Mean atmospheric temperature model estimation for GNSS meteorology using AIRS and AMSU data

Rata Suwantong¹, Panu Srestasathiern¹, Chalermchon Satirapod², Shi Chuang³ and Chaiyaporn Kitpracha²

¹Geo-informatics and Space Technology Development Agency (GISTDA), Thailand
²Department of Survey Engineering, Faculty of Engineering, Chulalongkorn University, Thailand
³GNSS Research and Engineering Center, Wuhan University, China

Abstract

In this paper, the problem of modeling the relationship between the mean atmospheric and air surface temperatures is addressed. Particularly, the major goal is to estimate the model parameters at a regional scale in Thailand. To formulate the relationship between the mean atmospheric and air surface temperatures, a triply modulated cosine function was adopted to model the surface temperature as a periodic function. The surface temperature was then converted to mean atmospheric temperature using a linear function. The parameters of the model were estimated using an extended Kalman filter. Traditionally, radiosonde data is used. In this paper, satellite data from an atmospheric infrared sounder, and advanced microwave sounding unit sensors was used because it is open source data and has global coverage with high temporal resolution. The performance of the proposed model was tested against that of a global model via an accuracy assessment of the computed GNSS-derived PWV.

Keywords: Precipitable Water Vapour (PWV), Global Navigation Satellite System (GNSS), Mean atmospheric temperature, Atmospheric Infrared Sounder (AIRS), Advanced Microwave Sounding Unit (AMSU)

1. Introduction

Physically, Precipitable Water Vapour (PWV) is referred to the amount of liquid water from water vapor condensation. Particularly, it is measured as the height of condensed water per unit area in vertical direction or an atmospheric column. The amount of PWV depends on the location on earth. For example, the amount of PWV at the equator is greater than that of PWV near the poles [1].

Since it is a significant factor for moisture and latent heat transportation [2], it is therefore a crucial information for climate studies, or disaster monitoring. For example, the monitoring of PWV was applied for flash flood prediction [3], and extreme rainfall events [2, 4]. Furthermore, the PWV is a crucial information for generating reliable weather forecast [5-6]. In other words, accurate PWV information is important for numerical weather prediction.

A popular approach for PWV estimation is the use of Continuously Operating Reference Stations (CORS) network [5, 7-9]. The CORS network is a network of GNSS stations that are setup to cover a large area and continuously receive the GNSS signals. Hence, high temporal resolution data covering a large area can be obtained. Namely, CORS network can provides data for continuous, accurate, all-weather, real-time PWV estimation. The atmospheric information is contained in the GNSS signal in terms of the signal propagation delay, particularly the Zenith Total Delay (ZTD) which can be extracted by the Precise Point Positioning (PPP) technique. PWV is then extracted from ZTD.

The conversion from ZTD to PWV is a function of the water vapor weighted mean atmospheric (tropospheric) temperature $T_m$. The difficulty is that $T_m$ cannot be measured directly in realtime. An indirect measurement is to convert the air surface temperature $T_s$, which is measured at or near the GNSS receiver, to $T_m$. In literature, there exists many global model for $T_m-T_s$ conversion [5. 10-11]. However, a local $T_m-T_s$ conversion model can provide GNSS-derived PWV with better accuracy [2].

Traditionally, the estimation of local $T_m-T_s$ conversion models uses radiosondes and ground-based Microwave Radiometers (MWR) data. Although radiosondes and MWR can provide accurate data for meteorology applications, the radiosonde network is expensive to operate. Namely, the obtained data has a sparse spatial coverage at low temporal frequency [12].

To achieve better coverage both temporally and spatially at smaller cost, in this paper, it is proposed to use the data from the Atmospheric Infrared Sounder (AIRS), and the Advanced Microwave Sounding Unit (AMSU) installed on NASA’s Aqua satellite to derive a local $T_m$ and $T_s$ relationship model. To formulate the relationship
mathematically between \( T_m \) and \( T_s \), the triply modulated cosine was adopted to model \( T_s \) as a periodic function. The surface temperature is then converted to \( T_m \) by a linear function. The parameters of the model are estimated using extended Kalman filter.

