Estimation of land surface temperature from a Geostationary Operational Environmental Satellite (GOES-8)

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[1] Two algorithms are developed and applied to observations from the Geostationary Operational Environmental Satellite (GOES) to enable frequent estimate of Land Surface Temperature (LST) representing the diurnal cycle. The derived LSTs are evaluated against a wide range of ground observations. Both algorithms are based on radiative transfer theory; one is similar to the classical split window approach used for deriving Sea Surface Temperature (SST), while the other is a three-channel algorithm. The three-channel LST algorithm aims to improve atmospheric correction by utilizing the characteristics of the middle-infrared (MIR) band. Effects of both the atmosphere and the surface emissivity are accounted for. The simulations from the proposed algorithms are compared with previously developed generalized split window algorithm, and a split window algorithm with water vapor correction. During daytime, the proposed new split window algorithm gives the best LST retrievals, while during nighttime, the proposed three-channel algorithm gives the best retrievals, both within a Root Mean Square (RMS) error of less than 1 K and without a significant bias. Evaluations against the Atmospheric Radiation Measurement (ARM) observations of radiometric surface temperatures and Surface Radiation Network (SURFRAD) observations of outgoing long wave (LW) radiation indicate that LST can be determined from the actual GOES-8 observations within an RMS accuracy of about 1–2 K, standard error of about 1 K, and bias of less than 1 K. When evaluated against the North Carolina Agricultural Research Service (NCARS) soil temperature as observed at depth of 8 in. and against air temperature observations, the amplitude of the retrieved LST is found to be significantly greater than that of the observed soil temperature, lower than the nighttime air temperature, and higher than the daytime air temperature. When the soil observations are “corrected” to account for the depth difference, they are in good agreement with the LST retrieved from the satellite observations. This indicates that observations of soil temperature, which are more readily available than measurements of “skin” temperatures, can be useful in evaluating satellite-based estimates. The LST retrieved from both of the proposed algorithms and from a NOAA/NESDIS algorithm, are generally very close to the converted skin temperature from the SURFRAD surface outgoing LW radiation. In most cases, the newly proposed algorithm shows better agreement with ground observations.


1. Introduction

[2] Surface skin temperature is an important climate parameter due to its control of the upward terrestrial radiation, and consequently, the control of the surface sensible and latent heat flux exchange with the atmosphere. Information on surface skin temperature is quite scarce. In the past, for large-scale needs, surface shelter temperatures were used as a proxy to surface skin temperatures. Observations from satellites have been found to be useful for inferring surface skin temperatures, but the inference schemes still remain challenging. Only few satellite sensors have the capability to observe all the necessary parameters needed to derive surface temperature at high accuracy. Some lack sufficient number of channels to derive surface
emissivity, while others do not observe the Earth surface frequently enough due to the presence of clouds. Land surface emissivity may be quite different from unity and is spectrally variable [Lyon, 1965; Nerry et al., 1990]. Because land surface emissivity is generally less than one, part of the atmospheric downward radiation is reflected by the surface and has to be considered [Lorenz, 1986].

[1] An early effort to retrieve Land Surface Temperature (LST) from satellites was made by Price [1984], by adopting the AVHRR Sea Surface Temperature (SST) split window algorithm over agricultural land. After a careful analysis of the relevant sources of error, he showed that the split window method for SST could be adopted with an accuracy of 3°C. Since most land surface emissivities are not close to unity as assumed for the sea surface, Becker [1987] presented a model that accounts for the LST error introduced by the spectral emissivity dependencies of the AVHRR channel 4 (10.8 μm) and channel 5 (11.9 μm). Becker and Li [1990] extended the split window method for SST to LST and took into account the variability in land surface emissivity. LST was expressed as a linear combination of the brightness temperature in the split window channels in a similar form as for SST [Nati and Smith, 1998] but with coefficients varying spectrally. They have shown that more accurate LST can be retrieved with this local split window method, once the surface emissivities are known with sufficient accuracy. This algorithm, the so-called “generalized split window” LST algorithm, has been widely used. At present, there is a lack of information on surface emissivity. There have been attempts to estimate surface emissivity from the Normalized Difference Vegetation Index (NDVI) [Vandeven-Griens and Ove, 1993; Valor et al., 1996; Tungalasaikhan et al., 1998]; however, the NDVI concept is not applicable to every surface type. Some scientists proposed to derive surface emissivity from the Advanced Space Thermal Emission and Reflection Radiometer (ASTER), the Thermal Infrared (TIR) Multispectral Scanner (TIMS), and the Moderate-resolution Imaging Spectroradiometer (MODIS) [Kealy and Hook, 1993; Gillespie et al., 1998; Wan and Snyder, 1996; Liang, 2001; Schmugge et al., 2001; Ma et al., 2002]. These algorithms need five to seven thermal window channels, and the GOES satellite has only two thermal window channels.

[2] Surface temperature derivation from satellites is made in the atmospheric windows where absorption water vapor is minimal, yet it is not negligible. Recently, several attempts have been made to improve atmospheric correction [Prata, 1993; Sobrino et al., 1994; Becker and Li, 1995; Francois and Otle, 1996; Coll and Caselles, 1997]. These split window type algorithms have coefficients changing with both surface emissivity and atmospheric transmittance or atmospheric water vapor content. These algorithms yield standard error of temperature estimate between ±1 and ±1.5 K with no significant bias [e.g., Coll and Caselles, 1997]. While water vapor can be derived from satellite instruments, information on atmospheric transmittance is not readily available.

[3] May [1993] introduced a three-channel nighttime SST algorithm to retrieve SST from NOAA/AVHRR imager observations during nighttime, and demonstrated improved accuracy relative to the split window algorithm. The transmittance of radiant energy from the surface through the atmosphere is greater for AVHRR channel 3 (3.75 μm) than for channels 4 and 5, resulting in smaller atmospheric attenuation in channel 3, and providing a more accurate SST retrieval when all three thermal channels are used. As yet, a three-channel LST algorithm has not been developed.

