Split-Window Coefficients for Land Surface Temperature Retrieval From Low-Resolution Thermal Infrared Sensors

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***Abstract*—In this letter, we provide a complete set of split-window coefficients that can be used to retrieve land surface temperature (LST) from thermal infrared sensors onboard the most popular remote-sensing satellites: ERS-ATSR2, ENVISAT-AATSR, TERRA/AQUA-MODIS, NOAA series-AVHRR, METOP-AVHRR3, GOES series-IMAGER, and MSG1/MSG2-SEVIRI. The coefficients have been obtained by minimization from an extensive simulated database constructed from MODTRAN radiative transfer code calculations, emissivity spectra extracted from spectral libraries, and spectral response functions of the thermal bands considered. This letter also analyzes the magnitude of the error on the LST retrieval and the contribution to the error of the different uncertainties. Results are summarized in a lookup table useful for scientists interested on land surface retrievals at global scale, thereby facilitating and homogenizing the task of retrieving this parameter from different common sensors.**

***Index Terms*—Atmospheric correction, land surface temperature (LST), MODTRAN, split window (SW), thermal infrared (TIR).**

I. Introduction

LAND surface temperature (LST), including also sea surface temperature (SST), is the main geo–biophysical variable to be retrieved from thermal infrared (TIR) remotely sensed data, since most of the energy detected by the sensor in this spectral region is directly emitted by the land surface. LST is a key parameter in many environmental studies related to different disciplines such as geology, hydrology, ecology, oceanography, meteorology, climatology, etc.

LST is being mapped in a global scale using different low-resolution sensors, which are onboard polar orbit as well as geostationary platforms. Several topics have been published during the last 30 years related to LST retrieval techniques, its accuracy, and its application to the study of surface processes that occur in our planet. In this letter, we present coefficients for the most popular thermal sensors used to calculate LST from a split-window (SW) algorithm. Details regarding the theory involved in TIR and SW algorithms can be found in [1]–[3].

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This letter is organized as follows. Section II introduces the proposed SW algorithm. Section III describes the simulation procedure employed to obtain the SW coefficients and describes the sensitivity analysis made in order to assess the expected accuracy of the retrieved LSTs. Section IV shows the results obtained for each thermal sensor, and Section V includes a partial validation of the algorithm. Finally, Section VI includes the main conclusion of this letter.

II. Proposed SW Algorithm

The SW technique, as presented in this letter, uses two thermal bands typically located in the atmospheric window between 10 and 12 μm. The basis of the technique is that the radiance attenuation for atmospheric absorption is proportional to the radiance difference of simultaneous measurements at two different wavelengths, each subject to different amounts of atmospheric absorption [4]. The idea behind this technique was probably first suggested by Saunders [5], followed by Anding and Kauth [6] and Prabhakara *et al.* [7]. A review of the SW technique and different published SW algorithms can be found in [8].

The SW algorithm proposed in this letter is given by

$$T_s = T_i + c_1(T_i - T_j) + c_2(T_i - T_j)^2 + c_0 + (c_3 + c_4W)(1 - \varepsilon) + (c_5 + c_6W)\Delta\varepsilon \quad (1)$$

where T_i and T_j are the at-sensor brightness temperatures at the SW bands i and j (in kelvin), ε is the mean emissivity, $\varepsilon = 0.5(\varepsilon_i + \varepsilon_j)$, $\Delta\varepsilon$ is the emissivity difference, $\Delta\varepsilon = (\varepsilon_i - \varepsilon_j)$, W is the total atmospheric water vapor content (in grams per square centimeter), and c_0–c_6 are the SW coefficients to be determined from simulated data. The algorithm given by (1) comes from the mathematical structure proposed by Sobrino *et al.* [2], later modified by Sobrino and Raissouni [9]. The main advantages of this algorithm are the following: 1) It is a physics-based algorithm, since it is obtained from the radiative transfer equation (RTE) applied to two different bands; 2) it takes into account both emissivity and water vapor effects; 3) it includes both LST and SST cases; and 4) it is totally operational.