The rest of this paper is organized as follows. In Section 2, the method for extracting PWV from GNSS observations is discussed. In Section 3, AIRS and AMSU satellite data preparation, and \( T_m \) and \( T_s \) relationship formulation will be presented. The extended Kalman filter technique for model parameter estimation will be explained in Section 4. The experimental results of the parameters for the local TN relation and the accuracy of the GNSS PWV derived using the global and local models will be studied in Section 5. The concluding remarks will be presented in the last section.

2. Precipitable water vapor estimation using satellie geodesy

A. Precipitable water vapour computation from the ZTD

In [13], Saastamoinen studied the effect of troposphere causing the delay on microwave propagation. Such delay depends on the temperature, the pressure, and the water vapor. These factors can change the reflective index along the signal traveling path. The variation of reflective index yield the delay in the signal propagation. Such delay is hence called tropospheric delay.

In the seminal work by Bevis et al. [5], the tropospheric delay of GPS signal was used to infer quantity of water vapor which is called Precipitable Water Vapor (PWV). Particularly, it is referred to the amount of water vapor in vertical direction after condensation in millimeter unit.

PWV can be calculated from the Zenith Total Delay (ZTD) which can be obtained using GNSS data processing technique called Precise Point Positioning (PPP). ZTD can be decomposed into two parts. The first one is the Zenith Hydrostatic Delay (ZHD) which is contributed by dry air and the nondipole component of water vapor. The second one is the Zenith Wet Delay (ZWD) which is associated solely with the dipole component of the water vapor in the atmosphere. Mathematically, ZTD can be simply formulated as \( ZTD = \text{ZHD} + \text{ZWD} \) or equivalently, \( \text{ZWD} = \text{ZTD} - \text{ZHD} \).

To extract the ZWD component from ZTD, the ZHD is modeled as the function of pressure, latitude, and height [13]:

\[
\text{ZHD} = \frac{2.2766 \rho_o}{1 - 0.00266 \cos(\phi) - 0.00000028 H^2},
\]

where \( \rho_o \) is the air surface pressure in bar, \( \phi \) the latitude of the receiver, and \( H \) the height above the ellipsoid in meter. After the ZWD is extracted, it can then be recast to PWV by:

\[
\text{PWV} = \Pi \cdot \text{ZWD}.
\]

The coefficient \( \Pi \) is given by equation:

\[
\Pi = \frac{10^{-6}}{R_w \left( k_2 + k_3 T_m \right)}
\]

where \( k_2 \) and \( k_3 \) are empirical coefficients. In this paper, the values are \( k_2 = 0.221 \text{K/Pa} \), \( k_3 = 3739 \text{K/Pa}^2 \). \( R_w = 461.525 \text{J/(kg·K)} \) is a specific gas constant of water vapor. \( T_m \) is the water vapor-weighted mean tropospheric temperature which is also called the mean tropospheric temperature in \( K \). Although the mean tropospheric temperature depends on the temperature profile in troposphere, it can be estimated using average of the surface temperature at the GNSS receiver.

It can be observed that the conversion from ZWD to PWV is a function of \( T_m \) which is difficult to be estimated especially in realtime. One of the solution is to estimate \( T_m \) using surface temperature \( T_s \) which is much easier to obtain. That is, \( T_m \) is modeled as a function of \( T_s \).

B. Existing tropospheric mean temperature models

A simple mathematical formulation is the linear function which can be simply expressed as:

\[
T_m = a T_s + b,
\]

where \( a \) and \( b \) are empirical coefficients given in many versions by different sources. The variation of such parameters is associated with location, height, season and weather. In [5], the relation between \( T_m \) and \( T_s \) is formulated as:

\[
T_m = 0.72 T_s + 70.2
\]

for the region between Alaska and Florida. However, It was mentioned in [11] that this parameters can be used globally. Mendes et al. [10] estimated the parameters \( a \) and \( b \) using radiosonde data. Particularly, the linear function (4) was fitted to 32,500 radiosonde profiles from 50 stations covering 62°S–83°N. The fitted model is:

\[
T_m = 0.789 T_s + 50.4
\]