[4] The above studies are focused on polar orbiting satellite systems, such as NOAA-AVHRR and the Along-Track Scanning Radiometer (ATSR). The temporal measurement frequency of these satellites is approximately 2 times per day, which is inadequate for many applications. Land Surface Temperature Diurnal Cycle (LSTD) is an important element of the climate system and is not captured by the polar orbiting satellites. Jin and Dickinson [1999] proposed to interpolate the derived surface temperatures from the NOAA-11 AVHRR instruments into a diurnal cycle, by using typical diurnal patterns of temperature for different latitudes, seasons, and vegetation types as derived from the Community Climate Model (CCM3)/Biosphere-Atmosphere Transfer Scheme (BATS). The spatial resolution of CCM3/BATS is 2.8° (about 280 km), too low for many applications. Geostationary satellites provide diurnal coverage, which makes them attractive for deriving information on LST. The geostationary satellite GOES observes the surface continuously at a nadir pixel resolution of about 4 km [Menzel and Purdom, 1994].

[5] In this paper, we introduce a new split window LST algorithm based on radiative transfer calculations, as well as a three-channel algorithm using the characteristics of the Middle-Infrared (MIR) band to overcome the atmospheric water vapor effect, presented independently for daytime and nighttime observations. Surface emissivities are assigned with spatial and temporal variability as represented by current classifications of land surface types. The latter is expected to reduce error effects due to land surface emissivity as conventionally assigned. The new LST algorithms are compared with the previously proposed generalized split window algorithm [Becker and Li, 1990] and the split window algorithm with water vapor correction [Becker and Li, 1995]. In section 2, data used in this study are described. In section 3, the characteristics of the GOES imager instrument are presented. Section 4 presents the algorithm methodology, which is based on linearization of the radiative transfer equation. Results from the simulations and from the evaluation of LST from real-time GOES observations are presented in section 5. Algorithm error analysis is discussed in section 6.

2. Data

[6] To make the LST simulation results applicable on global scale, input information on surface emissivity and corresponding atmospheric profiles is needed on similar scale for the forward radiative transfer simulations. The Department of Geography at the University of Maryland (UMD) generated a 1-km resolution global land cover product [Hansen et al., 1998] (http://gaia.umiacs.umd.edu:8811/landcover/index.html). These products include the following 14 International Geosphere-Biosphere Programme (IGBP) classes [IGBP, 1993]: (1) water, (2) evergreen needleleaf forest, (3) evergreen broadleaf forest, (4) deciduous broadleaf forest,
(6) mixed forest, (7) woodland, (8) wooded grassland, (9) closed shrub land, (10) open shrub land, (11) grassland, (12) cropland, (13) bare ground, and (14) urban and built-up. This product was first aggregated to the resolution of the global simulations of 2.5° and to the analyzed data resolution of 0.5°. In the aggregation process, the land cover type in each grid box was assigned on the basis of the dominant surface type, while the surface emissivity was calculated according to a linear mixing with weighted sum of the land cover percentage times the emissivity of this surface type.

During daytime, LST was calculated from the proposed split window algorithm according to the 14 surface types. During nighttime, LST was calculated by using the new three-channel algorithm, assuming emissivity according to surface types. A spectral library of surface emissivity and reflectivity over a wide range of spectral wavelengths from the Moderate Spectral Atmosphere Radiance and Transmittance (MOSART) data set [Cornette et al., 1994] was used. Surface emissivities at the GOES bands can be obtained by interpolation using sensor spectral response function. Figure 1 shows the surface emissivity in the GOES-8 three-window channels derived for the 14 IGBP surface types. As seen, surface emissivity in the thermal window channels of 11.0 and 12.0 μm is more stable than in the MIR channel of 3.9 μm, which may be one reason why most algorithms use the split window approach only (the other one being that during daytime, the contribution to the MIR channel from the solar part of the spectrum is negligible).

Satellite observations needed for testing the methodology are available as a by-product from the NOAA/NESDIS GOES-8 operational product of surface short-wave radiative fluxes [Turpyle et al., 1996; Pinker et al., 2003], generated in support of the GEWEX (Global Energy and Water Cycle Experiment) Continental-scale International project (GCIP) [Leese, 1994] activities, as archived at the UMD (http://www.meto.umd.edu/~srb/gcip). Ground observations from three different sources will be used for the evaluation of the LST algorithm. The following information will be used in this study:

(1) The National Centers for Environmental Prediction (NCEP) reanalyzed global surface temperature data set with matching atmospheric profiles for July 1993 at a resolution of 2.5°.
(2) GCP cloud cover fraction, target mean GOES-8 channel 2 (3.9 μm), channel 4 (10.8 μm), and channel 5 (12.0 μm) radiances and brightness temperature, satellite zenith angle, and solar zenith angle.
(3) UMD Department of Geography 1 km global land cover data with 14 IGBP classes aggregated to the NCEP data resolution of 2.5° and the GCIP resolution of 0.5°.
(4) The Atmospheric Radiation Measurement (ARM) observations of surface skin temperature and outgoing long wave (LW) radiation [Stokes and Schwartz, 1994] from the Central Facility (36.6°N, 97.5°W), Southwest Oklahoma, near Lamont, Southern Great Plains (SGP) region of the United States.
(5) North Carolina Agricultural Research Service (NCARS) Weather and Climate Network observations of soil temperature at 6–8 in. in the ground observed by soil probes, and the air temperature from the automated weather stations.

The GOES Imager Instrument
The GOES Imager is a multichannel instrument designed to sense radiant and solar-reflected energy from sampled areas of the Earth. The multielement spectral channels simultaneously sweep east west and west east along a north to south path by means of a two-axis mirror scan system.

The GOES imager has five channels centered at 0.67, 3.9, 6.7, 11.0, and 12.0 μm, respectively. The 3.9, 11.0, and 12.0 μm channels are infrared windows with little water vapor absorption, while the 6.7 μm band is a water vapor band that can be used to detect atmospheric vapor in the upper troposphere. The 0.67 μm is a visible band that can be used during daytime to detect clouds. In order to assess the characteristics of these channels, we performed simulations with inputs taken from the NCEP reanalyzed global data for July 1993 over land surfaces under clear-sky condition for GOES-8 five channels, by running the Moderate Resolution Atmospheric Radiance and Transmittance Model (MODTRAN 4.0) [Berk et al., 1987].

