An Advanced Scientific Gateway for Assessing Land Surface Temperatures Utilizing Landsat 8 and VIIRS Data

Alexei Belotserkovsky
United Institute of Informatics Problems, National Academy of Sciences
Minsk, Belarus
orcid.org/0000-0002-8544-8554

Rita Abrahamyan
Institute for Informatics and Automation Problems of the National Academy of Sciences of Armenia
Erevan, Armenia
orcid.org/0000-0003-0009-8899

Hayk Grigoryan
Institute for Informatics and Automation Problems of the National Academy of Sciences of Armenia
Erevan, Armenia
hayk.grigoryan.a@gmail.com

Hrachya Astsatryan
Institute for Informatics and Automation Problems of the National Academy of Sciences of Armenia
Erevan, Armenia
orcid.org/0000-0001-8872-6620

Arthur Lalayan
Institute for Informatics and Automation Problems of the National Academy of Sciences of Armenia
Erevan, Armenia
orcid.org/0000-0001-6695-3697

Pavel Lukashevich
United Institute of Informatics Problems, National Academy of Sciences
Minsk, Belarus
orcid.org/0000-0002-8544-8554

Andrey Shuliak
Belarusian State University of Informatics and Radioelectronics
Minsk, Belarus

***Abstract*—This The article presents an example of using a service-oriented platform based on data cube technology. This platform has been implemented in two versions, one in Belarus and the other in Armenia, serving as a gateway for estimating land surface temperature (LST) using Landsat 8 and VIIRS data. The gateway provides access to four LST search algorithms and two interpolation methods for generating LST time series. The study identified the most accurate LST estimates, and it confirmed that VIIRS LST products exhibit reasonable levels of accuracy.**

Keywords—LST, VIIRS, Landsat, remote sensing, scientific gateway, platform

I. Introduction

Accurate Land Surface Temperature (LST) data is pivotal for weather forecasts and climate change assessments, serving as a critical indicator of the Earth's surface heat and exerting a profound influence on various atmospheric and environmental processes. Precision in LST measurements is of utmost importance when monitoring climate shifts, identifying drought occurrences, assessing crop health, and understanding land surface evaporation patterns.

The retrieval of LST data from thermal infrared remote sensing sources, whether on a global, regional, or city-scale, offers unparalleled advantages, particularly in the investigation of urban heat island effects. While weather stations and remote sensing (RS) techniques traditionally serve as primary means for collecting LST data on a large scale [1, 2], their application underscores the broader significance of these measurements in comprehending and addressing environmental changes.

In contrast to weather stations, RS methods provide a more extensive observation range, capable of acquiring spatial LST data from satellite sources that complement in situ measurements and facilitate the reanalysis of near-surface air temperatures [3-5]. Methods employing Thermal Infrared (TIR) and passive microwave data are utilized for retrieving LST data from satellite sources [6-7]. Passive microwave data offer continuous LST monitoring with minimal susceptibility to weather conditions but tend to rely on retrieval models that exhibit lower accuracy compared to those established using TIR data. As a result, TIR data remains the preferred method for constructing precise LST models.

This article introduces SciGaP (Scientific Gateway Platform), which streamlines the process of scientific problem-solving [8]. The platform simplifies optimal algorithm selection, precise interpolation, and result visualization, as demonstrated through a comparison of VIIRS and Landsat LST products [9]. This study aims to enhance the coherence of Landsat 8 and VIIRS data for generating essential LST time series, particularly crucial for site-specific analyses.

To address altitudinal variances, we compare the effectiveness of Nearest Neighbor (NN) and Inversely Weighted Distance (IDW) interpolation methods. We align satellite-derived LST observations with ground-based meteorological stations to reveal temporal patterns and anomalies. Utilizing split-window algorithms, VIIRS data contributes to enriching environmental records. The evaluation of VIIRS LST data and Landsat-8 TIRS LST products is conducted in conjunction with ground-based meteorological stations in Armenia during the period from May to October 2022.

