# **Responses to Referee #1**

We have tried our best to answer all the questions raised by referee #1. Thanks for your time anyway.

# **Responses to Referee #2**

We thank the referee #2 for the insightful comments and constructive suggestions. We have revised manuscript according to the reviewer's suggestions. Below are our responses to the referee's specific comments (*Italics*). The page and line numbers in our responses refer to those in the revised manuscript.

a. It is necessary to mention a summary of the authors' responses (a,b,c) in the text. Authors: Thanks for the reviewer's reminding, we have deleted the unused reference 'Adavi and Mashhadi' in the revised manuscript, and this revised manuscript has been proofread by a native English speaker.

b. The reference "Adavi and Mashhadi" is not used in the text. Please delete this reference from the list of references.

Authors: Thanks for the reviewer's reminding, we accepted your suggestions and deleted it in the revised manuscript.

c. Please consult with a native speaker on the language of the paper to complete the paper's corrections.

Authors: Thanks for the reviewer's suggestion, this revised manuscript has been proofread by a native English speaker.

# **Responses to Referee #3**

We thank the referee #3 for the insightful comments and constructive suggestions. We have addressed all their comments in the revised manuscript. Below are our responses to the referee's specific comments (*Italics*). The page and line numbers in our responses refer to those in the revised manuscript.

*1 A brief introduction of the improved method needs to be included in the abstract.* Authors: Thanks for the reviewer's reminding, we accepted your suggestions and have added a brief introduction of the improved method into the abstract (Page 1, Lines 20-23).

2 The current English writing actually is not well. To be a high-quality journal paper, I would like to suggest author to polish the English by native speakers.

Authors: Thanks for the reviewer's suggestion, this paper has been polished by native English speakers.

3 The comparisons with the radiosonde show that the performance of the improved method is very poor. Especially in the lower troposphere, large differences exist. The poor performance will definitely restrict its applications in meteorology.

Authors: Thanks for the reviewer's reminding, to be frank we are not satisfied with the

comparison results in the lower troposphere as you mentioned. However, we are really sorry to find that the large differences in the water vapor profiles occur due to the wrong calculation. In the revised manuscript, all calculations have been checked to ensure the correctness and the accuracy of water vapor derived from two models. The comparison with radiosonde data has been revised (Page 16, Lines 424-426; Page 17, Lines 434-435). Besides, the Figure 6 has also revised and we find the differences in the lower troposphere have shrunk a lot, not as bad as before (Page 17, Lines 439-449).

4 The improved method consists of two parts: using the traditional method to get the initial water vapor fields; performing polynomial fitting for each layer. In my opinion, the polynomial fitting is just another kind of horizontal constraint. Why not directly impose that horizontal constraint to the tomography equation? I am afraid if you perform polynomial fitting for each layer, the finally reconstructed SWVs will differ the measured SWVs a lot. Assessments on the reconstructed SWVs are required.

Authors: Thanks for the reviewer's question, we really appreciate your suggestion of directly imposing the layered optimal polynomial fitting functions as horizontal constraints to the tomography equation. In this paper, unfortunately, we did not think of this method. In our future research we would try this method to see if the results derived from the mentioned method would be better. As for the final reconstructed SWVs, the assessments on that are performed in the revised paper and the results show that the two model have the similar accuracy (Page 17-18, Lines 450-461). Referring to the previous paper we published (Yao and Zhao, 2017), this accuracy of SWVs comparison would be okay.

Reference: Yao Y, Zhao Q. A novel, optimized approach of voxel division for water vapor tomography. Meteorology and Atmospheric Physics, 2017, 129(1):57-70, DOI: 10.1007/s00703-016-0450-4.

# An improved pixel-based water vapor tomography model

3 4 Yibin Yao<sup>1, 2, \*</sup>, Linyang Xin<sup>1</sup> and Qingzhi Zhao<sup>3</sup> 5 School of Geodesy and Geomatics, Wuhan University, Wuhan 430079, China; 6 ybyao@whu.edu.cn (Y.Y); linyangxin@whu.edu.cn (L.X); 7 Key Laboratory of Geospace Environment and Geodesy, Ministry of Education, Wuhan University, Wuhan 8 430079. China 9 <sup>3</sup> College of Geomatics, Xi'an University of Science and Technology, Xi'an 710054, China; 10 zhaoqingzhia@163.com 11 Correspondence: ybyao@whu.edu.cn; Tel.: +86-027-68758401 12 13 Abstract: As an innovative use of Global Navigation Satellite System (GNSS), GNSS water vapor 14 tomography technique shows great potential in monitoring three-dimensional water vapor variation. Most 15 of the previous studies employ the pixel-based method, i.e., dividing the troposphere space into finite voxels 16 and considering water vapor in each voxel as constant. However, this method cannot reflect the variations 17 in voxels and breaks the continuity of the troposphere. Moreover, in the pixel-based method, each voxel 18 needs a parameter to represent the water vapor density, which means huge numbers of parameters are 19 needed to represent the water vapor field when the interested area is large and/or the expected resolution is 20 high. In order to overcome abovementioned problems, in this study, we propose an improved pixel-based 21 water vapor tomography model, which uses layered optimal polynomial functions obtained from the 22 European Centre for Medium-Range Weather Forecasts (ECMWF) by adaptive training for water vapor 23 retrieval. Tomography experiments were carried out using the GNSS data collected from the Hong Kong 24 Satellite Positioning Reference Station Network (SatRef) from March 25 to April 25, 2014 under different 25 scenarios. The tomographic results are compared to the ECMWF data and validated by the radiosonde. Results show the new model outperforms the traditional one by reducing the Root Mean Square Error 26 27 (RMSE) and this improvement is more pronounced by 5.88% in voxels without the penetration of GNSS 28 rays. The improved model also has advantages in expression with more convenience. 29 30 Keywords: GNSS; water vapor tomography; ECMWF; Radiosonde

## 31 1. Introduction

As the most active component in the troposphere, water vapor is one of the most difficult parameters to monitor and describe (Rocken et al., 1997). A good understanding of the spatial-temporal variation of water vapor is very helpful for improving weather forecasting and early warning of disastrous weather (Weckwerth et al., 2004).

