Article ID: 1006-8775(2018) 02-0243-10

0–10 KM TEMPERATURE AND HUMIDITY PROFILES RETRIEVAL FROM GROUND–BASED MICROWAVE RADIOMETER

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Abstract: Deviation exists between measured and simulated microwave radiometer sounding data. The bias results in low-accuracy atmospheric temperature and humidity profiles simulated by Back Propagation artificial neural network models. This paper evaluated a retrieving atmospheric temperature and humidity profiles method by adopting an input data adjustment-based Back Propagation artificial neural networks model. First, the sounding data acquired at a Nanjing meteorological site in June 2014 were inputted into the MonoRTM Radiative transfer model to simulate atmospheric downwelling radiance at the 22 spectral channels from 22.234GHz to 58.8GHz, and we performed a comparison and analysis of the real observed data; an adjustment model for the measured microwave radiometer sounding data was built. Second, we simulated the sounding data of the 22 channels using the sounding data acquired at the site from 2011 to 2013. Based on the simulated rightness temperature data and the sounding data, BP neural network-based models were trained for the retrieval of atmospheric temperature, water vapor density and relative humidity profiles. Finally, we applied the adjustment model to the microwave radiometer sounding data collected in July 2014, generating the corrected data. After that, we inputted the corrected data into the BP neural network regression model to predict the atmospheric temperature, vapor density and relative humidity profile at 58 high levels from 0 to 10 km. We evaluated our model's effect by comparing its output with the real measured data and the microwave radiometer's own second-level product. The experiments showed that the inversion model improves atmospheric temperature and humidity profile retrieval accuracy; the atmospheric temperature RMS error is between 1K and 2.0K; the water vapor density's RMS error is between 0.2 g/m^3 and 1.93g/m^3; and the relative humidity's RMS error is between 2.5% and 18.6%.

Key words: ground-based microwave radiometer; BP neural network; atmospheric profiles; regression accuracy

CLC number: P407.7 **Document code:** A

doi: 10.16555/j.1006-8775.2018.02.012

1 INTRODUCTION

Atmospheric temperature and humidity are critical variables for atmospheric and environmental studies. Acquirement of temperature and humidity profiles in continuous time is very important for understanding weather development and predicting weather in various scales (Liu et al. [1]; Han and West [2]; Li and Zeng [3]). Although possessing a high degree of representation and credibility, conventional sounding data are increasingly unable to suit the needs of modern meteorological development because of low temporal resolution (Liu et al. [4]). Because the ground-based microwave radiometer has many advantages, such as high temporal resolution, high sounding accuracy and simple operation, it has become an important instrument for atmospheric sounding and has been applied in many fields (Yao and Chen [5]; Wang et al. [6]). The ground-based microwave radiometer can obtain atmospheric temperature, relative humidity and liquid water profile at a range of 0–10 km, and these data are continuous in time. These data, combined with continuous wind profile data, have

Received 2017-08-16; **Revised** 2018-01-30; **Accepted** 2018-05-15

Foundation item: National Key Research and Development Program of China (2017YFC1501704, 2016YFA0600703); Projects of International Cooperation and Exchanges NSFC (NSFC-RCUK_STFC) (61661136005); Major State Basic Research Development Program of China (973 Program) (2013CB430101); Six Talent Peaks Project in Jiangsu Province (2015-JY-013); Project Funded by the Priority Academic Program Development of Jiangsu Higher Education Institutions (PAPD), Key Laboratory of Radiometric Calibration and Validation for Environmental Satellites, National Satellite Meteorological Center, China Meteorological Administration

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become an important reference for short-term weather forecasting (Yao and Chen [5]). Some experts have suggested that the microwave radiometer should play a significant role in future atmospheric detection systems, as microwave detection technology is approaching maturity (Liu et al. [7]). Therefore, the study of the inversion of atmospheric temperature and the humidity profile using data from microwave radiometers has scientific significance and potential application value (Huang et al. [8]).

The models for atmospheric temperature and humidity retrieval mainly include regression models, physical models and artificial neural network models (Wang et al.[6]; Martin et al.[9]). Methods using regression models are relatively simple but do not achieve high accuracy for complicated relations. Methods using physical models are computationally intensive and time consuming. However, the artificial neural network algorithm has obvious advantages. For example, it does not need the complex relationships of physical models, nor does it need to exert great effort to find a formula for retrieving variables; however, it can describe the non-linear relation between radiance and atmospheric variables and is very convenient to use. Therefore, artificial neural networks were usually used to develop operational systems (Wang et al. [6]). With the advancement of artificial neural network technology, it is also used in the field of microwave remote sensing, in particular atmospheric profile inversion (Huang et al.[8]).

