | 71           |
| Shanghai | 58362| (31.40°N, 121.46°E)        | 4            |
| Sheyang  | 58150| (33.76°N, 120.25°E)        | 7            |
| Nanjing  | 58238| (32.00°N, 118.80°E)        | 7            |

3.2. Regression Analysis

The analysis was performed using data from seven radiosonde stations during 2015–2016, and the sample size is 5110. The SPSS (Statistical Product and Service Solutions) software was used to analyze the relationship between $T_m$ and $T_s$, $e_s$, and $P_s$. Table 2 shows the fitting indexes ($R^2$) of $T_m$ and $T_s$, $e_s$, $P_s$. $X$ represents the independent variable. Meanwhile, the $R^2$ was used to evaluate the fitting effect. The higher the value of the $R^2$, the better the fitting effect.

Table 2. The fitting indexes ($R^2$) of $T_m - T_s$, $T_m - e_s$ and $T_m - P_s$.

| Function       | Expression           | X=Ts   | X=es  | X=Ps  |
|----------------|----------------------|--------|-------|-------|
| Linear         | $T_m = aX + b$       | 0.854  | 0.772 | 0.705 |
| Power          | $T_m = aX^b$         | 0.853  | 0.832 | 0.705 |
| Logarithmic    | $T_m = a\ln X + b$  | 0.855  | 0.830 | 0.705 |

It can be seen from Table 2 that the $R^2$ of all the $T_m$ to $T_s$ is almost the same, so the simple linear function can well express the relationship between $T_m$ and $T_s$. The relationship between $T_m$ and $e_s$ is equally fitted by logarithmic function and power function, which are both better than the linear function. Therefore, $\ln e_s$ will be selected as the independent variable to establish linear RTM. It is better to use power function to express the nonlinear relationship between $T_m$ and $e_s$. The fitting indexes between $T_m$ and $P_s$ are exactly the same for the three functions. The correlation between $T_m$ and $P_s$ is lower than that between $T_m$ and $T_s$, $\ln e_s$, but the effect of $P_s$ on $T_m$ cannot be ignored.

3.3. Linear/Nonlinear Correlation and Collinearity

We performed correlation and collinearity analysis using the same data as regression analysis. Correlation and collinearity analysis were carried out as follows. Figure 2 shows the correlation analysis between $T_m$ and $T_s$, $p_s(b)$, $\ln e_s(c)$, $e_s(d)$, where $R$ is the correlation coefficient. $R$ can both show positive correlation and negative correlation between meteorological factors. It shows that $T_m$ has a strong positive linear correlation with the $T_s$ and $\ln e_s$, while $T_m$ has a negative linear correlation to $P_s$. Meanwhile, $T_m$ and $e_s$ have a nonlinear correlation.

Table 3 contains the statistics of linear correlation analysis. It can be seen that there is a strong correlation between factors, so a collinear relationship may exist between them. Collinearity is usually referring to the non-independence of the two or more predicting factors in a regression analysis. A high degree of multi-collinearity will have an impact on regression modeling, resulting in a reduction in modeling precision. Therefore, it is necessary to verify the collinearity before modeling. If collinearity exists, corresponding solutions should be taken first [47].
There exist coefficients \((a_1, \ldots, a_m)\) for factors \((X_1, \ldots, X_m)\) to make the following equation hold [48]

\[
a_1X_1 + a_2X_2 + \ldots + a_mX_m = a_0
\]

(11)

Supposing there exists a factor \(X_k\) can be expressed by other factors as follows

\[
X_k = \left(\frac{a_0 - \sum_{j \neq k} a_jX_j}{a_k}\right)
\]

(12)

and then \(X_1, \ldots, X_m\) show collinearity. Otherwise, there is no collinearity among \(X_1, \ldots, X_m\).

