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A new weighted mean temperature model in China

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Abstract

The Global Positioning System (GPS) has been applied in meteorology to monitor the change of Precipitable Water Vapor (PWV) in atmosphere, transformed from Zenith Wet Delay (ZWD). A key factor in converting the ZWD into the PWV is the weighted mean temperature (T_m), which has a direct impact on the accuracy of the transformation. A number of Bevis-type models, like $T_m - T_s$ and $T_m - T_s, P_s$ type models, have been developed by statistics approaches, and are not able to clearly depict the relationship between T_m and the surface temperature, T_s. A new model for T_m, called weighted mean temperature norm model (abbreviated as norm model), is derived as a function of T_s, the lapse rate of temperature, δ, the tropopause height, h_{trop}, and the radiosonde station height, h_s. It is found that T_m is better related to T_s through an intermediate temperature. The small effects of lapse rate can be ignored and the tropopause height be obtained from an empirical model. Then the norm model is reduced to a simplified form, which causes fewer loss of accuracy and needs two inputs, T_s and h_s. In site-specific fittings, the norm model performs much better, with RMS values reduced averagely by 0.45 K and the Mean of Absolute Differences (MAD) values by 0.2 K. The norm model is also found more appropriate than the linear models to fit T_m in a large area, not only with the RMS value reduced from 4.3 K to 3.80 K, correlation coefficient R^2 increased from 0.84 to 0.88, and MAD decreased from 3.24 K to 2.90 K, but also with the distribution of simplified model values to be more reasonable. The RMS and MAD values of the differences between reference and computed PWVs are reduced by on average 16.3% and 14.27%, respectively, when using the new norm models instead of the linear model.

Keywords: Tropospheric zenith delay; Precipitable water vapor; Weighted mean temperature; Norm model

1. Introduction

Water vapor is one of the most active gases on the Earth surface, and is unevenly distributed in time and space (Yao et al., 2012). It affects the long-term and short-term changes in weather and climate. It has been a main research focus for meteorologists to monitor the change of water vapor. In the ground-based GPS meteorology, the GPS signal delay due to the atmospheric refraction is used to study water vapor contents. The delay in the zenith direction is called zenith total delay, and the Zenith Wet Delay (ZWD) can be separated from the zenith total delay by removing the zenith hydrostatic delay. Bevis et al. (1992) discussed the principle of applying GPS technology to detect water vapor contents, derived from the relationship between the ZWD and the precipitable water vapor (PWV), and obtained a linear regression model relating the weighted mean temperature to the surface temperature using 8718 radiosonde data distributed in the middle latitude region of the USA. That makes the transformation of ZWD to PWV possible, and the GPS technology since then has become an important technology to monitor the change of water vapor contents.

GPS can obtain high spatial and temporal resolution of the precipitation, and has a wide range of applications. The variation characteristics of precipitable water vapor can be used as an indicator to detect the fog (Lee et al., 2010), to

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correct the InSAR data affected by the water vapor (Lindenbergh et al., 2009), and to estimate the arrival time of plum rain in China (Cao et al., 2007). Therefore, it has an important significance for numerical weather prediction and climate related research (Heise et al., 2015).

When the wet refractivity on a profile is available, the ZWD can be obtained from the following equation (Singh et al., 2014)

$$ZWD \approx 10^{-6}\sum_{i=1}^{n}\frac{N_w^i + N_w^{i+1}}{2}\Delta H_{i+1,i} \tag{1}$$

where N_w is the wet refractivity, i is a point on the profile, $H_{i+1,i}$ is the geopotential height difference between points $i+1$ and i, and n is the total number of points available along the profile. The wet refractivity N_w is given by Thayer (1974)

$$N_w = \left[k_2'\frac{e}{T} + k_3\frac{e}{T^2}\right]Z_w^{-1} \tag{2}$$

where e is the partial pressure of the water vapor in mbar, k_2' and k_3 are the atmospheric refractivity constants (Davis et al., 1985; Bevis et al., 1994), $k_2' = 16.5 \pm 10$ K/mbar, $k_3 = 377.600 \pm 3000$ K^2/mbar, and Z_w^{-1} is

$$Z_w^{-1} = 1 + 1650\left(\frac{e}{T^3}\right)[1 - 0.01317T_c + 1.75\times10^{-4}T_c^2 + 1.44T_c^3] \tag{3}$$

where T_c and T are the dew point temperatures in Celsius and Kelvin, respectively.

