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Research Article

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An Empirical Model for Atmospheric Temperature Estimation Using a Geographic Grid Neural Network Framework

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Abstract: Atmospheric temperature (T) is a critical parameter in Global Navigation Satellite System (GNSS) tropospheric tomography, and facilitates the conversion of wet refractivity (N_w) to water vapor density (ρ_v). This study presents an empirical model for T estimation based on a Geographic Grid Neural Network (GGNN) framework. The proposed GGNNTemp model has neural networks with a 1°×1° geographic grid. Each geographic grid node employs a multilayer feedforward neural network with inputs of month and altitude and output of temperature. Comparative evaluations against the GPT2w model demonstrate the superior performance of the GGNNTemp model, achieving a BIAS value of 0.01 K and an RMSE of 1.60 K—significantly outperforming GPT2w's 12.37 K RMSE. The model exhibits consistent accuracy across varying latitudes, altitudes (up to 10 km), and seasons, with ρ_v conversion errors maintained below 5‰. This work highlights the efficacy of GGNN technology in modeling atmospheric parameters and advances its potential for broader applications in GNSS meteorology.

Keywords: atmospheric temperature; Geographic Grid Neural Network; GNSS tropospheric tomography; wet refractivity; water vapor density

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1. Introduction

In the field of Global Navigation Satellite System (GNSS), accurate empirical models of atmosphere/tropospheric parameters have become increasingly vital for practical applications such as GNSS navigation positioning and GNSS meteorology. Among many atmospheric parameters, atmospheric temperature (T) is an important parameter. T is a necessary parameter in some zenith wet delay (ZWD) models like the Saastamoinen model (Saastamoinen, 1972) and the Hopfield model (Hopfield, 1971). However, more advanced ZWD models like the GPT2w model and the GTrop model do not depend on T. On the other hand, T remains crucial for GNSS tropospheric tomography. With dense GNSS networks, this technique can reconstruct 3D/4D wet refractivity (N_w) fields above the regions of GNSS networks. For practical applications, we pay more attention to water vapor density (ρ_v) rather than N_w and N_w should be converted into ρ_v. The formulas for calculating N_w and ρ_v can be described respectively as

$$N_w = k_2^{'} \cdot \frac{e}{T} + k_3 \cdot \frac{e}{T^2} \quad (1)$$

$$\rho_v = \frac{e}{R_v \cdot T} \quad (2)$$

where e is the partial pressure of water vapor, $k_2^{'}$ and k_3 are the refraction constants for water vapor, and R_v is the specific gas constant for water vapor. Thus, the conversion between N_w and ρ_v can be achieved through the following formula

$$\rho_v = N_{\mathrm{w}} \cdot \frac{1}{R_v \cdot (k_2' + k_3 / T)} \quad (3)$$

Since R_v, k_2' and k_3 can be regarded as constants, this conversion involves only a single variable *T*. Consequently, the conversion can be achieved through an empirical model of *T*. Several empirical models developed for calculating zenith tropospheric delay (ZTD). *T* is are key input parameter in some of the empirical ZTD models, and inherently serve a dual purpose as empirical models for *T*. Prominent examples include the EGNOS model (Penna et al. 2001), the UMB3m model (Leandro et al. 2008), and the GPT2w model (Böhm et al. 2015).

The Geographic Grid Model (GGM) has become a fundamental modeling framework for establishing empirical models of tropospheric parameters. GGMs can discrete geographic coordinates into 1°×1° to 5°×5° grids to resolve geographic variations of these atmospheric parameters. GGM techniques have been successfully implemented in several renowned models, including TropGrid, TropGrid2, ITG, WGTEM, GPT2w and GTrop (Sun et al. 2019). On the other hand, machine learning algorithms have advanced the modeling of tropospheric parameters (Ding et al. 2025; Zhu et al. 2022; Yue et al. 2025; Li et al. 2024; Li et al. 2023;Li et al. 2025; Yang et al. 2021; Huang et al. 2024; Huang et al. 2025; Bi et al. 2024). These machine learning algorithms are highly diverse, such as multilayer feedforward neural network, least squares support vector machine, generalized regression neural network,

and adaptive neuro fuzzy inference system. In atmospheric modeling, the parameters to be estimated typically serve as output variables in machine learning models, while the associated modeling variables (e.g., spatial coordinates, temporal parameters) constitute the input variables for these machine learning models.