The transmittance of four GOES-8 thermal channels versus surface skin temperature distribution is shown in Figure 2a. The transmittance at the 6.7 μm water vapor band is almost zero for skin temperatures above 240 K. The surface radiation is almost totally absorbed by water vapor; this band can be used to detect atmospheric water vapor distribution, but not to retrieve surface skin temper-
Table 1. Summary of Data Sources

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Institution</th>
<th>Instrument</th>
<th>Resolution</th>
<th>Date</th>
<th>Location</th>
</tr>
</thead>
<tbody>
<tr>
<td>IGBP land cover</td>
<td>UMD</td>
<td>AVHRR</td>
<td>1 km</td>
<td></td>
<td>Global</td>
</tr>
<tr>
<td>Surface temperature with matching</td>
<td>NCEP</td>
<td>ETA model</td>
<td>2.5°</td>
<td>July 1993</td>
<td>Global</td>
</tr>
<tr>
<td>atmospheric profiles</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Spectral library of reflectance</td>
<td>MOSART</td>
<td></td>
<td>0.02 μm</td>
<td></td>
<td></td>
</tr>
<tr>
<td>and emissivity</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Satellite zenith angles, imager data</td>
<td>UMD/NESDIS</td>
<td>GOES-8</td>
<td>0.5°</td>
<td>July to Dec. 1997, Jan. to June 1998</td>
<td>USA</td>
</tr>
<tr>
<td>Skin temperature</td>
<td>ARM</td>
<td>Radiometer</td>
<td></td>
<td>July to Dec. 1997, Jan. to June 1998</td>
<td>Central facility, OK</td>
</tr>
<tr>
<td>Soil temperature, air temperature</td>
<td>NCARS</td>
<td>Soil probe</td>
<td></td>
<td></td>
<td>Raleigh, NC</td>
</tr>
<tr>
<td>Upwelling LW</td>
<td>SURFRAD</td>
<td>PIR</td>
<td></td>
<td>SURFRAD*</td>
<td></td>
</tr>
</tbody>
</table>

Four of the SURFRAD stations: Bondville, IL; Fort Peck, MT; Goodwin Creek, MI; and Table Mountain, CO.

4. Radiative Transfer for LST Determination

[20] In clear-sky conditions, for far-IR bands, solar contributions are negligible and the outgoing infrared spectral radiance at the top of atmosphere can be represented by:

\[ L(\lambda, \mu) = \varepsilon_0(\lambda, \mu) B(\lambda, T_s) \tau_0(\lambda, \mu) + L_a(\lambda, \mu), \]  

(1)

where \( \varepsilon_0 \) is the surface spectral emissivity, \( B \) is the Planck’s function, \( \tau_0 \) is the transmittance at the Earth’s surface, \( L_a \) is the thermal path radiance, \( T_s \) is the skin temperature, \( \lambda \) is the wavelength, and \( \mu = \cos(\theta) \), where \( \theta \) is the satellite viewing angle, also known as satellite nadir angle.

[21] The first term represents the surface contribution term; it is the gray body radiance emitted by the Earth’s surface. The second term is the atmospheric contribution term, referred to as path thermal radiance in equation (1), and is the vertically integrated effect of emission from every atmospheric layer modulated by the transmittance of the air above that emitting layer, namely:

\[ L_a(\lambda, \mu) = \int_{\tau_0}^1 B(\lambda, T_p) d\tau(\lambda, \mu, p), \]  

(2)

where \( T_p \) is the air temperature at vertical layer \( p \), and \( p \) is the pressure of the vertical emitting layer.

4.1. Advanced Split Window Algorithm

[22] For a specific land surface type with surface emissivity close to unity, the radiance error introduced by the atmosphere, \( \Delta L \), can be represented as:

\[ \Delta L = B(\lambda, T_s) - L(\lambda, \mu) \]

\[ = B(\lambda, T_s) - B(\lambda, T_s) \tau_0(\lambda, \mu) - \int_{\tau_0}^1 B(\lambda, T_p) d\tau(\lambda, \mu, p) \]

\[ = \int_{\tau_0}^1 \left( B(\lambda, T_s) - B(\lambda, T_p) \right) d\tau(\lambda, \mu, p) \]  

(3)

Figure 2. (a) Transmittance versus skin temperature. (b) Temperature deficit versus precipitable water. The skin temperature \( T_s \) is shown as the input for simulations, \( T_b \) refers to the simulated brightness temperature, the symbol in Figure 2b is the symbol as Figure 2a. See color version of this figure at back of this issue.
From the Planck function we find:

\[ \Delta L = B(\lambda, T_s) - L(\lambda, \mu) = B(\lambda, T_s) - B(\lambda, T_{\lambda}) \]

\[ \approx \frac{\partial B}{\partial T} \bigg|_{T_{\lambda}} (T_s - T_{\lambda}), \]

(4)

where \( T_{\lambda} \) is brightness temperature at wavelength \( \lambda \).

[23] For an optically thin gas the following approximations can be made:

\[ d\tau = d\{\exp(-k_{\lambda}l)\} \approx d(1 - k_{\lambda}l) = -k_{\lambda}dl, \]

(5)

where \( k_{\lambda} \) is the absorption coefficient and \( l \) is the optical path length. \( dl = \rho dz \approx \rho_0 \exp(-z/H)dz, \rho \) is the density of the absorbing gas, \( \rho_0 \) is the density at 0 km, \( H \) is the atmospheric scale height, and \( z \) is the height. If we assume that the Planck function is adequately represented by a first-order-Taylor series expansion in each window channel, then:

\[ B(\lambda, T_s) - B(\lambda, T_p) \approx \frac{\partial B}{\partial T} \bigg|_{T_{\lambda}} (T_s - T_p). \]

(6)

Substituting equations (4), (5), and (6) into equation (3), we obtain:

\[ T_{s} - T_{\lambda} = k_{\lambda} \int_{0}^{h} (T_s - T_p)dl, \]

(7a)

\[ l_0 = \int_{0}^{\infty} \rho dz \approx \int_{0}^{\infty} \rho_0 \exp(-z/H)dz, \]

(7b)

where \( l_0 \) is the optical depth from the surface to the top of the atmosphere.

