HIGH TEMPORAL AND SPATIAL RESOLUTION AIR TEMPERATURE RETRIEVAL FROM SEVIRI AND MODIS COMBINED DATA

Attilio Gambardella[1], Klemen Zakšek[2,3], Thomas Huld[1], and Marion Schroeder-Homscheidt[4]

[1] Institute for Energy, EC Joint Research Center – Via E.Fermi 2749, I-21027 Ispra (VA), Italy

[2] Institute of Geophysics, University of Hamburg – Bundesstrasse 55, D-20146 Hamburg, Germany

[3] Space-SI (Slovenian Centre of Excellence for Space Sciences and Technologies) – Aškerceva 12, SI-1000 Ljubljana, Slovenia

[3] German Remote Sensing Data Center, German Aerospace Center (DLR) - Postfach 1116, D-82234 Wessling, Germany

1. Introduction

In the context of PV performance analysis and planning, as well as solar thermal or solar heating, the knowledge of the air temperature at ground level (commonly measured at two meters height above ground - T2m) plays an important role. For instance, high temperatures cause higher cooling loads and reduce electricity yields of photovoltaic solar power plants. For many applications it is desirable to have T2m values not just at high temporal, but also at high spatial resolutions, since local influences can be large in the case, for instance, of rough topography.

T2m is not driven directly by the sun, but indirectly by the land surface temperature (LST), thus T2m can be parameterized from the LST. Suitable remote sensing sensors are mostly aboard sun-synchronous polar orbiting satellites (e.g. Moderate Resolution Imaging Spectroradiometer – MODIS). LST derived from these data have good radiometric accuracy and high to medium spatial resolution (e.g. 1000 m for MODIS). The problem of the polar orbit is that the data are retrieved seldom. This results in the best case scenario (i.e. MODIS) in LST retrievals that are available only twice a day for a specific location, depending on cloud cover and geographical latitude. This is not adequate for applications needing continuous T2m measurements. A higher frequency of observation is necessary to monitor the diurnal development of LST. This is possible by satellites in geostationary orbit (e.g. GOESS, MSG). SEVIRI aboard MSG for example can retrieve the data even every 15 minutes. Hence, SEVIRI provides 96 images per day in comparison to MODIS Terra and Aqua with 4 images per day. These data have, however, a poor spatial resolution; ground sampling distance is in the case of SEVIRI is 3.1 km in nadir. The spatial resolution is even lower in the areas away from nadir. For instance, in Europe an average pixel has dimensions of about 3 km in the E–W direction and 5 km in the N–S direction. Some methods have been developed that make possible to estimate LST from geostationary data at sub-pixel spatial resolution. These methods are usually known as downscaling.

Recently, Zakšek and Schroedter-Homscheidt (2009) proposed a parameterization, based on remote sensing data, to provide T2m field of high spatial (1000 m) and temporal (30 min) resolution with a root mean square deviation (RMSD) of about 2 K. It was validated for the regions of France, Germany and Slovenia. The above mentioned parameterization combines SEVIRI and MODIS data for LST downscaling based on temperature-vegetation index (TVX) approach (Prihodko and Goward, 1997). The energy-balance approach proposed by Meteotest (2003) is used to parameterize the lapse rate between downscaled LST and measured T2m. The parameterization was developed to be applicable over large regions without having to take into account differences in the land cover type's surroundings the meteorological stations. A wide variety of land cover types was employed in the test data set. However, to increase the accuracy of the T2m parameterization, it might be further refined considering areas with land cover different from the actual validation areas. The purpose of this study is to extend the parameterization approach to the desert and pre-desert land cover. During the initial tests it was, however, discovered that the T2m is for the case study of North Africa poorly correlated to all explanatory variables except LST. Thus we improved the LST downscaling procedure and used the downscaled LST to parameterize the T2m.

2. The LST downscaling approach

In this section the highlights of the considered methodology are described. For a more detailed description of the approach the interested reader can refer to the papers Zakšek and Schroedter-Homscheidt (2009) and Zakšek and Oštir (2012).

The hypothesis behind the LST downscaling is that a linear correlation exists between a vegetation index (e.g. the normalized differential vegetation index – NDVI) and the LST. If vegetation index data of a better spatial resolution than the LST resolution are available (e.g. MODIS ones), the parameters of the regression line can be derived from low resolution NDVI and LST. These are then applied to high resolution vegetation index data to compute the corresponding LST (Fig. 1).

