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Identifying concentrated areas of trip generators from high spatial resolution satellite images using object-based classification techniques

Cláudia A. Soares Machado [a,*], Alessandra M. Knopik Beltrame [b], Eduardo J. Shinohara [c], Mariana A. Giannotti [a,1], Laurent Durieux [d], Tânia M.Q. Nóbrega [e], José A. Quintanilha [a,1]

[a] Laboratory of Geoprocessing of the Department of Transportation Engineering, Polytechnic School of the University of São Paulo (Escola Politécnica da Universidade de São Paulo – EPUSP), Av. Prof. Almeida Prado, Travessa 2, no. 83, São Paulo, SP, CEP 05508-070, Brazil
[b] SENAC – National Service of Commercial Learning (Serviço Nacional de Aprendizagem Comercial), Office of Graduate Geoprocessing, Brazil
[c] CETESB – SÃO PAULO STATE ENVIRONMENTAL AGENCY (COMPANHIA AMBIENTAL DO ESTADO DE SÃO PAULO), Av. Professor Frederico Hermann Júnior, 345. Prédio 12 – Alto de Pinheiros, São Paulo, SP, CEP 05459-900, Brazil
[d] IRD – Institute of Research and Development (Institut du Recherche et Developement), France
[e] Department of the Environment, Water Resources, Science and Technology of the State of Paraíba (Secretaria de Meio Ambiente, Recursos Hídricos, Ciência e Tecnologia do Governo do Estado da Paraíba – SEMARHCT), Brazil

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ABSTRACT

The urban environment is highly complex and heterogeneous and is characterised by rapid changes in its configuration and characteristics, which scholars have referred to as urban growth. However, urban growth is not synonymous with urban development. However, urban growth is not synonymous with urban development. For development to accompany growth, territorial ordinances must be adopted, which highlights the need for planning. The high frequency and broad scope of geographic alterations in the urban environment require quick and inexpensive methods to produce and update spatial information, such as those methods that depend on remote-sensing tools. The advent of remote-sensing satellite imagery with high spatial resolution introduced a new perspective from which to analyse and study urban areas, particularly with respect to the impact of transportation systems and human activities that operate in the midst of a global context that is looking for ways to promote a sustainable urban growth and development model. In this context, the present paper proposes a methodology for identifying useful urban features for transportation planning, particularly with respect to areas with higher concentrations of trip generators that are identified from satellite images, using object-based classification techniques. The proposed methodology for classifying images minimises costs and prioritises field activities related to research on trip generators, as well as origin/destination studies. The methodology was used in the city of João Pessoa, Paraíba State, Brazil with satisfactory and promising results.

Introduction

The urban environment is highly complex and heterogeneous and is characterised by rapid changes in its configuration and characteristics, which scholars have referred to as urban growth. However, urban growth is not synonymous with urban development. However, urban growth is not synonymous with urban development. Whereas the former indicates only an increase in the amount of urbanisation, the latter denotes an increase in quality combined with growth. For development to accompany growth, there must be territorial organisation and planning. However, for planning even to be possible, the urban growth observed in large- and medium-sized cities, such as those in Brazil, for example, requires constant and extensive mapping to update the applicable databases, particularly for spatial data (geographic). The intense urbanisation process demands substantial financial, time and human resource commitments to build and maintain geo-referenced databases that enable the government to manage and administer

* Corresponding author. Tel.: +55 11 30915174; fax: +55 11 30915716.
E-mail addresses: claudia.machado@usp.br, claudia.s.machado@uol.com.br, csmachado6@gmail.com (C.A. Soares Machado), alessandra.mkbeltram@sp.senac.br (A.M. Knopik Beltrame), eshinohara@sp.gov.br (E.J. Shinohara), mariana.giannotti@usp.br (M.A. Giannotti), laurent.durieux@ird.fr (L. Durieux), tanianobrega@aesa.pb.gov.br (T.M.Q. Nóbrega), jaquinta@usp.br (J.A. Quintanilha).
[1] Tel.: +55 11 30915174; fax: +55 11 30915716.

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the cities. As a result, there is a growing demand for accurate, reliable, fast and inexpensive information.

Thus, the high frequency and broad scope of geographical changes in the urban environment require fast and inexpensive methods to produce and update both medium- and large-scale spatial information for planning purposes (Freire, 2010). It is in this context that the use of remote-sensing tools has grown as an alternative to traditional methods of building and maintaining spatial databases because they are less costly, more agile and able to track changes and identify events in the physical environment that serve as tools for urban managers, particularly those working in transportation planning.

Remote–sensing techniques–image classification methods

The advent of remote-sensing satellite imagery with high spatial resolution introduced a new perspective to conducting analyses and studies of urban areas, particularly in examining the impacts of human activities on the planet (such as transportation systems); the introduction of such technology came at a time that is witnessing the growth of concerns about the need to find and promote a sustainable model for urban growth and urban development. The high resolution imagery expands the scope of research that detects changes in land use/land cover (LULC) and no longer restricts such research to environmental studies of natural resources and urban analysis on a global or regional scale. From that time forward, urban studies could be performed with much greater detail than previously. The classifications of LULC came to be determined more accurately; thus, urban sprawl could be detailed, for instance, through road system detection, the identification of different types of edification covers and the composition of bare soil, the determination of the species of urban vegetation, etc. The process of land urban image classification became systematic.

Based on the foregoing, many researchers have attempted to assess the impact of human activities on the urban areas and to understand and organise the contemporary and future urban environment. The demand for accurate and updated spatial information is essential for effective planning and managing cities. It is within this context that the use of remote-sensing science is emphasised because remote-sensing tools are capable of generating information for mapping, analysing and monitoring urban systems (Nóbrega et al., 2008).

Currently, pixel-based and object-based techniques are the most utilised methods of remote-sensing image classification. Pixel-based classification uses spectral information to categorise pixels into classes, whereas object-based classification uses contextual information (in addition to spectral information) to sort pixels into classes.

However, this rule is not absolute. It is possible to use some contextual information in the pixel-based approach. Stuckens et al. (2000) used the segmentation procedure to integrate contextual information with pixel-based methods to classify LULC in a metropolitan area and also in the postclassification, which led to improved results by reducing confusion among urban LULC categories, and overall accuracy was increased as a consequence of incorporating contextual information into the classification process. Puissant et al. (2005) examined the potential of the spectral/textural approach to improve pixel-based classification accuracy in classifying intra-urban LULC types and confirmed the utility of textural analysis to enhance the results, particularly in urban areas in which the images are spectrally more heterogeneous. Textural analysis utilising the post-classification process improves overall accuracy and reduces confusion among LULC classes. Esch et al. (2010) and Taubenböek et al. (2012) performed pixel-based classifications of urbanised areas on RADAR images and focused on a textural analysis to highlight regions that are extremely textured due to land surface heterogeneity, as is typical in urban areas.

