The development of a method for semi-automatic classification of built-up areas from aerial imagery

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Abstract

The identification of built-up areas from aerial imagery is essential for map updating and detecting changes for a national mapping organisation. At the Chief Directorate of National Geo-spatial Information (CD: NGI), South Africa's national mapping agency, this process relies on operators to manually digitise features of interest, which is very time consuming and labour intensive. It is therefore necessary to explore methods that will assist in automatic classification of such areas to speed up the process of updating topographic databases. This pilot project attempts to automate the classification of urban built-up areas, which are important as they can grow and change rapidly, and can indicate where other landscape changes may have occurred. The method of classification should be suitable in multiple South African landscapes. This research evaluates various image classification methods, and illustrates the development of the proposed methodology for urban scene land cover classification in South Africa. Three of the methods evaluated were tested and compared, and the results achieved indicate that object-based classifiers are more suitable than pixel-based classifiers in detecting urban built-up areas. The importance of generating suitable image objects in an object-based classification is indicated in this study, and the significance of texture measures used in classifying urban built-up areas is highlighted.

1. Introduction

The Chief Directorate of National Geo-spatial Information (CD: NGI), South Africa's national mapping agency, is responsible for the national topographic mapping, aerial imagery acquisition and control survey network of the country. One of its responsibilities is the capturing and revision of topographical data into the national, integrated database of geospatial information. All topographic data is currently manually digitised from aerial imagery, which is a laborious process that relies on the knowledge and interpretation of the operator performing the task. It is therefore necessary to move towards a more automated approach in the production process to allow for rapid map updates.

The focus of this research is on finding a method of classifying urban built-up areas automatically or semi-automatically from high-resolution aerial imagery in South Africa. The research is confined to the urban built-up areas, and no other features contained in the topographic map database. Built-up areas are identified as a priority feature because they can grow and change rapidly, and also may indicate where other topographic changes may have occurred (for example, new roads or schools). Once built-up areas are successfully classified, they can be compared to CD: NGI's existing topographic vector data so that changes may be discovered and map databases may be updated. This research is focused on image classification, but the possible applications of the results of the classification, such as change detection, and topographic map updating are the logical next steps to be followed.

Built-up urban or residential areas are described as areas where people live on a permanent or semi-permanent basis. This includes single story residential units, multi-story units, high rise buildings, as well as low settlement density of rural dwellings (Lück et al., 2010). The CD: NGI define residential land use, or high urban density, as a built-up area where many buildings have been built close together, generally with a spacing of less than 50m between buildings. This definition continues with the explanation that services such as electricity, water and sewage disposal may be available, except in informal settlements. A similar definition is given for low urban density (residential) with the difference being that the buildings are built closely together, but not as closely as in high urban density (Chief Directorate: National Geo-spatial Information, 2013). Such definitions, which include municipal services that are not visible in aerial imagery, were not developed for the purposes of classifying residential spaces from image scenes.

Deciding on the best methodology for classifying built-up areas automatically is not a trivial task when one considers the large geographical extent of South Africa, and its varying terrain and climate. Climatic conditions range from the dry Karoo, to lush and heavily vegetated regions, to the Mediterranean climate of Cape Town, to the varying coastal and mountainous regions. Rainfall, temperatures, terrain, and soil types vary greatly in different regions of South Africa resulting in vastly differing land cover and seasonal variations.

This pilot study aims to develop a method for classifying urban built-up areas in multiple South African landscapes. In the process of developing such a method, various methods of image classification were evaluated, and three of these are presented in this paper.

For the proposed methodology to be effective within a mapping production environment, it should be robust and applicable across the country, and should require minimal user input or knowledge about the scene being classified.

Similar studies comparing pixel and object-based classification methodologies have been done before (Myint et al., 2011; Shackelford & Davis, 2003), but the originality of this work lies in its application in the South African environment. The South African National Space Agency (SANSA) has also worked on land cover classification methodologies for South Africa, and has developed the land cover field guide (Lück et al., 2010). This field guide is currently used by CD: NGI as the basis for land cover class definitions.

