Uncertainty Quantification for the Extraction of Informal Roads from Remote Sensing Images of South Africa

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ABSTRACT
Informal unpaved roads in developing countries arise naturally through human movement without government authorities being informed. These roads are not authorised nor maintained by council, nor reliably mapped in quality-controlled online maps. Information on informal roads is critical for sustainable city growth, and may be gleaned from spatial big data. Attempts to extract such roads from satellite images are sparse, and no automatic or guided semi-automatic approach has yet been employed. In this paper, we consider possible definitions of informal roads, by investigating the effects of their often poorly defined boundaries. We aim to detect these roads using a **state-of-the-art** method and to address the uncertainties encountered. The method is applied to areas in Gauteng Province and North West Province, South Africa using very high resolution images. The conceptualisation of informal road boundaries, and hence the definition of an informal road, must be adapted to address challenges of informal road detection. These include the existence of clear boundaries, the visibility of road edges, road surface heterogeneity, and whether or not it is desirable to use only the central part of the road for transport. This paper contributes uniquely by considering the conceptual and practical challenges of informal road extraction in remote sensing.

KEYWORDS
image processing; information extraction; uncertainty modelling

1. Introduction

Many ad hoc unpaved roads exist throughout South Africa. These are created on a local level by citizens without informing the authorities, and do not necessarily comply with the standards or prescribed definition of roads as specified by South African **laws**, such as the National Road Traffic Act[1]. These roads are referred to as informal roads in this paper. In contrast, formal roads are roads sanctioned and maintained by government, and display different characteristics, due to being officially and uniformly maintained.

Information on informal roads is critical for municipalities to pro-actively plan and assess the impacts of policies and developments, including informal settlement up-

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[1]South African Legal Information Institute, National Road Traffic Act, 1996 [No. 93 of 1996] - G 17603. Available online: http://www.saflii.org/za/legis/num_act/nrta1996189/

grading strategies, such as the Tshwane municipality's Project Tirane[2] and current initiatives in Cape Town[3]. It is also useful for pre-informing town planning when performing accessibility analyses, e.g. to determine how many people have access to facilities such as clinics and schools, according to **standards** stipulated by government, such as those specified by the Council for Scientific and Industrial Research[4]. It may also be used by emergency services needing to navigate such roads.

Information on informal roads in rural settings is relevant to the Sustainable Development Goals (SDGs), in particular SDG 9 on Industry, Innovation and Infrastructure. Target 9.1 specifies the need for sustainable infrastructure leading to affordable and equitable access for all [5]. The Rural Access Index (RAI) is used to measure Indicator 9.1.1, namely the **share of the population who live within 2km of the nearest road in good condition in rural areas** (Iimi et al., 2016). Road density and condition significantly influence the RAI in African countries. Recently, digitised road networks have been used as inputs to calculate the RAI (Iimi et al., 2016).

Digitised informal roads, as well as other relevant information on informal roads, are not available in official databases since the roads arise without the government being informed. These roads are also not captured by data companies. **As an example, Figure 1 shows an area of Makanyaneng, North West Province, South Africa, along with the roads mapped manually by AfriGIS, and made available on Google Maps. The formal unpaved roads are available on Google Maps while the informal roads were not. Applications exist that allow users to map roads themselves, such as Open Street Maps and Tracks4Africa. However, the availability and quality of roads captured by private individuals is not guaranteed. While such information is useful, it may not be suitable for use in municipal decision-making.**

Given an efficient road extraction method, detecting informal roads from remote sensing images could make this information available in a time- and cost-effective manner. Little work has been done on the automatic extraction of informal roads from remote sensing images. Many uncertainties are associated with extracting informal roads, such as irregular boundaries and heterogeneous land cover at the scale of dwellings in informally developing areas (Nobrega, O'Hara, & Quintanilha, 2006). Nobrega et al. (2006) address the problem and highlight these and other difficulties within the context of informal settlements. However, their technique is not automatic and requires many tuning parameters and user inputs. In addition, informal roads appear in a variety of surroundings, including formal settlements, and take on a wide range of characteristics, **such as road surface reflectance and irregular boundaries**. In order to address the uncertainties of this problem, we explore the challenges associated with these divergent circumstances. Section 2 provides a thorough discussion of the definition of an informal road and their visual identification. We parametrise the Binary Partition Tree-based algorithm developed by M. Li, Stein, Bijker, and Zhan (2016) to identify these roads. This method is naturally suited to detect and model uncertainties. We furthermore identify sources of extraction uncertainty inherent to the characteristics of informal roads.

[2]Democratic Alliance: *DA-led Tshwane Selling Mayoral Mansion to Bring Better Services.* Available online: https://www.da.org.za/2017/07/da-led-tshwane-selling-mayoral-mansion-bring-better-services/

[3]IOL News: *City plans to spend over R850 million on informal settlement upgrades.* Available online: https://www.iol.co.za/capeargus/news/city-plans-to-spend-over-r850-million-on-informal-settlement-upgrades-14374452

[4]CSIR Guidelines for the Provision of Social Facilities in South African Settlements

[5]United Nations: https://unstats.un.org/sdgs/metadata/?Text=&Goal=9&Target=9.1

The rest of the paper is structured as follows. Section 2 explores the definition of an informal road. The chosen road extraction algorithm is discussed and justified in Section 3. The methodology is explained in Section 4. The results are given in Section 5. Section 6 discusses the results and posits future research questions, while Section 7 concludes.

2. Road Definition

From a legal standpoint, formal roads have either been created or recognised by government, whereas informal roads are created without government knowledge, and there are no official records of their existence. Informal roads arise naturally through human movement and the need for access to job opportunities and facilities. The routes along which roads are created are determined by convenience. For the purposes of road extraction from remote sensing images, an informal road must be recognisable in spatial and visual terms. **Herein, we choose to consider three components to the spatial definition of an informal road in any settlement, namely the surrounding area, the settlement characteristics, and the road characteristics. These components are chosen to provide a comprehensive definition of an informal road both in regards to its physical characteristics and the broader environmental context.**

The **surrounding** area under consideration can be either urban or rural. This influences the density of the surrounding houses, the immediate surroundings of the road (e.g. built-up or open space such as yards), and the prevalence of vegetation. The settlement can be formal or informal. **Herein, the term informal settlements refers specifically to areas that have been settled and developed by inhabitants in an unplanned fashion, without government approval. Informal settlements often exhibit irregular road and block structures (Nobrega et al., 2006). Settlements that exist with the knowledge and approval of government are herein referred to as formal. These can have one of two origins. They are either informal settlements that have been recognised by government, or they were developed by government from the beginning. The second type of formal settlement exhibits a regular structure. The type of settlement determines the kind of informal road that occurs in the area. The roads in informal settlements, as well as in settlements that used to be informal, tend to be narrow, have heterogeneous surfaces and exhibit semi-regular and irregular patterns.** Settlements that started out as formal are more likely to contain broad roads with a regular structure and homogeneous surface reflectance.

The road characteristics considered are road reflectance, shape and boundaries. **The reflectance of informal roads may be used to separate them from their surroundings, especially vegetation and built-up areas. However, reflectance is not sufficient in itself, as bare soil areas and roofs made from local clay may have similar reflectance to bare soil roads. Roads have a linear shape, which distinguishes them from non-linear objects of similar reflectance, e.g. yards and houses. Road boundaries define the shape of roads, and distinguish roads from non-road areas. Boundaries also define width.** Informal roads as considered herein are all unpaved. The surfaces are created and maintained by regular use. Informal roads that are well-used by the community may have surfaces and shapes that appear similar to formal paved roads, which have been specially prepared for use. These surfaces have homogeneous surface reflectance, though the reflectance values are different to those of paved roads. The shapes are regular and the width is uniform for the entire length of the road. Informal roads that are not as well-maintained exhibit heterogeneity in the surface reflectance, including dark and light patches. The shapes are not as regular and the width varies considerably along the length of the road. **Since we aim to detect roads that are candidates for formalisation, a minimum width is necessary. We consider roads that are navigable by vehicles. While Mackey, Van Zyl, and Vorster (1981) suggests a minimum, namely the vehicle width of 1.8m, a minimum road width is not enforced herein. Figure 2 gives an example of informal roads, demonstrating a typical unplanned, irregular network. All roads in this image are informal. The footpaths in areas A and D are too narrow to be considered roads. The road running from north to south in area C demonstrates an irregular winding shape, while the roads on either side (east and west) of the junction are not aligned. The road in area B demonstrates an abrupt change in width.**

Determining the width of a road requires that the road boundaries should be defined. The question now arises whether these boundaries should define only the part of the road that is navigable by vehicles, or should include adjacent sidewalk-like areas that are navigable by bicycles, pedestrians and animal transport. For informal roads, neither type of boundary is necessarily visually clear or rigorously definable. This is due largely to the fact that informal roads tend to blend into their surroundings, especially in areas with bare soil. Gauteng and North West Province are in general dry areas. In addition, residents of informal settlements often purposely clear away grass in order to discourage snakes. Strict rules may not apply regarding the inclusion or exclusion of areas adjacent to the centre parts of roads. It is rarely clear where a true road ends and a non-road adjacent area begins, since the centre parts of informal roads often fade into spectrally and visually similar adjacent areas, such as bare soil areas, yards and driveways.