II. Methodology and Data Propcessing

The proposed gateway incorporates VIIRS and Landsat 8/TIRS thermal bands to assess Land Surface Temperature (LST). This involves several key phases, including pre-processing, band selection, and radiance-to-temperature conversion.

During the pre-processing phase, we applied a 60-minute time window centered around the station observation time, with a ±30-minute buffer around the 3-hour observation point. Data falling outside of this defined window were excluded, resulting in a reduction of the dataset for both nighttime and daytime periods. Notably, the dataset experienced a significant reduction of over 40% during daytime hours. As a result, the study focused exclusively on nighttime data, as it provided a more comprehensive representation for analysis, while the daytime data were considered less suitable for our purposes.

A. *Landsat 8/TIRS processing*

Several split-window algorithms have been proposed in various studies, consistently showing superior performance compared to the single-channel algorithm [10-11]. However, a significant challenge arises from the TIRS instrument's notable absolute radiometric calibration error, leading to considerable stray light issues [12]. This issue is particularly prominent in Band 11, making it challenging to employ conventional split-window algorithms for Land Surface Temperature (LST) retrieval from the two TIR bands of Landsat 8 TIRS.

As a result, for our investigations, we have chosen to adopt the single-channel algorithm based on the recommendation provided by the United States Geological Survey [13]. This decision is driven by the technical limitations associated with the TIRS instrument and its radiometric calibration, which make the single-channel approach a more suitable option for our specific needs. The algorithm is described step by step in [14]

B. *VIIRS processing*

VIIRS offers global moderate-reso lution data twice daily, ensuring continuous coverage. Its advantages encompass reduced data delivery times, improved image quality owing to enhanced scan geometry, and the provision of novel and enhanced forecasting products. Operating with a full field of view spanning 112.56° in the cross-track direction, VIIRS functions as a scanning radiometer, providing complete global daily coverage around the clock. It operates at a nominal equatorial altitude of 829 km, with a swath width of approximately 3060 km.

For Land Surface Temperature (LST) retrieval, data from VIIRS channels M15 and M16 are employed in conjunction with a split-window technique. This approach rectifies for atmospheric absorption and explicitly incorporates surface emissivity in the retrieval process. Nevertheless, the precision of satellite-based LST measurements is constrained by factors such as atmospheric correction, surface emission characteristics, and sensor performance. These elements can impact the efficacy of LST algorithms under diverse retrieval conditions, including region, season, day/night, or dry/moist conditions [25-26].

LST estimation utilizes brightness temperatures recorded at 11µm (band M15) and 12µm (band M16) channels. The split-window technique mitigates atmospheric effects by leveraging two or more adjacent Thermal Infrared (TIR) channels, typically within the 10-12.5µm range. This approach is straightforward, computationally efficient, and does not necessitate precise atmospheric profiles.

Various algorithms, including those developed by Jiminez-Munoz [15], Kerr [16], McMillin [17], and Price [18], have been implemented for LST retrieval.

III. SCIENTIFIC GATEWAY PLATFORM

The advanced scientific gateway platform is constructed on top of a virtual scalable environment [19] and incorporates pre-existing services [20,21,14], seamlessly integrating data extraction and analytics modules, as depicted in Figure 5. This novel gateway, based on Jupyter [22], offers several benefits for data visualization, enabling the seamless integration of code and visual elements within a comprehensive notebook. This integration significantly streamlines the analysis workflow.

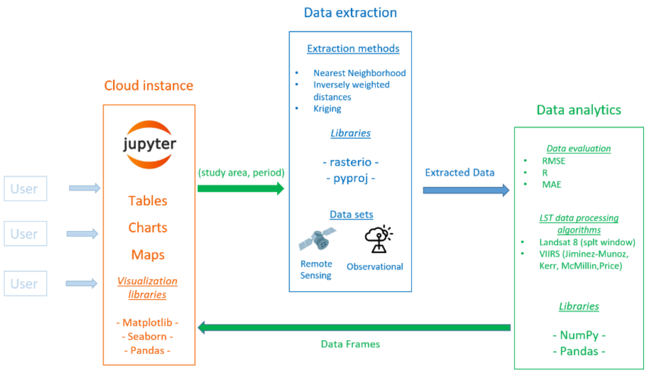

Fig. 1. Topography of the scientific gateway

Furthermore, the platform boasts a highly adaptable and robust framework explicitly tailored for the assessment of land-surface temperatures. This feat is accomplished by harnessing the capabilities of the esteemed Landsat 8 and VIIRS data sets, renowned for their accuracy and reliability in the field of remote sensing.

