

Towards development of a national human settlement layer using high resolution imagery: a contribution to SDG reporting

Naledzani Mudau*, Willard Mapurisa¹, Thomas Tsoeleng¹, Morwapula Mashalane¹

Earth Observation Directorate, South African National Space Agency, Pretoria, South Africa,

*NMudau@sansa.org.za

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Abstract

This study investigated the automation of the building extraction using SPOT 6 satellite imagery. The proposed methodology uses variance textural information derived from 1.5m panchromatic image to detect built-up areas from non-built-up areas. Once detected, detailed segmentation is performed on built-up class to create individual building objects. Canny edges, SAVI and spectral properties of the objects were used to classify building structures from other land use features using a thresholding technique. The methodology was tested in different areas including formal, rural village and informal and new development settlement types without modifying segmentation and classification parameters. The proposed methodology successfully detected built-up from non built-up areas in all different settlement types. The detection of individual structures achieved more than 70% in formal, rural village and new development areas while less than 50% of building structures in informal settlement were detected. The proposed method can contribute towards monitoring of human settlement developments over a larger area which is vital during spatial planning, service delivery and environmental management. This work will contribute towards the development of a National Human Settlement Layer developed and maintained by SANSA.

Keywords: SPOT 6, Building structures, texture, human settlements

1. Introduction

Data on the spatial distribution of built-up areas and buildings is required for a number of applications including spatial planning, population estimation, service delivery, environmental and disaster management. In the past two decades, the world witnessed unprecedented high levels of urbanisation with more than half of the world population living in urban areas in 2008. The global urban population is expected to grow by 2.5 billion between 2014 and 2050 with about 90 % of increase concentrated in developing countries (United Nations, 2015). The proportion of people living in urban areas in South Africa increased from 54% in 1990 to 62% in 2011. In addition to population growth, urbanisation in South Africa is also attributed to the abolishment of apartheid legislation (Mudau, *et al.*, 2014). Population increase results in the increase in the demand for land required for housing, infrastructure and services (Pesaresi, *et al.*, 2016). Sustainable human settlement development relies on the knowledge of the current and historical information on the extent and condition of human settlements. Prioritisation of development projects requires access to accurate

and up-to-date human settlement data (Gueguen, *et al.*, 2017). Traditional methods used to gather information on human settlements include census and ground surveys. These methods are resource intensive and time-consuming resulting in data unavailability and information gaps which necessitate the need to develop a methodology to automatically generate reliable and consistent data on the spatial distribution of built-up areas and building structures.

Remote sensing provides a cost-effective tool to map and monitor human settlements development over a large geographical area. The launch of Ikonos and Quickbird stimulated the development of higher scale urban applications. Availability of high to very high spatial resolution imagery makes it possible to extract man-made structures such as building structures (Mayunga, *et al.*, 2013). Efforts have been made to map human settlement layers at a global level. The Global Human Settlement Layer (GHSL) presents a global human settlement layer automatically mapped from Landsat satellite imagery acquired in different time period available at 38.2 m (fine) and 305.8 m (aggregated) resolutions (Pesaresi, *et al.*, 2016). Global Urban Footprint (GUF) presents a global human settlement layer automatically mapped from TanDEM-X and TerraSAR-X acquired between 2011 and 2012 available at of 12 m (fine) and 84 m (aggregated) resolution (Esch, *et al.*, 2017). These layers allow - assessment of human presence at a global level. High spatial resolution data on human settlement is required to support analysis of human settlements developments at higher scale. At a country level, a number of mapping agencies use aerial photography or very high resolution satellite imagery to manually digitise building structures and update topographical maps. In addition to cartographic applications, high spatial resolution data on human settlements provides information on location, distribution and characteristics of settlements required to support spatial planning, risk assessment and to manage urbanisation.

Automation of building extraction from high spatial resolution imagery has been one of the most interesting topics in remote-sensing (Grigillo, *et al.*, 2012). However, building extraction is amongst the most challenging tasks in remote sensing due to the heterogeneous nature and similar spectral information of urban materials (Wang, *et al.*, 2017; Ziaei, *et al.*, 2013). Object-based classification techniques have been applied to high spatial resolution imagery to automate the detection of human settlements and building structures. Object-based rule sets that utilise textural and morphological, edge density and line features are some of the commonly used techniques for automated human settlements or building extraction. Lin and Ning, 2017, used lines and angles to detect human settlements from very high spatial resolution images. Pushparaj and Hegde, 2017, extracted building structures from Quickbird imagery using morphological operators and achieved highly accurate results. Kemper *et al.*, 2015 investigated an automated methodology which utilises textural features and reference data to extract and monitor human settlements in South Africa using Satellite Pour l'Observation de la Terre (SPOT 5) satellite imagery. Textural features have been proven to be effective in mapping built-up areas from high resolution imagery (Shao, *et al.*, 2014; Huang and Zhang, 2012; Zhang, *et al.*, 2013; Pesaresi, *et al.*, 2013).

