

## EVALUATION OF RESTORATION TECHNIQUE IN COMPLEX LANDSCAPE AREAS

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### ABSTRACT

In remote sensing images, the problems related to spatial resolution, image degradation and pixel mixture could particularly affect heterogeneous areas. Restoration is a technique that aims to correct radiometric distortions and, combined with a resampling filter, generates images in a finer grid with improved visual quality. This study aims to evaluate the effectiveness of restoration technique to improve quantitative measurements of classification in complex landscape areas. For this purpose, a Landsat 5 Thematic Mapper image with 30 m spatial resolution was processed using restoration and resampling techniques, resulting in a 15 m spatial resolution image. Preliminary results applying a linear spectral mixing model, followed by supervised classification indicated that the restored image showed better visual quality, thus allowing to detect targets in the scene with more details. However, a quantitative comparison between processed and original images, resulted in slight differences ( $\pm 0.003$ ) in classification accuracy.

**Key words** — Linear spectral mixing model, supervised classification, Landsat-5 TM, image restoration.

### 1. INTRODUCTION

In remote sensing images, each pixel has a digital number that results from spectral responses of the elements inside the region delimited by the sensor field of view (FOV) plus atmospheric contribution [1]. The occurrence of different elements inside the pixel explains the mixture problems [1,2] and this fact can be further aggravated by the larger pixel size, in other words, the smaller spatial resolution of a sensor.

In addition to the sensor spatial resolution characteristics, the original signal can be degraded during imaging formation process due factors as optic diffraction, detector size and limitations of the electronic filter, for example. This degradation causes a blurred appearance in the image, characterizing the loss of details affecting the radiometric quality [3].

Thereby, the problems related to spatial resolution, degradation of image process and pixel mixture could particularly affect heterogeneous areas as studies of landscape complex zones, defined here as a subset of landscape boundaries representing different components such

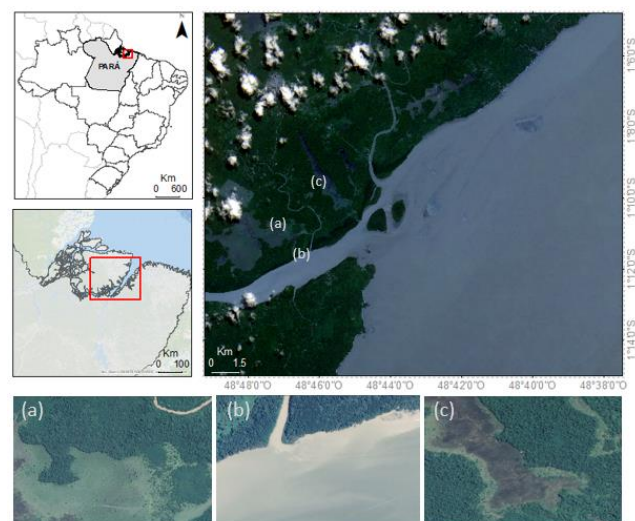
as plant communities [4], water bodies and soils. Due to mixture of targets in these complex zones, classification accuracy of lower spatial resolution remote sensing images could be affected that consequently impacts the monitoring of land use and land cover changes.

Restoration is a technique that aims to correct radiometric distortions inserted by the optical sensor in process of generating the digital images in order to reduce a blurring effect. The correction is performed by a linear filter, where weights are obtained from the sensor characteristics and not empirically as the case of traditional enhancement filters. In this manner, the filter is specific to each type of sensor and spectral band [5]. Moreover, the process combines a resampling filter to generate images in a finer grid with better visual quality.

The main purpose of this study is to evaluate the effectiveness of restoration technique to improve quantitative measurements of classification in landscape complex zones, using a Landsat 5 Thematic Mapper and separating surface targets by linear spectral mixing model.

### 2. MATERIAL AND METHODS

This research was carried out in a region situated in an estuary of the Amazon river – near to Marajó island – and located  $01^{\circ}12'00''$  of South latitude and  $48^{\circ}48'00''$  of West longitude in State of Pará, Brazil (Figure 1).



