IDENTIFYING MULTI-DECADAL CHANGES OF THE SAO PAULO URBAN AGGLOMERATION WITH MIXED REMOTE SENSING TECHNIQUES: SPECTRAL MIXTURE ANALYSIS AND NIGHT LIGHTS

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ABSTRACT

One of the first applications of satellite remote sensing imagery was to detect the size and shape of urbanized areas. Under many circumstances the mere identification of what is really urban is not clear. Smaller towns, diffuse development and varying degrees of spatial connectivity combined with the lack of an agreed upon definition of urban complicate the task. The proximity of urban development to spectrally similar fallow agricultural areas is a primary challenge of mapping urban development with satellite imagery.

As sensors on satellites became more sophisticated and technically advanced, urban applications of remote sensing used higher spatial resolution imagery. However, moderate spatial resolution is widely used on non-urban applications because the synoptic spatial and retrospective temporal coverage is superior that offered by high resolution sensors. The most widely available imagery over the longest time period is provided by the Landsat missions. However, the 30 m spatial resolution of Landsat imagery combined with the spectral heterogeneity of urban land cover results in most urban areas being imaged as spectrally mixed pixels. Spectral mixture models may provide a physically based solution to the urban spectral heterogeneity because it is possible to reduce the dimensionality of the multispectral reflectance by converting it to areal fractions of land cover components, thus making interpretation easier. The spectral ambiguity of urban land cover is unavoidable but the challenge of mapping urban extent may be mitigated by using multiple sensors to image different characteristics of the urban environment.

The present analysis was based on a three component linear mixture model incorporating substrate, vegetation and dark targets, directly used for visualization on false colour composites of red, green & blue respectively. Fraction composites suggest the location and extent of urban development – both at the periphery and within Sao Paulo's urban agglomeration and its surroundings – but the spectral ambiguities with non-urban land cover remain a challenge.

Winter and summer image pairs were selected for quality and consistency of solar illumination for two time intervals: 1986-2005 and 2000-2010. Changes over both time periods were quantified in terms of changes in endmember fractions. The results show increases of substrate, greater than 10% of the pixel area, with equivalent reduction of vegetation and/or shadow fractions. From these increases in substrate fraction, together with the presence of night lights of higher intensity and concentration, we infer an increase in urbanized land cover. A quantitative and visual analysis of these changes at different spatial scales is presented.

Wide field synoptic imagery provided by the Defence Meteorological Satellite Program Operational Line Scanner (DMSP-OLS) indicates the presence of urbanized areas by imaging nocturnal lights. This sensor has been used by the Earth Observation group at NOAA NGDC to produce annual global composites of temporally stable nighttime lights since 1992. OLS night light imagery helps to differentiate non-urban substrate (i.e. exposed soil) from urbanized surfaces with different degrees of development, according to the intensity of the emitted light.

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INTRODUCTION

The city of Sao Paulo has evolved from small town with about 20,000 inhabitants at the very end of the XIX century to one of the biggest metropolis of the world in less than 90 years. This explosive increase of population was very noticeably during the 70's of the XX century, when the city growth with a variety of economic uses that marked, and determined, the way it expanded its urbanized surface. Among the different uses that were given to the ground, most of the territory was residential – composed of both formal and informal dwellings. For a number of reasons, it is important to identify changes and map the growth of both types of settlements. However, it is very difficult to differentiate formal-non-precarious neighbourhoods from informal and precarious settlements using aerial photographs or satellite imagery.

The complexity of the physical characteristics of the urbanized surface is a well known fact, especially when the object of study is a global metropolis, such as the city of Sao Paulo. The characteristic imprint of this city, one of the most populous of the world, shows continuous urban occupation on a wide region that covers –most, all, or part- of the territory of 20 municipalities of the Metropolitan Region. This large area spanning multiple administrative units constitutes a challenge when it comes to produce spatio-temporal change mapping. As presented in Figure 1, the urbanized surface (2,139 km^2) alternating with built area, vegetation, exposed soil, and water bodies extends over the 7,944 km^2 of the 39 municipalities that integrate the Sao Paulo Metropolitan Region. According to IBGE (Brazilian Institute of Geography and Statistics) census from 2010 (1) the total population is 20.3 million inhabitants. The core and capital of the territory is the Municipality of Sao Paulo, with 1,523 km^2 and estimated population of 11.2 million with an elevated degree of urbanization.