[24] If two close spectral channels are selected to give equal values of \( T_{\mu} \), such as the GOES split window channels 11 and 12 \( \mu m \), we will have two equations with different absorption coefficients \( k_{\lambda} \) to solve simultaneously:

\[ \frac{T_s - T_{11}}{T_s - T_{12}} = \frac{k_{11}}{k_{12}} \]

(8a)

or

\[ T_s - T_{11} = \frac{k_{11}}{k_{12} - k_{11}} (T_{11} - T_{12}). \]

(8b)

Here \( T_{11} \) and \( T_{12} \) are the brightness temperatures of the 11 and the 12 \( \mu m \) channels, and \( k_{11} \) and \( k_{12} \) are the absorption coefficients of the 11.0 and 12.0 \( \mu m \) channels. This equation is frequently used as a basis for split window SST algorithms [McClain et al., 1985]. In our case, equation (8b) can be used for any surface type, land or water, as long as the surface emissivities in the split window channels are close to unity.

[25] Figure 3a shows simulation results for the relationship between band temperature deficits \( T_s - T_{11} \) and \( T_s - T_{12} \) for one surface type (evergreen needleleaf forest) compared with all surface types mixed together (Figure 3b). If all surface types are mixed together, there is much more variability and the relationship between \( T_s - T_{11} \) and \( T_s - T_{12} \) is nonlinear. For a specific surface type the relationship is rather linear, which confirms that for a particular land type, the linear split window algorithm used for SST retrieval can be adopted for LST retrieval. Since most land surface emissivity can depart significantly from unity, we can see in Figure 4 that a parabolic relationship exists between \( T_{11} - T_{12} \) and \( T_s \).

[26] The developed split window LST algorithm, referred to as advanced split window, is one where a separate equation is established for each surface type by using 11.0 and 12.0 \( \mu m \) split window. When the satellite viewing angle increases, the optical path increases and the atmospheric attenuation increases. Therefore McClain et al. [1985] added a zenith angle correction term (sec \( \theta \) - 1) to the SST split window algorithm equation. It was found that by adding a second term of the brightness temperature difference \( (T_{11} - T_{12})^2 \), the atmospheric effect can further be removed. If we add this term to the LST retrieval, the equation will have the following form:

\[ T_s(k) = a_0(k) + a_1(k)T_{11} + a_2(k)T_{12} + a_3(k) \cdot (T_{11} - T_{12})^2 + a_4(k)\sec \theta - 1 \]

(9)

where \( k \) is the index of the surface types and \( \theta \) is the satellite viewing angle.

4.2. Three-Channel LST Algorithm

[27] Starting with the radiative transfer equation, the radiance measured by channel \( i \) of a satellite sensor can be written as:

\[ B_i(T_s) = \left[ e_i B_i(T_s) + p_i R_i \right] T_s + R_i, \]

(10)
By inserting equations (11), (12a), and (12b) into equation (10):

\[ B_i(T_i) = \tau_i B_i(T^p_i) + (1 - \tau_i) B_i(T^a_i). \] (13)

[28] Linearizing the Planck function in equation (13) around \( T_i \) yields:

\[
\frac{\partial B}{\partial T} L(T_i) = \tau_i \frac{\partial B}{\partial T} \left( T^p_i - T_i + L(T_i) \right) + (1 - \tau_i) \frac{\partial B}{\partial T} \left( T^a_i - T_i + L(T_i) \right)
\]

with

\[ L(T_i) = B_i(T_i) \left. \frac{\partial B}{\partial T} \right|_{T_i}. \] (15)

The Planck function can be approximated by using a simple power function [Price, 1989]:

\[ B_i(T_i) \approx \alpha_i T_i^{n_i}. \] (16)

Parameters \( \alpha_i \) and \( n_i \) are constants obtained by a least squares regression fit. In order to achieve the best approximation of the Planck function, we divide the temperature range into two parts: (1) less than 285 K and (2) more than 285 K. The parameter \( n_i \) is given in Table 2 for each case.

[29] The power law approximation is useful for analyses involving the Planck function, with the following approximation:

\[
L(T_i) = B_i(T_i) \left. \frac{\partial B}{\partial T} \right|_{T_i} \approx \frac{\alpha_i T_i^{n_i}}{\alpha_i T_i^{n_i}} = \frac{T_i}{n_i}. \] (17)

Inserting equations (16) and (17) into equation (14), the atmospheric correction for brightness temperature can be written as:

\[ T^p - T_i = \frac{1}{1 - \tau_i} \left( T_i - T^a_i \right). \] (18)

We linearize Planck function in equation (11) around \( T^p_i \) and obtain the emissivity correction:

\[
T_s - T^p = \frac{(1 - \varepsilon_i) \left[ T^p_i \left( \frac{n_i - 1}{n_i} \right) \cdot (1 - \tau_i) \cdot T^p - (1 - \tau_i)T^a_i \right]}{\varepsilon_i n_i}. \]

Inserting equation (18) into equation (19) yields:

\[ T_s = C_1 T_i - C_2 T^a_i - C_3 T^p_i. \]

**Table 2.** Parameter \( n_i \) for Approximate Planck Function (Power Function) for GOES-8 Window Channels

<table>
<thead>
<tr>
<th>Channel, ( \mu m )</th>
<th>( n_i ) ( (T_i &lt; 285 \text{ K}) )</th>
<th>( n_i ) ( (T_i &gt; 285 \text{ K}) )</th>
</tr>
</thead>
<tbody>
<tr>
<td>3.9</td>
<td>13.88</td>
<td>12.90</td>
</tr>
<tr>
<td>10.8</td>
<td>4.99</td>
<td>4.57</td>
</tr>
<tr>
<td>12.0</td>
<td>4.51</td>
<td>4.15</td>
</tr>
</tbody>
</table>
Table 3. Atmospheric Transmittance for Standard Atmosphere Profiles