The ground-based microwave radiometer used in this experiment, MP-3000A, was purchased from Radiometrics in the United States. It uses an artificial neural network model to achieve the atmospheric temperature and humidity profile. However, the coefficients of the network cannot be modified; thus, it is difficult for users to adjust the network to improve the inversion accuracy. In addition, our experiments showed the persistence of a certain deviation between the measured and simulated brightness temperature, although the microwave radiometer was calibrated (see Fig.1). However, the inversion program combined with the instrument is unable to deal with these deviations. Therefore, this paper used the monochromatic radiative transfer model (MonoRTM, Liu et al.[7]) to simulate the brightness temperature according to the figuration of the ground-based microwave radiometer based on the sounding data at a meteorological observation station in Nanjing and compared the simulated and measured radiance to build bias-correction models for the measured radiance. Then, a localized backpropagation (BP) neural network was established for atmospheric temperature and humidity profile inversion based on the simulated radiance and sounding data. Finally, bias-correction models were used to correct the measured radiance at 22 spectral bands, and the corrected radiances were inputted into the BP neural network to estimate the atmospheric temperature and humidity profile. The inversion results were compared with the level-2 products of the ground-based microwave radiometric, and their accuracy was evaluated.

2 DATA AND METHOD

2.1 *Data introduction*

Obtained at the meteorological observation station of Jiangsu Meteorological Bureau, the data included the radiosonde data of the temperature and humidity profiles and ground-based microwave radiometer data. The microwave radiometer data were provided by the projects listed at the foot of the first page of this paper. In order to obtain enough samples to develop the BP neural network, the radiosonde data of the temperature and humidity profiles from 2011 to 2013 were downloaded from the Wyoming State University database (http://weather.uwyo.edu/upperair/seasia.html). In the experiment program, the MP-3000 microwave radiometer was placed in the station to obtain atmospheric microwave downwelling in June and July, 2014 and obtained 65 samples under clear or cloudy conditions at 8:00 a.m. or 8:00 p.m. Beijing time.

The MP-3000 microwave radiometer provides a total of 22 channels, and the center frequencies are between 22.234 GHz and 58.800 GHz. Among them, the first 14 channels correspond to water-vapor absorption channels detecting water vapor in the atmosphere and the last eight channels are oxygen absorption channels detecting atmospheric temperature. The microwave radiometer outputs a set of data every minute, which includes four kinds of data as shown below.

(1) Level-0 as unprocessed raw data;

(2) Level-1 as brightness temperature data from level 0 data;

(3) Level-2 as the atmospheric temperature, relative humidity and liquid water profile products on 58 levels of altitude, derived from the built-in neural network algorithm of MP-3000 microwave radiometer.

(4) TIP calibration file.

In the experiment, level-1 and level-2 data were used. Level-1 brightness temperature data were used to retrieve the atmospheric temperature and moisture profile, and level-2 data were used to evaluate the accuracy of MP-3000 products. The radiosonde data were used to simulate downwelling radiance, and then the bias-correction models were built. In addition, the radiosonde data were used to evaluate the accuracy of MP-3000 level-2 products and the inversion results.

In order to make the height of the levels of radiosonde data match that of the MP-3000 level-2 products, linear interpolation was performed on the radiosonde data, and a set of radiosonde data at the 58 levels was acquired in the 0-10 km atmospheric layer. Water vapor density data cannot be directly obtained by radiosonde. In order to study water vapor density inversion, formulas (1) and (2) were used to calculate the water vapor density of each level (Sheng et al.[10]).

$$e=6.1078*U*\exp\left[17.708*\frac{(T-273.16)}{(T+29.3298)}\right] \quad (1)$$

$$\rho=\frac{e}{0.004615*T} \quad (2)$$

where the parameter e represents water vapor pressure, t is atmospheric temperature, u is relative humidity and ρ is vapor density.

2.2 *Simulation of the downwelling radiance using MonoRTM*

In order to build a BP neural network for atmospheric temperature and moisture retrieval, a great deal of microwave radiometer data are needed. In general, the numerical simulation method is used to obtain the data. In the experiments, MonoRTM was used to simulate atmospheric downwelling radiance at the 22 MP-3000 microwave spectral bands based on the radiosonde data acquired at the Nanjing station from 2011 to 2013. The atmospheric parameters and microwave radiometer configuration parameters can be inputted by revising the 10 parameter files of MonoRTM according to the real atmospheric condition and instrumental configuration. The atmospheric variables include atmospheric temperature, pressure, relative humidity, and liquid water content, which are from the radiosonde data. The microwave radiometer configuration parameters include the number of spectral bands and their channel frequencies (Liu et al. [7]). The MonoRTM model has the input parameter of the liquid water content. Therefore, it can not only be used to simulate atmospheric downwelling radiance under clear-sky conditions but also to simulate downwelling radiance under cloudy conditions. However, due to the constraints of the objective conditions, the conventional radiosonde cannot provide cloudy liquid water content. In this paper, the method used by Liu [7] and Zhang [8] was applied to estimate the cloud liquid water content. If the relative humidity of the whole atmosphere was lower than 85%, the weather condition was considered clear sky, and the liquid water concentration was set to 0 g/m^3. If there were atmospheric layers for which relative humidity was not less than 85% , it was considered cloudy. For cloudy-sky conditions, two methods were applied to calculate cloudy liquid water content: The cloud water content was set to 0.5g/m^3 if the relative humidity was greater than 95%, whereas the cloud water content was calculated by a certain linear equation if the relative humidity was between 85% and 95% (Liu et al.[7]; Huang et al.[8]).