To optimize the user experience and cater to diverse visualization needs [23], the platform employs Matplotlib and Seaborn as its primary visualization libraries. These powerful tools enable the creation and customization of various visualization types and styles, ensuring that researchers and analysts can effectively convey their findings and insights through clear, visually appealing data representations.

The data extraction module leverages two potent Python libraries, Rasterio and Pyproj, to efficiently extract Landsat 8 and VIIRS data. Rasterio is a versatile library capable of reading, writing, and manipulating raster data, making it an invaluable asset for handling satellite imagery. On the other hand, Pyproj facilitates precise coordinate transformations between various reference systems, ensuring accurate alignment and processing of spatial data.

By incorporating NN and IDW interpolation methods through Python programming within the Jupyter Notebook environment, the module's capabilities have been significantly extended. This integration harmoniously combines the strengths of Rasterio and Pyproj with the adaptability of NN and IDW interpolation methods, offering a robust solution for managing Landsat 8 and VIIRS data. The use of the Jupyter Notebook environment enables users to interact seamlessly with the module, simplifying data manipulation, analysis, and visualization tasks.

The platform employs two distinct algorithms for estimating LST from Landsat 8 and VIIRS satellite data. Each algorithm is meticulously tailored to its respective data source, ensuring the accuracy and reliability of LST results. For Landsat 8 data, the split-window algorithm is employed to correct atmospheric effects and yield precise LST estimations.

Meanwhile, for VIIRS data, the Jimenez-Munoz, Kerr, McMillin, and Price algorithms are selected. These algorithms are implemented using the Python programming language within the Jupyter Notebook development environment. This choice guarantees efficient processing and visualization of LST outcomes and seamless integration with popular Python libraries like NumPy, pandas, and Rasterio, which facilitate data manipulation and analysis. The Jupyter Notebook environment also fosters a user-friendly and interactive workflow, enabling researchers to test, modify, and share their work efficiently.

IV. Methods and Algorithms Applied for LST Validation

Two methods have been carefully chosen to estimate satellite-derived Land Surface Temperature (LST) values at meteorological stations: Nearest Neighbor (NN), which assigns values from the nearest pixel, and the Inverse Distance Weighting (IDW) method [24].

The Nearest Neighbor method, a deterministic spatial interpolation approach, operates under the assumption of constant variable values within a defined neighborhood around each sample point. In contrast, the IDW method assigns weights to neighboring sample points based on their distance from the station's location. The objective of evaluating these methods using meteorological station observations was to enhance data availability in a cost-effective manner.

The evaluation employed various statistical metrics, including BIAS, the coefficient of correlation (R), the coefficient of determination (R^2), and Root Mean Square Error (RMSE). BIAS quantifies the average error magnitude between predicted and actual values, revealing any systematic overestimation or underestimation tendencies. R assesses the linear relationship between predicted and actual values, while RMSE calculates the square root of the average squared differences between the two value sets, providing an overall measure of error. R^2 elucidates the extent to which independent variables can explain variance in the dependent variable within a regression model. Collectively, these metrics establish a quantitative framework for assessing the accuracy of the spatial interpolation results.

The performance of different algorithms has been evaluated using VIIRS and Landsat data in three different terrain types: valley areas dominated by irrigated meadow and mountain-brown semi-desert soil, foothill areas, and mountain areas characterized by mid-mountain steppe soils and mountain meadow. According to estimates, the Price, Jiminez-Munoz, and McMillin algorithms provided the best results at nighttime in the valley, foothill, and mountain areas. At the same time, the Kerr algorithm showed very poor results and, according to our research, cannot be used in our region to estimate surface air temperature. The Landsat LST data also showed good agreement with the measured temperatures, with an RMSE of 3.0 0C and an R-value of 0.55.

