RETRIEVAL OF TEMPERATURE AND EMISSIVITY OF DUNE FIELDS USING LANDSAT8 AND QUARTZ SPECTRAL LIBRARY IN AN ITERATIVE APPROACH

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ABSTRACT

Retrieval of temperature emissivity (TE) for targets using thermal infrared (TIR) data is of great importance in climatology, urban heat island analysis, geological studies, and many more. In TIR, water vapor content is the largest source of errors in radiance data (common in humid climate) requiring an efficient atmospheric correction. Another source of error is that the radiance is a function (depend) of the TE of the target, making this an indeterminate problem. The objective of this work is to propose a method to recover TE for quartz from its radiance spectrum measured in a laboratory for mitigating the indeterminate problem. For this purpose, we used linear regression models in radiance laboratory spectrum quartz data, applied to LANDSAT 8 image. The results showed that it is possible to recover the TE with errors of 0.179K in temperature and 0.0031 in emissivity when compared to other classical methods referred as Reference Channel Method (RCM), and at the same time mitigating the indeterminate problem.

Key words — Quartz, Temperature, Emissivity, TES, LANDSAT 8.

1. INTRODUCTION

Radiance data in thermal infrared (TIR) can be used to obtain temperature and emissivity of a target, which has applications in several fields. Geology, climatology, analysis of biological processes, geophysical analysis, studies of atmospheric plume, land use, disaster assessment, pollution research and change detection are some of the these applications [1]-[2]. To use TIR for these applications, it is important to extract temperature and emissivity consistently because these information combined to form the radiance spectrum of the target.

Among the various fields of applications of TIR, the main one is geological mapping. The behavior of minerals and the observed spectral features have been found to be correlated, especially in relation to silicates. These features are related to the differences in the SiO content in the soil [3]-[4], which has minimal emissivity and therefore maximum absorption (reststrahlen effect). This behavior can be observed in silicates, such as quartz, having reststrahlen effects observed around 8,2µm and 9,3µm [4]-[5]. Thus, TIR (8µm to 15µm) is effective for this kind of study where the emissive properties of the material are predominant compared to their reflective properties [6] and hence used to get better results in geological mapping.

One of the main problems associated with TIR data is the difficulty in obtaining precise measurements for the temperature and emissivity of the target due to the nonlinearity in the temperature and radiance of the target [4]-[8]. To mitigate this problem, many researchers tried to develop better algorithms to separate temperature and emissivity for TIR as described by [4]-[9].

In the TIR, radiance is calculated using Planck's function and the emissivity of the target (for a given wavelength and temperature). However, regardless of the number of bands used for measurements of radiance, there will always be one more variable than the measured. For example, a spectral radiometer, which obtains radiation measurements from N bands, has $N + 1$ unknowns (N emissivity/radiance for each band and the temperature) [4]-[8]). This makes the system indeterminate, when there are more unknowns than equations, unless additional constraints are included in the system. It should be noted that another problem in TIR measurement is the atmospheric effects, particularly in humid environments, where high humidity interferes with the proper acquisition of data from earth's surface. Thus, whenever possible it is necessary to perform atmospheric correction since the error propagated in the calculation of the temperature/emissivity due to nonlinearity of the TIR itself can be significant.

This work proposes a new iterative approach to retrieve the temperature and emissivity of a target from the radiance data. It uses the linearized form of Wien's approximation for Planck's function and a regression model of the spectral library of a target at different temperatures. Thus, it is possible to estimate the temperature of the target knowing only its radiance. This work hypothesize that emissivity is temperature dependent, and the question to be answered is whether it is possible to reach a good accuracy and precision in TE retrieval from a single band sensor. In this way, the authors expect to develop a consistent approach for separation of temperature and emissivity, minimizing the errors, which can be easily extrapolated and applied at larger scales.

2. MATERIAL AND METHODS

2.1. Material

The study area is one of the last dune fields in the state of Rio Grande do Sul (RS), called Cabras Beach, located on the northern coast of the state, between the municipalities of Cidreira and Tramandaí, approximately 10 km long and 500 m wide (Figures 1 and 2).

