Sand Mining Lakes Along the Paraíba do Sul River: An Assessment Based on Sentinel 2B/MSI Sensor

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Abstract. *Sand mining activity is present along the Paraíba do Sul River, promoting changes in the landscape with the formation of lakes, that have different colors and spectral responses depending on their current status of activity. This study aims to identify and quantify the distribution of these lakes, using Linear Spectral Unmixing Model (LSUM) in a Sentinel 2B/ MSI image. From the water-sediment fraction originated, the lakes were segmented and classified. The cities of Tremembé, Pindamonhangaba and Taubaté were the areas with more active mining lakes, while in the Roseira region, the non-active mining lakes were predominant. Approximately 63% of lakes of the Vale do Paraíba Region were defined as active sand mining lakes.*

1. Introduction

The monitoring of natural resources in large regions, such as the Paraíba do Sul River outskirts, can be optimized through remote sensing and image processing. According to Reis et al. (2006), sand extraction occupies a prominent place among the region economic activities. In general, these mining activities have an important role in social and economic development, generating jobs and moving the construction market. However, the extractive activity of sand causes environmental problems and major landscape transformations, including the formation of sand pits known as mining lakes, which have different characteristics when observed by satellite images.

In the Vale do Paraíba region, sand extraction began on the Paraíba do Sul river and, later, it was explored in the river plain pits [Da Silva et al. 2011]. The color of the water observed in remote sensing images may be used to identify whether sand pits are active or not [Da Silva et al. 2011]. The blue tone indicates that mining is active, considering that the lighter shade of blue, the greater the intensity of mining activity, on the other hand, the dark tone represents the inactivity of mining practices [Da Silva et al. 2011]. Most mining pits, despite a request for use of fish farming or fish and pay in most degraded area recovery plans, often end up abandoned and in the process of eutrophication [Mechi and Sanches 2010]. The eutrophicated lakes usually appear in dark and brownish colors in the satellite images due to the coverage of macrophytes and the high content of organic compounds and nutrients.

Generally, mining causes significant impact over the environment, since this activity often involves suppression of vegetation, soil exposure and erosion, which results in important changes in the quantity and quality of surface and ground-waters and in air pollution, among other negative effects [Mechi and Sanches 2010], and so several recovery processes are needed. In many cases, the lakes originated are filled with the water provided by water table and rain, and the sediments in suspension decant over time, leaving the water relatively cleaner.

In this context, the aim of this study is to assess the current conditions of the sand mining lakes along the Paraíba do Sul River using Linear Spectral Unmixing Model (LSUM) and a segment-based classification for a scene derived from Sentinel 2B/MSI sensor. The analysis of lakes according to their content of suspended sediment, was based on their spectral response, and so providing the basis for inferences about the quantity of deactivated lakes and those that are under sand mining operation.

2. Material and Methods

A remote sensing image corresponding to June 26th, 2019 derived from Sentinel 2B/MSI (level 2A) was used to assess the study area. In this image was applied the Linear Spectral Unmixing Model (LSUM), a water mask to enhance the lakes and also techniques of segmentation and classification. The image processing was based in the MSI spectral bands B2 (447,6 - 545,6nm), B3 (537,5 - 582,5nm), B4 (645,5 - 683,5nm) and B8 (762,6 - 907,6 nm), all of them with a 10m spatial resolution. ENVI 5.1 and QGIS 3.8 softwares were chosen to apply the processes mentioned.

2.1. Study Area

The study area comprises the Vale do Paraiba region, located in the state of São Paulo. The Paraíba do Sul River results from the confluence of the Paraibuna and Paraitinga rivers, which sources are in the São Paulo state. During its course, it crosses, among others, the municipalities of Cachoeira Paulista, Lorena, Aparecida, Potim, Roseira, Pindamonhangaba, Tremembé, Taubaté and Caçapava; cities that compose our study area (Figure 1). Its discharge occurs in the Rio de Janeiro state, flowing to the Atlantic Ocean.

