The potential of remote sensing data in public works audit

Osmar Abílio de Carvalho Júnior
is a geologist and has a PhD in Geology from the University of Brasília (UnB) where he is a professor.

Roberto Arnaldo Trancoso Gomes
is a geographer and has a PhD in Geography from the Federal University of the State of Rio de Janeiro (UFRJ). He is also a professor at the University of Brasília (UnB).

Renato Fontes Guimarães
is a cartographic engineer with a PhD in Geology. He is also a professor at the University of Brasília (UnB).

SUMMARY

This paper analyzes the potential applications of remote sensing techniques in the audit and monitoring of infrastructure works. Currently, there is a wide availability of remote sensing data from different sensors and platforms, providing a fast and useful source of information to describe the composition of the elements present on the surface and their changes over time. The enhancement of remote sensing with increased spatial, temporal and spectral resolution on different platforms (satellites, aircraft, and unmanned aerial vehicles) has broadened the perspectives of studies and applications of remote sensing data, including the monitoring of public infrastructures in construction or concessions. The extraction of digital elevation models from remote sensors also constitutes an important attribute to describe the features of infrastructure works. The studies most commonly found in the literature are related to urban features and highways. Studies on audit and monitoring of construction works are still little reported, which constitutes a broad field of research and innovation. Several techniques of change detection have been proposed and evaluated for different environments and targets, and in each type of environment and target, they must compare and analyze precision to define the best procedure to be adopted. Specific research for each type of work should be undertaken demonstrating the real potential of remote sensing for oversight in urban or rural environments.

Keywords: Remote Sensing, change detection, digital elevation model, spectral classification.

1. INTRODUCTION

The effective oversight of public works is a key factor to minimize public expenditures. For example, audits carried out by the Fiscobras (the TCU annual plan for public works audit) in Rio Grande do Norte State during the 2011-2012 period provided savings to the public coffers of R$119,529,497.78 (SOUZA; BATISTA, 2013). The Fiscobras in 2015 carried out 97 audits, totaling R$ 31 billion in audited resources, in which 61 works (62.9%) demonstrated indications of serious irregularities (BRASIL, 2015).

However, the continental dimension of the Brazilian territory makes it difficult to conduct traditional audits, which requires constant work of professionals on-site. The growing need for infrastructures aiming at the long-term economic growth of the country combined with the high degree of irregularities makes it imperative to improve technology to inspect continuously public works in progress or under concession throughout the country (MIRANDA; MATOS, 2015; VITAL et al., 2015). During the audit, it is essential to obtain accurate information on the evolution of public works (construction, renovation, manufacture, restoring or expansion of public property), to detect any inconsistencies or lack of elements in the basic design and technical specifications. In this context, remote sensing can be an important tool, providing periodic monitoring of large areas at low cost. In recent years, extensive research efforts have been made to change detection using remote sensing images in different scenarios: (a) urban (HEGAZY; KALOOP, 2015; SUN et al., 2013); (b) agricultural (MENKE et al., 2009; OLIVEIRA et al., 2014); and (c) natural and environmental preservation areas (COPPIN; BAUER, 1996; YADAV; KAPOOR; SARMA, 2012). Therefore, remote sensing has been widely used to assess the spatial dynamics of the earth's surface and the effectiveness of territorial planning. Specifically, studies on oversight of public works using remote sensing are not frequently reported in scientific journals. The lack of research to apply this technique, demonstrates a large field for scientific innovations, having economic relevance and immediate return to society. The collection of multitemporal images enables providing subsidies for comparing what was planned with what was executed in each work, both in the spatial and temporal dimensions. This approach allows comparing the pre-defined work schedule with the actual work in progress, allowing total or partial reconstruction of the financial and executive background.

