Angular anisotropy of satellite observations of land surface temperature

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1 Satellite-based time series of land surface temperature (LST) have the potential to be an important tool to diagnose climate changes of the past several decades. Production of such a time series requires addressing several issues with using asynchronous satellite observations, including the diurnal cycle, clouds, and angular anisotropy. Here we evaluate the angular anisotropy of LST using one full year of simultaneous observations by two Geostationary Operational Environment Satellites, GOES-EAST and GOES-WEST, at the locations of five surface radiation (SURFRAD) stations. We develop a technique to convert directionally observed LST into direction-independent equivalent physical temperature of the land surface. The anisotropy model consists of an isotropic kernel, an emissivity kernel (LST dependence on viewing angle), and a solar kernel (effect of directional inhomogeneity of observed temperature). Application of this model reduces differences of LST observed from two satellites and between the satellites and surface ground truth - SURFRAD station observed LST. The techniques of angular adjustment and temporal interpolation of satellite observed LST open a path for blending together historical, current, and future observations of many geostationary and polar orbiters into a homogeneous multi-decadal data set for climate change research. Citation: Vinnikov, K. Y., Y. Yu, M. D. Goldberg, D. Tarpley, P. Romanov, I. Laszlo, and M. Chen (2012), Angular anisotropy of satellite observations of land surface temperature, Geophys. Res. Lett., 39, L23802, doi:10.1029/2012GL054059.

1. Introduction

After significant achievements in global satellite monitoring of sea ice extent decrease, sea level rise, Antarctic and Greenland ice sheet melting, tropospheric air warming, and sea surface temperature warming, the time has come to put together multi-decadal observations from the many geostationary satellites and polar orbiters with different geometry and timing of observations to create a comprehensive homogeneous land surface temperature (LST) data set for climate change studies.

There are three main obstacles to this task:

4 Diurnal cycle problem. Because of the variation of observation times, temporal adjustment is usually required for satellite observed LST. The simplest solution to this problem, proposed in this paper, is to use the climatology of LST diurnal and seasonal variations from geostationary satellites to interpolate or extrapolate satellite derived LST in time.

5 Cloudiness problem. As spatial resolution of satellite radiometers increases, detection of cloud contamination of LST observations becomes easier, spatial coverage improves, permitting the interpretation of satellite observed LST as a new meteorological variable – clear sky LST. Like other meteorological variables, clear sky LST has a time-dependent expected value and other statistical parameters at each geographical location and at each time, but it cannot be observed under cloudy conditions.

6 Angular anisotropy problem. Satellite observations show that at each specific location, and at each specific time, the dependence of LST on Sun position and viewing geometry is absolutely unique. Nevertheless, we expect that these angular dependencies have only a few important causes. Therefore, a universal empirical model of angular anisotropy of LST can be developed and its parameters can be statistically evaluated using available satellite observations. Angular correction of satellite retrieved LST must be applied before these data can be compiled into a long term data set, assimilated into weather prediction models or used in climate research.

There are several modeling, experimental, and case studies of the angular anisotropy of LST, which report variations of 2–4 K (and even larger) depending on the radiometer viewing angle and on the local Sun position [Minnis and Khayler, 2000; Sobrino and Cuenca, 1999; Cuenca and Sobrino, 2004; Lagouarde et al., 1995; Pinheiro et al., 2004, 2006; Rasmussen et al., 2010, 2011]. Experimental data show that bare soil emissivity decreases with increasing viewing zenith angle, but there is no angular dependence for grass emissivity [Sobrino and Cuenca, 1999; Cuenca and Sobrino 2004]. The same should be true for the emissivity of dense forest. At nighttime, when bare ground, near surface air, and vegetation canopy temperatures are closer to equilibrium and the temperature field is relatively homogeneous, angular anisotropy of LST should depend on the fractional amount of vegetation within the instrument’s field of view, which itself depends on the viewing angle. During daytime, incoming solar radiation, inhomogeneity of evaporation and shadowing produce an additional dependence of LST on the viewing zenith angle, its relative azimuth, and solar zenith
angle. This complexity causes physical models of anisotropy of LST to have a large number of spatially and time-dependent parameters describing the land cover, which greatly hinders their application to multi-decadal multi-satellite data.