2.3 *Building the bias-correction models for MP-3000 level-1 data*

Although MP-3000 had been calibrated before the observation experiments were conducted, the measured brightness temperature was not consistent with the simulated with a systematic error. Based on the 35 observation data for June 2014, a scatter diagram of the measured and simulated brightness temperature was plotted (Fig.1). Fig.1 shows that there is significant deviation between the measured and simulated brightness temperature at the spectral bands about the water vapor absorption channels (a-c) and oxygen absorption channels (d-i). The difference between the measured and simulated brightness temperatures of some samples even exceeds 10K.

In order to correct the deviation of the measured brightness temperature, static regression methods were used to develop the bias-correction models for 22 spectral bands (Table 1).

2.4 *Development of inversion model*

BP neural network algorithm is a relatively mature and widely used nonlinear inversion algorithm. It has been successfully used in atmospheric parameter inversion (Wang et al. [6]; Wang et al. [11]). In the experiment, three BP neural networks were established for the estimation of atmospheric temperature, relative humidity and water-vapor density. The input layer of networks had 25 neurons corresponding to the 22 band brightness temperature, atmospheric temperature, pressure and relative humidity of the near-surface layer. The output layer of each network contained 58 nodes corresponding to the 58 heights, which were consistent with the heights of the ground-based microwave radiometer level-2 product.

The performance of the neural network is affected by the number of nodes in the hidden layer. Insufficient hidden nodes will make the network lack sufficient information, thus reducing the accuracy of the whole network. However, an excessive number of hidden nodes requires too much training time, depressing the calculation efficiency of the network (Hecht-Nielsen[12]; Wang[13]). A number of research methods were proposed to calculate the number of hidden nodes (Cimini et al.[14]; Boukabara et al. [15]; Zhao[16]; Zhou[17]). In the experiment, these methods were compared. Considering the consumption time and inversion accuracy, 30 nodes were set in the hidden layer (Martin et al. [9]; Hecht-Nielsen [12]; Zhao [16]).

The performance of the neural networks is also related to their transfer function apart from the structure of the network. In the networks, the hidden layer employed the hyperbolic S transfer function named Tansig, whose input data might be an arbitrary value and output data was between -1 and 1. The output layer employed the linear transfer function named Purelin.

2.5 *Accuracy analysis*

In order to evaluate the inversion models, the mean error (ME) and root mean square error (RMSE) at the 58 heights were calculated with the radiosonde as the standard. In addition, the level-2 products of MP-3000 were also validated using the same method. ME and RMSE are defined as below.