<table>
<thead>
<tr>
<th>Atmosphere</th>
<th>Precipitable Water, g cm⁻²</th>
<th>10.8</th>
<th>12.0</th>
</tr>
</thead>
<tbody>
<tr>
<td>U.S. standard</td>
<td>1.13</td>
<td>0.8552</td>
<td>0.8014</td>
</tr>
<tr>
<td>Tropical</td>
<td>3.32</td>
<td>0.5574</td>
<td>0.4159</td>
</tr>
<tr>
<td>Midlatitude summer</td>
<td>2.36</td>
<td>0.6915</td>
<td>0.5786</td>
</tr>
<tr>
<td>Sub-Arctic winter</td>
<td>0.69</td>
<td>0.8903</td>
<td>0.8646</td>
</tr>
<tr>
<td>Sub-Arctic summer</td>
<td>1.65</td>
<td>0.7847</td>
<td>0.7011</td>
</tr>
<tr>
<td>Sub-Arctic winter</td>
<td>0.33</td>
<td>0.9336</td>
<td>0.9147</td>
</tr>
</tbody>
</table>

where

\[ C_{ji} = \frac{1}{\tau_i} \left[ 1 + \frac{(1-\varepsilon_j)(1-\tau_i)(n_j-1)}{n_j\varepsilon_j} \right] \]

\[ C_{2i} = \frac{(1-\tau_i)}{\tau_i} \left[ 1 + \frac{(1-\varepsilon_i)(1-\tau_i)(n_i-1)}{n_i\varepsilon_i} \right] \]

\[ C_{3i} = \frac{(1-\varepsilon_i)}{\varepsilon_i} (1-\tau_i). \quad (20) \]

[30] If surface emissivity and atmospheric transmittance are assumed to be known, and \( n_j \) is a constant that depends on the spectral channel, there are three unknown parameters, \( T_i, T_a, \) and \( T_d, \) and information in the three channels can be used to obtain surface temperature. Assuming the channel indices are \( i_1, i_2, \) and \( i_3, \) we get:

\[
T_i = C_{i_1} T_{i_1} - C_{i_2} T_{i_2}^d - C_{i_3} T_{i_3}^d
\]

\[
T_e = C_{i_1} T_{i_1} - C_{i_2} T_{i_2}^d - C_{i_3} T_{i_3}^d
\]

\[
T_a = C_{i_1} T_{i_1} - C_{i_2} T_{i_2}^d - C_{i_3} T_{i_3}^d
\]

\[
T_\theta = \frac{(C_{i_3} - C_{i_2})(C_{i_1} T_{i_1} - C_{i_2} T_{i_2}) - (C_{i_3} - C_{i_3})(C_{i_1} T_{i_1} - C_{i_2} T_{i_2})}{(C_{i_2} - C_{i_3})(C_{i_3} - C_{i_3})}
\]

\[
T_{\sigma} = \frac{(C_{i_1} T_{i_1} - C_{i_2} T_{i_2})}{(C_{i_1} - C_{i_2})}
\]

\[
T_s = C_{i_1} T_{i_1} - C_{i_2} T_{i_2}^d - C_{i_3} T_{i_3}^d. \quad (21)
\]

For MODTRAN profiles, the atmospheric transmittance can be calculated, assuming values given in Table 3.

[31] When atmospheric transmittance is not available, we use a regression method to find the appropriate coefficients of equation (20) as follows:

\[
C_{ji} = a_0(j) + a_1(j) \frac{(1-\varepsilon_j)}{\varepsilon_j}, \quad j = i_1, i_2, i_3. \quad (22)
\]

Subsequently, using equation (21), \( T_i \) can then be written as:

\[
T_i = a_0 + a_1 T_{i_1} + a_2 T_{i_2} + a_3 T_{i_3} + a_4 \frac{(1-\varepsilon_i)}{\varepsilon_i} T_{i_1} + a_5 \frac{(1-\varepsilon_i)}{\varepsilon_i} T_{i_1} + a_6 \frac{(1-\varepsilon_i)}{\varepsilon_i} T_{i_1}. \quad (23)
\]

[32] The three-channel algorithm developed here may be applied to a combination of any three thermal infrared channels. In the derivation of this algorithm the atmospheric downward radiation reflected by the surface is considered, however, the solar radiation reflected by the surface, which is a component of the MIR radiance signal during daytime, is not considered. During daytime, the MIR channel contains both reflected solar radiation and radiation emitted by the surface, while at night, there is no solar reflection. If the three-channel algorithm is applied to GOES-8 observations in the MIR channel 3.9 µm combined with the split window channels (11.0 and 12.0 µm), this combination may be used for LST retrieval at night. Therefore we will use the proposed three-channel algorithm for nighttime LST retrieval and the proposed new split window algorithm for daytime LST retrieval. The retrieval scheme for LST or LSTD from the GOES-8 observations is presented in Figure 5.

4.3. Selected Published LST Algorithms

[31] Since several split window LST algorithms have been developed in the past, we will compare our results with two widely used LST algorithms. One is a typical split window algorithm with emissivity correction, the so-called generalized split window algorithm [Becker and Li, 1990; Wan and Dozier, 1996]. The other one is a split window algorithm with water vapor correction [Becker and Li, 1995].

4.3.1. Generalized Split Window

[34] The split window (11.0, 12.0 µm bands) algorithm of Wan and Dozier [1996] is based on Becker and Li’s [1990] algorithm given as:

\[
T_s = a_0 + (a_1 + a_2 \varepsilon_1 + a_3 \varepsilon_2) T_1 + (a_4 + a_5 \varepsilon_1 + a_6 \varepsilon_2) T_2, \quad (24)
\]

where

\[
\varepsilon_1 = \frac{1 - (\varepsilon_{11} + \varepsilon_{12})}{(\varepsilon_{11} + \varepsilon_{22})}, \quad \varepsilon_2 = \frac{(\varepsilon_{11} + \varepsilon_{12})}{(\varepsilon_{11} + \varepsilon_{12})},
\]

and \( \varepsilon_{11} \) and \( \varepsilon_{12} \) are emissivities corresponding to 11.0 and 12.0 µm bands, respectively.

\[
T_1 = (T_{11} + T_{12})/2 \quad \text{and} \quad T_2 = T_{11} - T_{12},
\]

Figure 5. Flow diagram showing major steps to derive land surface temperature (LST) from GOES-8.
where $T_{11}$ and $T_{12}$ are brightness temperatures in the 11.0 and 12.0 $\mu$m bands, respectively.

