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A Comprehensive Evaluation of 4-Parameter Diurnal Temperature Cycle Models with In Situ and MODIS LST over Alpine Meadows in the Tibetan Plateau

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Abstract: Diurnal variation of land surface temperature (LST) is essential for land surface energy and water balance at regional or global scale. Diurnal temperature cycle (DTC) model with least parameters and high accuracy is the key issue in estimating the spatial–temporal variation of DTC. The alpine meadow is the main land cover in the Tibetan Plateau (TP). However, few studies have been reported on the performance of different DTC models over alpine meadows in the TP. Four semi-empirical types of DTC models were used to generate nine 4-parameter (4-para) models by fixing some of free parameters. The performance of the nine 4-para DTC models were evaluated with four in situ and MODIS observations. All models except GOT09-dT- t_s (dT means the temperature residual between T_0 and T ($t \rightarrow \infty$); t_s means the time when free attenuation begins) had higher correlation with in situ data ($R^2 > 0.9$), while the INA08- t_s model performed best with NSE of 0.99 and RMSE of 2.04 K at all sites. The GOT09- t_s - τ (τ is the total optical thickness), VAN06- t_s - ω_1 (ω_1 means the half-width of the cosine term in the morning), and GOT01- t_s models had better performance, followed by GOT09-dT- τ , GOT01-dT, and VAN06- t_s - ω_2 (ω_2 means the half-width of the cosine term in the afternoon) models. All models had higher accuracy in summer than in other seasons, while poorer performance was produced in winter. The INA08- t_s model showed best performance among all seasons. Models with fixing t_s could produce higher accuracy results than that with fixing dT . The comparison of INA08- t_s model driven by in situ and Moderate Resolution Imaging Spectroradiometer (MODIS) data indicated that the simulation accuracy mainly depended on the accuracy of MODIS LST. The daily maximum temperature generated by the nine models had high accuracy when compared with in situ data. The sensitivity analysis indicated that the INA08-dT and GOT09-dT- t_s models were more sensitive to parameter dT , while all models were insensitive to parameter t_s , and all models had weak relationship with parameters ω and τ . This study provides a reference for exploring suitable DTC model in the TP.

Keywords: diurnal temperature cycle model; sensitivity analysis; alpine meadow; Tibetan Plateau

1. Introduction

Land surface temperature (LST) is a key and basic parameter for land surface energy balance and water balance at regional and global scales [1,2]. The diurnal LST variation is crucial for meteorological,

hydrological and climatological research and applications [3–6]. Moreover, it is also a very sensitive parameter to describe the characteristics of surface energy balance, surface thermal inertia, and surface water-heat budget [4]. The larger error of diurnal temperature cycle (DTC) probably leads to high uncertainty in each component of the energy balance.

Tibetan Plateau (TP), with the average elevation of more than 4000 m above sea level (MASL) and an area of about $2.5 \times 10^6 \text{ km}^2$ [7,8], is regarded as the world's Third Pole and one of most sensitive areas for climate change [9,10]. TP has an important impact on the Asian Monsoon and even global climate through its orographic and thermal effects [11,12]. The complex interactions between land surface and atmosphere of TP play an important role in modulating these effects [13]. Serious challenges still existed in simulating land-surface processes of the TP (i.e., the surface energy balance) [14,15]. Since LST is a critical parameter for calculating land surface energy balance and water-heat budget [16], it is therefore very important to evaluate the different DTC models in TP.

The DTC is affected by many factors, and these factors can mainly be divided into two categories: one is surface energy balance, which depends on solar insolation, land surface properties, and atmospheric variables. The other is surface thermal inertia, which depends on soil type, soil moisture content, and vegetation cover [4,17]. The DTC is also very important to interpolate the missing data of LST, improve the cloud screening algorithms, and analyze urban thermal environment [18–20], which can be simulated by DTC models.

Many DTC models have been developed with various functions [18,19,21,22]. Generally, DTC models can be divided into four categories: (1) the physical method, such as land surface models (LSMs); (2) the quasi-physical method, based on surface energy flux or thermal inertia; (3) the semi-physical method, based on the thermal diffusion equation during daytime and Newton's law of cooling theory during nighttime; and (4) the statistical method, mainly based on the relationship between LST and local geographic information [23]. Among these, the semi-physical method was widely used [2,17,18,24–26] due to its flexibility.

For example, Parton and Logan [27] developed a semi-physical model for predicting diurnal variation in soil and air temperatures, which utilized a truncated sine function and an exponential function to simulate the diurnal temperature variations during daytime and nighttime, respectively. Göttsche and Olesen [22] improved the DTC model originally developed by Göttsche and Olesen [18] through smooth the increase of LST around sunrise and change the width of DTC by adding total optical thickness after validating at oak forest and desert sites.

On the other hand, some studies calibrated DTC model through satellite data or combining both in situ and satellite data. Ignatov and Gutman [4] derived a statistical model to reconstruct the monthly mean DTC by using data from the International Satellite Cloud Climatology Project (ISCCP). Schädlich et al. [21] proposed a simple semi-physical model to temporally interpolate brightness temperature by using Meteorological Satellite (METEOSAT) data. Göttsche and Olesen [18] developed a semi-physical model, which combined cosine and exponential functions with brightness temperature derived from geostationary METEOSAT satellites data. Based on Geostationary Operational Environmental Satellite (GOES-8) observations, Sun and Pinker [28] proposed a new fitting algorithm by using sine function during nighttime and cosine function during daytime, which was applied to estimate DTC with LSTs extracted from Advanced Very High-Resolution Radiometer (AVHRR). Van den Bergh et al. [29] presented a three-step semi-physical model by using Meteosat Second Generation (MSG) data to interpolate missing values. Jiang et al. [24] modified the model originally developed by Göttsche and Olesen [18] to interpolate temperature temporally for thermal infrared channels of METEOSAT data, and they found it performed well on vegetated and bare areas. Inamdar et al. [19] pointed out that a hyperbolic function was more suitable for modeling DTC during nighttime and modeled DTC with MODIS and GOES data. Duan et al. [25] compared six DTC models with in situ LST and that derived from Spinning Enhanced Visible and Infrared Imager (SEVIRI) data, and reported that the model proposed by Göttsche and Olesen [22] showed best performance. Huang et al. [23] proposed a generic framework for monitoring temperature variation, and the mean absolute error between observed LST

and the brightness temperatures of Moderate Resolution Imaging Spectroradiometer (MODIS) and SEVIRI data reduced from 1.71 to 0.33 °C. Hong et al. [26] comprehensively evaluated four-parameter DTC models with in situ and satellite (including SEVIRI and FengYun-2F) data.

