

ImgTools: a software for optical remotely sensed data analysis

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Resumo.

Neste artigo apresentamos as principais ferramentas de processamento de imagens de satélites da versão beta do software ImgTools. ImgTools foi desenvolvido para ser usado nos projetos de pesquisa e de monitoramento florestal do Imazon, mas rapidamente chamou a atenção de uma comunidade de usuários beta que começaram a testar e a usar o programa em seus projetos. A carência de programas comerciais ou de domínio público com ferramentas integradas para normalização de dados multi-espectrais, de diferentes sensores remotos, com classificadores automáticos genéricos, foi a principal motivação para o desenvolvimento do software. Apresentamos também exemplos de projetos que utilizam o ImgTools e o desenvolvimento futuro do software.

Palavras-chave/key words: sensoriamento remoto, processamento de imagens, monitoramento de florestas; remote sensing, image processing, forest monitoring, REDD+

1. Introduction

Software for processing large multi-sensor and temporal datasets are still lacking inhibiting quick extraction of key information for decision makers and policy formulation. Overall, only a small fraction of the remote sensing data available in the public domain space has been actually processed to extract information about forest change. For example, the Landsat program has been acquiring satellite imagery of Earth since July 23, 1972, but very few tropical forest areas have been systematically monitored. Brazil has a long operational forest monitoring program – named Prodes (*Monitoramento da Floresta Amazônica por Satélite*) – since 1988. Prodes deforestation statistics exists since then, but digital maps are available only from 1997-2000 to now on, at an annual basis. Therefore, there is still a gap of forest change information in the Brazilian Amazon for most of the 1980s and 1970s.

Several issues must be overcome to improve information extraction from the available and upcoming satellite imagery data. The lack of generic image classification algorithms is one of these issues. Generic Classification is an Algorithm (GCA) that is both spatial and temporally robust, based on a standardized set of data and classification rules that can be used to map land cover changes within the same environmental conditions. GCA has been proposed to monitor forest conversion (Woodcock et al., 2001), but has not been applied thoroughly in very large areas such as the Amazon region.

GCA applied to multi-sensor imagery requires data normalization techniques. Spectral Mixture Analysis (SMA) is a promising one since it generates fraction images that are physically interpretable and comparable across sensors, avoiding the comparison of reflectance band values that are not usually positioned in the same spectral region and are not inter-calibrated. The greatest challenge regarding the use of fraction images in GCA has to do with the generation of standardized fractions through time and space. The problem of temporal standardization has been solved previously with the use of reference endmembers and the application of radiometric inter-calibration techniques (Roberts et al., 2002). One difficulty with this approach is the acquisition of reference endmembers which requires a well-calibrated spectral library representative of the land-cover types found in the areas of interest. An alternative approach based on the exploration of the spectral n-dimensional space

has been proposed to define a standard set of image endmembers that can be used to generate spatially consistent fractions worldwide (Small, 2004). This generic endmember approach has been successfully tested over large areas in the Brazilian Amazon using different sensors (i.e., Landsat, Spot, MODIS and Aster) (Souza Jr. et al., 2005a and 2005b; Souza Jr., 2009). Finally, multi-resolution fusion can be automated through downscaling geostatistical techniques enabling comparison of fraction images obtained with different pixel sizes (Sales et al., no prelo).

So far, there is no software encompassing all these remote sensing techniques to deal with data normalization, GCA and multi-sensor data fusion. In 2002, several pieces of software started to be written in IDL (Interactive Data Language) as part of a Ph.D. dissertation of C. Souza Jr. (Souza Jr., 2005). In 2010, most of the image processing programs were developed to run in command line and scripting modes. An intuitive and user-friendly graphical user interface (GUI) was lacking making the use of these programs a challenge for most users. Then, J. Siqueira, an undergraduate environmental engineer student joined a trainee program at Imazon, and quickly developed the necessary IDL skills to push the development of the GUI interface for the core set of IDL programs already developed. We have called the alfa version of the software *ImgTools* (*thinking we would come up with a better name in the future!*). *ImgTools* has evolved quickly and reached a level of more than 30 users in 12 countries, applying it to forest monitoring projects. In this article, we describe the features of the current beta version of *ImgTools*, its applications and future developments of this software. We also discuss the challenges to develop generic image classification algorithms to apply in the Brazilian Amazon region. The main goal is to share these information to encourage new users to try and help the development of *ImgTools* to build a remote sensing community that optimizes the use of satellite imagery data to monitor tropical forest regions and potentially other biomes.