In stead of using the linear function, Schueler et al. proposed an alternative model called mixed harmonic/surface temperature model at the request day of year (DoY):

\[
T_m = T_m^0 + \tilde{T}_m \cos \left( 2 \pi \frac{\text{DoY} - \DoY_0}{365.25} \right) + q \sigma T_s
\]

where

- \( T_m^0 \) mean temperature at day DoY
- \( \tilde{T}_m \) the average of \( T_m \)
- \( q \) the amplitude of the annual cycle of \( T_m \)
- \( \DoY_0 \) the day of year
- \( \DoY_m \) the day of the year for maximum winter, equal to 28 for the Northern Hemisphere and to 211 for the Southern Hemisphere
- \( q \) an amplifier-weighting term for the \( T_s \)

Note that \( T_m^0 \), \( \tilde{T}_m \), and \( q \sigma \) are specific for each station. It can be observed that this model is just an combination of harmonic function of \( T_m \) and a linear function of \( T_s \). The global linear surface temperature model was also derived:

\[
T_m = 0.6477 T_s + 86.9
\]

which is different from the models given by Bevis et al. [5] and Mendes et al. [10] because those models were derived locally.

The important of accurate \( T_m \) for estimating PWV was pointed out in [2]. Namely, \( T_m \) is the largest source of error in PWV estimation. Moreover, local \( T_m \) model should be used to obtain accurate GNSS derived PWV [7]. Generally, the coefficients of each meteorological
in $T_m - T_s$ relation are estimated using radiosonde data. However, the obtained data does cover a large area and the operation cost is very costly.

To address this issue, in this paper, an alternative method for estimating the parameters of $T_m$ and $T_s$ relation is proposed. That is, the satellite data from the Atmospheric Infrared Sounder (AIRS) and the Advanced Microwave Sounding Unit (AMSU) equipped on Aqua satellite are used to derive the relation between $T_m$ and $T_s$. The advantage of this approach is that the data is free of charge. Moreover, this approach is suitable for the areas that radiosonde data is not available.

### Table 1 The data layers used for deriving $T_m$ model

<table>
<thead>
<tr>
<th>Data layer</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>pressStd</td>
<td>pressure level for atmospheric temperature profile</td>
</tr>
<tr>
<td>pressH2O</td>
<td>pressure level for water vapor profile</td>
</tr>
<tr>
<td>TAirStd</td>
<td>atmospheric temperature profile</td>
</tr>
<tr>
<td>H2OMMRLevStd</td>
<td>mixing ratio profile</td>
</tr>
<tr>
<td>TSurfAir</td>
<td>air surface temperature</td>
</tr>
</tbody>
</table>

3. **Mean tropospheric temperature retrieval from satellite data**

**A. AIRS and AMSU data**

AIRS and AMSU are sensors equipped on NASA’s Aqua satellite. It was designed to have 2 days revisiting time. The global coverage is thus possible with high temporal frequency. The data from AIRS and AMSU are processed together to have level 2 standard product called AIRX2RET where version 6 is the latest version as of April, 2016. The processed data is stored in Hierarchical Data Format (HDF) and can be download from NASA’s website. In one HDF file, there are many data layers. The data layers used in this paper are listed in Table 1. For further information on the AIRX2RET products, the readers are referred to [14].

In this paper, the region of interest in Thailand was used in the study. Since Aqua passes Thailand two times around 2 and 13 o’clock local time daily, the local $T_m$ models for day and night are thus possible to be derived separately.

The processed AIRS and AMSU data provide atmospheric temperature profile at 28 standard pressure levels from bottom atmosphere to the top, while the water vapor profile is provided at 15 pressure levels. Furthermore, the pressure level for water vapor profile is the same as the firs 15 pressure levels for atmospheric temperature profile.

In [15], the accuracies of AIRS and AMSU products i.e., atmospheric temperature and water vapor were evaluated. That is, the accuracy of estimated atmospheric temperature is about 1 K for 1-km resolution. For water vapor estimation, the uncertainty is about 15% for 2-km resolution.

**B. Computing mean tropospheric temperature from AIRS and AMSU**

Given the water vapor partial pressure $e_i$ and the air temperature $T_i$ at the pressure level $i$, the mean atmospheric temperature can be computed as the following:

$$T_m = \sum e_i T_i / \sum e_i$$  (9)

It can be observed that this formulation is the weighted harmonic mean of the air temperature $T_i$ with weight $e_i$.