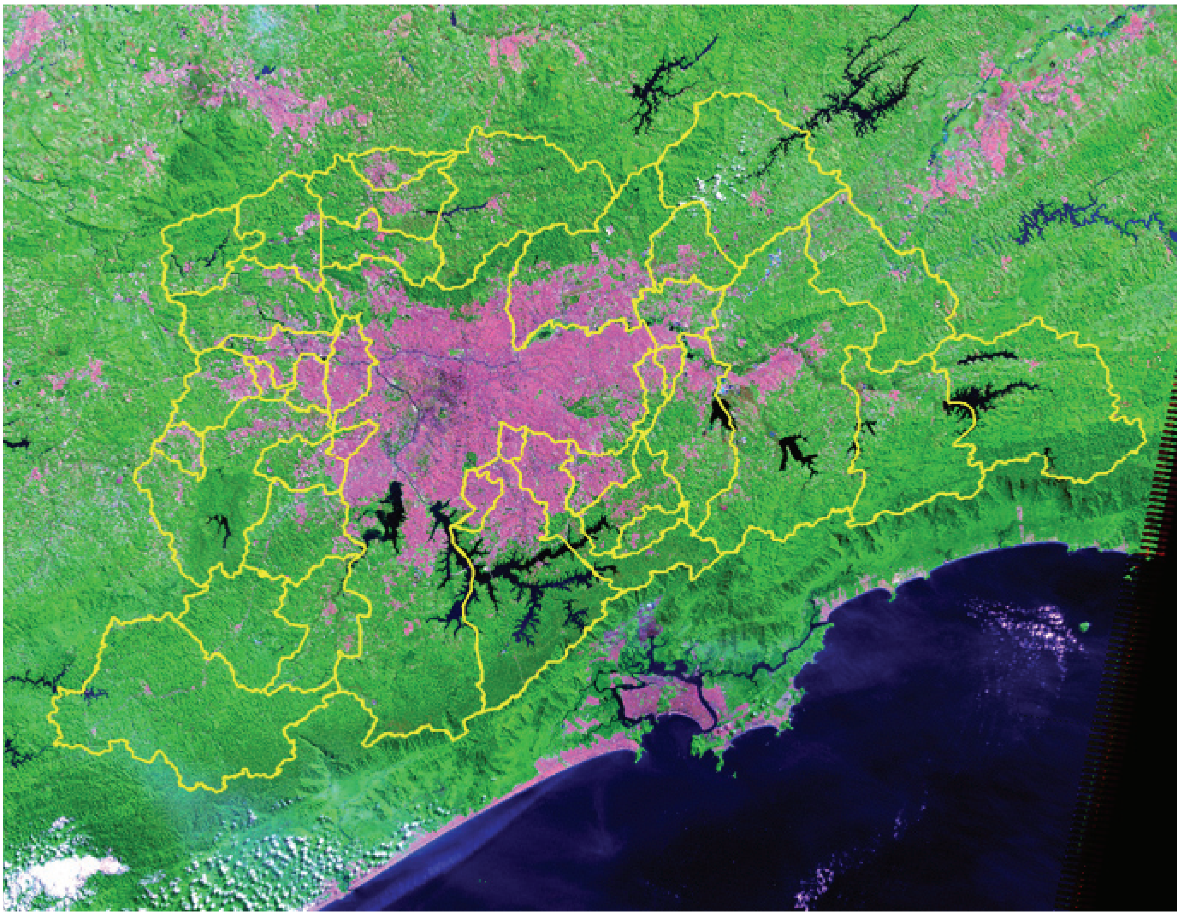

Figure 1: Visible/infrared false colour composition Landsat 5 image (TM bands 7, 4 and 2 - RGB) of the full study area. The municipality limits of Sao Paulo's Metropolitan Region are shown in yellow. Note that the urban continuum (in rose-pink) of the city extends over the municipality of Sao Paulo, at the centre. Water bodies are depicted as black. The image was collected 12:55 PM April 4th 2010.

Urban changes and remote sensing images

Spatio-temporal change mapping with remotely sensed imagery has the potential to inform a wide variety of urban research and management questions. Despite its great potential, remotely sensed imagery remains underutilized for urban applications.

With the increase of the spatial and spectral resolution of the modern sensors, urban applications of remote sensing tend to use high spatial resolution (<10 m) imagery, while moderate spatial resolution is primarily used for non-urban applications. But this decametre resolution imagery has proved sufficient for measurement of some environmental urban parameters that would be both very difficult and too expensive to measure directly. On the other hand, as the complexity of the urban surfaces prevail even when observed on high resolution imagery, detailed land use maps are very difficult to produce with conventional remote sensing classification methods.

The characteristic spatial scale and the spectral variability of urban land cover pose serious problems for traditional image classification algorithms. In urban areas where the reflectance spectra of the land cover vary appreciably at scales comparable to, or smaller than, the Ground Instantaneous Field Of View (GIFOV) of most satellite sensors, the spectral reflectance of a individual pixel will generally not resemble the reflectance of a single land cover class but rather a mixture of the reflectance of two or more targets present within the GIFOV. Because they are combinations of spectrally distinct land cover types, mixed pixels in urban areas are frequently misclassified as other land cover classes. Conversely, the definition of an urban spectral class will often misclassify pixels of other non-urban land cover.