The GNSS technique can not only retrieve the precipitable water vapor (Bevis et al., 1994; Emardson et al., 1998; Baltink et al., 2002; Bock et al., 2005) but also monitor the three-dimensional water vapor distribution by using the GNSS tomography method (Flores et al., 2000; Seko et al., 2000; Macdonald et al., 2002).

Braun et al. (1999) first proposed the concept of reconstructing the tropospheric water vapor structure using 20 GPS stations in a regional observational network. Flores et al. (2000) first applied the tomography technique to obtain wet refractivity from the GNSS slant wet delay (SWD). In the same year, Hirahara (2000) used a different method to conduct GNSS tomography experiments, which also successfully obtained three-dimensional water vapor fields. Since then, many scientists proposed new methods and applied them to GNSS water vapor tomography experiments (Rohm et al., 2014; Yao et al., 2016; Zhang et al., 2017; Ding et al., 2018; Zhao et al., 2018).

47 Hirahara (2000) conducted a four-dimensional tomography experiment and solved the tomography 48 equations using the damping least square method. Braun et al. (2003, 2004) overcame the sensitivity 49 problem in GNSS tomography by using the extended sequential filtering method. Perler et al. (2011) 50 presented a new parametric method for the water vapor retrieval. Nilsson and Gradinarsky (2006) obtained 51 the wet refractivity directly from the GNSS phase observations using the Kalman filter method. Rohm and 52 Bosy (2009) used the Moore-Penrose pseudo-inverse of variance-covariance to solve the linear equations 53 and emphasized the ill-posed tomography equation. Yao et al. (2016) obtained good tomographic results by 54 using the optimal grid-making method. Zhao and Yao (2017) proposed a method of using the side-55 penetrating signals for tomography and improved the utilization rate of the GNSS rays. Aghajany and 56 Amerian (2017) obtained the tomography results of water vapor profiles from ERA-I numerical weather 57 prediction data by applying 3D ray tracing technique. Dong and Jin (2018) reconstructed the water vapor 58 density using multi-GNSS systems and showed that the accuracy of GNSS tomography results are 59 improved by 5% from the GPS-only system to the dual-systems (GPS+GLONASS). Besides, the virtual 60 reference station approach (Marel, 1998; Vollath et al., 2013), an effective method to attenuate the effects 61 of atmospheric errors in long-distance dynamic positioning, was also used in GNSS tropospheric 62 tomography.

63 In previous studies, most of the GNSS tomography methods divided the interested troposphere into 64 finite voxels and the water vapor density in each voxel is considered as constant, these methods with the 65 above assumptions are defined as the pixel-based method. Apparently, this kind of method cannot retrieve the variations in voxels and breaks the continuous nature of the troposphere as well. Moreover, the pixel-66 67 based method requires each voxel to have a parameter to represent the water vapor density in it, which may lead to the situation that we have to use huge numbers of parameters when the research area is large and 68 69 the expected resolution is high. Last, over-parametrization may cause mathematical problems when we use 70 limited observations to invert for the parameters that may be correlated. Therefore, this paper analyzes the 71 limitations of the traditional pixel-based water vapor tomography method and proposes an improved model. 72 The improved model uses the water vapor density obtained from the traditional model as the input value 73 and outputs the fitting water vapor density by the layered optimal polynomial functions. This new model

has the advantages of reflecting the variations in voxels and keeping the continuity of water vapor in troposphere.

### 76 2. An improved pixel-based water vapor tomography model

77 2.1. Establishment of the traditional pixel-based water vapor tomography model

- 78 2.1.1. Retrieval of SWV
- For tropospheric tomography, the most important observation is the slant water vapor (SWV), which is related to the water vapor density and can be defined by

81 
$$SWV = \int_{S} \rho_V ds \quad (1)$$

82 where s represents the path of the satellite signal ray, and  $\rho_V$  is the water vapor density (units: g/m<sup>3</sup>).

83 SWV can be obtained by the following method:

84 
$$SWV = \frac{10^6}{R_{\omega}[(k_3/T_m) + k_2]} \cdot SWD \quad (2)$$

85 where  $k_2^{'} = 16.48$  K hPa<sup>-1</sup>,  $k_3 = 3.776 \times 10^5$  K<sup>2</sup> hPa<sup>-1</sup>, and  $R_{\omega} = 461$  J kg<sup>-1</sup> K<sup>-1</sup>, which represent the specific

gas constants for water vapor.  $T_m$  is the weighted mean tropospheric temperature, calculated from an empirical equation proposed by Liu et al. (2001) using the meteorological measurements. SWD is the slant wet delay, which may be given as

89 
$$SWD_{elv,\varphi} = m_{wet}(elv) \times ZWD + m_{wet}(elv) \times \cot(elv) \times (G_{NS}^{w} \times \cos\varphi + G_{EW}^{w} \times \sin\varphi) + R \quad (3)$$

where *elv* is the satellite elevation,  $\varphi$  is the azimuth,  $m_{wet}$  is the wet mapping function,  $G_{NS}^{w}$  and  $G_{EW}^{w}$ 90 91 are the wet delay gradient parameters in the north-south and east-west directions, respectively. R refers to 92 the unmodeled zero difference residuals that may involve unmodeled influence on the three-dimensional 93 spatial water vapor distribution, which can make up for the lack of tropospheric anisotropy using only the 94 gradient term (Bi et al., 2006). Since the GAMIT software only provides the double difference residuals, 95 the zero difference residuals in this paper are obtained from the double difference residuals according to 96 the method proposed by Alber et al. (2000). ZWD is the zenith wet delay, which is extracted from the zenith tropospheric delay (ZTD) by separating the zenith hydrostatic delay (ZHD) using equation ZWD=ZTD-97 98 ZHD. ZHD can be calculated precisely using surface pressure based on the Saastamoinen model 99 (Saastamoinen, 1972):

100 
$$ZHD = \frac{0.002277 \times P_s}{1 - 0.00266 \times \cos(2\varphi) - 0.00028 \times H}$$
(4)

101 where  $P_s$  is the surface pressure (unit: hPa),  $\varphi$  is the latitude of the station, and H is the geodetic 102 height (unit: km). The unit of ZHD is meter.