2. Software Framework

ImgTools was developed to integrate fundamental image processing steps to accomplish classification of very large data sets across space and time. These steps include: (1) Pre-processing; (2) Build reference spectral libraries; (3) Spectral Mixture Analysis; (4) Image Classification; (5) Post-Classification (Figure 1). All these steps are explained in detail below.

2.1 Pre-Processing

In this step, *ImgTools* requires high accurate pixel co-registration (i.e., <1 pixel off) and atmospherically corrected images for temporal and large areas forest change detection and image classification analyses. Image registration has been performed outside *ImgTools* and can be done in different commercial and free software. For image registration, we use the triangulation algorithm for pixel interpolation and nearest neighborhood resampling, with enough image control points (usually 10-20) to warranty low root mean squared (RMS) errors (i.e. <1 pixel) to assure that the changes detected over time are not contaminated by misregistration (Verbyla and Boles, 2000).

To account for spatially variable atmospheric contamination noise due to haze and smoke, the technique proposed by Carlotto (1999) was implemented in *ImgTools*. The Carlotto technique is based on the assumption that smoke and haze only adversely impact the visible bands, mostly in the blue spectral region, leaving the near-infrared (NIR) and short-wave infrared (SWIR) bands unaffected. Statistics are calculated for the entire image, in which average values for visible bands (e.g. bands 1, 2 and 3 for Landsat TM/ETM+) are calculated for each unique combination of NIR and SWIR bands (e.g., bands 4, 5 and 7 for Landsat TM/ETM+). After calculating these statistics, the original values for the visible bands for a specific combination of the NIR and SWIR bands are replaced with the scene averages for

that combination. This technique homogenizes contamination throughout a scene – thus clear sky portions of the image gain a slight amount of contamination, while contamination is significantly reduced in areas under smoke or haze, but improves atmospheric correction. We have successfully implemented Carlotto's technique applied to Aster, MODIS and MERIS.

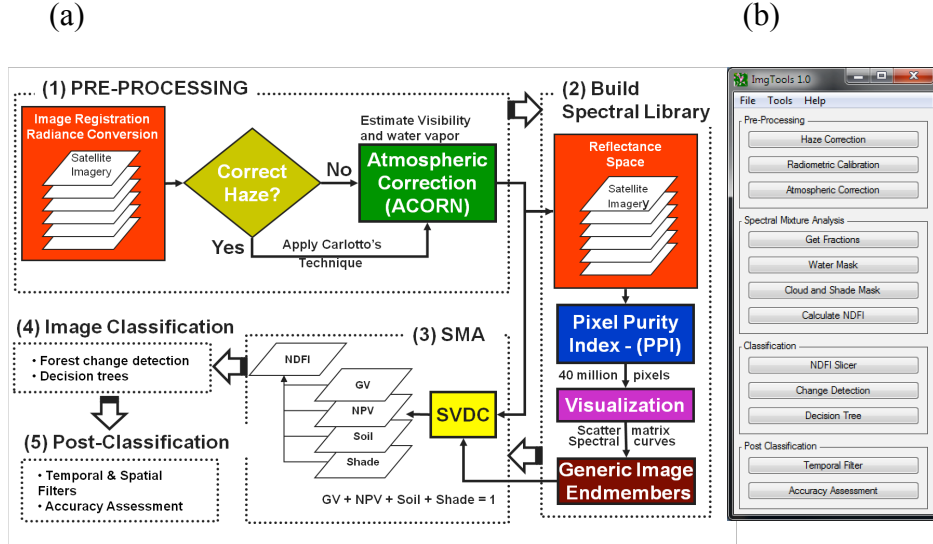


Figure 1. ImgTools conceptual framework (a) and main software interface (b).