Perhaps, the logical solution to avoid this situation would be to increase the spatial resolution of the input remote sensing imagery by selecting a sensor with a very small GIFOV. These images have been named as high resolution (1 to 5 metres pixel size) and very high resolution (less than 1 metre). The problem is that urban structure is still very complex as we “zoom in” increasing the spatial resolution, and the cost of the images and consequent processing increases as well.

The spatiotemporal distribution of the increase of urban built-up areas coincident with the apparent diminishing of the vegetation is an important relationship of the urbanized surfaces that can be quantified using multispectral imagery. However, conventional classifications methods used at scales compatible with the sensor spatial resolution have proven to be of limited utility in urban areas, due to the spectral heterogeneity of this dynamic and complex environment, which commonly combines several different materials of natural and artificial origin. Spectral Mixture Models - SMM, on the other hand, may provide a physically based solution to the urban spectral heterogeneity issue because spectral mixture models account for the contribution of features below pixel scale. In addition, it is possible to reduce the dimensionality of the multispectral reflectance by converting it to fractions of land cover components (spectral endmembers), thus facilitating the interpretation. The good news is that as the SMM assumes the spectral heterogeneity as a basis of its analysis (as Spectral Mixture Analysis – SMA); consequently it is possible to use coarse resolution imagery to study urban territories.

For instance, if an urban area contains significant amounts of vegetation then the reflectance spectra measured by the sensor will be influenced by the reflectance characteristics of the vegetation. Macroscopic combinations of homogeneous "endmember" materials within the GIFOV often produce a composite reflectance spectrum that can be described as a linear combination of the spectra of the endmembers (2). If mixing among the endmember spectra is predominantly linear and the endmembers are previously known, it may be possible to "unmix" individual pixels by estimating the fraction of each endmember in the composite reflectance of a mixed pixel (3,4). A variety of methods have been developed to estimate the areal abundance of endmember materials within mixed pixels - particularly for use with imaging spectrometers in geologic remote sensing e.g. (5,6,7,8) and vegetation mapping (9,10,11,12,13). Some authors (14,15,16,17) have used the endmember fractions provided by the Spectral Mixture Models to analyse urban reflectance.

The advantage of using the analysis by means of spectral mixture (SMA) is the possibility to enhance and facilitate image interpretation. To interpret an image in terms of proportions or approximate fractions of the different materials that forms each pixel is much easier to be done than considering separate values of radiance, reflectance and emitance of the present materials (18). Thus, on the concept of Spectral Mixture Model, an image representing soil fraction, for instance, would be analysed over its proportion within the pixel, that might vary from zero (0) – area totally covered by vegetation – to 100% – area of exposed soil where vegetation would be totally missing. The strength of the Spectral Mixture Analysis approach lies in the fact that it explicitly takes into account the physical processes responsible for the observed radiances (below pixel scale) and therefore accommodates the existence of mixed pixels.

Spectral mixture occurs in two ways: linear and non-linear. Linear mixing considers the mixture as a linear combination of the different components of the pixel weighted by their respective proportions. The non-linear mixture is more complex because the radiance interacts with more than one material, thus resulting in multiple and complex interactions.

In general, the linear mixture is considered dominant and the non-linear mixture a second degree effect. On the Linear Spectral Mixture Model (LSMM) the signal registered on the pixel is mathematically described by the following formula:

$$R = RaFa + RbFb + ... + RnFn + r$$

Where: *R* is the value of the mixture pixel; *Ra*, *Rb* and *Rn* the spectral responses of the components; *Fa*, *Fb* and *Fn* are the fractions of the components; *r* is the residual, that includes the fitting of the considered components, the error of the model as well as errors produced by the atmospheric effects, solar angle, and sensor degradation.

On spectral mixture analysis the spectral responses of the components (*Ra*, *Rb*,…,*Rn*) are known as “endmembers”. When the spectral responses are extracted directly from the image, the term “image-endmember” is used. The reference spectra produced on the laboratory or acquired on the field are known as “reference-endmembers”. Figure 2 illustrates the LSMM.