**Figure 1.** Location of the study area in Marajó Island, Para State – Brazil and representations of non-inundated areas (a); lowland areas bordering rivers (b) and inundated rainforest areas (c).

Hydrography directly influences the local vegetation, which defines the main regional ecosystems. There are four kinds of ecosystems: "terra firme" ("uplands" – non-inundated areas – (a) in Figure 1)), "várzea" ("wetland" – extensive lowland areas bordering the main river and its tributaries – (b)), "igapó" (inundated rainforest areas (c)), and natural grasslands (wide-open areas of pastures) [6].

To realize this study, we selected one cloud-free Landsat 5 Thematic Mapper (TM) scene from 07/29/2011 and path/row 224/61. The Landsat scene was acquired from the USGS (United States Geological Survey) already orthorectified and atmospherically corrected. We also selected one RapidEye scene from 08/09/2011 that provides 5 m spatial resolution data, obtained from <http://geocatalogo.mma.gov.br/>. A higher spatial resolution data was used to produce a validation map to supports the interpretation of targets on scenes and evaluation purposes.

Initially, the scenes were extracted to the interest area in order to minimize the presence of clouds and also registered geographically. After images pre-processing, all bands of Landsat TM were restored using the combined interpolation-restoration method from 30 m to 15 m spatial resolution (Figure 2: Step 1) and the process is realized on spectral band by spectral band of each sensor. It should be noted that this type of processing is recommended to be performed on the original image without any kind of processing such as enhancement and filtering, which alter the radiometric characteristics of image [7]. All procedure was realized on *SPRING software version 5.5* [8].

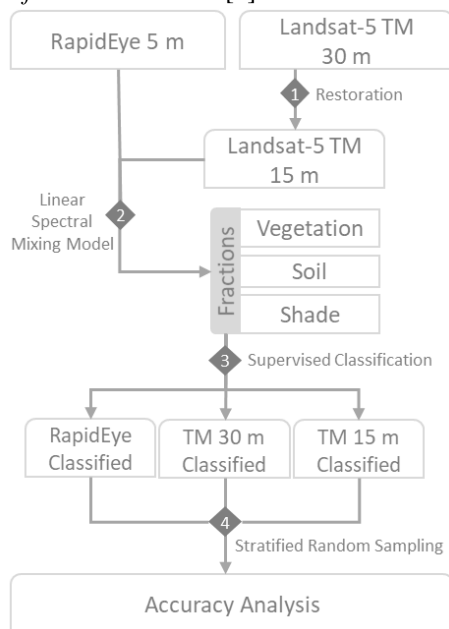


Figure 2. Methodological Flowchart.

Among techniques of image processing that allows quantifying the proportion of elements within a pixel, Linear Spectral Mixing Model (LSMM) is one of the most used to separate components as vegetation, soil and shade (also considered in this study such as water). From LSMM, the value of each digital element on image is the weighted

combination of pure pixels of soil, shade and vegetation present in each element on scene [2]. In step 2, the pure pixels (endmembers) used in the model were selected directly in the image and a linear relationship spectral reflectance mixture of surface endmembers was used to obtain the fraction images (Equation 1):

$$\rho_i = a * veg_i + b * soil_i + c * shade(water)_i + \epsilon_i \quad (1)$$

Where:  $\rho_i$  represents the spectral reflectance in band  $i$  of TM image;  $a$ ,  $b$ , and  $c$  are the proportion of vegetation, soil, and shade in each pixel;  $veg_i$ ,  $soil_i$ , and  $shade_i$  correspond to the spectral responses of each components;  $\epsilon_i$  is the error term for each band  $i$ .

Subsequently, after generating fractions images of vegetation, soil and shade for all three images (RapidEye, TM 30 m and TM 15 m), we classified the data using a supervised classification method by maximum likelihood, pixel by pixel, determining three classes for classification and using the same samples to both original and restored Landsat scenes (Step 3).