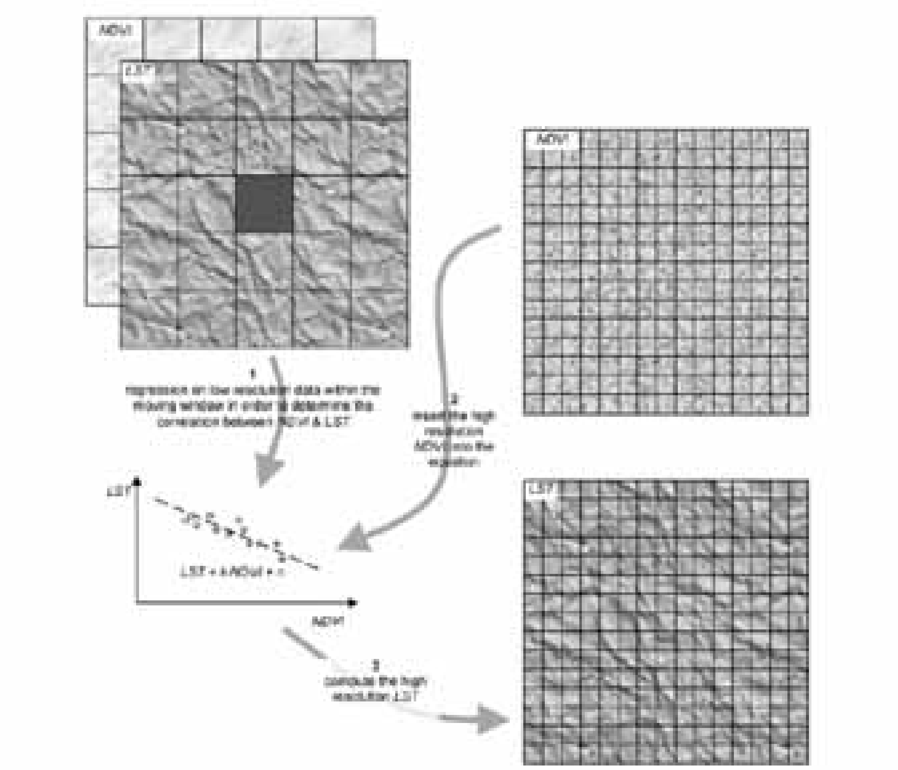

Fig. 1: Scheme of the LST downscaling procedure (adapted from Zakšek and Schroedter-Homscheidt, 2009)

In this study we extended the list of possible explanatory variables beyond NDVI. The downscaling consists of four steps:

- principal component analysis (PCA) of auxiliary data in the output spatial grid resolution,
- up-scaling (aggregation) of the highest ranked principal components,
- estimation of regression equation (between SEVIRI LST and up-scaled auxiliary data) with a moving window analysis,
- estimation of LST in the output spatial grid resolution.

Using PCA is possible to convert a set of observations of possibly correlated variables into a set of uncorrelated principal components. The number of principal components is less than or equal to the number of original variables. PCA is defined in such a way that the first principal component accounts for as much of the data variability as possible. Each succeeding component has the highest variance possible under the constraint that it is uncorrelated with the preceding components.

Before any further analysis the auxiliary data and LST are co-registered to the same grid. The input LST is our case given for a SEVIRI pixel.

The result of the proposed downscaling procedure is a regression equation that explains LST as a linear combination of the chosen principal components. The correlation between each principal component and LST is locally dependent. In the case we want to downscale LST for a large area we thus cannot search for a regression equation for the whole region of interest. It might even be that the first component is statistically insignificant for the spatial distribution of LST for a certain part of the region of interest. Therefore the optimal solution is to adapt the downscaling equation locally by moving window analysis; we set up the regression equation for each pixel based on the principal components and LST values within the moving window. In our study we decided for the moving window of 7 (columns) by 7 (rows). Once the regression equation is known it can be applied to the principal components in 1'm spatial resolution. This gives us an estimate of LST at the same resolution.