Classifying remote-sensing data by using spectral, spatial and textural information in methods that apply these individually or in combination has increased their applicability for feature extraction and mapping (Tehrany et al., 2014). Depending on the type of analysis and imagery characteristics, these approaches (pixel-based and object-based) have both merits and drawbacks.

In some studies, both methods are used together to improve classification accuracy. For example, in Shackelford and Davis (2003), the two approaches were applied to the classification process of multispectral high resolution imagery data over urban areas to map LULC, whereas in Gutiérrez et al. (2012), the methods were used for LULC classification of medium resolution imagery.

In general, for urban studies undertaken using remote sensing with high resolution imagery, the object-based approach has been the most useful and has yielded good results. Yan et al. (2006) tested pixel-based and object-based classifications for land cover mapping in a coal fire area located in Wuda, Mongolia, China. A statistically rigorous comparison of the two approaches was undertaken in that study and determined that the overall accuracy of the object-based classification was higher than that obtained using the pixel-based method.

Cleve et al. (2008) used high spatial resolution imagery in the USA to analyse the expansion of urban development into wildland areas in Napa County, California to distinguish LULC categories. The authors explored the accuracy of pixel-based and object-based classification methods for mapping the wildland–urban interface, and their results indicate that object-based classification yielded higher accuracy than the pixel-based method.

Blaschke (2010) presented an overview of the development of the object-based method by means of a comprehensive literature review and concludes that the pixel-based paradigm is flawed and that the object-based method is making considerable progress toward the spatially explicit information extraction workflow that is required for spatial planning and for many monitoring programmes. Thus, Blaschke (2010) concludes that the object-based technique represents a significant trend in remote sensing and GIScience by meeting the demands of increasing the spatial resolution in imagery and the use of large amounts of geospatial data.

Newman et al. (2011) compared pixel-based and object-based classification to determine the effects of these two methods in a fragmentation analyses of Cockpit Country in Jamaica. According to these authors, both methods showed similar trends in fragmentation metrics; however, there were significant differences between them regarding the metrics that quantified landscape configuration. The authors affirmed that the object-based approach presents better results for landscape analyses than the pixel-based method.

Ouyang et al. (2011) affirmed that the object-based classification has demonstrated many significant advantages over other methods of classifying urban and/or forest ecosystems. These authors compared the effectiveness of object-based classification and pixel-based classification methods for mapping plants in a saltmarsh ecosystem through very high resolution imagery, and they concluded that the object-based method yields better results in terms of accuracy than the pixel-based approach because the object-based technique performance employs membership functions and a hierarchical approach with multi-scale segmentation.

Robertson and King (2011) compared pixel- and object-based classifications of Landsat Thematic Mapper data for mapping and analyses of LULC change in the mixed land-use region of eastern Ontario, Canada during the 1995-2005 period. The quantitative and visual analyses showed no significant accuracy differences between the two methods. The object-based method produced thematic maps with more uniform and meaningful LULC classes, but it suffered from absorption of small classes into larger objects and the incapability of spatial attributes to contribute to class discrimination and separation. However, according to the authors, despite the similar map accuracies of the two approaches, temporal change maps produced using post-classification comparison and intensive visual analysis of errors of commission and omission revealed that the object-based maps depicted change more accurately than the pixel-based classification, even using medium spatial resolution.

As explained by Wang et al. (2004), the object-based method involves two steps: segmentation and classification. In the segmentation stage, the major task is to partition the entire image into a series of closed objects. The object-based image classification process is controlled by a knowledge base that describes the characteristics of output object classes (Darwish et al., 2003). The objects are generated through the segmentation procedure, which is the search for homogeneous areas in an image set with the aim of identifying and classifying these areas (Mather and Koch, 2011, p. 434).

The objects created by the segmentation procedure by one or more criteria of homogeneity in one or more dimensions of a feature space have the spectral information that is contained in the pixels that make up the objects (e.g., mean values per band, variance, etc.), and they also have spatial information (shape, texture and contextual information) that is present in both the meaningful image objects and in their relationships with one another (Blaschke, 2010; Darwish et al., 2003).

The classification of images based on objects is grounded in a given set of procedures that begin with the use of segmentation techniques on the images selected to create objects. Having defined the objects, geometric and spectral information is indirectly extracted from them. This information is then modelled based on contextual information to support intra- and inter-object analyses. The objects are defined based on the segments generated from the images using a segmentation procedure. Gonzalez and Woods (2000), p. 509 described segmentation as dividing images into smaller parts or objects of interest until they are isolated.

Detailed reviews of segmentation methods can be found in the following studies: Fu and Mui (1981) affirm that segmentation techniques can be categorised into three classes, i.e., characteristics that feature thresholding or clustering, edge detection, and region extraction; Pal and Pal (1993) critically review and summarise segmentation techniques (fuzzy and non-fuzzy methods); Haralick and Shapiro (1985) review a variety of image segmentation techniques and describe several specific examples of each class of algorithm on real images; Zhang (1996) describes different methods proposed for segmentation evaluation, shows a description of each one and provides a comparative discussion about them; and Cufí et al. (2003) review the segmentation techniques that integrate region and boundary information, in which several algorithms are described to highlight the strengths and weaknesses of such techniques.

Although the segmentation process can be performed in both pixel and object-based classification approaches, it has an essential role in the object-based technique because segmentation provides the building blocks of object-based image analysis, according to Blaschke (2010). Thus, the quality of object-based classification strongly relies on the quality of the segmentation process, particularly in urban environments in which the great heterogeneity and volume of information in the objects (spectral and contextual information) complicates matters.

Remote–sensing techniques–interaction between LULC and transportation systems

Notably, applications in transportation studies that employ remote-sensing data to study LULC identification have become more common. The interaction between transportation and LULC occurs mainly in terms of accessibility because this interaction is related to the ease of movement among locations throughout the transportation system. In turn, the higher the accessibility measure of a place (best transportation supply), the more value that is ascribed to the land, and interferes in the location of activities, which consequently leads and guides the use of urban land (Khisty and Lall, 1998, p. 720).

Currently, many researchers use remote sensing for studies involving the interaction of transportation and LULC. Zhang and Guindon (2006) used remote-sensing imagery for thematic mapping of LULC within the context of the relationship between urban transportation and energy consumption caused by urban expansion. The authors quantified sustainability indicators involved in extracting information related to urban form (density, compactness, and mixed LULC), and they analysed these indicators regarding their impacts on the efficiency of LULC, transportation systems and the environment.