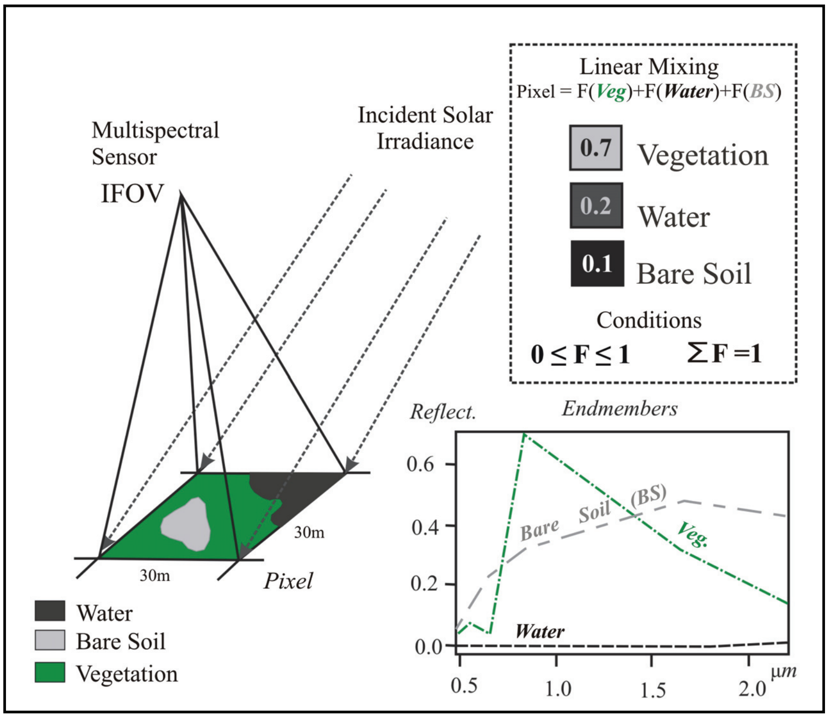

Figure 2: Perfect decomposition with a Linear Spectral Mixture Model (LSMM) on a 30 m pixel formed by a mixture of 3 components: vegetation, water and soil. On this case the residual is zero. Source: (19, p. 27).

As mentioned, it is possible to use Linear Spectral Unmixing with imagery such as generated by Landsat 5 & 7 satellites. As a result, the pixel values of these images indicate the fraction of the pixel that contains the endmember material corresponding to that image. For example a pixel from the #1 Profusion image with a value of 0.45 indicates that 45% of the pixel contains endmember

#1. If many pixels have values above 1 or below 0, this indicates that one or more of the endmembers chosen for the analysis are probably not well characterised, or that one or more additional endmembers are missing from the analysis. On the process of calculating three endmembers of an image, a fourth image containing the *RMS* error is generated. A good analysis of the *RMS* error image would help to determine areas of missing or incorrect endmembers.

Analysis of Landsat TM and ETM+ imagery suggests that the spectral reflectance of the Sao Paulo metropolitan area can be described as linear mixing of three distinct spectral endmembers: Substrate, Vegetation and Dark. This paper provides only a brief summary of urban Spectral Mixture Analysis (SMA) technique. A more detailed discussion of the use of Linear Spectral Mixture Analysis (LSMA) as well as the theory, analysis and validation is given by (18), for urban areas is given by (20,21,22,23,16).

In this case, the Substrate represents bare soil, rocks and built up areas, including impervious and non-impervious surfaces. Vegetation corresponds to dense forest, grass or agricultural areas. Forest and open canopy vegetation contain an internal shade component and are represented along the mixing line between the Vegetation and Dark endmembers. The Dark endmember corresponds to clear water or deep shadow. Water containing suspended sediment and biological productivity is more reflective so it occurs along the mixing line between the Substrate and Dark endmembers. But in some cases appears distinct Vegetation endmember on the water bodies due to the presence of algae and aquatic macrophytes which emergence and grow was boosted by different degrees of eutrophication. Clouds are not a significant problem in any of the scenes selected for this paper.

Scanner (DMSP-OLS) indicate the presence of urbanized coverage by means of showing night lights. This sensor has been used to produce annual global composites of temporally stable nighttime lights since 1992 (24). OLS imagery contributes to differentiate non-urban substrate (i.e., soil) from urbanized surfaces with different degrees of development, according to the intensity of the city lights (25).

Objectives

The purpose of this study is to analyse and map the most conspicuous changes occurred on the developed surface of the city of Sao Paulo using multi-decadal spectral mixture analysis of Landsat TM and ETM+ imagery provided by the Defense Meteorological Satellite Program Operational Line. Aiming to separate actually urbanized surface from the mere increases in substrate fraction, night lights (coming from the OLS), will provide the data to infer an increase in urbanized land cover.

METHODS

Change/growth analysis on the City of Sao Paulo

The analysis was based on a three component linear mixture model incorporating Substrate, Vegetation and Dark targets (also known as Endmembers), directly used for visualisation on false colour composites of red, green & blue respectively. Summer (April) and winter (August) image pairs were selected for quality and consistency of solar illumination for 1986-2005 and 2000-2010. Selected images were mosaicked to cover the study area (164 $\times$ 127 km^2), and cut accordingly. The two pairs were matched by date, as presented on the list in Table 1.

Fraction images with the three previously mentioned endmembers for each of the four selected scenes were produced. An example, showing the most recent image used (from 04/18/2010) is depicted on Figure 3.

After May 2003 the images from Landsat 7 ETM+ became negatively affected by gaps produced by a failure on the Scan Line Corrector – SLC, but only one of the images used on the research (08/02/2005) had this problem. As attenuating effect on this, should be considered that a stripe 21 km wide at the centre of the scene (slightly slant due the satellite orbit) is not affected by the SLC failure, and the gaps are not so wide as to ruin the entire surface of the image. They go from 2 pixels wide (60 m near the central non-gapped stripe) to 14 pixels wide (420 m at the periphery of both sides of the image). The average separation of this gaps with continuous imagery (on all the spectral bands of Landsat 7 with SLC off) goes around 1,000 metres. This item was finally solved by filling the gaps using a special algorithm and a non-gapped image of the same resolution (26).

