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# Short Communication

# Modelling the true monthly mean temperature from continuous measurements over global land

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**ABSTRACT:** The true monthly mean temperature is defined as the integral of the continuous temperature measurements in a month ($T_{d0}$), which is apparently different from the average ($T_{d1}$) of the monthly averaged maximum ($T_{max}$) and minimum ($T_{min}$) temperatures. Unfortunately, $T_{d1}$ instead of $T_{d0}$ has been widely used as the monthly mean temperature, not only as an input parameter for various models in ecology, climatology and hydrology but also as an effective factor for climate change studies. It has already been demonstrated in previous researches that the bias between $T_{d0}$ and $T_{d1}$ ($T_{bias} = T_{d1} - T_{d0}$) cannot be ignored; in some places, it could even be very large. Therefore, it is with great urgency that $T_{d0}$ should replace $T_{d1}$ to eliminate the impact of the imperfect monthly mean temperature on related researches. However, $T_{d0}$ cannot be obtained directly due to the lack of the historical observations of land surface air temperature ($T_a$) at a higher temporal resolution, e.g. hourly observations. In this study, a multiple linear regression (MLR)-based method is created to calculate $T_{d0}$ with the predictors of daylength, diurnal temperature range (DTR = $T_{max} - T_{min}$) and $T_{d1}$. The MLR method performs very well, with a mean $R^2$ of 0.61 over global land and 0.76 in arid or semi-arid areas. It can be used to improve studies on regional climate change and evaluations of climate model simulations.

KEY WORDS land surface air temperature; diurnal temperature range; climate change; global warming

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## 1. Introduction

Air temperature is a measurement of the atmospheric thermal state, which is one of the most fundamental variables widely used in ecology (O'Connor *et al.*, 2007), climatology (Jones and Moberg, 2003) and hydrology (Piani *et al.*, 2010) researches. The true monthly mean temperature (Brooks, 1921; Conner and Foster, 2008) is defined as the integral of the continuous temperature measurements in a month ($T_{d0}$), which is apparently different from the average of the monthly maximum and minimum temperatures ($T_{d1}$) (Jones *et al.*, 1999). There are three reasons why $T_{d0}$ cannot be replaced by $T_{d1}$. First, the timing of the occurrences of maximum and minimum temperatures ($T_{max}$ and $T_{min}$) can be widespread. Therefore, while $T_{max}$ and $T_{min}$ have a clear physical meaning, their monthly mean is difficult to interpret physically. Second, $T_{d1}$ may exaggerate the spatial heterogeneities compared with $T_{d0}$, because the impact of a variety of geographic (e.g. elevation) and transient (e.g. cloud cover) factors is greater on $T_{max}$ and $T_{min}$ (and hence in $T_{d1}$) than that on the hourly averaged mean temperature, $T_{d0}$ (Zeng and Wang, 2012). Finally, $T_{d1}$ samples land surface air temperature ($T_a$) only twice, leaving approximately two thirds of the day unmonitored and missing important information from weather events (Wang, 2014). However, $T_{d1}$ has been used as the monthly mean temperature instead of $T_{d0}$ in observations, modelling and other applications for historical and technical reasons (Thompson and Solomon, 2002; Kalnay and Cai, 2003; Schär *et al.*, 2004).

The bias between $T_{d1}$ and $T_{d0}$ ($T_{bias}$) cannot be ignored. Ye *et al.* (2002) drew the conclusion that $T_{bias}$ had seasonal and regional variations by comparing $T_{d1}$ with $T_{d0}$ in China. Bonacci *et al.* (2013) compared $T_{bias}$ at three main meteorological Croatian stations in different climate conditions and obtained the same conclusion. Wang (2014) compared the multiyear averages of bias between $T_{d1}$ and $T_{d0}$ during cold seasons and warm seasons and found that the multi-year mean bias during cold seasons in arid or semi-arid regions could be as large as 1 °C. Wang (2014) made a quantitative assessment of the bias in the use of $T_{d1}$ to estimate the trends of the mean $T_a$ and found that the use of $T_{d1}$ had an important impact on the warming rate on regional and local scales. Gough and He (2015) examined two methods to calculate the mean daily temperature, one based on the average of daily minimum and maximum

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temperatures and the other based on the average of 24 h at Churchill, Manitoba. Their results provide a cautionary note for the use of the min/max method of determining the mean temperatures, particularly in areas that are fog prone.

WMO (1983) suggested that it was advisable to use a true mean or a corrected value to correspond to a mean of 24 observations a day. Zeng and Wang (2012) argued from scientific, technological and historical perspectives that it is time to use the true monthly mean temperature in observations and model outputs. However, observations of $T_{max}$ and $T_{min}$ were the only available data sources that were widely used for the mean air temperature over land in the mid-19th century (Jones *et al.*, 2007), while the hourly $T_a$ observations have been available globally since the 21st century. Therefore, the existing length of the hourly time series drastically limits the use of $T_{d0}$ and hinders the replacement of $T_{d1}$ with $T_{d0}$.