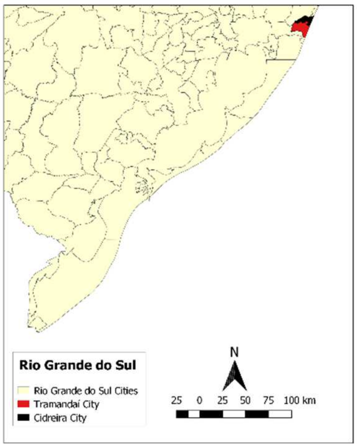

Figure 1: Study area location


Figure 2: LANDSAT 8 R4G3B2

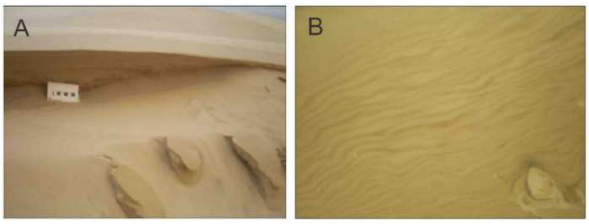

Figure 3: Dune fields from study area, a) side view b) nadir.

The dune fields (Figure 3) are characterized in such a way that they arranged side by side and are moving by the action of the wind, mobilizing the sandy particles. The region was formed by large sea level oscillations (up and down) controlled by glacial and interglacial climatic cycles. During the glacial period, the global climate is drier and the glaciers retain large amounts of water. Consequently, the level of the oceans falls and the coastline recedes, increasing the continental area. During interglacial periods, the average temperature of the earth surface increases, the glaciers partially melt and the level of the oceans rises, decreasing the coastline and the continental area. The spectral library was provided by the LabSRGeo (Laboratório de Sensoriamento Remoto e Geológico), CEPSRM (Centro Estadual de Pesquisa em Sensoriamento Remoto e Meteorologia) of UFRGS (Universidade Federal do Rio Grande do Sul). This laboratory has the μFT-IR model 102 equipment that allows measurements of radiance and emissivity of targets in the laboratory and in the field. In this work, we used the quartz spectral library obtained in laboratory at various temperatures. A LANDSAT8 image of the study area, acquired on 09/12/2018 was used and 16739 pixels over the inner dune field were selected. The parameters for its atmospheric correction were calculated using the online module https://atmcorr.gsfc.nasa.gov/.

2.1. Method

This study used an iterative process based on the Wien's approximation of Planck Function (Equation 1) to retrieve the emissivity and the temperature using only radiance data.

$$BB_{Wien}(\lambda,T) = \frac{C_1}{\lambda^5 \pi e^{C_2/\lambda T}} \quad (1)$$

where, BB_{Wien} is the Wien's approximation of blackbody radiation, ε is the emissivity, λ is the wavelength given in μm, T is the temperature in K, $C_1 = 3.74151\text{x}10^{-16} Wm^{-2}$ is the first radiation constant and $C_2 = 0.0143879mK$ is the second radiation constant. The laboratory data were then re-sampled according to:

$$L = \frac{\int f_{response} * L_{measurements}}{\int f_{response}} \quad (2)$$

where, L being the resampled data, $f_{response}$ the response function for LANDSAT8 band 10, $L_{measurements}$ the laboratory measurements of the target. As the data in their normal space (radiance-space) has a low enhance to variations of temperature, it is necessary transform the lab data into a space, where this enhance is optimized. To do this, the data is linearized (space-log radiance) using:

$$\frac{C_2}{T} = \lambda \ln(\varepsilon) + \lambda \ln(C_1) - 5\lambda \ln(\lambda) - \lambda \ln(\pi) - \lambda \ln(L_\lambda) \quad (3)$$

In this new space, the data is better discriminated than in the original space. With the laboratory data in space-log, the regressions are performed using the Equation 3. The left-hand side of the equation is the dependent variable and the right-hand side of the equation is the independent variable.–The iterative process initially uses the simplification of Equation

ISBN: 978-85-17-00097-3

2, given by Equation 4, to determine the initial temperature and emissivity values.

$$\frac{C_2}{T} = \lambda \ln(C_1) - 5\lambda \ln(\lambda) - \lambda \ln(\pi) - \lambda \ln(L_\lambda) \quad (4)$$

As can be seen in Figure 4, the emissivity can be neglected at the first step of the process, due to low contribution.