2. Data and test sites

The aerial imagery used in the study was captured at 0.5m resolution, using an Integraph Digital Mapping Camera (DMC). Both RGB and colour infrared (CIR) orthorectified imagery, obtained from CD: NGI, was used for each test area. Image pre-processing is performed by CD: NGI contractors, who radiometrically adjust the image bands, in terms of contrast and brightness, so that images within a specific flight job are similar in appearance. Since only standard products available to the CD: NGI were to be used in this study, no additional processing was performed on the imagery.

The size of an orthorectified image, which is the size of a single test scene, is approximately 5km by 6km. Two test areas were used for all methods of classification examined. The first test scene was an area in Table View, Cape Town captured in 2010 (**Error! Reference source not found.**). This area has grown rapidly since the last topographic map for this area was compiled in 2000 (**Error! Reference source not found.**). This scene in Cape Town was chosen as it covers a variety of built-up areas.

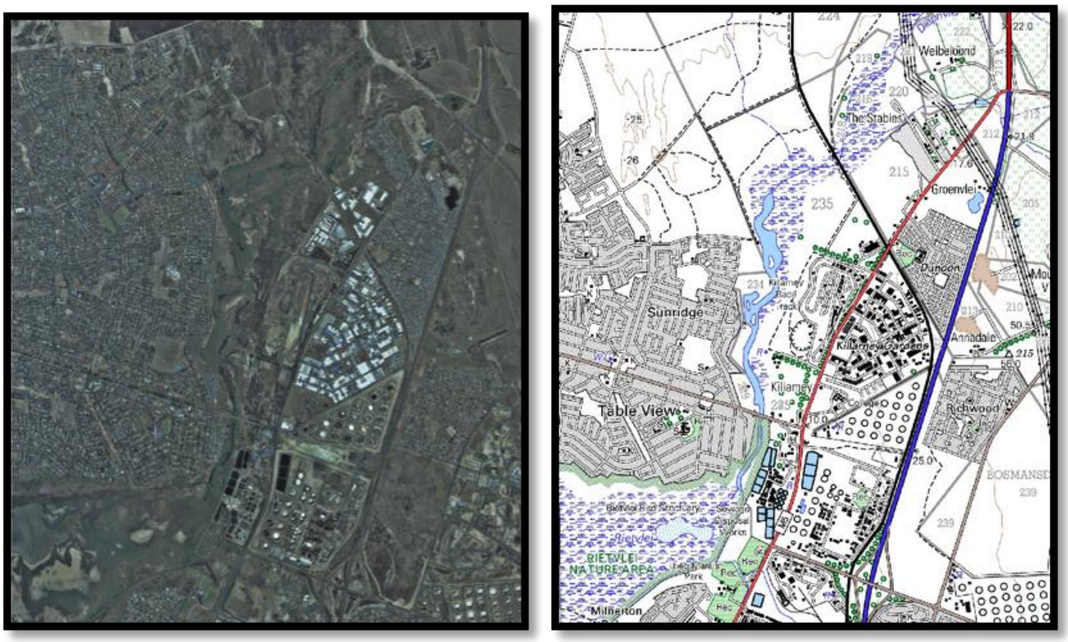

Figure 1. Test area 1 – left: aerial image (2010); right - portion of 1:50 000 topographic map (2000)

The second test area is an area called Tembisa in Johannesburg, also captured in 2010. This large built-up area has also expanded in size since the last topographic map was compiled in 2002 (**Error! Reference source not found.**). Tembisa is predominantly comprised of built-up areas and both formal residential and informal settlements can be seen in the image covering this area.