Taking this into consideration, we use the multiple linear regression (MLR) method with predictors of daylength, diurnal temperature range (DTR = $T_{max} - T_{min}$) and $T_{d1}$ to fit the historical bias between $T_{d1}$ and $T_{d0}$ at approximately 6600 global-distributed weather stations from 2000 to 2013. Then, the historical $T_{d0}$ can be obtained based on the relationship between $T_{bias}$ and $T_{d1}$. The study is organized as follows: the data and methodology are presented in Section 2. The analysis and discussion of the results are presented in Section 3. The conclusions appear in Section 4.

## 2. Materials and methods

### 2.1. Data

The hourly observations of $T_a$ over global land for the years 2000–2013 were downloaded from the NOAA National Climatic Data Center (NCDC) Integrated Surface Database (ISD) (Smith *et al.*, 2011). The ISD dataset comprises worldwide hourly surface weather observations from approximately 20 000 stations historically and has undergone extensive automated quality control (Lott, 2004). The ISD data used in this article are available online at ftp://ftp.ncdc.noaa.gov/pub/data/noaa/.

### 2.2. Predictor variable selections

Three predictor variables, daylength, DTR (DTR = $T_{max} - T_{min}$) and $T_{d1}$ ($T_{d1} = (T_{max} + T_{min})/2$), are chosen for two reasons below.

From the perspective of data length, the observations of $T_{max}$ and $T_{min}$ can be traced to the mid-19th century (Jones *et al.*, 2007); these are the longest observed variables available to date. $T_{d1}$ and DTR calculated from $T_{max}$ and $T_{min}$ are then very appropriate for the consideration of the data length. Daylength, the ratio of daytime to a 24-h period, is a function of the month, day and latitude and it is not restricted by data length. Therefore, daylength, DTR and $T_{d1}$ are the three suitable variables existed to model the historical $T_{bias}$ for historical and technological reasons.

From the perspective of physical mechanism, owing to the longwave cooling effect, the $T_a$ near surface reaches its minimum during the early morning after sunrise. Then $T_a$ rises because of sensible heating from the surface and reaches its maximum in the early afternoon. Generally, $T_{d1}$ samples $T_a$ twice a day during the daytime, while $T_{d0}$ includes air temperature information over both daytime and nighttime. As the daylength gets longer, there are less hourly $T_a$ observations at night, most of which are lower than $T_{d1}$, causing a decrease in the bias between $T_{d1}$ and $T_{d0}$. DTR represents the contrast of $T_a$ between daytime and nighttime. It responds to surface moisture and vegetation transpiration (Feddema *et al.*, 2005; Zhou *et al.*, 2007), which affect to what extent energy received by the surface is partitioned into latent and sensible heat fluxes. In arid or semi-arid regions, more energy is partitioned into sensible heat, heating the air above the surface and affecting the shape of the diurnal cycle that results in a higher DTR. $T_{d1}$ is closely associated with the atmospheric downward longwave radiation, which warms the air above the surface during both day and night. Under clear sky conditions, atmospheric downward longwave radiation can be empirically calculated as a fourth-power function of the surface air temperature (Wang and Dickinson, 2013).

### 2.3. Data reprocessing

The first step involved excluding temperature observations that were flagged as erroneous by ISD quality control. Next, we included hourly temperature observations that passed the time consistency check recommended by the WMO (Zahumenský and SHMI, 2004) to remove unrealistic jumps. The ISD data were then converted from coordinated universal time (UTC) to local solar time. MLR-based method can be used both on stations and grids and both the results are good. We have tried the regression at both station and 1° × 1° grid scale and found that the results are a little better at station scale. However, in most scientific researches such as temperature trend studies, grid data are required. Therefore, the results at 1° × 1° grid scale were reported in this article. It is easy to use current available datasets, e.g. GHCN to derived $T_0$.

The monthly averaged DTR was produced only if hourly temperatures were available for more than 22 h a day and at least 15 days a month. In this study, $T_{max}$ and $T_{min}$ were selected from hourly $T_a$. $T_{d1}$ was calculated as the average of $T_{max}$ and $T_{min}$. $T_{d0}$ was the integral of the monthly averaged 24-h temperatures. DTR was calculated as the difference between $T_{max}$ and $T_{min}$. According to Herbert Glarner's formula (www.gandraxa.com/length_of_day.xml, accessed 13 May 2015), monthly daylength was computed from the latitude and midpoint of each month (Reda and Andreas, 2004).