Table 1: The eight scenes of Landsat TM and ETM+ that were processed mosaicked and cut, as depicted on Figure 1. Note the date, time and solar elevation alignment on the two pairs (1986-2005) and (2000-2010).

Image	Satellite	Sensor	Acquisition		
			Date	Time	Solar elevation (°)
219076 & 219077 +1986218XXX04	Landsat 5	TM	08/06/1986	12:26 PM	33.22
219076 & 219077 +2005214EDC00	Landsat 7	ETM+	08/02/2005	12:53 PM	36.97
219076 & 219077 +2000121EDC00	Landsat 7	ETM+	04/30/2000	12:57 PM	40.90
219076 & 219077 +2010108CUB01	Landsat 5	TM	04/18/2010	12:55 PM	43.39

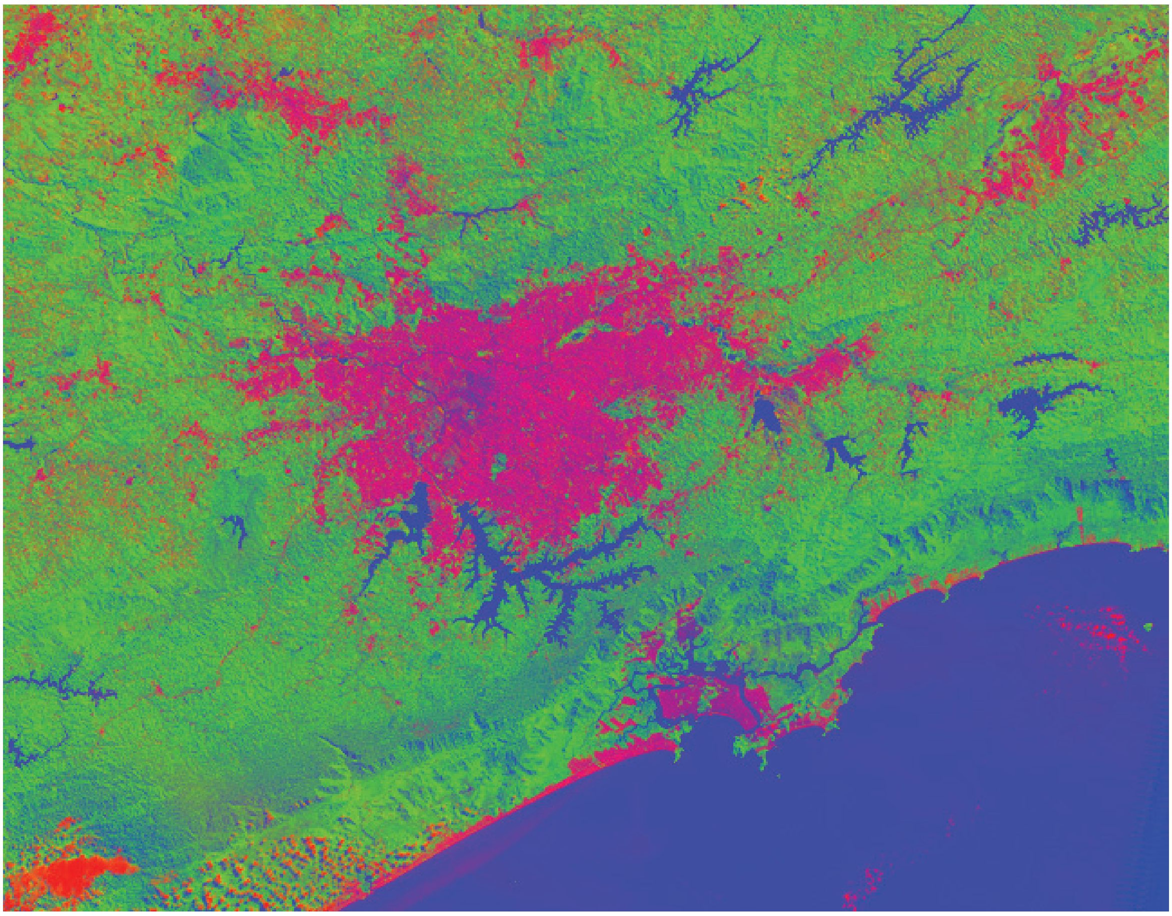

Figure 3: False colour composite fraction image generated with 2010 Landsat 5 TM multispectral bands. Red represents Substrate and high albedo surfaces, Green shows vegetation and Blue indicates dark and clear water body endmembers respectively. A linear stretch between 0.5 and 1.0 has been applied to each fraction band.