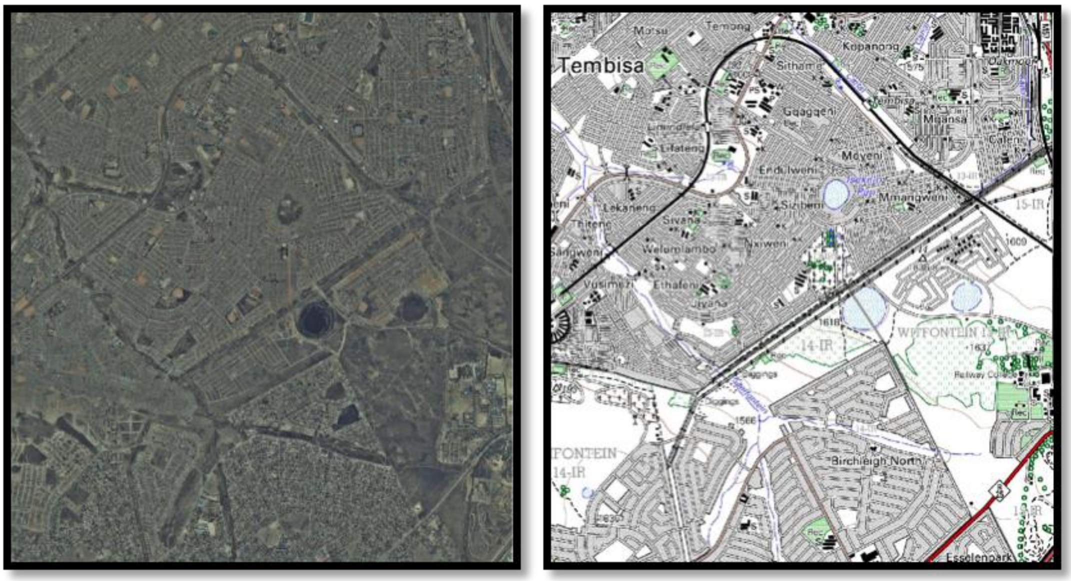

Figure 2. Test area 2 – left: aerial image (2010); right - portion of 1:50 000 topographic map (2002)

With the pixel-based image classification methods tested, the red, green and blue bands from the RGB images were combined with the near infrared band from the CIR images to make a single four-band image for each test area. Classification for both supervised and unsupervised pixel-based approaches were done using Erdas Imagine software.

All object-based approaches were carried out using eCognition Developer software. For the first method that relied on only the reflectance properties of the image bands for image segmentation, the red, green, blue and near infrared image bands were used as input for each test scene. For all subsequent object-based methods, additional cadastral data was included in the segmentation process. This data was comprised of erven and farm portions that were stored in shapefile format (vector data). Cadastral data is maintained and supplied by the Office of the Surveyor-General in South Africa. Data for Cape Town was dated at 2012, and Johannesburg data was from 2010.

3. Image classification

This research starts with a comparison of various methods of image classification that includes both pixel and object-based approaches, and is illustrated in Figure 3. The per-pixel methods consist of supervised and unsupervised approaches. With the object-based classification method, segmentation is a key factor (Blaschke, 2010) and various techniques are applied in order to find the most suitable method of image segmentation. Image segments should adequately represent features of interest (Smith & Morton, 2008). Since it is possible to generate image segments at various scales, one can create various objects of interest (segments) at different scales for different features (Blaschke & Strobl, 2001; Blaschke, 2010). It is also possible to include existing vector data in the segmentation approach. Vector data, such as that representing cadastral parcels, may be used to impose boundaries in order to create segments within an image (Smith & Morton, 2008). Cadastral segments can then be further segmented based on spectral, textural or context information (Baatz & Schäpe, 1999).

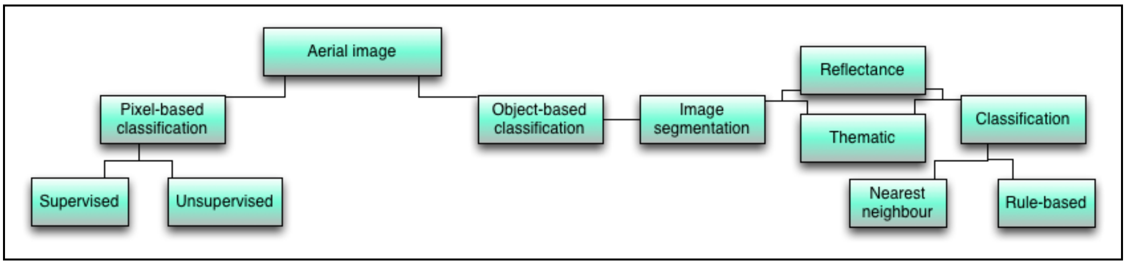

Figure 3. Image classification methodology

3.1 Pixel-based

Both supervised and unsupervised methods were assessed in this this study. The maximum likelihood classifier was chosen for the supervised classification method and the Iterative Self-Organizing Data Analysis Technique (ISODATA) was used for unsupervised classification. The maximum likelihood classifier is widely used for land cover classification and is often used as a reference for assessing other classification methods (Song et al., 2005). Assuming that the data has a Gaussian distribution, and that class signatures are well selected, the maximum likelihood method usually provides high classification accuracies (Jensen, 2005). The unsupervised ISODATA method is popular in classifying heterogeneous high resolution images since it is successful in finding spectral clusters that are inherent in images (Zhang, 2001).