However, the use of images to inspect public works has difficulties similar to those described in the mapping of features of urban areas. Some of them are (CAVALLI et al., 2008; WENTZ et al., 2014): (a) the spectra of the pixels of urban environments are constituted by spectral mixtures due to the high heterogeneity of these environments, and may generate confusion among the classes in the classification process (b) the physical structures of the urban classes vary spatially, taking into account different compositions of roofs, pavements, and architectural forms. Therefore, infrastructure works (buildings, bridges, roads, waterways, railways, etc.) are made of different materials (asphalt, paints, concrete, metal, glass, tiles, vegetation and soil); which are combined in various proportions (JENSEN; COWEN, 1999). For example, both the type of materials used and their architectural differences may differentiate two bridges. In addition, another factor of complexity is that during a construction work in progress an intense modification of the elements and patterns takes place. Therefore, the monitoring of works by remote sensing requires obtaining consistent and detailed information, as well as the elaboration of a specific methodology of digital image processing. Different techniques for the detection of urban features consolidated or under construction may be used. Usually, the method of visual interpretation is considered the most accurate, but it is also the most time consuming and expensive. An alternative to visual interpretation is to use supervised classifications, unsupervised classifications, and knowledge-based expert system approaches (JAT; GARG;

KHARE, 2006). In addition, change detection techniques should be adopted considering the different pre-classification or post-classification approaches.

This paper discusses the issues related to the use of remote sensing in the oversight of public works. The definition of the images to be used is evaluated considering the advances made in the improvement of spatial, spectral, temporal attributes and the extraction of altimetric data. The progress obtained with the increase of the different resolutions of the images result in new methods for the treatment and analysis of the data, with implications in the efficiency of the inspection by remote sensing. Besides, this paper reviews the main methods of change detection, which allows monitoring changes during the works and evaluating their adjustments to the initial project.

2. CHARACTERISTICS OF THE TEMPORARY, SPECTRAL AND SPATIAL RESOLUTION OF THE REMOTE SENSORS IN THE OVERSIGHT OF WORKS

2.1 SPATIAL RESOLUTION

The definition of classes related to engineering works by remote sensing and their implications in legal compliance is highly dependent on the spatial (pixel size), spectral (number of spectral bands) and temporal (revisit period of the same place on the earth's surface) resolution of an image. These three factors are important, but the image must contain high spatial resolution so that the objects in a construction work may be individualized. It is useless to have a high spectral resolution if a pixel contains different urban elements and mixed spectral behaviors. Normally, the identification of an urban object in an image must have a minimum representation of four pixels (COWEN et al., 1995; JENSEN; COWEN, 1999). According to Small (2003), the minimum spatial resolution for capturing urban structures is 5 meters, also applicable to engineering works.

High spatial resolution images in urban environments enable the use of the basic elements of interpretation (tone, color, texture, shape, size, orientation, pattern, shadow, location, and location of objects in the urban landscape) to identify and judge their meaning. Currently, different images of high spatial resolution orbital sensors (less than 4 meters) are available in the market. Among them, we highlight: GeoEye-1 (0.46m), WorldView-1 and 2 (0.46 m), WorldView-3 and 4 (0.31 m), Pleiades-1A and 1B (0.5 m), Kompsat-3A (0.55 m) and 3 (0.7 m), QuickBird (0.65), Gaofen-2 (0.8 m), TripleSat (0.8 m), Ikonos

(0.82m), SkySat-1 and 2 (0.9m) and Spot-6 and 7 (1.5 m) (Table 1). The increase in the availability of high-resolution spatial images from commercial satellites has led to the growth of digital image processing techniques for infrastructure studies, road networks, and urban elements.

A significant innovation in the mapping of urban areas using high spatial resolution images is the use of geospatial object-based image analysis (Geobia), which differs from traditional pixel-based methods. In Geobia, the image is segmented into relatively homogeneous regions (image objects) before classification (BLASCHKE, 2010; MYINT et al., 2011). Thus, the classification uses as a basic unit segments and their attributes instead of pixels. The high degree of spectral variability within a class (shadows, solar elevation angle, tree canopy gaps, etc.) may hamper pixel-based classification and favor object-based techniques that are represented by average segment values (YU et al., 2006).