The launch of SPOT 6 satellite provided access to wide swath higher resolution images that can be used to map human settlements. With a spatial resolution of up-to 1.5m, SPOT 6 satellite imagery

provides the ability to visually identify building structures in certain built-up areas. This study investigates the extraction of building structures from SPOT 6 satellite imagery. In this study, spectral, textural and edge properties of the features will be used to classify built-up areas and building structures from land cover and other land use features.

2. Data and Methodology

Data used for this study is SPOT 6 satellite imagery. The date of acquisition of imagery used varied between March and June 2016. SPOT 6 satellite acquires imagery using panchromatic and multispectral modes. The panchromatic sensor acquires images at 1.5m spatial resolution whereas the multispectral sensor acquires images at 5m spatial resolution. Both modes capture images in a 60km by 60km swath. The multispectral imagery contains four bands i.e. Blue, Green, Red and NIR. This imagery was sourced from South African National Space Agency (SANSA). The imagery was orthorectified to UTM coordinate system. To improve the spatial resolution of the multispectral imagery, panchromatic and multispectral images were pansharpened to create 1.5m multispectral image using Brovey Transformation pansharpening technique available in Erdas software package. During Brovey Transformation pansharpening process, every multispectral band is multiplied by a ratio of panchromatic band and the sum of multispectral bands to create new pansharpened multispectral band (Ashish and Veena, 2014; Ishpreet and Nirvair, 2017). This process retains the relative spectral contribution of each pixel resulting high contrast image is has proven to be successful in merging SPOT panchromatic and multispectral images (Yanmei, *et al.*, 2014; Ishpreet and Nirvair, 2017).

The study area covered the following human settlement types:

- Formal-low density: suburban areas characterised by low population density containing single houses planned as neighbourhood units with a closed road network system
- Formal-high density: Formally planned and mass-built settlements (often with backyard shacks)
- Informal settlement: illegal and unplanned settlement (mostly with shacks)
- Rural village: planned and located in non-urban areas with undeveloped roads
- New-development: planned single structures recently built in a greenfield area.

The proposed approach involves two main steps: detecting as built-up areas and detecting building structures using object-based classification techniques. Texture is one of the most significant characteristics of identifying similar patterns in remote sensing images. Textural analysis has been successfully used in human settlement classification (Stasolla and Gamba, 2007; Shao, *et al.*, 2014; Huang and Zhang, 2012; Zhang, *et al.*, 2013; Pesaresi, *et al.*, 2013). A variance texture image was derived from a panchromatic image using Erdas Imagine software package. A 3 x 3 moving window was selected. Variance operator measures the dispersion of the pixel values around the mean in a

moving window and is considered high when there is large grey-level standard deviation in local areas (Clausi and Zhao, 2002). The variance image is produced using the following formula:

$$\text{Variance} = \sum (x_{ij} - \text{Mean})^2 / n - 1 \quad [1]$$

Where: x_{ij} = DN value of pixel (i,j) , n= number of pixels in a window and M = Mean of the moving window (Irons and Petersen 1981).

The processing was done using Trimble eCognition software package. Multi-resolution segmentation technique was used for segmentation using all pan-sharpened bands to produce built-up image objects. This process is a bottom up region merging technique which uses shape, scale and compactness parameters to aggregate pixels into increasingly larger pixels at multiple levels (Benz, *et al.*, 2004; Baatz & Schape, 2000) and is one of the most popular segmentation algorithms (Esch, *et al.*, 2008). Level 1 segments were created using scale parameter of 100, shape and compactness values of 0.1 and 0.5 respectively. These parameters were determined through a trial and error approach until satisfactory building built-up objects were achieved. Classification of built-up from non-built-up areas was done using the variance textural and the spectral information of the image objects. Visual inspection of textural values was done to determine the thresholds corresponding to built-up areas and non-built-up area. Built-up areas generate high variance textural values caused by different features such as roads and building compared to other land cover features such as grassland which has little to no textural variation. Built-up areas have textural values of > 0.48 in the different human settlement types while other not-built-up objects including open spaces within built-up areas have lower textural values. Spectral properties of the pansharpened were used to classify areas where natural objects generate high textural values.