With the supervised method it was necessary to collect adequate training samples for the classes water, vegetation, road, built-up areas and bare ground or sand, which were present in the images. The unsupervised method is simple to use and does not require training data, making it faster to implement than the supervised approach. Since unsupervised classification is the identification of spectrally distinct classes in an image, the analyst must still use reference data to associate spectral classes with the land cover types of interest. The spectral classes identified may not be uniquely associated with a land cover type, and one may have several spectral classes representing a single feature class (Lillesand et al., 2004). This approach was tested with numerous classes, which were selected by trial and error, but having a greater number of classes did not add any value, as they needed to be reduced to the original five classes mentioned above.

3.2 Object-based

In many instances object-based classification has proven to be superior over pixel methods in classifying complex environments like built-up areas and patterned landscapes (Blaschke & Strobl, 2001).

The first and most important step in object-based image classification is the generation of homogeneous image objects or segments (Marpu et al., 2010), but the selection of suitable segmentation parameters is not a simple task, and users should have knowledge of the objects of interest (Hofmann, 2001b; Flanders et al., 2003; Smith & Morton, 2010). Segments are comprised of groups of pixels that are the basic input for further classification. Image segments can then be classified based on spectral, shape and texture properties (Benz et al., 2004; Hofmann, 2001a).

There are various approaches to image segmentation, one of which is the multiresolution segmentation technique. This technique starts with each pixel forming one image object. At each step a pair of image objects is merged into one larger object until a specific threshold is reached. The merging decision is based on local homogeneity criteria which describes the similarity of adjacent image objects (Baatz & Schäpe, 2000).

Since the selection of suitable segmentation parameters for a multiresolution segmentation is difficult (Hofmann, 2001b; Flanders et al., 2003; Smith & Morton, 2010; Drăguţ et al., 2010), an alternative approach is to start the segmentation process using thematic data and a ‘chessboard’ segmentation (Aminipouri et al., 2009). The nationally available cadastral dataset comprising erven and farm portions (Chief Surveyor-General, 2013) is a very useful thematic data source that can be used as part of the image segmentation approach (Smith & Morton, 2010). The chessboard segmentation algorithm follows a top-down approach and works by cutting the image or image objects into smaller objects (eCognition Developer Reference Book, 2012). With this algorithm, existing vector data can be used to create initial segments that can later be segmented based on image reflectance properties such shape, colour, texture, etc. (Aminipouri et al., 2009).

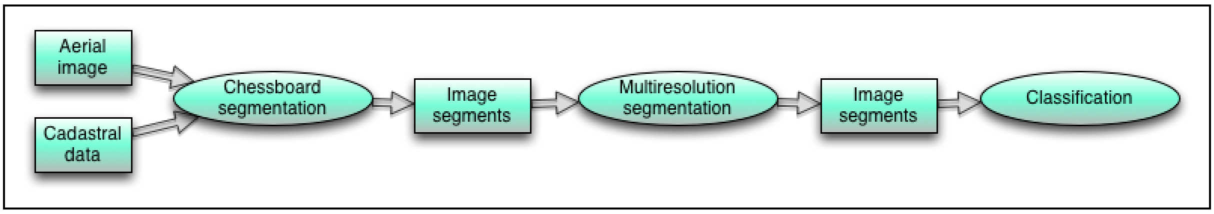

Figure 4. Image segmentation process

The image segmentation process developed from one that used only spectral properties of the imagery to one that included both imagery and thematic data. Suitable segments were generated using cadastral data and a chessboard segmentation followed by a multiresolution segmentation (see Figure 4).

The rationale for using cadastral data is that built-up areas will typically have cadastral data identifying land parcels and ownership, and this information can be used as a starting point for image segmentation. Land parcels may have varying land cover features within them, and should not necessarily be segmented based on their spectral properties alone, as this may result in multiple image objects that may need to be preserved as one object. Segments represented by cadastral boundaries can be further segmented based on image reflectance, shape, texture and context within the land parcels.

