

A predictive model for regional zenith tropospheric delay correction (Postprint)

Authors: Xie Lei, Danning Zhao, Xie Lei

Date: 2024-01-22T00:00:00+00:00

Abstract

The conventional zenith tropospheric delay (ZTD) model (known as the Saastamoinen model) does not consider seasonal variations affecting the delay, resulting in low accuracy and stability. This limitation may be addressed by incorporating adjustments for annual and semi-annual variations. This study utilizes ZTD data provided by the Global Geodetic Observing System to analyze seasonal variations in the bias of the Saastamoinen model across Asia, and subsequently constructs a model with seasonal variation corrections, designated as SSA. To overcome the model's dependence on in-situ meteorological parameters, the SSA+GPT3 model is formed by combining SSA with the GPT3 (global pressure-temperature) model. The results demonstrate that introducing annual and semi-annual variations substantially improves the Saastamoinen model, yielding small and temporally stable variations in bias and root mean square (RMS) error. In summer and autumn, the bias and RMS are noticeably smaller than those from the Saastamoinen model. Additionally, the SSA model performs better in low-latitude and low-altitude areas, with bias and RMS decreasing as latitude or altitude increases. The prediction accuracy of the SSA model is also evaluated for external consistency. The results show that the accuracy of the SSA model (bias: -0.38 cm, RMS: 4.43 cm) is superior to that of the Saastamoinen model (bias: 1.45 cm, RMS: 5.16 cm). The proposed method exhibits strong applicability and can therefore be used for predictive ZTD correction across Asia.

Full Text

Preamble

Astronomical Techniques and Instruments, Vol. 1, January 2024, 1–8 •
Article • A predictive model for regional zenith tropospheric delay correction

Yu Lei¹, Danning Zhao²

¹*School of Computer Science & Technology, Xi'an University of Posts & Telecommunications, Xi'an 710121, China*

²*School of Electrical & Electronic Engineering, Baoji University of Arts and Sciences, Baoji 721016, China*

Correspondence: leiyu@xupt.edu.cn

Received: March 5, 2023; Accepted: March 12, 2023; Published Online: June 26, 2023

<https://doi.org/10.61977/ati2024000>

© 2024 Editorial Office of Astronomical Techniques and Instruments, Yunnan Observatories, Chinese Academy of Sciences. This is an open access article under the CC BY 4.0 license (<http://creativecommons.org/licenses/by/4.0/>)

Citation: Lei, Y. and Zhao, D. N. 2024. A predictive model for regional zenith tropospheric delay correction. *Astronomical Techniques and Instruments*, 1(1): 1–8. <https://doi.org/10.61977/ati2024000>.

Abstract

The conventional zenith tropospheric delay (ZTD) model (known as the Saastamoinen model) does not consider seasonal variations affecting the delay, resulting in low accuracy and stability. This limitation may be addressed by incorporating adjustments for annual and semi-annual variations. This study utilizes ZTD data provided by the Global Geodetic Observing System to analyze seasonal variations in the bias of the Saastamoinen model across Asia, and subsequently constructs a model with seasonal variation corrections, designated as SSA. To overcome the model's dependence on in-situ meteorological parameters, the SSA+GPT3 model is formed by combining SSA with the GPT3 (global pressure-temperature) model. The results demonstrate that introducing annual and semi-annual variations substantially improves the Saastamoinen model, yielding small and temporally stable variations in bias and root mean square (RMS) error. In summer and autumn, the bias and RMS are noticeably smaller than those from the Saastamoinen model. Additionally, the SSA model performs better in low-latitude and low-altitude areas, with bias and RMS decreasing as latitude or altitude increases. The prediction accuracy of the SSA model is also evaluated for external consistency. The results show that the accuracy of the SSA model (bias: -0.38 cm, RMS: 4.43 cm) is superior to that of the Saastamoinen model (bias: 1.45 cm, RMS: 5.16 cm). The proposed method exhibits strong applicability and can therefore be used for predictive ZTD correction across Asia.