Note that application of (1) requires the knowledge of surface emissivity and water vapor. However, it is not in the scope of this letter to address these issues. A review of methods for ε retrieval can be found in [10]. Different methods for W estimations are described, for example, in [11].

III. Simulation

A. Coefficient Determination

SW coefficients involved in (1) are calculated after statistical fits (minimization) from a complete simulated database. For this purpose, at-sensor brightness temperatures T_i and T_j are reproduced from the RTE, in which values of ε are obtained from spectral libraries and values of atmospheric parameters ($L^{\mathrm{atm}\downarrow}$, τ, and $L^{\mathrm{atm}\uparrow}$) are extracted from atmospheric profiles and MODTRAN radiative transfer code [12]. All the spectral parameters are averaged using the spectral response functions of the different TIR sensors considered in this letter.

We have included in the simulation a total amount of 108 ε spectra for natural surfaces extracted from the ASTER spectral library [13], as described in [3], and 61 atmospheric profiles extracted from the Thermodynamic Initial Guess Retrieval database, as described in [14]. Simulations were performed at five different view angles, namely, 0°, 10°, 20°, 30°, and 40°, to account for angular effects due to the wide swath angle of low-resolution sensors. View angles higher than 40° were not considered since pixels located throughout the image at these angles are discarded in most cases. In the simulations, LST was chosen as $T_0 - 5$ K, T_0, $T_0 + 5$ K, $T_0 + 10$ K, and $T_0 + 20$ K, where T_0 is the temperature at the first layer of the atmospheric profiles, in order to account for differences between LST and near-surface air temperature. By taking into account the five different view angles, the five different LST values, the 61 atmospheric profiles, and the 108 ε spectra, SW coefficients were determined from the minimization of 164 700 data points.

B. Sensitivity Analysis

In order to provide an estimation of the theoretical error on the LST, and also the contribution of the different terms to that error, a sensitivity analysis has been performed based on the classical error theory using derivatives. Hence, the contribution to the error on the LST $e(\mathrm{LST})$ is given by the following terms:

$$e(\mathrm{LST}) = \sqrt{\delta_{\mathrm{alg}}^2 + \delta_{\mathrm{NE}\Delta T}^2 + \delta_{\varepsilon}^2 + \delta_W^2} \tag{2}$$

where δ_{alg} is the standard error of the algorithm obtained in the minimization (standard error of estimation), $\delta_{\mathrm{NE}\Delta T}$ is the contribution of the noise equivalent delta temperature $(\mathrm{NE}\Delta T)$, δ_{ε} is the error due to the uncertainty of the surface emissivity, and δ_W is the error due to the uncertainty of the atmospheric water vapor content. These contributions are, respectively, given by

$$\delta_{\mathrm{NE}\Delta T} = \sqrt{\left(\frac{\partial T_{\mathrm{s}}}{\partial T_i}\right)^2 e^2(T_i) + \left(\frac{\partial T_{\mathrm{s}}}{\partial T_j}\right)^2 e^2(T_j)} \tag{3}$$

$$\delta_{\varepsilon} = \sqrt{\left(\frac{\partial T_{\mathrm{s}}}{\partial \varepsilon_i}\right)^2 e^2(\varepsilon_i) + \left(\frac{\partial T_{\mathrm{s}}}{\partial \varepsilon_j}\right)^2 e^2(\varepsilon_j)} \tag{4}$$

$$\delta_W = \left(\frac{\partial T_{\mathrm{s}}}{\partial W}\right) e(W) \tag{5}$$