### 2.4. Multiple linear regression

The form of the regression equation can be expressed as Equation (1):

$$T_{bias} = a\,\text{daylength} + b\,\text{DTR} + c\,T_{d1} \quad (1)$$

where *a*, *b*, *c* are the regression coefficients (Figure S1, Supporting Information) of MLR. $T_{bias}$ can also be expressed as the difference between $T_{d1}$ and $T_{d0}$ (Equation (2)):

$$T_{bias} = T_{d1} - T_{d0} \quad (2)$$

Synthesizing Equations (1) and (2), $T_{d0}$ is a linear combination of daylength, DTR and $T_{d1}$. When the regression coefficients are known, the historical $T_{d0}$ can be calculated as:

$$T_{d0} = (1 - c)\, T_{d1} - a\,\text{daylength} - b\,\text{DTR} \quad (3)$$

In each grid, the multicollinearity among the predictor variables was evaluated by the variance inflation factor (VIF) (Chatterjee and Price, 1977). Chatterjee and Price (1977) suggested that if VIF was in excess of 10, the regression results were unreliable. There were 0.59% grids on land with a VIF > 10 excluded after this step. Then MLR-based method was conducted on each grid. The responding variable was $T_{bias}$, and the predictor variables were daylength, DTR and $T_{d1}$ with a full time series. All the variables were normalized previously. Note that there is no pattern to the residuals plotted against the fitted values, and no heteroscedasticity can be observed.

### 2.5. Model evaluation

We evaluated the model in two steps. The first step was to calculate the ratio between the $R^2$ from tenfold cross-validation (Efron, 1983), which represented the applicability of the regression equation, and the $R^2$ from the original MLR using all data groups. In the tenfold cross-validation, the sample is divided into ten subsamples. Each of the ten subsamples serves as a hold-out group and the combined observations from the remaining nine subsamples serve as the training group. The performance of the ten prediction equations applied to the ten hold-out samples is recorded and then averaged. Because the hold-out sample was not involved in the selection of the model parameters, the performance of this sample is a more accurate estimate of the operating characteristics of the model with new data (Kabacoff, 2011).

The second step was to compute the differences of observed and fitted $T_{bias}$ between cold seasons (November to April in the Northern Hemisphere or May to October in the Southern Hemisphere) and warm seasons (May to October in the Northern Hemisphere or November to April in the Southern Hemisphere). By comparing the spatial patterns of the observed and predicted differences of $T_{bias}$ between warm and cold seasons, one can check whether the model can accurately reflect the impact of DTR and $T_{d1}$ on $T_{bias}$ because daylength only depends on latitude. This step illustrates the applicability of the method in climatic study because daylength does not vary annually.

### 2.6. Contributions of the predictors

The relative weights method was computed to demonstrate the contribution each predictor made to $R^2$. This method approximates the average increase in the $R^2$ obtained by adding a predictor variable across all possible submodels, considering both predictor's direct effect and its effect when combined with other predictors (Johnson and LeBreton, 2004).

## 3. Results and discussion

### 3.1. Performance of the method (statistical analysis and model evaluation)

Regressions in nearly all the grids on the land (95.03%) passed the $\alpha = 0.05$ Student's *t*-test (Figure S2). Figure 1 shows a scatterplot of the observed $T_{bias}$ against the fitted $T_{bias}$ obtained by the MLR method in a grid located in France. The MLR explains 92.3% of the $T_{bias}$ from 2000 to 2013 with a mean square error (MSE) of 0.009. This indicates that the method can simulate $T_{bias}$ accurately at the grid. The MSE and $R^2$ of MLRs over all the grids on land are shown in Figures 2 and 3, respectively. A low MSE and a high $R^2$ suggest a good regression result. In Figure 2, 81.36% of the grids have an MSE <0.05. In Figure 3, 63.36% of the grids have an $R^2$ >0.5. The MLR method performs very well, with an $R^2$ median of 0.61 over global land and 0.76 in arid or semi-arid areas. The grids distributed in mid-latitude regions show a good result, while the performance of grids along the coast and in polar regions is poor.

To illuminate the reason for the differences of the simulated results in different regions, we chose two stations for further analysis. Figures 4 and 5 present the time series of $T_{bias}$, daylength, DTR and $T_{d1}$ at two stations. One is located in an arid area (Figure 4) and the other is located in a coastal area (Figure 5). In Figure 4, $T_{bias}$ has an obvious seasonal variation and a relatively large fluctuation in arid regions, such as Sardy Field, USA, daylength, DTR and $T_{d1}$, all have similar seasonal variations with $T_{bias}$. There is little seasonal variation of $T_{bias}$ in coastal areas, such as Bochambeau, French Guiana, as shown in Figure 5. In

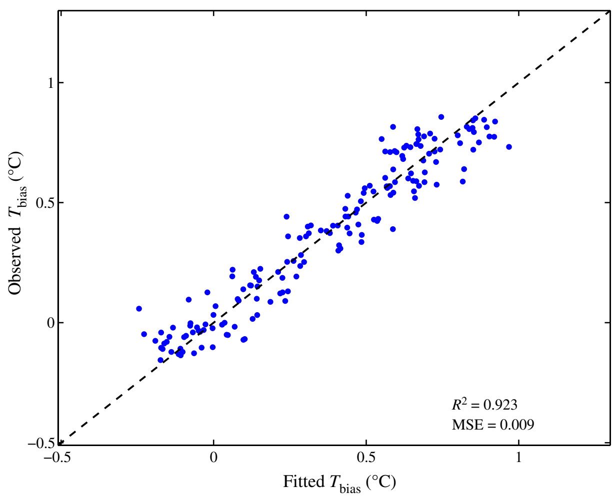


Figure 1. Scatterplot of the observed and fitted monthly $T_{bias}$ ($T_{bias} = T_{d1} - T_{d0}$) of a grid (4.5°W, 45.5°N) in France. $T_{d0}$ is the integral of the continuous temperature measurements in 1 month, and $T_{d1}$ is the average of the maximum ($T_{max}$) and minimum ($T_{min}$) temperatures. The dashed line is the 1 : 1 relationship.

