Automatic classification of roof objects from aerial imagery of informal settlements in Johannesburg

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Abstract

Improving the planning and provision of public services for those living in informal settlements depends on the availability of accurate demographic information. However, such data frequently do not exist because traditional survey and census methods are rarely successful in these environments. In this paper, the use of automatic feature extraction from aerial imagery is proposed as an alternative to these ground-based methods. We focus on the identification of roof and non-roof objects in an informal settlement called Diepsloot, situated close to Johannesburg in South Africa and home to approximately 200,000 people. Reference data provided by Johannesburg Metropolitan Municipality authorities are used to validate the results of our automated analysis, which achieved an overall accuracy of 80.5% when compared to manual delineation.

Keywords: Informal settlements; roof objects, feature extraction; aerial images; population estimation

Introduction

South Africa's socio-economic state is one of extreme polarization, and to generalize, those sandwiched in the middle reside in mainly informal dwellings either in the backyards of low cost housing or large 'slum' settlements. Informal settlements are increasingly widespread across the country with approximately 2.3 million people living without adequate shelter (Topham 2012). This is a well documented national problem and although post-apartheid governments in South Africa have maintained a pro-active stance on upgrading and re-housing, the efforts to close the gap have not been sufficient in scale. Having been described as *"running to a standstill"* (Topham 2012, slide 1), the current methods for re-housing are far behind the pace required; statistics show that for every newly re-housed family, there are three more families moving into the informal settlements (Housing Development Agency, 2012). In terms of absolute numbers, 1.5 million households in 1994 required adequate shelter, spawning a huge drive to provide a further 2.65 million households to date according to the National Upgrading Support Programme (NUSP 2012). However, in the twenty years since then, the deficit has actually gone up by 800,000 with 2.3 million now requiring adequate shelter (Housing Development Agency, 2012).

The most likely route out of informal habitation is through full-time employment, enabling those affected to pay their way out of poverty, but without more basic unskilled job opportunities and organisations that are dependent on generations of labour, such as processing and large-scale manufacturing (Sunter 2012), this goal will remain unachievable for the majority. It is therefore imperative that, where possible, tools used for city planning and urban development in developed countries are applied to these informal settings to ensure a better provision of services and maintain a quality of life above a certain threshold. Challenges remain, however, in collecting the accurate and continuous data that such planning tools require, a process that is notoriously difficult within the informal settlement environment (UNICEF 2012).

This paper aims to test the capability of an off-the-shelf feature extraction algorithm to delineate informal settlement characteristics and to detect patterns of change. The results that are generated can be used subsequently to better inform local planners and give an improved insight into likely future dynamics of these informal areas, providing the authorities with the opportunity to mitigate the impact of rapid urbanisation on both the populace and public infrastructure. The next section of the paper provides a short outline of what feature extraction involves with references to its previous application. This is followed by sections introducing the study area and explaining the method, before a presentation of results. Some conclusions are drawn in the final section.

Feature extraction and previous work

Feature extraction software uses aerial and satellite imagery to identify specific objects or features on the ground using Object Based Image Analysis (OBIA). It uses three main image criteria properties –

spectral, textural and spatial – to analyze the relationship between pixels and profile areas into chosen classes. The technology is dependent on fine resolution imagery (ideally sub metre) and benefits greatly when used with multispectral (i.e. multiple spectral bands) imagery (Carleer and Wolff 2004). Feature extraction differs from basic supervised and unsupervised pixel classifications in its ability to extract 'objects' rather than just pixels of a certain value. It does this by analysing bands in varying ratios, assessing the spatial patterns of pixel values to each other, and being able to identify recurring pixel combinations in the form of 'texture' analysis. In contrast, pixel-based classification tools rely solely on digital numbers (spectral reflectance values) to cluster pixels, with no consideration of adjacency or topology.

Previous work using feature extraction to automatically classify roof area and subsequently estimate population has focussed on informal settlements in Kenya, Tanzania, Brazil and India (Veljanovski et al. 2012, Aminipouri 2008). Veljanovski et al. (2012) successfully used feature extraction to calculate Roof Area per Person (RApP) and derived a population estimate of between 235,000 and 270,000 in Kibera, a slum area within the city limits of Nairobi, Kenya. The International Institute for Geo-Information Science and Earth Observation in the Netherlands used fuzzy membership to map roof area within three slums of Dar es Salaam, Tanzania, yielding an accuracy of 74.3%. The study concluded by outlining how simple, effective and cost-efficient the approach was, being able to *"*be applied by researchers and non-professional users*"*(Aminipouri 2008, p.05).