[8] The main goal of this paper is to introduce a simple statistical model of angular anisotropy of LST, and to estimate its parameters using available simultaneous GOES-EAST and GOES-WEST observations collocated at the US Surface Radiation (SURFRAD) stations. The model can then be used in an algorithm for angular correction of satellite retrieved clear sky LST data. The main requirement of the angular correction algorithm is to convert satellite observed directional LST, \( T(\gamma, \xi, \beta) \), that depends on the satellite zenith viewing angle \( \gamma \), Sun zenith angle \( \xi \), and relative Sun-satellite azimuth \( \beta \), into a direction independent equivalent physical temperature that can be used in climate change studies.

2. Data

[9] Data used in this article consist of a full year (2001) time series of ground truth LST computed from observed upward \( F_u \) and downward \( F_d \) wide band hemispheric infrared fluxes at the five SURFRAD stations listed in Table 1, and collocated hourly time series of LST retrieved under clear sky conditions from observations of two geostationary satellites, GOES-8 (GOES-EAST, 75°W) and GOES-10 (GOES-WEST, 135°W). Satellite observed LST was retrieved using the split window algorithm of \( T_\text{v} \), and \( T_\text{s} \) [Yu et al., 2009]. Random and systematic errors of these data were assessed and discussed by Vinnikov et al. [2008] and Yu et al. [2012]. LST at SURFRAD stations is computed from the traditional equation

\[
T_S = \left[ F_u - (1 - e)F_d \right] / (\sigma \cdot e) \right]^{0.25}, \tag{1}
\]

where \( \sigma \) is the Stefan-Boltzmann constant and \( e \) is surface emissivity. Monthly mean values of spectral and broad-band land surface emissivity at station locations is estimated using data from the Moderate Resolution Imaging Spectroradiometer (MODIS) operational land surface emissivity product. The baseline fit method, based on a conceptual model developed from laboratory measurements of surface emissivity, is applied to fill in the spectral gaps between available emissivity wavelengths [Seemann et al., 2008]. Surface broadband emissivity at each station is obtained by the regression of the collocated emissivity values at three spectral bands [Wang et al., 2005; Ogawa et al., 2003]. No information is available on the accuracy of pixel-to-site emissivity estimates, yet the maximum regression emissivity error is about 0.006 regardless of the surface types [Wang et al., 2005]. A threshold cloud-detection algorithm has been applied to determine whether the surface scene is under strict clear-sky conditions. The most important aspect of this algorithm is the use of both satellite and SURFRAD observations. To determine clear-sky background, the maximum brightness temperature of GOES Channel 4 during the previous 10 days is composited; and the standard deviation of downwelling sky irradiance measured during the past 15 minutes at a SURFRAD site is checked. Eight parameters are chosen to characterize the essential differences of a cloudy pixel from a clear one. These parameters enable us to identify the possible spectral, spatial, and temporal singularities of a target pixel due to cloud contamination.

2.1. Time Adjustment

[10] The 15 minute difference in the observation time of the two satellites has been taken into account using analytical approximations of seasonal and diurnal variations of LST following Vinnikov et al. [2004, 2008, 2011]. We approximate the seasonal and diurnal variations (time-dependent expected value \( \bar{T}_S(t) \)) in the time series \( T_S(t) \) of observed GOES-8 LST at locations of SURFRAD stations as the product of the first two Fourier harmonics of the annual cycle \( (n = -2, -1, 0, 1, 2) \) and the first two harmonics of the diurnal cycle \( (k = -2, -1, 0, 1, 2) \).

\[
\bar{T}_S(t) = \sum_{n} \sum_{k} a_{nk} e^{i(2\pi n(t + k))}, \tag{2}
\]

where \( t \) is time in days, \( N = 365.25 \) is the length of a year in days, and \( a_{nk} \) are empirical coefficients. For all the pairs of observed LST of satellites GOES-8 and GOES-10 with times \( t_{S1} \) and \( t_{S2} \) of observations \( |t_{S1} - t_{S2}| \leq 15 \) minutes, the interpolated values \( \bar{T}_S(t_{S1}) \) are computed as:

\[
\bar{T}_S(t_{S1}) = \bar{T}_S(t_{S2}) - \bar{T}_S(t_{S1}) + \bar{T}_S(t_{S1}). \tag{3}
\]