Nóbrega et al. (2008) used object-based classification in images from the remote-sensing satellite IKONOS 2 to map the LULC to detect and extract the road network in the area in the outskirts of São Paulo City, the capital of São Paulo State, Brazil. Pacifici et al. (2009) used panchromatic images from the QuickBird and Worldview 1 satellites (spatial resolution of 0.63 m and 0.50 m, respectively) to map and classify the LULC of the cities of Las Vegas, Washington, D.C., and San Francisco in the United States, and Rome, Italy. The authors applied the object-based approach to identify different types of pavement in local roads, highways and parking areas. Additionally, LULC was separated into classes regarding horizontal residences and apartment buildings, with high accuracy of the object-based image classification process.

Machado et al. (2010) used high resolution images from the IKONOS 2 satellite for thematic mapping of the LULC and occupation in the city of Osasco, São Paulo State, Brazil. The objective was to identify LULC classes related to industrial and commercial activities and to calculate the accessibility index of these economic sectors using the municipal road network.

Pinho et al. (2012) argue that recent studies regarding urban LULC are important with respect to planning and management. The authors provide a LULC classification through the object-based approach of high resolution images from the IKONOS 2 satellite (panchromatic band with 1.0 m of spatial resolution and multispectral bands with 4.0 m of spatial resolution), in the city of São José dos Campos, São Paulo State, Brazil.

Alfasi et al. (2012) conducted a study to evaluate the performance of the current LULC plan for the Central District of Israel by using data and information from remote-sensing tools (aerial photographs) and analyses in a GIS environment. The authors conclude that the current development of LULC in the study area is not in accordance with the public authority's planning, and they discuss the flexibility of LULC planning in relation to actual usage, to densely populated districts and to spatial complexity.

Hu and Wang (2013) analysed and mapped the urban LULC in Austin, Texas, United States using aerial photographs. The aim was to assess urban planning and environmental management actions. The study developed an automatic methodology to classify the urban LULC in detail, including the transportation facilities, and to identify transportation-related classes, such as railroads, transport terminals, airfields, parking lots, and so forth. The authors affirm that transportation-related classes are difficult to identify within the LULC classification system.

Remote–sensing techniques–transportation planning studies

Currently, with the enhancement of remote-sensing sensors resolutions, the use of images in studies and academic research regarding monitoring and mapping of the urban LULC for transportation planning purposes have been recurring themes in the scientific community. For instance, the remote-sensing tools can be applied to build the database for the transportation models to forecasting demand models.

According to McNally (2000), the history of transportation demand modelling for personal travel has been dominated by the Four Step Model (FSM). Although "travel" is derived from the demand for activity participation, the FSM is a trip-based – rather than activity-based – method. Trip origins-destinations (ODs) form the principle database of the FSM, which is the conventional and more typically applied approach to forecasting transportation demand.

The FSM results in a forecast of future travel demand per transportation link. These data (OD pairs) are then used to assess the future performance of the existing transportation system to identify transportation links that lack sufficient capacity and to forecast the impact of possible transportation investments on the performance of the system (Martens, 2006).

The range of information collected for conventional transportation demand modelling purposes (e.g., FSM) should be extended, mainly in terms of temporal and spatial data. Remote-sensing technologies are capable of providing a broader amount of data, continuously monitoring travel and activity systems, and the use of such technologies should be increased (McNally and Rindt, 2007). Deng et al. (2009) state that remote-sensing techniques are able to offer an entirely new type of data source for estimating OD matrices without surveys in a less costly and less time-consuming way.

Trip generators in Brazil

Brazil is a highly urbanised country: approximately 80% of the Brazilian population lives in urban centres, and 90% of the Gross Domestic Product (GDP) is created in cities. Therefore, the scale of urbanisation in Brazil is of great concern, and the distribution of the population across the urban hierarchy presents challenges to policymakers in cities of different sizes (Mata et al., 2007).

In particular, since the 1980s, the structuring of urban space in Brazil in its medium-sized and large cities has undergone a major transformation from a monocentric compact model to a sprawling model with multiple centralities. Townroe (1984) argued that the federal and state authorities responsible for planning urban development in Brazil in the mid-1980s were considering introducing a new policy initiative to decentralise the manufacturing industry from the metropolitan areas in the major Brazilian cities as a further strategy to accommodate future growth and to alter the pattern of urban forms.

During this time, large urban projects began operating as shopping malls, hypermarkets, office condominiums, etc., and had a negative impact on urban spaces due to the large transportation volume accompanying these projects, which contributed to increased congestion, pollution (air pollution due to vehicle emissions and noise pollution), and traffic accidents. This process also raised transportation costs, i.e., the negative externalities associated with transportation that affect the performance and safety of urban traffic (Janic and Vleugel, 2012; Miller et al., 2013; Van Wee, 2009; Verhoef, 1994). Timilsina and Dulal (2011) affirm that LULC analysis, urban and transportation planning, and infrastructure investment could contribute to reducing externalities, but these processes are expensive and play a small role in previously developed medium-sized and large cities.

Based on these developments, it is necessary to study and evaluate the impact of such projects and ventures. These large ventures were initially called "Traffic Generators" and were associated with locations or installations of different types that developed common activities in a size and on a scale capable of producing and/or attracting a significant number of human trips (Portugal and Goldner, 2003, p. 322).

The concept of Traffic Generators has evolved to Trip Generators (TGs). Whereas the former approach considers only the impact caused by motorised traffic – mainly individual transportation by cars and its effects on the road system (circulation, accessibility, and safety) – the new concept includes trips by other transportation modes, including public transportation and non-motorised means of travel, and the impact of all these transportation modes on socioeconomic development; the consequences of the use, occupation and value of urban land; and the effects on the quality of life of transportation system users (Gonçalves et al., 2012). This concept evolved because TGs have had broader impacts that exceed the scope of traffic and have transcended the road sector; these impacts cover the transport system as a whole and impact economic development and the population's quality of life. Therefore, the concept of TGs is not static; on the contrary, it is constantly evolving and confronting current societal concerns related to environmental issues, such as sustainability and quality of life (Portugal, 2012, p. 748).

Gonçalves et al. (2012) present an overview of the evolution of the concept of TGs, highlighting the concept that involves aspects of sustainable transport that they then refer to as Sustainable Trip Generators. These enterprises are located in areas with conditions that are conducive to enabling sustainable mobility, based on displacement by non-motorised transportation modes and public transportation and under the assumptions and concepts of transit-oriented development (TOD) areas, which are based on mixed LULC, the presence of public transport terminals near the projects, an emphasis on public transportation searching intermodality, spaces for pedestrians and cyclists to travel safely (sidewalks and bike lanes), short blocks, and transportation system amenities (e.g., shelter in the breakpoints of buses, benches, information boards, etc.).