### 4.3.2. Split Window With Water Vapor Correction

[35] Becker and Li’s [1995] algorithm is given as:

$$T_s = A_0 + PT^+ + MT^-$$

$$T^+ = \frac{T_4 + T_5}{2}$$

$$T^- = \frac{T_4 - T_5}{2}$$

$$A_0 = a_0 + a_1 W$$

$$P = a_2 + (a_3 + a_4 W \cos \theta)(1 - \varepsilon_4) - (a_5 + a_6 W) \Delta \varepsilon$$

$$M = a_7 + a_8 W + (a_9 + a_{10} W)(1 - \varepsilon_4) + (a_{11} + a_{12} W) \Delta \varepsilon$$

Here subscripts 4 and 5 refer to 11.0 and 12.0 $\mu$m bands, $T$ is the brightness temperature, $\varepsilon$ is the surface emissivity, $W$ is the total precipitable water or total column water vapor, $\Delta \varepsilon = \varepsilon_4 - \varepsilon_5$, and $\theta$ is the satellite viewing angle. The regression coefficients used in equations (24) and (25) are derived from the global forward simulations, with NCEP data as input.

### 5. Results

#### 5.1. Error Comparison

[36] In Figure 6, the Root Mean Square (RMS) error distribution for different algorithms during daytime and nighttime from the global simulations is presented. No sensor noise errors are added. The land cover and emissivity are the same as the input for forward simulations. Included are 5370 points over land with matching profiles at five satellite viewing angles. During daytime the solar zenith angle is between 0° and 87.5°; during nighttime the solar zenith angle is in the range of 87.5°–180°. During daytime, the LST retrieval error from the generalized split window algorithm is above 0.5 K over the entire temperature range, and is greater than 1 K for temperatures above 290 K. Becker and Li’s [1995] LST algorithm with water vapor correction shows big improvement over their generalized LST algorithm developed in 1990. The RMS error can be below 0.5 K for temperature below 290 K. The total precipitable water used in this algorithm was integrated from the NCEP reanalyzed atmospheric profiles and used as input for the simulations. The proposed new split window algorithm shows improvement when compared with the Becker and Li’s [1995] algorithm, with an RMS error of less than 1 K over the entire temperature range. During nighttime, the RMS error from the generalized algorithm is above 0.5 K. The LST derived from the newly developed three-channel algorithm shows improvements for temperatures above 285 K, while it is worse than the generalized split window LST algorithm for temperatures below 285 K. If the LST retrieval is separated into two categories based on channel 4 brightness temperature ($T_{41}$) threshold value of 280 K, namely, two sets of coefficients are used, the LST retrieval shows substantial improvement over most of the temperature range, with an RMS error below 0.5 K. The proposed advanced split window algorithm gave the best performance during daytime, while the three-channel LST algorithm with two $T_{11}$ categories gave the best LST retrieval during nighttime.

#### 5.2. Geometry Effects

[37] The RMS error for LST retrieval as a function of satellite viewing angle for different algorithms during daytime is shown in Figure 7. The satellite viewing angle is also known as the satellite nadir angle, and should not to be confused with the satellite zenith angle which is relative to the view point (VP). The convention followed here is described by Ruff and Gruber [1975] and Conlan [1973]. Specifically, if $\theta$ is the satellite viewing (nadir) angle and $\theta_s$ is the zenith angle of the satellite at the VP, $R$ is the Earth radius and $H$ is satellite height, then the following relationship exists:

$$\sin \theta_s = (R + H)/R \sin \theta.$$  \hspace{1cm} (26a)

[38] Since the height of the geostationary satellite is about 36,000 km for GOES, the GOES satellite zenith angle is about 6–10 times the GOES viewing (nadir) angle:

$$\sin \theta_s \cong (36,000 + 6700)/6700 \sin \theta \approx 6.37 \sin \theta.$$  \hspace{1cm} (26b)

[39] For example, a 2° satellite viewing (nadir) angle corresponds to a 12.8° satellite zenith angle and a 9° satellite viewing angle corresponds to a 85.2° satellite zenith angle. The retrieval error increases with the satellite viewing angle. Larger errors occur at warm temperatures and large viewing angles. The proposed split window algorithm shows improvement over the generalized split window algorithm.
due to increasing viewing angles. For the generalized split window algorithm [e.g., Becker and Li, 1990], for satellite viewing angles greater than 6° and surface skin temperatures warmer than 280 K, the RMS error is above 1 K. For the new split window algorithm, the RMS error is reduced for viewing angle less than 6°, temperatures above 290 K, and viewing angles greater than 6°; the RMS error is also smaller than that from the generalized split window algorithm. The bias error (Figure 8) shows underestimates at viewing angles greater than 6° and temperatures above 280 K. The bias from the new split window algorithm is lower (−2 K) than that from the Becker and Li's [1995] algorithm (−4 K) and the generalized split window algorithm (−4.5 K).

[40] During nighttime, the new three-channel algorithm shows improvements over the generalized split window algorithm (Figure 9). The maximum RMS error is about 3.5 K for the generalized split window algorithm, 1.5 K for the proposed split window algorithm, and 1 K for the proposed three-channel algorithm. For the generalized LST algorithm, the RMS error is above 1 K if the viewing angle is greater than 6° and the skin temperature is larger than 255 K. The RMS error for the proposed split window algorithm is less than 0.5 if the viewing angle is less than 6° and is greater than 1 K when viewing angle is greater than 6° and surface temperature is larger than 300 K. While the RMS error for the three-channel algorithm is less than 0.5 K for most situations, it is about 1 K for viewing angle larger than 7° and surface temperature higher than 300 K. The bias errors presented in Figure 10 indicate that the new split window and the three-channel algorithms present improvement over the generalized split window algorithm. The bias errors are reduced from about −4 K to −1.5 K and −1 K, respectively. From Figures 7–10 it is evident that the LST retrieval error is smaller during nighttime than during daytime.