To compute water vapor partial pressure $e_i$ at level $i$, the mixing ratio at level $i$ ($w_i$) is taken into account. That is, the total pressure level is converted to the water vapor partial pressure:

$$e_i = w_i / (w_i + \varepsilon p_i)$$  (10)

where $p_i$ is the total pressure level. $\varepsilon$ is ratio between the molecular weight of water $M_w$ and the apparent molecular weight of dry air $M_d$ i.e., $\varepsilon = M_w / M_d = 0.622$. It must be aware that the mixing ratio must be scaled by $10^{-3}$ before computing (10) because the unit of the mixing ratio from AIRS is g/kg.

**C. Mean tropospheric temperature and air surface temperature models**

In order to explain the rational behind the temperature model proposed in this paper, in Figure 1, the temperature data for Bangkok, Thailand from November 2013 to
November 2015 were illustrated. It can be observed that $T_x$ is a periodic function of time with a period of 1 year. Furthermore, $T_m$ and $T_s$ show a linear relationship. By combining these two observations, it is therefore hypothesized that the periodicity of $T_m$ is induced from $T_x$ through linear relationship. This hypothesis is different from the harmonic model proposed in [11] as shown in (7). That is, the $T_m$ itself in (7) is a periodic function.

To formulate the $T_m$ and $T_s$ relationship, $T_x$ is first modelled as a periodic function:

$$T_{sx} = \mu_k + A_k \sin \left(2\pi \frac{DoY}{365.25} + \Phi_k\right)$$  \hspace{1cm} (11)

where $\mu_k, A_k, \Phi_k$ are the mean, the amplitude and the initial phase of the sine function at instant $k$ respectively. This periodic function is also known as triply (mean, phase, and amplitude) modulated cosine function which is popular for modelling the time series of satellite data [16]. $T_x$ is then converted to $T_{mx}$ by a linear function:

$$T_{mx} = aT_{sx} + b$$  \hspace{1cm} (12)

The parameters $a$, $b$, $\mu_k$, $A_k$, and $\Phi_k$ are then estimated independently to obtain a local $T_m$ model for the area of interest.

4. Deriving the mean tropospheric temperature model using the Extended Kalman filter

A. State and measurement definitions

To estimate the parameters of $T_m$ and $T_s$ relationship expressed in (11) and (12), the sequential parameter estimation method called Extended Kalman Filter (EKF) is adopted and the data from AIRS and AMSU is used as measurement. According to (11) and (12), the state vector $x_k$ containing the parameters to be estimated at instant $k$ is expressed as:

$$x_k = [a_k, b_k, \mu_k, A_k, \Phi_k]^T.$$  \hspace{1cm} (13)

To define the state equation for EKF, it is assumed that the state vector does not change much from the previous instant. The state vector is thus propagated by:

$$x_k + 1 = f(x_k) + w_k = x_k + w_k,$$  \hspace{1cm} (14)

where $w_k \sim \mathcal{N}(0, Q)$ is a zero-mean white Gaussian process noise with covariance matrix $Q$. The function $f(\cdot)$ is called the state equation.

The measurement vector $y_k$ at instant $k$ is therefore the mean atmospheric and surface temperatures i.e., $y_k = [T_{mx}, T_{sx}]^T + v_k$ where $v_k \sim \mathcal{N}(0, R)$ is a zero-mean white Gaussian measurement noise with covariance matrix $R$. Remind that $T_{sx}$ and $T_{mx}$ are retrieved from AIRS and AMSU at instant $k$. Therefore, by combining (11) and (12), the measurement vector can be expressed as a function of the state as:

$$y_k = h(x_k) + v_k$$  \hspace{1cm} (15)

The function $h$ is called the measurement. Given both state and measurement equations, the parameters of the $T_m$ and $T_s$ relationship can then be estimated using EKF technique.