A new technology called geographic grid neural network (GGNN) integrates the advantages of both the GGM technology and the neural network technology (Zhu et al. 2021; Zhu et al. 2022). The GGNN technology, on one hand, characterizes geographic variations of the parameters to be predicted in the form of latitude-longitude grids, which is a modeling technique similar to GGMs. On the other hand, it models the influence of other parameters (such as altitude variations, annual variations, diurnal variations, etc.) on the target parameter at specific latitude-longitude locations using neural network techniques.

In GNSS meteorology, several atmospheric parameters exhibit multidimensional variations, including horizontal, vertical, annual, and diurnal variations (Krueger al. 2004; Wu et al. 2008; Böhm et al. 2015; Sun et al. 2019). Among many atmospheric parameters, the weighted mean temperature (T_m) is key for converting ZWD to precipitable water vapor. The successful application of the GGNN technology in T_m has been demonstrated. In this study, we apply the GGNN technology to

model another atmospheric parameter—namely, atmospheric temperature, and and introduce a new model (GGNNTemp).

2. Design of the GGNNTemp Model

Similar to empirical models of other tropospheric parameters, the GGNNTemp model is an empirical model of T for tropospheric range usage. Its input parameters are longitude, latitude, altitude, and month, and the output parameter is atmospheric temperature. GGNNTemp is developed by capturing the geographical, vertical, and seasonal variations of atmospheric temperature (Wu et al. 2008). Although atmospheric temperature variations exhibit marked diurnal variation characteristics (Wu et al. 2008), this factor was not considered in the modelling process of the GGNNTemp model.

The GGNNTemp model employs the modeling framework of the GGNN technology. A GGNN framework has a geographic grid system i.e. longitude-latitude grids (Fig. 1), and each geographic grid node hosts an independent neural network. The neural network corresponding to the geographic grid node with longitude L_j (j=1, 2, ..., m) and latitude B_i (i=1, 2, …, n) is defined as NN(L_i, B_j). In this way, there are $m \times n$ independent neural networks in Fig. 1.

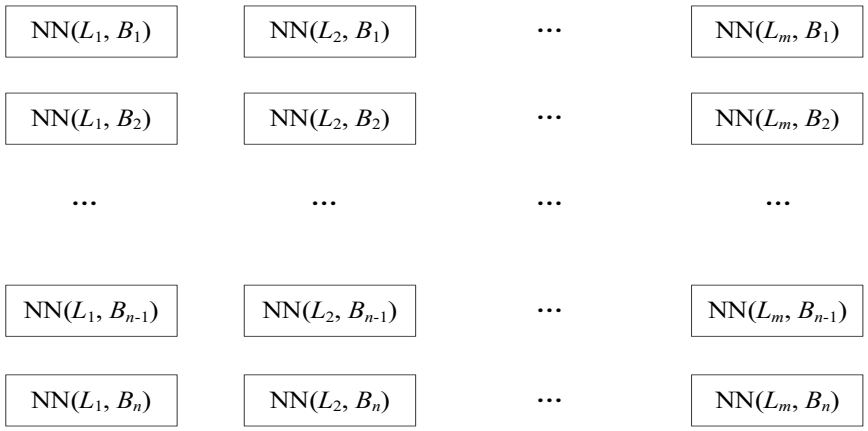


Fig. 1 The main architecture of a GGNN framework

Secondly, we should design each of the neural network NN(L_i, B_j). The neural network type used for modeling at each of the neural network NN(L_i, B_j) is a multi-layer feedforward neural network (Haykin, 1994). A `multi-layer feedforward neural network structure includes an input layer, hidden layer/layers, and an output layer. It belongs to supervised learning algorithms and is widely used in fields such as classification, regression, prediction, and nonlinear fitting. Due to its ability to effectively handle multi parameter nonlinear fitting problems, there have been numerous literature reports on its application in atmospheric modeling (Ding et al. 2025; Zhu et al. 2022; Yue et al. 2025). The design for each of NN(L_i, B_j) should fully consider the factors that affect T changes at this specific location and and we employ identical architectural configurations.

The design for each of NN(L_i, B_j) resembles the design of the traditional neural network models for atmospheric parameter modeling. However, the two parameters of latitude and longitude need not be

considered as input variables since the geographic grid technology already accounts for latitude and longitude variations. In this study, the 3``design for each of NN(L_i, B_j) mainly considers the temporal and vertical variations of *T*. Thus the design of each node in a single neural network is as follows. The input parameters are month (*M*) and height (*H*), and the output parameter is *T*. The output layer contains only one neuron and uses a linear transfer function (i.e., $f(x) = x$). The hidden layer of the GGNNTemp model is set to a single layer, containing 4 neurons, and the hyperbolic tangent function (i.e., $g(x) = \frac{2}{1+\exp(-2x)} - 1$) is used as the transfer function in these 4 neurons. In summary, the design structure of each neural network, i.e., NN(L_i, B_j), is shown in Fig. 2.