Pairs of observed GOES-10 LST, \( T_{S1}(t_{S1}) \), and interpolated GOES-8 LST, \( T_{S2}(t_{S1}) \), are considered to be simultaneous. The assumption that the LST anomaly \( T(t_{S2}) - T(t_{S1}) \) does

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Table 1. SURFRAD Stations and Statistics of Differences Between GOES-EAST and GOES-WEST Observed LST at Locations of These Stations

<table>
<thead>
<tr>
<th>Station Name</th>
<th>Lat. (°N)</th>
<th>Lon. (°W)</th>
<th>GOES-8 ( \gamma_e )</th>
<th>GOES-10 ( \gamma_m )</th>
<th>Number of Observations</th>
<th>Raw data Time Shift = 15 min.</th>
<th>Time Shift Adjusted</th>
<th>Angular Adjusted</th>
</tr>
</thead>
<tbody>
<tr>
<td>Desert Rock, NV</td>
<td>36.63</td>
<td>116.02</td>
<td>60.14</td>
<td>46.81</td>
<td>148</td>
<td>0.2</td>
<td>0.6</td>
<td>0.5</td>
</tr>
<tr>
<td>Boulder, CO</td>
<td>40.13</td>
<td>105.24</td>
<td>55.68</td>
<td>55.40</td>
<td>292</td>
<td>1.3</td>
<td>1.3</td>
<td>0.5</td>
</tr>
<tr>
<td>Goodwin Creek, MS</td>
<td>34.25</td>
<td>89.87</td>
<td>42.68</td>
<td>61.89</td>
<td>134</td>
<td>2.5</td>
<td>1.3</td>
<td>0.5</td>
</tr>
<tr>
<td>Fort Peck, MT</td>
<td>48.31</td>
<td>105.10</td>
<td>62.42</td>
<td>62.36</td>
<td>466</td>
<td>0.6</td>
<td>0.9</td>
<td>0.3</td>
</tr>
<tr>
<td>Bondville, IL</td>
<td>40.05</td>
<td>88.37</td>
<td>48.12</td>
<td>66.14</td>
<td>579</td>
<td>1.7</td>
<td>1.8</td>
<td>0.0</td>
</tr>
</tbody>
</table>

*SURFRAD stations coordinates, satellite viewing angles, nighttime and daytime number of pairs of simultaneous LST GOES-EAST and GOES-WEST observations. Bias and angular anisotropy adjustment (equations (16) and (17)) was applied with the coefficients: \( A = -0.0138 \) K \( ^{-1} \), \( B \gamma = 0.57 \) K, \( C = 0.9954 \), \( D = 0.0140 \) K \( ^{-1} \).
not change during a 15-minute time interval, \( T(t_8) = T(t_{10}) = T(t_{10}) \) for \( |t_8 - t_{10}| \approx 15 \text{ min} \), appears reasonable because this time interval is small compared to the ~3 day decay scale in lag-correlation functions of LST anomalies [Vinnikov et al., 2008, 2011]. The same approach can be applied for larger temporal adjustment of satellite observed LST and other meteorological variables with very strong diurnal cycle.

3. Three-Kernel Approach

[11] The proposed statistical model to approximate the angular dependence of satellite-observed LST can be expressed by the following simple equation:

\[
T(\gamma, \xi, \beta)/T_0 = 1 + A \cdot \varphi(\gamma) + D \cdot \psi(\gamma, \xi, \beta),
\]

where: \( T_0 = T(\gamma = 0, \xi) \) is LST in the nadir direction at \( \gamma = 0 \). The first term, 1, on the right side of (4), has the sense of a basic “isotropic kernel” that should be corrected by two other kernels; \( \varphi(\gamma) \) is the “emissivity kernel,” related to observation angle anisotropy; \( \psi(\gamma, \xi, \beta) \) is the “solar kernel,” related to spatial inhomogeneity of surface heating and shadowing of different parts of the land surface and its cover, \( [\psi(\gamma, \xi \geq 90^\circ, \beta) = 0 \text{ at nighttime}; A \) and \( D \) are coefficients that should be estimated from observations. These coefficients depend on land topography and the land cover structure. Such a model follows the traditional structure of BRDF (Bidirectional Reflectance Distribution Function) semi-empirical models based on a linear combination of “kernels” as generalized by Jupp [2000].