A problem of object-based classification is its dependence on the segmentation stage, which can generate excessive or reduced segments of terrain features (LIU; XIA, 2010). Usually, the lack of segments is considered worse than their excess (KIM; MADDEN; WARNER, 2009). The minimization of this type of error may be obtained through successive segmentation tests prior to classification (TRIAS-SANZ; STAMON; LOUCHET, 2008) and through the analysis of segment accuracy (DORREN; MAIER; SEIJMONSBERGEN, 2003; KIM; MADDEN; XU, 2010).

Table 1:
Description of the main orbital satellites. Images available for free are marked with an asterisk (*)

AVAILABLE SATTELITES	SPATIAL RESOLUTION	TEMPORAL RESOLUTION	SPECTRAL RESOLUTION (Band)
ALOS	2,5 m	Variable	1 panchromatic
	10 m	Variable	3 visible
	10 a 100 m	Variable	1 infrared
CARTOSAT	2,5 m	5 days	1 panchromatic
CBERS*	5 m	Variable	1 panchromatic
	10 m	Variable	2 visible
			1 infrared
	20 m	26 days	3 visible
			1 infrared
	40 m	26 days	1 panchromatic
			2 infrared
	80 m	26 days	1 thermal
	64 m	5 days	3 visible
			1 infrared
EROS	0,7 m	Scheduled	1 panchromatic
FORMOSAT	2 m	Scheduled	1 panchromatic
	8 m	Scheduled	3 visible
			1 infrared
GAOFEN	0,8 m	5 days	1 panchromatic
	3,2 m	5 days	3 visible
			1 infrared
GEOEYE	0,5 m	Scheduled	1 panchromatic
	2 m	Scheduled	3 visible
			1 infrared
IKONOS	1 m	Variable	1 panchromatic
	4 m	Variable	3 visible
			1 infrared
KAZEOSAT-1	1 m	Scheduled	1 panchromatic
	4 m	Scheduled	3 visible
			1 infrared
KOMPSAT 2	1 m	Scheduled	1 panchromatic
	4 m	Scheduled	3 visible
			1 infrared
KOMPSAT 3	0,7 m	Daily (possible)	1 panchromatic
	2,8 m	Daily (possible)	3 visible
			1 infrared
KOMPSAT 3A	0,55 m	Daily (possible)	1 panchromatic
	2,2 m	Daily (possible)	3 visible
	5,5 m	Daily (possible)	2 infrared
LANDSAT 5*	30 m	16 days	3 visible
			3 infrared
	120 m	16 days	1 thermal
LANDSAT 7*	15 m	16 days	1 panchromatic
	30 m	16 days	3 visible
			3 infrared
	60 m	16 days	1 thermal
LANDSAT 8	15 m	16 days	1 panchromatic
	30 m	16 days	4 visible
			3 infrared
			1 aerosol
			1 cirrus
	100 m	16 days	2 thermal

AVAILABLE SATTELITES	SPATIAL RESOLUTION	TEMPORAL RESOLUTION	SPECTRAL RESOLUTION (Band)
PLEIADES	0,5 m	Daily (possible)	1 panchromatic
	2 m	Daily (possible)	3 visible
			1 infrared
RAPIDEYE	5 m	Scheduled	4 visible
			1 infrared
SENTINEL 1*	5 a 20 m	12 days	Radar
SENTINEL 2*	10 m	10 days with possibility of 5 days	3 visible
			1 infrared
	20 m		4 red-edge
			2 infrared
	60 m		1 aerosol
			1 cirrus
			1 water vapor
SPOT	1,5 m	Daily (possible)	1 panchromatic
	6 m	Daily (possible)	3 visible
			1 infrared
SKYSAT	1,1 m	Scheduled	1 panchromatic (possibility of creating a 90-second video)
	2 m	Scheduled	3 visible
			1 infrared
TERRASAR-X	0,25 a 40 m	Scheduled	Radar
TH-01	2 m	Scheduled	1 panchromatic
	10 m	Scheduled	3 visible
			1 infrared
TRIPLESAT	1 m	Scheduled	1 panchromatic
	4 m	Scheduled	3 visible
			1 infrared
WORLD VIEW	0,3 m	Scheduled	1 panchromatic
	1,24 m	Scheduled	1 aerosol
			4 visible
			1 red-edge
			2 infrared
	3,7 m	Scheduled	8 infrared
	30 m	Scheduled	12 Cavis (cloud, aerosol, vapor, ice and snow)
TERRA/AQUA (Sensor-MODIS)*	250 m	1-2 days	1 visible
			1 infrared
	500 m		2 visible
			3 infrared
	1000 m		7 visible
			16 infrared
			6 thermal
TERRA (Sensor ASTER)*	15 m	Variable	2 visible
			1 infrared
	30 m		6 infrared
	90 m		5 thermal