Once classified, smaller segments were created within the built-up class using scale parameter of 10 and similar values of shape and compactness. Canny edges were created using the Red band of the pan sharpened image and were used with other pan-sharpened bands to segments into objects that represent building structures. To classify building structures within built-up areas, edge, spectral properties and Soil Adjusted Vegetation Index (SAVI) were used. Threshold values were assessed by visually inspecting the spectral, Canny edges and SAVI of building structures and other areas. Canny edges have been successfully used towards automation of the detection building structures from high resolution imagery (Singhal and Radhika, 2014, Bhadauria, *et al.*, 2013, Benarchid, *et al.*, 2013). Canny edge detection is a multi-stage edge detection approach which produces higher accurate edges compared to other edge detection techniques (Bhadauria, *et al.*, 2013). Building edges produce stronger edges than other land use features, so do other natural features such as trees depending on the surrounding surfaces material. Building structures have Canny edge values of > 0.3. The separation of building structures from other natural features with stronger edges was done using SAVI. The SAVI was developed by Huete, 1998, to minimise the effect of soil brightness on the vegetation indices involving the use of Red and NIR bands. A number of studies have applied SAVI with other vegetation indices during the classification of built-up areas using remote sensing data and achieved accurate results (Xu, 2007; Hidayati, *et al.*, 2018; Francis, *et al.*, 2013). Vegetation indices together with other feature extraction variables such as texture or morphology have been applied

towards automation of building extraction. The use of vegetation indices in building extraction enable the separation of natural from man-made features in urban environment (Rohit, *et al.*, 2012; Koc San & Turker, 2010). Natural features within built-up areas generated SAVI values of greater than 0.3. This value was used to separate natural objects with higher Canny edge values. The SAVI was calculated using the formula:

$$SAVI = ((NIR-Red) / (NIR+Red+L)) * (1+L) \quad [2]$$

Where NIR is Near-Infrared and L is canopy background adjustment which was set to 1 as the study area has low vegetation cover (Huete, 1998). Figure 1. shows a workflow of the proposed methodology:

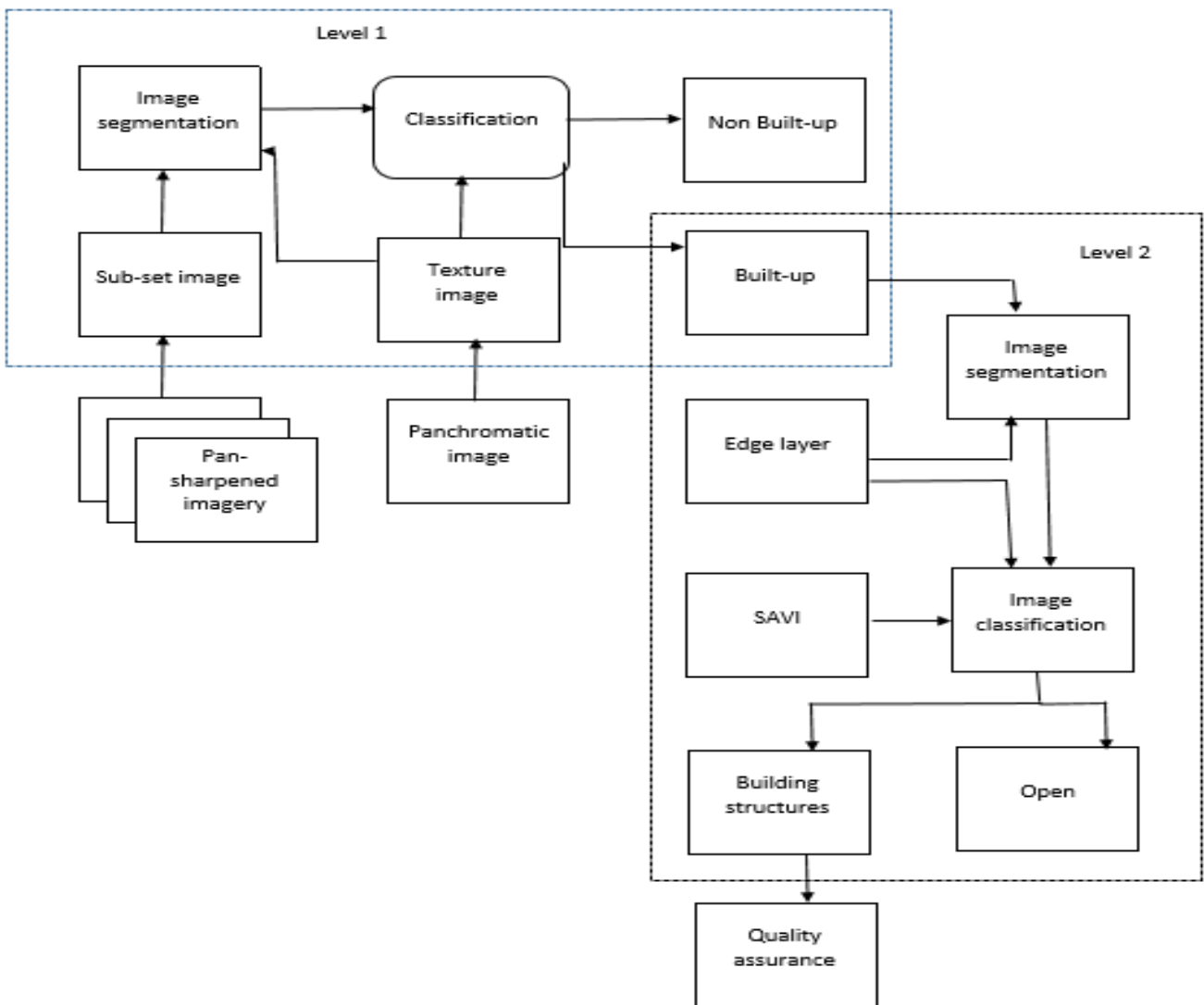


Figure 1. Proposed workflow for building extraction from SPOT 6 imagery

To assess the accuracy of automatically detected building structures, building outlines were manually digitised in formal-low density, rural village and new development areas using very high resolution imagery. The Worldview 2 images acquired between 2013 and 2016 was used. This data

was accessed through ArcGIS base maps. Accuracy assessment was done at an object level using statistical parameters define by McGlone and Shufelt, 1994. The following quality performance measurements were assessed:

$$DP = (100 \times TP)/(FP + FN) \quad [3]$$

$$CpP = (100 \times TP)/(TP + FN) \quad [4]$$

$$CrP = (100 \times TP)/(TP + FP) \quad [5]$$

Where, DP is Detection Percentage, CrP is Correctness Percentage, CpP is Completeness Percentage, TP are True positives representing reference building areas automatically detected as building structures, FP are False Positives representing non-building areas automatically detected as building structures and FN are False Negative representing number of building areas that were not automatically detected (McGlone and Shufelt, 1994). This quality assessment method has been applied in several studies to assess the detection accuracy of building structures (Hermosilla, et al., 2011); Khoshelhama, et al., 2009; Pushparaj & Vittal Hegde, 2017).

For accuracy assessment of building structures detected in informal and formal-high, location of reference building structures were mapped by points due to the size and high density of structures. Detection percentage was done through assessment of areas where reference points overlap with automatically detected building structures. Correctness and Completeness Percentages were not assessed in informal settlement and formal-high density areas due to the higher density of the structures which makes the visual interpretation of individual structures difficult.

3. Results and discussions

The results show that the proposed methodology is able to detect built-up areas in formal-low density, formal-high density, informal settlement, new development and rural village. The application of variance textural information on scale parameter of 100 multi-resolution segmentation objects was successful in classifying built-up and non-built up areas, see Figure 2. a and b. Open areas within built-up areas were successfully delineated from built-up areas. Vegetated areas, water and other land cover features were also successfully classified as non-built-up areas due to their lower textural values. There were however, areas where portions of roads were classified are built-up and in other instances as non built-up. This was due to variation of road surfaces and surrounding material. Few edges of the land use features such as mining were also detected.