The choice of boundary influences how the reference data are determined. Figure 3 shows typical informal unpaved roads with two different sets of reference data. The reference data determine the measured accuracy of the extracted results, hence different levels of accuracy will be achieved with the same set of results. The effects of more inclusive versus more exclusive rules for capturing reference data are investigated in this study.

Finally, informal roads may appear similar to unpaved informal roads. The roads extracted in this paper are thus not all necessarily informal. **Consider Figure 4. The unpaved roads in (a) and (c) appear regular and may be formal**. However, challenges in terms of road extraction remain unchanged for these roads, only that their true nature is known.

3. Road Extraction Algorithms

Various techniques exist that are capable of extracting formal roads (Mena, 2003; Wang et al., 2016), but no automatic or guided semi-automatic method currently exists for efficiently extracting all types of informal roads from remote sensing imagery. In our implementation we intend to parametrise an existing road extraction method to suit the problem of informal and unpaved roads, to allow for investigation of uncertainties of informal road extraction. Recent methods for the detection of rural roads have shown that rural roads experience some of the same challenges as informal roads, in particular the varying widths of roads and heterogeneity of road surface reflectance and colour (Liu, Zhang, Li, & Tao, 2017). Unlike rural roads, however, informal roads are often found in urban settings. An urban road extraction method with adjustable parameters is preferred since urban road extraction methods may also achieve success when extracting rural roads (Coulibaly, Spiric, Lepage, & St-Jacques, 2018).

In order for a road extraction approach to be suitable for informal roads, it must rely only on characteristics possessed by informal roads and take the circumstances of these roads into account. Incorporating geometric and structural properties instead of relying on spectral information decreases the risk of confusion with spectrally similar features (J. Li, Hu, & Ai, 2018; Liu et al., 2017). Other informal road characteristics also need to be considered. For instance, centreline extraction has been used in several recent methods. This fails when the road widths change suddenly (R. Li & Cao, 2018). Also, methods relying on clearly defined road boundaries will fail, such as the multiscale method in Coulibaly et al. (2018) or approaches incorporating edge detection such as that of Liu et al. (2017). Uniform colour of roads is another assumption that is used by recent methods (Abdollahi, Bakhtiari, & Nejad, 2017), but is not met by informal roads. An approach which overcomes the above problems is desired.

The technique chosen for this paper was proposed by M. Li et al. (2016) and is based on binary partition trees (BPT). This is a flexible method with adaptable parameters which can be modified to suit different road and environmental characteristics. Buildings, shadows and vegetation are automatically removed. Building removal is critical since long, linear buildings may be geometrically similar to roads (Liu et al., 2017). Shadow removal has also been mentioned as an advantage (J. Li et al., 2018). Vegetation is removed reliably using near-infrared (NIR) data, an advantage above many recent techniques that have made use of optical VHR data only (Miao, Shi, Samat, Lisini, & Gamba, 2016; Xu, 2016; Zhang et al., 2017). The removal of buildings, vegetation and shadows prior to road extraction gives this method a significant advantage over other techniques.

Once vegetation, shadows and buildings have been removed, the image is represented hierarchically using a Binary Partition Tree (BPT). A review of the literature of BPTs and an algorithm for BPT construction may be found in Valero, Salembier, and Chanussot (2013). The BPT outperforms traditional pixel-based spectral classifiers (Valero, Salembier, Chanussot, & Cuadras, 2011). The region characteristics used are the compactness and elongation of regions, and two features based on morphological profiles and orientation histograms. These shape features are not specific to formal roads.

The method incorporates fuzzy logic for building and shadow removal as well as for road extraction. Fuzzy logic has been employed by recent approaches to accommodate for many uncertainties associated with road extraction (Maboudi, Amini, Malihi, & Hahn, 2018; Wang et al., 2016).

The objective here is to quantify the uncertainty during the automatic detection of informal roads, using a state of the art urban road extraction method, and to determine the success of informal road extraction. The chosen method facilitates the detection and quantification of uncertainty. The considered uncertainties are comprised of existential uncertainty, related to the presence or absence of roads, and extensional uncertainty, related to the boundaries of roads. The use of M. Li et al. (2016) in this paper provides a state of the art urban road extraction approach to an application area not yet investigated thoroughly.

4. Materials and Methods

4.1. Study Area and Data

The datasets are all taken from a multispectral VHR Pléiades-1B image with an estimated azimuth angle of 65° and a spatial resolution of 0.5 m[6]. **The image is from 2014**. The areas considered herein were chosen to represent a variety of typical road and settlement types. The focus is on formalisable roads, i.e. roads with extent wide enough for use by cars. The areas to be studied are situated in the north-western parts of Gauteng Province and the south-eastern parts of North West Province, South Africa. The informal settlements in these areas are in many cases starting to formalise and the informal roads are beginning to take on a grid-like structure. The areas are shown in Figure 4. These feature a variety of road types, both formal and informal, paved and unpaved, and various settings including urban and rural. **Area 1 in Figure 4(a) exhibits broad, straight urban unpaved roads as well as formal paved roads. The unpaved roads in this image are wide enough to accommodate two lanes and are strong candidates for future paving. Area 2 is shown in Figure 4(b). It contains dusty formal paved roads and narrow, irregular informal roads. These roads are not likely to be formalised, but are nevertheless navigable. Both areas 1 and 2 are in Mabopane, Tshwane Municipality, Gauteng. Area 3, in Figure 4(c), is located in Soshanguve, Tshwane. It displays broad unpaved urban roads with heterogeneous surface reflectance and colour. This variation in reflectance is typical in areas with varying soil type or recently after rain, when different areas of the roads have dried to various extents. Area 4 is shown in Figure 4(d) and is located in Kgabalatsane, North West. It shows mostly straight unpaved roads against a spectrally similar background, being typical in drier areas. Area 5, shown in Figure 4(e), is in Brits, North West. This area displays narrow unpaved roads in a setting with many bare soil areas and plentiful vegetation.**

The reference data for accuracy assessment was obtained via manual digitisation. The same image was used as the source, due both to limited data availability, and to ensure that the results were comparable, e.g. that no roads exist in the reference that do not exist in the extraction or vice versa.

4.2. Road Extraction

The methodology of M. Li et al. (2016) was parametrised to suit roads under consideration here. After vegetation and shadow removal, a fuzzy landscape of building shadows is created. This specifies the directional relationship of each non-vegetation image pixel to the shadow regions. The fuzzy landscape is thresholded at a building extraction threshold value to remove buildings. Tree shadows are similarly removed using the directional relationship between vegetation and their shadows. The segments that are not classified as trees, buildings or shadows form the Road Region of Interest (Road ROI). This is used to construct the Binary Partition Tree (BPT). Figure 5 provides an overview of the method.

A Binary Partition Tree (BPT) provides a natural representation of images which

[6]The authors would like to thank the CSIR, South Africa, for the provision of the VHR images.

stores only the most important relationships between regions, allowing for the quick application of complex image processing techniques. It is a hierarchical representation of the regions that can be obtained from an initial partition of an image (Valero et al., 2011). The hierarchy results from the steps of some region merging algorithm based on a region model and a region merging order (Valero et al., 2013). The region model specifies which region characteristics are of interest. The region model has four components: two geometrical properties, based on region elongation and region compactness, and two structural properties based on histograms of oriented gradients (HOG) and morphological profiles respectively.

Road regions are then extracted from the BPT. For each image region R_i, a possibility measure and a necessity measure are calculated, whether an object is a road or a non-road. A non-road is any image segment that does not comply with the definition of an informal road as given in Section 2, i.e. the complete segmented image is made up of road and non-road segments. The notation is given below:

$$\begin{aligned}
\text{Possibility of a road } &= \Pi(R_i) \\
\text{Possibility of a non-road } &= \Pi(\bar{R}_i) \\
\text{Necessity of a road } &= N(R_i) = 1 - \Pi(\bar{R}_i) \\
\text{Necessity of a non-road } &= N(\bar{R}_i) = 1 - \Pi(R_i)
\end{aligned}$$

R_i is classified as a road if $\Pi(R_i) > \Pi(\bar{R}_i)$ and $N(R_i) > N(\bar{R}_i)$, that is if both the possibility and necessity of the region being a road is larger than the possibility and necessity, respectively, of the region being a non-road. The uncertainty associated with an extracted road segment R_i is given by $\Pi(\bar{R}_i) = 1 - N(R_i)$. The method produces certainty (necessity) maps of the regions that were classified as road. For the final results, the necessity maps are converted to binary datasets, thresholded at zero. Any region classified as a road receives a value of 1, while all other areas receive a value of 0. The non-thresholded necessity values are used to construct the uncertainty maps in Section 5.3.