There is little evidence of feature extraction algorithms being used in South Africa to date. Manual digitisation of aerial imagery remains the predominant method for extracting demographic data using remote sensing, although the Council for Scientific and Industrial Research (CSIR) in Pretoria recently used multi-temporal data to analyze the spread of human settlements in South Africa's Gauteng Province (Salmon et al. 2009). This study, however, was carrying out analysis on change patterns in general land cover at a coarser resolution that did not incorporate a roof-count methodology, resulting in a wider study area that could not account for population growth in specific communities.

Area of Study: Diepsloot Johannesburg

Diepsloot is located on the northern boundary of Johannesburg centre (Figure 1) and has existed for almost twenty years as an informal settlement. Created in 1995, Diepsloot began as a transit camp for displaced persons following a re-housing effort by the Government (removal of persons occupying land illegally). In the interim, a community has developed made up of both formal tenured property and informal settlements. Current estimates suggest it is home to 200,000 people (Harber 2011), with a small river clearly forming a division between those living in low-cost housing or Rehabilitation and Development Programme (RDP) dwellings, and those living in an area commonly referred to as the squatter camp (Informal Units) (Figure 2). The name 'Diepsloot' comes from the Afrikaans word for 'ditch', referring to the deep furrow created by the river. Land is left vacant adjacent to the banks of the river due to repeated flooding, and so provides the communities main dumping ground for domestic waste. Located approximately 30 kilometres north of the centre of Johannesburg, it is cited as being a hub of criminal activity, ruled by gangs who are growing in numbers as a result of the high unemployment figures (BBC 2008).

Public services exist in the area of RDP dwellings and water and electricity are available to the majority of residents. However, those in the neighbouring informal units reside with few domestic connections to electricity, water or sanitation, and abused community toilet blocks in very poor condition shared by hundreds of people, posing a serious health hazard (Johannesburg Development Agency 2011). In 2011, the National Census conducted a survey in Diepsloot, but reports soon followed of a flawed methodology with South African Census Agency, STATSSA, citing that there were "very difficult working conditions" whilst trying to gather data from shack environments (Anderson 2013, personal communication).

In addition, this study incorporated analysis on two comparable informal settlements called Alexandra and Zandspruit in other corners of the Metro. In this case, no ground survey was carried out, only feature extraction on the respective imagery (Figure 3). This provided additional results with which to measure the Diepsoolt findings against.

Data and Methods

The efficacy of feature extraction algorithms depends largely on the spatial and spectral resolutions of the imagery used. Medium and fine-resolution imagery often comprises data collected at visible, near-infrared and panchromatic wavelengths – at spatial resolutions ranging between 2 to 90 metres (Joint Research Centre 2013). Although feature extraction is extensively used at such resolutions, it is mainly at regional scales for continuous land-cover types. In contrast, aerial photography provides the necessary detail for clear delineation of fine-scale artificial objects, in this case using two sets of imagery with pixel resolutions of 15 cm and 50 cm (Figure 4). When identifying informal units that cover no more of an area than five metres squared, such fine resolution is crucial.

For the current study, the City of Johannesburg Corporate GIS Department and the Chief Directorate National Geo-spatial Information (CDNGI) provided two sets of orthorectified aerial imagery for the Diepsloot area (Table 1). In addition, vector shapefiles of local authority boundaries and delineation of informal settlement borders were provided by STATSSA.

Table 1 Data used in the current study

Description	Year Flown	Bands/Channels
0.15 metre time series aerial imagery	2000 / 2003 / 2009 / 2012	RGB
0.50 metre aerial imagery	2010	RGB and NIR

Locations allocated for feature extraction were chosen to be representative of homogenous areas of informal units rather than comprising an entire informal settlement. Once identified, the delineated areas were extracted from the original image tiles and classified using pixel-based algorithms to remove spectrally-distinct areas of non-roof land cover. Methods of classification included fuzzy criteria analysis, maximum likelihood criteria and supervised classification using training polygons. We used ENVI EX, the feature extraction module of ENVI (EXELIS 2013a, 2013b) to delineate roof tops within the remaining land cover data. We experimented with both available algorithms provided by the ENVI feature extraction module (Figure 5). Firstly example based, which comprises manually identifying examples of objects that the software then analyses using a k-means clustering algorithm into chosen 'clusters' or classes, pre-defined by the user. The second method is rule based whereby the user has three extensive lists of rules to choose from, spectral, textural and spatial. Within each rule-set there are varying attributes (of each rule), and the user can define a chosen class by several varying rules. Largely a trial and error process, it should be repeated until an optimum segmentation/extraction result is produced, before finally exporting the results into ArcMap in both vector and raster format for final analysis.