The above studies suggested that the quasi- and semi-physical methods can successfully model DTC through discrete values, especially when models combined with remote sensing data. The semi-physical method was applied with free parameters ranging from three to six, while the quasi-physical method with free parameters ranging from two to twelve when modelling DTC [16]. Many semi-physical DTC models need more than six input data, which makes it difficult to obtain high accuracy DTC variation at regional or global scale.

Some geostationary satellites can provide the DTC with temporal resolution of 15 or 30 minutes (i.e., SEVIRI and METEOSAT). Geostationary satellites scan large areas, i.e., their specific Earth orbits. However, only some regions can be scanned, which could not describe the diurnal temperature characteristics in large regions or at global scale by these satellites. MODIS provides the global reasonable LST product with transiting four transit times per day, which have been widely effective and applied in many regions, and brings the possibility of DTC estimation at global scale. Thus, it is one of key issues to reduce the free parameters of DTC models to less than or equal to four parameters. For example, Duan et al. [17] modified the model of Inamdar et al. [19] to estimate the DTC variation by reducing free parameters to four by using MODIS data. Hong et al. [26] reduced the number of free parameters to four and compared eight four-parameter DTC models under various bio-climates with multi-source (SEVIRI and FY-2F) data.

DTC models showed varied performances with in situ data and different satellite images over different land covers [25,26]. For example, Duan et al. [25] evaluated six DTC models over different land cover types using in situ data and satellite data, and found JNG06 and GOT09 models may performed better. Hong et al. [26] compared four-parameter DTC models over four land cover types with in situ data and satellite data, and they found the GOT-dT- τ model was more suitable for most land covers. Alpine meadow and steppe account for about 50% of the total area of the TP [30]. However, few studies focus on the performance of DTC models over alpine meadows in the TP due to limited in situ data. Most in situ stations are located in the eastern and southern TP, and there are few stations in the western TP due to the extreme fragile environment [31].

On the other hand, there are many poor-quality remote-sensing productions of LST in the Tibetan Plateau (TP) due to the influence of clouds [32], while reanalysis data also have large biases and uncertainties [33,34]. It is difficult to quantify the physical processes of land surface energy and water balance at regional scale in the TP. There are many studies that have focused on LST estimation and validation in the TP [35–37]. Seldom studies which investigated the diurnal variation of LST in the TP regions have reported. Therefore, it is very important to evaluate the performances of different DTC models in the TP, especially when it combined with remote sensing data (i.e., MODIS LST).

In this study, nine 4-para DTC models were compared for monitoring the DTC variations over alpine meadows in the TP with half-hour observation data. The aim is to compare the performances of different models with in situ data and MODIS LST data, and identify the best semi-physical method over alpine meadows in the TP.

2. Data and Methods

2.1. Data

To explore the suitable DTC model for the TP, alpine meadow as one of the main underlying surfaces was selected as representative. In addition, we incorporated both in situ data and LSTs extracted from satellite products (i.e., MODIS) for study.

2.1.1. In Situ Data

The half-hourly LST observation data at five sites with alpine meadow were selected to evaluate the performance of the nine 4-para models (Figure 1). The detail information of the stations and observation data are shown in Table 1. Due to the availability of observation stations, only five sites were chosen for representing alpine meadows. The half-hourly LST is calculated by Yang et al. [38], based on the upward and downward longwave radiation:

$$LST = \left(\frac{L_{\uparrow} - (1 - \varepsilon)L_{\downarrow}}{\varepsilon\sigma} \right)^{1/4} \quad (1)$$

where $L_{\uparrow}$ and $L_{\downarrow}$ are the observed upward and downward long-wave radiation fluxes (W m^{-2}), respectively; σ is Stefan-Boltzmann constant ($5.67 \times 10^{-8} \text{ W m}^{-2} \text{ K}^{-4}$); ε is the land surface emissivity, with 0.99 at all alpine meadow sites [25] and the reasonability of the value will be discussed in Section 4.1.

Figure 1. Geolocations of the alpine meadow observation sites in the Tibetan Plateau, the land cover distribution were based on Zhang et al. [30].

Table 1. Information of the land surface temperature (LST) observation sites in the Tibetan Plateau.

Site Name	Latitude (°)	Longitude (°)	Elevation (MASL)	Year	Data Source
Arou	38.05	100.46	3033	2014	Liu et al., 2018 [39]
Hulugou	38.25	99.88	3232	2013	Han et al., 2018 [40]
Suli	38.42	98.32	3885	2010	Chang et al., 2018 [41]
Naqu	31.37	91.9	4509	2011	Sun et al., 2018 [42]
Tanggula	33.07	91.93	5100	2010	Yao et al., 2011 [43]

Considered the observation date of different stations varied, the representative days are selected to evaluate the performance of nine DTC models. Furthermore, several days for each season at one representative site were randomly selected for evaluating the universality of each DTC model. Four necessary conditions were considered for selecting the represent days and running the model: (1) all

models are generated under clear-sky condition without obvious change in wind speed, generally standard deviation of wind speed at the height of 2 m less than 2 m s^{-1} ; (2) sunrise only appears once per day; (3) temperature decays freely after “thermal sunset” at time t_s ; (4) The MODIS satellite temperatures acquired four times per day. Therefore, the half-hour LSTs (48 values per day) were used to validate the model performances; while the day with four observations corresponding to the MODIS transit time (10:30, 13:30, 22:30, and 01:30 at local time) were chosen for fitting DTC model. Under the premise of meeting the above conditions, four days in each season were randomly selected at each site to compare the performance of different models.