4.3. Misclassification Assessment

The misclassification rate is obtained by comparing the extracted roads with a reference set. Roads were manually digitised, rasterised and spatially aligned with the road extraction results. Due to the often unclear extent of an informal road, in terms of the exact boundaries and the extent of pavements, verges and driveways, a pixel-based quality assessment method is used **over a region-based approach.** Our digitised reference dataset allows investigation of the effects of the road definition in terms of road boundaries, accuracy and the types of errors.

Misclassification of pixels can occur by false positives (FP) or false negatives (FN). False positives occur when non-road pixels are classified as road. False negatives are pixels that correspond to road in the reference but are classified as non-road. Correct classifications are either true positives (TP) or true negatives (TN). True positives result from pixels that correspond to road in the reference being correctly classified as road, while true negatives are non-road pixels correctly identified as non-road. The following four metrics are used to evaluate the quality.

$$\text{Misclassification Rate} = \frac{\text{FP} + \text{FN}}{\text{FP} + \text{FN} + \text{TP} + \text{TN}} \tag{1}$$

$$\text{Quality} = \frac{\text{TP}}{\text{TP+FP+FN}} \tag{2}$$

$$\text{Commission} = \frac{\text{FP}}{\text{TP+FN}} \tag{3}$$

$$\text{Omission} = \frac{\text{FN}}{\text{TP+FN}}. \tag{4}$$

The misclassification rate given in Equation 1 provides a general measure of misclassification over the entire image. Quality (Equation 2) is an overall measure of the extracted results (Heipke, Mayer, Wiedemann, & Jamet, 1997). It expresses the number of pixels correctly identified as road, as a proportion of all the pixels identified as road, whether correctly or incorrectly. The commission metric (Equation 3) measures the false positive rate and omission (Equation 4) measures the false negative rate.

4.4. Uncertainty Analysis

Misclassification of pixels translates to errors and uncertainty in the classification of road segments. The uncertainty associated with an extracted road segment is defined as the possibility that the segment was misclassified. The uncertainties investigated here relate to the roads themselves, rather than being specific to the extraction process. The road-related uncertainties originate from the definition used, from the recognisability of roads on remote sensing images, and from inherent uncertainties in the data caused by e.g. atmospheric disturbance.

These uncertainties may be existential or extensional (Molenaar, 2000). Existential uncertainty refers either to the possibility that a road segment is classified as road but does not correspond to a road on the ground, or to the possibility that a road on the ground is not detected. Extensional uncertainty occurs when the presence of a road is certain, but the extent of its boundaries is not clear. This is the case when a road segment contains road and non-road pixels, or when parts of the edges of a road are not detected.

Explicitly, only the geometry of the road segments is taken into account. Misclassification at the level of the pixels and the presence of pixels of heterogeneous land cover type directly influence the geometry of the segments. They are hence an implicit part of the uncertainty. These sources of uncertainty will therefore be taken into account in the interpretation. Errors at the level of the radiance, caused by atmospheric interference, are more complicated to quantify. We consider those as noise and will not further address them.

4.5. Parameter Effects

In this application area, human intervention in some parameter choices is suggested, due to the variation in environment and road type. This would be required for any extraction algorithm in general, when adapted for the unique and varying circumstances of informal roads. There are two types of parameters for the road extraction method considered herein, namely external and internal.

The external parameters relate to the azimuth, which can be obtained from the image metadata, and the scale, which specifies the initial segmentation. Variation in over-segmentation input has little effect on the BPT construction (M. Li, Bijker, & Stein, 2015).

The internal parameters, lower and upper bounds related to the compactness and elongation, are set using expert knowledge, as in M. Li et al. (2016). The expert knowledge rarely changes between various cases and can be reasonably employed for different areas. The window size and number of bins used in constructing the HOGs are also internal, as is the length of the morphological path. The theoretical background in M. Li et al. (2016) suggests fixing the path length and number of bins while varying the window size. The effect of the window size is investigated, as small changes to its value may result in significantly different extracted results. The threshold used to extract buildings during BPT creation is also considered. The effects of these two parameters on the quality and misclassification rate were investigated for all areas under study. Note that the spatial resolution was 0.5m for all the images. **Table 1 gives the internal parameters that had the same value for all areas, namely the compactness and elongation parameters, the path length and number of bins.**

The effects of the window size for area 2 are shown in Figure 6. A range of possible window sizes from 10 to 100 were considered and the results were compared quantitatively. The metrics in Figure 6(b) were normalised by dividing by their totals. A window size of 55 shows a local maximum in the quality, suggesting its suitability. Figure 7 shows similar results for area 3. A window size of 80 is appropriate since it results in high quality and a lower misclassification rate.

The effects of the building extraction threshold are shown in Figure 8. For both areas 2 and 3, a threshold of 0.5 results in the maximum quality and a lower misclassification rate. Table 2 gives the window sizes and building thresholds for all areas.

From the above results, it is clear that optimal parameter choices can vary considerably depending on the image, and there is no single overall best choice. This suggests that human intervention remains necessary for choosing the parameters.

5. Results

The obtained results are given in Figure 9, with corresponding quality assessment in Table 3, as compared to the reference data. They highlight the difficulty of extracting informal roads. In spite of the challenges, our method was able to identify roads of different types in all of the areas. The accuracy varies.

All areas exhibited a high false positive rate (commission). The fact that high commission rates were experienced for all areas, agrees with the problem of false positive detection experienced in Nobrega et al. (2006). **Areas 1 and 4, shown in Figure 9(a) and (d) respectively, experienced the lowest commission rates. Areas 3 and 5 (Figure 9(c) and (e), respectively)** experienced the highest. **The removal of shadows, vegetation and buildings prevented such areas being misdetected as roads. Therefore, the false positives were almost exclusively caused by bare soil areas such as dusty yards, driveways, and other open areas adjacent to roads. These had similar reflectance to unpaved roads, and formed part of image objects that included roads, and therefore possessed the required geometric properties to be classified as roads. In area 1, a few buildings were not removed during the creation of the road ROI,**

despite the correct removal of their corresponding shadows. Some of these buildings were misdetected as roads.

The false negative (omission) rates were lower for all areas than the corresponding commission rates. Areas 4 and 5 exhibited the highest omission rates. Trees, tree shadows and other objects on the sidewalks, as well as tree shadows occluding the central parts of the roads, caused many misclassifications in all of the areas. This is especially clear in area 2, **as shown in Figure 9(b)**. Since the method eliminates trees and shadows prior to identifying roads, detecting occluded roads is a challenge not within the scope here. The heterogeneity of land cover at the scale of narrow informal roads was another source of false negatives, agreeing with problems experienced in Nobrega et al. (2006). Some road pixels grouped with vegetation pixels during segmentation were wrongfully detected as vegetation, and hence removed during the creation of the Road ROI. This can be seen especially in areas 2, 4 and 5, where many narrow semi-rural roads were not detected when bordered by vegetation. In area 4, some of the undetected roads were narrow with road surface areas.

Surface colour heterogeneity was not such a serious problem for wider roads, as in area 3. Although the roads in area 3 exhibited dark, muddy and grassy patches, the method correctly classified many of these roads. Cars on the road did not in general negatively affect the results for these roads, except where a substantial shadow was cast by a car, leading to the detection of the car as a building and its exclusion from the Road ROI.

Overall, area 4 had the lowest misclassification rate, however, its false negative rate was the highest of the datasets. Area 1 provided best values in terms of all metrics except misclassification rate, and was the only area for which the quality was above 50%. **The road and environmental characteristics were favourable for road extraction. The roads exhibit mostly homogeneous reflectance, and have broad width. Their boundaries are clearly defined and constrained by the presence of houses and walls. The road surfaces do not tend to fade into their surroundings at the edges, as they are not adjacent to open bare soil spaces. In addition, there are relatively few trees, shadows, and objects on the roads.** The results were acceptable for area 1, but demonstrate the difficulty of road extraction for areas 2 to 5.

5.1. Comparison of the Results for Paved and Unpaved Roads

Table 4 compares the results for areas 1 and 2 considering the paved and unpaved roads separately. The method performed better on the paved roads in terms of misclassification and quality, due to the lower commission rate. This was an expected result since the algorithm was originally developed for paved roads. For the unpaved roads, a considerably lower false negative rate led to higher quality. This was a surprising result, indicating the equal suitability of this algorithm for unpaved road extraction. For both paved and unpaved roads in area 1, the quality was higher than in Table 4. For area 2, the paved roads obtained slightly higher misclassification and commission rates than the unpaved roads. The omission rate was considerably lower. This nearly doubles the quality. The results for the paved roads in area 2 were also better than when the paved and unpaved roads were both taken into consideration as in Table 4. The method obtained less false positives on the paved roads of area 1 than its unpaved roads, but more false negatives.