[12] Analytical expressions for the kernels \( \varphi(\gamma) \) and \( \psi(\gamma, \xi, \beta) \) have been developed using, as described above, synchronous clear sky LST observations of two satellites, GOES-8 and GOES-10, at the location of five satellite pixels coincident with representative SURFRAD stations during one full year 2001.

3.1. Emissivity Kernel

[13] We used nighttime only (\( \xi > 90^\circ \)) observations of these satellites at locations of all five SURFRAD stations together to find the best expression for the emissivity kernel \( \varphi(\gamma) \) and to estimate \( A \). Using LST estimates derived from GOES-EAST (\( T_E \)) and GOES-WEST (\( T_W \)), it is assumed that one of them, chosen arbitrarily, is unbiased and the other one has a constant bias in observed LST due to instrumental or calibration imperfections. Assuming that LST observed by GOES-WEST, \( T_W \), is biased compared to GOES-EAST, the \( T_W \) value is then substituted by \( T_W + B_W \), where \( B_W \) is an unknown constant bias. Using expression (4) for nighttime observations, i.e., solar kernel \( \psi(\gamma, \xi, \beta) \equiv 0 \), we can write:

\[
T_E/[1 + A \cdot \varphi(\gamma_E)] = (T_W + B_W)/[1 + A \cdot \varphi(\gamma_W)].
\]

This equation in the following form can be used for testing different approximations of \( \varphi(\gamma) \) and least square estimation of the unknowns \( B_W \) and \( A \):

\[
T_E - T_W \approx B_W + A[(T_W + B_W) \cdot \varphi(\gamma_E) - T_E \cdot \varphi(\gamma_W)].
\]

The satellite zenith angles \( \gamma_E \) and \( \gamma_W \) are given in Table 1. The angular sampling is very limited, with only two zenith angles per site. One could fit many functions that match these two angles, yet have different shapes. With the assumption that a common universal shape of \( \varphi(\gamma) \) exists and can be found, equation (6) has been written for each pair of simultaneous nighttime observations of the satellites at the locations of all five SURFRAD stations, giving a total of 1619 equations. Applying the ordinary least squares technique, fewer than three iterations are needed to resolve the rather weak nonlinearity in (6). We obtained the best results using the following analytical expression for \( \varphi(\gamma) \) and values for \( B_W \) and \( A \):

\[
\varphi(\gamma) = 1 - \cos(\gamma), B_W = 0.57K, A = -0.0138K^{-1}.
\]

3.2. Solar Kernel

[14] Following the same procedure as for the emissivity kernel, the following simple analytical expression can be used to approximate the solar kernel for \( \xi \leq 90^\circ \) is recommended:

\[
\psi(\gamma, \xi, \beta) = \sin(\gamma) \cos(\xi) \sin(\xi) \cos(\xi - \gamma) \cos(\beta).
\]

In this approximation, \( \cos(\xi) \) represents dependence of incoming solar radiation on solar zenith angle; \( \sin(\xi) \cos(\beta) \) represents the effect of solar shadows; \( \cos(\xi - \gamma) \) represents the LST hot spot effect at \( \gamma \to \xi \) and \( \beta \to 0 \); and \( \sin(\gamma) \) is needed to satisfy the definition requirement \( \psi(\gamma = 0) = 0 \). Nevertheless, the expressions (7) and (8) are purely empirical. The equations for daytime observations, analogues to (5) and (6), which are for nighttime, can be written as:

\[
T_E[1 + A \varphi(\gamma_W)] - (T_W + B_W)[1 + A \varphi(\gamma_E)] \\
\approx D[(T_W + B_W)\psi(\gamma_E, \xi, \beta_E) - T_E \psi(\gamma_W, \xi, \beta_W)].
\]

Assuming \( A \) and \( B_W \) are known, equation (9), written for each pair of daytime simultaneous observations, has been used to obtain the least squares estimate of the amplitude \( D \):

\[
D = 0.0140K^{-1}.
\]

The function \( T(\gamma, \xi, \beta)/T_0 \) for different solar zenith angles \( \xi \) is shown in Figure 1.