To assess the accuracy of the resulting classification, a reference area of actual roof coverage was manually delineated from randomly placed 50m x 50m 'accuracy polygons'. Two accuracy polygons per area of study were used, with the actual roof coverage being delineated by hand (Figure 6). Roof coverage delineated by hand can be considered as the standard for feature extraction to aim for, as in 100% accurate. The feature extraction result, when compared to the actual roof coverage shows clearly a 10% margin, where the feature extraction process has recorded 10% more roof area than there really is. The far-right image (c) in Figure 6 highlights this 10% margin.

At 2,500 square metres per polygon, with 12 polygons randomly placed over Diesploot and the two remaining areas of study in Alexandra and Zandspruit, the 'actual roof area' reference data are taken from a sample totalling three hectares. From analyzing the feature extraction roof coverage from within the same accuracy polygons, comparable data for roof coverage using the sample provides an initial indication of accuracy. Additionally, a standard accuracy assessment using randomly placed points was carried out to calculate errors of commission and errors of omission.

Results

After the two imagery data sets were tested for their feature extraction capabilities, and the various parameters set within the module, in general the process was a repetitive one of trial and error until a satisfactory result/output was achieved. By simply documenting the results of one test, and comparing it with the previous, the method involved finding an optimum balance of segmentation versus scale, versus attribute and rule settings (Squarzoni 2013). The results format is two-fold. First, the extent and growth of the backyard units (Figure 7), and second, analysis of the existing number of dwellings in the squatter camp (Figure 8).

Backyard unit analysis

The main objective for using feature extraction on an RDP plot was to ascertain how many additional homes an RDP plot was supporting. Part of that process was to differentiate clearly between an RDP plot and the adjoining shacks, which proved to be a relatively straightforward process due to the absolute uniformity of an RDP roof at 5.5 metres by 6.0 metres and all made out of the same roof material. Analysis was conducted using time series imagery for 2000, 2006, 2009 and 2012.

The sample field survey results for the average number of households per RDP stand (5.18) is multiplied by the RDP count to estimate the total number of households. So if there are 413 RDP counts in the Diepsloot sample area, the total estimated households is 2,139.

The feature extraction results show that roof coverage area has grown by more than 250% since 2000, when the RDP development was completed. However, in terms of households, the 'total estimated households' figure shows more than 400% growth. The main factor for differences in growth figures between roof coverage and households is that a backyard unit is considerably smaller, at an average of 15m², than the RDP house at 33m².

As with both the study in Kenya and Tanzania, estimations of population were acquired by a roof area per person (RApP) method, using a sample of population data related to the study location, and multiplying it by the feature extraction results. Specifically for the backyard unit population, estimates were derived by multiplying the extracted RDP roof count (413), by the average population recorded per RDP stand during the sample field survey (11.51), giving a total estimated population of 4,754. This result was then compared to the 2011 Census total of 4,764 for the exact same area (Figure 5), a discrepancy of only 10 persons, or an error of 0.3%. The close proximity of the two counts was surprising for two reasons: (i) because there has been a two-year interim period between the census survey and the field survey sample in which a degree of growth might have been expected; and (ii) several recent reports on the execution of the Census in the informal settlement environment make reference to an undercount of households and population statistics (STATSSA 2012). Assumptions can be made that the existing formality of the RDP setting meant that, despite the backyard units being of 'informal shack' description, the uniformity and accessibility made the census results for this area relatively accurate.

Informal Unit Analysis

The main objective for using a feature extraction procedure on an informal settlement is to formulate a population estimation method and compare the results to the 2011 Census data. The major benefit of such an approach is that sensitive information can be identified through feature extraction that the census would struggle to record. Unlike the RDP location study, levels of growth were not recorded as there had not been significant expansion of the settlement within the 10 years of available data.