In step 4, we analyse the results by visual interpretation and accuracy assessment in both classifications in TM 30 m and TM 15 m in order to evaluate the use of Restoration technique. The approach to accuracy assessment was based on the work of [9] as indicated by [10]. A random sampling design was performed considering each stratum according to all classes of this work, based on the frequency of the pixels for each class.

[9] indicate the use of error matrix based on stratified sampling to convert into a new error matrix (Equation 2) by estimated area proportions. From this new matrix, the 95% confidence interval is obtained by multiplying the standard error and also user's, producer's, and overall accuracies. The diagonal values in matrix present the number of correctly identified pixels. The other values represent the number of pixels classified into another class.

$$\hat{p}_{i,j} = \frac{W_i \times n_{i,j}}{n_i} \quad (2)$$

Where:  $\hat{p}_{i,j}$  – is the estimated area proportion for each cell in the matrix error;  $W_i$  – is the class weight (the area proportion mapped as class  $i$ ) and can be calculated by dividing the number of pixels per class by the total number of pixels [10];  $n_{i,j}$  – is the sample count in cell  $i, j$  and  $n_i$  is the total number of sample counts in class  $i$ .

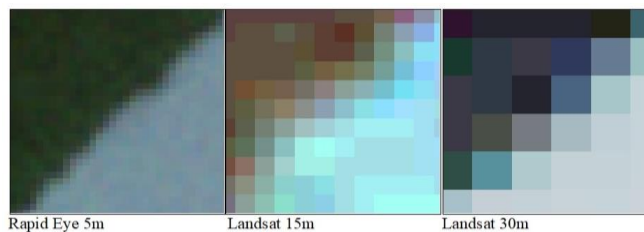
All samples and accuracy analysis were obtained using the R programming environment and algorithms developed by [10] (<https://github.com/openforis/accuracy-assessment>) [11, 12] comparing with our ground truth.

### 3. RESULTS AND DISCUSSION

The results obtained through the interpolation-restoration process are illustrated in Figure 3. It is observed that the restored image brings a visual gain in the highlighting of elements present on scenes. This effect is better visualized in edges areas.

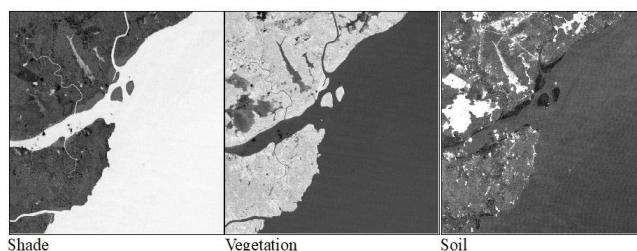
The result allows greater detailing of targets, since that the blurring effect is reduced when compared to original

image with lower spatial resolution. Due to interpolation method through cubic convolution, it is generated a more natural appearance on image, after assigning a new value to the pixel.



**Figure 3. Result of interpolation-restoration to 15 m compared to validation (left) and original scene (right) in 1:2000 scale.**

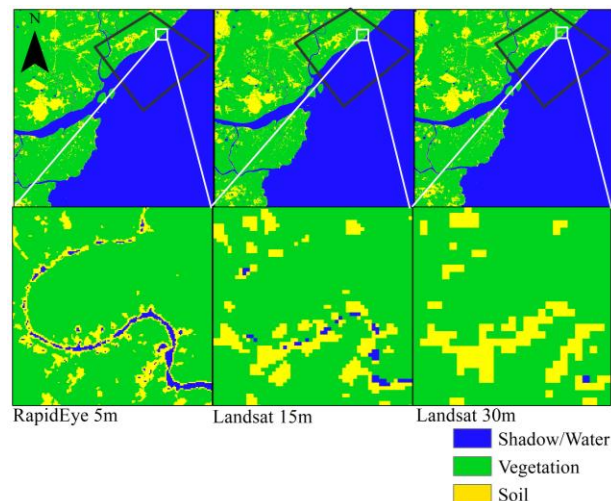
The use of LSMM highlighted the targets of interest and reduces dimensionality of data, simplifying the classification process. The components of soil, vegetation and shade are highlighted in the correspondent fraction images, considering that the shade fraction highlighted areas of low reflectance (Figure 4).