After an image has been segmented into suitable image objects, the image objects can be classified by assigning each image segment to a class based on features and criteria decided on by the user (Baatz & Schäpe, 1999; Baatz & Schäpe, 2000; Blaschke, 2010). The scope of classification algorithms within the eCognition Developer environment range from sample-based nearest neighbour, to logic membership function to specialised context driven analysis (eCognition Developer, 2014). Initial object-based classifications focused on classifying water, vegetation, road, built-up areas and bare ground using the nearest neighbour method, but as the classification method developed and shifted to a rule-based approach, the emphasis changed to only focus on urban-built-up areas.

Spectral information alone may not be sufficient to map urban areas in high-resolution imagery, and studies show that textural approaches based on co-occurrence matrix statistical measures have been used in the classification of remotely sensed imagery with significant improvements over traditional radiometric approaches (Pesaresi, 2000; Pesaresi et al., 2008; Su et al., 2008; Puissant et al., 2005; Zhang et al., 2003).

Various spectral, shape and textural features were used in the classification of image objects, and this progressed from one method to the next, based on results obtained in each test. Since image texture is particularly useful in discriminating built-up from non-built-up areas (Puissant et al., 2005), numerous texture measures were evaluated to assess the texture of image objects representing built-up areas.

4. Results and Analysis

4.1 Pixel-based

The results of the unsupervised classifications were not satisfactory and classes were not easily separated, due to the large variability among them. Classes were left as numbered items, as no single class could be clearly identified. This method resulted in many mixed classes and therefore meaningful names, e.g. road or water, could not be assigned.

Even though water appears to be classified reasonably well, as can be seen with the dam in Figure 5, there are pixels that are not water but are also classified as the same class. This is evident from parts of the road and built-up areas that are incorrectly classified as water, while other water features present in the image were not grouped in the same class as the dam. There also appears to be overlap between what should be the built-up class and the bare ground class. The road class cannot be isolated and seems to be represented by various classes. Vegetation was mostly split across two classes, but there is too much overlap between classes to confirm exactly which classes represent any one particular feature.

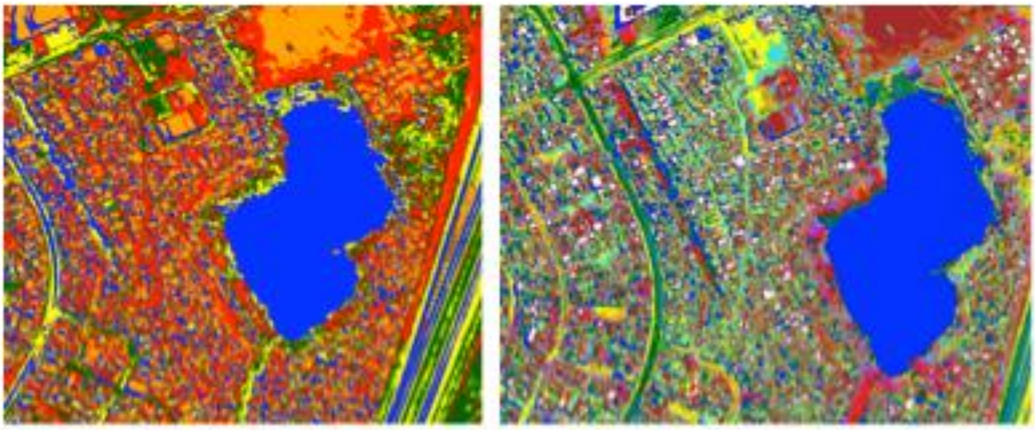

Figure 5. Unsupervised ISODATA classification – test area 1 - left: 5 classes, right: 12 classes

By increasing the number of classes in the ISODATA classification, more discrete classes were isolated, but these classes would need to be reduced to the desired five output classes mentioned previously. The results for unsupervised classifications with varying number of classes for both test areas were not satisfactory, and classes were not easily separated due to the large variability among them.

The accuracy of this method was based on a visual inspection only, as without knowing with certainty what particular classes were, this made it difficult to perform a robust numerical accuracy assessment.

Results for the supervised methods showed some improvement over the unsupervised methods, but there were also difficulties in separating classes of interest.

Training samples were digitised from high-resolution aerial imagery based on prior knowledge of land cover features in scenes tested. Approximately 30 samples per class were randomly selected throughout the test areas.

