Response to reviewer 2

We would like to thank the reviewer for the constructive comments concerning our manuscript. We have examined all the comments carefully, and the following are our responses for the questions or comments:

(1) In the Introduction, you wrote that "not all GNSS stations are equipped with meteorological sensors." then you said the Tm models independent of meteorological observations "had to be constructed". Really? I don't think it is the only solution while there are some other methods to solve such a problem. For example, we can interpolate the measurements from nearby surface meteorological sensors to the GNSS stations followed by using the Ts-Tm model, or we can also interpolate the reanalysis vertical profiles over the sites. Right? So you should write more to convince me of the significance of your study.

This is a good question. As is correctly said by the reviewer, there are different ways to obtain Ts values, such as the interpolation method using the actual meteorological measurements nearby or the reanalysis data in the area. However, the performance of different methods varies due to the inherent nature of the individual method. This includes for example, the interpolation error due to different terrain elevations between the meteorological sensor's location and the point of interest in addition the interpolation methods used. As for the Bevis-like model (Ts-Tm) method, its fundamental assumption is the availability of local long-term radiosonde observations which may not be readily accessible for some regions. One of the possible ways to solve the availability issue is to use reanalysis data to to develop Ts-Tm models. However, such a reanalysis-based Ts-Tm model may not be as accurate as that derived from local radiosonde profiles. In addition, the timely availability is another concern. Another drawback in using the reanalysis data is its latency issue. For some time-critical applications, near real-time (NRT) / real-time (RT) Tm is essential for NRT/RT GNSS-PWV determination. All these form the basis for this research, the development of an empirical model that is independent of actual on-the-fly meteorological observations.

To clarify these points, relevant revisions have been made.

(2) *What is the application area of your Tm model? For time-critical applications? Your Tm model is based on the ERA5 monthly mean reanalysis data. Theoretically, such monthly mean reanalysis data has no ability to capture the short-term variations of Tm. Furthermore, your Tm model is independent of real-time meteorological observations. Therefore, I am not sure about the ability of your Tm model for near-real-time applications. Maybe the error statistics of your Tm model is good. But these statistics indexes were also the "mean precision index" over a specific period. For near-real-time application, we should also pay attention to the short-term performances of the Tm estimations, especially under some extreme weather conditions. I would like to see your discussions about these issues in detail. Giving some time series of Tm over some points may be helpful.*

Again, the reviewer has raised a very good question about the performance of our method since the monthly-mean data were used. In our research, ERA5 hourly reanalysis data at UTC 12:00 and globally distributed radiosonde profiles in 2018 were utilized to evaluate the performance of our new model. Both 24-hour and 12-hour variations of Tm have been used in the reference data for the evaluation of our new model in the form of "mean precision index". The performance of our model under extreme weather conditions has also been assessed (summer storm period in August and September 2018). The Tm values integrated from the radiosonde profiles at KingsPark radiosonde station (No.45005, Hong Kong) from August to September in 2018 were taken as the reference data. As is shown in Fig.1, the Tm values at the station predicted by our new model, as well as a Tm-Ts model (Tm=0.6195Ts+103.3452) developed using Tm and Ts series at KingsPark station (He et al., 2019) were compared against corresponding radiosonde measurements during the "summer storm" periods. The daily total rainfall data (published by Hong Kong Observatory, https://www.hko.gov.hk) during the two months are also shown in the figure. Heavy rainfall occurred frequently in Hong Kong during the two months, and a super typhoon, named "Mangkhut" landed near HongKong and caused torrential rain on 16th September. As is shown in the figure, our model shows clear outperformance during the two months. More experiments showed that the coefficients of a Ts-Tm models vary significantly with time (i.e. 0.6195 vs 0.58 for the linear part, 103.3452 vs 115.71 for the constant part, respectively), which means that a Tm-Ts model may have large errors during some periods.

