

Article

A China-Specific Near-Real-Time GNSS Water Vapor Retrieval Model Based on LightGBM

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Highlights

What are the main findings?

- The proposed CLZP-ZHD model consistently outperforms GPT3-ZHD and CTrop-ZHD in accuracy, and its accuracy does not degrade with increasing distance above ground level within the vertical range from the surface to near the tropopause.
- By integrating near-real-time GNSS ZTD with a residual compensation mechanism, the CLZP-PWV model effectively suppresses systematic bias and random errors, achieving substantially higher accuracy than mainstream models.

What are the implications of the main findings?

- Once trained, the CLZP model enables high-accuracy ZHD estimation and near-real-time PWV retrieval without requiring co-located meteorological observations during operational application.
- This model provides a practical and robust technical solution for regional GNSS meteorological applications and atmospheric water vapor monitoring.

Abstract

Atmospheric water vapor is a key atmospheric variable that regulates weather variability, the hydrological cycle, and climate processes. GNSS-based water vapor retrieval provides an effective approach for continuous and near-real-time monitoring of atmospheric water vapor. However, conventional meteorology-independent models still have limitations in regional adaptability, vertical accuracy, and the representation of nonlinear atmospheric variability. To address these limitations, this study proposes a China-specific near-real-time GNSS water vapor retrieval model, termed China LightGBM-based Zenith Hydrostatic Delay and Precipitable Water Vapor Model (CLZP), by integrating LightGBM with near-real-time GNSS observations. First, a high-accuracy gridded ZHD model, CLZP-ZHD, was developed using LightGBM to estimate ZHD from the surface to near the tropopause. Subsequently, a PWV residual compensation model, CLZP-PWV, was developed by incorporating multi-source features, including near-real-time GNSS ZTD, to mitigate error propagation in PWV retrieval. Validation results from both ERA5 and independent radiosonde datasets indicate that CLZP-ZHD reduces RMSE by approximately 25.4% and 28.2% relative to GPT3-ZHD and CTrop-ZHD in the ERA5-based validation, and by 21.7% and 23.0% in the radiosonde-based validation, respectively, while maintaining stable accuracy across different heights. For PWV retrieval, the ERA5-based validation of CLZP-

Academic Editor: Chung-yen Kuo

Received: 22 June 2026

Revised: 5 August 2026

Accepted: 5 August 2026

Published: 6 August 2026

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PWV shows that it reduces RMSE by approximately 32.7% and 38.2% relative to GPT3-PWV and CTrop-PWV, respectively, and demonstrates improved performance in humid and climatically complex regions. These results suggest that, once trained, CLZP improves the accuracy and stability of near-real-time GNSS water vapor retrieval over China without requiring in situ meteorological observations during operational application, providing a practical approach for regional GNSS meteorological applications.

Keywords: GNSS meteorology; zenith hydrostatic delay; precipitable water vapor; Light Gradient Boosting Machine; near-real-time retrieval

1. Introduction

Water vapor is one of the most dynamic constituents of the troposphere and plays a vital role in the global hydrological cycle, atmospheric energy exchange, and processes governing weather and climate change [1–3]. It not only directly affects precipitation formation and atmospheric stability but is also closely associated with the occurrence and development of extreme weather events. Therefore, accurate and continuous monitoring of atmospheric water vapor is essential for weather forecasting, climate research, and disaster prevention [4]. Conventional techniques for observing atmospheric water vapor primarily include radiosondes [5,6], microwave radiometers [7,8], and satellite remote sensing [9]. Although these methods can provide water vapor with a certain degree of accuracy, they are generally limited by low temporal resolution, high operational costs, and sensitivity to weather conditions. With the rapid development of the Global Navigation Satellite System (GNSS), atmospheric water vapor retrieval based on GNSS signal propagation delays has emerged as an increasingly important technique. GNSS offers several advantages including all-weather capability, high temporal continuity, low cost, and broad spatial coverage, demonstrating substantial potential for atmospheric water vapor monitoring [10].

When GNSS signals propagate through the neutral atmosphere, they experience a delay commonly referred to as the zenith tropospheric delay (ZTD). The ZTD can be decomposed into two components: the zenith hydrostatic delay (ZHD) and the zenith wet delay (ZWD). The ZHD is primarily caused by dry atmospheric gases and is relatively stable, whereas the ZWD is strongly associated with atmospheric water vapor and exhibits significant spatiotemporal variability. The ZWD can therefore be obtained by separating the ZHD from ZTD. In combination with the atmospheric weighted mean temperature (T_m), the ZWD can then be converted into precipitable water vapor (PWV), thereby enabling GNSS-based water vapor retrieval [11,12]. During GNSS data processing, the ZTD can be estimated as an unknown parameter with high accuracy [13–15]. Consequently, accurate determination of ZHD and T_m is critical for improving the accuracy of GNSS-derived water vapor retrieval.

Existing methods for obtaining ZHD and T_m can generally be divided into two main categories. The first category relies on models driven by measured meteorological parameters, such as the Saastamoinen model [16], Hopfield model [17], and the Bevis model [11]. These approaches generally provide high accuracy [18,19]. However, their widespread application is limited by the absence of meteorological sensors at many GNSS stations. The second category consists of empirical models that do not require meteorological inputs, such as the UNB series [20,21] and the GPT series [22–25]. These models rely solely on positional and temporal information, making them suitable for real-time or near-real-time applications. However, because the atmosphere exhibits pronounced nonlinear be-

havior and strong spatiotemporal variability, conventional empirical models remain limited when applied to regions with complex climate conditions. For example, Zhang et al. quantitatively evaluated the ZHD results of the UNB3m, GPT2, and GPT2w models and found that the RMSE of the three models increases with increasing latitude [26]. To overcome these limitations, region-specific models with higher spatial resolution and improved accuracy have been developed. Mao et al. developed an improved TZTD model based on UNB3m and reanalysis data from the National Centers for Environmental Prediction (NCEP) [27]. Li et al. investigated the temporal variations in zenith hydrostatic delay (ZHD) residuals from the GPT3 model and developed a Fourier-function-based correction model for China and its surrounding regions, referred to as CGPT3 [28]. Yuan et al. established a global weighted mean temperature model, GT_m -R, using ECMWF Re-Analysis Interim (ERA-Interim) data [29]. Subsequently, Sun et al. employed ECMWF Re-Analysis v5 (ERA5) data to develop CTrop, a tropospheric delay and weighted mean temperature model for China and adjacent areas. CTrop accounts for the diurnal variations in ZHD, zenith wet delay (ZWD), and weighted mean temperature (T_m), as well as the seasonal variations in their vertical lapse rates. The model can directly provide ZHD, ZWD, and T_m estimates and achieves substantial improvements in spatial resolution, temporal resolution, and accuracy compared with conventional models [30]. These models are generally gridded and are constructed based on the periodic variations in ZHD or T_m , thereby improving the accuracy of GNSS water vapor retrieval over China. However, most of these models rely solely on surface data and assume a linear decrease with altitude. Although they can achieve high accuracy near the surface, their accuracy tends to decrease with increasing elevation. For instance, Mao et al. found that the ZHD accuracy of the GPT2w model decreases rapidly with height above the ground [31].

In recent years, machine learning approaches have attracted considerable attention because of their strong nonlinear modeling capabilities and data-driven nature. Compared with conventional empirical models, machine learning methods can automatically extract complex spatiotemporal relationships from multi-source data, thereby substantially improving the representation of nonlinear atmospheric variability. Ding developed a T_m model using a multilayer feedforward neural network (MFFNN), achieving substantial accuracy improvements over four existing models, including GPT2w and GT_m [32]. Li et al. constructed the GZHD model using a backpropagation artificial neural network (BP-ANN) based on the relationship between ZHD and ZTD, improving accuracy by approximately 21% relative to GPT3 [33]. Zhu et al. used ERA5 data to develop a regional T_m gridded model for China, namely CT_m -FNN, based on a feedforward neural network (FNN). This model effectively captures the nonlinear relationship between T_m and elevation, enabling accurate estimation of T_m from the surface to the vicinity of the tropopause [34]. As an efficient ensemble learning algorithm, Light Gradient Boosting Machine (LightGBM) offers high computational efficiency, strong generalization capability, and suitability for large-scale data modeling. It is particularly effective in capturing nonlinear relationships among multiple variables and therefore has strong potential for tropospheric delay modeling. For example, Li et al. constructed four T_m models using radiosonde data from the Yangtze River Delta region and four machine learning algorithms: LightGBM, support vector machine (SVM), random forest (RF), and classification and regression tree (CART). Their results showed that the LightGBM-based model achieved the highest accuracy among the four methods [35].