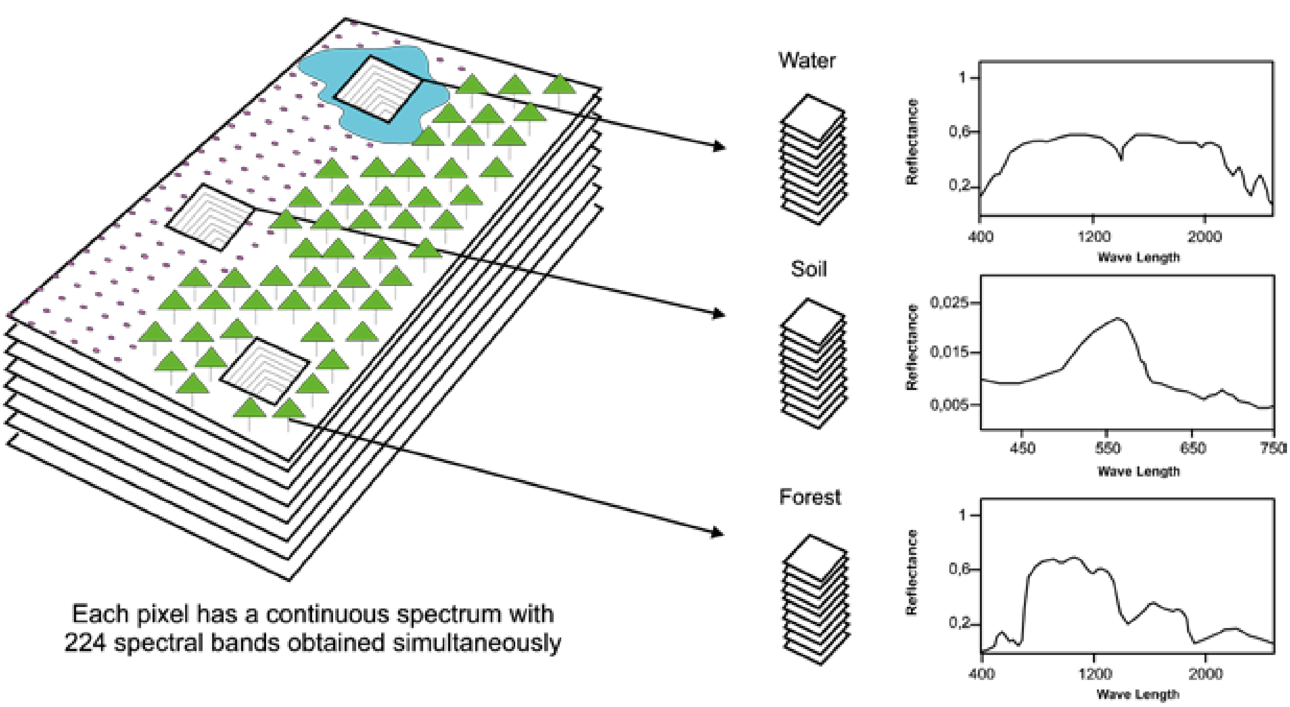
2.2 SPECTRAL RESOLUTION

The detailed knowledge of spectral characteristics enables an accurate identification of surface elements. To this end, several studies have developed specific spectral libraries for different targets from field or laboratory spectrometers to support classification, such as urban elements (BEN-DOR; LEVIN; SAARONI, 2001; HEROLD et al., 2004), mineral elements (CLARK et al., 2007), plantations (RAO; GARG; GHOSH, 2007) and flooded areas(ZOMER; TRABUCCO; USTIN, 2009).

The emergence of hyperspectral images (Figure 1), characterized by hundreds of narrow and continuous spectral bands in the reflected solar spectrum, and enabled the development of new techniques that improved the detection and quantification of materials (CARVALHO JÚNIOR et al., 2003). Spectral classification seeks to convert the spectral signals that reflect the urban coverage into categories that represent the physical nature of the surface. In addition, these images enable a subpixel spectral analysis through the estimate of abundance of the surface materials contained in pixels from the linear mixing analysis (PHINN et al., 2002; WU; MURRAY, 2003) and its Multiple Endmember Spectral Mixture Models (MESMA) variation (DEMARCHI et al., 2012; FRANKE et al., 2009). This approach makes it possible to address the problem of spectral heterogeneity within the same class, which is one of the main difficulties in urban areas (HEIDEN; SEGL; KAUFMANN, 2007). A same type of class may be characterized by several spectrally distinct materials or have differentiated compositions due to deterioration over time (DEMARCHI et al., 2012). For example, roofs may consist of different materials and, in addition, modify their spectral behavior due to the accumulation of fungi and dirt.

Normally, the most used hyperspectral images in urban studies are the Hyperion sensor onboard the EO-1 satellite and those from aircraft-embedded sensors such as Airborne Visible Infrared Imaging Spectrometer (AVIRIS), Compact Airborne Spectrographic Imager (CASI), and Hyperspectral Mapper (HyMap).

Figure 1:
Design of AVIRIS hyperspectral sensor, which high-spectral resolution makes the information of a given pixel similar to that obtained by means of laboratory and / or field measurements. (Modified from GREEN et al., 1998).