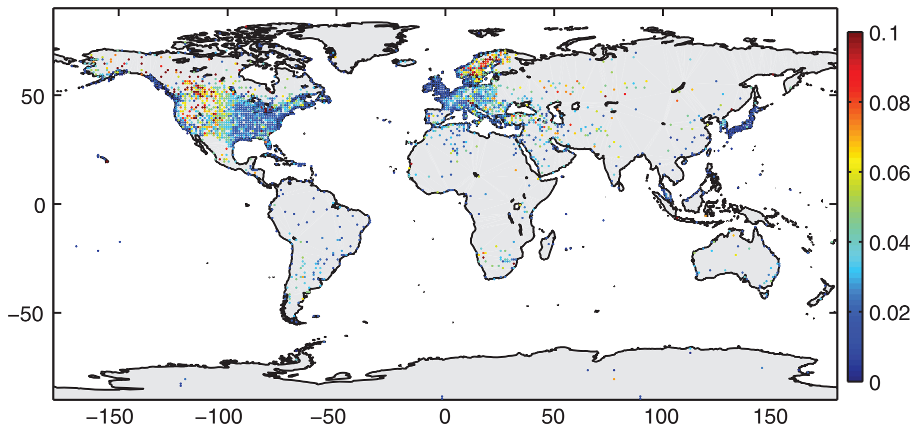


Figure 2. MSE of MLR of $T_{bias} = T_{d1} - T_{d0}$. $T_{d0}$ is the integral of the continuous temperature measurements in 1 month, and $T_{d1}$ is the average of the maximum ($T_{max}$) and minimum ($T_{min}$) temperatures. A low MSE indicates a good regression result. Of all of the grids, 81.36% have an MSE <0.05.

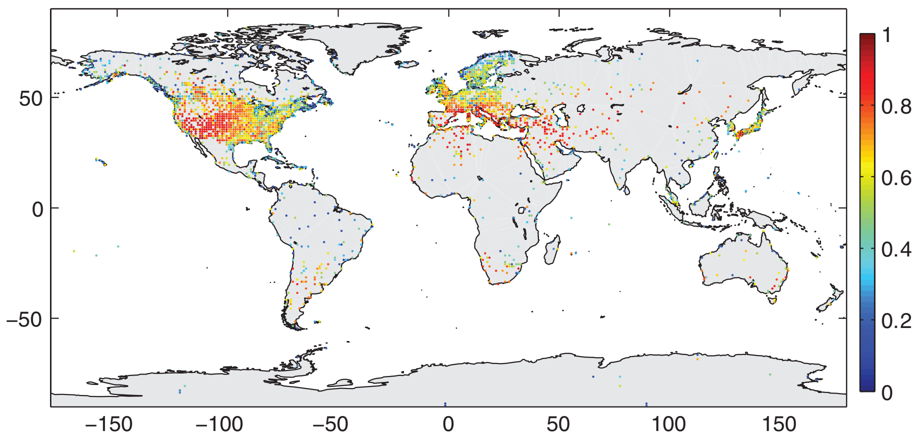


Figure 3. *R*-square of the MLR of $T_{bias} = T_{d1} - T_{d0}$. $T_{d0}$ is the integral of the continuous temperature measurements in 1 month, and $T_{d1}$ is the average of the maximum ($T_{max}$) and minimum ($T_{min}$) temperatures. Values closer to 1 indicate a good regression result. Of all of the grids, 63.36% over land have an $R^2$ value >0.5. The MLR method performs very well with a median $R^2$ value of 0.61 over global land and 0.76 in arid or semi-arid areas.

addition, the amplitude of the variation is small. Thus, it is difficult to depict $T_{bias}$ along the coast. Stations in polar regions have similar temporal variations of $T_{bias}$ along the coast. This is because in coastal regions, changes of $T_a$ are largely determined by advection rather than local impacts (e.g. land–atmosphere interaction). In polar regions, the main energy comes from longwave radiation, and there is no obvious seasonal variation. Furthermore, cold front that occurs randomly significantly affects the DTR over polar regions.

### 3.2. Contributions of the predictor variables

The relative weights (%) of the predictor variables (Figure 6) are used here to evaluate the contribution each predictor makes to the $R^2$ quantitatively, considering both its direct effect (e.g. its correlation with the criterion) and its effect when combined with the other variables in the regression equation (Johnson and LeBreton, 2004). The sum of the relative weights of the three predictor variables, daylength (Figure 6(a)), DTR (Figure 6(b)) and $T_{d1}$ (Figure 6(c)), is 1. A larger value represents more contributions a specific predictor makes to the $R^2$. In most of the grids on land, daylength contributes the most to the explanation of the $T_{bias}$ variation. The mean relative weights of daylength, $T_{d1}$ and DTR are 54.2, 25.6 and 20.2%, respectively.