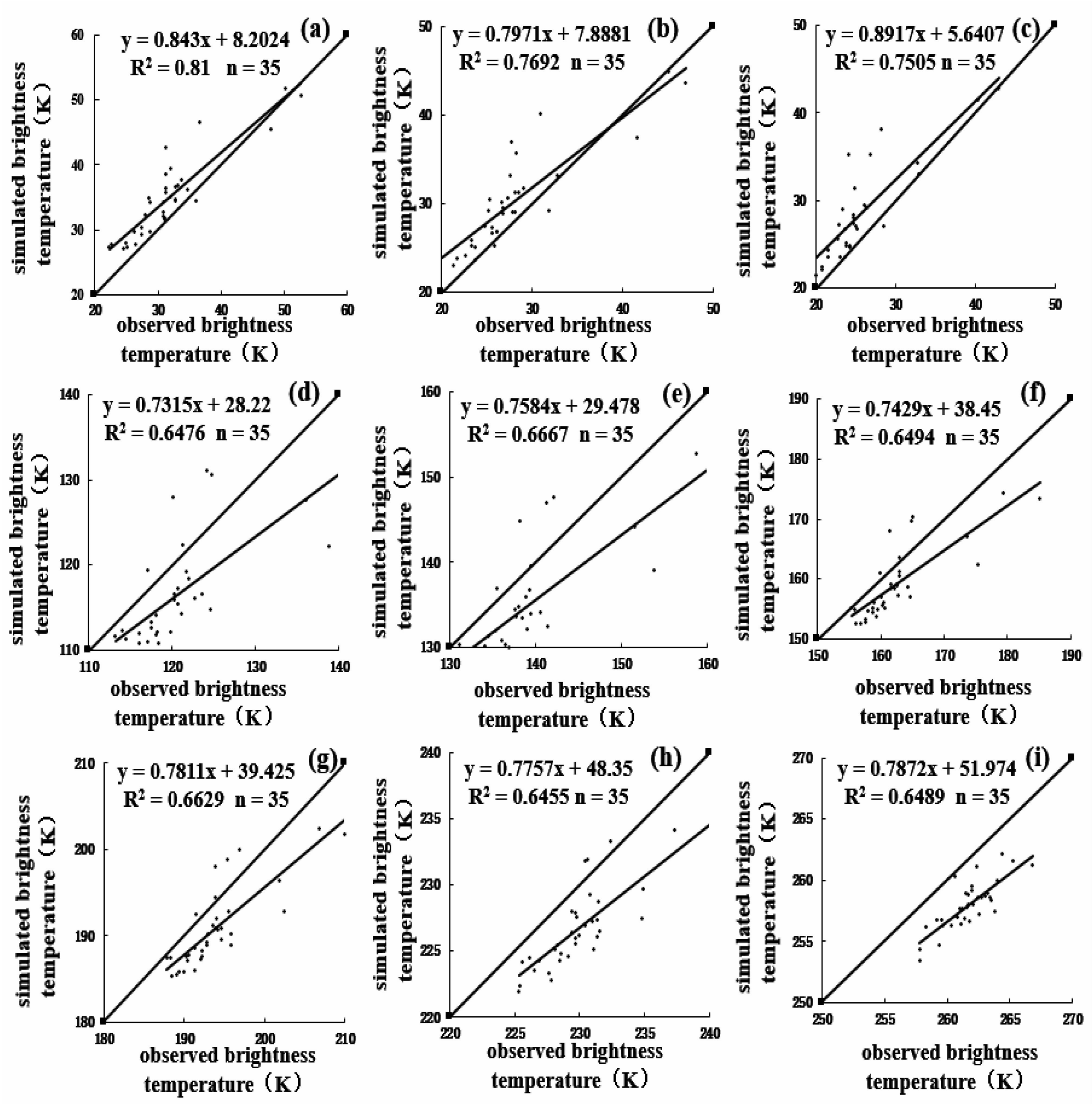

Figure 1. Scatter diagrams of the simulated and observed brightness temperatures in 26.234GHz through 53.848GHZ channels.

Table 1. The correction models for MP-3000 22 channels

f/GHz	Linear fitting equation	R^2	f/GHz	Linear fitting equation	R^2
22.234	Y=0.99575X+2.1078	0.9384	52.804	Y=0.7811X+39.425	0.6629
22.5	Y=0.9615X+1.9817	0.9357	53.336	Y=0.7757X+48.35	0.6455
23.034	Y=0.9515X+3.2138	0.9248	53.848	Y=0.7872X+51.974	0.6489
23.834	Y=0.964X+5.1675	0.8845	54.4	Y=0.8911X+27.975	0.8577
25	Y=0.894X+7.0311	0.8582	54.94	Y=0.866X+38.929	0.9288
26.234	Y=0.843X+8.2024	0.81	55.5	Y=0.8807X+33.555	0.8901
28	Y=0.7971X+7.8881	0.7692	56.02	Y=0.8329X+49.003	0.9215
30	Y=0.8917X+5.6407	0.7505	56.66	Y=0.8952X+30.796	0.9216
51.248	Y=0.7315X+28.22	0.6476	57.288	Y=0.9173X+24.405	0.9265
51.76	Y=0.7584X+29.478	0.6667	57.964	Y=0.9015X+28.978	0.9506
52.28	Y=0.7429X+38.45	0.6494	58.8	Y=0.9119X+26.061	0.9509

$$\mathrm{ME}=\frac{1}{n}\sum_{i=1}^{n}(u_i-v_i) \tag{3}$$

$$\mathrm{RMSE}=\sqrt{\frac{1}{n}\sum_{i=1}^{n}(u_i-v_i)^2} \tag{4}$$

where n is the number of total samples at a certain level, v_i is the radiosonde data, u_i is the inversion data or the MP-3000 level-2 products including atmospheric temperature, relative humidity or water vapor density (Liu et al.[7]).

The main process of estimation of atmospheric temperature and humidity profile based on the BP neural networks is as follows. First, the BP neural networks were trained using the simulated microwave radiometer data and radiosonde data obtained from 2011 to 2013 in order to fit the coefficients of the network and build the inversion models. Second, the 30 groups of observation from MP-3000 in July 2014 were bias-corrected and were then inputted to the trained neural networks to estimate atmospheric temperature, relative humidity and water vapor density. Finally, the inversion results and MP-3000 level-2 products were validated by the radiosonde data, and the accuracy was evaluated.

3 RESULTS AND ANALYSIS

3.1 *Atmospheric temperature inversion*

3.1.1 CASE STUDIES

In the experiments, two cloudy-sky cases were studied at 0000 UTC and 1200 UTC on 8th July. Fig.2 (a and b) shows the atmospheric temperature profiles from the inversion experiments, MP-3000 and radiosonde data. As shown in Fig.2, the variation trends in atmospheric temperature are similar, which increase as the height increases. However, the MP-3000 data underestimate atmospheric temperature, in particular above 3km. In addition, the temperature profiles from the inversion experiments are closer to the radiosonde profile. The estimated temperature profiles of the experiments more accurately reflect the actual vertical distribution of atmospheric temperature.

3.1.2 STATISTICAL ANALYSIS FOR THE MAE AND RSME ATMOSPHERIC TEMPERATURE

Figure 3 shows the mean absolute error (MAE) and root mean square error (RMSE) of the estimated atmospheric temperature and MP-3000 level-2 temperature products. In Fig.3, BPNN represents the retrieved temperature of the experiments, and RadiomeNN represents the temperature product of the microwave radiometer. As seen in Fig.3, the difference in MAE and RMSE of the MP-3000 level-2 temperature products at different heights is very apparent in the layer below 4 km. The MAE at surface, 1km and 3km is positive, while it is negative at the heights of 0.5km and 1.5km. The RMSE near the surface is approximately 1.5K; nevertheless, it is relatively high (about 4K) at a height of 1 km. Above 4km, the MAE and RMSE of the microwave radiometer temperature products increase rapidly, and their values reach 5.78K and 6.78K at 10km, respectively. Plainly, the error of MP-3000 is very high.