The international literature has generated Traffic Impact Studies (TISs), which utilise a definition similar to that of TGs. According to Muldoon and Bloomberg (2008), transportation regulatory agencies use TISs to develop projects that are associated with transportation systems and to predict the lifespan of a transportation project based on future estimates in a LULC scenario. The TISs help transportation agencies make decisions about LULC, assess whether the proposed development projects are suitable for their intended locations and determine the type and extent of improvements required by a transportation system. A similar application was discussed by Wang and Trauth (2006), who used pixel-based image classification techniques to identify large commercial and industrial ventures as places of origins and destinations of urban trips, and these were used to measure distances in order to determine transportation system accessibility.

Bornstein (2010) refers to TGs as megaprojects and conducted a study about their effects in the North American cities of Montreal, Vancouver and Los Angeles. The author also indicates that megaprojects are expensive and complex and can be beneficial at the regional level, although the residents of local neighbourhoods must bear the externalities because these types of projects often generate congestion, pollution, and accidents, i.e., at the local level, such projects contribute to the negative externalities related to increased transportation requirements and can lead to increased socioeconomic polarisation in contemporary cities.

Objective

This paper aims to present an alternative methodology that uses remote-sensing tools to identify and locate urban features spatially that are relevant to transportation studies. Specifically, this paper describes a method for identifying useful urban features for transportation planning, particularly projects and ventures associated with locations or installations of different types that might generate a substantial amount of urban trips. The objective is to identify areas whose LULC classes imply that a substantial amount of urban trips (origins and destinations) might be generated and these areas are thus called TG concentration areas.

The proposed methodology consists of using object-based image classification to obtain the TGs' ODs. The rationale for this methodology is that remote-sensing tools are cheaper and faster than traditional approaches for identifying the TGs' ODs, which are the main database of the FSM. Thus, the results of this study can be used as an input database for transport demand models. In addition, these tools are able to monitor large areas and their LULC changes in near real time by means of analyses and studies of multitemporal satellite imagery.

The paper is structured as follows. Section 2 describes the materials used and methodology adopted to conduct the study, Section 3 describes the results obtained, and Section 4 presents the conclusions of the article.

Materials and methods

The area under study consists of the political-territorial limits of the municipality of João Pessoa, the capital of the State of Paraíba, located in northeastern Brazil.

The municipality of João Pessoa encompasses an area of approximately 211 km^2 and is located in the extreme east of the State of Paraíba, between the coordinates 7°14′29″ S and 34°58′36″ W, and 7°03′18″ S and 34°47′36″ W.

The city transportation system utilises buses as its sole mode of legalised public transportation, and these are maintained through public grants from the municipal government. The approximate capacity of the transportation service is 424,600 passengers on weekdays. In addition to buses, there is a taxi service (automotive fleet) that includes 1440 vehicles (April 2011), according to data and information from the Department of Transportation and Traffic of João Pessoa (STTRANS).

The study utilised SPOT 5 satellite images (acquired in 2009) with multispectral bands at a spatial resolution of 10 m for the green, red and near- and mid-infrared wavelengths, with a 2.5-m spatial resolution for the panchromatic band. Vector data (georeferenced) are provided by the City of João Pessoa and contain the information listed below, which was used for comparison with the final results obtained after applying the proposed method:

- Public, commercial and social facilities that were considered TGs by the City of João Pessoa, classified by activity type;
- Boundary limits of the municipality, neighbourhoods and parks;
- Digital database of census sectors according to the IBGE (Brazilian Institute of Geography and Statistics - Instituto Brasileiro de Geografia e Estatística).

Digital processing of the remote-sensing images, which resulted in the object-based classification, was performed using the following software: SPRING 5.1.7, ENVI 4.2 and eCognition Developer 8.0.

TRIP generators

Determining potential locations to identify TGs begins with adopting a representation system for mapping LULC. In this study, the CORINE system (Bossard et al., 2000, p. 105) was chosen because it is best suited to the purposes of the research. In classifying LULC, two systems are used worldwide: a) the system developed by Jensen (2000), p. 379, which is an adaptation of the system developed by Anderson et al. (1976), p. 28 and adopted by the United States Geological Survey (USGS); and b) the Coordination of Information of the Environment (CORINE), a programme created to provide environmental information to the European Union.

Both systems are structured using a hierarchical scale, and the classification of LULC determines the greatest differences between them. Whereas the USGS system focuses more on using classified areas, such as those associated with commercial and public services, CORINE seeks to characterise areas based on their composition and spatial arrangements (Beltrame and Quintanilha, 2009).

To identify TGs, an initial visual interpretation of the LULC from the satellite images was performed, which looked for surface materials that correspond to the LULC classes that are considered TGs. To achieve this goal, the challenge in this phase of the study was to find LULC classes that could be identified as TGs, i.e., LULC that have the ability to generate large quantities of trips. The classes used for this interpretation correspond to buildings with metal and asbestos

Table 1
Definition of the mapped classes — CORINE system.

Level I	Level II	Level III	Level IV
Artificial areas	Urban fabric	Continuous urban fabric	Private housing estates, residential neighbourhoods consisting of individual houses (horizontal residential areas) Construction of residential flats (vertical residential areas)
	Industrial, commercial and transport units	Industrial and commercial units Road network and associated land (routes)	
	Mine, dump and construction sites	Mineral extraction Construction sites (sand)	
	Artificial, non-agricultural vegetated areas	Urban greenery Sport and leisure facilities	
Natural areas	Heterogeneous agricultural areas Forest, shrubs and/or herbaceous vegetation associations		

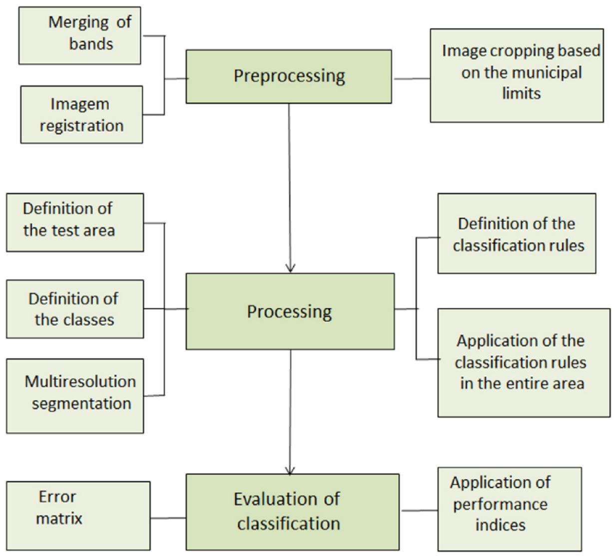


Fig. 1. Schematic diagram of the methodology used for image classification.

roofing (no ceramic roofing), which are commonly used in large and medium-sized industrial or commercial buildings; health facilities; schools, colleges, universities, etc.; sports and leisure facilities; religious temples; and so forth. Conversely, residential units (ordinary houses), that are not the focus of this study, typically have ceramic roofing. Likewise, areas with large concentrations of high-rise condominiums (residential and commercial building), which generate a significant number of trips, were also identified and associated with the TGs.