2.3 TEMPORAL RESOLUTION

The advent of orbital sensors with high temporal resolution has promoted a new approach to the classification of superficial targets, which consider aspects of cyclical changes or with known trajectories of an event or an object that may be described and identified by a temporal signature. The spectral similarity between the different types of vegetation, which are constituted by the same absorption features, may be difficult to distinguish from a single image in time. However, time series of remote sensing enable the establishment of a typical phenological signature, identifying different types of natural ecosystems (ABADE et al., 2015), phytophysiognomies (CARVALHO JÚNIOR; HERMUCHE; GUIMARÃES, 2006; CARVALHO JÚNIOR et al., 2008) and plantations (COUTO JÚNIOR; CARVALHO JÚNIOR; MARTINS, 2012; SAKAMOTO et al., 2005). This approach enables the detection of individual natural events, such as fire (CARVALHO JÚNIOR et al. 2015) and floods (AIRES et al., 2014).

In the oversight of engineering works, it is fundamental to evaluate the temporal resolution of remote sensors. Construction works evolve through a programmed schedule that enables the definition of which sensors have adequate temporal resolutions for their audit. Weather conditions (atmospheric interference and cloud coverage) also affect the acquisition of images and may be essential to optical sensors in some locations, such as in the Amazon region. In this case, high frequency revisit satellites should be sought for the selection of images or radar image sensors should be used.

High temporal resolution sensors usually have low spatial resolution, such as the MODIS sensor and the Advanced Very High Resolution Radiometer (AVHRR). However, many missions use a constellation of identical satellites that orbit the Earth in a synchronized manner, enabling a succession of high-resolution images with high spatial resolution, such as the following orbital programs: Rapideye (5 satellites); Triplesat (3 satellites); Pleiades (2 satellites) and Spot 6-7 (2 satellites). Although time series constituted with images with the same specifications facilitate the development of automated methods, studies that reconcile images of different sensors have become a research challenge.