To address the limitations of conventional empirical models that do not require meteorological inputs—such as regional adaptability, reduced accuracy at high altitudes, and limited capacity to express nonlinear relationships—previous studies have largely focused on refining T_m models. However, Ning et al. showed that ZHD contributes 10–20% to PWV uncertainty, whereas T_m contributes less than 5% to PWV [36]. Motivated by these

considerations, this study develops a LightGBM-based near-real-time GNSS water vapor retrieval model for China referred to as CLZP. First, a high-accuracy gridded ZHD model for China is developed using the LightGBM algorithm to provide accurate ZHD estimates from the surface to the vicinity of the tropopause at arbitrary locations. Building on this model, an improved near-real-time GNSS water vapor retrieval model is constructed by integrating the LightGBM algorithm with GNSS ZTD data, thereby enhancing the accuracy and stability of PWV retrieval. The specific contribution of CLZP lies in combining a gridded ZHD model with stable vertical performance from the surface to near the tropopause and a near-real-time GNSS ZTD-driven PWV residual compensation model, thereby supporting station-level PWV retrieval over China without requiring in situ meteorological observations as operational inputs.

2. Data and Methods

2.1. Data

2.1.1. ERA5 Reanalysis Data

The ERA5 reanalysis dataset, produced by the European Centre for Medium-Range Weather Forecasts (ECMWF), provides global meteorological variables with high spatial and temporal resolution and has been widely used in tropospheric delay modeling and water vapor retrieval studies. ERA5 integrates multi-source observations with numerical weather prediction models to provide a range of meteorological parameters, including pressure, temperature, relative humidity and specific humidity, with high accuracy and consistency. Compared with earlier reanalysis products, ERA5 provides substantially improved spatial and temporal resolution, enabling a more detailed characterization of the spatiotemporal variability of atmospheric parameters. This high-resolution capability helps improve both the accuracy and stability of tropospheric delay modeling. In GNSS meteorology, ERA5 data are commonly used as reference data for developing empirical and machine-learning-based models [37–39]. Hourly ERA5 temperature, relative humidity, and geopotential data at 37 standard pressure levels from 1000 to 1 hPa were used in this study. The study area covers 15–55°N and 73–135°E. Data from 2014 to 2017 were used for model training, and data from 2018 were used for testing. These data were used to calculate ZHD, T_m , and the reference PWV. The CLZP-ZHD model was developed on a $0.5^\circ \times 0.5^\circ$ grid, while a $0.4^\circ \times 0.4^\circ$ grid was used for the ERA5-based validation. A $0.4^\circ \times 0.4^\circ$ grid was selected to avoid systematic coincidence with the $0.5^\circ \times 0.5^\circ$ CLZP-ZHD grid and to evaluate the model at off-grid locations, which is more representative of practical GNSS station applications.

2.1.2. Radiosonde Data

Radiosonde observations provide an essential means of obtaining information on atmospheric structure and water vapor content in meteorological studies. During balloon ascents, radiosonde instruments measure vertical profiles of meteorological variables, including temperature, humidity, pressure, and wind speed. The radiosonde data used in this study were obtained from the Integrated Global Radiosonde Archive (IGRA), which is maintained by the National Centers for Environmental Information (NCEI) under the National Oceanic and Atmospheric Administration (NOAA). The variables used included pressure, temperature, relative humidity, and geopotential height. Observations at 00:00 and 12:00 UTC from 78 stations in 2018 were used as an independent dataset to evaluate the ZHD models.

2.1.3. GNSS Data

In this study, hourly GNSS ZTD products provided by the Crustal Movement Observation Network of China (CMONOC) were used for model development and for evaluating the applicability of the proposed model to near-real-time GNSS water vapor retrieval. CMONOC is a major national scientific infrastructure jointly established by several institutions, including the China Earthquake Administration and the National Administration of Surveying, Mapping and Geoinformation. Its GNSS reference station network covers mainland China and surrounding regions and comprises approximately 260 continuously operating stations. Owing to their high solution accuracy and fine spatiotemporal resolution, CMONOC data have been widely used in crustal deformation monitoring and GNSS meteorology research [40–42]. The CMONOC ZTD products used in this study have a temporal resolution of 1 h. Historical ZTD products were used for model training and testing. During operational application, once a newly estimated ZTD value is available, it can be directly input into the CLZP-PWV model together with the station location and temporal information, without requiring in situ meteorological observations.

2.2. Methods

2.2.1. The Method of Calculating ZHD

In this study, hourly temperature, relative humidity, and geopotential data at 37 pressure levels from ERA5 were used to derive the ZHD profiles required for model training. The geopotential was first converted into orthometric height and subsequently transformed into ellipsoidal height. The ZHD was then calculated using the integral method, as expressed in Equation (1):

$$\text{ZHD} = 10^{-6} \int_{h_s}^{\infty} N_h(z) dz \quad (1)$$

where h_s is the surface height and N_h is the hydrostatic refractivity, which can be calculated using Equation (2):

$$N_h = k_1 R_d \rho \quad (2)$$

where $k_1 = 77.689 \text{ K/hPa}$ is the refractivity constant, $R_d = 287.053 \text{ J}\cdot\text{kg}^{-1}\cdot\text{K}^{-1}$ is the specific gas constant for dry air, and ρ denotes air density, which can be calculated using Equation (3). In this study, the refractivity constants were adopted from the best average solution proposed by Rüeger [43]:

$$\rho = \frac{P - e}{T \times R_d} + \frac{e}{T \times R_w} \quad (3)$$

where P is the atmospheric pressure (hPa), e is the water vapor pressure (hPa), T is the temperature (K), and $R_w = 461.495 \text{ J}\cdot\text{kg}^{-1}\cdot\text{K}^{-1}$ is the specific gas constant for moist air. The water vapor pressure e was calculated using the Buck formulation [44], as expressed in Equations (4) and (5):

$$e = 6.1121 \times (1.0007 + 3.46 \times 10^{-6} \times P) \times \text{RH} \times \exp(a) \quad (4)$$

$$a = \frac{[18.729 - (T - 273.15)/227.3](T - 273.15)}{T - 15.28} \quad (5)$$

where RH is the relative humidity (%).

2.2.2. The Method of Calculating T_m

Similarly, the T_m profile at each grid point was obtained using the integral method [11], as expressed in Equation (6):

$$T_m = \frac{\int_{h_s}^{\infty} (e/T) dz}{\int_{h_s}^{\infty} (e/T^2) dz} \quad (6)$$

2.2.3. The Method of Calculating PWV

After ZTD, ZHD, and T_m were obtained, the PWV was calculated using Equation (7) [11]:

$$PWV = \frac{10^5}{R_v \left(\frac{k_3}{T_m} + k_2' \right)} \times (ZTD - ZHD) \quad (7)$$

where $R_v = 461 \text{ J} \cdot \text{kg}^{-1} \cdot \text{K}^{-1}$ is the specific gas constant for water vapor, $k_2' = 22.97 \text{ K/hPa}$ and $k_3 = 375,463 \text{ K}^2/\text{hPa}$.

2.2.4. LightGBM Model

LightGBM is an efficient ensemble learning algorithm based on gradient boosting decision trees (GBDT). It iteratively constructs multiple decision trees by using the negative gradient as the optimization objective, thereby enabling effective modeling of complex nonlinear relationships. To overcome the computational limitations of conventional GBDT algorithms when applied to large-scale datasets, LightGBM incorporates two key optimization strategies: gradient-based one-side sampling (GOSS) and exclusive feature bundling (EFB). GOSS improves the estimation of information gain by preferentially retaining samples with larger gradients, whereas EFB reduces feature dimensionality by bundling mutually exclusive features, thereby substantially reducing computational complexity. In addition, LightGBM employs a histogram-based decision tree algorithm that discretizes continuous features, further accelerating training and improving memory efficiency. These strategies enable LightGBM to maintain high prediction accuracy while achieving high computational efficiency, making it particularly suitable for large-scale data-driven modeling tasks [45].

2.2.5. Construction of the CLZP Model

To address the limitations of existing models while exploiting the high-resolution characteristics of ERA5 data, this study developed a LightGBM-based near-real-time GNSS water vapor retrieval model for China, referred to as CLZP. The CLZP model consists of two main components: the CLZP-ZHD gridded model and the CLZP-PWV correction model. A schematic overview of the CLZP model is shown in Figure 1.

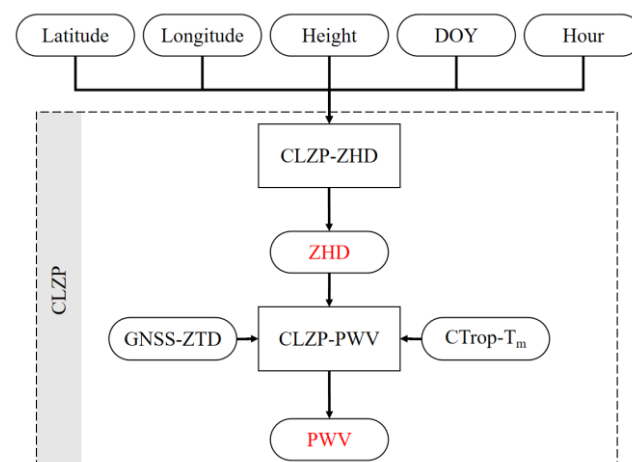


Figure 1. Schematic Diagram of the CLZP Model.

The CLZP-ZHD gridded model was constructed on a $0.5^\circ \times 0.5^\circ$ spatial grid. At each grid point, day of year (DOY), ellipsoidal height (m), and hour of day were used as input features to train a LightGBM model, with ZHD (m) as the output. During model application, the latitude and longitude of a GNSS station were first used to identify the corresponding grid cell. The LightGBM models at the four surrounding grid points were then used to estimate ZHD at the station elevation, and bilinear interpolation was applied to derive the station-specific ZHD.