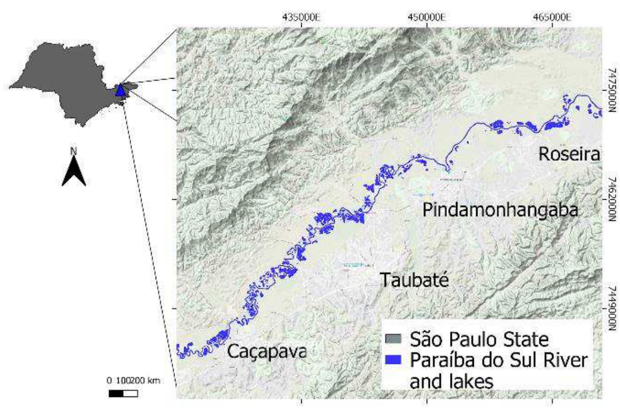

Figure 1. Study area.

It is important to highlight that in the city of São José dos Campos, the sand mining is prohibited since 1984, but the effects of the past mining activities can be seen until today. For this reason, this city was excluded from the follow analysis.

2.2. Linear Spectral Unmixing Model (LSUM)

In this model, a linear relation is used to represent a spectral mix of targets in each image pixel, requiring the selection of pure components (endmembers) of a scene. In this study was determined a representative pixel of water with high suspended sediment content, eutrophicated water and clean water. Thus, the response of each pixel, in any spectral band, can be defined as a combination of the responses of these constituents, generating the synthetic bands called fraction images [Shimabukuro et al. 1998]. Although three synthetic bands were generated, only the water-sediment fraction image was used for the next steps of this study, due to the quality and clarity of the information provided. According to Valerio et al. (2013), the LSUM can be calculated as equation 1:

$$n = \sum_{i=1}^{n} (a_{ij} x_{ij}) = e_i \qquad [1]$$

Where r_i is the resulting pixel reflectance in band i for a pixel composed by components (from a total of components); a_{ij} is the in band individual component reflectance, which corresponds to a proportion x_{ij} of the pixel ($0 \leq x_{ij} \leq 1$), and e_i is the error of each spectral band.

2.3 NDWI - Water mask

The Normalized Difference Water Index (NDWI) was calculated in order to enhance only the water features, focusing on the aim of this study. This index makes use of reflected near-infrared radiation and visible green light, since NIR is as strongly absorbed by water as reflected by terrestrial vegetation and dry soil [Mcfeeters 1996]. Therefore, the NDWI maximizes the typical reflectance of water features by using green light, minimizing the low reflectance of NIR by water features. It takes advantage of the high reflectance of NIR by terrestrial vegetation and soil features that results in a negative index value. In this way, the image processing to eliminate negative values, retaining just the water bodies information for analysis (the range of NDWI is then from zero to one). Thus, the NDWI for Sentinel2B/MSI sensor is calculated by the equation 2:

$$\text{NDW}I = \frac{B3 - B8}{B3 + B8} \qquad [2]$$

Where B3 is the green band and B8 the NIR band of the MSI sensor. The NDWI was used as a water mask (pixels with NDWI values lower than 0 were excluded from the study, as were considered non-water pixels) in the water-sediment fraction derived from the LSUM.

2.4 Segmentation

The image segmentation is a process that divides the spatial data into meaningful regions, based on the homogeneity and heterogeneity criteria [Haralick and Shapiro 1992]. For this paper, was used a Ruled Based segmentation algorithm, implemented on ENVI 5.3. This algorithm allows the user to define the degree of segmentation (smaller or bigger segments) and specify rules to classify these segments.

In order to achieve the proposed goal, the segmentation was applied in the masked water-sediment fraction with a scale level of 100%, assuring that each lake would be classified in a single class. Based on the image analysis, the specified classification rule was that lakes with sediment fraction lower than 0.2 would be classified as non-active sand mining lakes and those with values higher than 0.2, as active lakes. This threshold of 0.2 was empirically determined after several tests. Another condition was that the lakes should have an area larger than 10.000 m², preventing the classification of other water bodies and isolated in-land pixels.