The process was centred on extracting solely informal unit roof coverage within a designated census boundary, and calculating the average number of households using the sample field survey data. This method differed to the backyard unit process as the feature extraction had to perform sufficiently well on extracting all variants of shack roof, in an area considerably more heterogeneous than the RDP location.

Although the feature extraction results could differentiate between 'no roof' and 'roof' data, it was unable to separate different shack households by roof material alone. Therefore, to estimate the number of households the total area was divided by the average shack size identified from the sample field survey. The formula used is identified as the following:

$$Total\ Number\ of\ Households = \frac{Total\ FE\ Area}{Average\ Shack\ Size} = \frac{234{,}920\ m^2}{15.5\ m^2} = \ 15{,}156$$

In comparison with a western city, which records approximately 100 households per hectare (Patel et al. 2012), Diepsloot has a density of 645 households per hectare, a figure considerably higher than some of the slum areas of Kibera, Nairobi (Kamande 2013).

Based on the same principle as the RDP location, the RApP method was used to estimate the population of the informal settlement with the feature extraction results. Using the identified 'total number of households' (15,156) and the sample field survey data on average number of persons per household, the total estimated population is 53,955.

When compared to the 2011 Census results of 23,214 people for the same area, the feature extraction results show double the estimate at 53,956. This information is more in line with the empirical data on Diepsloot and its expansion over the years, such as those conclusions made by the University of Witwatersrand in South Africa, citing the 'mushrooming' and 'ballooning' recorded in the last ten years as a serious urban planning problem (Huchzermeyer et al. 2011). In addition, these results would reflect the reports of an undercount of population statistics during the Census.

Conclusions

The findings reported in this paper show that when used with standard GIS spatial analyst tools, feature extraction has a place within public sector urban development teams as an infrastructure planning tool. In conjunction with the provision of up-to-date accurate imagery, an experienced user is able to provide relatively quick and cost effective analysis of the extent to which an informal settlement is impacting the public sector, with the estimated population and demographic data providing a strong foundation for informal settlement upgrading. A basic quantum can be obtained to measure consumption, provide basic risk analysis on existing hazards, and help to understand patterns of growth during interim census periods (Ahmad, 2013). In addition, the feature extraction outputs offer an insight into how best to monetise geospatial value (Hattingh 2013) to recuperate business and residential revenue, that can ultimately be put back into the same community to raise the standard of living. Feature extraction is dependent on how well the imagery used represents the exact features the user is aiming to identify. In the case of roof area coverage, the time elapsed between the date the imagery was flown and the time of analysis can obviously affect how up-to-date the results will be. The level to which vegetation, foliage, shadows and cloud cover are obstructing the features to be extracted can also render a certain location inapplicable for feature extraction, and so need to be considered before investing time and money in lengthy analysis. The spectral properties of an aerial photograph should also be briefly assessed for their levels of homogeneity, as extreme levels of object variance, such as hundreds of differing types of roof material, can result in poor extraction results. Infrared and NIR data should be considered to help further refine the results. In the case of Diepsloot, NIR data were not used due to the available 0.5 metre data being at too coarser scale, and ultimately outperformed by the sharper 0.15 metre RGB imagery (Figure 4). However, what was evident during trials is NIR's ability to separate vegetation from artificial objects which, if applied at the sub 0.5 metre resolution, is likely to have significantly enhanced accuracy (Tanner 2013).

Successes of feature extraction in informal settlement environments across other areas of the globe can be mirrored in South Africa, and are particularly applicable within the country's metropolitan authorities, where sub-metre (very high) resolution imagery can be made available either in the private or public sector. Benefits are magnified significantly when integrated with field survey data as an element of 'ground truthing', and the results should be viewed in tandem with existing GIS practices, not as a substitute. Like any software tool, there must be an appreciation that the results provide a virtual assessment that can only give part of the answer, and in most cases only give enough information to inspire further investigation. Particularly within the scope of socio-economic work, there must be a level of resistance to obtaining answers remotely, and desk-top studies of human impact must be matched with intervention within the community. However, when using up-to-date accurate imagery, an experienced user of feature extraction is able to provide relatively quick and cost effective analysis on the extent to which an informal settlement is impacting the public sector. A basic quantum can be obtained to measure consumption, provide basic risk analysis on existing hazards, and help to understand patterns of growth between census periods.