The tolerance (\(Tol\)) is used to verify collinearity in this paper and expressed as

\[
Tol = 1 - R^2
\]

(13)

where \(R^2\) is the square of correlation coefficients between two factors. As a matter of fact, a threshold value of \(Tol\) larger than 0.1 is often accepted [48]. If the value of \(Tol\) exceeds 0.1, then there is no collinearity. The statistical tolerances among the variables are shown in Table 4. It is observed that there is no collinearity among \(\ln e_s, e_s, T_s\) and \(P_s\), since the \(Tol\) values are much larger than 0.1. Therefore, these variables can be used to establish the RTMs.
Table 4. Statistical tolerances among independent variables.

| Factor       | $R^2$ | Tol |
|--------------|-------|-----|
| $T_s - P_s$  | 0.60  | 0.40|
| $e_s - P_s$  | 0.54  | 0.46|
| $T_s - e_s$  | 0.60  | 0.34|
| $\ln e_s - T_s$ | 0.71  | 0.29|
| $\ln e_s - P_s$ | 0.58  | 0.42|
| $\ln e_s - e_s$ | 0.64  | 0.36|

4. Results

In this section, firstly, yearly and seasonal linear RTMs will be established based on the linear correlations of $T_m$ to $T_s$, $\ln e_s$ and $P_s$, and their precision comparison with previous RTMs will be performed. Then, based on the nonlinear correlation between $T_m$ and $e_s$, nonlinear RTMs will also be established. Finally, the precision of these RTMs will be compared.

4.1. Yearly Linear RTM

4.1.1. Establishing RTM

1. One-factor RTM

According to the correlation analysis of $T_m$ and $T_s$, the linear fitting method is used to set as following

$$T_m = a_1 + b_1 T_s$$  \hspace{1cm} (14)

The residual vector $V$ is expressed in matrix as [49]

$$V = [1 \ T_s] \begin{bmatrix} a_1 \\ b_1 \end{bmatrix} - T_m$$ \hspace{1cm} (15)

where $V$ is the residual error vector. After the $T_m$ and $T_s$ from all the aforementioned 7 radiosonde stations during 2015–2016 were taken into Equation (15), the coefficients of $a_1$, $b_1$ can be calculated based on the least square principle ($V^T PV = \min$), then the yearly one-factor RTM in the Yangtze River Delta region can be obtained as

$$T_m = 44.5054 + 0.8148 T_s$$ \hspace{1cm} (16)

2. Two-Factor RTM

According to the correlation analysis of $T_m$ (as reference value), $T_s$ and $\ln e_s$, the multiple linear fitting method is used as follows

$$T_m = a_2 + b_2 T_s + c_2 \ln e_s$$ \hspace{1cm} (17)

The residual vector $V$ is expressed in matrix as

$$V = [1 \ T_s \ \ln e_s] \begin{bmatrix} a_2 \\ b_2 \\ c_2 \end{bmatrix} - T_m$$ \hspace{1cm} (18)

After the $T_m$, $T_s$, and $e_s$ from all the aforementioned 7 radiosonde stations during 2015–2016 were taken into Equation (18), the coefficients $a_2$, $b_2$, $c_2$ can be calculated based on the least square principle, then the yearly two-factor RTM of the Yangtze River Delta region can be obtained as

$$T_m = 124.9910 + 0.4922 T_s + 4.9104 \ln e_s$$ \hspace{1cm} (19)
3. Three-Factor RTM

According to the correlation analysis of $T_m$ (as reference value), $T_s$, $e_s$ and $P_s$, the multiple linear fitting method is used as follows

$$T_m = a_3 + b_3 T_s + c_3 ln e_s + d_3 P_s$$ (20)

The residual vector $V$ is expressed in matrix as

$$V = [1 \ T_s \ ln e_s \ P_s] \begin{bmatrix} a_3 \\ b_3 \\ c_3 \\ d_3 \end{bmatrix} - T_m$$ (21)

After the $T_m$, $T_s$, $e_s$ and $P_s$ from all the aforementioned 7 radiosonde stations during 2015–2016 were taken into Equation (21), the coefficients $a_3$, $b_3$, $c_3$ and $d_3$ can be calculated based on the least square principle, then the yearly three-factor RTM of the Yangtze River Delta region can be obtained as

$$T_m = 247.0598 + 0.4372 T_s + 4.2812 ln e_s - 0.1032 P_s$$ (22)

4.1.2. Precision of RTMs

To test the precision of yearly multifactor RTMs, the reference values of $T_m$ from 2016 to 2017 were used to compare with the $T_m$ derived from the Bevis model, yearly one-factor RTM, yearly two-factor RTM and yearly three-factor RTM in the Yangtze River Delta region. Figure 3 shows the bias statistical histograms of the Bevis model and one-factor, two-factor and three-factor yearly RTMs. The bias of each RTM is normally distributed (Figure 3). The bias of the Bevis model is mainly distributed in the range of $-8$ K–$4$ K, and the symmetry axis of the bias distribution of the Bevis model applied in the Yangtze River Delta is not 0 but $-2$. The biases of the one-factor, two-factor and three-factor RTMs are mainly distributed in the range of $-6$ K–$6$ K, and the symmetry axis of the bias distribution is closer to the theoretical value of 0. There is no bias less than $-8$ K or greater than $8$ K for the two-factor and three-factor models, so the multifactor models are much better than the one-factor model in the Yangtze River Delta region.