4. Algorithm for Angular Correction of Satellite-Observed LST

[15] Satellite observed angular dependent LST needs to be converted into the isotropic, direction-independent, equivalent physical temperature, \( \theta \), which can then be used in climate change studies. Such an equivalent temperature can be defined by the expression:

\[
\theta \equiv \pi^{-1} \int_0^{2\pi} \int_0^{\pi/2} T(\gamma, \xi, \beta)^4 \sin(\gamma) \cdot d\gamma \cdot d\beta.
\]
\[ T(\gamma, \xi, \beta) = T^*(\gamma^*, \xi^*, \beta^*) / \left[ 1 + A \phi(\gamma^*) + D \psi(\gamma^*, \xi^*, \beta^*) \right] \]

\[ \theta = C \cdot T^*(\gamma^*, \xi^*, \beta^*) / \left[ 1 + A \phi(\gamma^*) + D \psi(\gamma^*, \xi^*, \beta^*) \right] \]

\[ C = \left( \int_{0}^{\pi/2} \int_{0}^{2\pi} \left[ 1 + A \phi(\gamma^*) + D \psi(\gamma^*, \xi^*, \beta^*) \right]^4 \sin(\gamma) \cos(\gamma) \cdot d\gamma \cdot d\beta \right)^{0.25} \]

In such a way we can estimate the unbiased angular-corrected equivalent values of LST observed by the GOES-EAST and GOES-WEST satellites.

\[ \theta_E = C \cdot T_{E}^* / \left[ 1 + A \phi(\gamma_E^*) + D \psi(\gamma_E^*, \xi_E^*, \beta_E^*) \right] \]

\[ \theta_W = C \cdot \left( T_{W}^* + B_W \right) / \left[ 1 + A \phi(\gamma_W^*) + D \psi(\gamma_W^*, \xi_W^*, \beta_W^*) \right] \]

For two observations for the same location, the best estimate should be obtained by averaging observations from both satellites \( \theta_{\text{ave}} = (\theta_E + \theta_W)/2 \).

### 5. Statistics of Errors

The decrease of mean and root mean square (RMS) differences between GOES-EAST and GOES-WEST observed LST can be used as a measure of the efficiency of the applied data adjustment. The estimates are shown in Table 1. Raw data (uncorrected LST retrievals) at the location of SURFRAD stations have mean difference (\( T_E - T_W \)) ranging from 0.2 to 2.5 K and RMS differences from 1.3 to 2.2 K. Adjustment for the 15-minute shift in the time of observation of these two satellites noticeably decreases the range of the mean (\( T_E - T_W \)) differences to 0.6 to 1.8 K and the RMS differences to values between 1.3 and 1.9 K. Angular adjustment, which includes the mean bias correction, improves the error statistics further. Mean differences for SURFRAD stations are in the range of ±0.5 K and RMS differences are in the range from 1.2 to 1.4 K.

As a result of the angular adjustment at all five stations (Table 2), we obtained a significant decrease of the systematic error in differences between LST observed by GOES-EAST and GOES-WEST. At the first three stations in the Table (Desert Rock, NV; Boulder, CO; Goodwin Creek, MS) we obtained a very substantial decrease of random error in this difference. The last two stations (Fort Peck, MT; and Bondville, IL), located in regions with very flat topography and homogeneous vegetation cover, exhibit only small decreases of this random error.

Let us compare the temporally and angular adjusted satellite observed \( \theta_E \) and \( \theta_W \) with \( T_S \) observed at SURFRAD stations (columns 2–5 in Table 2), which represent the available ground truth LST. However, it is expected that \( T_S \) could be noticeably biased because of the small footprint of the station radiometer measuring the upward flux \( F_u \) compared to the much larger satellite pixel. This may also explain the larger RMS error \( (\theta_E - T_S) \) or \( (\theta_W - T_S) \) in Table 2 than for \( (\theta_E - \theta_W) \) in Table 1. Averaging of the two LST temporal- and angular-adjusted observations obtained for the same pixel at the same time from two satellites GOES-EAST and GOES-WEST further decreases the random error of observation (last column in Table 2). The largest bias of SURFRAD LST data compared to satellite LST is at the Desert Rock, NV station, −1.5 K. This could mean that the in situ measurements at Desert Rock do not represent the surrounding areas well, that the emissivity is underestimated, or that there is an instrumental problem. Biases at other stations do not exceed ±0.5 K.
Table 2. Statistics of Differences Satellite (GOES-EAST, GOES-WEST) and Surface (SURFRAD) Observed LST

