ERROR PROPAGATION IN THE LSA-SAF ALGORITHM FOR LAND SURFACE TEMPERATURE

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Abstract

The Satellite Applications Facility on Land Surface Analysis (LSA-SAF) generates a set of products related with land, land-atmosphere interactions, and bio-geophysical parameters. The LSA-SAF products are available on a pixel basis, in the satellite nominal resolution (3 km at nadir in the case of SEVIRI/Meteosat, centred at 0°E). Furthermore, an indication of the expected accuracy of each retrieved value is also given, either in the form of quality flags, or as estimated error bars. In the case of Land Surface Temperature (LST), the quality information is still qualitatively. Here we present a statistic characterization of estimates provided by the LST algorithm, which allow the determination of a realistic error bars for each retrieved value.

The error statistics of the LST algorithm are based on sensitivity studies, which take into account the expected errors of the main inputs, namely: (i) sensor noise for SEVIRI channels 10.8μm and 12.0μm; (ii) emissivity uncertainties – mostly dependent on the dominant land cover for each pixel; and (iii) error statistics of ECMWF forecasts of total column water vapour (TCWV). LST is estimated for clear-sky pixels, and thus, the impact of undetected clouds is out of scope of the present study. The uncertainties in the input variables are assumed to have a Gaussian distribution, with known standard deviation. In the case of TCWV this is available from ECMWF error statistics, while in the case of surface emissivity the error standard deviation is estimated as a function of the pixel land cover class. The propagation of the different error sources in the LSA-SAF LST algorithm allows the estimation of the respective error standard deviation, as a function of input variables.

The results of the sensitivity study show that sensor noise, by itself, is responsible for LST inaccuracies of the order of 0.3°C. Uncertainties in surface emissivity have a higher impact for dry atmospheres (reaching values of the order of 0.6°C to 0.8°C). Although the emissivity impact is smaller for moist conditions, the overall LST error tends to increase with TCWV; it is estimated that LST inaccuracies higher than 2°C occur for less than 10% of the retrieved values.

INTRODUCTION

During the last years several algorithms have been proposed to retrieve land surface temperatures (LST) from remote sensing data. Most of these techniques were first developed to determine the sea surface temperature and later adapted to land surfaces where emissivity becomes a huge challenge since it depends on the different materials that compose the surface and has high spatial and temporal variability. The most used algorithms to retrieve LST are based on multi-channel methods often called split-window algorithms. In these methods the atmospheric correction is based on the differential absorption of the two adjacent channels operating on the thermal atmospheric window 8-14μm.

Since Price (1984), who proposed a split-window algorithm using only on the AVHRR data, the methods have been improved by adding additional parameters as inputs such as NDVI (e.g. Kerr et al., 1992). Others (e.g. Becker and Li, 1990) preferred not include new parameters but derived parameters like the square root of the two spectral emissivities. One of the last
algorithms, proposed by Wan and Dozier (1996), has their regression coefficients dependent on the total column water vapour and satellite view angle.

Most authors analyse the error of the algorithm itself ignoring the uncertainties in the respective inputs. Wan and Dozier (1996) make sensitivity studies to analyse the impact of emissivity and sensor noise on the retrieved $LST$.

The LSA-SAF generates and disseminates $LST$ retrieved from SEVIRI data on an operational basis. Since the uncertainties of the final product depend on a wide range of forecasts, it is essential that an error indication be also disseminated preferably in a quantitative way and on a pixel basis.

**LST-GSW ALGORITHM**

Currently the LSA-SAF is producing operationally a Land Surface Temperature ($LST$) product based on the Generalized Split-Window (GSW) algorithm proposed by Wan and Dozier (1996) and adapted to SEVIRI channels (Madeira, 2002). The algorithm determines $LST$ (Eq.1) as a function of brightness temperatures and emissivities of the two SEVIRI window channels centred at 10.8$\mu$m and 12.0$\mu$m (IR10.8 & IR12.0), respectively, with coefficients $A$, $B$ and $C$ dependent on classes of total column water vapour ($TCWV$) and satellite zenith angle (VZA).

$$LST = \left(A_1 + A_2 \frac{1 - \varepsilon}{\varepsilon} + A_3 \frac{\Delta \varepsilon}{\varepsilon^2}\right) \frac{T_{10.8} + T_{12.0}}{2} + \left(B_1 + B_2 \frac{1 - \varepsilon}{\varepsilon} + B_3 \frac{\Delta \varepsilon}{\varepsilon^2}\right) \frac{T_{10.8} - T_{12.0}}{2} + C \quad \text{Eq.1}$$

with $\Delta \varepsilon = \varepsilon_{10.8} - \varepsilon_{12.0}$ and $\varepsilon = 0.5(\varepsilon_{10.8} + \varepsilon_{12.0})$.