Although the results obtained for the daytime were not satisfactory, it can be concluded from the results that the four algorithms Price, Jimenez-Muñoz, and McMillin, can be successfully used to evaluate the LST study regardless of the region (plain, foothills, mountains) at night.

V. Discussion and Conclusing

The article introduces a scientific gateway that conducted temperature-based validation by directly comparing ground-based Land Surface Temperature (LST) measurements with satellite-derived LST values. It thoroughly examined and analyzed the statistical differences between these two variables. The article underscores the capabilities of Landsat-8 TIRS and VIIRS data in producing high-temporal-frequency, medium-spatial-resolution LST maps, showcasing their potential for various applications.

Future research endeavors will focus on amalgamating VIIRS and Landsat-8 data to create denser time series, expected to yield superior results compared to this study. In conclusion, this study contributes to the expanding body of research exploring the potential of remote sensing data in comprehending temperature fluctuations and their implications across various applications, including urban heat island analysis, environmental monitoring, and agriculture.

Acknowledgment

The research was supported by the Science Committee of the Republic of Armenia within the State Target Program project entitled "Creating a Cloud Computing Environment for Solving Scientific and Applied Problems" (№ 1-8/TB-23) and joint Armenian-Belarusian research project entitled “Remote sensing data processing methods using neural networks and deep learning to predict changes in weather phenomena and air pollution”.

References

[1] Li, Z. L., Tang, B. H., Wu, H., Ren, H., Yan, G., Wan, Z., … Sobrino, J. A. (2013, April 5). Satellite-derived land surface temperature: Current status and perspectives. Remote Sensing of Environment.

[2] Sobrino, J. A., Jim?nez-Mu?oz, J. C., & Paolini, L. (2004). Land surface temperature retrieval from LANDSAT TM 5. Remote Sensing of Environment, 90(4), 434-440.

[3] Tomlinson, C.J.; Chapman, L.; Thornes, J.E.; Baker, C. Remote sensing land surface temperature for meteorology and climatology: a review. Meteorological Applications 2011, 18(3), 296-306, DOI: 10.1002/met.287.

[4] Sobrino, J. A., Jim?nez-Mu?oz, J. C., & Paolini, L. (2004). Land surface temperature retrieval from LANDSAT TM 5. Remote Sensing of environment, 90(4), 434-440.

[5] Qin, Z. H., Zhang, M. H., Karnieli, A., & Berliner, P. (2001). Mono-window algorithm for retrieving land surface temperature from Landsat TM6 data. Acta Geographica Sinica, 56(4), 456-466.

[6] Liu, D.; Pu, R. Downscaling Thermal Infrared Radiance for Subpixel Land Surface Temperature Retrieval. Sensors 2008, 8, 2695-2706. Sensors 2014, 14 21406

[7] Duan, S.B.; Li, Z.L.; Tang, B.H.; Wu, H.; Tang, R.L. Generation of a time-consistent land surface temperature product from MODIS data. Remote Sens. Environ. 2014, 140, 339-349.

[8] github,https://github.com/ArmHPC/Remote-Sensing-Data-Processing-Services

[9] Guerschman, J. P., McVicar, T. R., Vleeshower, J., Van Niel, T. G., Pea-Arancibia, J. L., & Chen, Y. (2022). Estimating actual evapotranspiration at field-to-continent scales by calibrating the CMRSET algorithm with MODIS, VIIRS, Landsat and Sentinel-2 data. Journal of Hydrology, 605, 127318.

[10] Jimnez-Muoz, J.-C.; Sobrino, J.A.; Skokovi, D.; Mattar, C.; Crist?bal, J. Land Surface Temperature Retrieval Methods from Landsat-8 Thermal Infrared Sensor Data. IEEE Geosci. Remote Sens. Lett. 2014, 11, 1840-1843.