According to the criteria of the CORINE system, which were adopted in this study, the classes associated with the TGs include the following: industrial and commercial units, residential clusters (mainly buildings' condominiums), and sports and leisure facilities, as explained below in Table 1.

The first, second and third levels of the CORINE system consist of 5, 15 and 44 classes, respectively. The subsequent levels are open, and each analyst may thus define them according to the research interests and areas analysed.

The present study focused on the urban areas for which the following classes were defined (as in Table 1).

Image classification

The process was divided into three macro-processes: image preparation/pre-processing, processing (including the classification itself) and classification evaluation. Fig. 1 presents these three phases schematically. The procedures used in each phase are described below.

Although they do not fit into the TG definition, other classes (e.g., urban greenery and sand (bare soil)) were included in the classification to refine the classes of interest and avoid misclassification errors.

Object-based classification frequently adopts image merging (Schowengerdt, 2007, p. 515) because spatial resolution is considered more important than spectral resolution for characterising interurban targets (Barragán et al., 2011; Durieux et al., 2008; Myint et al., 2011). In this case, because the targets were not characterised based on their spectral response, merging the images with different scales resulted in better TG identification.

In this work, the fusion between the panchromatic band (spatial resolution of 2.5 m) and the multispectral bands (spatial resolution of 10 m) was performed – which resulted in a colour composite with 2.5 m spatial resolution – to make greater use of the spatial and spectral information contained in the original image set (Lu et al., 2011).

There are certain techniques of image fusion available in digital image processing software, such as principal components, RGB (Red – Green – Blue) and IHS (Intensity – Hue – Saturation) transformations, etc. The fusion result consists of a synthetic image with the original image's colours preserved in addition to the level of detail of the panchromatic band. Among the methods that were tested, the principal components showed the best quality and final results.

The principal component method was used at this stage to reduce the number of bands to be treated without a significant loss of information, which is even more important when handling merged images.

The digital database for the IBGE census sectors was overlaid on each image to serve as a reference for image registration. The registered image was cropped using the municipal limits of Joao Pessoa.

Multiresolution segmentation

The image was segmented into three distinct levels, following a “top-down” strategy. According to Hofmann (2001), the segmentation strategy affects the boundaries of the objects; thus, it is recommended to start at the level where the objects of interest are located.

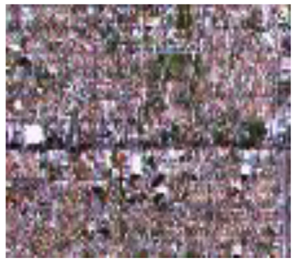
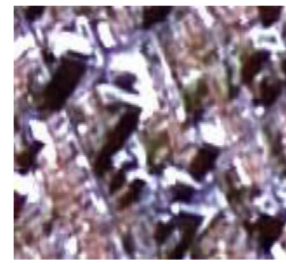
The city of João Pessoa has a significant portion of natural areas, consisting of native vegetation, agricultural land, water bodies and mineral extraction. Once the classes of interest of this study were found in the urban environment, they were used as the first segmentation level (level I) that was able to extract the urban area (the urban fabric class).

The second level (level II) was applied to select the areas of concentration of horizontal residential; industrial, commercial, and transport units; urban greenery; sports and leisure facilities; and

Table 2
Segmentation levels and their respective parameters.

Levels	Objects	Objectives	Scale	Shape (weight)	Colour (weight)
III	Vertical residential Road network Auxiliary classes	Identifying objects of interest in a more detailed scale	50	0.4	0.9
II	Horizontal residential Industrial, commercial and transport units Urban greenery Sport and leisure facilities Sand	Identifying larger objects of interest. Serve as the basis for the occurrence of other classes in level I	100	0.4	0.9
I	Urban fabric Natural areas	Select the urban area, restricting the presence of natural areas in the subsequent levels. Select and remove clouds and their shadows.	500	0.1	0.5

Table 3
Description of the LULC classes.

Segmentation levels	Characterisation	Image
I	Urban fabric: predominance of impervious coverage (structures and the transport network), and sparse vegetation.	
	Natural areas: prevalence of vegetation with agricultural areas and mineral extraction. Presence of water bodies.	
II	Horizontal residential areas: predominance of ceramic roofing, well-defined city blocks and the presence of vegetation (gardens, lawns, and trees).	
	Industrial, commercial and transport units: predominance of metallic roofing, concrete, asbestos, and asphalt, generally with well-defined geometric shapes.	
	Sports and leisure facilities: soccer fields and stadiums.	
	Sand: because this is a coastal area, a significant portion of the bare soil is covered with sand.	
	Urban greenery: presence of trees and grass areas.	
III	Vertical residential areas: buildings and predominance of bright concrete, with a greater concentration near the beach.	
	Road network: asphalt-covered streets, avenues, roads and highways.	

bare soil (sand). Among the three segmentation levels adopted, this level concentrated most of the objects of interest.

The third segmentation level (level III) aimed to divide and reorganise the objects of the previous level. The objects generated in level III formed more detailed classes (derived from the classes obtained in level II). For instance, the "vertical residential" and "road network" classes (level III) were extracted from the "industrial, commercial and transport units" class (level II) (see Table 3).

The final classes are: urban greenery, sand, sports and leisure facilities, industrial and commercial units, horizontal residential, vertical residential, and road networks.

Several tests were performed in the search for parameters that best delimit the objects of interest, considering the attributes' sizes, colours and shapes. Table 2 shows the segmentation levels applied, with their respective parameters and objectives.

Hierarchical network

Adopting a hierarchical network helps in the classification process as a strategy to be followed. Initially, classes are selected that are more easily distinguishable and then other derived classes are set through these first classes.

Because the classes of interest to the work are concentrated in urban areas, the classification process should begin with extracting the urban fabric, which is quite different from the natural areas. Subsequently, other classes were defined within the urban fabric, as shown in Fig. 2. Some tests were conducted to obtain this structure, which is the most functional within the proposed objective.

The vegetation class was identified using the Normalised Difference Vegetation Index (NDVI), which is commonly employed when classifying this element (Liu and Huete, 1995).

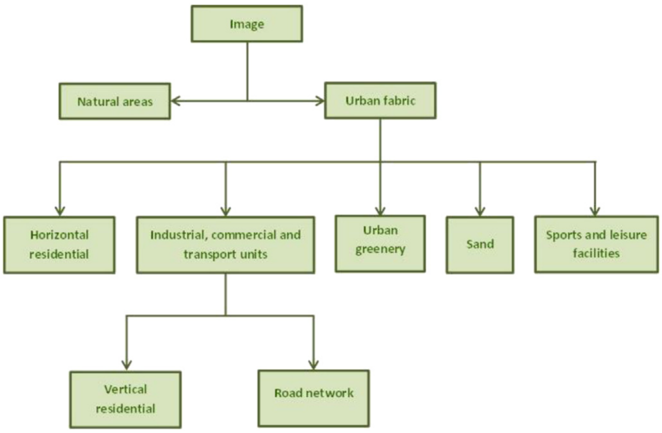


Fig. 2. Hierarchical network scheme.