103 Since the SWV is obtained, the tomographic area can be discretized into a number of voxels, in which 104 the water vapor density is a constant during a given period of time. Therefore, a linear equation relating the 105 SWV and the water vapor density can be established as follows (Chen and Liu, 2014): 106

107 
$$SWV^{p} = \sum_{ijk} (D^{p}_{ijk} \bullet \rho_{ijk}) \quad (5)$$

108 where  $SWV^{p}$  is the slant water vapor of  $\rho$  th signal path (unit: mm). i, j, and k are the positions of

109 discrete tomographic voxels in the longitudinal, latitudinal and vertical directions, respectively.  $D_{iik}^p$  is

110 the distance of the  $\rho$  th signal in voxel (i, j, k) (unit: km).  $\rho_{ijk}$  is the water vapor density in a given voxel

(i, j, k) (unit: g/m<sup>3</sup>). A matrix form of this observation equation can be rewritten as follows (Flores et al.,
2000; Chen and Liu, 2014):

113 
$$y_{m\times 1} = A_{m\times n} \bullet \rho_{n\times 1} \quad (6)$$

114 where *m* is the number of total SWVs, and *n* is the number of voxels in the tomographic area. *y* is the 115 observed value here as the SWV, which penetrates the whole interest area, *A* is the coefficient matrix of the 116 signal transit distances through the voxels, and  $\rho$  is the column vector of the unknown water vapor 117 density.

118 2.1.2. Constraint equations of the tomography modeling

119 Solving for the unknown water vapor density in Eq. (6) is actually an inversion algorithm issue as the 120 design matrix A is a large sparse matrix, whose normal equation is singular, leading to numerical problems when using a direct inversion method (Bender et al., 2011). To overcome this rank deficiency problem, 121 122 constraint equations are often introduced to the tomography equation (Flores et al., 2000; Troller et al., 123 2002; Rohm and Bosy, 2009; Bender et al., 2011). In our study, the horizontal constraint equation is imposed 124 by the Gauss-weighted functional method (Guo et al., 2016) and the vertical constraint equation is imposed 125 by the functional relationship of the exponential distribution (Cao, 2012), respectively. The final 126 tomography model is then obtained as

127 
$$\begin{pmatrix} A_{m \times n} \\ H_{m \times n} \\ V_{m \times n} \end{pmatrix} \bullet \rho_{n \times 1} = \begin{pmatrix} y_{m \times n} \\ 0_{m \times n} \\ 0_{m \times n} \end{pmatrix}$$
(7)

where H and V are the coefficient matrices of horizontal and vertical constrains, respectively. In order to obtain the inverse matrix shown in Eq. (7), singular value decomposition is used in this paper (Flores et al., 2000).

131 2.2. An improved pixel-based water vapor tomography model

The improved pixel-based water vapor tomography model proposed in this paper can take advantage of facilitating the continuity of water vapor expression efficiently in spatial-temporal distribution and calculating the water vapor density conveniently. The improved tomography model firstly obtains the water vapor density from voxels penetrated by GNSS rays using the traditional pixel-based tomography model, then obtains the optimal polynomial function of each layer through adaptive training. With known coefficients of the layered optimal polynomial functions, the water vapor density can finally be calculated by given the latitude, longitude and the altitude. Specific steps are as follows:

First, use the traditional pixel-based water vapor tomography model to obtain the initial water vapor density from voxels penetrated by GNSS rays as the observation values for obtaining the optimal 141 polynomial function coefficients of each layer.

142 Second, normalize the coordinates of each voxel center in the tomographic area. Since the polynomial 143 fitting of the water vapor at each tomographic layer is in essence to establish the relationship between the 144 latitude as well as the longitude of the tomographic region and the water vapor density. The general 145 expression is:

146 
$$V_d = a_0 + a_1 B + a_2 L + a_3 B L + a_4 B^2 + a_5 L^2 + a_6 B^2 L \cdots$$
(8)

where B is the latitude, L is the longitude, and  $V_d$  represents the water vapor density. Polynomial 147

coefficients such as  $a_i$  are obtained via the least squares method. In the process of data solving, the 148 149 numerical values of the latitude and longitude may not be small, then the magnitude of multiple power may 150 be larger than  $10^4$ , which will lead to the ill-posed problem of the design matrix in the inversion process and eventually affect the reliability of the estimated coefficients. To ensure the design matrix will be 151 152 relatively stable in the inversion process, the latitude and longitude coordinates B and L need to be 153 normalized. The specific methods are as follows:

$$B^{*} = \frac{B - \mu_{B}}{\sigma_{B}}$$
154
$$L^{*} = \frac{L - \mu_{L}}{\sigma_{L}}$$
(9)

where  $B^*$  and  $L^*$  are the normalized latitude and longitude, respectively, and B and L are the 155 latitude and longitude in the initial region range.  $\mu$  is the average value of the latitude or longitude, and 156  $\sigma$  is the standard deviation of the latitude or longitude. 157 Third, determine the layered optimal polynomial functions of the improved model through adaptive 158

159

training. 160 First, based on the size of the selected tomographic region, determine the highest 161 polynomial fit order. In this paper, the highest polynomial fit order chosen as 5 turns out to 162 be generally sufficient.