Figure 3 shows that the error of the inversion experiments is relatively small. Below a height of 1 km, the MAE of temperature is positive, less than 0.3K; above 3 km, the MAE of temperature is negative, less than 0.7K. The RMSE of retrieved temperature continues to increase from 1K to 2K as the height increase in the 10km atmospheric layer. Compared to the MP-3000 temperature products, the estimated temperature has higher accuracy. In addition, the brightness temperature without bias correction was also inputted into the BP neural network to retrieve the atmospheric temperature. Comparing the inversion results with bias-correction and without bias-correction, it is apparent that bias-correction significantly improves the accuracy of the estimated atmospheric temperature.

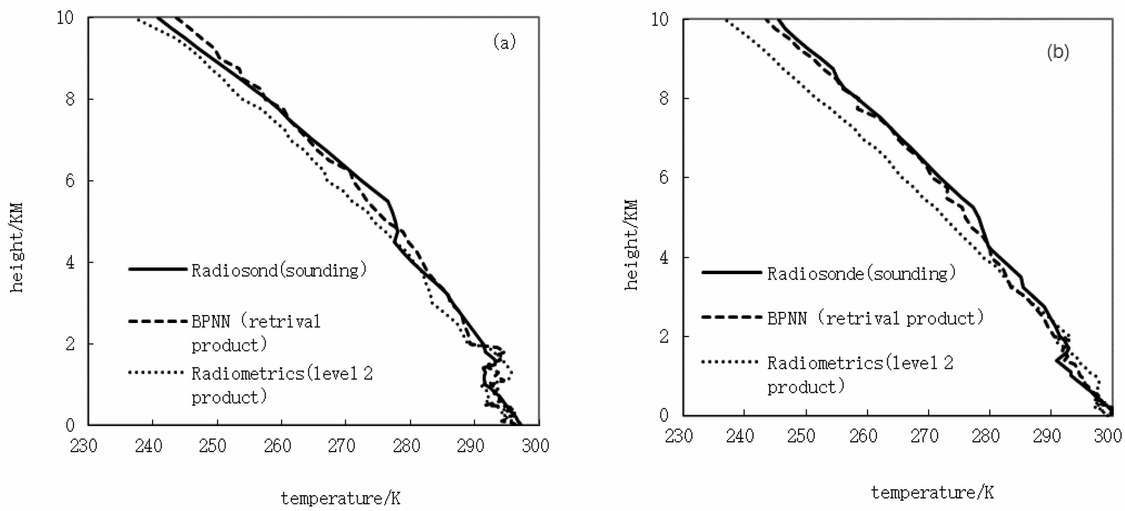

Figure 2. The retrieved temperature, MP-3000 level-2 temperature products and radiosonde data at 0000 UTC (a) and 1200 UTC (b) on 8th July, 2014.

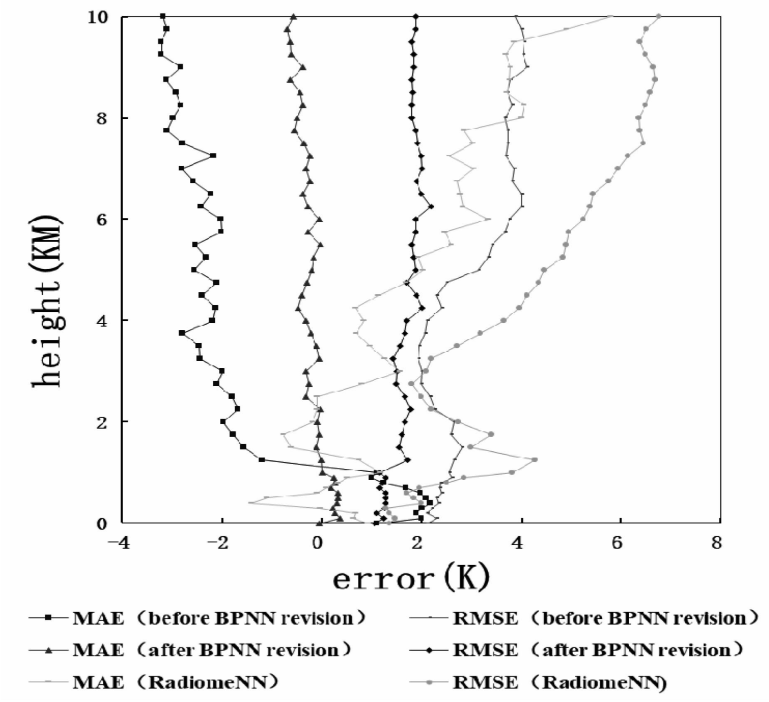

Figure 3. Mean error and root mean square error of retrieved atmospheric temperature and level-2 products of microwave radiometer at the 0–10km height.

3.2 *Atmospheric water vapor density*

3.2.1 CASE STUDY

Figure 4 (a) and (b) show the atmospheric water vapor density profiles from the inversion experiments, MP-3000 and radiosonde data at 00 UTC and 12 UTC on 8th July, respectively. As shown in Fig. 5, the water vapor density profiles are very close, which illustrates that the three kinds of data are similar, but the retrieved water vapor density profile is closer to the radiosonde data, especially at 0 to 1 km. The microwave radiometer products overestimate water vapor density; nevertheless, the inversion results of this paper can better represent the actual vertical distribution of water vapor density.