ImgTools can radiometrically correct satellite data (Landsat, Aster, Spot, RapidEye) using the gains and offset provided in the image metafile. Radiance data must be converted to reflectance, which is an input data requirement for SMA. The current version does not have a module for atmosphere correction, and this step is usually performed using other software (Atmospheric Correction Now 4.0 – ACORN: Analytical Imaging & Geophysics, Boulder, CO; or FLAASH) or taken reflectance products generated by other sources.

2.2 Spectral Mixture Analysis (SMA)

SMA decomposes the spectral mixture – commonly found in the pixel reflectance values of remotely sensed data – into fractions of purer materials, known as endmembers. The SMA model assumes that the image spectra are formed by a linear combination of n pure spectra, such that:

$$R_b = \sum_{i=1}^n F_i R_{i,b} + \epsilon_b \quad \text{for} \quad (1)$$

$$\sum_{i=1}^n F_i = 1 \quad (2)$$

where R_b is the reflectance in band b , $R_{i,b}$ is the reflectance for endmember i , in band b , F_i the fraction of endmember i , and ϵ_b is the residual error for each band. The SMA model error is estimated for each image pixel by computing the **RMS** error, given by:

$$\text{RMS} = \left[n^{-1} \sum_{b=1}^n \epsilon_b^2 \right]^{1/2} \quad (3)$$

SMA has been applied extensively in the Amazon region to generate fractions images that are further used as input variables in image classification techniques (Adams et al., 1995;

Roberts et al., 2002; Souza et al., 2003;) or to estimate biophysical properties of vegetation and soils (Asner et al., 2003; Numata et al., 2003; Souza et al., 2003).

The SMA model results were evaluated as proposed by Adams et al. (1995). First, the RMS images were inspected and models with RMS values greater than 5% were discarded from the fraction change analysis. Next, fraction images were evaluated and interpreted in terms of field context and spatial distribution. Finally, the histograms of the fraction images were inspected to quantify the percentage of pixels lying outside the range of zero to 100% and to evaluate fraction value consistency over time (i.e., that intact forest values were similar over time). Only models with at least 98% of the values within zero to 100% and those that showed mean fraction value consistency over time were kept. For the models that did not pass one of these tests, we redo the atmospheric correction with new parameter models (i.e., visibility, atmosphere type, etc.) and repeat the steps.

2.2.1 Building Endmember Spectral Library

Small (2004) showed that it is possible to obtain standard global endmembers from the Landsat n-dimensional spectral space. The methodology proposed by Small (2004) has been applied to determine generic image endmembers of green vegetation (GV), non-photosynthetic vegetation (NPV) and soil to generate standard fraction images of these endmembers over the Brazilian Amazon (Souza Jr., et al., 2005a).

The identification of the nature and number of pure spectra (i.e., endmembers), in the image scene is imperative for a successful application of SMA models. Four mixed endmembers are expected in forested environments, GV, NPV, Soil and Shade. More recently we have introduced a Cloud endmember to facilitate cloud masking. Image endmembers representing GV, NPV, Soil and Cloud were extracted from reference reflectance images selected across the region. Shade endmember was assigned zero percent reflectance at all wavelengths (photometric shade). The pixel-purity-index (PPI), available in ENVI 4.0 (Boardman et al., 1995) was used to identify image endmember candidates. Five image subsets (500x500 pixels), representing the variety of land cover types found in the images, were used as inputs for the PPI algorithm. The PPI result was used to identify the pixel location in the original image and extract the spectral curves of these pixels. The final image endmembers were selected based on the pixel location in the Landsat reflectance spectra with the aid of an n-dimensional visualization tool available in ENVI. The pixels located at the extremes of the spectral data were selected as candidate endmembers. The final endmembers were selected based on the spectral shape and image context (e.g., soil spectra are mostly associated with unpaved roads and NPV with pasture having senesced vegetation). ImgTools provide a set of generic endmembers obtained with the procedures described above, for the following sensors: Landsat TM/+ETM, Aster, MODIS and MERIS, (Figure 2).