2.1.2. MODIS Data

The MODIS LST products (MOD11A1 and MYD11A1) were retrieved through the generalized split-window algorithm [44] with spatial resolution of 1 km and transit 2 times per day, respectively. The high quality (QC = 0) LST and local solar time at the observation sites were extracted from the MODIS LST products. Four days at the Suli (21 April and 2 October 2010) and Tanggula sites (26 April and 4 May 2010) were used to evaluate the performance of the best model with MODIS data. The MODIS Aqua and Terra LST products (collection 5) were downloaded from NASA website (<https://search.earthdata.nasa.gov>).

2.2. Methods

Four popular semi-physical (SEM) DTC methods, including GOT01 model developed by Göttsche and Olesen [18], VAN06 model proposed by Van den Bergh et al. [29], INA08 model founded by Inamdar et al. [19] and GOT09 model developed by Göttsche and Olesen [22], were chosen for experiment on reducing the number of free parameters to four.

2.2.1. GOT01 Model

Göttsche and Olesen [18] assumed that DTC of daytime could be simulated by a cosine function based on the thermal diffusion equation, and an exponential function to describe the decay of nighttime LST with the assumption of obeying Newton’s law of cooling. The model can be expressed as follows:

$$\begin{aligned} T_{day}(t) &= T_0 + T_a \cos\left(\frac{\pi}{\omega}(t - t_m)\right), \quad t < t_s \\ T_{night}(t) &= T_0 + dT + \left[T_a \cos\left(\frac{\pi}{\omega}(t_s - t_m)\right) - dT\right] e^{\frac{-(t-t_s)}{k}}, \quad t \geq t_s \end{aligned} \quad (2)$$

where $T_{day}(t)$ and $T_{night}(t)$ are the LST of daytime and nighttime, respectively; T_0 is the residual temperature around sunrise; T_a is the temperature amplitude; ω is the duration of daytime (DD), which represents the width over the half-period of the cosine term and can be expressed as a function of latitude (φ) and the solar declination (δ); t_m is the time when the temperature reaches peak; t_s is the time when free attenuation begins; dT is the temperature residual between T_0 and $T(t \rightarrow \infty)$; k is the attenuation constant. There are five free parameters in this model (T_0 , T_a , t_m , t_s , and dT).

In order to apply the model with MODIS LST, it is essential to reduce the number of free parameters to four. Base on previous studies [17,26], two schemes were made: (a) fix dT as zero ($dT = 0$), named as GOT01-dT; (b) set t_s to be one hour before sunset ($t_s = t_{ss} - 1$, where t_{ss} is the sunset time, which can be calculated from website <https://www.esrl.noaa.gov/gmd/grad/solcalc>), named as GOT01- t_s (Table 2).

Table 2. Summary of parameters for the nine diurnal temperature cycle (DTC) models.

Cases	All Parameters	Fixed Parameters	Category	Reference
GOT01-dT	T_0, T_a, t_m, t_s, dT	$dT = 0$	SEM	Schädlich et al. [21]
GOT01- t_s	T_0, T_a, t_m, t_s, dT	$t_s = t_{ss} - 1$	SEM	Hong et al. [26]
Van06- t_s - ω_1	$T_0, T_a, t_m, t_s, \omega_1, \omega_2$	$t_s = t_{ss} - 1; \omega_1 = DD$	SEM	this study
Van06- t_s - ω_2	$T_0, T_a, t_m, t_s, \omega_1, \omega_2$	$t_s = t_{ss} - 1; \omega_2 = DD$	SEM	this study
INA08-dT	T_0, T_a, t_m, t_s, dT	$dT = 0$	SEM	Hong et al. [26]
INA08- t_s	T_0, T_a, t_m, t_s, dT	$t_s = t_{ss} - 1$	SEM	Hong et al. [26]
GOT09-dT- τ	$T_0, T_a, t_m, t_s, dT, \tau$	$dT = 0; \tau = 0.01$	SEM	Hong et al. [26]
GOT09-dT- t_s	$T_0, T_a, t_m, t_s, dT, \tau$	$dT = 0; t_s = t_{ss} - 1$	SEM	Hong et al. [26]
GOT09- t_s - τ	$T_0, T_a, t_m, t_s, dT, \tau$	$t_s = t_{ss} - 1; \tau = 0.01$	SEM	Hong et al. [26]

2.2.2. VAN06 Model

Van den Bergh et al. [29] proposed a three-stage model to describe DTC due to different width of the half-period cosine term on the rising slope (in the morning) and falling slope (in the afternoon). This model is expressed as follows:

$$\begin{aligned}
 T_{day1}(t) &= T_0 + T_a \cos\left(\frac{\pi}{\omega_1}(t - t_m)\right), \quad t < t_m \\
 T_{day2}(t) &= T_0 + T_a \cos\left(\frac{\pi}{\omega_2}(t - t_m)\right), \quad t_m \leq t < t_s \\
 T_{night}(t) &= T_0 + T_a \cos\left(\frac{\pi}{\omega_2}(t_s - t_m)\right) e^{\frac{-(t-t_s)}{k}}, \quad t \geq t_s
 \end{aligned} \quad (3)$$

where $T_{day1}(t)$ and $T_{day2}(t)$ are the daytime temperatures before and after t_m ; ω_1 and ω_2 are the half-width of the cosine term in the morning and afternoon, respectively. There are six free parameters in the VAN06 model ($T_0, T_a, t_m, t_s, \omega_1$, and ω_2). Two of the six free parameters need to be fixed in this model, while ω_1 and ω_2 are different. Therefore, two schemes generate: (a) $t_s = t_{ss} - 1$ and $\omega_1 = DD$, named as Van06- t_s - ω_1 ; (b) $t_s = t_{ss} - 1$ and $\omega_2 = DD$, named as Van06- t_s - ω_2 (Table 2).