Although DTR explained the $T_{bias}$ least, it has an important effect on the spatial distribution of $T_{bias}$. Figure 7 shows the differences of multiyear averaged $T_{bias}$ between cold seasons (November to April in the Northern Hemisphere or May to October in the Southern Hemisphere) and warm seasons (May to October in the Northern Hemisphere or November to April in the Southern Hemisphere). Figure 7(a) shows the observed $T_{bias}$, while Figure 7(b) shows the fitted $T_{bias}$ using the MLR model. Both demonstrate that $T_{bias}$ is higher in cold seasons than in warm seasons around the globe, especially in arid or semi-arid regions, which have the same pattern with Wang (2014). This pattern may be related to the contribution of DTR for the reasons that the values of daylength and $T_{d1}$ increase with latitude, while the distribution of DTR (Figure S3) is in good agreement with the distribution of the differences

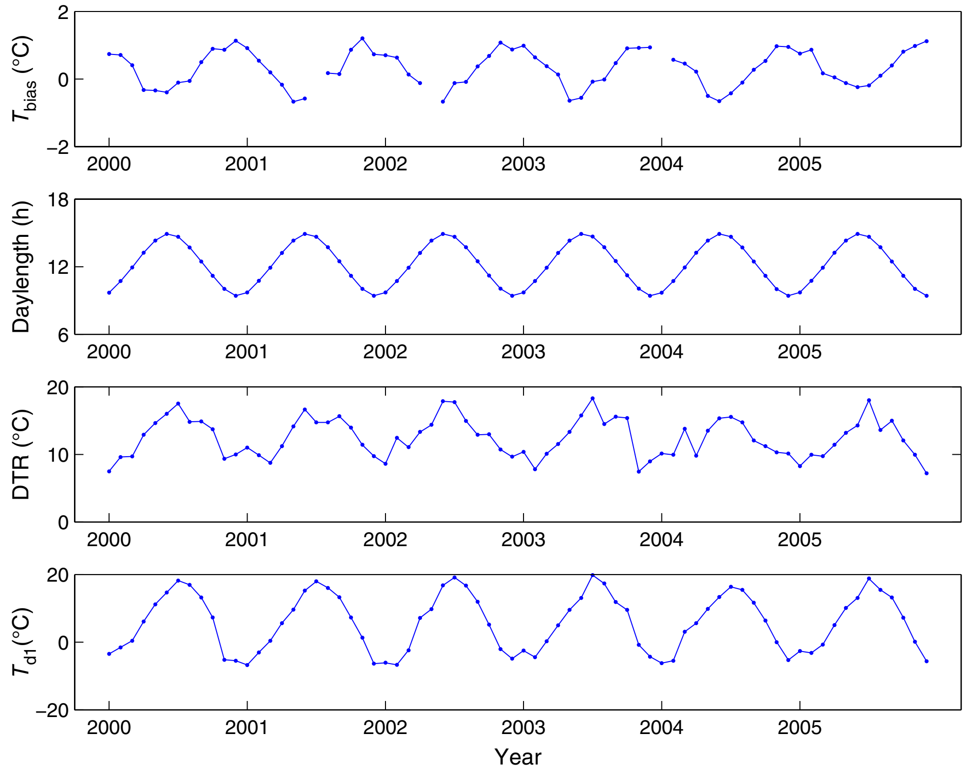


Figure 4. Time series of $T_{bias} = T_{d1} - T_{d0}$, daylength, DTR and $T_{d1}$ [the mean temperatures of the daily maximum ($T_{max}$) and minimum ($T_{min}$) temperatures] at Sardy Field, USA, which is located in an arid region. $T_{bias} = T_{d1} - T_{d0}$ has an obvious seasonal variation and a relatively large range of fluctuation; $T_{d0}$ is the integral of the continuous temperature measurements in 1 month. Daylength, DTR and $T_{d1}$ all have similar seasonal variations with $T_{bias}$.