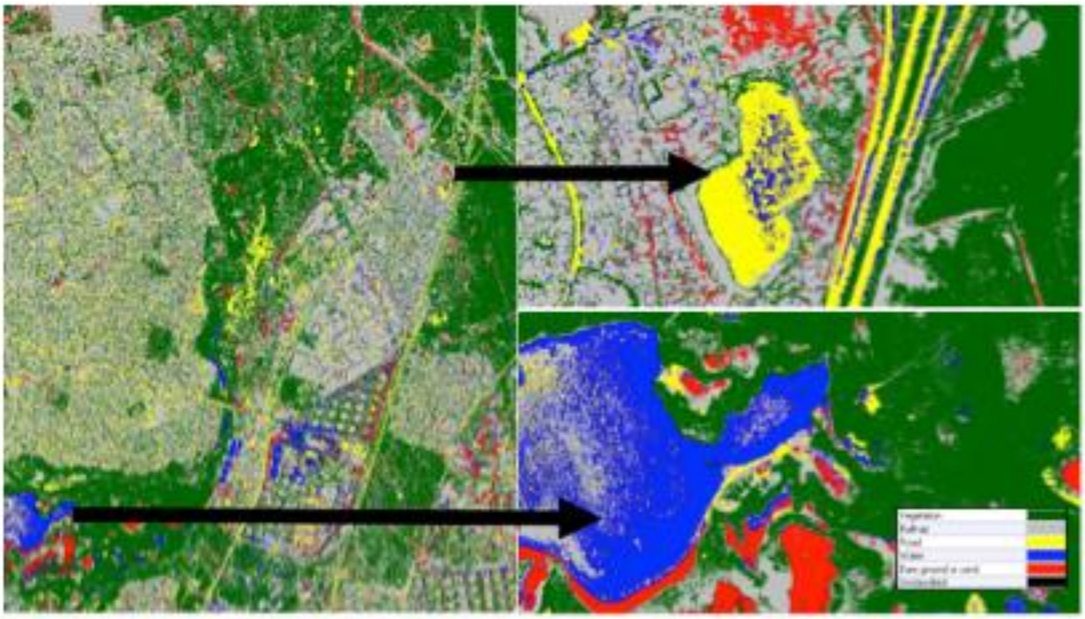

Figure 6. Supervised maximum likelihood classification – test area 1

It is clear that there is confusion between some classes, and this is illustrated in the enlarged image on the top right (Figure 6), where a large water body has been incorrectly classified as part of the road class. It should be noted that samples were taken from this water body and used as part of the training data for the classification, which explains why some of the pixels have been classified as water, but the remainder and majority of pixels are incorrectly classified as road. In the image of the classified wetland on the lower right, it can be seen that some pixels representing water were incorrectly classified as built-up areas and roads.

Table 1. Accuracy assessment and kappa statistics for supervised pixel-based classification: test area 1

Class name	**Producer accuracy**	**User accuracy**	**KIA per class**
Built-up	0.36	0.40	0.23
Bare ground or sand	0.69	0.90	0.86
Vegetation	0.62	0.80	0.73
Water	0.80	0.40	0.33
Road	0.63	0.50	0.40
Overall accuracy	**0.60**		
KIA	**0.50**		

Table 2. Accuracy assessment and kappa statistics for the supervised pixel-based classification: test area 2

Class name	**Producer accuracy**	**User accuracy**	**KIA per class**
Built-up	0.43	0.60	0.44
Bare ground or sand	0.55	0.60	0.49
Vegetation	0.60	0.90	0.86
Water	1.00	0.90	0.88
Road	0.00	0.00	-0.02
Overall accuracy	**0.60**		
KIA	**0.50**		

The overall accuracy and the kappa index of agreement (KIA) for both scenes were not very encouraging, and the user and producer accuracy of the built-up class were also very low. The KIA per class for built-up areas was poor in both test areas. The user and producer accuracies, as well as the KIA per class for built-up areas, were significantly lower for test area 1 compared to test area 2. Test area 2 was comprised of considerably more built-up areas than test area 1, and the built-up areas in the second test area were very similar in appearance, whereas in the first test area there was more variation within the type of built-up areas. User and producer accuracies for the remaining classes differed substantially between scenes, excepting for results for vegetation, which were similar. The accuracy of the road class in the second test area was particularly poor, with both user and producer accuracy equal to 0.00, and KIA of -0.02, indicating that the agreement is slightly worse than that expected by chance. Overall, the pixel-based supervised maximum likelihood classification resulted in unsatisfactory results in this study.