5.2. Effects of Including Sidewalks and Verges

The effects of including only the central or most clearly delineated parts of roads in the road definition, excluding sidewalks and verges were investigated. The extent of sidewalks and verges was determined via visual inspection. These included areas on the edges of roads that were not covered by vegetation or buildings, and therefore traversable on foot, but not apparently navigable by cars, due to e.g. direct adjacency to houses or abrupt termination.

The effects are quantified for area 2 in Table 5. This relates to extensional uncertainty. These quality measures were calculated by excluding sidewalks, and may be compared to those in Table 3, which were calculated by including sidewalks. The results excluding sidewalks are shown in Figure 11, and can be compared to the results including sidewalks, shown in Figure 9(b).

While the commission rate was significantly higher when the sidewalks and verges were excluded, the false negative rate reduced. However, the quality decreased, while the overall misclassification rate did not change.

5.3. Uncertainty Maps

Uncertainty maps were generated using the necessity scores calculated by the algorithm. These maps show the uncertainty associated with the extracted road segments, and demonstrate which segments are more likely to truly be roads. Identifying uncertain areas allows the investigation of possible reasons for the road extraction uncertainty. Uncertainty maps for areas 1 and 2 are given in Figure 12. These display the largest merged regions of the BPT that were classified as road, with their associated uncertainty. Darker areas represent segments with higher certainty. For area 1, the formal road in the northern part of the image experienced the lowest uncertainty at 0.15. Short road segments, such as in the north-eastern corner of the image, and bare soil yard areas experienced the highest uncertainty with values between 0.8 and 0.9. In area 2, the minimum uncertainty of 0.31 was attained for segments associated with the broad paved road. Higher uncertainty was experienced by narrower road segments. The narrow informal road segment in the south-western part of the image attained the highest uncertainty of 0.87.

6. Discussion

This section discusses the obtained results, with particular attention given to sources of uncertainty.

6.1. Sources of Uncertainty

The misclassifications led to uncertainty in the extraction results. The method used is naturally good at identifying and modelling uncertainties. Both existential and extensional uncertainty were experienced. In this method, as well as any other similar approach based on region merging, the misclassification of regions and hence uncertainty could be due to errors occurring at the pixel level, during segmentation or region merging. A schematic representation of the possible sources of existential and extensional uncertainty is given in Figure 13.

At the pixel level, uncertainty was introduced through mixed pixels and corrupted radiance. Mixed pixels were caused by land cover heterogeneity or irregular road boundaries at a level too small to be captured by the pixels. Atmospheric disturbance could cause corrupted radiance. During segmentation, pixels of heterogeneous land cover type were in some cases erroneously grouped together. The inclusion of mixed pixels in segments could also lead to confusion. This occurred especially in the case of narrow roads bordered by vegetation (see areas 2 and 3). Road pixels grouped with shadow or building pixels would also have been misdetected. On the other hand, non-road pixels grouped with road pixels were erroneously detected as road. Errors in the segmentation influenced the merging order during the construction of the BPT, leading to segments consisting of non-road pixels being merged with road segments and eventually being classified as road.

Figure 14 illustrates ways in which existential and extensional uncertainty were caused by the physical characteristics of informal roads. Areas A, B and C contain sources of existential uncertainty. Area A displays a narrow dusty stretch that connects to a road in the north but fades into the adjacent dusty yard. At this point also, a broader road begins. It is possible that this road connects to the narrow stretch and hence to the road in the north of the image. However, if this stretch were a commonly-used road, one would expect it to be wider and to connect clearly to the broader road. Doubt therefore exists as to whether or not it is a road. Areas B and C exhibit short, navigable stretches that appear to have been smoothed, with faintly distinguishable boundaries. In C, the stretch connects to a road at the eastern end, but ends abruptly in vegetation at the western end, implying that it not used as a through road. The stretch in B similarly does not connect to the rest of the network although it is clearly navigable.

Areas D, E and F demonstrate extensional uncertainty. In D, the east-west road appears wide at the edges of the area, but narrows drastically at the centre and is bordered by vegetation. In E, the north-south road is delineated at its eastern border, but fades into the yards to the west. It is not clear where the road ends and where the yards begin. The north-south road in F fades into the dusty yard to the west and into vegetation towards the east. The tree and shadow occluding the east-west road in F also cause extensional uncertainty. While it is clear that the road continues in the shade and under the tree, the occluded road boundary cannot be detected.

6.2. Connectivity of Extracted Roads in the Road Network

For areas 1 and 2, both paved and unpaved roads were considered. The unpaved road networks connected to the paved road networks in both the image and reference data. Figure 15 illustrates how this topology was reflected by the extracted roads. In area 1, all connections were captured. In area 2, the undetected connection 1 and the partial connections 2 and 4 corresponded to informal roads that were not fully captured. Connection 3 was correctly captured and corresponded to a more fully extracted informal road. Connection 5 was not fully captured. The formal and informal roads, despite being detected, were separated by a small gap. The extracted networks were in general topologically sound. They maintained connectivity where roads from both networks were detected, with this exception.

6.3. Effects of the Road Definition on Uncertainty and Misclassification

The effects of the definition of a road on misclassification and extensional uncertainty was investigated for area 2. Although the centres of the unpaved roads are clearly visible for area 2, it is unclear how far the boundaries of the roads truly extend. This is clearer when the entire width of the navigable surface is considered road, as in Figure 9. Considering only the central part of the road did not **substantially** influence the misclassification rate. However, the false positive rate was higher by 76% than in the case where sidewalks and verges were included in the definition. This is due to the fact that the method identified the side areas as road. When the adjacent areas were included, trees and other objects on these areas led to a 6% increase in false negatives. The way in which we define roads, therefore, fundamentally involves uncertainty.

6.4. Directions for Future Research

This method achieved the most accurate results for **broad roads with clear boundaries that were not occluded by objects or shadows**. However, in order to be captured accurately, roads must be distinguishable from their backgrounds. The only restriction on the satellite images is that they should be cloud-free. The images used herein are from a dry winter. Images showing healthier vegetation as well as grass growing in many of the open dusty areas, will reduce uncertainty of roads in vegetated areas, due to the effective removal of vegetation by NDVI.

To extend this technique to suit less favourable conditions of informal roads, knowledge-based rules specifying informal road characteristics could be implemented, by incorporating expert knowledge in the BPT via fuzzy sets (M. Li et al., 2016). Ways of dealing with occlusions could also be investigated, for instance incorporating SAR images to penetrate trees. The utilisation of height data from LiDAR datasets could allow for the complete removal of all buildings and other tall objects.

Various ways of obtaining reference data could be explored. Crowd sourced mapping has become a valuable source of information in recent years. However, inhabitants of informal settlements in South Africa **often do not own** smart phones or have access to data and WiFi that will allow them to contribute to crowd sourced mapping, while inhabitants of other areas do not necessarily enter informal settlements, due to safety concerns. Finding ways to promote crowd sourced mapping could lead to the availability of more reliable reference data in the future.

7. Conclusion

This paper contributes to the identification of the sources of uncertainties associated with informal road extraction and to the modelling of uncertainty when identifying unpaved, informal roads from remote sensing images. A flexible state of the art road detection method was parametrised, and applied in a South African context. Spatial shape information of image objects, as well as the relationships between image objects was exploited. This is the first use of an automatic road extraction method for informal roads. This method naturally provided for the identification and modelling of uncertainties. Sources of uncertainty and reasons for possible misclassification were explored. The best classification was obtained for broad, unpaved roads in an urban setting, while the least accurate results were obtained for irregular roads where the surrounding areas were spectrally similar to the roads, and vegetation was prevalent.

We conclude that the method detects roads in a variety of settings and is most suitable for broad, unpaved, non-occluded roads in an suburban context, with few adjacent dusty areas.

Sources of uncertainty and inaccuracy were identified, including unclear and irregular road boundaries, surface type heterogeneity, stationary objects on the roads, and the occlusion of roads by trees and tree shadows. The sources of uncertainty were related to the possible presence or absence of roads, or to irregularities in road boundaries.

Adapting the road definition was found to reduce certain types of errors, while increasing others to a greater or lesser extent. Defining roads to include sidewalks and bare soil verges **substantially** decreased the false positive rate. We conclude that the way in which we conceptualise roads introduces uncertainty. Certain types of errors may be reduced by adapting the definition of a road to suit local circumstances. Future work could address these sources of uncertainty, improve extraction accuracy and explore conceptualisations of informal roads.

We achieved the objectives of exploring the definition of an informal road and identifying sources of uncertainty associated with extracting informal roads.

Declaration of Interest

The authors declare no conflict of interest.

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Parameter	Value for All Areas
Compactness parameter (lower bound)	0
Compactness parameter (upper bound)	0.6
Elongation parameter (lower bound)	0
Elongation parameter (upper bound)	0.4
Number of bins	60
Morphological path length	400

Table 1. Internal parameters that were the same for all areas.