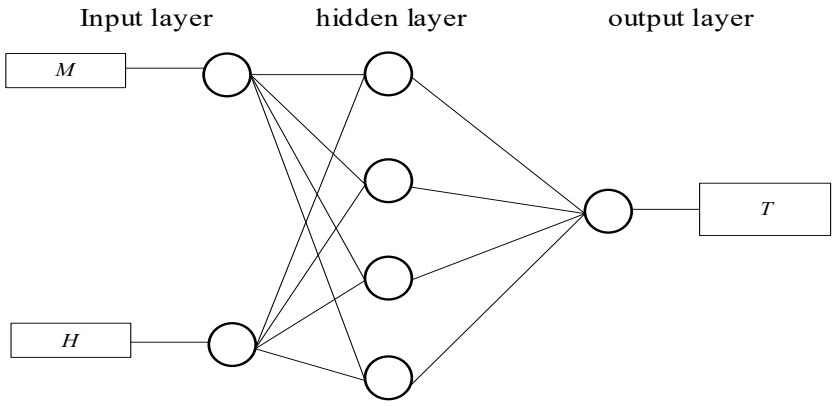


Fig. 2 Neural network architecture for a single geographic grid node of the The GGNNTemp model. It includes the input layer, the hidden layer, and the output layer.

3. Data Preparation

3.1 Study area

The study area of this research is situated between 90 °E to 140 °E longitude and 10 °S to 24 °N latitude. This zone encompasses Southeast Asia and the western Pacific region, and exhibits pronounced land-sea interactions. This zone has predominantly tropical conditions.

3.2 Training Data

For the traditional neural network, generally, it only requires a single set of training data. The GGNN framework is completely different, and it requires each grid point to have its own individual dataset for training the neural network NN(L_i, B_j). Thus, matching geographic grid data are required for modeling. This study selects ERA5 data for modeling GGNNTemp. ERA5 is a high-resolution global atmospheric reanalysis dataset developed by the European Centre for Medium Range Weather Forecasts (ECMWF), providing continuous meteorological and climate variable data from 1940 to the present. Replaced the original ERA Interim reanalysis product, ERA5 dataset integrates global observational data and numerical models through data assimilation techniques, and generates high-quality spatiotemporal continuous datasets using physical laws. In this study, ERA5 monthly averaged data on pressure levels from 1940 to present is used. The dataset features multi-scale spatial resolutions with 0.25° ×0.25° for reanalysis products and 0.5° ×0.5° for ensemble members. Vertically, it spans the

full atmospheric column from 1000 hPa to 1 hPa, discretized across 37 standardized pressure levels. Temporally, the records extend continuously from 1940 to present with monthly resolution, providing comprehensive coverage of atmospheric variability across synoptic to climate timescales. This configuration ensures consistent representation of both tropospheric and stratospheric processes while maintaining computational tractability for long-term climate studies.The ERA5 product selected in this article covers data from 2010 to 2020. The grid resolution of the selected modeling data is 1°. The vertical coverage is for site below the height of 12 km. Figure 3 shows the geographical distribution of training sites