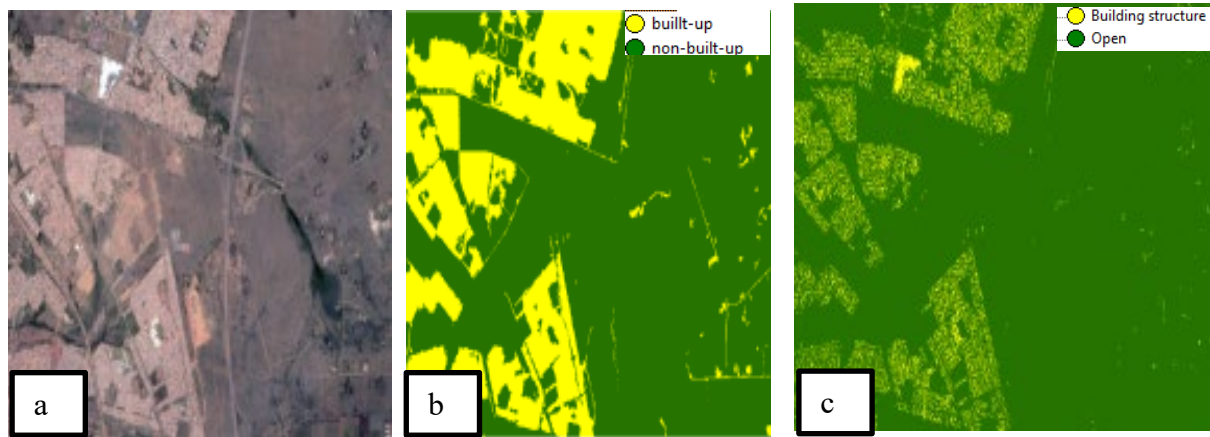


Figure 2. Building structures classification results: a, Formal- township SPOT 6 image, b, built-up and non-built-up classification c, building structure classification results

In terms of the detection of building structures, Detection Percentage accuracy was 73% in formal-low density area, 83.8% in new development area and 81% in rural village area, see Table 1. for the accuracy assessment results and Figure 3. for the building structures classification results. Lower Correctness Percentage in formal-low density area could be attributed to existences of trees which cover some parts of the building roofs. The highest correctness was achieved in rural village areas followed by new development area. Higher Correctness Percentage in rural village can be attributed to lower density of building structures and lack of tall trees closer to the building structures, whereas, higher completeness in new development area is due to stronger edges of the buildings and lack of trees or other man-made features. The assessment of the results shows that the segments of a building structure are affected by the surrounding surfaces and features which affect the shape of boundary of the building. Open areas closer to the building structures are classified with building structures resulting in an irregular building boundary whereas buildings closer to natural features such as short trees and grassland tend to have more accurate building boundaries.

Table 1. Accuracy assessment results

Settlement type	TP	FN	FP	Detection Percentage	Correctness Percentage	Completeness Percentage
Formal-low density	22475m ²	5765m ²	2547m ²	73.00%	79.59%	89.82%
New development	12919m ²	1688m ²	795m ²	83.88%	88.44%	94.20%
Rural village	18487m ²	884m ²	3405	81.17%	95.44%	84.45%
Informal	379	331	468	47.43%	-	-
Formal-high density	175	35	204	75.45%	-	-

Accuracy assessment of building structures in formal high-density and informal settlement resulted in detection percentages of 75% and 45% respectively. The proposed methodology failed to separate individual structures in areas with high density of building structures in formal-dense density

areas. These are areas where backyard shacks exist. Even though 75% Detection Percentage was achieved in form-high density areas, most of the building boundaries were not fully detected. This shows that the detection of edges is affected by the surrounding features.

Lower detection accuracy of building detection in informal settlement was influenced by size and higher density of building structures. The edges of most of the building structures in informal settlement are not strong enough due to heterogeneous roof materials. The results show that edges detected informal settlement from 1.5m SPOT 6 image are suitable for classifying building structures from other land use areas. There is therefore a need to apply other spatial or geometric features during detection or use of very high spatial resolution imagery in the detection of building structures outlines detection in areas with high density of building structures.

The use of SAVI did not show high impact on the detection accuracy of building structure boundaries, however, it reduced commission errors caused gullies and natural features around building structures in formal-low density areas and rural villages.