![Bias statistical histograms of Bevis model and yearly one-factor, two-factor and three-factor RTMs.](image)

Figure 3. Bias statistical histograms of Bevis model and yearly one-factor, two-factor and three-factor RTMs.

Figures 4 and 5 list the time series variation of $T_m$ and their biases of the Bevis model, the one-factor, two-factor and three-factor yearly RTMs to the radiosonde-derived $T_m$ at Anqing and Sheyang stations during 2016–2017. It can also be seen from Figure 4a to Figure 5a that the $T_m$ shows seasonal changes all through a year. The highest $T_m$ value is recorded in summer, whilst the lowest is in winter. The bias of the three-factor RTM is relatively concentrated towards 0, which is relatively small compared to the other models,
as shown in Figures 4b and 5b. The reason may be that using the three factors to establish RTMs can reflect the changes in $T_m$ throughout the year in a relatively more accurate way.

Figure 4. Comparison of the time series of $T_m$ (a) and the biases (b) of Bevis, the one-factor, two-factor and three-factor RTMs to the radiosonde-derived $T_m$ at Anqing station during 2016–2017.

Figure 5. Time series of $T_m$ (a) and the biases (b) of Bevis, one-factor, two-factor and three-factor RTMs to the radiosonde-derived $T_m$ at Sheyang station during 2016–2017.

Table 5 shows the previous RTMs in the Yangtze River Delta [50]. Table 6 shows the precision statistics of previous RTMs and new proposed RTMs in 2016 and 2017, respectively. It can be seen that the Bevis model has the lowest precision among all the models. The precision of one-factor, two-factor and three-factor RTM increases in turn. Based on the average of the bias and RMSE of the two years, precision analysis was performed. Compared to the Bevis model, the bias of newly established one-factor, two-factor and three-factor yearly RTM was reduced by 0.55 K, 0.68 K and 0.69 K, respectively, and the RMSEs improved by 0.56 K, 0.80 K and 0.83 K, respectively. The precision of the newly established three-factor RTM was slightly better than that of the two-factor RTM.

Compared to the previous two-factor RTM, the bias and the RMSE of the newly established two-factor RTM improved by 0.08 K and 0.15 K, respectively. Compared to the previous three-factor RTM, the bias of the newly established three-factor RTM improved by 0.07 K, and the RMSE improved by 0.14 K. The newly established yearly three-factor RTM has the highest precision, and it was chosen to establish the seasonal linear three-factor RTMs in the following section.

Table 5. Previous RTMs in the Yangtze River Delta [50].

| Model       | Previous RTMs          |
|-------------|------------------------|
| One-factor  | $T_m = 44.5054 + 0.8148T_s$ |
| Two-factor  | $T_m = 255.1953 + 0.6614T_s - 0.1643P$ |
| Three-factor| $T_m = 257.4974 + 0.5548T_s - 0.1384P + 0.1447c_s$ |
Table 6. Precision statistics of yearly multifactor RTMs (K).

| Year | Previous RTMs | Bias | RMSE | New RTMs | Bias | RMSE |
|------|---------------|------|------|----------|------|------|
| 2016 | Bevis         | 3.06 | 3.71 | Bevis    | 3.06 | 3.71 |
|      | One-factor    | 2.41 | 3.08 | One-factor| 2.41 | 3.08 |
|      | Two-factor    | 2.33 | 2.94 | Two-factor| 2.25 | 2.80 |
|      | Three-factor  | 2.25 | 2.80 | Three-factor| 2.22 | 2.74 |
| 2017 | Bevis         | 2.77 | 3.46 | Bevis    | 2.77 | 3.46 |
|      | One-factor    | 2.32 | 2.98 | One-factor| 2.32 | 2.98 |
|      | Two-factor    | 2.30 | 2.94 | Two-factor| 2.23 | 2.78 |
|      | Three-factor  | 2.28 | 2.90 | Three-factor| 2.24 | 2.78 |

4.2. Seasonal Multifactor Linear RTMs

4.2.1. Establishing RTMs

$T_m$ shows seasonal dynamic regularity all through a year. Therefore, the $T_m$, $T_s$, $e_s$ and $P_s$ from the 7 radiosonde stations during 2015–2016 were divided on a seasonal basis to establish the seasonal three-factor linear RTMs. The seasonal three-factor linear RTMs are shown in Table 7.