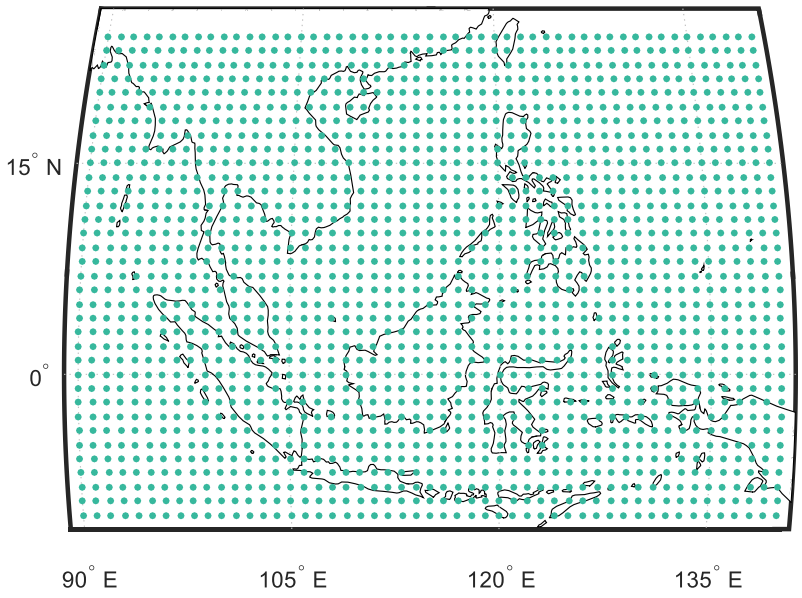


Fig. 3 Geographical Distribution of Training Sites

3.3 Validation Data

The test data is another data source, namely radiosonde data (Durre et al.

2006). The radiosonde is one of the most traditional and highly accurate methods for in-situ atmospheric observations. Radiosonde meteorological observation data includes key meteorological atmospheric parameters such as temperature, humidity, pressure, wind speed and wind direction, and is a benchmark data source for meteorological research and model validation. This article selected data from 44 radiosonde stations within the study area, covering the period from 2000 to 2015. The geographical distribution of the 44 sounding stations is shown in Fig. 4.

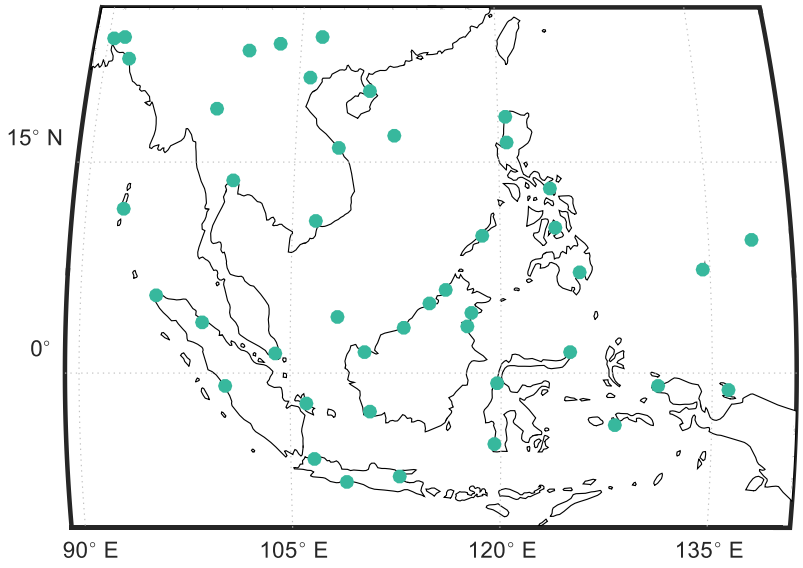


Fig. 4 Geographical Distribution of the 44 Test Stations

4. Accuracy Assessment

4.1 Model to be compared

The GPT2w model was selected as a comparative model. From the perspective of empirical model of *T*, the GPT2w model is significantly more

advanced than the standard atmospheric model (Minzner 1977). The T values from the GPT2w model are determined by

$$T = T_S + dT \tag{4}$$

where T_S is temperature at the Earth's surface (T_S) and dT is the vertical lapse rate of T. Both T_S and dT were stored in a grid format with a geographic grid resolution of 1°. T_S and dT were considered with the annual and semi annual variations and can be formulated respectively as

$$\begin{aligned} T_S &= A_1 + A_2 \cdot \cos(2\pi DOY / 365.25) \\ &+ A_3 \cdot \sin(2\pi DOY / 365.25) + A_4 \cdot \cos(4\pi DOY / 365.25) + A_5 \cdot \sin(4\pi DOY / 365.25) \end{aligned} \tag{5}$$

$$\begin{aligned} dT &= B_1 + B_2 \cdot \cos(2\pi DOY / 365.25) \\ &+ B_3 \cdot \sin(2\pi DOY / 365.25) + B_4 \cdot \cos(4\pi DOY / 365.25) + B_5 \cdot \sin(4\pi DOY / 365.25) \end{aligned} \tag{6}$$

Finally, T at the user's position is determined based on the calculated T values from nearby grid points using bilinear interpolation.