3.2.2 STATISTICAL ANALYSIS FOR THE MAE AND RSME OF WATER VAPOR DENSITY

Figure 5 shows the mean absolute error (MAE) and root mean square error (RMSE) of the estimated atmospheric water vapor content and MP-3000 level-2 products. As shown in Fig.5, the MAE (−3.7 g/m^3) and the RMSE (3.9 g/m^3) of the water vapor density product of MP-3000 are relatively high in the atmospheric layer

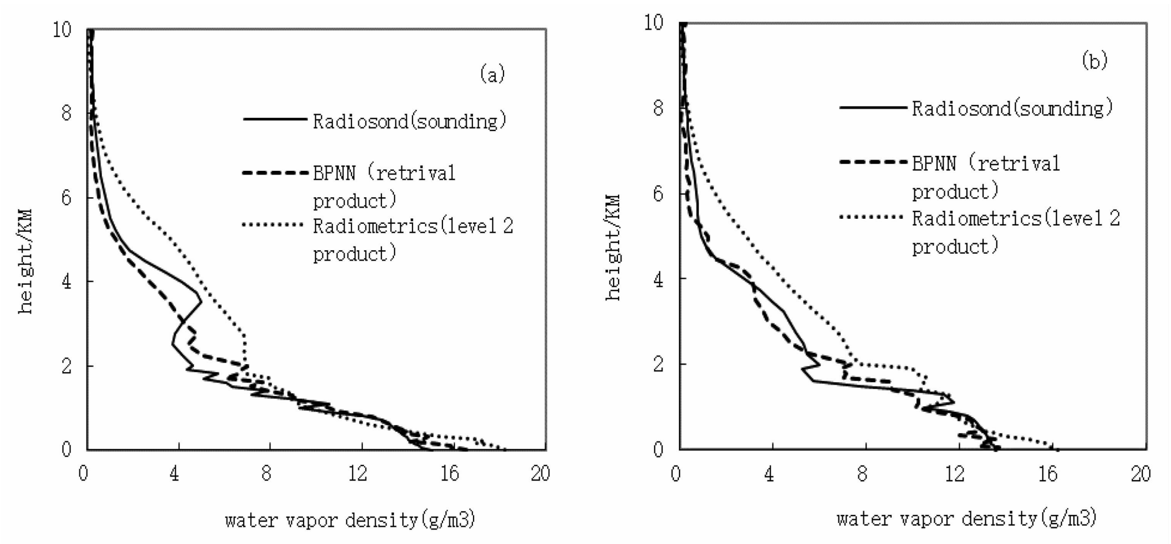

Figure 4. The retrieved atmospheric water vapor density, MP-3000 level-2 products and radiosonde at 0000 UTC (a) and 1200 UTC (b) of July 8.

below 0.3 km. In the layer of 0.5–2.25 km, the MAE (from –0.7 g/m^3 to 0.7 g/m^3) and RMSE (<2.2 g/m^3) are relatively small. The MAE and RMSE rapidly increase above a height of 2.3 km and reach the maximum of –4.89 g/m^3 and 6.8 g/m^3 at the 2.75 km height. Then, the MAE and RMSE gradually decrease, and positive deviation appears from the 6.75 km height.

As seen in Fig.5, the MAE and RMSE of the estimated water vapor density product are relatively small (from –0.24 g/m^3 to 0.23 g/m^3 and 0.2 g/m^3 to 1.93 g/m^3, respectively), and the maximal RMSE appears at a height of 1 km. Compared with the MP-3000 products, the accuracy of estimated water vapor density is greatly improved, in particular in the layers below 0.5 km and heights within the range 2.25–6.25km. In addition, the results show that the bias-correction significantly improves the accuracy of estimated water vapor content.

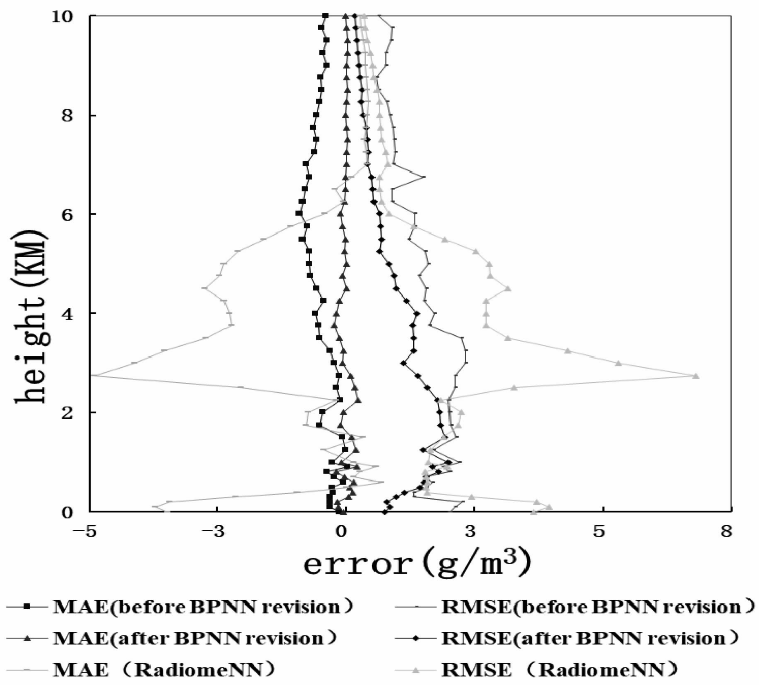

Figure 5. Mean error and root mean square error of retrieved atmospheric humidity and level-2 products of microwave radiometer at the 0–10km height.