Table 7. Seasonal three-factor linear RTMs during 2015–2016.

| Seasons | Seasonal RTMs                                                                 |
|---------|-------------------------------------------------------------------------------|
| Spring  | $T_m = 253.7193 + 0.4272 T_s + 5.0205 \ln e_s - 0.1090 P_s$                  |
| Summer  | $T_m = 79.5517 + 0.7115 T_s + 2.3678 \ln e_s - 0.0121 P_s$                  |
| Autumn  | $T_m = 380.0851 + 0.3516 T_s + 3.3502 \ln e_s - 0.2068 P_s$                  |
| Winter  | $T_m = 380.0981 + 0.3293 T_s + 4.4980 \ln e_s - 0.2045 P_s$                  |

4.2.2. Precision of RTMs

In order to test the precision of the seasonal three-factor RTMs, the $T_m$ predicted from the Bevis model, yearly and seasonal three-factor RTMs in the Yangtze River Delta region from 2016 to 2017 were compared to the radiosonde-derived $T_m$. Figure 6 shows the statistical histograms of the biases of the Bevis model, yearly and seasonal three-factor RTM-derived $T_m$ in spring (a), summer (b), autumn (c) and winter (d).

It can be seen that the biases of all RTMs are distributed normally, while the symmetric axis of the bias of the Bevis model deviates from 0. In spring, autumn and winter, the bias distribution of the seasonal three-factor RTMs is nearly equivalent to yearly RTMs. In summer, the bias distribution of the seasonal three-factor RTMs is better than that of the yearly three-factor RTM. Table 8 shows the deviation statistics of the Bevis model, yearly and seasonal three-factor RTMs. It can be seen from the number of deviations that the seasonal three-factor RTM has the best improvement.

Table 8. Deviation distribution of Bevis model, yearly and seasonal three-factor RTMs (K).

| Model  | (< −8) | (−8, −6) | (−6, −4) | (−4, −2) | (−2, 0) | (0, 2) | (2, 4) | (4, 6) | (6, 8) | (>8) |
|--------|--------|----------|----------|----------|---------|--------|--------|--------|--------|------|
| Bevis  | 148    | 668      | 1548     | 2515     | 2629    | 1452   | 763    | 301    | 143    | 32   |
| Yearly | 10     | 153      | 705      | 1535     | 2503    | 2741   | 1912   | 535    | 93     | 12   |
| Seasonal| 10    | 139      | 694      | 1539     | 2544    | 2939   | 1741   | 510    | 67     | 16   |

Figures 7 and 8 list the time series of $T_m$ and their biases of the Bevis model, the yearly and seasonal three-factor RTMs to the radiosonde-derived $T_m$ at Nanjing and Hangzhou during 2016–2017. Similar to the yearly RTM, the $T_m$ calculated by seasonal RTMs have similar changes over time. The $T_m$ calculated by the seasonal RTMs is much closer to the reference value, while the deviations of the Bevis model are larger.
Figure 6. The statistical histograms of the biases of Bevis model, yearly and seasonal three-factor RTMs in spring (a), summer (b), autumn (c) and winter (d).

Figure 7. Time series of $T_m$ (a) and biases (b) of Bevis, the yearly and seasonal three-factor RTMs to the radiosonde-derived $T_m$ at Nanjing station during 2016–2017.

Figure 8. Time series of $T_m$ (a) and the biases (b) of Bevis, the yearly and seasonal three-factor RTMs to the radiosonde-derived $T_m$ at Hangzhou station during 2016–2017.
The statistics of the $T_m$ are listed in Table 9. It can be seen that biases and RMSE of seasonal three-factor RTMs are smaller than that of the yearly three-factor RTMs, especially in summer. Based on the average of the bias and RMSE of four seasons, a precision analysis was performed. Compared to the Bevis model, the mean biases of yearly and seasonal three-factor RTMs improved by 0.70 K and 0.76 K, and the mean RMSE of them improved by 0.86 K and 0.96 K, respectively. The mean biases and RMSE of the seasonal three-factor RTMs decreased by 0.06 K and 0.10 K compared to the yearly three-factor RTM. It means that the seasonal three-factor RTMs can reflect the seasonal characteristics of $T_m$ and their precisions are better than that of yearly three-factor RTM.