Subsequently, near-real-time GNSS ZTD data were combined with T_m derived from the CTrop model to calculate the initial station-level PWV according to Equation (7). The CTrop-derived T_m was selected because CTrop has demonstrated good performance in China and surrounding regions [46] and does not require meteorological observations as model inputs. However, the predicted ZHD and T_m values may contain substantial errors under complex weather conditions. These errors may propagate into the final PWV estimates and accumulate during the retrieval process, thereby limiting retrieval accuracy. To mitigate these propagated errors, the CLZP-PWV correction model was developed. Longitude (degrees), latitude (degrees), elevation (m), DOY, hour, and ZTD (m) were used as input features, while the correction term for the initial station-level PWV (mm), denoted as dPWV (mm), was used as the output to train a unified LightGBM model. The final PWV (mm) was obtained by adding dPWV to the initial PWV, thereby enabling accurate near-real-time PWV retrieval at the station. Because in situ meteorological observations were unavailable at the GNSS stations, ERA5 data were used to obtain station-specific ZHD and T_m , from which PWV was calculated and used as the reference value. Schematic diagrams of the CLZP-ZHD and CLZP-PWV models are shown in Figures 2 and 3, respectively.

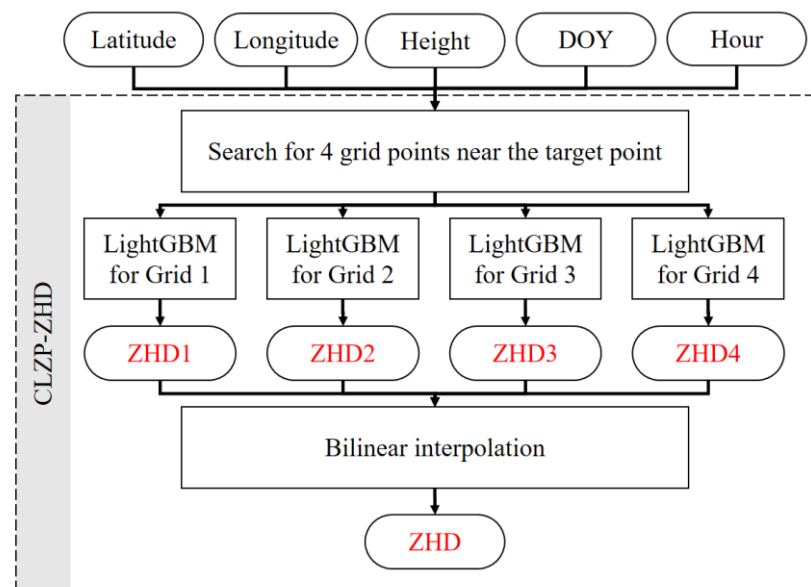


Figure 2. Schematic Diagram of the CLZP-ZHD Model.

The CLZP-ZHD gridded model divides the study area ($15\text{--}55^\circ\text{N}$, $73\text{--}135^\circ\text{E}$) into grids with a spatial resolution of $0.5^\circ \times 0.5^\circ$, resulting in 10,125 grid points. ERA5 data from 2014 to 2017 were used as the training set, whereas 2018 data served as the testing set. Each grid point included 37 pressure levels with hourly sampling, yielding 1,297,368 training samples per grid point ($37 \times 24 \times 1461$).

Unlike the gridded CLZP-ZHD model, the CLZP-PWV model adopts a unified modeling strategy for all stations. Data from 100 CMONOC stations during 2014–2017 were used for training, whereas data from 43 stations in 2018 were used for testing. The spatial

distribution of the training and testing stations is shown in Figure 4. The hyperparameters of the LightGBM models were optimized using a two-step strategy: first, Bayesian optimization was applied to identify promising regions of the parameter space, followed by a local exhaustive search for fine-tuning. The final hyperparameter settings are listed in Table 1. On a computer equipped with an NVIDIA GeForce RTX 4060 GPU and an Intel Core i7-12700KF CPU, one complete retrieval cycle, from the input of the required data to the output of the final PWV result, required approximately 1.33 s. This processing efficiency satisfies the practical requirements of near-real-time GNSS-based PWV retrieval.

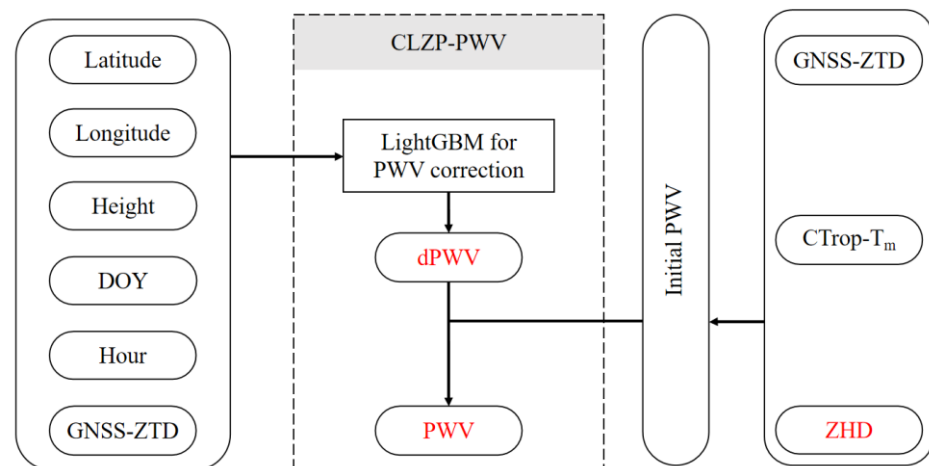


Figure 3. Schematic Diagram of the CLZP-PWV Model.

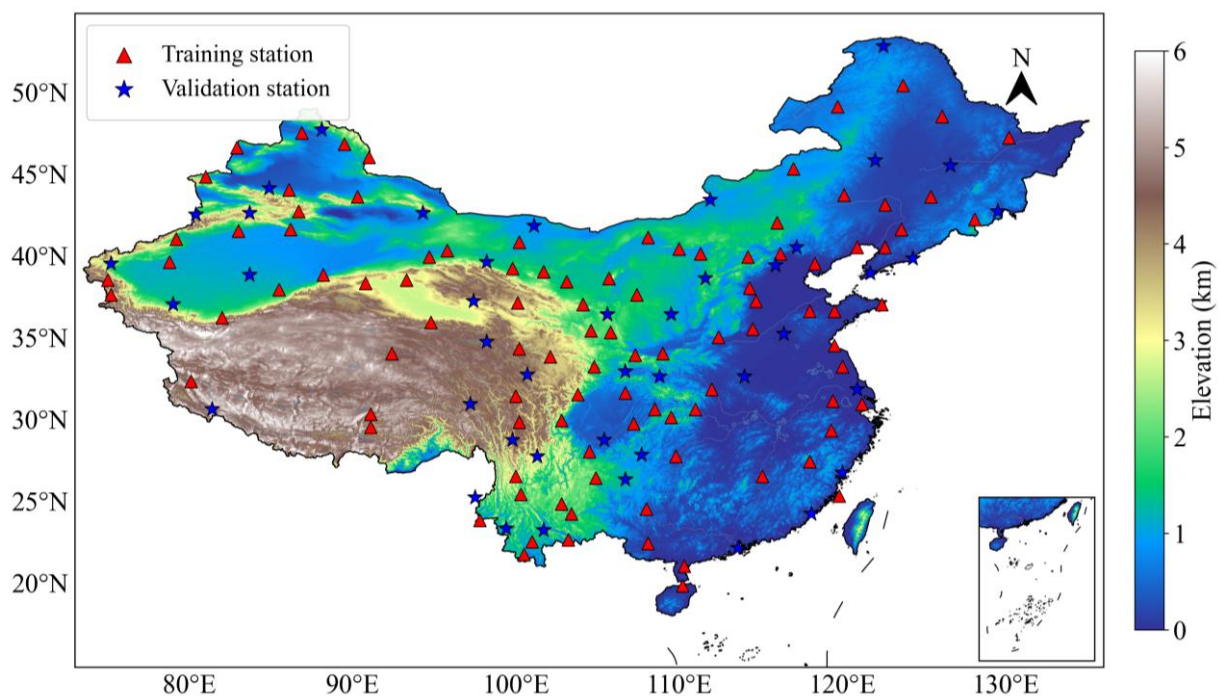


Figure 4. Distribution of Training and Testing Stations. Red triangles denote training stations, and blue stars denote testing stations.

Table 1. LightGBM Hyperparameter Settings.