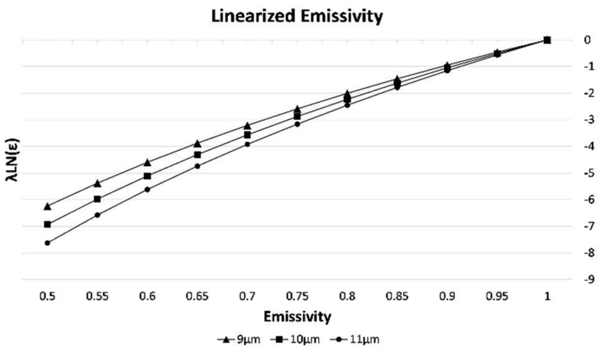

Figure 4: Log-space linearized emissivity component contribution from different emissivity values.

After the initial determination of temperature and emissivity, an interactive process begins. In this process, corrections for differences between Wien's approximation and Planck function are performed and the temperature/emissivity is adjusted using Equations 5 and 6.

$$RHS^n = \lambda \ln(\varepsilon^{n-1}) + \lambda \ln(C_1) - 5\lambda \ln(\lambda) - \lambda \ln(\pi) - \lambda \ln(L_\lambda^{n-1}) + A(T^{n-1}) \quad (5)$$

$$T^n = \frac{C_2}{f(RHS^n)} \quad (6)$$

where, n is the iteration, $A(T)$ is the correction factor for the difference between the Planck functions and its approximation given by Wien and $f(RHS)$ is the linear regression modeled based on linearized lab data in the log-space. The process runs while a threshold is not reached. In this work, the threshold has been reached when:

$$L_{img} - \bar{L} < -0.18 \quad (7)$$

where, L_{img} is the radiance of the LANDSAT8 image in the pixel analyzed and $\bar{L}$ is the radiance calculate in the iterative process. A flowchart of the process is presented in Figure 5 and more details of the process are given in [9] and Grondona et al. (in preparation).

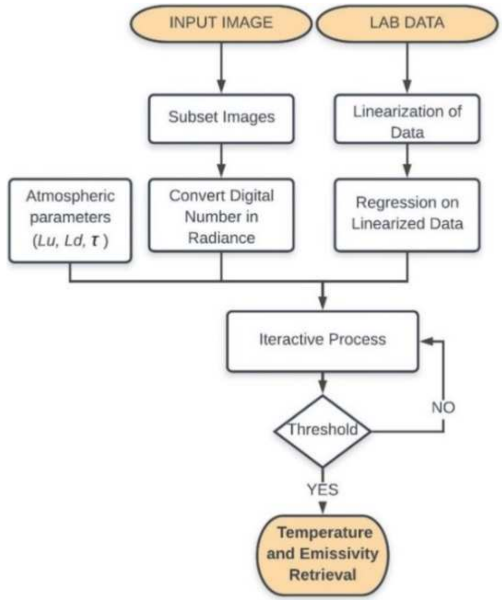

Figure 5: Flowchart of the proposed iterative method.

3. RESULTS

The results are presented as temperature maps. Figure 6 shows the result of the proposed method and Figure 7 is a temperature map generated using a constant emissivity of 0.8832 from band 10 of LANDSAT8 by the application of inverse Reference Channel Method (RCM).