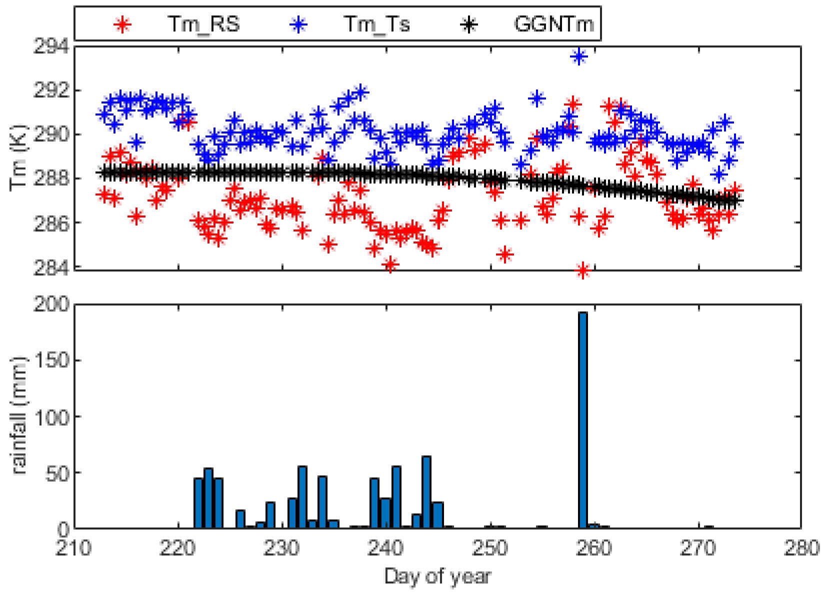

Figure 1. Tm derived from radiosonde profiles, Ts-Tm model, GGNTm from August to September in 2018 at KingsPark station and the daily total rainfall at Hong Kong International Airport

(3) Or you can use your Tm model for climate research. Unfortunately, I didn't see any discussions about this. In fact, there are still some questions about climate

application. What is the advantage of your model compared with other solutions, e.g. interpolation of reanalysis data? Are there enough GNSS observations located in "the ocean area, a high mountainous area, or even a flight vehicle" for demonstrating the advantages of your model in climate or weather issues?

We agree that the reanalysis data are important and reliable products for climate research. Different from the reanalysis data, GNSS receivers are regarded as cost-effective equipment for meteorological research, the main advantage of the GNSS-based method is its real-time, stable, high-temporal-resolution and relative long-term capabilities. In fact, some preliminary research in relation to the long-term feature of the GNSS ZTD/PWV series and the relationship between GNSS-PWV and weather or climate issues have already been carried out (Bianchi et al., 2016; Bonafoni and Biondi, 2016; Calori et al., 2016; Chen et al., 2018; Choy et al., 2013; He et al., 2019; Junbo Shi et al., 2015, 2015, 2015; Rohm et al., 2014; Wang et al., 2018; Zhang et al., 2015).

As for the potential applicability of this research in ocean, mountain and flight-based etc. areas, We have noticed that some studies have extended the GNSS-PWV sensing to a shipborne GNSS receiver, or GNSS receiver that onboard other moving vehicles (Fan et al., 2016; Wang et al., 2019; Webb et al., 2016). Thus, we concentrated on developing a high-accuracy unbiased empirical model for predicting Tm values in any possible places, which is meaningful for GNSS meteorology.

(4) *I agree that Tm is "a crucial variable for the determination of the conversion factor II". However, the significance of II in determining GNSS PWV depends. Equation (13) in your study is not quite accurate. It may greatly exaggerate the impact of Tm errors on PWV calculations in many cases. Detailed discussions about the uncertainty budgets of GNSS PWV can be found in https://doi.org/10.5194/amt-9-79-2016 or https://doi.org/10.5194/amt-12-1233-2019. We can see that under some situations the barometric pressure observations may introduce much larger errors into the GNSS PWV estimations. So your serious discussions about the improvement in GNSS PWV calculations brought by your Tm model will be grateful.*

This is a good question. The revised paper has incorporated more discussions (see below) about the improvement of the GNSS -PWV brought by our new model.

