Uncertainty indices of high spatial resolution Land Surface Temperature over urban areas

Zina Mitraka1, Michele Lazzarini2, Georgia Doxani3, Fabio Del Frate1, Hosni Ghedira2

1 Tor Vergata University, Earth Observation Lab, Rome, Italy

2 Research Center for Renewable Energy Mapping and Assessment, Masdar Institute, United Arab Emirates

3 European Space Agency, ESRIN, Frascati, Italy



- > Land Surface Temperature (LST) and uncertainties
- > High resolution LST methodology briefing
- > Uncertainty estimation method
- > Results on a test site
- > Conclusions

Why Land Surface Temperature

Land Surface Temperature (LST) is a *key variable* for studying *land surface processes* and *interactions with the atmosphere*.

Detailed, *frequent* and *accurate* satellite-derived *LST products* may support various urban applications, related to *urban microclimate*, like the monitoring urban heat island.

For the derived products to be used as effectively as possible, it is important to *provide uncertainty estimates*.



Uncertainties in LST retrieval

- Freitas, S.C., Trigo, I.F., Bioucas-Dias, J.M., Göttsche, F. (2010). Quantifying the Uncertainty of Land Surface Temperature 525 Retrievals from **SEVIRI/Meteosat**, *IEEE Trans. Geosci. Remote Sens.* 48, 523-534.
- Hulley, G.C., Hughes, C.G., Hook, S.J. (2012). Quantifying uncertainties in land surface temperature and emissivity retrievals from ASTER and MODIS thermal infrared data. J. Geophys. Res. 117(D23), D23113.
- Ghent, D., Remedios, J. (2013). Developing first time-series of land surface temperature from **AATSR** with uncertainty estimates. EGU General Assembly, Vienna (AUT), 7-12 April.

Uncertainty sources in LST retrieval:

radiometric noise, surface emissivity, atmospheric contribution (water vapor), sensor view angle and the model

High resolution LST methodology



Surface Cover Fractions



^{400 800 1200 1600 2000 2400} Wavelength (nm)



$$R_i = \sum_{k=1}^n a_k R_{ik} + ER_i$$

 $\sum_{k=1}^{n} a_k = 1, a_k \ge 0 \ \forall k$

Emissivity



Fractions (a_k) derived from high resolution image **image**



Emissivity (ε_k) information from spectral libraries adjusted to the sensor





High Resolution TIR Band





 $\mathbf{E}^{(L)} = \min_{\mathbf{E}} \left\| \mathbf{S}^{(L)} - \mathbf{A}^{(L)} \cdot \mathbf{E}^{(L)} + a \frac{w^2}{n} (\mathbf{E}^{(L)} - \overline{\mathbf{S}}^{\prime(L)}) \right\|_2^2 \qquad \mathbf{S}^{(H)} = \mathbf{A}^{(H)} \cdot \mathbf{E}^{(L)}$

LST

from a split-window algorithm

$$LST = T_i + c_1 (T_i - T_j) + c_2 (T_i - T_j)^2 + c_0 + (c_3 + c_4 wv)(1 - \varepsilon) + (c_5 + c_6 WV) \Delta \varepsilon$$

where T_i , T_j are the brightness temperatures for bands i and j $\varepsilon = (\varepsilon_i + \varepsilon_j)/2$ is the mean emissivity of bands i and j $\Delta \varepsilon = \varepsilon_i - \varepsilon_j$ wv is the atmospheric water vapor content c_0 to c_6 are coefficients (Jiménez-Muñoz et al., 2008)

Uncertainty Propagation

Monte Carlo

an experimental probabilistic method to solve difficult deterministic problems by *simulating a large number of experimental trials*

Advantages

- > closer to the underlying physics of actual measurement processes
- > can handle both *small and large uncertainties*
- > do *not* require *complex* partial differentiations
- > accounts for input covariances or dependencies

Disadvantage

> *computationally expensive* especially for EO data \rightarrow hundreds of simulation for each pixel

Bootstrap

repeatedly **resample** from the given sample (Monte Carlo simulation results) and estimate the confidence intervals for each new sample

Uncertainty Propagation



Test site and data



<u>Study site:</u> Heraklion, Greece Urban and rural area ~315 km2

<u>Data:</u>

MODIS Level 1 (MOD021KM), Water Vapor Product (MOD05) 1 km spatial resolution

ASTER Level 1b (AST_L1b)



Surface Cover Fractions

Vegetation Abundance Map



Low-Albedo Impervious Surface Abundance



High-Albedo Impervious Surface Abundance



Soil Abundance Map







Surface Cover Type	Emissivity MODIS Band 31 10.78 -11.28 µm	Emissivity MODIS Band 32 ^{11.770-12.270 µm}
Vegetation	0.988 ± 0.003	0.991 ± 0.001
High Albedo Manmade	0.95 ± 0.02	0.96 ± 0.02
Low Albedo Manmade	0.977 ± 0.007	0.978 ± 0.003
Soil	0.973 ± 0.07	0.981 ± 0.003



 $\begin{array}{c} \textbf{Emissivity} \\ \textbf{MODIS Band 31: } 10.78 \ \text{-}11.28 \ \mu\text{m} \end{array}$

Uncertainty (%) MODIS Band 31: 10.78 -11.28 μm



Low Resolution TIR Band

 $\begin{array}{c} \textbf{Radiance} \\ \textbf{MODIS Band 31: } 10.78 \ \textbf{-}11.28 \ \mu m \end{array}$





High Resolution TIR band

 $\begin{array}{c} \textbf{Radiance} \\ \textbf{MODIS Band 31: } 10.78 \ \textbf{-}11.28 \ \mu m \end{array}$

Uncertainty (%) MODIS Band 31: 10.78 -11.28 μm



LST

High Resolution LST (K)

Uncertainty (K)



LST



Conclusions – Further Research

> Users require uncertainty estimates for EO-based LST products

- > Uncertainty estimates of LST products provide *insights for both the data and the algorithms*, thus they provide valuable source of information for the EO community for data quality and models sensitivity analysis
- > Statistical methods based on simulations can be proven valuable for the estimation of uncertainty in satellite-derived products
- > Those methods are computationally demanding, but solutions to overcome this limitation, may arise in assumptions for the behavior of the remote sensors as well as for the algorithms
- > Assessment of the efficiency of different uncertainty propagation methods on EO data and algorithms and intercomparison
- > Other techniques (i.e. jackknife method) and *combinations of uncertainty methods* can be tested

Thank you for your attention...