4.2 Development and use of the GGNNTemp model

In this case study, the GGNNTemp model uses a grid resolution of 1°×1° and thus consists of 1785 (51×35) neural networks. Each of the 1785 neural networks requires independent training. Once all the 1,785 neural networks have been trained, the GGNNTemp model becomes fully functional. Model users identify the four nearest neural networks based on latitude and longitude coordinates of their sites. Then they compute the 4 values of T for nearby points using altitude and month parameters. Finally, the T value for the user's site can be obtained through bilinear interpolation based on the

four grid points.

4.3 Accuracy of *T*

For all test data mentioned in Section 3.3, the GGNNTemp model exhibits a BIAS of 0.01 K and an RMSE of 1.60 K, while the GPT2w model demonstrates alarmingly low accuracy, showing a BIAS of -8.28 K and an RMSE of 12.37 K. This result indicates that the GGNNTemp model outperforms the GPT2w model with an improvement of 10.77 K in accuracy. Single-station statistical results in Fig.5 indicate: RMSE of the GGNNTemp model ranges between 1.04 K and 3.63 K; BIAS ranges between -1.21 K and 1.32 K. For most stations, the GPT2w model shows larger BIAS values (ranging from -17.31 K to 2.54 K), and this elevated BIAS directly contributes to its higher RMSE.

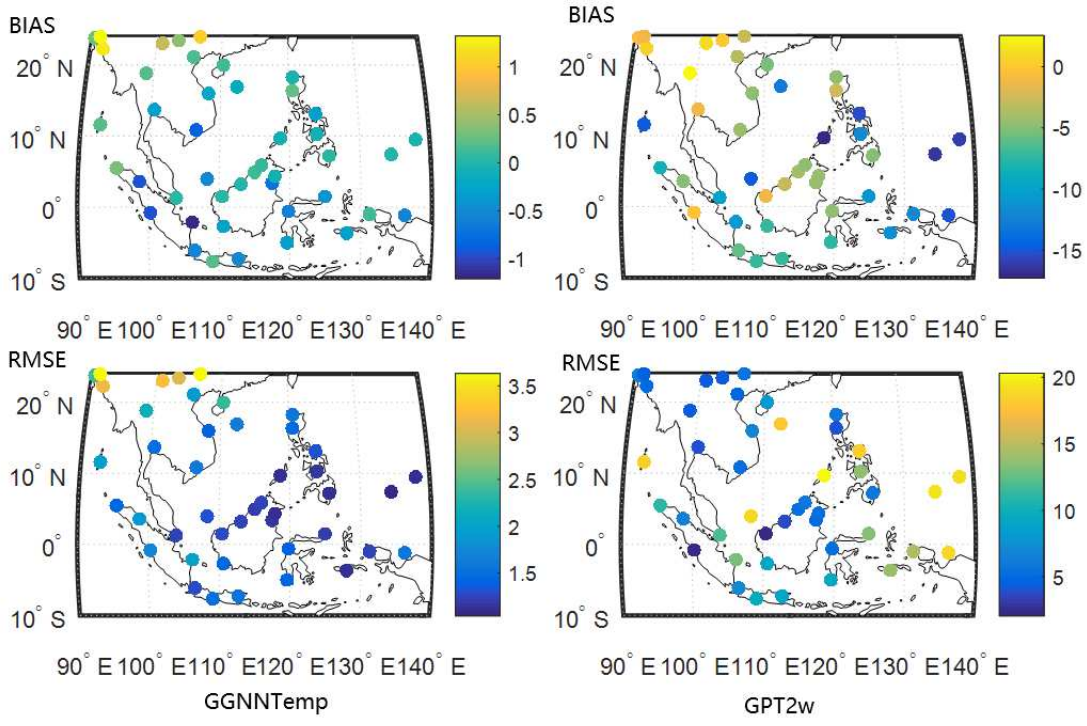


Fig. 5 Geographic Distribution of Station-Statistical Accuracy for Two Models

Atmospheric temperatures exhibit distinct geographical variations, particularly with significant latitudinal dependence. As shown in Fig. 6, this latitudinal influence is analyzed through comparative accuracy assessments of the two models across different latitude bands. The RMSE variation of the GPT2w model exhibits certain changes across different latitude bands, primarily correlated with its BIAS fluctuations. The GGNNTemp model demonstrates consistently low BIAS values across various latitude bands, with RMSE showing minor variations as latitude bands shift. The reason for the relatively small changes in RMSE with latitude is that the study area is primarily located in the tropical region. Analysis shows that the error of the GGNNTemp model significantly increases with latitude, while the GPT2w model exhibits significant fluctuations in inter latitude errors, mainly related to its system BIAS values. In contrast, the GGNNTemp model maintains smaller error fluctuations in different latitude bands, demonstrating better stability.