Keywords: Zenith tropospheric delay; Saastamoinen model; Seasonal variations; Asian area; Accuracy analysis

1. INTRODUCTION

Tropospheric delay represents the primary error source in Global Navigation Satellite System (GNSS) positioning, navigation, and timing. The effect of the troposphere on GNSS signals manifests as an additional delay in the measurement of the signal traveling from satellite to receiver. The error caused by the troposphere is approximately 2 m in the zenith direction and 20 m for lower elevations [?], necessitating correction in GNSS applications. Unlike ionospheric delay [?], tropospheric delay is frequency-independent and consequently cannot be eliminated by combining signals of different frequencies. Therefore, an empirical model of zenith tropospheric delay (ZTD) is typically employed for correction. Accordingly, constructing a high-precision ZTD empirical model is of great practical significance.

Currently, commonly used ZTD empirical models can be divided into two categories. The first category comprises meteorological parameter models, which use surface pressure, temperature, and water vapor pressure to calculate ZTD. Among these models, the accuracy of the Hopfield model decreases with increasing altitude, while the Saastamoinen model is less affected by altitude, making it more widely applicable. The ZTD correction accuracy of these models can approach centimeter precision when using measured meteorological parameters, but the accuracy can degrade by a factor of 2 to 3 when using standard meteorological parameter models, limiting their applicability in high-precision GNSS positioning, navigation, and timing. To remove dependence on measured parameters, Liu et al., Yang et al., Yao et al., and Du et al. have used meteorological parameters provided by the global barometric temperature GPT/GPT2/GPT2w models as input for the Saastamoinen model [?], effectively improving the applicability of these models in high-precision GNSS applications.

The second category consists of non-meteorological parameter models, such as the European Geostationary Navigation Overlay Service (EGNOS) [?, ?], which represents the ZTD correction model adopted by European and American wide-area augmentation systems. These models require only station location information, without surface meteorological parameters, to calculate ZTD, and the global average ZTD calculation accuracy is comparable to that of Saastamoinen and Hopfield models based on measured parameters. However, the EGNOS and University of New Brunswick (UNB) models divide the Earth into 15° latitude intervals, resulting in poor spatial resolution and neglecting longitude effects, which prevents them from capturing local ZTD variations. Furthermore, the ZTD correction calculated by these models is ineffective in areas outside Europe and North America. To meet the demand for ZTD correction in high-precision GNSS applications, new non-meteorological parametric ZTD models have been successively established. Some utilize atmospheric reanalysis data from the European Centre for Medium-Range Weather Forecasts (ECMWF) and National Centers for Environmental Prediction to establish global non-meteorological empirical ZTD models such as SHAO-H and IGGTrop [?, ?]. Others use Global Geodetic Observing System (GGOS) Atmosphere data and International GNSS

Service (IGS) ZTD data for direct modeling, such as the GZTD and GGZTD models [?, ?]. Additionally, regional ZTD models have been developed for China and surrounding areas [?].

While the aforementioned ZTD models are fully empirical and established using global atmospheric reanalysis or ZTD data, achieving high global average accuracy, their accuracy and applicability for ZTD correction in local areas may still be insufficient. To improve the accuracy and applicability of the ZTD model in Asia, this paper establishes a seasonal ZTD model, designated as SSA (Saastamoinen model with seasonal corrections), which incorporates annual and semi-annual variations based on the widely used Saastamoinen model. This is accomplished using ZTD grid products with a spatial resolution of $1^\circ \times 1^\circ$ and a temporal resolution of 6 h released by GGOS Atmosphere. The SSA model is combined with a new version of the global pressure-temperature model, GPT3 [?], to form a predictive model for ZTD correction called SSA+GPT3, which does not require measured meteorological parameters. Using high-precision ZTD data from 66 GNSS tracking stations in the Asian region, provided by GGOS Atmosphere and IGS as references, the ZTD correction accuracy of the SSA model is evaluated for the Asian region, and the spatial and temporal distribution characteristics of the ZTD correction errors are analyzed.