4.2 Object-based

Various features, such as spectral properties, shape and texture were examined in an attempt to find those that isolated built-up areas from other classes. The texture measures *GLCM mean, GLCM homogeneity*, and *GLCM contrast* were evaluated and it was found that *GLCM contrast* could be used to successfully discern between *built-up* and *not built-up* image segments. This is because built-up areas are highly textured in comparison to other features, such as vegetation, bare areas and water.

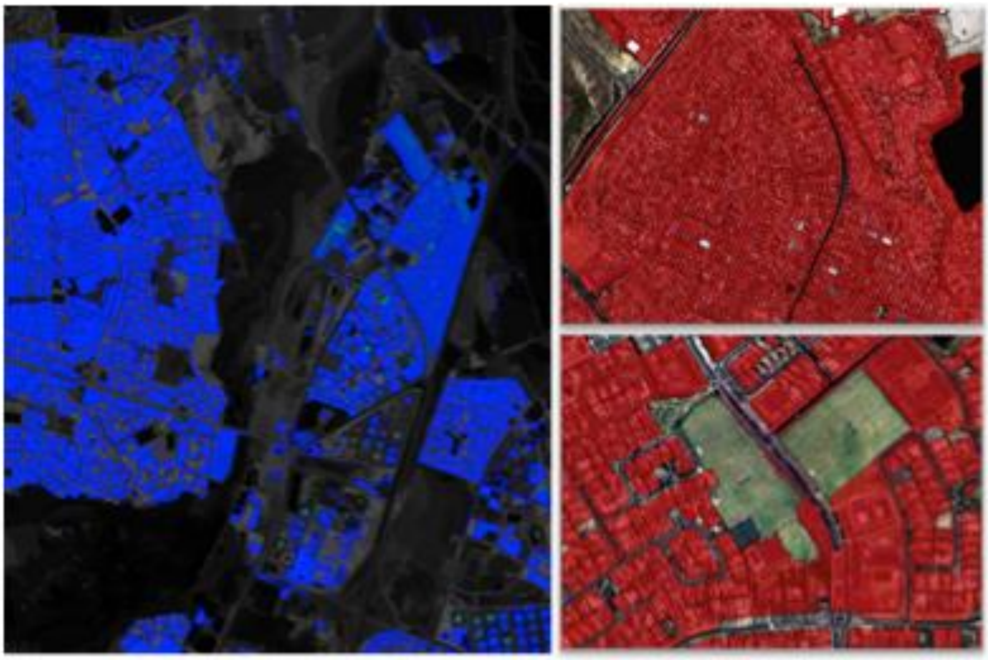

Figure 7. Object-based classification (test area 1): Left: highlighted segments based on GLCM contrast; right: enlarged areas showing classified built-up segments

The built-up class was classified using the threshold condition for *GLCM contrast*. Any segments with a value higher than the specified threshold for *GLCM contrast* were classified as built-up and all other segments were classified as not built-up.

With the second test area a minor change in the threshold value for *GLCM contrast* was effective in identifying built-up areas. This suggests that the method can be transferred from one scene to another without changing the process, and only editing the threshold value to be better suited to a specific scene.

The use of the texture measure *GLCM contrast* proved to be very effective in differentiating built-up areas from non-built-up areas when included in the process of an object-based classification methodology. The overall accuracy and KIA were 92% and 81% respectively for the first test area, and 95% and 89% for the second area. The producer and user accuracies for built-up area for both test areas were 90% or greater. This classification resulted in the highest accuracies of all the methods tested (Duncan, 2013).