2.4 DIGITAL ELEVATION MODELS

Digital elevation models (DEM) are 3D representations of the terrestrial surface that reproduce the natural and anthropic features of landscapes. The construction of these models starts from analog aerial photographs and is then developed by other technologies, such as: digital aerial photography, high-resolution orbital optical sensor, interferometric radar and airborne laser radar. Currently, unmanned aerial vehicles (UAVs) carry on board the different sensors that make DEMs. Recently, mobile laser radar sensors may be mounted to any platform (a boat, a car, etc.).

Optical sensors on board satellites map the Earth's surface from two different points of view, enabling the extraction of DEMs. Among them are satellites with different spatial resolutions, developed by space agencies such as the Spot series, IRS, Cartosat-1, Alos-Prism, WorldView-2, QuickBird-2, Ikonos-2, Aster, among many others. Data may be acquired across a single line of scanning (Spot) or acquired in parallel with a superposition area (QuickBird) (POLI; TOUTIN, 2012). Orbital images have filled the gap in the production of accurate DEMs, but next-generation airborne cameras such as the ADS 80 now produce precision compatible with high-resolution remote sensor images such as Worldview (HOBI; GINZLER, 2012).

DEMs made by Interferometric Synthetic Aperture Radar (InSAR) are obtained from the return of the phase differences of the waves to the satellite. Among the DEMs from this method, we highlight Radarsat 1 and 2, Sentinel 1 and SRTM, and the latter is the most used worldwide (JARIHANI et al., 2015; MUSA; POPESCU; MYNETT, 2015). These products have the advantage of a continuous mapping, even with cloud coverage. **Figure 2** shows an example of an urban area DEM (A) and an aerial photograph overlapping this DEM (B).

The production of DEMs from laser radar, which measures the distance between a sensor and a target based on half the time spent between pulse emission and detection (BALTSAVIAS, 1999), has already existed for a few decades. However, great technological advances in recent years have made it possible to identify subtle elevation changes from a thick cloud of points, making it possible to map and distinguish objects with small texture variations (MENG; CURRIT; ZHAO, 2010). Laser sensors may be mounted to aircraft, satellites and unmanned aerial vehicles. Recently, a mobile laser scanning system that acquires data in 2D and 3D was developed. Such data is inserted in any land or sea mobile platform (PUENTE et al., 2013). This technology has major advantages, such as: (a) cost reduction due to high-speed data capture; (b) high density of points, ensuring a complete planialtimetric survey that reduces the number of questionable data; and (c) 3D visualization that enables to verify if the mapped objects correspond to the conditions of the real world.

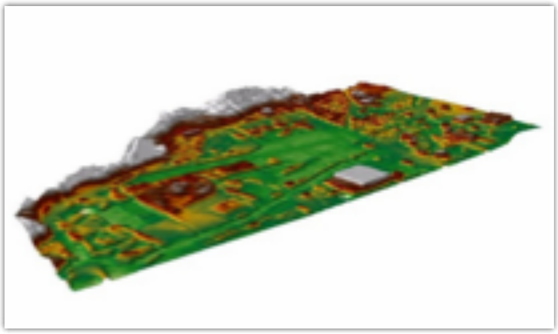
The DEMs are widely used to detect and describe urban features (KIM; NEVATIA, 2004). However, obstructions in dense urban environments are still a major obstacle to mapping, and methodologies are essential to cover the lack of information and insufficient texture to identify features (DURUPT; TAILLANDIER, 2006). New technologies that use laser radar, such as Light Detection and Ranging (Lidar), are being developed to reproduce in 3D high-resolution anthropic features, but their coverage is limited, and data acquisition and processing demand a high cost (BAUGH et al., 2013).