Area	Window Size	Building Threshold
1	19	0.5
2	55	0.5
3	80	0.5
4	75	0.3
5	50	0.4

Table 2. Window sizes and building thresholds used for each area.

Quality Measure	Area 1	Area 2	Area 3	Area 4	Area 5
Misclassification	18%	22%	24%	16%	20%
Quality	53%	33%	36%	30%	25%
Commission	52%	83%	105%	63%	129%
Omission	20%	39%	26%	50%	43%

Table 3. Assessment of the quality of the results for areas 1-5.

Quality Measure	Area 1: Paved Roads	Area 1: Unpaved Roads	Area 2: Paved Roads	Area 2: Unpaved Roads
Misclassification	16%	21%	18%	16%
Quality	53%	49%	40%	27%
Commission	45%	75%	85%	81%
Omission	22%	15%	23%	52%

Table 4. Quality assessment comparing paved and unpaved roads for areas 1 and 2.

Quality Measure	Area 2: Excluding Sidewalks
Misclassification	23%
Quality	26%
Commission	159%
Omission	33%

Table 5. Quality assessment quantifying the effect of excluding sidewalks and verges.

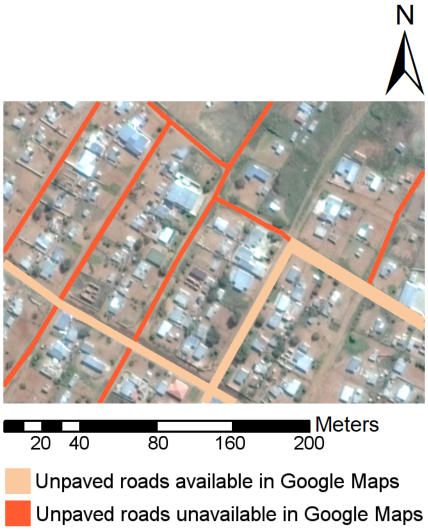

N
Meters
20
40
80
160
200
Unpaved roads available in Google Maps
Unpaved roads unavailable in Google Maps

Figure 1.

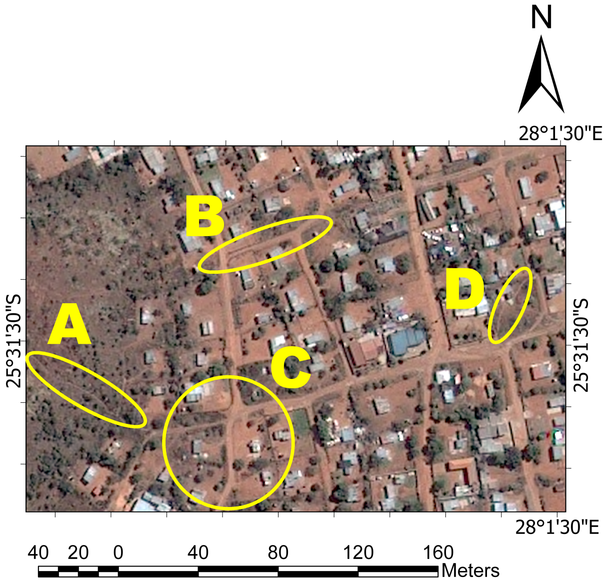
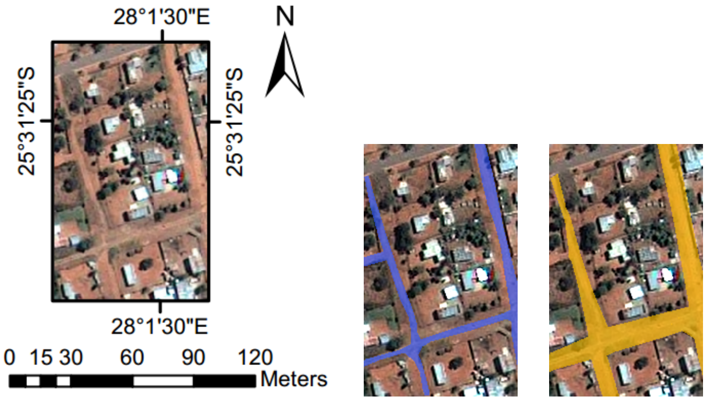


Figure 2.

Image captions:

(1) Formal and informal roads in Makanyaneng, demonstrating informal roads not available in Google Maps. (Imagery ©2017 DigitalGlobe, Map data ©2017 AfriGIS (Pty) Ltd.)
(2) Examples of informal roads in an unplanned network. Areas A and D contain footpaths (not considered roads herein). Area B shows a road with a sudden width change. Area C contains a road with an irregular shape, as well as a junction between roads that are not aligned with each other.
(3) The influence of the conceptualisation of roads on the road extraction process. a) An area containing informal roads. Coordinates: 28°1'28"E 25°31'25"S. b) & c) Reference data according to two different conceptualisations of roads.
(4) The areas under study. a) Area 1 exhibits formal paved roads and broad, straight unpaved roads. b) Area 2 shows paved roads and irregular unpaved informal roads. c) Area 3 illustrates regular structured roads with heterogeneous surfaces. d) Area 4 shows unpaved roads set among spectrally similar unpaved yards and open areas. e) Area 5 exhibits narrow unpaved roads in a semi-rural setting.
(5) Flowchart of the methodology used in the application.
(6) Effects of different window sizes used in the HOG construction on classification accuracy, for area 2. a) Error metrics on the same graph. b) Normalised error metrics.
(7) Effects of different window sizes used in the HOG construction on classification accuracy, for area 3. a) Comparison of error metrics. b) Normalised error metrics.
(8) Effects of different building extraction thresholds on the normalised assessment metrics for areas 2 and 3. Both show a viable threshold value at 0.5. a) Results for area 2. b) Results for area 3.
(9) Road extraction for the different areas: a) Area 1, b) Area 2, c) Area 3, d) Area 4, and e) Area 5.
(10) The portions of the areas that were used to compare the results for paved and



a) b) c)

Figure 3.

unpaved roads: a) Paved and unpaved roads of area 1, b) Unpaved roads of area 2, c) Paved roads of area 2.

(11) Results when roads are defined to exclude sidewalks, verges and adjacent areas, for area 2.

(12) Uncertainty maps of road areas in areas 1 (a) and 2 (b). Darker areas were classified as road with a higher certainty.

(13) A diagram illustrating the possible sources of uncertainty for road extraction, at pixel, segmentation and region merging level.

(14) Sources of uncertainty in an informal road network. Areas A, B and C indicate sources of existential uncertainty: it is not clear whether or not roads actually exist in these areas. Areas D, E and F exhibit extensional uncertainty: roads are present in these areas, but the extents of these roads are not clear.

(15) Connections between the extracted unpaved and paved road networks. a) For area 1, all connections were captured, b) For area 2, only connection 3 was fully captured.