The resulting image was segmented into three different levels, as shown in Table 3; the first segmentation level was extracted from the municipality layer, and the next two were based on the nomenclature that defined the mapped classes (Table 1).

Defining parameters capable of describing the classes of interest required prior analysis and class characterisation, as shown in Table 3. The object classification process was performed by defining attributes and rules for remaining in each class. Samples were selected for various classes at their respective levels. These samples allowed the characteristics of each class to be identified according to previously selected characteristics, including the average reflectance in each band of the image and its relationship with other object classes.

At level I, the separation between the natural areas and urban fabric classes was made using spectral attributes and the condition that the object classified as urban fabric should always be neighbouring another object of the same class; otherwise, it would be classified as natural area.

Subsequently, the level II classification was performed. The first condition for all classes analysed at this level was to belong to the urban fabric class (similarity). At this stage, according to the CORINE system, it was possible to identify the classes: horizontal residential; industrial, commercial and transport units; sand (bare soil); urban greenery; and sports and leisure facilities (soccer fields and stadiums).

The classification performed at level III remained unchanged with respect to the following classes: horizontal residential, urban greenery, sand, and sports and leisure facilities. However, the industrial, commercial and transport units class was divided into the following classes: industrial and commercial units, road network, and vertical residential. The road network class was created at level III only to refine the industrial and commercial units class and avoid labelling wide roads, avenues and streets improperly.

To better characterise the vertical residential class, the shadow auxiliary class was created. Thus, the edge relation between the shadow and industrial and commercial units classes was used as a parameter to distinguish industrial and commercial buildings from vertical residential buildings, as illustrated in Fig. 3.

After having tested and validated all the classification parameters in the test area, these parameters were applied throughout the study area.

To evaluate the LULC classification, four areas within the project were selected based on the following criteria:

- Mixed, where it was possible to find most, if not all, classes assessed;
- Predominance of the horizontal residential class;
- Predominance of the vertical residential class; and
- Predominance of the industrial and commercial class.

Within each of these areas, polygons (objects) were selected to comprise the confusion matrix and for the calculation of the Kappa, that are measures that assess the accuracy of the classification process. The confusion matrix is a descriptive statistical technique that consists of a square matrix in which the LULC classes detected by the image classification process are arranged in rows and columns. Each matrix cell shows the quantity of pixels assigned to each class. Therefore, the main diagonal of the matrix shows the number of pixels classified correctly. The overall accuracy is calculated by dividing the number of pixels correctly classified (sum of the main diagonal of the matrix) by the total number of pixels contained in the confusion matrix (Congalton, 1991).

The confusion matrix detects two types of errors: commission errors and omission errors. The commission errors are the pixels of other classes included in the class being evaluated. The omission errors consist of pixels that should belong to the class under consideration but were not classified as such (Congalton, 1991; Lillesand et al., 2008, p. 756; Campbell and Wynne, 2011).

Another accuracy test that is widely used in the classification evaluation is the Kappa statistic. It is a measure based on the agreement between the classification performed (actual or observed) and the reference classification (or expected, which is the main diagonal of the confusion matrix), and the probability of

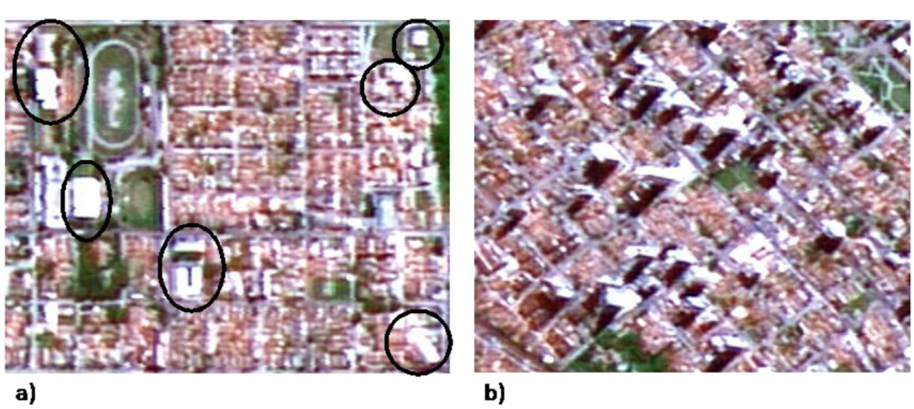


Fig. 3. a) Example of industrial or commercial buildings and their shadow patterns and b) shadow patterns of the residential buildings (vertical residential).

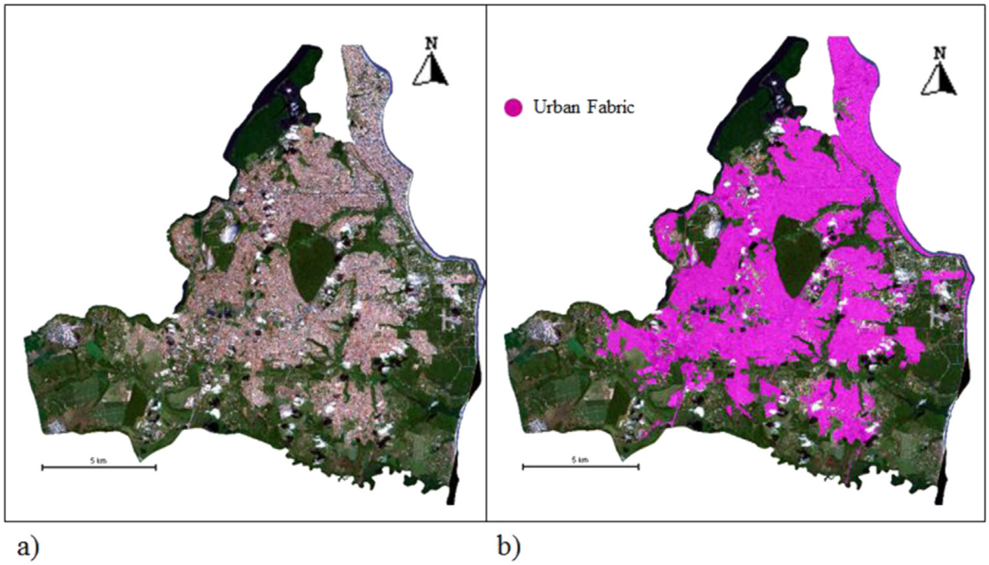


Fig. 4. a) Image of the total area of João Pessoa; and b) Urban fabric identification, according to level I.

agreement (the sum of the cells that are outside the main diagonal) (Campbell and Wynne, 2011; Congalton, 1991).