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3. Results and Discussion

The LSUM generated four fraction images, whereas the water-sediment fraction was capable of highlighting the lakes condition (Figure 2. A). This fraction emphasizes the features with higher sediment contents by showing them with lighter shades of gray and white. This information obtained is confirmed by the RGB 432 composition (Figure 2. D), in which lakes with light blue and white are known a current mining lakes. As the clean-water and eutrophicated-water fraction (Figures 2.B and 2.C) did not provide relevant information for study purpose, they were not used.

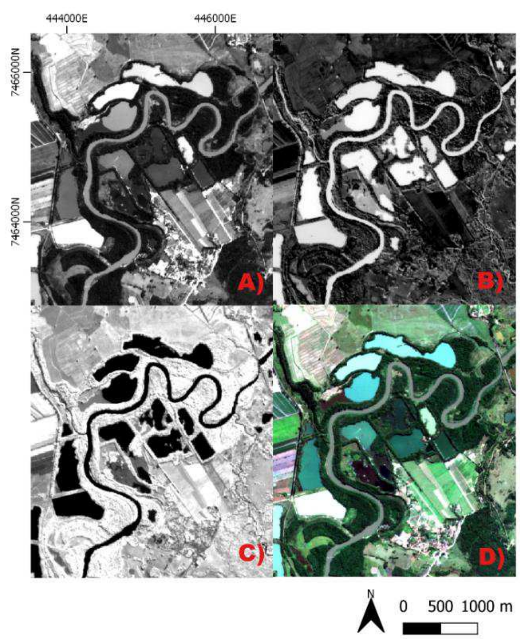

Figure 2. Fraction images generated from LSUM (A) water-sediment fraction, B) clean-water fraction, C) eutrophicated-water fraction and D) RGB 432 composition.

The application of the water mask in the water-sediment fraction was crucial to eliminate the non-water features. The segmentation and classification techniques resulted in the discrimination of the lakes in active (lakes with a sediment fraction higher than 0.2) and non-active (lakes with sediment fraction lower than 0.2), all of them with a superficial area bigger than 10.000 m² (Figure 3).

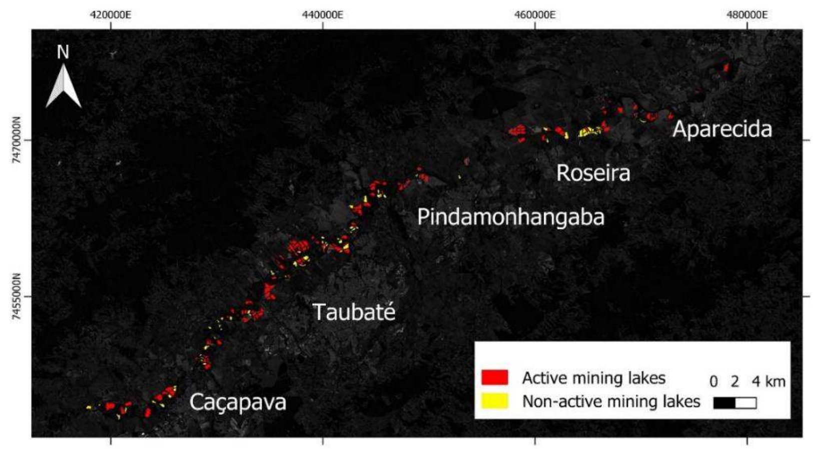

Figure 3. Segmentation and classification results of the lakes in active and non-active classes.

A closer look at the segmentation lakes in two sand mining regions, and the quantity of lakes from each class are presented in Figure 4. The results show consistency, as the lighter blue and white lakes were classified as active mining lakes and the darker lakes as non-active mining lakes, according to the true color RGB Sentinel 2B.