<table>
<thead>
<tr>
<th>Station Name</th>
<th>((\theta_E - T_3)_A), K</th>
<th>((\theta_W - T_3)_A), K</th>
<th>([\theta_E + \theta_W]/2 - T_3), K</th>
<th>Solar Kernel (D_{station}), K (-1)</th>
<th>((\theta_E - B_W), K)</th>
<th>([\theta_E + \theta_W]/2 - T_3), K</th>
</tr>
</thead>
<tbody>
<tr>
<td>Desert Rock, NV</td>
<td>-1.1 1.4 -1.6 1.0 -1.4 1.0</td>
<td>0.0165</td>
<td>0.4 1.3 -1.5 1.0</td>
<td>Boulder, CO</td>
<td>-0.2 1.5 -0.7 1.3 -0.5 1.2</td>
<td>0.0149</td>
</tr>
<tr>
<td>Goodwin Creek, MS</td>
<td>-0.6 1.2 -0.1 1.4 -0.3 1.2</td>
<td>0.0126</td>
<td>-0.5 1.2 -0.5 1.2</td>
<td>Fort Peck, MT</td>
<td>0.1 1.6 -0.2 1.4 0.0 1.3</td>
<td>0.0097</td>
</tr>
<tr>
<td>Bondville, IL</td>
<td>0.3 1.4 0.3 1.4 0.3 1.3</td>
<td>0.0068</td>
<td>0.1 1.2 0.3 1.3</td>
<td>Boulder, CO</td>
<td>-0.2 1.5 -0.7 1.3 -0.5 1.2</td>
<td>0.0126</td>
</tr>
</tbody>
</table>

*Results are for angular anisotropy adjustment based on universal solar kernel coefficient value \(D = 0.0140\) K \(-1\) (estimated for all stations together) and for the adjustment based on solar kernel coefficients \(D_{station}\) estimated separately for each of the stations. Infrared kernel coefficient \(A = -0.0138\) K \(-1\) and GOES-WEST LST \(B_W = 0.57\) K and \(C = 0.9954\) are common for all estimates.

[19] In order to illustrate the overall improvements achieved by the statistical distribution of the difference between LST observed from GOES-EAST and GOES-WEST at Desert Rock, NV, it is presented in Figure 2 (top). The first panel displays the initial distribution of the raw differences \((T_E - T_W)\), which still contain the 15-minute time mismatch between the observations of the two satellites. After time shift (and constant bias) adjustment, the distribution of \((T_E - T_W - B_W)\) is getting noticeably taller and narrower (second panel). Angular correction makes the distribution \((\theta_E - \theta_W)\) significantly taller and significantly narrower (third panel). This progressive narrowing of the statistical distribution proves the effectiveness of the proposed angular adjustment technique. In the third panel a significant part of angular anisotropy is corrected, which mainly leaves the residual random error of satellite-retrieved LST. This random error can be decreased \(2^{0.5}\) times by averaging observations of two satellites, \(\theta_{ave} = (\theta_E + \theta_W)/2\). The statistical distribution of the difference of \(\theta_{ave}\) and \(T_S\) is shown in Figure 2 (right). \(T_S\) here is the in situ LST obtained at the SURFRAD station. This distribution has an even sharper shape than the others and has a standard deviation of 1.0 K. If we use the estimate of RMS(\(\theta_E - \theta_W\)) = 1.3 K given in Table 1 and the known standard error of \(T_S\) which is 0.6 K at Desert Rock [Vinnikov et al., 2008], we conclude that these estimates are consistent with the assumption that random errors in the angular adjusted satellite LST and in the SURFRAD station observed LST are not just random, but also statistically independent. Variations of atmospheric temperature and water vapor profiles are not the source of these errors since both satellites are looking at the same scene.

[20] Systematic seasonal/ diurnal pattern of the time adjusted debiased difference \((T_E - T_W - B_W)\) between GOES-EAST and GOES-WEST observed LST at Desert Rock, NV, is shown in Figure 2 (bottom left). This difference is approximated here with an expression analogous to (2). The bottom-middle panel presents the same difference but for angular adjusted temperatures \((\theta_E - \theta_W)\). The main components of seasonal and diurnal cycles have been removed by application of the angular adjustment (16-17). The bottom-right panel displays seasonal-diurnal cycles in the difference between the average of the two angular adjusted satellite temperatures and SURFRAD observed temperatures \([(\theta_E + \theta_W)/2 - T_3]\). This pattern clearly shows that the proposed angular adjustment technique removes much of the geometric inhomogeneity of satellite LST.