2.2.3. INA08 Model

Inamdar et al. [19] proposed a hyperbolic function to describe the decay of LST at night by replacing the exponential function developed by Göttsche and Olesen [8], which can be given as follows:

$$\begin{aligned}
 T_{day}(t) &= T_0 + T_a \cos\left(\frac{\pi}{w}(t - t_m)\right), \quad t < t_s \\
 T_{night}(t) &= T_0 + dT + \left[T_a \cos\left(\frac{\pi}{w}(t_s - t_m)\right) - dT\right] \frac{k}{k + t - t_s}, \quad t \geq t_s
 \end{aligned} \quad (4)$$

INA08 model contains five free parameters (T_0, T_a, t_m, t_s , and dT), the same parameters as GOT01 model. Thus, the same schemes can be made: (a) $dT = 0$, named as INA08-dT; (b) $t_s = t_{ss} - 1$, named as INA08- t_s (Table 2).

2.2.4. GOT09 Model

Based on the energy balance, Göttsche and Olesen [22] considered that LST increased relative slowly around sunrise due to the higher total atmospheric optical thickness (TOT) at large sun zenith angles, which can be described by the following equations:

$$\begin{aligned}
 T_{day}(t) &= T_0 + T_a \frac{\cos(\theta_z)}{\cos(\theta_{z,min})} e^{(m_{min} - m(\theta_z))\tau}, \quad t < t_s \\
 T_{night}(t) &= T_0 + dT + \left[T_a \frac{\cos(\theta_{zs})}{\cos(\theta_{z,min})} e^{(m_{min} - m(\theta_{zs}))\tau} - dT\right] e^{\frac{-12}{\pi k}(\theta - \theta_s)}, \quad t \geq t_s
 \end{aligned} \quad (5)$$

where θ is the thermal hour angle; θ_z is the solar zenith angle; $\theta_{z,min}$ is the zenith angle when $t = t_m$; θ_{zs} is the thermal angle when $\theta = \theta_s$; m_{min} , $m(\theta_z)$ and $m(\theta_{zs})$ are the relative air mass at $\theta_{z,min}$, θ_z and θ_{zs} , respectively; τ is TOT. GOT09 model contains six free parameters (T_0, T_a, t_m, t_s, dT , and τ). The total atmospheric optical thickness was generally regarded as a constant value for modeling DTC [3]. Therefore, τ can be regarded as a reduced parameter, and we selected τ as 0.01 based on

Hong et al. [26]. There are three parameters that can be fixed and three schemes can be obtained by combining two of the three parameters: (a) $dT = 0$ and $\tau = 0.01$, named as GOT09-dT; (b) $dT = 0$ and $t_s = t_{ss} - 1$, named as GOT09-dT- t_s ; (c) $t_s = t_{ss} - 1$ and $\tau = 0.01$, named as GOT09- t_s - τ (Table 2).

2.2.5. Solution of These Models

All the parameters of the nine 4-para DTC models were listed in Table 2. The Levenberg-Marquardt algorithm [45] was adopted to evaluate the performance of the nine 4-para DTC models. The initial values of the free parameters for each model were listed in Table 3.

Table 3. Initial values of the free parameter for the nine 4-para DTC models.

Parameter	GOT01-dT	GOT01- t_s	Van06- t_s - ω_1	Van06- t_s - ω_2	INA08-dT	INA08- t_s	GOT09-dT- τ	GOT09-dT- t_s	GOT09- t_s - τ
T_0 (K)	T_{min}	T_{min}	T_{min}	T_{min}	T_{min}	T_{min}	T_{min}	T_{min}	T_{min}
T_a (K)	$T_{max} - T_{min}$	$T_{max} - T_{min}$	$T_{max} - T_{min}$	$T_{max} - T_{min}$	$T_{max} - T_{min}$	$T_{max} - T_{min}$	$T_{max} - T_{min}$	$T_{max} - T_{min}$	$T_{max} - T_{min}$
t_m (h)	13.5	13.5	13.5	13.5	13.5	13.5	13.5	13.5	13.5
t_s (h)	$t_{ss} - 1$	—	—	—	$t_{ss} - 1$	—	$t_{ss} - 1$	—	—
dT (K)	—	0.5	—	—	—	0.5	—	—	0.5
ω_1 (h)	—	—	—	DD	—	—	—	—	—
ω_2 (h)	—	—	DD	—	—	—	—	—	—
τ	—	—	—	—	—	—	—	0.01	—

2.3. Evaluation Metrics

The coefficient of determination relationship (R^2), root mean square error (RMSE), mean bias (MB), and Nash—Sutcliffe efficiency coefficient (NSE) were used for statistical evaluation on different models. The equations are listed in Table 4.

Table 4. Statistical indexes used in this study.

Index	Abbreviation	Equation
Coefficient of determination	R^2	$\frac{(n \sum_{i=1}^n (T_{est} T_{obs}) - \sum_{i=1}^n T_{est} \sum_{i=1}^n T_{obs})^2}{(n \sum_{i=1}^n T_{est}^2 - (\sum_{i=1}^n T_{est})^2)(n \sum_{i=1}^n T_{obs}^2 - (\sum_{i=1}^n T_{obs})^2)}$
Root mean square error	RMSE	$\sqrt{\frac{\sum_{i=1}^n (T_{est} - T_{obs})^2}{n}}$
Mean bias	MB	$\frac{\sum_{i=1}^n (T_{obs} - T_{est})}{n}$
Nash—Sutcliffe efficiency coefficient	NSE	$1 - \frac{\sum_{i=1}^n (T_{obs} - T_{est})^2}{\sum_{i=1}^n (T_{obs} - \overline{T_{obs}})^2}$

Note: T_{est} stands for simulations, T_{obs} is the observed values, $\overline{T_{obs}}$ is the average of T_{obs} , and n is the sample number.