- Then set the water vapor density from voxels penetrated by GNSS signal rays as the input 163 value and keep trying out new polynomial functions, the optimal polynomial function of 164 165 each layer is obtained by adaptive training. What needs to be noted here is the number of 166 estimated coefficients need to be less than that of the voxels penetrated by GNSS rays in 167 each layer. Otherwise the over-fitting problem would happen.
- 168 Finally, after comparing training results of multi-group polynomial functions at different levels, the polynomial function with the minimum RMSE value obtained from the water 169 vapor density of the post-fitting layer and that of the ECMWF is the best fitting equation 170 171 for this layer. Each layer could have the individual optimal polynomial function in general.

172 Fourth, after finding the optimal polynomial function of each layer in different heights, taking the 173 latitude, longitude and altitude information into the function could obtain the three-dimensional water vapor 174 distribution in the tomographic region. The continuous water vapor density can be easily described by 175 broadcasting the estimated coefficients of the layered optimal polynomial functions.

176 2.3. The optimal polynomial selection based on adaptive training

Since the polynomial form can well reflect the continuity of water vapor and has the advantage of high-efficiency computing as well as easy expression, this paper chooses the polynomial form as the layered fitting function. Based on adaptive training, the selection process of the layered optimal polynomial function is as follows:

First, construct a polynomial equations training library, which contains a wide variety of polynomial function forms of the latitude and longitude as independent variables while of the water vapor density in the voxels as the dependent variable. After many experiments, the maximum power of the latitude and longitude found as 5 is sufficient to describe the water vapor changes. Therefore, the maximum power of the fitting function part is adopted as 5 in the training library.

Second, according to the water vapor density observations from the voxels penetrated by the GNSS signals at each level, the form of the candidate polynomial function of each layer is automatically determined from the polynomial function training library, ensuring that the number of observations at all levels is always greater than that of estimated coefficients of candidate polynomials.

190 Third, calculate the water vapor variation index (WVVI) of each layer in both east-west and north-191 south directions using the traditional water vapor tomography results as shown in Eq. (10).

192 
$$WVVI = \frac{\nabla wv_{EW}}{\overline{\nabla wv_{NS}}}$$
(10)

193 where  $wv_{EW}$  and  $wv_{NS}$  are the water vapor density in east-west and north-south direction, separately.

The WVVI is a changing rate indicator of the water vapor density in a given direction. According to 194 195 the water vapor variation index of each layer in the east-west and north-south direction, it can be determined 196 whether the water vapor exists mainly in the east-west distribution or the north-south distribution. As an 197 aid, WVVI can decide the main body of the alternative polynomial function with higher order whether in 198 longitude or latitude and then efficiently find the layered optimal polynomial function. If the water vapor 199 density of a layer indicates a horizontal gradient of east-west distribution, the polynomial function with 200 higher-order term of the longitude should be given the priority. It suggests that when the water vapor shows 201 an east-west gradient distribution there is a better correlation between the longitude and the water vapor 202 variation, furthermore the high-order term in longitude can better reflect the nuanced water vapor variation. 203 A simple example of the polynomial function with a higher-order term in longitude is shown in Eq. (11):

$$V_d = a_0 + a_1 B + a_2 L + a_3 B L + a_4 L^2 + a_5 B L^2 + a_6 L^3$$
(11)

205 Otherwise, when the water vapor density of a layer indicates a horizontal gradient of north-south 206 distribution, the polynomial function with higher-order term of the latitude should be given the priority. A 207 simple example is shown in Eq. (12):

208 
$$V_d = a_0 + a_1 B + a_2 L + a_3 B L + a_4 B^2 + a_5 B^2 L + a_6 B^3$$
(12)

204

While the distribution regularities of the water vapor density gradient are not clear or obvious, the polynomial function with the same order of the latitude and longitude can be considered as the example shown in Eq. (13):

212 
$$V_d = a_0 + a_1 B + a_2 L + a_3 B L + a_4 B^2 + a_5 L^2$$
(13)

Fourth, the candidate polynomials of all levels screened by the WVVI gradient auxiliary information are used as the next comparative polynomials, and the required estimated coefficients of the comparative polynomial are solved according to the principle of least squares through Eq. (14) and automatically recorded into the coefficients data set. M is the matrix of the longitude and latitude, and the vector xcomprises the unknown coefficients of the comparative polynomial functions as shown in Eq. (15).

218 
$$V_d = Mx \qquad (14)$$

$$x = \begin{bmatrix} a_0 \\ a_1 \\ \vdots \\ a_n \end{bmatrix}$$
(15)

220 Fifth, through the comparative polynomials with the estimated coefficients in each layer, the wholevoxel water vapor fitting of each layer is automatically fit with the information of the latitude and longitude. 221 In order to obtain the RMSE, the fitting result would be compared with the ECMWF water vapor density 222 223 of each layer in this period. The results are then saved to the accuracy data sets of each layer. The 224 comparative polynomials with the estimated coefficients are constantly selected to train the fitting of the 225 layered water vapor density and then compared with the water vapor density of ECMWF at each layer. 226 Thus, large accuracy data sets of RMSE can be obtained, where the smallest RMSE value of the 227 comparative polynomial form can be chosen, and then the optimal polynomial of each layer could come into being. It is noteworthy that the optimal polynomial of each layer might be different. With the layered 228 229 optimal polynomial, the continuous three-dimensional water vapor density in the tomographic region can 230 be expressed conveniently by transmitting the estimated coefficients information.

## 231 3. Experiment

219

232 3.1. Experimental description and data-processing strategy

To study whether the accuracy and stability of the improved water vapor tomography model are better than that of the traditional model, the following experiment is designed.

235 Tomographic data is obtained from the SatRef Network for Hong Kong from 25 March 2014 to 25 236 April 2014. Two epochs are taken each day (0:00 and 12:00 UTC). The corresponding meteorological data 237 is also used to calculate the PWV. The tomographic area ranges between latitude 22.24°N to 22.54°N and longitude 113.87°E to 114.29°E. Taking the mean sea level as the height of the base level, the vertical 238 239 resolution is 0.8 km, and total grid number is  $5 \times 7 \times 13$ . In the selected area, a total of 11 GNSS stations 240 and 1 radiosonde station (located at King's Park, Hong Kong) are selected, and the ECMWF grid data are 241 extracted twice daily at 00:00 and 12:00 UTC from 25 March 2014 to 25 April 2014 (grid resolution of 242  $0.125 \times 0.125$ ). See Fig. 1 for details.