The algorithm was trained (Madeira, 2002) with a set of atmospheric profiles extracted from TIGR-like database (Chevallier et al, 2000), 50 radiosondes covering a wide variety of atmospheric conditions and the US-standard atmospheres. For each profile emissivity was assigned values within the intervals $0.94 \leq \varepsilon \leq 1.0$ and $-0.0135 \leq \Delta \varepsilon \leq 0.0227$ and viewing angles covering the SEVIRI viewing angle $0^\circ \leq VZA \leq 55^\circ$. The optimal GSW coefficients were determined by means of separate regression analysis performed over the simulated data for 12 classes of VZA and 8 classes of TCWV.

In the present study the error budget on $LST$-GSW algorithm is estimated using a subset of 15,094 clear sky global profiles representative of surface and atmospheric conditions within MSG disk from the SeeBor training database (Borbas et al., 2005). This database, composed by surface temperatures, IGBP Landover classification and temperature and humidity profiles, together with the satellite view angle for the specific geo-location and the SEVIRI response functions, is used as input to the radiative transfer model MODTRAN4 (Berk et al., 1999) to simulate brightness temperatures for the two window channels. The surface emissivity follows the methodology by Peres and DaCamara (2004) that relates the spectral emissivities with IGBP classification.

The error on $LST$-GSW algorithm is then computed as the difference between: 1) the reference $LST$ provided by SeeBor database ($LST_{\text{SeeBor}}$) and 2) the $LST$ retrieved by applying Eq.1 to the simulated brightness temperatures ($LST$). As expected, the error increases with VZA and TCWV being generally $< 1$K. Values over 1.5K occur for VZA $> 25^\circ$ & TCWV $> 4$cm (Figure 1).
Figure 1: RMSE of LST algorithm (differences between SeeBor LST and MODTRAN estimations) as a function of total column water vapour (TCWV) and satellite view angle (VZA).

Figure 2 indicates an overall RMSE lower than 1K and a negligible bias. The LST error correlates with (is independent of) the temperature profile near surface for moist (dry) atmospheres. Figure 3 shows that the atmospheric water content again dominates LST errors.

Figure 2: Scatterplot of LST bias (LST_{SeeBor} - LST) as a function of the difference between surface and air temperature separated by classes of total column water vapour (TCWV).

Figure 3: Scatterplot of LST bias (LST_{SeeBor} - LST) as a function of surface temperature separated by classes of total column water vapour (TCWV).

**ERROR PROPAGATION**

In the previous section described we described the LST errors ignoring the uncertainties in the inputs. When the GSW is applied operationally uses estimates of surface emissivity and TCWV, which also contain errors. In the current section the different errors sources will be identified as well as their impact on the total LST error.

Potentially all inputs may introduce errors in retrieved LST values, although the impact of satellite view angle errors can be ignored when using rectified images from geostationary satellites. For the current application the expected error on VZA (only dependent on the geo-location) is sufficient low for us to assume that it will not imply the wrong choice of Eq.1 coefficients. All the other inputs (emissivity (ε), total column water vapour (TCWV) and sensor noise) are relevant error sources for the LST algorithm.
Impact of TCWV on LST Errors

The procedure to determine the impact of TCWV uncertainties assumes that \( LST \) can be estimated as a function of TCWV and other parameters represented by \( \Theta \), i.e.,

\[
LST = f_{GSW} (TCWV, \Theta).
\]

Eq.2

Since TCWV is not known but only an estimate \( TCWV = TCWV + n \), where \( n \) is assumed as a gaussian random variable with null mean and standard deviation \( \sigma_n \), it is possible to compute the variance of \( LST \) estimations, obtained from the GSW algorithm, knowing \( TCWV \) :

\[
\sigma^2_{LST|TCWV} \equiv E \left[ \left( LST - LST \right)^2 \mid TCWV \right].
\]

Eq.3

The GSW algorithm considers only classes of TCWV, where the probability of an estimate \( TCWV \) being part of class \( I_i = [\omega^-, \omega^+] \) may be determined by:

\[
P(TCWV \in I_i \mid TCWV) = \frac{1}{2} \left\{ \text{erfc} \left( \frac{\omega^- - \hat{\omega}}{\sqrt{2}\sigma_n} \right) - \text{erfc} \left( \frac{\omega^+ - \hat{\omega}}{\sqrt{2}\sigma_n} \right) \right\}
\]

Eq.4

where \( \text{erfc}(.) \) represents the complementary error function, and \( \sigma_n \) is the standard deviation of TCWV forecast errors for each class \( i \). Finally, the error of \( LST \) estimations associated to the uncertainties of the GSW method and the uncertainties of TCWV classifications is given by:

\[
\sigma^2_{LST|TCWV} = \sum_i \sigma^2_{LST|TCWV,\omega} P(TCWV \in I_i \mid TCWV),
\]

Eq.5

Probability values (Eq.4) are shaded in Figure 4 and the results of Eq.5 are represented by contours in the same figure, which shows that errors in LST above 1K have a very low probability (<0.2).