2.1. Data Source

GGOS Atmosphere provides ZTD grid data with a spatial resolution of $1^\circ \times 1^\circ$ and a temporal resolution of 6 h, based on ECMWF atmospheric reanalysis data from 1980 to the present, available from Vienna Mapping Functions Open Access Data [?]. The GGOS Atmosphere products not only have very high spatial resolution but are also of high quality and can therefore be used as a standard dataset for ZTD research and applications [?].

2.2. Seasonal Effects on the Saastamoinen Model

High-precision ZTD data provided by GGOS Atmosphere from 2015 to 2017 for 66 IGS GNSS tracking stations distributed across the Asian region are used as reference values to calculate the daily averaged bias of the Saastamoinen model. Spectral analysis of the bias from 2015 to 2017 is conducted separately, and the daily averaged bias of these IGS stations in each latitude range shows significant annual and semi-annual seasonal variations. These variations and their spectral analysis results for 2015–2017 at the eastern YSSK, southern CUUT, western URUM, and northern PETS stations in the Asian region are presented in Fig. 1 [Figure 1: see original paper]. Variations at other stations are similar.

As can be seen from Fig. 1, the daily bias of the Saastamoinen model exhibits annual and semi-annual seasonal effects, which can be approximated using a

cosine function:

$$\text{Bias} = \text{Bias}_{\text{mean}} + A_1 \cos\left(\frac{2\pi(\text{doy} - d_1)}{365.25}\right) + A_2 \cos\left(\frac{2\pi(\text{doy} - d_2)}{182.625}\right) \quad (1)$$

where $\text{Bias}_{\text{mean}}$ is the annual mean value of bias; bias and day of year (doy) are known quantities; A_1 and A_2 are the amplitudes of the annual and semi-annual variations, respectively; and d_1 and d_2 are the phases of the annual and semi-annual variations, respectively. These amplitudes and phases can be determined using the nonlinear least squares method. The spatial and temporal distribution characteristics of the amplitudes and phases are not discussed or analyzed here due to space limitations.

2.3. The SSA Model

Considering the seasonal effects on the Saastamoinen model, this paper proposes a new seasonal ZTD model by adding annual and semi-annual terms to the Saastamoinen model, referred to as SSA:

$$\text{ZTD} = 0.002277 \cdot P + \left(0.05 + \frac{1255}{T}\right) \cdot e \cdot [1 - 0.00266 \cos(2\varphi) - 0.00028h] + \text{Bias} \quad (2)$$

where P , T , e , φ , and h are the surface pressure in hPa, temperature in Kelvin, water vapor pressure in hPa, station latitude in radians, and height in km, respectively.

To overcome the dependence of the SSA model on measured meteorological parameters and improve its applicability, the GPT3 model is introduced to provide relatively accurate pressure, temperature, and water vapor pressure values. To accomplish this, we construct a refined SSA+GPT3 model using the following process:

Step 1. Calculate the pressure, temperature, and water vapor pressure parameters of the four horizontal grid points nearest to the station using the GPT3 model, based on the station latitude, longitude, altitude, and time information, while finding the ZTD_0 of the four points adjacent to the station in the GGOS Atmosphere grid file.

Step 2. Use equation (3) to make altitude corrections to the meteorological parameters of the grid points. We calculate the ZTD of each of the four grid points relative to the station altitude according to:

$$\text{ZTD}(h) = \text{ZTD}_0 \cdot e^{-\beta h} \quad (3)$$

where β is the height imputation factor. We then use bilinear interpolation to calculate the meteorological parameters and ZTD at the station, expressed as:

$$\begin{cases} T = T_0 + \frac{dT}{dh} \cdot \Delta h \\ P = P_0 \cdot \exp \left\{ -\frac{g_m}{R_g \cdot T_0 \cdot (1 + 0.6077Q)} \cdot \Delta h \right\} \\ e = e_0 \cdot \left(\frac{100 - P}{P_0} \right)^{\lambda + 1} \end{cases}$$

where P_0 , T_0 , and e_0 represent the pressure, temperature, and water vapor pressure at the grid point surrounding the sites, respectively; λ is the water vapor descent factor; $\frac{dT}{dh}$ is the temperature lapse rate in degrees/m; g_m is the mean acceleration due to gravity; Δh is the difference between the site height and grid height; Q is the specific humidity in kg/kg; R_g is the gas constant; and M_{tr} represents the molar mass of dry air.