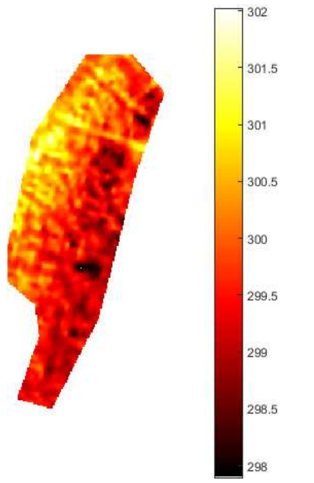

Figure 6: Temperature image from proposed method

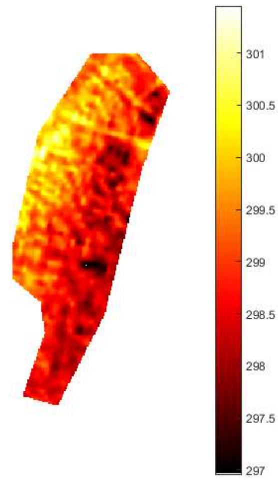

Figure7: Temperature image from RCM method

As seen in figures 6 and 7, there is no visual difference between the two methods. In other words, the new method shows that the temperature can be retrieved with an error less than 1k from laboratory spectra. In fact, the error between these two methods is less than 0.32K. Figure 8 shows the image difference between the Temperature from RCM and that from the method proposed in this work.

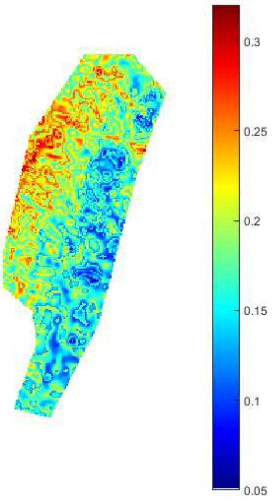

Figure 8: Temperature difference image (RCM Temperature – Iterative Temperature)

In Figure 8, the regions in blue were the greatest differences occurred and it is possible to see that it was in the coldest area of dune field. In contrast, the smallest differences occurred over the areas with the highest temperature in the dune field. In terms of quantitative values, 0.32K gives the maximum difference between the reference and the calculated temperatures, the minimum difference is 0.06K, the mean error is 0.179K with standard deviation of ±0.04K with 0.185 K of RMSE errors. For emissivity, these values are: -0.0013 for maximum difference, -0.0052 for minimum difference, the mean error of 0.0031 with standard deviation of ±0.0006 and RMSE error of 0.0031.

4. DISCUSSION

The mean error of the proposed method in this work for temperature is 0.179K and for emissivity is 0.0031 for a temperature of about 299.5K, for RCM is 299.75K and by the proposed method is 299.57K. It represents an error less than 0.06% for a reference temperature of 299.5K. The proposed method achieved compatible precision when compared with the orbital thermal sensor of LANDSAT8 that has NEΔT = 0.4K at T = 300K (USGS, 2018). Furthermore, the results showed that the error in the proposed method is 2.2 times less than the error given for the sensor at 300K. Although the results are satisfactory, it must be noticed that the difference is a positive number, which means that there is a systematic error that needs to be fixed. This error can be caused mainly by 2 factors: (1) the correction facto *A(T)* in the equation 5, and (2) by the threshold applied in the iterative process.

5. CONCLUSIONS

Thermal infrared data, specifically the temperature-emissivity retrieval, has a well-known problem: without some assumptions to constrain the problem there is no possible solution, given that always are *N* equations (radiances) and *N + 1* unknowns (N emissivity and 1 temperature). With this in mind, the main objective of this work was to propose an approach capable of using some alternate data source, mitigate this problem and retrieve the temperature and emissivity with a good accuracy and precision. The proposed method is an iterative approach that uses laboratory radiance spectra to retrieve temperature and emissivity using only the radiance data. In this way, the method showed great potential for applications in field, with errors are compatible with those specified by the USGS – LANDSAT. Some points need more research in the future, such as the correction factor and the threshold determination. Improvements in these parameters may lead to better results.

ACKNOWLEDGMENT

We would like to acknowledge CAPES (Coordenação de Aperfeicoamento de Pessoal de Nível Superior) for providing financial assistance for this research, and the LabSRGeo for the laboratory data.

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