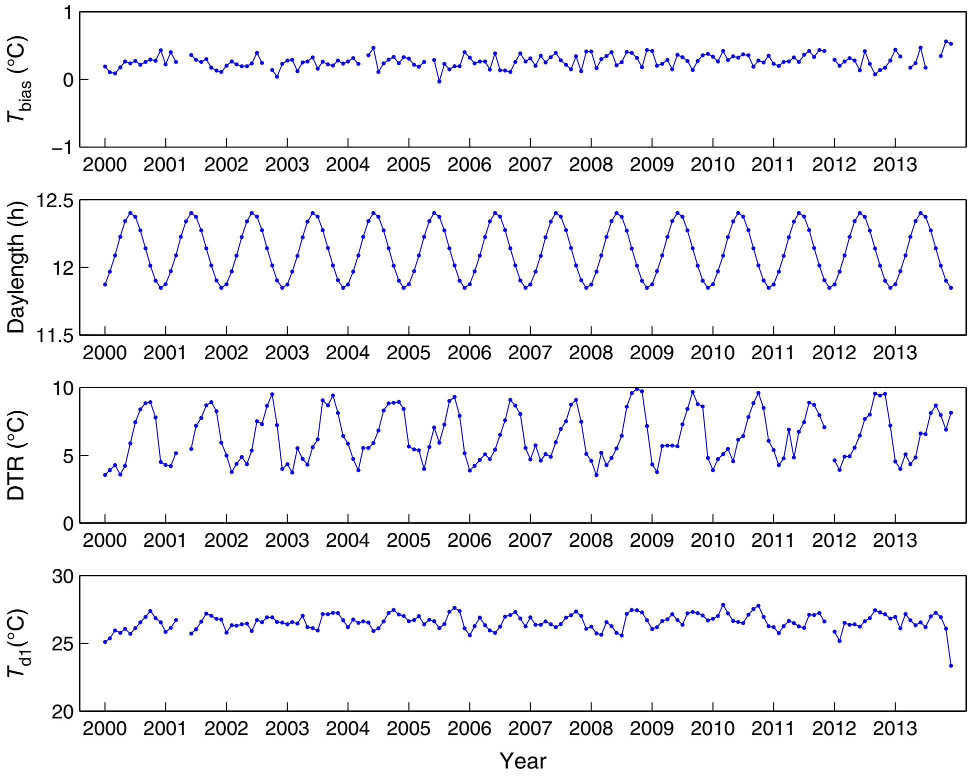


Figure 5. Time series of $T_{bias} = T_{d1} - T_{d0}$, daylength, DTR (DTR = $T_{max} - T_{min}$) and $T_{d1}$ [the mean temperatures of the daily maximum ($T_{max}$) and minimum ($T_{min}$) temperatures] at the Bochambeau, French Guiana station (52.4°W, 4.8°N) along the coast. $T_{d0}$ is the integral of the continuous temperature measurements in 1 month. There is little seasonal variation of $T_{bias}$. In addition, the amplitude of variation is small. It is difficult to depict the $T_{bias}$ along the coast with the predictor variables of daylength, DTR and $T_{d1}$.