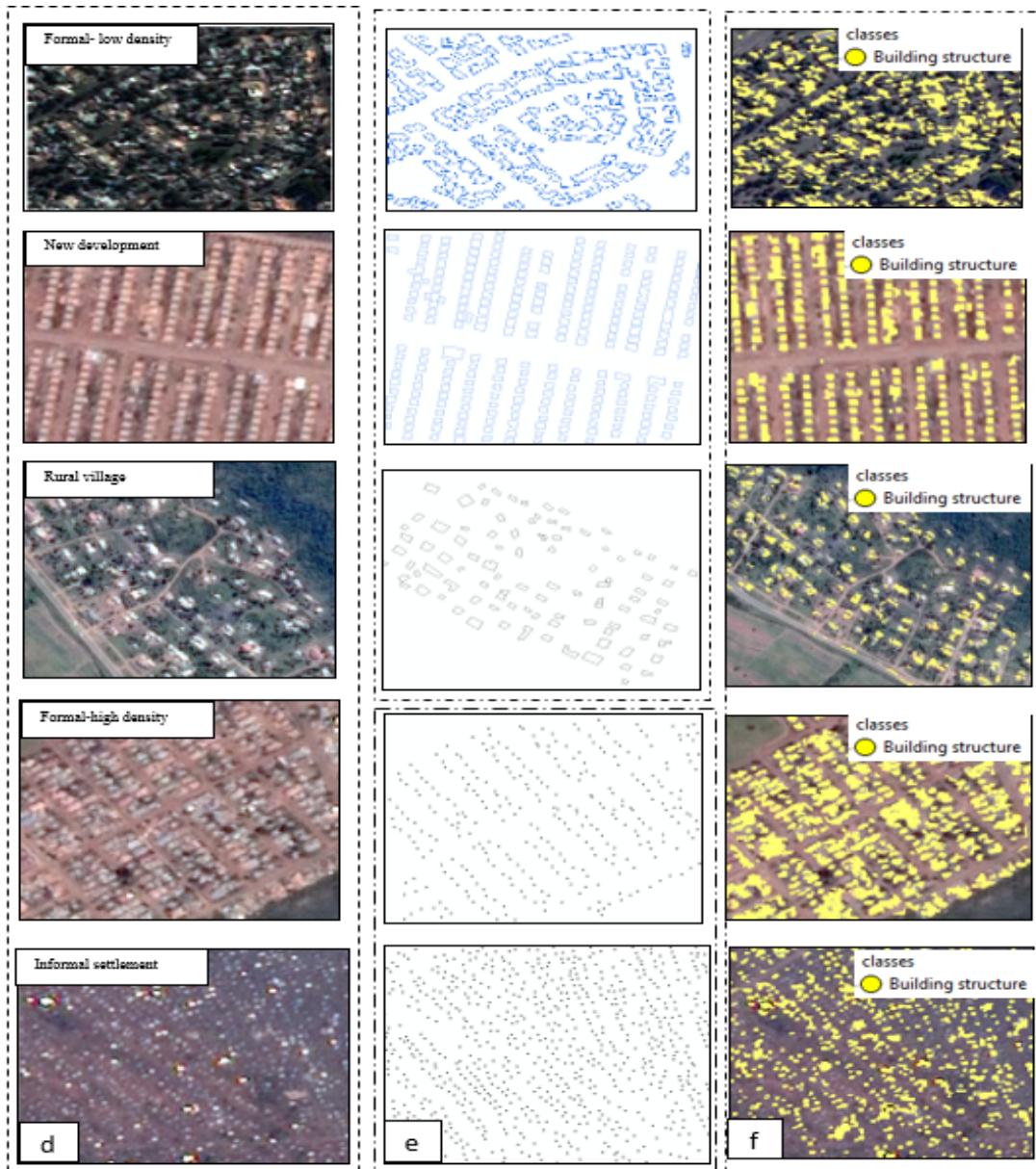


Figure 3: Building classification results; d represents the natural colour images of the areas assessed; e represent reference building boundaries and points used for accuracy assessment and f represents the building structures automatically detected using the proposed methodology.

4. Conclusions

The proposed two-level classification approach shows that variance texture, SAVI and Canny edge detection algorithm can be used to detect and map the spatial distribution of built-up areas and building structures using SPOT 6 satellite imagery. The study shows that spatial and spectral characteristics of SPOT 6 panchromatic band for the extraction of variance textural features that are dominant in built-up areas than in non-built-up areas hence enabling the classification of built-up areas and non-built-up areas such as water bodies, open areas and vegetated areas. The detected built-up area shows the boundaries of the different settlement types from low density to high-density human settlement. The Canny edge detection algorithm applied on SPOT 6 imagery yields stronger edges of man-made structures including building structures providing features that can be used to detect and

classify building structures from other land use features. The use of SAVI slightly reduce the errors of commission caused by non-built-up features such as bare areas. The lower detection accuracy of building structures in informal settlements and dense formal residential areas can be attributed to the spatial resolution of SPOT 6 and size of the structures and higher density of building structures within these areas. Very high resolution imagery is recommended for the detection of individual building structures in such areas.