Step 3. Calculate the ZTD by substituting the meteorological parameters at the stations obtained in Step 2 into the Saastamoinen model and treating them as true values to obtain the bias of the Saastamoinen model.

Step 4. Perform periodic fitting of the ZTD bias to determine the amplitude and phase of the annual and semi-annual variations. According to the above model construction process, the combined SSA+GPT3 model can perform ZTD calculation at any position.

3.1. Experimental Setup

Sixty-six IGS GNSS tracking stations in the Asian region are selected to analyze and evaluate the effectiveness of the model. The research area spans 10°N–63°N and 66°E–159°E. The geographical distribution of the 66 IGS stations in the Asian region is shown in Fig. 2 [Figure 2: see original paper]. ZTD products from 2015 to 2017 provided by GGOS Atmosphere are used as reference values to analyze the spatial and temporal distribution characteristics of the SSA model errors. Final ZTD data from 2018 from the IGS are used to evaluate the accuracy of the ZTD prediction values of the SSA model, with bias and RMS error taken as error measurements.

3.2. Temporal Distribution of Bias and RMS

3.2.1. Variations of Daily Averaged Bias and RMS

To analyze the day-by-day variation of bias and RMS of the SSA and Saastamoinen models, the daily averaged bias and RMS of each IGS station are calculated by day of year. The daily averaged bias and RMS variations in

2015–2017 calculated from SSA+GPT3 and Saastamoinen+GPT3 (abbreviated to SA+GPT3) for the eastern YSSK, southern CUUT, western URUM, and northern PETS stations in the Asian region are shown in Fig. 3 [Figure 3: see original paper]. Variations at other stations are similar and therefore are not presented.

The daily averaged bias and RMS of the Saastamoinen model for the four IGS stations show clear seasonal variations—small in winter and large in summer. These variations occur because wet delay decreases due to dry air in winter, causing a reduction in ZTD estimate error, whereas wet delay increases due to humid air in summer, leading to increased error. The bias and RMS at the western URUM station are relatively small compared with those at other stations in Asia, whereas the bias and RMS at the eastern YSSK station are larger in summer, owing to the effect of the marine climate causing drastic variations in water vapor. In contrast to other stations, the bias and RMS change rapidly at the southern CUUT station, which is located at low latitude and influenced by tropical and marine climates. These results illustrate that the Saastamoinen model can be improved if these seasonal variations are taken into account in ZTD estimation. The bias and RMS of the SSA model are not only smaller than those of the Saastamoinen model but also more stable, demonstrating that introducing annual and semi-annual terms into ZTD estimates yields noticeable improvements.

3.2.2. Variations of Monthly Averaged Bias and RMS

To analyze the month-to-month variations of the bias and RMS of the two models, the monthly averaged bias and RMS of 66 IGS stations in the Asian region from 2015 to 2017 are calculated, as shown in Fig. 4 [Figure 4: see original paper]. The bias of the Saastamoinen model is generally positive, indicating that this model usually underestimates ZTD in the Asian region and exhibits a systematic bias. By comparison, the monthly averaged bias and RMS from the SSA model are relatively small and stable, with no clear periodic variation in bias, while periodic variation in RMS is substantially reduced. The bias and RMS of the SSA model do not show significant fluctuations even in summer and autumn when water vapor levels change dramatically, indicating that the SSA model, with seasonal terms, achieves higher accuracy than the conventional Saastamoinen model, especially in summer and autumn.