 $\blacklozenge$  GNSS Station  $\star$  Radiosonde  $\blacklozenge$  ECMWF

243

244

Figure 1. The GNSS stations (11 black rhombuses) and the radiosonde station (1 red star) and the ECMWF comparative
 points (12 ochre circles) in Hong Kong. The grid lines display tomography grids.

According to the official website of the Hong Kong Observatory (http://www.weather.gov.hk/contentc.htm) for the weather review, Hong Kong had a total of 15 days of rainy weather from 25 March 2014 to 25 April 2014, as shown in Table 1.

250

 Table 1. Rainfall information for March and April 2014.

Date	Rainfall situation
3.29	Thunderstorms turn to heavy rain
3.30	Thunderstorms turn to heavy rain
3.31	Thunderstorms turn to heavy rain
4.1	Showers accompanied by wind, thunderstorms
4.2	Showers, reports of hail in some areas
4.3	Showers, some parts of the rain are quite large
4.6	Cloudy showers, low temperature
4.7	Heavy showers, low temperature
4.8	Showers, low temperature
4.14	Showers
4.21	Cloudy turns to the showers
4.22	Showers and foggy
4.23	Showers turn to the rain
4.24	Showers turn to the cloudy
4.25	Cloudy turns to the rain

In this paper, GAMIT (v10.50) (Herring et al., 2010) software was used for processing the GPS observations based on the double-differenced model at a sampling interval of 30 s, and the global mapping function was adopted. The zenith total delay (ZTD) and wet horizontal gradient intervals were estimated at 0.5 h and 2 h, respectively. Based on the surface pressure obtained from observed meteorological 255 parameters, the ZHD could be obtained by the Saastamoinen model, and ZWD was isolated from ZHD.

256 Via GMF projection, the SWD could be obtained by transforming the observed SWV.

257 *3.2. Experimental introduction and comparison* 

The RMSE and bias of the improved tomography model residuals were calculated by subtracting the ECMWF water vapor density from the water vapor density of the improved pixel-based water vapor tomography model (hereinafter referred to as the improved model). In a similar way, the RMSE and bias of the traditional tomography model residuals can also be obtained from the difference between the ECMWF water vapor density and the water vapor density obtained by the traditional pixel-based water vapor tomography model (hereinafter referred to as the traditional model).

In order to evaluate the improved model, this paper investigates 6 scenarios, comprising the spatial distribution scenario, the everyday distribution scenario, the rainy scenario and the non-rainy scenario. Moreover the scenarios of residuals of the water vapor density in voxels with and without penetrating GNSS rays are inspected. The definitions of 6 scenarios abovementioned are as follows:

The spatial distribution scenario is investigated by obtaining the RMSE and bias of the residuals from all ECMWF comparative points at all time intervals.

The everyday distribution scenario is found by obtaining the RMSE and bias of the residuals from all
ECMWF comparative points in two epochs each day. Besides the overall accuracy of 32 days between 25
March 2014 and 25 April 2014 was calculated.

The rainy scenario is based on 15 rainy days between 25 March and 25 April, 2014, as referred to in Table 1. The RMSE and bias of the residuals are obtained from all ECMWF comparative points in all the epochs during rainy days. Similarly, the non-rainy scenario is found with the accuracy analysis of the non-rainy days.

The scenario of residuals of the water vapor density in voxels without GNSS rays penetration is found by obtaining the RMSE and bias of the residuals from ECMWF comparative points without rays passing through in all the epochs each day. Conversely, the scenario with GNSS rays penetration is found by obtaining the RMSE and bias of the residuals from ECMWF comparative points with rays penetrating in all the epochs each day.

According to the above classifications, the accuracy of the improved model residuals and the traditional model residuals were calculated, and the accuracy of the improved model was compared with the traditional one to find out which one is better. Furthermore, the water vapor comparison with radiosonde data was designed to show if the improved model would be more efficient than the traditional one.

286 **4. Interpretation of 6 scenario results** 

287 4.1. Accuracy information of the spatial distribution scenario

To verify whether the accuracy of the improved model is better than that of the traditional model, the layered RMSE and bias of the residuals are obtained from the tomography results (using both the optimal polynomial function of each layer and the traditional way) and the ECMWF data in all ECMWF comparative points (shown in Table 2). The calculation of RMSE improvement percentage involved in the following tables is shown in Eq. (16).

293 
$$\Delta RMSE\% = \left(RMSE_{trad} - RMSE_{impr}\right) / RMSE_{trad} \cdot 100\% \quad (16)$$

294 where  $RMSE_{impr}$  is the RMSE value of the residuals calculated from the improved model, and

295  $RMSE_{trad}$  is the RMSE value of the residuals obtained from the traditional model.

296 Table 2 shows that RMSE and bias values obtained by the improved model are smaller than those of 297 the traditional model, and the RMSE improvement percentage is positive, which indicates that the improved 298 model has a higher accuracy than the traditional model in general. The reason of the appreciable RMSE 299 improvement percentage in the upper region is that the value of the water vapor density in high altitudes is 300 very small (see Fig. 2 for details), even small water vapor changes could cause a large percentage fluctuation. 301 In addition, the bias and RMSE in the bottom from Table 2 are not as good as those of the other higher layers, regardless of which model is used. These results could be mainly ascribed to a certain system 302 303 deviation between the comparison data of ECMWF and the GNSS tomographic data. Besides, due to less 304 voxels with GNSS rays penetration in the lower layers, the observations are too insufficient to get good 305 accuracy. Figure 2 also shows that the water vapor content in the bottom region is so abundant and 306 changeable that tomography results from models could not reflect it accurately. These above reasons lead 307 to large bias and RMSE values in the bottom tropospheric area.