We agree that the atmospheric pressure may introduce larger errors if the atmospheric pressure was observed with poor accuracy. However, we think that the errors in Tm should not be neglected in such conditions, as a large error in Tm could amplify the impact of the atmospheric pressure and hence may lead to more errors in the predicted GNSS-PWV. As for the improvement of the GNSS-PWV brought by GGNTm, a new experiment was conducted to study the impact of the errors in Tm on the GNSS-PWV using the ERA5 hourly reanalysis data that were utilized in Section 3.1. The ZWDs at each of the pressure levels over the globally distributed grid points (2664 grid points in total) were calculated through integration:

$$ZWD = 10^{-6}\int_{H}^{\infty}(k_2'\frac{e}{T} + k_3\frac{e}{T^2})\,dh \quad (1)$$

where H is the height of the reference pressure level. Then the reference PWVs can be obtained using the ZWDs and the corresponding conversion factors resulting from the reference Tm values:

$$PWV = ZWD \cdot \Pi(T_m) \quad (2)$$

Similarly, the PWVs resulting from different empirical Tm models can be obtained. The statistical results of the RMSEs of the PWVs resulting from different model-predicted Tm values by comparing the PWVs resulting from the reference Tm values (as references) are shown in Figure 2. As we can see, the performance of both GGNTm and GTrop are better than GWMT_D. The mean RMSE of the predicted PWVs resulting from GTrop and GGNTm over 2664 grid points were almost the same. But the maximum RMSEs of the PWVs resulting from GGNTm were better than GTrop from 1000 hPa to 775 hPa. This is because the nonlinear variation of Tm in the vertical direction was properly modelled in some regions. We can also find that there are not significant differences between the RMSEs of the predicted PWVs resulting from GGNTm and GTrop due to fewer water vapor at the pressure levels with high altitudes, although the accuracy of the model-predicted Tm values resulting from GGNTm was better than GTrop. However, due to the fact that the water vapor content varies with latitude, terrain, season and weather, the improvement in the model-predicted Tm values at pressure levels with high altitudes is still meaningful.

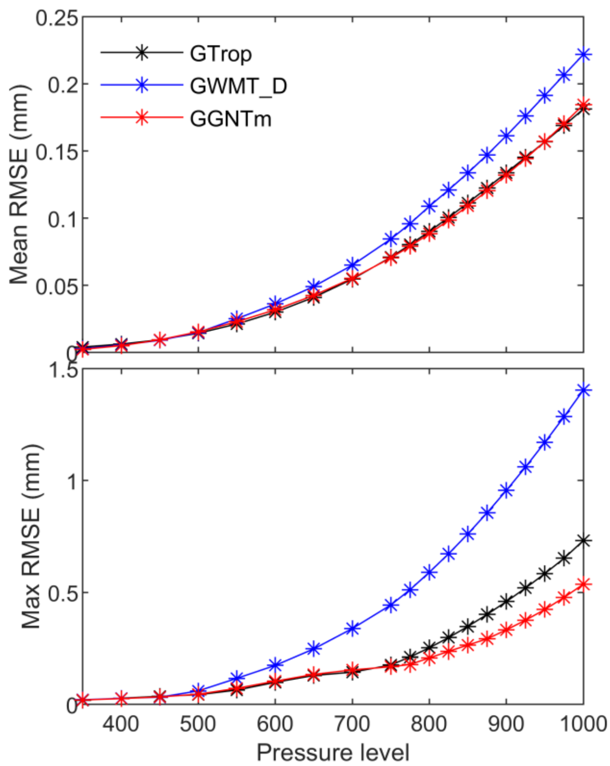

Figure 2. Mean RMSE and maximum RMSE of PWV values at each of the pressure levels at UTC 12:00 at all global grid points in 2018 resulting from each of the three models selected.

We hope the above explanations have clarified all the questions raised by the reviewer (#2). Again, we are very grateful for the constructive comments and suggestions made.

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