	CLZP-ZHD	CLZP-PWV
Learning_rate	0.026	0.078
Num_leaves	36	73
Max_depth	10	12
Min_data_in_leaf	302	66
Feature_fraction	0.93	0.85
Bagging_fraction	0.98	0.92
Bagging_freq	5	3
Lambda_l1	0.076	0.0011
Lambda_l2	0.059	0.013
Min_gain_to_split	0.00053	0.016

To quantitatively evaluate model accuracy, three statistical metrics were used in this study: mean bias (MB), root mean square error (RMSE), and standard deviation (STD). The calculation formulas for each metric are as follows:

$$\text{Bias} = \frac{1}{n} \sum_{i=1}^n x_{\text{model}} - x_{\text{truth}} \quad (8)$$

$$\text{RMSE} = \sqrt{\frac{1}{n} \sum_{i=1}^n (x_{\text{model}} - x_{\text{truth}})^2} \quad (9)$$

$$\text{STD} = \sqrt{\frac{1}{n-1} \sum_{i=1}^n ((x_{\text{model}} - x_{\text{truth}}) - \text{Bias})^2} \quad (10)$$

where x_{model} is the predicted value from the model, x_{truth} is the true value, and n is the number of samples.

3. Results

3.1. Validation of the CLZP-ZHD Model

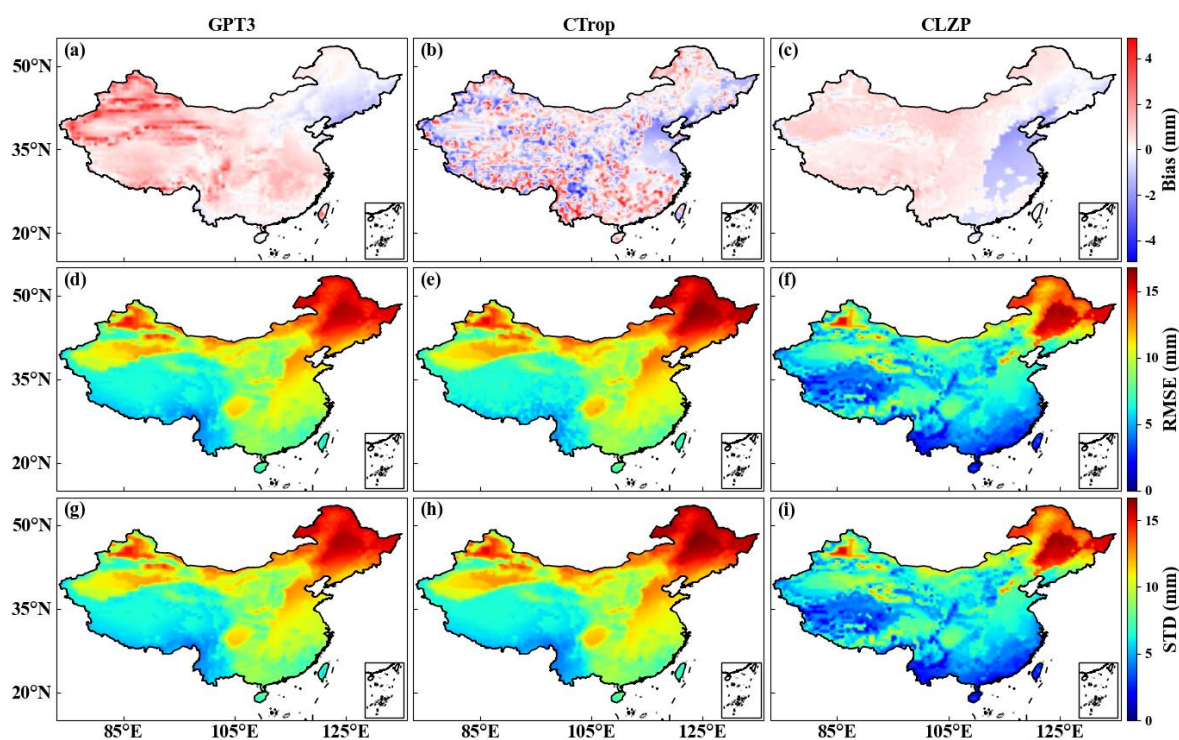
3.1.1. Overall CLZP-ZHD Model Analysis

Hourly ERA5 data with a spatial resolution of $0.4^\circ \times 0.4^\circ$ over China in 2018 were used to evaluate the accuracy of the CLZP-ZHD model, with GPT3-ZHD and CTrop-ZHD models used as benchmark models. Table 2 summarizes the statistical results, and Figure 5 shows the spatial distributions of Bias, RMSE, and STD for the three models.

The ERA5-based validation indicates that CLZP-ZHD achieves the best overall performance among the three models. The mean bias of GPT3-ZHD, CTrop-ZHD, and CLZP-ZHD are 0.65, -0.34 , and 0.15 mm, respectively. The bias of CLZP-ZHD is closest to zero, suggesting that it provides better control of systematic deviations. In terms of RMSE, CLZP-ZHD reaches the lowest value of 7.09 mm, compared with 9.51 mm for GPT3-ZHD and 9.88 mm for CTrop-ZHD. This corresponds to RMSE reductions of approximately 25.4% and 28.2% relative to GPT3-ZHD and CTrop-ZHD, respectively. Paired Student's t -tests conducted using grid points indicated that the RMSE of CLZP-ZHD was significantly lower than those of GPT3-ZHD and CTrop-ZHD (both $p < 0.001$). The STD of CLZP-ZHD is 7.06 mm, which is also lower than those of GPT3-ZHD (9.44 mm) and CTrop-ZHD (9.71 mm), indicating reduced error dispersion and improved stability (both $p < 0.001$).

Table 2. Accuracy Comparison of ZHD Derived from the GPT3, CTrop, and CLZP Models Against ERA5 Data.

Model	Bias/mm	RMSE/mm	STD/mm
GPT3-ZHD	0.65 [−1.70, 4.90]	9.51 [3.99, 16.14]	9.44 [3.96, 16.14]
CTrop-ZHD	−0.34 [−4.54, 4.87]	9.88 [4.21, 16.76]	9.71 [3.93, 16.72]
CLZP-ZHD	0.15 [−1.97, 1.81]	7.09 [0.10, 16.07]	7.06 [0.10, 16.07]

**Figure 5.** Distribution of Bias, RMSE, and STD of ZHD from the GPT3, CTrop, and CLZP models relative to ERA5 data. Panels (a–c), (d–f), and (g–i) represent Bias, RMSE, and STD, respectively, for the three models.

The spatial distributions further confirm the superior performance of CLZP-ZHD. GPT3-ZHD exhibits pronounced positive bias in several high-altitude regions of western China, whereas CTrop-ZHD shows stronger spatial variability, with alternating positive and negative deviations. By contrast, the bias of CLZP-ZHD is generally closer to zero and more spatially uniform, with fewer areas showing large deviations. For RMSE and STD, all three models show broadly similar spatial patterns, with relatively larger values in high-latitude regions and smaller values in low-latitude regions. Nevertheless, CLZP-ZHD produces lower RMSE and STD values across most of the study area, demonstrating better spatial adaptability and more stable ZHD estimation.

To further assess the independent applicability of CLZP-ZHD, observations from 78 radiosonde stations in 2018 were used for validation. Surface-level ZHD was calculated from radiosonde data using the same procedure as that applied to ERA5. The results are summarized in Table 3 and Figure 6. GPT3-ZHD and CTrop-ZHD both show positive overall bias values of 2.21 and 2.05 mm, respectively, indicating mild systematic overestimation. CLZP-ZHD has a smaller bias of 1.20 mm, again showing better control of systematic errors. For RMSE, GPT3-ZHD and CTrop-ZHD obtain values of 11.57 and 11.77 mm, whereas CLZP-ZHD reduces the RMSE to 9.06 mm. This represents improvements of 21.7% and 23.0% relative to GPT3-ZHD and CTrop-ZHD, respectively. Paired Student's *t*-tests based on the station results indicated that the RMSE of CLZP-ZHD was significantly lower than those of GPT3-ZHD and CTrop-ZHD (both $p < 0.001$). The STD values

of GPT3-ZHD, CTrop-ZHD, and CLZP-ZHD are 10.36, 10.22, and 8.21 mm, respectively, confirming that CLZP-ZHD also reduces error dispersion in the independent radiosonde validation (both $p < 0.001$).

The radiosonde-based spatial distributions are generally consistent with the ERA5-based results. CLZP-ZHD yields lower RMSE and STD values across most regions, with particularly evident improvements in eastern coastal areas. Although local differences remain due to the uneven distribution of radiosonde stations and the complex regional atmospheric conditions, CLZP-ZHD exhibits better spatial consistency than GPT3-ZHD and CTrop-ZHD. These findings indicate that the proposed model is not only well fitted to the ERA5-derived reference data but also maintains good generalization ability when evaluated using independent radiosonde observations.

Overall, both ERA5- and radiosonde-based validations demonstrate that CLZP-ZHD outperforms GPT3-ZHD and CTrop-ZHD in terms of Bias, RMSE, and STD. The proposed model provides more accurate and spatially stable ZHD estimates over China, mainly because the LightGBM framework can better capture nonlinear relationships among temporal variation, height, and atmospheric conditions. These improvements provide a more reliable ZHD basis for subsequent near-real-time GNSS PWV retrieval.

Table 3. Comparison of ZHD accuracy from the GPT3, CTrop, and CLZP models relative to radiosonde data.