3.3 *Relative humidity*

3.3.1 CASE STUDY

Figure 6 (a and b) shows the atmospheric relative humidity profiles from the inversion experiments, MP-3000 and radiosonde data at 0000 UTC and 1200 UTC on 8th July, respectively. As shown in Fig.6, the three types of data are similar. Compared with MP-3000 production, the estimated relative humidity profile is more consistent with the radiosonde. In particular in the layer at 0~1km, the microwave radiometer product underestimates the relative humidity; however, the estimated relative humidity more accurately illustrates the vertical distribution of relative humidity.

3.3.2 STATISTICAL ANALYSIS FOR MAE AND RSME

Figure 7 shows the mean absolute error (MAE) and root mean square error (RMSE) of the estimated atmospheric relative moisture and MP-3000 level-2 products. As shown in Fig.4, the MAE of MP-3000 product is positive in the layers below 2.5 km and above 6.8 km, and the MAE is highest (22.8%) at a height of 0.6 km. In the atmospheric layer between 2.75 and 6.75 km, the MAE of the MP-3000 product is negative, and the MAE is highest (–43%) at a height of 4.25 km. Obviously, the MP-3000 overestimated atmospheric relative moisture in the layers below 2.5 km and above 6.8 km but underestimated relative moisture in the layer between 2.75 and 6.75 km. The RMSE of atmospheric relative moisture is small (6.5%–17.8%) in the layer below 0.5 km, but it is higher (19.8%–50.5%) in the layer above it. Fig.7 shows that the MAE of relative humidity is between –3.7% and 3.8%, and the RMSE is between 2.5% and 18.6%. Compared with MP-3000 relative humidity production, the accuracy of the inversion data is higher. In addition, bias correction significantly improves the accuracy of relative humidity estimation.

3.4 *Analysis of the inversion error*

Although the developed inversion method acquired higher accuracy for the estimation of atmospheric temperature and humidity profiles compared with the MP-3000 products, there is still some deviation compared with the radiosonde. The possible causes of the error are as follows: (1) A linear empirical model was used to calculate cloudy liquid water content that

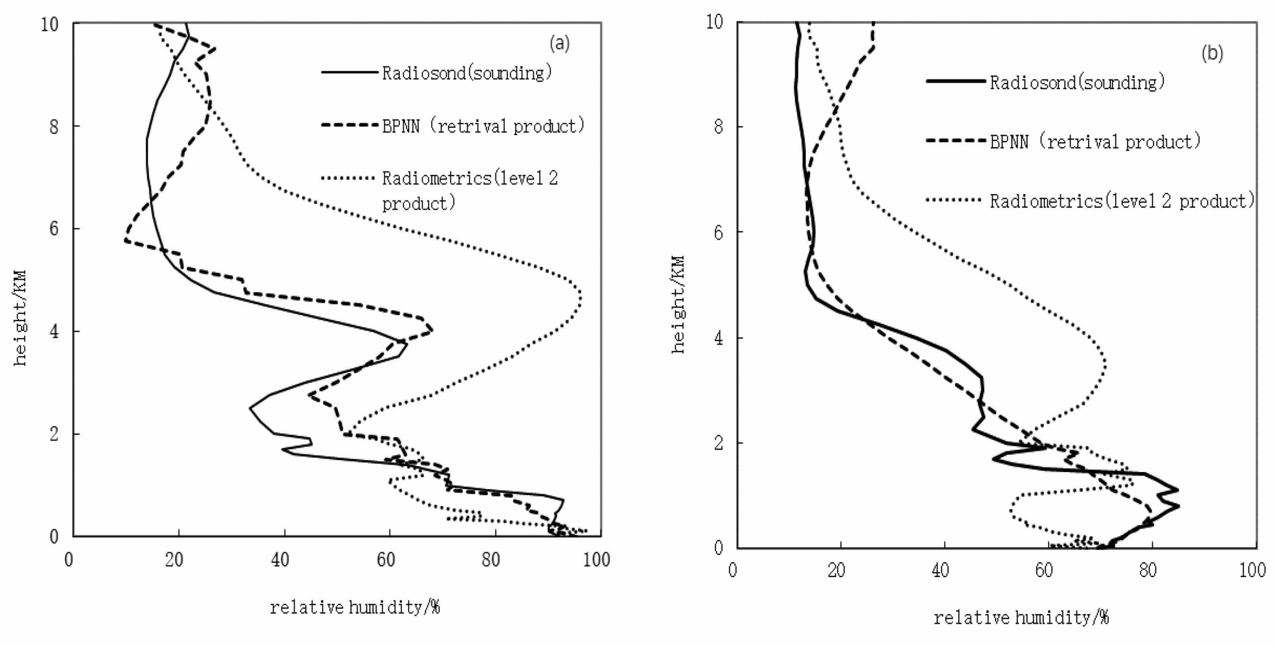

Figure 6. The retrieved atmospheric relative humidity, MP-3000 level-2 products and radiosonde at 0000 UTC (a) and 1200 UTC (b) of 8th July.