3.3. Spatial Distributions of Bias and RMS

The three-year averaged bias and RMS statistics from 2015 to 2017 are calculated and shown for 66 IGS stations in the Asian region in Fig. 5 [Figure 5: see original paper]. The bias and RMS of the Saastamoinen model are relatively small in the high-latitude region of western and northern Asia but larger in the southern low-latitude region characterized by oceanic and tropical climates.

The bias and RMS are also relatively large in the eastern coastal region, which is influenced by an oceanic climate with drastic water vapor changes. Furthermore, the bias of the Saastamoinen model is positive at most stations in the Asian region, again indicating that this model often underestimates the actual value of ZTD. The bias and RMS of the SSA model are smaller than those of the Saastamoinen model. Specifically, the bias is close to zero, indicating that the SSA model, with seasonal terms, has little systematic bias. The mean values of the bias and RMS across all 66 IGS stations are 1.91 cm and 5.18 cm, respectively, between 2015 and 2017 for the Saastamoinen model, while the mean RMS is 4.2 cm for the SSA model, representing an overall reduction of 19% relative to the Saastamoinen model.

3.3.1. Variations of Bias and RMS with Height

To analyze the height distribution characteristics of the bias and RMS of the two models, the altitudes of 66 stations were divided into brackets of <500 m, >500–1,000 m, 1,500–2,000 m, and >2,000 m. The bias and RMS at each height range from 2015 to 2017 are shown in Fig. 6 [Figure 6: see original paper], in which the bias from the SSA model is small enough to be insignificant and has been omitted. The RMS of both models shows a noticeable decreasing trend with increasing station height. The RMS of the SSA model is smaller than that of the Saastamoinen model in each height range. Also noteworthy is the fact that the bias of the Saastamoinen model is positive from 0 to 2,000 m and becomes larger with increasing height. However, the bias shows a sudden increase when altitude exceeds 2,000 m. One possible explanation is that there are few IGS stations in this height range. Furthermore, the accuracy of both models is better at high altitudes because the integration interval of tropospheric refractivity is shortened at high altitudes, with drier air causing reduced wet delay at high-altitude stations such as URUM and LHAZ in China. In all latitude ranges, the accuracy of the SSA model is improved to different degrees compared with the Saastamoinen model. Overall, the improvement is most significant in low-altitude regions. Compared with the Saastamoinen model, the RMS of the SSA model is reduced by 20.31%, 11.25%, 4.01%, and 11.05% in the height ranges of <500 m, >500–1,000 m, 1,500–2,000 m, and >2,000 m, respectively.

3.3.2. Variations of Bias and RMS with Latitude

To analyze the latitude distribution characteristics of the bias and RMS of both models, the latitudes of 66 stations were divided into 16°N–30°N, 30°N–45°N, and 45°N–63°N regions. The averaged bias and RMS of 66 stations in each latitude range from 2015 to 2017 are shown in Fig. 7 [Figure 7: see original paper], in which the bias of the SSA model is very low and has been omitted. The RMS shows a decreasing trend with increasing latitude, and the accuracy of the SSA model is superior to that of the Saastamoinen model in all latitude ranges. The bias of the Saastamoinen model also shows a decreasing trend with increasing station latitude. Additionally, the accuracy of the SSA model

is substantially better at high-latitude areas above 30°N compared with that of the Saastamoinen model. This is because ZTD estimation error is larger in the lower latitudes of Asia due to oceanic and tropical climates, where water vapor changes are more complex. The accuracy of the SSA model improves to different degrees in all latitude ranges compared with that of the Saastamoinen model, and this enhancement is more obvious in regions below 30°N. In contrast with the Saastamoinen model, the RMS of the SSA model decreases by 30%, 9.55%, and 10.3% in the latitude ranges from 16°N–30°N, 30°N–45°N, and 45°N–63°N, respectively.

3.4. Prediction Assessment of the SSA

To further assess the accuracy of the SSA model, the model is tested with ZTD grid products released by GGOS Atmosphere between 2015 and 2017. This SSA model is then employed to predict the ZTD of 66 IGS stations in the Asian region in 2018. The final ZTD data from the IGS are taken as the real values for model assessment. Fig. 8 [Figure 8: see original paper] shows the spatial distribution of the yearly averaged bias and RMS of the ZTD predictions, and the bias and RMS statistical measures are given in Table 1 .