Acknowledgements

The authors would like to thank the following individuals and organisations for their time and support during the term of this project:

R Anderson (STATSSA), H Pienaar (Johannesburg Dept' Dev' and Planning), C Simms (ESRI South Africa), C Tanner (AOC GeoSpatial), M Thompson (Geo-TerraImage), D Tjia (Jo'burg Corporate GIS), J Verhulp (CDNGI Cape Town), I Guest (SATPLAN), P Ahmad (The City of Johannesburg), C Squarzoni (EXELIS), D Anagnostopoulos (Adonis Design), K Parry (STATS SA), S Williams (Welsh Branch), , ESRI South Africa, Corporate Geo-Informatics City of Johannesburg, CDNGI South Africa and finally L Petricevic.

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9. Figures

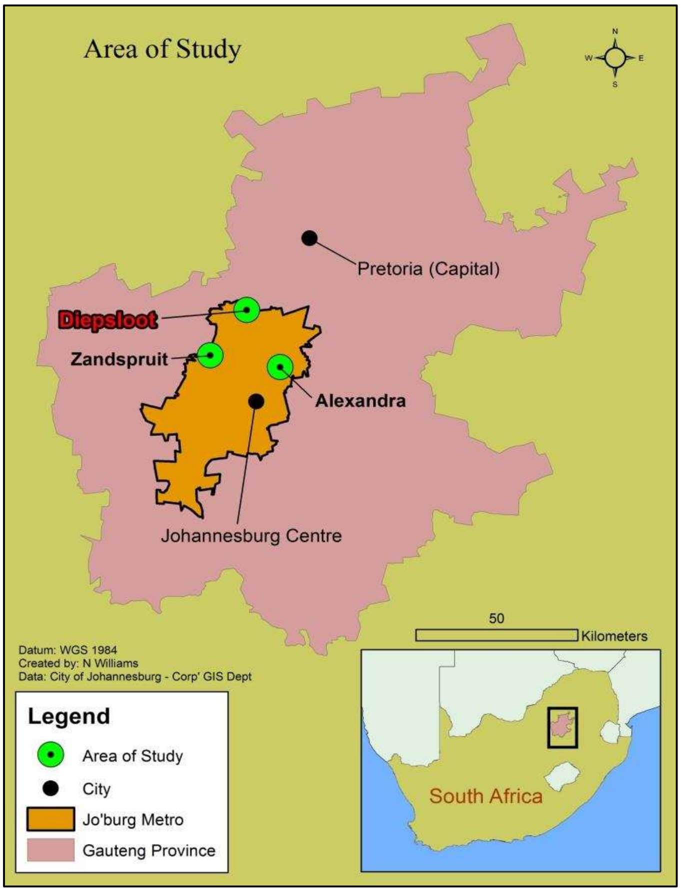


Fig. 1 The study area within its regional context and (inset) its national context

Fig. 2 The Diepsloot settlement with formal (foreground) and informal (background) dwellings