The success of the proposed methodology, in detecting built-up areas provides an alternative to monitor settlement expansion. Detection of building structures enable for detailed monitoring of urban built environment which can contribute towards sustainable urbanisation and monitoring of SDG indicator 11 and related goals.

5. REFERENCE

- Ashish, D. & Veena, C., 2014. A New Pan-Sharpening Method Using Joint Sparse FI Image Fusion Algorithm. *International Journal of Engineering Research and General Science*, 2(4), pp. 447-455.
- Baatz, M. and Schape, A. (2000) Multiresolution Segmentation: An Optimization Approach for High Quality Multi-Scale Image Segmentation. In: Strobl, J., Blaschke, T. and Griesbner, G., Eds., *Angewandte Geographische Informations-Verarbeitung, XII*, Wichmann Verlag, Karlsruhe, Germany, 12-23.
- Benarchid, O & Raissouni, N & Samir, El Adib & El Abbous, Abdellah & Azyat, Abdelilah & Ben Achhab, Nizar & Lahraoua, Mohammed & Chahboun, A., 2013. Building Extraction using Object-Based Classification and Shadow Information in Very High Resolution Multispectral Images, a Case Study: Tetuan, Morocco. *Canadian Journal on Image Processing and Computer Vision*.
- Benz, U. C., Hofmann, P., Willhauck, G., Lingenfelder, I., Heynen, M2004. Multi-resolution, object-oriented fuzzy analysis of remote sensing data for GIS-ready information. *ISPRS Journal of Photogrammetry & Remote Sensing*, Volume 58, p. 239 – 258.
- Bhadoria, H., Singh, A. & Kumar, A., 2013. Comparison between Various Edge Detection Methods on Satellite Image. *International Journal of Emerging Technology and Advanced Engineering*, 3(6), pp. 324-328.
- T. Esch, M. Thiel, M. Bock, A. Roth, and S. Dech, 2008. Improvement of Image Segmentation Accuracy Based on Multiscale Optimization Procedure. *IEEE Geoscience and Remote Sensing Letter*.
- Francis, M., Evaristo, L. & Japhet, K., 2013. Usage of Indices for Extraction of Built-up Areas and Vegetation Features from Landsat TM Image: A Case of Dar Es Salaam and Kisarawe Peri-Urban Areas, Tanzania. *International Journal of Agriculture and Forestry*, 3(7), pp. 273-283.
- Grigillo, D., Fras, M. K. & Petrovič, D., 2012. Automated building extraction from IKONOS images in suburban areas. *International Journal of Remote sensing*, 33(16).
- Gueguen, L. et al., 2017. Mapping Human Settlements and Population at Country Scale From VHR Images. *IEEE journal of selected topics in applied earth observations and remote sensing*, 10(2).
- Hermosilla, T., Ruiz, L. A., Recio, J. A. & Estornell, J., 2011. Evaluation of Automatic Building Detection Approaches Combining High Resolution Images and LiDAR Data. *Remote Sensing*, Volume 3.
- Hidayati, i. N., Suharyadi, R. & Danoedoro, P., 2018. Developing urban built-up extraction method based on remote sensing imagery index transformation. *Geoplanning: Journal of Geomatics and Planning*, 5(1), pp. 131-142.
- Huang, X. & Zhang, L., 2012. Morphological Building/Shadow Index for Building Extraction From High-Resolution Imagery Over Urban Areas. *EEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, 5(1), pp. 161-172.