3. Results

3.1. Performance of the Nine DTC Models at Each Observation Site

At the Arou site which has lower elevation and relative humid climate, the statistical indicators of DTC (Figure 2) suggested that all models performed well with higher R^2 (>0.9) and NSE (>0.9) except GOT09-dT- t_s model, which performed worst with lowest R^2 (0.89), highest RMSE (6.0 K) and lowest NSE (0.86). The INA08- t_s model produced the best result with the highest R^2 (0.99) and lowest RMSE (1.76 K). The VAN06- t_s - ω_1 , GOT01-dT and GOT09- t_s - τ models showed better performance with almost similar lower RMSE of 1.9, 1.9, and 1.97 K, respectively. The GOT01- t_s and GOT09- t_s - τ models showed reduced performance with RMSE of 2.12 and 2.18 K, respectively. Though the INA08-dT model had higher R^2 (0.95) and NSE (0.94), it still performed worse with larger RMSE (3.15 K).

Figure 2. Statistical indicators (coefficient of determination: (R^2) (a); mean bias (MB) (b); root mean square error ($RMSE$) (c); and Nash—Sutcliffe efficiency coefficient: (NSE) (d) of Diurnal Temperature Cycle (DTC) between estimated by the nine 4-para DTC models and in situ data at each observation site under clear-sky day.

At the Hulugou site which has relative lower elevation and humid climate, the GOT01-dT model had good performance with highest R^2 (0.98), lowest $RMSE$ (2.27 K) and highest NSE (0.98). The INA08-ts and GOT09-dT- τ models showed better performance with similar lower $RMSE$ (2.39 and 2.42 K) and higher NSE (0.97 and 0.97) followed by the INA08-dT, GOT09-ts- τ , and GOT01-ts models. The INA08-dT and GOT09-ts- τ models showed same performance with higher R^2 (0.97), lower $RMSE$ (2.74 K), and higher NSE (0.97). The VAN06-ts- ω_2 model showed reduced performance with higher $RMSE$ (3.28 K) and lower NSE (0.95). The GOT09-dT-ts model performed worst with highest $RMSE$ (4.77 K) and lowest NSE (0.9).

At the Suli site which has relative middle elevation and arid climate, all models performed well with higher R^2 (>0.9) and NSE (>0.9). The INA08-ts and GOT01-ts models produced the highest R^2 (0.98), lowest $RMSE$ (1.81 K), and highest NSE (0.98), respectively. The GOT09-ts- τ performed better with lower $RMSE$ (1.9 K) followed by the VAN06-ts- ω_1 , GOT01-dT and VAN06-ts- ω_2 models. The INA08-dT model showed reduced performance with higher $RMSE$ (3.19 K), while the GOT09-dT-ts model had worst performance with highest $RMSE$ (6.08 K) among all models.

At the Naqu site which has higher elevation and arid climate, the INA08-ts model performed best with highest R^2 (0.99), lowest $RMSE$ (2.01 K) and highest NSE (0.99) among all models. The GOT09-ts- τ and GOT01-ts models performed better with higher R^2 (0.99 and 0.99), lower $RMSE$ (2.08 and 2.16 K), and higher NSE (0.99 and 0.99), respectively, and followed by the VAN06-ts- ω_1 and VAN06-ts- ω_2 models. The GOT09-dT- τ and GOT01-dT models showed reduced performance with higher $RMSE$ (2.9 and 3.07 K), respectively. The INA08-dT model had larger error with $RMSE$ of 4.17 K, while the GOT09-dT-ts model performed worst with lowest R^2 of 0.86, highest $RMSE$ of 8.25 K and lowest NSE of 0.79.

At the Tanggula site which has relative higher elevation and arid climate, all models performed well with higher R^2 (>0.9) and higher NSE (>0.9). The GOT09-ts- τ , INA08-ts and VAN06-ts- ω_2 model performed best with same highest R^2 (0.98), similar lowest $RMSE$ of 2.05 and 2.18 K and same highest NSE (0.98). The GOT01-ts, VAN06-ts- ω_1 , and GOT09-dT- τ models performed better, which had lower $RMSE$ ranging from 2.21 to 2.3 K and followed by the GOT01-dT model. The INA08-dT and

GOT09-dT- t_s had largest errors with *RMSE* of 3.07 and 3.2 K, respectively. Moreover, all models had higher *NSE*, which suggested that all models produce better results for evaluating DTC at the Tanggula site.

In a short summary, among the nine models, INA08- t_s performed best than the other models with lowest average *RMSE* of 2.04 K and highest *NSE* of 0.99 at all alpine meadow sites (Figures 2 and 3). The GOT09- t_s - τ , VAN06- t_s - ω_1 and GOT01- t_s models had similar better performance with lower *RMSE* of 2.26 K, and higher average *NSE* of 0.98, followed by the GOT09-dT- τ , GOT01-dT, and VAN06- t_s - ω_2 models, which showed better performance with *RMSE* ranging from 2.37 to 2.6 K, respectively. All models were highly correlated with measured values with R^2 above 0.9 except GOT09-dT- t_s model. The INA08-dT model showed poorer performance with higher average *RMSE* (3.3 K), while GOT09-dT- t_s model produced poorest performance with highest average *RMSE* of 5.9 K and lowest *NSE* of 0.86 (Figure 3d).

Figure 3. The average statistical indicators (R^2 , (a); *RMSE*, (b); *MB*, (c); and *NSE*, (d) of the nine 4-para DTC models at all sites compare with in situ data under clear-sky day.