5.3. Evaluation of LST Retrievals

[41] The LST algorithms developed in section 4 for clear-sky condition have been applied to the GOES-8 satellite
observations as available from the GCIP/SRB database. Since observations from all five channels are stored and clear-sky determination was done while preparing inputs to an algorithm to derive short-wave radiative fluxes, it is possible to use the same clear-sky classification for the thermal channels. The results are evaluated against different types of variables that measure directly or indirectly surface skin temperatures. These include observations made with hand held Infrared Thermometers, soil temperature observations by contact soil probes, and fluxes of outgoing LW radiation. Such an approach is necessary since radiometric observations of surface skin temperature are not readily available.

[42] The GCIP domain is an area that extends from 25°N to 50°N in latitude and 125°W to 70°W in longitude, at 0.5° resolution. The UMD Department of Geography 1 km land cover information was aggregated to this resolution. The LST algorithms developed and described in section 4 were applied to the clear-sky radiances using coefficients obtained from the forward simulations.

5.3.1. Evaluation Against Observations From Infrared Thermometers

[43] Observations from Infrared Thermometers were available from the ARM SGP region located in southwest Oklahoma at 36.5°N, 97.5°W. The clear periods were selected according to reported cloud cover fraction as derived at NOAA/NESDIS from the GOES-8 satellite observations. A comparison of LST derived from equation (9) as well as that obtained from the NOAA/NESDIS operational algorithm [Wu et al., 1999] was done against ground observations. The NOAA/NESDIS operational SST algorithm was developed at the Cooperative Institute for Meteorological Satellite Studies (CIMSS). Results for selected months of 1997 and 1998 are shown in Figure 11, while results for a full year (1998) divided into four seasons are presented in Figure 12. During certain months

![Figure 9. RMS error versus satellite viewing angle and surface skin temperature for different algorithms during nighttime.](image)

![Figure 10. Bias error versus satellite viewing angle and surface skin temperature for different algorithms during nighttime.](image)
the LST as retrieved from the NOAA/NESDIS algorithm is in close agreement with the proposed algorithm and with observations.

[44] The histogram of the percentage probability distribution versus LST bias error is shown in Figure 12. In spring, the highest errors were between 0.5 and 1.5 K; in summer, errors centered at −0.5 and 2.5 K; in fall, a 1.5 K bias-error was of the highest percentage; while in winter, the errors were smaller, between −0.5 and 0.5 K.

5.3.2. Evaluation Against Soil Probes

[45] Evaluation against soil temperature and air temperature observations made by the NCARS network allowed to illustrate issues faced when evaluating satellite-based retrievals against soil observations, or the more readily available air temperatures. Using the proposed and the NOAA/NESDIS algorithm to retrieve LST yielded higher values than the air temperature during daytime and lower values than the air temperature during nighttime, consistent with the diurnal radiative forcing (Figure 13). Generally, the maximum LST is larger than maximum air temperature; the minimum LST is smaller than the minimum air temperature; the amplitude of soil temperature is reduced below the surface and its phase lags behind the surface skin temperature, as presented in the following equation:

\[
T_{\text{skin}}(t) = T + \Delta T_s \exp(-z/(\omega/2k)^{1/2}) \cdot \sin \left[ \omega t - \left( \frac{\omega}{2k} \right)^{1/2} z \right].
\]  

(27)

where \( T \) is the daily or the annual mean soil temperature, \( \Delta T_s \) is the amplitude of the surface skin temperature wave, \( k \) is the thermal diffusivity, \( z \) is the depth below the surface, and \( \omega \) is the angular frequency, \( \omega = 2\pi/p \), where \( p \) is the period [Carslaw and Jaeger, 1959].

[46] If the thermal diffusivity \( k \) is known, assumed here to be \( 2.8 \times 10^{-3} \text{ cm}^2 \text{ s}^{-1} \) as appropriate for loam, two soil temperature observations can be used to solve equation (27) for the daily mean soil temperature \( T_s \) and the amplitude of the surface skin temperature \( \Delta T_s \). The surface soil temperature at \( z = 0 \) can be calculated, taking \( t \) in equation (27) to be in UTC time. As seen in Figure 13, the adjusted LST from the observations at depth of 8 in. to represent the surface value is similar to the one retrieved from the satellite observations with the proposed algorithm. Observed differences could be partly due to the fact that the actual LST does not fit a perfect sine wave, as assumed in the mathematical formulation. The results presented in Figure 13 illustrate that the use of beneath surface observations of soil temperature, where most observations are made, would still be useful for evaluating remotely sensed retrievals.

5.3.3. Evaluation Against Outgoing LW Radiation

[47] The upwelling thermal irradiance measured in the spectral range 3–50 μm from the SURFRAD network observations, needs first to be converted to a surface skin temperature \( T_s \) according to:

\[
R^I = \varepsilon \sigma T_s^d \quad \text{or} \quad T_s = (R^I/\varepsilon \sigma)^{1/4}.
\]  

(28)

[48] The surface emissivity is assigned according to surface type, \( \sigma \) is the Stefan-Boltzmann constant. The retrieved LST versus the converted \( T_s \) are shown in Figure 14. The LST retrieved from both of our proposed algorithm and the NOAA/NESDIS algorithm is generally very close to the converted skin temperature. Most of the time, the newly proposed algorithm shows better agreement with the observations.

6. Algorithm Error Analysis

[49] Retrieved LST versus observed LST during different seasons are shown in Figure 15. In winter, when the temperature is the coldest, the RMS error is smaller, of only 1.38 K. When the LST increases in the spring, the RMS increases to 1.94 K. During summer, where the surface skin temperature over land is the highest, the RMS error is 2.30 K. In fall, the surface temperature range is between 280 and 310 K, the RMS error is 2.38 K, the largest among the four seasons. These results agree quite well with the simulation results, the largest error occurs at LST range of 280–310 K, while the error is smaller for lowest skin temperatures.

[50] As shown, the RMS error of the simulated LST is lower than 0.5 K in most cases (Figure 6), while, for real-
time data, the RMS error is about 2 K (Figure 15). It needs to be noted that in the LST retrieval from the simulated data, the sensor error is not considered. The land cover and emissivity used in the forward simulations are considered as true values. The sources of error can be several: (1) an error related to the sensor, known as sensor error; (2) an algorithm error, can be caused due to emissivity and atmospheric correction error; (3) the “clear-sky” radiances used can be contaminated with clouds; (4) the inherent problems with the evaluation process, for example, ground observations represent a point value, while satellites measure at a pixel level, which is a $4 \times 4$ km area for the GOES-8; (5) spatial inhomogeneity within a pixel area; (6) ground observations used as “ground truth” can also have errors; (7) variability in the satellite viewing angle; and (8) aerosols are not accounted for. Since in the present evaluation process, three different measurements were used, differences can arise. We will discuss these error sources in what follows.