308 <b>Table 2.</b> Statistics of two models' tomography accuracy with respect to ECMWF data in the spatial distribution	on scenario
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		t	vias	RM	ISE	RMSE
L	ayer	Traditional	Improved	Traditional	Improved	Improvement
		model	model	model	model	Percentage
	1	-7.81	-7.65	8.17	8.00	2.06%
	2	-3.52	-3.42	3.95	3.83	3.14%
	3	-0.90	-0.80	1.66	1.60	4.05%
	4	0.72	0.61	1.39	1.36	2.00%
	5	1.62	1.58	1.87	1.83	2.28%
	6	1.95	1.77	2.10	2.09	0.39%
	7	1.98	1.90	2.25	2.20	2.07%
	8	1.76	1.68	2.15	2.10	2.32%
	9	1.62	1.60	2.06	2.04	1.10%
	10	1.34	1.11	1.85	1.47	20.68%
	11	1.04	0.87	1.60	1.25	21.75%
	12	0.74	0.61	1.26	0.96	23.67%
	13	0.44	0.38	0.71	0.58	18.36%

309 for the experimental period (Unit: g/m<sup>3</sup>).



Figure 2. The layered maps of the water vapor density from (a) (b) the traditional model and (c) (d) the improved model at specific epochs, (a) (c) 0:00 UTC 9 April 2014 and (b) (d) 0:00 UTC 11 April 2014.

312 4.2. The accuracy information of the everyday distribution scenario

313 To prove whether the accuracy of the improved model is better than that of the traditional model on 314 the everyday time scale, the RMSE improvement percentage is obtained from all ECMWF comparative points (a total of 12) at two epochs each day, using both the layered optimal polynomial functions and the 315 316 traditional method. Figure 3 shows that the percentage of RMSE improvement per day is mostly positive, 317 and the percentage of April 11th can even approach 12%, indicating that the improvement seems to be 318 appreciable. This improvement shows that the accuracy of the improved model is mostly superior to that of 319 the traditional model in everyday distribution; however, on April 7, April 9 and April 15, the RMSE 320 improvement percentage is negative. This might be due to the heavy showers bringing rapid water vapor 321 changes from April 7 to April 8 and on April 14, which is difficult to fit the polynomial function well with 322 the unstable water vapor. However, since negative percentages do not exceed -1%, the accuracy of the 323 improved model could be considered basically equivalent to that of the traditional model for these four 324 days.

11



325

Figure 3. Everyday distribution statistics of daily RMSE improvement percentage between 25 March and 25 April,
 2014.

328 In addition, the overall RMSE and bias of the residuals are obtained from the ECMWF comparative 329 points (a total of 12) in two epochs under the entire everyday distribution scenario. The statistical results 330 are shown in Table 3 below.

331 Table 3. Statistics of two models' tomography accuracy with respect to ECMWF data in the everyday distribution

332 scenario for the experimental period (Unit: g/m<sup>3</sup>).

Statistics	Traditional	Improved	RMSE	
Statistics	model	model	improvement	
type	moder	moder	percentage	
RMSE	2.97	2.87	3.44%	
bias	0.07	0.02		

Table 3 shows that the RMSE obtained by the improved model is smaller by 3.44% compared to that of the traditional one. The bias of the improved model more closes to zero, indicating that the improved model has better stability and less systematic deviation from the comparative data. The better accuracy shows the superiority of the improved model.

337 4.3. The accuracy information of rainy and non-rainy scenarios

To further analyze the reliability of the improved model compared with the traditional model in different weather conditions, according to the distribution of rainy days in Table 1, all the rainy days data and non-rainy days data are used separately for tomography to obtain the RMSE and bias of the residuals under corresponding weather conditions. The number of matching points is still 12 (see Fig. 1). The overall statistical results are shown in Table 4.

343 Table 4. Statistics of two models' tomography accuracy with respect to ECMWF data in the rainy scenario and the non-

(a) The overall rainy scenario statistics						
Statistics type	Traditional model	Improved model	RMSE improvement percentage			
RMSE	3.05	2.94	3.68%			
bias	0.05	-0.01				
	stics					
Statistics type	Traditional model	Improved model	RMSE improvement percentage			
RMSE	2.89	2.80	3.21%			

rainy scenario for the experimental period (Unit: g/m<sup>3</sup>).

345 Table 4 (a) shows that the RMSE and bias of the residuals calculated by the improved model are better than those of the traditional model using rainy days' data. The RMSE of the improved model is 3.68% 346 347 better than that of the traditional model, indicating the accuracy of the new model is superior. The improved model bias closes more to zero than that of the traditional one, which means the improved model has an 348 349 increase in stability and a reduction in the system error. Using non-rainy days' data, the RMSE and bias of 350 the residuals calculated by the improved model are also better than those of the traditional model (see Table 351 4 (b)). The RMSE improvement percentage is 3.21%, also indicating the improved model has enhanced 352 accuracy. Besides, the improved model bias is more close to zero, making the system error weakened. Table 353 4 also shows that the RMSE improvement percentage of the rainy-day is better than that of the non-rainy 354 days. This finding shows that the improved model is more suitable for obtaining the tomographic results 355 when heavy water vapor changes occur.

356 4.4. The accuracy information of voxels with and without GNSS rays penetrating scenarios

In the traditional pixel-based water vapor tomography model, the water vapor density in the voxels 357 without GNSS rays passing through depends on the accuracy of the water vapor density in the adjacent 358 359 voxels with GNSS rays penetration. However, the improved model uses the layered optimal polynomial 360 functions for overall fitting to obtain the water vapor density in voxels without penetrating GNSS rays. To determine if the layered optimal polynomial function of the improved model contributes better to the 361 accuracy of the water vapor density, the scenarios of voxels with and without GNSS rays penetration as 362 363 described in section 3.2 were designed. After obtaining the RMSE and bias of the residuals using the improved and traditional tomography models separately under designed scenarios, the overall accuracy 364 365 information of voxels with and without GNSS rays penetrating shows in Table 5.