3.2. Diurnal Temperature Variation over Different Seasons

The comparisons between simulated by the nine 4-para DTC models and observed diurnal LST variations in four seasons at all sites (Figure 4) indicated that all models performed better at hours after sunrise, while LSTs were substantially underestimated around sunrise due to the ignorance of the slow increase in temperature around sunrise, which corresponding with the results reported by Hong et al. [26]. At the Suli site, the INA08- t_s and GOT01- t_s models produced better result in winter (Figure 4a), while all models except INA08-dT and GOT09-dT- τ models produced higher accuracy with lower *RMSEs* (<2 K) in spring (Figure 4b). At the Arou site, the INA08- t_s , VAN06- t_s - ω_1 , and GOT01-dT models produced better results in winter (Figure 4e), spring (Figure 4f) and summer (Figure 4g), while the INA08- t_s , GOT01- t_s and GOT09-dT- τ models performed better in winter and summer. At the Hulugou site, the GOT09-dT- τ , GOT01-dT and INA08- t_s models performed better in spring (Figure 4j) and summer (Figure 4k). The INA08-dT model produced lowest error in winter (Figure 4i). While the INA08- t_s and GOT01-dT models performed better in autumn (Figure 4l). At the Naqu

site, VAN06- t_s - ω_1 , INA08- t_s and GOT01- t_s models produced better results in winter. The INA08- t_s , GOT01- t_s and GOT09- t_s - τ models performed better in spring and autumn, while the GOT09-dT- t_s , INA08- t_s and GOT09- t_s - τ models performed better in summer. At the Tanggula site, all models except the INA08-dT and GOT09-dT- t_s models performed better in winter, while all models except the INA08-dT model could produce higher accuracy in summer. GOT09-dT- τ , GOT09- t_s - τ and INA08- t_s models performed better in spring, while GOT09-dT- t_s and INA08- t_s models produce higher accuracy results in autumn.

Figure 4. Simulated by the nine 4-para DTC models and in situ observed diurnal variations of LST at each site (Arou, (a–d); Hulugou, (e–h); Suli, (i–l); Naqu, (m–p); Tanggula, (q–t)) in four seasons.

In general, all models showed similar patterns at each site in each season, most models performed worse in spring and autumn than summer. However, the performances of different models had large difference in some seasons. According to the performance of each model at all sites in four seasons, models with fixing t_s seems produce higher accuracy results than that with fixing dT .

The $RMSE$ s of the nine 4-para DTC models over four seasons (Figure 5) suggested that all models had good performance with lower $RMSE$ in summer, which also had higher R^2 (>0.9), NSE (>0.9) (not shown here), and while performances of all models were relatively lower in winter.

Figure 5. RMSEs of the nine 4-para DTC models over four seasons in the TP.

In winter, INA08- t_s model had best performance with lower RMSE (2.4 K). VAN06- t_s - ω_1 , GOT01-dT, and GOT09-dT- τ models had relatively good performance with lower RMSE of 2.64, 2.66, and 2.81 K, and same higher NSE of 0.94. GOT01- t_s and GOT09- t_s - τ models showed reduced performance, while INA08-dT model produced larger error with higher RMSE of 3.56 K. GOT09-dT- t_s model performed worst with highest RMSE (9.1 K) and lowest NSE (0.35) in winter. In spring, INA08- t_s model performed best followed by GOT01- t_s model, while GOT09-dT- t_s model showed poor performance. In summer, all models performed well with higher NSE (>0.9). GOT09- t_s - τ and INA08- t_s models performed best with highest R^2 (0.97), lowest RMSE (1.58 and 1.66 K), and highest NSE (0.97). Noting that GOT09-dT- t_s model had good performance in summer while it performed poor in other seasons. In autumn, INA08- t_s model produced highest accuracy, while GOT09-dT- t_s performed worse with highest RMSE (5.93 K) and lowest NSE (0.72).

In a short summary, both the simulations in single day (Figure 3) and in different seasons (Figure 5) suggested that INA08- t_s model can be used to combine with LST derived from remote sensing data.

3.3. Diurnal Temperature Variation over Days

In order to evaluate the simulation effect of DTC models on any days, five days in 2010 at the Suli site were randomly chosen for representing each season, and 20 days were selected in this study (Figure 6). Compared with observed values, the VAN06- t_s - ω_1 (Figure 6e), INA08- t_s (Figure 6d) and GOT09- t_s - τ (Figure 6i) models could evaluate DTC better with lower RMSEs (1.98, 2.03, and 2.04 K, respectively). The GOT09-dT- t_s (Figure 6h) model performed worst with highest RMSE (4.28 K). These results indicated that models with fixing t_s could produce higher accuracy, while models with fixing dT had large bias.

Figure 6. Scatter plots of observed LST and that estimated by the GOT01-dT (a), GOT01-ts (b), INA08-dT (c), INA08-ts (d), Van06-ts- ω_1 (e), Van06-ts- ω_2 (f), GOT09-dT- τ (g), GOT09-dT-ts (h) and GOT09-ts- τ (i) models, respectively.

3.4. Performance of the INA08-ts Model with MODIS Data under Clear-Sky Day

Considering the data availability, the MODIS LST data of four clear-sky days in 2010 at the Suli and Tanggula sites were selected to test the performance of INA08-ts model with remote sensing data (Figure 7). As expected, the INA08-ts model forced by the observed data performed better than that driven by the MODIS data at the Suli site on 21 April 2010 (Figure 7a) and the Tanggula site on 4 May 2010 (Figure 7d). This is most likely due to the large error of MODIS LST, which obviously overestimated at daytime and underestimated at nighttime at the Suli site on April 2010.

LST estimated by MODIS was underestimated during daytime at the Tanggula site on 4 May 2010. The INA08-ts model forced by the observed data and MODIS data showed similar performances at the Suli site on 2 October 2010 (Figure 7b) and the Tanggula site on 26 April 2010 (Figure 7c) due to the relatively high accuracy of MODIS LST. The different performances of the INA08-ts model forced by MODIS data (Figure 7) indicated that the accuracy of driving data was a primary factor for simulation accuracy [17] and the simulation accuracy of the INA08-ts model around sunrise will need further exploration. It indicated that day-to-day temporal simulation of LST is essential for improving the simulation accuracy around sunrise, which corresponding with that reported by Duan et al. [46].