3. DIGITAL IMAGE PROCESSING AND CHANGE

Remote sensing change detection techniques may provide important information for the monitoring of engineering and infrastructure works. Some examples are (a) the area and rate at which buildings are developed; (b) the distribution and spatial relationship of types of changes by evaluating the relative performance of civil construction activities with the planned schedule; (c) the definition of the trajectory of change establishing a sequence of events and possible stoppages; and (d) the preparation of a cartographic representation that helps and shows existing spatial problems, favoring oversight

Figure 2:
urban area DEM (A) and aerial photograph overlapping this DEM (B).

A



B

actions. For this purpose, a detailed analysis should be performed concerning the existing methods, performing tests and combinations of procedures to obtain the best treatment of the data from an accuracy analysis.

3.1 PREPROCESSING

Usually, two preprocessing steps are described in change detection: (a) geometric correction; and (b) radiometric calibration (ALMUTAIRI; WARNER, 2010). The geometric correction transform the image coordinate system in a spatial coordinate system. This process enables to compare pixels values over time, eliminating the existence of some systematic distortion. Incorrect geometric registration impairs the accuracy of change detection, generating false artificial artifacts that do not match surface features. Thus, the images must have a perfect overlap, with a root mean square error of at most 0.2 pixels to reach an error of only 10% (TOWNSHEND et al., 1992; DAI; KHORRAM, 1999).

Radiometric calibration removes changes caused by external factors, such as: changes in sensor calibration over time, sun elevation angle, variability in Earth-Sun distance, and atmospheric interference. These methods are subdivided into two types: absolute and relative.

Absolute radiometric correction uses radiative transfer codes to obtain reflectance on the Earth's surface, eliminating atmospheric interference. Key atmospheric interferences derive from two effects: (a) scattering (diffusion or dispersion) that changes the direction of propagation of solar radiation by elastic interaction with particulates, mainly aerosols; and (b) atmospheric absorption, with effective loss of energy at specific wavelengths, mainly from seven gases: water vapor (H2O), carbon dioxide (CO2), ozone (O3), nitric oxide (N2O), carbon monoxide (CO), methane (CH4) and oxygen (O2) (ZULLO JÚNIOR, 1994). However, the correction of the atmospheric effects is more effective using hyperspectral sensors that contain bands exclusive to the different gases and makes a correction for each pixel. In relation to multispectral images, constant values are adopted for the whole image.

Relative corrections normalize digital values to a common scale, in which invariant features between two images are adjusted to a single reference, assuming that these pixels are linearly correlated (DU; TEILLET; CIHLAR, 2002). Therefore, the central question is to obtain the invariant features to conduct the linear regression between temporal images, and they may be determined by visual or computational inspection. Several

automated methods were proposed to find the invariant points and to normalize the images. We highlight the following methods: robust linear regression (HEO; FITZHUGH, 2000) frequency density diagram (SONG et al., 2001; CHEN; VIERLING; DEERING, 2005); distance and similarity spectral measures (CARVALHO JÚNIOR et al., 2013), spectral measurements among canonical components (CANTY; NIELSEN; SCHMIDT, 2004); and non-change zones around the regression line (ELVIDGE et al., 1995) or main components (DU et al., 2002). With the purpose of agglutinating all these techniques, Carvalho Júnior et al. (2013) proposed a sequential method to determine invariant points composed of the following methods: (a) spectral measurements in the original temporal images or in the canonical components; (b) density of the dispersion diagram; and (c) robust regression. The current method is in the Abílio program.

3.2 CHANGE DETECTION

Different methods have been proposed to change detect from remote sensing images, with important bibliographical reviews on the subject (COPPIN et al., 2001; HALL; HAY, 2003; LAMBIN, 1999; LU et al., 2003; SINGH, 1989; TEWKESBURY et al., 2015).