3. Input Parameters

3.1 Input for LST downscaling

The main input parameter, LST, is the radiative skin temperature over land. It is an operational LSA SAF product derived every 15 minutes for cloud-free pixels. SEVIRI IR channels at 10.8 and 12.0 μm are used in a generalized split-window algorithm (Wan and Dozier, 1996). The quality of the derived LST relies mainly on cloud detection accuracy. A significant parameter for LST accuracy is land surface heterogeneity, which can produce a significant variation in LST measurements as a function of view zenith angle.

From MODIS several auxiliary data are used the downscaling scheme. Both the NDVI and the enhanced vegetation index (EVI) are used. Both indices are a standard NASA product (Huete et al., 2002) available for Terra MODIS (product code MOD13) and Aqua MODIS (product code MYD13). The product is a 16-day composite of normalized differential vegetation indexes at 250, 500 and 1000 m spatial resolution. Land surface albedo quantifies the part of the energy that is absorbed and transformed into heat and latent fluxes thus it is also correlated with LST. NASA provides 8-day albedo product MCD43 from combined Terra and Aqua MODIS measurements (Schaaf et al., 2002). In this approach both black and white sky albedo in 500 m spatial resolution are considered. Another parameter correlated with LST is emissivity which is a relative ability of a body's surface to emit energy by radiation. NASA provides an average emissivity and an average LST as 8-day products (Wan, 2008) both for Terra MODIS (product code MOD11) and Aqua MODIS (product code MYD11). MODIS LST is not used since the goal is to downscale LST independently of any other LST data. Only emissivity is considered used. These data are available in only 1000 m spatial resolution. All the above mentioned data are first re-projected to the 1' output grid.

LST is also influenced by topography (Hais & Kucera, 2009; Neteler, 2010). LST usually decreases with elevation and increases with higher values of solar insolation. Steeper slopes are usually more exposed to the winds and areas with larger sky-view factor are more exposed for long-wave surface cooling. Thus we used SRTM digital elevation model data and derived elevation, slope (the first gradient of the terrain surface), aspect (the direction of the steepest slope) and sky-view factor (portion of the visible sky). These datasets were then up-scaled to the output grid spatial resolution. The aspect was used in the further analysis only to estimate the solar incidence angle according to the Earth-Sun geometry.

3.2 Additional input for T2m parameterization

The above described data are used for the LST downscaling (Zakšek and Oštir, 2012). In our attempt to parameterize T2m we used two additional LSA SAF products (used already in Zakšek and Schroedter-Homscheidt, 2009): down-welling surface short-wave radiation flux (DSSF), and albedo (AL). DSSF refers to the radiative energy in the wavelength interval 0.3–4.0 µm reaching the Earth's surface per unit of time and surface area as given in Wm^{-2}. It depends on solar zenith angle, cloud coverage, atmospheric extinction and surface albedo; it is derived every 30 minutes from SEVIRI bands at 0.6, 0.8, and 1.6 µm. Land surface albedo (AL) quantifies the part of the energy that is absorbed and transformed into heat and latent fluxes. AL product is generated once per day from three short-wave channels (0.6, 0.8 and 1.6 µm. Except LST, all parameters listed in sections 3.1 and 3.2 showed poor correlation with the lapse rate between LST and T2m. Thus we decided to fit T2m directly to LST: T2m = *f*(LST).

3.3 Ground data

Estimated T2m data are validated with T2m measurements obtained from JRC-MARS meteorological database maintained by the JRC-MARS Unit. Five T2m values, measured at time horizons 6:00, 9:00, 12:00, 15:00 and 18:00 hours at Greenwich Mean Time (GMT), are recorded each day, In Figure 2 the geographic distribution of the ground stations for the North Africa region is shown.