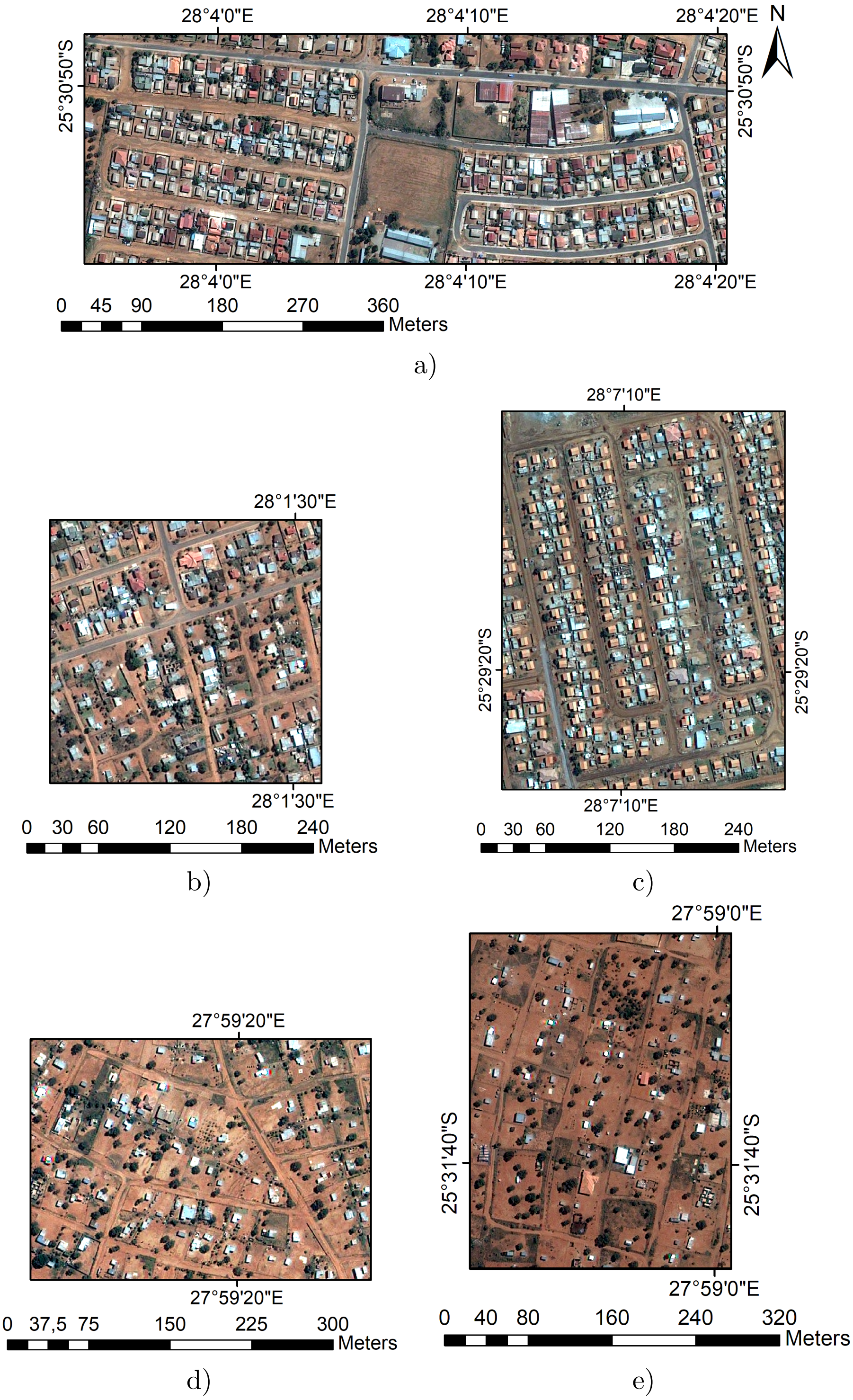

28°4'0"E
28°4'10"E
28°4'20"E
N
25°30'50"S
25°30'50"S
28°4'0"E
28°4'10"E
28°4'20"E
0 45 90 180 270 360
Meters
a)
28°1'30"E
28°1'30"E
0 30 60 120 180 240
Meters
b)
28°7'10"E
25°29'20"S
25°29'20"S
28°7'10"E
0 30 60 120 180 240
Meters
c)
27°59'20"E
27°59'20"E
0 37,5 75 150 225 300
Meters
d)
27°59'0"E
25°31'40"S
25°31'40"S
27°59'0"E
0 40 80 160 240 320
Meters
e)

Figure 4.

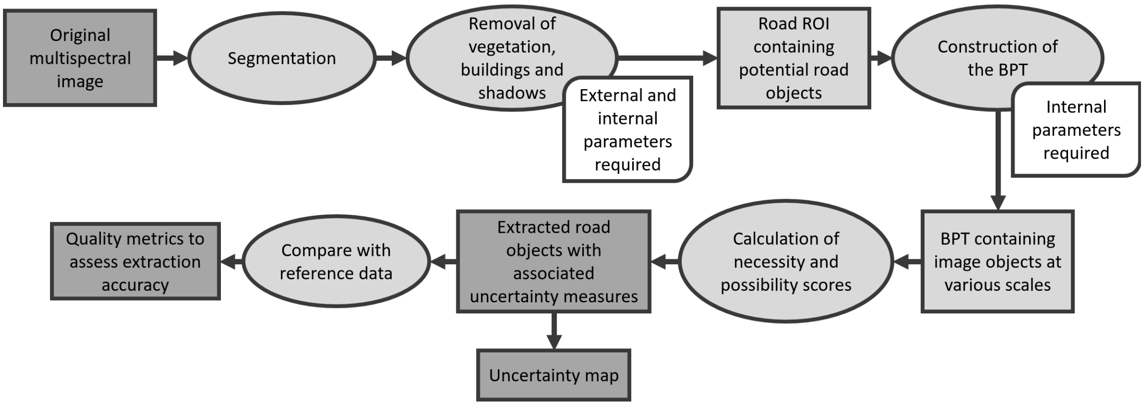


Figure 5.

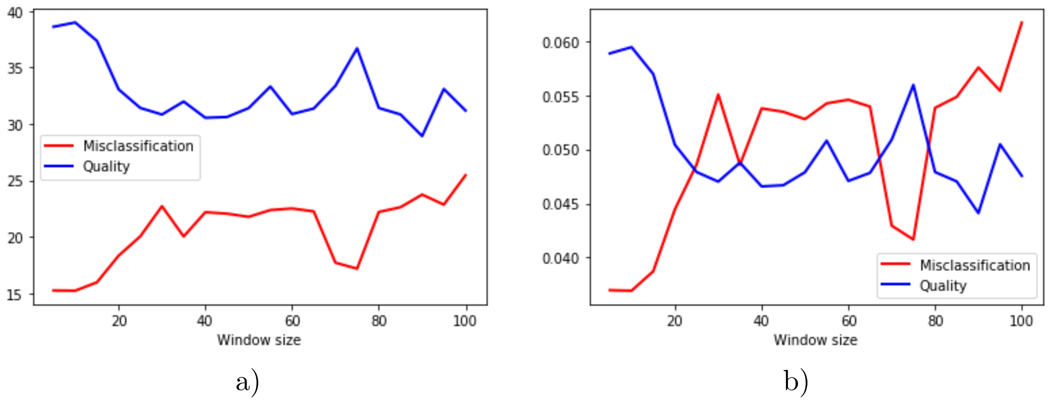


Figure 6.

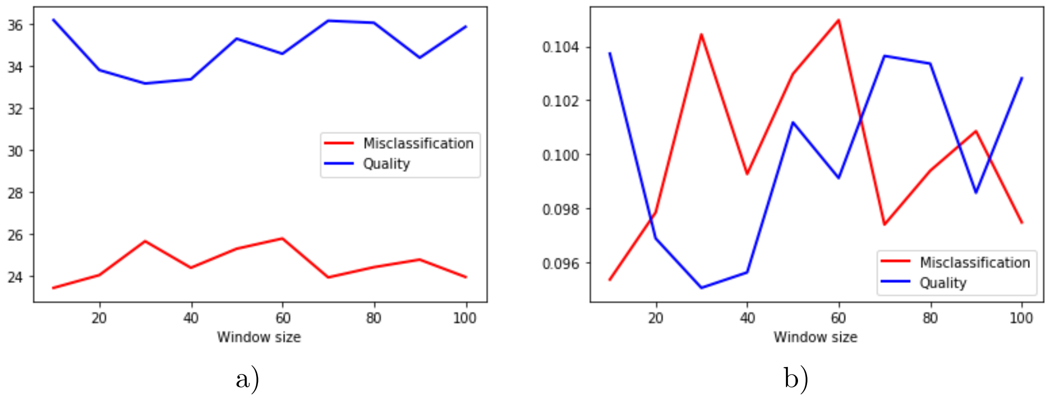
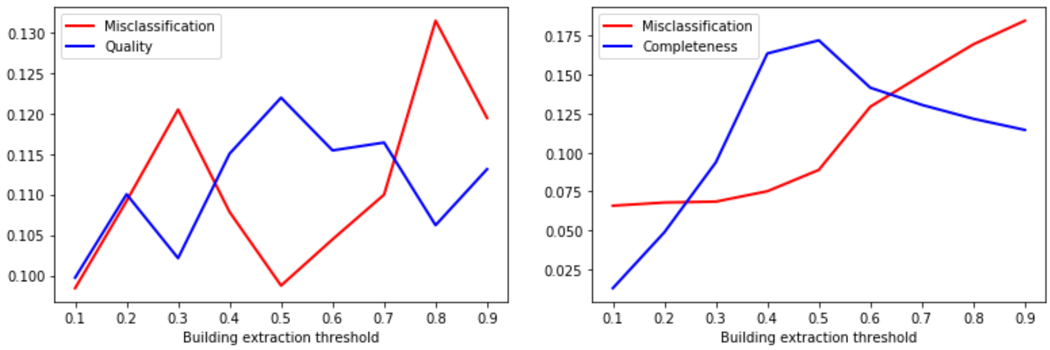


Figure 7.


Misclassification
Quality
0.130
0.125
0.120
0.115
0.110
0.105
0.100
0.1 0.2 0.3 0.4 0.5 0.6 0.7 0.8 0.9
Building extraction threshold
Misclassification
Completeness
0.175
0.150
0.125
0.100
0.075
0.050
0.025
0.1 0.2 0.3 0.4 0.5 0.6 0.7 0.8 0.9
Building extraction threshold

a) b)

Figure 8.