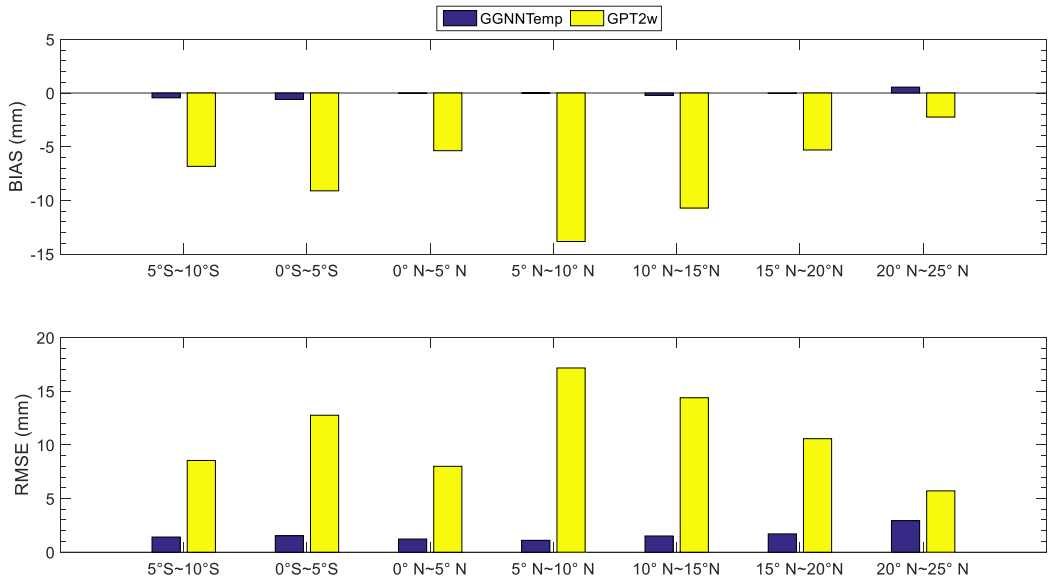


Fig. 6 Model accuracy for statistical range of different latitude bands within the study area

For some tropospheric parameters in GNSS meteorology such as precipitable water vapor, tropospheric delay, and T_m, they are mainly applied near the Earth's surface. However, accuracies of T at different heights of troposphere are of equal importance in the GNSS tropospheric tomography process. Figure 5 further illustrates the accuracy characteristics of the two models at different height ranges below the height of 10 km. Although the atmospheric temperature in the tropospheric region decreases with increasing altitude, RMSE of the GGNNTemp model fluctuates between 1.20 K and 2.00 K and does not exhibit significant vertical variation characteristics. The system deviation of the GGNNTemp model is less than 0.25 K in all height ranges. The accuracy of the GPT2w model is comparable to that of the GGNNTemp model in the altitude range below 1000 meters, but as the

altitude increases, its error significantly increases, mainly due to the influence of its BIAS. In Fig. 7, the highest BIAS value for the GPT2w model is -15.26 K, with a corresponding RMSE of 19.00 K. It should be pointed out that since the GPT2w model is mainly designed for near ground applications, it is not recommended to apply it to heights above 2000 meters. This fully demonstrates that *T* values from the GPT2w model are not suitable for GNSS tomography. In summary, GGNNTemp maintains higher accuracies than GPT2w across varying height ranges.