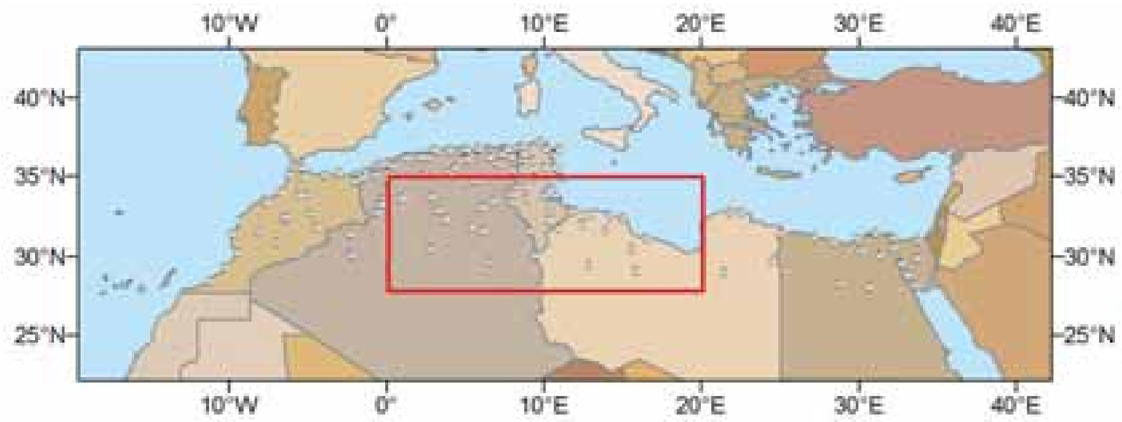

Fig. 2: Geographic distribution of the ground stations for the North Africa region. 34 stations are within the selected case study area (red rectangle).

4. Results

4.1 Case study: Algeria, Libya, Tunis

As case study we considered the area in North Africa spanning 0–20°E, 28–34°15'N. This area corresponds to MODIS level 3 tiles (h18v05, h18v06, h19v05 and h1906). The area covers parts of Algeria, Lybia and Tunis (see Fig.3). The analyzed data-set covers the entire year 2009 (some albedo data for April May and June were missing).

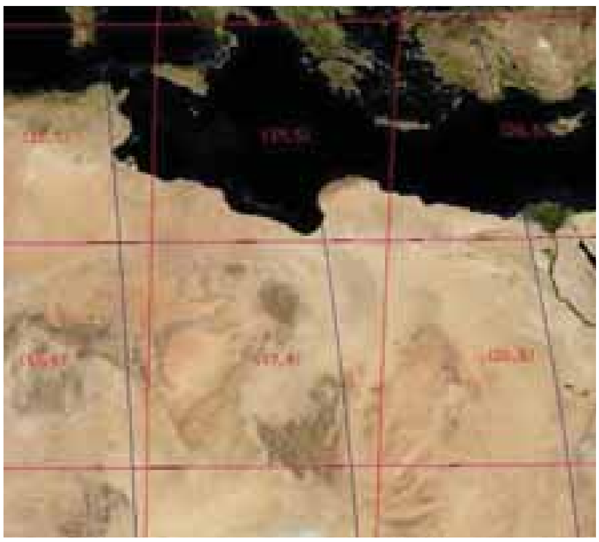

Fig. 3: Scheme of MODIS tiles for the region of central North Africa

4.2 T2m parameterization setup and validation

T2m was in the end parameterized from LST on the basis of 2766 measurements. Only the measurements, were all variables were available, were considered. From these values with down-welling surface short-wave radiation flux (DSSF) less then 100 W/m2 (sun low on the horizon) and those with extreme albedo values were not considered. Albedo values range mostly between 0.3 and 0.4; but sometimes below 0.2 and over 0.4. These latter are the considered thresholds.

None of the considered variables (except LST) explains the T2m, thus we decided to use following parameterization:

$$T2m = 4.03 + 0.865 \cdot LST + 0.00233 \cdot LST^2 . \qquad \text{(eq.1)}$$

Validation was based on 2922 measurements (Fig. 4). RMSD is 2.9 K with correlation coefficient *r* equal to 0.96, together with a minimum residual of -14.2 K and a maximum residual of 12.7 K. The resulting RMSD of 2.9 K can be considered acceptable also considering the estimated error of the input LST (the input LST has accuracy slightly better than 2 K).

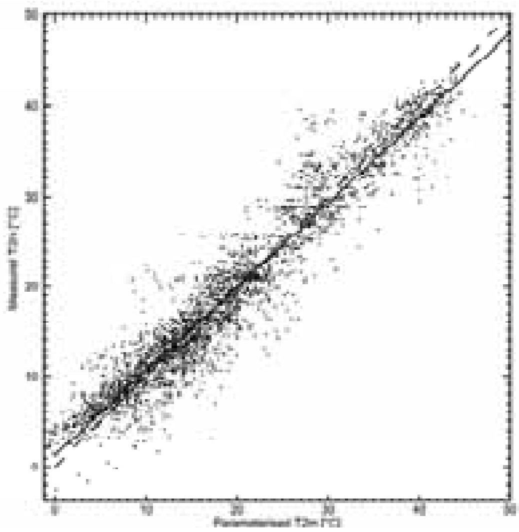

Fig. 4: Parameterized vs. measured T2m values validation scatter plot.