RESULTS

The next step was generating the fraction difference images in order to emphasize and calculate the rate of changes. The more important changes to be sought would be those of Vegetation/Shadow fraction that turned into Substrate, as in principle, they would characterise urbanization in detriment of reducing a natural, or at least a well vegetated portion or land coverage.

Fraction difference images reveal the location and extent of urban development/growth – both at the periphery and within Sao Paulo. Changes in fraction mixtures and texture also highlight high rise construction as well as vegetation abundance. Red on the difference images means deep changes: Vegetation that turned into Substrate, as depicted on Figures 4 and 5.

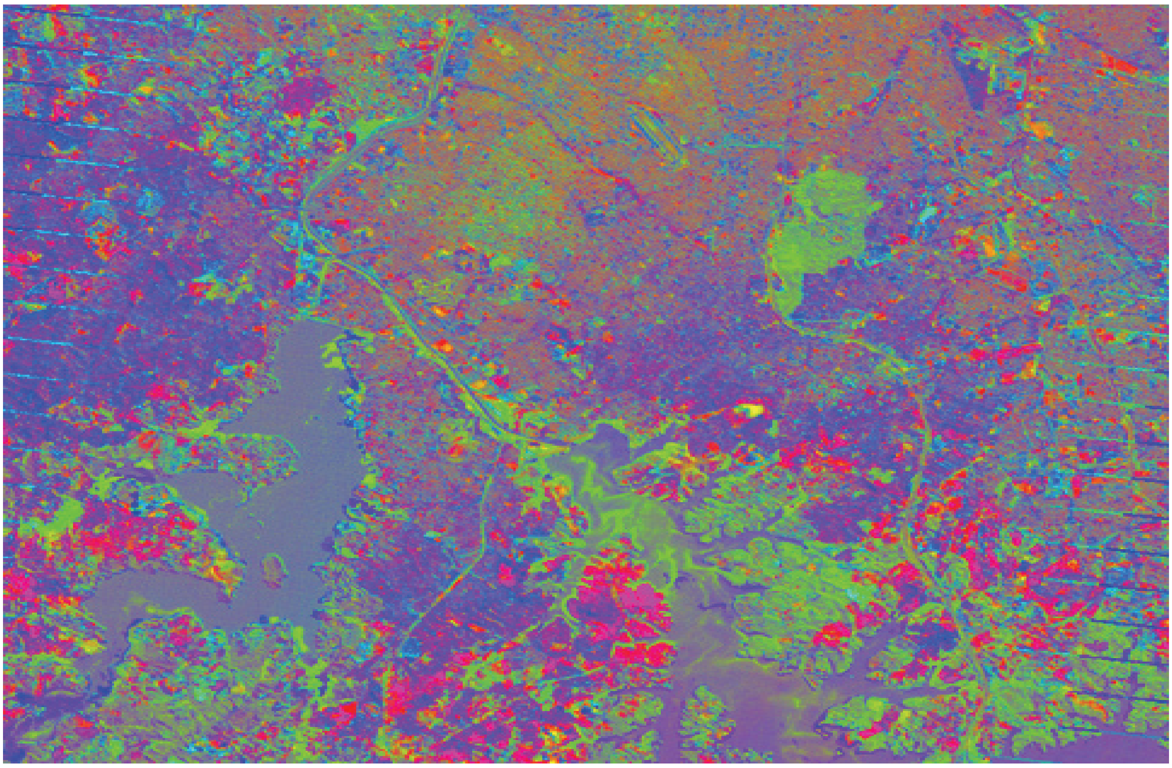

Figure 4: Detail (24 $\times$ 20.7 km^2) from the south part of the city of Sao Paulo. False colour composite fraction difference image generated with 2005-1986 Landsat 7 ETM+/ Landsat 5 TM multispectral bands. Red, Green and Blue represent Substrate, Vegetation and Dark fraction, respectively. In this case intense/bright Red means important changes from Vegetation into Substrate. Relevant changes concentration occurs at the south centre area of the city, on the region among the two water reservoirs.

Many changes became evident on the two difference fraction images that were produced. Indicating a growth on the Substrate surfaces of 208.06 km^2, 105.2 km^2 and 18.6 km^2 (relatives to the whole study area, Sao Paulo's Metropolitan Region and Municipality of Sao Paulo boundaries respectively) for the 1986-2005; and showing alteration of 277.33 km^2, 68.3 km^2 and 10.2 km^2 (same spatial references) for the 2000-2010 periods, regarding the quantity of changed surface that altered its fraction predominance into substrate, as presented on Table 2. The three territories considered offered quite diverse change rates.

Table 2: The figures indicate the amount of changed surface that altered its fraction predominance from Vegetation/Shadow into Substrate within the limits of the three territories considered: a) Total image surface, b) Sao Paulo's Metropolitan Region, c) Municipality of Sao Paulo (all shown on Figure 1).