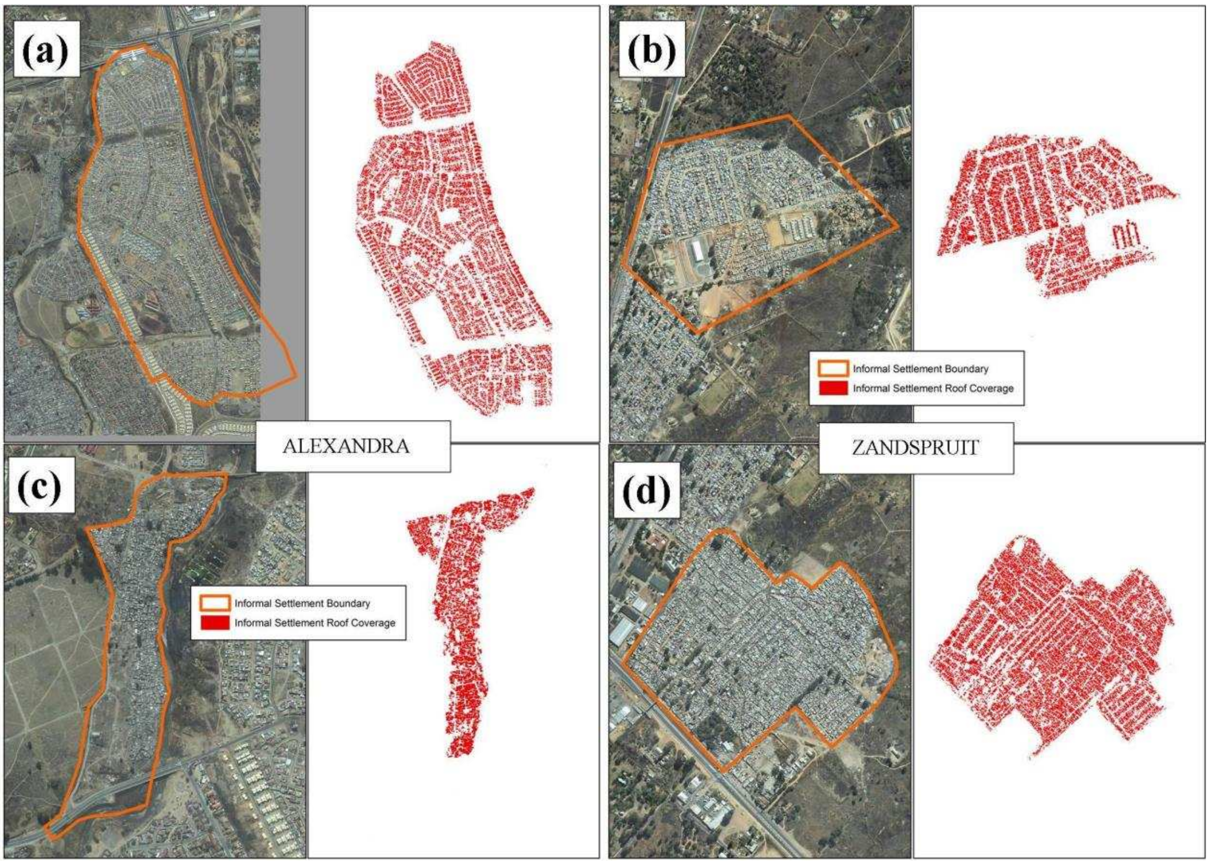


Fig. 3 Feature extraction results clearly show growth around RDP houses, (a) and (b), and the extent of roof coverage in informal settlements, (c) and (d), for the suburbs of Alexandra and Zandspruit.

Fig. 4 Example of two different resolutions of aerial imagery used for the study. Outside layer being the 50 cm resolution, inside layer being the 15 cm resolution.