The yearly averaged bias and RMS from the Saastamoinen model are smaller in the western region and high-latitude region of Asia and larger in the eastern and low-latitude regions, with a maximum bias of 6.07 cm. Compared with the Saastamoinen model, the yearly averaged bias of the SSA model is smaller across the entire Asian region, with a maximum value of 2.43 cm. The RMS is approximately 5 cm in northwestern Asia and larger in other regions for the Saastamoinen model, whereas the value for the SSA model is under 5 cm in regions with latitudes above 40°N and larger in lower latitudes. Additionally, the enhancement of the SSA model is most obvious in lower-latitude regions. The RMS of both models becomes smaller with increasing latitude. The SSA model reduces the bias and RMS by 73.79% and 14.15%, respectively, compared with the Saastamoinen model.

To further analyze seasonal variations of the bias and RMS, the monthly averaged bias and RMS of 66 IGS stations in 2018 are shown in Fig. 9 [Figure 9: see original paper]. The monthly averaged bias and RMS of the Saastamoinen model show obvious seasonal variations—large in summer and small in winter—whereas the RMS of the SSA model changes slowly each month and does not show large fluctuations even in summer and autumn. The bias of the SSA model, shown in Fig. 9A, is significantly smaller than that of the Saastamoinen model except in January, March, and October. This is because the bias of the SSA model has more negative values in these months than the Saastamoinen model, leading to a large calculated monthly averaged bias. However, although the monthly averaged RMS of both models is comparable in spring and winter, the monthly averaged RMS of the SSA model in autumn and summer is signifi-

cantly lower than that of the Saastamoinen model, and the RMS is reduced by 36.36% at maximum.

Fig. 8, Fig. 9, and Table 1 not only demonstrate that the ZTD prediction accuracy of the SSA model in the Asian region is better than that of the Saastamoinen model but also verify that the spatial and temporal variation characteristics of the prediction errors are generalized.

4. CONCLUSIONS

The widely used Saastamoinen model requires in-situ meteorological parameters and is also affected by seasonal changes in environmental conditions. In this study, the bias of the Saastamoinen model shows clear seasonal variations, and spectrum analysis indicates that these variations are dominated primarily by annual and semi-annual cycles. To improve the Saastamoinen model, we propose an enhanced model, dubbed the SSA model, to compensate for seasonal annual and semi-annual variations using meteorological parameters from the empirical GPT3 model. The results demonstrate that the SSA model, with annual and semi-annual terms, achieves high ZTD prediction accuracy in the Asian region with a yearly averaged RMS of approximately 4.5 cm. Both the bias and RMS of the SSA model are smaller and more stable than those of the Saastamoinen model, even in summer and autumn. The enhancement in summer can reach 36.36% compared with the Saastamoinen model.

The extent of this improvement is also related to geographic location; the improvement is very noticeable in the low-latitude and low-altitude areas of Asia. Moreover, accuracy enhances with increasing latitude or altitude. Because the SSA model is constructed based on $1^\circ \times 1^\circ$ high-resolution GGOS Atmosphere data products, and the required meteorological parameters can be provided by GPT3, we conclude that the combined SSA+GPT3 model is a potentially very effective method for tropospheric delay corrections in high-precision GNSS applications over Asia and can be used to predict tropospheric delays in real-time high-precision GNSS positioning, navigation, and timing.

ACKNOWLEDGEMENTS

This work was supported by the Basic Science Research Program of Shaanxi Province (2023-JC-YB-057 and 2022JM-031).

AUTHOR CONTRIBUTIONS

Yu Lei conceived the ideas, designed and implemented the study, and wrote the paper. Danning Zhao collected the meteorological tropospheric delay data,

performed the statistical analysis, and revised the paper. All authors read and approved the final manuscript.

