Satellite Datasets and there Scaling Factor for Land Surface Temperature

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Satellite remote sensing, which can continually observe various surface processes on a global scale, has explicitly facilitated such studies [1–3]. While remote sensing plays an increasingly important role in large-scale environmental monitoring, it has also been criticized for its inherently limited spatial resolution [4–6]. This limitation weakens the reliability of studies based on satellite data due to uncertainty generated from spatial heterogeneity.

Among all the land surface parameters, land surface temperature (LST) is an important factor controlling most physical, chemical, and biological processes of the Earth system. It is generally defined as the skin temperature of the Earth’s surface [7]. Because the surface is generally heterogeneous and non-isothermal within an IFOV, the pixel-wise LST is an integral quantity representing the integrated effects of the whole ensemble [8].

Retrieved LST is validated with ground measurements, which are often performed over large, flat, and relatively homogeneous test sites to avoid uncertainty due to spatial heterogeneity [9,10]. However, the accuracy of LSTs retrieved from heterogeneous or mixed pixels remains questionable. Moran et al. (1997) evaluated uncertainty in LSTs due to heterogeneity. LSTs were up scaled from airborne data using two aggregation schemes for a semiarid rangeland. The average LST difference was less than 0.1 K, and the error due to emissivity differences was negligible for relatively homogeneous sites [11,12].

To explore issues related to scaling satellite-retrieved LST data, this study used data from the AMSR-2, Landsat, ASTER and AMSR-E sensors on board NASA’s Earth Observation Satellites. In this research work, first take sample sites and then derive land surface temperature from satellite brightness temperature values by the help of following scaling factors for different satellite data [13,14].

The study area has six training sites on globe in different continent to compare temperature in different satellites datasets on same location. Sample sites are located on following place: (1) Karl Stefan Memorial Airport (USA); (2) Mondai, Santa Catarina (Brazil); (3) Belgrade, Serbia (Europe); (4) Khartoum, Sudan (Africa); (5) Chengdu, China; (6) Kalgoorlie, Australia.

• AMSR-2

For AMSR2 data scale factor is set as 0.01[K]. For instance, if brightness temperature data is stored as 28312, original value of the data is 283.12[K].

• Aster

ASTER surface temperatures are computed from spectral radiance so begins by converting DN’s to radiance and for that equation is following:

\[ L_\lambda = (DN - 1) \times UCC \]

Where \( L_\lambda \) is the spectral radiance, DN are the TIR band digital numbers, and UCC are the published Unit Conversion Coefficients (0.005225 w/m²sr⁻¹/µm⁻¹).

Temperature (measured in degrees Kelvin) is then given by:

\[ T = \frac{K2}{\ln \left( \frac{K1}{L_\lambda + 1} \right)} \]

Where \( K1 = 641.32 \) and \( K2 = 1271.22 \) are constants derived from Planck’s radiance function.

• Landsat

OLI and TIRS band data can be converted to TOA spectral radiance using the radiance rescaling actors provided in the metadata file:

\[ L_\lambda = M_\lambda Q_{cal} + A_\lambda \]

Where:

\[ L_\lambda = \text{TOA spectral radiance (w/m}^2\text{sr}^{-1}\mu\text{m}^{-1}) \]
\[ M_\lambda = \text{Band-specific multiplicative rescaling factor from the metadata} \]
\[ Q_{cal} = \text{Quantized and calibrated standard product pixel values (DN)} \]
\[ A_\lambda = \text{Band-specific additive rescaling factor from the metadata} \]

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• **Analysis**

In the following section, 1°×1° spatial subsets of the products were co-registered so that the resulting subsets cover the same area as the Landsat, ASTER, AMSR-2 and AMSR-E images. Where necessary, spatial re-sampling was performed using the nearest neighbour method [15,16]. The gravel plains are highly homogenous in space and time and outside globe two seasons (around September and June) the chances for precipitation are remote therefore, it is safe to assume that the land surface was completely dry for the results presented in this paper. The following section briefly discusses the actual land surface temperature on the same area and time from different satellite data sets.

• **AMSR-2 and AMSR-E**

AMSR-2 June 2014 data show minimum 166.67 K and highest 305.34 K temperature. In June highest temperature is present in Sahara desert, west centre of North America and northeast part of Brazil, west part of India and china. AMSR-E is showing 327.68 k highest temperatures in deserted part of the globe such as Sahara and Thar Desert. 292.34 K temperature in green vegetation part of globe. 271.02 k temperature is in high altitude and Northern hemisphere part. It’s also show very cold temperature on poles.

• **Landsat**

In 2014 sample site in Europe, Landsat 8 band number 11 shows 267.11 K as lowest temperature and 312.92 highest temperatures. Maximum region show around 290 to 300 k temperatures. In North America its 287.7 to 310.5 K and in South America is 274.3 to 293.71 K but maximum region have high temperature, above than 285 K.

In 2013 in Australia temperature range is in between 271.67 to 299.53 K and this region show an average temperature. For Africa its 284 to 310 but maximum area have above than 305 K temperature, which show high temperature. In Asia it’s from 267.74 to 277.58 K and maximum area has average temperature.