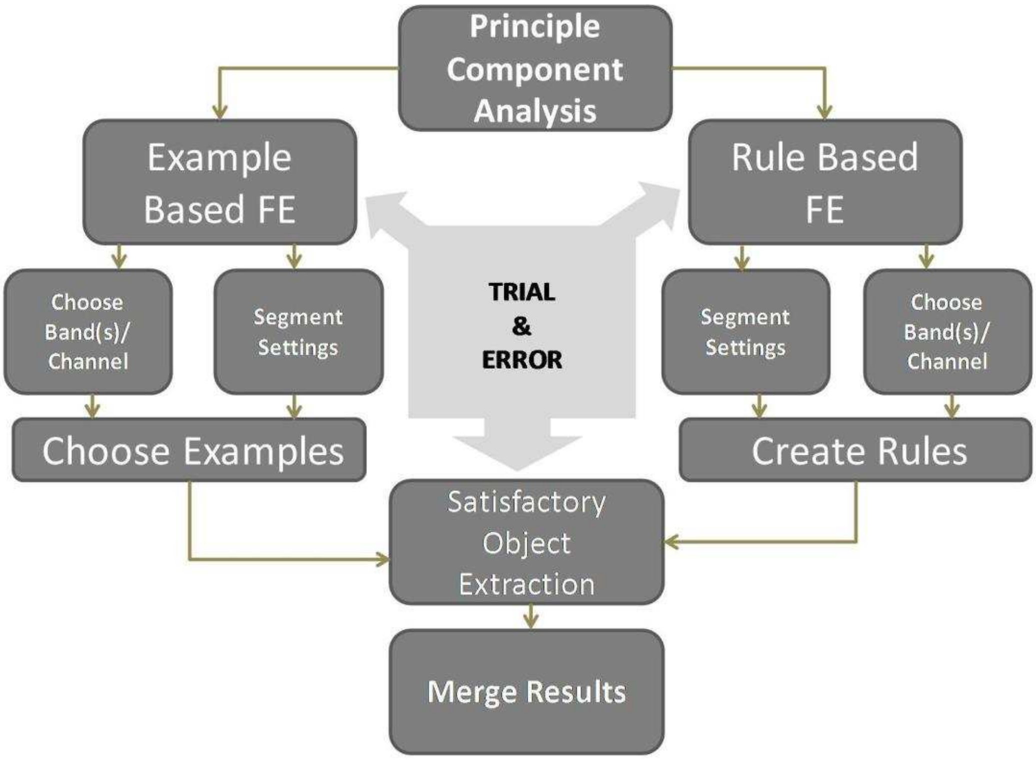
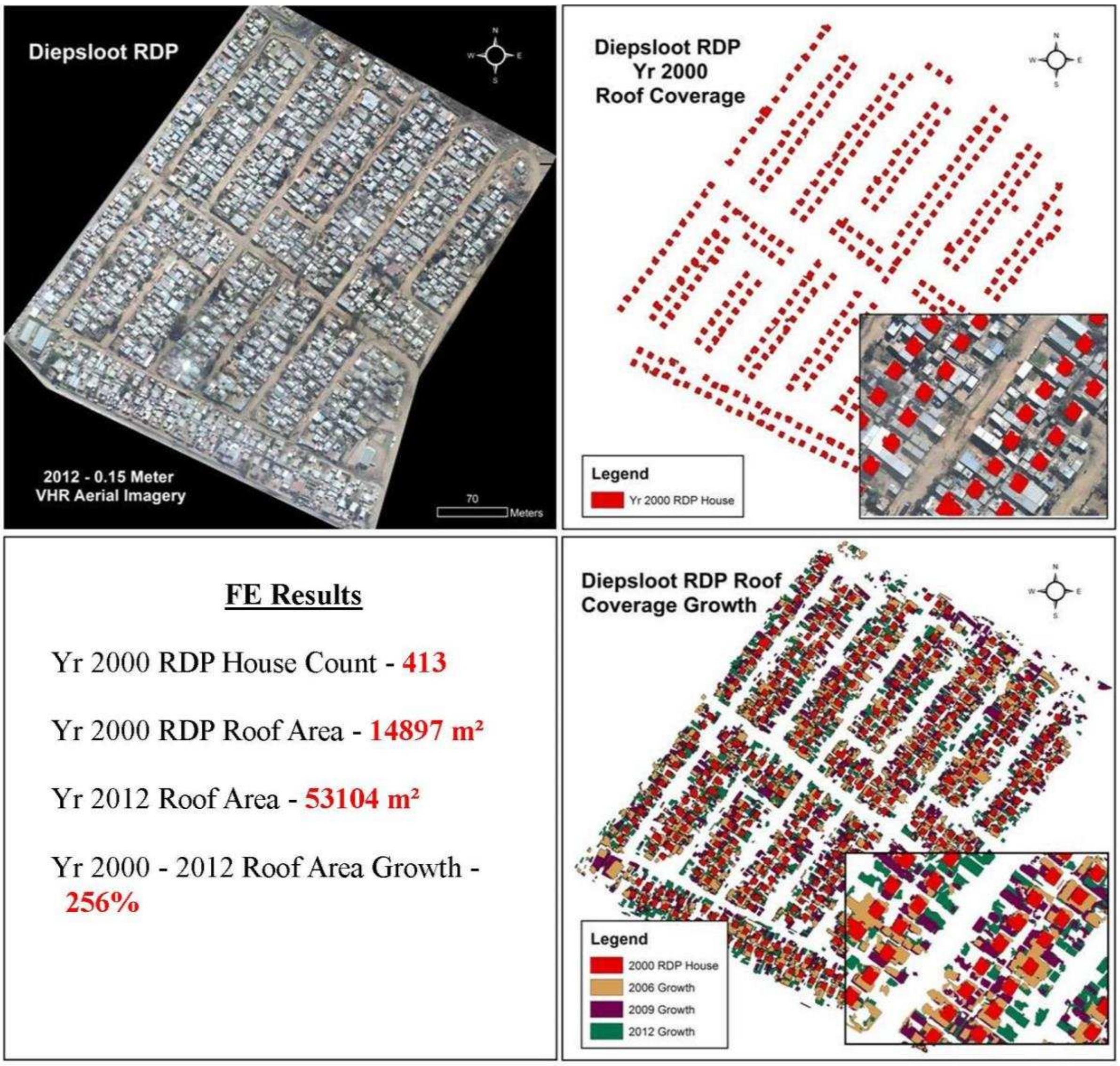


Fig. 5 The workflow used to delineate rooftops by feature extraction using ENVI EX.