2.2.2 Normalized Difference Fraction Index – NDFI

In order to enhance the degradation signal caused by selective logging and burning, a Normalized Difference Fraction Index (NDFI) has been proposed and is one of the input variable of ImgTools for several image classification techniques available in the software. NDFI is computed using the fraction images obtained with SMA by:

$$\text{NDFI} = \frac{\text{GV}_{\text{Shade}} - (\text{NPV} + \text{Soil})}{\text{GV}_{\text{Shade}} + \text{NPV} + \text{Soil}} \quad (4)$$

where GV_{shade} is the shade-normalized GV fraction given by,

$$GV_{\text{Shade}} = \frac{GV}{100 - \text{Shade}} \quad (5)$$

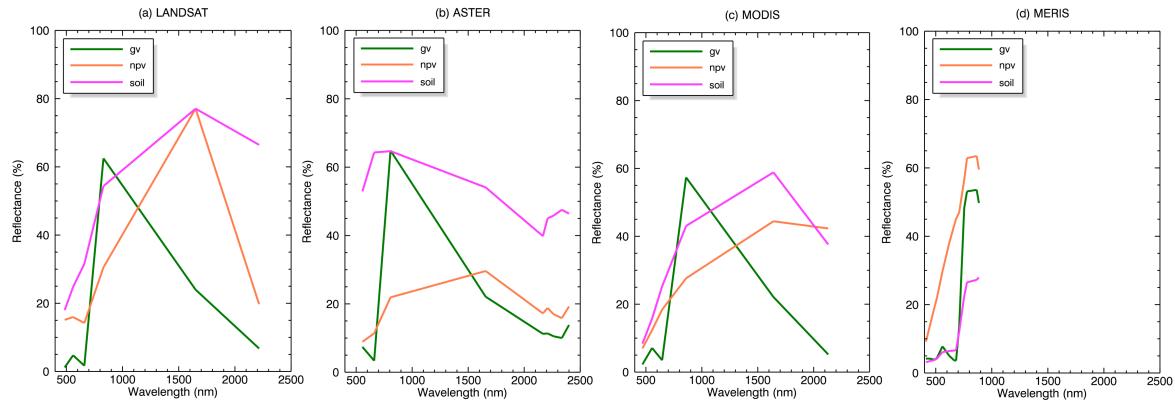


Figure 2. Generic image endmembers available in ImgTools: (a) Landsat TM/+ETM, (b) Aster, (c) MODIS, (d) MERIS,

The NDFI values range from -1 to 1. Theoretically, the NDFI value in intact forest is expected to be high (i.e., about 1) due to the combination of high GV_{shade} (i.e., high GV and canopy Shade) and low NPV and Soil values. As the forest becomes degraded, the NPV and Soil fractions are expected to increase, lowering the NDFI values relative to intact forest. Therefore, the NDFI has the potential to enhance the detection of forest degradation caused by selective logging and burning. The NDFI has the advantage of combining, in one synthetic band, all the information that has been shown to be relevant for identifying and mapping degraded forests in the Amazon region.

2.3 Image Classification

ImgTools has several image classification techniques implemented aiming to speed up the extraction of information from satellite imagery through GCAs. The overall principle of these GCAs implemented in ImgTools relies on: i) normalized and noise reduced data sets; ii) specific objectives regarding information extraction; 3) combination of spectral, spatial and temporal pixel information to detect and map specific targets; and 4) minimum analyst interference in the image classification process. A description of the image classification algorithms available in ImgTools is presented below:

i. Water mask. Detects and map exposed water bodies associated with rivers, dams and lakes. Uses “GV (≤ 10) and Shade (≥ 75) and Soil (≤ 5)” as a default rule. The water mask output is used as input to generate NDFI, and to improve the Cloud/Mask results. The inputs are GV, Shade (calculated on the fly) and Soil fractions. Spatial filter can be applied to eliminate isolated pixels. Topography shadow can generate classification errors. The output is a binary image with water (=1) and no water (=0) classes.