Difference image	Total surface (km^2)	Total changes (km^2)	Total changes (%)	SPMR surface (km^2)	SPMR changed (km^2)	SPMR changed (%)	MSP surface (km^2)	MSP changed (km^2)	MSP changed (%)
2005-1986	21,037.5	208.06	0.99	7,942.3	105.2	1.32	1,525	18.6	1.22
2010-2000	21,037.5	277.33	1.32	7,942.3	68.3	0.86	1,525	10.2	0.67

A conspicuous change of great proportions considering the shorter time period (2010-2000), was the appearance of the southern portion of the road ring of the city, as shown on Figure 5. The construction of this part of the ring was concluded at the beginning of 2010 and the road was officially inaugurated on April 1st 2010, just few days before the capture of the Landsat 5 image at April 18th 2010.

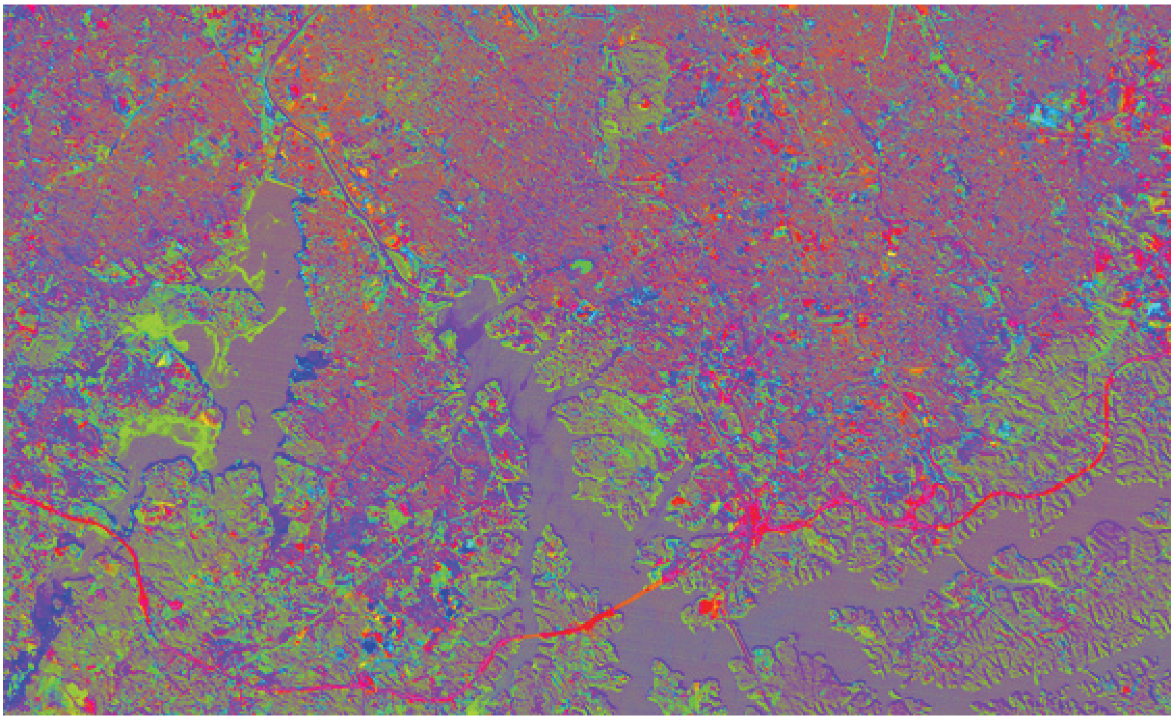

Figure 5: Detail (34 $\times$ 20.5 km^2) from the south part of the city of Sao Paulo. False colour composite fraction difference image generated with 2010-2000 Landsat 5 TM/ Landsat 7 ETM+ multispectral bands. As in Figure 4 Red, Green and Blue represent Substrate, Vegetation and Dark fraction, respectively. Some of the most evident changes occur at the south and eastern area of the city, where the sinuosities of the road ring stands out as a major change of metropolitan dimensions. The highway crosses over the two reservoirs.

To produce the data presented on Table 2, first was generated a single band image for each of the change difference images used, as explained above, afterwards, a process of logical classification (decision tree algorithm) was applied using the following formula:

$$(b1 > 0.2)\,\mathrm{AND}\,((b2 < -0.1)\,\mathrm{OR}\,(b3 < -0.1))$$

where $b1$ = change in Substrate, $b2$ = change in Vegetation and $b3$ = change in Dark fraction.

The logic behind this operation was: “find all the pixels that meet the condition of increase more than 20% on the Substrate fraction AND a decrease of more than 10 % on the Vegetation OR Shadow fractions”. If the condition is true, the resulting image will have a value of 1, otherwise will be 0, that is a binary map.