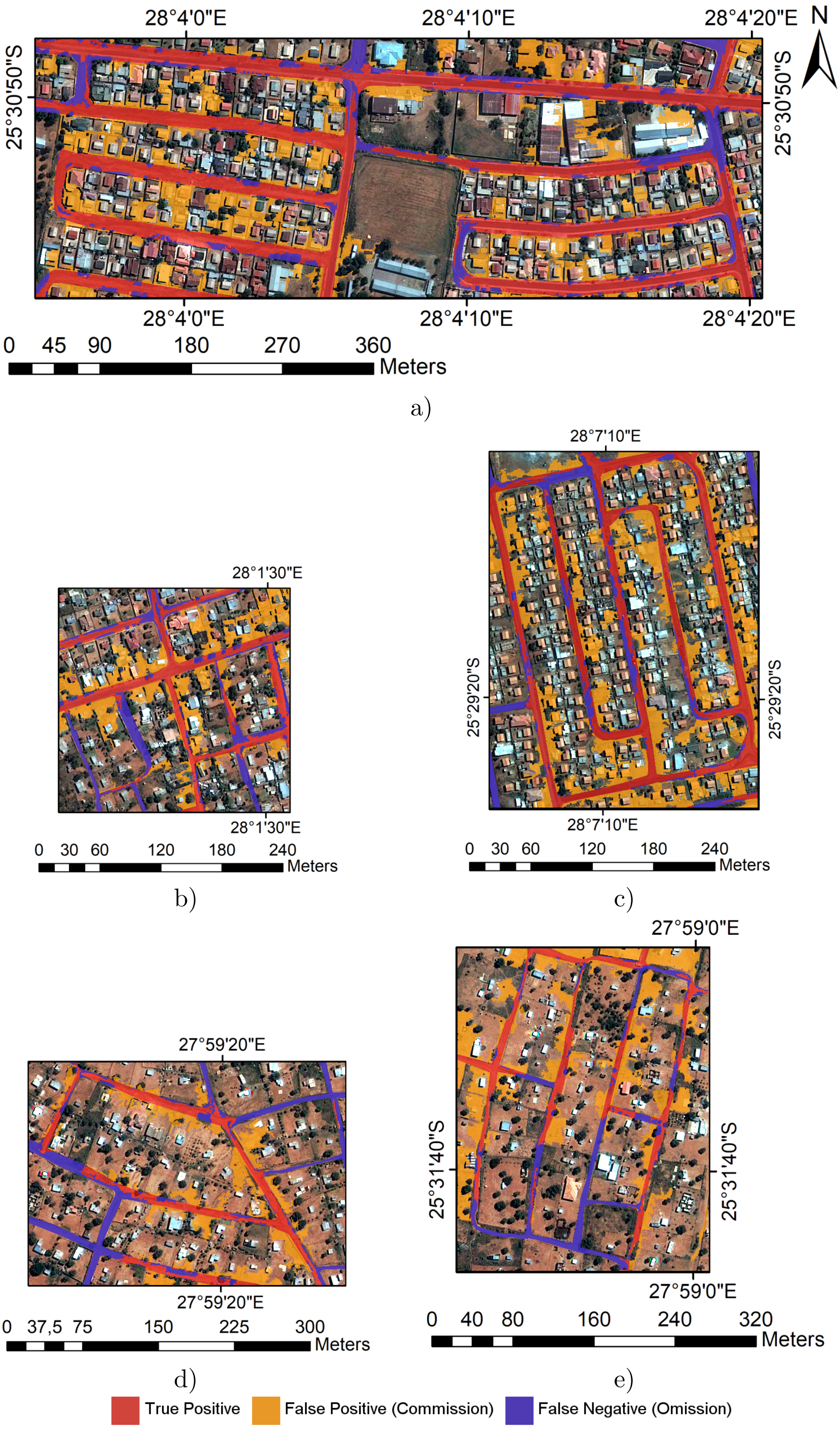

28°4'0"E
28°4'10"E
28°4'20"E
N
25°30'50"S
0 45 90 180 270 360
Meters
a)
28°7'10"E
28°1'30"E
25°29'20"S
0 30 60 120 180 240
Meters
b)
c)
27°59'0"E
27°59'20"E
25°31'40"S
0 37,5 75 150 225 300
Meters
0 40 80 160 240 320
Meters
d)
e)
True Positive
False Positive (Commission)
False Negative (Omission)

Figure 9.

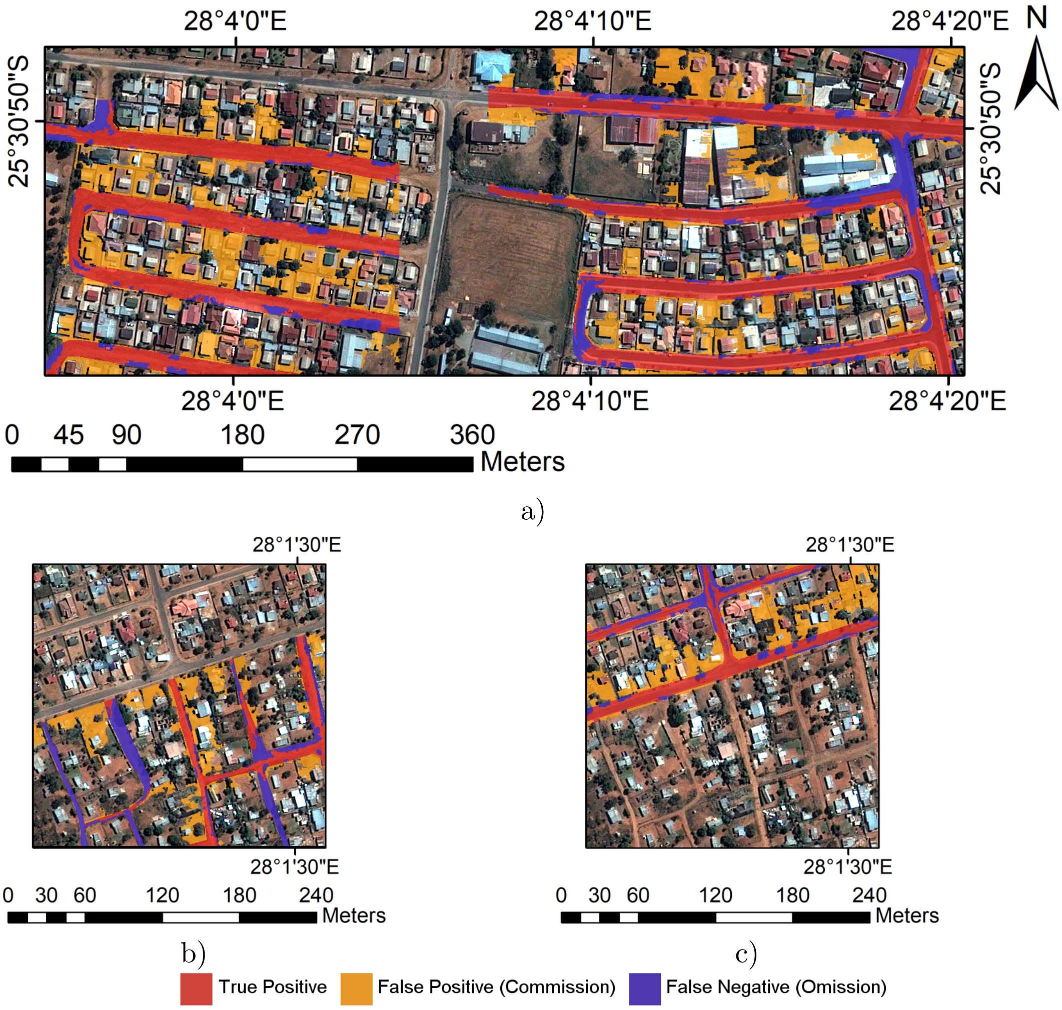


Figure 10.