where e refers to the error of the parameter considered in brackets. The different derivatives of the T_{s} given by (1) can be easily calculated. Values of $e(T_i) = e(T_j) = 0.1$ K, $e(\varepsilon_i) = e(\varepsilon_j) = 0.01$, and $e(W) = 0.5\ \mathrm{g} \cdot \mathrm{cm}^{-2}$ have been considered for all the sensors. These selected values are considered to be representative of typical errors when working in remote sensing. Note that some error values can change depending on the sensor considered. For example, based on the technical specifications for the AATSR sensor, the $\mathrm{NE}\Delta T$ is 0.05 K, which will therefore slightly improve the $\delta_{\mathrm{NE}\Delta T}$ value, whereas the technical specifications for the SEVIRI sensor provide a $\mathrm{NE}\Delta T$ of 0.2 K, which will therefore slightly worsen the $\delta_{\mathrm{NE}\Delta T}$ value. However, the same values have been considered for all the sensors to allow a direct comparison of errors, as will be discussed in the next section.

IV. Results

The results obtained for each sensor are summarized in Table I, which includes effective wavelengths for the two thermal bands considered in the SW algorithm (λ_i and λ_j), the SW coefficients (c_0–c_6), the Pearson's correlation coefficient (r), the contribution to the total error of the different terms (δ_{alg}, $\delta_{\mathrm{NE}\Delta T}$, δ_{ε}, and δ_W), and the total error in LST $e(T_{\mathrm{s}})$.

Note that errors on LST have been calculated by applying (2)–(5) to each of the 164 700 simulated data points. Then, a mean value (bias) with its standard deviation (σ) and the root-mean-square error (rmse) obtained as $[\mathrm{bias}^2 + \sigma^2]^{1/2}$ has been calculated. Therefore, error values presented in Table I should be considered as a mean global error and not simply as a particular value for a certain situation.

Before the presentation of some validation results, we can say that the validity of the mathematical structure of the SW algorithm given by (1) and the reliability of the SW coefficients presented in Table I are ensured by the results obtained for the standard error of the algorithm (δ_{alg}). Hence, δ_{alg} values range between 1.1 and 0.9 K, except for GOES12 and GOES13, with $\delta_{\mathrm{alg}} > 2.7$ K, due to the change of the band located at 12 μm by the band located at 13.3 μm, which implies that the LST retrievals from these two sensors will not be as accurate as it was with their predecessors neither with the other sensors. In terms of total errors on LST $e(\mathrm{LST})$, values range between 1.5 and 1.8 K, except for MODIS sensor, with a slight increase to 2.1 K, and GOES12 and GOES13 with values higher than 2.8 K due to the aforementioned reasons.

In terms of the different contributions to $e(\mathrm{LST})$, it is clearly shown that the main contribution is due to the ε uncertainty, with δ_{ε} values ranging between 1.1 and 1.8 K. However, in this case, δ_{ε} values for GOES12 and GOES13 decrease to 0.6 K, which shows that the ε effect is minimized when the second SW band is displaced to 13.3 μm. This fact also occurs with $\delta_{\mathrm{NE}\Delta T}$ values, which range between 0.4 and 0.6 K except a decrease to 0.16 K for GOES12 and GOES13. The minimum contribution to the total error is due to the uncertainty on W, δ_W, typically below 0.1 K.

V. Validation

We do not have a complete data set of *in situ* measurements coinciding with all the sensor overpasses; thus, in this section, we provide a partial validation using some *in situ* measured LSTs in coincidence with certain sensors' overpasses. Results

TABLE I

SW COEFFICIENTS (c_0-c_6) OBTAINED FOR THE DIFFERENT LOW-RESOLUTION TIR SENSORS CONSIDERED IN THIS LETTER. EFFECTIVE WAVELENGTHS (λ_i AND λ_j) FOR THE TWO SW THERMAL BANDS ARE ALSO GIVEN, AS WELL AS THE RESULTS OBTAINED IN THE SENSITIVITY ANALYSIS (δ_{alg}: ERROR DUE TO THE MINIMIZATION, $\delta_{\mathrm{NE}\Delta T}$: ERROR DUE TO THE NOISE EQUIVALENT DELTA TEMPERATURE, δ_{ε}: ERROR DUE TO THE UNCERTAINTY OF THE SURFACE EMISSIVITY, δ_W: ERROR DUE TO THE UNCERTAINTY OF THE ATMOSPHERIC WATER VAPOR CONTENT, AND e(LST): TOTAL ERROR IN THE LST). PEARSON'S CORRELATION COEFFICIENT (r) OBTAINED IN THE MINIMIZATION IS ALSO INCLUDED