When the ZWD is available, the PWV can be computed by

$$PWV = \Pi \times ZWD \tag{4}$$

where $\prod$ can be expressed by equation

$$\Pi = \frac{10^6}{\rho_w R_v[k_3/T_m + k_2']} \tag{5}$$

where ρ_w is the density of water, R_v is the specific gas constant.

Therefore, the ZWD can be estimated from radiosonde data using Eqs. (1)–(3). The estimated PWV from radiosonde data using Eq. (4) will serve as reference in analyzing the performance of estimating the PWV using different T_m models.

The weighted mean temperature, T_m, is given by Bevis et al. (1994)

$$T_m = \frac{\int e/Tdh}{\int e/T^2dh} \tag{6}$$

where the integration is made from the station to the tropopause, their heights being h_s and h_{trop}, respectively.

Achieving accuracy of 1% and 2%, respectively, in PWV would require errors in T_m less than 2.74 K and 5.48 K on average, respectively (Wang et al., 2005). This means the accuracy of T_m has to be improved. For an area without radiosonde data, it is impossible to calculate T_m from Eq. (6). So many regional or global linear models have been developed, such as linear models between T_m and T_s (Bevis et al., 1992; Mendes et al., 2000; Solbrig, 2000), and T_m and (T_s, e) (Singh et al., 2014). In addition, a non-meteorological parameter model for computing T_m was suggested by Yao et al. (2012), only requiring the input parameters of time and 3D coordinates of the observing station. All models mentioned above have been developed by using mathematical fitting techniques, but they lack theoretical basis, and thus it is subjective in determining which parameters are included in the fitting.

In the following, Eq. (6) is re-formulated into a new function form by using the functional inner product and functional norm. The resulting equation is called the weighted mean temperature norm equation. The norm equation gives theoretical descriptions of how the influencing parameters affect T_m. In site-specific situations, the effects of temperature lapse rate, δ, and $(h_{trop} + h_s)$, on the fitting performance are assessed to propose a simplified model. The norm model and its simplified model are then determined using the radiosonde data of 84 stations in China between 2008 and 2010, and compared with linear models of T_m. Finally, four radiosonde stations at different latitudes are chosen to study the performance of the simplified model in retrieving the PWV. In the performance evaluation, the ZWD, T_m and PWV, computed respectively from Eq. (1), (6) and (4), are used as reference.

2. Derivation of the weighted mean temperature norm model

By using the functional norm, Eq. (6) can be expressed as (Yao et al., 2015)

$$T_m = \frac{\|T\|\cdot\varphi}{\sqrt{h_{trop} - h_s}} \tag{7}$$

where T is the norm of the temperature along the profile above the observing station. The derivation process from Eq. (6) to Eq. (7) is given in Appendix A. The models deduced from Eq. (7) are collectively called the weighted mean temperature norm models, norm models for short.

The temperature at a height h over an observing station can be expressed by $T = T_s + \delta(h - h_s)$, assuming that the temperature decreases linearly with the height. And the expression of $T = T_s + \delta(h - h_s)$ can be simplified as follow

$$T = T_k + \delta h \tag{8}$$

where $T_k = T_s - \delta h_s$, the expression of T is then obtained as

$$\|T\| = \sqrt{\int_{h_s}^{h_{trop}}(T_s + \delta(h - h_s))^2dh} = \sqrt{\int_{h_s}^{h_{trop}}(T_k + \delta h)^2dh} = \sqrt{\frac{1}{3\delta}(T_k + \delta h)^3\Big|_{h_s}^{h_{trop}}}$$