Change detection algorithms are composed of two processing steps: (a) classification; and (b) change detection. A classification of the change detection methods considers whether the change detection step comes before or after the classification step. They are called (YUAN et al., 2005): (a) pre-classification, in whi-

ch a new image highlighting the change features is created and then the classification stage is performed; and (b) post-classification, in which an independent classification is initially performed for each period and then extraction and quantification of changing areas are performed from the cross-tab between temporal images.

Many methods of pre-classification were proposed: (a) the use of algebraic techniques for subtracting and dividing multitemporal images (COPPIN et al., 2001; FRANKLIN et al., 2003; SKAKUN; WULDER; FRANKLIN, 2003); (b) change vector analysis (CARVALHO JÚNIOR et al., 2011; JOHNSON; KASISCHKE, 1998); (c) spectral mixing (ADAMS et al., 1995); and (d) several linear transformations, such as principal components analysis (BYRNE et al., 1980; FUNG e LEDREW, 1987), correspondence analysis (CAKIR et al., 2006), canonical analysis (NIELSEN; CONRADSEN; SIMPSON, 1998) and Tasseled-Cap (HEALEY et al., 2005). Pre-classification methods, although effective in locating changes, are often difficult to identify the nature of the change, thus needing another stage in classification.

Thus, the post-classification method is the most widely used method in change detection studies in urban environments, because it is effective in describing the magnitude, location and nature of the changes that have occurred (HARDIN; JACKSON; OTTERSTROM, 2007). The main advantages of the post-classification method are: (a) an independence in the classification process of temporal images compensates the variations in atmospheric conditions, phenological changes and soil moisture; (b) the process of updating data is simple, benefiting monitoring; (c) it enables comparing sensor data with different types of resolutions; and (d) enables individualizing the different categories of change, not restricted to highlighting the features of changes (COPPIN et al., 2001; MENKE et al., 2009). In contrast, the two main disadvantages of this method are: (a) it usually is not fully automatic, which makes the method time-consuming; and (b) the precision of change detection depends on the accuracy of the classification at each period, and this may facilitate the propagation of errors (YUAN et al., 2005; MENKE et al., 2009).

According to Silva et al. (2012), direct classification of the various spectrum-temporal bands does not fit into the post-classification and pre-classification methods, since the stages of classification and change detection are synchronized. In this type of classification, group analysis (WEISMILLER et al., 1977) and artificial neural networks (DAI; KORRAM, 1999) are normally used.

4. CONCLUSIONS

This paper reviewed the main potentialities and challenges regarding the use of remote sensing in the oversight of works within TCU activities, focusing on the following aspects: (a) quality of image attributes; (b) steps of digital image processing; and (c) possible adjustments and efforts required to quantify and understand the stages of public works. Auditing public works through remote sensing is a complex process, with some degree of interference between classes and a strong component of spatial-temporal changes. Only a continuous representation in the time of the construction work elements enable precise analysis and oversight. For this purpose, repetitive measurements of the spectral and spatial components of the Earth's surface should preferably be obtained in high resolution. Each attribute provides a specific type of information about the construction work and should be combined for a detailed description of the surface processes. Different models of change detection should be tested, considering the conditions of the surroundings and the environments.

Oversight and monitoring from geoprocessing and remote sensing techniques enable monitoring different works simultaneously, virtually in real time. This new approach requires a set of methodological investigations in order to reinforce the relationship between the original design of the works and the magnitude of change detected in the image. The advance of expert models to detect automated or semi-automated change in public works will enable the establishment of an alert system focusing on field inspection. To this end, computational research efforts should be employed to develop a set of standard detection techniques that will enable improving the management of the construction work phases, reducing uncertainties. This technological arsenal adapted to the different targets will allow the definition of strategies to curb the action of possible fraud or delays in schedule.

The key factor for successful mapping of engineering works is to use high-resolution images (spectral, spatial and temporal) and the DEM integrated with the intended response described by the executive project, containing all factors specific to the activity. Differently, from other studies of remote sensing in urban areas, this case has previously provided the spatial location and the intended changes, enabling a new approach to the development of automated techniques considering a previous model.

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