Platform-Sensor	$\lambda_i;\lambda_j$ (μm)	c_0 (K)	c_1 (-)	c_2 (K^{-1})	c_3 (K)	c_4 ($K \cdot cm^2 \cdot g^{-1}$)	c_5 (K)	c_6 ($K \cdot cm^2 \cdot g^{-1}$)	r	δ_{alg} (K)	$\delta_{NE\Delta T}$ (K)	δ_ε (K)	δ_w (K)	e(LST) (K)
ERS-ATSR2	10.94;12.07	-0.151	1.064	0.342	37.1	1.81	-131	15.7	0.970	1.1	0.45	1.2	0.05	1.7
ENVISAT-AATSR	10.86;12.05	-0.172	1.016	0.299	39.7	0.97	-124	14.8	0.971	1.1	0.42	1.2	0.06	1.7
TERRA-MODIS	11.02;12.04	-0.004	2.625	0.424	41.4	0.04	-201	26.6	0.981	0.9	0.60	1.8	0.13	2.1
AQUA-MODIS	11.03;12.04	0.012	2.601	0.424	41.3	0.14	-199	26.3	0.980	0.9	0.59	1.8	0.12	2.1
NOAA07-AVHRR	10.81;11.92	-0.060	1.752	0.326	45.2	-0.88	-152	18.9	0.979	0.9	0.48	1.4	0.09	1.8
NOAA09-AVHRR	10.78;11.86	-0.003	2.054	0.333	47.3	-1.64	-164	20.6	0.981	0.9	0.51	1.5	0.11	1.8
NOAA11-AVHRR	10.80;11.90	-0.037	1.897	0.329	46.3	-1.30	-158	19.7	0.980	0.9	0.50	1.5	0.10	1.8
NOAA12-AVHRR	10.89;11.97	0.027	1.602	0.352	42.5	0.04	-147	18.1	0.976	1.0	0.48	1.4	0.08	1.8
NOAA14-AVHRR	10.79;12.00	0.025	1.458	0.273	44.0	-0.47	-133	16.4	0.977	1.0	0.44	1.3	0.09	1.6
NOAA15-AVHRR	10.83;11.93	-0.031	1.826	0.327	44.7	-0.71	-155	19.3	0.979	0.9	0.49	1.4	0.10	1.8
NOAA16-AVHRR	10.88;12.02	-0.110	1.277	0.321	40.1	0.86	-134	16.3	0.973	1.1	0.45	1.3	0.07	1.7
NOAA17-AVHRR	10.81;11.93	-0.032	1.783	0.311	45.1	-0.87	-151	18.9	0.979	0.9	0.48	1.4	0.10	1.7
NOAA18-AVHRR	10.81;12.02	-0.098	1.281	0.276	42.0	0.18	-129	15.7	0.975	1.0	0.43	1.2	0.07	1.6
METOP-AVHRR3	10.82;11.97	-0.045	1.733	0.307	44.3	-0.61	-150	18.7	0.978	0.9	0.47	1.4	0.09	1.7
GOES8-IMG	10.72;11.99	0.048	1.447	0.244	45.4	-0.97	-129	15.8	0.977	0.9	0.42	1.2	0.09	1.6
GOES9-IMG	10.73;12.02	-0.011	1.335	0.236	44.2	-0.53	-124	15.3	0.976	1.0	0.41	1.2	0.09	1.6
GOES10-IMG	10.70;12.06	-0.111	1.083	0.219	43.0	-0.21	-114	13.9	0.974	1.0	0.38	1.1	0.08	1.5
GOES11-IMG	10.75;12.03	-0.030	1.275	0.245	43.0	-0.15	-123	15.1	0.975	1.0	0.41	1.2	0.08	1.6
GOES12-IMG	10.74;13.33	1.815	-0.311	0.020	-46.3	27.26	-50	7.6	0.769	2.8	0.16	0.6	0.31	2.9
GOES13-IMG	10.69;13.30	1.833	-0.331	0.022	-40.7	25.64	-51	7.9	0.783	2.7	0.16	0.6	0.29	2.8
MSG1-SEVIRI	10.79;11.94	0.006	1.736	0.297	45.3	-0.97	-147	18.3	0.979	0.9	0.47	1.4	0.10	1.7
MSG2-SEVIRI	10.78;11.99	-0.021	1.503	0.273	44.2	-0.58	-135	16.7	0.977	0.9	0.44	1.3	0.09	1.6