B. Extended Kalman Filter equations and parameter initialization

a) EKF Equations: To estimate the state vector, the EKF algorithm traditionally consists of two steps i.e., prediction and update as follows [17]:

**Prediction**:\[ \hat{x}_k = x_k \quad \text{and} \quad P_k = P_k \]

**Update**:\[ \hat{x}_k = \hat{x}_k + K_k(y_k - h(\hat{x}_k)) \quad \text{and} \quad P_k = \tilde{P}_k - K_k S_k R_k^{-1} K_k^T \]

where $\hat{x}_k$ and $P_k$ are the a priori estimate at instant $k$, $\tilde{P}_k$ is the a priori estimation error covariance matrix, $\hat{x}_k$ is the a posteriori estimate, and $P_k$ is the a posteriori error covariance matrix.

b) Parameter initialization: Since EKF is an iterative process, the state vector $x_0$ (13) or parameters must be initialized. The mean $\mu_k$ can be initialized by using the average of all $T_x$ measurements. The initial $A_k$ and phase $\Phi_k$ can be computed using Fourier transformation of the $T_x$ time series. That is, the magnitude and phase of the first harmonic are used as the initial values for $A_k$ and $\Phi_k$. The parameters of global $T_m$-$T_s$ models can then be used to initialize $a_k$, $b_k$, and $\Phi_k$ e.g., the parameters of (8).

The initial a priori error covariance matrix $P_0$ which represents the confidence in the a priori initial state is chosen such that:

$$P_0 = \text{diag}(1, 0.5, 0.5, 5 \cdot \pi/180)^T.$$  \hspace{1cm} (16)

To model the process noise, $a$ and $b$ are assumed to be constant as done for the global models in (5), or (8). That is, the process noise on $a$ and $b$ are supposed to be zero. The process noise covariance matrix $Q$ is then:

$$Q = \text{diag}(0, 0, 0.5, 0.1 \cdot \pi/180)^T.$$  \hspace{1cm} (17)

Regarding the analysis in [15], the accuracy for atmospheric and surface temperatures is about 1 K for 1 km resolution, the measurement noise covariance matrix is chosen as:

$$R = \text{diag}(0.5, 0.5)^T.$$  \hspace{1cm} (18)

By the nature of EKF, $a$ and $b$ parameters are updated at each iteration. However, the estimated $a$ and $b$ at the final instant will be used as the local $T_m$ model. The rationale for selecting $a$ and $b$ parameters is that $a$ and $b$ parameters are assumed to converge as the time goes by.

5. Experimental results

A. Estimated parameters for $T_m$ and $T_s$ models

To evaluate the performance of the proposed $T_m$ model estimation method, the experiment was conducted using the AIRS and AMSU data from September, 2010 to September,
The estimated parameters $a$ and $b$ for nighttime. The positions of CORS stations are plotted with green dots.

2015. Particularly, the $T_m$ and $T_s$ data at the CORS station was used.

The estimated $\hat{a}$ and $\hat{b}$ parameters in the $T_m$ and $T_s$ relationship (4) at each CORS station for day and night times are illustrated in Figure 2. The parameters $a$ and $b$ at each CORS stations, which are shown as green dots on the plot, were first estimated. The parameters for other positions were then calculated by bilinear interpolation technique. It can be observed that the parameters $a$ and $b$ depend on the spatial location. Moreover, they are also function of time.

To evaluate the accuracy of the obtained parameters from the proposed method, $T_m$ and $T_s$ obtained from AIRS and AMSU respectively at the CORS station in Bangkok is plotted along with global $T_m$ models (5), (6), (8), and the derived local $T_m$ models are plotted in Figure 3 where it can be observed that the local models fit more the AIRS and AMSU observations than the global models.

B. Accuracy of GNSS PWV using Local and Global models

To demonstrate the efficiency of the estimated $a$ and $b$ parameters i.e., local $T_m$ model, the accuracy of GNSS-derived PWV was used. That is, the PWVs extracted from GNSS using local and global $T_m$ models i.e., (6) were compared with a reference one. Traditionally, PWV obtained from the microwave radiometer is utilized. An alternative is to use satellite imagery i.e., AIRS, and AMSU as reference. In [18], it was reported that the PWV retrievals using AIRS, and AMSU have a strong agreement with the microwave radiometer with a bias of -0.233 mm and root mean squared
There exists a bias in atmospheric PWV and the alternative hypothesis testing is used to test whether there exists a bias in the GNSS-derived PWV using the local or global models. Therefore, the null hypothesis $H_0$, and the alternative hypothesis $H_1$ were set as $H_0: \theta = 0$ and $H_1: \theta \neq 0$, where $\theta$ is the error of GNSS-derived PWV compared with PWV from AIRS and AMSU e.g., $PWV_{\text{GNSS}} - PWV_{\text{AIRS}}$. For the two tailed test, the null hypothesis is rejected, if the absolute value of the t-statistics is less than the $t$ distribution $t_{\alpha/2, n}$ where $n$ is the number of samples and $\alpha$ is the significant level.