Results

Fig. 4 shows the visual result of the phase corresponding to level I.

The classes analysed in level II were horizontal residential; industrial, commercial and transport units; green urban; sand; and sports and leisure facilities. In this phase, objects had a size that favoured cluster classification, which minimised confusion between the classes.

The horizontal residential class was extracted without major difficulties. Its distinct characteristics, i.e., predominance of a ceramic colour, enabled its identification without significant confusion with other classes.

The class of industrial, commercial and transport units resulted in some confusion because of the variety of materials that were found in their objects, including metallic roofing, which could be confused with sand, concrete and asbestos, both in light and dark shades.

The sports and leisure facilities class was extracted using manual classification after visual identification of the scene. This procedure was performed as a result of the great difficulty in the automatic identification of this class.

Fig. 5 presents the final results of the level II classification.

Classification of the urban greenery, sand, sports and leisure facilities, and horizontal residential classes was replicated in level III, with the sub-objects in this level inheriting the class corresponding to the super-object of level II. All areas classified in level II with specified labels remained classified as such in level III, although the number and size of the objects changed.

The industrial, commercial and transportation units class was reclassified, which resulted in the industrial and commercial unit, vertical residential and road network classes. Because the spectral attributes of these classes are similar, other criteria were used to

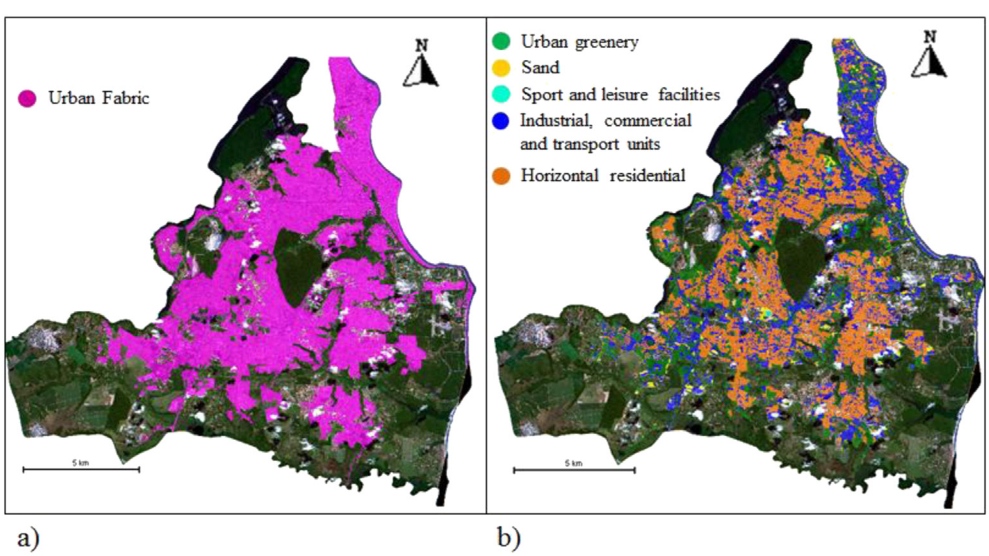


Fig. 5. a) Identification of the artificial areas in the level I classification; and b) Reclassification of the artificial areas into new classes, according to level II.

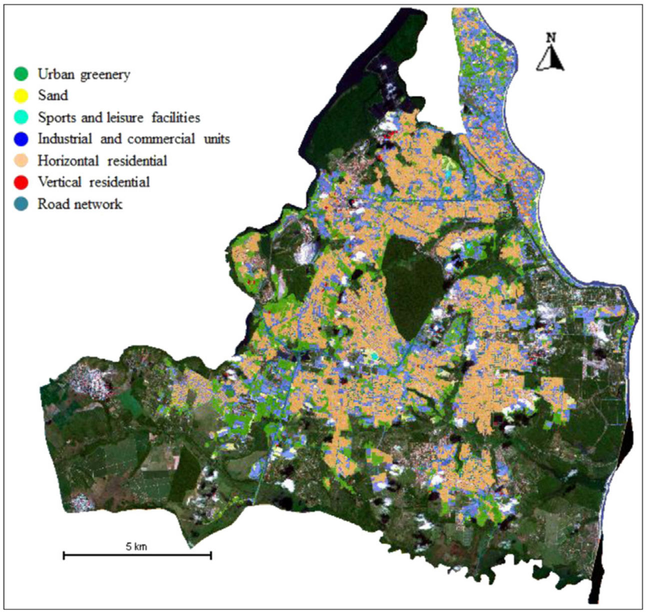


Fig. 6. Visualisation of the level III – Final classification.

characterise them, including the neighbouring relationship with the shadow class for the vertical residential area and geometric attributes and the length and width for the transportation route (road network) class. Fig. 6 shows the visual result of the level III classification.

Table 4 shows the final classification values, for which an overall accuracy rate of 71.4% and a Kappa coefficient of 0.68 were obtained.

According to the results of the confusion matrix, the classification of residential classes, both vertical and horizontal, yielded good results. However, the “Industrial and Commercial Units” class failed to produce results that were as good as those for the other two classes, and the largest confusions are associated with the “road network” and “sand” classes.

This result can be explained by the fact that the commercial establishments are concentrated in the coastal zone of João Pessoa, where the high-income population live. Moreover, as the asbestos and metal roofing, typical of these type of buildings, have an analogous spectral response to the sand present in the coast (beaches) and the coastal roads, made of concrete instead of asphalt, the confusion between the classes occurs, reducing the accuracy of these classes.

Although the “road network” and “sand” classes are not among the priorities of this project, given the confusion associated with the “Industrial and Commercial Units” class, these classes may be misleading when analysing trips because they do not consider real trip attractors.

Because the objective is to identify areas with TG concentrations, the classes of interest in this study are the “vertical residential” (large condominium buildings), “industrial and commercial units”, and “sports and leisure facilities” classes.

The “vertical residential” class is concentrated near the northern coast of the town in which there is a predominance of high-income residents. This high-income population requires diversified commercial activities and services, which results in establishments being concentrated in these areas, including shopping malls, cinemas, restaurants, hotels and shops (Bezerra and Araújo, 2007, p. 16). The density of condominiums, the concentration of service and commercial offerings and the high purchasing power of the inhabitants in these areas that indicates a high number of private vehicles causes many trips to be generated in these regions, which therefore characterises them as TGs.

The “industrial and commercial units” class is distributed over almost the entire urbanised area of the city, with a higher density in the coastal area to the north (described above) and at the traditional axis of the city, in which, in accordance with Bezerra and Araújo (2007), p. 16, the first commercial, residential, industrial and administrative facilities were installed and the sociospatial structure of the municipality was defined. These areas have the

Table 4
Confusion matrix of the level III classification.