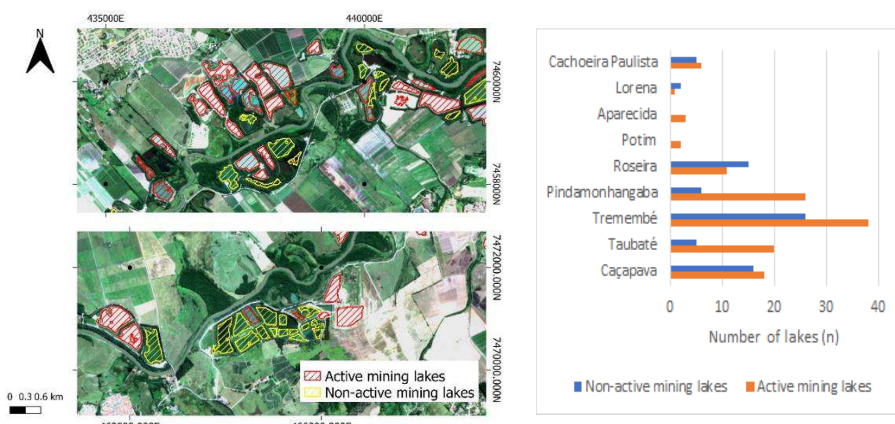

Figure 4. Classification of mining lakes (left) and quantity of non-active and active mining lakes (right).

Tremembe, Pindamonhangaba and Taubaté were the areas with more active mining lakes, while in Roseira region, the non-active mining lakes were predominant. Cachoeira Paulista, Lorena, Aparecida and Potim were regions with a lower number of mining and non-mining lakes. In total, 200 lakes in the region were identified, of which 62,5% classified as active mining lakes. In terms of area, the active sand mining lakes accounted for approximately 74% (active lakes tend to be bigger), stating that they are predominant in the Vale do Paraíba Region.

4. Conclusions

LSUM succeeded in the estimation of sediment proportion in the studied lakes, when applied in a high spatial resolution image, based on visual interpretation. The use of a specific fraction image allows a greater interpretation of the scenario and with relatively simple techniques applied posteriori, it was possible to quantify the number of active lakes in a more efficient way.

This approach has the potencial for the mining lakes monitoring in the Vale do Paraiba region. Thus, it would be capable of supporting surveillance agencies and adequate public policies.

Future studies could compare the changes in the situation of lakes through a time series analysis. In this way, it would be possible to identify when the sand mining started in a region, and also to confirm the regularity of licensed áreas. Moreover, among the detected active lakes, validation procedures based on in situ data and environmental licensing verification could endorse the obtained results.

5. References

Da Silva, G. B. S., Simi, R. and Rudorff, B. F. T. (2011) "Monitoramento da extração de areia nos municípios não pertencentes ao Zoneamento Ambiental Minerário do trecho paulista da várzea do rio Paraíba do Sul", In: *XV Simpósio Brasileiro de Sensoriamento Remoto*, Curitiba. Anais... São José dos Campos: INPE.

Haralick, R. M. and Shapiro, L. G. (1992) "Computer and robot vision", Addison-Weasley, 1st edition.

Mcfeeters, S. K. (1996) "The use of the Normalized Difference Water Index (NDWI) in the delineation of open water features", International journal of remote sensing, v. 17, n. 7, p. 1425-1432.

Mechi, A. and Sanches, D. L. (2010) "Impactos ambientais da mineração no Estado de São Paulo", Estudos avançados, v. 24, n. 68, p. 209-220.

Reis, B. J. et al. (2006) "Influência das cavas de extração de areia no balanço hídrico do vale do Paraíba do Sul", Revista Escola de Minas, v. 59, n. 4, p. 391-396.

Shimabukuro, Y. E., Novo, E. M. and Ponzoni, F. J. (1998) "Índice de vegetação e modelo linear de mistura espectral no monitoramento da região do Pantanal", Pesquisa Agropecuária Brasileira, v. 33, n. 13, p. 1729-1737.

Valerio, A. M. and Kampel, M. (2013) "Uso de Imagens LISS-III para a caracterização espectral da pluma do Rio Paraíba do Sul", In: *XVI Simpósio Brasileiro de Sensoriamento Remoto,* Foz do Iguaçu. Anais... São José dos Campos: INPE.