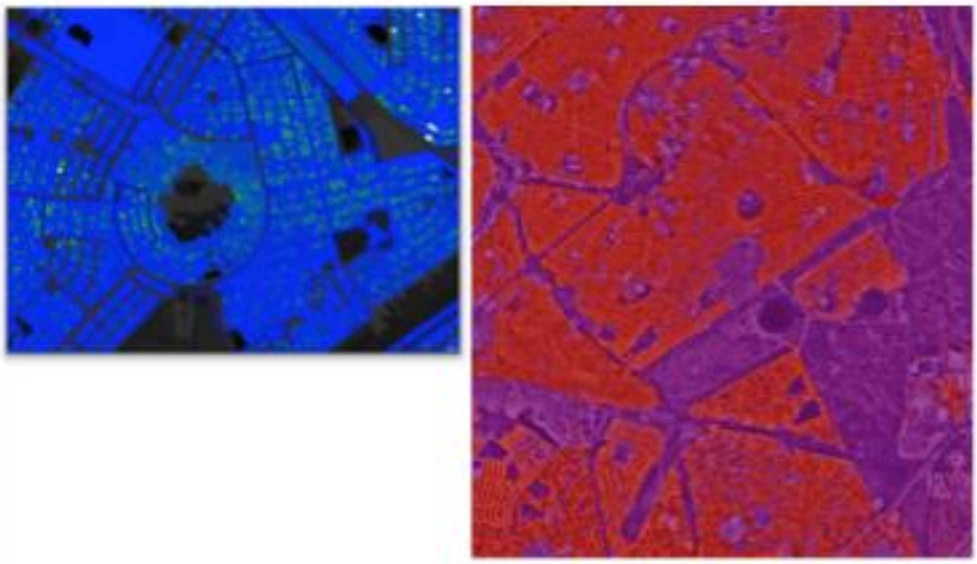

Figure 8. Object-based classification (test area 2): Left: enlarged portion of image showing highlighted segments based on GLCM contrast; right: classified image (red – built-up, purple – not built-up)

Table 3. Accuracy assessment and kappa statistics for object-based classification – test area 1

Class name	Producer accuracy	User accuracy	KIA per class
Built-up	0.90	0.98	0.72
Not built-up	0.95	0.81	0.93
Overall accuracy	**0.92**		
KIA	**0.81**		

Table 4. Accuracy assessment and kappa statistics for object-based classification – test area 2

Class name	Producer accuracy	User accuracy	KIA per class
Built-up	0.97	0.96	0.91
Not built-up	0.92	0.94	0.88
Overall accuracy	**0.95**		
KIA	**0.89**		

5. Conclusions

The objective of this study was to develop a process for automatic or semi-automatic classification of urban built-up areas from aerial imagery in South Africa. The methodology proposed should be robust and applicable across South Africa, and should require minimal user input or knowledge about the scene being classified. A generalised method is needed, as South Africa is a country with highly varied landscape and climatological conditions.

Generally, the pixel-based classifiers did not perform very well, and the classification of manmade features, such as built-up areas and roads, was unsatisfactory with these classifiers. This may be due to the large spectral variations within manmade features, as opposed to natural features, which tend to be more homogeneous.

The success rate of classifying built-up features was much higher with the object-based methods compared to the pixel-based methods. The improvement in accuracy is due to the classification of homogeneous segments as opposed to individual pixels, since groups of pixels represent classes of interest more appropriately than individual pixels.

Segmentation using image reflectance values works, but may not generalise well. Typically segments representing features of interest will need to be created through an iterative process of segmentation that may rely on various image segment properties. Depending on the features of interest and the spectral characteristics of the image, this process can vary substantially from one scene to the next. Thematic data is useful in constraining image segmentation and proved to be beneficial in achieving suitable image objects that could then be classified. Using thematic data provides a robust method of image segmentation.

The texture measure, *Texture after Haralick – GLCM contrast,* yielded very encouraging results in differentiating built-up areas from other features. The threshold value for *GLCM contrast* is scene dependent, and must be found by fine-tuning the value to find the optimal solution for the area of interest.

The results achieved add to the view that object-based classifiers are more suitable than pixel-based classifiers in urban scenes. This was a pilot study and future work is needed to add more land cover features and evaluate the methodology developed across a broader landscape range.

Future research in the following areas could be considered:

- The robustness of the methodology should be further evaluated by increasing the number of test sites.
- The purpose of this investigation was not to distinguish between different types of built-up areas, but rather to find a collective ‘urban built-up’ land cover class. However, for future work, one may wish to distinguish between different types of built-up areas; for example, residential, commercial and industrial areas.
- Only standard image products available to CD: NGI were used in this study. Emerging research is demonstrating the value of including Lidar data for image segmentation (Chen et al., 2005; Chen et al., 2009).

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