Expected Results (Ground Reference)	Reported Results (Classification)																
	Horizontal Residential Areas		Vertical Residential Areas		Industrial & Commercial Units		Road Network		Urban Greenery		Sand		Shade		Total	Omission %	Commission %
	Pixels	%	Pixels	%	Pixels	%	Pixels	%	Pixels	%	Pixels	%	Pixels	%	Pixels		
Horizontal Residential Areas	49887	81.08	0	0.00	5965	9.69	872	1.42	0	0.00	3243	5.27	1561	2.54	61528	19	17
Vertical Residential Areas	0	0.00	2991	94.35	179	5.65	0	0.00	0	0.00	0	0.00	0	0.00	3170	6	68
Industrial & Commercial Units	6565	10.50	6474	10.35	40971	65.51	3117	4.98	0	0.00	3243	5.19	2170	3.47	62540	34	39
Road Network	0	0.00	0	0.00	2009	15.62	9645	75.00	776	6.03	0	0.00	430	3.34	12860	25	31
Urban Greenery	3851	8.73	0	0.00	3188	7.23	396	0.90	35847	81.30	809	1.83	0	0.00	44091	19	2
Sand	0	0.00	0	0.00	14844	62.21	0	0.00	0	0.00	9018	37.79	0	0.00	23862	62	45
Shade	0	0.00	0	0.00	0	0.00	0	0.00	0	0.00	0	0.00	934	100.00	934	0	82
Total	60303	28.86	9465	4.53	67156	32.13	14030	6.71	36623	17.52	16313	7.81	5095	2.44	208985		
Overall Accuracy	71.4%																
Kappa Coefficient	0.68																

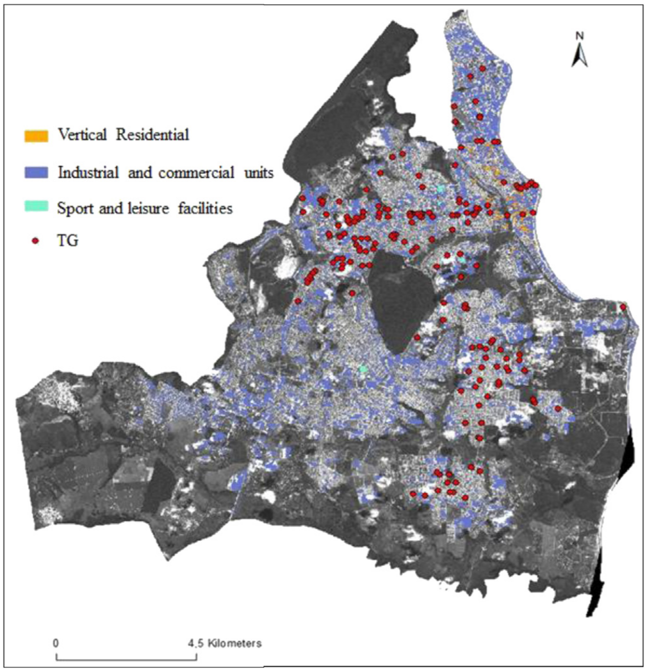


Fig. 7. Final results of the classification of areas with TG concentrations in João Pessoa (PB, Brazil).

potential to generate (produce and attract) many trips, thus characterising them as TGs.

Areas classified as "sports and leisure facilities" areas generate seasonal transportation demand because trips in these areas occur during events at these locations. Thus, the characteristics of these TGs differ from those of other TGs, in which trip generation can be considered continuous and intermittent. Sports and leisure facilities areas are scattered throughout the municipality.

Fig. 7 shows the areas of the city with the highest TG concentrations (the classes described above) and, for comparison, includes those projects that the City Hall of João Pessoa have registered and consider TGs. Overlap in these information layers indicates that the proposed method identifies the areas mapped by the city as TGs but extends this characteristic to other locations that are not identified as such by the municipal government.

Conclusions

With respect to its initial objective of identifying areas with concentrations of TGs in the city of João Pessoa, the methodology described in the article generated satisfactory results in terms of overall accuracy (71.4%) and Kappa coefficient (0.68) for the urban environment. As observed in the confusion matrix (Table 4), the most relevant classes to the TG investigation (the "Vertical Residential Areas" and "Industrial and Commercial Units") presented accuracies of 94.35% and 65.51%, respectively.

The better performance of the "Vertical Residential Areas" class over the "Industrial and Commercial Units" class is due to fact that the second class has, predominantly, asbestos or metal roofing. These materials present a very similar spectral response to the "Sand" class. Additionally, there are a high concentration of commercial buildings along the coastal area, which is the zone with the highest income level of João Pessoa. Even though not being a problem away from the coastal area, the confusion between these classes is enough to reduce the accuracy of the "Industrial & Commercial Units" class.

In turn, even with the same kind of roofing, the "Vertical Residential Areas" class can be clearly distinguished from the others by the presence of shadow. It leads to very good results to "Vertical Residential Areas" (94.35%) and "Shade" (100%) classes.

However, the interpretation of the results by the analyst is crucial because the automatic procedure of image classification can analyse the characteristics of materials and substances but cannot determine the real LULC. The LULC can be inferred by the analyst who investigates the types of materials and substances related to the spectral response, texture, shape, geometric and topological relationships, etc.

Regarding the "sand" class, there are 14,844 pixels that were misclassified as belonging in the "Industrial & Commercial Units" class, which occurred because the spectral response of the sand (along the coast) is similar to the spectral response of the metal roofs that typify industrial and commercial buildings. Moreover, because it is a narrow strip of sand (7.8% of the total study area), the use of context information was not enough to solve this problem, but this usage does not occur apart from at coastal areas.

In addition, 34.49% of pixels containing industrial and commercial units were misclassified as other classes, which corresponds to 10.3% of the total study area. In terms of the impact on this project, this problem is reduced because 60% of the misclassified pixels were actually residential areas, and several buildings used for commerce and services were buildings that previously had been residential units. The remaining misclassified pixels (roads, sand, and urban greenery) represent approximately 4% of the total area.

Some of the difficulties encountered in performing this work were caused by the characteristics of João Pessoa, which has a relatively homogeneous LULC compared with the urban fabric of interest for identifying TGs. The images used were those that are currently available and not others that were acquired specifically for this type of research.

Refining the research would involve including geocoded responses that are derived from the results of questionnaires used in the field (a simplified OD research project) and using spatial analysis methods to create a plan for obtaining specialised information that can be added as additional data – in the form of a classification rule – for object-based project classification.

The classification of satellite images using information generated from field surveys to identify TGs or better understand the uses and dynamics of urban space opens a new path that is indicated by the developments in this study. One challenge that remains is to develop field research methodology that is less expensive than the commonly used OD study methodologies and that can compensate for the lack of information in larger studies by taking advantage of the benefits of remote sensing, which include providing satellite images at any time.

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