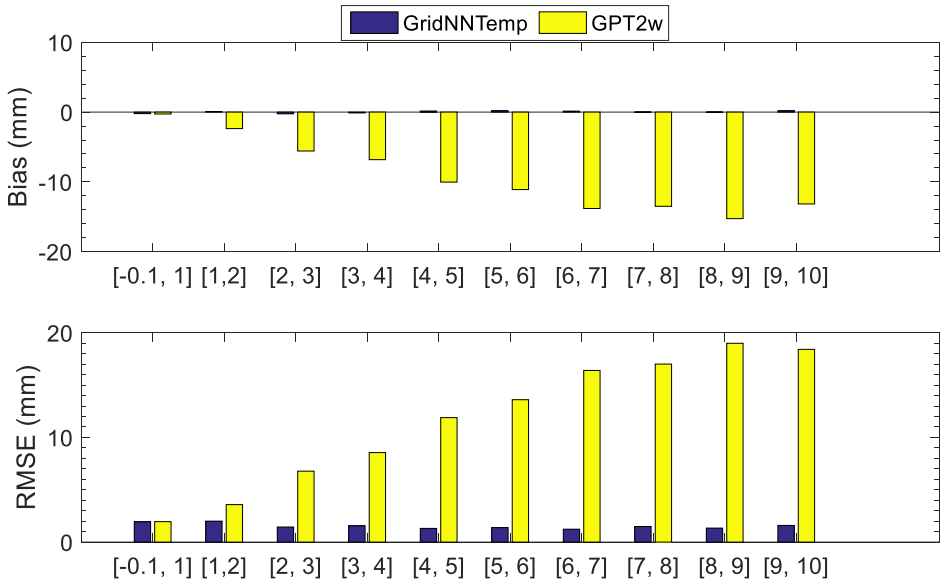


Fig. 7 Model Accuracy at Different Height Ranges

The seasonal variation of atmospheric temperature is another important manifestation of its spatiotemporal distribution pattern. Research has shown that the *T* model error exhibits significant monthly variations in both surface and tropospheric regions below 10 km. Figures 8 and 9 show the model

accuracy performance of 22 Southern Hemisphere stations and 23 Northern Hemisphere stations across different months, respectively. The results in Figs. 8 and 9 show that the GPT2w model exhibits significant high BIAS and RMSE values across different months. The GGNNTemp model demonstrates slight variations in RMSE across seasons, with overall lower RMSE values in summer and higher values in winter. Specifically, the GGNNTemp model outperforms the GPT2w model in all seasons in terms of accuracy, and its system deviation absolute value remains below 2.00 K.