366 Table 5. Statistics of two models' tomography accuracy with respect to ECMWF data in the voxels with and without

(a) The overall scenario statistics of voxels without rays penetrating						
Statistics type	Traditional model	Improved model	RMSE Improvement Percentage			
RMSE	3.40	3.20	5.88%			
Bias	1.59	1.51				
(b) The overall scenario statistics of voxels with rays penetrating						
Statistics type	Traditional model	Improved model	RMSE Improvement Percentage			
RMSE	3.27	3.24	1.00%			
bias	1.70	1.65				

367 penetrating GNSS rays for the experimental period (Unit: g/m<sup>3</sup>).

368 Table 5 (a) shows that the RMSE and bias of the residuals calculated by the improved model are better than those of the traditional model in the scenario of voxels without GNSS rays penetrating. Moreover the 369 370 RMSE of improved tomography model is 5.88% better than that of the traditional model, and the bias 371 decreased from 1.59 to 1.51 g/m<sup>3</sup>. To a certain extent, results show that the improved model is more 372 advantageous for obtaining the water vapor density from the voxels without GNSS rays penetrating, which 373 is consistent with the initial hypothesis: the traditional model uses empirical constraint equations in section 374 2.1.2, Eq. (7), which is unable to well represent the actual distribution of the water vapor density from 375 voxels without GNSS rays penetrating. However, the improved model uses the relatively accurate water 376 vapor density from voxels with GNSS rays penetrating as the observation values to further fit the water 377 vapor density in voxels without GNSS rays penetrating. Therefore, the improved model can better reflect 378 the actual layered situation of continuous water vapor changes, and the accuracy is naturally better. What's 379 more, in the scenario of voxels with GNSS rays penetrating, the RMSE and bias obtained by the improved model are also superior to those of the traditional models, see Table 5 (b). The RMSE calculated by the 380 improved model is 1% higher than that of the traditional model, and the bias reduced from 1.7 to 1.65 g/m<sup>3</sup>, 381 382 which could prove the reliability of the improved model.

383 In order to double-check if the improved model in the scenario of voxels without GNSS rays penetration shows a better result in the vertical water vapor distribution, the water vapor density profiles 384 for different altitudes at specific times are given in Fig. 4. Two times (0:00 UTC 11 April 2014 and 12:00 385 386 UTC 11 April 2014) are chosen for they correspond to the maximum percentage of RMSE improvement during the experiment period of 32 days. Figure 4 shows that in the scenario of voxels without GNSS rays 387 388 penetration, the water vapor profile of the improved model better matches that of ECMWF data than the 389 traditional model, especially in the bottom layers, which again implies that the water vapor density derived 390 from the improved model is superior to that of the traditional one in the scenario of voxels without GNSS 391 rays penetrating.



Figure 4. Water vapor profiles derived from ECMWF and two models in the scenario of voxels without penetrating
 GNSS rays, (a) and (b) are periods of 0:00 UTC 11 April 2014 and 12:00 UTC 11 April 2014, respectively.

Furthermore, to compare directly the vertical accuracy of the water vapor density derived from different altitudes in the scenario of voxels without penetrating GNSS rays, the tomographic results (25 March 2014 to 25 April 2014) from two different tomography models are analyzed. Figure 5 shows the percentage of RMSE improvement and the relative error of the water vapor density changing with altitudes. The percentage of RMSE improvement in Fig. 5 is defined as the same as Eq. (16), and the relative error is defined by using the Eq. (17).

$$RE = \frac{\rho - \rho_{ECMWF}}{\rho_{ECMWF}} \tag{17}$$

401 where *RE* is the relative error,  $\rho$  represents the water vapor density derived from the traditional or

402 improved tomography model, and  $\rho_{ECMWF}$  is the water vapor density derived from ECMWF grid data.

It can be observed in Fig. 5 that in the scenario of voxels without GNSS rays penetration the percentage 403 404 of RMSE improvement is positive in lower layers while negative in some middle and upper layers, which 405 could prove that the improved model enhances the accuracy of tomography results in most layers when 406 there are seldom voxels with GNSS rays penetrating especially in the bottom layers. Due to the lack of 407 GNSS observation data, the bottom accuracy of tomographic results is generally low. In addition, Figure 5 408 shows in the scenario of voxels without GNSS rays penetration, the relative error begins to decrease with 409 the altitude and then increases above 3 km. When the altitude is higher, the relative error becomes larger 410 because of the small water vapor values in the upper layers, a very tiny difference could cause a large 411 relative error between the models and the ECMWF data.



Figure 5. In the scenario of voxels without GNSS rays penetration (a) the percentage of RMSE improvement and (b) the relative error change with height (the blue curve and red curve are derived from the differences between the profiles of the improved model, the traditional model and ECMWF grid data, separately for 64 epochs from 25 March 2014 to 25 April 2014).

# 416 5. Water vapor comparison with radiosonde data

As radiosonde data can provide fairly accurate vertical profiles of tropospheric water vapor (Niell et 417 418 al., 2001), in this paper, the water vapor profiles derived from radiosonde data, as a reference, are used to 419 validate the tomographic results from two models for showing if the improved model would be more efficient than the traditional one. In Hong Kong, there is one radiosonde station located at King's Park 420 421 (shown in Fig. 1) where radiosonde balloons are launched twice daily at 0:00 and 12:00 UTC, respectively. 422 Water vapor profiles derived from the improved model and the traditional model for the location of the 423 radiosonde station are compared with that derived from radiosonde data at 00:00 and 12:00 UTC daily for 424 the experimental period of 32 days. The overall statistical results are shown in Table 6. The RMSE and the bias of the improved model are 1.03 and -0.06 g/m<sup>3</sup>, respectively, and the values of the traditional model 425 426 are 0.82 and -0.17 g/m<sup>3</sup>, respectively, which indicates that the RMSE of the improved model is not as good 427 as the traditional model while the bias of the improved model is a little better than that of the traditional 428 one. The reason for poor accuracy of the improved model could be due to systematic differences between 429 the training source ECMWF data and the radiosonde data. Besides, shown in Fig.1, the location of the 430 radiosonde station is close to one GNSS station (HKSC), leading to the voxels for the location of the 431 radiosonde station having GNSS rays penetration. Since the improved model has advantages of obtaining 432 water vapor density just from voxels without GNSS rays penetration, this situation cannot show the 433 superiority of the improved model.