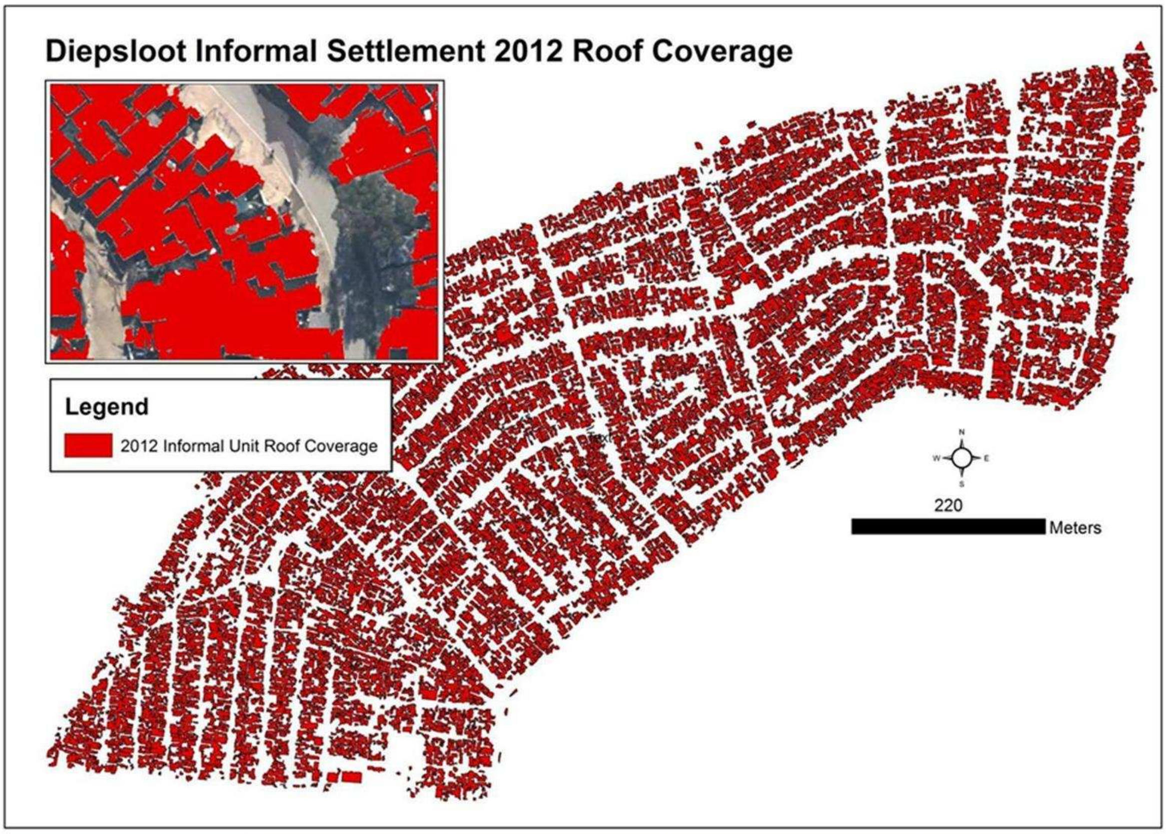
Actual Roof Coverage (a)	Feature Extraction (b)	% Difference (c)
12,301 m²	13,577 m²	10%

Fig. 6 Manual delineation of actual roof area (a), used to assess the accuracy of the feature extraction (b), with the identified error of the extraction (c).



2011 Census Population	FE Population	FE Households	FE Pop' Density	FE HH Density
4764	4754	2139	35 m² p/p	76 m² p/h

Fig. 7 The outputs and results from feature extraction on the backyard unit location with growth. The growth clearly visible surrounding each RDP House, differentiated by colours sperating the years the imagery was flown.



2011 Census Population	FE Population	FE Households	FE Pop' Density	FE HH Density
23214	53956	15156	11 m² p/p	39 m² p/h

445

Fig. 8 The outputs and results of feature extraction on the informal settlement location in the resultant polygon shapefile forming an excellent base map for informal settlement upgrading and planning, showing access routes and boundaries clearly.