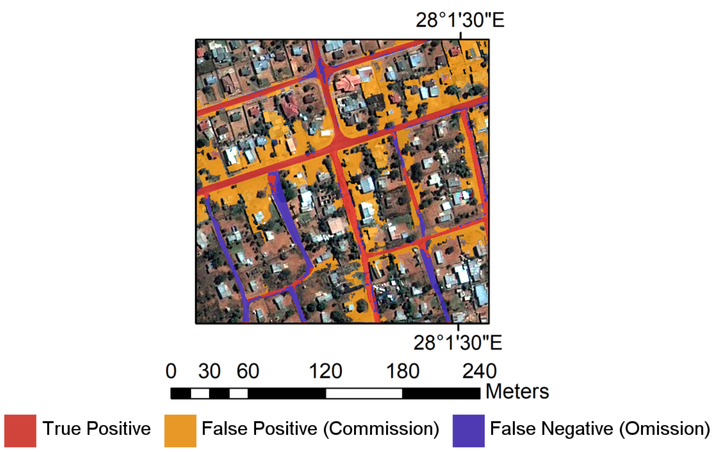
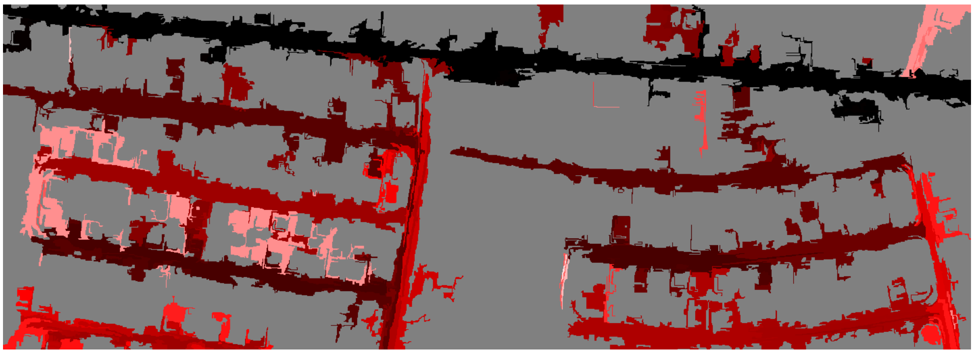
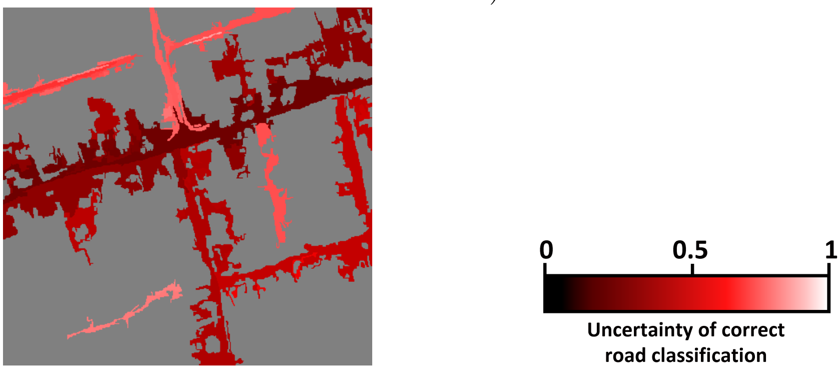


Figure 11.



a)



b)

Figure 12.

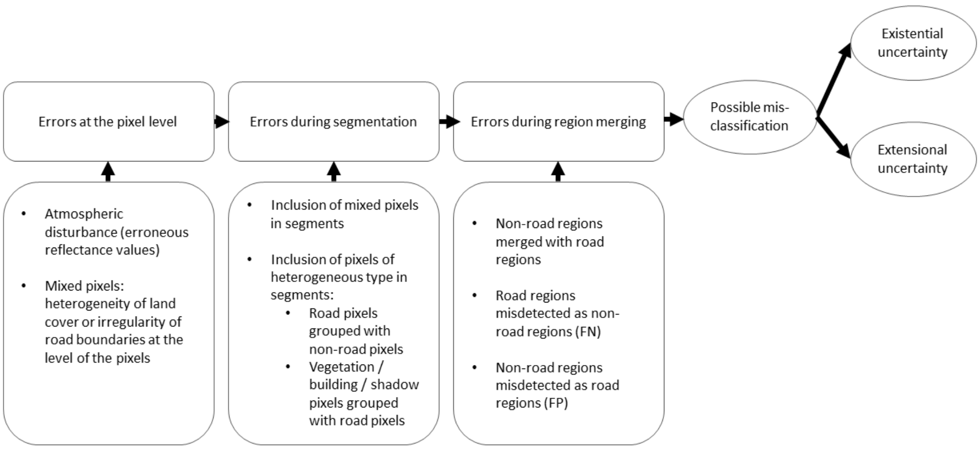
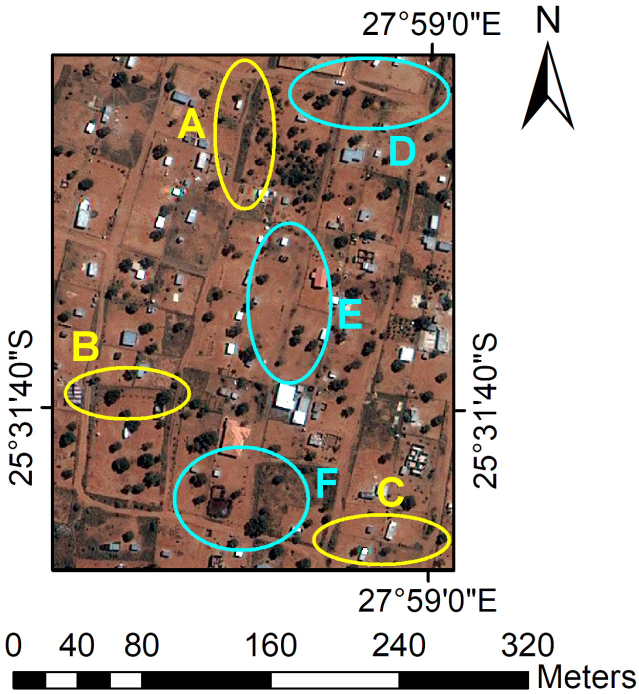


Figure 13.


27°59'0"E
N
A
D
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25°31'40"S
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F
C
27°59'0"E
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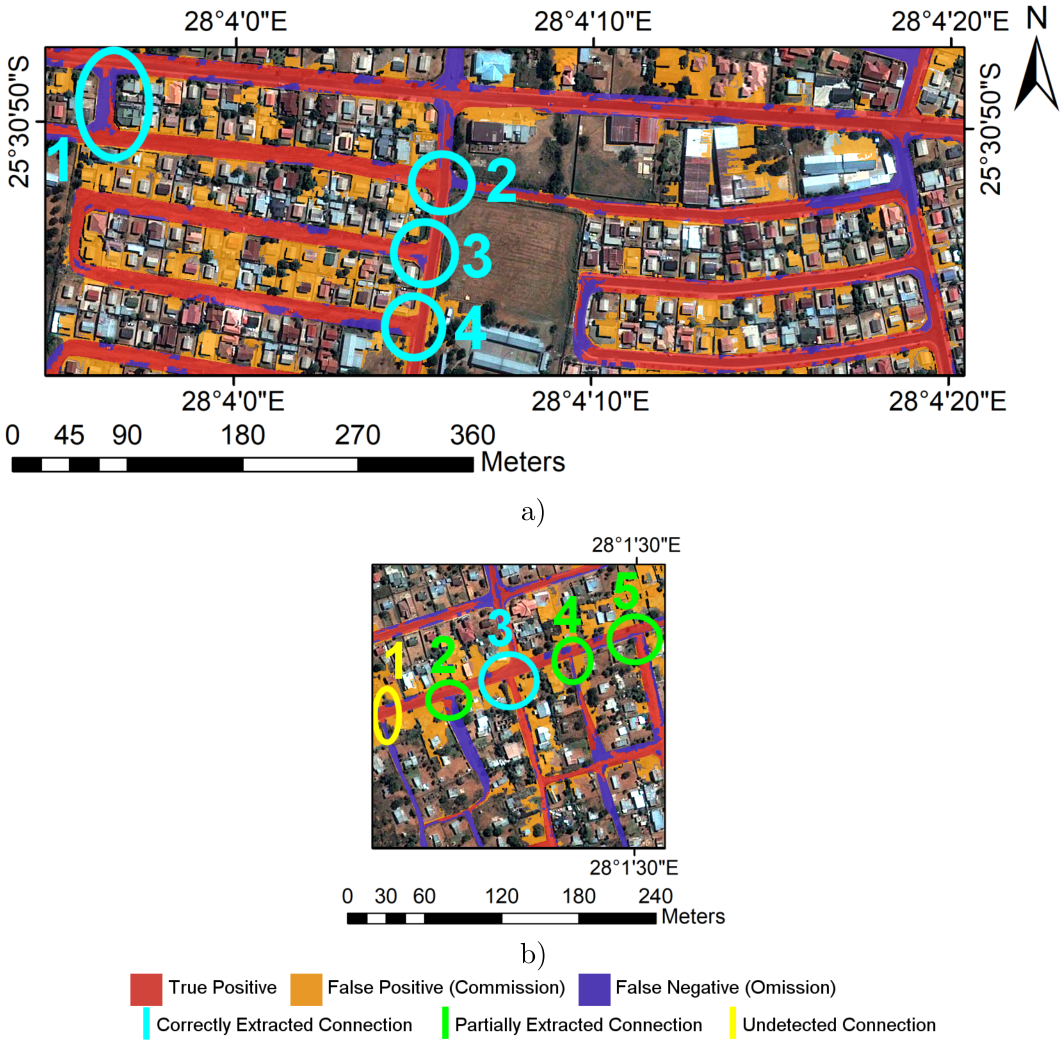
40
80
160
240
320
Meters

Figure 14.


28°4'0"E
28°4'10"E
28°4'20"E
N
25°30'50"S
25°30'50"S
1
2
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4
28°4'0"E
28°4'10"E
28°4'20"E
0 45 90 180 270 360
Meters
a)
28°1'30"E
1
2
3
4
5
28°1'30"E
0 30 60 120 180 240
Meters
b)
True Positive
False Positive (Commission)
False Negative (Omission)
Correctly Extracted Connection
Partially Extracted Connection
Undetected Connection

Figure 15.