**Figure 4. Shade, vegetation and soil fraction images derived from LSMM.**

Considering the final results, based on supervised classification, could be observed in the image detail that the restoration technique brings a better result visually. Although based on the original data of TM 30 m, the scene applied restoration technique presented greater detailing compared to lower original resolution. As observed in zoom (Figure 5), it is possible to detecting features and more similarities compared of our 5 m validation data. Considering studies about complex zones, forest fragments, forest degradation, areas bordering the main river and its tributaries and also landscape boundaries, this result can bring a better definition of each element seen on scene.

Table 1 and 2 presents the statistical analysis by comparing the results obtained from both original and restored Landsat TM with RapidEye in terms of estimated area proportion. In overall, the comparisons showed a high accuracy between 0.967 and 0.970, with results slightly superior in the restoration technique. Our comparison showed that the “Soil” class is more confused in both results, specifically, what we mapped as “Soil” in TM classification’s in our reference was defined as “Vegetation”. This result implies in the lowest user’s accuracies.



**Figure 5. Classification scene (above) and zoom (below) representing improved detail of the river in 1:10000 scale.**

**Table 1 – Error matrix expressed in terms of estimated area proportion based on stratified sampling (Equation 2).**

		Reference RapidEye 5 m				
		Shade	Vegetation	Soil	Total	$W_i$ *
Classified Map TM 30 m	Shadow	0.629	0.003	0.005		0.637
	Vegetation	0.000	0.308	0.010		0.318
	Soil	0.003	0.012	0.030		0.045
	Pixels	52,095	26,009	3,718	81,822	
	Area (km <sup>2</sup> )	46.52	23.74	3.37	73.64	
S(Area) (Km <sup>2</sup> )		0.33	0.44	0.48		
95% CI (km <sup>2</sup> )		0.653	0.869	0.948		
User's		0.988	0.968	0.670		
Producer's		0.996	0.954	0.665		
Overall		0.967				

**Table 2 – Error matrix expressed in terms of estimated area proportion based on stratified sampling (Equation 2).**

		Reference RapidEye 5 m				
		Shade	Vegetation	Soil	Total	$W_i$
Classified Map TM 15 m	Shadow	0.633	0.002	0.002		0.638
	Vegetation	0.000	0.315	0.005		0.320
	Soil	0.005	0.015	0.022		0.042
	Pixels	208,711	104,740	13,833	327,284	
	Area (km <sup>2</sup> )	46.99	24.51	2.14	73.64	
S(Area) (Km <sup>2</sup> )		0.26	0.33	0.34		
95% CI (km <sup>2</sup> )		0.52	0.66	0.66		
User's		0.993	0.985	0.520		
Producer's		0.992	0.947	0.757		
Overall		0.970				

\*Where S means Standard deviation and CI means confidence interval of the classes.

The overall results of classification accuracies could be explained by the fact that restoration technique is based from own sensor characteristics to correct distortions inserted by the optical sensor. Though our results were similar to quantifying targets as water/shade, vegetation and soil, different areas in terms of characteristics and plot size could be tested. However, is important to considerate that restoration technique will increase the time spent in data processing, since its application is made on spectral band by spectral band.

#### 4. CONCLUSIONS

The application of restoration techniques combined with resampling process resulted in images with improved visual quality that supports to detect features of different targets on scenes due to greater detailing in comparison to original image.

Particularly in studies about complex landscape zones, this technique could provide, for example, better detection of forest as also areas bordering the main river and its tributaries. Although this technique will increase the time spent in data processing, the application could support studies when higher spatial resolution images are not available.

#### 5. ACKNOWLEDGMENTS

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