Impact of Emissivity & Sensor Noise on LST Errors

\( LST \) depends explicitly on the two spectral emissivities \( \varepsilon_{108} \) and \( \varepsilon_{120} \) (Peres and DaCamara, 2004), which are obtained from a relation between IGBP-USGS Landover classes and emissivity values and also expected errors, \( \Delta\varepsilon_{108} \) and \( \Delta\varepsilon_{120} \), respectively. Assuming the errors on those emissivities are independent, their impact on \( LST \) errors can be derived as:
\[
S^2_T = \left( \frac{\partial LST}{\partial \varepsilon_{108}} \Delta \varepsilon_{108} \right)^2 + \left( \frac{\partial LST}{\partial \varepsilon_{120}} \Delta \varepsilon_{120} \right)^2 \quad \text{Eq. 6}
\]

Figure 6 (left panel) show that the impact of uncertainties in surface emissivity is always below 1K for dry atmospheres (TCWV<3cm); only for a small number of cases (<5%) this impact is about 2K. The emissivity impact is always <0.5K for moist conditions (TCWV>3cm).

When using the SEVIRI channels IR10.8 and IR12.0 we can expect a noise of the order of \( \Delta T_{108} = 0.11K \) and \( \Delta T_{120} = 0.15K \), respectively (Schmetz et al., 2002). Since \( LST \) also depends explicitly on the brightness temperatures of those channels their impact can be estimated by:

\[
S^2_{Tb} = \left( \frac{\partial LST}{\partial T_{108}} \Delta T_{108} \right)^2 + \left( \frac{\partial LST}{\partial T_{120}} \Delta T_{120} \right)^2 \quad \text{Eq. 7}
\]

**Figure 5:** Histograms of \( LST \) errors [K] due exclusively to emissivity uncertainties (left panel) and to sensor noise (right panel).

The sensor noise has a higher impact for moist atmospheres (TCWV>3cm), ranging between 0.5K and 1K, than for dry atmospheres where its impact is below 0.5K (Figure 5 – right panel).

**LST Total Error & Error Bars**

Assuming all sources of errors as being independent, the total error on \( LST-GSW \) algorithm can be computed simply as the square root of the sum of the different contributions:

\[
S = \sqrt{S^2_{Tb} + S^2_T + S^2_{TCWV}} . \quad \text{Eq. 8}
\]

Where \( S^2_{Tb}, S^2_T \) and \( S^2_{TCWV} \) are given by Eq.7, Eq.6 and Eq.5. The error inherent to \( GSW \) algorithm, discussed in the previous sections, is embedded in the \( S^2_{TCWV} \) term.

Figure 6 shows the histograms of the total error \( S \), accounting all uncertainties in the inputs, grouped by TCWV (left) and by emissivity (right). It can be seen that errors tend to increase with TCWV except for values around 2K that are mainly dominated by the emissivity uncertainties since they occur for lower values of emissivity associated with higher emissivity uncertainties.
Figure 6: Histograms of LST errors [K] including all sources of errors grouped by TCWV (left panel) and by emissivity (right panel).

Note that the total error $S$ is a function of the emissivities, brightness temperatures, water vapour content and satellite view angle (and the respective uncertainties) so that it has a temporal and spatial variability. Figure 7 shows an example of the LSA-SAF LST error bars (corresponding to one standard deviation) for each pixel. Diagrams illustrate the impact of each source of errors on the total LST error for specific locations.

Figure 7: Map of LST Error Bar [K] for 2006/10/05 at 09:00 UTC. The diagrams show the contribution of each error source for the total error [K] for selected locations.

CONCLUSIONS

The LST product operational in LSA-SAF since 2005 is based on a GSW algorithm adapted to SEVIRI sensor with coefficients determined by MODTRAN simulations for TIGR-like database and US-standard profiles among others. The algorithm is a regression where LST depends explicitly on the spectral emissivities and brightness temperatures of the two SEVIRI window channels with the coefficients depending on the atmospheric total column water vapour and satellite view angle.

SeeBor training database and MODTRAN radiative transfer model were used to simulate brightness temperatures for clear sky conditions generating a sample of about 15000 sets of
[LST and brightness temperatures] representative of surface and atmospheric conditions within the MSG disk.

The error budget of LST algorithm was computed based on this set of data first ignoring the uncertainties on input data and later identifying and quantifying the different sources of errors.

In the absence of input uncertainties the errors in the LST–GSW algorithm tend to increase with view angle and water vapour in the atmosphere, i.e., with the optical thickness. Although the overall RMSE is less than 1K and the bias is negligible.

The impact of input errors depends not only on each simple error but also on the value of each input parameter (spectral emissivity, water content, brightness temperatures and view angle). The LST–GSW is particularly sensitive to uncertainties in TCWV and emissivity.

In the near future it is foreseen to disseminate an error bar for LST product estimated as a standard deviation of the total error.

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REFERENCES