Figure 7. DTC estimated by the INA08-ts model driven by the observed and MODIS data at the Suli (a,b) and Tanggula (c,d) sites, respectively.

4. Discussion

4.1. Sensitivity to the Surface Emissivity

There is no observation surface emissivity in the study area, which is a necessary parameter for calculating LST estimation. Moreover, there is no valid method for calculating surface emissivity. In order to study the sensitivity of LST to the surface emissivity, a semi-empirical method was applied based on heat transfer theory [10]. Once ε is overestimated or underestimated under near-neutral conditions, the estimated sensible heat flux (H_{est}) would produce large bias compared with observed sensible heat flux (H_{obs}). Thus, the difference between H_{est} and H_{obs} could be a judgment for LST. Therefore, RMSEs between H_{est} and H_{obs} were used to explore the sensitivity of LST to ε .

$$H_{est} = \rho c_p (LST - T_a) / r_h \quad (6)$$

where ρ is the air density (kg m^{-3}), c_p is the specific heat of air at constant pressure ($1004 \text{ J kg}^{-1} \text{ K}^{-1}$), T_a is temperature at specific height (2 m), and r_h is the heat transfer resistance.

Figure 8 showed that RMSE between H_{est} and H_{obs} changed with surface emissivity varying from 0.85 to 1.0 for all sites. Sensible heat flux was not sensitive to surface emissivity for all sites, which suggested that LST was not sensitive to surface emissivity. Therefore, a value of 0.99 recommended by Duan et al. [25] for surface emissivity is reasonable in the study. Moreover, the uncertainty of surface emissivity would not affect the evaluation on DTC models [25].

Figure 8. Sensitivity of sensible heat flux to the surface emissivity.

4.2. Influence of DTC Models on Energy Balance Components

The effect of each DTC model on energy balance components is essential for the adaptability of these models. We focused on the impact on net radiation flux, and sensible heat flux in the study (Figure 9).

Figure 9. RMSEs of the nine 4-para DTC models for net radiation and sensible heat flux in the TP.

Nine models were adopted for estimating net radiation and sensible heat flux over alpine meadows. The INA08- t_s model performed best with lowest RMSEs both for net radiation (9.23 W m^{-2}) and sensible heat flux (15.29 W m^{-2}). Moreover, models with fixing t_s produced better results than that with fixing dT or τ , which suggested that models with fixing t_s was more suitable for estimating DTC and energy components over alpine meadows in the TP.

4.3. Comparison of the Model Parameters

As aforementioned, all nine models have three free parameters (T_0 , T_a , and t_m), thus five variables include T_0 , T_a , T_{max} ($T_{max} = T_0 + T_a$), t_m , and k can be obtained. To evaluate the accuracy of the free parameters obtained by the other eight 4-para DTC models, T_{max} was used to compare with in situ observation, while T_0 , T_a , t_m , and k were compared with that estimated from INA08- t_s model (Figure 10).

Figure 10. RMSEs of the differences between values of the parameters (T_0 , T_a , and T_{max} : (a); t_m , and k : (b)) generated from the nine 4-para DTC models and that of the INA08- t_s model (or observed values, like T_{max}).

To facilitate understanding, RMSE between the value of parameters in each model and that of the INA08- t_s model (or observed value) was calculated and compared. The results suggested that GOT01- t_s and GOT09- t_s - τ models overestimated T_0 , while T_0 obtained from other models were underestimated when compared with that of the INA08- t_s model (Figure 10a). GOT01- t_s and GOT09- t_s - τ models showed lower RMSEs, while the RMSEs of other models were more than 3 K, especially that INA08-dT model had a high RMSE of 9.9 K (Figure 10a). Moreover, T_a values for all models showed similar characteristic with that of T_0 . Although RMSEs of T_0 and T_a were different for each other, values of T_{max} are similar ranging from 1.23 K for the GOT09- t_s - τ to 1.68 K for VAN06- t_s - ω_2 model (Figure 10a), indicating that all models could accurately produce daily maximum temperature.

RMSEs of t_m ranged from approximately 0.12 h for the GOT09- t_s - τ and GOT01- t_s models to 0.72 h for the INA08-dT model (Figure 10b). INA08-dT generated largest bias for k with RMSE of 1.71 h, while k values for other models showed similar RMSEs ranging from 0.37 h for the VAN06- t_s - ω_1 model to 0.69 h for GOT01-dT model.

4.4. Sensitivity Analysis for the Parameters of Nine 4-Para DTC Models

To further understand the sensitivity of the free parameter to each model, a sensitivity analysis of parameters of each model was performed with reasonable ranges in practical situations at the Suli site (Table 5).

Table 5. Sensitivity parameters and variation range for each model.

Cases	Sensitive Parameter	Ranges of Variation; Steps
GOT01-dT	dT	−8:8; 1
GOT01- t_s	t_s	$t_s - 1:t_s + 1; 0.1$
VAN06- t_s - ω_1	t_s	$t_s - 1:t_s + 1; 0.1$
	ω_1	$DD - 1:DD + 1; 0.1$
VAN06- t_s - ω_2	t_s	$t_s - 1:t_s + 1; 0.1$
	ω_2	$DD - 1:DD + 1; 0.1$
INA08-dT	dT	−8:8; 1
INA08- t_s	t_s	$t_s - 1:t_s + 1; 0.1$
GOT09-dT- τ	dT	−8:8; 1
	T	0:0.2; 0.01
GOT09-dT- t_s	dT	−8: 8; 1
	t_s	$t_s - 1:t_s + 1; 0.1$
GOT09- t_s - τ	t_s	$t_s - 1:t_s + 1; 0.1$
	T	0:0.2; 0.01

For dT , $RMSEs$ of the GOT01-dT and GOT09-dT- τ models showed similar characteristics as dT varied in four seasons, which fluctuated from appropriately 1 to 3 K in summer and from nearly 2 to 4 K in other seasons (Figure 11). It suggested that dT had low sensitivity to the GOT01-dT and GOT09-dT- τ models. $RMSEs$ of the INA08-dT model rapidly decreased at first and then slowly increased with increasing dT in winter, while it increased rapidly with increasing dT in spring and summer. However, the INA08-dT model displayed the similar trends with GOT01-dT and GOT09-dT- τ models in autumn, indicating that the INA08-dT model had high sensitivity to dT in winter, spring, and summer and low sensitivity in autumn. For the GOT09-dT- t_s model, $RMSEs$ rapidly increased in winter and followed a decreasing and then an obviously increasing trend with increasing dT in other seasons, indicating that dT was a very sensitive parameter in the GOT09-dT- t_s model.