[11] Du, C.; Ren, H.; Qin, Q.; Meng, J.; Zhao, S. A Practical Split-Window Algorithm for Estimating Land Surface Temperature from Landsat 8 Data. Remote Sens. 2015, 7, 647-665.

[12] Montanaro, M.; Barsi, J.; Lunsford, A.; Rohrbach, S.; Markham, B. Performance of the Thermal Infrared Sensor on-board Landsat 8 over the first year on-orbit. Earth Obs. Syst. XIX 2014, 9218, 921817.

[13] Barsi, J.A.; Schott, J.R.; Hook, S.J.; Raqueno, N.G.; Markham, B.L.; Radocinski, R.G. Landsat-8 Thermal Infrared Sensor (TIRS) Vicarious Radiometric Calibration. Remote Sens. 2014, 6, 11607-11626.

[14] Pavel Lukashevich, Alexei Belotserkovsky, Hayk Grigoryan, Rita Abrahamyan, Hrachya Astsatryan, Aliaksei Sasnovich, LST Quality Evaluation Service for Heterogeneous, IEEE Proceedings of the International Conference on Information and Digital Technologies 2023, pp. 195-199.

[15] Jim?nez-Mu?oz, J. C., Sobrino, J. A., Skokovi?, D., Mattar, C., & Cristobal, J. (2014). Land surface temperature retrieval methods from Landsat-8 thermal infrared sensor data. IEEE Geoscience and remote sensing letters, 11(10), 1840-1843.

[16] Kerr, Y. H., Wald, L., & Duguay-Tetzlaff, A. (1992). Theoretical and experimental comparison of the "split window" and "single channel" algorithms for retrieving land surface temperature from space. Remote sensing of Environment, 42(1), 71-89.

[17] McMillin, L.M., Yoe, C.M., & Goodrum, P.M. (1975). Satellite determination of surface temperature from the 8 to 14 micron region. Proceedings of the 11th International Symposium on Remote Sensing of Environment, 23-27.

[18] Price, J. C. (1984). Land surface temperature measurements from the split window channel of the NOAA 7 Advanced Very High Resolution Radiometer. Journal of Geophysical Research: Atmospheres, 89(D4), 7231-7237.

[19] H. Astsatryan, A. Lalayan, G. Giuliani, Scalable Data Processing Platform for Earth Observation Data Repositories, Scalable Computing: Practice and Experience, 24(1), pp. 35-44, doi: 10.12694/scpe.v24i1.2041, 2023.

[20] Hrachya Astsatryan, Hayk Grigoryan, Rita Abrahamyan, Shushanik Asmaryan, Vahagn Muradyan, Garegin Tepanosyan, Yaniss Guigoz, Gregory Giuliani, Shoreline delineation service: using an Earth Observation Data Cube and Sentinel 2 images for coastal monitoring, Springer Earth Science Informatics, 15, 2022, 1587-1596, doi: 10.1007/s12145-022-00806-7.

[21] Hrachya Astsatryan, Hayk Grigoryan, Aghasi Poghosyan, Rita Abrahamyan, Shushanik Asmaryan, Vahagn Muradyan, Garegin Tepanosyan, Yaniss Guigoz, Gregory Giuliani, Air temperature forecasting using artificial neural network for Ararat valley, Springer Earth Science Informatics, vol 14, no. 2, pp. 711-722, DOI: 10.1007/s12145-021-00583-9, 2021.

[22] Kluyver, T., Ragan-Kelley, B., P?rez, F., Granger, B. E., Bussonnier, M., Frederic, J., ... & Willing, C. (2016). Jupyter Notebooks-a publishing format for reproducible computational workflows (Vol. 2016, pp. 87-90).

[23] Sahoo, K., Samal, A. K., Pramanik, J., & Pani, S. K. (2019). Exploratory data analysis using Python. International Journal of Innovative Technology and Exploring Engineering (IJITEE), 8(12), 2019.

[24] Li, J.; Heap, A.D. Spatial interpolation methods applied in the environmental sciences: A review. Environ. Model. Softw. 2014, 53, 173-189.