TABLE II

VALIDATION OF THE SW ALGORITHM FOR DIFFERENT SENSORS. BIAS REFERS TO THE LST DERIVED WITH THE SW ALGORITHM MINUS THE LST MEASURED *IN SITU*. RMSE IS CALCULATED BY RMS SUM OF BIAS AND STANDARD DEVIATION (σ)

Sensor	Sites	No. Data	W range ($g \cdot cm^{-2}$)	Bias (K)	σ (K)	RMSE (K)
NOAA11 AVHRR	Hay Walpeup	191	0.8-1.2	-0.8	1.6	1.8
NOAA12 AVHRR	Hay Walpeup	118	0.8-1.2	-1.4	1.2	1.8
ERS ATSR2	Uardry	36	0.6-2.1	-0.9	1.8	2.0
NOAA11 AVHRR	BOREAS	110	0.1-5.4	1.3	1.5	2.0

are provided in Table II. Validation data used in this table are the same as those explained in [15]: data acquired in three Australian test sites (Hay, Walpeup, and Uardry) [16] and in central Canada as part of the Boreal Forest Ecosystem Study experiment [17].

RMSE values obtained in the validation agree with expected errors of the SW algorithm as obtained in the sensitivity analysis (see Table I), typically below 2 K. In spite of the facts that the SW algorithm is the same for all the sensors, that the coefficients are obtained using the same simulated data, and that the errors of the same order of magnitude are expected for all sensors, the algorithm predictions should still be compared with the *in situ* measurements.

VI. CONCLUSION

The SW algorithm presented in this letter and given by (1) provides an operative methodology to retrieve LST from different low-resolution sensors with two TIR bands located in an atmospheric window, typically between 10 and 12 μm. The main advantage of SW algorithms is that they perform the atmospheric correction using at-sensor registered data The main disadvantage is that they require knowledge of ε and W, but these parameters can be estimated from remote-sensing data. The expected accuracy of the LST retrievals is below 2 K, with the major contribution to the total error being the uncertainty in the ε, assumed to be 1% in this letter. Higher errors have been found for the imager sensor onboard GOES12 and GOES13 platforms, since the band traditionally located at 12 μm was displaced to 13.3 μm. Note that the SW algorithm presented in this letter is applicable to both land and sea surfaces. For the SST retrieval, $\varepsilon = 1$ and $\Delta\varepsilon = 0$ can be considered as a first approximation. The SW coefficients calculated for most used TIR sensors provide a kind of lookup table useful for scientists interested on LST retrievals at global scale. We encourage these users to apply the algorithm and the coefficients presented here and report the results achieved in the validation.

REFERENCES

[1] F. Becker and Z.-L. Li, "Temperature-independent spectral indices in thermal infrared bands," *Remote Sens. Environ.*, vol. 32, no. 1, pp. 17–33, Apr. 1990.

[2] J. A. Sobrino, Z.-L. Li, M. P. Stoll, and F. Becker, "Multi-channel and multi-angle algorithms for estimating sea and land surface temperature with ATSR data," *Int. J. Remote Sens.*, vol. 17, no. 11, pp. 2089–2114, Jul. 1996.