6.1. Sensor Error

Sensor error includes calibration error and sensor noise error. Noise Equivalent Difference Temperature (NEDT) is usually used to represent the sensor noise error. Table 4 shows NEDT for GOES-8 infrared channels (http://rsd.gsfc.nasa.gov/goes/text/goestechnotes.html).

6.2. Land Cover Classification Error

It is believed that land cover classification accuracy in the range of 70 to 90% can be achieved [DeFries et al., 1995, 1998; Hansen et al., 1996, 1998; Strahler et al., 1996; Friedl and Broadley, 1997]. The correct typing probability for 1 km global land cover classification of Loveland and Belward [1997] is expected to reach 85%. Errors in land cover classification will introduce errors in the coefficients derived from the forward simulations for the fourteen land cover types, which are used to represent emissivity variability. An experiment was performed to assess the brightness temperature error due to land cover classification error. It can be seen (Figure 16a) that the brightness temperature error in wavelength of 10.8 and 12 $\mu$m is very small and is less than the error in the MIR 3.9- $\mu$m channel. This is a major reason for introducing the proposed split window algorithm.

6.3. Surface Emissivity Error

In the previous section, discussed were effects of land cover classification errors on brightness temperatures, as applicable during daytime, using the proposed split window algorithm. During nighttime, the proposed threecolumn algorithm is used, with assigned values of emissivity. An emissivity error causes brightness temperature error and therefore an LST retrieval error. As shown in Figure 16b, the brightness temperature error increases with the increase in the emissivity error and is larger in the 11.0 and 12.0 $\mu$m bands and smaller in the 3.9 $\mu$m band. The brightness temperature error due to emissivity error in Figure 16b is the average of all global data points over the entire temperature range. For a specific temperature the error may be larger. As shown in a previous section (Figure 1), emissivity variations are fairly small in the thermal IR bands (11.0 and 12.0 $\mu$m) but somewhat larger in the MIR band (3.9 $\mu$m); namely, an emissivity error causes a smaller brightness temperature error in the MIR band than in the thermal IR bands. This is another reason for introducing a three-channel algorithm.

6.4. Atmospheric Correction Error

Water vapor is the major absorbing gas in the window channels. Thus the main atmospheric effect comes from the water vapor absorption when window channels are used to retrieve LST. Figure 17 shows total column water vapor vs. LST distribution. As can be seen, most water vapor is concentrated at the warmer temperature range of 280–305 K and can vary from 0.25 to 7 cm due to increased evaporation from warmer surfaces, except for rocks, sand,
and desert areas. This is why bigger errors occurred at warmer temperature above 280 K.

7. Conclusions

In this paper a new split window and a new three-channel algorithm have been developed to retrieve LST from GOES-8 observations. It was demonstrated that the new split window algorithm gives best retrieval during daytime, while the three-channel algorithm gives the best LST retrievals during nighttime, when compared with currently available methods. In the simulation, where sensor error is not considered and land cover and emissivity used are assumed to be the “true” values, the RMS error was found to be less than 1 K and the bias was not significant. Evaluation against the ARM observations shows that LST as derived from actual GOES-8 observations can be determined within an RMS error of about 1–2 K, standard error of about 1 K, and a bias of less than 1 K. When evaluated against the NCARS soil temperature and the more readily available air temperature observations, the amplitude of LST is significantly greater than that of the observed soil temperature. It was found to be lower than air temperature at night and higher than air temperature during the day. Evaluation against the ARM observations show that LST retrieved from the NOAA/NESDIS algorithm is quite close to the observed skin temperature during certain months while the proposed LST algorithm shows improvements during most of the year. Evaluations against the SURFRAD

![Figure 13](image)

Figure 13. Evaluation of estimated LST from GOES-8, based on proposed and NOAA/NESDIS algorithms, versus observed soil temperature at depth of 8 in., calculated surface temperature from measured value at depth of 8 in., and air temperature at 2 m, as measured at the NCARS Raleigh site during different months. See color version of this figure at back of this issue.

![Table 4](image)

Table 4. GOES-8 Noise (in K@300 K)

<table>
<thead>
<tr>
<th>Channel</th>
<th>GOES-8</th>
</tr>
</thead>
<tbody>
<tr>
<td>2A</td>
<td>0.20</td>
</tr>
<tr>
<td>2B</td>
<td>0.22</td>
</tr>
<tr>
<td>3</td>
<td>0.18</td>
</tr>
<tr>
<td>4A</td>
<td>0.12</td>
</tr>
<tr>
<td>4B</td>
<td>0.10</td>
</tr>
<tr>
<td>5A</td>
<td>0.22</td>
</tr>
<tr>
<td>5B</td>
<td>0.22</td>
</tr>
</tbody>
</table>

![Figure 14](image)

Figure 14. Evaluation of estimates of LST for GOES-8, based on proposed and NOAA/NESDIS algorithms, versus skin temperature derived from surface outgoing long wave radiation as observed at four SURFRAD stations during different months.
surface outgoing long wave radiation observations show that LST retrieved from both the proposed and the NOAA/NESDIS algorithms are in close agreement with the inferred skin temperature, the newly proposed algorithm showing better agreement with observations during certain months of the year.

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References


SUN AND PINKER: LAND SURFACE TEMPERATURE FROM SATELLITES

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Figure 2. (a) Transmittance versus skin temperature. (b) Temperature deficit versus precipitable water. The skin temperature $T_s$ is shown as the input for simulations, $T_b$ refers to the simulated brightness temperature, the symbol in Figure 2b is the symbol as Figure 2a.

Figure 13. Evaluation of estimated LST from GOES-8, based on proposed and NOAA/NESDIS algorithms, versus observed soil temperature at depth of 8 in., calculated surface temperature from measured value at depth of 8 in., and air temperature at 2 m, as measured at the NCARS Raleigh site during different months.