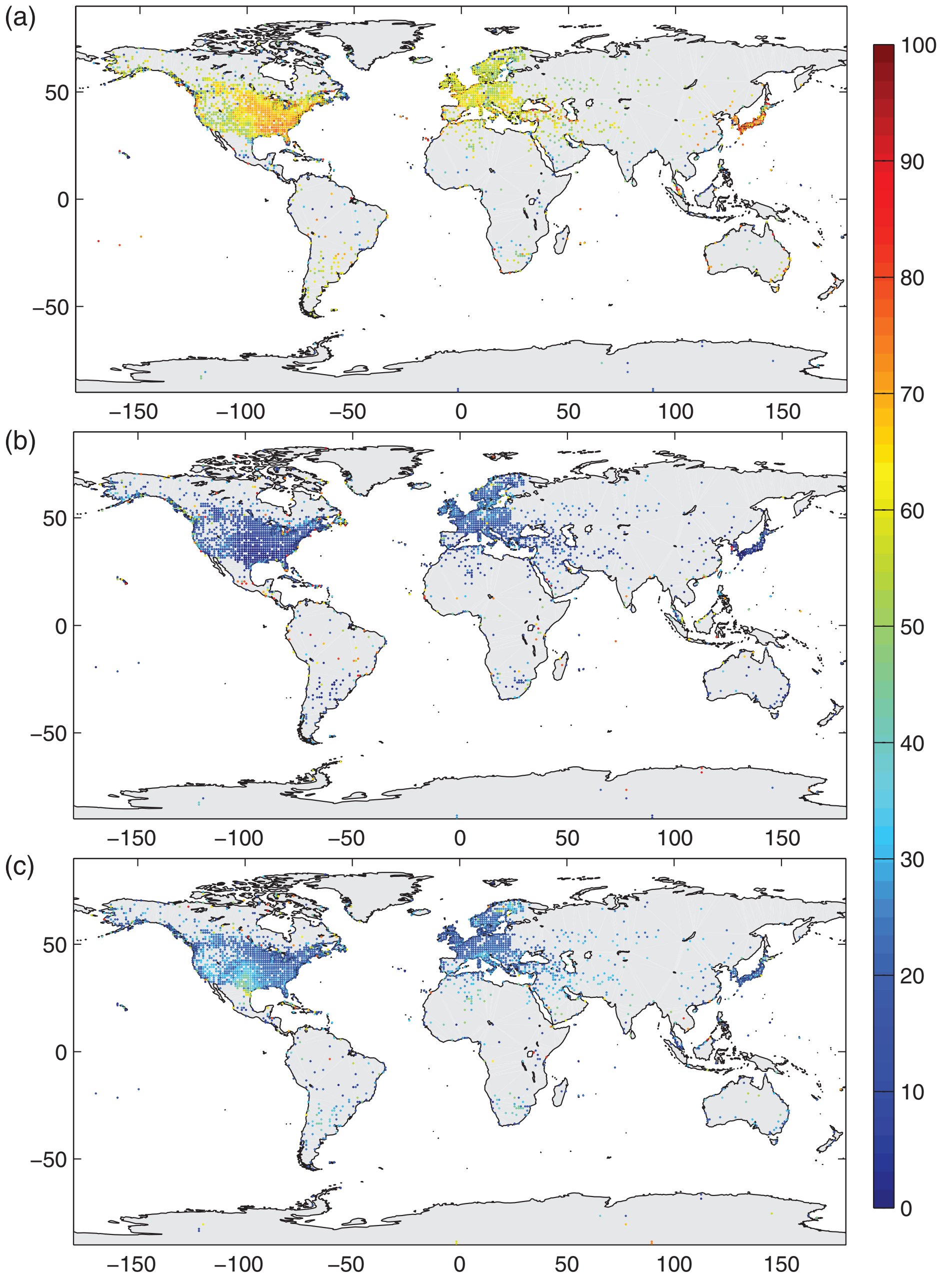


Figure 6. Relative weights (%) of predictor variables of $T_{bias} = T_{d1} - T_{d0}$: (a) daylength, (b) DTR (DTR = $T_{max} - T_{min}$) and (c) $T_{d1}$ [the mean temperatures of the daily maximum ($T_{max}$) and minimum ($T_{min}$) temperatures]. A larger value represents a larger contribution that a specific predictor makes to the $R^2$. The mean relative weights of daylength, $T_{d1}$ and DTR are 54.2, 25.6 and 20.2%, respectively.

of $T_{bias}$, high in arid or semi-arid regions and low in humid regions.

Compared with observed $T_{bias}$ (Figure 7(a)), the fitted $T_{bias}$ (Figure 7(b)) shows almost the same distribution, again verifying the reliability of our methods.

### 3.3. Predictability of the method

How well will this regression model perform in the prediction of the historical $T_{bias}$? The tenfold-validation method (Efron, 1983) was used to evaluate the applicability of the regression equation at each site. The ratio between the $R^2$ from tenfold cross-validation and the $R^2$ from the original MLR (Figure 8) is close to 1 at most of the land sites, except for those along the coast and in polar regions. This indicates that the regression equation is applicable and that this method can be used to predict the historical $T_{bias}$ over land globally, except for coastal and polar areas.

## 4. Conclusion

The mean land surface air temperature ($T_{d1}$) calculated from observations of $T_{max}$ and $T_{min}$ has been widely used in climatic change studies. However, studies have shown that $T_{d1}$ may have significant biases in depicting climatology and long-term trends of the mean air temperature over land in particular for regional studies. This is because

 