- Huete, A.R., 1988. A Soil-Adjusted Vegetation Index (SAVI). *Remote sensing of environment*, 25, 295-309.
- Iron, James R., and Gary W. Petersen. 1981. "Texture Transforms of Remote Sensing Data," *Remote Sensing of Environment*, Vol. 11: 359-370.
- Ishpreet, K. & Nirvair, N., 2017. A study of remote sensing using image fusion: a review. *International Journal of Advanced Research in Computer Science*, 8(7), pp. 585-595.
- Jiang, N., Zhang, J., Li, H. & Lin, X., 2008. Object-oriented building extraction by DSM and very high-resolution orthoimages. Beijing, China, s.n., pp. 441-446.
- Kemper, T., Mudau, N., Mangara, P. & Pesaresi, M., 2015. Towards an automated monitoring of human settlements in South Africa using high resolution SPOT imagery. Berlin, Germany, *The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences*.
- Khoshelham, K. et al., 2009. Performance evaluation of automated approaches to building detection in multi-source aerial data. *ISPRS Journal of Photogrammetry and Remote Sensing*, Volume 65, pp. 123-133.
- Koc San, D. & Turker, M., 2010. Building extraction from high resolution satellite images using Hough transform. *Remote Sensing and Spatial Information Sciences - ISPRS Archives*.
- Lin, X. & Ning, X., 2017. Extraction of human settlements from high resolution remote sensing imagery by fusion both rightangle cornes and roight angle sides. Wuhan, China, *The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences*.
- Mayunga, S. D., Coleman, D. J. & Zhang, Y., 2013. Semi-automatic building extraction in dense urban settlement areas from high-resolution satellite images. *Survey Review*, 42(315), pp. 50-61.
- McGlone, J. & Shufelt, J., 1994. Projective and Object Space Geometry for Monocular Building Extraction. Seattle, WA, USA, Computer Vision and Pattern Recognition.
- Mudau, N., Mhangara, P. & Gebreslasie, M., 2014. Monitoring urban growth around Rustenburg, South Africa, using SPOT 5. *South African Journal of Geomatics*, 3(2).
- Pesaresi, M. et al., 2016. The Global Human Settlement Layer from Landsat imagery. Beijing, China, *IEEE International*.
- Pushparaj, J. & Vittal Hegde, A., 2017. A comparative study on extraction of buildings from Quickbird-2 satellite imagery with & without fusion. *Cogent Engineering*.
- Shao, Z., Tian, Y. & Shen, X., 2014. BASI: a new index to extract built-up areas from high-resolution remote sensing images by visual attention model. *Remote Sensing Letters*, 5(4), pp. 305-214.
- Singhal, S. & Radhika, S., 2014. Automatic Detection of Buildings from Aerial Images Using Color Invariant Features and Canny Edge Detection. *International Journal of Engineering Trends and Technology*, 11(8), pp. 393-396.
- Stasolla, M. & Gamba, P., 2007. Exploiting soatial patterns of informal settlement detection in arid environments using optical spaceborne data. *International Archives of Photogrammetry, Remote Sensing and Spatial Information Sciences*, Volume 36, pp. 31-36.
- Tian, J. & Reinartz, P., 2013. Fusion of multi-spectral bands and DSM from Worldview-2 stereo imagery for building extraction. Sao Paulo, Brazil, pp. 135-138.
- United Nations, 2015. World Urbanization Prospects: The 2014 Revision, s.l.: ST/ESA/SER.A/366).
- Wang, C., Zhang, Y., Diao, W. & Wang, H., 2017. Extracting rooftops from remote sensing images using both top-down and bottom-up processes. *Remote Sensing Letters*, 8(6), pp. 586-595.
- Xu, H., 2007. Extraction of Urban Built-up Land Features from Landsat Imagery Using a Thematicoriented Index Combination Technique. *Photogrammetric Engineering and Remote Sensing*, 73(12), p. 1381-1391
- Xu, Y., Pu, L., Zhang & Lifang, 2014. Spatial Pattern and the Process of Settlement Expansion in Jiangsu Province from 1980 to 2010, Eastern China. *Sustainability*, Volume 6, pp. 8180-8194.
- Yanmei, L., Haiyang, Y., Yang, G. & Dong, R., 2014. Study on Efficiency of Fusion Techniques for IKONOS Images. Beijing, China, *IOP Conference Series: Earth and Environmental Science*.

- Yastikli, N. & Uzar, M., 2013. Building extraction using multi sensor systems. Hannover, Germany, pp. 379-382.
- Zhang, J., Li, P. & Xu, H., 2013. Urban built-up area extraction using combined spectral information and multivariate texture. Melbourne, Australia , *IEEE*.
- Ziaei, Z., Pradhan, B. & Mansor, S. B., 2013. A rule-based parameter aided with object-based classification approach for extraction of building and roads from WorldView-2 images. *Geocarto International*, 29(5), pp. 554-569.