Model	Bias/mm	RMSE/mm	STD/mm
GPT3-ZHD	2.21 [−16.20, 17.85]	11.57 [5.20, 19.56]	10.36 [4.34, 15.59]
CTrop-ZHD	2.05 [−14.76, 19.55]	11.77 [4.77, 21.10]	10.22 [3.96, 15.58]
CLZP-ZHD	1.20 [−12.79, 12.34]	9.06 [2.43, 17.67]	8.21 [2.42, 16.12]

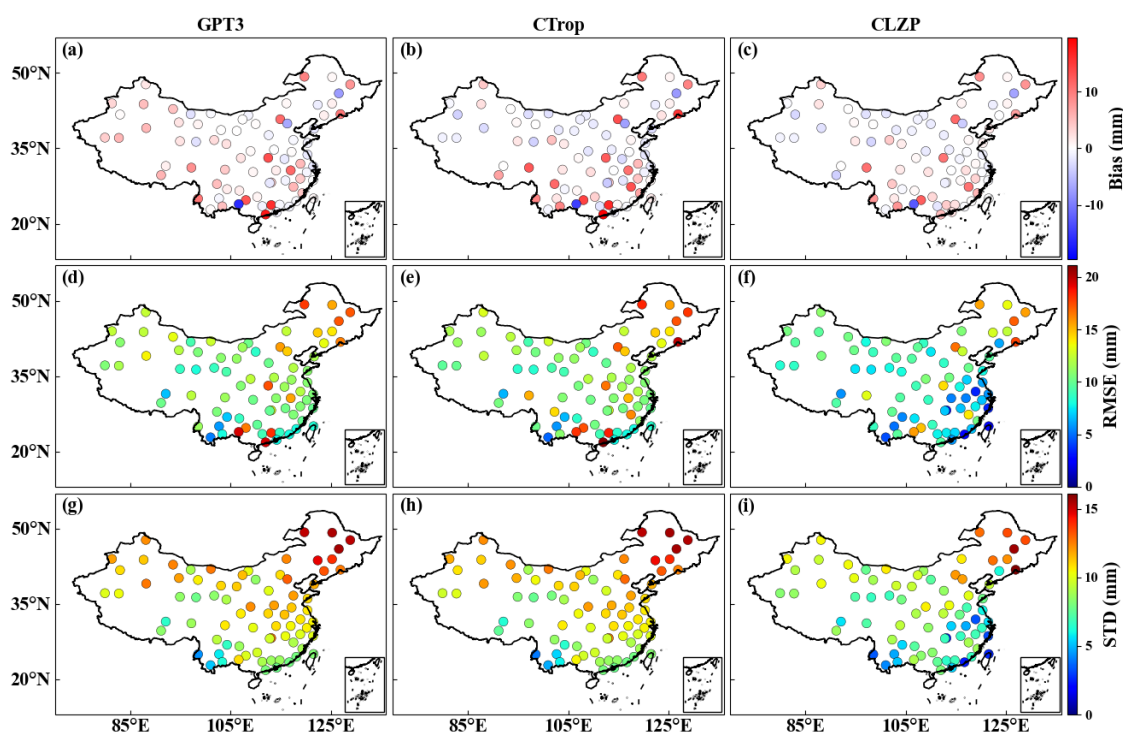


Figure 6. Distribution of Bias, RMSE, and STD of ZHD from the GPT3, CTrop, and CLZP models relative to radiosonde data. Panels (a–c), (d–f), and (g–i) represent Bias, RMSE, and STD, respectively, for the three models.

3.1.2. Daily Variation Analysis of Model Accuracy

A representative point (33.4°N, 115.4°E) was randomly selected to analyze the daily variation in model accuracy. ERA5-derived ZHD was used as the reference, and the daily variations in the accuracy metrics are shown in Figure 7. All three models exhibit noticeable temporal fluctuations in bias, RMSE, and STD. These variations mainly reflect the influence of seasonal ZHD changes and synoptic-scale disturbances on model accuracy. It should be noted that GPT3-ZHD, CTrop-ZHD, and CLZP-ZHD are models constructed from long-term reanalysis meteorological data. Although these models can capture mean atmospheric variability, they remain limited in representing short-term non-stationary atmospheric changes.

In terms of bias, GPT3-ZHD and CTrop-ZHD show similar daily variation patterns, with relatively large fluctuations and frequent alternations between positive and negative values, indicating that their systematic errors are sensitive to temporal changes. In contrast, the bias curve of CLZP-ZHD is smoother and shows smaller day-to-day variations, suggesting more stable systematic error behavior under varying atmospheric conditions. Regarding RMSE, GPT3-ZHD and CTrop-ZHD exhibit higher error levels, with frequent pronounced peaks, indicating reduced stability during periods of strong atmospheric variability or transitional weather conditions. By comparison, CLZP-ZHD maintains a generally lower RMSE level with weaker temporal fluctuations. During most high-error periods, its peak values are lower than those of GPT3-ZHD and CTrop-ZHD, demonstrating stronger robustness to short-term atmospheric variability. In terms of STD, the differences among the three models are more evident. GPT3-ZHD shows the highest STD overall, indicating larger random errors and greater error dispersion. Although CTrop-ZHD improves upon GPT3-ZHD, noticeable fluctuations remain. In contrast, CLZP-ZHD exhibits the lowest STD on most days, with a more stable temporal pattern.

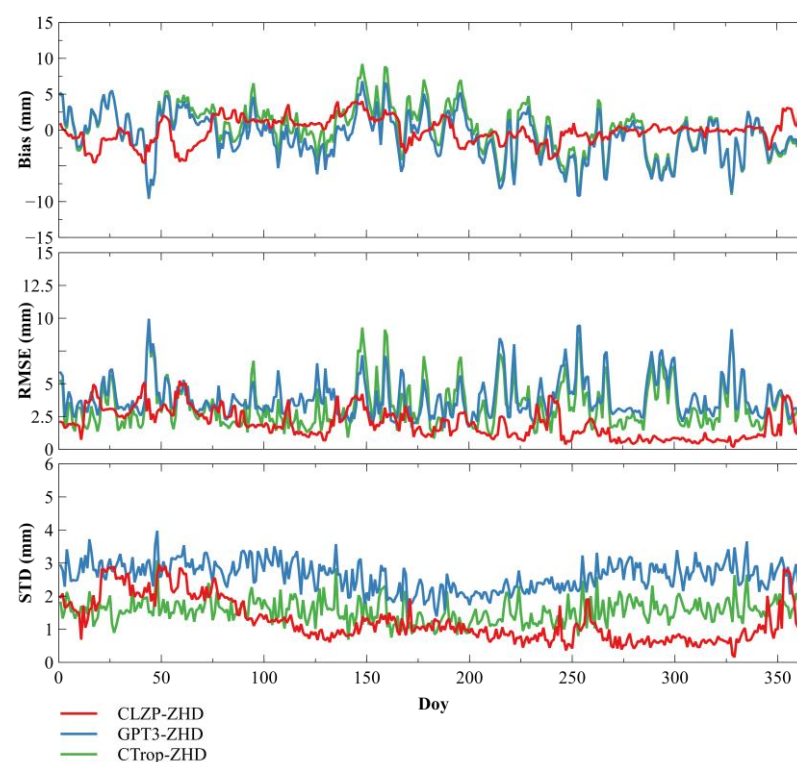


Figure 7. Daily variation in Bias, RMSE, and STD of ZHD from the GPT3, CTrop, and CLZP models relative to ERA5 data. The red, blue, and green lines represent CLZP, GPT3, and CTrop, respectively.

3.1.3. Analysis of Accuracy Variation with Height Above Ground

To evaluate the height-dependent performance of the three ZHD models, ZHD profiles from all ERA5 grid points and radiosonde stations were divided into six 1 km height intervals above ground level. Bias, RMSE, and STD were calculated for each interval, as summarized in Tables 4 and 5.

The GPT3-ZHD model shows a pronounced height-dependent systematic error. In the ERA5-based validation, its Bias increases from -0.42 mm below 1 km to 42.56 mm above 5 km, while RMSE increases from 3.95 to 42.83 mm. A similar pattern is observed in the radiosonde-based validation, where Bias and RMSE reach 57.61 and 57.85 mm, respectively, above 5 km. In contrast, STD remains relatively stable across height intervals, indicating that the error growth of GPT3-ZHD is mainly driven by systematic overestimation rather than increased error dispersion. This behavior is likely related to its reliance on gridded pressure fields and an exponential pressure-decay formulation, which may not adequately represent vertical atmospheric variability at high altitudes.

CTrop-ZHD reduces the height-dependent errors compared with GPT3-ZHD but still exhibits altitude-related deviations. Its Bias changes from negative values in the lower atmosphere to positive values at higher elevations, reaching 13.36 mm in ERA5 and 15.08 mm in radiosonde validation above 5 km. Although CTrop-ZHD generally yields lower RMSE than GPT3-ZHD, its errors still increase at high altitudes, suggesting that its vertical correction strategy only partly mitigates height-related systematic bias.

By contrast, CLZP-ZHD maintains the most stable accuracy across all height intervals. Its Bias remains close to zero in both ERA5 and radiosonde validations, and its RMSE stays at a low level, approximately 3–4 mm for ERA5 and 4–6 mm for radiosonde data. STD is also consistently low and generally lower than or comparable to those of the benchmark models. These results demonstrate that CLZP-ZHD effectively controls height-dependent systematic errors and provides more reliable ZHD estimates from the surface to near the tropopause.