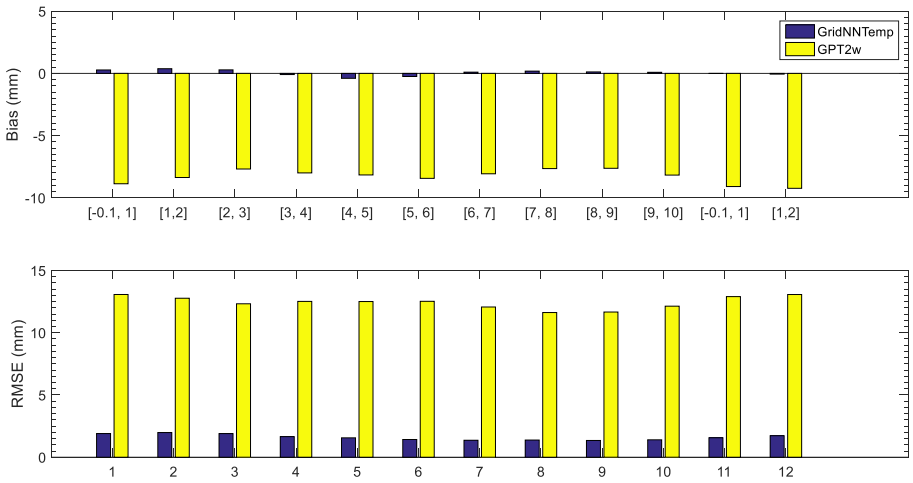


Fig. 8 Accuracy of Southern Hemisphere Station Data Across Different Months

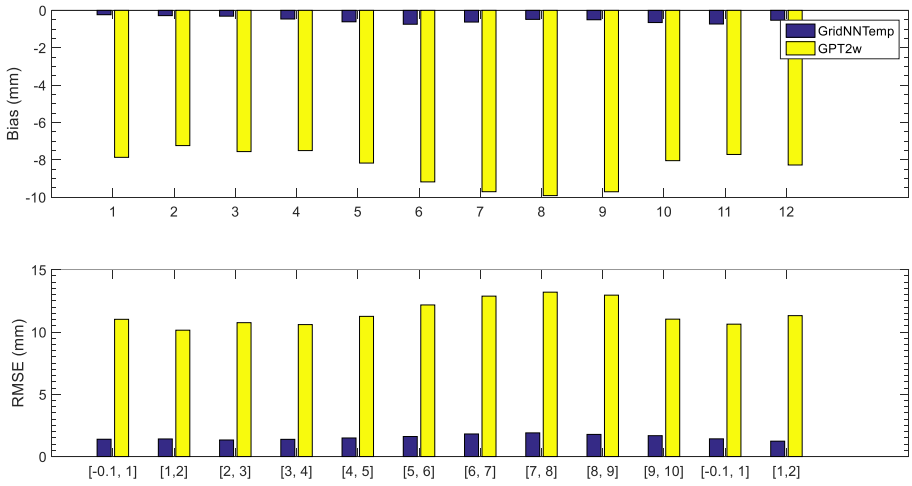


Fig. 9 Accuracy of Northern Hemisphere Station Data Across Different Months

4.4 Relative accuracy of ρ_v

T is an intermediate parameter used for converting N_w extracted from GNSS observations to ρ_v. Therefore, the error of the T model should be converted into the error of ρ_v. In this study, the relative error of ρ_v is used to measure the impact of T model error on ρ_v forecast values, because ρ_v error is not only affected by T error but also by N_w. The accuracy analysis of ρ_v relative error can eliminate the influence of N_w on ρ_v. According to the basic relationship between N_w on ρ_v described by equations (1) and (2), the relationship between T error and relative error of ρ_v can be derived:

$$RE = \frac{|\Delta\rho_v|}{\rho_v} = \frac{|\Delta T|}{T} \cdot \frac{1}{\left[k_2' \cdot (T+\Delta T)/k_3\right]+1} \tag{7}$$

The mean RE (MRE) for all test data of the 44 testing stations is 4.1‰. This indicates that the conversion error of due to T modeling can reach a

relatively ideal range. The MRE values for each of the 44 testing stations are shown in Fig. 10. This result indicate that the relative errors at 32 stations are less than 5‰. Among these, the results for 11 stations are less than 1.00 %, with the highest being 1.01% at one station.

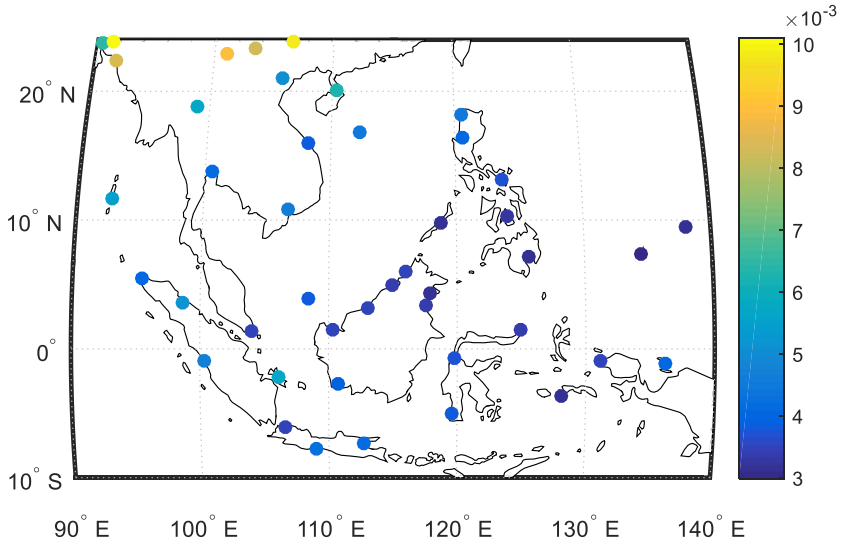


Fig. 10 ρ_v relative errors for 44 testing stations. The MRE values are displayed.

5. Conclusion

Atmospheric temperature is an important parameter in GNSS tropospheric tomography and serves as a critical variable for the conversion between N_w and ρ_v. The GGNNTemp model is an empirical model for atmospheric temperature prediction for tropospheric range usage. This work use a novel methodology (i.e. the GGNN technology) for geophysical parameter prediction, with significant theoretical and

practical implications. It uses the GGNN technology in the modeling process and reach with an accuracy of 1.60 K within the study region spanning 90°E to 140°E and 10°S to 24°N. For the GGNNTemp model, accuracy performance across different elevation ranges, latitudes, and seasons demonstrates its accuracy superiority. The variations in atmospheric temperature with respect to latitude and longitude are effectively captured through the deployment of the geographic grid method, which involves establishing individual neural network models at each grid point. Variations associated with month and altitude, however, are modeled by setting these two parameters as input variables to the neural network. The results of this study also demonstrate the successful application of grid neural network technology in modeling atmospheric parameters. Future work will extend the GGNN technology to other tropospheric parameters in GNSS meteorology. Beyond GNSS meteorology, the GGNNTemp model also finds applications in aerospace.

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Medium-Range Weather Forecasts (ECMWF) for sharing the ERA5 reanalysis dataset (accessible via: https://cds.climate.copernicus.eu/datasets), both of which were instrumental for the GGNNTemp model.

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