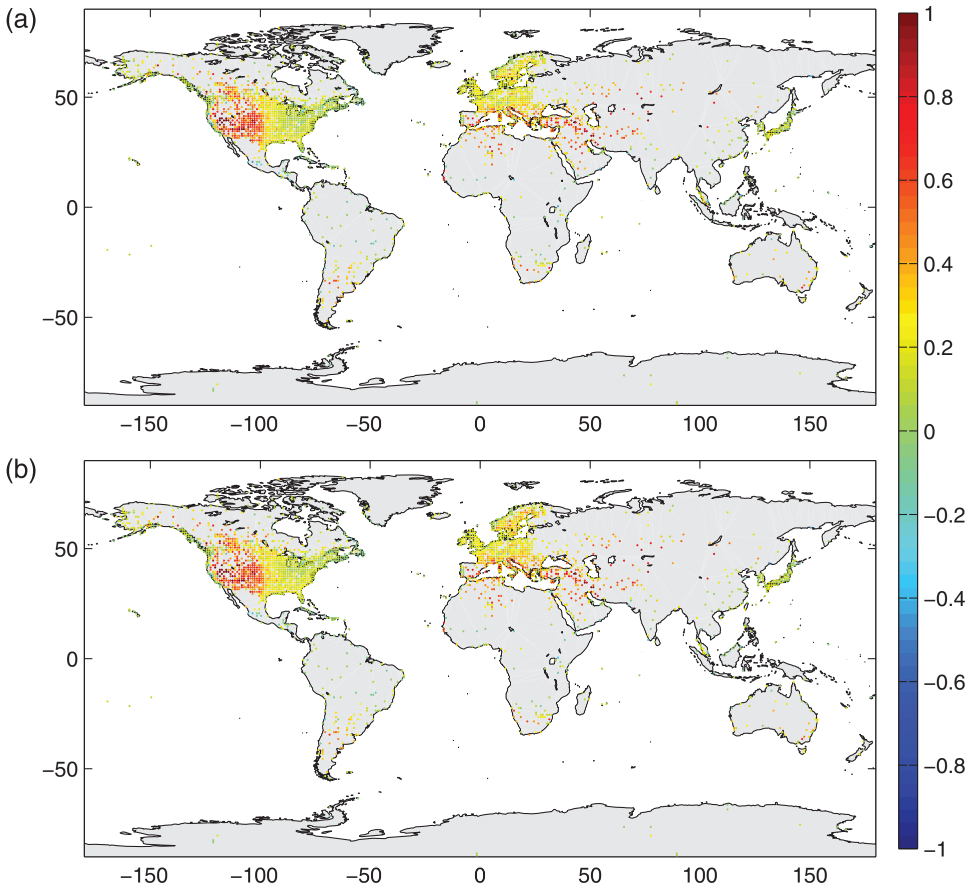


Figure 7. Differences of multiyear averaged $T_{\text{bias}} = T_{\text{d1}} - T_{\text{d0}}$ (unit: °C) between cold seasons (November to April in the Northern Hemisphere or May to October in the Southern Hemisphere) and warm seasons (May to October in the Northern Hemisphere or November to April in the Southern Hemisphere). $T_{\text{d0}}$ is the integral of the continuous temperature measurements in 1 month, and $T_{\text{d1}}$ is the average of the maximum ($T_{\text{max}}$) and minimum ($T_{\text{min}}$) temperatures. (a) Observed $T_{\text{bias}}$ and (b) fitted $T_{\text{bias}}$ using a MLR model. Both demonstrate that $T_{\text{bias}}$ is higher in cold seasons than warm seasons around the globe, especially in arid or semi-arid regions. Compared with observed $T_{\text{bias}}$ (a), the fitted $T_{\text{bias}}$ (b) shows almost the same distribution, which again verified the reliability of our methods.

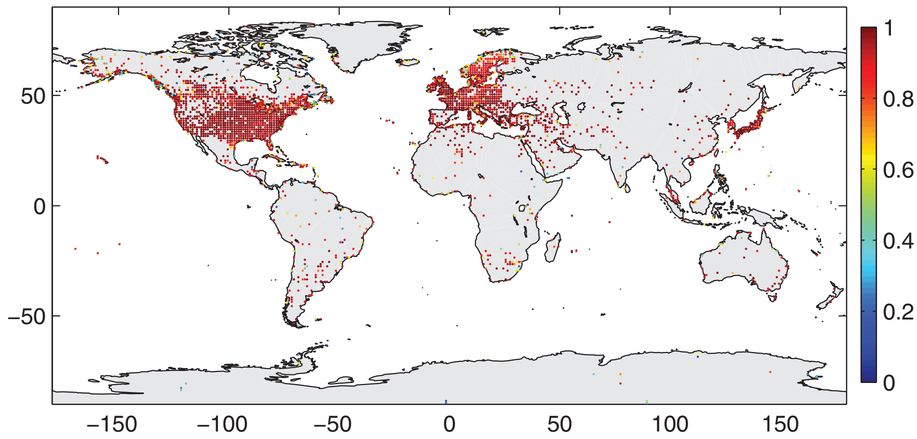


Figure 8. The ratio between the $R^2$ from tenfold cross-validation and the $R^2$ from the original MLR of $T_{\text{bias}} = T_{\text{d1}} - T_{\text{d0}}$ using all data groups. A ratio closer to 1 indicates the high applicability of the regression equation.

the diurnal cycle of $T_a$ depends on surface conditions, i.e. surface wetness and vegetation coverage.

In this study, we propose an MLR-based method with three predictor variables of daylength, DTR and $T_{\text{d1}}$ to model the bias of $T_{\text{d1}}$ ($T_{\text{bias}} = T_{\text{d1}} - T_{\text{d0}}$, where $T_{\text{d0}}$ is the mean $T_a$ calculated from 24 observations of hourly temperature). The MLR method performs very well, with a mean $R^2$ of 0.61 over global land and 0.76 in arid or semi-arid areas. The mean relative weights of daylength, $T_{\text{d1}}$ and DTR are 54.2, 25.6 and 20.2%, respectively.

Although ranking last, DTR has an important effect on the spatial distribution of $T_{bias}$.

The limitation of this method is that a uniform global regression equation cannot be obtained directly. However, this method has the potential to change the situation of the lack of historical $T_{d0}$ and facilitates the transformation from $T_{d1}$ to $T_{d0}$.

## Acknowledgements

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## Supporting Information

The following supporting information is available as part of the online article:

**Figure S1**. Regression coefficients of multiple linear regression (MLR) of $T_{bias} = T_{d1} - T_{d0}$. (a) Daylength, (b) daily temperature range (DTR = $T_{max} - T_{min}$) and (c) $T_{d1}$ [mean temperatures of the daily maximum ($T_{max}$) and minimum ($T_{min}$) temperatures].

**Figure S2**. The cyan dots indicate that the regressions pass the $\alpha = 0.05$ Student's *t*-test, and the red pluses indicate that the regressions do not pass the confidence test.

**Figure S3**. Annual mean diurnal temperature range (DTR = $T_{max} - T_{min}$) in units of °C from 2000 to 2013. The value of DTR is high in arid or semi-arid region, and low in humid regions, which shows a good agreement with the distribution of $T_{bias} = T_{d1} - T_{d0}$ differences between cold seasons and warm seasons. $T_{d0}$ is the integral of the continuous temperature measurements in a month, $T_{d1}$ is the average of the maximum ($T_{max}$) and minimum ($T_{min}$) temperatures.

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