Table 9. The biases and RMSE of the Bevis model, seasonal and yearly three-factor RTM-derived $T_m$ in the Yangtze River Delta region during 2016–2017 (K).

| Season  | Model  | Seasonal RTM | Yearly RTM |
|---------|--------|--------------|------------|
|         |        | Bias | RMSE | Bias | RMSE |
| Spring  | Bevis  | 3.07 | 3.76 | 3.07 | 3.76 |
|         | Three-factor | 2.53 | 2.88 | 2.53 | 3.03 |
| Summer  | Bevis  | 2.86 | 3.46 | 2.86 | 3.46 |
|         | Three-factor | 1.77 | 2.20 | 1.99 | 2.39 |
| Autumn  | Bevis  | 3.09 | 3.77 | 3.09 | 3.77 |
|         | Three-factor | 2.18 | 2.70 | 2.19 | 2.74 |
| Winter  | Bevis  | 2.68 | 3.35 | 2.68 | 3.35 |
|         | Three-factor | 2.19 | 2.73 | 2.20 | 2.75 |

4.3. Nonlinear Three-Factor Seasonal RTMs

4.3.1. Establishing RTMs

Since the seasonal RTMs can reflect the seasonal characteristics, and the three-factor RTM has more advantages compared to the two-factor RTM, the nonlinear seasonal three-factor RTMs are established using the data of 7 radiosondes in the Yangtze River Delta region from 2015 to 2016 based on the nonlinear correlation between $T_m$ and $e_s$. Table 10 shows the established nonlinear seasonal three-factor RTMs during 2015–2016.

Table 10. The nonlinear seasonal three-factor RTMs in the Yangtze River Delta region during 2015–2016.

| Season  | RTM                                           |
|---------|-----------------------------------------------|
| Spring  | $T_m = -47.601 + 0.55473T_s + 203.60e_s^{0.02083} - 0.04712P_s$ |
| Summer  | $T_m = 81.713 + 0.70566T_s + 1.6097e_s^{0.41430} - 0.01098P_s$ |
| Autumn  | $T_m = 117.25 + 0.44669T_s + 178.35e_s^{0.01623} - 0.14967P_s$ |
| Winter  | $T_m = -107.63 + 0.40852T_s + 420.59e_s^{0.01002} - 0.15991P_s$ |

4.3.2. Precision of RTMs

In order to test the precision of nonlinear seasonal multifactor RTMs, the reference values of $T_m$ from 2016 to 2017 were used to compare with the $T_m$ derived from Bevis model, linear and nonlinear seasonal three-factor RTMs in the Yangtze River Delta region. Figure 9 shows the statistical histograms of the biases of Bevis model, linear and nonlinear seasonal three-factor RTM-derived $T_m$ in spring (a), summer (b), autumn (c) and winter (d).

It can be seen the biases of all RTMs are distributed normally. The best improvement of bias distributions is recorded in summer. The biases of the linear and nonlinear seasonal three-factor RTMs are concentrated in the range $-6$ K to $6$ K, while the biases of the Bevis model are in the range $-10$ K to $6$ K in summer. Table 11 shows the deviation statistics of the Bevis model, linear and nonlinear seasonal three-factor RTMs. It can be seen from the number distribution of the deviations that the precision of the nonlinear seasonal three-factor RTMs is approximately equivalent to the linear seasonal three-factor RTMs.
Table 11. Deviation statistics of Bevis model, linear and nonlinear seasonal three-factor RTMs in the Yangtze River Delta region during 2016–2017 (K).

| Range            | Bevis | Linear | Nonlinear |
|------------------|-------|--------|-----------|
| \((-\infty, -8)\) | 148   | 10     | 12        |
| \((-8, -6)\)     | 668   | 139    | 122       |
| \((-6, -4)\)     | 1548  | 694    | 660       |
| \((-4, -2)\)     | 2515  | 1539   | 1561      |
| \((-2, 0)\)      | 2629  | 2544   | 2567      |
| \((0, 2)\)       | 1452  | 2939   | 2886      |
| \((2, 4)\)       | 763   | 1741   | 1769      |
| \((4, 6)\)       | 301   | 510    | 514       |
| \((6, 8)\)       | 143   | 67     | 87        |
| \((8, +\infty)\) | 32    | 16     | 17        |

Figures 10 and 11 shows the time series of $T_m$ and the biases of the Bevis model and the linear and nonlinear seasonal three-factor RTMs compared to the radiosonde-derived $T_m$ at Nanjing and Shanghai during the period 2016–2017.