Table 4. Comparison of the accuracy of ZHD from the three models with increasing height above ground level based on ERA5 data.

	Model	<1 km	1–2 km	2–3 km	3–4 km	4–5 km	>5 km
Bias/mm	GPT3-ZHD	−0.42	4.76	10.66	20.50	30.83	42.56
	CTrop-ZHD	−3.47	−7.66	−6.96	−2.24	4.39	13.36
	CLZP-ZHD	−0.06	0.08	−0.02	−0.01	0.41	0.14
RMSE/mm	GPT3-ZHD	3.95	6.13	11.23	20.96	30.97	42.83
	CTrop-ZHD	5.45	8.29	7.61	4.03	5.15	13.98
	CLZP-ZHD	3.44	3.02	2.83	3.62	3.98	3.55
STD/mm	GPT3-ZHD	3.95	3.85	3.54	4.37	2.96	4.82
	CTrop-ZHD	4.21	3.16	3.08	3.35	2.70	4.11
	CLZP-ZHD	3.44	3.02	2.83	3.62	2.57	3.55

Table 5. Comparison of the accuracy of ZHD from the three models with increasing height above ground level based on radiosonde data.

	Model	<1 km	1–2 km	2–3 km	3–4 km	4–5 km	>5 km
Bias/mm	GPT3-ZHD	−0.24	4.50	11.28	17.63	27.57	57.61
	CTrop-ZHD	−0.81	−5.12	−6.17	4.75	5.84	15.08
	CLZP-ZHD	−0.17	0.28	0.69	0.47	0.50	0.39
RMSE/mm	GPT3-ZHD	6.91	6.95	12.55	18.47	28.30	57.85
	CTrop-ZHD	6.33	7.09	8.01	5.96	8.16	15.92
	CLZP-ZHD	4.12	5.68	5.23	5.01	4.72	4.32

STD/mm	GPT3-ZHD	6.91	5.29	5.50	5.50	6.40	5.26
	CTrop-ZHD	6.28	4.90	5.13	3.60	5.70	5.11
	CLZP-ZHD	4.12	5.67	5.18	4.99	4.69	4.31

3.2. Validation of the CLZP-PWV Model

3.2.1. Overall CLZP-PWV Model Analysis

To evaluate the performance of the models in GNSS-based PWV retrieval, ZTD data from 43 CMONOC stations in 2018 were used to derive PWV using GPT3-PWV, CTrop-PWV, and CLZP-PWV. The overall validation results are summarized in Table 6. In terms of systematic error, all three models exhibit positive bias values of 0.24 mm, 0.15 mm, and 0.10 mm, respectively, indicating slight overall overestimation. Among the three models, CLZP-PWV has the smallest bias, which is closest to zero, indicating the best systematic error control, followed by CTrop-PWV and GPT3-PWV. In terms of RMSE, GPT3-PWV and CTrop-PWV yield values of 1.71 mm and 1.86 mm, respectively, whereas CLZP-PWV achieves the lowest RMSE of 1.15 mm. This corresponds to reductions of approximately 32.7% and 38.2% relative to GPT3-PWV and CTrop-PWV. Paired Student's *t*-tests based on the station results indicated that the RMSE of CLZP-PWV was significantly lower than those of GPT3-PWV and CTrop-PWV (both $p < 0.001$). Regarding STD, GPT3-PWV and CTrop-PWV have values of 1.71 mm and 1.86 mm, respectively, whereas CLZP-PWV shows a lower STD of 1.13 mm, indicating reduced error dispersion. Overall, CLZP-PWV outperforms GPT3-PWV and CTrop-PWV across all three metrics—bias, RMSE, and STD—indicating that it reduces systematic errors, overall magnitude, and random errors, thereby improving the accuracy and stability of PWV retrieval.

Table 6. Comparison of PWV accuracy from the GPT3, CTrop, and CLZP models relative to ERA5 data.

Model	Bias/mm	RMSE/mm	STD/mm
GPT3-PWV	0.24 [−1.35, 1.85]	1.71 [0.52, 2.37]	1.71 [0.51, 2.34]
CTrop-PWV	0.15 [−3.06, 1.70]	1.86 [0.48, 3.36]	1.86 [0.48, 2.41]
CLZP-PWV	0.10 [−1.10, 1.53]	1.15 [0.47, 1.98]	1.13 [0.46, 1.40]

As shown in Figure 8, in terms of the spatial distribution of bias, all three models exhibit relatively small systematic errors, with most stations falling within ± 1 mm. In terms of RMSE, GPT3-PWV and CTrop-PWV generally show larger values (approximately 1.5–3.0 mm) in central-eastern and southern China, whereas lower values are observed in western regions. This pattern may be associated with higher water vapor content and more complex atmospheric variability in these regions. In contrast, CLZP-PWV exhibits lower RMSE values overall than the two benchmark models. Notably, in the humid regions of central and eastern China, its RMSE is substantially reduced, with most stations remaining below 1.5 mm, indicating that CLZP-PWV maintains high retrieval accuracy under complex climatic conditions. Regarding the spatial distribution of STD, GPT3-PWV and CTrop-PWV show relatively large error dispersion in northeastern and northern China. This pattern is likely associated with pronounced seasonal variability, large temperature gradients, and uneven water vapor distributions in these regions, which lead to greater error dispersion. In contrast, CLZP-PWV shows lower STD values overall, indicating better stability under varying climatic conditions. This improvement can be attributed to the LightGBM algorithm, which integrates multi-source features and near-real-time ZTD data, enabling the model to adapt to varying spatiotemporal conditions and thereby reduce error dispersion.

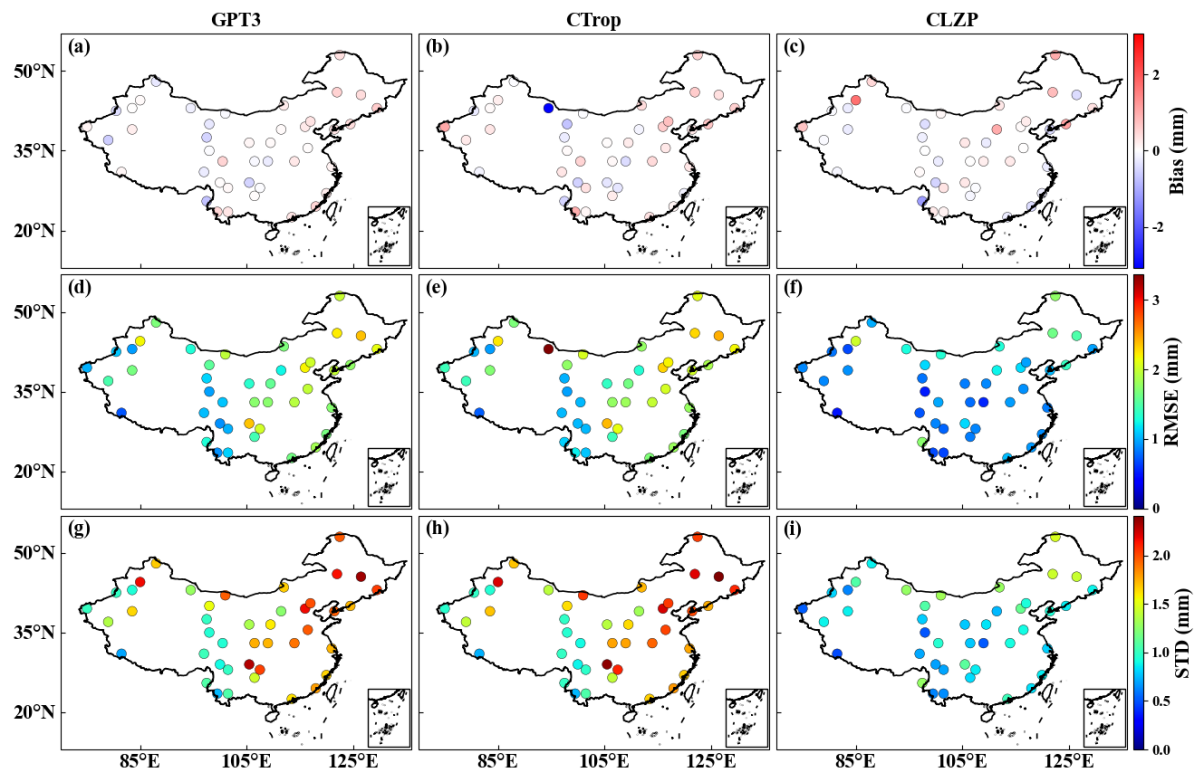


Figure 8. Distribution of Bias, RMSE, and STD of PWV from the GPT3, CTrop, and CLZP models relative to ERA5 data. Panels (a–c), (d–f), and (g–i) represent Bias, RMSE, and STD, respectively, for the three models.