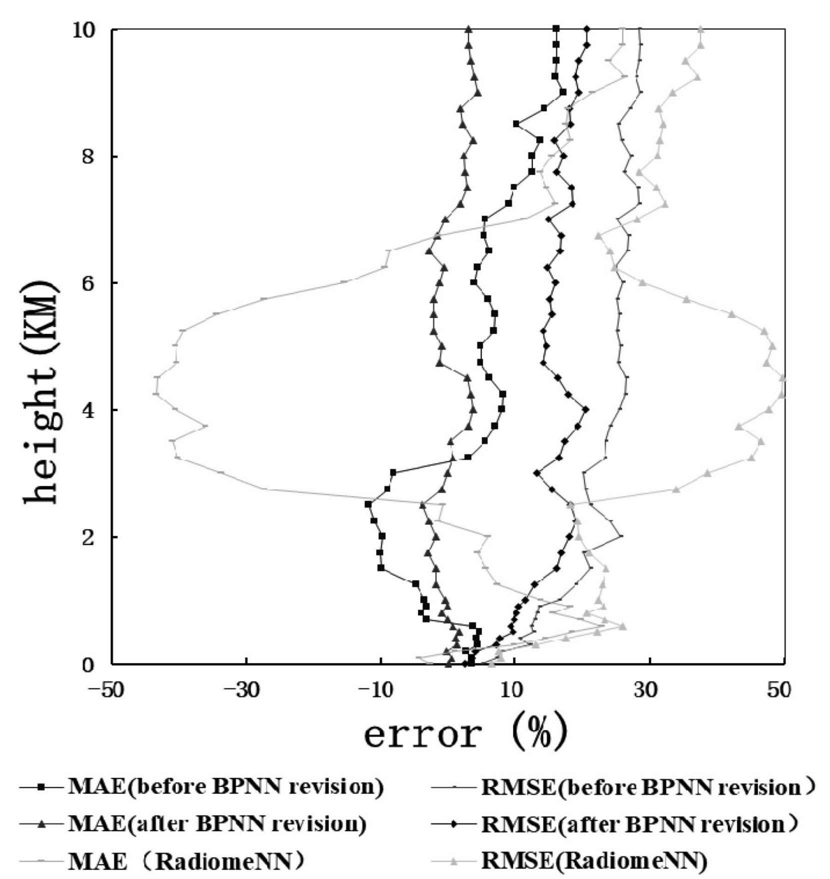

Figure 7. Mean error and root mean square error of retrieved atmospheric relative humidity and level-2 products of microwave radiometer at the 0–10km height.

will introduce error in brightness temperature simulation; (2) the BP neural network model's inversion accuracy is affected by the samples for training; thus, enough accurate and representative samples make the network more accurate. However, both the simulated microwave data and radiosonde data exhibit errors. They also bring the error to the inversion results; (3) radiosonde data error will pass on to the simulated data, affecting the accuracy of the inversion models. In addition, radiosonde data are the standard to calculate MAE and RMSE; thus, its error affects the calculation of inversion accuracy.

4 CONCLUSIONS

This paper focused on a method to retrieve atmospheric temperature, water vapor density and relative humidity from a ground-based microwave radiometer. Three inversion models were developed using the MonoRTM radiative transfer model and BP neural network. The models were used to estimate the atmospheric temperature and humidity profiles, and the accuracies were analyzed. Some conclusions were drawn as follows.

(1) In the troposphere, the estimated atmospheric temperature is very similar to the radiosonde data, and the MAE between the two data is not bigger than 0.4 K. However, the maximal MAE of the MP-3000 temperature products reaches 6 K. Comparing the estimated atmospheric temperature and MP-3000 temperature product, the developed BP neural network model significantly improves the accuracies of the atmospheric temperature estimation.

(2) The retrieved atmospheric water vapor density and relative humidity consist of radiosonde data, and the MAEs are from −0.24 to −0.23 g/m^3 and from −3.7% to −3.5%, respectively; the RMSEs are from 0.20 to 1.93 g/m3 and from 2.5% to 18.6%, respectively. However, the maximal RMSEs of MP-3000 products are 6.8 g/m3 and 49% , respectively. Comparing the estimated atmospheric humidity and MP-3000 products, the BP neural network models developed in the study significantly improve the accuracy of atmospheric humidity estimation. In addition, the bias-correction for the measured brightness temperature also improves the inversion accuracies.

(3) In the experiment, we just acquired two-month measurement data. In order to improve the accuracies of the atmospheric temperature and humidity estimation, we need more data to calibrate and validate the models in future work. In addition, building inversion models for clear sky and cloudy sky conditions is a method to improve the inversion accuracies.

Acknowledgement: The authors would like to appreciate all their colleagues who participated in field trips to help collect ground measurements. Thanks especially go to AER's Radiative Transfer Working Group for providing the MonoRTM model.

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Citation: BAO Yan-song, CAI Xi, QIAN Cheng, et al. 0-10 km temperature and humidity profiles retrieval from ground-based microwave radiometer [J]. J Trop Meteor, 2018, 24(2): 243-252.