DECLARATION OF INTERESTS

The authors declare no competing interests.

REFERENCES

- Zhang, J. H., Lachapelle, G. 2001. Precise estimation of residual tropospheric delays using a regional GPS network for RTK applications. *Journal Geodesy*, 75(5-6): 255–266.
- Lu, W. J., Ma, G. Y. 2022. Near-real-time ionospheric TEC derivation from single station with neural network. *Astronomical Research & Technology*, 19(2): 141–148. (in Chinese)
- Liu, J. Y., Chen, X. H., Sun, J. Z., et al. 2017. An analysis of GPT2/GPT2w+Saastamoinen models for estimating zenith tropospheric delay over Asian area. *Advances in Space Research*, 59(3): 824–832.
- Yang, et al. 2013. A comprehensive algorithm using fusion of tropospheric delay models. *Journal of Southeast University (Natural Science Edition)*, 43(S2): 418–422. (in Chinese)
- Yao, Y. B., Zhang, B., Yan, F., et al. 2015. Two new sophisticated models for tropospheric delay corrections. *Chinese Journal of Geophysics*, 58(5): 1492–1501. (in Chinese)
- Du, X. Y., Qiao, Q., Wei, P. P. 2019. Real-time correction model for zenith tropospheric delay applied to the Chinese region. *Journal of Electronics & Information Technology*, 41(1): 156–164. (in Chinese)
- Kos, T., Botincan, M., Markezic, I. 2009. Evaluation of EGNOS tropospheric delay model in south-eastern Europe. *Journal of Navigation*, 62(2): 341–349.
- Leandro, R., Santos, M. C., Langley, R. B. 2006. UNB neutral atmosphere models: development and performance. In *Proceeding of ION NTM 2006*.
- Zhao, J. Y., Song, S. L., Chen, Q. M., et al. 2014. Establishment of a new global model for zenith tropospheric delay based on functional expression for its vertical profile. *Chinese Journal of Geophysics*, 57(10): 3140–3153. (in Chinese)
- Li, W., Yuan, Y. B., Ou, J. K., et al. 2012. A new global zenith tropospheric delay model IGGtrop for GNSS applications. *Chinese Science Bulletin*, 57(17): 2132–2139.

Li, W., Yuan, Y. B., Ou, J. K., et al. 2015. New versions of the BDS/GNSS zenith tropospheric delay model. *Journal of Geodesy*, 89(1): 73–80.

Huang, L. K., Chen, H., Liu, L. L., et al. 2021. A new high-precision global model for calculating zenith tropospheric delay. *Chinese Journal of Geophysics*, 64(3): 782–795. (in Chinese)

Chen, J. P., Wang, J. G., Wang, A. H., et al. 2020. SHAtropE—a regional gridded ZTD model for China and the surrounding areas. *Remote Sensing*, 12(1): 165.

Chen, J. P., Wang, J. G., Wang, J. X., et al. 2019. SHAtrop: empirical ZTD model based on CMONOC GNSS network. *Geomatics and Information Science of Wuhan University*, 44(11): 1588–1595. (in Chinese)

Lei, Y., Zhao, D. N., Xu, J. S. 2023. Multi-model fusion method to estimate zenith tropospheric delay. *Astronomical Research & Technology*, 20(2): 111–122. (in Chinese)

re3data.org: VMF Data Server; editing status 2020-12-14; re3data.org - Registry of research data repositories. <http://doi.org/10.17616/R3RD2H>.

Landskron, D., Böhm, J. 2018. VMF3/GPT3: refined discrete and empirical troposphere mapping functions. *Journal of Geodesy*, 92(4): 349–360.

Yao, Y. B., Xu, X. Y., Hu, Y. F. 2017. Precision analysis of GGOS tropospheric delay product and its application in PPP. *Acta Geodaetica et Cartographica Sinica*, 46(3): 278–287. (in Chinese)

Note: Figure translations are in progress. See original paper for figures.

Source: ChinaXiv — Machine translation. Verify with original.