3.2.2. Daily Variation Analysis of PWV Accuracy

Figure 9 illustrates the daily variations in bias, RMSE, and STD for PWV derived from GPT3-PWV, CTrop-PWV, and CLZP-PWV at station DLHA (37.4°N, 97.4°E) using ERA5 data as the reference. All three models exhibit noticeable temporal fluctuations in daily bias. GPT3-PWV and CTrop-PWV show relatively large amplitudes, with frequent alternations between positive and negative deviations, indicating temporally unstable systematic errors. In contrast, the bias series of CLZP-PWV is smoother, with smaller fluctuation amplitudes and values remaining close to zero for most periods, suggesting more stable systematic error control. In terms of RMSE and STD, GPT3-PWV and CTrop-PWV exhibit relatively large fluctuations, with several pronounced peaks, indicating that their overall errors are strongly affected by temporal variability. CLZP-PWV maintains lower RMSE and STD values with smaller fluctuations, indicating greater stability and robustness in PWV retrieval.

3.2.3. Analysis of Accuracy Variation Under Different ZTD Intervals

Table 7 presents the PWV retrieval accuracy of the three models under different ZTD intervals. Since ZTD is closely related to atmospheric moisture content and tropospheric state, this analysis provides further insight into model robustness under different water vapor conditions. For bias, both GPT3-PWV and CTrop-PWV exhibit alternating positive and negative deviations across ZTD intervals, with negative bias dominating under low-ZTD conditions and gradually shifting to positive bias under higher-ZTD conditions. This indicates that their systematic errors vary with atmospheric moisture content. In contrast, CLZP-PWV maintains smaller bias values across all ZTD intervals, indicating more stable systematic-error control under different moisture conditions. For RMSE and STD, both GPT3-PWV and CTrop-PWV increase with ZTD, indicating error expansion under rising

water vapor conditions. In contrast, although CLZP-PWV also increases with ZTD, it does so only slowly and consistently achieves the lowest RMSE and STD across all intervals. These results confirm that the proposed residual compensation strategy effectively mitigates error amplification in high-moisture environments.

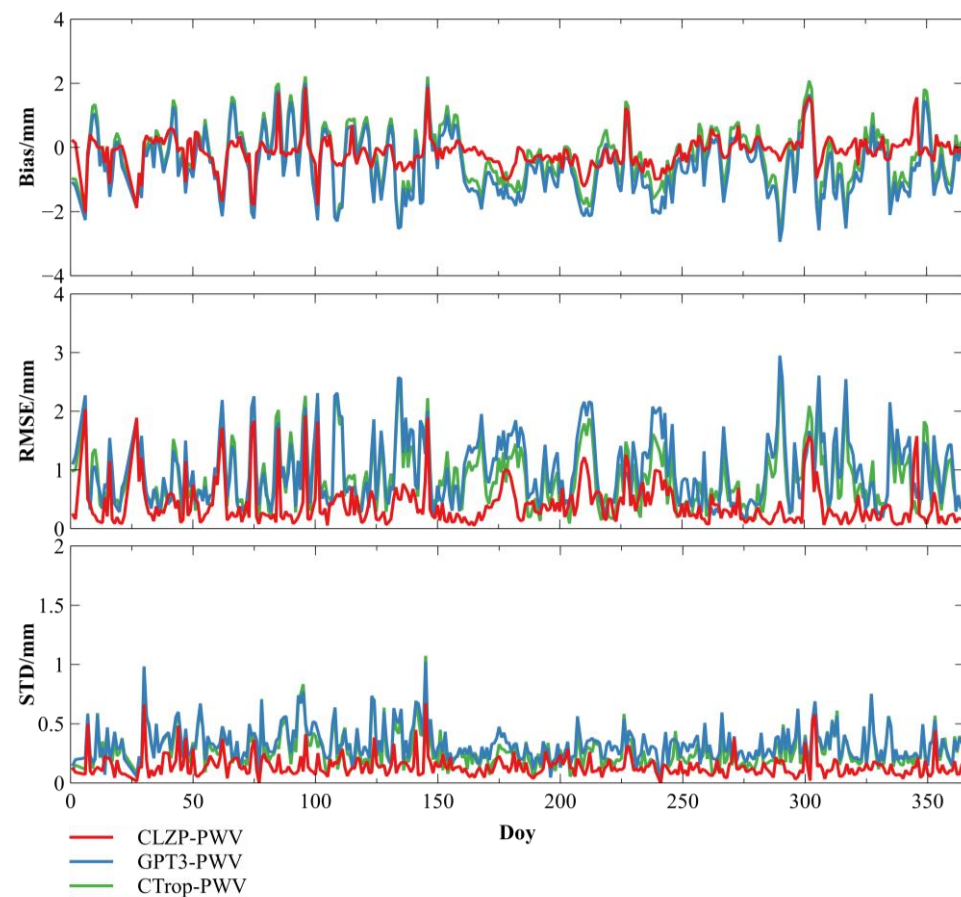


Figure 9. Daily variation in Bias, RMSE, and STD of PWV from the GPT3, CTrop, and CLZP models relative to ERA5 data. The red, blue, and green lines represent CLZP, GPT3, and CTrop, respectively.

Table 7. Comparison of PWV accuracy from the GPT3, CTrop, and CLZP models across different ZTD intervals relative to ERA5 data.

	Model	<1.5 m	1.5–1.7 m	1.7–1.9 m	1.9–2.1 m	2.1–2.3 m	>2.3 m
Bias/mm	GPT3-PWV	−0.03	−0.36	−0.29	−0.12	0.10	0.31
	CTrop-PWV	0.06	−0.11	−0.15	−0.61	0.19	0.50
	CLZP-PWV	−0.02	−0.05	0.04	0.44	0.43	−0.06
RMSE/mm	GPT3-PWV	0.94	1.08	1.17	1.47	1.91	1.99
	CTrop-PWV	0.95	1.02	1.17	1.93	1.99	2.08
	CLZP-PWV	0.50	0.77	0.80	1.15	1.37	1.09
STD/mm	GPT3-PWV	0.94	1.01	1.13	1.46	1.91	1.97
	CTrop-PWV	0.95	1.02	1.16	1.84	1.98	2.02
	CLZP-PWV	0.50	0.77	0.80	1.06	1.30	1.09

4. Discussion

The results demonstrate that the proposed CLZP model improves both ZHD estimation and GNSS-based PWV retrieval over China. Validation results from ERA5 and independent radiosonde datasets show that CLZP-ZHD reduces RMSE by 25.4% and 28.2%

(ERA5) and by 21.7% and 23.0% (radiosonde) relative to GPT3-ZHD and CTrop-ZHD, respectively. The GNSS-based validation of CLZP-PWV yields RMSE reductions of 32.7% and 38.2% compared with GPT3-PWV and CTrop-PWV, respectively. Paired Student's *t*-tests based on the corresponding grid and station results confirmed that the reductions in RMSE and STD were statistically significant in all comparisons ($p < 0.001$). Therefore, the improvements achieved by CLZP are not merely marginal statistical fluctuations but are both statistically significant and practically meaningful. The improvement of CLZP-ZHD is particularly evident in its vertical stability. Unlike GPT3-ZHD, which exhibits a pronounced monotonic increase in bias and RMSE with height, and CTrop-ZHD, which shows a transition from negative to positive bias across altitudes, CLZP-ZHD maintains bias consistently close to zero, low RMSE, and stable STD across all height intervals. This demonstrates that CLZP-ZHD effectively suppresses the accumulation of systematic bias with height and provides more reliable error control throughout the vertical range. Widely used empirical models such as GPT3-ZHD and CTrop-ZHD generally rely on simplified representations of pressure decay or predefined vertical correction functions. Although these strategies are effective for broad climatological applications, they may introduce height-dependent systematic errors, especially in regions with complex terrain or at high elevations. By contrast, CLZP-ZHD directly incorporates height and temporal variables into a LightGBM-based modeling framework, allowing for nonlinear relationships between ZHD, altitude, and atmospheric variability to be represented more flexibly. This explains why CLZP-ZHD maintains relatively low Bias, RMSE, and STD from the surface to near the tropopause. Previous studies have shown that GNSS positioning accuracy is affected by multiple error sources, including satellite geometry, receiver characteristics, observation environment, and atmospheric delay modeling. Improvements in observation strategies, stochastic modeling, and multi-frequency or multi-constellation processing have been shown to enhance positioning performance [47,48]. Nevertheless, residual tropospheric delay remains one of the major error sources in high-precision GNSS applications [49]. Therefore, improving the accuracy of zenith hydrostatic delay (ZHD) estimation is important not only for GNSS water vapor retrieval but also for enhancing the reliability of high-precision GNSS positioning.

The improvement in CLZP-PWV further indicates that accurate PWV retrieval requires not only reliable ZHD estimation, but also effective compensation for residual errors propagated from multiple sources. In conventional GNSS-PWV retrieval, uncertainties in ZHD, T_m , and ZTD may accumulate and eventually affect the final PWV estimate. The CLZP-PWV model addresses this issue by learning the residuals of the initial PWV estimates using multi-source predictors, including station location, elevation, temporal information, and near-real-time GNSS ZTD. This design allows the model to capture systematic and nonlinear error patterns that are difficult to represent using purely empirical formulations. The lower RMSE and STD of CLZP-PWV, especially in humid regions of central and eastern China and under high-ZTD conditions, suggest that the residual compensation mechanism is effective in reducing error amplification under complex moisture environments.