For t_s , $RMSEs$ of the GOT09-dT- t_s model rapidly increased in winter, spring, and autumn, while it slowly decreased first and then slowly increased within the range from 1.1 to 1.5 K in summer (Figure 11). $RMSEs$ of other models slowly increased between 2 and 4 K in winter and decreased slowly between 1 and 1.6 K in summer, while it slowly fluctuated in spring and autumn. $RMSEs$ of all models fluctuated slowly in summer within a shallow range from 1 to 1.6 K. These results indicated that t_s was sensitive to the GOT09-dT- t_s model and insensitive to other five models in winter, spring, and autumn, while it had little impact on all models in summer.

For ω_1 , $RMSEs$ of VAN06- t_s - ω_1 slowly decreased in all seasons (Figure 11). As for ω_2 , $RMSEs$ of VAN06- t_s - ω_2 insignificantly decreased from 3.5 to 2.8 K in autumn and slowly increased in other seasons. Therefore, ω_1 and ω_2 were insensitive to VAN06- t_s - ω_1 and VAN06- t_s - ω_2 models, respectively. For τ , $RMSEs$ of both GOT09-dT- τ and GOT09- t_s - τ models insignificantly decreased in winter and autumn, while they slowly increased in spring and summer. Moreover, $RMSEs$ of the GOT09-dT- τ model were higher than that of GOT09- t_s - τ in whole four seasons.

In short summary, the INA08-dT and GOT09-dT- t_s models are more sensitive to dT , indicating that fixing dT as zero in the INA08-dT and GOT09-dT- t_s models probably yield large error. There exists an optimal value for dT in the GOT09-dT- t_s model to acquire high accuracy result. t_s is an insensitive parameter in the GOT01- t_s , INA08- t_s , VAN06- t_s - ω_1 , VAN06- t_s - ω_2 and GOT09- t_s - τ models, while it had large impact on the GOT09-dT- t_s model in winter, spring and autumn, indicating that large error may yield when fix t_s as a constant for GOT09-dT- t_s model in these seasons. ω and τ had little impact on the related models, however, optimal values of these parameters are difficult to determine. Therefore, models with fixing t_s (except the GOT09-dT- t_s model) could produce high accuracy result, however, further study still need to reduce its error in winter, spring, and autumn.

Figure 11. RMSEs of the nine 4-para models with ranging the corresponding fixed parameters (dT , t_s , ω , and τ) in four seasons.

4.5. Uncertainties and Limitations of the Evaluation on the Performance of the Nine 4-Para DTC Models

The uncertainty of the estimation on surface emissivity may influence the accuracy of the LST observations, thus affects the accuracy of model simulations, while values of the model parameters with and without error-added (Gaussian random error) were almost same [25]. Generally, the spatial resolution of MODIS is 1 km, while the observation data only represents the temperature characteristics around each observation site. The error between observation value and MODIS LST is inevitable due to the inconsistent scale [47]. Moreover, angular anisotropy of MODIS LSTs would also affect the accuracy of model performance. There is no ideal solution to make angular normalize due to its complexity [17]. Therefore, the accuracy of remote sensing products still needs to verify before application, especially in high altitude mountains. Moreover, there are at most four available data one day for MODIS, which may limit the DTC model operation.

All experiments in this study were performed under clear-sky conditions. However, clouds are common for high altitude mountains, which may limit model application in the TP. As Hong et al. [26] pointed out, one possible solution was to temporally aggregate clear-sky MODIS LSTs with a certain number of days to obtain representative clear-sky LST. However, it just reflects the thermal characteristics of the land surface, not the surface dynamics of a specific day. Further study is still needed to explore the universality of model application with and without cloud conditions. Previous studies have mainly focused on the model operation with single day [2,25,26], which caused the physical discontinuity around sunrise for modeling day-to-day DTC [46]. Therefore, further study is still needed to improve the LST accuracy around sunrise and verify in various underlying surfaces.

5. Conclusions

The performance of the nine 4-para DTC models were comprehensively evaluated and compared in the study. Some conclusions are made:

- (1) The INA08- t_s model showed best performance among all models over alpine meadows under in situ data. All models had highest accuracy in summer, though poorest performance displayed in winter.
- (2) Models with fixing t_s (i.e., INA08- t_s) could produce higher accuracy over random days. Moreover, the INA08- t_s model could evaluate high accuracy DTC with MODIS data.
- (3) T_0 values obtained from the GOT01- t_s and GOT09- t_s - τ models were overestimated compared with that generated by the INA08- t_s model, while other models underestimated T_0 value. T_a values for all models showed similar characteristics with that of T_0 values. The estimated daily maximum temperature for all models showed high accuracy compared with in situ data.
- (4) The sensitive analysis indicated that the INA08-dT and GOT09-dT- t_s models was more sensitive to dT , while t_s was an insensitive parameter for the related models. ω and τ had little impact on the related models. Models with fixing t_s could produce higher accuracy result than that with fixing dT .

This research provides guidance for evaluating suitable 4-para DTC models in various applications in different regions. Day-to-day temporal simulation of LST is essential for improving the simulation accuracy and helpful for describing surface energy balance and surface thermal inertia in the TP. Further study is still needed to consider day-to-day DTC simulation. Alpine meadows were chosen to investigate the performance of nine 4-para DTC models in the TP. Further study will focus on other underlying surfaces.

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