Table 6. Statistics of two models' tomography accuracy with respect to radiosonde data for the experimental period
 (Unit: g/m<sup>3</sup>).

<b>Statistics</b>	Traditional	Improved
type	model	model
<b>RMSE</b>	<mark>0.82</mark>	<mark>1.03</mark>
<mark>bias</mark>	<mark>-0.17</mark>	<mark>-0.06</mark>

436 In addition, water vapor profiles obtained by two models and radiosonde data are compared for the 437 specific two epochs at 0:00 UTC 25 March 2014 and 0:00 UTC 7 April 2014, shown in Fig. 6. Those two 438 times are selected because they correspond to the non-rainy day and heavy rainfall day, which could be 439 more comprehensive and representative for the comparison results of water vapor profiles. It can be seen from Fig.6 that two models in the non-rainy day match the radiosonde data a little better than that in the 440 441 rainy day. The traditional model shows better comparison results in upper layers than that of the improved 442 model while the two models have almost the same comparison results in the middle and lower layers. The 443 reason for poor performance in the lower layers might due to abundant water vapor in the bottom troposphere as well as the division of the vertical resolution. Compared to the radiosonde data, with almost 444 445 the same accuracy and profile matching results as the traditional model, the improved model still has the 446 advantage of the convenient and efficient expression.



447



449 day at 0:00 UTC 25 March 2014, (b) a rainy day at 0:00 UTC 7 April 2014.

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450 6. SWV comparison
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In order to further verify the reliability of the improved model, five days are randomly selected from different weather conditions to make assessments on the reconstructed SWVs of two models (see Table 7). The comparison between measured SWVs and the ones derived from tomography results of two models is performed and the average RMSE and bias are shown in Table 8. The RMSE and bias of SWVs obtained from tomography results of two models are almost the same under different weather conditions, which indicates the reconstructed SWVs of the improved model has the similar accuracy with that of the traditional one. Since the improved model has the advantage in expressing the water vapor distribution more

- 458 expediently, the similar accuracy of two models in SWVs comparison shows the reliability and superiority
- 459 of the improved model.

460	Table 7. Statistics of two models' accuracy of SWVs for different weather conditions for 5 days (Unit: mm).										
	<mark>Data</mark>	<mark>3.3</mark>	<mark>0</mark>	<mark>4.</mark>	2	<mark>4.</mark> 9	<mark>)</mark>	<mark>4.</mark>	<mark>13</mark>	<mark>4.2</mark>	2 <mark>5</mark>
	<b>Condition</b>	Thunderston to heav	orms turn y rain	Showers, : hail in so	reports of me areas	Non r	ainy	Sui	ıny	Cloudy tur rai	rns to the n
	<mark>Model</mark>	Traditional	Improved	<b>Traditional</b>	Improved	Traditional	Improved	<b>Traditional</b>	Improved	<b>Traditional</b>	Improved
	<mark>RMS</mark>	<mark>10.14</mark>	<mark>10.28</mark>	<mark>15.03</mark>	<mark>15.48</mark>	<mark>2.47</mark>	<mark>2.56</mark>	<mark>8.22</mark>	<mark>8.55</mark>	<mark>12.21</mark>	<mark>12.84</mark>
_	Bias	<mark>-2.67</mark>	<mark>-3.03</mark>	<mark>-1.94</mark>	<mark>-2.08</mark>	0.14	<mark>-0.06</mark>	<mark>-1.51</mark>	<mark>-1.54</mark>	<mark>-3.40</mark>	<mark>-3.89</mark>
4 < 1			1.1.5		COLU	L G1		· 1 / TT ·	<u>_</u>		

|--|

<b>Statistics</b>	<b>Traditional</b>	<b>Improved</b>
type	model	model
<b>RMSE</b>	<mark>9.63</mark>	<mark>10.06</mark>
<mark>bias</mark>	<mark>-1.89</mark>	<mark>-2.15</mark>

#### 462 7. Conclusion

In this paper, an improved pixel-based water vapor tomography model has been proposed, which is 463 464 much more concise and convenient in expression than the traditional one. Only using the layered optimal 465 polynomial coefficients, the three-dimensional water vapor distribution in the tomography region could be 466 described. By using the SatRef GNSS network observation data in Hong Kong between 25 March and 25 467 April, 2014, the RMSE and bias have been assessed in 6 scenarios. The scenarios include the spatial distribution scenario and the everyday distribution scenario, the rainy scenario and the non-rainy scenario, 468 and the voxels with and without GNSS rays penetrating scenarios. The results demonstrate that in either 469 case, the RMSE and bias of the improved model are better than that of the traditional model. Among these 470 471 scenarios, when there are voxels without GNSS rays penetrating, the RMSE improvement percentage can 472 be significantly increased up to 5.88%, which shows that the improved model is more advantageous for 473 obtaining the water vapor density from voxels without GNSS rays penetration. Using radiosonde data for 474 evaluation, it is proved that with the almost similar accuracy the improved model is more efficient in 475 expression than the traditional one. However, some shortcomings still remain in the improved model. For 476 example, more or less the water vapor accuracy of the improved model is still affected by the traditional 477 model, and the layered optimal polynomial functions are limited by the size of the tomographic area and 478 the situation of dividing voxels. In the future, the function-based water vapor tomography model, which is 479 free from the above limitations, should be studied. It is expected that the function-based water vapor 480 tomography model will be more conveniently used when the expression parameters of the function part 481 could be obtained directly from SWVs.

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