For a comparison we tried to set up also a parameterization as proposed by Creswell et al. (1999). They proposed to explain the difference between LST and T2m in southern Africa with solar zenith angle (z). Following their study we developed the following parameterization:

$$T2m = 13.7 + 0.960 \cdot LST - 14.8 \cdot z + 5.10 \cdot z^2 , \qquad \text{(eq.2)}$$

and the RMSD is 2.9 K with correlation coefficient *r* equal to 0.96, together with a minimum residual of -13.9 K and a maximum residual of 12.7 K. So following the method of Creswell et al. (1999) brings no significant improvement.

5. Conclusions

The purpose of this study was to extend the T2m parameterization from SEVIRI and MODIS data to the desert and pre-desert land cover regions.

The overall accuracy of the estimates T2m values is 2.9 K is not completely satisfactory mostly because usual variables that have been used so far in the HRES-SEB parameterization (Zakšek and Schroedter-

Homscheidt, 2009) failed to explain the T2m variability. Thus we parameterized T2m as a second order polynomial of LST .A possible improvement may be achieved considering other possible factors that drive the T2m in the desert are, e.g. Down-welling Surface Long-wave Radiation Flux (DSLF), geological maps, etc.

6. Acknowledgments

Authors would like to thank the Land Surface Analysis Satellite Applications Facility (LSA SAF) and National Aeronautics and Space Administration (NASA) for the easy access to their data via the Web, and the AGRI4CAST Action team from JRC-MARS Unit for collecting and providing the JRC-MARS meteorological database.

7. References

Cresswell, M.P., 1999. Estimating surface air temperatures, from Meteosat land surface temperatures, using an empirical solar zenith angle. International Journal of Remote Sensing 20 (6), 1125-1132

Hais, M., & Kucera, T. (2009). The influence of topography on the forest surface temperature retrieved from Landsat TM, ETM + and ASTER thermal channels. ISPRS Journal of Photogrammetry and Remote Sensing, 64(6), 585-591. doi:10.1016/j.isprsjprs.2009.04.003

Huete, A., Didan, K., Miura, T., Rodriguez, E. P., Gao, X., & Ferreira, L. G. (2002). Overview of the radiometric and biophysical performance of the MODIS vegetation indices. Remote Sensing of Environment, 83(1-2), 195-213. doi:10.1016/S0034-4257(02)00096-2

Neteler, M. (2010). Estimating Daily Land Surface Temperatures in Mountainous Environments by Reconstructed MODIS LST Data. Remote Sensing, 2(1), 333-351. doi:10.3390/rs1020333

Meteotest, 2003. Meteonorm handbook, Part III: Theory Part 2, http://www.meteotest.ch.

Prihodko, L., Goward, S.N., 1997. Estimation of air temperature from remotely sensed surface observations. Remote Sensing of Environment 60 (3), 335-346.

Schaaf, C. B., Gao, F., Strahler, A. H., Lucht, W., Li, X., Tsang, T., Strugnell, N. C., et al. (2002). First operational BRDF, albedo nadir reflectance products from MODIS. Remote Sensing of Environment, 83(1-2), 135-148. doi:10.1016/S0034-4257(02)00091-3

Wan, Z. (2008). New refinements and validation of the MODIS Land-Surface Temperature/Emissivity products. Remote Sensing of Environment, 112(1), 59-74.

Wan, Z., Dozier, J., 1996. A generalised split-window algorithm for retrieving land surface temperature from space. IEEE Transactions on Geosciences and Remote Sensing 34 (4), 892-905.

Zakšek K., Schroedter-Homscheidt M., 2009. Parameterization of air temperature in high temporal and spatial resolution from a combination of the SEVIRI and MODIS instruments, J. of Photogrammetry and Remote Sensing, 64, 414-421.

Zakšek K., Oštir K., 2012. Downscaling land surface temperature for urban heat island diurnal cycle analysis, Remote Sensing of Environment, in print.