[21] The estimates presented in Tables 1 and 2 show that the effect of the angular adjustment of satellite observed LST is very strong for the first three stations and is almost insignificant for the last two. Assuming that our earlier estimates of parameters \(A\) and \(B_W\) are correct, we estimated optimal values of \(D_{station}\) anisotropy coefficients for each of the five SURFRAD stations. The estimates of these coefficients and error statistics are given in Table 2. It is most interesting that estimates of the \(D_{station}\) coefficients seem to depend on topography and vegetation cover smoothness. They vary from 0.0165 K \(-1\) at Desert Rock, NV to 0.0068 K \(-1\) at Bondville, IL. It looks as if this parameter can be used as a measure of thermal angular anisotropy for different land surfaces. However, using optimal local estimates of \(D_{station}\) instead of its universal value increases the accuracy of angular adjusted satellite observed LST. In this study this improvement of accuracy is not significant and can be ignored.

6. Concluding Remarks

[22] This analysis assumes that satellite retrieved LST is an aggregate of the real physical temperature of land surface components within the field of view of a satellite radiometer. However, currently available algorithms for LST retrieval may inadvertently modify angular dependence of LST on viewing angle. Therefore, the empirical model (4) has to be validated using independently observed data and different retrieval algorithms, for example, other algorithms listed by Yu et al. [2009].

[23] Surface observed \(T_S\) at SURFRAD stations is used here for the model validation, but not for model development. There are two pieces of evidence that we are moving in the proper direction. The first is a significant decrease in systematic and RMS differences between observed \(T_E\) \& \(T_W\) after angular adjustment (Table 1). Some decrease is guaranteed by using equations (6) and (9) to estimate the model’s parameters. The second, more important, evidence is the decreasing systematic and RMS difference between the angular adjusted satellite observed surface temperature \((\theta_E, \theta_W, \theta_{ave})\) and independently observed ground truth \(T_S\), shown in Table 2.

[24] The weakest part of this research is that all five SURFRAD stations are observed from satellites at a very
limited range of viewing zenith angles ranging from 43° to 66°. All observations at the same location have constant satellite viewing angles $\gamma_E$ and $\gamma_W$. Because of this limitation we are not able to properly estimate the value of the emissivity kernel coefficients, $A$, for each station separately. Another limitation consists in the lack of observations at small solar zenith angles, $\xi < 10.75^\circ$, in our data set. Nevertheless, we have the advantage of using data for a full year so all seasonal and diurnal variations of solar zenith and azimuth angles and evolution of land surface cover are well represented.

[25] There are some research problems for which correct results can be obtained without angular adjustment of satellite observed LST data. However, climate change research usually needs multisatellite multi-decadal observations in which temporal and spatial homogenization include their temporal synchronization and angular adjustment. The proposed climatological approach for such homogenization needs more work before it can be recommended for application. Fortunately, there is a very large territory overlapped by multi-year LST observation from the US GOES-EAST and GOES-WEST satellites. These data can be used to improve representation of satellite and solar zenith angles, to improve analytical expressions for kernel functions $\phi(\gamma)$ and $\psi(\gamma, \xi, \beta)$ in (4). The main difficulty in using these data is the absence of an appropriate algorithm for the detection of cloud contaminated pixels. It would also be desirable to obtain estimates of $A$ and $D$ anisotropy coefficients for the main types of landscapes and surface covers. A climatological approach is only one of the possible approaches to angular correction of satellite observed LST.

[26] The results obtained in this paper have numerous further research applications:

- Evaluation of angular anisotropy of LST based on overlapping observations of several satellites. This can be two geostationary satellites, as GOES-EAST and GOES-WEST in this paper, but it can be a combination of two or more geostationary and polar orbiters.
- Conversion of directionally-observed LST into direction-independent equivalent physical temperature of land surface.
- Temporal interpolation of satellite-observed LST with a very strong diurnal cycle. In this paper, this was very small 15-minute adjustment of GOES-8 observed LST. The same technique can be applied for larger temporal adjustment of LST observations from polar orbiters. In such a case all satellite observed LST should be first corrected for angular dependence.
- Finally, the proposed approaches to angular and temporal adjustments of satellite observed LST do not modify observed climatic trends and are appropriate for satellite monitoring of long-term climate change.

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References