Figure 10. Time series of $T_m$ (a) and the biases (b) of Bevis, linear and nonlinear seasonal three-factor RTMs to the radiosonde-derived $T_m$ at Nanjing station during 2016–2017.
Table 12. The biases and RMSE of the linear and nonlinear seasonal multifactor RTMs-derived 
$T_m$ in the Yangtze River Delta region during 2016–2017 (K).

| Models            | Spring | Summer | Autumn | Winter |
|-------------------|--------|--------|--------|--------|
| Linear            | Bias   | 2.53   | 1.77   | 2.18   | 2.19   |
|                   | RMSE   | 3.09   | 2.20   | 2.70   | 2.73   |
| Nonlinear         | Bias   | 2.49   | 1.77   | 2.18   | 2.18   |
|                   | RMSE   | 3.07   | 2.19   | 2.71   | 2.73   |

5. Discussions

Yearly RTMs are universal for all seasons and are easy to use in the Yangtze River Delta region. Different from the previous studies on the linear relationship between $T_m$ and $T_e$, $e_s$, $P_e$, this study modified the linear expression through collinearity and correlation analysis by replacing the coefficient $e_s$ with $\ln e_s$, which improved the precision to a certain extent. It indicates that these coefficients are statistically significant. Additionally, it makes sense to find a more statistical expression.

However, from the time series analysis of $T_m$, it can be seen that $T_m$ exhibits regular dynamic changes throughout the year. The Yangtze River Delta region has four distinctive seasons, and the seasonal changes in $T_m$ are in line with the climate. Establishing RTMs on a seasonal basis may better reflect the seasonal characteristics of $T_m$. The results show that the seasonal three-factor linear RTMs have the best precision among the Bevis model and RTMs, especially in summer. The reason may be that the $T_m$ shows a high peak in summer due to the higher temperature than the other three seasons, and seasonal three-factor RTMs can exhibit their superiority in predicting $T_m$ in summer.

Moreover, we established multifactor RTMs based on the nonlinear relationship between $T_m$ and $e_s$. Although its modeling is more complex than linear RTMs, it is also meaningful if the precision has further improved. However, the results show that it is equivalent to express the relationship between $T_m$ and $e_s$ by using a power function or a logarithmic function. Therefore, the linear seasonal three-factor RTMs can be chosen to calculate the $T_m$ in the Yangtze River Delta Region, serving the prediction and research of GNSS-PWV due to their simple expressions and higher precision compared to existing RTMs.
6. Conclusions

In this study, several one-factor and multifactor RTMs were established by using 7 radiosondes during 2015–2016 in the Yangtze River Delta region. The numerical integration and least squares principle were adopted to obtain $T_m$ time series and RTMs, respectively. The newly established linear RTMs include yearly and seasonal one-factor, two-factor and three-factor RTMs. The new nonlinear RTMs include seasonal three-factor RTMs. These RTMs were validated by comparing to the radiosonde-derived $T_m$ (as the reference value) during 2016–2017.

Results showed that the yearly three-factor RTM performs much better than the Bevis model, with improvements of 0.69 K and 0.83 K in bias and RMSE, respectively. The precisions of the seasonal three-factor RTMs are better than that of the yearly three-factor RTM, and it can better reflect the seasonal changes in $T_m$, especially in summer. Compared to the linear seasonal three-factor RTMs, the mean bias of nonlinear seasonal three-factor RTMs improved by 0.01 K. Using a power function or a logarithmic function to express the relationship between $T_m$ and $e_s$ has the same effect. Therefore, due to the complicated expressions of nonlinear RTMs and the limitation of its precision improvement compared to the linear RTMs, the linear seasonal three-factor RTMs are recommended to calculate the $T_m$ and GNSS-PWV in the Yangtze River Delta region.

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