ii. Cloud/Shade mask. The inputs are Cloud and Shade fractions. Spatial filter and buffer technique can be applied to improve the results. The output is a raster image with Shade (=1), Cloud (=2) and No Cloud (=0) classes.

iii. NDFI Slicer. This is a simple classification-slicing algorithm applied to NDFI. The main goal of this algorithm is to produce a quick forest baseline map to be used as an input to forest change detection of large temporal data sets. The image slicing default rules applied area: deforestation = $0 \leq \text{ndfi} \leq 175$, degradation = $175 < \text{ndfi} \leq 185$ and forest = $\text{ndfi} > 185$. NDFI with water and cloud and shade applied is used as input. The output is a raster image with the

following classes: forest (=1), regeneration (=2), degradation (=3), non-forest (=4), water (=5), cloud (=6) and deforestation (=7).

iv. Forest change detection. This algorithm was designed to detect deforestation and forest degradation between two dates. New deforestation detected between two dates is used to update the forest mask used for the next pair of image dates. A default change detection rule is applied to the NDFI differencing images such as: deforestation = $0 \leq (t_1 - t_0) \leq -35$, degradation = $-35 < (t_1 - t_0) \leq -20$ and Forest = $(t_1 - t_0) > -20$. The input for this algorithm is a data stack of NDFI images (at least two images) and the forest baseline. The output is a time series change detection raster image with deforestation and forest degradation age classes such as: forest (=1), regeneration (=2), degradation (=3), non-forest (=4), water (=5), cloud (=6), deforestation $t_1:t_n$ (=11:11+n). Spatial filters can be applied across through all the time series or to specific pair of dates.

v. Decision Tree Classification. This implements a hierarchical classification rules obtained through a recursive partition process of classification training samples or knowledge-based (i.e., empirical) classification rules. A default set of empirical knowledge-based rules is provided by ImgTools, but users have the flexibility to build their own set of decision rules or input statistically derived rules (using R language). Preferably, the data input for classification is a set of fraction images obtained from SMA or reflectance images. We suggest the users to choose between these two sets of inputs and avoid mixing them since their information comes from different pixel scales. The output classes depend on the classification scheme defined by the image analyst. ImgTools comes with pre-defined and tested set of rules useful to generate specific maps.