From an application perspective, the main advantage of CLZP is that it does not require in situ meteorological observations while retaining near-real-time capability through the use of GNSS ZTD. This feature is important for GNSS meteorology because many GNSS stations are not equipped with co-located meteorological sensors. The proposed framework therefore provides a practical solution for high-resolution regional water vapor monitoring, particularly in areas where dense GNSS networks are available but surface meteorological observations are sparse. Recent studies have increasingly applied regional modeling and machine learning methods to improve GNSS-based PWV retrieval. Adavi et al. developed regional RF- and ANN-based models for hourly PWV estimation

over Austria, demonstrating that machine learning can represent the nonlinear relationships between GNSS observations, spatial and temporal variables, and atmospheric water vapor without requiring measured meteorological parameters during model operation [50]. Pang et al. applied a generalized regression neural network to adjust ERA5 PWV by considering seasonal and geographical differences, showing that regional and seasonal modeling can reduce systematic discrepancies between reanalysis and GNSS-derived PWV [51]. More recently, Liu et al. developed an RF-based PWV model for Hong Kong using a prior PWV estimate, geographical and temporal variables, and GNSS ZTD. Their results demonstrated that residual learning can improve regional PWV retrieval while avoiding the use of in situ meteorological observations during operational estimation [52].

Although these studies demonstrate the value of regional information and nonlinear modeling, their objectives and model structures differ from those of CLZP. The model developed by Adavi et al. focused on regional hourly PWV estimation, whereas the model of Pang et al. was designed to adjust ERA5 PWV products rather than to retrieve station-level PWV directly from near-real-time GNSS observations. The model of Liu et al. is more similar to CLZP-PWV because both use geographical, temporal, and GNSS ZTD information to model the residuals of an initial PWV estimate. However, that model was developed for the Hong Kong region and focused primarily on PWV inversion. In contrast, CLZP was developed for China and combines a gridded ZHD estimation model with a unified PWV residual compensation model. This design allows the height-dependent and temporal variability of ZHD and the accumulated residuals in the subsequent PWV retrieval process to be considered within the same framework.

Recent studies of ZHD modeling have also shown that the biases of conventional hydrostatic delay models vary with geographical location and season. Fan et al. developed a gridded correction model for conventional ZHD formulations and demonstrated that regional and periodic correction can mitigate systematic model biases [53]. Unlike an output correction applied to an existing empirical ZHD model, CLZP-ZHD directly models ZHD at each spatial grid point using elevation, DOY, and hour as predictors. This approach provides a more flexible representation of regional, temporal, and height-dependent variations in ZHD.

Despite these advantages, several limitations should be acknowledged. First, CLZP is a data-driven regional model, and its performance depends on the representativeness and quality of the training data. Although ERA5 provides high-quality reanalysis fields, reanalysis uncertainties may still be transferred into the model. Second, the model was trained and validated mainly within China, and its applicability to other regions with different climatic regimes and topographic characteristics requires further assessment. Third, CLZP was compared only with GPT3 and CTrop in this study. Although these models provide representative benchmarks, the evaluation did not include more recent open-source tropospheric models, such as PVoxel and IGPZWD, which provide more refined representations of vertical atmospheric variations. Therefore, the present results only demonstrate the relative performance of CLZP against the two selected benchmark models and cannot establish whether it outperforms these newer models. Further comparisons under consistent data sources, validation periods, spatial domains, and height intervals are required. Fourth, the complete 37-level ERA5 pressure profiles were retained during model construction. In high-elevation regions, some lower pressure levels may lie below the actual terrain, and the corresponding ERA5 values are model-derived fields rather than direct atmospheric observations. Their inclusion may therefore introduce additional uncertainty, although the surface-level and radiosonde evaluations cannot separately quantify this influence. Fifth, although near-real-time GNSS ZTD improves the responsiveness of CLZP-PWV to short-term atmospheric changes, the model still relies on statistical relationships derived from historical data. Under extreme weather events or rapidly

evolving atmospheric conditions, these relationships may not fully capture the underlying physical processes, potentially leading to increased errors during certain periods. Future work should therefore incorporate longer validation periods, independent extreme-weather cases, higher-resolution numerical weather prediction products, and ERA5 model-level or terrain-screened pressure profiles. Systematic comparisons with PVoxel, IGPZWD, and other recent open-source tropospheric models should also be conducted under a unified evaluation framework. Moreover, introducing physical constraints or hybrid physical – machine learning strategies may further improve the robustness and interpretability of near-real-time GNSS water vapor retrieval.

5. Conclusions

This study proposed a regional near-real-time GNSS water vapor retrieval model for China, termed CLZP, to address the limited regional adaptability and insufficient representation of nonlinear atmospheric variability in conventional meteorology-independent models. The model integrates LightGBM with near-real-time GNSS observations and consists of two components: CLZP-ZHD for high-accuracy ZHD estimation and CLZP-PWV for PWV residual compensation. By combining a gridded ZHD modeling strategy with a multi-source PWV error compensation mechanism, the trained CLZP model enables high-accuracy near-real-time PWV retrieval without requiring in situ meteorological observations as real-time inputs.

1. CLZP-ZHD uses LightGBM to model ZHD at each grid point, allowing nonlinear temporal and height-dependent variations to be represented more flexibly. Validation against ERA5 and radiosonde data shows that CLZP-ZHD outperforms GPT3-ZHD and CTrop-ZHD in terms of Bias, RMSE, and STD. Relative to GPT3-ZHD and CTrop-ZHD, CLZP-ZHD reduces RMSE by approximately 25.4% and 28.2%, respectively, and also yields lower STD, indicating reduced error dispersion. Further height-dependent analysis demonstrates that CLZP-ZHD maintains stable accuracy from the surface to near the tropopause, effectively mitigating the high-altitude over-estimation observed in GPT3-ZHD and the increasing high-elevation errors of CTrop-ZHD.
2. To mitigate the propagation of errors from ZHD, T_m , and ZTD into PWV retrieval, CLZP-PWV was developed as a residual compensation model using multi-source features, including near-real-time GNSS ZTD. The GNSS-based validation shows that CLZP-PWV achieves lower Bias, RMSE, and STD than GPT3-PWV and CTrop-PWV. Specifically, CLZP-PWV reduces RMSE by approximately 32.7% and 38.2% relative to GPT3-PWV and CTrop-PWV, respectively, and produces lower STD, indicating improved retrieval stability. Spatial, temporal, and ZTD-dependent analyses further show that CLZP-PWV performs particularly well in humid and climatically complex regions and maintains robust accuracy under high-ZTD conditions.

Overall, the proposed CLZP model provides an effective technical approach for high-accuracy ZHD estimation and near-real-time GNSS-based PWV retrieval over China. Its independence from in situ meteorological observations makes it suitable for operational GNSS meteorology applications, especially at stations without co-located meteorological sensors. Future work will focus on validating the model under extreme weather conditions, extending it to other climatic regions, and incorporating higher-resolution numerical weather prediction data or physical constraints to further improve model robustness and interpretability.

Author Contributions: Conceptualization, M.Z. and X.F.; methodology, H.C.; software, Q.Z.; validation, M.Z. and H.C.; formal analysis, H.C.; investigation, Q.Z.; resources, M.Z.; data curation, H.C.

and Z.L.; writing—original draft preparation, M.Z. and H.C.; writing—review and editing, M.Z. and X.F.; visualization, H.C.; supervision, M.Z.; project administration, M.Z.; funding acquisition, X.F. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by Jiangsu Provincial Natural Science Foundation (Grant No. BK20250211).

Data Availability Statement: The ERA5 data used in this study are available at <https://cds.climate.copernicus.eu/datasets/reanalysis-era5-pressure-levels?tab=download> (accessed on 7 October 2025). The IGRA radiosonde data can be accessed at: <https://www.ncei.noaa.gov/data/integrated-global-radiosonde-archive/archive/> (accessed on 20 October 2025). The GPT3 model is available at: <https://vmf.geo.tuwien.ac.at/codes> (accessed on 21 December 2025). The CTrop model is available at: <https://github.com/sun1753814280/CTrop> (accessed on 21 December 2025). The source code, trained model files, and relevant processing instructions for the CLZP model are publicly available at <https://github.com/changhui-njupt/CLZP-model/tree/master> (accessed on 22 July 2026).

Acknowledgments: The authors would like to thank the ERA5 gridded data provided by the European Centre for Medium-Range Weather Forecasts, radiosonde data provided by the NOAA National Centers for Environmental Information through the Integrated Global Radiosonde Archive (IGRA), and GNSS ZTD products provided by the China Earthquake Administration.

Conflicts of Interest: The authors declare no conflicts of interest.

Abbreviations

The following abbreviations are used in this manuscript:

GNSS	Global Navigation Satellite System
ZTD	zenith tropospheric delay
ZHD	zenith hydrostatic delay
ZWD	zenith wet delay
T _m	weighted mean temperature
PWV	precipitable water vapor
LightGBM	Light Gradient Boosting Machine
ERA5	ECMWF Re-Analysis v5
CMONOC	Crustal Movement Observation Network of China
IGRA	Integrated Global Radiosonde Archive

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