Detailed analysis of the difference maps revealed several points of interest, such as large and contiguous built up spots that should have remain untouched because they belong to the Environmental Protected Areas - EPA[1] determined by law. Unfortunately, the legislation that should have protected these regions turned out to be one of the causes of its occupation; mainly due to lack of public management, integrated metropolitan fiscalization and social control. Several forms of precarious and informal housing, including on this category not only slums, but irregular allotments as well, proliferated on the southern part of the Municipality of Sao Paulo after 1976, when the protection law was promulgated.

[1] Known as *Área de Proteção Ambiental* or *APA* in Portuguese.

A substantial amount of pixels of scattered changes occur on both difference images; not only because of the conversion of Vegetation into Substrate, but due to the increase of Dark fraction as well.

Night Lights Results

We use a similar compositing approach to illustrate changes in night light since 2000. Figure 6 shows a tri-temporal (2010/2006/2000 = R/G/B) composite of radiance calibrated night lights provided by Christopher Elvidge and the Earth Observation Group at NOAA NGDC. The radiance calibrated stable light product is produced by combining unsaturated pixels from the annual composite with reduced gain composite coverages collected within the individual years shown in each band. The reduced gain coverages are used to replace pixels that are saturated in the standard high gain product. The use of low gain data allows us to resolve changes in the otherwise saturated urban cores that are most brightly lighted. The radiance calibrated composites clearly distinguish the brighter light sources from the surrounding overglow while resolving any changes in brightness that occur within the core areas.

Figure 6: Tri-temporal composite of radiance calibrated night lights from 2010 (r), 2006 (g) and 2000 (b) for the southeast corridor of Brazil. The $Log_{10}(DN)$ transform shows both bright urban cores and smaller dim lights. Note relative stability of most lights with more recent increases in brightness appearing red and yellow.

The regional composite shows the relative stability of the southeast corridor spanning São Paulo and Rio de Janeiro. Because the data have been intercalibrated across years with an equivalent linear stretch applied to each channel of the image, areas unchanged appear in shades of gray while colour implies change. To accommodate the full range of brightnesses in the radiance calibrated data, we show Log_{10}(DN). Some conspicuous areas of increased brightness can be seen in red throughout the image. Most of these areas of growth occur at the periphery of medium to small settlements. The growth that has occurred on the periphery of São Paulo are not apparent because they occur within the overglow of the brighter urban core. However, the strong brightness contrast of the smaller settlements distinguish them from spectrally similar areas of exposed soil that mimic the impervious surfaces found in developed areas.

CONCLUSIONS

A quantitative and visual analysis of the changes at different spatial scales has been carried out during the execution of this research. Results so far indicate that the methodology here presented opens venue to the development of a change cartographic base map for the whole Sao Paulo's Metropolitan Region that would have the potential to inform a wide variety of urban research and crucial management questions, such as the appearance and growth of slums pockets and irregular allotments, monitoring of protected areas including the prevention of deforestation and other relevant land cover changes.

On this study, the whole analysis has been carried out using moderate spatial resolution with imagery with satisfactory results. In our opinion, the main objective of the research can be accomplished when the most conspicuous changes are detected by means of using multi-temporal spectral mixture analysis of Landsat TM and ETM+ imagery. The analysis is based on a three component linear mixture model incorporating substrate, vegetation and dark targets, directly used for visualization on false colour composites of red, green & blue colours respectively. Further study will focus on quantitative analysis of the results and application to the areas given above. Winter and summer image pairs were used for quality and consistency of solar illumination for 1986-2005 and 2000-2010.

Fraction difference images revealed the location and extent of urban development – both at the periphery and within the city of Sao Paulo. Changes in fraction mixtures and texture also point out high rise construction as well as vegetation abundance. In some cases, shadows of individual high rises can be seen. Many pixels of scattered changes occur on both difference images; not only because of the conversion of Vegetation into Substrate, but due to the increase of Dark fraction as well. This last kind of change points out to the increase of high rise buildings on different parts of Sao Paulo Metropolitan area, when occurred on conjunction with the augment of Substrate. The three territories considered offered quite diverse change rates, probably due to the different time span (19 versus 10 years) as well as the crop season. There should be certainly more changes that aren't resolvable by the satellite spatial and spectral resolution, or they lay near the detection limit.

Further analysis of the quantity, quality, location and rate of change occurring within the city of Sao Paulo will build on this research. Even though the amount of changes measured on both periods of time are very similar, it should be considered that a small number of large changes can outweigh the majority - even on small intervals. However, it is important to know where those changes are, and how they relate with the evolution of the metropolitan region during the considered time span.

Compared to urban agglomerations in Asia, Sao Paulo's metropolitan night lights don't show much change over the decade at this scale of analysis. Not surprising, since the city was already developed by 2000. Maybe growth happened by intensification of existing settlements - but this does not appear as brightening.

Night lights are a great complement to reflectance in the tropics where lush vegetation complicates image interpretation. In spite of relatively apparent little change, the lights do resolve the ambiguity of SWIR-bright targets like concrete and soil.

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