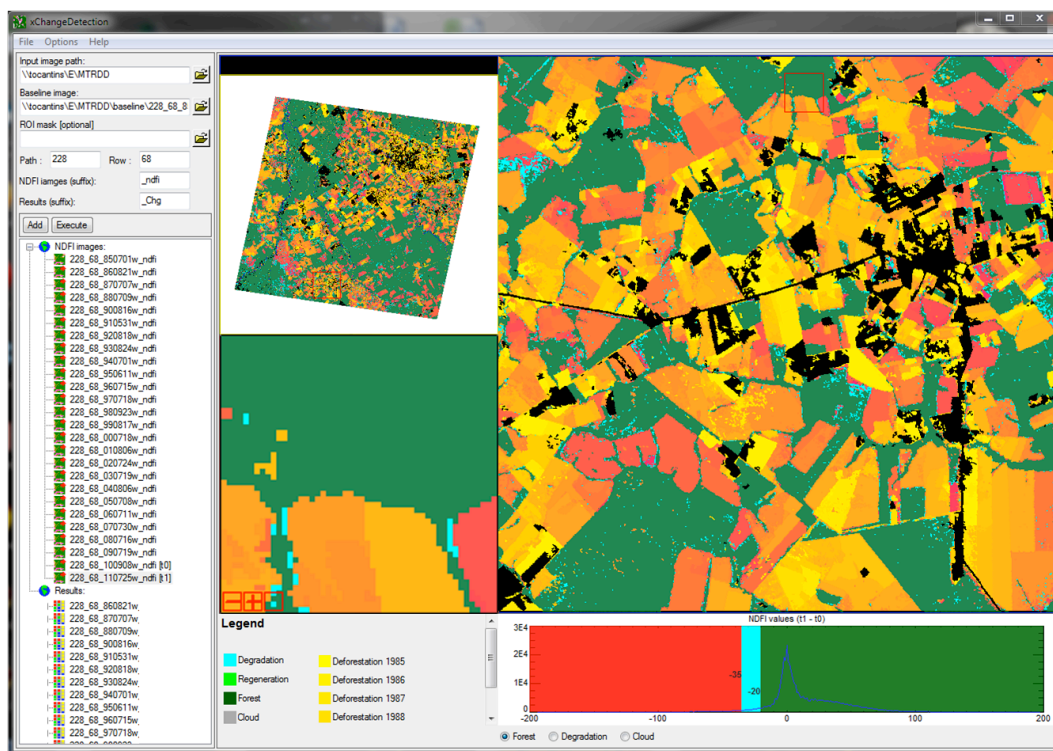


Figure 3. Example of the user interface of the change detection module.

2.5 Post-Classification

In terms of post-classification, we have implemented two set of programs in ImgTools. First, a temporal filter to track disallowed transitions over time and to remove cloud pixels when possible. For example, cloud pixel removal can occur when, for instance, in date t_1 the

area was classified as forest, t_2 as cloud and t_3 as forest. Under these conditions, cloud pixels in t_2 can be changed to forest class. We have implemented several temporal rules in ImgTools and new ones can be added.

The second post-classification software is an implementation of the accuracy assessment protocol defined by Powell et al. (2004). This protocol implements a series of procedures for statistical selection of reference samples, evaluation and labeling (or classification) rules of reference data, and an unbiased corrections of the reference data (e.g., geolocation, mixed pixels, edges, and reference data classification errors), to eliminate errors in the process. Very high spatial resolution imagery (from satellite or aerial videographer sources) can be used in ImgTools for this purpose and a user-friendly GUI was built to implement this accuracy assessment protocol.

3. Applications and Future Steps

ImgTools was originally designed to support Imazon's projects on forest monitoring but there is a growing interest on this software by several research groups. Since 2011, ImgTools has been used into several projects outside Imazon creating a user community despite its implementation is still in the beta version by the time this article was written. Here we present some examples of these projects and successful application of this software.

In the scope of Imazon, two large projects have been using ImgTools. The first project aims to reconstruct deforestation and forest degradation time series from 2000 to 2010 for the Brazilian Amazon. The software was designed to originally support this project activity, which is entering in a final stage to produce research papers and reports. The second project that uses ImgTools at Imazon is the operational monitoring of forest management projects (Monteiro & Souza Jr, 2012). All NDFI products used to assess forest management approved projects of Mato Grosso and Pará state, and illegal logging activities have been monitored using the software. Bi-annual reports of the status of forest management activities in these states have been produced and applications to monitor forest concessions in the Amazon region and small scale logging in the Amazonas state are underway.

Two large area pan-tropical projects have also benefit from ImgTools. First, a seemliness classification methodology of deforestation and forest degradation applied to the entire Pan-Amazonia region lead by the RAISG network. This project results with deforestation and forest degradation maps and statistics are being published in 2012 and there is a new project being put together to implement an operational monitoring platform for this region. The second project is in the Congo Basin region and first results have been produced.. Both projects required short training (<40 hours) capacity building and proved that the learning curve is fast allowing quick production of results.

Currently, several users are using ImgTools in their projects. This growing interest by its beta version has encouraged us to speed the development to reach version 1.0 of the software. For that, we will finalize the integration of atmospheric correction third party and public domain software (6S and potentially LEDAPS), improve GUI and fix minor bugs, write the users manual and tutorials, and build a website for the user community. We hope that by the time we will be presenting this results in this symposium we will be able to announce the release of version 1.0 of ImgTools, and that the software can contribute to improve information extraction of satellite imagery data.

Acknowledgements

We would like to thank the Imazon's research donors for supporting the development of ImgTools including: Gordon and Betty Moore Foundation, Climate Land Use Alliance (CLUA) and Fundo Vale. We also would like to thank the entire community of ImgTools' beta users for their support and encouragement to keep us developing the software.

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