[3] J.-C. Jiménez-Muñoz and J. A. Sobrino, "Feasibility of retrieving land-surface temperature from ASTER TIR bands using two-channel algorithms: A case study of agricultural areas," *IEEE Geosci. Remote Sens. Lett.*, vol. 4, no. 1, pp. 60–64, Jan. 2007.

[4] L. M. McMillin, "Estimation of sea surface temperatures from two infrared window measurements with different absorption," *J. Geophys. Res.*, vol. 80, no. 36, pp. 5113–5117, 1975.

[5] P. M. Saunders, "Aerial measurement of sea surface temperature in the infrared," *J. Geophys. Res.*, vol. 72, no. 16, pp. 4109–4117, Aug. 1967.

[6] D. Anding and R. Kauth, "Estimation of sea surface temperature from space," *Remote Sens. Environ.*, vol. 1, no. 4, pp. 217–220, Dec. 1970.

[7] C. Prabhakara, G. Dalu, and V. G. Kunde, "Estimation of sea surface temperature from remote sensing in the 11- to 13-μm window region," *J. Geophys. Res.*, vol. 79, no. 33, pp. 5039–5044, 1974.

[8] Y. H. Kerr, J. P. Lagouarde, F. Nerry, and C. Ottlé, "Land surface temperature retrieval techniques and applications: Case of the AVHRR," in *Thermal Remote Sensing in Land Surface Processes*, D. A. Quattrochi and J. C. Luvall, Eds. Boca Raton, FL: CRC Press, 2004, pp. 33–109.

[9] J. A. Sobrino and N. Raissouni, "Toward remote sensing methods for land cover dynamic monitoring: Application to Morocco," *Int. J. Remote Sens.*, vol. 21, no. 2, pp. 353–366, Jan. 2000.

[10] J. A. Sobrino, J.-C. Jiménez-Muñoz, G. Sòria, M. Romaguera, L. Guanter, J. Moreno, A. Plaza, and P. Martínez, "Land surface emissivity retrieval from different VNIR and TIR sensors," *IEEE Trans. Geosci. Remote Sens.*, vol. 46, no. 2, pp. 316–327, Feb. 2008.

[11] J.-C. Jiménez-Muñoz and J. A. Sobrino, "Atmospheric water vapour content retrieval from visible and thermal data in the framework of the DAISEX campaigns," *Int. J. Remote Sens.*, vol. 26, no. 15, pp. 3163–3180, Aug. 2005.

[12] A. Berk, G. P. Anderson, P. K. Acharya, J. H. Chetwynd, L. S. Bernstein, E. P. Shettle, M. W. Matthew, and S. M. Adler-Golden, *MODTRAN4 User's Manual*. Bedford, MA: Air Force Res. Lab., Hanscom AFB, 1999.

[13] S. J. Hook, *The ASTER Spectral Library*. Pasadena, CA: Jet Propulsion Lab., 1999. [Online]. Available: http://speclib.jpl.nasa.gov

[14] J. A. Sobrino, Z.-L. Li, and M. P. Stoll, "Impact of the atmospheric transmittance and total water vapor content in the algorithms for estimating satellite sea surface temperatures," *IEEE Trans. Geosci. Remote Sens.*, vol. 31, no. 5, pp. 946–952, Sep. 1993.

[15] J.-C. Jiménez-Muñoz and J. A. Sobrino, "A generalized single-channel method for retrieving land surface temperature from remote sensing data," *J. Geophys. Res.*, vol. 108, no. D22, p. 4688, Nov. 2003. DOI:10.1029/2003JD003480.

[16] A. J. Prata, "Land surface temperatures derived from the advanced very high resolution radiometer and the along-track scanning radiometer 2. Experimental results and validation of AVHRR algorithms," *J. Geophys. Res.*, vol. 99, no. D6, pp. 13 025–13 058, 1994.

[17] P. J. Sellers *et al.*, "The Boreal ecosystem atmosphere study (BOREAS): An overview and early results from the 1994 field year," *Bull. Amer. Meteorol. Soc.*, vol. 76, no. 9, pp. 1549–1577, Sep. 1995.