In the testing, samples from 64 days were used. The t-statistics of error using local and global $T_m$ models in GNSS derived PWV are reported in Table 2. For 2-tailed $\alpha = 0.2$ (90% confidence) and 63 degree of freedom, the critical value for the $t$ distribution is about 1.29. Therefore, it cannot be rejected that the GNSS-derived PWV using local $T_m$ model has no bias. In contrast, for the global model, the null hypothesis cannot be accepted. That is, we cannot accept that there is no bias in the GNSS-derived PWV using global model.

Moreover, it can be observed from the mean error of global model that PWV is underestimated because the mean error is less than zeros. Referred to Figure 3, $T_m$ from global model is less than the measured one. This yields the shrinkage in the value of coefficient $\Pi$ in (3) and the extracted PWV.

### Table 2 t-statistics for bias detection, where the error is $PWV_{\text{GNSS}} - PWV_{\text{AIRS}}$

<table>
<thead>
<tr>
<th>$T_m$ model</th>
<th>Mean error [K]</th>
<th>Standard error of the mean difference [K]</th>
<th>t-statistics</th>
</tr>
</thead>
<tbody>
<tr>
<td>Local model</td>
<td>0.199</td>
<td>0.786</td>
<td>0.253</td>
</tr>
<tr>
<td>Global model (6)</td>
<td>-1.063</td>
<td>0.764</td>
<td>-1.391</td>
</tr>
</tbody>
</table>

In this experiment, GNSS observations from the CORS owned by the Department of Public Works and Town & Country Planning (DPT) of Thailand from January 2015 to November 2015 were utilized. The PPP technique implemented in the PANDA software from Wuhan university was used for data processing i.e. ZTD extraction. The surface temperature at the CORS station was used to compute $T_m$ using local, and global models. The obtained $T_m$ was then used to compute coefficient $\Pi$ in (3) for PWV extraction. In Figure 4, the time series of estimated PWV using local, and global $T_m$ models together with the PWV from AIRS and AMSU are illustrated.

The efficiency of the estimated $T_m$ model was evaluated by bias detection in PWV computation. The bias detection was performed by single sample $t$-test. Particularly, the hypothesis testing is used to test whether there exists a bias in the GNSS-derived PWV using the local or global models. Therefore, the null hypothesis $H_0$, and the alternative hypothesis $H_1$ were set as $H_0: \theta = 0$ and $H_1: \theta \neq 0$, where $\theta$ is the error of GNSS-derived PWV compared with PWV from AIRS and AMSU e.g., $PWV_{\text{GNSS}} - PWV_{\text{VARS}}$. For the two tailed test, the null hypothesis is rejected, if the absolute value of the t-statistics is less than the $t$ distribution $t_{\alpha/2, n}$ where $n$ is the number of samples and $\alpha$ is the significant level.

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### 6. Concluding remarks

In this paper, the data from AIRS, and AMSU equipped on NASA’s Aqua satellite were used to derive a local $T_m$ and $T_s$ relationship. The algorithm utilized for solving the local model parameters was the extended Kalman filter. Air surface temperatures was modeled using the triply modulated cosine because of its periodicity. The surface temperature is then converted to mean atmospheric temperature by a linear function. Traditionally, the radiosonde data is used as measurement. In this paper, the satellite data from atmospheric infrared sounder, and advanced microwave sounding unit sensors was used because it is free of charge and has global coverage and high temporal resolution. The performance of the proposed model was tested against the global model. It was shown that there were no biases in the GNSS-derived PWV using local $T_m$ model. In contrast, using global $T_m$ yielded bias in the PWV estimation.

### 7. Acknowledgement

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8. References