• **ASTER**

In ASTER data on same location in 2014 in Europe, temperature range is in between 289.31 to 318.16 K and for North America is from 277.88 to 300.22 K. In both regions, maximum area is cool. In South America and Asia temperature range is 277.88 to 300.22 K and 256.85 to 300.68 K respectively. Maximum area has average temperature. In Africa and Australia it’s 275.14 to 320.80 and 285.79 to 303.80 K respectively.

• **Comparing in land surface temperature in AMSR-2, AMSR-E, Landsat and ASTER satellite data**

In North America Landsat data showing highest and AMSR-2 and AMSR-E data is showing lowest temperature in all locations. ASTER data temperature values are in between in North America. In South America ASTER show highest temperature and AMSR-2 and AMSR-E lowest and Landsat is in between. For Europe is same like South America. In Africa Landsat have highest and AMSR-2 and AMSR-E lowest temperature and ASTER data temperature is in between. In Asia ASTER is highest, than Landsat and AMSR-2 and AMSR-E is the lowest temperature. For Australia, Highest is AMSR-2 and AMSR-E than ASTER and Landsat is lowest temperature. The analysis results show that Landsat and ASTER data temperature is close to ground measurements in compare of AMSR-2 and AMSR-E data temperature due to their high resolution and scale [17].

**References**

1. Boori MS, Vozenilek V (2014) NASA EOS Aqua Satellite AMSR-E data for snow variation. Journal of Geology and Geosciences 3: 1-6.
2. Boori MS, Vozenilek V (2014) Socio-hydrological vulnerability: A new science through remote sensing and GIS. Advances in Environmental Science, Development and Chemistry 281-285.
3. Boori MS, Vozenilek V (2014) Remote Sensing and land use/land cover trajectories. Journal of Geophysics and Remote Sensing 3: 1-7.
4. Boori MS, Vozenilek V, Burian J (2014) Land-cover disturbances due to tourism in Czech Republic. Advances in Intelligent Systems and Computing, Springer International Publishing Switzerland 303: 63-72.
5. Boori MS, Vozenilek V (2014) Land use/cover, vulnerability index and exposers intensity. Journal of Environments 1: 1-7.
6. Boori MS, Vozenilek V (2014) Remote sensing and GIS for Socio-hydrological vulnerability. Journal of Geology and Geosciences 3: 1-4.
7. Boori MS, Ferraro RR (2013) Microwave polarization and gradient ratio (MPGR) for global land surface phenology. Journal of Geology and Geosciences 2: 1-10.
8. Boori MS, Ferraro RR (2012) Northern Hemisphere snow variation with season and elevation using GIS and AMSR-E data. Journal of Earth Science and Climate Change 512: 001.
9. Boori MS, Amaro VE, Targino T (2012) Coastal risk assessment and adaptation of the impact of sea-level rise, climate change and hazards: A RS and GIS based approach in Apodi-Mossoro estuary, Northeast Brazil. International Journal of Geomatics and Geosciences 2: 815-832.
10. Boori MS, Amaro VE (2011) Natural and eco-environmental vulnerability assessment through multi-temporal satellite data sets in Apodi valley region, Northeast Brazil 4: 216-230.
11. Boori MS, Amaro VE (2011) A remote sensing and GIS based approach for climate change and adaptation due to sea-level rise and hazards in Apodi-Mossoro estuary, Northeast Brazil 1: 14-25.
12. Boori MS, Amaro VE (2011) A remote sensing approach for vulnerability and environmental change in Apodi valley region, Northeast Brazil. World Academy of Science, Engineering and Technology (WASET), International Science Index 50, International Journal of Environmental, Earth Science and Engineering 5: 01-11.
13. Boori MS, Amaro VE, Vital H (2010) Coastal ecological sensitivity and risk assessment: A case study of sea level change in Apodi River (Atlantic Ocean), Northeast Brazil. International Journal of Environmental and Earth Sciences 1: 127-136.
14. Boori MS (2010) Coastal vulnerability, adaptation and risk assessment due to environmental change in Apodi-Mossoro estuary, Northeast Brazil. International Journal of Geomatics and Geosciences 1: 620- 638.
15. Boori MS, Amaro VE, Vital H (2010) Coastal ecological sensitivity and risk assessment: A case study of sea level change in Apodi River (Atlantic Ocean), Northeast Brazil. World Academy of Science, Engineering and Technology, International Journal of Environmental, Earth Science and Engineering 4: 44-53.
16. Boori MS, Amaro VE (2010) Detecting and understanding drivers of natural and eco-environmental vulnerability due to hydro geophysical parameters, ecosystem and land use change through multispectral satellite data sets in Apodi estuarine, Northeast Brazil. International Journal of Environmental Sciences 1: 543-557.
17. Boori MS, Amaro VE (2010) Land use change detection for environmental management: using multi-temporal, satellite data in Apodi Valley of northeastern Brazil. Applied GIS International Journal 6: 1-15.